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

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Abstract

Do safety nets affect investment? If so, how? Combining a natural experiment that gave guaranteed income to landowning farmers in India with transaction-level bank account data and loan-level credit bureau data, we evaluate the impact of unconditional and perpetual guaranteed income on small farmer entrepreneurs. We find that guaranteed income leads to an increase in income from farming. A promise of $1 guaranteed income each year generates an additional $1.7 of income from farming. We then study the mechanisms behind this effect. We find that instead of *reducing* ambition and initiative, guaranteed income allows recipients to work *differently*. Specifically, guaranteed income provides protection against downside risk, which increases demand for credit and allows farmers to invest in a more capital-intensive mode of production. We estimate that a $1 guaranteed income each year increases credit demand by $15.7. Our results show that uninsured risk inherent in an entrepreneurial venture may be a binding demand-side constraint inhibiting growth. The availability of basic income support increases entrepreneurs' financial resilience and significantly improves their production activity.

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1 Introduction

Do safety nets encourage investment? Specifically, how is investment affected by a guaranteed income program? Over the last decade, guaranteed income programs that give unconditional and perpetual cash transfers, such as Universal Basic Income (UBI) or Basic Income (BI) proposals, have garnered considerable attention, with several small pilots launched across the globe and support from a wide range of proponents.[1] However, such proposals have also attracted criticism and an extensive debate among both academics and policymakers. 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 indicate that entrepreneur's 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.[2] On the other hand, most classical macroeconomic models predict that the income effect of such transfers disincentivize ambition, initiative, and hard labor. As a result, detractors argue that guaranteed income will discourage investment or productive activity.[3] It has been challenging to resolve the ambiguity over which force is pivotal due to the lack of direct empirical evidence examining the relationship between guaranteed income and investment.

Guaranteed income programs – such as UBI – is an identical, unconditional, recurring and guaranteed cash transfers sized to meet basic needs given to everyone within a well-defined community. While the topic of conditional or one-time cash transfers has been the subject of substantial prior research (Bastagli et al. (2016)), the extant literature does not provide direct empirical evidence on the effect of unconditional and perpetual cash transfers (Banerjee, Niehaus and Suri (2019), Hoynes and Rothstein (2019)).[4] 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. One cannot simply extrapolate from studies of conventional cash transfers as the impacts of perpetual and unconditional cash transfers could be different in at least three ways. First, perpetual cash transfers provide better protection than one-time cash transfers against future risk (Bianchi and Bobba (2013)). Second, households may respond differently to such transfers due to behavioral frictions such as present bias, lack of self-control, etc (Ganong and Noel (2019), Gerard and Naritomi (2021)). Third, unconditionality uncouples income, wealth, and effort from eligibility, thus eliminating incentives to manipulate these variables to avoid failing the means test.

We make progress on the debate by directly estimating the impact of unconditional and

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

[2] The core of the argument in the support for guaranteed income is best captured in Mark Zuckerberg's Harvard commencement speech: *"But I know lots of people who haven't pursued dreams because they didn't have a cushion to fall back on if they failed."*

[3] Former Speaker of the US House of Representatives, Paul Ryan explains: *"But we don't want to turn the safety net into a hammock that lulls able-bodied people to lives of dependency and complacency, that drains them of their will and their incentive to make the most of their lives."*

[4] A notable exception is Banerjee et al. (2020*b*). They conduct a randomized controlled trial across 15,000 households in Kenya and analyze the effect of UBI-like transfers on hunger, sickness, and depression during COVID-19.

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

Our results have two main implications. First, we provide evidence that safety nets – like guaranteed income programs – can increase production by catalyzing a shift to a high capital-intensive mode of production rather than turning into a *hammock* that drives 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 increase financial resilience and dilute demand-side barriers originating from uninsured risk. 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 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 natural experiment generates temporal and cross-sectional variation in the receipt of guaranteed income based on a fixed characteristic – landownership. Launched in March of 2019, the Indian BI program – Pradhan Mantri Kisan Samman Nidhi (PMKSN) or Prime Minister's Farmer's Tribute Fund – gave a guaranteed, unconditional, and perpetual cash transfer of ₹6,000 ($1,735 in PPP terms) per year to all landowning farmers in India.[5] The program covered 67% of all farmers and 27% of the total Indian population. The cash transfers accounted for 7% of farmers' average annual income. The present discounted value of these transfers is significant and is 28 times the average stock of savings held by landowning farmers. Three characteristics of our natural experiment allow for credible identification. First, landownership status was defined as of December 2018, making it an immutable characteristic and ensuring the stability of our treatment and control units over time. Second, the transfers are orthogonal to the income, wealth, or effort of landowning farmers. Such a variation is necessary to isolate the effects of these transfers, holding fixed other determinants of entrepreneurial activity such as preferences and productivity. Third, the announcement of the policy was completely unexpected, precluding the possibility of anticipatory effects.

We employ a differences-in-differences (DID) framework by combining the nationwide guaranteed income program (PMKSN) with granular transaction-level data from a private bank and loan-level data from the credit bureau. Specifically, we compare the outcomes of the treatment group (landowning farmers) and the control group (non-landowning or tenant farmers) before and after the policy. Our unique data allows the joint measurement of the key outcomes – income

[5] We use the terms guaranteed income and basic income (BI) interchangeably.

and credit. We build farmer-by-month measures of income from farming, PMKSN cash transfers, term loans, credit card usage, savings, and spending. We supplement the bank data with the survey data allowing us to measure investment. Our identification strategy includes farmer fixed effects to control for all time-invariant heterogeneity due to differences in preferences and productivity and ZIP X month fixed effects to control for all time-varying geographic variation. We interpret the estimate of Treatment × Post as a within-ZIP estimator comparing landowning and non-landowning farmers within the same ZIP code while controlling for unobserved differences in individual-level preferences or productivity.

The paper's first result identifies the effect of guaranteed income on farmers' income from agricultural work, excluding transfers. Our DID estimate indicates that the treatment group's work income increased by 10% relative to the control group. Specifically, we estimate a promise of $1 guaranteed income each year generates an additional $1.7 of income from farming over the twelve months following the announcement. Our estimate of the guaranteed income multiplier is 2.7, with $1 coming from direct transfers and $1.7 from increased agricultural revenue as a result of the transfers.

We supplement our baseline analysis with a dynamic assessment of the treatment effect. Three takeaways emerge. First, the policy led to an increase in the income for the treatment group, while leaving the control group largely unaffected. Second, the significant difference in income is realized during the second harvest season after the policy. Third, the first harvest season after the policy does not exhibit differences in income as the announcement occurred after most production decisions had been made. This suggests that the change in the agricultural production process primarily drives the increased income for the treatment group. Furthermore, we establish that the increased income for farmers is related to an increased efficiency in their entrepreneurial activity, i.e., agricultural productivity. Combining the ZIP code-level administrative data on the number of PMKSN beneficiaries with the remote sensing data on agricultural yields at the ZIP code-level, we document that a 10% increase in the number of beneficiaries is associated with an 8.1% rise in agricultural yields.

The causal interpretation of the treatment effect relies on two identifying assumptions. First, the treatment group received cash transfers under PMKSN. We verify the first-stage assumption and find that 96.03% of farmers in the treatment group received PMKSN transfers. Second, in the absence of PMKSN, outcomes for farmers in the treatment and control groups would have evolved according to parallel trends. We provide evidence for this assumption by analyzing outcomes for the treatment and control groups prior to the policy and find no indication of pre-existing trends. Furthermore, we conduct a falsification test by exploiting the case of the state of West Bengal, which did not comply with the policy. We document that the average treatment effect for landowning farmers in West Bengal is statistically insignificant and economically negligible. The falsification test provides direct evidence for the assumption that the treatment and control groups would have evolved according to the parallel trends in the absence of the policy.

The paper's second result identifies factors that determine the increase in agricultural income and production. Specifically, we examine the policy's effect on investment in agriculture and allied activities. Combining the natural experiment with detailed survey data on household assets, we find treated households increase their ownership of productive assets such as tractors, livestock, and two-wheelers. Additionally, in regions with a greater share of policy beneficiaries, we find an increased usage of fertilizers and irrigation facilities, along with a greater entry of new agri-based micro-enterprises. On a conservative note, we estimate that lumpy investment increases by 10%. This increase is equivalent to 45% of the present discounted value of guaranteed income, and is large ($\approx$ 7.75X) relative to the size of the annual cash transfer of ₹6,000.

The third result of the paper identifies the source of funding for the increased investment. We document that the increased investment is financed using debt. We combine the natural experiment with the detailed loan-level data on farmers from the Indian credit bureau matched with our bank data. On the extensive margin, we find that the probability of a new loan to the treatment group increases by 10.91%. Similarly, on the intensive margin, we document an increase of 12.9% in the number of loans and a 16.8% increase in loan amount to the treated farmers. We find that almost all new credit is used to finance the productive capacity of farmers. We estimate that additional \$1 in guaranteed income increases term loans by \$11.2 and credit card utilization by \$4.5. This implies a total increase in credit of \$15.7, which is equivalent to 91% of the perpetuity value of guaranteed income.

We further establish the critical role of credit markets in generating the positive income effect of the recipients. First, 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 following a permanent income shock (Friedman (1957), Carroll (2001)). We find that farmers facing high credit market frictions either due to prior default or low credit scores had negligible effects on their income and credit. Second, using the Sobel-Goodman mediation test we document that 94% of the total effect of the policy on income is mediated through credit.

The fourth result 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 increasing their financial resilience to adverse shocks.

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). We focus on KCC, given that the credit limit and the interest rates on the product are unrelated to farmers' creditworthiness. Additionally, we document economically and statistically insignificant changes in KCC credit limit and interest rates for the treatment group after the policy. Hence, any credit supply-side changes due to the increased creditworthiness – because of an income shock – are not reflected in this product. 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 KCCs increase by six percentage points for the treatment group after the policy. The treatment effect is economically significant relative to the average utilization rate of 21.3% and represents a $4.5 increase in credit utilization in response to $1 guaranteed income each year. Moreover, the evolution of the treatment effect in the post-policy period indicates that the utilization rate increases slowly after the policy announcement, peaks during the Kharif cultivation season, and declines during the harvest season. The results indicate that the demand for credit increases among the treatment group.

We further supplement our analysis by examining the policy's effect on suggestive proxies for credit demand and supply for the universe of loan data for our sample farmers. We find that loan applications – measured by the number of inquiries – rise by 36%, whereas the acceptance rate is unaffected. This result suggests that the supply side is mainly unresponsive to these transfers. We argue that the lack of supply-side response is due to institutional frictions. Loan officers typically use three data inputs to make decisions on agricultural loans — average expected agricultural yields in the region, collateral, and credit scores. All these inputs are based on historical data, and changes in farmers' income are not reflected in either of the metrics, at least not in the short run. Furthermore, the absence of supply-side reaction supports the notion that cash-flow based lending is less prevalent for small businesses due to practical and feasibility concerns arising from low contractility, small cash flow sizes, and ex-post reorganization being expensive for lenders (Lian and Ma (2021)).

Next, we investigate the factors that drive the credit demand effect. Using voter data as a proxy for trust in program perpetuity, we find the policy's effect is significantly higher in regions where beneficiaries have greater expectations in the ability of these transfers to protect against future risk. This result complements the conjecture that perpetual cash transfers can stimulate demand and generate greater effects by providing protection against future risks (Bianchi and Bobba (2013), Banerjee, Niehaus and Suri (2019)). Additionally, we document a greater effect of the policy on credit markets in areas with high agricultural risk and incomplete insurance markets. This result indicates that greater income risk and incompletely insured income volatility are partly a cause of low take-up of loans, and the availability of basic income support can have substantial positive effects on loan demand.

A key part of our mechanism is that guaranteed income reduces the covariance between expected marginal returns on investment and marginal utility of consumption by increasing resilience to adverse shocks. We provide a direct test for this hypothesis by examining the policy's effect on consumption, default, and savings across different states of the world. We document that the direct cash transfers under the policy mitigates the negative effects of adverse shocks on consumption fluctuations and loan-repayment ability. Thereby reducing the magnitude of the covariance term. Furthermore, we complement the results examining the effect of guaranteed income on safety nets by documenting a decline in perceptions of current and future financial constraints among treated households and a reduction in extreme distress of farmers – measured using farmer suicides.

We conduct a battery of robustness tests to address potential issues with our analysis. First, we implement a border regression discontinuity design comparing contiguous district-pairs that straddle the state boundaries of West Bengal and the five neighboring states and find similar results. This test exploits the non-compliance of the policy by the state of West Bengal to address concerns about the comparability of the treatment and control groups. We further supplement the analysis using a matched sample of treatment and control groups and find similar results. Second, we present a formal test for the effect of spillovers á la Berg, Reisinger and Streitz (2021) to address concerns about the violation of Stable Unit Treatment Value Assumption (SUTVA). We find that spillovers are likely to be of little concern as the input and output markets are heavily regulated.

We discuss two alternative explanations. First, the policy can directly increase investment by increasing cash-in-hand as in Gertler, Martinez and Rubio-Codina (2012). BI cash transfers are basic, by definition, and hence small relative to the annual average income of farmers. Therefore, ability of such transfers in directly relaxing liquidity constraints for the purchase of large fixed assets is severely limited.[6] 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. (2020*a*)). While we view these channels as complementary and do not deny the presence of these effects, our documented mechanism operates through a shift towards capital intensive mode of production.

1.1 Related Literature

The contribution of this paper is two-fold. First, this paper evaluates the impact of the world's largest welfare program. We are the first to evaluate the effect of a guaranteed income on production activity of small entrepreneurs. Second, we are the first to present a systematic empirical analysis of the demand-side channel through which safety nets can spur credit demand and thus investment.

This paper contributes to the literature understanding the role of risk tolerance on entrepreneurship (Knight (1921), Kihlstrom and Laffont (1979), Miller (1984), Iyigun and Owen (1998), Levesque and Minniti (2006)).[7] The mechanism of our paper complements Hombert et al. (2020) and Gottlieb, Townsend and Xu (2021) who document an increase in entrepreneurship following an increase in downside protection due to unemployment insurance and protected maternity leave, respectively. We add to these papers in three ways. First, we examine the effect of a different protection mode – guaranteed income in a developing country. 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, and financial literacy, among others (Cole and Xiong (2017), Platteau, De Bock and Gelade (2017)). Second, we focus on the demand-side barriers to the *reorganization* of business activity among

[6] 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.

[7] The paper is also related to the literature that explores the characteristics of entrepreneurs. We direct readers to Astebro et al. (2014) and Kerr et al. (2018) for a detailed review of the literature on the individual determinants of entrepreneurship.

existing small entrepreneurs, i.e., the capital-intensity of existing firms, rather than barriers to the *level* of entrepreneurial activity, i.e., the number of new firms created. Third, we identify a novel mechanism through which safety net expansions can increase credit demand, investment, and income for small entrepreneurs. Therefore, 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 (Kanbur (1979), Kihlstrom and Laffont (1979), Banerjee and Newman (1991), Morduch (1995), Bryan, Chowdhury and Mobarak (2014)).

Our paper is related to the literature examining the impact of financial constraints on entrepreneurial activity.[8] Specifically, this paper presents 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.[9] However, randomized experiments providing standard loans to microenterprises show little or no effect of loans on enterprise profitability or sales.[10] 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 little effect. In contrast, policies – such as basic income support – that relax demand-side constraints by increasing safety nets can generate greater effects. Guaranteed income mitigates the under-investment problem by providing an additional layer of safety net when small entrepreneurs are hit by a shock, i.e., when their marginal utility of additional consumption is high and expected marginal returns on investment is low.[11] Therefore, our results complement the experimental-setting results of Karlan et al. (2014), Emerick et al. (2016), and Lane (2020), who document that absence of risk protection may be the binding constraint for small and poor entrepreneurs, such as farmers. Moreover, our results are consistent with the theoretical predictions of Rosenzweig and Wolpin (1993) and Donovan (2021), that incompletely-insured income volatility is in part a cause of agricultural inefficiency and the availability of certain non-agricultural guaranteed income has a substantial positive effect on agricultural output.

This paper is related to the corporate finance literature examining the effect of debt contracts on investment. An essential feature of debt contracts is the imposition of a large cost of financial distress when the borrower is unable to repay the loan (Townsend (1979), Diamond (1984)). As a result, if borrowers operate in a risky environment, the cost of financial distress lowers their demand for credit and consequently discourages investment. Prior work has focused on

[8] Kerr and Nanda (2009) provide a review of the literature examining the relevance of financing constraints for entrepreneurship. Woodruff (2018) presents a detailed review of the financial constraints – among other constraints – faced by small businesses in developing countries.

[9] Some studies that identify high returns to 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).

[10] 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) documents that the impact of credit on household business is likely to be negligible.

[11] An alternative way of framing the argument is that the magnitude of the covariance term increases with risk-aversion, and guaranteed income reduces risk-aversion through the classic wealth effect of Pratt (1964)

attenuating the low credit demand problem by reducing the cost of financial distress. Using a randomized controlled trial, Field et al. (2013) argues that altering debt contract specifications to reduce the cost of financial distress by giving a grace repayment period can increase credit usage and investment in high-return projects. We contribute to this literature by documenting that safety nets – such as guaranteed income – can act as an alternative tool for reducing the under-investment problem associated with traditional debt contracts. Additionally, we document that credit demand stimulated by guaranteed income does not lead to greater default. This finding stands in contrast to the increase in default following interventions aimed at reducing the cost of financial distress, as documented in Field et al. (2013).

Another contribution of this paper is to provide a systematic assessment of a basic income program on productive activity in a developing country rolled out on a large scale.[12] Our paper is closest to Banerjee et al. (2020*b*), 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 hunger, sickness, and depression among recipients in spite of the pandemic. Our findings complement their analysis by documenting the role of guaranteed income in creating a safety net against adverse shocks. However, our paper differs from them in that we evaluate the effect of such transfers during normal times and primarily focus on the role of such transfers in stimulating credit demand. Other closely related work has focused on labor supply, estimating the effects of long-term cash transfers in Alaska (Jones and Marinescu (2022)) and Iran (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. 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.

Our work is also related to the literature that examines the effect of wealth shocks on self-employment and entrepreneurship. This literature has primarily focused on the importance of such wealth shock in alleviating liquidity constraints (Holtz-Eakin, Joulfaian and Rosen (1994), Blanchflower and Oswald (1998), Andersen and Nielsen (2012), Blattman, Fiala and Martinez (2014), Adelino, Schoar and Severino (2015), Corradin and Popov (2015), Harding and Rosenthal (2017), Schmalz, Sraer and Thesmar (2017), Hanspal (2018), and Bellon et al. (2021) among others). An exception is Bianchi and Bobba (2013) who exploit the welfare program *Progresa/Oportunidades*,

[12] Prior assessments of UBI have primarily focused on short-lived small pilot studies such as the examination of the effects of UBI on health, nutrition, schooling, economic activity, women's agency, and the welfare of those with disabilities in eight villages in Madhya Pradesh, India (Eskelinen (2016)). Between 1974 and 1979, Canada ran a UBI randomized controlled trial in the province of Manitoba. Forget (2013), Strobel and Forget (2013), Forget, Peden and Strobel (2013), and Forget (2011) document that UBI in Manitoba seemed to benefit residents' health and education. Another pilot conducted by BIG (Basic Income Grant) in two villages in Namibia, with some analysis but without statistical inference also indicates improvement in health, education, and employment. Similarly, Hämäläinen et al. (2017) evaluate the employment effects of a small pilot basic income program in Finland that only targeted the initially unemployed (not universally) and required them to forego other social benefits. While these pilot studies are informative, Hoynes and Rothstein (2019) argue that such small-scale UBI pilot studies do little to resolve outstanding questions due to their failure to meet the conditions of the canonical program. Moreover, these pilot studies suffer from issues of inference and generalizability due to their small sample size.

which targets poor households in rural Mexico and provides cash transfers conditional on their behaviors in health and children education. They provide suggestive evidence that the program increased incidence of entrepreneurship by enhancing the willingness to bear risk. Using the same natural experiment, Gertler, Martinez and Rubio-Codina (2012) find that the these cash transfers did not increase credit but increased production as a portion of the transfer was used to finance investment. While our results complement these papers, we differ from them as we analyze the effects of unconditional cash transfers on the reorganization of business activity of self-employed farmers and provide a detailed empirical description of the credit demand channel through which safety nets increase production. Broadly, we add to this literature by presenting a potential demand-side explanation for the facts documented in Hurst and Lusardi (2004) – (1) no discernible relationship between household wealth and the probability of starting a business for the majority of the wealth distribution, and (2) borrowing constraints are not empirically important in deterring the majority of small business formation.

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 outlines the empirical strategy of the paper. Section 5 lays down the key results of the paper. Section 6 presents the details of the mechanism. Section 7 presents a discussion of the results and section 8 concludes.

2 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, agriculture 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 and decreased by 4.6% in 2014 and 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. 2019 All India Debt Investment Survey states 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 to the farmers but have subsequently been 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 $1,735 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.[13] The list of landowning farmers and their bank accounts is provided by each state to the federal government based on land registration records, Aadhar cards, and soil health cards. The policy is confined to only landowning farmers as the lack of systematic identifying data on landless farmers imposed legal restrictions on the GOI.[14] 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 B.1 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.

[13] 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 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 with the individual Aadhar Cards, analogous to social security cards in the United States. The primary account for farmers is usually the account opened for them under the PMJDY.

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

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 ≈ ₹103,448 or $29,907 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.[15] 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.

3 Data

This section discusses the various datasets used in our analysis including transaction-level bank data, loan-level data from the credit bureau, data on beneficiaries of PMKSN, remote-sensing data on agricultural yields, administrative data on gross sown area under various crops, and data on survey of household assets.

3.1 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, consumption, 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, 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.

[15]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 interest, 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.

Our bank data is a sample of 91,419 non-institutional farmers with active saving accounts from January 2011 through December 2021.[16] The sample spans all farmers that have a savings account with our bank in one of the Indian states of Karnataka, Maharashtra, Punjab, Telangana, and West Bengal. 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 86,873 farmers with 2.2 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 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 the Unified Payments Interface (UPI). UPI is the primary mode of transaction for self-employed individuals in India, such as farmers.[17] 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.

A concern is if bank data can characterize the income and spending behavior of farmers in rural economies. First, we note that focusing on bank data is unlikely to exclude a large 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 C.1). 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. Second, we compare the key metrics of income and expenditure in our bank data with the data reported by the 2018 Situation Assessment Survey of farmers. Appendix Table C.1 reports the comparison. The average monthly income and expenditure in the bank data for the year 2018 are ₹8,334 and ₹11,578, respectively. The two metrics are close, though somewhat dissimilar, to the average monthly agricultural income and expenditure of ₹7,996 and ₹11,858 in the 2018 SAS survey. Overall, the comparison indicates that our bank data can characterize farmers' income

[16] Following the World Bank standard, we define an account as active if it has at least one transaction per year. The median number of transactions for our sample is 5 per year, with a mean value of 13.43.

[17] 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 such as farmers in India since the demonetization in 2016. UPI is similar to Venmo in the United States.

and spending behavior in rural India. However, 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.[18]

3.2 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 inquiry was made. The data captures all formal sector 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. Moreover, credit cards and kisan credit cards are excluded from this data because the credit bureau reporting format for these products makes analysis difficult.[19] We collapse our data at the farmer-by-month level and include zeros when no loan or inquiry was made. Our analysis of the borrowing data centers on four variables – the probability of getting a loan, probability of inquiry, number of loans, and loan amount.

3.3 Beneficiaries of PMKSN

We collect a novel administrative dataset on the beneficiaries of PMKSN from the Ministry of Agriculture, GOI. The data covers all beneficiaries of the scheme across the country and provides information on the number of unique beneficiaries at the village or town level. We geo-reference this data using village names to compute the number of unique PMKSN beneficiaries at the ZIP code level. Appendix figure C.2 presents the geographic distribution of beneficiaries.

3.4 Remote-sensing data on agricultural yields

Remote-sensing data is used to measure agricultural yields otherwise unavailable at the granular ZIP code level. We use a satellite-based enhanced vegetative index (EVI) to construct for ZIP code-level agricultural production, as no ZIP code-level agricultural production data exists in India. EVI is a chlorophyll-sensitive composite measure of plant matter generated by NASA's

[18]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.

[19]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.

Earth Observation satellite – Landsat 8. We direct the readers to Huete et al. (2002) for details on the construction of EVI.

We construct a measure of agricultural yield by subtracting the early cropping season value of EVI (the mean of the first six 8-day composites) from the maximum value of EVI during the season. The measure allows us to effectively control for non-crop vegetation, such as forest cover, by measuring the change in vegetation from the planting period to the point of peak vegetation. This measure has previously been used by Labus et al. (2002) and Rasmussen (1997) to construct agricultural yields. Asher and Novosad (2020) document that this measure is highly correlated with annual agricultural yields at the district level in India. A contribution of this paper is to extend the remote-sensing data used in Asher and Novosad (2020) to cover a more recent period from January 2017 through December 2019. For robustness, we use two other measures of agricultural production – average and median values of EVI. Appendix figure C.3 presents the geographic distribution of average EVI from January 2017 through December 2019. Lastly, we match this data with the data on number of PMKSN beneficiaries.

3.5 Consumer Pyramids Household Survey

We obtain detailed data on the ownership of durable assets 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.[20] We use this data to investigate the effect of cash transfers on ownership of fixed assets such as tractors, cows, and two-wheelers. Moreover, this dataset also provides information on the income of households, and their sentiments regarding current and future financial prospects.

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, bank branch location data from the Reserve Bank of India, 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, and the 2019 Situation Assessment Survey (SAS) for farmers conducted by the National Sample Survey Office (NSSO).

[20] Internal discussions with CMIE indicate that agricultural laborers are more likely to be landless farmers and work for landowning farmers.

4 Empirical Strategy

This paper estimates the effects of guaranteed income on income from work, production, and credit market outcomes of self-employed farmers. We exploit the cross-sectional and time-series variation due to the introduction of PMKSN. PMKSN was introduced in March 2019 and gave perpetual and unconditional cash transfers to landowning farmers – the treatment group. However, the policy did not provide cash transfers to non-landowning (tenant) farmers – the control group. We begin by estimating the following empirical specification:

$$\frac{y_{i,Post} - y_{i,Pre}}{y_{i,Pre}} = \beta \cdot Treatment_i + \theta_z + \varepsilon_i \tag{1}$$

where, $y_{i,Pre}$, and $y_{i,Post}$ denote the sum of the dependent variable of interest over the 12 months before and after the policy, respectively. $Treatment_i$ is an indicator variable taking the value of one for landowning farmers and zero for non-landowning farmers. The estimate of β provides the average treatment effect of the program on studied outcomes. Specifically, it measures the annual growth rate of the outcome of interest for the treatment group relative to the control group. We include ZIP code fixed effects denoted by θ_z as farmers within a geography are exposed to similar idiosyncratic shocks and have similar cropping patterns. Therefore, the specification evaluates the relative outcomes at the farmer level by comparing the treatment and the control groups within a ZIP code.

A concern with specification 1 is that the systematic differences between the treatment and control groups could drive the estimate of β. Table 1 reports the sample average of the key variables for the treatment and control groups as well as unconditional and within ZIP average differences between the two groups. While the unconditional differences between the two groups are statistically significant, the economic magnitude of the difference is small relative to the overall sample average. Moreover, the differences between the two groups shrink further while comparing the two groups within a ZIP code. The within-ZIP differences become not only economically small but also statistically insignificant. Nevertheless, it is implausible to argue that the two groups are similar across all observed and unobserved dimensions.

We address this concern by augmenting the empirical strategy outlined in equation 1 with a standard difference-in-differences (DID) design comparing the treatment and the control groups before and after the introduction of the policy. The specification includes farmer fixed effects and ZIP × month fixed effects. Farmer fixed effects address the concern that a direct comparison of the treatment and the control group may pose an empirical challenge if the two groups are different. Farmer fixed effects allow us to control for all time-invariant heterogeneity due to differences in preferences, productivity, and other unobserved traits. Another issue with a direct comparison is that the agricultural production, which determines income from farming, is a function of the geography, determining the types of crops cultivated. Moreover, the eventual output also depends on local idiosyncratic shocks such as fires, rainfall, pest infestation, etc., and the local government's monetary or non-monetary assistance. ZIP × month fixed effects allow us to non-parametrically control for all time-varying granular differences arising from geography that may determine farmer's income from work. Therefore our baseline empirical specification is as follows:

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t} \tag{2}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. $Avg(y_{Pre})$ denotes the average over the entire sample 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. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ month fixed effects, where z refers to the ZIP code where farmer i operates.

The estimate of interest is the coefficient of the interaction term of $Treatment_i$ and $Post_t$ given by β. β is the estimate of the treatment effect capturing the treatment group's response, relative to the control group, to the policy. Specifically, β is a within ZIP code estimator comparing the average difference in the treatment and the control groups operating in the same ZIP code after controlling for all observed and unobserved time-invariant heterogeneity across farmers. We calculate the standard error of the point estimate by clustering at the ZIP code level since our empirical strategy effectively compares the treatment and the control group within a ZIP code.

The causal interpretation of β relies crucially on two assumptions. First, the treatment group received the cash transfers, whereas the control group did not. We verify the first-stage relevance assumption by examining the fraction of farmers in the treatment group who received the transfers. Second, in the absence of a policy change, the outcomes for the farmers in the treatment and control groups would have evolved according to parallel trends. We investigate the parallel trends assumption by estimating a dynamic specification as in equation 3 to analyze the outcomes for the treatment and control groups before the policy. An added advantage of the dynamic specification is that it allows us to evaluate the evolution of the treatment effect after the policy. Examining the temporal evolution of the treatment effect in a high-frequency setup is important as the policy shock was an aggregate shock, and the effect may be confounded by the presence of other contemporaneous aggregate shocks.

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \sum_{k=-22,k\neq-1}^{k=12} \beta_k \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t} \tag{3}$$

As before, $y_{i,t}$ 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. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ month fixed effects, where z refers to the ZIP code where farmer i operates. β_k refers to the treatment effect estimated at $t = k$ relative to the treatment effect at $t = -1$. As before, standard errors are estimated by clustering at the ZIP code level.

4.1 Other Assumptions

The DID estimator relies on three other assumptions – homogeneity in the intensity of treatment across treatment units, stability of the treatment and control groups, and no spillovers.

Homogeneity in the intensity of treatment: Saez (2002), and Hanna and Olken (2018) show that in the presence of a progressive tax schedule, BI-like cash transfers will not raise the after-tax income of all recipients by the same amount. Therefore, a concern with unconditional 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 and farm-based enterprises 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 assumption is the stability of the treatment and the control unit over time. Specifically, buying and selling of agricultural land can allow individuals to select in or out of the treatment group. The stability 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 that bought agricultural land after December 2018 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.

No Spillovers Assumption: We evaluate the assumption of no spillovers by examining the evolution in the income of the control group after the policy. We find that the control group was largely unaffected by the policy. Additionally, we follow Berg, Reisinger and Streitz (2021) to present a formal test for the effect of heterogeneous spillovers on the treatment and the control group within a district. The results indicate that the spillovers are likely to be of little concern.

5 Results

This section presents the results of the effect of guaranteed income under PMKSN on income from work, agricultural yields, investment, and credit.

5.1 First-Stage Relevance of the Policy

We begin our analysis by evaluating the first-stage relevance of the policy, i.e., the treatment group received these cash transfers whereas the control group did not. Cash transfers under PMKSN were made in three installments of ₹2,000 on fixed dates. We compare the amount and the dates of the transfer provided by the GOI with our transaction-level bank data to identify if the treatment group received transfers.[21] Figure 1 presents the first-stage results. Our analysis indicates that 96.03% of the farmers in the treatment group received transfers.[22] The 4% gap could be attributed to farmers having another bank account wherein the transfers were disbursed or a delay in the disbursal of cash transfers due to errors in information recording. No farmers in the control group received these transfers.[23]

5.2 Second-Stage: Effect of the Policy on Income from Work

This section examines the effect of cash transfers under PMKSN on income from work. We begin by analyzing the differential effect of the policy on the treatment and control groups. Figure 2 presents the unconditional temporal analysis of the average income from work (Panel 2a) and the difference in income (Panel 2b) for the treatment and control groups. There are four key takeaways from the analysis. First, Panels 2a and 2b provide prima-facie evidence suggesting an increase in the income for the treatment group, following the policy, while leaving the control group largely unaffected. Second, the income for the farmers in the treatment and control groups evolved according to parallel trends in the pre-policy period. Third, the significant difference in income is realized during the second harvest season after the policy. Fourth, the first harvest season after the policy does not exhibit significant differences in income as the announcement of the policy occurred after the majority of the production decisions had already been made. This suggests that the change in agricultural practices primarily drives the increased income for the treatment group.

Next, we examine the policy's effect on income from work for the treatment and control groups following specification 1. Table 2 reports the results from the farmer-level analysis. The estimate of interest is positive, statistically significant across all specifications, and stable in magnitude.[24] Specifically, the estimate indicates a 10% increase in the relative income for the treatment group after the policy. Economically, this effect indicates a relative increase in income of ₹10,121-₹10,441 for the treatment group. Comparing, the annual increase in income with the magnitude of cash transfers indicates that a $ 1 annual guaranteed income generates additional income of $1.7 over the next twelve months. Therefore, the total average increase in income

[21] We look between -5 and +5 days of the scheduled transfer to identify transfers. We use this window instead of the precise date to circumvent any issues related to the book-keeping and recording of the date of the transfer at the bank level. In our sample, no transfers were recorded between -1 and -5. Most of the transfers were recorded between 0 and +2 days of the scheduled transfer date.

[22] We do not include the treatment group farmers in the state of West Bengal as the state did not comply with the policy. Using the same methodology, we verify that the treatment group farmers in West Bengal did not receive these cash transfers.

[23] This result is not surprising since our sample bank spends a lot of time as well as legal and monetary resources in verifying land deeds and the ownership of the land.

[24] The values of Oster (2019) lower bound based on changes in the magnitude of the estimate of interest and model R^2 are 0.0906 (moving from column 2 to 3) and 0.1011 (moving from column 2 to 4). The lower bound values indicate that the identified set safely excludes zero, and we can reject the null that the policy's effect on income is driven by omitted variables under standard Oster (2019) assumptions. Alternatively, the respective values of Oster (2019) lambda are 9.42 (moving from column 2 to 3) and 52.35 (moving from column 2 to 4), indicating that the relative strength of unobservables to observables has to be very large for the documented effect to be driven by omitted variables.

following these transfers is \$2.7, where\$1.7 comes from the policy's effect on farming income and \$1 from direct transfers.

5.2.1 Results from the Differences-in-Differences (DID) Design

This section presents the results from the estimation of our baseline DID specification. Table 3 reports the results from the estimation of specification 2. The estimate of interest associated with the interaction term of treatment and post is positive and statistically significant across all specifications. The model R^2 increases from 0.02% to 27.05% from columns 1 to 5, whereas the estimate of interest is fairly stable. The estimate increases in magnitude with the addition of fixed effects indicating that the omitted variables are likely to downward bias the estimate of β (Altonji, Elder and Taber (2005), Oster (2019)). The estimate indicates that income from work increases by 9.3-12.6% for the treatment group, relative to the control group, for the twelve months following the policy announcement. Economically, this effect indicates an increase in income of ₹9,276-₹12,612 for the treatment group over the twelve months following the policy announcement. Comparing the annual increase in income from work with the magnitude of cash transfers indicates that for each \$1 of annual guaranteed income. there is an increase in income from work of \$1.55-\$2.10.

Next, we examine the treatment effect using the dynamic specification. Figure 3 presents the results from the estimation of specification 3. Figure 3 complements the prima-facie evidence presented in Figure 2 by adding farmer and ZIP × month fixed effects. The results show that the income for the farmers in the treatment and control groups evolved according to parallel trends in the pre-policy period. The parallel trends result allows us to interpret the estimate of β in Tables 2 and 3 as causal. Moreover, the treatment effects appear immediately after the policy's launch in March 2019. The treatment effects increase slowly over time and are most significant during the second harvest season after the policy.

We demonstrate that our empirical design is consistent with our identification assumption of parallel trends using a falsification test. 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. Hence, West Bengal presents itself as a natural falsification test setup whereby the hypothesized treatment effect is unlikely to be present, despite the presence of the treatment and control groups, due to non-compliance by the state. Figure 4 presents the results from the estimation of dynamic specification 3 for the state of West Bengal. The results indicate no differential effect on income across the treatment and control groups after the policy. The coefficients are statistically and economically insignificant, with a magnitude close to zero. The falsification test provides direct evidence for the assumption that the treatment and control groups would have evolved according to the parallel trends in the absence of the policy. Additionally, the test helps address other concerns that our results may be driven by other aggregate contemporaneous shocks with asymmetric effects on the treatment and control groups.

5.2.2 Results from Border Discontinuity Design

We further utilize the non-compliance of the state of West Bengal to supplement our baseline results with a border discontinuity design. 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. The test effectively compares landowning farmers exposed to similar cultural, geographic, climatic, or economic conditions, which may affect the economic outcomes of interest. The intuition is to construct a counterfactual for landowning farmers who benefited from PMKSN using *similar* landowning farmers in West Bengal. The key identifying assumption of this test is that the plausible confounding variables are likely to vary smoothly rather than discretely at jurisdictional boundaries. Under this assumption, the test overcomes the concern related to the comparability of landowning and non-landowning farmers as well as the comparability among landowning farmers in far-away geographies.

Table 4 reports the results from the border discontinuity design using the sample of contiguous district-pairs shown in appendix Figure D.1.[25] 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. Effectively, the test compares the average difference between landowning and non-landowning farmers within a complier district with that of a non-complier contiguous district in West Bengal. The estimate of the triple interaction term is statistically significant and positive. The results from the border discontinuity design further strength our faith in the baseline results discussed in Tables 2 and 3.

5.2.3 Robustness

This section examines several potential concerns related to the robustness of the findings presented in Tables 2 and 3 and Figures 2 and 3.

Placebo Test: 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 Figure D.2 presents the results from the estimation of equation 2 for the placebo years – 2017, 2015, 2014, and 2013.[26] The coefficients for all placebo years are statistically and economically insignificant, with a magnitude close to zero. Thus, the *null* results for the placebo years indicate that our results are unlikely to be spurious, and the absence of the treatment effect in the year 2014

[25]There are two points to note about this test. First, this test uses the CPHS data instead of the bank data because the bank data is unavailable for the states bordering West Bengal. Second, the most granular geographic unit in the CPHS data is district.

[26]We do not include 2016 in the test since it was the year of demonetization, which made 86% of cash in circulation illegal tender overnight.

indicates that the results are unlikely to be driven by the differential effects of federal elections on the treatment and control groups. Additionally, the test reinforces our parallel trends assumption.

Spillovers: A major concern with the interpretation of the treatment effect is the violation of the Stable Unit Treatment Value Assumption (SUTVA) in the presence of spillovers on the control group. The spillovers can be due to the increased economic activity of the treatment group or non-landowning farmers anticipating receiving the PMKSN benefits in the future. Positive spillovers on the control group do not threaten the economic interpretation of the treatment effect. They simply downward bias the estimate, in which case one can interpret the estimated treatment effects in this paper as the lower bound. However, negative spillovers on the control group pose a serious threat to the economic interpretation of the treatment effect. Figure 2a shows that the income from work for the control group is largely unperturbed after the implementation of the policy, hence spillovers are likely to be of little concern. Nevertheless, we follow Berg, Reisinger and Streitz (2021) and present a formal test for the effect of spillovers. We assume that the cash transfers affect farmers' input and output prices, which generates heterogeneous spillovers on both the treatment and control groups.[27] Since farmers are likely to purchase inputs and supply their outputs in the same market within a district, we assume district as the unit of spillovers.[28] Moreover, we assume that these spillovers are a function of district-level treatment intensity, i.e., the fraction of treated farmers in the district. Appendix Table D.1 presents these results. The results indicate that the spillovers are likely to be of little concern as the estimate assuming no spillovers (column 1) is statistically similar to the estimate assuming homogeneous spillovers (column 2) and heterogeneous spillovers (column 3) across the treatment and control groups.

Controlling for Covariates: Another concern with our analysis is that the treatment effect may be driven by differences in covariates across the treatment and control groups. We address this concern by augmenting specification 2 with the interaction term of $Post_t$ with farmer level controls (X_i) measured before the policy. Appendix Table D.2 presents the results. We add several control variables such as average savings, spending, credit card usage, other investments in fixed deposits, recurring deposits, provident fund deposits, stock market holdings, number of banking transactions per day, credit score, interest rate, limits on Kisan credit cards, farmer age, account age, religion, and prior default tag. The results show that the estimate of $Treatment_i \times Post_t$ is robust to the addition of the farmer-level covariates indicating that the estimate is unlikely to be driven by differences in covariates.

Treatment Effect in Matched Sample: We further address the issue of comparability of the treatment and control groups in a matched sample. We match treatment and control farmers within a ZIP code based on observable characteristics in the pre-policy period. We match based on average savings, spending, credit card usage, other investments in fixed deposits, recurring deposits, provident fund deposits, stock market holdings, number of banking transactions per day, credit score, interest rate, farmer age, account age, and prior default tag. Appendix Table D.3 presents the comparison of the treatment and control groups in our matched sample, indicating

[27] Cash transfers to farmers can increase demand for inputs in agriculture, generating a positive price effect on inputs. Moreover, increased productivity in agriculture can reduce output prices.

[28] Results are also robust to assuming ZIP code as the unit of spillovers.

balance on the matched characteristics. Notably, while we do not match the treatment and control groups based on their income from work, we find that our matched sample has relatively similar incomes. Appendix Table D.4 presents the baseline results from the matched sample and finds results similar to Table 3. Taken together, the results in appendix Table D.2 and D.4 indicate that the pre-existing differences in the treatment and control groups are unlikely to drive the results.

Representativeness and Measurement Issue: A concern with our analysis is the representativeness of our sample and the measurement of income from work using banked income. We address this concern by estimating specification 2 using the reported household-level income from the CPHS survey in an all-India sample. Appendix Table D.5 presents the results. The estimate of the interaction term of interest is qualitatively similar to the baseline results, indicating that issues regarding the representativeness and income measurement in our bank data are likely to be of little concern.

Alternative Transformation of the Dependent Variable: Appendix Tables D.6, D.7, and D.8 show that our results are robust to different empirical specifications, such as having outcome variables in inverse hyperbolic sine (IHS), logs, and levels instead of scaling by the pre-period average.

5.3 Effect of the Policy on Agricultural Productivity

This section presents direct evidence that the increased income from work is driven by increased agricultural productivity. Crop yield measures agricultural output harvested per unit of land area and is a standard measure of agricultural productivity. We merge the remote-sensing data on agricultural yield with the number of PMKSN beneficiaries at the ZIP code level to estimate the following specification:

$$LN(y_{z,t}) = \beta \cdot LN(\#Beneficiaries_z) \times Post_t + \theta_{z,s} + \theta_{s,t} + \varepsilon_{i,t} \tag{4}$$

where, $LN(y_{z,t})$ denotes the natural logarithm of agricultural yield constructed using Enhanced Vegetation Index (EVI) in ZIP code z at time t. t refers to season-year as the unit of time. s refers to the cropping season. There are two cropping seasons in India – Rabi and Kharif. Each season-year includes the Kharif season from year y and the Rabi season from year $y+1$. Our preferred measure of agricultural yield is constructed by subtracting the early cropping season value of EVI (the mean of the first six 8-day composites) from the maximum growing season value of EVI as in Asher and Novosad (2020). The differenced measure allows us to effectively control for non-crop vegetation, such as forest cover, by measuring the change in vegetation from the planting period to the moment of peak vegetation. $LN(\#Beneficiaries_z)$ denotes the natural logarithm of the number of PMKSN beneficiaries in ZIP code z. $Post_t$ takes a value of one for months following March 2019. $\theta_{z,s}$ denotes ZIP code × season fixed effects and controls for ZIP code specific time-invariant factors that influence yield during a cropping season. $\theta_{s,t}$ denotes season × year fixed effects and controls for all aggregate shocks that may affect the yield during a cropping season.

Identification in equation 4 comes from the cross-sectional variation in the number of PMKSN beneficiaries across ZIP codes and the timing of the roll out of the policy. There is considerable geospatial variation in the number of beneficiaries, as shown in appendix Figure C.2. Moreover, the multi-year nature of the remote-sensing data covers periods of cash transfer and times when no transfers were made. Additionally, ZIP code fixed effects allow us to control for endogeneity concerns related to the geospatial variation in the number of PMKSN beneficiaries.[29] Finally, the estimate of β gives the elasticity of agricultural production to change in the number of beneficiaries.

Table 5 presents results from the estimation of equation 4. The estimate of interest – the interaction term of $LN(\#Beneficiaries_z)$ and $Post_t$ – is positive and statistically significant. Moreover, the magnitude of the estimate is fairly stable despite the large increase in model R^2 from 4.20% in column 1 to 88.45% in column 5. The estimate indicates that a 10% increase in the number of PMKSN beneficiaries increases agricultural yield by 8.1%.[30] The estimated effect is sizable, representing the tenth percentile of agricultural yield. We also document a modest decline in prices of agricultural commodities sold locally consistent with the result of an increase in agricultural productivity (see Appendix section E.1).

We verify the effect is not driven by pre-trends. Figure 5 presents the results from the estimation of a dynamic specification. The estimates indicate the absence of any pre-trends that could explain the observed treatment effects documented in Table 5. Additionally, we present the robustness of our results to alternative measures of yield using the mean and the median values of EVI. Appendix Table D.9 reports results from the robustness test which are qualitatively similar to the results reported in table 5.

5.4 Effect of the Policy on Investment

We hypothesize that the increases in agricultural income and yields are driven by greater investment in agriculture. This section provides direct evidence of greater investment in agriculture by the treatment group.

We begin by examining the policy's effect on lumpy investment in assets such as tractors, cattle, and two-wheelers. Using the CMIE household survey data, we document a greater accumulation of these investment goods by the treatment group – relative to the control group – after the policy. Table 6 presents the policy's effect on investment. The estimate of interest is the interaction term of treatment and post. The estimation strategy includes household fixed effects and district × month fixed effects. The coefficient of interest is positive and statistically significant. Economically, the results indicate that the treatment group increased their ownership of tractors, cattle, and two-wheelers by 13.5%, 26.8%, and 6.77%, respectively. These effects are economically significant and indicate that the treatment group increases their investment in fixed assets, which are likely to generate long-run returns.

We present robustness of our results using a Poisson fixed-effect regression specification

[29] The simultaneous implementation of other policies that may have a varied influence on various geographies depending on their share of landowning farmers can confound our conclusions. However, to the best of our knowledge, no additional policies that would differ geographically in their effects due to variations in the share of landowning farmers were put into place at the same time as PMKSN.

[30] The estimate is standardized to report the effect in terms of a 10% increase in the number of beneficiaries.

as suggested by Cohn, Liu and Wardlaw (2022) to address econometric issues associated with skewed, non-negative count outcome variables (see appendix Table D.10). Additionally, we supplement the analysis in Table 6 by examining the policy's effect on state-level tractor sales in all states relative to the state of West Bengal. Moreover, we conduct ZIP code-level analysis by comparing sales of tractors for agricultural and non-agricultural purposes within a ZIP code-month. Appendix Tables F.1 and F.2 present the results from the state-level and the ZIP code-level analysis, respectively. The analysis provides complimentary evidence of an increase in tractor sales after the policy.

The income and capital stock information in the survey data allows us to compute the marginal revenue product of capital (MRPK). We use a two-stage least square (2SLS) methodology to compute the MRPK. We impute the stock value by combining the stock of tractors, livestock, and two-wheelers with the average cost for each item. Table 7 presents the results. Column 2 presents the first-stage estimate regressing the capital stock on the interaction term of treatment and post. The first-stage f-statistic is 25.65, indicating the relevance of the instrument. The magnitude of the first-stage estimate indicates a 10% increase in capital. This estimate is economically large, equivalent to the 45% of the present discounted value of guaranteed income, and is 7.75 times the size of the annual cash transfer of ₹6,000.[31]

Column 1 presents the second-stage estimate from regressing the household income on predicted capital from the first-stage. Our second-stage coefficient implies a capital elasticity of income of 0.80. Multiplying the elasticity estimate with the pre-period annual average income and dividing it by the pre-period average capital stock indicates that the value of MRPK is 0.22. Therefore, the estimate implies an average return on capital of 22%. Our estimate of the MRPK can be used to discipline macroeconomic models of developing economies in future work.

Next, we examine the policy's effect on other investment in agriculture at the district level – consumption of fertilizers and irrigation. Appendix Table F.3 reports the policy's effect on fertilizer consumption. Results indicate that a 1% increase in the number of beneficiaries increases the total consumption of fertilizers by 6%. Appendix Table F.4 reports the policy's effect on irrigation. Results show that a 1% increase in the number of beneficiaries increases irrigation by 5.5%, and the increase in irrigation is driven by private sources of irrigation, such as tube-wells, wells, private canals, etc., in which farmers can directly invest. Additionally, we document an increase in new agri-based micro-enterprises, following the policy. Appendix section E.2 discusses the effect on firm entry in detail.

5.5 Effect of the Policy on Credit

This section examines the role of credit in financing the increased investment, as documented in section 5.4. We combine the natural experiment with the detailed loan-level data from the Indian credit bureau (TransUnion-CIBIL) to identify the policy's effect on credit.

We examine the policy's effect on the extensive margin – the probability of getting a new

[31] Note that this is a lower bound, as the survey data only allows us to measure a fraction of household investment.

loan – and the intensive margin – the number of new loans and the loan amount. We collapse our loan-level data such that each farmer has only two observations, one for the pre-policy period and another for the post-policy period. Specifically, we collapse the data for the twelve months before and after the policy to compute whether the farmer got a loan in either period, the number of new loans in each period, and the total amount associated with new loans in each period.

Column 1 of Table 8 reports the policy's effect on the extensive margin of credit outcome – the probability of a new loan. The estimate of interest is positive and statistically significant. Results indicate that the probability of a new loan increases by 11% for the treatment group after the policy. The estimate represents a 17% increase over the pre-period sample mean of 62%.

Columns 2 and 3 of Table 8 report the policy's effect on the intensive margin – the number of new loans and the loan amount, respectively. The estimate of interest is positive and statistically significant. The number of new loans increases by 13% over the pre-period sample mean. Specifically, the treatment group gets 0.15 additional new loans relative to the control group after the policy. Similarly, the loan amount for the treatment group increases by 17% over the next twelve months after the policy. On average, the loan amount increases by ₹67,000 for the treatment group. For robustness, we repeat our intensive margin analysis using the loan-level data and find similar results (see Appendix Table D.11).

The policy's effect on credit is economically significant. Specifically, the effect is 11.2 times larger than the yearly cash transfer of ₹6,000 and is equal to 65% of the present discounted value of guaranteed income.[32]

5.5.1 Does the New Credit Finance Consumption or Productive Capacity?

This section documents 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.[33] 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 D.12.

Table 9 reports the policy's effect on credit market outcomes for productive loans (panel A) and consumption loans (panel B). The results in panel A are similar to the results reported in Table 8. On the extensive margin, the probability of a new loan increases by 9%. On the intensive margin, the number of new loans increases by 22% over the mean and the loan amount increases by 28% over the mean. Meanwhile, we do not find any economically or statistically significant

[32] We obtain the value of 0.65 by comparing the increase in loan amount of ₹67,000 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%.

[33] Another reason for investigating if the new credit finances productive capacity or consumption is that if the majority of the new credit goes into financing household consumption, it could potentially generate a *"bad"* credit boom (Mian, Sufi and Verner (2017), Mian and Sufi (2018), Mian, Sufi and Verner (2020), Müller and Verner (2021)).

results for consumption loans (panel B). The result indicates that almost all new credit is used to finance the productive capacity of farmers.

For robustness, we replicate the analysis using a long-form dataset that combines the two loan types. The estimate of interest is the triple interaction term of loan type, treatment status, and the post variable. An added advantage of this specification is that it allows us to include farmer × time fixed effects controlling for all time-varying heterogeneity at the farmer-level. Appendix Table D.13 reports the estimate of interest and finds results similar to Table 9. Specifically, we find increases in the probability, number, and loan amount used to finance productive capacity relative to consumption.

6 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.

6.1 Importance of Credit Markets in Driving the Effect

This section evaluates the role of credit markets in driving the effect of guaranteed income on income from work. Friedman (1957) and Carroll (2001) emphasize the role of the credit market in the transmission of permanent income shocks, i.e., a permanent income shock can change household behavior only if households can borrow against the unearned income component.[34] Ganong and Noel (2020) show that the link between housing wealth and consumption breaks down when borrowers are underwater. Since such borrowers are cut off from future access to credit markets, wealth shocks to these borrowers do not translate into real effects. 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 unfavorable interest rates or credit rationing. Hence, a farmer with a prior default tag is severally limited in their ability to secure credit.

Therefore, we investigate the role of credit markets by estimating our baseline specification 2 separately for two sub-groups of farmers – farmers with a default tag before March 2018 and farmers with no default tag through March 2018. PMKSN beneficiaries receive a significant wealth or a permanent income shock equal to 27 times the average stock of savings. This implies that the unearned income component is a large part of this permanent income shock. An unearned income shock can affect investment only if the recipients can access credit markets. Farmers with a default tag are likely to be cut off from credit markets and cannot convert their unearned income into current investment. Table 10 reports the results. Column 1 reports the estimate for the full sample.

[34] Unearned income component is defined as the component of a permanent income shock that has yet not been realized, but will occur sometime in the future.

Columns 2 and 3 report the estimate for the sample of farmers without and with prior default, respectively. The estimate of interest for the sample of farmers with no prior default is positive and statistically significant. Economically, the estimate implies that a $1 of annual guaranteed income will increase income from work by $2.7. This estimate is larger than the baseline estimate of $2.1. The estimate of interest for the sample of farmers with a prior default tag is economically negligible ($0.1) and statistically insignificant. The results indicate that credit markets play an important role in the documented positive income effect of BI transfers.

We supplement the results on heterogeneity in income – documented in Table 10 – with the heterogeneity in credit market outcomes by prior default status. We find the increased credit for the treatment group is driven by farmers with no prior default tag (see Appendix Table F.5). Meanwhile we do not find any increase in credit for the treatment group with prior default. The results reinforce the hypothesis that the presence of credit market frictions can impede the ability of a wealth shock to affect income.

Furthermore, we validate the role of credit markets by focusing on sub-groups of farmers with different 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. Therefore, the permanent income shock due to PMKSN is likely to have a smaller effect on farmers with low credit scores. Figure 6 reports the policy's economic effect on income from work (Panel 6a) and credit (Panel 6b) for the treatment group – relative to the control group – estimated separately for each sub-group of credit score. The sub-groups are defined based on the pre-policy credit scores. Results indicate that the treatment effect monotonically increases with credit scores. Economically, the effect on income (credit) rises from 0.18 (-0.01) for the lowest decile of the credit scores to 3.2 (0.90) for the highest.

Next, we quantify the salience of credit markets in driving the effect. Specifically, we conduct the Sobel-Goodman mediation test to identify the proportion of the total effect of the policy on income that is mediated through credit. The intuition behind the test is that if an intervening variable – in this case, new credit – is an important pathway for an explanatory variable's – the policy – influence, the former has to be both strongly predicted by the latter, and including the intervening variable should reduce the coefficient on the explanatory variable. The reduction in the coefficient of the explanatory variable is informative about the magnitude of the effect of the explanatory variable mediated through the intervening variable (Baron and Kenny (1986)). Appendix H discusses the details of the test. Our Sobel-Goodman test results indicate that 94.4% of the total effect of the policy on income is mediated through credit (see Appendix section H.1).

The results of the Sobel-Goodman test also allow us to rule out an alternative explanation, i.e., cash transfers increase investment directly by increasing the amount of cash-in-hand available for investment. However, our results indicate that, at maximum, only 6% of the effect can be explained by the cash-in-hand channel of BI, making it relatively unimportant. This is 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. 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.

6.1.1 Quantifying the Effect of Credit on Income

We quantify the credit elasticity of income using the two-stage least square (2SLS) methodology with first- and second-stage given by equations 5 and 6, respectively. Specifically, we use the interaction term of treatment and post as an instrument for loan amount and project the predicted loan amount on income.

$$Credit_{i,p} = \beta \cdot Treatment_i \times Post_p + \theta_i + \theta_{z,p} + \varepsilon_{i,t} \tag{5}$$

$$Income_{i,p} = \psi \cdot \hat{Credit}_{i,p} + \theta_i + \theta_{z,p} + \mu_{i,t} \tag{6}$$

Table 11 presents the results from the 2SLS estimation. Column 1 presents the estimate of the income elasticity of credit and column 2 presents the estimate of credit-to-income multiplier. We suppress the first-stage results since they are identical to column 3 of Table 8. The first-stage f-statistic is 73.05, indicating the relevance of the instrument. Our estimate of elasticity is 0.71 and the estimate of the credit-to-income multiplier is 0.22. Economically, the results indicate a $1 increase in credit increases income by $ 0.22, or a 1 percentage point increase in credit increases income by 0.71 percentage point. The multiplier can be interpreted as the short-term increase in income due to an increase in credit, including both short-term and long-term credit.

6.2 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 explain the increased credit to the treatment group documented in section 6.1. We begin by identifying changes in credit demand 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. Additionally, we examine the effect on income and credit based on the heterogeneity of factors that determine credit demand – ability of guaranteed income to protect against future risk, salience of idiosyncratic risk, and incomplete insurance markets. Lastly, we show that the insurance effect of the policy reduces hedging activity.

6.2.1 Effect of the Policy on Credit Demand – 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.[35] The credit limit and the interest rates for KCCs are

[35] 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

unrelated to farmers' creditworthiness. Therefore, this product provides an ideal laboratory to examine the effect guaranteed income has on farmers' demand for credit.

The KCC program was introduced to issue a line of credit to farmers, which they can use to purchase agriculture 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. KCC is issued for a term of five years. These cards' first-year credit limit is based on the amount of land held and the crops being grown. The credit limit on the cards is increased for subsequent years by a fixed percentage of the last year's limit.[36] The 2017 RBI circular provides illustrations for the details of the calculations. Appendix Figures G.1, G.2, and G.3 present these illustrations.[37] Our conversations with the bank managers suggest that banks directly follow the illustrations provided by the Reserve Bank of India to calculate the credit limits. Moreover, the interest rates are fixed for each credit limit as per the bank's internal guidelines. 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 G.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 G.1 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 12 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 six percentage points for the treatment group after the policy. The treatment effect is large relative to the average utilization rate of 21.3% and represents an average increased usage of ₹27,000.

Additionally, we present the dynamic assessment of the treatment effect on KCC utilization rate. Figure 7 presents the results. Specifically, the evolution of the treatment effect in the post-policy period indicates that the utilization rate increases slowly after the policy announcement, peaks during the Kharif cultivation season, when the majority of capital expenditure is incurred in the cultivation process, and declines during the harvest season. Overall, we document an increase in the KCC utilization rate. The results indicate that the demand for credit increases among the treatment group following the policy.

The increased credit usage of ₹27,000 on KCC combined with the increased credit of ₹67,000, documented in section 5.5, implies a total credit increase of ₹94,000, which is equal to 15.7 times

monthly utilization of credit cards. Therefore, we use the detailed information on KCC issued by our sample bank to conduct this analysis.

[36] The fixed percentage is usually set to 10%. So if the first-year credit limit is ₹100, the credit limit in the second year is ₹110. The credit limits for the third, fourth, and fifth years are ₹121, ₹133.10, and ₹146.41, respectively.

[37] The illustrations are taken for the 2017 RBI circular and can be accessed at LINK

the size of yearly cash transfer of ₹6,000. The total effect on credit is equivalent to 91% of the present discounted value of guaranteed income.

6.2.2 Effect on Credit Inquiries & Acceptance

We supplement the analysis by examining the policy's effect on a proxy for credit demand – the probability of inquiry and number of inquiries on all loans.[38] Table 13 presents the results. We estimate an 8.3% increase in the probability of inquiry and a 36.5% increase in the number of inquiries over the sample mean for the treatment group. Additionally, we examine the effect on a proxy for credit supply – the probability of acceptance conditional on inquiry. Column 3 of Table 13 presents the policy's effect on acceptance rate. We estimate that the probability of acceptance conditional on inquiry – or acceptance rate – was largely unchanged by the policy. On the demand side, we find that credit inquiries rise, whereas on the supply side, acceptance rate is unaffected.

The results suggest the credit supply is largely unresponsive to permanent income shocks. 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 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.[39] 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. 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. Third, the institutional structure of agricultural lending in India complements the lack of a supply-side response to a permanent income shock. 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.

[38] However, we note that inquiries are an equilibrium outcome which may be influenced by the marketing practices of lenders and households' perceptions of lending standards, making them an imperfect proxy for demand. Additionally, we only have the data on inquiries and not the data on applications. Mishra, Prabhala and Rajan (2021) note that inquiries may understate applications, especially for state owned banks. 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.

[39] 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.

6.2.3 Role of Trust in Government Commitment

The policy's effect in stimulating credit demand crucially depends on the expectations of the treatment group that the cash transfers will continue perpetually and protect against future risk (Bianchi and Bobba (2013), Banerjee et al. (2020*b*)). 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 2014 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.

We augment the specification employed in section 5.5 to include a triple interaction term of BJP vote share, treatment, and post. Table 14 presents the results. The coefficient of interest is positive and statistically significant. Economically, the estimates indicate that a ten percentage-point increase in BJP vote share is associated with a 0.3% increase in the probability of a new loan, 0.3% increase in the number of loans, and 0.5% increase in the loan amount over the sample average. Overall, the total treatment effect increases with BJP vote share and is economically small when the BJP vote share is zero.

The monotonic increase in the treatment effect can be interpreted to be driven by higher demand under the assumption that the credit supply is based on the centralized policy at the bank level. Conversely, credit demand based on the ability of these transfers to protect against future risk is decentralized and a function of granular-level trust in the government commitment. Appendix Figure F.1 shows that there is no economic relationship between pre-policy lending and the 2014 BJP vote share, validating the assumption that credit supply does not vary with BJP vote share. We provide additional support for this assumption by examining the heterogeneity in the policy's effect on the interest rates of new loans for the treatment group. Column 1 of Appendix Table F.6 presents the results from the DID analysis on the interest rates of new loans and finds no statistically or economically significant variation in the treatment effect by BJP vote share.

This result indicates that the ability of guaranteed income to protect against future risk is a crucial driver of credit demand and complements the results of Bianchi and Bobba (2013). Moreover, this result adds to the burgeoning literature examining the role of human frictions in the transmission of fiscal policy (Francesco et al. (2021)).

6.2.4 Role of Risk

This section examines the heterogeneity in policy's effect on credit market outcomes based on the rainfall risk faced by farmers. We hypothesize that the credit demand effect due to the policy is likely to be higher when farmers face greater risk. The intuition behind this test is that the negative covariance between marginal returns to investment and marginal utility of consumption is likely to attenuate credit demand when the likelihood of adverse shocks is high. In other words, farmers sacrifice profitable investment opportunities when faced with higher risk. Thus, the marginal benefit of an increased safety net is likely to be greater when farmers face higher risk, thereby increasing credit demand. We focus on monsoon rainfall risk for two reasons. First, 60% of agricultural land is rainfall dependent and monsoons account for nearly 80% of the rainfall in India (Ahmad et al. (2017)). Second, poor rainfall affects all farmers in a local area, limiting risk-sharing between neighbors (Townsend (1994)).

We begin by defining the rainfall risk faced by each ZIP code. We compute ZIP code level rainfall as the monthly average of the precipitation levels of each 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.[40] ZIP code-year observations with positive z-scores are coded as zero, i.e., no drought, and negative z-scores are coded as one, i.e., below-average rainfall. We use the average value of our drought measure from 2014 through 2017 to compute the probability of drought for each ZIP code. ZIP codes with the above- and below-median probability of drought are coded as high- and low-risk areas, respectively. Lastly, we combine this dataset with the loan-level dataset to examine the heterogeneity in the treatment effect by rainfall risk.

Figure 8 presents the heterogeneity in the treatment effect on credit market outcomes by rainfall risk. We estimate the regression specification employed in section 5.5 separately for ZIP codes with high and low rainfall risk. Figures 8a reports the policy's effect on the extensive margin of credit outcomes – the probability of a new loan. The treatment group experiences a 15.32% increase in the probability of a new loan relative to the control group, after the policy, in high-risk areas. In comparison, the treatment effect in low-risk areas is 4.12%. Figure 8b and 8c report the policy's effect on the intensive margin of credit outcomes – the number of new loans and loan amount – for ZIP codes with high and low rainfall risk. The treatment group experiences a 15.01% increase in the number of loans over the sample average in high-risk areas as opposed to an increase of 4.54% in low-risk areas. Similarly, the treatment group experiences a 14.16% increase in loan amount over the sample average in high-risk areas. In comparison, the treatment effect in low-risk areas is 11.48%. All estimates for the two sub-samples are statistically different from each other. Overall, the results imply that the treatment effect on borrowing is higher in areas with high 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 interest rates. Column 2 of Appendix Table F.6 presents the results from the DID analysis on interest rates of new loans. We find no statistically or economically significant variation in the treatment effect on interest rates 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.[41]

[40] India receives 90% of its annual rainfall within the monsoon months of June, July, August, and September.

[41] 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), Mobarak and Rosenzweig (2013)).

6.2.5 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.

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 (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 percent. Using primary data from India, Cole, Giné and Vickery (2017) document that farmers do view basis risk as a significant drawback of an insurance product.

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. We define ZIP code-level basis risk as one minus the regression R^2. Appendix Figure F.2 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 documented in Mobarak and Rosenzweig (2012) and Cole, Giné and Vickery (2017).

Figure 9 presents the heterogeneity in treatment effect on credit market outcomes by basis risk. We separately estimate the regression specification employed in section 5.5 for ZIP codes with high and low basis risk. Figure 9a reports the policy's effect on the extensive margin of credit outcomes – the probability of a new loan – for ZIP codes with high and low basis risk. Figures 9b and 9c report the policy's effect on the intensive margin – the number of new loans and loan amount – for ZIP codes with high and low basis risk. Overall, the results indicate the treatment effect on borrowing is higher in areas with high basis risk. We interpret the relative increase in borrowing in high basis risk areas to be driven by demand. We support this interpretation by documenting no statistically or economically significant heterogeneity in the interest rate response to the policy by basis risk (see Column 3 of Appendix Table F.6). The results imply the relative impact of safety nets is higher in areas where insurance cannot effectively provide safety nets. Therefore, the results speak directly to the underlying assumption that farmers are ex-ante constrained by uninsured risk and the safety nets provided by guaranteed income can dampen the effect of uninsured risk on credit demand.

6.2.6 Effect of the Policy on Hedging Activity

This section examines the policy's effect on hedging activity in farming. Karlan et al. (2014) show that an insurance effect in the presence of imperfect risk markets can generate a negative impact on hedging activity. Traditional agriculture employs several risk management strategies to offset losses due to idiosyncratic shocks. One such hedging activity is mixed farming. Mixed farming is less risky relative to monoculture as the former allows the farmer to diversify away crop-specific idiosyncratic risk. Appendix Table F.7 reports the policy's effect on several measures of agricultural diversification. The estimate of interest is negative and indicates a decline in agricultural diversification after the policy. Specifically, a 1% increase in the number of PMKSN beneficiaries reduces agricultural diversification by 1.4-1.9% at the district-level. Another risk-mitigation strategy that farmers employ includes growing more subsistence crops instead of cash crops, as the former is less affected by erratic rainfall. 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 find similar effects of the policy, wherein districts with a greater number of PMKSN beneficiaries have a greater cultivated area under cash crops after the policy (see Appendix table F.8). Hence, following Karlan et al. (2014), we interpret the decline in hedging activity to imply that the guaranteed income increases down-side risk protections.

6.3 Does the policy really create a safety net?

The key hypothesis of this paper is that guaranteed income creates a safety net that increases credit demand and, consequently, capital and income. This hypothesis is motivated by the formal argument presented in Dercon and Christiaensen (2011). The underinvestment problem arises because the marginal return to risky investment and the marginal utility of consumption can move in the opposite direction after a risk-averse entrepreneur is hit by a negative shock. In other words, in bad states of the world the covariance between marginal returns and marginal utility is negative, when liquidity constraint is likely to bind. The problem of negative covariance is made worse when investment is financed using debt, as debt contracts impose a large cost of financial distress on the borrower when she is unable to pay.[42] As a result, it is optimal to reduce demand for credit to finance investment in a risky economic activity. We argue that guaranteed income reduces the magnitude of the covariance by mitigating fluctuations in consumption and increasing loan repayment ability during bad states of the world. This section provides a direct test of this hypothesis.

We test this hypothesis by examining the policy's effect on consumption fluctuations and default during bad states of the world, such as droughts. We define drought by computing the deviation of the monsoon rainfall in a ZIP code from its historical average and code all ZIP codes with negative deviation as having a drought. We focus on droughts for two reasons.

[42] The cost of financial distress includes future exclusion from credit markets (Garmaise and Natividad (2017)) and other economic prospects (Bos, Breza and Liberman (2018), Herkenhoff, Phillips and Cohen-Cole (2021), Cahn, Girotti and Landier (2021)) as well as social stigma (Gross and Souleles (2002)) and other fixed costs (Livshits, MacGee and Tertilt (2010)).

First, agriculture in India is highly dependent on monsoon rainfall. Second, poor rainfall affects all farmers in a local area, limiting risk-sharing between neighbors. We examine the safety net hypothesis of guaranteed income by estimating the following regression specification:

$$\begin{aligned} y_{i,t} = &\beta_1 \cdot Treatment_i \times Post_t \times Non-Drought_t + \beta_2 \cdot Treatment_i \times Post_t \times Drought_t \\ &+ \beta_3 \cdot Treatment_i \times Drought_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

where, $y_{i,t}$ is the variable of interest for farmer i at month t residing in ZIP code z. Table 15 reports the results from the estimation of equation 7 for consumption and default as dependent variables in columns 1 and 2, respectively. The estimate of interest in columns 1 and 2 is β_2, the coefficient associated with the triple interaction terms of treatment, post-policy, and drought.

The estimate of β_2 is positive and statistically significant in column 1, indicating that the treatment group's consumption relative to the control group is 7.05% higher during droughts in the post-policy period compared to droughts in the pre-policy period. The higher relative consumption of the treatment group is not driven by systematic differences in the response of the two groups to droughts as evidenced by the economically small and statistically insignificant coefficient on the interaction term of treatment and drought. The estimate of β_2 is economically significant since droughts are associated with an 8.3% decline in consumption in the pre-policy period (see Appendix Table F.9). While the estimate of β_2 is smaller in magnitude than the estimate of β_1, the f-test on the equality of the two estimates fails to reject the null that the two estimates are statistically equivalent. Therefore, the results reported in column 1 suggests that the policy allows the treatment group to mitigate consumption fluctuations across different states of the world. Additionally, the estimate of β_2 indicates that guaranteed income cushions against 85% of consumption decline experienced by households during periods of droughts.

Similarly, column 2 finds that the probability of default on KCCs decreases by 1.4% for the treatment group following the policy. Moreover, the decline in default is economically and statistically significant during normal times, as well as during periods of droughts. The f-test indicates that the estimates of β_1 and β_2 are statistically equivalent, suggesting that guaranteed income improves the repayment ability of the treatment group across different states of the world. As before, lower post-policy likelihood of default for the treatment group is not driven by systematic differences in the response of the two groups to droughts as evidenced by the economically small and statistically insignificant coefficient on the interaction term of treatment and drought. The result on reduction in default is consistent with the results presented in section 6.1 that document an increase in credit to high-quality farmers as indicated by an ex-ante quality measure: credit score. An important implication of this result is that greater credit demand induced by guaranteed income does not lead to greater default. Hence, guaranteed income programs seem to be a more feasible solution for increasing credit demand relative to other interventions, that directly reduce the cost of financial distress on borrowers as in Field et al. (2013), and result in greater default.

6.3.1 Effect of the policy on savings

A key assumption of the proposed hypothesis is that the policy allows farmers to mitigate negative effects of adverse shocks. This section directly tests the assumption by examining the savings behavior of the treatment across different states of the world. Column 3 of Table 15 estimates the policy's effect on the savings of the treatment group. Results indicate an average 27.7% increase in savings of the treatment group, amounting to ₹1,055. However, the increase in savings differ substantially across the states of the world. Farmers facing a drought experience a 13.4% increase in savings as opposed to a 45.5% increase in savings for farmers facing no droughts. The difference in savings across states of the world corresponds to ₹1,222. From an accounting perspective, this difference in savings across farmers experiencing droughts and no droughts is sufficient to match the increased consumption of ₹817 for the treatment farmers experiencing droughts as well as additional ₹405 to meet minimum debt service requirements. Therefore, we argue that guaranteed income reduces the covariance term by mitigating the effect of adverse shocks on consumption fluctuations and debt repayment ability. In other words, guaranteed income increases credit demand by increasing financial resilience.

6.3.2 Effect of the Policy on Financial Conditions and Extreme Distress

This section provides direct evidence of the policy's effect on financial constraints and extreme distress. Using the Aspirations survey data collected by CMIE, we show that the treatment households report having better financial conditions today relative to last year and expect better financial conditions next year as well (Appendix Table F.10). Additionally, using detailed data on suicides from the state of Karnataka, we document that the incidence of farmer suicides reduces after the policy, indicating a reduction in extreme stress (Appendix Table F.11). Specifically, the number of farmer suicides reduced by 6.63% over the sample mean after the policy. Moreover, using detailed closing reports filed by local police on farmer suicides, we document that the reduction in farmer suicides is driven by reduction in incidence of suicides due to indebtedness (Appendix Table F.12). The results indicate the effectiveness of the safety net provided by guaranteed income in improving the current and expected financial conditions, as well as extreme stress.

7 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. We find that unconditional and perpetual cash transfers increase income by 10%. Specifically, a promise of an additional \$1 in guaranteed income generates an additional \$1.7 of income from work. The increase in income is driven by a shift towards a more capital-intensive mode of production financed using credit. Our conservative estimate of the policy's effect on capital indicates that it increases by 10.2%. The estimate implies that an additional \$1 in guaranteed income increases capital by \$7.75. This increase in capital is equivalent to 45% of the perpetuity value of an annual stream of \$1 in guaranteed income discounted at 5.8%. We refer to this estimate as a conservative estimate because we can observe only a fraction of household assets in our data. Our estimates of the capital elasticity of income and the marginal revenue product of capital are 0.80 and 0.22, respectively. These estimates are likely to be an upper bound as our data allows us to observe large fixed assets that are likely to be more productive. On the policy's effect on credit, we estimate that additional $1 in guaranteed income increases term loans by $11.2 and credit card utilization by $4.5. This implies a total increase in credit of $15.7, which is equivalent to 91% 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 $14-$18.5, equivalent to 81%-107% of the perpetuity value of guaranteed income.

The magnitude of effect on credit and investment is surprisingly large. So, how can such a small transfer each period have such a sizeable effect on investment? Dercon and Christiaensen (2011) show that 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 highlight two caveats of our findings. First, 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 6.1 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. Second, our results should not be taken to imply that risk averse entrepreneurs who forgo profitable opportunities are to be blamed for their under-investment problem or lack of growth. Our results do not suggest that underinvestment is a result of a behavioral bias, but a choice that is not freely made and is driven by binding consumption or liquidity constraints and uninsured risk.

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.

We compare our results with Egger et al. (2021) 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. (2021). 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. (2021) 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.[43] 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. This can be a fruitful area of research. Banerjee et al. (2020*b*) already make some progress on this front and we seek to take up this question in future research.

[43]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.

8 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 is 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, when the marginal utility consumption is high and the marginal returns on risky investment is low. Therefore, guaranteed income increases credit demand and investment by increasing financial resilience and the willingness to bear risk.

Our results have implications for both policymakers and academics. First, our results highlight the role played by the cost of the financial distress associated with traditional debt contracts in generating the under-investment problem among small entrepreneurs. Specifically, our results suggest the importance of safety nets in attenuating the adverse effects of the cost of financial distress on investment. 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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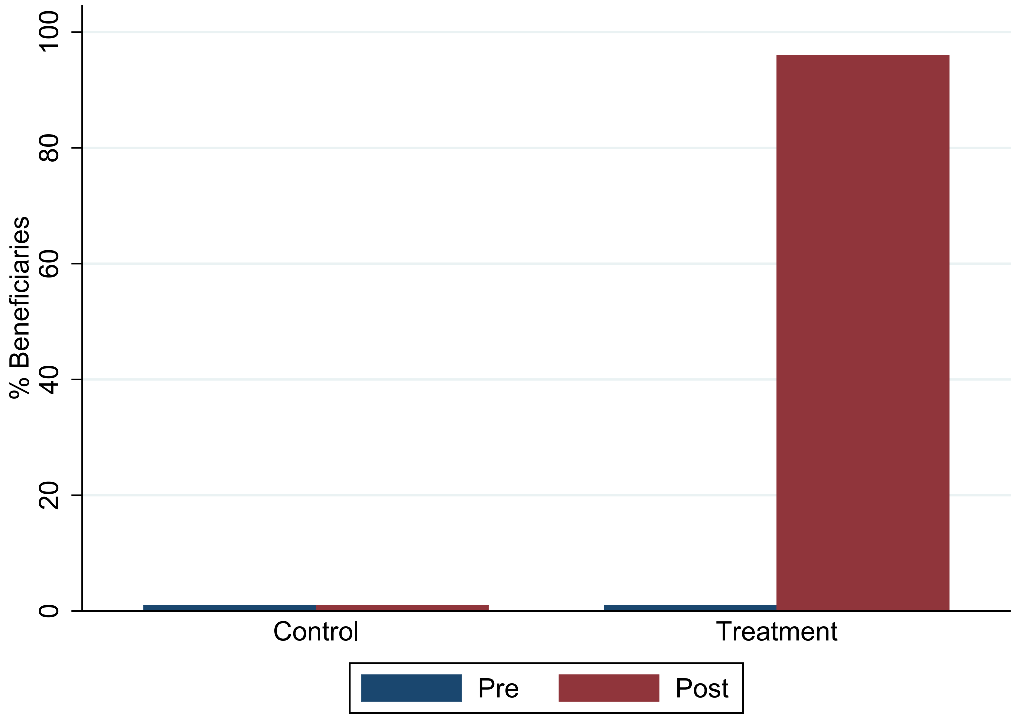
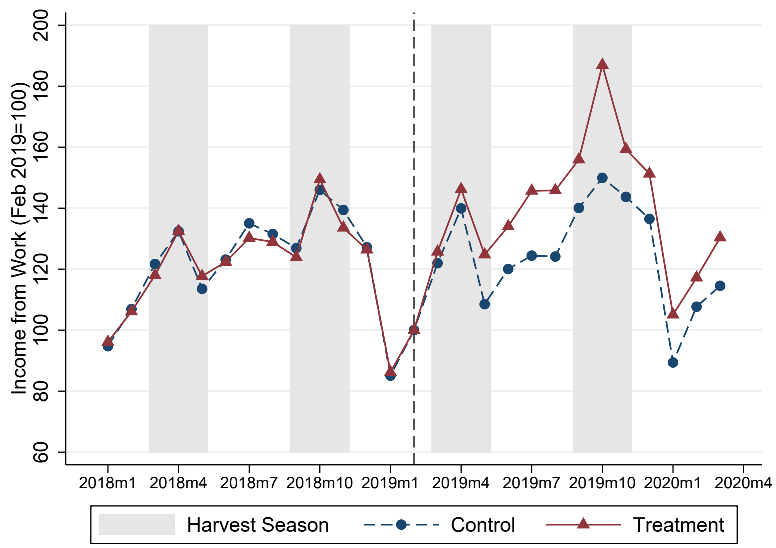
Figure 1: First-Stage Relevance of the Policy

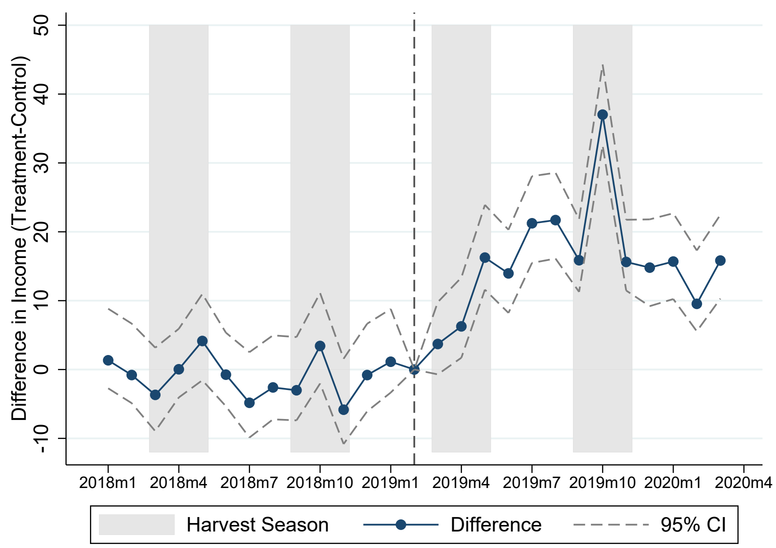


The figure presents the evaluation of the first-stage relevance of the policy, i.e., the treatment group received these cash transfers whereas the control group did not. Cash transfers under PMKSN were made in three installments of ₹2,000 on fixed dates. We combine the amount and the dates of the transfer provided by the Government of India with our bank data to identify if the treatment group received transfers. We look between -5 and +5 days of the scheduled transfer to identify transfers. The treatment group refers to the landowning farmers, and the control group refers to the non-landowning farmers. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 until March 2020. Pre-period refers to the sample period before the policy, and the post-period refers to the sample period after the policy. The policy was launched in March 2019.

Figure 2: Univariate Results: Effect of the policy on Income from Work



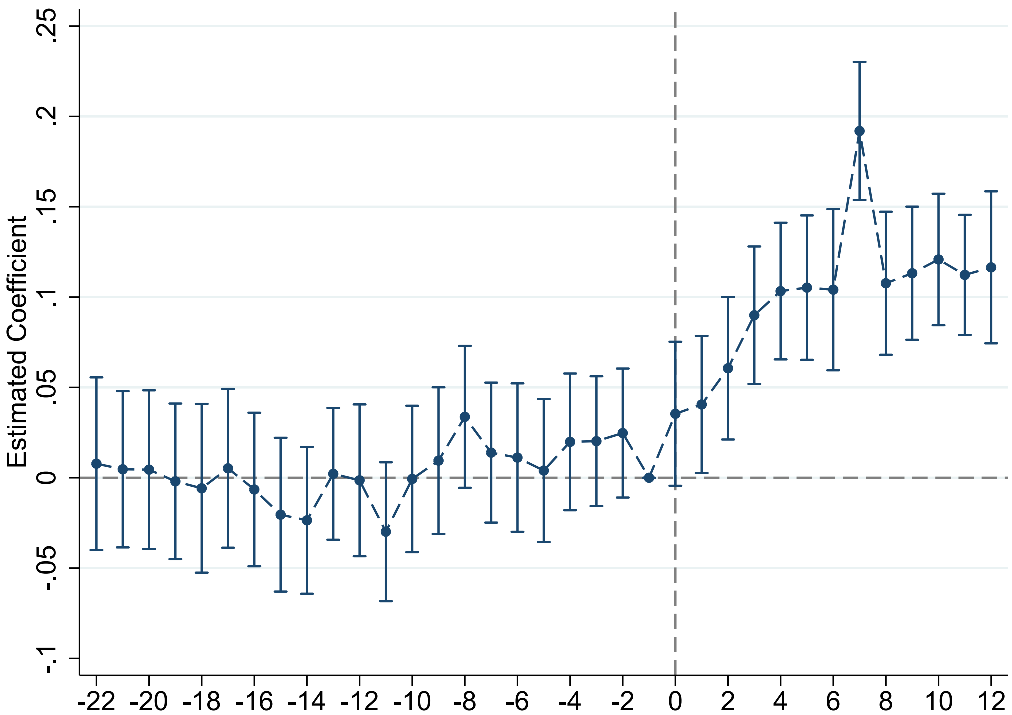
(a) Income from Work



(b) Difference in Income (Treatment-Control)

The figure presents the effect of the policy on farmer's income from work. Panel 2a reports the evolution of the average income from work for the treatment and control groups over time. Panel 2b reports the evolution of the average difference in the income from work for the treatment and control groups over time, along with the 95% confidence intervals. 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 market investments, and the PMKSN transfers. Income from work is standardized to a value of 100 for the treatment and the control groups in February 2019. The dashed vertical line denotes one month before the policy's launch in March 2019. The sample comes from the transaction-level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through March 2020. The gray bars denote the harvest seasons. Each year has two harvest seasons – March (Rabi season) and October (Kharif season). The treatment group refers to landowning farmers and the control group refers to non-landowning farmers.

Figure 3: Dynamic Treatment Effects: Effect of the policy on Income from Work

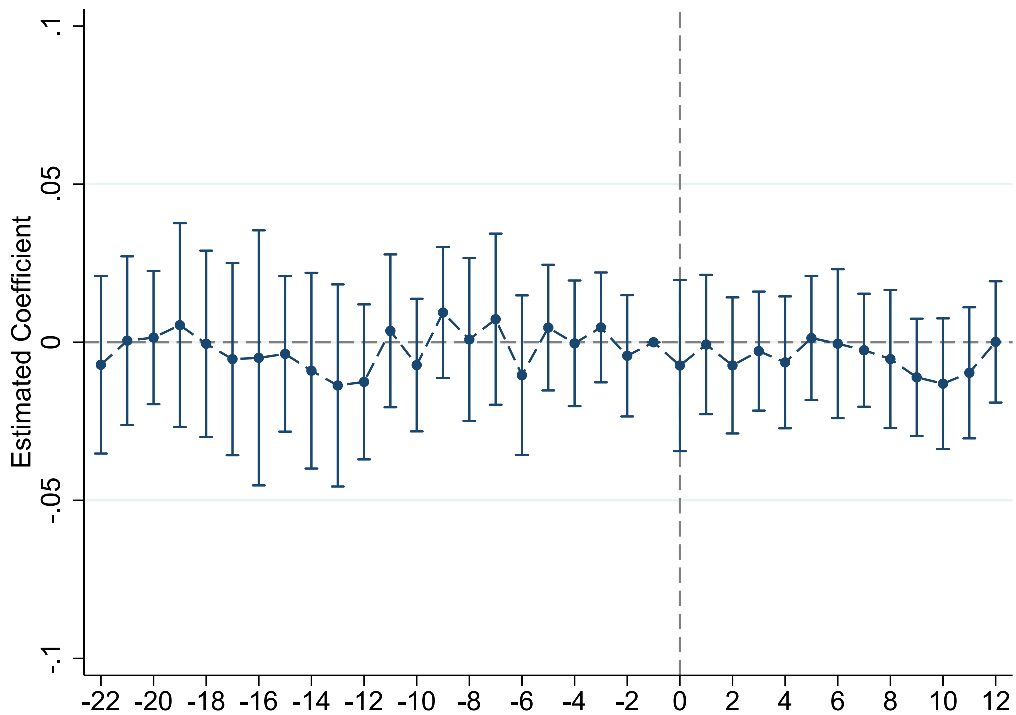


The figure presents the estimates of $\{\beta_k\}$ based on the following dynamic specification:

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \sum_{k=-22,k\neq-1}^{k=12} \beta_k \cdot Treatment_i \times 1(t=k) + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the income from work measured for farmer i at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the income from work during the pre-policy period. $Treatment_i$ takes a value of one for landowning farmers and a value of zero for non-landowning farmers. $1(t=k)$ is a time indicator, with $t=-1$ being the omitted month. $t=0$ denotes March 2019. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ month fixed effects, where z refers to the ZIP code where farmer i operates. β_k refers to the treatment effect estimated at $t=k$ relative to the treatment effect at $t=-1$. The sample comes from the transaction-level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2017 through March 2020. The key dependent 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. Capped spikes drawn with the estimated coefficients $\{\beta_k\}$ indicate 95% confidence intervals obtained from standard errors clustered at the ZIP code level.

Figure 4: Falsification Test: Treatment Effect in the State of West Bengal

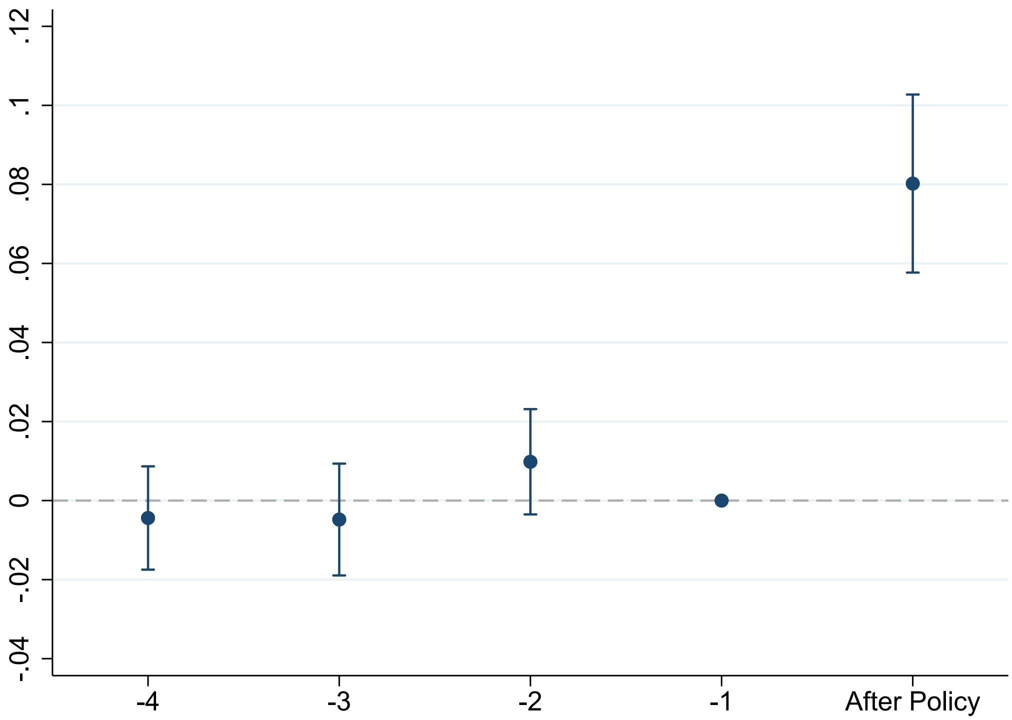


The figure presents the estimates of $\{\beta_k\}$ based on the following dynamic specification:

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \sum_{k=-22,k\neq-1}^{k=12} \beta_k \cdot Treatment_i \times 1(t = k) + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the income from work measured for farmer i at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the income from work during the pre-policy period. $Treatment_i$ takes a value of one for landowning farmers and a value of zero for non-landowning farmers. $1(t = k)$ is a time indicator, with $t = -1$ being the omitted month. $t = 0$ denotes March 2019. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP × month fixed effects, where z refers to the ZIP code where farmer i operates. β_k refers to the treatment effect estimated at $t = k$ relative to the treatment effect at $t = -1$. The sample comes from the transaction-level bank data and includes farmers in the states of West Bengal from March 2017 through March 2020. The key dependent 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. Capped spikes drawn with the estimated coefficients $\{\beta_k\}$ indicate 95% confidence intervals obtained from standard errors clustered at the ZIP code level.

Figure 5: Dynamic Treatment Effects: Effect of the policy on Agricultural Yields

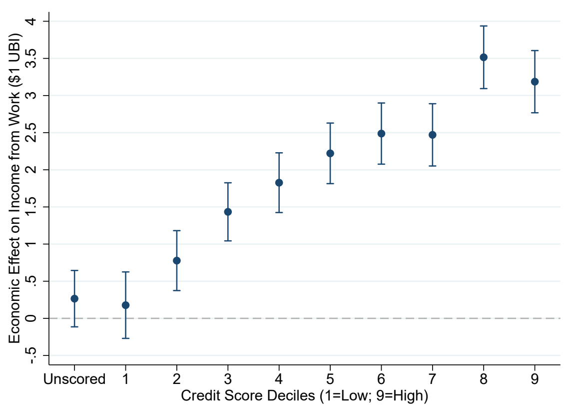


The figure presents the estimates of $\{\beta_k\}$ based on the following dynamic specification:

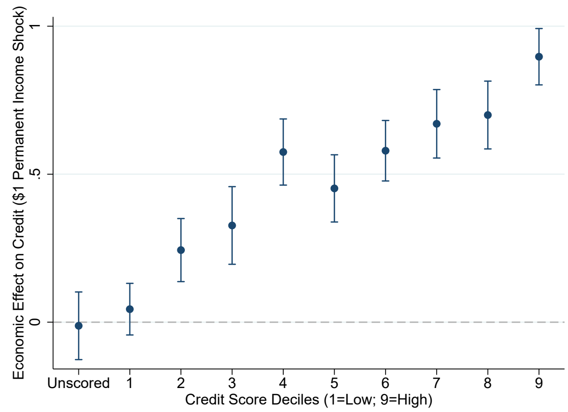
$$LN(y_{z,t}) = \sum_{k=-4,k\neq -1}^{k=\text{After Policy}} \beta_k \cdot LN(\#Beneficiaries_z) \times 1(t=k) + \theta_{z,s} + \theta_{s,t} + \varepsilon_{z,t}$$

where, $LN(y_{z,t})$ denotes the natural logarithm of agricultural yield in ZIP code z at time t. t refers to season-year as a unit of time. s refers to the cropping season. There are two cropping seasons in India – Rabi and Kharif. Each season-year includes Kharif season from year y and the Rabi season from year $y+1$. $LN(\#Beneficiaries_z)$ denotes the natural logarithm of number of PMKSN beneficiaries in ZIP code z. $1(t=k)$ is a time indicator, with $t=-1$ being the omitted year. t = After Policy denotes agricultural yield in the year 2019 after March. $\theta_{z,s}$ denotes ZIP code $\times$ season fixed effects. $\theta_{s,t}$ denotes season $\times$ year fixed effects. The data spans all states of India from January 2015 through December 2019. The states of West Bengal, Jammu and Kashmir, and the north-eastern states are excluded from the analysis. The data on yields comes from the remote-sensing satellite Landsat 8. We construct agricultural yield by subtracting the early cropping season value (the mean of the first six 8-day composites) from the maximum growing season value. The data on the number of beneficiaries comes from the Government of India. The estimate is standardized to report the effect in terms of a 10% increase in the number of beneficiaries. β_k refers to the treatment effect estimated at $t=k$ relative to the treatment effect at $t=-1$. Capped spikes drawn with the estimated coefficients $\{\beta_k\}$ indicate 95% confidence intervals obtained from standard errors clustered at the ZIP code level.

Figure 6: Effect of the policy on Income from Work & Credit by Credit Scores



(a) Effect on Income



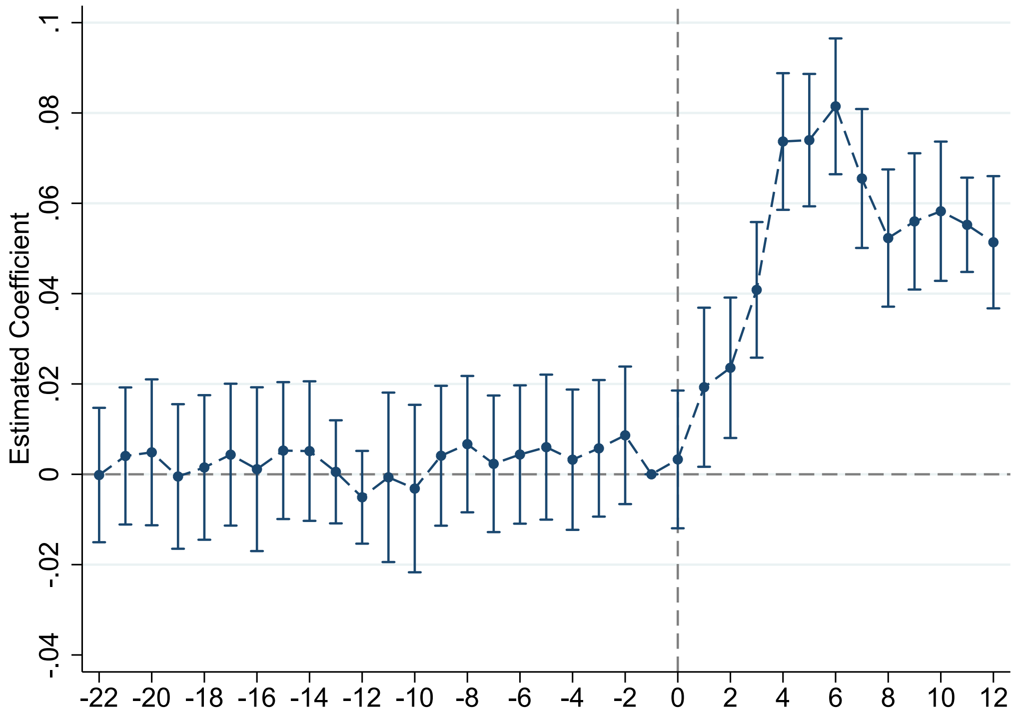
(b) Effect on Credit

The figure presents the estimates of the policy's economic effect on income from work and credit amount implied by the coefficient $\{\beta\}$ based on 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 income from work (Panel 6a) and loan amount (Panel 6b) measured for farmer i at time t. The unit of time is month in Panel 6a and the pre- and post-policy period in Panel 6b. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Avg(y_{Pre})$ denotes the sample average of the income from work (Panel 6a) and loan amount (Panel 6b) 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 following March 2019. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP × time fixed effects, where z refers to the ZIP code where farmer i operates. We divide our sample into ten sub-groups based on farmers' credit score before the policy. The first sub-group includes farmers with no credit scores. The second sub-group includes the farmers with the lowest credit scores, and the tenth sub-group includes farmers with the highest credit scores. We estimate the specification separately for each sub-group, each with different $Avg(y_{Pre})$, and report the economic effect. Economic effect is computed by multiplying the estimate with average annual income before the policy and dividing the product by 6000 in Panel 6a. Economic effect is computed by multiplying the estimate with average loan amount before the policy and dividing the product by the present discounted value of ₹6000 at 5.8% annual risk-free rate in Panel 6b. The sample used in Panel 6a comes from the transaction-level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through March 2020. The key dependent variable income from work is calculated as the sum of all cash inflows in the account after subtracting the inflows due to disbursal of loans, maturity of financial market investments, and PMKSN transfers. The sample used in Panel 6b comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. This sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. The key dependent variable is the loan amount associated with new loans. Capped spikes drawn with the estimated economic effects indicate 95% confidence intervals obtained from standard errors clustered at the ZIP code level.

Figure 7: Dynamic Treatment Effects: Effect of the policy on Utilization Rates of Kisan Credit Cards

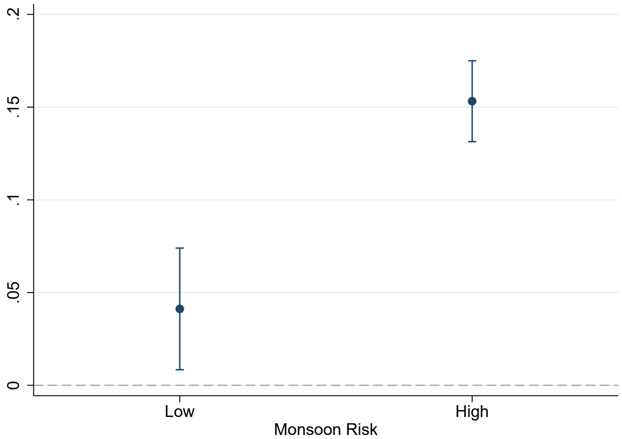


The figure presents the estimates of $\{\beta_k\}$ based on the following dynamic specification:

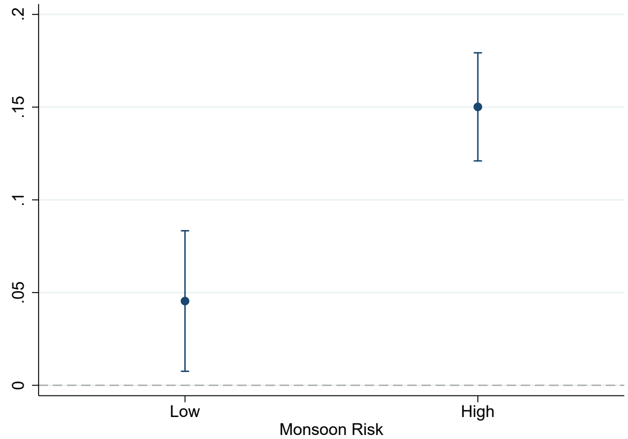
$$UR_{i,t} = \sum_{k=-22,k\neq-1}^{k=12} \beta_k \cdot Treatment_i \times 1(t = k) + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where, $UR_{i,t}$ denotes the utilization rate on kisan credit card for farmer i at time (month) t. $Treatment_i$ takes a value of one for landowning farmers and a value of zero for non-landowning farmers. $1(t = k)$ is a time indicator, with $t = -1$ being the omitted month. $t = 0$ denotes March 2019. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ month fixed effects, where z refers to the ZIP code where farmer i operates. β_k refers to the treatment effect estimated at $t = k$ relative to the treatment effect at $t = -1$. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 until February 2020. The sample only consists of farmers with outstanding kisan credit cards before March of 2019 with at least one year remaining term. Capped spikes drawn with the estimated coefficients $\{\beta_k\}$ indicate 95% confidence intervals obtained from standard errors clustered at the ZIP code level.

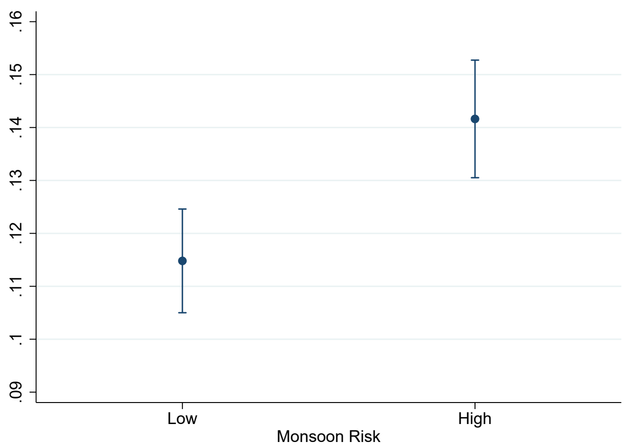
Figure 8: Heterogeneous Treatment Effect on Borrowing by Rainfall Risk



(a) Probability of Loan



(b) # Loans



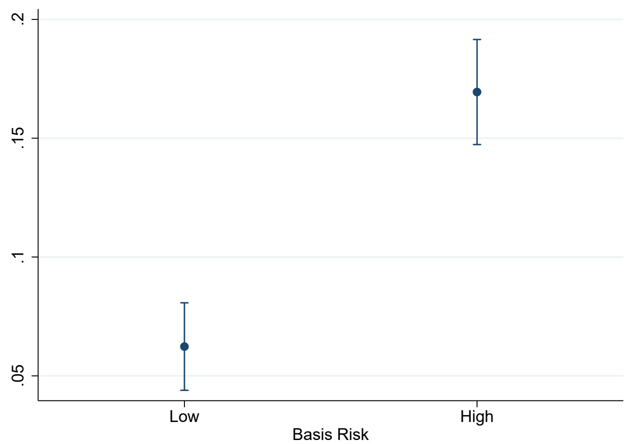
(c) Loan Amount

The figure presents the heterogeneity in the treatment effect on borrowing according to the risk faced by farmers. The figure plots the point estimate associated with the interaction term of treatment and post according to the following specification estimated separately for two sub-samples of ZIP codes with high and low rainfall risk:

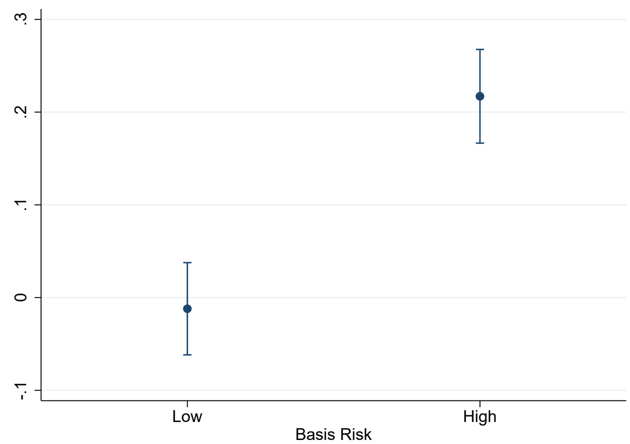
$$\frac{y_{i,p}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_p + \theta_i + \theta_{z,p} + \varepsilon_{i,t}$$

where $y_{i,p}$ denotes the dependent variable of interest measured for farmer i at time p. There are only two time-periods in the analysis – pre-policy period and the post-policy period. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Avg(y_{Pre})$ 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. $Post_p$ takes a value of one for the post policy period defined as the twelve months from March 2019. θ_i denotes farmer fixed effects. $\theta_{z,p}$ denotes ZIP $\times$ post 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 sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. Panel 8a 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. Panel 8b uses the number of new loans as the dependent variable divided by the pre-period sample average. Panel 8c uses the total loan amount as the dependent variable divided by the pre-period sample average. We compute ZIP code level rainfall as the monthly average of the precipitation levels of each 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 rainfall periods from 2014 through 2017. ZIP code-year observations with positive z-scores are coded as zero, i.e. no drought, and negative z-scores are coded as one, i.e. below average rainfall. We use the average of the drought measure from 2014 through 2017 to compute the probability of drought for each ZIP code. ZIP codes with above- and below-median probability of drought are coded as high and low risk areas, respectively. Capped spikes drawn with the estimated economic effects indicate 95% confidence intervals obtained from standard errors clustered at the ZIP code level.

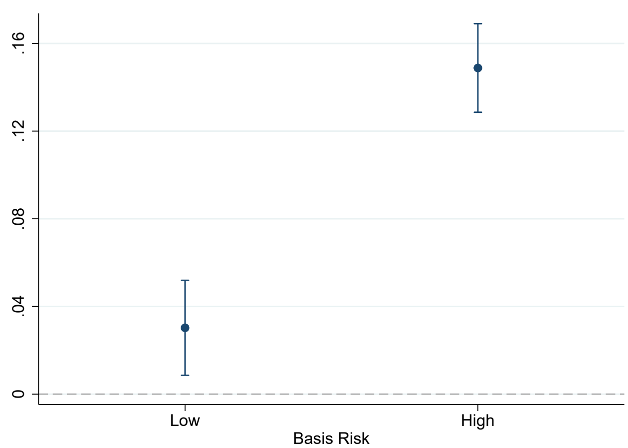
Figure 9: Heterogeneous Treatment Effect on Borrowings by Basis Risk



(a) Probability of Loan



(b) # Loans



(c) Loan Amount

The figure presents the heterogeneity in the treatment effect on borrowings according to the basis risk faced by the farmers in rainfall insurance contracts. The figure plots the point estimate associated with the interaction term of treatment and post according to the following specification estimated separately for two sub-samples of ZIP codes with high and low basis risk:

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

where $y_{i,p}$ denotes the dependent variable of interest measured for farmer i at time p. There are only two time-periods in the analysis – pre-policy period and the post-policy period. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Avg(y_{Pre})$ 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. $Post_p$ takes a value of one for the post-policy period defined as the twelve months from March 2019. θ_i denotes farmer fixed effects. $\theta_{z,p}$ denotes ZIP $\times$ post 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 sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. Panel 9a 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. Panel 9b uses the number of new loans as the dependent variable divided by the pre-period sample average. Panel 9c uses the total loan amount as the dependent variable divided by the pre-period sample average. 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. ZIP codes with above- and below-median basis risk are coded as high and low basis risk areas, respectively. Capped spikes drawn with the estimated economic effects indicate 95% confidence intervals obtained from standard errors clustered at the ZIP code level.

Table 1: Systematic Differences across Treatment and Control groups

	Sample Average	Group-wise Average		Difference (T-C) *unconditional*		Difference (T-C) *within ZIP code*	
		Control (C)	Treatment (T)	Magnitude	t-stat	Magnitude	t-stat
Income	8,334.24	9,665.96	8,271.60	-1394.36***	3.23	-752.91	1.47
Savings	3,803.82	6,011.95	3,699.26	-2,312.69***	10.36	-569.37**	2.35
Expenditure	11,578.78	13,489.92	11,488.25	-2,001.67***	2.90	-1,348.14	1.54
Credit Score	524.90	526.96	524.80	-2.16	0.50	0.51	0.11
Interest Rate	11.08	10.55	11.10	0.55***	7.90	-0.18***	4.73
Frac. Default	0.297	0.300	0.297	-0.003	0.21	0.035***	2.88
KCC Credit Limit	496,862.30	424,171.40	500,241.80	76,070.41***	4.97	-19,054.52	1.01
Frac. CC User	0.007	0.015	0.007	-0.008***	3.71	-0.002	0.69
Frac. Oth Inv	0.004	0.016	0.003	-0.013***	4.27	-0.004*	1.66
Account Age	5.31	5.83	5.29	-0.54***	6.50	-1.94***	29.35
# Trnx per day	0.022	0.029	0.021	-0.008***	6.20	-0.006***	3.44
Farmer Age	45.23	44.07	45.29	1.22***	4.59	-0.43	1.28
Frac. Female	0.056	0.027	0.058	0.031***	9.63	0.015***	2.64

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, Karnataka, and Telangana. 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 stock markets. Column 1 reports variable names, column 2 reports the overall monthly sample average of the variables. Columns 3 and 4 report the sample average of the control and treatment groups, respectively. Columns 5 and 6 report the unconditional difference of averages across the treatment and control groups and the associated t-statistics, respectively. Columns 7 and 8 report the within-ZIP difference of averages across the treatment and control groups and the associated t-statistics, respectively. T-statistics (T-stats) are computed using Standard errors clustered at the ZIP code level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Farmer Level Analysis: Effect of the Policy on Income from Work

Dep Var: Income Growth	(1)	(2)	(3)	(4)
Treatment	0.1012***	0.1044***	0.1014***	0.1031***
	(0.0185)	(0.0244)	(0.0305)	(0.0338)
State FE		Yes		
District FE			Yes	
ZIP Code FE				Yes
# Obs	86,873	86,873	86,873	86,873
R^2	0.0007	0.0185	0.0278	0.0890
Economic Effect (in ₹)	10,121	10,441	10,141	10,311
Economic Effect ($1 UBI)	$1.69	$1.74	$1.69	$1.72

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:

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

where $y_{i,Pre}$, and $y_{i,Post}$ denote the sum of the income from work for farmer i over the 12 months before and after the policy, respectively. $Treatment_i$ is an indicator variable taking the value of one for landowning farmers and zero for non-landowning farmers. The coefficient β on $Treatment_i$ provides the average treatment effect of the policy. θ_z denotes ZIP code fixed effects. Column 1 reports the estimate of β without any fixed effects. Columns 2, 3, and 4 report the estimate of β with state, district, and ZIP code fixed effects, respectively. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. The key dependent 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. 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 3: Differences-in-Differences Analysis: Effect of the Policy on Income from Work

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)	(5)
Treatment X Post	0.0928***	0.0947***	0.1088**	0.1229***	0.1261***
	(0.0313)	(0.0311)	(0.0241)	(0.0469)	(0.0119)
Treatment	-0.1673***	-0.1670***	-0.0286		
	(0.0223)	(0.0218)	(0.0200)		
Post	-0.0012				
	(0.0303)				
Month FE		Yes		Yes	
Farmer FE				Yes	Yes
ZIP Code X Month FE			Yes		Yes
# Obs	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451
R^2	0.0002	0.0035	0.0605	0.2483	0.2705
Economic Effect (in ₹)	9,276	9,468	10,884	12,228	12,612
Economic Effect ($1 UBI)	$1.55	$1.58	$1.81	$2.05	$2.10

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. $Treatment_i$ 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. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ 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 equation 2 in column 5. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. The key dependent 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 market investments, and PMKSN transfers. 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 4: Evidence from Border Regression Discontinuity Design

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)
Treatment X Complier X Post	0.1627**	0.1627**	0.1626**	0.1959**
	(0.0742)	(0.0747)	(0.0748)	(0.0956)
Household FE	Yes	Yes	Yes	Yes
District X Month FE	Yes	Yes	Yes	Yes
Treatment X Month FE	Yes	Yes	Yes	
District-Pair X Month FE		Yes	Yes	
District-Pair X Treatment FE			Yes	
District-Pair X Treatment X Month FE				Yes
# Obs	41,253	41,253	41,253	41,253
R^2	0.6306	0.6306	0.6306	0.6334

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

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

where $y_{i,t}$ denotes the dependent variable of interest measured for household i at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. $Treatment_i$ takes a value of one for 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 defined to be treatment households. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes household fixed effects. $\theta_{z,t}$ denotes district $\times$ month fixed effects, where z refers to the district where farmer i operates. $\theta_{p(z\in p),T,t}$ 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. The sample comes from the CPHS survey conducted by the CMIE across from March 2018 through February 2020. The sample employed in the analysis is shown in Appendix Figure D.1. All regressions are weighted by survey weights of each household. The key dependent variable is the reported household income from work. The key independent variable is the triple interaction term of treatment, complier and post. Complier takes a value of one for all the bordering districts in state of West Bengal, shown in navy blue in Appendix Figure D.1. Standard errors clustered at the household level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Effect of the Policy on Agricultural Production

Dep Var: LN(Yield)	(1)	(2)	(3)	(4)	(5)
LN(#Beneficiaries) X Post	0.0785***	0.0787***	0.0787***	0.0810***	0.0808***
	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0078)
LN(#Beneficiaries)	0.0139***	0.0140***	0.0140***		
	(0.0003)	(0.0003)	(0.0003)		
Post	0.0069***	-0.0126***			
	(0.0018)	(0.0018)			
Season FE		Yes			
Season X Year FE			Yes	Yes	Yes
ZIP Code FE				Yes	
ZIP Code X Season FE					Yes
# Obs	114,614	114,614	114,614	114,614	114,614
R^2	0.042	0.3986	0.404	0.7199	0.8845
Sample Mean (Y Variable)	0.168	0.168	0.168	0.168	0.168
St Dev (Y Variable)	0.156	0.156	0.156	0.156	0.156
Sample Mean (X Variable)	4,766	4,766	4,766	4,766	4,766
St Dev (X Variable)	6,701	6,701	6,701	6,701	6,701

The table estimates the elasticity of agricultural yield to change in the number of PMKSN beneficiaries at the ZIP code level according to the following specification:

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

where, $LN(y_{z,t})$ denotes the natural logarithm of agricultural yield in ZIP code z at time t. t refers to season-year as a unit of time. s refers to the cropping season. There are two cropping seasons in India – Rabi and Kharif. Each season-year includes Kharif season from year y and the Rabi season from year $y+1$. $LN(\#Beneficiaries_z)$ denotes the natural logarithm of the number of unique PMKSN beneficiaries in ZIP code z. $Post_t$ takes a value of one for months following March 2019 and zero otherwise. $\theta_{z,s}$ denotes ZIP code $\times$ season fixed effects. $\theta_{s,t}$ denotes season $\times$ year fixed effects. The data spans all states of India from January 2017 through December 2019. The states of West Bengal, Jammu and Kashmir, and the north-eastern states are excluded from the analysis. The data on yields comes from the remote-sensing satellite Landsat 8. We construct agricultural yield by subtracting the early cropping season value (the mean of the first six 8-day composites) from the maximum growing season value. The data on the number of beneficiaries comes from the Government of India. The estimate is standardized to report the effect in terms of a 10% increase in the number of beneficiaries. 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 6: Effect of the Policy on Investment: Tractors, Cattle & Two-wheelers

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1) Tractors	(2) Cattle	(3) Two-Wheelers
Treatment X Post	0.1350***	0.2679***	0.0677***
	(0.0335)	(0.0352)	(0.0109)
Household FE	Yes	Yes	Yes
District X Month FE	Yes	Yes	Yes
Education group X District FE	Yes	Yes	Yes
Education group X Month FE	Yes	Yes	Yes
Gender group X District FE	Yes	Yes	Yes
Gender group X Month FE	Yes	Yes	Yes
Age group X District FE	Yes	Yes	Yes
Age group X Month FE	Yes	Yes	Yes
HH Size group X District FE	Yes	Yes	Yes
HH Size group X Month FE	Yes	Yes	Yes
# Obs	170,163	170,163	170,163
R^2	0.8124	0.5594	0.7933
Sample Mean	0.0900	1.6155	0.7195

The table estimates the relative effect of cash transfers under PMKSN on investment for the treatment and control groups according to the following specification:

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

where $y_{i,t}$ denotes the dependent variable of interest measured for household 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 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 defined to be treatment households. $Post_t$ takes a value of one for months following March 2019. θ_i denotes household fixed effects. $\theta_{z,t}$ denotes district $\times$ month fixed effects, where z refers to the district where farmer i operates. $\Gamma_{i,t}$ denotes additional fixed effects associated with the interaction of education group, gender group, age group and household size group with district and time (month) dummies. The sample comes from the CPHS survey conducted by CMIE across all states in India from March 2018 through March 2020. The states of West Bengal, Jammu and Kashmir, and the north-eastern states are not included in the sample. All regressions are weighted by survey weights of each household. The key dependent variable is the number of tractors in column 1, the number of cattle or livestock in column 2, and the number of two-wheelers in column 3. Standard errors clustered at the district level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Quantifying the Effect of Capital on Income

	(1)	(3)
	Second-Stage	First Stage
	$\frac{Income_{i,t}}{Avg(Income_{Pre})}$	$\frac{Capital_{i,t}}{Avg(Capital_{Pre})}$
$\frac{Capital_{i,t}}{Avg(Capital_{Pre})}$	0.7995*	
	(0.4710)	
Treatment X Post		0.1020***
		(0.0201)
Household FE	Yes	Yes
District X Month FE	Yes	Yes
Education group X District FE	Yes	Yes
Education group X Month FE	Yes	Yes
Gender group X District FE	Yes	Yes
Gender group X Month FE	Yes	Yes
Age group X District FE	Yes	Yes
Age group X Month FE	Yes	Yes
HH Size group X District FE	Yes	Yes
HH Size group X Month FE	Yes	Yes
# Obs	97,609	97,609
First Stage f-statistic		25.650

This table estimates the effect of capital on income using the following 2SLS specification:

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

$$\frac{Income_{i,t}}{Avg(Income_{Pre})} = \psi \cdot \frac{\hat{Capital}_{i,t}}{Avg(Capital_{Pre})} + \theta_i + \theta_{z,t} + \Gamma_{i,t} + \mu_{i,t}$$

where $Income_{i,t}$ denotes income from agriculture measured for household i at time (month) t. $Avg(Income_{Pre})$ denotes the sample average of income from agriculture during the pre-policy period. $Capital_{i,t}$ denotes the imputed value of capital stock measured for household i at time (month) t. $Avg(Capital_{Pre})$ denotes the sample average of imputed value of capital stock 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 defined to be treatment households. $Post_t$ takes a value of one for months following March 2019. θ_i denotes household fixed effects. $\theta_{z,t}$ denotes district $\times$ month fixed effects, where z refers to the district where farmer i operates. $\Gamma_{i,t}$ denotes additional fixed effects associated with the interaction of education group, gender group, age group and household size group with district and time (month) dummies. The group definitions are adopted directly from the survey. The sample comes from the CPHS survey conducted by CMIE across all states in India from March 2018 through March 2020. The states of West Bengal, Jammu and Kashmir, and the north-eastern states are not included in the sample. All regressions are weighted by survey weights of each household. Column 1 reports the second-stage estimate and column 2 reports the first-stage estimate. Standard errors clustered at the district level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Effect of the Policy on Credit

	(1)	(2)	(3)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Treatment X Post	0.1091***	0.1295***	0.1685***
	(0.0086)	(0.0160)	(0.0101)
Farmer FE	Yes	Yes	Yes
ZIP × Post FE	Yes	Yes	Yes
# Obs	87,238	87,238	87,238
R^2	0.5256	0.6797	0.7805
Sample Mean	0.618	1.182	396,970

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:

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

where $y_{i,p}$ denotes the dependent variable of interest measured for farmer i at time p. There are only two time-periods in the analysis – pre-policy period and the post-policy period. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Avg(y_{Pre})$ 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. $Post_p$ takes a value of one for the post-policy period defined as the twelve months from March 2019. θ_i denotes farmer fixed effects. $\theta_{z,p}$ denotes ZIP × post 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 sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana 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 9: Does the New Credit Finance Consumption or Productive Capacity?

Panel A: Productive Capacity Loans			
	(1)	(2)	(3)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Treatment X Post	0.0886***	0.2169***	0.2813***
	(0.0117)	(0.0087)	(0.0145)
Farmer FE	Yes	Yes	Yes
ZIP X Post FE	Yes	Yes	Yes
# Obs	87,238	87,238	87,238
R^2	0.596	0.705	0.806
Sample Mean	0.316	0.401	245,964

Panel B: Consumption Loans			
	(1)	(2)	(3)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Treatment X Post	0.0064	0.0197	-0.026
	(0.0040)	(0.0121)	(0.0183)
Farmer FE	Yes	Yes	Yes
ZIP X Post FE	Yes	Yes	Yes
# Obs	87,238	87,238	87,238
R^2	0.527	0.608	0.636
Sample Mean	0.430	0.709	149,599

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:

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

where $y_{i,p}$ denotes the dependent variable of interest measured for farmer i at time p. There are only two time-periods in the analysis – pre-policy period and the post-policy period. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Avg(y_{Pre})$ 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. $Post_p$ takes a value of one for the post policy period defined as the twelve months from March 2019. θ_i denotes farmer fixed effects. $\theta_{z,p}$ denotes ZIP $\times$ post 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 sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana 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. Panel A uses the sample of loans used to finance productive loans. Panel B uses the sample of loans used to finance consumption. 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. 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 Income from Work by Prior Default Status

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)
Treatment X Post	0.1261***	0.1390***	0.0080
	(0.0119)	(0.0477)	(0.0080)
Farmer FE	Yes	Yes	Yes
ZIP Code X Month FE	Yes	Yes	Yes
# Obs	2,169,451	1,733,886	433,694
R^2	0.2705	0.2769	0.2712
Sample	Full	No Prior Default	Prior Default
Economic Effect (in ₹)	12,612	16,003	709
Economic Effect ($1 UBI)	2.1	2.7	0.1

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. $Treatment_i$ 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 following March 2019. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ month fixed effects, where z refers to the ZIP code where farmer i operates. 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. The sample comes from the transaction-level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. The key dependent variable income from work is calculated as the sum of all cash inflows in the account after subtracting the inflows due to disbursal of loans, maturity of financial market investments, and PMKSN transfers. 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: Quantifying the Effect of Credit on Income

	(1)	(2)
	$\frac{Income}{Avg(Income)_{Pre}}$	Income
$\frac{\text{Loan Amount}}{\text{Avg(Loan Amount)}_{Pre}}$	0.7080***	
	(0.0603)	
Loan Amount		0.2241***
		(0.0191)
Farmer FE	Yes	Yes
ZIP Code X Post FE	Yes	Yes
# Obs	87,238	87,238
First Stage f-statistic	73.0503	73.0503
Instrument	Treatment X Post	Treatment X Post

The table estimates the effect of credit on income using the following 2SLS specification:

$$Credit_{i,p} = \beta \cdot Treatment_i \times Post_p + \theta_i + \theta_{z,p} + \varepsilon_{i,t}$$

$$Income_{i,p} = \psi \cdot \hat{Credit}_{i,p} + \theta_i + \theta_{z,p} + \mu_{i,t}$$

There are only two time-periods in the analysis – pre-policy period and the post-policy period. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Treatment_i$ takes a value of one for landowning farmers and a value of zero for non-landowning farmers. $Post_p$ takes a value of one for the post-policy period defined as the twelve months from March 2019. θ_i denotes farmer fixed effects. $\theta_{z,p}$ denotes ZIP × post 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 sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. Column 1 uses $\frac{Income}{Avg(Income)_{Pre}}$ as the second-stage dependent variable and $\frac{\text{Loan Amount}}{\text{Avg(Loan Amount)}_{Pre}}$ as the first-stage dependent variable. $Avg(Income)_{Pre}$ and $\text{Avg(Loan Amount)}_{Pre}$ denote the sample average of income and loan amount during the pre-policy period. Column 2 uses the level form of income as the second-stage dependent variable and the level form of credit as the first-stage 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.

Table 12: Effect of the Policy on Utilization Rates for Kisan Credit Cards

Dep Var: Utilization Rate	(1)	(2)	(3)	(4)	(5)
Treatment X Post	0.0735***	0.0735***	0.0788***	0.0764***	0.0675***
	(0.0258)	(0.0258)	(0.0261)	(0.0230)	(0.0233)
Treatment	-0.0055***	-0.0055***	-0.0064***		
	(0.0004)	(0.0004)	(0.0006)		
Post	-0.0008				
	(0.0006)				
Month FE		Yes		Yes	
Farmer FE				Yes	Yes
ZIP Code X Month FE			Yes		Yes
# Obs	1,512,367	1,512,367	1,512,367	1,512,367	1,512,367
R^2	0.0001	0.0005	0.0439	0.2688	0.2938
Sample UR Mean	0.2134	0.2134	0.2134	0.2134	0.2134
Sample KCC Limit	397,161.20	397,161.20	397,161.20	397,161.20	397,161.20
Increased Usage	29,191.35	29,191.35	31,296.30	30,343.12	26,808.38

The table estimates the relative effect of cash transfers under PMKSN on utilization rates for the treatment and control groups according to the following specification:

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

where $UR_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. The key dependent variable is the utilization rates for kisan credit cards. $Treatment_i$ 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 following March 2019. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ 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 the key specification in column 5. The sample comes from the transaction-level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. The sample only consists of farmers with outstanding kisan credit cards before March of 2019 with at least one year remaining term. 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 13: Effect of the Policy on Applications and Acceptances

	(1)	(2)	(3)
	Inquiry (=1)	$\frac{\#Inquiry}{Avg(\#Inquiry_{Pre})}$	Accept (=1)
Treatment X Post	0.0828***	0.3646***	-0.0038
	(0.0244)	(0.1010)	(0.0195)
Farmer FE	Yes	Yes	Yes
ZIP X Post FE	Yes	Yes	
ZIP X Month FE			Yes
# Obs	87,238	87,238	79,606
R^2	0.403	0.408	0.077
Sample Mean	0.259	1.074	0.085

The table estimates the relative effect of cash transfers under PMKSN on credit inquiries for the treatment and control groups according to the following specification:

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

where $y_{i,p}$ denotes the dependent variable of interest measured for farmer i at time p. There are only two time-periods in the analysis – pre-policy period and the post-policy period. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Avg(y_{Pre})$ 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. $Post_p$ takes a value of one for the post-policy period defined as the twelve months from March 2019. θ_i denotes farmer fixed effects. $\theta_{z,p}$ denotes ZIP $\times$ post fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the inquiry-level data from the Indian credit bureau merged with the transaction-level data from the bank. The sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. Column 1 uses a binary variable as the dependent variable taking a value of one if an inquiry was made for the farmer in the credit bureau during the period, and zero otherwise. Column 2 uses the number of inquiries as the dependent variable divided by the pre-period sample average. Column 3 uses a binary variable as the dependent variable taking a value of one if the inquiry was accepted and zero otherwise. Column 3 uses inquiry-level data. We define an inquiry to be accepted if there was a corresponding loan for the inquiry within 45 days. 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 by Trust in Government Commitment

	(1)	(2)	(3)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
BJP Vote Share X Treatment X Post	0.3064**	0.2971**	0.5280***
	(0.0882)	(0.0637)	(0.0522)
Treatment X Post	0.0204***	0.0483	0.0322
	(0.0019)	(0.0280)	(0.1106)
Farmer FE	Yes	Yes	Yes
ZIP X Post FE	Yes	Yes	Yes
# Obs	87,238	87,238	87,238
R^2	0.525	0.680	0.781

The table estimates the heterogeneity in the relative effect of cash transfers under PMKSN on credit market outcomes for the treatment and control groups by BJP vote share according to the following specification:

$$\frac{y_{i,p}}{Avg(y_{Pre})} = \beta_1 \text{BJP Vote Share}_z \cdot Treatment_i \times Post_p + \beta_2 \cdot Treatment_i \times Post_p + \theta_i + \theta_{z,p} + \varepsilon_{i,t}$$

where $y_{i,p}$ denotes the dependent variable of interest measured for farmer i at time p. There are only two time-periods in the analysis – pre-policy period and the post-policy period. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. BJP Vote Share_z measures the the share of votes cast for BJP in the 2014 federal elections. The data on vote shares of all political parties comes from the Election Commission of India at the electoral constituency level. We map electoral constituencies to ZIP codes. $Treatment_i$ takes a value of one for landowning farmers and a value of zero for non-landowning farmers. $Post_p$ takes a value of one for the post-policy period defined as the twelve months from March 2019. θ_i denotes farmer fixed effects. $\theta_{z,p}$ denotes ZIP × post 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 sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana 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 15: Testing the Safety Net Hypothesis: Droughts, Consumption, Default, and Savings

		(1) Consumption	(2) Default	(3) Savings
Treatment X Post	Non-Drought	0.1153***	-0.0218**	0.4549***
		(0.0289)	(0.0081)	(0.0394)
	Drought	0.0705***	-0.0115***	0.1337***
		(0.0122)	(0.0030)	(0.0092)
Treatment X Drought		0.0044	0.0082	-0.0114
		(0.0394)	(0.0053)	(0.0334)
Farmer FE		Yes	Yes	Yes
ZIP X Month FE		Yes	Yes	Yes
Cohort X Month FE			Yes	
# Obs		2,169,451	1,512,367	2,169,451
R^2		0.4835	0.6827	0.6923
Test: Drought = Non-Drought				
f-statistic		2.09	2.34	319.52
Prob >F		0.1764	0.1544	0.0000
Coef: Treatment X Post		0.0969***	-0.0139***	0.2774***
		(0.0140)	(0.0040)	(0.0137)

The table estimates the relative effect of cash transfers under PMKSN on consumption, default, and savings during periods of drought and non-droughts according to the following specification:

$$y_{i,t} = \beta_1 \cdot Treatment_i \times Post_t \times Non-Drought_t + \beta_2 \cdot Treatment_i \times Post_t \times Drought_t$$

$$+\beta_3 \cdot Treatment_i \times Drought_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

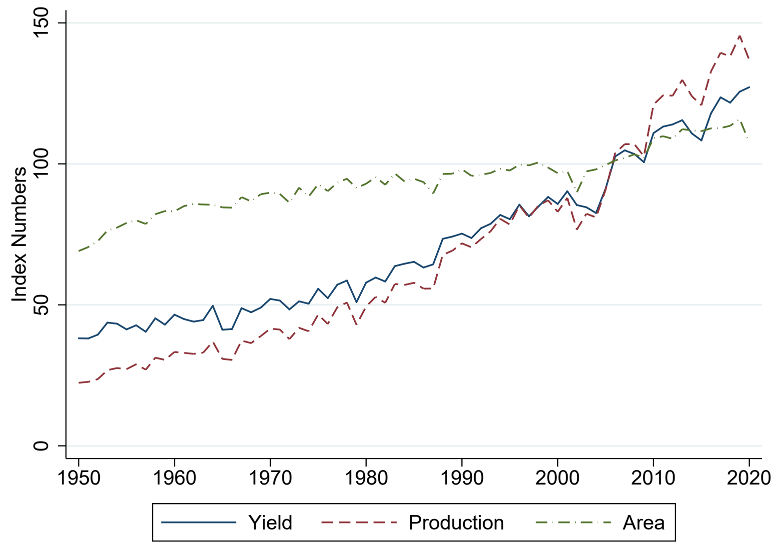
where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. $Treatment_i$ takes a value of one for landowning farmers and a value of zero for non-landowning farmers. $Post_t$ takes a value of one for months following March 2019. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP × month fixed effects, where z refers to the ZIP code where farmer i operates. We define drought by computing the deviation of the Kharif season rainfall in a ZIP code from its historical average rainfall and code all ZIP codes with negative deviation as drought. The sample comes from the transaction-level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. We measure consumption using all outflows from the bank account, including in-person and Automated Teller Machine (ATM) withdrawals, wire transfers, and credit and debit card transactions. We remove all outflows classified as spending for durable goods using the Merchant Category Code (MCC) associated with each transaction. We measure savings using month ending balance in bank accounts. Default is calculated if the farmer's kisan credit card was more that 90 days past due during month t. Column 1 uses consumption in month t for farmer i scaled by pre-policy average. Column 2 uses a binary variable taking a value of 1 if the kisan credit card is more than 90 days past due and 0 otherwise. Column 3 uses savings in month t for farmer i scaled by pre-policy average. All columns report the f-statistic associated with the test examining the equality of coefficients β_1 and β_2, as well as the combined coefficient associated with Treatment X Post. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Internet Appendix for:

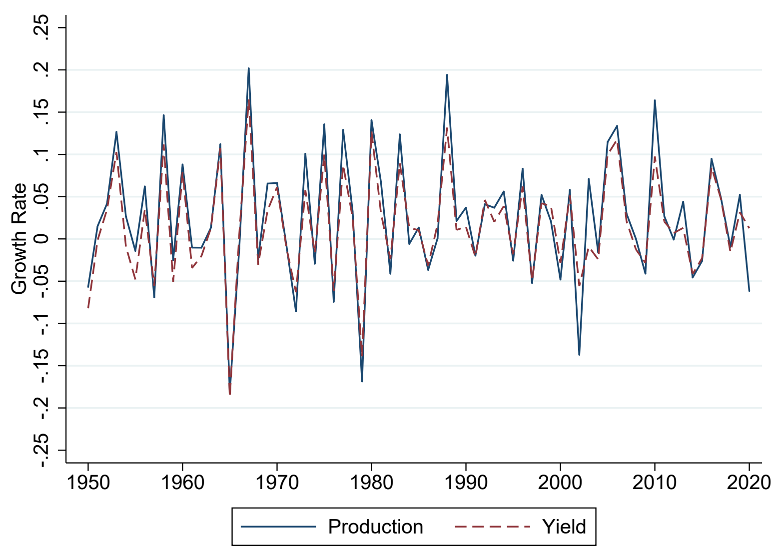
"Safety Nets, Credit, and Investment: Evidence from a Guaranteed Income Program"

Appendix A Agriculture in India

Figure A.1: Agricultural Growth in India



(a) Index Numbers over time

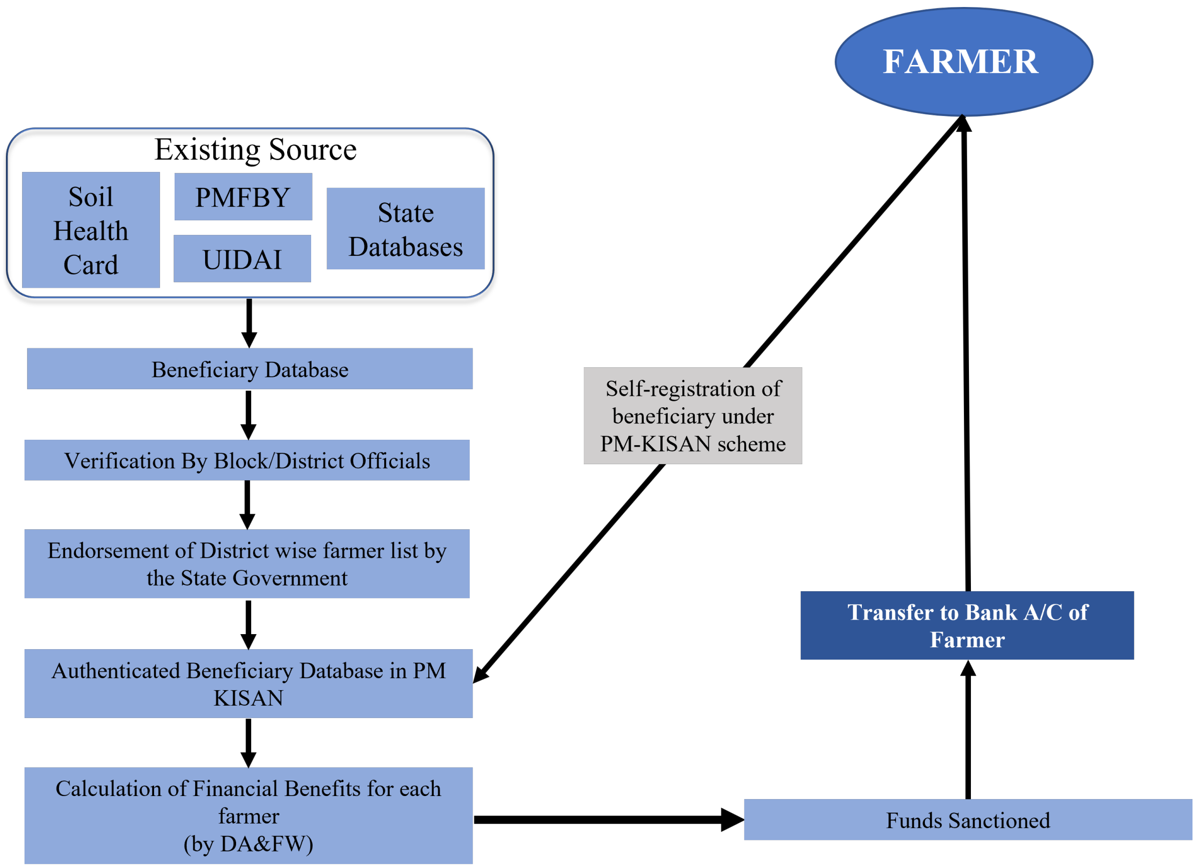


(b) Growth over time

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.

Appendix B Transfer process under PMKSN

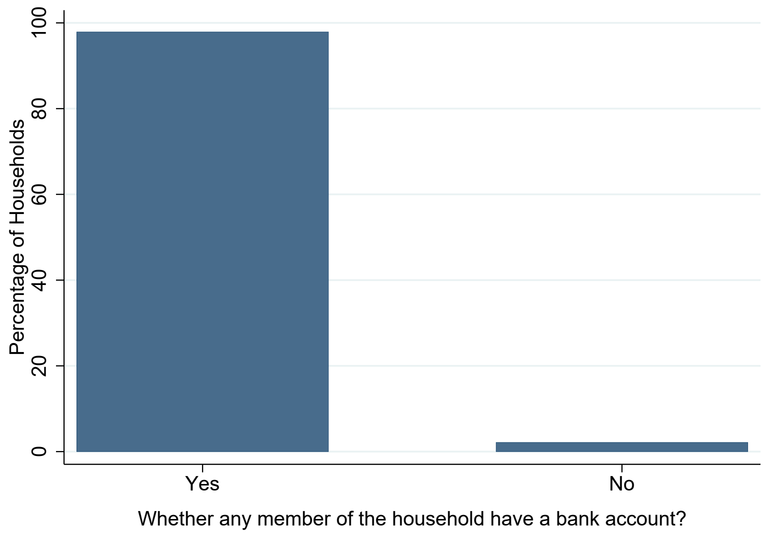
Figure B.1: Data: Beneficiaries of PMKSNY by ZIP code



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 C Data

Figure C.1: Fraction of Farmer Households with Bank Accounts



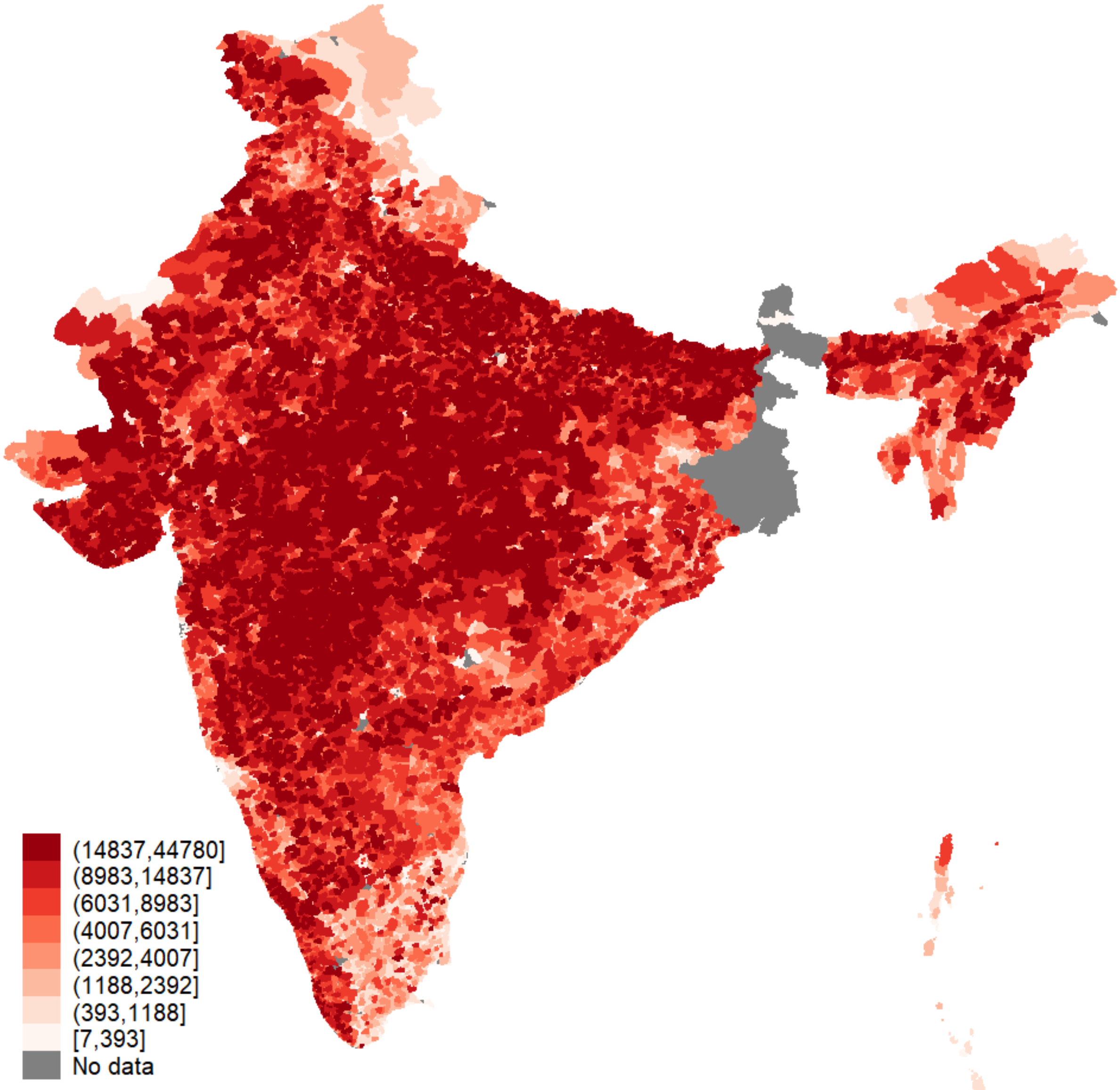
The figure plots the percentage of farmer households with at least one bank account. The data comes from the 2018 Situation Assessment Survey (SAS) conducted by the National Sample Survey Office (NSSO) during their 77^{th} round in the calendar year 2019. The survey records farmer responses as of 2018. 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 C.1: Comparison of sample data with national data

	Bank Data	SAS Survey Data
Income	8,334.00	7,996.89
Expenditure	11,578.78	11,858.00
Age	45.23	48.91
% with Credit	50.2%	40.3%

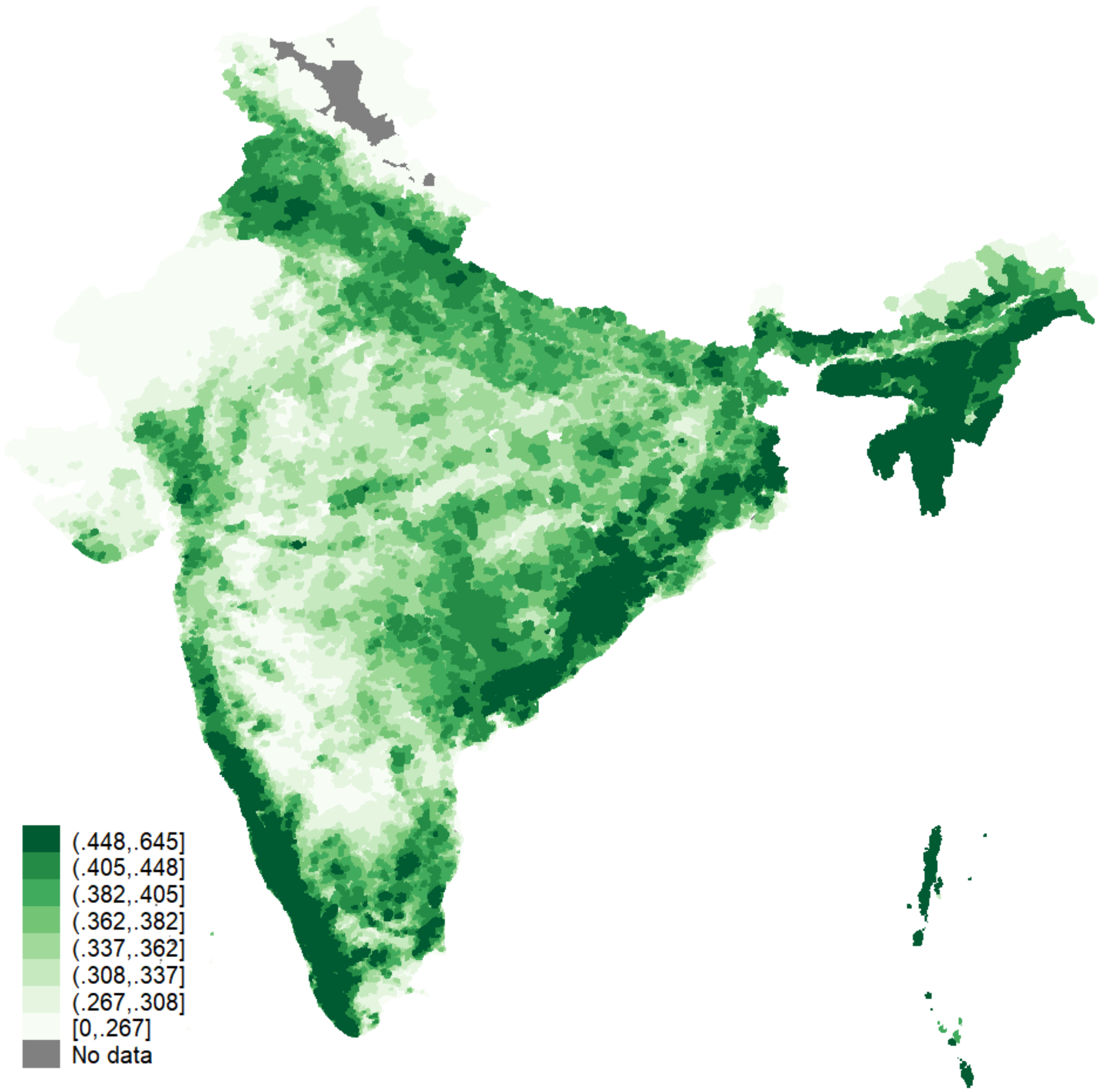
The table compares key metrics of income and spending in our sample data with the national data in the 2018 Situation Assessment Survey (SAS). The 2018 Situation Assessment Survey (SAS) was conducted by the National Sample Survey Office (NSSO) during their 77^{th} round in the calendar year 2019. The survey records detailed information on receipts and expenditure of the agricultural household members during 2018. Detailed description of the survey as well as the data can be accessed at the Ministry of Statistics and Program Implementation (MOSPI) website.

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



The figure plots the geographic distribution of the number of PMKSN beneficiaries by ZIP code. Darker shades of red denote a greater number of beneficiaries. The data comes from the Ministry of Agriculture, Government of India and is constructed by geo-referencing villages to ZIP codes. Note that we have not verified any boundaries and do not claim authenticity of the same. We do not endorse the international geographic boundaries shown here.

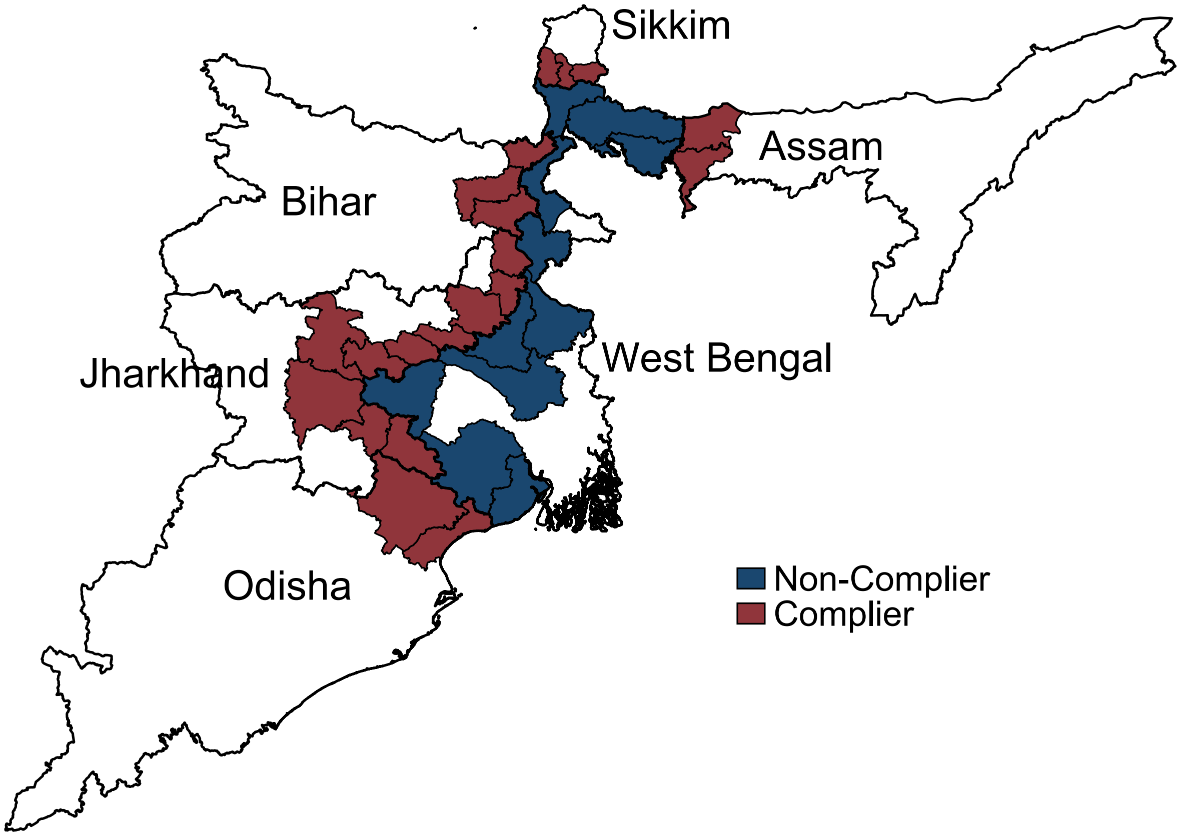
Figure C.3: Data: Enhanced Vegetative Index (EVI) by ZIP code



The figure plots the geographic distribution of the average value of enhanced vegetative index (EVI) from January 2017 through December 2019 by ZIP code. Darker shades of green denote greater value of EVI. EVI is a chlorophyll-sensitive composite measure of plant matter, generated by NASA's Earth Observation satellite – Landsat 8. EVI is generated from each scene's near-infrared, red and blue bands. 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 aggregate EVI at the ZIP code level and present the average EVI from January 2017 through December 2019. Note that we have not verified any boundaries and do not claim authenticity of the same. We do not endorse the international geographic boundaries shown here.

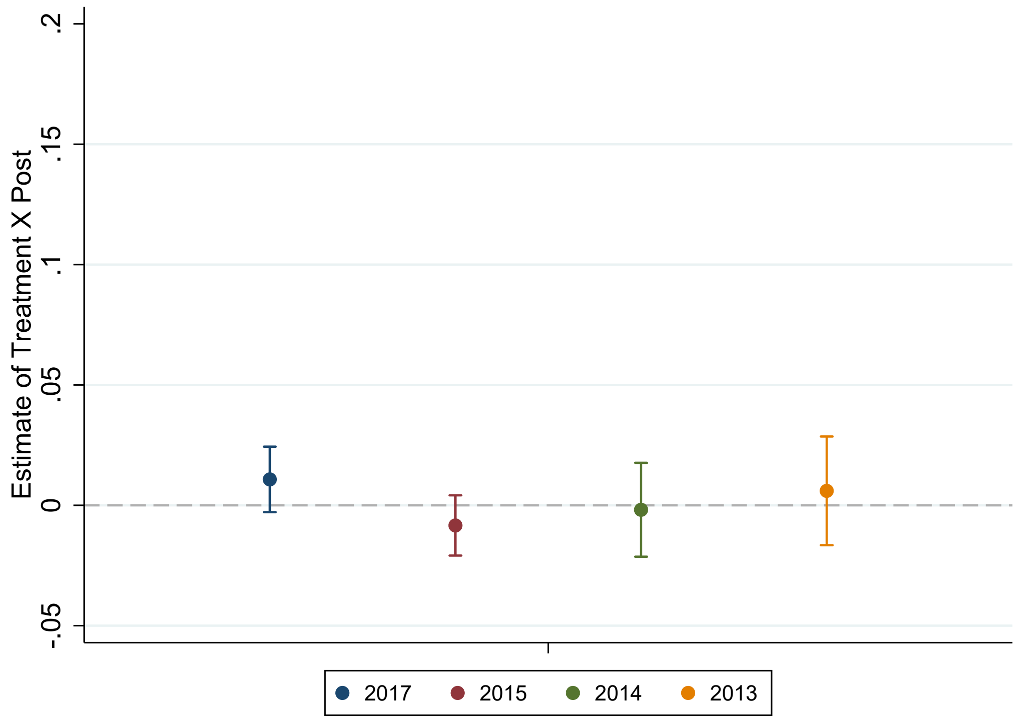
Appendix D Robustness Tests

Figure D.1: 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.

Figure D.2: Placebo Test: Treatment Effect in prior years when policy was not launched



The figure presents the estimates of $\{\beta\}$ based on the following specification estimated for the years 2017, 2015, 2014, and 2013:

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

where, $y_{i,t}$ denotes the income from work measured for farmer i at time (month) t. $Avg(y_{Pre})$ denotes the sample average of the income from work 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 of year x and zero otherwise. x takes values of 2019, 2017, 2018, 2014, and 2013. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the transaction level bank data and includes farmers in the state of Punjab, Maharashtra, Karnataka, and Telangana from March of year $x - 1$ through February of year $x + 1$. The key dependent 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. Capped spikes drawn with the estimated coefficients $\{\beta\}$ indicate 95% confidence intervals obtained from standard errors clustered at the ZIP code level.

Table D.1: Robustness: Spillovers and the Treatment Effect

Dep Var: Income Growth	(1)	(2)	(3)
Treatment	0.1044***	0.1057***	0.1255**
	(0.0244)	(0.0261)	(0.0635)
Frac. Treated		-0.0078**	
		(0.0031)	
Treatment X Frac. Treated			-0.0075***
			(0.0016)
(1-Treatment) X Frac. Treated			-0.0224***
			(0.0057)
State FE	Yes	Yes	Yes
# Obs	86,873	86,873	86,873
R^2	0.0185	0.019	0.0191

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

$$\frac{y_{i,Post} - y_{i,Pre}}{y_{i,Pre}} = \beta \cdot Treatment_i + \beta_T \cdot Treatment_i \times Frac.Treated_d$$

$$+\beta_T \cdot (1 - Treatment_i) \times Frac.Treated_d + \theta_s + \varepsilon_i$$

where $y_{i,Pre}$, and $y_{i,Post}$ denote the sum of the income from work for farmer i over the 12 months before and after the policy, respectively. $Treatment_i$ is an indicator variable taking the value of one for landowning farmers and zero for non-landowning farmers. The coefficient β on $Treatment_i$ provides the average treatment effect of the policy. θ_s denotes state fixed effects. The empirical specification of the test is based on Berg, Reisinger and Streitz (2021). Column 1 reports the estimate of β with state fixed effects. 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 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 augments the specification in column 2 by including the interaction of fraction of treated farmers with the treatment and control status of the farmer. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. The key dependent 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. Data on district-level fraction of treated farmers comes from the Government of India. 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 D.2: Robustness: Adding other farmer-level covariates measured before the policy

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Treatment X Post	0.1261***	0.1263***	0.1235***	0.1271***	0.1214***	0.1373***	0.1251***	0.1251***	0.1153***	0.1089***	0.1109***	0.1247***	0.1242***	0.1404***	0.1298***
	(0.0119)	(0.0208)	(0.0208)	(0.0204)	(0.0206)	(0.0199)	(0.0207)	(0.0207)	(0.0204)	(0.0193)	(0.0204)	(0.0207)	(0.0207)	(0.0204)	(0.0189)
Age X Post		-0.2124***													-0.3876***
		(0.0270)													(0.0260)
KCC Limit X Post			0.0050***												0.0236***
			(0.0013)												(0.0014)
Default X Post				-0.3065***											-0.3118***
				(0.0145)											(0.0174)
Int Rate X Post					0.0088*										-0.0154***
					(0.0046)										(0.0046)
Relationship X Post						0.3491***									0.3259***
						(0.0333)									(0.0370)
CC User X Post							0.3379***								1.0222***
							(0.1161)								(0.1246)
Other Inv X Post								0.2022							0.3082*
								(0.1691)							(0.1670)
Liquid Wealth X Post									-0.0183***						0.0087***
									(0.0013)						(0.0015)
Consumption X Post										-0.0390***					-0.0444***
										(0.0014)					(0.0016)
% Visits X Post											-0.0356***				-0.0287***
											(0.0020)				(0.0023)
Credit Score X Post												0.0911***			0.0901***
												(0.0044)			(0.0049)
Female X Post													-0.0123		-0.0352
													(0.0234)		(0.0227)
Hindu X Post														-0.1426***	-0.0068
														(0.0159)	(0.0170)
Farmer FE	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
# Obs	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451	2,142,572	2,169,451	2,169,451	2,169,451	2,169,451	2,142,572
R^2	0.434	0.4341	0.434	0.4344	0.434	0.4342	0.434	0.434	0.4342	0.4316	0.4346	0.4344	0.434	0.4341	0.4331

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, natural logarithm of one plus credit limit on Kisan credit cards, default tag which takes a value of one for farmers with a prior default history and zero otherwise, interest rates on Kisan credit cards, 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, Liquid Wealth is measured as the natural logarithm of the average savings in liquid bank deposits, consumption measured as the natural logarithm of the total spending by farmers in the previous year, % 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 × month fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. The key dependent 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 market investments, and PMKSN transfers. 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 D.3: Matched Sample: Comparing the Treatment and the Control Group

	Overall	Sample		Difference	
		Control	Treatment	Magnitude	t-stat
Income from Work	12,925.51	12,448.91	13,402.11	-953.20	1.63
Savings	8,243.09	8,759.10	7,994.84	764.26	1.02
Consumption	7,420.02	7,382.83	7,457.93	-75.11	0.24
Frac. CC User	0.019	0.019	0.018	0.001	0.09
# Trnx per day	0.048	0.045	0.049	-0.005	0.96
Credit Score	561.63	553.03	565.78	-12.76	1.36
Interest Rate	9.19	9.11	9.22	-0.11	0.97
Frac. Default	0.210	0.219	0.205	0.014	0.58
Farmer Age	44.33	44.21	44.39	-0.18	0.24
Account Age	6.40	6.49	6.36	0.13	1.27
Frac. Female	0.048	0.029	0.057	-0.029**	2.26
Frac. Other Investment	0.010	0.019	0.006	0.013**	2.25
Sanction Limit	397,161.20	344,278.40	422,603.10	78,324.7**	2.26

The table compares the characteristics of the treatment and control groups in the matched sample. We match the treatment and control farmers based on observable characteristics in the pre-policy period within a ZIP code. We match based on average savings, spending, credit card usage, other investments such as fixed deposits, recurring deposits, provident fund deposits, and stock market holdings, number of banking transactions per day, credit score, interest rate, farmer age, account age, and prior default tag. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2019. T-stats clustered at the ZIP code level are reported in the last column. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.4: Robustness: Estimating Treatment Effects Using Matched Sample

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)
Treat X Post	0.1160**	0.1107**
	(0.0530)	(0.0531)
Farmer FE	Yes	Yes
ZIP Code X Month FE	Yes	
Matched Pair X Month FE		Yes
# Obs	42,052	42,052
R^2	0.6036	0.8347

The table estimates the relative effect of PMKSN cash transfers on income from work for the treatment and control groups according to the following specification using the matched sample:

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

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. $Treatment_i$ 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. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ month fixed effects, where z refers to the ZIP code where farmer i operates. Column 1 replicates baseline specification 2 for the matched sample. Column 2 presents the within matched pair estimate by including Matched Pair $\times$ month fixed effects. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. The key dependent 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. Standard errors clustered at the match-group level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.5: Robustness: Addressing issues of Representativeness and Measurement Error using CPHS Survey

Dep Var: $\frac{y_{i,t}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)	(5)
Treatment X Post	0.1103***	0.1043***	0.1104***	0.1087***	0.1098***
	(0.0239)	(0.0240)	(0.0238)	(0.0238)	(0.0238)
Household FE	Yes	Yes	Yes	Yes	Yes
District X Month FE	Yes	Yes	Yes	Yes	Yes
Education group X District FE		Yes	Yes	Yes	Yes
Education group X Month FE		Yes	Yes	Yes	Yes
Gender group X District FE			Yes	Yes	Yes
Gender group X Month FE			Yes	Yes	Yes
Age group X District FE				Yes	Yes
Age group X Month FE				Yes	Yes
HH Size group X District FE					Yes
HH Size group X Month FE					Yes
# Obs	466,600	466,600	466,600	466,600	466,600
R^2	0.6677	0.6746	0.6793	0.6841	0.6894
Sample Mean	8,278.44	8,278.44	8,278.44	8,278.44	8,278.44

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

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

where $y_{i,t}$ denotes the dependent variable of interest measured for household 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 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 defined to be treatment households. $Post_t$ takes a value of one for months beginning March 2019 and zero otherwise. θ_i denotes household fixed effects. $\theta_{z,t}$ denotes district $\times$ month fixed effects, where z refers to the district where farmer i operates. Column 2-5 include additional fixed effects associated with interaction of education group, gender group, age group and household size group with district and time (month) dummies. The group definitions are adopted directly from the survey. The sample comes from the CPHS survey conducted by the CMIE across all states in India from March 2018 through February 2020. The states of West Bengal, Jammu and Kashmir, and the north-eastern states are not included in the sample. All regressions are weighted by survey weights of each household. The key dependent variable is the reported household income from work. Standard errors clustered at the district level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.6: Robustness: Alternative Transformation – Inverse Hyperbolic Sine Transformation

Dep Var: $LN(y + \sqrt{(1+y^2)})$	(1)	(2)	(3)	(4)	(5)
Treat X Post	0.1034***	0.1050***	0.1000***	0.1298***	0.1240***
	(0.0206)	(0.0207)	(0.0210)	(0.0200)	(0.0207)
Treat	-0.1480***	-0.1479***	-0.0476**		
	(0.0177)	(0.0177)	(0.0191)		
Post	-0.0392				
	(0.0394)				
Month FE		Yes		Yes	
Farmer FE				Yes	Yes
ZIP Code X Month FE			Yes		Yes
# Obs	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451
R^2	0.0012	0.0165	0.0915	0.4143	0.4340

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

$$LN(y_{it} + \sqrt{(1 + y_{it}^2)}) = \beta \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. $Ln(y_{it} + \sqrt{(1 + y_{it}^2)}$ denotes the inverse hyperbolic sine transformation of the dependent variable. $Treatment_i$ 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. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ 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 equation 2 in column 5. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. The key dependent 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 market investments, and PMKSN transfers. 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 D.7: Robustness: Alternative Transformation – Natural Logarithm Plus One

Dep Var: LN(1+Income)	(1)	(2)	(3)	(4)	(5)
Treat X Post	0.0964***	0.0979***	0.0932***	0.1213***	0.1158***
	(0.0192)	(0.0193)	(0.0197)	(0.0188)	(0.0194)
Treat	-0.1374***	-0.1373***	-0.0450**		
	(0.0165)	(0.0165)	(0.0178)		
Post	-0.0359				
	(0.0369)				
Month FE		Yes		Yes	
Farmer FE				Yes	Yes
ZIP Code X Month FE			Yes		Yes
# Obs	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451
R^2	0.0012	0.0165	0.0915	0.4128	0.4327

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

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

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. $LN(1 + y_{it})$ denotes the one plus natural logarithmic transformation of the dependent variable. $Treatment_i$ 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. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ 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 equation 2 in column 5. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. The key dependent 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 market investments, and PMKSN transfers. 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 D.8: Robustness: Alternative Transformation – Level Transformation

Dep Var: Income	(1)	(2)	(3)	(4)	(5)
Treat X Post	773.42**	789.07**	681.57*	1024.58***	840.45**
	(382.82)	(385.47)	(386.24)	(390.93)	(402.40)
Treat	-1394.37***	-1391.62***	-831.92**		
	(380.92)	(382.56)	(413.08)		
Post	-10.14				
	(368.76)				
Month FE		Yes		Yes	
Farmer FE				Yes	Yes
ZIP Code X Month FE			Yes		Yes
# Obs	2,169,451	2,169,451	2,169,451	2,169,451	2,169,451
R^2	0.0002	0.0035	0.0381	0.2483	0.2705

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

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

where $y_{i,t}$ denotes the dependent variable of interest measured for farmer i at time (month) t. $Treatment_i$ 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. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP × 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 equation 2 in column 5. The sample comes from the transaction level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. The key dependent 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 market investments, and PMKSN transfers. 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 D.9: Robustness: Alternative Measures of Agricultural Yield

	(1)	(2)
	LN(Mean EVI)	LN(Median EVI)
LN(#Beneficiaries) X Post	0.0307***	0.0327***
	(0.0046)	(0.0047)
ZIP Code FE	Yes	Yes
Month FE	Yes	Yes
# Obs	657,002	657,002
R^2	0.8811	0.8762
Sample Mean (Y Variable)	0.364	0.364
St Dev (Y Variable)	0.141	0.145

The table estimates the elasticity of agricultural yield to change in the number of PMKSN beneficiaries at the ZIP code level according to the following specification:

$$LN(y_{z,t}) = \beta \cdot LN(\#Beneficiaries_z) \times Post_t + \theta_z + \theta_t + \varepsilon_{z,t}$$

where, $LN(y_{z,t})$ denotes the natural logarithm of agricultural yield in ZIP code z at time t. t refers to month as a unit of time. $LN(\#Beneficiaries_z)$ denotes the natural logarithm of the number of PMKSN beneficiaries in ZIP code z. $Post_t$ takes a value of one for months following March 2019 and zero otherwise. θ_z denotes ZIP code fixed effects. θ_t denotes month fixed effects. The data spans all states of India from January 2017 through December 2019. The states of West Bengal, Jammu and Kashmir, and the north-eastern states are excluded from the analysis. Column 1 uses the mean value of Enhanced Vegetation Index (EVI) and column 2 uses the median value of EVI as the key dependent variable. The data on EVI comes from the remote-sensing satellite Landsat 8. The data on the number of beneficiaries comes from the Government of India. The estimate is standardized to report the effect in terms of a 10% increase in the number of beneficiaries. 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 D.10: Robustness: Effect of the Policy on Investment (Poisson Regression)

Dep Var: $y_{i,t}$	(1) Tractors	(2) Cattle	(3) Two-Wheelers
Treatment X Post	0.6851**	0.3019***	0.0329**
	(0.2724)	(0.0389)	(0.0142)
Household FE	Yes	Yes	Yes
District X Month FE	Yes	Yes	Yes
Education group X District FE	Yes	Yes	Yes
Education group X Month FE	Yes	Yes	Yes
Gender group X District FE	Yes	Yes	Yes
Gender group X Month FE	Yes	Yes	Yes
Age group X District FE	Yes	Yes	Yes
Age group X Month FE	Yes	Yes	Yes
HH Size group X District FE	Yes	Yes	Yes
HH Size group X Month FE	Yes	Yes	Yes
# Obs	21,756	136,795	141,273
Pseudo R^2	0.1541	0.2525	0.0663

This table estimates the effect of cash transfers under PMKSN on investment for the treatment and control groups according to the following Poisson specification:

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

where $y_{i,t}$ denotes the dependent variable of interest measured for household 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 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 defined to be treatment households. $Post_t$ takes a value of one for months following March 2019. θ_i denotes household fixed effects. $\theta_{z,t}$ denotes district $\times$ month fixed effects, where z refers to the district where farmer i operates. $\Gamma_{i,t}$ denotes additional fixed effects associated with the interaction of education group, gender group, age group and household size group with district and time (month) dummies. The group definitions are adopted directly from the survey. The sample comes from the CPHS survey conducted by CMIE across all states in India from March 2018 through March 2020. The states of West Bengal, Jammu and Kashmir, and the north-eastern states are not included in the sample. All regressions are weighted by survey weights of each household. The key dependent variable is the number of tractors in column 1, the number of cattle or livestock in column 2, and the number of two-wheelers in column 3. Standard errors clustered at the district level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.11: Robustness: Effect of the Policy on Credit (Loan Level Analysis)

Dep Var: LN(Loan Amount)	(1)	(2)	(3)	(4)	(5)
Treatment X Post	0.1671***	0.1218*	0.1459**	0.1472**	0.1566**
	(0.0584)	(0.0647)	(0.0649)	(0.0674)	(0.0698)
Farmer FE	Yes	Yes	Yes		
Month FE	Yes				
ZIP X Month FE		Yes	Yes	Yes	Yes
ZIP X Bank Type FE			Yes		
Farmer X Bank Type FE				Yes	Yes
Bank Type X Month FE					Yes
# Obs	196,654	196,654	196,654	196,654	196,654
R^2	0.4385	0.514	0.5556	0.5956	0.5995

The table estimates the effect of cash transfers under PMKSN on loan amount for the treatment and control groups according to the following specification:

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

where $LN(y_{i,b,t})$ denotes the natural logarithm of the dependent variable of interest (loan amount) measured for farmer i at time (month) t given by bank-type b. $Treatment_i$ 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 following March 2019. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP × month fixed effects, where z refers to the ZIP code where farmer i operates. $\theta_{i,b}$ denotes farmer × bank-type fixed effects, where b refers to the bank-type which gave the loan to the farmer. $\theta_{b,t}$ refers to bank-type × month fixed effects. The sample comes from the loan-level data from the Indian credit bureau merged with the transaction-level data from the bank. The sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana 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 D.12: 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.

Table D.13: Robustness: Does the New Credit Finance Consumption or Productive Capacity?

	(1)	(2)	(3)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Productive Loan X Treatment X Post	0.0879***	0.3347**	0.3385***
	(0.0092)	(0.0693)	(0.0445)
Farmer X Post FE	Yes	Yes	Yes
Loan Type X ZIP X Post FE	Yes	Yes	Yes
# Obs	174,476	174,476	174,476
R^2	0.543	0.565	0.678
Sample Mean	0.373	0.555	197,782

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:

$$\frac{y_{i,t,p}}{Avg(y_{Pre})} = \beta \cdot \text{Productive Loan}_t \cdot Treatment_i \times Post_p + \theta_{i,p} + \theta_{t,z,p} + \varepsilon_{i,t,p}$$

where $y_{i,t,p}$ denotes the dependent variable of interest measured for farmer i at time p for loan type t. There are only two time-periods in the analysis – pre-policy period and the post-policy period. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. There are two loan types – loans used to finance productive capacity and loans used to finance consumption. $Avg(y_{Pre})$ 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. $Post_p$ takes a value of one for the post policy period defined as the twelve months from March 2019. Productive Loan$_t$ takes a value of one for loans used to finance productive capacity and a value of zero for loans used to finance consumption. $\theta_{i.p}$ denotes farmer $\times$ post fixed effects. $\theta_{t,z,p}$ denotes Loan Type $\times$ ZIP $\times$ post 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 sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana 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. Loans meant to purchase farm equipment or loans tagged as priority sector loans for business-related activities are classified as defined as loans for enhancing productive capacity. All other loans are classified as loans for consumption. 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 E Effect of the Policy on Prices & Firm Entry

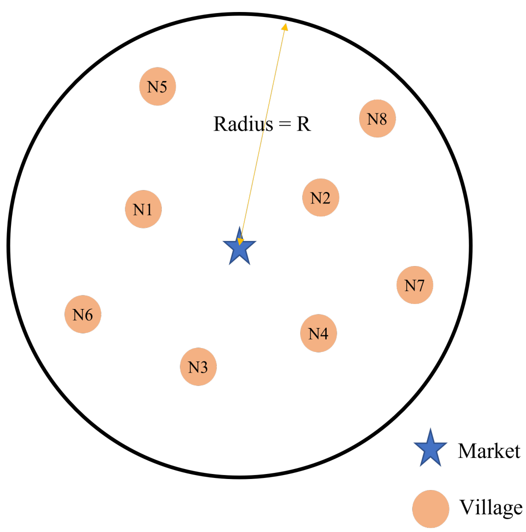
E.1 Effect of the Policy on Prices

This section documents the policy's effect on prices of agricultural commodities.

E.1.1 Data

We collect detailed new data on prices of agricultural commodities at the wholesale market (*mandi*) level. The data comes from the AgMARKNET database maintained by GOI. This data provides information on the prices of agricultural commodities across all wholesale agricultural markets in India. We match wholesale markets with the number of PMKSN beneficiaries at the village level using Geographic Information System (GIS). First, we use Google's Geocoding API to obtain spatial coordinates for each market.[44] Second, we superimpose the coordinates of these markets with village coordinates. We draw circles of radius R_m, ranging from 5 to 15 km in intervals of 1 km, around the market and add the number of beneficiaries of PMKSN for all villages inside the circle. We attribute these beneficiaries to the wholesale market. Appendix figure E.1 presents a schematic representation of the process to match wholesale markets with beneficiaries of PMKSN at the village level.

Figure E.1: Matching agriculture wholesale markets with villages



The figure presents the schematic representation of matching of the wholesale markets with PMKSN beneficiaries at the village level. We match wholesale markets with the number of PMKSN beneficiaries at the village level using Geographic information system (GIS). First, we use Google's Geocoding API to obtain spatial coordinates for each market. Second, we superimpose the coordinates of these markets with village coordinates. We draw circles of radius R_m, ranging from 5 to 15 km in intervals of 1 km, around the market and add the number of PMKSN beneficiaries for all villages inside the circle. We attribute these beneficiaries to the wholesale markets. Stars denote the wholesale market or *mandi*, and circles denote villages. N_i denotes the number of PMKSN beneficiaries in each village i. The total number of beneficiaries attributed to the market in this diagram is the sum of all N_i within the circle of radius R_m.

Additionally, we classify all crops into perishable and non-perishable to identify the local

[44] Documentation: https://developers.google.com/maps/documentation/geocoding/start

effect of cash transfers on prices. The distinction between perishable and non-perishable commodities is important for our analysis since perishable commodities are sold locally and hence are a function of local conditions. In contrast, non-perishable commodities can be easily transported to other locations and are more likely to be a function of global market conditions. Perishable commodities include tomatoes, potatoes, and onions. Non-perishable commodities include split pulses, millets, rice, soybean, and wheat.

E.1.2 Results

We supplement the analysis of agricultural yield by examining the policy's effect on the prices of agricultural commodities. On the one hand, greater agricultural production can lower prices by increasing the supply in the markets. On the other hand, cash transfers can also increase the demand for agricultural goods, translating into higher prices. Therefore, an issue is the extent to which cash transfers to farmers affect local agricultural output prices and, thus, the extent to which the effects on yield and agricultural income are nominal or real.

We document the price effect of the policy by combining the ZIP code-level administrative data on the number of PMKSN beneficiaries with the prices of several agricultural commodities sold in wholesale markets. We map wholesale agricultural markets (*mandis*) to beneficiaries using the methodology outlined in section E.1.1 and appendix Figure E.1. We exploit the spatial variation in the number of PMKSN beneficiaries across mandis and the temporal variation due to the timing of the policy. Additionally, we exploit another feature of the data which allows us to classify agricultural goods into non-perishable and perishable.[45] Perishable agricultural goods are not easily transportable and hence are non-tradable. Standard international trade theory predicts that prices of non-tradable goods are likely to be a function of local economic conditions. In contrast, the prices of tradable goods are likely to be a function of global economic conditions.

We examine the policy's effect on prices by estimating the following regression specification:

$$\begin{aligned} LN(P_{c,m,t}) =& \beta \cdot Perishable_c \cdot LN\{\sum_{v \in R_m} b_v\} \cdot Post_t + \gamma LN(P_{c,m,t-1}) \\ &+ \theta_{m,t} + \theta_{c,t} + \theta_{c,m} + \varepsilon_{c,m,t} \end{aligned} \tag{E.1}$$

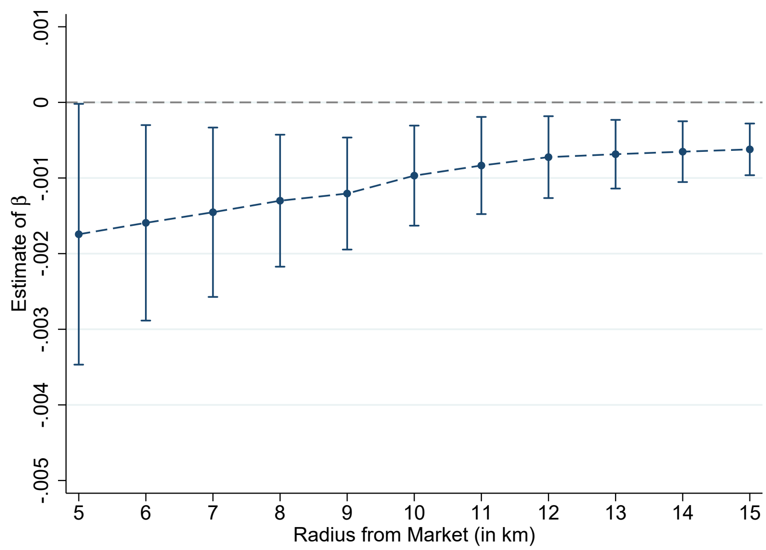
where, $LN(P_{c,m,t})$ denotes prices of agricultural commodity c in mandi m at time (month) t. $Perishable_c$ takes a value of one for perishable commodities that include tomatoes, potatoes, and onions, and zero otherwise. $LN\{\sum_{v \in R_m} b_v\}$ refers to the natural logarithm of the total number of PMKSN beneficiaries mapped to mandi m using radii of R_m. $Post_t$ takes a value of one for months following March 2019. We saturate our specification by including market × month fixed effects ($\theta_{m,t}$), commodity × month fixed effects $\theta_{c,t}$, and commodity × market fixed effects ($\theta_{c,m}$). Market × month fixed effects control for all time-varying shocks to the local economy and endogeneity concerns related to the spatial variation in the number of PMKSN beneficiaries. Commodity

[45] Perishable commodities include tomatoes, potatoes, and onions. Non-perishable commodities include lentils (split pulses), millets, rice, soybean, and wheat.

$\times$ month fixed effects control for all time-varying shocks to each commodity's production and supply process. Commodity $\times$ market fixed effects control for all time-invariant factors related to a market-commodity pair. β is our estimate of interest and is estimated for different values of R_m ranging from 5 to 15 km in intervals of 1 km.

Figure E.2 reports the results from the estimation of equation E.1 for values of R_m ranging from 5 to 15 km in intervals of 1 km. The estimate of interest is negative and statistically significant. Moreover, the estimate smoothly decreases in magnitude as the distance from the mandi increases, indicating spatial diffusion of prices as we include faraway villages into the mandi. The estimate indicates that a 10% increase in the number of beneficiaries decreases the prices of perishable commodities by 0.1%.[46] The effect on prices indicates that the supply-side effect of the cash transfers dominates the demand-side effect and lowers the prices of output in the market.

Figure E.2: Effect of the policy on Prices of Agricultural Commodities



The figure presents the estimates of $\{\beta\}$ based on the following specification:

$$LN(P_{c,m,t}) = \beta \cdot Perishable_c \cdot LN\{\sum_{v \in R_m} b_v\} \cdot Post_t + \gamma LN(P_{c,m,t-1}) + \theta_{m,t} + \theta_{c,t} + \theta_{c,m} + \varepsilon_{c,m,t}$$

where, $LN(P_{c,m,t})$ denotes price of agricultural commodity c in mandi m at time (month) t. $Perishable_c$ takes a value of one for perishable commodities that include tomatoes, potatoes, and onions, and zero otherwise. $LN\{\sum_{v \in R_m} b_v\}$ refers to the natural logarithm of the total number of PMKSN beneficiaries mapped to mandi m using a radii of R_m. b_v refers to the number of beneficiaries in village v that lies inside the radius R_m. $Post_t$ takes a value of one for months following March 2019. The specification includes market $\times$ month fixed effects ($\theta_{m,t}$), commodity $\times$ month fixed effects $\theta_{c,t}$, and commodity $\times$ market fixed effects ($\theta_{c,m}$). β is our estimate of interest and is estimated for different values of R_m ranging from 5 to 15 km in intervals of 1 km. The unit of analysis is ZIP code-commodity-month. The data spans all states of India from January 2017 through December 2019. The states of West Bengal, Jammu and Kashmir, and the north-eastern states are excluded from the analysis. The data on prices of agricultural commodities comes from the AgMARKNET database. The data on the number of beneficiaries comes from the Government of India. We map wholesale agricultural markets (*mandis*) to beneficiaries using the methodology outlined in section E.1.1 and appendix Figure E.1. The estimate is standardized to report the effect in terms of a 10% increase in the number of beneficiaries. Capped spikes drawn with the estimated coefficients $\{\beta\}$ indicate 95% confidence intervals obtained from standard errors clustered at the mandi level.

[46] The estimate is standardized to report the effect in terms of a 10% increase in the number of beneficiaries.

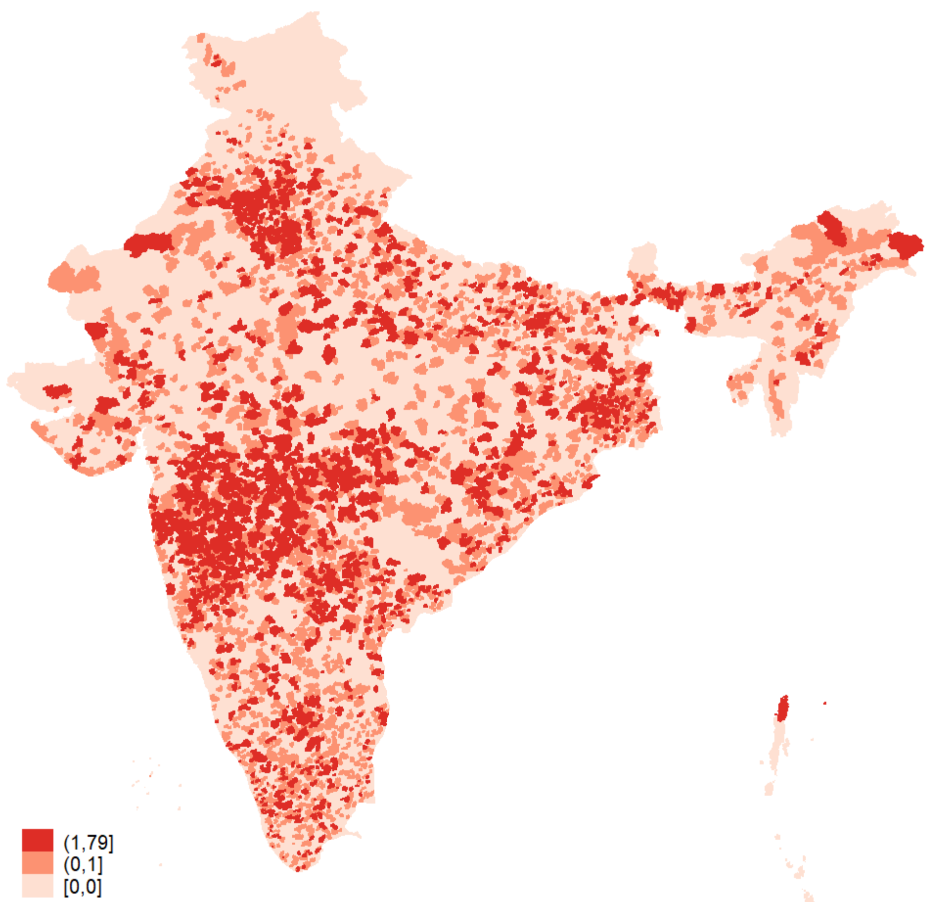
E.2 Effect of the Policy on Firm Entry

This section documents the effect of the policy on the entry of new agri-based micro-enterprises.

E.2.1 Data

We obtain data on the registration records of approximately 55,716 firms from the Ministry of Corporate Affairs (MCA), GOI. The data covers registration records of all new for-profit private firms established in India from January 2017 through December 2019. The data provides us with information on the industry code of the new firms. We focus our analysis on firms in the agricultural sector, which accounts for 21% of all new firms. The data also provides us with the precise address of operations for the firm. We extract the ZIP code information from the address file to construct a spatio-temporal dataset of India's agricultural private sector economic activity from 2017 until 2019. Appendix figure E.3 illustrates the spatial distribution of new private agricultural firms registered across all ZIP codes in India from 2017 through 2019.

Figure E.3: Data: Entry of agricultural firms by ZIP code



The figure plots the geographic distribution of the total number of new agriculture firms from January 2017 through December 2019 by ZIP code. Darker shades of red denotes greater number of agricultural firms. Our data comes from the Ministry of Corporate Affairs and includes all for-profit agri-based firms in India registered from 2017 through 2019. Note that we have not verified any boundaries and do not claim authenticity of the same. We do not endorse the international geographic boundaries shown here.

E.2.2 Results

This section examines the policy's effect on the entry of new agricultural enterprises. Appendix Table E.1 presents the results. The estimate of interest is the coefficient associated with the interaction term of Ln(# Beneficiaries) and Post. The estimate of interest is positive and statistically significant. We include ZIP code fixed effects to address issues related to the endogeneity in the spatial distribution of PMKSN beneficiaries across ZIP codes. Moreover, the estimate of interest is stable in magnitude as we sequentially add fixed effects from columns 1 to 5, and the model R^2 increases from 1.3% to 15.0%. Economically, the estimate indicates that a 10% increase in the number of beneficiaries increases the entry of new agricultural enterprises by 5.3%. The majority of the new firms captured in our data are very small, so the results indicates an increase in the entry of small agri-based businesses in areas with greater number of PMKSN beneficiaries.

Table E.1: Effect of the Policy on Entry of New Agricultural Enterprises

Dep Var: # New Firms	(1)	(2)	(3)	(4)
LN(# Beneficiaries) X Post	0.0570***	0.0601***	0.0458***	0.0527***
	(0.0138)	(0.0138)	(0.0131)	(0.0131)
LN(# Beneficiaries)	0.0735***	0.0699***		
	(0.0129)	(0.0129)		
Post	-0.1242			
	(0.1124)			
Month FE		Yes	Yes	Yes
ZIP Code FE			Yes	Yes
Avg(# New Firms$_{Pre}$) X Post				Yes
# Obs	34,658	34,658	34,658	34,658
Pseudo R^2	0.0132	0.0199	0.1496	0.1497
Sample Average	0.1977	0.1977	0.1977	0.1977

The table estimates the elasticity of entry of new agricultural firms to change in the number of PMKSN beneficiaries at the ZIP code level according to the following Poisson specification:

$$y_{i,t} = exp\{\beta \cdot LN(\#Beneficiaries_i) \times Post_t + \theta_i + \theta_t + \varepsilon_{i,t}\}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for ZIP code i in month t. $LN(\#Beneficiaries_i)$ refers to the natural logarithm of the number of PMKSN beneficiaries in ZIP code i. $Post_t$ takes a value of one following March 2019. θ_i denotes ZIP code fixed effects. θ_t denotes month fixed effects. Avg(# New Firms$_{Pre}$) denotes the sample average of the variable of interest during the pre-policy period at the ZIP code level. The data on entry of new agricultural firms comes from the Ministry of Corporate Affairs, Government of India and spans from January 2017 through February 2020. The key dependent variable is the total number of new agricultural firms. The estimate is standardized to report the effect in terms of a 10% increase in the number of beneficiaries. 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 F Other Results

Table F.1: Effect of the Policy on Tractor Sales – State level Analysis

Dep Var: Tractor Sales	(1)	(2)	(3)	(4)	(5)	(6)
Treat X Post	0.3514**	0.3515**	0.3513**	0.3433**	0.3495**	0.3525**
	(0.1625)	(0.1626)	(0.1627)	(0.1619)	(0.1475)	(0.1463)
Treat	0.1697	0.1689				
	(0.3459)	(0.3457)				
Post	-0.0879					
	(0.1585)					
Month FE		Yes	Yes	Yes		
State FE			Yes			
State X Model FE				Yes	Yes	
State X Make FE				Yes	Yes	
Month X Model FE					Yes	
Month X Make FE					Yes	
Month X Model X Make FE						Yes
State X Model X Make FE						Yes
# Obs	23,439	23,439	23,439	23,439	23,439	23,439
Pseudo R^2	0.0076	0.0338	0.1759	0.8392	0.8492	0.9095
Sample Mean	63.9756	63.9756	63.9756	63.9756	63.9756	63.9756

The table estimates the effect of the policy on state-level sales of tractors according to the following Poisson specification:

$$y_{s,m1,m2,t} = exp\{\beta \cdot Treatment_s \times Post_t + \theta_{s,m1,m2} + \theta_{m1,m2,t} + \varepsilon_{s,m1,m2,t}\}$$

where, $y_{s,m1,m2,t}$ denotes the sales of tractor of make $m1$ and model $m2$ in state s at time t. $Treatment_s$ takes a value of zero for the state of West Bengal and a value of one for all other states. $Post_t$ takes a value of one for months following March 2019. $\theta_{s,m1,m2}$ and $\theta_{m1,m2,t}$ denote state × model × make fixed effect and model × make × month fixed effect, respectively. The data for monthly state-wide sales of tractors by model and make come from an e-commerce website – Tractor Junction and spans from April 2018 through March 2020. Standard errors clustered at the state-model-make level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table F.2: Effect of the Policy on Tractor Sales – ZIP code level Analysis

Dep Var: $\frac{y_{z,t,a}}{Avg(y_{Pre_a})}$	(1) Number	(2) Amount
Agricultural Purpose X Post	0.1732***	0.1763***
	(0.0252)	(0.0320)
Zipcode X Month FE	Yes	Yes
Agricultural Purpose X Zipcode FE	Yes	Yes
# Obs	347,468	347,468
R^2	0.8157	0.6569
Sample Mean	3.021	1,863,074

The table estimates the effect of the policy on ZIP code-level sales of tractors according to the following specification:

$$\frac{y_{z,t,a}}{Avg(y_{Pre_a})} = \beta \cdot \text{Agri Purpose}_a \times Post_t + \theta_{z,a} + \theta_{z,t} + \varepsilon_{z,t,a}$$

where $y_{z,t,a}$ denotes the dependent variable of interest measured for ZIP code z at time (month) t. $Avg(y_{Pre_a})$ denotes the sample average of the variable of interest during the pre-policy period. Tractor sales can either be for agricultural purposes or non-agricultural purposes. Agri Purpose$_a$ takes a value of one for sales of tractors for agricultural purposes. $Post_t$ takes a value of one for months following March 2019. $\theta_{z,a}$ denotes ZIP code $\times$ purpose fixed effect. $\theta_{z,t}$ denotes ZIP $\times$ month fixed effects, where z refers to the ZIP code where sales happen. Column 1 and 2 use the number of tractor sales and the rupee amount of tractor sales as the dependent variable. The sample comes from the tractor registration data maintained by the Niti Aayog and spans from March 2018 through February 2020. The data covers the states of Bihar, Chattisgarh, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerela, Maharashtra, Odhisa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and Uttarakhand. 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 F.3: Effect of the Policy on Investment: Consumption of Fertilizers

Dep Var: $\frac{y_{i,s,t}}{Avg(y_{Pre})}$	(1) Total	(2) Nitrogen	(3) Phosphorus	(4) Potassium
LN(Beneficiaries) X Post	0.0598***	0.0543***	0.1016***	0.0274
	(0.0210)	(0.0191)	(0.0297)	(0.0367)
District X Season FE	Yes	Yes	Yes	Yes
State X Season X Year FE	Yes	Yes	Yes	Yes
# Obs	3,995	3,995	3,995	3,995
R^2	0.9344	0.9241	0.9146	0.8339
Sample Mean (in tonnes)	17,500	11,100	4,207	985

The table estimates the effect of change in the number of PMKSN beneficiaries on the consumption of fertilizers according to the following specification:

$$\frac{y_{i,s,t}}{Avg(y_{Pre})} = \beta \cdot LN(\#Beneficiaries_i) \times Post_t + \theta_{i,s} + \theta_{z,s,t} + \varepsilon_{i,s,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for district i in year t and season s. Each year has two seasons – Rabi and Kharif. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. $LN(\#Beneficiaries_i)$ refers to the natural logarithm of the number of PMKSN beneficiaries in district i. $Post_t$ takes a value of one for seasons following the 2019 Kharif season. $\theta_{i,s}$ denotes district $\times$ season fixed effects. $\theta_{z,s,t}$ denotes state $\times$ season $\times$ year fixed effects. District i is located in state z. The data on fertilizer consumption comes from the Ministry of Agriculture, Government of India and spans from the Rabi season in 2017 through the Rabi season in 2020. The key dependent variable is the total consumption of all fertilizers in column 1, total consumption of all Nitrogen-based fertilizers in column 2, total consumption of Phosphorus-based fertilizers in column 3, and total consumption of Potassium-based fertilizers in column 4. The estimate is standardized to report the effect in terms of a 10% increase in the number of beneficiaries. Standard errors clustered at the district level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table F.4: Effect of the Policy on Investment: Irrigation

Dep Var: $\frac{y_{i,t}}{Avg(y_{Pre})}$	(1) All Sources	(2) Government Sources	(3) Private Sources
LN(Beneficiaries) X Post	0.0549**	0.0347	0.0618**
	(0.0230)	(0.0270)	(0.0271)
District FE	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes
# Obs	1,296	1,296	1,296
R^2	0.9881	0.9868	0.9873
Sample Mean (in ’000 tonnes)	112.50	27.42	85.08

The table estimates the effect of change in the number of PMKSN beneficiaries on the utilization of irrigation facilities according to the following specification:

$$\frac{y_{i,t}}{Avg(y_{Pre})} = \beta \cdot LN(\#Beneficiaries_i) \times Post_t + \theta_i + \theta_{s,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest measured for district i in year t. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. $LN(\#Beneficiaries_i)$ refers to the natural logarithm of the number of PMKSN beneficiaries in district i. $Post_t$ takes a value of one following March 2019. θ_i denotes district fixed effects. $\theta_{s,t}$ denotes state $\times$ year fixed effects. District i is located in state s. The data on irrigation comes from the Ministry of Agriculture, Government of India and spans from March 2017 through March 2020. The key dependent variable is the total irrigation from all sources in column 1, total irrigation from government sources in column 2, and total irrigation from private sources in column 3. The estimate is standardized to report the effect in terms of a 10% increase in the number of beneficiaries. Standard errors clustered at the district level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table F.5: Effect of the Policy on Credit: Role of Prior Default

Panel A: No Prior Default

	(1)	(2)	(3)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Treatment X Post	0.1077***	0.1597***	0.1717***
	(0.0137)	(0.0090)	(0.0156)
Farmer FE	Yes	Yes	Yes
ZIP X Post FE	Yes	Yes	Yes
# Obs	69,790	69,790	69,790
R^2	0.526	0.699	0.796
Sample Mean	0.614	1.110	410,496

Panel B: Prior Default

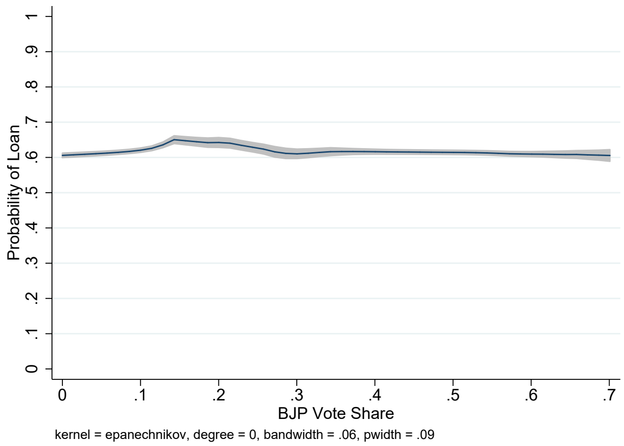
	(1)	(2)	(3)
	Loan (=1)	$\frac{\#Loan}{Avg(\#Loan_{Pre})}$	$\frac{\text{Loan Amt}}{Avg(\text{Loan Amt}_{Pre})}$
Treatment X Post	0.0265	0.0093	-0.0091
	(0.0258)	(0.0316)	(0.0191)
Farmer FE	Yes	Yes	Yes
ZIP X Post FE	Yes	Yes	Yes
# Obs	17,448	17,448	17,448
R^2	0.568	0.682	0.653
Sample Mean	0.611	1.076	256,441

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

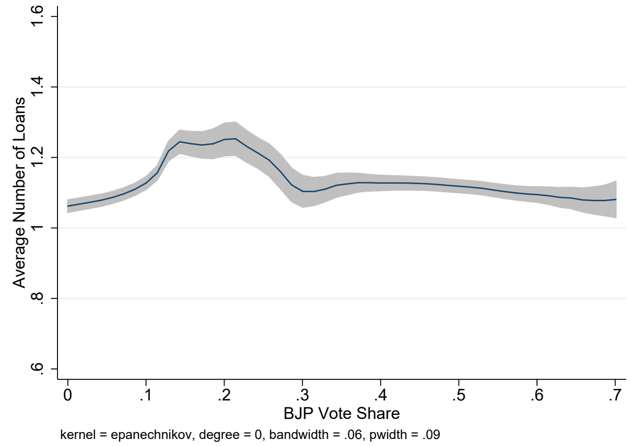
$$\frac{y_{i,p}}{Avg(y_{Pre})} = \beta \cdot Treatment_i \times Post_p + \theta_i + \theta_{z,p} + \varepsilon_{i,p}$$

where $y_{i,p}$ denotes the dependent variable of interest measured for farmer i at time p. There are only two time-periods in the analysis – pre-policy period and the post-policy period. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Avg(y_{Pre})$ 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. $Post_p$ takes a value of one for the post policy period defined as the twelve months from March 2019. θ_i denotes farmer fixed effects. $\theta_{z,p}$ denotes ZIP $\times$ post 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 sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana 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. Panel A uses the sample of farmers with no prior default tag. Panel B uses the sample of farmers with prior default tag. Standard errors clustered at the ZIP code level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

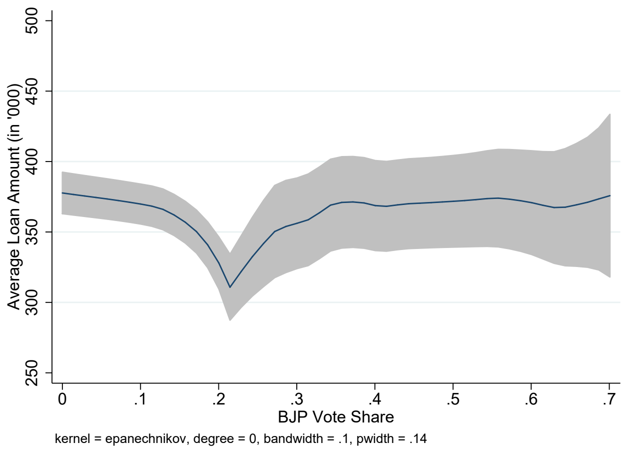
Figure F.1: Pre-Policy Lending and 2014 BJP Vote Share



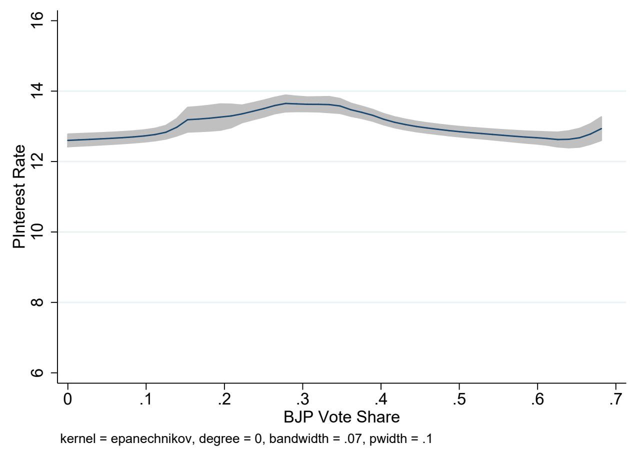
(a) Probability of Loan



(b) # Loans



(c) Loan Amount



(d) Interest Rates

The figure presents the relationship between pre-policy lending and BJP vote share. Panel F.1a presents the local linear polynomial fit between probability of loan in the pre-period and 2014 BJP vote share. Panel F.1b presents the local linear polynomial fit between the average number of loans in the pre-period and 2014 BJP vote share . Panel F.1c presents the local linear polynomial fit between the average amount of loans in the pre-period and 2014 BJP vote share. Panel F.1d presents the local linear polynomial fit between the average interest rates on loans in the pre-period and 2014 BJP vote share. The blue line represents the local linear polynomial and the gray shaded regions represents the 95% confidence intervals.

Table F.6: Effect of the Policy on Interest Rate

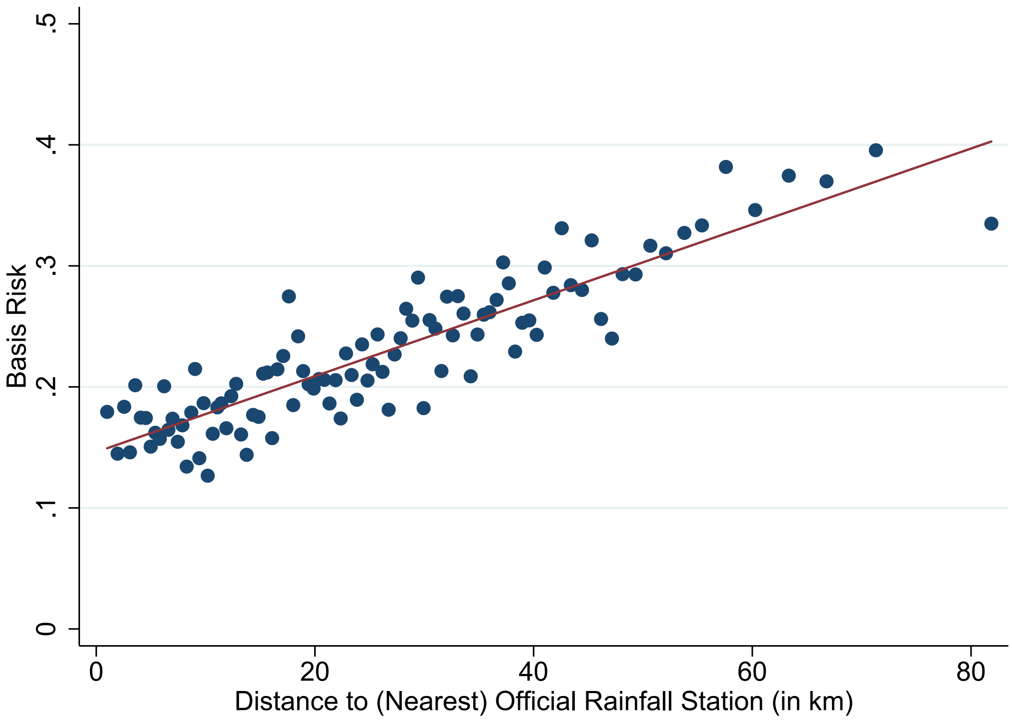
Dep Var: Interest Rates	(1)	(2)	(3)
BJP Vote Share X Treatment X Post	-0.0030		
	(0.0347)		
High Rainfall Risk X Treatment X Post		-0.0093	
		(0.0249)	
High Basis Risk X Treatment X Post			-0.0062
			(0.0075)
Treatment X Post	0.0194	0.0114	0.0207*
	(0.0331)	(0.0319)	(0.0109)
Farmer FE	Yes	Yes	Yes
ZIP Code X Post FE	Yes	Yes	Yes
# Obs	166,432	166,432	166,432
R^2	0.9567	0.9572	0.9449

The table estimates the heterogeneity in the relative effect of cash transfers under PMKSN on credit market outcomes for the treatment and control groups by different variables according to the following specification:

$$y_{i,t} = \beta_1 \cdot X_z \cdot Treatment_i \times Post_t + \beta_2 \cdot Treatment_i \times Post_t + \theta_i + \theta_{z,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ denotes the dependent variable of interest –interest rates on loans – measured for farmer i at time t (month). X_z denotes the key ZIP code level variable of interest. Column 1 uses BJP Vote Share$_z$ as X_z. BJP Vote Share$_z$ measures the share of votes cast for BJP in the 2014 federal elections. The data on vote shares of all political parties comes from the Election Commission of India at the electoral constituency level. We map electoral constituencies to ZIP codes. Column 2 uses High Drought Risk$_z$ as X_z. We compute ZIP code level rainfall as the monthly average of the precipitation levels of each 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 to 2017. ZIP code-year observations with positive z-scores are coded as zero, i.e. no drought, and negative z-scores are coded as one, i.e. below average rainfall. We use the average value of the drought measure from 2014 through 2017 to compute the probability of drought for each ZIP code. ZIP codes with above- and below-median probability of drought are coded as high and low risk areas, respectively. Column 3 uses High Basis Risk$_z$ as X_z. We map the latitude and longitudes of the ZIP codes to the latitude and longitudes of the nearest official rainfall station. We compute the model R^2 of the regression of total monthly rainfall in a ZIP code on total monthly rainfall at the nearest official rainfall station. We define basis risk as one minus the model R^2. ZIP codes with above- and below-median basis risk are coded as high and low basis risk areas, respectively. $Treatment_i$ 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 the post policy period defined as months following March 2019. θ_i denotes farmer fixed effects. $\theta_{z,t}$ denotes ZIP $\times$ time fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the loan-level data from the sample bank. The sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana 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.

Figure F.2: Basis Risk and Distance to Nearest Rainfall Station



The figure presents the 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.

Table F.7: Effect of the Policy on Hedging Activity: Diversification

	(1)	(2)	(3)	(4)
	$1-\sum s_i^2$	$\sum s_i \cdot LN(\frac{1}{s_i})$	$1-s_1-\sum s_i^2 \cdot (2-s_i)$	$-2\sum i \cdot s_i$
LN(# Beneficiaries) X Post	-0.0139***	-0.0188***	-0.0192***	-0.0182***
	(0.0033)	(0.0030)	(0.0036)	(0.0024)
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
# Obs	2,272	2,272	2,272	2,272
R^2	0.8271	0.8516	0.8519	0.8862
Sample Mean	0.5997	0.5437	0.5800	0.2978

The table estimates the effect of the policy on district-level agricultural diversification according to the following specification:

$$y_{z,t} = \beta \cdot LN(\#Beneficiaries_z) \times Post_t + \theta_z + \theta_t + \varepsilon_{z,t}$$

where, $y_{z,t}$ denotes the level of diversification in district z at time t. t refers to year as the unit of time. $LN(\#Beneficiaries_z)$ denotes the number of PMKSN beneficiaries in district z. $Post_t$ takes a value of one for years following 2019. θ_z denotes district fixed effects. θ_t denotes year fixed effects. The unit of analysis is district-year. The data spans all states of India from April 2017 through March 2020. The states of West Bengal, Jammu and Kashmir, and the north-eastern states are excluded from the analysis. Columns 1-4 use four different measures of agricultural diversification. Column 1 uses one minus standardized HHI. HHI is calculated as the squared sum of share of gross sown area under crop i in each district z. HHI is then standardized to a take value between 0 and 1. Column 2 uses entropy index. Entropy Index is calculated as the sum of the product of share of gross sown area under crop i and the natural logarithm of one divided by the share of gross sown area under crop i. Column 3 uses one minus the standardized concentration index. Concentration index is calculated as the share of gross sown area under crop i with the largest share in district z, denoted by s_1 plus the sum of the square of share of gross sown area under crop i multiplied with two minus share of gross sown area under crop i. The index is standardized to take value between 0 and 1. Column 4 uses the negative sum of share of gross sown area under crop i multiplied with its order i. The data on gross sown area under each crop at the district-year level comes from the Ministry of Agriculture. The data on the number of beneficiaries comes from the Government of India. The crops used to compute the diversification measures include rice, wheat, coarse cereals, jowar, bajra, maize, ragi, small millets, barley, pulses, major oilseeds, cotton, jute, mesta, hemp, tea, coffee, natural rubber, spices and condiments, vegetables, roots and tubers, fruits, sugarcane, tobacco, and guarseed. The estimate is standardized to report the effect in terms of a 1% increase in the number of beneficiaries. Standard errors clustered at the district level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table F.8: Effect of the Policy on Hedging Activity: Area Under Cash Crops

Dep Var: Share of GSA Under Cash Crops	(1)	(2)	(3)
LN(# Beneficiaries) X Post	0.0086***	0.0086***	0.0105***
	(0.0027)	(0.0027)	(0.0024)
LN(# Beneficiaries)	0.0211***	0.0211***	
	(0.0024)	(0.0024)	
Post	-0.0751***		
	(0.0280)		
Year FE		Yes	Yes
District FE			Yes
# Obs	2,276	2,276	2,276
R^2	0.0595	0.0600	0.9006
Sample Mean	0.0732	0.0732	0.0732

The table estimates the effect of the policy on district-level share of gross sown area under cash crops according to the following specification:

$$y_{z,t} = \beta \cdot LN(\#Beneficiaries_z) \times Post_t + \theta_z + \theta_t + \varepsilon_{z,t}$$

where, $y_{z,t}$ denotes the share of gross sown area under cash crops in district z at time t. t refers to year as the unit of time. $LN(\#Beneficiaries_z)$ denotes the number of PMKSN beneficiaries in district z. $Post_t$ takes a value of one for years following 2019. θ_z denotes district fixed effects. θ_t denotes year fixed effects. The unit of analysis is district-year. The data spans all states of India from April 2017 through March 2020. The states of West Bengal, Jammu and Kashmir, and the north-eastern states are excluded from the analysis. The data on gross sown area under each crop at the district-year level comes from the Ministry of Agriculture. The data on the number of beneficiaries comes from the Government of India. The crops used to compute the gross sown area include rice, wheat, coarse cereals, jowar, bajra, maize, ragi, small millets, barley, pulses, major oilseeds, cotton, jute, mesta, hemp, tea, coffee, natural rubber, spices and condiments, vegetables, roots and tubers, fruits, sugarcane, tobacco, and guarseed. Cash crops include cotton, jute, mesta, tobacco, and sugarcane. The estimate is standardized to report the effect in terms of a 1% increase in the number of beneficiaries. Standard errors clustered at the district level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table F.9: Effect of Drought on Consumption

Dep Var: $\frac{y_{i,p}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)
Drought	-0.1419***	-0.1265***	-0.0801***	-0.0829***
	(0.0045)	(0.0097)	(0.0076)	(0.0072)
Month FE		Yes	Yes	Yes
ZIP Code FE			Yes	Yes
Farmer FE				Yes
# Obs	2,078,451	2,078,451	2,078,451	2,078,451
R^2	0.0014	0.0309	0.0982	0.3629

The table estimates the effect of adverse drought shocks on consumption according to the following specification:

$$\frac{y_{i,p}}{Avg(y)_{Pre}} = \beta Drought_t + \theta_i + \theta_t + \varepsilon_{i,t}$$

where $\frac{y_{i,p}}{Avg(y)_{Pre}}$ denotes the dependent variable of interest for farmer i at time (month) t. θ_i denotes farmer fixed effects. θ_t denotes month fixed effects. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. We define drought by computing the deviation of Kharif season rainfall in a ZIP code from its historical average rainfall and code all ZIP codes with negative deviation as drought. The sample comes from the transaction-level bank data and includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from January 2014 through December 2018. We measure spending using all outflows from the bank account, including in-person and ATM withdrawals, wire transfers, and credit and debit card transactions. We remove all outflows classified as spending for durable goods using the Merchant Category Code (MCC) associated with each transaction. 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 F.10: Effect of the Policy on Financial Conditions

	(1)	(2)
	Financial Condition Today, Relative to Last Year	Financial Condition Next Year, Relative to Last Year
Treatment X Post	0.0432***	0.0443***
	(0.0142)	(0.0128)
Household FE	Yes	Yes
Education group X District FE	Yes	Yes
Education group X Month FE	Yes	Yes
Gender group X District FE	Yes	Yes
Gender group X Month FE	Yes	Yes
Age group X District FE	Yes	Yes
Age group X Month FE	Yes	Yes
HH Size group X District FE	Yes	Yes
HH Size group X Month FE	Yes	Yes
District X Month FE	Yes	Yes
# Obs	159,940	159,940
R^2	0.616	0.584

The table estimates the relative effect of the policy on reported financial conditions today and the expected financial conditions next year relative to last year for the treatment and control groups. *Treatment* 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 defined to be treatment households. *Post* takes a value of one for months following March 2019. Specification includes household fixed effects and district $\times$ month fixed effect. Additionally, we include fixed effects associated with the interaction of education group, gender group, age group and household size group with district and time (month) dummies. The group definitions are adopted directly from the survey. The sample comes from the Aspirations survey conducted by CMIE across all states in India from March 2018 through March 2020. The states of West Bengal, Jammu and Kashmir, and the north-eastern states are not included in the sample. All regressions are weighted by survey weights of each household. The key dependent variable is the reported financial conditions today (column 1) and expected financial conditions in the next year, relative to the last year (column 2). Standard errors clustered at the district level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table F.11: Effect of the Policy on Farmer Suicides

Dep Var: $\frac{y_{z,f,p}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)
Farmer X Post	-0.0663***	-0.0663***	-0.0663***	-0.0663***
	(0.0166)	(0.0166)	(0.0166)	(0.0166)
Farmer	-0.5973***	-0.5973***	-0.5973***	
	(0.0343)	(0.0343)	(0.0343)	
Post	0.0883***			
	(0.0149)			
ZIP Code FE		Yes		
Post FE		Yes		
ZIP Code X Post FE			Yes	Yes
ZIP Code X Farmer FE				Yes
# Obs	2,220	2,220	2,220	2,220
R^2	0.2096	0.6097	0.6298	0.9801
Sample Mean	16.271	16.271	16.271	16.271

The table estimates the effect of the policy on farmer suicides in the state of Karnataka. We collapse the data to our unit of analysis at the ZIP code-pre/post-individual type level. Individual type is either a farmer or a non-farmer. Therefore each ZIP code unit has four observations – two observations for time (pre and post) and for each unit of time two observations for individual type (farmer or non-farmer). An individual is identified as a farmer based on the farmer tag in the police report data. The state authorities maintain this database to report the number of farmer suicides. *Post* takes a value of one for months following March 2019. The data spans across the state of Karnataka from March 2018 through March 2020. Specification includes farmer × zip fixed effects and zip × post fixed effects. $y_{z,f,p}$ denotes the dependent variable of interest measured for ZIP code z at time p for farmer type f. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. The key dependent variable is the the number of suicides. 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 F.12: Effect of the Policy on Farmer Suicides due to Debt

Dep Var: $\frac{y_{z,d,p}}{Avg(y)_{Pre}}$	(1)	(2)	(3)	(4)
Debt X Post	-0.0642*	-0.0642*	-0.0642*	-0.0642*
	(0.0348)	(0.0348)	(0.0348)	(0.0348)
Debt	-0.0281	-0.0281	-0.0281	
	(0.0412)	(0.0412)	(0.0412)	
Post	0.0092			
	(0.0267)			
ZIP Code FE		Yes		
Post FE		Yes		
ZIP Code X Post FE			Yes	Yes
ZIP Code X Debt FE				Yes
# Obs	1,384	1,384	1,384	1,384
R^2	0.0038	0.4892	0.5792	0.9227
Sample Mean	5.038	5.038	5.038	5.038

The table estimates the effect of the policy on farmer suicides due to debt in the state of Karnataka. We collapse the data to our unit of analysis at the ZIP code-pre/post-suicide type level. Suicide type is either due to debt or other reasons. Therefore each ZIP code unit has four observations – two observations for time (pre and post) and for each unit of time two observations for suicide type (debt or non-debt). An individual is identified as a farmer based on the farmer tag in the police report data. We restrict our sample to farmers. The state authorities maintain this database to report the number of farmer suicides. We identify if the reason for suicide was related to debt by examining the summary of the closing report filed by the police authorities. We tag a farmer suicide due to debt if any of the following words appear in the closing report – debt, loan, bank, and lender. *Post* takes a value of one for months following March 2019. The data spans across the state of Karnataka from March 2018 through March 2020. Specification includes farmer × zip fixed effects and zip × post fixed effects. $y_{z,f,p}$ denotes the dependent variable of interest measured for ZIP code z at time p for suicide type d. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Avg(y_{Pre})$ denotes the sample average of the variable of interest during the pre-policy period. The key dependent variable is the the number of suicides. 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 G Kisan Credit Cards

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

Figure G.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 G.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 G.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**

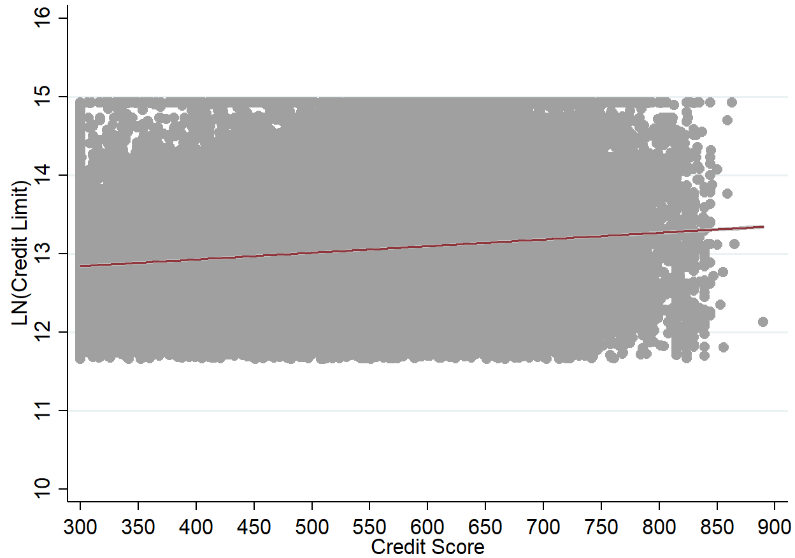
Maximum Permissible Limit /

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

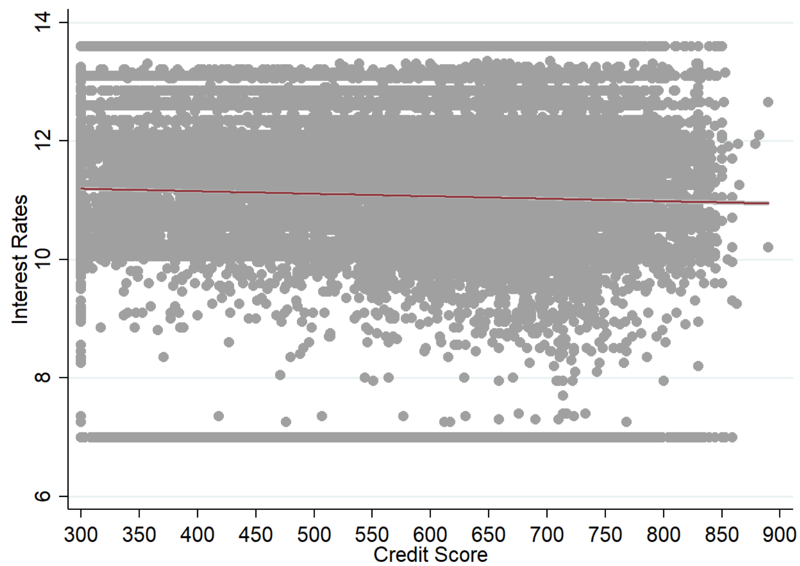
Drawing Limit will be reduced every year based on repayment schedule of the term loan(s) availed and withdrawals will be allowed up to the drawing limit.

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.

Figure G.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, Karnataka, and Telangana before March of 2019. The data on credit limit and interest rates comes from my sample bank. The gray dots represents the scatter plot and the red line represents the best fit line

Table G.1: Effect of the Policy on KCC Credit Limit and Interest rates

	(1)	(2)
	LN(Credit Limit)	Interest Rates
Treat X Post	0.0018	-0.0119
	(0.0037)	(0.0025)
Farmer FE	Yes	Yes
ZIP Code X Post FE	Yes	Yes
# Obs	126,432	126,432
R^2	0.9970	0.9784
Sample Mean	12.7457	11.1181

The table estimates the relative effect of cash transfers under PMKSN on KCC credit limit and interest rates for the treatment and control groups according to the following specification:

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

where $y_{i,p}$ denotes the dependent variable of interest measured for farmer i at time p. There are only two time-periods in the analysis – pre-policy period and the post-policy period. The pre- and post-policy periods refer to the twelve months before and after the policy, respectively. $Treatment_i$ takes a value of one for landowning farmers and a value of zero for non-landowning farmers. $Post_p$ takes a value of one for the post policy period defined as the twelve months from March 2019. θ_i denotes farmer fixed effects. $\theta_{z,p}$ denotes ZIP × post fixed effects, where z refers to the ZIP code where farmer i operates. The sample comes from the bank data that provides information on all changes to the credit limit and interest rates on KCC issued by the bank. The sample includes farmers in the states of Punjab, Maharashtra, Karnataka, and Telangana from March 2018 through February 2020. Column 1 uses the natural logarithm of credit limit on KCC as the dependent variable. Column 2 uses the interest rates on KCC 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 H Sobel-Goodman Mediation Test

This section outlines the steps involved in Sobel-Goodman mediation test based on Sobel (1982). The test examines the effect of a variable x on y that is mediated through z. Three different regression models are examined while evaluating the mediation effect.

$$y = \gamma_1 + c \cdot x + \varepsilon_1 \tag{H.1}$$

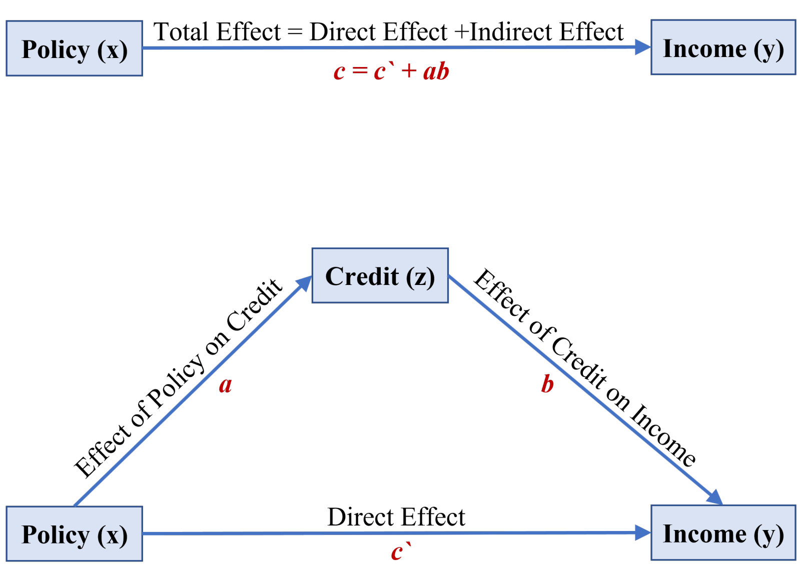
$$z = \gamma_2 + a \cdot x + \varepsilon_2 \tag{H.2}$$

$$y = \gamma_3 + c^{'} \cdot x + b \cdot z + \varepsilon_3 \tag{H.3}$$

where y is the dependent variable of interest, x refers to the independent variable, and z refers to the mediating variable. γ_1, γ_2, and γ_3 represent the intercepts for each model, while ε_1, ε_2, and ε_3 represent the error term for each equation. Figure H.1 presents the schematic description of the test and the quantities of interest. The description of four quantities of interest that emerge from the above regressions is as follows:

1. The total effect of x on y is given by c
2. The effect of x on z is given by a. This is the effect of the independent variable on the mediating variable
3. The direct effect of x on y is given by $c^{'}$
4. Effect of x on y that is mediated through z is given by:
   (a) Indirect Effect = $c - c^{'} = a \times b$

Figure H.1: Schematic Description of Sobel-Goodman Mediation Test



We directly estimate equations H.1 and H.2 by running the following regressions that allow us to estimate the total effect of the policy on income (c) and the effect of the policy on the mediating variable (a).

$$\frac{Income_{i,p}}{Avg(Income_{Pre})} = c \cdot Treatment_i \times Post_p + \theta_i + \theta_{z,p} + \varepsilon^1_{i,p} \tag{H.4}$$
$$\frac{Credit_{i,p}}{Avg(Credit_{Pre})} = a \cdot Treatment_i \times Post_p + \theta_i + \theta_{z,p} + \varepsilon^1_{i,p} \tag{H.5}$$

Estimating equation H.3 poses a concern since credit is an endogenous variable. This creates an econometric issue in directly estimating c'. However, we can estimate the coefficient b by running the following 2SLS regression. The second stage stage coefficient allows us to estimate b.

$$\frac{Credit_{i,p}}{Avg(Credit_{Pre})} = a \cdot Treatment_i \times Post_p + \theta_i + \theta_{z,p} + \varepsilon^1_{i,p} \tag{H.6}$$
$$\frac{Income_{i,p}}{Avg(Income_{Pre})} = b \cdot \frac{\hat{Credit}_{i,p}}{Avg(Credit_{Pre})} + \theta_i + \theta_{z,p} + \varepsilon^1_{i,p} \tag{H.7}$$

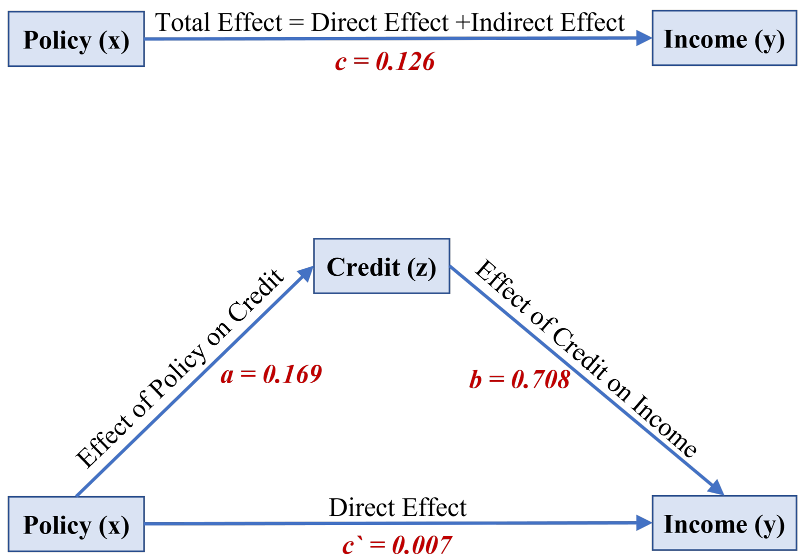
Hence, we compute the indirect effect using the product of coefficients a and b. Sobel (1982) shows that the standard error of the product is given by $\sqrt{a^2 \cdot \sigma_b^2 + b^2 \cdot \sigma_a^2}$ where σ_b^2 is the variance of b and σ_a^2 is the variance of a. The distribution of the product term is only normal at large sample sizes and Sobel (1982) proposes usage of z distribution to determine significance. Aroian (1947) and Goodman (1960) propose alternative z-statistics to determine significance. The three z-statistics are given as follows:

$$\text{Sobel Test: } z = \frac{a \times b}{\sqrt{a^2 \cdot \sigma_b^2 + b^2 \cdot \sigma_a^2}}$$
$$\text{Aroian Test: } z = \frac{a \times b}{\sqrt{a^2 \cdot \sigma_b^2 + b^2 \cdot \sigma_a^2 + \sigma_a^2 \cdot \sigma_b^2}}$$
$$\text{Goodman Test: } z = \frac{a \times b}{\sqrt{a^2 \cdot \sigma_b^2 + b^2 \cdot \sigma_a^2 - \sigma_a^2 \cdot \sigma_b^2}}$$

H.1 Results

Figure H.2 presents the estimates of interest used in the Sobel-Goodman mediation test. The estimates of c, a, and b comes from the estimation of equations H.4, H.5, and H.7, respectively. The direct effect c' is computed as difference between c and the product of a and b. The estimate of c' is equal to 0.007. The fraction of policy's effect on income mediated through credit is given by $\frac{a \times b}{c}$ which is equal to 0.944. The z-statistics associated with the indirect effect are shown in Table H.1.

Figure H.2: Results from Sobel-Goodman Mediation Test



The figure presents the estimates of different quantities of interest from the Sobel-Goodman mediation test. The estimates of c, a, and b comes from the estimation of equations H.4, H.5, and H.7, respectively.

Table H.1: Z-statistics associated with Indirect Effect ($a \times b$)

Test	Z-Statistic
Sobel (1982)	8.161***
Aroian (1947)	8.160***
Goodman (1960)	8.162***

The table presents the z-statics associated with the Sobel (1982), Aroian (1947), and Goodman (1960) for test of significance of the indirect effect. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.