Policy Paper 41

Can Finance Mitigate Climate Risks in Agriculture?

Farm-level Evidence from India

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Preface

Climate change is one of the biggest challenges to sustainable development of agriculture, and consequently to the livelihood of farming communities, and the governments' efforts to improve food and nutrition security and reduce poverty, especially in countries more exposed to climate risks and dominated by small-scale producers who often lack finance for investment in risk management. During the past two decades, climate finance for agriculture has attracted considerable attention in policy debates, yet agriculture's share in the total climate finance has remained minimal.

Empirical evidence presented in this paper distinctly highlight the role of finance in building resilience of agriculture. These provide a basis for a change in policy stance to emphasize climate finance in investment and credit planning in agriculture, and the need for innovative approaches to deliver finance that is climate sensitive.

Climate risks are predicted to be severe in plausible future climate scenarios; hence, the need for climate finance for agriculture cannot be understated. Current level of climate finance for agriculture is not commensurate with its requirement. Today's investments in climate actions will shape future trajectory of agricultural growth, and its economic and social outcomes. I hope this paper will be useful for policymakers, financial institutions and other stakeholders to take informed decisions on financing agriculture for risk management.

P S Birthal
Director, ICAR-NIAP

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Authors

Executive Summary

Climate change is one of the biggest threats to sustainable development of agriculture. In the absence of adaptation and mitigation, climate change will reduce crop yields and food supplies, affecting livelihoods of farming communities and consumers alike, and effectiveness of governments' efforts towards improving food security, combating malnutrition, and reducing poverty. Climate threat is more pronounced in developing countries located in tropics and sub-tropics, which often lack technologies and finances for risk management.

Inter alia, investments in agricultural research, early-warning and climate advisory systems, agri-food supply chains and rural infrastructure, and financial support to farmers for adoption of stress-tolerant crop varieties, crop diversification, precision farming and natural resource management can significantly help improve productivity and resilience of agriculture. Nonetheless, financial and credit planning in agriculture in developing countries has remained anchored to productivity enhancement. Only recently, policies have started addressing agriculture's vulnerability to climate risks.

During the past two decades, much has been talked about climate finance for agriculture at several international and national forums. Yet, the achievements have been too little. In 2020, agricultural sector shared not even 3 percent of the global climate finance (CIP, 2023), probably due to high real and perceived risks in agriculture and lack of scale for investment, especially in smallholder-dominated developing countries.

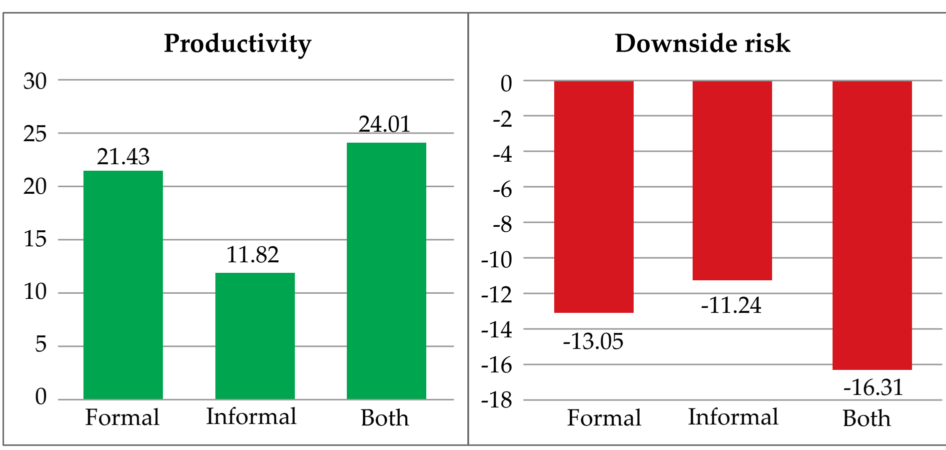
Notwithstanding, agriculture can deliver higher crop yields, food supplies and farm incomes using fewer resources while reducing greenhouse gas emission, if the technological, institutional and financial barriers to climate-resilient agriculture are overcome. Through a rigorous analysis of data from a large-scale nationally representative farm survey in India, this paper has assessed the contribution of finance to risk mitigation and productivity improvement in agriculture. Followings are key findings of this investigation.

Farmers require financial support for risk mitigation: Climate risks compel liquidity-constrained farmers to rely on external finance for meeting the revenue and capital needs in farming to improve productivity and reduce vulnerability to risks. Our findings show that only one-third of the farm households access external finance of which — 73 percent of them rely exclusively on formal or public finance, and 15 percent on informal or private finance.

Finance provides co-benefits: Finance has a measurable impact on farm productivity and its resilience to climate change. Its productivity-enhancing effect, however, is comparatively large (24%) than its risk-reducing effect (16%) (Figure 1).

Formal finance has a bigger effect than informal finance: Compared to informal finance, formal finance is twice more effective in enhancing farm productivity (Figure 1). Its risk-reducing effect is also bigger but at the margin. Nevertheless, there is a complementarity in the effects of the two — productivity as well as risk benefits are enhanced when informal finance complements formal finance.

Figure 1: Effects of finance on farm productivity and downside risk



Finance for capital investment is more productive: Long-term finance for capital investment has a bigger effect compared to short-term finance for revenue expenses; and the effect gets magnified in case of their conjunctive use.

There exists a lending bias in rural financial markets: Households with small landholdings, headed by females, and belonging to lower castes have smaller access to finance due to lack of assets acceptable as collateral to lenders.

Diversification, information, insurance, and markets enhance prospects of securing finance: Prospects of securing finance from formal sources are brightened if farmers practice diversified agriculture (i.e., horticultural crops and animal husbandry), and have a greater access to information, insurance, and product markets.

Building resilience in agriculture is, thus, contingent upon farmers' access to finance. Today's investments in climate transition will shape future trajectory of agricultural growth and its economic and social outcomes. In this context, findings of this study provide crucial feedback for financial and credit planning for risk management in agriculture.

Risk management should be an integral component of financial and credit planning in agriculture: Traditionally, financial and credit planning in agriculture has largely targeted enhancing productivity of agriculture. However, the growing threat of climate change necessitates a shift in policy stance towards financing agriculture for adaptation and mitigation.

Financial institutions must build their capacity in risk assessment: Climate impacts and their management strategies are context- and location-specific; hence, risk management strategies should be tailored to agro-ecological and socio-economic conditions. However, financial institutions lack capacity in identifying mitigation and adaptation measures at farm level for extending financial support for their implementation. Hence, they must interact and collaborate with a range of stakeholders, including research and extension institutions, non-governmental organizations, agribusiness firms, self-help groups, and village-level institutions that have better understanding of climate-smart interventions and their financial requirements.

Financial institutions should be responsive to the needs of farming communities: Socially and economically disadvantaged farming communities, who need finance the most, have comparatively low access to it due to lack of collateral, and high transaction costs and lending risks associated with small loans. Hence, financial institutions must innovate financial products and services suited to the needs of marginalized communities. One such innovation could be provision of collateral-free concessional finance conditional upon farmers' adoption of climate-smart technologies and practices. Another could be extending financial support to a group of farmers for creating shared assets such as community tube-wells and pressurised irrigation systems, solar farming and farm machinery.

Integrate financial support and crop insurance: Crop insurance is an important means of risk transfer. However, the premium for insurance is paid before start of the crop season when liquidity-constrained farmers face competing demands on their limited financial resources. Linking credit to insurance not only mitigates liquidity constraints for farmers but also reduces transaction costs and lending risks for financial institutions. Until 2020, crop insurance in India was compulsory for borrowers of institutional credit, but it has now been delinked and made voluntary. This may reduce farmers' participation in insurance programme. Rather de-linking insurance from credit, a better option could have been to overcome the problems of credit-linked insurance.

Value chains offer scope for integration of climate finance: Currently, bulk of climate finance in agriculture aims at post-harvest supply chain activities such as storage, warehouse, and refrigerated transport; and a little for adaptation and mitigation at farm level. Nonetheless, there is a considerable scope of integrating climate finance with supply chains through tripartite contracts involving their sponsors (i.e., agribusiness firms, start-ups, cooperatives, and farmer producer organizations), farmers, and financial institutions.

Financial institutions can facilitate market for carbon or green credits: Government of India has recently announced creation of a national market for carbon or green credits to incentivise farmers and other stakeholders to adopt climate-smart technologies and practices. Financial institutions can play a catalytic role in upcoming market for green credits by linking financial support to the adoption of sustainable agricultural practices.

Improve metrics and tools for valuation of ecosystem services of sustainable agricultural practices: Unlike in other economic sectors, the process of quantification, valuation and certification of carbon and green credits in agriculture is complex due to interactions among different activities of the agricultural ecosystem. Current metrices and tools to estimate costs and benefits of climate-smart interventions or ecosystem services are insufficient. More research is required to accurately assess economic, environmental and social costs and benefits of different climate-smart interventions.

♦♦♦

1 Introduction

Agriculture is both a source and a victim of climate change, yet it also offers a solution to mitigate climate change. Agriculture contributes approximately 18 percent to the total emission of greenhouse gases (GHG), which are responsible for global warming or climate change. At the same time, compared to other sectors, it is more vulnerable to climate change, especially in developing countries that tend to be hot, and lack resources for mitigation and adaptation (Dell *et al*., 2012; Ortiz-Bobea *et al*., 2021). Ortiz-Bobea *et al*.(2021) have estimated that since the early 1960s, despite rapid technical progress in agriculture, climate change has slowed down productivity growth of world agriculture by 21 percent, and the slow-down has been more pronounced in tropical countries. There exists similar evidence from India — the climate impacts are more significant in ecologically fragile arid and semi-arid tropics (Birthal *et al*., 2014) and in economically underdeveloped states (Birthal *et al*., 2021).

Predictions suggest climate change to be more severe, and accompanied by increasing frequency of extreme events like droughts, floods and heat-waves in plausible future climate scenarios (IPCC, 2022). In the absence of mitigation and adaptation, such extreme changes in climate will significantly affect agricultural productivity and food supplies, endangering livelihoods of farming communities, and reducing effectiveness of governments' efforts to improving food security, combating malnutrition, and reducing poverty.

Hallegatte *et al*. (2016) have estimated comparatively large negative effects of droughts on poverty and nutrition in sub-Saharan Africa and South Asia. Several other studies too have reported reduction in household income and consumption due to deficit rainfall (e.g., Bhandari *et al*., 2007; Hill and Mejia-Mantilla, 2015; Amare *et al*., 2018). Long-term consequences of frequent exposure to climate risks could be devastating, resulting in depletion of household savings, sale of non-productive and productive assets, increase in indebtedness, and degradation of natural resources (Rosenzweig and Binswanger, 1993; Dercon, 2004; Dercon and Christiaensen, 2011; Bhandari *et al*., 2007). In the absence of adaptation and mitigation, poor farmers as well as consumers may remain in a perpetual low-income or poverty trap (Dercon and Christiaensen, 2011; Vargas and Angelino, 2012). Thus, the need for building resilience in agriculture is indispensable for rural welfare.

Resilience strategies must be built upon technologies, innovations, infrastructure, markets, and institutions (i.e., credit and extension) and synchronized and coordinated across spatial scales. Delivering higher and stable outputs requires utilizing land, water and energy optimally taking into consideration regional heterogeneity in resource endowments and socio-economic conditions. In common parlance, such a strategy is termed as 'climate-smart agriculture'.

Governments and farmers in developing countries however confront several challenges in transition to climate-smart agriculture. Agriculture is dominated by smallholders (Lowder *et al*., 2016), and traditionally, finance has been an important barrier to adoption of improved technologies and practices (Feder *et al*., 1990; Nagarajan and Meyer, 2005; Huang *et al*., 2008; Banerjee, 2009; Miller and Jones, 2010; Swinnen and Maertens, 2014; Chen *et al*., 2015). The same holds in case of transition to climate-smart agriculture. In India, only about one-third of the farm households meet their financial requirements through borrowings from formal and informal sources (GoI, 2021a).

Finance contributes to agricultural development in several ways. First, by easing liquidity constraints, it enables timely purchase of inputs and services by farmers. Finance helps optimize resource allocation, leading to higher technical and allocative efficiency. Binswanger and Khandker (1995) and Narayanan (2016) have shown that flow of formal finance preserves agricultural productivity *via* increased use of inputs. Second, access to finance may be an incentive for farmers to adopt improved technologies, and to invest in irrigation, land and water conservation and mechanization, which can potentially shift production function upward or cost function downward.

Third channel through which finance contributes to farm outcomes is that it allows farmers to use their fixed resources (i.e., land) intensively (Carter, 1989), and benefit from economies of scope due to enterprise complementarity. In mixed farming systems, cultivation of land at its intensive margin augments biomass supply as feed for animals, which, in turn, can lead to an improvement in animal productivity and scale of production. Fourth, access to finance may motivate farmers to diversify into more-remunerative enterprises, including horticulture and livestock, which often require higher initial investment.

Diversification also helps mitigate climate risks (Birthal and Hazrana, 2019), reduce pest risks, and improve resource-use efficiency (Tamburini *et al*., 2020; van Zonneveld *et al*., 2020). Studies have shown that diversification into high-value horticulture and animal husbandry is significantly associated with low poverty rates (Birthal and Negi, 2012; Birthal *et al*., 2015). However, smallholder farmers facing liquidity constraint may not diversify their product portfolio beyond a threshold (Birthal *et al*., 2015)

Finally, finance improves farm households' capacity to manage climate or other production risks. Liquidity-constrained risk-averse farmers are often reluctant to adopt improved technologies and innovations or undertake long-term investment in soil and water conservation, farm mechanization and precision agriculture, which can improve crops' resilience to climate change. By relaxing liquidity constraint, access to finance can empower farmers to recover from adverse effects of climate shocks. Further, availability of finance may motivate farmers to purchase insurance to transfer a part of expected output loss to financial institutions for a fee or premium (Ali *et al*., 2020; Birthal *et al*., 2022). The insurance premium has to be paid before start of the crop season; a time when farmers confront competing demands on their limited financial resources.

In recent times, financing adaptation and mitigation in agriculture has attracted considerable attention in academic and policy debates. At the 15th Conference of Parties (COP 15) of the UNFCC (United Nations Framework Convention on Climate Change) in Copenhagen in 2009, developed countries pledged to mobilize US$100 billion per annum by 2020 for financing climate actions in developing countries that are comparatively more exposed and vulnerable to climate risks, and lack resources for their management. The pledge, however, has remained unfulfilled — in 2020 a total US$83.3 billion was mobilized. Climate finance was also high on agenda of the COP 27 in Glasgow in 2022 and is expected to be a topic of significant discussion in future also.

Despite being highly vulnerable to climate change, the reality is that agriculture has remained neglected in climate finance. In 2020, it shared less than 3 percent of the total climate finance (CPI, 2023). One of the reasons for poor flow of finance to agriculture is that financial and credit planning in agriculture has mostly targeted productivity improvements, which is reflected in literature exploring nexus between finance and agricultural development (Binswanger and Khandker, 1995; Burgess and Pande, 2005; Cole, 2009; Ramkumar and Chavan, 2007; Naryanan, 2016; Misra *et al*., 2016; Maitra *et al*., 2017; Kumar *et al*., 2017; Kumar *et al*., 2020).

Finance supports climate actions in agriculture to reduce GHGs and increase carbon sink without any adverse effect on its productivity (UNFCCC, 2018). Nevertheless, quantifying the effect of finance on agricultural outcomes is complex. Its effects are embedded in input effects, the unscrambling of which is a real empirical challenge (Carter, 1989; Feder *et al*., 1990; Binswanger and Khandker, 1995). The other challenge relates to fungibility of money — there is always a possibility of diversion of borrowed money from its intended use, leading to an under-estimation of its effects on agricultural outcomes (Carter, 1989; Binswanger and Khandker, 1995; Burgess and Pande, 2005). Also, there is high probability of targeting and selection biases, i.e., a financing scheme can target a specific group of farmers or farmers can self-select to participate in the scheme (Binswanger and Khandkar, 1995).

This paper assesses the effects of finance on farm outcomes, i.e., productivity and risk in agriculture. Specifically, it investigates the following questions:

(i) What determines farmers' access to finance, and their choice of a source of finance, formal or informal?

(ii) Does access to finance improve farm outcomes, i.e., productivity and risk?

(iii) Do the productivity and risk outcomes of finance differ by its source and intended use?

(iv) Is there a complementarity in the effects of different sources of finance and its purposes?

Generating empirical evidence on the effects of finance is essential for providing evidence-based feedback to policymakers and financial institutions to take informed decision in revisiting investment and credit planning in agriculture. This is particularly important when climate change is emerging as a significant threat to agriculture and agriculture-based livelihoods.

This paper makes three contributions to literature. First, it isolates effects of finance embedded in input effects and explicitly brings out the contribution of finance to productivity improvement and risk reduction in agriculture. Second, it assesses contribution of long-term and short-term finance, a key to prioritize financing mitigation and adaptation strategies. Third, it looks for complementarity in the effects of different sources of finance, which can be important for financial institutions in smoothening flow of public finance.

Rest of the paper is organized as follows. Next chapter discusses data and provides the descriptive statistics. Econometric framework for assessing the effects of finance on farm outcomes is provided in Chapter 3. Chapter 4 identifies factors influencing farmers' decisions to seek financial support by source. Concomitantly, it discusses effects of finance on farm outcomes. A brief account of status of climate finance in Indian agriculture in relation to global context is given in Chapter 5. Conclusions and implications are summarized in the last section.

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2 Data and Descriptive Statistics

Over the past five decades, Government of India has introduced several reforms in the financial sector to enhance flow of institutional finance to agriculture and reduce farmers' dependence on informal finance. In 1969, in the backdrop of the Green Revolution, 14 major commercial banks were nationalized, making it mandatory for them to earmark a certain proportion of their lending portfolio for agriculture and rural development. A big boost to agricultural finance came in 1976 when Regional Rural Banks were established aiming at improving targeting, delivery, and monitoring of rural credit. Further, National Bank for Agriculture and Rural Development (NABARD) was established in 1982 to serve as an apex bank for refinancing agriculture and rural development. Successive reforms in financial sector aimed at easing financing norms and procedures regarding collateral requirement, interest rate, and inclusiveness and outreach of banking system.

The reforms had a significant impact — a 15-fold increase in supply of institutional credit to agriculture (at constant 2010 prices) between 1980-81 and 2019-20 (Kumar and Afroz, 2022), leading to doubling of its intensity (i.e., ratio of outstanding credit to agricultural gross domestic product) from 0.21 to 0.41. Farmers' dependence on informal finance reduced considerably — share of informal credit in the total rural credit declined from 71 percent in 1971 to 30 percent in 2019-20 (GoI, 2021b).

2.1 Data

To assess effects of finance on farm outcomes, i.e., productivity and risk, we have used household-level data from a nationally representative farm survey, viz., Situation Assessment Survey of Agricultural Households, conducted in 2018-19 by National Sample Survey Office (NSSO), Government of India (GoI, 2021a). Survey was implemented in two rounds: July-December 2018 and January-June 2019 covering same households in each round. A total 56,899 households from 5940 villages spread over all states and union territories were covered in the survey.

Households have further been categorised as agricultural households and non-agricultural households. A household was considered an agricultural household if it earned at least Rupees 4000 per month from agricultural activities, including cultivation of crops, animal husbandry, and fisheries, and also had at least one member self-employed in agriculture in the past 365 days. Accordingly, agricultural households comprised 79 percent of the total households. Most agricultural households possessed and cultivated land, but some did not. Hence, in our analysis, we considered all those households who had earned income from crop farming.

The Situation Assessment Survey provides information on several aspects of farming and farmers. These include area, production, and value of crops; landholding size, land leased-in and leased-out, and irrigated area; ownership of livestock and farm assets; income sources; cost of production; access to information and technical advice; formal training in agriculture; and membership of farmer organizations. Besides, it provides information on social and demographic characteristics such as age, sex, and education of household heads, and the caste they belong to.

Information on finance pertains to its source and purpose for which it had been sought (i.e., capital investment and revenue expenses). Information on risk management relates to farmers' self-reported losses due to different climate shocks, subscription to crop insurance contract, and sale of crop output at government-determined minimum support prices (MSP).

2.2 Descriptive statistics

Farm households supplement their financial requirements over their savings through borrowings either from a formal or informal source.[1] Table 1 presents the proportion of households seeking financial support from formal and informal sources. One-third of the farm households have borrowed from any source — 73 percent of them exclusively from formal sources, 15 percent solely from informal sources, and the rest from both.

Further, about 57 percent of the households have acquired short-term finance for meeting their revenue or operational expenses, i.e., for purchase of inputs and services, and the rest for acquiring farm machinery and

[1] Formal sources of finance comprise the commercial banks, regional rural banks, co-operative societies, co-operative banks, insurance companies, provident fund, employers, financial corporations/institutions, non-banking financial companies (NBFC) including micro-financing institutions, bank-linked self-help groups (SHGs), joint liability groups (JLGs), and non-bank-linked SHGs/JLGs; and informal sources includes landlords, agricultural moneylenders, professional moneylenders, input suppliers, relatives and friends, chit funds, commission agents, and traders.

Table 1. Frequency distribution of borrowers by source and purpose of finance

Source of finance	Capital expenses (Long-term)		Revenue expenses (Short-term)		Total	
	No.	%	No.	%	No.	%
Formal	4697	75.25	6072	72.59	10769	73.72
Informal	962	15.41	1174	14.03	2136	14.62
Both	583	9.34	1119	13.38	1702	11.65
Total	6242	100	8365	100	14607	100

equipment, and for investment in land and water conservation. Notably, the proportion of short-term finance exhibits parity between formal and informal sources.

Table 2 shows that farmers availing financial support have larger landholdings and better access to irrigation, and are differentially engaged in animal husbandry, horticulture, and non-farm business activities. Farmers availing credit are also more educated and have a stronger association with farmer organizations. Besides, they are better-informed about crop insurance and minimum support prices (MSP). This is pertinent as 43 percent farmers have sold their produce (mainly paddy and wheat) to government agencies at MSP, and 24 percent have purchased crop insurance. Importantly, the proportion of households reporting crop loss due to any climate risk is higher among those seeking financial support. Such farmers also spend more on inputs (i.e., seeds, fertilizers, and pesticides). This reflects the role of finance in alleviating liquidity constraint on farmers' purchase of inputs.

Table 2 also compares characteristics of households availing finance from formal and informal sources. Formal-sector borrowers expectedly have comparatively large landholdings, allocate more area to high-value crops, spend more on inputs, and are engaged to a greater degree in non-farm business activities. The pecking order in education and membership of organization extends to accessing formal *versus* informal finance.

A specificity in Indian context is the division of society along ethnicity, religion, and caste lines. India has a long history of social division based on caste, which is an important determinant of households' social status and their access to inputs, including credit and information and also to public resources. Social identity has, however, rarely been considered in assessing the effects of finance or farm services on farm outcomes. In the caste hierarchy, scheduled castes (SCs) and scheduled tribes (STs) are at the

Table 2. Summary statistics

Variables	Non-borrowers		Borrowers		Borrowers					
					Formal		Informal		Both	
Net returns (Rs/ha)	43762	(316377)	59042	(524029)	58477	(499445)	54964	(295142)	66273	(776458)
Household characteristics										
Family size (No.)	4.67	(2.28)	5.04	(2.49)	5.12	(2.56)	4.91	(2.27)	4.76	(2.25)
Age of the household-head (years)	49.21	(14.01)	52.28	(12.99)	53.06	(12.92)	49.28	(13.28)	50.77	(12.55)
Gender of the household-head (Male=1 Female=0)	87.65		94.39		94.25		94.91		94.67	
Education level (%household-heads)										
Illiterate	35.15		29.87		26.96		40.12		36.44	
Below primary	9.92		9.25		9.30		9.77		8.43	
Primary	14.80		15.54		1.00		2.00		3.00	
Middle	15.89		16.16		15.38		15.69		16.33	
Secondary	11.81		14.20		16.80		13.76		14.84	
Higher secondary	6.73		7.81		15.05		10.12		13.36	
Graduate and above	5.69		7.17		8.41		5.78		6.34	
Caste (% households)										
Scheduled caste	22.08		9.23		8.63		14.80		7.22	
Scheduled tribe	17.44		12.22		11.08		17.34		13.77	
Other backward caste	38.90		47.31		46.87		46.46		50.67	
Upper or other caste	21.58		31.24		33.43		21.40		28.34	
Net assets (Rs/per person)	629.08		2653.53		2610.80		1242.74		4281.42	
Formal training in agriculture (% households)	1.42		3.06		3.22		2.27		2.97	
Non-farm income (% households)	6.46		10.31		10.97		7.78		8.97	
Farm characteristics										
Operated land (ha)	0.47	(0.76)	1.33	(1.67)	1.33	(1.66)	0.96	(1.08)	1.71	(2.06)

Contd.

Table 2 contd.

Variables	Non-borrowers		Borrowers		Borrowers					
					Formal		Informal		Both	
Area irrigated (%)	35.57		66.67		66.51		64.71		69.49	
No. of animals (cattle and buffalo)	1.29	(2.40)	2.39	(3.01)	2.39	(2.98)	2.30	(3.30)	2.53	(2.89)
Area under high-value crops (%)	19.79		25.65		26.87		20.78		23.48	
Fertilizers (Rs/ha)	2861.59	(6026.66)	5983.70	(7485.97)	5909.37	(7466.09)	5309.10	(7308.87)	7070.66	(7663.40)
Seeds (Rs/ha)	2679.65	(9038.74)	4377.81	(8568.44)	4447.41	(7150.50)	4096.48	(15604.39)	4255.06	(5860.43)
Pesticides ((Rs/ha)	885.63	(3844.63)	2749.06	(7297.13)	2556.01	(7016.75)	2352.27	(7351.48)	4243.50	(839.91)
Labour (Rs/ha)	7963.46	(16716.30)	12980.95	(17644.28)	12968.33	(17055.50)	11496.48	(12145.64)	14508.63	(24184.51)
Institutional characteristics (% households)										
Access to information	64.95		66.26		65.81		60.63		74.36	
Access to crop insurance	3.68		23.50		25.28		9.15		27.40	
Member of a farmer organization	2.78		6.97		7.41		4.20		7.15	
Crop sale at MSP	17.02		42.92		43.77		33.41		47.33	
Risk characteristics (% households)										
Loss due to pests and diseases	10.70		17.74		18.41		14.38		17.21	
Loss due to droughts	15.02		27.77		27.52		27.25		29.76	
Loss due to floods	2.65		4.54		4.51		5.64		3.64	
Loss due to other natural causes	2.25		7.02		6.85		6.61		8.43	

Note: Figures in parentheses are standard deviations.

bottom, upper castes at the top, and the rest termed as other backward castes (OBCs) lie in the middle. Literature suggests that lower-caste households often face discrimination in accessing credit (Kumar, 2013; Birthal *et al*., 2017; Karthick and Madheswaran, 2018), and extension services (Birthal *et al*., 2015).

Table 2 also compares level of farm productivity, measured as net returns per unit of cropped area, between non-borrowers and borrowers. In general, farm productivity appears positively associated with farmers' access to finance, which is a preliminary indication of the likely effect of finance on productivity and resilience of agriculture.

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3 Method for Estimating Effects of Finance

As discussed above, estimating effects of finance on farm outcomes is a significant empirical challenge on account of its effects being embedded in input effects, and possibility of self-selection and targeting biases. Thus, effects of finance if estimated using ordinary least square (OLS) method may be biased and inconsistent. The challenge can be addressed through a two-step bias-correction approach (Carter, 1989; Feder *et al*., 1990; Binswanger and Khandker, 1995; Khandekar and Faruqee, 2003; Narayanan, 2016; Kumar *et al*., 2017, Kumar *et al*., 2020). Binswanger and Khandker (1995) and Narayanan (2016) have estimated time-series panel regressions of aggregate output supply, input demand, farm investment, and wage as a function of predicted flow of finance, controlling for exogenous factors. Other studies have employed either instrumental variable (IV) (e.g., Kumar *et al*., 2017; Kumar *et al*., 2020) or endogenous switching regression (e.g., Carter, 1989; Feder *et al*., 1990; Mukasa *et al*., 2017).

Liquidity-constrained households supplement their savings through borrowings from formal or informal sources anticipating that additional liquidity would lead to sustainable improvement in farm outcomes. The utility of borrowed funds is generally unobserved. What is observed is the farmers' decisions to seek financial support from one or other source. Hence, we employ a multinomial endogenous switching regression (MESR), which first identifies factors that influence farm households' decisions 'whether to avail financial support or not, and from whom'; and then, correcting for selection and targeting biases it estimates the effects of finance on farm outcomes. Besides, MESR can address challenges of endogeneity and inadequate counterfactuals.

Theoretically, a liquidity-constrained farm household seeking financial support compares its expected utility across different sources of finance and chooses the one that he/she expects to deliver a higher return.[2] This can be represented by a latent variable U_{ij}^{*}.

[2] Utility can be defined in terms of access, interest rate, and repayment schedule.

$$U_{ij}^{*} = \beta X_i + \varepsilon_{ij} \quad (1)$$

Where, i denotes the household and j the source of finance. X_i is a vector of observed characteristics of farms and farm households, and ε_{ij} is a vector of unobserved characteristics. Let I be an index denoting farmers' choice of source of finance:

$$I = j \text{ iff } U_{ij}^{*} > \max_{m \neq j}(U_{im}^{*}) \quad \text{or} \quad \eta_{ij} < 0 \quad \text{for all } m \neq j \quad (2)$$

Where, $\eta_{ij} = \max_{m \neq j}(U_{im}^{*} - U_{ij}^{*}) < 0$. Eq. (2) implies that household i avails finance from source j if it delivers greater utility than any other source, m≠j, and its probability can be specified as a multinomial logit function (McFadden, 1973).

$$P_{ij} = \Pr(\eta_{ij} < 0 | X_i) = \frac{\exp(\beta_j X_i)}{\sum_{m=1}^{J}(\beta_m X_i)} \quad (3)$$

Here, non-borrowers comprise reference category, i.e., j=1, against households availing finance from formal or informal source or both, i.e., j = 2, …, 4.

In its second step, MESR estimates the farm outcome functions with a set of explanatory variables Z_i for each source of finance.

$$R_{ij} = \alpha_j Z_i + u_{ij} \qquad \text{if } I = j \quad (4)$$

Where, R_{ij} is represents the farm outcome for household i who has acquired finance from source j. The unobserved term u_{ij} is distributed with $E(u_{ij}|X, Z) = 0$ and var $(u_{ij}|X, Z) = \sigma_j^2$. R_{ij} is observed if source j has been chosen by household i.

If error term (ε) in selection equation is correlated with error term (u) in outcome equation, then OLS estimates will be biased and inconsistent. Hence, following Bourguignon *et al*. (2007), a bias-corrected equation is estimated as:

$$R_{ij} = \alpha_j Z_i + \sigma_{j\varepsilon}\hat{\lambda}_{ij} + \omega_{ij} \qquad \text{if } I = j \quad (5)$$

Where, σ_j is the covariance between ε and u; and ω is the error term with an expected value of zero. λ_j is the Inverse Mills Ratio (IMR) computed from probabilities estimated from Eq. (3).

$$\lambda_j = \sum_{m \neq j}^{j} \rho_j \left[\frac{\hat{P}_{im}\text{In}(\hat{P}_{im})}{1-\hat{P}_{im}} + \text{In}(\hat{P}_{ij})\right] \quad (6)$$

Where, ρ is the correlation between ε and (u).

Outcome equation includes means of expenditures on farm inputs (i.e., fertilizers, pesticides, seeds, and labour) to account for possible correlation between household-invariant unobserved heterogeneity and observed covariates (Mundlak, 1978).

There is a possibility that factors that influence farmers' access to finance may influence farm outcomes as well. This means that outcome equation shares covariates of selection equation. Hence, instrumental variables are used to capture exogenous variation in borrowing decisions. Our instrumental variables are formal training in agriculture, and household's net asset position. The choice of instruments is guided by literature, and the commonly used instruments include information sources, households' access to technical advice and extension services, and their socioeconomic status (Di Falco and Veronesi, 2011; Di Falco and Veronesi, 2014; Kassie *et al*., 2015, Collins-Sowah *et al*., 2019). Formal training in agriculture is expected to contribute to farmers' understanding of risks, their adaptation and mitigation strategies, and costs and benefits associated with their implementation. Likewise, households' resource endowment also influences their borrowing decisions — resource constrained households are more likely to depend on financial support. Instrumental variables are expected to not directly influence farm outcomes, but indirectly *via* adoption of risk management measures (Di Falco and Veronesi, 2011).

To quantify the effects of finance on farm outcomes, coefficients from MESR are used to predict outcomes for borrowers and non-borrowers against some counterfactuals. We estimate expected actual (observed) and counterfactual outcomes for borrowers, and the difference between actual and counterfactual outcomes is the average treatment effect on treated (ATT) or alternatively the effect of finance on farm outcomes. Following Carter and Milon (2005), expected actual and counterfactual utility can be computed as:

Actual*: Households who had availed finance*

$$E\left(R_{ij}\middle|I = j\right) = \alpha_j Z_{ij} + \sigma_j \lambda_{ij} \tag{7}$$

Counterfactual*: Had borrowers not availed finance*

$$E(R_{i1}|I = j) = \alpha_1 Z_{ij} + \sigma_1 \lambda_{ij} \tag{8}$$

Difference between Eq. (7) and Eq. (8) provides the ATT.

$$\text{ATT} = Z_i\left(\alpha_j - \alpha_1\right) + \lambda_{ij}(\sigma_j - \sigma_1) \tag{9}$$

First term on the right-hand side in Eq. (9) provides expected change in outcome due to difference in observed characteristics; and second term due to difference in unobserved characteristics. Our outcome variables are farm productivity (i.e., net returns per hectare) and its skewness, which captures risk more accurately than variance (Di Falco and Chavas, 2009; Kassie *et al*., 2015).

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4 Effects of Finance on Productivity and Risk

To test 'whether MESR model is correctly identified', we perform a falsification test for goodness of exclusion restrictions. Test results are presented in Table A1 (in appendix). Both instrumental variables, viz., farmers' formal training in agriculture, and their net asset position, are statistically significant in selection equations but not in outcome equations, meaning that MESR is correctly specified.

Instrumental variables are also tested for their exogeneity. Durbin and Wu-Hausman tests for 2SLS (Durbin, 1954; Wu, 1974; Hausman, 1978), and Sargan C test for GMM estimators (Sargan, 1958) are not statistically significant (Table A2 in appendix). Thus, the null hypothesis that instruments are exogenous is rejected.

4.1 Factors influencing access to and choice of source of finance

Table 3 presents the estimates of selection equations. Diagnostic tests show a good fit of all multinomial logit functions. Wald statistic rejects the null hypothesis that regression coefficients are jointly equal to zero. Chi-squared test for joint significance of instruments is also statistically significant.

Coefficients on all risk variables[3] are positive and significant, suggesting that climate risks compel farmers to seek financial support.

Age and schooling of household heads are positively and significantly associated with their access to formal finance. This is expected as experience (proxied by age) and education make farmers informed about their financial requirements, and also procedures of accessing finance from formal sources.

Nevertheless, access to finance is differentiated by farmers' resource endowment, social identity, and gender. Coefficient on land size is positive and significant in case of formal finance, suggesting that smallholders

3 The risk indicators are farmers' self-reported crop loss due to droughts, floods, pests, and other natural hazards.

Table 3. First stage estimates of multinomial logit model (dependent variables: sources of finance)

Explanatory variables	Formal		Informal		Both	
Demographic characteristics						
Family size	-0.1162***	(0.0264)	-0.2178***	(0.0512)	-0.4073	(0.0522)
Age of the household-head	0.1819***	(0.0488)	-0.7880***	(0.0885)	-0.8400	(0.0949)
Gender of the household-head	0.3720***	(0.0501)	0.6966***	(0.1043)	0.7148	(0.1129)
Education level						
Below primary	0.1018**	(0.0463)	-0.2211	(0.0844)	-0.3526***	(0.0939)
Primary	0.1028**	(0.0400)	-0.3259***	(0.0735)	-0.3023***	(0.0755)
Middle	0.0717*	(0.0397)	-0.5329***	(0.0762)	-0.5963***	(0.0799)
Secondary	0.0194	(0.0424)	-0.7218***	(0.0881)	-0.6217***	(0.0835)
Higher secondary	-0.0529	(0.0524)	-0.7977***	(0.1116)	-1.0266***	(0.1148)
Graduate and above	-0.1084**	(0.0546)	-1.0054***	(0.1273)	-1.4045***	(0.1339)
Caste						
Scheduled caste	-1.0485***	(0.0453)	-0.3496***	(0.0843)	-1.2235	(0.1060)
Scheduled tribe	-0.1404**	(0.0421)	0.3181***	(0.0795)	0.2135**	(0.0836)
Other backward caste	-0.0632**	(0.0299)	0.2281***	(0.0639)	0.1695**	(0.0602)
Non-farm income	0.2807***	(0.0419)	0.0860	(0.0892)	0.1652*	(0.0887)
Farm characteristics						
Operated land	0.5752***	(0.0130)	0.4019***	(0.0226)	0.9176***	(0.0301)
Area irrigated	0.4512***	(0.0291)	0.6517***	(0.0570)	0.5979***	(0.0610)
No. of animals	0.1994***	(0.0192)	0.2278***	(0.0363)	0.1728***	(0.0368)
Area under high value crops	0.0044	(0.0298)	-0.1290**	(0.0608)	-0.0296	(0.0606)
Institutional characteristics						
Access to information	0.1355***	(0.0262)	0.1231**	(0.0499)	0.4515***	(0.0565)
Access to crop insurance	1.3934***	(0.0368)	0.1280	(0.0918)	1.3371***	(0.0621)
Crop sale at MSP	0.0212**	(0.0062)	0.0265**	(0.0125)	0.0317***	(0.0101)
Member of a farmer organization	0.3288***	(0.0552)	-0.0444	(0.1292)	0.3497***	(0.1019)
Risk characteristics						
Loss due to pests and diseases	0.0708**	(0.0337)	-0.0269	(0.0680)	0.0410	(0.0668)
Loss due to droughts	0.3029***	(0.0286)	0.4337***	(0.0534)	0.4110***	(0.0549)
Loss due to floods	0.0786	(0.0593)	0.3114**	(0.1050)	-0.1172	(0.1267)
Loss due to other natural causes	0.5785***	(0.0538)	0.8588***	(0.0928)	0.8156***	(0.0914)
Instrument variables						-
Net assets	0.0415***	(0.0042)	0.0411***	(0.0082)	0.0623***	(0.0079)
Formal training in agriculture	0.2153**	(0.0818)	0.3264**	(0.1668)	0.1282	(0.1593)
Constant	-3.6530***	(0.2051)	-1.2862**	(0.3715)	-1.9541***	(0.3995)
Joint significance of selected instruments	30.24***		32.36***		20.89***	
Joint significance of farm varying covariates $\chi2$ (3)	31.41***		22.32***		31.22***	

Notes: Non-borrowers are the reference category. Figures in parentheses are bootstrapped standard errors. *** ** and * indicate significance at 1%, 5% and 10%, respectively.

have comparatively low access to formal finance. Putting it differently, collateral is potentially important in accessing finance. A positive and significant coefficient on households' asset position also provides support to this. Access to formal finance is also differentiated by caste and gender of household heads — female-headed and lower-caste households have comparatively small access to formal finance.

Besides, repayment capacity of potential borrowers is an important consideration for lenders, which we proxy by irrigated area. Irrigation plays a dual role of enhancing productivity and reducing risk (Birthal *et al*., 2015; Birthal *et al*., 2022). A positive and significant coefficient on irrigation indicates that higher the repayment capacity higher is farmers' access to finance. On the other hand, diversification of crop portfolio in favour of high-value crops reduces households' reliance on informal sources. So does the engagement in non-farm business activities. Nevertheless, access to technical advice and information and markets (i.e., sale of grains at government-determined MSP) enhances prospects for securing finance from formal sources. Likewise, their association with farmer organizations helps secure formal finance.

4.2 Factors influencing productivity and risk

Estimates of productivity and risk functions are presented in Table A3 in the appendix. In most outcome equations, bias-correction term (i.e., Inverse Mills Ratio) is statistically significant, suggesting need for correcting self-selection and targeting biases in estimating effects of finance on farm outcomes.

As expected, climate risks adversely affect farm productivity. Nevertheless, irrigation and diversification into high-value crops and animal farming lead to an improvement in farm productivity. Coefficients on farm inputs are positive and statistically significant, confirming their crucial role in improving productivity. Further, productivity is positively and significantly associated with information and markets.

On the other hand, most of the explanatory variables in skewness functions are statistically insignificant (Table A 4 in the appendix).

4.3 Effects of finance on productivity and risk

4.3.1 Effects on farm productivity

Table 4 presents the average treatment effects on treated (ATTs). Correcting for self-selection and targeting biases and controlling for the influence of several other covariates, finance has a significantly positive effect on farm productivity. It, however, is differentiated by source of finance. Compared to informal finance, formal finance is twice more effective — formal finance leads to 21.4 percent higher productivity, which is almost twice the effect of informal finance (11.8%). And the effect is bigger when informal finance complements formal finance.

Table 4. Effects of sources of finance on farm productivity (ATTs)

Source of finance	Actual	Counterfactual	Difference	% change
Formal	6.6440 (0.2785)	5.2200 (0.5556)	1.4240*** (0.0286)	21.43
Informal	5.7968 (0.6205)	5.1115 (0.8996)	0.6852*** (0.0760)	11.82
Both	6.2643 (0.5076)	4.7603 (0.6731)	1.5039*** (0.0721)	24.01

Notes: Figures in parentheses are standard errors. ***, **, and * denote significance at 1, 5 and 10%, respectively. Reference category comprises non-borrowers.

Effect of finance is also differentiated by its use (Table 5). Long-term finance for capital investment is more effective than short-term finance for revenue expenses, and it gets magnified if both are used in conjunction. This means that gains from long-term finance for capital investment may remain small in the absence of finance for operational expenses.

Table 5. Effects of long-term finance on farm productivity (ATTs)

Purpose of finance	Actual	Counterfactual	Difference	% change
Capital expenses	6.5464 (0.4850)	6.9294 (0.4123)	-0.3830*** (0.0316)	5.53
Capital and revenue expenses	5.9710 (3.4068)	6.6337 (2.3500)	-0.6627*** (0.2134)	9.99

Notes: Figures in parentheses are standard errors. ***, **, and * denote significance at 1, 5 and 10%, respectively. Reference category is short-term credit.

4.3.2 Effects on risk

Table 6 presents the ATTs of finance for downside risk. Access to finance positively skews productivity distribution, meaning a reduction in probability of output loss due to risks and uncertainties. Yet, there is a source effect, *albeit* small. Formal finance has a slightly bigger risk-reducing effect (13.1%) than informal finance (11.2%). And expectedly, risk benefits are enhanced when formal finance is supplemented by informal finance.

Table 6. Effects of sources of finance on downside risk (ATTs)

Source of finance	Actual	Counterfactual	Difference	% change
Formal	0.0256 (0.0172)	0.0294 (0.0168)	0.0038 (0.0002)***	13.05
Informal	0.0296 (0.1058)	0.0333 (0.1788)	0.0037 (0.0001)***	11.24
Both	0.0233 (0.0865)	0.0279 (0.0564)	0.0046 (0.0001)***	16.31

Note: Figures in parentheses are standard errors. ***, **, and * denote significance at 1, 5 and 10%, respectively. Reference category comprises non-borrowers.

4.3.3 Robustness check

There is a possibility that farm outcomes and their determinants are spatially correlated. MESR cannot control for such spatial correlation. The way is to estimate a spatial econometric model using location of farm households. Such an information, however, is not available in the dataset.

Nevertheless, assuming that spatial dependence is group-specific, fixed effects regression can account for spatial correlation (Anselin and Arribas-Bel, 2013). Table A5 (in the appendix) presents the estimates of farm productivity functions including district fixed effects and bootstrapped standard errors clustered at district and village levels. Such a clustering of standard errors can account for possible correlations in the residuals of productivity functions across spatial units.

Table 7 presents the ATTs estimated with bootstrapped standard errors clustered at district, and district and village levels simultaneously. When standard errors are clustered at district and village levels simultaneously, ATTs are almost similar to those obtained from MESR. This indicates the robustness of our findings.

4.4 Discussion

Frequency of climate risks, i.e., droughts, floods, and heatwaves, in India is predicted to increase in future climate scenarios, which, in the absence of adaptation and mitigation, will significantly affect agricultural productivity, food supplies, farm incomes, and poverty. Bhandari *et al*. (2007), based on a household survey in eastern India, have shown a 25-60 percent reduction in household income, and a 12-33 percent increase in head-count poverty in a drought year. Birthal *et al*. (2021) have estimated impact of climate risks on overall productivity of agriculture and found that since 1980 climate risks have reduced productivity growth of Indian agriculture by 25 percent, and more in underdeveloped and agrarian states.

Table 7. ATTs for farm productivity estimated from fixed effects regression

Source of finance	Non-borrowers	Borrowers	Difference	% change
	District fixed effects: Standard errors clustered at district level			
Formal	5.2197 (0.4430)	6.6440 (0.3528)	1.4243 (0.0286)***	21.44
Informal	5.0689 (0.7611)	5.7968 (0.5780)	0.7278 (0.0766)***	12.56
Both	5.3692 (0.7380)	6.2643 (0.4987)	0.8951 (0.0770)***	14.29
	District and village fixed effects: standard errors clustered at village and district levels			
Formal	5.2098 (0.4272)	6.6440 (0.3213)	1.4342 (0.0283)***	21.59
Informal	5.0526 (0.7696)	5.7968 (0.6443)	0.7442 (0.0728)***	12.84
Both	4.7590 (0.8020)	6.2643 (0.5750)	1.5052 (0.0704)***	24.03

Note: Figures in parentheses are standard errors. ***, **, and * denote significance at 1, 5 and 10%, respectively. Regressions with district fixed effects take into account within-district cross-correlation and heteroscedasticity of errors. Regressions with village fixed effects consider within-village cross-correlation and heteroscedasticity of errors.

Nevertheless, recent advances in agricultural research, i.e., stress-tolerant crop varieties, sensor-based micro-irrigation, zero-tillage, and laser land-levelling, offer considerable scope for risk mitigation in agriculture (Teklewold *et al*., 2017; Issahaku and Abdulai, 2019; Ali *et al*., 2021; Birthal *et al*., 2022). Besides, agricultural diversification and crop insurance are other important means of risk mitigation.

Agriculture is exposed to multiple risks, and a single measure cannot provide an efficient solution to all types of risks. Studies have shown that joint application of two or more adaption/mitigation measures is more effective (Kassie *et al*., 2015; Issahaku and Abdulai, 2019; Birthal *et al*., 2022). Thus, bundling of technologies is essential to improve resilience of agriculture. In this context, Altieri, et al. (2017) from an extensive review of literature conclude that joint application of traditional practices and modern technologies is a robust path to improving efficiency, sustainability and resilience in agriculture.

Transition to climate-smart agriculture, however, requires upfront investment in rural infrastructure, agricultural research, early warning systems, resource conservation, among others (see, Lybbert and Sumner 2012). Several studies have pointed out that investment in mitigation and adaptation at higher geographical scales (i.e., national, and subnational levels), and alleviating financial constraints on farmers' adoption of technologies can help mitigate risks in agriculture (Teklewold *et al*., 2017; Birthal *et al*., 2019; Issahaku and Abdulai, 2019; Ali *et al*., 2021; Birthal *et al*. 2022).

Rates of returns on investment in risk management in agriculture have been shown as quite attractive. ECA-Economics of Climate Adaptation Group (2009) have shown that 40-68 percent of the loss in agricultural output due to climatic shocks can be avoided by investing in early warning systems, management of land and water resources, and research on crop breeding for stress-tolerance. Coger *et al*. (2021) have estimated that every dollar spent on adaptation pays US$2-10 in return. Importantly, returns on investment in agricultural research have been comparatively large than on other adaptation and mitigation measures. Likewise, returns on investment in agromet services have also been estimated to be quite attractive (Rathore and Chattopadhyay (2016).

Our findings show that financial support to farmers has a measurable impact on risk mitigation in agriculture. Nevertheless, financial and credit planning in agriculture in India or for that matter in most developing countries has concentrated on productivity enhancement, with little consideration to risk management.

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5 Status of Climate Finance for Agriculture

The need for climate finance has been echoed time and again. At the 15th Conference of Parties (COP 15) of the UNFCC in Copenhagen in 2009, developed countries, which contribute two-third to the total greenhouse gas emissions, pledged to mobilize US$100 billion per annum by 2020 for supporting climate actions in developing countries, which are more exposed to climate risks but lack finances for their mitigation. The pledge, however, has remained unfulfilled (Chowdhury and Jomo, 2022). In 2020, developed countries could mobilize US$83.3 billion, two-third of which, went for mitigation and the rest for adaptation (OECD, 2022).

CPI (2023) tracked global climate finance and noted doubling of climate finance between 2011 and 2020, from US$ 364 billion to US$ 665 billion. Nearly half of it came from public sources, and 89 percent of it was targeted to mitigation. Further, it reports a significant regional concentration of climate finance — the East Asia and Pacific share 43 percent while South Asia share merely 5 percent.

By activity, climate finance has remained concentrated on energy and transport. Agriculture has received a meagre share in climate finance. In 2020, of the total US$83.3 billion mobilized by developed countries for climate actions in developing countries, agricultural sector (agriculture, forestry, and fisheries) received only 9 percent (OECD, 2022). On the other hand, CPI (2023) has estimated share of agriculture in total climate finance at 2.55 percent, equally distributed between mitigation and adaptation.

Current level of climate finance for agriculture is much less than what is required. At the COP 21 in Paris in 2015, countries agreed to contain rise in global temperature below 1.5°C by end of this century over its pre-industrial level. Towards this, the countries have set targets for reduction in GHG emissions for 2030 by switching over to low-carbon activities in different sectors, including agriculture. However, for agricultural sector to shift to a low-carbon climate-resilient path by 2030, an annual investment of US$ 423 billion is required, which is almost 26 times of the current level of investment (CPI, 2023).

India has been proactive in addressing issues related to climate mitigation and adaptation in agriculture. In 2008, as a part of National Action Plan on Climate Change (NAPCC), it initiated National Mission on Sustainable Agriculture (NMSA). In 2011, a network project National Innovations in Climate Resilient Agriculture (NICRA) was launched under the aegis of Indian Council of Agricultural Research (ICAR). In 2015, it launched National Adaptation Fund on Climate Change (NAFCC), with National Bank for Agriculture and Rural Development (NABARD) as National Implementing Entity (NIE). NABARD also serves as NIE for Adaptation Fund (AF) under Kyoto Protocol.

In its Nationally Determined Commitments (NDCs) in 2015 (subsequently revised in 2020) India has set following targets for 2030: (i) achieve half of its cumulative electric power installed capacity from non-fossil fuel sources, (ii) reduce GHG emission intensity (of its gross domestic product) to 45 percent, and (iii) create an additional carbon sink of 2.5-3 billion tonnes (CO_2-equivalent). The country will require a total US$ 2.5 trillion or US$ 170 billion per annum to realize the NDCs (cited in GoI, 2021c; CPI, 2022).

No specific target has been set for agriculture, yet enhancing its resilience through adaptations is indicated in the NDCs. For adaptation actions in agriculture, forestry, fisheries, infrastructure, water resources and ecosystems, an investment requirement of US$206 billion (i.e., 8.2% of the total US$2.5 trillion) has been indicated.

CPI (2022) tracked India's green finance at an average of US$44 billion in 2019/2020, which is approximately one-fourth of the total annual requirement of US$ 170 billion. Importantly, climate actions have largely been financed from domestic resources (85%), and the rest have been sourced from international sources (CPI, 2022). Of the domestic investment, about 59 percent came from private sources.

CPI (2022) could not track green finance for agriculture due to non-availability of data on investment in climate actions. Nevertheless, it has reported that an investment of US$5 billion in disaster monitoring and emergency response system, flood mitigation and drought management, and mostly through budgetary support (95%).

Sareen and Shankar (2022), on the other hand, have estimated India's private sector investment requirement for climate actions at US$ 1.01 trillion between 2022 and 2030, i.e., US$112 billion per annum. Of this, sustainable food system must receive about 28 percent. Further, Sareen and Shankar (2023) have reported that currently agri-tech investment in India remains targeted to supply chain start-ups, ignoring investment at farm level, where there is a considerable scope for investing in on-farm solutions such as soil and crop monitoring, pest surveillance, precision agriculture and input automation systems.

NABARD refinances agriculture and rural development activities. Commercial banks, regional rural banks and cooperatives provide short-term finance for operational expenses, and medium to long-term finance for investment in irrigation, land and water conservation, farm mechanisation, plantation, animal husbandry and fisheries. Both long-term and short-term finances are aimed to be flexible to adjust in the event of an extreme climate event. Short-term finance is converted into medium-term finance, and long-term finance is rescheduled by relaxing repayment commitments. Besides, NABARD finances several other development projects related to irrigation, watersheds, and rural infrastructure through grants-cum-loans to state governments. Note, many of these activities address climate concerns also. NABARD has set up a Climate Change Fund with a corpus of Rs 20 crores for supporting climate actions in agriculture.

In 2021-22, NABARD provided credit support of Rs 18634 billion to agriculture, shared in a ratio of 3:2 between short-term and long-term finance. Our findings, however, show a larger contribution of long-term or mitigation finance to productivity enhancement (60%) than its share in the total credit (40%). However, capital formation in agriculture has slowed down — its share in gross capital formation has gradually declined to 6.6 percent in 2020-21 from 8.5 percent in 2011-12 (GoI, 2023). Private sector accounts for 85 percent of the gross capital formation in agriculture. Farm households are the largest private players in agriculture, but they hardly invest 3 percent of their income in capital formation (Bathla *et al*. 2022). Public investment induces private investment, and therefore, accelerating flow of long-term finance for capital formation is imperative for risk mitigation in agriculture.

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6 Conclusions and Policy Implications

Climate finance for agriculture has attracted considerable attention in academic and policy debates. However, our understanding of the effects of finance on productivity and resilience in agriculture remains limited *inter alia* due to empirical challenges in segregating its effects from input effects.

By employing multinomial endogenous switching regression to cross-section household-level data, this paper has simultaneously estimated the contribution of finance to risk mitigation and productivity enhancement in agriculture. The main conclusions emerging from this investigation are as follows:

First, finance has a measurable effect on farm outcomes. It enhances productivity by 24 percent and reduces downside risk by 16 percent. However, there is a source effect — compared to informal sources of finance, formal finance is almost twice more effective. Risk-reducing effect of formal finance is also bigger *albeit* at margin. Nevertheless, both productivity-enhancing and risk-reducing effects get enhanced when formal finance is complemented by informal finance. Our findings suggest an allocation of 40 percent of the financial resources for climate actions.

Second, long-term finance for capital investment is more effective than short-term finance for revenue expenses. And the effect gets magnified when both are used in conjunction. Current allocation of agricultural credit is in a ratio of 3:2 between short-term and long-term credit. Our findings suggest a reversal of this. A greater share of long-term credit is desirable given the low level of capital formation in agriculture and increasing requirement of finance for mitigation.

Third, there is a lending bias in rural financial markets against female-headed, lower-caste, and small farm households, who need finance the most, but have smaller access to it due to perceived higher transaction costs and lending risks associated with small loans.

Fourth, diversification of income portfolio into horticultural crops, animal husbandry and non-farm business activities along with an accelerated flow of information on technologies, inputs and services, and crop insurance, and an assured access to markets enhance the prospects of accelerating flow of finance from formal sources.

Given the increasing exposure of agriculture to climate change, there is a need for a change in policy stance emphasizing risk management. Some important issues that merit attention of financial institutions and policymakers are as follows:

First, India's agricultural policy or for that matter credit policy has primarily targeted productivity enhancement. Given the increasing threat of climate change the mitigation and adaptation must comprise an important aspect of financial and credit planning in agriculture.

Second, climate-smart interventions are often context- or location-specific; hence, adaptation and mitigation measures should be tailored to local contexts. Financial institutions must, therefore, interact and collaborate with a range of stakeholders, including research organizations, public extension agencies, non-governmental organizations, agribusiness firms, self-help groups, and village-level institutions. Such a collaboration can help identify efficient adaptation and mitigation measures for different agroclimatic conditions.

Third, financial institutions must be responsive to the needs of farming communities, especially smallholders who need finance the most but face discrimination in financial markets due to lack of assets to offer as collateral, and higher transaction costs and lending risks. It is, therefore, imperative for financial institutions to design innovative financial products suited to smallholders' requirements while reducing transaction costs and risks. One such innovation could be extending collateral-free concessional credit to farmers conditional upon their adoption of climate-smart interventions. Another could be to support to a group of farmers, not individuals, for investment in community-managed assets with group guarantee as collateral.

Fourth, currently private agri-tech investment is concentrated on post-production supply chain operations. Nonetheless, there is a considerable scope of financing climate actions along the supply chains through tripartite contracts involving their sponsors (i.e., agribusiness firms, start-ups, cooperatives, and farmer producer organizations), farmers, and financial institutions.

Sixth, Government of India has recently announced creating a national market for carbon and green credits to incentivise farmers and other stakeholders to adopt technologies and practices that mitigate climate risks and conserve natural resources. By extending finance to farmers and other stakeholders for adoption of sustainable agricultural practices, financial institutions can play an important role in such upcoming markets.

Seventh, assessing costs and benefits of climate-smart interventions in agriculture is not straightforward because of complex interactions among different components of production system. Current metrics and tools to evaluate costs and benefits of climate-smart interventions are insufficient (Sadier, 2016). More research is needed to develop methods to accurately assess their costs and contributions to risk mitigation.

Finally, crop insurance is an important means of risk transfer, but premium for it must be paid before start of the growing season when farmers confront competing demands on their limited financial resources. In India, until 2020 crop insurance was compulsory for borrowers of commercial banks and other financial institutions, primarily to reduce transaction costs for insurance agencies and lending risk for banking system. Purchase of insurance for borrowers is now voluntary. It is apprehended that that delinking insurance from credit may adversely affect uptake of insurance.

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Appendix Tables

Table A1. Validity tests for instrumental variables

Variables	OLS: Dependent variable: Ln productivity	Multinomial logit model: Dependent variable: source of finance		
		Formal sector	Informal sector	Both
Net assets	0.1058 (0.4047)	0.0415*** (0.0043)	0.0411*** (0.0086)	0.0623*** (0.0082)
Formal training in agriculture	0.0953 (0.0924)	0.2153* (0.0837)	0.3264* (0.1653)	0.1282 (0.1602)
Constant	4.2852*** (0.7340)	-11.3590*** (0.8535)	-6.9569*** (1.5887)	-12.2630*** (1.8087)

Notes: Regressors include complete set of controls. Figures in parentheses are standard errors. *** ** and * indicate significance at 1%, 5% and 10%, respectively.

Table A2. Results of endogeneity tests

Test type	Dependent variable: Ln farm productivity	
	2SLS	GMM
Durbin χ2 (p-value)	0.9776 (0.3228)	
Wu-Hausman F (p-value)	0.9744 (0.3236)	
C Sargan χ2 (p-value)		0.8387 (0.3598)

Notes: Regressors include complete set of controls. Figures in parentheses are standard errors.

Table A3. Estimates of outcome equations (Dependent variable: Ln farm productivity)

	Non-borrowers		Borrowers					
Explanatory variables			Formal		Informal		Both	
Demographic characteristics								
Family size	0.1640***	(0.0087)	0.0667	(0.1119)	0.1738***	(0.0268)	-0.0697	(0.1587)
Age of the household-head	0.1393	(0.2316)	-0.2475**	(0.0749)	1.5378	(0.7458)	-1.0618***	(0.0844)
Gender of the household-head	-0.0375	(0.1775)	0.0926	(0.1577)	-0.8539***	(0.0130)	0.0356	(0.0263)
Education level								
Below primary	0.0809***	(0.0227)	0.0520	(0.1542)	0.7941	(0.5722)	0.0005	(0.1482)
Primary	0.1634*	(0.0861)	-0.0497	(0.1286)	1.0210*	(0.6091)	-0.4500**	(0.1578)
Middle	0.2096*	(0.1122)	0.0604	(0.1294)	1.0977*	(0.5823)	-0.1330	(0.2145)
Secondary	0.1553	(0.2701)	0.0541	(0.2497)	1.4492**	(0.4588)	-0.4252**	(0.1257)
Higher secondary	0.2485	(0.2074)	0.0000	(0.1342)	1.6890**	(0.5835)	-0.2546**	(0.0757)
Graduate and above	0.1627	(0.1466)	0.0223	(0.2926)	2.7057**	(0.8064)	0.0605	(0.1188)
Caste								
Scheduled caste	0.0444	(0.0647)	0.3671***	(0.0691)	-0.3860	(0.9395)	1.1846***	(0.1337)
Scheduled tribe	-0.2696	(0.1896)	-0.4582**	(0.1503)	-0.7501	(0.5031)	0.4961***	(0.0527)
Other backward caste	-0.0986	(0.0692)	0.0174	(0.0729)	-0.4325**	(0.1440)	0.3307***	(0.0864)
Non-farm income	0.4830***	(0.1031)	-0.1386***	(0.0310)	0.4115	(0.5421)	-0.1964	(0.2842)
Farm characteristics								
Operated land	0.5094***	(0.0215)	0.0954***	(0.0168)	0.4094	(0.2886)	-0.0622	(0.1159)
Area irrigated	3.0639***	(0.1714)	1.7555***	(0.0174)	1.2931***	(0.1245)	1.7647***	(0.0970)
No. of animals	0.3906***	(0.0828)	0.3399***	(0.0032)	0.3524***	(0.0311)	0.2523*	(0.1312)
Area under high value crops	1.7402***	(0.1352)	0.6047***	(0.0421)	0.4445**	(0.1944)	0.3966**	(0.1210)

Contd.

Table A3 contd.

	Non-borrowers		Borrowers					
Explanatory variables			**Formal**		**Informal**		**Both**	
Institutional characteristics								
Access to information	-1.1394***	(0.0672)	0.0614***	(0.0176)	-0.1192	(0.3977)	0.5464**	(0.1697)
Access to crop insurance	1.1670**	(0.3455)	-0.1586	(0.3078)	3.2367**	(1.4041)	-1.1347***	(0.2763)
Crop sale at MSP	0.1268***	(0.0102)	0.0901***	(0.0059)	0.0642***	(0.0072)	0.0258	(0.0225)
Member of farmer organization	0.6872***	(0.1272)	-0.0998	(0.1228)	0.7326	(0.8528)	-0.6409***	(0.1403)
Risk characteristics								
Loss due to pests and diseases	0.3987***	(0.0149)	-0.2272***	(0.0180)	-0.2634	(0.7529)	-0.4553**	(0.1477)
Loss due to droughts	0.3186*	(0.1751)	-0.5209***	(0.0197)	-0.9049***	(0.0814)	-0.7929***	(0.0533)
Loss due to floods	-0.2575	(0.2479)	-0.8105***	(0.1541)	-1.5844***	(0.0177)	-0.9589***	(0.1246)
Loss due to other natural causes	-0.2328	(0.3646)	-0.5195***	(0.0904)	-1.6436**	(0.5197)	-0.5858***	(0.0522)
Mundlak fixed effects								
Fertilizers	0.0158	(0.5784)	-0.2159	(0.3531)	0.4356***	(0.1015)	0.0001***	(0.0000)
Seeds	0.0001***	(0.000)	0.0001***	(0.0000)	0.0001***	(0.0000)	0.0001***	(0.0000)
Pesticides	0.7353***	(0.1318)	-0.0639	(0.0948)	0.9893	(1.0171)	-0.3778	(1.9490)
Labour	-0.9669***	(0.0410)	-0.3421	(0.9011)	-3.3587	(2.6259)	-3.2322	(3.6692)
Ancillary								
Non-borrowers	-1.1385***	(0.3046)	-0.9765***	(0.2446)	-0.1152	(0.6339)	-0.5422***	(0.0816)
Formal sector borrowers	-1.0696***	(0.2338)	-0.4027***	(0.0815)	0.8231	(0.6685)	-1.0867***	(0.2649)
Informal sector borrowers	-1.0818	(1.7002)	0.9104	(0.9473)	-0.8545**	(0.4175)	1.9336***	(0.4010)
Both	-1.6542	(1.3444)	-0.5715***	(0.1156)	0.5423	(2.0146)	-0.1215**	(0.0614)
Constant	4.3305	(4.2457)	11.3504	(12.7186)	26.9815	(23.7936)	38.6266	(18.9382)
Joint significance of selected instruments	34.44**		44.55***		56.88***		38.23***	
Joint significance of farm varying covariates $\chi2$ (4)	29.53**		23.39**		24.26**		30.99***	

Note: Figures in parentheses are bootstrapped standard errors. ***, ** and * indicate significance at 1%, 5% and 10%, respectively

Table A4. Estimates of outcome equations (Dependent variable: Skewness in farm productivity)

	Non-borrowers		Borrowers					
Explanatory variables			Formal		Informal		Both	
Demographic characteristics								
Family size	-0.0039*	(0.0022)	0.0066***	(0.0027)	-0.0294	(0.2825)	0.0156	(0.0101)
Age of the household-head	-0.0045	(0.0141)	0.0308***	(0.0114)	0.1163	(0.3470)	0.0552	(0.0579)
Gender of the household-head	0.0019	(0.0236)	0.0058	(0.0176)	-0.0984	(0.1409)	-0.0391	(0.1311)
Education level								
Below primary	0.0006	(0.0141)	-0.0130	(0.0174)	0.0467	(0.1192)	0.0308	(0.1173)
Primary	-0.0075	(0.0062)	-0.0105	(0.0238)	0.0952**	(0.0397)	0.0242	(0.1012)
Middle	0.0076	(0.0103)	0.0058	(0.0452)	0.1500***	(0.0091)	0.0328	(0.0524)
Secondary	-0.0038	(0.0029)	0.0133	(0.0116)	0.0914**	(0.0284)	0.0703	(0.1134)
Higher Secondary	0.0080	(0.0296)	0.0114	(0.0426)	0.1376	(0.2186)	0.0650**	(0.0264)
Graduate and above	0.0095	(0.0150)	0.0017	(0.0130)	0.0956	(0.0901)	0.1074***	(0.0198)
Caste								
Scheduled caste	-0.0073	(0.0072)	0.0025	(0.0167)	0.0275	(0.0635)	0.0078***	(0.0009)
Scheduled tribe	0.0076	(0.0110)	0.0024	(0.0042)	0.1146	(0.0960)	-0.0209	(0.0847)
Other backward caste	-0.0046	(0.0030)	0.0021	(0.0047)	0.0131	(0.0867)	-0.0115***	(0.0032)
Non-farm income	0.0049***	(0.0002)	-0.0092***	(0.0001)	0.0586	(0.1458)	0.0206	(0.0654)
Farm characteristics								
Operated land	0.0101	(0.0084)	0.0187	(0.0135)	0.1161	(0.1331)	0.0167	(0.0888)
Area irrigated	0.0034	(0.0391)	0.0262	(0.0225)	0.2023	(0.2035)	0.0627	(0.1737)
No. of animals	0.0019	(0.0024)	-0.0017	(0.0018)	0.0206	(0.0472)	-0.0028	(0.0489)
Area under high value crops	-0.0043***	(0.0006)	0.0102**	(0.0053)	0.0719	(0.1291)	0.0057	(0.0322)
Institutional characteristics								
Access to information	0.0013	(0.0092)	0.0073	(0.0066)	0.0255	(0.0278)	-0.0444	(0.0843)
Access to crop insurance	0.0164	(0.0116)	0.0498**	(0.0213)	0.1823	(0.4053)	0.0303	(0.1290)

Contd.

Table A4 contd.

	Non-borrowers		Borrowers					
Explanatory variables			**Formal**		**Informal**		**Both**	
Crop sale at MSP	-0.0008	(0.0054)	-0.0061***	(0.0008)	-0.0075	(0.0410)	-0.0192	(0.0253)
Member of a farmer organization	0.0071	(0.0129)	0.0002	(0.0206)	0.0599	(0.3010)	0.0195	(0.0833)
Risk characteristics								
Loss due to pests and diseases	-0.0094	(0.0141)	0.0063	(0.0088)	0.0391***	(0.0070)	0.0274	(0.0612)
Loss due to droughts	0.0077*	(0.0044)	0.0125	(0.0150)	0.1685	(0.2402)	0.0293	(0.1100)
Loss due to floods	-0.0017	(0.0160)	0.0121	(0.0485)	0.0511	(0.1221)	-0.0839**	(0.0357)
Loss due to other natural causes	0.0346	(0.0235)	0.0309	(0.0455)	0.1871	(0.2750)	0.0518	(0.2256)
Mundlak fixed effects								
Fertilizers	-0.0101***	(0.0005)	-0.0293	(0.0236)	0.1454	(0.1050)	0.1264	(0.1375)
Seeds	-0.0176	(0.0172)	0.0092**	(0.0033)	0.0017	(0.1209)	-0.0315	(0.0361)
Pesticides	0.0070	(0.0086)	0.0026	(0.0156)	-0.0441	(0.1846)	-0.0572	(0.0439)
Labour	-0.0056	(0.0095)	-0.0018	(0.0021)	-0.0302	(0.0941)	-0.0225	(0.0526)
Constant	0.2791***	(0.0161)	-0.0894	(0.1136)	-1.3114***	(0.0054)	-0.1036	(1.0539)
Ancillary								
Sigma2	0.0018	(0.0038)	0.0131***	(0.0004)	0.1809	(0.7403)	0.0186	(0.1359)
Non-borrowers	-0.3357	(0.3890)	-1.4953	(1.8118)	-1.4835	#VALUE!	0.5842	(1.0670)
Formal sector borrowers	0.3664	(1.7014)	-0.0393	(0.0765)	1.2306	(1.4340)	1.1529	(0.7333)
Informal sector borrowers	-0.9382***	(0.0406)	-1.3927	(1.6920)	-0.2969	(0.8935)	-1.5946	(0.6502)
Both	1.2454***	(0.2917)	-0.8243	(0.6609)	0.6039	#VALUE!	-0.5235	(0.3164)
Joint significance of selected instruments	45.99***		63.74***		33.17***		25.12***	
Joint significance of farm varying covariates $\chi 2$ (3)	15.48**		25.89**		14.87**		12.10**	

Note: Figures in parentheses are bootstrapped standard errors. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table A5. Fixed effects regressions (Dependent variable: Ln farm productivity)

Explanatory variables	Non-borrowers			Non-borrowers: Formal			Non-borrowers: Informal			Non-borrowers: Both		
Demographic characteristics												
Family size	0.1640***	(0.0335)	[0.0296]	-0.0601	(0.0809)	[0.0762]	-0.1832	(0.1748)	[0.1787]	-0.2781	(0.1975)	[0.1931]
Age of the household-head	0.1393*	(0.0695)	[0.0650]	0.0548	(0.2579)	[0.2347]	0.1150	(0.5730)	[0.5276]	-1.2341*	(0.5857)	[0.6331]
Gender of the household-head	-0.0375	(0.0526)	[0.0504]	0.3210*	(0.1483)	[0.1577]	0.0965	(0.4090)	[0.4159]	0.3690	(0.3781)	[0.3423]
Caste												
Scheduled caste	0.0443	(0.0839)	[0.0770]	-0.7087***	(0.1786)	[0.2153]	-0.5968	(0.4754)	[0.4949]	0.3120	(0.4843)	[0.5558]
Scheduled tribe	-0.2696***	(0.0660)	[0.0563]	-0.6723***	(0.1244)	[0.1497]	-0.1756	(0.3281)	[0.3407]	0.4858	(0.2553)	[0.3567]
Other backward caste	-0.0986	(0.0621)	[0.0505]	-0.0954	(0.0827)	[0.0970]	-0.0460	(0.2347)	[0.2540]	0.3252	(0.2689)	[0.2602]
Education level												
Below primary	0.0809	(0.0462)	[0.0506]	0.1647	(0.1339)	[0.1381]	0.3877	(0.2742)	[0.3055]	-0.0554	(0.3162)	[0.3506]
Primary	0.1634***	(0.0409)	[0.0476]	0.1317	(0.1167)	[0.1310]	0.4500	(0.2782)	[0.3003]	-0.4879	(0.2694)	[0.3278]
Middle	0.2096**	(0.0617)	[0.0506]	0.2387	(0.1765)	[0.1622]	0.1908	(0.3692)	[0.3690]	-0.2627	(0.3797)	[0.4306]
Secondary	0.1553*	(0.0655)	[0.0620]	0.2469	(0.1820)	[0.1848]	0.2682	(0.4284)	[0.4591]	-0.5763	(0.3753)	[0.4533]
Higher Secondary	0.2485***	(0.0614)	[0.0712]	0.0786	(0.2066)	[0.2087]	0.3555	(0.4965)	[0.4893]	-0.5480	(0.4738)	[0.5389]
Graduate and above	0.1627*	(0.0714)	[0.0810]	0.0496	(0.2334)	[0.2425]	1.0661*	(0.5017)	[0.5626]	-0.3846	(0.4743)	[0.6485]
Non-farm income	0.4830***	(0.0927)	[0.0789]	0.1323	(0.1006)	[0.1059]	0.4482	(0.4139)	[0.3118]	-0.0232	(0.3422)	[0.3024]
Farm characteristics												
Area irrigated	3.0639***	(0.1204)	[0.0817]	2.0535***	(0.1525)	[0.1410]	2.2043***	(0.2978)	[0.3380]	2.1274***	(0.3266)	[0.3294]
Operated land	0.5094***	(0.0339)	[0.0231]	0.7059***	(0.0718)	[0.0847]	0.9131***	(0.1592)	[0.1591]	0.5624**	(0.2039)	[0.1953]
No. of animals	0.3906***	(0.0465)	[0.0373]	0.4440***	(0.0742)	[0.0621]	0.6225**	(0.1812)	[0.1686]	0.3748	(0.2076)	[0.1528]
Area under high value crops	1.7402***	(0.1049)	[0.0646]	0.6641***	(0.1009)	[0.0847]	0.2574	(0.2509)	[0.2204]	0.4369*	(0.2178)	[0.2231]

Contd.

Explanatory variables	Non-borrowers			Non-borrowers								
				Formal			Informal			Both		
Risk characteristics												
Loss due to pests and diseases	0.3987***	(0.0679)	[0.0688]	-0.1255	(0.0920)	[0.0905]	-0.3219	(0.2092)	[0.2171]	-0.3893*	(0.1797)	[0.2078]
Loss due to droughts	0.3186**	(0.0928)	[0.0715]	-0.3330**	(0.1035)	[0.1020]	-0.3370	(0.1839)	[0.2533]	-0.5649*	(0.2487)	[0.2319]
Loss due to floods	-0.2575	(0.1720)	[0.1384]	-0.9308***	(0.2225)	[0.2072]	-1.1353**	(0.3705)	[0.4229]	-0.9926*	(0.4098)	[0.5045]
Loss due to other natural causes	-0.2328	(0.2183)	[0.1625]	-0.2287	(0.2142)	[0.2022]	-0.5376	(0.4648)	[0.5090]	-0.1468	(0.3797)	[0.4153]
Institutional characteristics												
Access to information	-1.1394***	(0.0781)	[0.0494]	0.2494**	(0.0843)	[0.0828]	0.0831	(0.1834)	[0.1882]	0.7805**	(0.2263)	[0.2224]
Access to crop insurance	1.1670***	(0.1687)	[0.1396]	1.3203***	(0.2621)	[0.2955]	2.7619**	(0.8424)	[0.7238]	-0.0240	(0.7752)	[0.8093]
Member of a farmer organization	0.6872***	(0.1164)	[0.1124]	0.2809	(0.1502)	[0.1500]	0.5483	(0.3391)	[0.4581]	-0.3482	(0.3389)	[0.3629]
Crop sale at MSP	0.1267***	(0.0138)	[0.0102]	0.1006***	(0.0137)	[0.0127]	0.1001**	(0.0321)	[0.0411]	0.0409	(0.0248)	[0.0285]
Selectivity terms												
Non-borrowers	-5.9625***	(0.4829)	[0.4489]	-1.4568**	(0.5154)	[0.4398]	-2.2635*	(1.1135)	[1.2376]	-2.4359**	(0.8334)	[0.9762]
Formal sector borrowers	-5.6016***	(0.8552)	[0.6169]	1.7605	(1.0638)	[1.1407]	1.2786	(3.0291)	[3.1130]	-5.6864	(3.3079)	[3.0598]
Informal sector borrowers	-5.6655**	(2.0100)	[1.5004]	-3.5496	(3.0411)	[2.7100]	-6.9780	(5.2049)	[6.2949]	11.1626*	(5.2279)	[6.3244]
Both	-8.6633***	(1.5462)	[1.3412]	1.9793	(2.0882)	[1.6001]	3.9137	(3.9664)	[4.4117]	0.1921	(2.5427)	[3.4692]
Constant	3.2553***	(0.5301)	[0.4847]	4.8461***	(1.0720)	[1.0323]	4.4223*	(2.1338)	[2.0414]	8.7434***	(2.0974)	[2.5420]

Notes: All regressions include district fixed effects. Robust standard errors clustered at district and village levels are in parentheses and braces, respectively. ***, **, and * denote significance at 1, 5 and 10%, respectively.

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