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Kisan Credit Card and Smallholder Farmers' Economic Performance in Eastern India

A Panel Data Analysis

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ABSTRACT

Farmers in India continue to be deprived of adequate and timely institutional credit. The Kisan Credit Card (KCC) scheme, introduced in 1998, sought to address this issue by providing credit support under a single window with simplified procedure. Using a panel data of 2,586 farming households from five states in Eastern India, namely, Bihar, Uttar Pradesh, Jharkhand, Odisha, and West Bengal in 2018 and 2023, we examine the determinants of access to KCC and its credit limit. We also analyze the impact of KCC on farmers' input usage, dependence on moneylenders and farm income using propensity score weighted fixed effects model which controls for selection bias and unobservable time-invariant heterogeneities. We find that farmers' participation in agricultural training, demonstrations and development programs encourage farmers to adopt KCC. Furthermore, KCC access increases farmers' input usage and reduces their dependence on money lenders. This evidence comes from an economically challenged region whose economy significantly depends on agriculture. The findings of the study raise concerns over the limited penetration of the scheme among smaller-scale farmers and provide key insights into the underlying issues hindering the efficacious functioning of the scheme.

Keywords: Institutional credit, Farmers, Eastern India, Panel data, Input usage, Economic welfare

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1. INTRODUCTION

A key determinant of the economic welfare of Indian farmers is their ability to purchase inputs or adopt new technologies for agricultural production activities. Financially challenged farmers with little or no landholdings are heavily dependent on credit, which enables them to use sufficient inputs, facilitates their adoption of modern technologies, and thus results in increased production (Akudugu, 2012; Asante-Addo et al., 2017; D'Souza, 2020; Kinuthia, 2018; Kumar et al., 2017, 2020; Narayanan, 2016; Tadesse, 2014). The availability of crop loans helps farmers to realize higher returns from farming (Akoijam, 2012; Hoda and Terway, 2015; Kumar et al., 2023; Singh and Sekhon, 2005). However, poor Indian farmers often fail to meet eligibility criteria to receive credit from institutional sources or face barriers related to high transaction costs, including transportation expenses from repeatedly visiting banks and opportunity costs from missed wage labor. Moneylenders offer credit with lower transaction costs, but this involves exorbitant interest rates that can drain farmers' earnings. In view of these issues, the government introduced the Kisan Credit Card (KCC) scheme in 1998 to provide adequate and timely credit support through the banking system, with flexible and simplified procedures for farmers (RBI, 2017). This scheme not only equips farmers to enhance their agricultural production but also helps promote inclusive growth and alleviate poverty among farmers, 80 percent of whom are categorized as marginal or small scale (Singh and Gupta, 2020). Initially meant for only crop loans, the scheme has been subject to several revisions to include allied and non-farm activities[1], offering farmers the necessary credit support for diverse agricultural and related value-chain needs. The KCC scheme's increased ease of borrowing and lower transaction costs differs from traditional crop loans. To qualify for a loan of up to INR[2] 160,000, beneficiaries are only required to provide documentation of land possession (in Bihar, for example, this is usually the land possession certificate), rather than collateral or a security deposit. The scheme charges a simple interest rate

[1] In 2004, the scheme was extended to investment credit requirement in allied and nonfarm activities including animal husbandry, poultry farming, fisheries, forestry, horticulture, and agro-processing since a majority of rural households also rely on allied and non-farm activities for income generation. The scheme was further revisited in 2012 by a working group under the chairmanship of Shri T.M. Bhasin, of Indian Bank, to simplify the scheme and facilitate the issuing of electronic Kisan Credit Cards. In the year 2018-19, the fisheries and animal husbandry farmers also became eligible to avail KCC for working capital requirements.

[2] INR: Indian rupee

of 7 percent, with a subvention of 3 percent upon prompt repayment (NABARD, 2019)[3]. Monitoring of KCC loans is less stringent than the traditional formal loans, and eligible farmers can also renew loans, even digitally (Kabirdoss, 2022). The operational flexibility has led to improvements in loan repayments (Vedini and Durga, 2007) as farmers are able to repay during periods of liquidity. Ensuring the renewal of KCC loan also incentivizes the farmers to make timely repayments. The scheme has also reduced transaction costs for farmers, as there is no processing fee, up to a limit of 3 lakhs (Kaur and Singh, 2016). The scheme is implemented by commercial banks, rural regional banks, and cooperative banks in line with the operational guidelines provided by the government. Commercial banks are the largest lenders, though rural regional banks and cooperative banks play an important role in many Indian states (Chanda, 2020). To bring more farmers under the umbrella of KCC benefits, the Government launched the KCC saturation drive in February 2020 which particularly targets PM KISAN beneficiaries[4].

Although the scheme has attracted many farmers, the program's coverage is inadequate, with a number of socioeconomic factors influencing the adoption of KCC. Based on a sample of 120 farmers from Tamil Nadu, Prakash and Kumar (2016) find that education, distance from a bank as well as the market have significant impacts on a farmer's access to KCC. A more extensive study by Kumar et al. (2023) finds operational land size, education, age, social group, and access to government schemes are key determinants of KCC adoption for nearly 3,000 farmers from eastern India. Similar findings were observed for more than 1,000 farmers in Haryana (Kumar et al., 2011) and 300 farmers in Assam (Bordoloi and Das, 2015). At the macroeconomic level, lagged values of KCC adoption, as indicated by the proportion of KCC accounts in rural population, were found to significantly affect KCC penetration, as measured by the proportion of KCC accounts among rural populations (Chanda, 2020). However, these studies did not investigate factors affecting credit limits for KCC holders.

[3] From 2011-12, government provides a subvention of 3% on prompt repayment of KCC loan to farmers as an incentive, i.e. on or before the due date or the date fixed by the bank, subject to a maximum period of one year. It was introduced as 1% subvention in 2009-10 and increased to 2% for 2010-11. The banks were also provided a subvention of 2% which has now been reduced to 1.5% for the year 2022-23 and 2023-24.

[4] Pradhan Mantri Kisan Samman Nidhi (PM KISAN) is an initiative by the government of India that give farmers up to ₹6,000 (US$72) per year as minimum income support.

The existing literature has little discussion or empirical exploration on the impacts of the KCC scheme. Most studies are region specific and focus on the scheme's progress in terms of number of cards issued (Bista et al. 2012; Kumar et al. 2011). Evidence using econometric methods to establish causation is largely limited (Mani, 2016; Singh & Sekhon, 2005). A few small-sample state-specific studies have used cost-benefit analysis to observe differences in expenditures and returns per acre between KCC beneficiaries and nonbeneficiaries. Using a sample of 60 farmers from Western Maharashtra, Hile and colleagues (2016) found KCC holders to have higher net returns on their crops than non-holders. Similar results were obtained by Prakash and Kumar (2016) and Agarwal and colleagues (2016) for 120 farmers from Tamil Nadu and 64 farmers from Uttarakhand, respectively. A study by Bista and colleagues (2012) showed that 60 KCC holders from Bihar had higher gross returns. Based on a sample of 210 observations from Karnataka, Jainuddin and colleagues (2013) also found KCC holders had higher gross returns for all crops considered in the analysis, in addition to higher net returns for most crops. Srivani (2023) observed that more than half of the study's 120 respondents reported an increase in income due to KCC. A recent study by Kumar and colleagues (2022) makes a more comprehensive empirical contribution by estimating the impact of KCC possession on farm income, household income, input usage, and dependence on moneylenders. Dwivedi and colleagues (2016) also evaluated the impact of KCC on input expenditure, productivity, net profit, farm business income, and farm labor income for Basmati cultivation in Jammu.

To contribute to the existing literature, which is primarily comprised of state-specific cross-sectional studies, our study utilizes panel data from 2018 and 2023 that captures information on more than 2,600 farmers from eastern India, a region whose population significantly depends on agriculture for employment. This region includes the states of Bihar, Eastern Uttar Pradesh, Jharkhand, Odisha, and West Bengal. We conducted an empirical examination of the determinants of access to KCC and of credit limits, as well as the impact of accessing KCC on farm income, expenditure on inputs, and borrowing from moneylenders. The study provides key insights into underlying issues that hinder the KCC scheme's functioning, namely

its adoption. It also provides substantive evidence on improved economic welfare and input usage due to KCC adoption.

The paper is organized as follows: Section 2 provides an overview of the KCC scheme, Section 3 presents the data and descriptive statistics of the variables used in the analysis, Section 4 discusses the empirical strategy used to arrive at the findings, Section 5 delves into the results, and Section 6 concludes with policy implications of the study's findings.

2. OVERVIEW OF THE KISAN CREDIT CARD SCHEME IN INDIA

As of 2023, the KCC scheme benefits 73 million farmers and has an outstanding debt of INR 8.85 trillion. When the scheme started in 1998, 800,000 cards were issued, and adoption rates experienced a compound annual growth rate of 40 percent until 2009-2010 (Kumar et al., 2011). However, analysis of the scheme's current state reveals a stagnant trend (Figure 1): the number of KCC beneficiaries has remained around 73 million since 2014-2015, even though the outstanding debt has risen steadily. While there are ambiguities surrounding these statistics,[5] the trend suggests that the scheme's outreach has stagnated—either due to a slowdown in enrolling new farmers or because the rate of disadoption is at par with the rate of enrolment. Meanwhile, the upward trend in outstanding debt indicates that existing beneficiaries are borrowing increasingly larger amounts- these are most likely largeholder farmers, as the KCC loan amount is directly dependent on landholding size. Taken together, these trends indicate that the scheme's benefits could be getting concentrated among relatively wealthier farmers, raising concerns about its inclusivity and effectiveness in reaching marginal and smallholders, which form majority of India's farming population. This makes poor farmers more vulnerable to debt traps of moneylenders, pushing them into poverty and worsening income inequalities in rural India.

[5] Note that the number of reported KCC beneficiaries may include dormant or renewed accounts that are counted as new ones (Kumar et al., 2011; Prakash & Kumar, 2016; Kumar et al., 2023).

Figure 1. Farmers' Kisan Credit Card accounts from 2014-2015 to 2022-2023: Number of accounts, sources, and outstanding debt

Source: RBI; NABARD.
Note: KCC = Kisan Credit Card.

The rise in outstanding debt could also indicate reborrowing and renewal of existing KCC accounts by beneficiaries. However, a steep rise in the amount of money loaned in 2021-2022 elicited concern from experts, who warned against non-performing assets (NPAs)(Parmar, 2023). Low agricultural productivity and the diversion of funds from productive investments to consumption needs could lead beneficiaries to default on their loans. This situation has culminated in a need to rethink the scheme and incorporate mechanisms to scrutinize how loans are used (Unnikrishnan, 2019).

Table 1 presents the number of KCC accounts and outstanding debt across different states. Among the country's major agricultural states, Andhra Pradesh, Kerala, Punjab, Tamil Nadu, and Telangana perform well on KCC access per 1,000 ha of net sown area, whereas the eastern Indian states of Jharkhand, Bihar, and West Bengal lag behind. Uttar Pradesh[6] and Odisha are closer to the national average of 789 KCC holders per 1000 households. There may be barriers to accessing KCC, such as lack of awareness and

[6] These statistics are for the entire Uttar Pradesh area, whereas our study focuses on Eastern Uttar Pradesh.

literacy to complete the application or understand the eligibility criteria, psychological hesitation to switch from traditional noninstitutional sources of credit, and reluctance or stringency of banks fearing nonrepayment of loans. In some cases, agricultural households may not be interested in accessing KCC because they were either engaged substantially in another occupation or they were absentee farmers (Mani, 2016). Social network and negative experiences associated with enrolment also infleunce farmers against paratcipation in the scheme (Das & Sharma, 2024).

Table 1. Number of operative KCC accounts and outstanding debt, by state

State/U.T	Operative KCC as of 3/31/2023 (in '000)	Amount outstanding (Billion INR) as of 3/31/2023	Net area sown ('000 ha)	Estimated number of agricultural households ('000)	Operative KCC (No./'000 households)	Outstanding amount per unit NSA ('000 INR/ ha)	Outstanding amount ('000 INR/household)
Andhra Pradesh	4552	609	5,884	3159	1441	103	193
Arunachal Pradesh	10	1	235	152	66	3	5
Assam	647	39	2,699	3100	209	14	13
Bihar	2577	174	5,077	7012	367	34	25
Chhattisgarh	1917	108	4,635	2985	642	23	36
Goa	9	1	127	-	-	9	-
Gujarat	3019	624	9,787	4037	748	64	155
Haryana	2287	500	3,552	1906	1200	141	263
Himachal Pradesh	460	76	530	1028	448	144	74
Jammu & Kashmir	911	64	720	1256	725	88	51
Jharkhand	968	52	1,291	2808	345	40	19
Karnataka	4721	542	10,804	4250	1111	50	127
Kerala	2594	434	2026	1467	1769	214	296
Madhya Pradesh	6269	781	15,512	7274	862	50	107
Maharashtra	7177	704	16,722	7294	984	42	96
Manipur	20	2	331	241	82	5	7
Meghalaya	72	4	255	365	197	14	10
Mizoram	35	3	146	76	459	22	41
Nagaland	30	2	384	192	157	5	9
Odisha	3971	217	4,102	4815	825	53	45
Punjab	2198	554	4,127	1467	1498	134	378
Rajasthan	6541	996	18,032	7038	929	55	141
Sikkim	9	1	77	65	133	7	9
Tamil Nadu	3581	421	4,738	2583	1387	89	163
Telangana	4337	444	5,500	2656	1633	81	167
Tripura	155	5	255	289	536	20	18
Uttarakhand	509	64	638	984	517	100	65
Uttar Pradesh	10705	1281	16,368	17758	603	78	72
West Bengal	3132	145	5,250	6689	468	28	22
Other	0	0	98	-	-	1	-

State/U.T	Operative KCC as of 3/31/2023 (in '000)	Amount outstanding (Billion INR) as of 3/31/2023	Net area sown ('000 ha)	Estimated number of agricultural households ('000)	Operative KCC (No./'000 households)	Outstanding amount per unit NSA ('000 INR/ ha)	Outstanding amount ('000 INR/household)
Total	73470	8855	13,9902	93094	789	63	95

Source: RBI; NABARD

Note: "-" indicates that data are unavailable, U.T. = Union Territory

An analysis of the amount of outstanding debt by net sown area indicates that the farmers of Andhra Pradesh, Haryana, Punjab, and Kerala have received generous credit through KCC. The eastern Indian states display lower performance in this area, with Bihar and West Bengal particularly lagging behind. A similar trend is observed in the outstanding amount of debt by agricultural household, where households from eastern Indian states have received a KCC credit of less than INR 95,267, the national average.

3. DATA AND DESCRIPTIVE STATISTICS

3.1 Data

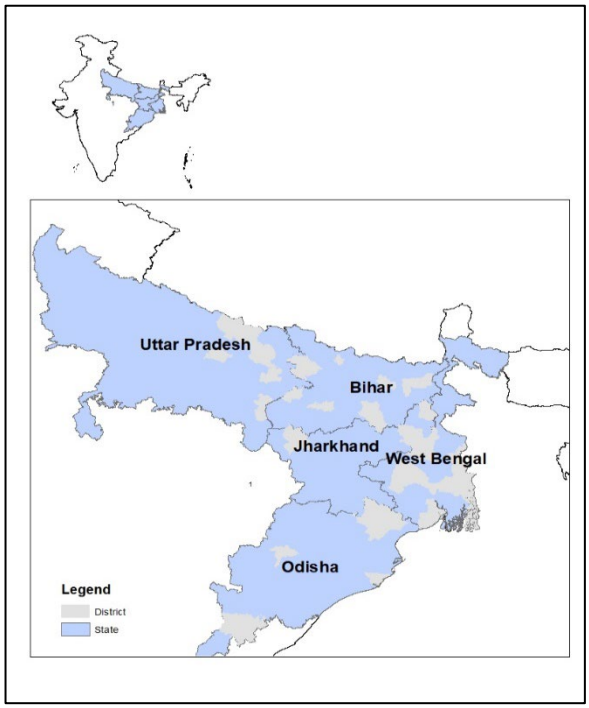
This study is based on panel data from a primary survey conducted during 2018/19 and a follow-up survey from 2023. In both rounds, we collected data using a thoroughly pretested questionnaire and trained enumerators. The focus region comprises five eastern states in India: Bihar, Eastern Uttar Pradesh, Jharkhand, Odisha, and West Bengal (Figure 2). The study region was chosen because of its significant dependence on agriculture and lower level of economic development, as compared to India's other major agricultural regions. The number of sample households selected in each state was determined in proportion to that state's rural population. Of the five surveyed states, Bihar had the largest rural population. For the sample, we randomly selected ten districts from Bihar, four districts from Jharkhand and Odisha each, and eight districts from Eastern Uttar Pradesh and West Bengal each. We then randomly chose two blocks from each district, two villages from each block, and, finally, 30 households from each village for the survey, based on household lists. The first round in 2018 comprised of 4,083 observations, however, only 3,375 households could be traced in the follow-up survey of 2023, of which 2,537 were farming households. This reduction in the number of observations is mainly attributed to emigration from the study region. Additionally, many households were no longer engaged in farming. Such attrition is common in longitudinal surveys, particularly in rural areas where migration for employment, education, or other socioeconomic reasons is prevalent. Table 2 shows the distribution of the surveyed sample by state.

Table 2. Distribution of sampled farmers by state and farm size in 2023

State	Total	%
Bihar	767	30.2
Eastern Uttar Pradesh	472	18.6
Jharkhand	276	10.9
Odisha	265	10.5
West Bengal	757	29.8
All	2,537	100.0

Source: IFPRI-ICAR survey, 2018-2019 and 2023

Figure 2. Sampled districts in eastern India



Source: ICAR-IFPRI Survey 2018-2019 and 2023

3.2 Descriptive statistics

Table A1 provides an overview of the key characteristics of the sampled households, including their description and summary statistics. The average household head is aged 51 years and holds six years of education in both the years. A vast majority of the sampled households are headed by men (96%). Across social groups,[7] 26% of these households belong to the General category, 31% belong to the scheduled castes/scheduled tribes while the remaining 44% belong to other backward classes. Farmers hold nearly 2 acres of land, on an average, and more than 75% of the farmers are marginal farmers[8], i.e., they hold less than 1 hectare of land[9]. Farmers' annual farm income per capita has gone up from INR 5,800 INR in 2018 to INR 11,300 in 2023.

[7] The caste system in India is a social hierarchy that divides people into groups based on their caste, or social class. SCs and STs are backward, uneducated, poor and officially regarded as socially disadvantaged people in India. Other Backward Class (OBC) is a collective term used by the Government of India to classify castes that are socially and educationally disadvantaged. It is one of several official classifications of the population of India, along with Scheduled Castes and Scheduled Tribes (SCs and STs).

[8] We categorize farmers as marginal if their net operational land is less than one hectare, small if the operational land is one to two hectares, medium if it is between two and four hectares, and large if it exceeds four hectares.

[9] 1 hectare = 2.47 acres.

Next, we compare key characteristics of KCC holders and non-holders between 2018 and 2023, as well as those who became KCC holders in 2023 (Table 3). The statistical t-test reveals that across all three scenarios, farm income was significantly higher for KCC holders than for non-holders. KCC holders were also significantly less dependent on moneylenders for their credit needs. For farmers who transitioned from being non-holders to holders between 2018 and 2023, the percentage of irrigated area increased.

Table 3. Descriptive characteristics of KCC and non-KCC holders, 2018 and 2023

Characteristics	Particulars	Non-holders, 2018	KCC holders, 2018	t-score	Non-holders, 2023	KCC holders, 2023	t-score	Non-holders, 2018	KCC holders, 2023	t-score
Household characteristics	Age of household head (years)	50.3	51.9	−1.8*	51.3	54.2	−4.7***	51.7	53.7	−1.9*
	Education of household head (years)	5.7	7.6	–7.6***	5.9	7.8	−8.3***	7.3	7.7	−1.1
	Household size (no.)	6.0	6.1	−0.5	6.7	6.4	1.0	5.5	6.4	−2.6**
	Household headed by male	0.97	0.98	−1.4	0.96	0.99	−3.1***	0.99	0.97	1.3
Farming activity	Experience in farming (years)	25.1	27.6	–3.9***	26.1	29.9	−5.9***	27.6	29.4	−1.6
	Size of landholding (acres)	1.7	2.8	–9.1***	1.8	2.7	−7.9***	2.2	2.5	−1.1
	Size of gross cropped area (acres)	2.5	4.1	–8.0***	2.5	3.6	−6.5***	2.9	3.3	−0.9
	Cropping intensity	1.5	1.5	−0.3	1.6	1.5	1.5	1.3	1.4	−2.3**
	Area under irrigation (%)	61.6	73.9	–5.8***	85.0	86.3	−0.8	68.9	85.3	−5.3***
Institutional variables	Political party[10]	0.11	0.13	-1.4	0.1	0.1	-3.7***	0.2	0.1	1.4
	Ration card	0.90	0.88	1.2	0.9	0.9	1.0	0.9	0.9	-1.2
	Agricultural trainings/demonstrations/Krishi mela/Kisan call center[11]	0.28	0.50	-9***	0.3	0.6	-10.9***	0.3	0.6	-6.1***
	Market	0.7	0.8	-6.9***	0.7	0.8	-8.0***	0.7	0.8	-2.9***
Outcome indicators	Input Expenditure (‘000 INR per acre)	9.1	9.8	−3.5***	9.6	9.5	0.4	8.9	9.5	−1.6
	Credit from moneylenders (as % of total credit)	25.0	3.0	10.6***	14.6	5.8	5.8***	12.7	7.0	1.9*
	Annual farm per capita~ (‘000 INR)	5.2	8.5	–11.3***	10.0	16.2	−9.3***	6.4	14.7	−8.1***
	Number (N)	2,071	466		2,003	534		253	253	

Source: Author’s calculations based on IFPRI-ICAR survey, 2018-2019 and 2023
Note: ***, **, * present significance at 1, 5, and 10 percent. ~Base year is 2011.

[10] Association with political parties is considered as an enabler of easier access to resources and networking.
[11] Krishi mela is an agricultural fair or exhibition that showcases new technologies, products, and practices. The Kisan call center provides countrywide toll-free number to answer farmers' questions in their own language.

3.3 Progress of KCC among sample households

Next, we present the progress of KCC from 2018 to 2023 (Table 4). KCC penetration increased from 18% in 2018 to 21% in 2023, and it is higher among farmers with larger landholdings. The latter finding may have resulted from lower credit demands from smaller farmers, due to their relatively lower production needs, or could imply that smaller farmers face challenges in accessing the KCC scheme, thereby raising concerns about its inclusiveness. Public commercial banks remain the largest supplier of KCCs, despite a 9% reduction in their share of KCC accounts. Private commercial banks have also emerged as notable sources of KCC from 0.9% of farmers in 2018 to 7.3% in 2023. The share of KCCs from cooperative banks registered a slight uptick during the period. Farmers prefer to receive KCCs from cooperative banks as cooperatives provide high-quality fertilizer and seed, among other inputs (Mani, 2016)[12]. From 2018 to 2023, the top reasons for applying for KCC remained the same: to purchase inputs and invest in farming equipment. This indicates that farmers continue to prioritize productive agricultural uses as they use funds from the scheme.

[12] Cooperative banks, in the form of Primary Agricultural Credit Societies (PACS), provide easy access to inputs such as fertilizer and pesticides as well as government programs for farmers.

Table 4. KCC characteristics by farm size, source, purpose, and interest rate from 2018 to 2023

	2018	2023
KCC holders	466	534
KCC holders across farm categories (%)		
Marginal	15.4	17.6
Small	25.4	30.9
Medium	31.8	32.2
Large	51.3	39.4
All	18.4	21.1
KCC source (%)		
Public/government bank	69.3	59.9
Private bank	0.9	7.3
Cooperative bank	29.8	32.8
KCC purpose (%)		
To purchase seeds, fertilizers, pesticides, etc.	71.1	66.6
To purchase farming equipment such as a tractor, thresher, etc.	15.3	8.9
For daughter's marriage	2.2	5.1
To purchase cattle	2.2	2.6
To pay back moneylender	2.0	2.0
To pay back debt from bank	1.3	2.8
For son's business	0.3	2.6
To lend to others	0.3	2.0
To purchase motorcycles	0.0	0.3
To purchase land	0.7	0.0
Other	4.7	7.4
KCC interest rate	6.9	5.5

Source: IFPRI-ICAR survey, 2018-2019 and 2023

However, except for purchasing cattle, few KCC holders allocate their funds toward other consumption needs, such as paying for a daughter's marriage, paying off old debts, purchasing motorcycles, or even lending money to others.

Table 5 presents KCC holders' credit limits across the different surveyed states from our sample. In real terms, the credit limit increased for farmers from Eastern Uttar Pradesh, Jharkhand, and West Bengal. However, farmers from Bihar and Odisha experienced a decline in their credit limits, with KCC holders from Odisha witnessing a considerable decline. The scheme's credit limit depends on many factors, such as credit worthiness, cropping patterns, and cost of cultivation. More smallholding farmers from Odisha received credit in 2023 than in 2018. It is also possible that lending has declined in these states due to the higher risk of defaults.

Table 5. Credit limit of KCC holders across states, in INR

State	2018	2023
Bihar	43,356	41,183
Eastern UP	69,496	83,156
Jharkhand	25,696	34,819
Odisha	33,908	25,928
West Bengal	20,236	27,780
All	39,426	42,304

Source: IFPRI-ICAR survey, 2018-2019 and 2023
Note: INR amounts are given in 2011-2012 prices.

4. CONCEPTUAL FRAMEWORK AND METHODOLOGY

The following subsections describe the empirical methods used to identify determinants of KCC access, as well as credit limits and the association of KCC access with outcome variables.

4.1 Determinants of KCC access and credit limit

To identify the determinants of KCC access and of credit limits from our panel data, we deployed the Heckman selection model, suspecting the possibility of an endogenous sample selection (Heckman, 1979). To check for this, we first estimated the selection equation using a probit model. A farmer's access to KCC is represented as:

$$KCC_{it} = \begin{cases} 1, \ if \ \alpha X_{it} + u_{it} > 0 \\ 0, otherwise \end{cases} \quad (1)$$

where, for every farmer, i=1,2…. N and year 't', KCC_{it} is a binary dependent variable that takes a value of 1 if i^{th} farmer has KCC in t^{th} year and 0, otherwise. X_{it} is a vector of explanatory variables and u_{it} represents the error term, $u_{it} \sim IID(0, \sigma^2)$.

Given the observed binary decision (KCC_{it}), the regression equation of the unobserved variable 'latent' KCC_{it}^* is given as:

$$KCC_{it}^* = X_{it}\alpha + u_{it} \quad (2)$$

We derived the Inverse Mills Ratio[13] (IMR) from (2) and used it as a regressor in the fixed/random effects model (depending on the result of the Hausman Specification test) to find the determinants of KCC credit limit. IMR captures the probability of being selected into the sample (Heckman, 1979). Therefore, including it in the outcome equation corrects for the selection bias, if it is present. The panel model is specified as:

$$KCC\_limit_{it}^* = \beta_1 w_{it} + \lambda_{it} \beta_2 + \varepsilon_{it} \quad (3)$$

Where '$KCC\_limit_{it}^*$' is a continuous variable representing the latent credit limit of Kisan Credit Card for farmer i in time period t, w_{it} is a vector of exogenous variables in the model, β_1 is a K × 1 vector of parameters, and β_2 is the estimated coefficient on the IMR, represented by $\lambda_{it.}$ εit is the composite error term, defined as: $e_{it} = u_i + \varepsilon_{it}$, where $u_i \sim IID(0, \sigma^2)$ and $\varepsilon_{it} \sim IID(0, \sigma^2_{\varepsilon})$.

[13] The IMR is given by the predicted KCC access estimates and is derived as $\lambda_{it} = \vartheta(\alpha' X_i)/\phi(\alpha' X_i)$, where ϑ is the probability density function and ϕ is the cumulative distribution function of the standard normal distribution (Heckman, 1979).

If the coefficient of IMR is not statistically significant in (3), it implies that sample selection bias is absent. In that case, determinants of KCC access can be estimated using standard probit model, as specified below:

$$P\ (KCCit = 1|\ Xit) = G(Xit'\alpha) \quad (4)$$

where P(KCCit=1| Xi) represents the likelihood of accessing KCC, G(.) gives the cumulative distribution function (CDF) of the standard normal distribution, Xit is a vector of explanatory variables which includes educational level, ration card, farming experience, gender, land size, household size, participation in government programs, state, social group, decision to sell and political links (See Table A1 for detailed description). The factors affecting the KCC credit limit, can be determined separately using fixed effects or random effects model, based on the outcome of the Hausman Specification test. The framework is specified as:

$$KCC\_limit_{it} = \beta_0 + \beta_1 X_{it} + \gamma_i + \varepsilon_{it} \quad (5)$$

Where Xit is a vector of explanatory variables, same as in Equation (4), γ_i represents the unobserved individual-specific effects and ε_{it} is the idiosyncratic error term. Both the equations (4) and (5) are estimated with state-fixed effects[14].

4.2 Association of KCC access with farmer's economic welfare and input usage using PSM-FE

The Fixed effects models can be instrumental in conducting impact evaluation using panel data as they account for unobservable, time-invariant factors that affect the outcome indicators (Angrist and Pischke, 2009). However, the fixed effects model does not take into account the bias arising from self-selection of farmers into the KCC scheme. Since our data is not based on an experimental setting with randomly assigned treatment, there may be a possibility of self-selection bias as farmers may have self-selected themselves into treatment. The self-selection bias arises from the possibility that KCC holders may be systematically different compared to non-holders. The propensity score matching is a widely used method to reduce self-selection bias and obtain a sample of treated and untreated groups, that are comparable based on observed characteristics. Therefore, to address both the issues of unobserved time-invariant

[14] State fixed effects help control for unobserved factors that are unique to each state but constant over time.

heterogeneities and self-selection, we combine PSM with Fixed Effects. The steps for conducting the same are given below.

Step 1: Propensity Score Matching

The propensity score matching method, a nonparametric analysis method, addresses the estimation issues arising from self-selection bias. It first eliminates the systematic difference between the treated and control group by conditioning the probability of getting treated on a wide set of covariates and then estimates the average treatment effects on the treated. The propensity score thus generated is used to pair treated observations with controls (Rosenbaum and Rubin, 1983). PSM relies on three crucial assumptions: unconfoundedness assumption, common support assumption and balancing property assumption.[15] Given these assumptions are satisfied, first a logit or probit model is deployed estimate the probability of receiving treatment based on a set of covariates. Covariates included in the regression should affect both outcome and treatment variables simultaneously (Caliendo and Kopeinig, 2008). Based on a large body of literature, we include educational level, ration card, farming experience, gender, land size, household size, participation in government programs, state, social group, decision to sell and political links as covariates. Next, the treated observations are matched with untreated observations. This paper chooses the kernel matching with common support and bandwidth of 0.01 to ensure reduction in bias and enhanced accuracy (Caliendo and Kopeinig, 2008). The matching is performed for all three outcome variables, i.e., 'per capita farm income', 'input expenditure per acre', and 'dependence on moneylenders' separately in each year.

Step 2: Fixed Effects Model with Propensity Score Weighting

The Hausman test confirms the suitability of fixed effects model, for each of the three outcome indicators. The fixed effects equation that we estimate is:

$$Y_{it} = \alpha_1 + \alpha_2 KCC_{it} + \alpha_3 X_{it}' + \phi_{it}' + \epsilon_{it}$$

[15] The unconfoundedness assumption requires the outcome variable to be independent of treatment given the propensity score generated by the logit regression. This rule is also called the Conditional Independence Assumption. The common support assumption ensures that there is sufficient overlap in the characteristics of units to find adequate matches. The balancing property assumption requires for any given propensity score, the treatment and control group should, on average, look identical (World Bank, n.d.).

Where Y_{it} is the outcome variable (expenditure on inputs, per capita farm income and dependence on moneylenders) for farmer i in round t (2018 and 2023). α_2 is the parameter estimate for KCC_{it} (as indicated above, KCC_{it} takes takes the value one if the farmer is a KCC holder and zero otherwise) and indicates the average effect of accessing KCC for each outcome. X_{it}' represents the vector of other time-varying control variables which includes the educational level, ration card, farming experience, gender, land size, household size, participation in government programs, state, social group, decision to sell and political links. Φ' represents the time-invariant unobserved farmer level heterogeneities. ϵ_{it} is the error term at the household level.

Next, we combine PSM with FE to address the bias in the estimate that may arise if KCC holders and non-holders are not comparable. For example, rich farmers without any need to borrow from KCC are included in the control group. By conducting fixed effects estimation on matched sample of comparable treated and untreated observations, we can account for the bias from both self-selection and time-invariant unobservable characteristics (Khandker and colleagues., 2009; Linden & Adams, 2010). Furthermore, we weigh the regression using the propensity score under the assumption of Conditional Independence by assigning the sample weight of 1 to all the farmers in the treatment group and P(X)/(1-P(X)) to farmers in the control group and obtain the (conditional) average treatment effect on treated (Hirano and Imbens, 2001; Hirano, Imbens, and Ridder, 2003; Michalopoulos, Bloom, and Hill, 2004). The empirical framework of combining PSM with fixed effects has been deployed by many studies (Kim et al., 2008; Imai and Azam, 2012; Luo and Escalante, 2019; Unnikrishnan and Imai, 2020). However, it is noted that PSM-FE does not take into account the effect of time-variant unobservable factors such as risk aversion and motivation. Yet, the bias introduced by these factors may not be a major concern as they may not affect the outcome directly (Imbens, 2004; Imbens and Rubin, 2015).

5. RESULTS AND DISCUSSION

5.1 Determinants of access to KCC and credit limit

The investigation of the determinants of access to KCC and its credit limit involved checking the suitability of the Heckman Selection model using the IMR. It was found that the IMR did not significantly impact farmers' KCC credit limits (Table A2 in Appendix), implying the absence of selectivity bias. Therefore, we estimated (4) and (5) using probit and random effects models,[16] respectively (Table 6). Column 1 of the table shows marginal effects of the estimated probit regression. Education has a positive impact on a farmer's decision to possess the KCC (Bordoloi and Das, 2015; Kumar et al., 2011, 2023), as well as on the KCC's credit limit.

Table 6. Determinants of access to KCC and of KCC credit limits

	(1)	(2)
Variables	**KCC access**	**KCC credit limit**
	Marginal effect dy/dx	
Social group (Base: General category)		
Scheduled caste/scheduled tribe	-0.116***	-1.724
	(0.019)	(3.610)
Other backward classes	-0.091***	-3.631
	(0.019)	(3.191)
Education	0.007***	0.673***
	(0.001)	(0.231)
Household size	0.000	0.523
	(0.002)	(1.221)
Ration card (1 = Has a ration card, 0 = otherwise)	0.031	-19.239**
	(0.020)	(8.694)
Farming experience	0.002***	0.114
	(0.000)	(0.098)
Gender (1= Male, 0 otherwise)	0.023	-8.204
	(0.033)	(10.188)
Land size category (Base: Marginal)		
Small	0.059***	18.790***
	(0.015)	(3.491)
Medium	0.070***	31.208***
	(0.022)	(5.708)
Large	0.145***	42.318***
	(0.036)	(15.327)
Agricultural trainings/demonstrations/Krishi mela/Kisan call center (1 = Attended, 0 = otherwise)	0.111***	4.275*

[16] The random effects model was chosen after conducting the Hausman specification test.

Variables	(1) KCC access	(2) KCC credit limit
	Marginal effect dy/dx	
	(0.010)	(2.224)
Market (1 = Sold agricultural produce in markets, 0 = consumed)	0.063***	4.486**
	(0.012)	(1.981)
Political party (1 = Member, 0 = otherwise)	0.030*	5.549*
	(0.017)	(3.303)
State (Base: Bihar)		
Eastern UP	0.151***	42.874***
	(0.019)	(4.666)
Jharkhand	0.192***	0.894
	(0.024)	(4.739)
Odisha	0.081***	-5.849
	(0.020)	(7.196)
West Bengal	0.096***	2.906
	(0.018)	(6.347)
Constant		31.117**
		(15.131)
Observations	5,074	1,000
Number of unique identifications	2,537	719

Note: Figures in parentheses present robust standard errors. ***, **, * present significance at 1, 5, and 10 percent.

Farmers who market their agricultural produce have higher credit limits and are also more likely to possess the KCC. This seems plausible, since farmers who produce for commercial purposes require more capital to enhance production. Furthermore, they may be influenced by the market network to adopt the KCC. Small, medium and large farmers are more likely to have access to KCC than marginal farmers, with the likelihood increasing with land size. The observation aligns with the findings of Bordoloi and Das (2015) and Kumar and colleagues (2011, 2022). The size of landholding is a deciding factor in determining a farmer's credit limit, as per governmental guidelines, hence, the positive coefficients for larger farmers in column 2. While farmers with larger landholdings may have a greater need for the KCC and thus be more likely to choose it, when it comes to accessing KCC, however, small-scale farmers may face difficulties in procuring the card. Various reasons could cause these difficulties, such as limited awareness of the scheme's benefits or the procedure to acquire the card. Banks may be reluctant to loan to these farmers, fearing defaults from less productive marginal farmers (Mani, 2016).

Among other covariates, attending agricultural trainings, demonstrations, or Krishi Mela or accessing the Kisan call center positively influence farmers' KCC adoption and credit limit. Political links are also seen as an enabler to KCC access and enhanced KCC credit limit. Those with more extensive farming experience are also more likely to access the KCC.

Access to ration cards has a significantly negative association with KCC credit limits, as poor households primarily use ration cards. KCC credit limits are higher for larger and more prosperous farmers. The negative coefficient of certain social groups with respect to KCC access indicates social disparities that hinder vulnerable populations from benefiting from such programs. Similar disparities were also observed by Kumar and colleagues (2011, 2022).

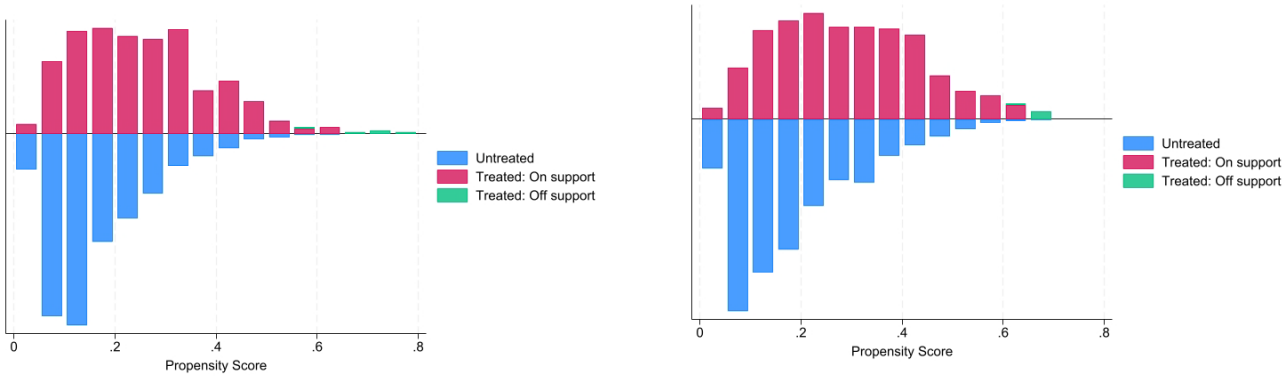
5.2 Impact of KCC with income, input usage and dependence on moneylenders

First, we conduct Propensity Score Matching to estimate the propensity score, i.e., the probability that a farmer has access to KCC, using the default probit model in Stata's 'pscore' command for each round[17]. Table A3 presents the probit regression estimates obtained from regressing the access to KCC variable on the covariates discussed above. Results indicate that in both the years, education, farming experience, land size, participation in agricultural trainings, demonstrations, or Krishi Mela or accessing the Kisan call center, belonging to upper castes and participation in market are positively associated with access to KCC. In 2023, political links and possessing ration card also exhibit a positive linkage with access to KCC.

The kernel matching is performed on observations from common support region with bandwidth of 0.01. Figure 3 gives graphs for common support regions and shows adequate overlap area in the propensity scores (common support) between treated and untreated groups. Only the observations that come under the common support region are used in matching. To ensure the validity of the balanced characteristics of the matched sample as well as the common support condition, we assess the covariate balance between treated and untreated groups using balancing test based on Rubin (2001) and find that covariates are strongly balanced in each round.

[17] The assumption of balancing property is satisfied for a total of 7 blocks in each year/round (Leuven & Sianesi, 2003).

Figure 3. Common Support Region

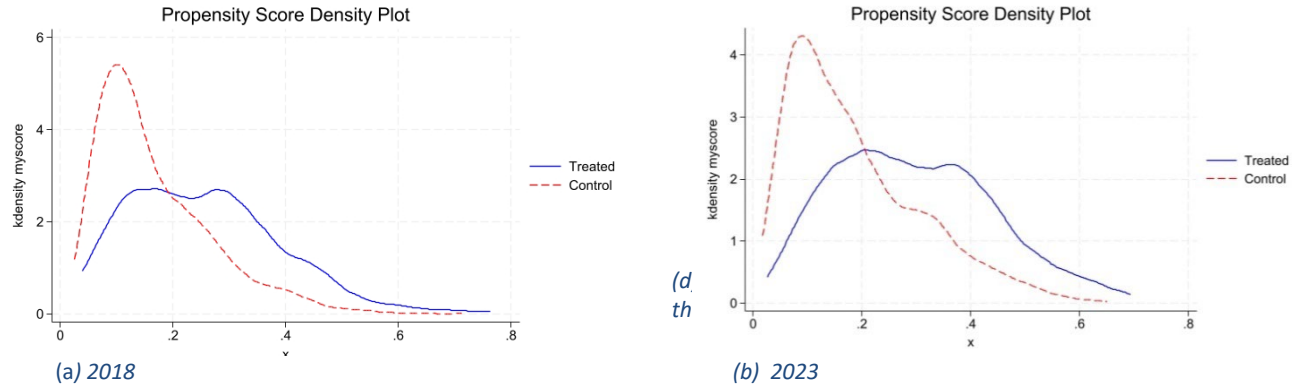


(a) Common Support Region for 2018

(b) Common Support Region for 2023

Source: Author's calculations based on ICAR-IFPRI Survey 2018 and 2023.

Figure 4. Propensity Score in 2018 and 2023



(a) 2018

(b) 2023

Source: Same as Figure 3.

Next, we present the results for PSM-FE inTable 7. Column (1), (4) and (7) display the estimates for the impact of access to KCC on per capita income from farming, expenditure on inputs and dependence on moneylenders, respectively, using FE model. Columns (2), (5) and (8) displays the FE model results for the matched panel data, i.e., after dropping the unmatched observations. Finally, column (3), (6) and (9) report the results for propensity score weighted model deployed on the matched sample. The estimation weighted by the propensity scores shows a differential incentive into the scheme for farmers over 2018 and 2023. Table A4 in Appendix reports a full set of results where the control variables included in the models display the expected sign.

Table 7. Impact of KCC with income, input usage and dependence on moneylenders

Variables	Expenditure on inputs ('000 INR/ Acre)			Dependence on moneylenders (%)			Farm income per capita ('000 INR/ household member)		
	FE	Matched FE	PSM-FE	FE	Matched FE	PSM-FE	FE	Matched FE	PSM-FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
KCC (1 = Has KCC, 0 otherwise)	1.136***	1.145***	1.070***	-9.404***	-9.065***	-9.024***	1.256	1.340*	1.266
	(0.289)	(0.291)	(0.302)	(2.313)	(2.297)	(2.360)	(0.779)	(0.785)	(0.848)
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of unique identifications	2537	2531	2531	1,121	1,110	1110	2537	2531	2531
R-squared	0.033	0.033	0.534	0.041	0.041	0.645	0.078	0.080	0.606

Note: Figures in parentheses present robust standard errors. ***, **, * present significance at 1, 5, and 10 percent.

In case of our first outcome variable, the FE model indicates KCC holders incur higher expenditure on farming inputs at 1% significance level. The matched sample with 6 lesser observations, shows a similar outcome. The propensity score-weighted FE model applied to the matched sample accounts for bias from both time-invariant unobservable factors and self-selection and confirms the nature of relationship between access to KCC and input expenditure per acre of land at 1% significance level, although the magnitude of impact registers a decline by 5.8%. Specifically, participation in KCC scheme allows farmers to spend INR 1,070 greater on agricultural inputs annually. This implies that KCC may ease liquidity constraints for farmers and financially empower them to access greater quantity and quality of farming inputs. Similar findings were obtained by Dwivedi and colleagues (2016) in the case of rice cultivation in Jammu.

The results for farmers' borrowing from moneylenders[18] display a negative and statistically significant coefficient across all three models. As discussed, the difference in magnitude across the three models arises from excluding unmatched observations and applying differential weighting. However, the difference is small, indicating consistency and robustness of the estimates. Availing credit through KCC can reduce farmers' dependence on moneylenders by over 9%. This finding is line with one of the primary aims of the Kisan Credit Card scheme which is designed to provide easy credit at low interest rates, eventually leading to decreased reliance on moneylenders. Kumar et al. (2023) found similar results from their analysis of Eastern India farmers in 2018.

FE model in column (7) shows that KCC has a positive, although statistically insignificant influence on farmers' per capita farm income. The matched sample with 6 lesser observations, reveals a positive impact at 10% significance level. However, conducting the estimation with weights yields a positive but statistically insignificant coefficient of 1.266. Unlike the findings of Kumar et al. (2023), our panel data study does not provide evidence indicating KCC's role in increasing income from farming. There could be multiple factors responsible for it, for instance, merely accessing better agricultural inputs and machinery

[18] This analysis of the impact of KCC on moneylender dependence only includes farmers who have taken loan (from any source) in the last 5 years. Therefore, the sample size reduces to 1,121 farmers.

does not guarantee the know-how of their proper utilization and may not enhance productivity. Additionally, despite availing loan from the scheme, the credit limit may not be sufficient to fulfill the farmers' requirements[19]. The occurrence of COVID 19 pandemic between 2018 and 2023, may have also led farmers to divert KCC amount to non-productive consumption needs, limiting its potential in bringing substantial gains from farming. Furthermore, since our panel comprises only two years, it is possible that the positive effects of acquiring KCC on farming income may appear with a lag and not get captured in our dataset, especially for those who accessed KCC in 2023.

[19] Indeed, recognizing farmers' increasing need for credit, the government revised the KCC credit limit to INR 500,000 in its Budget of 2025-26 (Business Standard, 2025).

6. CONCLUSIONS AND POLICY IMPLICATIONS

Easy access to credit has been a longstanding barrier that prevents farmers from accessing key inputs and infrastructure to realize productivity gains. The KCC scheme sought to address these issues by removing various challenges involved in receiving institutional credit. The program has shown impressive progress since it first began. However, the number of KCC holders has stagnated in recent years, even as the amount of outstanding debt has increased. Disregarding any discrepancies in the estimated number of KCC holders, this situation could imply that few farmers— possibly, large-scale farmers with high credit limits—are actually benefiting from the KCC scheme. Thus, it is important to explore which factors influence the adoption of KCC and its credit limit among farmers. We conducted this study in eastern India, one of the country's most economically vulnerable yet highly agriculture-dependent regions: specifically, we focused on Bihar, Eastern Uttar Pradesh, Jharkhand, Odisha, and West Bengal. The study was conducted using panel data from two years (2018 and 2023), consisting of 2,586 agricultural households. The empirical assessment of determinants of KCC access shows that among other factors, agricultural programs such as trainings, demonstrations, Krishi Mela, and Kisan call centers are important sources of information that can encourage farmers to adopt KCC. Policies can aim to strengthen agricultural extension programs to increase KCC adoption through targeted training, outreach, and financial literacy initiatives. Despite its success in improving input usage and reducing reliance on moneylenders, as suggested by PSM-FE empirical results, KCC penetration was found to be the lowest among smaller-scale farmers. This may explain the trend in rising KCC debt, even as the number of cardholders stagnates. While it is possible that smaller-scale farmers may be less willing to apply for KCC, may not meet the scheme's requirements, or may choose other sources of credit, they are economically disadvantaged, compared to larger-scale farmers, and largely excluded from accessing formal credit. Given that the scheme is designed to cater to all land sizes and production needs, it is important to ensure that smaller-scale farmers who want to use KCC are not excluded from the program. The scheme may need to be strategically reformed to become more inclusive for smaller-scale farmers through mechanisms that bridge the trust deficit between banks and farmers, including

through close monitoring of loaned amounts and background checks on beneficiaries to avoid defaults. Reforms to the KCC scheme can address loopholes that impede its efficacy and make credit accessible to farmers who need it. Finally, the empirical evidence regarding the role of KCC in enhancing farming income remains ambiguous. Income gains from KCC credit may not be realized instantly, hence, future research could deploy longer panel datasets to arrive at a more comprehensive picture.

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APPENDIX

Table A1. Key characteristics of sample households

Characteristics	Particulars	Description	2018	2023
Household characteristics	Age	Age of household head in number of years	50.4	51.9
	Education	Education of household head in number of years	6.1	6.3
	Gender	Dummy variable that takes a value of 1 if the household head is male, 0 otherwise.	0.9	0.9
	Social group	The social group that the household belongs to		
	• General	Dummy variable that takes a value of 1 if the household belongs to the general social group, 0 otherwise	0.3	0.3
	• Scheduled caste/ Scheduled tribe	Dummy variable that takes a value of 1 if the household belongs to the scheduled caste or scheduled tribe social group, 0 otherwise	0.3	0.3
	• Other backward classes	Dummy variable that takes a value of 1 if the household belongs to other backward classes, 0 otherwise	0.4	0.4
	Household size	Number of family members in the household	6.1	6.6
Farming activity	Farming experience	Years of farming experience of household head	25.5	26.9
	Net Operational Land	Land owned + land leased in – land leased out	1.9	2.0
	Land size category			
	• Marginal	Net operational land< 1 ha	0.78	0.76
	• Small	Net operational land> 1 ha and <=2 ha	0.15	0.17
	• Medium	Net operational land> 2 ha and <=4 ha	0.05	0.05
	• Large	Net operational land> 4 ha	0.01	0.01
	Gross cropped area (GCA)	the total area of land that is sown with crops once or more than once in a given year, in acres	2.8	2.8
	Cropping intensity	Ratio of GCA to Net operational land	1.5	1.6
Institutional variables	Political party[20]	Dummy variable taking a value of 1, if the household has a political party member, 0 otherwise	0.1	0.1

[20] Association with political parties is considered as an enabler of easier access to resources and networking.

Characteristics	Particulars	Description	2018	2023
	Ration card	Dummy variable taking a value of 1 if the household has a ration card, 0 otherwise	0.9	0.9
	Agricultural trainings/demonstrations/ Krishi mela/Kisan call center[21]	Dummy variable taking a value of 1 if the household has participated in Agricultural trainings or demonstrations or Krishi mela or Kisan call center, 0 otherwise	0.3	0.4
	Market	Dummy variable taking a value of 1 if the farmer sells his agricultural produce in the market, 0 if entire produce is self-consumed	0.7	0.7
Outcome indicators	Credit from moneylenders	Amount of money borrowed from moneylenders as a % of total credit from all sources	17.2	12.6
	Farm income	Income from farming divided by household size in '000 INR	5.8	11.3
	Input expenditure	Includes expenditures on fertilizer, manure, seeds, micronutrients, machinery, herbicides, pesticides, and irrigation, calculated per unit of cropped area ('000 INR/acre)	9.2	9.5
	Irrigated land	Percentage of net operational land that has access to irrigation	63.8	85.3

Source: IFPRI-ICAR survey, 2018-2019 and 2023

[21] Krishi mela is an agricultural fair or exhibition that showcases new technologies, products, and practices. The Kisan call center provides countrywide toll-free number to answer farmers' questions in their own language.

Table A2. Determinants of access to KCC and of credit limit (with Inverse Mills Ratio)

Variables	KCC credit limit
Inverse Mills Ratio	-2.411
	(5.586)
Education	0.595*
	(0.331)
Household size	0.511
	(1.222)
Ration card (1 = Has a ration card, 0 = otherwise)	-20.048**
	(8.306)
Farming experience	0.086
	(0.120)
Gender (1= Male, 0 otherwise)	
Land size category (Base: Marginal)	
Small	18.182***
	(4.003)
Medium	30.362***
	(5.965)
Large	40.812***
	(15.086)
Agricultural trainings/demonstrations/Krishi mela/Kisan call center (1 = Attended, 0 = otherwise)	3.020
	(4.226)
Market (1 = Sold agricultural produce in markets, 0 = consumed)	3.666
	(2.882)
Political party (1 = Member, 0 = otherwise)	4.954
	(3.298)
State (Base: Bihar)	
Eastern UP	40.666***
	(7.061)
Jharkhand	-1.900
	(8.110)
Odisha	-6.955
	(9.096)
West Bengal	2.309
	(8.209)
Constant	30.101
	(22.998)
Observations	1,000
Number of unique identifications	719

Note: Figures in parentheses present robust standard errors. ***, **, * present significance at 1, 5, and 10 percent

Table A3. Probit results of whether a farmer has access to KCC

Variables	KCC access	KCC access
	Year 2018	Year 2023
Social group[22] (Base: Scheduled caste/scheduled tribe)		
General category	0.390***	0.287***
	(0.083)	(0.081)
Other backward classes	0.127	0.037
	(0.078)	(0.075)
Education	0.028***	0.038***
	(0.007)	(0.007)
Household size	-0.014	-0.012
	(0.009)	(0.008)
Ration card (1 = Has a ration card, 0 = otherwise)	0.147	0.273**
	(0.105)	(0.118)
Farming experience	0.009***	0.013***
	(0.002)	(0.002)
Gender (1= Male, 0 otherwise)	0.203	0.158
	(0.203)	(0.205)
Land size category (Base: Marginal)		
Small	0.194**	0.223***
	(0.083)	(0.078)
Medium	0.296**	0.224*
	(0.128)	(0.124)
Large	0.812***	0.498**
	(0.217)	(0.240)
Agricultural trainings/demonstrations/Krishi mela/Kisan call center (1 = Attended, 0 = otherwise)	0.412***	0.465***
	(0.063)	(0.061)
Market (1 = Sold agricultural produce in markets, 0 = consumed)	0.301***	0.307***
	(0.073)	(0.073)
Political party (1 = Member, 0 = otherwise)	0.043	0.193*
	(0.094)	(0.110)
Constant	-2.168***	-2.357***
	(0.249)	(0.254)
Number of unique identifications	2,537	2,537

ote: Figures in parentheses present standard error. ***, **, * present significance at 1, 5, and 10 percent

[22] Due to a technical glitch in Stata software, the base categories for social group dummy is Scheduled caste/ scheduled tribe

Table A4. A full set of results of PS weighted FE model for matched panel.

Variables	Expenditure on inputs ('000 INR/ Acre)			Dependence on moneylenders (%)			Farm income per capita ('000 INR/ household member)		
	FE	Matched FE	PSM-FE	FE	Matched FE	PSM-FE	FE	Matched FE	PSM-FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
KCC (1=Has KCC, 0 otherwise)	1.136***	1.145***	1.070***	-9.404***	-9.065***	-9.024***	1.256	1.340*	1.266
	(0.289)	(0.291)	(0.302)	(2.313)	(2.297)	(2.360)	(0.779)	(0.785)	(0.848)
Education	0.031	0.031	0.030	-0.378	-0.398	-0.426	0.168***	0.171***	0.182***
	(0.026)	(0.026)	(0.026)	(0.271)	(0.272)	(0.285)	(0.062)	(0.062)	(0.065)
Household size	0.076**	0.076**	0.073**	-0.509	-0.480	-0.607			
	(0.031)	(0.031)	(0.031)	(0.441)	(0.451)	(0.466)			
Ration card (1 = Has a ration card, 0 = otherwise)	-0.519*	-0.538*	-0.555*	-9.773**	-10.161**	-10.499**	0.851	1.050	1.357
	(0.291)	(0.295)	(0.313)	(4.283)	(4.430)	(4.686)	(1.018)	(1.008)	(1.191)
Farming experience	-0.001	-0.001	0.003	-0.112	-0.115	-0.121	0.065***	0.063***	0.061***
	(0.009)	(0.009)	(0.009)	(0.104)	(0.106)	(0.110)	(0.019)	(0.019)	(0.020)
Gender (1= Male, 0 otherwise)	-0.768	-0.770	-0.857	-0.447	-0.461	-1.433	-0.856	-0.827	-0.850
	(0.546)	(0.546)	(0.556)	(7.153)	(7.159)	(7.182)	(0.834)	(0.829)	(0.912)
Land size category (Base: Marginal)									
Small	-0.071	-0.070	-0.085	6.096*	6.255*	7.126**	3.405***	3.398***	3.631***
	(0.258)	(0.259)	(0.260)	(3.185)	(3.224)	(3.379)	(0.614)	(0.617)	(0.649)
Medium	0.166	0.186	0.168	10.231*	11.258**	12.256**	7.003***	6.982***	6.693***
	(0.365)	(0.369)	(0.402)	(5.344)	(5.455)	(5.579)	(1.710)	(1.734)	(1.934)
Large	-0.199	-0.124	-0.022	-4.469	-2.207	-2.507	5.742	6.447	8.397
	(0.936)	(0.998)	(1.125)	(8.409)	(8.477)	(8.850)	(5.577)	(5.995)	(6.522)
Agricultural trainings/demonstrations/Krishi mela/Kisan call center (1 = Attended, 0 = otherwise)	0.598***	0.598***	0.611***	-1.398	-1.264	-0.839	1.426***	1.434***	1.635***
	(0.201)	(0.201)	(0.204)	(1.933)	(1.940)	(2.030)	(0.514)	(0.516)	(0.545)
Market (1 = Sold agricultural produce in markets, 0 = consumed)	1.203***	1.204***	1.191***	8.705***	8.649***	8.789***	4.314***	4.316***	4.325***
	(0.197)	(0.197)	(0.199)	(2.146)	(2.148)	(2.191)	(0.294)	(0.294)	(0.308)
Political party (1 = Member, 0 = otherwise)	0.163	0.135	0.145	1.541	1.686	1.762	-1.759**	-2.041**	-1.961**

Variables	Expenditure on inputs ('000 INR/ Acre)			Dependence on moneylenders (%)			Farm income per capita ('000 INR/ household member)		
	FE	Matched FE	PSM-FE	FE	Matched FE	PSM-FE	FE	Matched FE	PSM-FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	7.424***	7.441***	7.495***	28.785***	28.989***	31.115***	1.281	1.112	0.871
	(0.670)	(0.671)	(0.694)	(8.583)	(8.630)	(8.885)	(1.443)	(1.435)	(1.613)
Number of unique identifications	2537	2531	2531	1,121	1,110	1110	2537	2531	2531
R-squared	0.033	0.033	0.534	0.041	0.041	0.645	0.078	0.080	0.606

Note: Figures in parentheses present robust standard error. ***, **, * present significance at 1, 5, and 10 percent.

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