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Assessing the Impact of Lending through Kisan Credit Cards in Rural India

Evidence from Eastern India

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List of acronyms

ATM	Automated Teller Machine
CAGR	Compound Annual Growth Rate
CEM	Coarsened Exact Matching
DBT	Direct Benefit Transfer
DCT	Direct Cash Transfer
GoI	Government of India
ICAR	Indian Council of Agricultural Research
IFPRI	International Food Policy Research Institute
INR	Indian Rupee
KCC	Kisan Credit Card
MFIs	Micro-Finance Institutions
MGNREGA	Mahatma Gandhi National Rural Employment Guarantee Act
MIB	Monotonic Imbalance Bounding
OBC	Other Backward Caste
OLS	Ordinary Least Square
PAIS	Personal Accident Insurance Scheme
PCAHI	Per Capita Annual Household Income
PMFBY	Pradhan Mantri Fasal Bima Yojana
PMJDY	Pradhan Mantri Jan Dhan Yojana
POS	Point of Sale
PSM	Propensity Score of Matching
RBI	Reserve Bank of India
SC	Scheduled Caste
SHGs	Self-Help Groups
ST	Scheduled Tribe
TE	Treatment Effect

Abstract

This paper attempts to identify the determinants of access to the KCC program and empirically evaluate its impact on farmers' use of agricultural inputs and farm household incomes in Eastern India. We have also examined whether the possession of KCC reduces the farmer's dependence for borrowing on moneylenders. The estimation is based on Coarsened Exact Matching (CEM) approach, which is an increasingly popular method of estimating causal effects. The study uses a large survey of rural/farming households in eastern India (Bihar, Eastern Uttar Pradesh, Jharkhand, Odisha, and West Bengal). Findings reveal that access to KCC is strongly associated with the socioeconomic and demographic characteristic of farming households. We find that access to KCC increases farmers' use of the agricultural inputs and households and farm income especially for marginal and small farmers. Finally, access to KCC reduces farmer's dependency on moneylenders for borrowing credits by 25 percent.

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1. Introduction

The Kisan Credit Card (KCC1) scheme is a multipurpose credit card program for Indian farmers, which has provisions for crop loans, consumption credit, and term credit (GoI, 2017). The KCC scheme was introduced in 1998 to provide a single-window system of credit to the agricultural sector and to ensure that farmers have access to timely, hassle-free credit (Diwas et al., 2012; Kumar et al., 2011). The program also considerably reduces the amount of paperwork required to access credit. Once sanctioned, the credit card is valid for up to three to five years, subject to revision by banks. The credit limit of KCC is decided based on the cropping pattern and scale of finance as recommended by District Level Technical Committee (Mani, 2016).

Though the program offers a host of benefits, data indicate that only 43% of agricultural households have an active KCC (RBI, 2018). KCC coverage is even lesser in India's eastern states, which are characterized by acute poverty and a higher dependence on agriculture (Diwas et al., 2012; Kumar et al., 2011). In this paper, we attempt to identify the determinants of access to the KCC program and its impact on farmers' use of agricultural inputs and farm household incomes in Eastern India. We have also examined whether the possession of KCC reduces the farmer's dependence for borrowing on moneylenders.

The population of eastern India is highly dependent on agriculture as a source of income. The region is characterized by high poverty rates and small land-holding size. Due to resource constraints and limited savings, farmers often need credit to finance various agricultural operations. The time gap between investment and realization of returns also necessitates the use of credit (Aditya et al., 2019; Kumar et al., 2020; Giné, 2011). Though credit is not a direct agricultural input, it allows farmers to achieve an optimal level of inputs and facilitates adoption of modern technologies, and thus results in increased production and income (Akudugu, 2012; Asante-Addo et al., 2017; Awunyo-Vitor et al., 2014; Kumar et al., 2017;

Kumar et al., 2020; Kinuthia, 2018; Narayanan, 2016; Rahman et al., 2014; Tadesse, 2014;). Farmers can access credit either through formal financing entities like commercial banks, cooperatives, and microfinance institutes or through informal lending agencies like moneylenders. Though formal credit is cheaper, it generally involves high transaction costs, including travel expenses associated with repeat visits to banks and subsequent opportunity costs stemming from lost wages. Thus, many farmers still depend on moneylenders as a primary source of credit (Chenaa, 2018; de Castro and Teixeira, 2012; Diwas et al., 2012; Pal and Laha, 2015). In 1998, the Indian Government introduced the KCC scheme as an innovative credit delivery mechanism that would simplify the process of obtaining credit and ensure farmers had timely access to affordable financing (GoI, 2017; Kumar et al., 2011; Singh and Sekhon, 2005).

The KCC program bundles different types of credit into one multipurpose credit card; the credit limit comprises a crop loan (with terms that are based on the cropping pattern of the farmer), loans for post-harvest management and marketing, working capital for maintaining assets and dairy animals, consumption credit for other expenses, and term credit as needed. The program also gives farmers the option to access other financial products like crop insurance, asset insurance, and the Personal Accident Insurance Scheme (PAIS). The advantage of the KCC scheme is that it is a single-window system that addresses a wide variety of farmer credit needs and provides hassle-free credit access. A KCC also gives farmers financial flexibility. Kisan Credit Cards can be used to withdraw money at a bank branch or ATM or to make purchases from input shops via a point-of-sale (POS) machine. The crop loan component of the KCC program is also covered under the interest subvention scheme (to a ceiling of 3 lakh rupees) and has a 12-month repayment period. Presently, the annual interest rate is 7% (on the maximum eligible amount); however, timely repayment is rewarded by a 3% interest rate reduction (GoI, 2017). Another advantage is that once the KCC is approved/issued, farmers do not need to provide any spending receipts to lenders. In other words, card usage is not monitored. In terms of collateral security, KCC limit up to 1 Lakh rupees, can be sanctioned by is hypothecating the crop farmer is growing without the need of additional collateral. With tie up mechanism for recovery (for example bank tie up with processor to recover the credit), banks have the discretion to sanction a credit limit up to 3 lakhs without any additional collateral. However, banks are insisting on land mortgage (mortgaging entire land which are recorded in the Land Possession Certificate (LPC)) for KCC limit above 1 Lakh rupees (Mani, 2016). Banks also have the discretionary powers to request collateral security in case of sanctioning a higher KCC limit. If the loan amount dispersed under the KCC is not repaid, banks can treat it like any other agricultural loan and recover them as per RBI guidelines. In spite of these advantages, KCC adoption still remains low, especially in the eastern part of India (GoI, 2018).

Despite the importance of the KCC scheme as an innovative credit delivery channel, very few studies have attempted to explore the determinants of access to the program and its impact. Most existing literature looks at the progress of the program in terms of number of cards issued, with a focus on growth and regional issues (Diwas et al., 2012; Kumar et al., 2011). The few studies that do attempt to assess impact generally rely on small samples and do not use econometric methods to establish causation (Mani, 2016; Singh and Sekhon, 2005). We complement the literature by using detailed primary data from eastern India. Empirically estimating the impact of KCC access is difficult on account of self-selection and endogeneity issues, and most of the earlier studies do not account for those in their estimation strategies. In this study, we assess the determinants of access to a KCC and its impact on a number of outcomes, including amount of fertilizer used per hectare, per capita annual household income (PCAHI), farm income per hectare, and farmer dependency on moneylenders. We use rich data from farming household surveys conducted in five eastern states in India.

The paper has two significant contributions. First, we use a detailed primary survey of 2,932 agricultural households across five eastern states to map the access of farming households to the KCC scheme and to identify the determinants of access. Primary studies on program access are important to understanding its prevalence, as secondary data on the number of cards issued are not very accurate. Secondly, we estimate the impact of KCC access on agricultural household incomes after accounting for self-selection and endogeneity. Our findings indicate that obtaining timely credit helped farmers to spend more on inputs and resulted in higher income. Results also show that farmers with access to a KCC are less dependent on moneylenders as a source of financing. Considering eastern India has the nation's highest poverty incidence, our findings on the clear income-enhancing effects of Kisan Credit Cards have important implications for poverty alleviation. Also, the Indian Government has launched a series of flagship programs for agricultural development in eastern India with stated goals that include 'doubling farmers' income' and 'Bringing Second Green Revolution to Eastern India'. The results of our study clearly demonstrate the effectiveness of the KCC scheme in particular and agricultural credit in general in increasing input use and farm income, thus advancing these objectives.

The paper is organized as follows. Section 2 describes the sample data used for the study. Section 3 explains the approach and econometric models used to assess the determinants of access to KCC and the program's impact. Section 4 examines the growth and functioning of the KCC scheme in India. Section 5 discusses characteristics of KCC and non-KCC holders. Section 6 discusses the determinants of KCC access and Section 7 discusses the impact of holding a KCC as it relates to input use, farm income, household income, and dependence on moneylenders for loans. Finally, Section 8 concludes and discusses policy implications.

2. Data

This study uses data from a primary survey conducted during 2018-19 in five eastern states of India; namely, Bihar, Jharkhand, Odisha, eastern Uttar Pradesh, and West Bengal. The total sample size is 4,082 of which 2,932 samples are agricultural households.[1] For this study we have considered only agricultural households, as only these households are eligible for a Kisan Credit Card. Of these, 892 households are from Bihar (30.42%), 698 from eastern Uttar Pradesh (23.81%), 352 from Jharkhand (12.01%), 268 from Odisha (9.14%), and 722 are from West Bengal (24.62%). The number of sample households in a state was allocated in proportion to the rural population of that state, with Bihar having the highest rural population among the five surveyed states. We randomly selected ten districts from Bihar, four districts each from Jharkhand and Odisha, and eight districts each from eastern Uttar Pradesh and West Bengal. Then, we randomly selected two blocks from each district, two villages from each block, and 30 households from each village for the survey based on household listing. The purpose of the field survey was to map the financial pattern of farming households and assess the impact of different instruments of credit on farmers' economic welfare. The survey collected information on household characteristics, such as family size, age, education, and sex of the household head, resource endowment, access to the KCC program and other credit sources, and awareness of various government schemes, including, Jan Dhan Yojana, Pradhan Mantri Fasal Bima Yojana (PMFBY), loan waiving schemes, and Direct Benefit Transfer (DBT). These data also provide detailed information related specifically to KCC usage, such as purpose of loan, extent of utilization, credit limits, and number of bank visits to obtain a card, and thus are particularly well-suited for our analysis.

[1] In addition to 4080 observations from 136 villages (30 observations from each village), two more observations were collected as precautionary measure for any inconsistency or incomplete information. However, since we did not find any inconsistency, all the data points were used.

3. Conceptual and Empirical Framework

3.1. Conceptual framework and impact pathways

Farmers decide on the level of inputs needed to maximize their utility function based on various constraints, one of which is liquidity (Akudugu, 2012; Mani, 2018; Narayanan, 2015). Small and marginal farmers, with little savings, cannot invest in a profit-maximizing level of inputs unless they get credit (Guirkinger and Boucher, 2008; Karlan et al., 2014; Barrett et al., 2010). Not only does access to financing matter, but also its timeliness matters. The farmers who have access to a Kisan Credit Card are assured of credit and can withdraw the amount they see fit (Diwas et al., 2012; GoI, 2017; Kumar et al., 2011; Narayanan, 2016), which can promote an optimum use of resources. The program also has provisions for short-term and long-term investments in terms of assets, which can further increase productivity. The income increase resulting from higher input use and short-term investments creates what is called a 'liquidity effect' in literature (Binswanger and Khandkher, 1992; Narayanan, 2016). In addition, the KCC scheme has provisions for consumption credit to facilitate consumption smoothening and prevent credit diversion for consumption purposes. With access to a KCC, farmers' dependence on informal sources of credit—like moneylenders who charge exorbitant interests' rates—can also be reduced. In this study, we empirically estimate the impact of the KCC scheme on input use, income, and farmers' dependence on moneylenders for credit. In this study, we use Coarsened Exact Matching (CEM) as the data pre-processing step in estimating the causal effect. In observational studies, uneven distributions across treatment and control groups result in model dependence and biased estimates of treatment effects. Matching methods like PSM are commonly used to estimate causal effects in such cases.

3.2 Empirical Framework

Matching is a non-parametric method used to account for the data imbalance caused by confounding variables (Iacus, King, and Porro, 2012). The objective of matching is to ensure that two groups are similar, on an average, with respect to covariates. Balancing data by matching has been found to reduce the bias that occurs when using unmatched data. (Ho et al., 2007). Matching methods estimate the Treatment Effects (TE) based on the assumption that after conditioning on X, there will be some randomness which resembles the experimental setting.

Let us denote the pre-treatment variables by a vector X. In the first step, all those treated and control units outside the common support region will be dropped. In the second step, treated units are matched with the control units with respect to some metrics. Mahalanobi's matching uses Mahalanobi's distance between the units as metrics, whereas Propensity Score Matching (PSM) uses propensity score, a scalar derived from combining the covariates to be used as a balancing score.

Univariate matching methods like PSM do not guarantee any reduction in imbalance and depend on a set of unverifiable assumptions (Conditional Independence Assumption, for example). Further, when the matching is used for pruning observation as a data pre-processing approach, commonly used methods like PSM could result in increased imbalance, due to what is known as PSM paradox (Gary and Richard, 2019). Propensity scores also depend on the specification of the model used to estimate it. PSM can sometimes lead to improvements in balance with respect to one covariate while increasing the bias with respect to some other covariates, even though the mean values are similar (QIN, 2007). Univariate balancing methods aim to obtain univariate balance on mean of covariate. But such methods may not remove imbalance due to interaction with and the nonlinear function of X (vector of confounders). CEM is one alternative to commonly used univariate balancing methods.

CEM belongs to a class of Monotonic Imbalance Bounding (MIB) methods. (Blackwell, Iacus, King, and Porro, 2009). These methods use multivariate distributions for balancing and studies have shown them to be more effective than others in reducing data imbalance and model dependence. The method can be best described with the following set of equations following QIN (2007) and Iacus, King, and Porro (2009).

$$\left\{\begin{array}{c} D\left(f_1\left(x_{m_{T(\pi)}}\right), f_1\left(x_{m_{C(\pi)}}\right)\right) \leq \gamma_1(\pi_1) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ D\left(f_k\left(x_{m_{T(\pi)}}\right), f_k\left(x_{m_{C(\pi)}}\right)\right) \leq \gamma_k(\pi_k) \end{array}\right\}$$

In every dimension of X, Distance D between function f (.) of X in treated and f (.) X in control should be smaller than the monotonically increasing function of γ (π). This directly led us to

$$D\left(f_j\left(x_{m_{T(\pi)}}\right), f_j\left(x_{m_{C(\pi)}}\right)\right) \leq \gamma_j(\pi - \epsilon) < \gamma_j(\pi), j = 1, \ldots, k.), \text{ if } \epsilon > 0$$

Where π are the tuning parameters for each variable which researchers can specify. When the X of treated and control units meet the above set of inequalities, they can be matched. This is the fundamental principle of all Monotonic Imbalance Bounding matching techniques.

Further, let us consider x_i, one element of vector X. In CEM, x_i is divided to V_i number of classes or intervals based on researchers' understanding/intuitions.

$$\gamma_i(\pi_i) = \gamma_{i1}(\pi_{i1}), \gamma_{i2}(\pi_{i2}) \ldots \gamma_{iV_i}(\pi_{iV_i})$$

The approach of CEM can be summarized in three simple steps, following (Datta, 2015) (QIN, 2007) (Blackwell et al., 2009) (Iacus et al., 2012)(Gary and Richard, 2019):

- Temporarily Coarsen the variables in X into classes, which we refer to as strata or hypercuboids
- Sort units within the hypercuboid/rectangles according to original values of X

- Keep only the matched units; Units with strata with at least one treated and control unit are retained (the original values of X can be used for adjusting remaining imbalance)

Generally, the univariate difference in mean values of covariates across treated and control groups is considered as a measure of imbalance. But this doesn't reflect multivariate imbalance and imbalance due to other moments. Iacus et al. (2012) suggest an alternate measure.

$\mathcal{L}_1$ represents the distance between the multivariate histograms of X. Let us denote $H(X_1)$ which indicates the number of bins (or unique values) chosen for the variable X_1. Multivariate histograms are constructed by Cartesian product of $H(X_1)\ X\ H\ (X_2) \ldots H(X_k) = H$, which forms the cells for constructing the multivariate histograms. Denote the relative frequency of the treated and control groups by f and g. Let $l_1 \ldots l_k$ be the relative frequency corresponding to a particular cell. Then $\mathcal{L}_1$ is calculated through the following formulae

$$\mathcal{L}_1(f, g; H) = \frac{1}{2} \sum_{l_1 \ldots l_k \in H(X)} | f\, l_1 \ldots . l_k - g l_1 \ldots . l_k |$$

If the value of $\mathcal{L}_1$ is 1, it indicates perfect separation and if the value is 0, it indicates perfect matching of the multivariate distributions. A good matching process should result in decreased value of $\mathcal{L}_1$.

In this study we measured the value of $\mathcal{L}_1$ for the original data and then employed the CEM algorithm. Few important variables such as education level and social group of the household head, cultivable land, information about accessing KCC, awareness about Direct Cash Transfer (DCT) scheme, and number of livestock owns which determine KCC access are used for matching. Only matched units across treatment and control groups were retained. This serves as a pre-processing step to reduce the imbalance. Causal effect was estimated with Nearest Neighbour Matching as suggested by Iacus, King, and Porro (2008). To estimate causal effect, statistical software Stata 16.0 was used.

4. Extent and Growth of the KCC Program in India

The importance of enhanced and convenient access to credit for farmers has always been recognized and various programs and policies have been formulated to support agricultural financing. However, the agricultural finance and credit institutions in India prior to 1998 were deemed inefficient by several experts and thus the Kisan Credit Card Program was envisaged. The scheme was launched in 1998 and within a year of its inception about 5 million cards were issued against a target of 2 million; banks surpassed the target by almost two and half times. In 2005-06, the number of cards issued increased to 80 million, almost 16 times the number of KCCs issued in 1998-99 (Table 1). The number of operative KCCs increased with a 16.3% Compound Annual Growth Rate (CAGR) from 2005-06 to 2018-19. Presently, at national level, about 43% of agricultural households hold KCCs (Table 1). However, we should note that many studies have found discrepancies in reporting of the number of KCCs (e.g., counting renewed cards as new KCCs). Also, many households have more than one KCC. If we account for these factors, the actual percentage of households with a KCC is even less (Kumar et al., 2011).

In the eastern states of India, namely, Bihar, Jharkhand, Orissa, Uttar Pradesh, and West Bengal, KCC coverage is even slightly lower in comparison to the rest of India (Table 1). In 2018-19, in these five eastern states of India, about 39% of agricultural households were covered under the KCC scheme, while nearly 46% of agricultural households held KCCs in the rest of India. Many farming households in states like Punjab and Haryana have multiple cards. For instance, on average, 29% of agricultural households in Haryana and 73% in Punjab have more than one KCC. Though the percentage of agricultural households covered under the program in eastern states has increased from 5.5% in 2005-06 to 38.7% in 2018-19, more than 60% of agricultural households are still not covered.

Table 1: Progress in KCC Coverage

State/UT	% of agricultural households covered under the KCC scheme						
	2005-06	2010-11	2018-19	CAGR (%)	2005-06	2010-11	2018-19
Andhra Pradesh*	1345.8	1897.5	8473.0	14.0	11.2	14.4	54.6
Arunachal Pradesh	2.2	2.2	12.0	13.0	2.0	2.0	10.3
Assam	65.0	117.1	839.0	20.1	2.4	4.3	30.4
Bihar	209.2	567.3	2883.0	20.6	1.4	3.5	17.4
Chhattisgarh	238.5	272.3	1396.0	13.5	6.9	7.3	33.1
Gujrat	238.5	243.3	2420.0	18.0	5.1	5.1	41.7
Haryana	254.0	148.1	2104.0	16.3	15.8	9.2	128.6
Himachal Pradesh	35.2	56.6	357.0	18.0	3.8	5.9	34.8
Jammu and Kashmir	9.1	16.4	394.0	30.9	0.7	1.1	28.3
Jharkhand	126.6	154.6	996.0	15.9		5.7	34.6
Karnataka	505.0	650.3	3992.0	15.9	6.7	8.3	42.6
Kerala	240.1	300.5	1296.0	12.8	3.5	4.4	15.8
Madhya Pradesh	497.9	626.5	6732.0	20.4	6.3	7.1	61.5
Maharashtra	778.4	726.2	5795.0	15.4	5.7	5.3	34.9
Orissa	494.0	571.0	3940.0	16.0	11.3	12.2	78.5
Punjab	179.2	213.5	1946.0	18.6	17.8	20.3	173.2
Rajasthan	346.5	843.0	5726.0	22.2	5.6	12.2	69.1
Tamil Nadu	527.9	827.7	2065.0	10.2	6.4	10.2	26.5
Tripura	11.5	31.7	238.0	24.2	2.0	5.8	40.3
Uttar Pradesh	1333.1	1347.9	11137.0	16.4	5.9	5.9	45.4
Uttaranchal	60.0	73.2	481.0	16.0	6.5	8.0	56.0
West Bengal	479.7	448.6	2866.0	13.6	6.9	6.3	39.1
Eastern States**	2642.7	3089.5	21822.0	16.3	5.5	5.8	38.7
Total	8012.3	10168.6	66300.0	16.3	6.2	7.4	43.2

Note: * Andhra Pradesh includes the Telangana State. **Eastern states include Bihar, Eastern Uttar Pradesh, Jharkhand, Odisha, and West Bengal.
Source: RBI: TREND AND PROGRESS OF BANKING IN INDIA.

4.1. Pattern of KCC distribution in eastern India

The study sample consisted of 2,932 agricultural households, 560 (19.1%) of which did have a Kisan Credit Card, while the remaining 2,372 (81.9%) did not (Table 2). These numbers depict variation across states; Jharkhand having the highest percentage of KCC holders (27.3%) and Bihar the lowest (14.2%) among surveyed states. The variation in possession of KCCs is also apparent across caste and land-size categories. About 28% of agricultural households belonging to the general caste have a KCC, while only 14% of those in the Scheduled Caste

(SC) or Scheduled Tribe (ST) categories have a KCC.[2] Similarly, around 34% of medium and large farmers have a KCC while just about 17% of small farmers[3] have one. In a nutshell, farmers who belong to upper social strata and have larger landholdings have better access to the KCC scheme.

Table 2: KCC Distribution by State, Social Groups, and Land Size

State	Percentage of agricultural households holding a KCC						
	All	Social Group			Farmer Types		
		SC & ST	OBC	General	Marginal	Small	Medium & Large
Bihar	14.0	6.9	10.6	25.7	9.7	16.7	29.3
Eastern UP	20.9	11.6	19.3	35.5	16.7	30.8	46.0
Jharkhand	26.7	25.0	26.5	36.0	22.0	33.8	46.7
Odisha	19.4	15.8	20.6	26.1	18.1	23.9	15.4
West Bengal	19.8	12.1	25.6	25.7	18.9	37.0	66.7
Eastern India	19.1	13.4	17.6	27.8	16.4	24.4	34.2

Source: IFPRI-ICAR credit survey, 2018-19.

Table 3: Distribution of Average Amount of KCC Credit Limit, Eastern India, 2018-19

States	Social Group			Farmer types			KCC Households
	SC & ST	OBC	General	Marginal	Small	Medium & Large	
Average amount of KCC credit limit (INR/Households)							
Bihar	48500	63167	83869	54741	67621	104529	72096
Eastern UP	66765	97713	147551	76934	155375	183000	110836
Jharkhand	31483	41536	69222	35407	41692	61857	41085
Odisha	37575	32869	36583	31589	35174	66495	35446
West Bengal	38063	41200	35046	35171	55199	45000	36709
Eastern India	41534	65231	75865	48353	79573	116688	64551
Average amount of KCC credit limit (INR /Ha)							
Bihar	82224	70310	62759	101681	50517	31981	72096
Eastern UP	107792	162636	120646	175078	110593	55824	110836
Jharkhand	65638	57692	36722	80707	31335	20845	41085
Odisha	35408	54426	56224	63199	26271	21150	35446
West Bengal	71679	89819	84477	85945	40145	20207	36709
Eastern India	70396	99470	82989	108031	57958	36210	87247

Source: IFPRI-ICAR credit survey, 2018-19.

[2] "Scheduled caste" and "scheduled tribe" includes designated groups of historically disadvantaged indigenous people in India. The terms are recognized in the Constitution of India, and the various groups are designated in one of the categories. Since independence, scheduled castes and scheduled tribes were given reservation status, guaranteeing political representation. "General caste" includes groups of people who do not qualify for any of the affirmative action schemes operated by the government of India (excludes scheduled castes, scheduled tribes, and other backward classes).

[3] We have defined medium and large farmers as who having operational land of ≥ 2 hectares of land; small farmers having operational land 1 to 2 hectares and the marginal farmers are those having <1 hectare.

Table 2 shows the distribution of average credit limit of KCC per household and per hectare of land among social and farmer groups. The average credit limit of the KCC-holder households is about INR 64551 Among the social groups, the average credit limit for the general caste households is INR 75865, while for the SC & ST households, it is just INR 41533, which might also be due to differences in land-holding size. Among the farmer groups, medium and large farmers have an average credit limit of INR 116688 which is almost 2.5 times the average credit limit of the marginal farmer. There are many disparities among states in terms of average credit limit. Among all states surveyed, eastern Uttar Pradesh has the highest average credit limit of INR 110836, while West Bengal has the lowest average credit limit of INR 36709. When the government introduced the KCC scheme in 1998, one of the important motives was to provide short-term credit to farmers with a special focus on marginal and small farmers. Though marginal and small farmers are indeed getting some benefit from the scheme, medium and large farmers are getting more as they are able to obtain a greater number of KCCs with a higher average credit limit.

During the sowing season, farmers generally lack input resources such as fertilizers, seeds, and pesticide, and thus turn to informal credit sources such as moneylenders or commission agents to obtain financing at excessively high interest rates (Kumar et al, 2020). In contrast, banks charge a nominal rate (maximum of 7% if repayment is delayed, otherwise just 4%) on capital borrowed through the Kisan Credit Card program. Therefore, farmers benefit from taking credit through the KCC scheme and spend it on agricultural inputs. Our survey results support this notion. Table 4 presents the purpose for which the borrowed KCC amount has been spent. Two-thirds of the borrowed KCC amount were used to purchase agricultural inputs such as fertilizers, seeds, and pesticides, while only about 13% of the borrowed amount was used to purchase durable farming equipment like tractors and threshers.

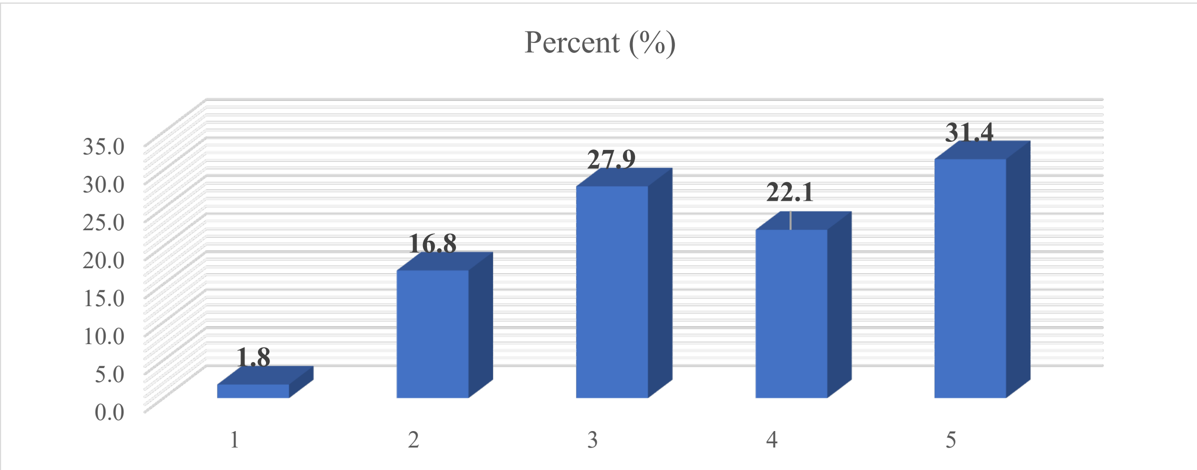
Table 4: Purposes of taking credit through KCC, Eastern India, 2018-19

Purpose	Percent (%)
To purchase fertilizers, seeds, pesticide	67.9
To purchase farming equipment (e.g., tractor, thresher)	12.6
For daughter's marriage	4.3
To purchase cattle	3.1
To return money to a moneylender	2.9
To return bank's old debt	1.4
To purchase land	1.4
For son's business	0.4
To lend out to others	0.1
Other (specify)	5.8

Source: IFPRI-ICAR credit survey, 2018-19.

Further, we asked respondents how many times they visited banks to get their KCC, and the results were surprising. Only about 2% of agricultural households reported that they got their KCC in just one visit while the majority of households reported having to make at least five bank visits in order to get their KCC (figure 1).

Figure 1: Number of visits to banks to get a Kisan Credit Card (KCC)



Source: IFPRI-ICAR credit survey, 2018-19

5. Characteristics of KCC and Non-KCC Holders

Table 5 presents the descriptive statistics of key interest variables used in this study. The average number of family members in surveyed households was around six and the average age of the heads of the households was about 51 years. On average, household heads among KCC holders were older than their counterparts among non-holders. The KCC-holder households had an average operational landholding of 1.13 hectares (ha) while non-KCC-holder households had 0.77 hectares (ha). The difference in average operational landholding between KCC and non-KCC holders is statistically significant at a one-percent level of significance. On terms of social group distribution, Other Backward Caste (OBC), accounted for about 45% of agricultural households in both categories, followed by Scheduled Caste (SC) and Scheduled Tribe (ST), which comprised around 29% of the sample households. Approximately, 39% of the agricultural households who held a KCC were from the general caste, while only 24% of the non-KCC households were from the same social group. The difference between these two is also statistically significant. Similarly, among agricultural households from the lower strata of society (i.e., SC & ST), about 20% were in the KCC-holder group while nearly 31% were in the non-KCC holder group. We can infer from the summary statistics that the probability of getting a KCC is higher among households in higher social strata.

Most of the agricultural household heads were literate (around 69%) and, on average, had about six years of education. The average years of education was greater among KCC holders (seven years of education) than among non-KCC-holder households (around five years of education). The difference between the groups is statistically significant at a one-percent level of significance. In terms of awareness of government schemes such as Pradhan Mantri Fasal Bima Yojana (PMFBY), Direct Cash Transfer (DCT), and loan waiving schemes, the KCC-holder households were more aware of these schemes than the non-KCC holders. The share of income from non-farm activities was about 50%, while the share of remittance in income was 20%.

Farm income per hectare, quantity of fertilizer used per hectare, per capita annual household income, and dependency on moneylenders are outcome indicators used in this study. The average quantity of fertilizer used per hectare among KCC-holder households is about 60 kg. It is approximately 55 kg among non-holders. This difference is statistically significant at a one-percent level of significance. The average per capita annual household income for the KCC-holder households is about INR 24611 and nearly INR 22049 for non-KCC holders. The difference between the household income is also statistically significant at five-percent level of significance. Approximately 30% of non-KCC-holder households have borrowed from a moneylender compared to just 5% of KCC holders. However, direct causation between KCC access and the outcome variables cannot be drawn due to endogeneity and selection bias.

Table 5: Descriptive statistics of the Sample Agricultural Households, Eastern India, 2018-19

Variables	KCC	Non-KCC	Difference	All
Per Capita Annual Household Income (INR)	24610.52	22048.74	2561.78**	22538.03
	(18388.04)	(14980.63)		(15717.58)
Farm income (Rs/Ha)	67709.38	69092.04	-1382.67	68827.96
	(45572.52)	(44129.1)		(44403.86)
Quantity of fertilizer used (Kg/Ha)	59.89	54.65	5.25***	55.65
	(45.78)	(41.67)		(42.53)
Borrowing credits from money lenders (%)	5.30	30.42	-25.12***	21.31
	(22.43)	(46.03)		(40.96)
Age (years)	52.05	50.44	1.61**	50.75
	(11.94)	(12.41)		(12.34)
Household size (number of people)	6.11	6.12	-0.01	6.12
	(3.37)	(3.20)		(3.24)
Operational land (ha)	1.13	0.77	0.36***	0.83
	(1.18)	(0.95)		(1.01)
Scheduled Caste and Scheduled Tribe (%)	20.18	30.69	-10.51***	28.68
	(40.17)	(46.13)		(45.24)
Other Backward Castes (OBCs) (% of households)	41.25	45.66	-4.41	44.82
	(49.27)	(49.82)		(49.74)
Other castes (% of households)	38.57	23.65	14.92***	26.50
	(48.72)	(42.5)		(44.14)
Education (years)	7.29	5.39	1.90***	5.75
	(4.92)	(4.87)		(4.94)
Possessing a social safety net card (% of households)	86.96	87.77	-0.81	87.62
	(33.70)	(32.77)		(32.94)
Heard of loan waiver (% of households)	90.89	80.82	10.07***	82.74
	(28.8)	(39.38)		(37.79)
Aware of direct cash transfer (% of households)	83.21	71.88	11.33***	74.05
	(37.41)	(44.97)		(43.85)
Aware of Pradhan Mantri Fasal Bima Yojana (PMFBY) (% of households)	76.25	51.85	24.40***	56.51
	(42.59)	(49.98)		(49.58)
Aware of Mahatma Gandhi National Rural Employment Guarantee Act (MNREGA) (% of households)	94.46	93.68	0.78	93.83
	(22.89)	(24.34)		(24.07)
Employed under MGNREGA (% of households)	31.43	31.53	-0.10	31.51
	(46.46)	(46.48)		(46.47)
Association with a political party (% of households)	13.57	9.11	4.47**	9.96
	(34.28)	(28.78)		(29.95)
Share of income from non-farm activities (%)	35.89	52.97	-17.08***	49.71
	(48.01)	(49.92)		(50.01)
Share of income from remittances (%)	14.29	20.78	-6.50***	19.54
	(35.02)	(40.58)		(39.66)
Possessing an account through the Pradhan Mantri Jan Dhan Yojana (PMJDY) (% of respondents)	31.07	33.64	-2.57	33.15
	(46.32)	(47.26)		(47.08)
Have sought information from any source (% of respondents)	46.79	42.96	3.83	43.69
	(49.94)	(49.51)		(49.61)
Own livestock (% of households)	80.89	78.58	2.31	79.02
	(39.35)	(41.03)		(40.72)
Number of observations	560	2372		2932

Source: IFPRI-ICAR credit survey, 2018-19.
Note: Standard errors in parentheses; INR/ha = (Indian) rupees/hectare; q/ha = quintal per hectare

6. Determinants of Access to KCC

Table 6 presents the coefficients and marginal effects of the probit regression estimated with 2,864 observations and results for the Linear Probability Model (LPM) with 2864 observations. The model is significant at a one-percent level of significance.[4] Size of operational landholding had a positive and significant effect on access to KCC. Agricultural households with larger operational landholdings were more likely to get access to KCC from a bank. This factor is one of the important determinants of KCC access because, generally, banks (both public and private) are hesitant to lend to marginal farmers due to higher risks associated with information asymmetry and lack of collateral. Larger operational landholdings are associated with a roughly 36-percent higher chance of access to the KCC program.

In the eastern states of India, and especially in Bihar and Uttar Pradesh, where SC, ST, and landless farmers continue to suffer social and economic exclusion, social group (caste) plays an important role in access to any financial service (Bhagat, R. B., 2013). Also, the backward classes are characterized by smaller landholdings and fewer additional resources. The regression results show that the agricultural households from general castes were more likely to get access to a KCC than the SC and ST households.

[4] Note that the model included block fixed effects as control variables

Table 6: Determinants of Access to KCCs for Agricultural Households, Eastern India, 2018-19

Variables	LPM	Probit	Marginal Effect
	Coefficient	Coefficient	*dy/dx*
Age (years) (log)	0.050**	0.282**	0.062*
	(0.025)	(0.137)	(0.032)
Household size (number) (log)	0.017	0.112	0.025
	(0.015)	(0.069)	(0.016)
Other backward caste $^{\alpha,\wedge}$	0.029	0.160*	0.035*
	(0.019)	(0.092)	(0.021)
General caste $^{\alpha,\wedge}$	0.072***	0.389***	0.093***
	(0.020)	(0.100)	(0.026)
Household head education (years) (log)	0.091***	0.466***	0.102***
	(0.029)	(0.141)	(0.034)
Access to social-safety-net card ^	-0.004	-0.021	-0.005
	(0.026)	(0.117)	(0.023)
Operational land (hectare) (log)	0.506***	1.625***	0.357***
	(0.141)	(0.520)	(0.103)
Loan-waiving scheme ^	0.051***	0.307***	0.060***
	(0.017)	(0.105)	(0.018)
Direct cash transfer ^	0.027**	0.152**	0.032**
	(0.013)	(0.074)	(0.016)
Have Pradhan Mantri Fasal Bima Yojana ^	0.608***	2.101***	0.694***
	(0.047)	(0.201)	(0.061)
Received MGNREGA ^	0.014	0.075	0.017
	(0.017)	(0.091)	(0.021)
Association with any political party ^	0.075**	0.330***	0.083**
	(0.030)	(0.123)	(0.034)
Share of nonfarm income (log)	-0.011**	-0.063***	-0.014***
	(0.005)	(0.023)	(0.005)
Income from remittances ^	-0.050***	-0.267***	-0.053***
	(0.018)	(0.098)	(0.018)
Have Prime Minister Jan Dhan Yojana account ^	-0.006	-0.024	-0.005
	(0.015)	(0.075)	(0.017)
Seek information from any source ^	-0.013	-0.076	-0.017
	(0.014)	(0.070)	(0.015)
Have livestock ^	0.007	0.021	0.005
	(0.017)	(0.091)	(0.021)
Constant	-1.738***	-8.961***	
	(0.349)	(1.375)	
Block Fixed Effects	Yes	Yes	Yes
Log pseudo-likelihood		-989.503	
Correctly classified		20.029	
Observations	2,864	2,796	2,796
R-squared	0.308		

Note: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. Robust standard errors are in parentheses. The observations in the columns 2, 3 and 4 were dropped from the analysis due to using block fixed effects. Circumflex (^) indicates dummy variable. α: Base group is scheduled casts and scheduled tribes.

Households in which the household head had more years of education were more likely to get access to the KCC scheme. Since accessing any type of agricultural credit from formal sources requires some paperwork, it is intuitive that households with educated persons will have a better access (Aditya et al., 2019). Education is also typically related to awareness of government programs in general.

Awareness of government schemes also affected households' decisions to obtain a KCC. For instance, agricultural households that had heard about loan waiving schemes more likely to obtain a KCC. Similarly, awareness of direct cash transfer schemes such as PM-Kisan, also had a significantly positive effect on accessing the KCC program. Agricultural households that had taken crop insurance under Pradhan Mantri Fasal Bima Yojana (PMFBY) were more likely to obtain a KCC. Those associated with any political party were also more likely to get access the program. On the other hand, agricultural households that were more dependent on remittance and non-farm income were less likely to obtain a KCC. Many past studies have also indicated that households with other sources of income have less liquidity constraints and generally do not prefer to be indebted.

7. Impact of KCC Access on Outcome Indicators

Table 7 presents the impact (treatment effects) estimates of KCC access on outcome indicators. As noted earlier, we have taken four outcome indicators; namely, farm income per hectare, per capita annual household income, quantity of fertilizer used per hectare, and dependency on moneylenders for credit. We have used the Coarsened Exact Matching (CEM) method to estimate the impact of KCC access on these outcome indicators. Initially the multivariate imbalance was 0.49, but after the CEM it became 0.42.

Table 7: Treatment Effect of KCC Access on Outcome Indicators

Outcome indicators	Marginal & Small Farmers	Medium & Large Farmers	All Agricultural households
Farm Income (INR/Ha)	7936.7***	-2158[ns]	7058.3***
	(2760.6)	(2545.6)	(2680.5)
Per Capita Annual Household Income (INR)	1864.9**	1173.4[ns]	2237.2**
	(930.8)	(2491.9)	(893.1)
Quantity of fertilizer used (Kg/Ha)	4.4*	3.9[ns]	5.7**
	(2.5)	(8.4)	(2.5)
Borrowing credits from money lenders	-24.2***	-36.9***	-24.7***
	(2.2)	(7.5)	(2.3)

Note: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. Figures in parentheses are robust standard errors. ns: Not significant.

As discussed above, the KCC can be used for multiple purposes, one of which is to increase farmer income. For all agricultural households, we find a positive and significant impact of KCC access on farm income per hectare. In terms of magnitude, the result show that the KCC-holder households have INR 7058 more farm income per hectare than the non-KCC holders. Further, we have estimated the impact of KCC access on farm income per hectare by landholding size. The marginal and small farmers with a KCC have, on average, INR 7936 more farm income per hectare than the non-KCC holders of the same land category. The impact of KCC access on farm income per hectare for medium and large farmers is negative and insignificant. Similarly, the impact of KCC access on per capita annual household income is positive and significant at a 5-percent level of significance. In terms of magnitude, the KCC households have INR 2237 more per capita annual household income than the non-KCC households.

Further, we have estimated the impact of KCC access on input usage (amount of fertilizer used per hectare), finding a positive and significant impact. KCC holders used an average of 5.7 kg more fertilizer per hectare than non-KCC households. In terms of landholding size, marginal and small farmers with a KCC used more fertilizer per hectare than the farmers of the same category without a KCC. Similar to farm income per hectare and per capita annual household income, the impact of KCC on quantity of fertilizer used per hectare among medium and large farmers is insignificant.

We have also estimated the treatment effects of KCC access on borrowing from moneylenders. Farmers with access to a KCC are about 25% less likely to borrow from moneylenders than non-KCC households. When also accounting for landholding category, medium and large farmers with KCC access are around 37% less likely to borrow from moneylenders than non-KCC holders of the same category. Marginal and small farmers with a KCC are approximately 24% less likely to borrow from moneylenders than non-KCC holders of the same category.

8. Conclusion and Implications

Kisan Credit Cards offer hassle-free, timely, and multipurpose credit facilities to farmers. In this paper we analysed the status, correlates, and impact of KCC access in eastern India. We found that only a small proportion of agricultural households have access to a KCC, and they are more likely to be of upper socio-economic strata. The impact of KCC access was positive and significant on both input use and income. Importantly, farmers with a KCC had lesser dependence on moneylenders.

The results clearly show that the KCC scheme can help farmers by providing timely credit which facilitates optimal input use. However, program access is limited to a relatively small group of educated farmers. Creating more awareness of the program and improving access can stimulate agricultural development in eastern India. Timely credit through the KCC scheme can help promote technology adoption and increase input intensity. Given Indian policy efforts aimed at doubling the income of farmers, the KCC scheme can play a catalytic role in boosting income among farming households.

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