

# Effects of Agricultural Credit Reforms on Farming Outcomes: Evidence from the Kisan Credit Card Program in India.\*

Somdeep Chatterjee

*Department of Economics*

*University of Houston*

*schatterjee2@uh.edu*

November 27, 2015

**Preliminary Draft - Please Do Not Cite**

## **Abstract**

This paper analyzes a major agricultural credit reform in India, known as the Kisan Credit Card (KCC) scheme, which intended to simplify the process of credit delivery in the agricultural sector. I use plausibly exogenous variation in the reach of the program to find the causal effects of the policy on agricultural output and technology adoption using a district panel data set. I also use a household dataset to analyze the effects of differential exposure to this policy on a wide range of household outcomes. I find evidence of increases in agricultural output of rice, which is the major crop of the country. I also find that on average the use of high yielding variety (HYV) seeds increases at the district level providing evidence of technology adoption. The increase in output at the district level is corroborated by suggestive increase in sales revenue and output of rice farmers at the household level. In addition, I observe increases in farm income for agrarian households suggesting that this program may have improved the condition of the poor people. The results indicate changes in composition of consumption and borrowing which are consistent with existing evidence for enhanced consumer well-being following the relaxation of credit constraints and expansion of credit to the unconstrained. I find evidence that bank borrowing increased for households due to this program and effects on income and production are higher for such borrowers.

---

\*I am grateful to Aimee Chin for her guidance and support all through this project. I would also like to acknowledge and thank Gergely Ujhelyi and Chinhui Juhn for their regular feedback and comments. I thank Dietrich Vollrath and Andrew Zuppann for comments and suggestions on various versions of this paper. I thank Chon-Kit Ao for useful discussion. I also thank participants at University of Houston Graduate Student Workshop and Brown Bag presentation sessions for valuable feedback. All errors are my own.

# 1 Introduction

Providing access to financial resources to the poor continues to be an important policy prescription in the literature even though the empirical evidence on impacts of credit constraint relaxations and expansion of credit options for the unconstrained in developing countries is mixed (Karlan and Murdoch 2009). To design effective policies that provide or expand access to credit, one would first need to understand the mechanisms through which credit access helps the poor and also the impact of implementing such a policy on the targeted beneficiaries. To estimate these impacts, the ideal experiment would be to randomly provide credit products to households and compare the outcomes of the ones getting access to the ones without access to this product. The January 2015 issue of AEJ Applied has six papers on this subject using randomized evaluations.<sup>1</sup> These papers find little to no impact of providing access to finance. Other papers like de Mel, McKenzie and Woodruff (2008) using experimental designs find positive impacts.

While randomized evaluations are ideal to identify the causal effects of credit constraint relaxations, by design these cater to a relatively small sample of the entire population. Whether a large scale national reform would replicate these findings is important to understand. In this paper, I look at a major overhaul in the agricultural credit delivery process in India in 1998, known as the Kisan Credit Card (KCC) program, and evaluate the impacts of this policy. The targeted group for this credit reform was rural agricultural households, generally involved in farming and other related occupations. Ease of delivering agricultural credit, reasonable interest rates and relaxation of monitoring norms were the key features of this program. Reports from the Planning Commission of India (2002) suggest that by 2000-01, KCCs constituted almost 71% of the total production credit disbursement by commercial banks. It was also the dominant mode of production credit delivery for other banks. The report also suggests that in the first two years, close to 4 million credit cards were issued with a total disbursement of credit lines worth 50 billion INR (1 billion USD approximately).

Although this was a major policy reform, to date there has been little convincing evidence

---

<sup>1</sup>All the 6 papers are cited in the references.

of the impacts of this program. Chanda (2012) uses post-policy state level data from 2004-2009 to see if growth in KCC issues lines up with increases in agricultural productivity. There are other government of India commissioned descriptive reports like the Planning Commission report mentioned above and Samantara (2010). In this paper, I use a country wide district panel dataset to evaluate the causal effects of this program on agricultural output and technology adoption. I also use household data to estimate the impacts of this program on a wide range of outcomes including income, consumption and borrowing.

The reach of formal financial institutions is not universal in most developing countries. This is because banks would want to select into richer regions unless they are administratively required to setup branches in unbanked locations. This makes formal credit markets less accessible to the poor in these areas. The KCC reform therefore provides an opportunity to add to this literature of how access to formal credit institutions can help the poor sections of the society in line with Burgess and Pande (2005). The unique feature of the KCC program was that it catered exclusively to the agricultural sector. Although in this paper, I am not able to distinguish whether the effects of KCC operate through channels of new access to credit or expansion of credit to the ones who already had some access. As a result most of my estimations should be viewed as a bundle of reduced form effects.

This paper takes advantage of rules in implementation of the policy to generate plausibly exogenous variation in access to this program to identify causal effects of the reform. The identification strategy relies on variation across three main dimensions. First is the time dimension. The policy was implemented in 1998 and I look at the outcomes in years before and after the policy. Second, is the political alignment dimension, ie, whether the state government is ruled by a party aligned with the central government in the federal structure of India. Political alignment has been widely regarded to be important for policy implementation and performance (see Chibber et al 2004, Iyer and Mani 2012 and Asher and Novosad 2015). The final source of variation comes from how the rolling out of these credit cards was implemented. The KCCs could only be issued through formal banks and not by any other agency. I use district level variation in the number of bank branches already setup prior to

the policy to proxy for access to this program.

I propose to identify the causal effect of the policy by the interaction of these three variables. The effect is identified by looking at the difference in outcomes after and before the policy in districts with more bank branches over districts with fewer bank branches in states that are ruled by political parties aligned with the central government after controlling for these differences in districts in the states not aligned with the center. I use pre-policy data to show that these regions were not already different along the relevant dimensions to provide support to the identifying assumption that any differences post-policy are attributable to the program.

I find that increased access leads to significantly higher production levels. Rice is the major crop of India and I find an aggregate increase in production by 88 thousand tonnes (metric ton) per year on average which is between 1/3 to 1/4 of an increase compared to the mean.<sup>2</sup> Corresponding to this large change, I find that technology adoption has also been significant. Crop production area under high yielding variety (HYV) seeds increased by around 71 thousand hectares at an aggregate level which is just under a 1/3 increase compared to the mean. This suggests that with increased access to credit, districts exposed to the program fared significantly better in terms of production and technology adoption. Using household data, I corroborate some of these results. I find suggestive evidence of increases in rice production for farmers even though estimated imprecisely. I am constrained by the fact that the household data comes only from a sample of farmers and not the universe, unlike the district panel data described above which contains all rice production in the districts. I find that revenue from sales of rice is higher for farmers potentially exposed to KCC.

The advantage of using household data is being able to observe borrowing patterns. Using a cross-section of households, I find that households are more likely to have fewer but larger loans with exposure to KCC. I also find that they are more likely to have larger bank loan

---

<sup>2</sup>The Food and Agricultural Organization's FAOSTAT indicates that in 2012, the value of rice produced in India is over 40 billion US dollars which makes it the most valuable crop of India. Rice has consistently been the major crop of India in terms of overall value for years. See - [faostat.fao.org](http://faostat.fao.org)

sizes if exposed to KCC. These effects seem to be larger for those households which report cultivation as their main source of income and for rice farmers. This is reassuring because most of the production effects observed using the district data seem to suggest that rice farmers would be most affected by this policy.

I find that even though on average there is no effect on income but farm income is higher by 129 Indian rupees (USD 2) per month for households whose main income source was cultivation. Compared to the mean, the magnitude of this effect is almost 25%. This is consistent with the findings on production and sales. With higher sales, we might expect higher profits, *ceteris paribus*. I find no overall impacts on consumption expenditure but composition of consumption changes. I find higher daily expenditures but lower expenditure on consumption like tobacco and beetel leaves.

I do not find any effects on the margin of whether a household is likelier to have a bank loan in response to the policy. Since I do find that households have a higher bank loan size conditional on borrowing, this allows me to analyze a sub sample of households seperately. I look at all the outcomes for only those households who borrow from banks and I find that all the effects described above are much more pronounced for this group. Since KCC had to operate through banks, this gives us confidence that our estimated effects are likely to be mediated through bank borrowing which should include KCC borrowing.

The rest of the paper is organized as follows. Section 2 provides background information. Section 3 describes the empirical strategy. Section 4 explains the Data. Section 5 presents results and Section 6 concludes.

## **2 Background**

### **2.1 The Kisan Credit Card Program**

Agriculture constitutes roughly a fifth of the total GDP of India and employs two out of three Indian workers. In the late nineties, agriculture started opening up to the market rather than being limited to subsistence farming. Agricultural credit has played an important role in

developing the market for such produce and help improve the condition of farmers in the country. However, the finance and credit institutions present in the country prior to 1998 were deemed inefficient by several reports and experts and as a result the Kisan Credit Card program was envisaged. This scheme was launched in 1998 and was introduced for the first time in the budget speech of the Finance Minister of India in the parliament. Within a year after its inception around 5 million cards were issued to farmers. Prior to 1998, the system of agricultural credit delivery was complicated. A multi agency approach was used where borrowers had to go through several layers of bureaucracies depending on the purpose of their loans (Samantara 2010). KCC also brought about a revolving credit regime as opposed to the existing demand loan system (Chanda 2012).

At its inception, the KCC was not a traditional credit card that is commonly used. The card was a mere documentation for identifying the individual and his credit line with a given bank. It did not have features that allowed payments at merchant outlets. This also makes the presence of banks an important dimension for identifying the intensity of reach of the program. The way to use a KCC was to visit the bank branch in person and withdraw a certain amount of money which could then be used for purchases. This also ruled out the possibility of banks monitoring the usage of the loans.

The most important feature of this credit product was the ease of availability of loan. Some banks laid down rules for eligibility like having title to an acre of irrigated land. On fulfilling this criterion, the farmer would be eligible for a loan with a bank without any collateral requirement for an amount upto 50,000 INR (around 1000 USD back then). The KCC accounts were largely valid for 3 years and repayment time frames spanned upto a year. On successful repayments and responsible credit use, these accounts were renewable but the initial approval was given largely without any background checks. As pointed out above, a big difference from existing crop loans was that the usage of the KCC loans were not monitored whereas most agro-credit was tied to agricultural use or purchase of inputs, fertilizers etc. So, a farmer could get a KCC account and use the amount for personal consumption.

In a way KCC provided the best available source of personal credit to poor farmers. The

biggest advantage over microfinance institutions were that KCC was operational through formal banks and charged a very reasonable interest rate of around 7% per annum as opposed to as large as 36-40% rates charged by self help group microcredit institutions. The approval process was also very simple and was a single window exercise as the only criterion was ownership of an acre of irrigated land. Many banks have recorded allowance of credit limits in excess of 50,000 INR but in such cases they often asked for collaterals. Therefore larger scale farmers who are financially in a better off situation were only likely to go for these loans. There was no clause to my knowledge which restricted large farmers from opening a KCC account.

Samantara (2010) points out that a major reason why KCC was launched was to integrate the various credit needs of farmers, from personal consumption to festival expenditure, education, health and agricultural needs, into one comprehensive product. Earlier a farmer had to weigh multiple options based on the purpose of his loan. KCC made it a one stop procedure wherein he could withdraw the requisite amount and use it for any purpose whatsoever. All the bank cared about was the timely repayment and not the usage. This was a major shift from the pre-existing agro-credit policy in India which was called the Agricultural Credit Delivery System. Under that system, a multi-product multi-agency approach was adopted. Policy makers in the country had planned this in a way such that specific needs of farmers could be addressed by specific credit products. A farmer could go to a bank for purchase of a particular input and get a loan against that purchase. The idea was more like financing purchases rather than giving out cash loans. From such a scheme KCC came as a welcome change which sought to replace the multi-product approach in favor of a cash credit approach in a single comprehensive product. As might be already evident from this discussion, KCC was intended to address the short term credit needs of farmers and not the longer term needs. Since there was no monitoring, one could not rule out the possibility of withdrawing cash from these accounts and using them for consumption purposes. At present, Kisan Credit Cards are available as differentiated products with various banks coming out with various varieties and features.

Overall the Kisan Credit Card program should be viewed as a bundle of reforms in one. It not only aimed to relax credit constraints by making loans available to the ones constrained prior to 1998 but also provided a source of flexible credit. KCCs could potentially finance a lot of purchases, not just agricultural inputs and therefore have wider social consequences. Since KCCs were a source of cheaper credit, one might also view it as expansion of credit options for the ones already having access to other forms of credit. Unconstrained farmers may now be attracted to borrow at cheaper rates and finance their short term credit needs.

## **2.2 Conceptual Framework and Related Literature**

To estimate the true causal effects of access to credit one would ideally want to generate random variation in access to financial institutions. There is a rich literature comprising of experimental studies along these lines (Angelucci, Karlan and Zinman 2015, Attanasio et al 2015, de Mel, McKenzie and Woodruff 2008, Augsburg et al 2015, Banerjee et al 2015, Crepon et al 2015, Tarozzi, Desai and Johnson 2015). Apart from this there is a quasi-experimental literature which looks at policy reforms in the formal financial sector to answer a similar question (Burgess and Pande 2005, Banerjee and Duflo 2014). Government policy reforms are usually not randomly assigned, therefore identifying the causal effects of such programs is challenging even though it is important to understand the mechanisms behind such policies aimed at removal of borrowing constraints.

Most recent studies on the role of credit access focus largely on this aspect of mechanisms of credit delivery (Karlan and Morduch 2009). This paper is the first to objectively evaluate the Kisan Credit Card scheme using a district panel dataset and extends this literature by looking at this large scale national reform in credit delivery mechanism. In the Indian context, Banerjee and Munshi (2004) and Banerjee and Duflo (2014) study the role of credit constraints on firms and businesses. However the role of credit constraints in agricultural occupations has been little studied till date. This paper also contributes to the literature by attempting to fill this void.

An important question that arises here is whether this program should be viewed as



enhanced ‘access’ to agricultural credit or ‘expansion’ of credit to the ones who already had access to credit? The existence of credit constraints and impediments to borrowing are major roadblocks in developing economies which is why governments may want to innovate by reforming the system of credit delivery. If the main objective is to improve the condition of the poor, one would imagine that removing the borrowing constraints would be important, or in other words a program like KCC should have given ‘access’ to credit to the ones who never had the chance to borrow before. The starting point of the analysis is to understand how we expect credit access to affect the credit constrained? If KCC relaxed credit constraints and people unable to borrow elsewhere could now borrow under this program, economic theory and existing empirical evidence would lead us to expect multiple effects.

First, if households invest in productive assets or the borrowed funds are used to finance improvements in technology of agricultural production, we expect their agricultural income to be higher. Second, if we aggregate these effects, overall production of crops should be higher and overall adoption of new technology should also be higher. Third, composition of consumption may change. Banerjee et al (2015) find such evidence in a microfinance experiment but the idea is applicable to a broader country wide setting as well because in essence we are thinking of the impact of relaxation of credit constraints per se. Finally, since this was a national level formal lending program, one would expect that with enhanced access informal lending would go down and be substituted by more formal sector loans.

The flip side however, is that from a lender’s perspective, such a policy may attract poor quality borrowers. This leads to issues of adverse selection. Asubel (1991) discusses credit card markets in the US and how lowering interest rates are far from ideal from a bank’s perspective as bad borrowers may select into borrowing at lower rates. KCC lending was usually at a much lower rate of interest than market rates or informal lending rates prevalent among microfinance institutions. This would have meant that the adverse selection issue was likely to be severe under this program. Also since new borrowers are unlikely to have ever engaged in credit dealings, their perception about their own future stream of income determining their repaying ability is likely to be myopic. Melzer (2011) and Bond, Musto

and Yilmaz (2009) point out these problems about ‘misinformed’ borrowers underestimating their future repayment commitments.

It is also important to think about potential general equilibrium effects of this program. Are there any spillovers? For example, if some farmers get credit cards whereas others do not, maybe they have a competitive advantage over the ones who did not get this card and this might lead to perverse welfare implications. Similarly, if KCCs are very attractive and result in high profits for farmers, this maybe an incentive for non-farmers to take up agricultural occupations which in turn may affect non-agricultural sectors in the rural areas.

### 3 Empirical Strategy

There are two parts in my empirical strategy. I have the twin objective of evaluating the overall effects of access to credit on production outcomes on average and also whether access to credit through such a reform is useful for intended beneficiaries. To this end, I use two different datasets. The first is a district panel dataset and the second is a cross-sectional household dataset.

Identifying the causal effects of having a KCC on agricultural outcomes using survey data is difficult because KCCs were not randomly assigned to households. Also, using a cross sectional dataset, it is not possible to use time varying access to the scheme either.<sup>3</sup> To overcome these issues, I propose an identification strategy that relies on plausible exogenous variation in the reach of this program to find causal effects of the program. Apart from the time dimension (program introduced in 1998) which provides variation in the access to the program over the span of the data, there are two different cross sectional dimensions that give us a sense of which regions might have had more access to these cards after the policy. I use an interaction of these dimensions to identify effect of the policy.

The KCC program was announced by the Finance Minister of India in his budget speech in 1998 and the implementation began soon after. The government at the center was ruled by the Bharatiya Janata Party (BJP) led National Democratic Alliance (NDA) coalition.

---

<sup>3</sup>Even though there is no clear idea even in government documents in terms of how these cards were rolled out.

However, not all state governments were run by the NDA coalition. Since the implementation of this policy required a lot of work at the grass roots in terms of setting up infrastructure, spreading awareness, nudging banks to implement this policy and the like, one can understand that the role that state governments and officials at the village and block levels who are employed by the state governments would have had an important role to play in the penetration of this policy in those states. This gives one potential source of variation in the policy. I use an indicator variable *aligned* which takes the value 1 if the state in question was ruled by the BJP or one of its NDA allies in 1998 and 0 otherwise. The idea is that *aligned* states would probably have earlier or quicker access to this policy whereas the opposition parties may choose to be slack in the policy implementation in the states where they are in power, out of several motives including the fact that they would want the scheme to be projected as a failure for the ruling coalition and take advantage of this in future elections themselves.

The first real governmental study on the program outreach was done in 2002 by the Planning Commission of India. They published a report with tables on the state wise coverage of Kisan Credit Cards as of March 2000, which is 2 years into the program. The coverage rates were basically the number of KCCs issued by various banks as a percentage of total operational land holdings in the concerned state. So this gave an idea as to how many farmers were potentially reached or covered under the policy within the first two years of the policy at a state level. If we observe that *aligned* states actually were implementing the policy faster than the other states, we might be more confident about the use of this dimension to identify the effects of the program. Table 1 provides supportive evidence. I find that coverage in aligned states is almost 2.5 times the coverage in rest of the states and the difference is statistically significant at the 99% level of confidence.

The second dimension that I bring to this analysis of variation in access is a technicality that the policy had. These credit cards could only be given out through banks. So it is understandable that areas with more banks are likely to be able to roll out these cards faster than the ones which are unbanked or have fewer banks. However, there may be concerns that

banks opened up or positioned or repositioned themselves based on the policy announcement in markets where KCC lending would flourish more. To account for this issue I use bank data at the baseline year, ie, 1998 and not after the policy. I use district level existing bank branches data from 1998 to enumerate the number of branch offices of banks at the time of announcement of the policy. This gives us another potential exogenous source of variation in the intensity of coverage of the program. I create the variable *bank98* to denote the number of bank branches in a given district in 1998 and use the indicator variable *morebanks* which takes the value 1 for districts with number of banks above the mean of *bank98*.

Finally, I use the indicator variable  $I(YEAR > 1998)$  to capture the time of exposure to the policy and controlling for pre-existing differences along the above cross sectional dimensions over time. I run the following regression for district ‘d’ in state ‘s’ at time ‘t’:

$$\begin{aligned}
Y_{dst} = & \alpha_s + \delta_t + \beta_1 aligned_s \cdot morebanks_d \cdot I(YEAR > 1998) + \beta_2 morebanks_d \\
& + \beta_3 aligned_s \cdot morebanks_d + \beta_4 morebanks_d \cdot I(YEAR > 1998) \\
& + \beta_5 aligned_s \cdot I(YEAR > 1998) + \gamma X_{dst} + \epsilon_{dst} \quad (1)
\end{aligned}$$

The coefficient of interest is  $\beta_1$  which captures the causal effect of the policy on outcomes  $Y$ . I use state fixed effects captured by  $\alpha_s$ . Demographic controls at the household level are included in  $X$ . I control for the number of persons in the family, number of children, number of married men and women and also the age and education levels of men and women.

The interpretation of  $\beta_1$  is that it gives us the difference over time (post- and pre-policy) in  $Y$  for households in districts with more banks compared to households in districts with lesser banks in aligned states after controlling for these same differences in non-aligned states. The identifying assumption is that the outcome  $Y$  would not have been different for these groups of households had there been no KCC policy. There is no standard way to validate this assumption and identification always assumes this, but the panel structure of the data provides an opportunity to check whether these districts were historically different

and already had differential trends even before the policy. If we find that before the policy, differences in outcomes along the above dimensions were not different, we gain confidence that the identifying assumption is plausible. I describe a check for this at a later section and find that before 1998 there were indeed no differences in outcomes in these areas.

The fact that prior to the policy, the cross sectional dimensions seem to be similar, leads us into the cross sectional analysis. The dataset that I use is from 2005 which is a post-policy year. I still use the above cross sectional dimensions to generate exogenous variation in access to the policy but do not have the time dimensions anymore. Since there were no differences in these regions prior to the policy, any difference that I find for 2005 can be attributed as a causal effect of the program.

Using the household dataset, I therefore propose to run the following regression for household  $h$  in district  $d$  and state  $s$ :

$$Y_{hds} = \alpha_s + \theta_1(\text{aligned} \cdot \text{morebanks})_{ds} + \theta_2(\text{morebanks})_d + \omega X_{hds} + u_{hds} \quad (2)$$

In this specification,  $\theta_1$  is the causal impact of the policy on outcomes  $Y$ . The identifying assumption here, similar to above, is that in the absence of the policy, the differences in household outcomes between districts with more and less banks in aligned states would not have been any different from the differences in household outcomes in more and less bank districts in non-aligned states.

The main outcome that I look at is crop production. As mentioned earlier, rice is the major crop of the country in terms of value. I focus primarily on rice production but also look at the other important crops like wheat and maize. The idea is that with access to credit, farmers may be able to invest more and increase output. Since there is an element of investment behavior attached to credit access, I look at the use of high-yielding variety (HYV) seeds. If farmers would adopt more HYV seeds to increase their production, this would be evidence of technology adoption. I observe all of these outcomes at the district level and use the panel dataset to find effects on these. The cross sectional dataset however has a wide range of other outcomes that are of interest. I briefly describe some of those

below.

If access to credit leads to higher agricultural production, an immediate hypothesis that follows is, access to credit leads to higher incomes for farmers. I use the household survey data to test this hypothesis. I also hypothesize that since KCC is a formal source of credit, this might lead to crowding out of informal lending sources like local money lenders and employers. I do not observe usage of HYV seeds at the household level but a feature of the agricultural sector is that most poor farmers are not able to preserve and/or grow seeds for indigenous production. I hypothesize that with access to credit, farmers become more efficient and will be able to use home grown seeds as a result. I also look at various measures of consumption to see if household consumption expenditure changed with exposure to the policy or if composition of their expenditure on different types of consumption changed.

## 4 Data

### *District Production Data*

The data for this study mainly comes from 2 sources. First, ICRISAT-VDSA database provides a district panel data set for agricultural outcomes.<sup>4</sup> For this analysis I am only focussing on production of rice, wheat, maize and use of HYV seeds. The data contains information on total production, total area under production, gross and net cropped and irrigated areas,, number of markets in district, rainfall etc. Although the dataset provides data from 1966-2011, I focus on the post-1985 period. This is because of two reasons. Firstly, the empirical strategy would require that pre-trends are accounted for among the geographic classifications used to identify the causal effect of the program. One would be worried that in years long before the policy, potential treatment and control groups would have had very different trends in outcomes which would invalidate the analysis. Also, the period before 1986 marks a long history of political turmoil including the emergency days and war with neighboring countries. 1986 gives us a reasonable starting point for the analysis and it is at

---

<sup>4</sup>The ICRISAT has a rich database known as the Village Dynamics of South Asia (VDSA) and makes this available for 19 major states of India

least 12 years before the KCC program began. Secondly, the dataset for the early 60s and 70s has lots of missing information, so analysis using those years would in any way lead to lesser power.

### *Household Survey Data*

The second dataset is the Indian Human Development Survey (IHDS)-2005. The first official release of the survey was in 2008 for a survey they conducted in 1503 Indian villages and 971 urban neighborhoods in the year 2005. So, the data in this edition of the survey is based on respondents interviewed in 2005. It was jointly conducted by a team from the University of Maryland, USA and the National Council of Applied Economic Research (NCAER), India. The 2005 survey covered 41,554 households and compiled responses from two interviews each of which lasted for an approximate duration of one hour. I have a wide range of outcome variables to look at including income, consumption per capita, asset ownership, loan and debt details etc. I focus only on the rural sample and exclude the urban households which yields a sample of 26734 households.

### *Household Crop Data*

The IHDS-2005 also surveyed households to collect data at the crop level. There are multiple households producing multiple crops. As will become clear later, most of my main results appear to be driven by rice producers. So I merge the household survey data with the crop files using only those farmers who produce any rice. For my regressions using this dataset, I focus on the households below the 99th percentile to exclude some large outliers. In the sample the mean of rice production for a household is around 25 units measured in tenths of a quintal, the maximum is 2600 which is unusually high. Therefore, I exclude the large outliers who produce above the 99th percentile, which is 200 units in tenths of a quintal.

### *Household Data from 1993*

To provide support to my identification strategy, described in the following section, I do a falsification exercise using a cross section of households from the 1993 Human Development Profile of India (HDPI) which was a household survey and interviewed several households who would later be reinterviewed in the IHDS.

### *Other Data*

My identification strategy also relies on variations across three dimensions, coverage of KCCs, number of bank branches in 1998 and political alignment of state governments with the center as of 1998. I look up media reports and open source information available online to match whether the political party ruling a state was part of the ruling coalition at the center.<sup>5</sup> I use data from the Reserve Bank of India website to list the number of bank branches and branch offices in each district. I also use data from the Planning Commission of India publication of 2002 for state level access to KCCs by number of land holding covered under the scheme in 2000 to support the idea that political alignment was important in terms of the reach of the program.

### *Do households own a Kisan Credit Card?*

The IHDS-2005 includes a question for households on whether anybody in the family owns a KCC or not. This is only a dummy variable. The ideal scenario to describe the true causal effect of access to credit on outcomes would be to do a 2SLS regression by instrumenting for access to credit. So if the KCC program was an instrument for access to credit, then ideally we would want to run a first stage regression of access to credit on the identifying variables and divide the reduced form estimates above by the first stage coefficient. However, regressions using this dummy variable as the dependent variable should not be interpreted as the ‘first-stage’ because of two main reasons explained as follows.

First, the ideal first stage we have in mind would be actual borrowings and usage of the

---

<sup>5</sup>In particular I look up the name of the Chief Minister of the states in 1998 and note down his political party. Then I check if that political party was part of the ruling coalition at the center, ie, National Democratic Alliance or NDA.



credit card and not the mere possession of this card. The only way that enhanced access to credit through possession of this card would lead to increases in income is if people actually borrowed using this card. Second, since we have just a single time point, the year 2005, which is seven years after the policy was implemented, all the coefficients reported using this dummy variable would be under-estimates of the first stage coefficients. For example, if a household had the KCC for 7 years, and we believe it was constrained prior to that, then the coefficients from the reduced form estimates I report are relevant over a period of time while the household has benefitted from access to credit. So if for this household we consider a change in some outcome  $Y$ , it is not just an instantaneous rise but an overall change. If we divide this by the first stage which just takes into account 1 period of time, the potential 2SLS estimate would be hugely overestimated. So we would either need to multiply the so called first stage coefficient by the number of years the household had the card for (the information for which is unavailable) or deflate the reduced form by some factor.

Second, the dummy variable for having a KCC is not the perfect proxy for ‘access to credit’ which would be the main dependent variable in our structural regression model to do the 2SLS regressions. It is also quite possible that a single household had multiple KCCs but this would show up as a 1 on the dummy, the same as a household with just 1 KCC. To avoid these problems, I do not use this as an outcome variable in my regressions. However, roughly comparing the means of this dummy variable in areas potentially exposed more to the program to the areas exposed less, I seem to find a positive difference, but this is merely suggestive and therefore I do not interpret this as causal. The mean of this dummy variable for the entire sample is around 4% which makes any estimation using this as a dependent variable less convincing.

## 5 Results

### 5.1 Results using District-Panel Dataset

#### 5.1.1 Effects on Crop Production

Table 2 reports results on reduced form effects of credit access through more exposure to KCC program on crop production outcomes. I run regressions using the specification in equation (2) as above and report the coefficients  $\hat{\beta}_1$  for each outcome. Rice is by far the major crop of India in terms of value of output. I find from column 1 that annual district production of rice increases by about 88 thousand tonnes with more exposure to KCC. This is quite a big effect compared to the mean of 285 thousand tonnes which suggests that impediments to borrowing severely constrain the scale of production. One possible interpretation of this is while farmers are credit constrained, they can put a smaller area under crop production, use lesser inputs and have little or no access to advanced production technology. With access to credit, these are less of problems and as a result we expect to see a surge in production, to the extent that is found in Table 2. <sup>6</sup>

One possible concern could be that there are state specific or district specific time trends that are driving these results. To address this concern, I allow for trends in the identifying variables in columns (2) and (3) and I find that the point estimate is robust. In columns 7 and 8, I look at two other crops and do not find any significant effect of this policy. Again, a reason could be that these crops are much less important in terms of value and not all states produce these whereas rice is a more universal crop in a country like India. So, with access to credit, given rice is more profitable in India, farmers are expected to invest more in rice production. However, it is reassuring that even though not significant, the point estimates on these are still positive which suggests an increase in overall production.

---

<sup>6</sup>India had a major drought in 2002 which affected several rice farmers. Rainfall was about 56% below normal in July and almost 22% less rain was recorded overall (see Bhat 2006). In general this should not impact my analysis. However, there maybe concerns that banked districts in aligned states might have responded differently in terms of providing support to the agricultural system and therefore it confounds the estimate somewhat. I find that the point estimates are not very different if we exclude 2002 which alleviates these concerns. These results are not reported but are available upon request.

### 5.1.2 Technology Adoption

A possible mediating channel for an increase in rice production could be adoption of technology. Existing studies have shown that credit constraints are important hindrances in adoption of technology (Croppenstedt, Demeke and Meschi 2003). Mukherjee (2012) uses Indian household data to show that access to banks leads to better adoption of High Yielding Variety (HYV) seeds in production. Since the KCC program intended to provide more credit access, it is interesting to examine whether the relaxing of credit constraints has a similar effect as Mukherjee (2012) on aggregate.

Column 4 in Table 2 suggests that overall crop area put under HYV seeds usage is higher by 71 thousand hectares with exposure to KCC. This is suggestive evidence that access to credit leads to some technology adoption. As with overall production, the point estimate here is also robust to linear de-trending as reported in columns 5-6. These reduced form effects can be viewed as mediating channels for an increase in rice production.

### 5.1.3 Threats to Identification: Check for Pre-Trends

The identification strategy would be invalidated in the case of pre-existing differential trends in the areas plausibly exposed more to KCCs compared to the ones not exposed as much. One example would be if some districts in aligned states are traditional strong holds of the political party in the center, those districts may in any case get preferential treatment historically and the coefficient we are picking up is not the true causal effect of the policy. To alleviate concerns such as these, in Figure 1 I plot all the  $\hat{\beta}_1$  coefficients for crop production outcomes by year instead of interacting with  $I(YEAR > 1998)$ . The dotted lines represent 95% confidence intervals. In other words, instead of using all the previous years as the omitted reference group, I exclude the year 1986 and compare the year specific effects with respect to this excluded year. Each point of the graph represents the following object for year  $t$ :

$$\begin{aligned}
& [(\bar{Y}_{aligned,morebanks} - \bar{Y}_{aligned,lessbanks}) - (\bar{Y}_{nonaligned,morebanks} - \bar{Y}_{nonaligned,lessbanks})]_t \\
& - [(\bar{Y}_{aligned,morebanks} - \bar{Y}_{aligned,lessbanks}) - (\bar{Y}_{nonaligned,morebanks} - \bar{Y}_{nonaligned,lessbanks})]_{1986} \quad (3)
\end{aligned}$$

I find that these coefficients, for all the outcomes are not statistically different from zero prior to the policy year (marked by a vertical line) and for rice production, they become positive since 1998. These suggest that the areas identified as exposed more to KCCs were not systematically different from the areas without as much KCC exposure as per my identification strategy.

In figure 2, I perform the same exercise but for HYV area as an outcome. The coefficient does not jump at 1998 as sharply as for rice production but at least prior to 1998 it is never significant, which supports the identifying assumption somewhat.

## 5.2 Do Households Change their Borrowing Patterns?

In this section I look at the impacts of these agricultural credit reforms on outcomes related to borrowing and lending. I report reduced form regressions using the household data. Unfortunately the district panel dataset (VDSA) does not provide any information on credit and therefore it is not possible to compare these findings at the district level. So all of the following analyses are based on the cross sectional dataset.

### 5.2.1 Total Borrowing

Panel A of Table 3 reports regression results for the outcomes I discuss here. Throughout the table I report results for all available households and 2 sub categories. First, columns titled ‘cultivator’ represent those households whose main income source is cultivation. Second, columns titled ‘Rice’ are for those households who produce any rice. I find from columns 1-3 that on average there is no effect on whether people exposed to KCC are more likely to borrow. The dependent variable is based on answers to the survey question of whether the

household had any loans in the last 5 years. The policy was implemented from 1998 and the survey is based on 2004-05, so it is hard to make conclusive statements about the estimated coefficients, especially because of the lack of precision. I also do not find any significant effect on total outstanding debt.

The more interesting results come from columns 7 to 12. I find that on average, households have lesser number of loans in the last 5 years. For every 2 rice farmers, I estimate 3 fewer loans with exposure to the KCC program. I do not find any evidence of the policy impacting the margin of whether the main creditor is a bank for the households. I define bank as the main creditor if the largest loan, conditional on borrowing, comes from a bank. The fact that this margin is unaffected by the policy allows me to look at effects of the program on a sub sample of households who borrow from banks. The KCC policy was expected to operate through banks, so the households who actually borrow from banks are likely to be affected by this program the most. I look at outcomes like production, consumption and income for this sub sample of households in the following sections.

### **5.2.2 Analysis of the Largest Loans**

In Panel B, I restrict attention only to the largest loans of households in the 5 years before the survey. Columns 1-6 focus on the largest loan from any source. The rest of the columns focus on the largest loans if the source is reported to be a bank. I do not find any difference in interest rates across the board. Although for bank loans, the negative coefficient (and the lower mean interest rates) are suggestive that the policy led to availability of cheaper credit because one feature of the reform was to allow borrowing at lower rates of interest. Again, these estimates are imprecise, so we have to be cautious with interpreting these.

The effects on loan size are significant. Not only do I find that the average household increasingly exposed to KCC borrows almost 9 thousand INR more than the average household less exposed to KCC, but this number is 16 thousand INR for the average rice farmer. This is with respect to loans from any source. If I restrict the sample to largest loans coming from banks, these numbers are considerably higher. The average household borrowing from

banks and exposed more to KCC has a largest loan that is 41 thousand INR bigger in size than the one with less exposure to KCC. These numbers are very similar for the cultivator and the rice farmer samples. These results are consistent with theories of expansion of credit as a result of KCC as well as access to credit. Whether the higher borrowing is because in the counterfactual households are constrained or due to the fact that loans are now cheaper cannot be separated with this exercise though the point estimates on the borrowing margins in panel A suggests that most of the effect is driven by existing borrowers and not new borrowers. Eitherway, this helps corroborate the findings on production. If borrowing increased, irrespective of the channel, we would expect more investment and therefore higher production.

### **5.3 Effects on Household Production, Income and Consumption**

It is interesting to examine how the higher borrowing estimated above translates into spending and income. The following sections are devoted to this exercise. I first check if production and sales increased for rice at the household level, which was the crop that appeared to have been most affected by the policy in the district analysis. Then I estimate effects of the program on household income and finally look at consumption expenditure.

#### **5.3.1 Rice Production and Sales**

I use the IHDS crop level data, as described above, to estimate the reduced form effects of the KCC program on production outcomes. Results are reported in Table 4. Most estimates are imprecise with large standard errors clustered by district. I restrict attention to only those households that produce some positive amount of rice. Column 1 suggests minimal effects on overall household production levels but if I restrict the sample to only those farmers who sell their output, as in columns 3 and 5, I find suggestive evidence of large increases in production levels and revenue. The increase in revenue is almost 40 thousand INR per year.

In columns 2, 4 and 6 I look at these outcomes for the subsample of bank borrowers only. I find significant increases in production and revenue from sales of rice. This is consistent

with earlier findings of increase in production at the district level and bigger bank loans. In the counterfactual, if households did not have access to larger loans prior to the introduction of KCC, they may have faced difficulties in financing their production technology. With KCC they can secure larger formal sector loans which allows productive investments and that transpires into higher output and revenue.

### 5.3.2 Income

Another way to corroborate the idea of higher agricultural output with increased access to credit is to see if this translates into effects on household outcomes. Increased agricultural output is only expected to have welfare effects if there is an observable increase in income of the farmers. Table 5 reports results that look at this dimension. When I restrict the sample to households whose main income source is cultivation and look at the reduced form policy effects on incomes from their farms, I find incomes higher by 129 INR (USD 2) which is about 25% compared to the mean. This is approximately a 24 INR monthly increase per capita for rice farmers.<sup>7</sup>

I also check for non-farm income and find no effects. If the reduced form effects are operating through enhanced credit access, especially for households with previously no access to credit, then we would only expect farm incomes to be higher because the policy was directed towards farming households.

When I restrict the sample to only bank borrowers, which we have now identified as the group of people most likely to be affected by the policy, I largely find significant effects on income. Both per-capita income and per-capita farm income is likely to be higher for these households if exposed to the KCC program more.

---

<sup>7</sup>Effects are imprecise as before but if we compare this to the estimated effects on revenue of rice farmers we can do some rough calculations. A 24 INR per capita increase in income (profits) of rice farmers would imply a yearly per capita increase in income of 288 INR. The average household has five or six members, so this translates to a total annual profit of around 1600 INR. With estimated sales revenue increases of 40 thousand INR annually, this implies that costs and investments would have been higher by around 38 thousand for rice farmers.

### 5.3.3 Consumption Expenditures

I do not find any effect of enhanced credit access on overall consumption expenditures but as reported in Table 6, composition of consumption expenditure changes. Banerjee et al (2015) in their microfinance experiment find that spending categories are sensitive to credit access and my results are consistent with their findings in a larger nationwide setting. Similar to their experimental results, I find a decrease in expenditure on what is coined as ‘temptation goods’. These are expenses on tobacco, beetel leaves etc and credit access has been believed to be a ‘disciplining device’ of sorts and therefore exposure to credit reduces expenditure on these items. I also find an increase in expenditure on recurring purchases of day to day household items.

The vast health economics literature also predicts that with increases in income, stress levels decline and as a result consumption of goods like tobacco and alcohol would go down (Cotti, Dunn and Tefft 2015). If access to credit led to higher production and higher income, it is not surprising that consumption expenditures decrease on temptation goods.

Expenditure on temptation goods is lower by 29 INR per month whereas day to day spending is higher by about 11 INR. For cultivators, this effect is 36 INR and 16 INR respectively and is estimated with greater precision. The effects are even higher for the sample of households who borrow from banks. One possible explanation consistent with the findings would suggest that with credit constraints being relaxed, households now can plan out their future spending stream better and spend money on more productive uses that would be welfare enhancing in the long run whereas they cut back on less productive consumption like tobacco etc. Even if the effects are not through relaxation of credit constraints, expansion of credit could also have similar effects.

## 5.4 Falsification Exercise

In this section, I perform a robustness check for my identification strategy and describe a falsification test. The identifying assumption for my analysis was that any differences in districts with more banks compared to districts with less banks in 2005 in aligned states



is attributable to the KCC program after controlling for trend differences in these districts using the non-aligned states. However, one maybe worried that prior to the policy, these areas were already different and what we are picking up is an existing trend. Figures 1 and 2 using the district panel data alleviates this concern but here I present an alternate test using household data.

The cross sectional data is from the 2005 Indian Human Development Survey (IHDS). A portion of the households interviewed in 2005 were drawn from an earlier survey known as the Human Development Profile of India (HDPI) conducted in 1993. Since HDPI was in a year before the policy, I use the above identification strategy for the households that can be traced back and run the regression equation (1) for some comparable outcome variables but for the year 1993. If  $\theta_1$  is the potential effect of the KCC policy with the 2005 data, then for the same regression with the 1993 data, we would not expect it to be significantly different from zero. Columns (1) and (2) of Table 8 report the  $\theta_1$  coefficients for the above regression for both 1993 and 2005 data using the comparable  $X$ s and for the comparable  $Y$ s. I report the regression results for per capita income in Table 7.

I find that coefficients are systematically higher in 2005 whereas they are never significantly different from zero in 1993. This suggests that the regions being compared in my estimation were not different prior to the policy and any difference arising post-policy may therefore be attributable as a reduced form impact of the program.

In column (3), I repeat the regressions from column (2) using the same sample but adding other controls as used in the main analysis above. These additional controls like number of persons in the family, number of children and married persons were not available in 1993. I find that most of the effects are still pretty much the same as in column (2) though the point estimates are marginally bigger.

## 6 Conclusions

In this paper I looked at a major agricultural credit reform in India known as the Kisan Credit Card policy which simplified the functioning of the agricultural credit market. A stated goal of the policy was to relax credit constraints on the poor. I used plausibly exogenous geographic variation in the outreach of the program to identify the causal impact of the policy. I find evidence that the reform led to large scale increases in aggregate agricultural output. Rice, the major crop of India seems to have been the most affected with a surge in production post-policy. There seems to have been significant adoption of technology by putting more area under cultivation to use of HYV seeds.

Using a household dataset, I estimated effects of this policy on borrowing compositions. I find households are likely to have fewer but bigger loans with exposure to the program. Also, size of the largest loan coming from banks is bigger for households in areas exposed to KCC. No significant effects are estimated on interest rates.

I further looked at the impacts of this policy on outcomes like consumption, production and income. I find suggestive evidence of increase in rice production and sales revenue. I estimate an increase in farm income of around 129 INR (USD 2) monthly per capita with enhanced credit access. The reduced form effects of the policy further suggest that credit access acts a potential disciplining device where people spend less on unproductive consumption and spend more on productive or investment goods. There is no effect however, on overall consumption expenditure.

I identify households with a bank loan as the most affected category and find that all estimated effects are much more pronounced for this sub sample of households suggesting that a mediating channel for the reduced form estimates are bank loans. Since KCC by design had to operate through banks, this provides confidence about our identification strategy picking up the effect of the KCC policy.

## References

1. Angelucci, M., Karlan, D. and Zinman, J (2015). ‘Microcredit Impacts: Evidence from a Randomized Microcredit Program Placement Experiment by Compartamos Banco’ *American Economic Journal - Applied Economics*
2. Asher, S and Novosad, P. (2015). ‘Politics and Local Economic Growth’ *Working Paper - Dartmouth* - <http://www.dartmouth.edu/novosad/asher-novosad-politicians.pdf>
3. Asubel, L. (1991). ‘The Failure of Competition in the Credit Card Market’ *American Economic Review*
4. Attanasio, O., Augsburg, B., De Haas, R., Fitzsimons, E. and Harmgart, H. (2015). ‘The Impacts of Microfinance: Evidence from Joint Liability Lending in Mongolia’ *American Economic Journal - Applied Economics*
5. Augsburg, B., De Haas, R., Harmgart, H., and Meghir, C. (2015). ‘The Impacts of Microcredit: Evidence from Bosnia and Herzegovina’ *American Economic Journal - Applied Economics*
6. Banerjee, A. V. and Duflo, E. (2014). ‘Do firms want to Borrow More? Testing Credit Constraints using a Directed Lending Program.’ *Review of Economic Studies*
7. Banerjee, A. V., Duflo, E., Glennerster, R. and Kinnan, C. (2015) ‘The Miracle of Microfinance. Evidence from a Randomized Evaluation’. *American Economic Journal - Applied Economics*
8. Banerjee, A. V. and Munshi, K. (2004). ‘How Efficiently is Capital Allocated? Evidence from the Knitted Garment Industry in Tirupur.’ *Review of Economic Studies*
9. Bhat, G. S (2006). ‘The Indian Drought of 2002 - a sub seasonal Phenomenon?’ *Quarterly Journal of the Royal Meteorological Society*
10. Bond, P., Musto, D and Yilmaz, B. (2009). ‘Predatory Mortgage Lending’ *Journal of Financial Economics*
11. Burgess, R. and Pande, R. (2005) ‘Do Rural Banks matter? Evidence from the Indian Social Banking Experiment.’ *American Economic Review*

12. Chanda, A. (2012). ‘Evaluating the Kisan Credit Card Scheme’ *International Growth Center Working Paper 12/0345*
13. Chibber, P., Shastri, S and Sisson, R. (2004). ‘Federal Arrangements and the Provision of Public Goods in India’ *Asian Survey*
14. Chin, A., Karkoviata, L and Wilcox, N. (2011) ‘Impact of Bank Accounts on Migrant Savings and Remittances: Evidence from a Field Experiment.’ *Working Paper, University of Houston*
15. Cotti, C., Dunn, R and Tefft, N. (2015). ‘The Dow is Killing Me: Risky Health Behaviors and the Stock Market’ *Health Economics*
16. Crepon, B., Devoto, F., Duflo, E and Pariente, W. (2015) ‘Estimating the Impact of Microcredit on Those Who Take It Up: Evidence from a Randomized Experiment in Morocco’ *American Economic Journal - Applied Economics*
17. Croppenstedt, A., Demeke, M. and Meschi, M. (2003) Technology Adoption in the Presence of Constraints: the Case of Fertilizer Demand in Ethiopia’ *Review of Development Economics*
18. De Mel, S., McKenzie, D. and Woodruff, C. (2008). ‘Returns to Capital in Microenterprises. Evidence from a Field Experiment.’ *Quarterly Journal of Economics*
19. Iyer, L. and Mani, M (2012). ‘Traveling Agents: Political Change and Bureaucratic Turnover in India’ *Review of Economics and Statistics*
20. Karlan, D. and Murdoch, J (2009). ‘Access to Finance’. *Handbook of Development Economics - Chapter 2*
21. Melzer, B. (2011). ‘The Real Costs of Credit Access: Evidence from the Payday Lending Market’ *Quarterly Journal of Economics*
22. Mukherjee, S (2012). ‘Access to Formal Banks and Technology Adoption: Evidence from Indian Household Panel Data’ *University of Houston - Working Paper*
23. O’Donoghue, T. and Rabin, M. (1999). ‘Doing it Now or Later’ *American Economic Review*

24. Planning Commission of India (2002). 'Support from the Banking System: A case Study of the Kisan Credit Card' *Study Report 146, Socio Economic Research Division*
25. Samantara, Samir (2010). 'Kisan Credit Card - A Study" *Occasional Paper 52, National Bank of Agriculture and Rural Development, Mumbai*
26. Tarozzi, A. Desai, J and Johnson, K (2015). 'The Impacts of Microcredit: Evidence from Ethiopia' *American Economic Journal - Applied Economics*

Table 1: Comparing Means of statewise spread of KCC in 2000 by *aligned*

	Aligned State (1)	Not Aligned State (2)	$\Delta$ (1)-(2)
KCC Coverage (in percentages)	30.596	12.710	17.886
Standard Deviation	17.223	12.617	$H_0 : \Delta = 0$ p-value < 0.001

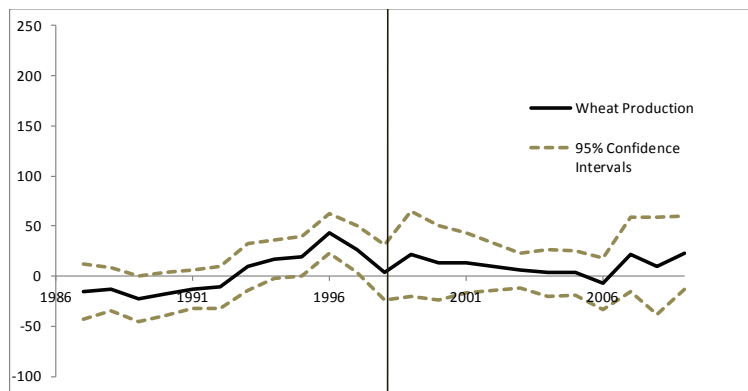
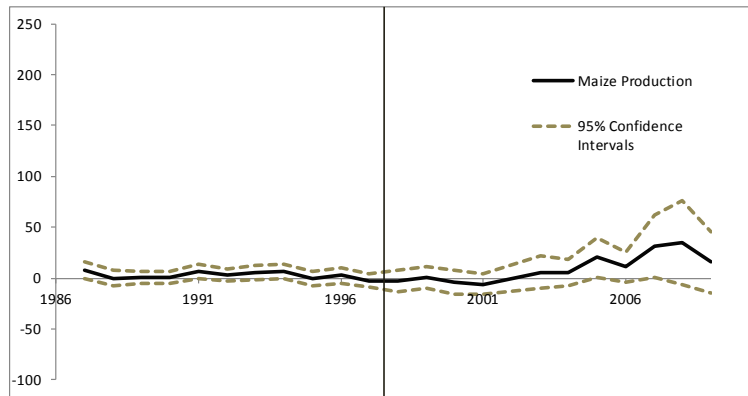
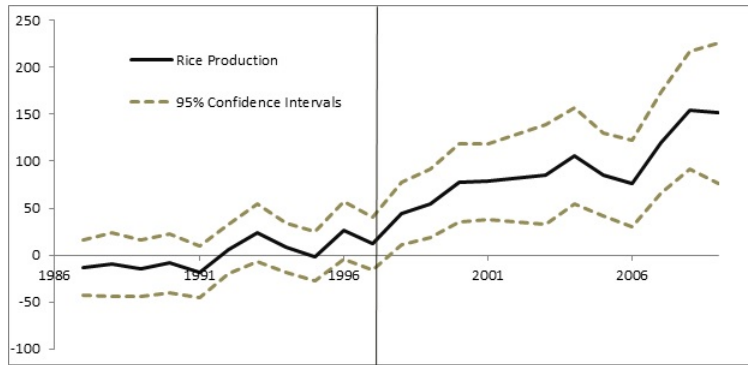
Notes: KCC coverage is obtained from Planning Commission of India reports. It is calculated as the number of KCCs issued as percentage of total operational holdings in a given state in the year 2000. I use the definition of *aligned* as described for states aligned in 1998 and use the coverage figures 2 years on. This table suggests that aligned states had much higher initial growth of the policy which provides support to the use of aligned as a dimension of identification.

Table 2: VDSA District Dataset: Effects on Crop Production and HYV Use

	Rice Production			Area under HYV Seeds			Wheat	Maize
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$aligned_s \cdot morebanks_d \cdot I(YEAR > 1998)$	88.7*** (21.4)	89.2*** (21.5)	89.8*** (21.4)	71.5*** (20.8)	72.7*** (21.2)	72.6*** (21.6)	9.99 (16.1)	6.51 (6.7)
Linear Trend in <i>aligned</i>		Yes	Yes		Yes	Yes		
Linear Trend in <i>morebanks</i>			Yes			Yes		
$R^2$	0.94	0.94	0.94	0.75	0.75	0.75	0.97	0.83
Observations	4992	4992	4992	4172	4172	4172	4978	4992
Mean of Dep Var		284.3			213.7		181.7	38.1

Notes: Analyses in this table are based on the district panel dataset. Each column presents a different regression. Production figures are annual, units 1000 tonnes and HYV area is in terms of 1000 hectares. All regressions include state and year fixed effects and control for all the double interaction terms and baseline variables *aligned*, *after* and *morebanks*. I control for the area put under rice cultivation and also irrigation specific to rice. Additional controls include rainfall, gross cropped and irrigated area, presence of markets. Clustered Errors are at the district level in parentheses. \*\*\* p<0.01 \*\*p<0.05 \*p<0.1

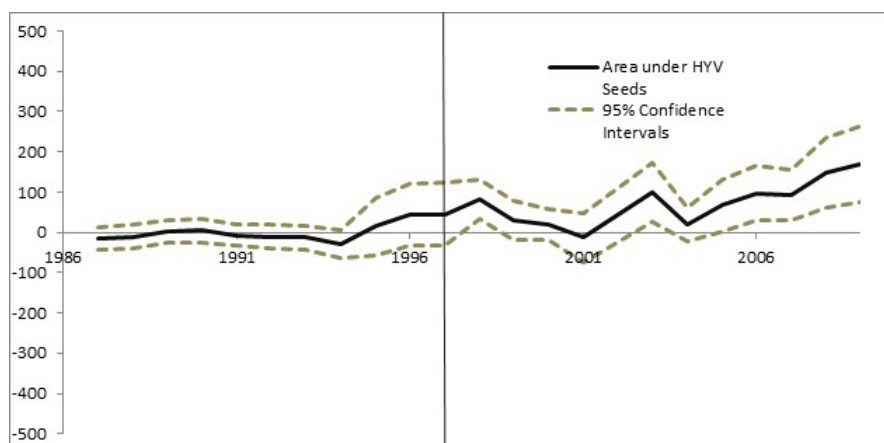
Figure 1: Coefficients of the interactions YEAR.(aligned.morebanks) for crop production outcomes



Notes: The vertical line marks the policy year whereas the dotted line represent 95% confidence intervals. Regressions use the VDSA district panel dataset and control for crop specific area under production, rainfall, crop specific irrigated area, markets nearby, gross cropped and irrigated areas and state fixed effects.



Figure 2: Coefficients of the interactions YEAR.(aligned.morebanks) for area under hyv seeds as outcome



Notes: The vertical line marks the policy year whereas the dotted line represent 95% confidence intervals. Regressions use the VDSA district panel dataset and control for rainfall, markets nearby, gross cropped and irrigated areas and state fixed effects.

Table 3: IHDS Dataset: Effects on Borrowing Composition

PANEL A	If Borrows			Total Outstanding Debt			Number of Loans			Main Creditor is Bank		
	All (1)	Cultivator (2)	Rice (3)	All (4)	Cultivator (5)	Rice (6)	All (7)	Cultivator (8)	Rice (9)	All (10)	Cultivator (11)	Rice (12)
<i>aligned · morebanks</i>	-0.072 (0.049)	-0.059 (0.060)	-0.138* (0.075)	-0.514 (6.589)	-7.984 (9.441)	-0.027 (9.670)	-1.351** (0.651)	-0.998 (0.667)	-1.590** (0.743)	-0.039 (0.023)	-0.067 (0.047)	-0.068 (0.062)
Mean	0.458	0.508	0.509	38.638	49.252	34.827	3.170	3.232	3.385	0.121	0.174	0.151
Observations	21450	7907	5700	10250	4021	2678	10111	4147	2827	21450	7907	5700

PANEL B	Only Largest Loans			Only Largest Loans from Banks								
	Interest Rates			Loan Size			Interest Rates			Loan Size		
All (1)	Cultivator (2)	Rice (3)	All (4)	Cultivator (5)	Rice (6)	All (7)	Cultivator (8)	Rice (9)	All (10)	Cultivator (11)	Rice (12)	
<i>aligned · morebanks</i>	0.080 (0.239)	0.014 (0.207)	0.192 (0.310)	9.414*** (4.759)	12.068 (7.672)	16.725* (10.197)	-0.037 (0.072)	-0.085 (0.082)	-0.114 (0.082)	41.364*** (2.973)	37.817** (14.576)	44.181** (19.470)
Mean	2.105	1.886	2.157	32.719	40.828	32.928	1.059	1.079	1.045	62.961	65.314	58.979
Observations	10114	4145	2827	10117	4151	2878	2696	1437	880	2696	1437	880

Notes: Each column represents a different regression. The sample in Panel B includes answers to questions about the largest loan in last 5 years for the households. Monetary Values (for loan size and outstanding loans) are in INR 1000 units. Columns 1-3 in Panel A report regressions where the dependent variable is a dummy for whether the household has any borrowing in the past 5 years. Total outstanding debt is the variable for how much the household currently owes others conditional on non-zero outstanding debt. The number of loans variable is also with respect to number of loans in past 5 years. The dependent variable, Main Creditor is Bank, is a dummy indicating if the largest loan of a borrower comes from a bank and takes the value zero for borrowers from other sources as well as non borrowers. The coefficients reported are for *aligned · morebanks*. All regressions include state fixed effects and control for baseline *morebanks* variable. Additional demographic controls include number of persons in each family, number of children in each household, number of married men and married women, age and education levels of men and women. Cultivator represents the sample of households whose main income source is reported to be cultivation and allied agriculture. Rice farmers are households who produce a positive amount of rice. Clustered Standard Errors are at the district level. \*\*\* p<0.01 \*\*p<0.05 \*p<0.1

Table 4: IHDS Dataset: Effects on Rice Production and Sales

	All Producers		If Sells Output			
	Quantity		Quantity		Price X Quantity	
	Full Sample (1)	Bank Borrowers (2)	Full Sample (3)	Bank Borrowers (4)	Full Sample (5)	Bank Borrowers (6)
<i>aligned · morebanks</i>	0.917 (4.033)	10.809** (5.299)	7.719 (6.355)	18.982** (7.636)	40.88 (38.62)	107.63** (43.12)
Observations	7118	997	2583	464	2583	464
Mean	21.067	25.244	40.736	40.365	238.54	228.67

Notes: The sample is restricted to only rice farmers in the IHDS dataset. Each column represents a different regression. All regressions include state fixed effects and control for baseline *morebanks* variable. Additional demographic controls include number of persons in each family, number of children in each household, number of married men and married women, age and education levels of men and women and area under rice production. The dependent variable in columns (1) to (4) is rice production in tenths of a quintal. The dependent variable in column 5 is the revenue from sale of rice conditional on selling rice. The units are INR 1000. Bank Borrowers represent the sample of households who have borrowed in the past 5 years and their largest loan comes from a bank. Clustered standard errors at the district level in parentheses. Number of clusters is 282. \*\*\* p<0.01 \*\*p<0.05 \*p<0.1

Table 5: IHDS Dataset: Effects on Income

	<u>Per Capita Income</u>			<u>Per Capita Farm Income</u>			<u>Per Capita Non Farm Income</u>	
	All (1)	Cultivator (2)	Bank Borrower (3)	All (4)	Cultivator (5)	Bank Borrowers (6)	All (7)	Business Person (8)
<i>aligned · morebanks</i>	-0.016 (0.069)	0.053 (0.141)	0.323* (0.197)	0.043 (0.063)	0.129 (0.140)	0.424* (0.223)	0.03 (0.060)	0.012 (0.159)
Mean	0.715	0.731	0.951	0.207	0.476	0.411	0.463	0.808
Observations	21117	7634	2634	20291	7262	2501	3769	677

Notes: Each column represents a different regression. The coefficients reported are for *aligned · morebanks*. All regressions include state fixed effects and control for baseline *morebanks* variable. Additional demographic controls include number of persons in each family, number of children in each household, number of married men and married women, age and education levels of men and women. In this table, monetary figures are in monthly INR 1000 which is approx monthly USD 20. The sample size is variable in this table based on the gradations ‘if cultivator’ and ‘if business person’. A household is denoted as a cultivator if the respondent reported that their main income source is from cultivation or allied activities. Similarly if the reported main source of income is business, I classify these households as ‘business persons’. Bank Borrowers represent the sample of households who have borrowed in the past 5 years and their largest loan comes from a bank. Clustered Standard Errors are at the district level. \*\*\* p<0.01 \*\*p<0.05 \*p<0.1

Table 6: IHDS Dataset: Effects on Consumption Expenditure

	Per Capita Monthly Cons			Household Items			Temptation Goods		
	All (1)	Cultivator (2)	Bank Borrowers (3)	All (4)	Cultivator (5)	Bank Borrowers (6)	All (7)	Cultivator (8)	Bank Borrowers (9)
<i>aligned · morebanks</i>	-0.0019 (0.0037)	0.0002 (0.0064)	0.0084 (0.0074)	0.0113 (0.0073)	0.0161* (0.0093)	0.0215** (0.0108)	-0.0283*** (0.0103)	-0.0360*** (0.0125)	-0.0114 (0.0178)
Mean	0.0644	0.0658	0.0854	0.0729	0.0791	0.0877	0.0817	0.0829	0.0928
Observations	21437	7899	2695	21437	7899	2695	21437	7899	2695

Notes: Each column represents a different regression. The coefficients reported are for *aligned · morebanks*. All regressions include state fixed effects and control for baseline *morebanks* variable. Additional demographic controls include number of persons in each family, number of children in each household, number of married men and married women, age and education levels of men and women. Monetary figures are in INR 1000 units here. The temptation goods include beetel leaves/tobacco etc. Banerjee et al (2015) find that microfinance as a disciplining device reduces per capita consumption of these goods by INR 9. The per capital equivalent of my finding of INR 28 reduction is INR 4. The HH items include regular purchases like soaps, bulbs, buckets, insecticides etc. I use the IHDS 2005 sample of rural households which have 26734 observations. Cultivator represents the sample of households whose main income source is reported to be cultivation and allied agriculture. Bank Borrowers represent the sample of households who have borrowed in the past 5 years and their largest loan comes from a bank. Clustered Standard Errors are at the district level. \*\*\* p<0.01 \*\*p<0.05 \*p<0.1

Table 7: Falsification Exercise

	1993	2005 Comparable Controls	2005 All Controls
	(1)	(2)	(3)
Per Capita Monthly Income	0.019 (0.045)	0.094 (0.125)	0.127 (0.120)
Per Capita Monthly Income (if principal occupation is cultivation)	0.037 (0.064)	0.292 (0.198)	0.329 (0.191)

Notes: I run reduced form regressions following the same identification strategy as described in the text for 2005 and using the HDPI data from 1993. I use the same households (8947) for both years. For the sample looking only at cultivators, I have 3731 households. In columns 1 and 2, I run regressions using only the comparable controls which are age, education of male, education of female and state fixed effects. In column 3, I re-run regressions of column 2 using the same sample but adding the controls used in the original analysis which are available for 2005. The additional controls in column 3 are number of persons in family, number of children and number of married males and females. I only report the comparable outcome variables. Clustered standard errors at the district level in parentheses. \*\*\* p<0.01 \*\*p<0.05 \*p<0.1