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Impact Evaluation of Cash Transfer: Case Study of Agriculture, Telangana

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Abstract

With Unconditional Cash Transfers in Agriculture emerging as a significant policy instrument in India in recent years, evaluating such interventions has become imperative and policy relevant. This study aims to estimate the causal impact of one such program implemented by the state of Telangana in 2018, on the agricultural input spending. This study uses the data from National Sample Survey's 77th round which is a nationally representative survey conducted in 2018-19. The analysis applies propensity score matching combined with inverse probability weighting method to estimate the causal impact of the cash transfer program. The findings from the study suggested a 36 percent raise in agricultural input spending for the average treatment effect estimate that is highly significant and can be traced to the cash transfer program. Additionally, after accounting for the selection bias, the average treatment effect on the treated estimates reveals a highly significant 18 percent increase in the input spending by the farmers. The results further suggest that the intervention shifts expenses away from imputed labour toward paid labour, and facilitates increased use of fertilizers.

Keywords: Agricultural Policy; Cash transfers; Input Spending
JEL Codes: *Q18; I38; O13*

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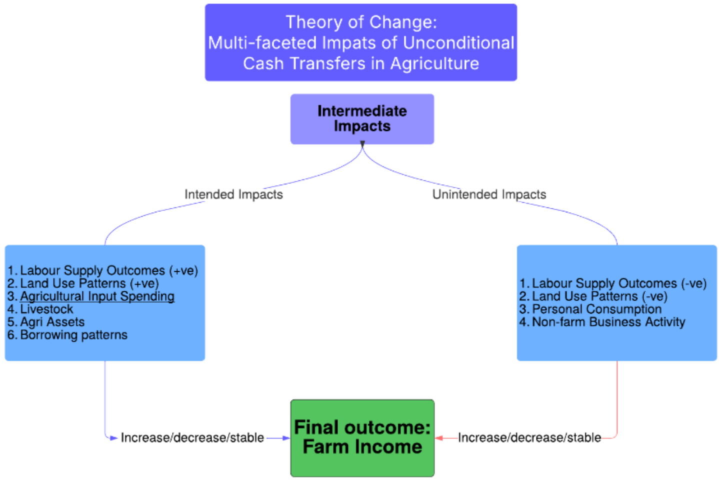
INTRODUCTION

The emergence of Unconditional Cash Transfers in Agriculture (UCTA) in India was spearheaded by the state of Telangana through the implementation of the flagship program *'Rythu Bandhu* Scheme*'* (RBS) in the year 2018. This program by the state government of Telangana has served as a model in this spectrum, encouraging several other states in India to implement similar programs (see Table A1 in Appendix) for the farmer's welfare. These UCTA programs can have multi-faceted effects on the beneficiary households (i.e., agricultural households). Moreover, if the cash transfers are large there might be potential spillover effects which can lead to boom in the rural economy. In this respect of UCTAs, a Theory of Change (ToC) can be framed for the program. The concept of ToC is often widely used in the literature and plays an instrumental role in the impact evaluation studies as it delineates pathways, causal relationships, mechanisms, and underlying assumptions about how change occurs (Browne, 2013). Generally, ToC is constructed in accordance with the policy context and it varies as the objective of the policy changes. Several studies in the literature, for example Leroy et al. (2009), Baird et al. (2012), Bailey and Hedlund (2012) and Jones and Shahrokh (2013), have proposed ToC for various policy contexts. Likewise, for the present analysis ToC is envisaged according to the underlying policy framework, and the expected outcomes are categorized as: immediate (or intermediate) outcomes, and final outcomes (see Figure 1).

The Theory of Agricultural Household Model advocated by Singh et al. (1986) delineates the decisions of agricultural households which are inseparable from production and consumption processes and these households are constrained by resources. The cash transfers in this scenario can act as resource push enhancing liquidity. It is also argued in the literature by Banerjee and Newman (1993), Aghion and Bolton (1997), Lindh and Ohlsson (1998), Lloyd-Ellis and Bernhardt (2000), and Banerjee (2001) that poor households remain trapped in poverty due to initial startup costs which exceeds their resources. One way to overcome such constraints, especially among poor farmers who are most likely to be credit-constrained which hinder them to invest optimally (Rosenzweig and Wolpin, 1993; Fenwick and Lyne, 1999; Lopez and Romano, 2000; Barrett et al., 2001; Winter-Nelson and Temu, 2005; Zezza et al., 2011), is through cash transfers. The cash transfers can act as a mechanism to reduce farmer's aversion to risk. And lower risk aversion may encourage farmers to take on more risk which can potentially boost the production levels (Dercon and Krishnan, 1996; Hennessy, 1998; Daidone et al., 2019). Therefore, the enhanced liquidity or reduced risk aversion resulting from cash transfers might incentivize farmers to invest in various agricultural activities. Since the cash transfers provide a guaranteed income at regular intervals and can increase liquidity, farmers move closer to the optimal level of inputs when credit markets fail to provide liquidity.

Figure 1: Theory of Change for UCTA



Source: Author's own preparation.

This study endeavours to find the causal impact of the *'Rythu Bandhu* Scheme*'* on the agricultural input spending using the 77th Round visit 1[1] of the National Sample Survey (NSS) corresponding to the year 2018-19. Since the RBS was introduced in 2018 and initial disbursals took place by the time 77th Round of NSS was conducted, the data collection provides natural setting for evaluation of the impact of RBS on agricultural input spending. The study focusses on input spending in agriculture as cash transfers could immediately reflect in enhanced spending by the farmers on variable costs. A study by Asfaw et al. (2012) underpins two key arguments to why intermediate outcomes (such as input spending) can be evaluated better than the final outcome (i.e., Farm income). Firstly, it would help to understand the impact mechanism – through what channels the impact occurs, such as investments on

[1] The Situation Assessment Survey of agricultural households was conducted in two visits by NSS. The first visit was from July – December 2018 (*Kharif* Season) and second visit was from January – June 2019 (*Rabi* Season).

labour allocation, inputs, land use measures etc. Second, the agricultural outputs and farm income are also determined by exogenous factors such as access to markets, prices, and weather conditions etc., which are beyond the farmer's or the program's control. The hypothesis in the evaluation of input spending is that the cash transfers made in the initial intervals are more likely to be spent on variable costs (i.e., expenses on seeds, fertilizers, land improvements, pesticides, and labour etc.). The idea of evaluating this outcome is important to determine whether cash transfers translate into more expenditure on inputs, which in turn could lead to better yields. Apart from input spending outcome, it is improbable that the cash transfers made in the early intervals would be used for purchasing agricultural machinery, livestock etc. For instance, Handa et al. (2018) argue that these investments on fixed assets are more plausible through a multiplier effect as they need more gestation period to occur. Thus, evaluating the intermediate outcome (i.e., agricultural input spending) is necessary and logical to understand whether unconditional cash transfer is used for the intended purpose.

This study employed one of the quasi-experimental methods for impact evaluation, propensity score matching (PSM) combined with Inverse Probability Weighting (IPW), to ensure a robust adjustment for potential selection biases and confounding. Impact evaluations of transfer programs are popularly assessed using Randomized Controlled Trials (RCTs), as they are widely regarded as the gold standard for establishing a credible control group - one that mirrors the treatment group but does not receive the transfer. Apart from RCTs, various quasi-experimental designs are also used in the impact evaluation studies when the RCTs are infeasible due to various challenges such as political sensitivities, monetary costs, ethical considerations, and logistical complexities (Baker, 2000; Angrist and Pischke, 2008; Imbens and Woolridge, 2009; Ravallion, 2009). In addition, programs that demonstrate promising results in RCTs have been observed to often face difficulties during large-scale implementation. As the scope of the program expands to encompass a broader and more diverse population, targeting precision diminishes, heterogeneity increases, and leakages become more prevalent, affecting the overall efficacy (Glennerster and Takavarasha, 2013). Moreover, it is well-established within the framework of PSM that, under the condition of random treatment assignment, the methodology effectively emulates the causal inference properties of RCTs.

The rest of the paper is structured as follows: it begins with a review of the relevant literature, followed by description of the data and empirical strategy. The paper concludes with a detailed discussion of the results and limitations.

REVIEW OF LITERATURE

Cash transfer (conditional and unconditional) programs are extensively implemented in South America and Sub-Saharan African countries. Generally, cash transfer programs around the world are designed to improve educational and health outcomes. But these programs have demonstrated positive spillover effects on various agricultural aspects, including increased agricultural output, enhanced agricultural assets, livestock development, higher agricultural investments, and improved living standards of agricultural households (Handa et al., 2018; Boone et al., 2013; Todd et al., 2010; Gertler et al., 2012; Sadoulet et al., 2001). Even though cash transfer programs targeted at agriculture are found only in a few countries, positive agricultural outcomes have been noted in countries that execute programs focused at improving human resources in general. As agriculture, especially subsistence farming, is the main source of income in many Sub-Saharan African nations, Asfaw et al. (2012) stress the need of examining the agricultural effects of cash transfer programs intended to improve human capital. Therefore, increased engagement in agricultural activities is fostered by the positive spillover effects of expanded human capital resulting from these transfers. As a result, studies on the effectiveness of these cash transfer programs often show that they have a major impact on agricultural output and other aspects related to agriculture. The body of research on cash transfers and agricultural outcomes has examined a wide range of outcomes in different nation and policy contexts, such as agricultural yield, input costs, asset accumulation, livestock management, and labour supply decisions etc. Available evidence across countries suggests that the impacts of cash transfers on the agricultural outcomes vary significantly. While there could be a number of reasons for the observed variation in causal effects, Daidone et al. (2019) argues that the size of the cash transfers, the socioeconomic and demographic traits of the target populations, and the design and implementation of the program contribute significantly to the observed variations.

Even in the analysis of agricultural input spending this heterogeneity in results is evident in the literature. For instance, Martinez (2004) examined a pension cash transfer program targeting elderly beneficiaries in rural Bolivia and found no statistically significant evidence to suggest that the transfers led to increased expenditures on agricultural inputs. In contrast, Todd et al. (2010) found that the input spending increased by 11 percent in October 1998 while evaluating Oportunidades, a conditional cash transfer program in Mexico. Subsequent assessments carried out in May 1999, however, did not maintain this effect, suggesting possible temporal variations in program impact that are consistent with Haushofer and Shapiro (2016, 2018). On the other hand, Handa et al. (2018) present strong empirical support based on their examination of Zambia's Multiple Categorical Cash Transfer Program (MCP) and Child Grant Program (CGP). Their results suggest that under MCP, households' agricultural input expenditures have increased significantly and steadily, increasing by an average of 242 percent over the course of the 24- and 36-month follow-up periods. This long-lasting effect highlights the significance of program-specific elements in influencing results, as it stands in stark contrast to the short-term impacts noted by Todd et al. (2010). These conflicting results underline the difficulty of assessing effects of cash transfer schemes and the necessity of context-sensitive approaches to comprehend their diverse effects on the investing behaviour of farmers. In addition, Daidone et al. (2019) provide a comprehensive examination of the impacts of cash transfer programs on agricultural input use across multiple countries, highlighting the heterogeneity in outcomes with magnitudes changing considerably by programs and by population subgroups, and only partially consistent with expected signs from theory. In a recent study on Malawi and Liberia, Aggarwal et al. (2024) also show the same trend of heterogenous results. Malawi has witnessed a spike in agricultural input spending by 25 percent as a result of unconditional cash transfer program. Liberia, on the other hand, showed no discernible benefits, which is probably because of its undeveloped market for agricultural inputs. Katewa and Pal (2024) conducted a study employing matching Difference-in-Difference method (using NSS Situation Assessment Survey of Agricultural Households (SAS) 2012 & 2018 datasets) that looked at agricultural productivity within the context of the RBS program in Telangana and found that yield has increased by 11 percent. Given that input spending and agricultural productivity are inextricably related, this finding suggests possible positive impact of RBS on input spending. The same study also found a significant increase in labour expenses due to RBS. However, a key limitation of their analysis was the absence of detailed data on total input expenditures i.e., paid-out and imputed expenses separately. Since the 2012-13 NSS SAS dataset does not elicit information separately for imputed and paid-out spending on agricultural inputs, their study was restricted towards estimating aggregate labour expenses. This gap in literature underscores the need for a much careful exploration of agricultural input spending, delving deeper into both imputed and paid-out expenditures to offer a more comprehensive understanding of the program's impact on agricultural input spending.

RBS – A BRIEF OVERVIEW

The state Government of Telangana in India launched 'Agriculture Investment Support Scheme - *Rythu Bandhu* Scheme for farmers in the state on 10th May 2018 (rechristened to *Rythu Bharosa* since 2024-25). Telangana's RBS is the first UCTA program implemented in India as an unconditional investment support scheme for farmers. The stated objective of RBS is, "Government of Telangana has come up with a new concept of providing Investment Support @ INR 4000 per acre per season (enhanced to INR 5000 since 2019-20 & later to INR 6000 since 2024-25) to all the farmers (*Pattadars*[2]) in the state towards purchase of various inputs like seeds, fertilizers etc., as initial investment before the crop season" (Government of Telangana, 2019).

There is no cap on the number of acres eligible for support. For example, a farmer who owns 1 acre would receive INR 10000 annually which is disbursed in equal instalments (i.e., INR 5000) in two cropping seasons (*Kharif* and *Rabi*). The scheme provides coverage for all land-owning farmers, regardless of whether they are actively engaged in farming. The disbursed amount is unconditional, allowing farmers full discretion over its use. They may allocate the funds toward activities such as purchasing fertilizers, seeds, machinery and labour, or for personal consumption and other expenditures of their choice. The total estimated outlay for the RBS was approximately INR 12000 - 15000 crore per

[2] It is a legal proof of ownership for agricultural land issued by the government.

cropping season. This accounts to 7 - 8 percent of the annual state budget and 1.5 - 1.7 percent of Telangana's GDP (Government of Telangana, 2023). In relation to GDP, the financial commitment to RBS was more than three times that of two of the most well-known cash transfer programs world-wide — Mexico's Progresa, which accounted for 0.4 percent of GDP (Davila Larraga, 2016), and Brazil's Bolsa Familia, which comprised 0.5 percent of GDP (Gazola Hellman, 2015).

Under the Telangana Land Reforms (Ceiling on Agricultural Holdings) Act[3], 1973, individuals cannot hold more than 27 acres of wetland or 54 acres of dryland, ensuring minimal scope for larger inequality in the distribution of benefits from RBS. Moreover, the proportion of large farmers is just 0.20 percent of total farmers, and the land operated by them is 2.30 percent of total landholding (Government of Telangana, 2018). The first instalment for the *Kharif* season in 2018-19 was disbursed through cheques, allowing farmers to withdraw funds directly from banks. However, since the *Rabi* season of 2018-19, payments have been made directly to farmers' bank accounts via the Direct Benefit Transfer (DBT) mechanism. To prevent legal disputes arising from tenancy issues (as per the Hyderabad Tenancy and Agricultural Lands Act[4], 1950), tenant farmers are excluded from the program. The introduction of new *Pattadar* Passbooks and the digitization of land records have streamlined the process, enabling the government to transfer benefits to farmers efficiently (Thomas et al., 2020).

DATA AND EMPIRICAL STRATEGY

Data

As mentioned above, this study evaluates the causal relationship between RBS and agricultural input spending using unit record data from

[3] See https://www.indiacode.nic.in/bitstream/123456789/8693/1/act_1_of_1973.pdf
[4] See https://www.indiacode.nic.in/bitstream/123456789/8575/1/act_21_of_1950.pdf

the 77th Round of the National Sample Survey. In each round, the NSS focuses on particular themes and gathers specific data in accordance with those themes. The 77th Round encompasses two distinct subjects: 'Land and Livestock Holdings of Households and Situation Assessment of Agricultural Households' (Schedule 18.1) and 'Debt and Investment' (Schedule 18.2). Schedule 18.1, which pertains exclusively to rural households, offers comprehensive data on various aspects of agricultural activity, including cultivated land, crop production, input expenditures, and investments in farm assets. Schedule 18.2 on the other hand, provides information on household borrowing, including loan sources, purposes, and interest rates, and covers both rural and urban households. For this analysis, Schedule 18.1 is used. The RBS in Telangana was implemented in May 2018, while the visit 1 of the survey had happened between July and December 2018. As the program's rollout and the survey period are so close together, this temporal alignment presents a special chance to examine the program's immediate post-implementation consequences. According to an evaluation of the program's implementation and reach by Muralidharan et al. (2021), 69 percent of the intended beneficiaries encashed their cheques prior to the start of the monsoon and the percentage rose to 83 percent subsequently. Thus, a substantial number of beneficiaries had cash in hand through the RBS prior to the NSS survey timeline. In other words, most recipients successfully accessed their funds, minimizing concerns about implementation flaws, and the high uptake justifies the use of observational data for analysis. Such an analysis enables a robust assessment of the program’s causal impact during its early stages.

Attrition

The input spending in agriculture is determined by several factors which are not in the control of farmers and these factors such as topographic, edaphic and weather conditions can largely influence the nature of spending. The NSS doesn't elicit this narrow information which limits the present analysis to only consider data from specific agro-climatic zone(s) [5] pertaining to the study area. This consideration acts as a proxy to control the extremities and address the diversities in various above-mentioned factors (topographic, edaphic, cropping patterns and irrigation etc.). For this analysis, Agro-climatic zone 10, i.e., Southern Plateau and Hills is chosen. Telangana which is the treated group and some parts of Karnataka, Andhra Pradesh and Maharashtra which fall under the untreated (or, control) group are covered in this zone (see Figure A1 in Appendix). Moreover, in order to control for more diversity, the standard errors are clustered at the district level as different agricultural parameters change from district to district. Rainfall is also a key factor in determining the input spending in agriculture due to which district-wise rainfall information for the monsoon months i.e., June, July and August (JJA) are considered, and individuals are assigned the rainfall information corresponding to their district.

The cash transfer intervention is only for the farmers who own agricultural land and tenant farmers are excluded from the benefit. Hence, for the sample validity, the farmers who own land are only considered. Thus, the sample restricts to 3,144 agricultural households from the original 4,606 agricultural households. This attrited sample is utilized for the causal impact analysis, incorporating several other control variables to ensure the impacts are attributable to the intervention and not due to confounding effects. The size of land holdings is considered as the main control variable and is also the treatment identification variable. Generally, larger landowners experience greater input expenses, making this an important factor to consider. The annual number of crops cultivated affects input costs, since a higher number of

[5] The agro-climatic zones are specified by the Indian Council for Agricultural Research; see https://www.imdagrimet.gov.in/

crops demands more inputs (cropping intensity) and also type of crop, i.e., food crops versus cash crops which might also influence input expenditures, as cash crops tend to necessitate a higher input level. The presence of water can encourage farmers to grow more crops or opt for crops that require more water (i.e., area irrigated), thus impacting input costs. Gaining technical guidance from sources like innovative farmers, agricultural universities, Krishi Vigyan Kendras, or media outlets can lead to an increase in input expenditures. Apart from these controls, demographic and economic factors like age, monthly per-capita consumption expenditure, education, gender are also used for controlling cofounding effects.

Empirical Strategy

Using the econometric methodology described by Dehejia (2004), Average Treatment Effects (ATE) and Average Treatment Effects on the Treated (ATT) are computed in order to assess the causal impacts of the RBS on agricultural input spending. A direct estimation of ATE can lead to bias as the treatment is non-random in the case of RBS (as the program is specific to a geographic location, policy-driven and inherent systematic dissimilarities that may exists between the states) and hence, ATT is more appropriate to account for selection bias. The ATT measures the expected difference between the observed outcomes of the treated group and their counterfactual outcomes (i.e., what their outcomes would have been had they not received the treatment) as indicated in equation (1).

$$\tau_{ATT} = E(\tau \mid T_i = 1) = E[Y_{1i} \mid T_i = 1] - E[Y_{0i} \mid T_i = 1] \qquad (1)$$

The ATT is difficult to estimate in non-experimental studies since the counterfactual outcome for treated people is not observed. If treatment selection is associated with the outcome variable, using the mean result of untreated individuals as a stand-in may induce selection bias. The untreated group is an imperfect counterfactual for the treated group, which leads to this bias. The treatment effect (τ_{ATT}) can be detected only when the treated and untreated groups do not exhibit systematic variations in their potential outcomes. In quasi-experimental studies one has to invoke some identifying assumptions (such as propensity score matching, PSM) to solve these problems.

PSM estimates the likelihood of an individual being assigned to the treatment group based on a set of observed covariates using either probit or logit model. These calculated probabilities, also known as propensity scores, are then used to pair members of the treatment group with members of the control group who have similar traits. For the analysis, PSM combined with Mahalanobis distance matching on covariates is used. PSM balances observed covariates on the propensity score and Mahalanobis distance matching ensures matching on important covariates within matched pairings choosing the nearest neighbour. Thus, this hybrid strategy reduces bias by providing a type of double robustness, provided that the covariate distance metric or the propensity score model is appropriately set (Rubin and Thomas, 2000). Following the matching procedure, outcome comparisons between the matched pairs are conducted to assess the intervention effect. Heckman et al. (1997, 1998) and Dehejia and Wahba (1999, 2002) indicates that, when matching is performed with precision, PSM can closely approximate experimental conditions. The efficacy of this method is contingent upon the inclusion of a sufficiently comprehensive set of covariates to ensure the proper alignment of treatment and control groups. Conditioning of the propensity score will eliminate the bias in the estimated treatment effect by ensuring the independence of treatment status and covariates. Rosenbaum and Rubin (1983) argue that treatment allocation can still be rendered conditionally random, adhering to the unconfoundedness assumption. Furthermore, conditioning on the propensity score $P(X_i)$ is conceptually equivalent to conditioning directly on X_i (see equation 2). But still, concerns might persist that this adjustment may be insufficient to fully mitigate potential bias arising from imbalances in covariates between the two groups (see columns of Unweighted Means in Table 1).

$$(Y_{1i}, Y_{0i} \perp T_i \mid X_i) \Leftrightarrow \left(Y_{1i}, Y_{0i} \perp T_i \mid P(X_i)\right) \qquad (2)$$

Table 1: Summary Statistics

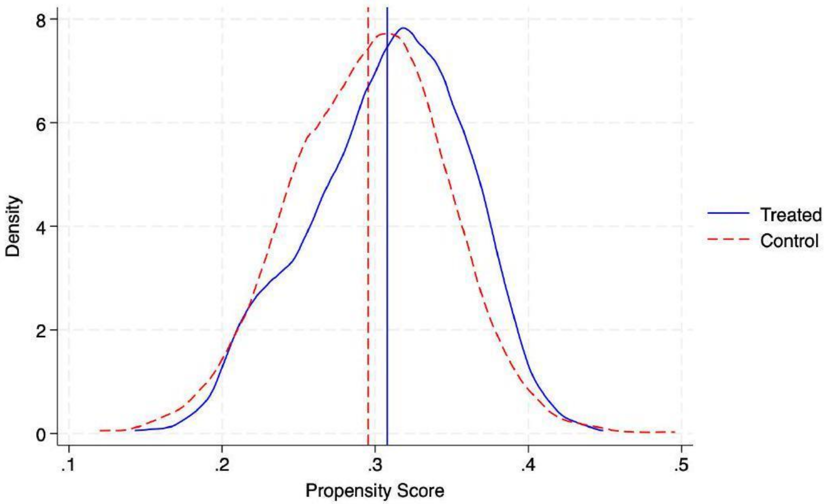
	Unweighted Means			Weighted-SMD		
Variables	**Control**	**Treat-ment**	**P-value**	**Control**	**Treat-ment**	**P-value**
Household Head Characteristics						
Age	51.22	48.92	**0.000**	49.40	48.91	0.380
Gender (Male)	0.901	0.900	0.928	0.900	0.900	1.000
Gender (Female)	0.098	0.099	0.928	0.099	0.099	1.000
Has agricultural training	1.982	1.993	**0.017**	0.994	0.993	0.763
Has formal education	0.537	0.439	**0.000**	0.443	0.439	0.853
Household Characteristics						
Log of MPCE	8.881	8.957	**0.000**	8.953	8.957	0.843
Farm Characteristics						
Land category (marginal)	0.418	0.393	0.189	0.391	0.393	0.925
Land category (small)	0.321	0.309	0.521	0.313	0.309	0.881
Land category (semi-medium)	0.196	0.224	**0.074**	0.222	0.223	0.956
Land category (medium)	0.056	0.066	0.244	0.066	0.066	1.000
Land category (large)	0.007	0.005	0.540	0.005	0.005	1.000
Log of Land irrigated	5.483	2. 149	**0.000**	2.223	2.222	0.702
Number of crops harvested	1.519	1.454	**0.030**	1.404	1.454	0.129
Cash cropss	0.330	0.324	0.731	0.323	0.324	0.961
Others						
Access to technical advice	0.556	0.671	**0.000**	0.671	0.671	1.000
RainfaII (in mm)	357.6	217.3	**0.000**	219.9	217.3	0.623
Observations	2202	942		2202	942	

Note: Weights constructed from estimated propensity score, $p(X)$. Individuals are weighted by $1/p(X)$ in the treatment group and by $1/[1 - p(X)]$ in the control group; p-values in bold indicate significance at 90 per cent or greater. The reduction in covariate imbalance achieved through weighting results in an increase in the p-value.

Source: Author's estimations based on unit record data from NSSO (2018).

Figure 2 shows the kernel density plot of estimated propensity scores for control and treatment groups. The scores for both groups largely fall within the range of common support, indicating that standard regression methods can be appropriately applied to evaluate the impact. The mean propensity score in the Treatment group is 0.30 (solid vertical line) and the mean in the Control group is 0.29 (dashed vertical line) suggesting a sufficient overlap.

Figure 2: Estimated Propensity Scores with Mean lines



Source: Author's own estimations

Since selection based on observables might result in confounding and potentially produce heterogeneous results, conditioning only on X does not yield accurate estimates. Weights are calculated as the inverse of the propensity score in order to overcome this challenge (see equation 3). By applying these weights to the study population, a pseudo-population with confounders uniformly split between the treated and control groups is created. The balance test conducted after weighting provides the Standardized Mean Differences (SMD) between treated and untreated groups show that the both groups are very similar (see Weighted-SMD columns in Table 1). Moreover, this method takes into account every observation in the sample (see Table 2), unlike matching or stratification/blocking techniques where individuals who do not fall under common support are pruned leading to a smaller sample (Sacerdote, 2004). τ_w provides a consistent estimate of the ATE and ATT and is thus a viable alternative to matching or stratifying based on the propensity score (Hirano et al., 2000; Sacerdote, 2004). It is given by:

$$\tau_w \; = E[Y_1] - E[Y_0] = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{T_i Y_i}{p(X_i)} - \frac{(1-T_i)Y_i}{1-p(X_i)}\right] \quad (3)$$

Table 2: Summary of observations after weighting

	Raw	**Weighted**
Number of obs.	3,144	3,144
Treated obs.	942	1,468
Control obs.	2,202	1,676

Source: Author's estimations based on unit record data from NSSO (2018)

Thus, the weighting estimator based on propensity scores, can be combined with regression analysis to enhance the estimation of the treatment effect. By including covariates X in the regression model, this combination helps improve robustness and reduces bias. The regression model is given by:

$$Y_i = \alpha_0 + \tau T_i + \alpha_1 X_i + \varepsilon_i \quad (4)$$

While individual techniques such as PSM or regression adjustment can remove bias, Imbens (2004) contends that combining them improves inference. A consistent estimate of ATE and ATT is provided by the weighted regression model, which guarantees that there is no correlation between treatment and covariates. The regression may produce erratic results if weights are not used making them inconsistent. Consequently, weighted regression (4) is used to increase consistency and provide a robustness check against possible confounding from observable characteristics.

EMPIRICAL FINDINGS AND DISCUSSION

While assessing the impact of RBS on agricultural input spending, it is important to control for other factors that can influence the expenditure on agricultural inputs. The estimates based on equation 4 are reported in Table A2 (see Appendix). The marginal estimates for log of total input spending highlights that as landholding size increases the amount spent on inputs also increases, which is to be expected. Higher crop intensity and the availability of agricultural advice are other factors that contribute to higher spending. Moreover, if the crop is a cash crop the input spending increases. Rainfall is not significant which is likely attributable to the limited variation within the sample due to the smaller sample size and the existence of irrigation, which reduces the reliance on rainfall. In terms of demographic factors, as expected younger and male farmers tend to spend more.

The analysis shows that due to the RBS, total agricultural input spending, which includes a range of costs like those on labour, fertilizer, and seeds, has increased by 36 percent overall, according to ATE estimates (see col. 1 in Table 3). More specifically, imputed input spending has dropped by 40 percent, whereas paid-out input spending has increased significantly by 55 percent and are statistically highly significant. This implies that farmers are changing their spending habits as a result of the cash transfer program by replacing imputed expenses with paid-out expenses. The Average Treatment Effects on the Treated are also calculated to account for potential selection bias, and the results indicate a highly statistically significant 18 percent increase in total input spending (see col. 2 in Table 3). An interesting finding is that the overall imputed expenses show a mammoth dip of approximately 50 percent, attributable to the RBS.

Table 3: Impact of RBS on Total Agricultural Input Spending

	IPW-ATE (1)	IPW-ATT (2)
Log of Total Input Spending	0.368 (0.073)***	0.183 (0.076)***
Observations	3144	3144
Log of Total Paid-out Input Spending	0.556 (0.080)***	0.354 (0.081)***
Observations	3134	3134
Log of Total Imputed Input Spending	-0.401 (0.105)***	-0.499 (0.127)***
Observations	3045	3045

Source: (1) Author's estimations based on unit record data from NSSO (2018); (2) Robust SE clustered at the district level are in parentheses. (3) *** p<0.01, ** p<0.05, * p<0.1

The changes in farming methods brought about by the cash transfer program can be better understood by examining agricultural input spending in greater detail, paying particular attention to important inputs like labour and fertilizer (see Table 4). Contrary to the findings of

Ervin et al. (2017), Handa et al. (2018), and Covarrubias et al. (2012), which indicate that cash transfers cause a reallocation of household labour from agricultural casual labour to own-farm labour, the 30 percent decrease in imputed labor spending in the present study points to a significant reduction in the reliance on family labour for farming (see col. 2 in Table 4). However, this observation is in consonance with the Becker's time allocation theory (1965) which indicate that an increase in non-labour income (here, cash transfer) causes the income effect, due to which the farmers can access more market goods thereby decreasing the expenses on imputed family labour. The 36 percent increase in paid-out labour spending reflects a gradual shift toward a more professionalized and efficient farming operation, where labour is sourced from outside (i.e., market) rather than relying on family members. This shift may be caused by a number of factors, including a decrease in the availability of family members for farming activities (due to household responsibilities, leisure, and reallocation of time etc.), or the ability to afford hired labour – due to the cash transfer. This trend could indicate that farmers are focusing on higher-value activities or diversifying their operations, as hiring labour allows them to scale production regardless of the availability of imputed labour. This change in labour dynamics also has broader implications. Family labour shifting away from farming could affect household labour dynamics and indicate that non-agricultural activities are becoming more significant as a means of diversifying income away from agriculture. Additionally, it implies that farmers are getting more adept at adopting more market-based, organized labour into their farming operations, which may increase productivity and efficiency (Shakeel et al., 2024).

Table 4: Impact of RBS on Agricultural Input Spending – Labour & Fertilizers

	Labour		**Fertilizers**	
	IPW-ATE (1)	**IPW-ATT (2)**	**IPW-ATE (3)**	**IPW-ATT (4)**
Log of Total Input Spending	0.262 (0.076)***	0.135 (0.088)*	0.518 (0.082)***	0.378 (0.086)***
Observations	3071	3071	3002	3002
Log of Paid-out Input Spending	0.473 (0.071)***	0.363 (0.069)***	—	—
Observations	2859	2859	—	—
Log of Imputed Input Spending	-0.173 (0.114)	-0.300 (0.133)**	—	—
Observations	2850	2850	—	—

Source: (1) Author's estimations based on unit record data from NSSO (2018); (2) Robust SE clustered at the district level are in parentheses. (3) *** p<0.01, ** p<0.05, * p<0.1

The analysis indicates that farmers are spending more on inputs due to improved liquidity and resource access, demonstrated by the notable (37 percent) rise in fertilizer expenditures (see col. 4 in Table 4). The increased expenditure on fertilizers indicate that farmers are enhancing their agricultural methods, which is expected to boost yields and this evidence is corroborated by Katewa and Pal (2024). While increased fertilizer use may boost crop yields in the short run, there may be long-term environmental consequences as well. An over-reliance on chemical fertilizers can eventually degrade soil fertility and health because they typically disturb the soil's natural nutritional balance. A trade-off between immediate agricultural output and long-term environmental sustainability may result from this, as local ecosystems and water quality may suffer in the long-run (see Pingali, 2012).

The shift from imputed to paid-out expenditure in the analysis shows that farmers' economic behaviour has altered significantly as a result of the cash transfer program. Farmers are now able to invest more strategically in their agricultural operations because of the availability of resources. Their increased flexibility allows them to purchase additional inputs (such labour, fertilizer, and seeds etc.), which boosts the efficiency and productivity of their farming operations. By boosting liquidity, the program assists farmers in improved resource management and the shift to more formal market-based transactions. As a result, farmers will have access to higher-quality inputs, their operations will be more sustainable (for example, organic farming may be encouraged), and they will be increasingly integrated into the formal agricultural system. For instance, paid labour and purchased seeds might lead to more consistent and efficient production methods, which could increase yields. However, this shift from imputed to paid-out spending may potentially have unanticipated consequences. Imputed seeds come from a variety of traditional, native crops that are sourced locally, offer a greater genetic diversity, and are occasionally better adapted to the local environment. If farmers prioritize commercial cultivars with high yields or more easily accessible inputs, and purchase more inputs from formal markets, there is a risk that this diversity may decrease. This possible decrease in diversity may result in mono-cropping. The post-1960s Green Revolution era, when a few high-yielding crop varieties displaced many traditional ones, that witnessed a decrease in crop-diversity. The study by Pattanayak et al. (2023), is a perfect illustration of this trend. While these high-yield varieties offer more productivity, they often lack resilience to pests and climate change issues, making farmers more vulnerable to crop failures.

ROBUSTNESS CHECKS

A falsification test is performed to evaluate the robustness of the estimated causal impact and rule out concerns regarding spurious correlations or model misspecification. In particular, the analysis incorporates a placebo treatment test (Rosenbaum, 2002; Imbens & Rubin, 2015; Eggers et al., 2024) by randomly assigning half of the sample to pseudo-treatment from the entire sample. By using this technique, it is possible to ensure that the observed effects are actually due to the intervention and not due to systematic biases or unobserved confounders. The results confirm the validity of the intervention impact by showing no statistically significant effect of the program on the pseudo-treatment group (see Table A3 in Appendix). In addition, a sensitivity analysis test is also undertaken using Rosenbaum's (1987) framework to check for unobserved confounding factors in the model. This method evaluates the degree to which treatment assignment would have been impacted by unmeasured confounders in order to jeopardize the reliability of the estimated impacts. The point estimates and confidence intervals' upper and lower bounds progressively diverge as Gamma rises (Gamma is a parameter which quantifies the extent of hidden bias in the model due to unobserved confounders), indicating the raising impact of unobserved factors. Nonetheless, the significance levels and the comparatively tight confidence intervals hold true even at Gamma = 2.0 (see Table A4 in Appendix) implying that the treatment effect is impervious to a reasonable amount of unobserved bias.

CONCLUSIONS

This study analysed the causal effects of RBS on farmers' spending on agricultural inputs in Telangana, India. The results show that farmers are becoming more dependent on paid-out expenditures and moving toward formal market mechanisms as a result of the cash transfers' enhanced liquidity. These findings, however, mostly show immediate effects. It is unclear if these effects will last in the long run. The literature points out that while some program benefits fade after the program ends, others persist. In case of RBS, the program has been in implementation since its inception in 2018, the benefits might have persisted in the long-run as well due to the guaranteed income (i.e., in the form of cash transfer) and the multiplier effect. In terms of available empirical evidence on liquidity-driven expenditure, the observed 18 percent rise in input spending shows a notable short-term boost. Input spending may eventually level out as mostly observed in the literature, necessitating additional research to completely comprehend the program's long-term dynamics. Given that the cash transfer is unconditional, the results from this study demonstrate that the money is being used (at least to an extent) for agricultural purposes as intended by the policy.

The fact that the results are based on Intent-to-Treat estimates, which do not take program non-compliance into account, is one of the study's main shortcomings. This, in turn, could result in a slight margin of bias (Shrier et al., 2014). The other limitation is that treatment status was determined from the observational data using land area as the treatment identification variable. The accuracy of the anticipated treatment effects could be slightly impacted by the possibility that a small percentage of farmers, even though they own land, may not have benefited from the program due to implementation challenges. Further, due to data limitations, important variables like soil fertility and other possible predictors of agricultural input spending are not included in the analysis. Nevertheless, with the control variables considered, the model shows reasonable explanatory power and thus provides credence to the study findings (see Table A2 in Appendix).

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Appendix

Figure A1: Treated and Untreated Parts of Study Area (Agro-climatic zone 10)

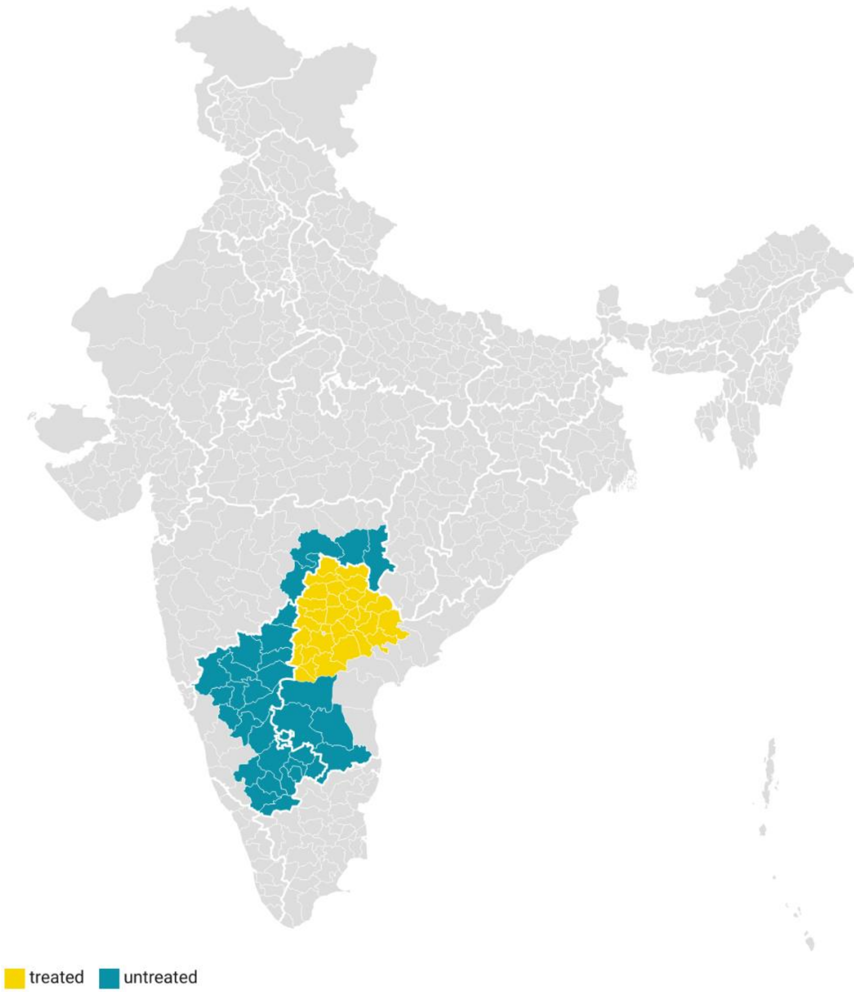

Table A1: Agricultural Cash Transfer Schemes in India

Government	Scheme	Year	Provisions	Spending (% of total expenditure in 2019-20)
Telangana	Rythu Bandhu	2018-19	INR 10000 per acre per year to all land- holding farmers	8%
Andhra Pradesh	Rythu Bharosa	2019-20	INR 13500 per family per year, including tenants	5%
Odisha	KALIA	2018-19 to 2021-22	INR 25000 per family for cultivators over 5 seasons & INR 12500 for landless agricultural households	4%
Jharkhand	Mukhyamantri Krishi Aashirvaad Yojana	2019-20	Marginal and small farmers will be given INR 5000 per acre per year (maximum up to 5 acres)	2%
West Bengal	Krishak Bandhu	2019-20	Farmers with 1 acre or more of cultivable land are entitled to INR 10000 per annum. Farmers with cultivable land holdings of less than 1 acre will get assistance on a pro-rata basis (minimum INR 4000)	1%
India	PM-Kisan Samman Nidhi	2019-20	INR 6000 per annum to all eligible land- holding farmers	2%

Source: Author's compilation from various Government documents.

Table A2: Marginal Estimates of log of Total input spending (Aggregate, Labour, and Fertilizers)

VARIABLES	lntotal (1)	lnlabour (2)	lnfert (3)
UCTA	0.324***	0.243***	0.498***
	(0.0885)	(0.0867)	(0.0862)
Age	-0.00277*	-0.00182	-0.00112
	(0.00145)	(0.00152)	(0.00142)
Gender (base: male)	-0.156**	-0.121**	-0.153**
	(0.0640)	(0.0603)	(0.0589)
Has Agri training	0.0687	0.0917	0.170
	(0.126)	(0.155)	(0.159)
Has formal education	-0.0423	-0.0487	0.00862
	(0.0437)	(0.0469)	(0.0419)
Log of MPCE	0.0254	0.0269	-0.00138
	(0.0374)	(0.0427)	(0.0431)
Land category (base: marginal)			
Land category (small)	0.660***	0.583***	0.716***
	(0.0384)	(0.0364)	(0.0457)
Land category (semi-medium)	1.081***	0.960***	1.148***
	(0.0456)	(0.0499)	(0.0528)
Land category (medium)	1.639***	1.379***	1.734***
	(0.0809)	(0.0887)	(0.0827)
Land category (large)	2.215***	2.092***	2.244***
	(0.170)	(0.178)	(0.267)
Log of land irrigated	-0.0494***	-0.0431***	-0.0382***
	(0.00562)	(0.00561)	(0.00646)
Access to technical advice	0.203***	0.208***	0.0622
	(0.0697)	(0.0739)	(0.0674)

Table continued

Table continued

No. of crops harvested	0.102***	0.0663**	0.0846**
	(0.0261)	(0.0314)	(0.0333)
Cash crop	0.318***	0.142**	0.325***
	(0.0585)	(0.0573)	(0.0673)
Rainfall (JJA)	0.000145	0.000132	0.000389**
	(0.000189)	(0.000198)	(0.000170)
Constant	9.304***	8.254***	7.374***
	(0.375)	(0.417)	(0.451)
Observations	3,144	3,071	3,002
R-squared	0.503	0.370	0.450

Source: (1) Author's estimations based on unit record data from NSSO (2018); (2) Robust SE clustered at the district level are in parentheses. (3) *** p<0.01, ** p<0.05, * p<0.1

Table A3: Marginal Estimates of log of Total input spending for Placebo Treatment group

VARIABLES	lntotal
Placebo_treat	**0.00954** **(0.0235)**
Age	-0.00401** (0.00167)
Gender (base: male)	-0.147** (0.0648)
Has Agri training	0.114 (0.122)
Has formal education	-0.0711 (0.0474)
Log of MPCE	0.0286 (0.0371)
Land category (base: marginal) Land category (small)	0.658*** (0.0378)
Land category (semi-medium)	1.084*** (0.0452)
Land category (medium)	1.651*** (0.0846)
Land category (large)	2.188*** (0.184)
Log of land irrigated	-0.0574*** (0.00578)
Access to technical advice	0.219*** (0.0707)
Number of crops harvested	0.0924*** (0.0251)
Cash crop	0.331*** (0.0622)
Rainfall (JJA)	2.16e-05 (0.000174)
Constant	9.474*** (0.349)
Observations	3,144
R-squared	0.486

Source: (1) Author's estimations based on unit record data from NSSO (2018); (2) Robust SE clustered at the district level are in parentheses. (3) *** p<0.01, ** p<0.05, * p<0.1

Table A4: Results of Sensitivity Analysis

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	10.2685	10.2685	10.2314	10.3056
1.1	0	0	10.2246	10.3123	10.1873	10.3493
1.2	0	0	10.1845	10.3521	10.1471	10.3893
1.3	0	0	10.1477	10.3887	10.1101	10.4261
1.4	0	0	10.1136	10.4225	10.0758	10.4602
1.5	0	0	10.0818	10.4541	10.0440	10.4919
1.6	0	0	10.0524	10.4835	10.0144	10.5215
1.7	0	0	10.0249	10.5111	9.98663	10.5490
1.8	0	0	9.99895	10.5367	9.96048	10.5751
1.9	0	0	9.97454	10.5611	9.93565	10.5995
2	0	0	9.95137	10.5840	9.91236	10.6227

Source: Author’s estimations based on unit record data from NSSO (2018)

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