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Impact of Cash Transfer Program on Time-Use Patterns of Agricultural Households: Evidence from India

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Abstract

While many developing countries, including India, increasingly started using unconditional cash transfers in agriculture (UCTAs) to improve welfare of people, the effectiveness of such policies are still being evaluated. The impact of UCTAs can be evaluated from multiple perspectives, including expenditure on inputs, allocation of time across different activities by the farmers etc. Using data from the 2019 and 2024 NSSO's Time Use Survey, this study aims to investigate the effects of a cash transfer program – *Rythu Bandhu* Scheme - introduced in Telangana on the time use patterns of rural agricultural households.The time allocation in a day has been classified into activities corresponding to four broad categories: System of National Accounts (SNA) (e.g., Employment and Production-related), Extended SNA (ESNA) (e.g., Unpaid domestic services and caregiving), Non-SNA (NSNA) (e.g., Learning, Socialization and Leisure etc), and Self-care (SC) (e.g., Eating, Sleeping etc). The program's causal impacts are evaluated separately for both periods using a Seemingly Unrelated Regression (SURE) framework to address cross-equation residual correlation. Additionally, to address selection bias, Average Treatment effects on the Treated (ATT) has been estimated ignoring residual correlation. The study also employed Propensity Score Matching (PSM), to ensure a valid quasi-experimental design. The 2019 findings demonstrate an initial trend towards more engagement in SNA and SC activities, coupled with a contraction in time spent on ESNA and NSNA activities. This pattern indicates an immediate response to the cash transfer, possibly driven by short-term adjustments in labour supply and household well-being. The 2024 estimates, on the other hand, show time use pattern that is more sustained: households engage more time on NSNA and, to a lesser extent, ESNA activities while spending less time on SNA and SC. These shifts indicate a settling into a new equilibrium facilitated by assured income from the UCTAs, where households diversify their time usage beyond the market production and prioritise leisure, learning, and social activities.

Keywords: Cash Transfers; Agriculture; Time-Use Patterns
JEL Classification: D13, I38, J22, Q18

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Sonna Vikhil
K. S. Kavi Kumar

1 Introduction

While many developing countries, including India, increasingly started using unconditional cash transfers in agriculture (UCTAs) to improve welfare of farmers, the effectiveness of such policies are still being evaluated. The impact of UCTAs can be evaluated from multiple perspectives, including expenditure on inputs, borrowing patterns, land use patterns, allocation of time across different activities by the farmers (particularly, labour supply), etc. The cash transfer programs, whether conditional or unconditional, will directly increase household liquidity with an overall goal of reducing poverty, vulnerability, and improving welfare outcomes (Fiszbein and Schady, 2009; Muralidharan et al., 2023). These cash transfer programs are thought to influence various outcomes of the beneficiary households (Todd et al., 2010; Baird et al., 2011; Asfaw et al., 2014; Banerjee et al., 2017; Baird et al., 2018) as outlined in the respective Theory of Change (ToC) constructed for the particular program. The idea of ToC is frequently used in the literature and is crucial in impact evaluation studies since it outlines the mechanisms, causal links, pathways, and underlying assumptions regarding the process of change (Browne, 2013). ToC is usually developed in accordance with the policy context and changes with the policy objective. The ToC for the UCTA program under evaluation in this study i.e., *Rythu Bandhu* Scheme (RBS) implemented by the state government of Telangana (India) was adapted from Vikhil and Kumar (2025). In the ToC for RBS, Vikhil and Kumar (2025) delineate the causal pathways that this cash transfer program might have on various outcomes and one among of them is the impact on time-use (TU) patterns (see Figure 1).

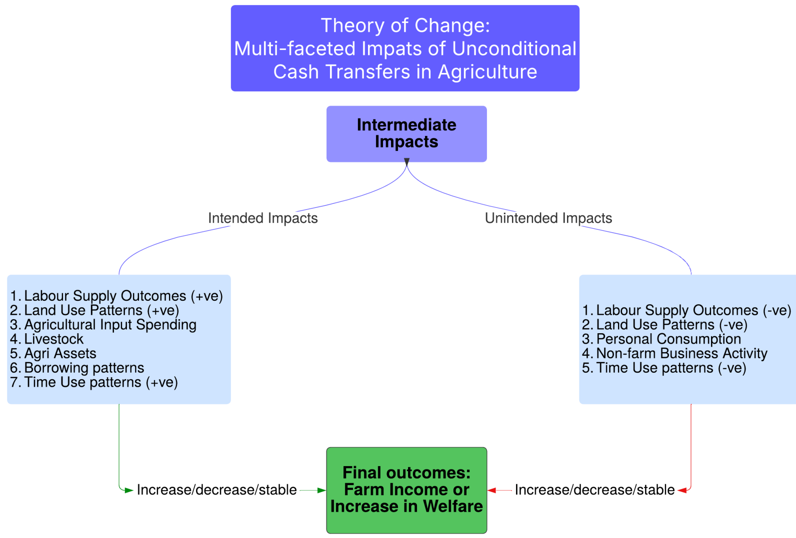
In general, unconditional cash transfers (UCTs) provide more flexibility in resource allocation than conditional transfers, enabling beneficiaries to address their most urgent needs. Numerous studies have examined their effects on asset accumulation, education, health, and consumption (Daidone et al., 2019; Bastagli et al., 2016). However, the implications of such transfers on intra-household time allocation – specifically, labour supply, unpaid domestic work, and leisure activities etc., among various household members received comparatively less attention. Cash Transfers (CTs[1]) have the ability to change leisure, caregiving, and work participation choices by easing financial constraints and delivering steady income. Thus, to assess the complete welfare impact of cash transfers, it is imperative to comprehend these

[1]The terms CTs and UCTs are used interchangeably in the initial sections of this paper for ease of discussion.

effects. Antonopoulos and Hirway (2010) in their study noted that time-use is becoming more widely acknowledged as a multifaceted measure of well-being that reflects not only economic output but also freedom and quality of life. The importance of time-spent on non-work activities that enhance economic welfare was highlighted by Becker (1965) and other studies (e.g., Mincer, 1962; Owen, 1971). Time-use data has been utilized in various empirical studies to investigate gender differences in unpaid labour, labour productivity, and educational outcomes etc. (Hirway and Jose, 2011; Janiso et al., 2021; Gibson and Shrader, 2018; Stinebrickner and Stinebrickner, 2004). Given the importance of analysing TU patterns, researchers' efforts to assess these patterns have gained traction over time. The relation between TU patterns and cash transfer programs has garnered interest in recent years; nevertheless, a few studies exist, while those that do predominantly concentrate on time allocated to work-related activities. These studies rarely examine the amount of time people spend on care, leisure, or socialization etc., in the presence of such transfers. However, in the context of India, modelling such interactions is still in its infancy due to several limitations. Firstly, with UCTs being a recent phenomenon, even the first nationwide Time Use Survey was carried out only in 2019, posing significant data challenges. Secondly, there are also challenges associated in finding a valid counterfactual group in the quasi-experimental framework.

The current study uses Singh et al. (1986) Agricultural Household Model as a linkage to understand how cash transfer programs affect the decisions of agricultural households. According to the Agricultural Household Model, the agricultural households make decisions pertaining to the production and consumption processes jointly by optimizing the distribution of time and resources among various activities subject to budget constraints, labour availability, and imperfections in the market. The unconditional transfers, which function as exogenous non-labour income shock, are expected to impact the consumption–leisure trade-off, labour supply decisions, and the distribution of time between domestic and agricultural responsibilities, all of which are key behavioural dimensions that the Agricultural Household Model captures.

In light of these considerations, the current study assesses the impact of *Rythu Bandhu* Scheme, an unconditional cash transfer program introduced by the Government of Telangana (India) in 2018 on the TU patterns of agricultural households using two rounds of National Sample Survey Office's (NSSO) Time Use Survey (TUS) (2019 and 2024). The



Source: Adapted from Vikhil and Kumar (2025)

Figure 1: Theory of Change for UCTA

program targets agricultural households and offers timely liquidity support through providing a certain amount per acre of land owned. The study uses two popular analytical techniques: Generalized Structural Equation Modelling, which enables the simultaneous estimation of multiple interrelated equations involving both observed and latent variables, and Propensity Score Matching, a well-known quasi-experimental technique for estimating causal effects. The findings suggest that immediately after the implementation of UCT program (i.e., in 2019) the time spent on employment activities has increased by a substantial percentage, whereas with sustained implementation of UCT program (i.e., in 2024) the time allocated to leisure has spiked up significantly indicating negative labour supply.

The remainder of the paper is organized as follows: an overview of the pertinent literature is presented first, then the data and empirical approaches are described. The short-run and long-run results are discussed in detail in the results section. Conclusions and policy implications are given in the final section.

2 Literature Review

According to Household Time Allocation models, individuals, given time and budget constraints, allocate time among a variety of activities, including paid employment, leisure, and domestic work etc., in order to maximize utility (Becker, 1965; Ghez and Becker, 1975). Given that wages remain constant, an increase in non-labour income (due to cash transfer) eases the budgetary constraint and leads to a pure income effect. This could lead people to reallocate their time from paid employment to leisure, household duties, or other non-market activities, as per standard labour-leisure trade-off argument. However, this model overlooks several kinds of market failures that could be addressed by the provision of cash transfers. CTs can reduce credit constraints in emerging and underdeveloped nations, allowing households to invest in productive activities which could drive how time is allocated and in turn boosts the labour supply (Gertler et al., 2012; Asfaw et al., 2014; Baird et al., 2018; Daidone et al., 2019). Banerjee et al. (2017) argues that the theoretical effect of CTs on work is thus ambiguous, suggesting that both the sign and magnitude of the treatment effects may be driven by the details of the program design (e.g., the targeting methods, the size of the transfers), as well as the underlying economic conditions. Therefore, it is important to analyse the effects of CTs empirically and document evidence across a variety of contexts.

2.1 Empirical Evidence

Cash transfer programs implemented across the globe are primarily intended to improve the human capital outcomes. Originally, the CT program were implemented in the Latin American and Sub-Saharan Africa regions. Existing research on cash transfer programs has mostly concentrated on Conditional Cash Transfers (CCTs), analyzing their short-term or immediate effects, particularly on health, education, and labour supply (Fiszbein and Schady, 2009; Bastagli et al., 2016). These studies largely highlight the ways in which conditionalities affect household behaviour by mandating particular behaviours, like going to school or getting regular checkups, which has short-term, measurable effects. However, this focus has led to significant gaps in understanding broader behavioural changes, such as, how households allocate their time away from formal work towards other activities such as domestic work, leisure etc. Even though cash transfers are important for overall welfare, particularly in rural and low-income contexts, very little attention has been paid to how they affect non-market activities including leisure, unpaid domestic labour etc. (Antonopoulos and Hirway, 2010; Gustavo and Monica, 2015). Although some studies has examined shifts in the dynamics of household labour and the distribution of time within households (Gammage, 2010; Hidrobo et al., 2016), it is still not common to explicitly analyze time-use patterns as outcomes. As such, the literature on assessing the effects of unconditional cash transfers, where responses from individuals may vary as there are no imposed compliance constraints, is very scanty.

The existing literature on the association between CTs and TU patterns, particularly, labour supply, are inconsistent and context-dependent. According to a significant amount of empirical research, cash transfers do not significantly affect labour supply patterns adversely, with a few studies reporting null or positive effects (Baird et al., 2018; Banerjee et al., 2017; Handa et al., 2018; Alzúa et al., 2013, Bandiera et al., 2017, Salehi-Isfahani and Mostafavi-Dehzooei, 2018; Gustavo and Monica, 2015). The studies conducted while evaluating several CCT programs in the Latin American countries have yielded inconclusive findings for wage employment participation. For instance, no statistically significant change in adult labour market participation following CCT interventions was found, as noted by Parker and Skoufias (2000), Teixeira (2010), Maluccio (2010), and Ribas and Soares (2011). These results suggest that either the transfer amounts are insufficient to substantially alter economic behaviour or the behavioural characteristics linked to transfers, like school attendance or health visits, do not directly affect the amount of time spent on labour-related activities. In contrast, other studies have revealed that beneficiaries exhibit a negative effect of labour supply, indicating that even modest and conditional non-labour income increase can have a significant effect on time spent on working (Maluccio and Flores, 2005; Hasan, 2010). This is in accordance with the standard labour supply theory, which elucidates that households may work less hours and spend more time on leisure or household duties when they have more non-labour income.

The evidence pertaining to UCTs also shows a similar mixed evidence. Evidence from several studies suggests that there is no proof that receiving unconditional payments results in any labour market disincentives (Gilligan et al., 2009; Asfaw et al., 2014; Banerjee et al., 2017; Baird et al., 2018). However, Covarrubias et al. (2012) reported reduced participation in low-skilled wage labour in Malawi, indicating an increased availability of the household for other activities, such as home-based agriculture. On the other hand, Ardington et al. (2009) found the positive effects of labour supply while studying CTs to elderly in South Africa which had significant spillover effects among prime-aged adults.

Although the majority of research on cash transfers discussed above focused on labour market engagement, it can be perceived that the increase in labour market engagements lead to an increase in time-spent in that activity. An increasing amount of research has begun to look at how CTs affect time-use patterns, namely leisure, childcare, and household work etc. According to Hidrobo et al. (2020), CTs can have a favourable impact on leisure time, particularly for women living in low- and middle-income countries. This suggests that welfare-enhancing behavioural changes may occur in response to increased household liquidity. Gustavo and Monica (2015) also noted an increase in time spent on leisure activities, whereas Hidrobo et al. (2020) found increase in the caregiving responsibilities undertaken by women after receiving transfers, and Hasan (2010) records increased time spent on childcare and domestic tasks in Bangladesh. Additionally, Molyneux and Thomson (2011) investigated the effects of CCTs on women's roles and unpaid caregiving and domestic work in Peru, Ecuador, and Bolivia. They observed that women are now more burdened with unpaid caregiving and domestic tasks as a result of CCTs. Women usually take up responsibility for meeting program requirements, such as school attendance or child health examinations. Because of this, women spend more time taking care of others and taking care of the home, which reinforces traditional gender roles.

Whether the CTs are unconditional or conditional, these disparate findings highlight the intrinsic heterogeneity in program outcomes. Numerous reviews by Banerjee et al. (2017) and Daidone et al. (2019) highlight how program design (conditional vs. unconditional), transfer amount and frequency, household structure, local labour market dynamics, and cultural norms interact in a complicated way to impact on how cash transfers affect time allocation towards paid work, unpaid labour, or leisure. For example, although the direction and amount of impacts vary significantly that even modest transfers can affect gender roles, time allocation, and intra-household bargaining. Further demonstrating the context-dependence of time-use patterns, Osei and Lambon-Quayefio (2021) show that CTs in Ghana reduced the burden of unpaid labour while increasing the engagement of women in informal employment suggesting that the CTs enabled women to reallocate their time more productively.

Even though, the literature remains inconclusive, it is widely acknowledged that CTs affect behavioural aspects like time allocation in addition to material effects such as income. To map the entire range of these effects, more rigorous and systematic study is required, especially in understudied regions like South Asian countries and particularly, India, where leisure and unpaid labour are significant yet often overlooked. In order to better understand these processes, a nuanced and context-specific analytical approach is necessary, particularly when looking at time-use pattern as a multifaceted welfare indicator and acknowledging that income is not the only aspect of well-being. Thus, using the survey data from two rounds of NSSO's Time Use Survey (2019 and 2024), this study tries to fill in the gap in literature by looking closely at the impact of unconditional cash transfers on how people spend their time in various areas, such as work, leisure, self-care, and unpaid household duties etc. This analysis adds significantly to the body of existing literature and has major implications for policy. First of all, it contributes to the field of research on how cash transfers affect the labour market in lower-income nations (Banerjee et al., 2017, Bastagli et al., 2019; Ervin et al., 2017; Gertler et al., 2012; Daidone et al., 2019; Salehi-Isfahani and Mostafavi-Dehzooei, 2018). Second, this study adds to the literature on the effects of cash transfer programs on labour dynamics among agrarian economies (viz., India) by focusing on agricultural labour supply and time-use of rural households – which is still understudied in comparison to effects on consumption, health, or education (Baird et al., 2014; Banerjee et al., 2017; Bastagli et al., 2016). Finally, this study contributes to the nascent field of research by examining how observed time allocation is impacted by exogenous income shocks (via transfers), thus providing empirical support for the behavioural underpinnings of Agricultural Household theory. The results based on two separate rounds of Time Use Survey – one immediately after the implementation of CTs, and the other after sustained implementation of the transfers – are explained through the underlying income and substitution effects by analyzing both short-run and long-run behavioural responses due to the effect of CTs. This is in contrast to the significant amount of the existing research, which mostly concentrates on immediate or short-run impacts (Haushofer and Shapiro, 2016; Banerjee et al., 2017; Handa et al., 2018).

3 Cash Transfer Program: Rythu Bandhu Scheme

On May 10, 2018, the state Government of Telangana, India introduced the "Agriculture Investment Support Scheme" for farmers in the state, known as the *Rythu Bandhu* Scheme (RBS) (rechristened as *Rythu Bharosa* starting from 2024–25). The RBS program in Telangana is the first UCTA program in India to be launched as an unconditional investment assistance program for farmers. RBS's stated goal is to "provide investment support of INR 4,000 per acre per season[2] (enhanced to INR 5,000 since 2019-20 & later to INR 6,000 since 2024-25) to all farmers (*Pattadars*[3]) 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 limit to the amount of acres that can be funded. For instance, a farmer with one acre would receive INR 12,000 per year, divided into equal instalments of INR 5,000 over the two cropping seasons (*Kharif* and *Rabi*). All landowners are included by the program, regardless of whether they are actively farming or not. The amount disbursed is unconditional, giving farmers complete control over how they utilize it. The money may be used for personal consumption and other expenses of their choice, or it may be used for things like buying seeds, fertilizer, equipment, and labour etc. The RBS was expected to cost between INR 12,000 and 15,000 crores every agricultural season. This represents 1.5 to 1.7 percent of Telangana's GDP, and 7 to 8 percent of the state budget each year (Government of Telangana, 2023).

The Telangana Land Reforms (Ceiling on Agricultural Holdings) Act,[4] 1973, prohibits any individual from owning more than 27 acres of wetland or 54 acres of dryland, thereby limiting the potential for further disparity when RBS benefits are distributed. Furthermore, only 0.20 percent of all farmers are classified as large farmers, and they account for just 2.30 percent of the total agricultural landholdings (Government of Telangana, 2018). During the 2018–19 *Kharif* season, the first instalment was distributed via cheques, enabling farmers to withdraw the funds directly from banks. However, since the 2018–19 Rabi season, payments have been transferred automatically to farmers' bank accounts through the Direct Benefit

[2]The disbursements are made for two seasons in a year (*Kharif* – which commences around June and *Rabi* – which commences around December). The annual sum received under the program thus amounts to INR 12,000 per acre (in 2024-25).

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

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

Transfer (DBT) mechanism. Tenant farmers are excluded from the scheme to avoid potential legal challenges under the tenancy laws, specifically those outlined in the Hyderabad Tenancy and Agricultural Lands Act,[5] 1950. With the digitization of land records and the introduction of new *Pattadar* passbooks, the process has been streamlined, allowing the government to effectively transfer benefits directly to farmers' bank accounts (Thomas et al., 2020).

4 Data and Empirical Strategy

The study uses observational data from two rounds of the National Sample Survey Office's (NSSO) Time Use Survey (TUS) — conducted in 2019 and 2024 — to investigate the effects of a cash transfer program — RBS — introduced in Telangana in 2018, on the time-use patterns of rural agricultural households. In India, the nationally representative TUS was first implemented in 2019 and repeated in 2024. Prior to this, a pilot study was conducted in 1998, though it was limited to six states.

Time-use data were recorded for all individuals aged 5 years and above over a 24-hour reference period, spanning from 4:00 a.m. on the day preceding the survey to 4:00 a.m. on the day of the survey, in thirty-minute intervals. Respondents were asked to report the time spent on various activities undertaken during this reference period, and each activity was coded according to the ICATUS[6] (2016) classification. The dataset also includes demographic, socio-economic, and household-level characteristics. The UCTA program in Telangana was implemented in 2018, the TUS data from 2019 facilitates analysis of short-run impacts of the program, and the estimates based on 2024 TUS data offer a long-run perspective.

As outlined by Neetha and Rajni (2010), the time allocation in a day has been classified into activities corresponding to three broad categories: System of National Accounts (SNA) – e.g., employment and related activities and production of goods for own final use, Extended-SNA (ESNA) – e.g., unpaid domestic services for household members, unpaid caregiving services for household members, and Unpaid volunteer, trainee, and other unpaid work, and Non-SNA (NSNA) – e.g., learning, socializing and communication, commu-

[5] https://www.indiacode.nic.in/bitstream/123456789/8575/1/act_21_of_1950.pdf

[6] The International Classification of Activities for Time-Use Statistics (ICATUS) 2016 is a global framework for classifying time-use activities. See https://unstats.un.org/unsd/classifications/Family/Detail/2083 for more details.

nity participation, and religious practise, culture, leisure, mass media and sports practices.[7] In addition, Self-Care (SC) – e.g., eating, sleeping, self-maintenance, and personal care, which was embedded in NSNA was also treated as a separate category. As Maheshwari and Viswanathan (2025) note, SC can dominate total time use, so it has been excluded from NSNA to capture other leisure activities. This study focuses on the TU patterns among these above-mentioned categories.

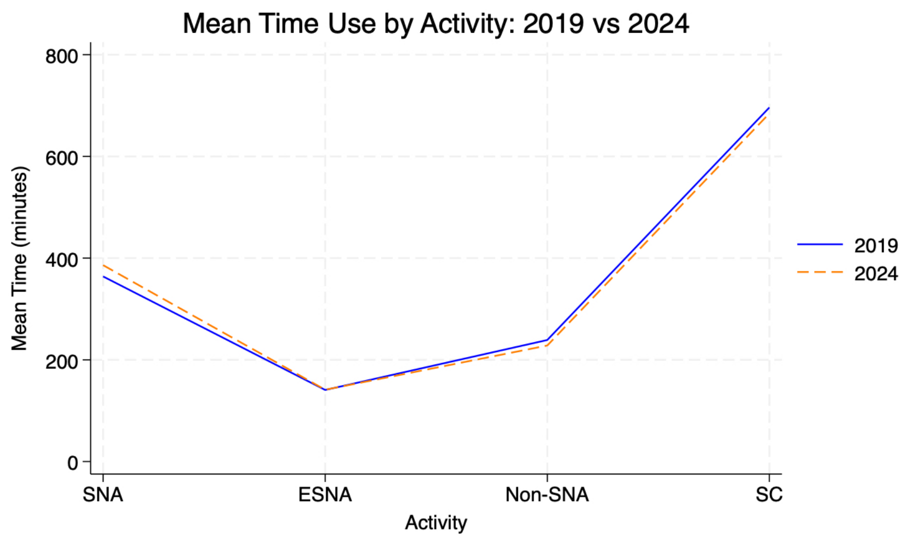


Figure 2: Mean Time Use by Activity in 2019 and 2024 in the Study Area

For sample validity, a specific study area was identified, and a subset of observations was excluded due to attrition, ensuring the reliability and consistency of the analytical sample. The study area comprises individuals from Telangana and its bordering districts in states such as Karnataka, Chhattisgarh, and Maharashtra. Andhra Pradesh, which also shares a border with Telangana, was excluded from the analysis due to the implementation of a similar cash transfer program within the state, which could confound the evaluation. The program's causal effects are assessed separately for 2019 and 2024 for the individuals in same study areas (i.e., a repeated cross-section). The Figure 2 compares the mean amount of time spent on the main activity categories (SNA, ESNA, NSNA, and SC) between 2019 and 2024 for the study sample comprising both treated and untreated groups. The TU pattern

[7] In the subsequent analysis, paid work, unpaid domestic work, and leisure are used synonymously with SNA, ESNA, and NSNA activities, respectively, as they form the major chunk of these TU categories.

remained relatively stable over the two periods. This implies that the study populations in 2019 and 2024 allocate their time in a manner that is essentially similar, supporting the notion that there haven't been any significant changes in the composition of activities. This provides validation that the study populations remained similar over two time periods for a causal inference. This reduces the risk of baseline bias and yields appropriate estimates that can be aligned to the treatment effect.

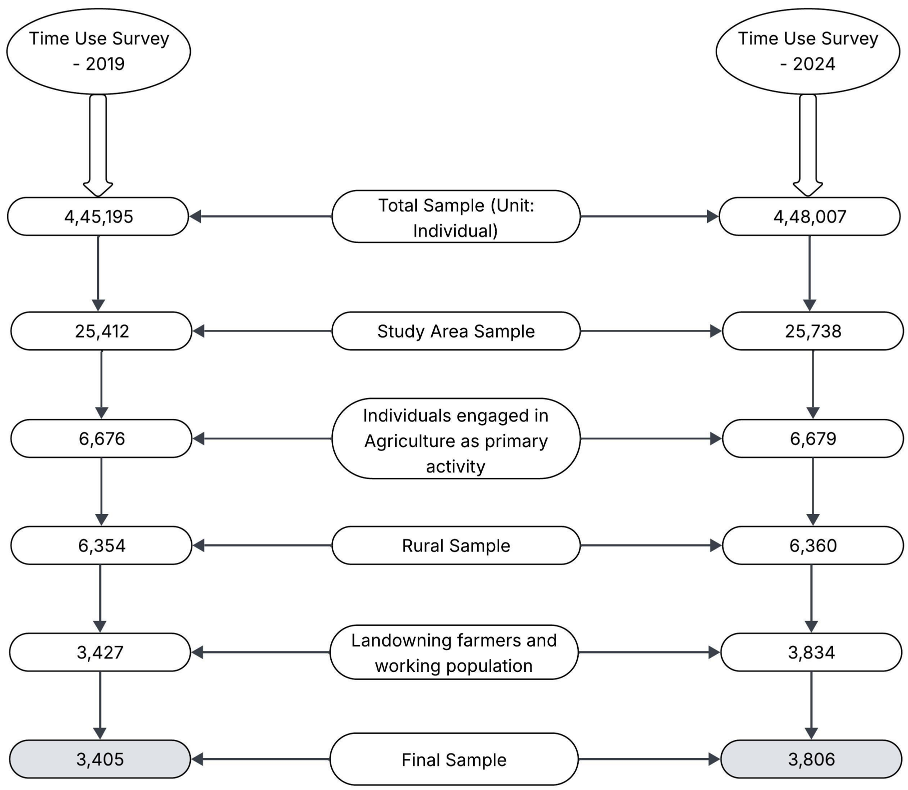


Figure 3: Exclusion Criteria Used and Sample Size – 2019 and 2024

The analysis focuses exclusively on individuals from rural areas, particularly engaged primarily in agriculture, as they are the primary beneficiaries of the cash transfers under consideration. Rural households typically face higher levels of income volatility, limited access to formal employment, and a greater reliance on unpaid labour, making them more sensitive to policy-induced changes in time allocation. Moreover, time-use dynamics in rural settings are distinct from urban contexts, where market integration, infrastructure, and opportunity costs differ significantly. The RBS is implemented for landowning farmers in the state, thus, landless farmers and tenant farmers are excluded from the sample as they do not receive the program benefit. Figure 3 shows the exclusion criteria followed and the sample attrition for the years 2019 and 2024.

4.1 Empirical Strategy

This study investigates how a cash transfer program affects rural agricultural households' time-use allocations among various categories. Prior to the regression analysis, this work has adopted a popular quasi-experimental design, viz., Propensity Score Matching (PSM), to ensure a valid causal inference design by identifying a proper counterfactual group. After the counterfactual group, which is similar in the observed characteristics to the treatment group, is established, the study used two empirical frameworks to estimate the unbiased causal impacts of the UCT program on TU patterns.

The two empirical frameworks employed in the analysis are: First, Generalized Structural Equation Modelling (GSEM) as specified by Skrondal and Rabe-Hesketh (2004) is used. The GSEM framework incorporated the Seemingly Unrelated Regression Equations (SURE) model as proposed by Zellner (1962), to jointly estimate multiple dependent variables (see equation 1) by explicitly modelling the residual correlation. This framework allows for the presence of correlated error terms across equations because time allocations for different activities such as labour, leisure, and domestic work etc., are jointly determined and may share unobserved factors (e.g., household preferences, seasonal variations), thereby improving estimation efficiency when outcomes (namely, the time spent on different activities) are interrelated (see Tables A2 and A3 in Appendix for residual correlation matrix). The reason for estimating SURE model within GSEM is, when estimating the causal impacts, the traditional SURE model poses challenges in the use of sample or treatment weights in the model. Thus, estimating SURE model within GSEM framework offers more reliable and effective estimates while accounting for associated cross-equation residual correlation (Wooldridge, 2010).

$$y_{ik} = \alpha_k + \beta_k D_i + \gamma_k \boldsymbol{X}_i + \varepsilon_{ik}, \quad k = 1, 2, \ldots, K \tag{1}$$

$$\mathrm{Cov}(\varepsilon_{ik}, \varepsilon_{il}) = \sigma_{kl} \quad \text{for } k \neq l$$

where:

- y_{ik} denotes the time spent on activity k (i.e., SNA, ESNA, NSNA, and SC) by individual i,
- $D_i \in \{0, 1\}$ is a binary treatment indicator equal to 1 if the household received the cash transfer and 0 otherwise,
- $\boldsymbol{X}_i$ is a vector of observed covariates,
- $\varepsilon_{ik} \sim \mathcal{N}(0, \sigma_k^2)$ are error terms, which are correlated across k.

Second, the study also investigated separate equation estimations for each time-use outcome category by employing the treatment effects combined with Inverse Probability Weighting with Regression adjustment (IPWRA) technique. This is largely due to the computational limitations within the GSEM framework to apply complex weights in the model which could bias the estimates. However, as mentioned above, ignoring cross-equation residual correlation could lead to efficiency loss if not estimated simultaneously. In this context, it is important to establish some literature to corroborate the separate estimation of different TU categories using treatment effects is also valid under few circumstances with certain compromises. Zellner (1962) notes that each outcome equation estimated separately will yield consistent results but less efficient. Zellner (1962) also notes if the joint estimation is not feasible due to the computational challenges, the outcome equations that are estimated separately would yield valid, albeit potentially less efficient estimates. Few other studies also argue that the efficiency loss from the estimation of multiple outcome equations is negligible when the explanatory variables are more or less similar across multiple outcome equations or if the residual correlations are modest (Balestra and Nerlove, 1966; Theil and Fiebig, 1979; Judge et al., 1991; Bartels and Fiebig, 1992).[8] Dwivedi and Srivastava (1978) also

[8] In this study, to maintain comparability and capture common structural determinants, most of the explanatory variables, including household-level characteristics and demographic controls, are consistently included in all outcome equations; however, some outcome equations include additional variables. These additional explanatory variables used are exclusively applicable to specific time-use categories. This strategy maintains a balance between flexibility and comparability, enabling the model to incorporate outcome specific time-use categories. Given that majority of the explanatory variables remain common across multiple outcome equations and residual correlations being moderate (see Tables A2 and A3 in Appendix for residual correlation matrix), the efficiency loss due to separate equation estimation is likely to be minimal.

analysed the optimality of least squares in SURE framework and concluded that separate estimation is acceptable when joint estimations poses computational challenges.

The results obtained from either SURE or GSEM models will be Average Treatment Effect (ATE) estimates which could lead to bias when selection problem is present.[9] In order to mitigate this bias, the GSEM needs to incorporate the Average Treatment Effect on the Treated (ATT) weights derived using propensity scores in the model. Still, this will not yield the doubly robust estimates as IPWRA does. In which case, inverse probability weights have to be accounted in the GSEM model which is technically not feasible. Due to GSEM's limitations in handling complicated survey weights or post-estimation reweighting, it is challenging to address selection bias changes in this framework which necessitates to estimates equations independently using treatment effects (i.e., IPWRA).

Given these limitations with the joint estimation of multiple outcomes using the GSEM framework—an alternative strategy has been adopted. In particular, the IPWRA method, which is implemented via the *teffects ipwra*[10] command in Stata can be used to estimate separate equations for each of the four outcome categories. This method addresses potential selection bias more robustly by integrating outcome regression model with propensity score weighting to enable consistent estimation of the ATT. Additionally, estimating each result independently allows for flexible model definition and covariate adjustment while avoiding the processing complexity associated with systems of equations. Despite modelling trade-offs, the estimations using equation 2 offers a realistic and theoretically supported substitute that guarantees reliable treatment impact estimations.

$$y_i = \alpha + \tau D_i + \gamma \boldsymbol{X}_i + \varepsilon_i \tag{2}$$

where:

- y_i denotes the time spent on each TU activity (i.e., SNA, ESNA, NSNA, and SC) by

[9]The estimates of ATE under selection bias tends to be inaccurate as the basic premise of similarity between treated and untreated groups has been compromised. When individuals self-select into treatment based on observed or unobserved attributes, the ATE requirement that the untreated group function as an appropriate counterfactual for the treated group is compromised (Heckman et al., 1997). Consequently, naive cross-group comparisons will be unable to identify the treatment's causal impact. In these situations, the ATT, which solely considers the treatment impact for those who actually received the intervention, is considered as a more relevant metric. ATT reduces selection bias and offers policy-relevant insights for assessing targeted programs by limiting the analysis to treated units and creating a counterfactual using observational techniques like matching, inverse probability weighting, or synthetic control (Imbens and Wooldridge, 2009). Consequently, the ATT provides a more accurate assessment of causal effects than the ATE in observational studies with non-random treatment assignment.

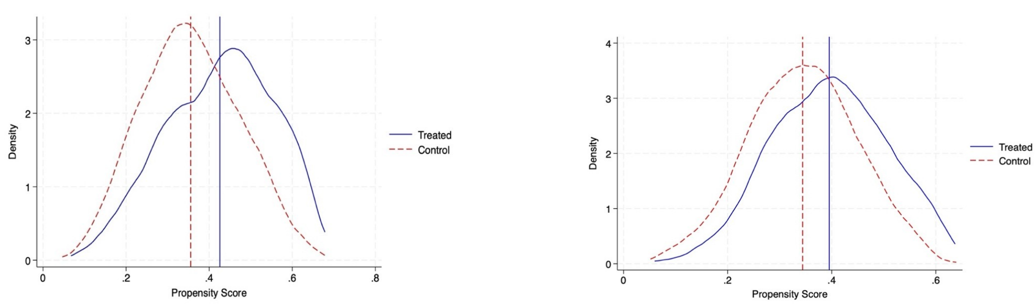
[10]Methodological note on Treatment effects (IPWRA) is discussed in the Appendix (not yet appended).

individual i,

- $D_i \in \{0, 1\}$ is a binary treatment indicator equal to 1 if the household received the cash transfer and 0 otherwise,
- $\boldsymbol{X}_i$ is a vector of observed covariates,
- ε_i is the error term.

5 Results and Discussion

As mentioned in the empirical strategy, there were possible computational difficulties, such as model non-convergence in the GSEM framework and the model's inability to apply IPW during estimation. These estimates should therefore be interpreted cautiously. Therefore, the discussion here is based on estimations derived from individual outcome equations ignoring residual correlations, in accordance with empirical guidelines as mentioned in the previous section. These results were estimated using the propensity score matching framework combined with Inverse Probability Weighted Regression Adjustment (IPWRA) method. The ATT estimates are derived from this analysis to account for the potential selection bias which is prevalent in quasi-experimental studies. The GSEM estimates are also presented along with the individual equation results estimated using *teffects ipwra* for the purpose of comparison. It is observed that the efficiency loss from disregarding residual correlation is insignificant, as evidenced by the small differences between the two sets of estimates.



(a) 2019 (b) 2024

Figure 1: Common support region based on TUS sample for 2019 and 2024

It is important to show the treatment and control groups' summary statistics before and

Table 1: Covariate Balance before and after Matching – TUS Sample, 2019

Variables	**Means – Unmatched sample**			**Means – Matched sample**		
	Treated (1)	Control (2)	p-value (3)	Treated (4)	Control (5)	p-value (6)
Age	39.78	38.21	**0.000**	39.78	39.44	0.425
Male	0.548	0.588	**0.025**	0.548	0.537	0.554
Female	0.452	0.412	**0.025**	0.452	0.463	0.554
Married	0.871	0.826	**0.000**	0.871	0.875	0.813
Unmarried & Others	0.129	0.174	**0.000**	0.129	0.125	0.813
Hindu	0.974	0.973	0.742	0.974	0.977	0.702
Muslim	0.018	0.021	0.541	0.018	0.010	0.093
Other Religion	0.008	0.007	0.704	0.008	0.013	0.176
Small Farmer	0.753	0.717	**0.021**	0.753	0.753	1.000
Medium & Large Farmer	0.247	0.283	**0.021**	0.247	0.247	1.000
log(MPCE)	8.982	8.867	**0.000**	8.982	8.991	0.627
Proportion Child	0.092	0.104	**0.037**	0.092	0.092	0.998
Proportion Elderly	0.024	0.044	**0.000**	0.024	0.028	0.241
Years of Education	3.790	5.482	**0.000**	3.790	3.862	0.695
Observations	1,291	2,114		1,291	2,114	

Note: (1) p-values greater than 0.05 indicate both groups are indifferent.

after propensity score matching prior to proceeding on to the discussion of the estimated causal effects. This initial stage reduces selection bias by confirming that the matching process has effectively balanced the covariates between the two groups reinforcing that both the groups are indifferent in all observed characteristics except the treatment. Prior to matching, slight differences were observed in key covariates. Nonetheless, post-matching diagnostics show a significant improvement in covariate balance, with the majority of variables showing a significant reduction in the mean differences (see Tables 1 and 2). Additionally, standardized mean differences (SMD) are also checked for all the covariates as seen in Figures A1 and A2 in Appendix. The figures show that the SMDs have reduced significantly after matching for the both the groups compared to before matching.

Using the propensity scores estimated from the discrete choice probit model (see Table A1 in appendix) for the treatment and control groups, the degree of overlap or common support is plotted. According to Rosenbaum and Rubin (1983), the matching requirement is met when there is a visible overlap between the two curves, which allows reliable counterfactual comparisons. From the both panels in Figure 4, it is evident that sufficient common support (or overlap) exists for 2019 and 2024 allowing the valid causal inference frame-

Table 2: Covariate Balance before and after Matching – TUS Sample, 2024

Variables	**Means - Unmatched sample**			**Means - Matched sample**		
	Treated (1)	Control (2)	p-value (3)	Treated (4)	Control (5)	p-value (6)
Age	40.74	39.82	**0.010**	40.74	40.24	0.223
Male	0.565	0.604	**0.019**	0.565	0.530	0.065
Female	0.435	0.396	**0.019**	0.435	0.470	0.065
Married	0.878	0.845	**0.005**	0.878	0.872	0.644
Unmarried & Others	0.122	0.155	**0.005**	0.122	0.128	0.644
Hindu	0.970	0.949	**0.002**	0.970	0.950	**0.006**
Muslim	0.008	0.028	**0.000**	0.008	0.013	0.191
Other Religion	0.022	0.023	**0.840**	0.022	0.037	**0.018**
Small Farmer	0.762	0.707	**0.000**	0.762	0.752	0.562
Medium & Large Farmer	0.238	0.293	**0.000**	0.238	0.248	0.562
log(MPCE)	9.365	9.278	**0.000**	9.365	9.386	0.189
Proportion children	0.080	0.087	0.151	0.080	0.075	0.292
Proportion elderly	0.062	0.086	**0.000**	0.062	0.068	0.191
Years of Education	5.034	6.175	**0.000**	5.034	5.072	0.834
Observations	1,367	2,439		1,367	2,439	

Note: (1) p-values greater than 0.05 indicate both groups are indifferent.

work. Nonetheless, the non-identical distributions implying some imbalance were trimmed to enhance the credibility of counterfactual comparative analysis (Wooldridge, 2010; Stuart, 2010). Trimming makes sure that the weighting and outcome models are estimated on a similar sample, which improves IPWRA's double robustness feature. According to Caliendo and Kopeinig (2008), ensuring this overlap is crucial to minimizing bias in causal inference based on propensity scores.

A variety of control variables are incorporated into the analysis to precisely assess the program's causal impact on individual time-use outcomes. Given their known impact on time allocation and labour-leisure trade-offs as evidenced in the labour economics literature, individual-level factors like age, gender, marital status, and educational attainment are taken into consideration. Although labour supply decisions are frequently modelled at the individual level, this study also takes household-level controls such as economic status, demographics, and socioeconomic statuses into account, acknowledging that these decisions are a part of socioeconomic settings and household-level decision-making processes that can influence individuals' choices (Blundell and MaCurdy, 1999). Furthermore, proxies for household infrastructure, specifically the type of lighting and cooking fuel used are accounted

Table 3: ATT Estimates for Different Categories of TU – Single Equation Estimates based on TUS Sample, 2019

Variables	**SNA**	**ESNA**	**NSNA**	**SC**
	(1)	(2)	(3)	(4)
Treatment	33.44***	-20.07***	-22.41***	14.23***
	(6.228)	(4.366)	(4.548)	(3.628)
Gender: Female	-0.07	-0.09	-0.06	-0.07
	(0.078)	(0.084)	(0.078)	(0.084)
Age	-0.01	-0.02***	-0.01	-0.02***
	(0.004)	(0.004)	(0.004)	(0.004)
Marital status: Married	0.28**	0.31**	0.27**	0.29**
	(0.112)	(0.119)	(0.112)	(0.119)
1.Hindu	-0.17	-0.37	-0.19	-0.41
	(0.423)	(0.444)	(0.425)	(0.439)
1.Muslim	-0.51	-0.78	-0.50	-0.77
	(0.500)	(0.540)	(0.499)	(0.534)
Farmer: Medium and above	-0.29***	-0.27***	-	-
	(0.086)	(0.092)	-	-
log(MPCE)	0.76***	0.40***	0.71***	0.34***
	(0.083)	(0.092)	(0.081)	(0.090)
Years of Education	-0.09***	-0.12***	-0.09***	-0.13***
	(0.009)	(0.010)	(0.009)	(0.010)
Proportion of Children	-0.78***	-0.53*	-0.75***	-0.47*
	(0.256)	(0.271)	(0.256)	(0.272)
Proportion of Elderly	-2.75***	-2.59***	-2.82***	-2.65***
	(0.550)	(0.540)	(0.554)	(0.542)
2.Cooking energy (1=clean fuels; 2=biomass fuels)	-	-2.04***	-	-2.04***
	-	(0.113)	-	(0.113)
1.Lighting energy (1=electricity; 0=other sources)	-	2.09***	-	2.05***
	-	(0.487)	-	(0.478)
1.Sweeping floor (1=manual; 0=other sources)	-	-0.20	-	-
	-	(0.699)	-	-
1.Washing clothes (1=manual; 0=other sources)	-	1.85**	-	-
	-	(0.845)	-	-
Constant	-6.44***	-5.57***	-5.97***	-3.40***
	(0.838)	(1.353)	(0.826)	(1.023)
Observations		3,405		

Note: (1) Robust standard errors in parentheses.
(2) $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: ATT Estimates for Different Categories of TU – Single Equation Estimates based on TUS Sample, 2024

Variables	**SNA** (1)	**ESNA** (2)	**NSNA** (3)	**SC** (4)
Treatment	-31.99***	2.15	36.26***	-6.24**
	(5.567)	(3.888)	(4.296)	(3.073)
Gender: Female	0.05	0.08	0.06	0.09
	(0.073)	(0.082)	(0.072)	(0.081)
Age	-0.01	-0.02***	-0.01	-0.02***
	(0.004)	(0.004)	(0.004)	(0.004)
Marital status: Married	0.16	-0.04	0.17	-0.04
	(0.110)	(0.125)	(0.109)	(0.124)
1.Hindu	0.30	-0.42	0.29	-0.33
	(0.269)	(0.319)	(0.267)	(0.312)
1.Muslim	-1.06**	-2.03***	-1.12***	-2.00***
	(0.421)	(0.469)	(0.420)	(0.464)
Farmer: Medium and above	-0.40***	-0.51***	-	-
	(0.085)	(0.088)	-	-
log(MPCE)	0.77***	0.49***	0.66***	0.38***
	(0.096)	(0.101)	(0.091)	(0.097)
Education years	-0.06***	-0.08***	-0.06***	-0.09***
	(0.009)	(0.010)	(0.009)	(0.009)
Proportion of Children	-0.69***	-0.73***	-0.64***	-0.65**
	(0.245)	(0.273)	(0.245)	(0.272)
Proportion of Elderly	-1.37***	-1.36***	-1.43***	-1.44***
	(0.302)	(0.313)	(0.303)	(0.315)
2.Cooking energy (1=clean fuels; 2=biomass fuels)	-	-3.30***	-	-3.26***
		(0.167)		(0.167)
1.Lighting energy (1=electricity; 0=other sources)	-	-0.79	-	-0.79*
		(0.517)		(0.470)
1.Sweeping floor (1=manual; 0=other sources)	-	1.18***	-	-
		(0.451)		-
1.Washing clothes (1=manual; 0=other sources)	-	-0.03	-	-
		(0.268)		-
Constant	-7.41***	-3.14***	-6.42***	-1.18
	(0.964)	(1.162)	(0.915)	(1.081)
Observations		3,806		

Note: (1) Robust standard errors in parentheses.
(2) $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

for, as they may directly affect the time needed to perform tasks at home. In order to measure the burden of unpaid domestic labour, which may have a substantial impact on how people divide their remaining time between productive and leisure activities, indicators for sweeping and washing tasks are also included as control variables.

Based on household and individual factors, the results from the Tables 3 and 4 show significant heterogeneity in time utilization. This result suggests that within the sample, gender-based variations in time-use are either negligible or obscured by other factors like wealth, education, household composition, and marital status. However, when more immediate factors are taken into account, the absence of statistical significance does not necessarily indicate gender equity in time usage; rather, it indicates that gender is not the only factor that explains difference in time-use. All time-use categories are positively impacted by marital status, which reflects the increased responsibility and shared effort in married households. Time spent on all activities is continuously decreased by the increase in education, indicating access to greater opportunities or time-saving alternatives. A higher household economic status (MPCE) highlights the role that economic well-being plays in facilitating diverse time usage by increasing the amount of time allotted to both productive and self-care activities. The role of childcare on time-use is demonstrated by the fact that a higher proportion of children significantly cuts down on time spent on all activities. Time utilization is also adversely affected by the presence of elderly family members, most likely as a result of caring responsibilities. Due to resource availability, farmers other than marginal and small landholdings devote less time to both SNA and ESNA activities. Having access to amenities like clean cooking energy increases efficiency by decreasing the time spent on ESNA activities. Overall, the findings highlight influence of several socioeconomic and demographic factors in the time-use of rural residents. The role of UCTs after controlling for all other factors on time-use patterns based on 2019 and 2024 Time Use Survey samples is discussed below.

5.1 Short-run Impacts of UCTs on Time-use

As mentioned earlier, given that the UCT program in the study area started in 2018, the effect of the transfers on time-use as evidenced by the 2019 sample are considered as short-run impact of UCT on time-use pattern. The impact of UCT on various categories of time-use shown in Table 5 are estimated separately for each individual outcome category.

For comparison the estimates based on GSEM framework are also reported along with the single equation estimates.[11]

The findings based on the Time Use Survey sample, 2019 demonstrate an initial trend towards more engagement in SNA and SC activities, coupled with a contraction in time spent on ESNA and NSNA activities. Paradoxically, even though higher income might reduce work (given leisure is a "normal" good), UCTs induce an increase in time spent in SNA activities by 9.5% (see col. 5 in Table 5) for the treated group compared to the counterfactual group, nullifying the pure income effect. As cash transfers increase the non-labour income, the standard labour-leisure trade-off theory advocates that, one should work less and less. But in the short-run, this necessarily need not hold true.

Table 5: Impact of UCTs on TU Patterns & Percentage Change Compared to Control Group – TUS Sample, 2019

TU category	GSEM (non-convergent)			TEFFECTS		
	ATT Coef.	**% Change**	**Sig.**	**ATT Coef.**	**% Change**	**Sig.**
	(1)	(2)	(3)	(4)	(5)	(6)
SNA (24.3%)	30.9	8.8	***	33.4	9.5	***
ESNA (10%)	−18.0	−12.4	***	−20.1	−13.8	***
NSNA (17.2%)	−22.9	−9.1	***	−22.4	−8.9	***
SC (48.3%)	10.0	1.4	***	14.2	2.0	***

Note: (1) Values in parentheses show the mean time allocation (%) in each TU category for the control group in 2019.
(2) $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

On the other hand, ESNA and NSNA activities exhibit a contraction in time spent by 13.8% and 8.9% (see col. 5 in Table 5), respectively indicating a stronger substitution effect, given that UCTs make the opportunity cost of leisure temporarily high. This pattern indicates an immediate response to the cash transfer, possibly driven by short-term adjustments in labour supply as UCTs might be used to invest in productive activities (inputs, livestock etc.) that require more labour, thus raising labour demand. The conventional labour-leisure trade-off model (Becker, 1965; Killingsworth, 1983) also states that individuals maximize their utility by turning time from leisure or unpaid activities into paid work if they discern that the cash transfer is transitory, thus maximizing their utility through spending more time on SNA activities in relation to time spent on other activities. Furthermore, an early

[11] The estimates from SURE and GSEM frameworks are reported in Tables A5 to A8 in Appendix for the purpose of comparisons to check for the potential efficiency loss stemmed from estimating the models independently.

increase in the time spent on SC activities is consistent with Grossman's (1972) model of health capital, which holds that future labour results are improved by investments in rest and nourishment.

5.2 Long-run Impacts of UCTs on Time-use

The impact of UCTs on time-use as evidenced by 2024 sample are treated as long-run effects since the transfers were in place for close to seven years by this survey period. Table 6 shows both the GSEM and single equation estimates of the impact of UCTs on various categories of time-use.

The estimates reported in Table 6 suggest that compared to the effects of UCTs on various time-use categories, the trend in 2024 is reversed – time spent on ESNA and NSNA activities increased due to UCTs, while that on SNA and SC decreased. This change is consistent with the classical income effect, which states that households choose non-market utility-enhancing activities and tend to reduce market employment as they internalize the cash transfer as a component of their permanent income (Friedman, 1957). It is consistent with the findings of Deaton and Muellbauer (1980) and Aguiar and Hurst (2007), who demonstrate that individuals often shift from market labour to better-quality leisure or caring activities as their income stabilizes over time. In the case of RBS, due to the program's uninterrupted operation since its inception in 2018, farmers now view it as a steady and permanent source of non-labour income rather than a short-term welfare measure.

Table 6: Impact of UCTs on TU Patterns & Percentage Change Compared to Control Group – TUS Sample, 2024

TU Category	**GSEM (non-convergent)**			**TEFFECTS**		
	ATT Coef. (1)	**% Change** (2)	**Sig.** (3)	**ATT Coef.** (4)	**% Change** (5)	**Sig.** (6)
SNA (27.6%)	−33.3	−8.3	***	−32.0	−8.0	***
ESNA (9.6%)	2.2	1.5		2.2	1.5	
NSNA (15%)	37.3	17.2	***	36.3	16.7	***
SC (47.6%)	−6.1	−0.8	**	−6.2	−0.9	**

Note: (1) Values in parentheses indicate the control group's mean time allocation share (%) in each TU category in 2024.
(2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results reported above suggest that the amount of time spent on SNA activities has decreased by around 8% (see col. 5 in Table 6) in the treated group compared to the untreated group, suggesting a significant decrease in labour participation focused on the market. Due to the stabilised investments, the opportunity cost of leisure falls, thus, individuals substitute more work time with unpaid domestic work and leisure activities. The magnitude of time spent on NSNA has increased by 16.7% which is approximately 36 minutes in a day (see col. 5 in Table 6) and is highly significant, thereby weakening the substitution effect. ESNA, which exhibited a downtrend in the short-run, has now increased by 1.5% but insignificant. These time shifts in the long-run indicate a settling into a new equilibrium facilitated by assured income from the cash transfers, where households diversify their time usage beyond the market production and prioritise leisure, learning, and societal-related activities.

5.3 Discussion

From the analysis reported above, a smooth transition from short-run to the long-run is observed as mentioned in the standard labour-leisure trade-off theory. Initially, as soon as the UCT is made the households increase their labour supply to complement the UCT or smooth consumption, and in the long-run they shift to more NSNA activities (i.e., leisure etc.,) as the economic security gets better. The study identifies the two key channels of transition in this respect. First, Dynamic Time Allocation, where, as the stability increases, households rebalance toward social and recreational activities after prioritizing their immediate requirements (SNA activities). Second, Investment cycles, while long-term productivity gains lessen the requirement for labour, short-term investments enhance employment.

The majority of empirical research indicates either positive or null effects on labour supply (e.g., Baird et al., 2018; Banerjee et al., 2017; Alzúa et al., 2013; Bastagli et al., 2016), and there is relatively less evidence regarding negative effects on labour supply (Bertrand et al., 2003), and it is largely context-dependent. One of the reasons for this is that the majority of studies focus on short-term effects, which often reveal the positive or null effects of labour participation. The liquidity that transfers offer has the potential to improve welfare and facilitate labour market participation in the short-run. However, uninterrupted income support may gradually change household labour preferences, resulting in more time being spent on leisure, unpaid care tasks, or subsistence activities, if conditions or productivity-linked incentives are not present. Similar conclusions are reached by Majid and Riaz (2022), who noted a negative effect in women's labour force participation in their panel study's second round, suggesting possible long-term behavioural changes.

Enhanced time spent on NSNA activities i.e., leisure, socialization etc., in the long-run can be understood as an indication of better household and individual welfare, especially when financial stress and time constraints limit the amount of time that can be used for discretionary activities. Leisure is viewed as a normal good in the standard labour-leisure trade-off framework and an increase in its consumption usually corresponds to an increase in economic well-being and utility. The capacity to shift from employment activities or unpaid domestic responsibilities to leisure time implies increased financial stability and less compulsion to participate in subsistence or income-generating activities (Aguiar and Hurst, 2007). Such changes may represent improvements in material circumstances as well as improvements in subjective well-being and health outcomes, particularly in low-income situations where time poverty may be acute (Bardasi and Wodon, 2010). Furthermore, Sen's Capability Approach (1999) suggests that the increase of time spent on leisure activities may also be a reflection of individual's expanded substantive freedoms, or their actual chances to lead the lives they believe in. In this sense, time is not just a resource but also a dimension of capability that allows people to participate in activities that are essential to wellbeing, such as rest, introspection, caregiving, cultural, religious, and community life. Therefore, more leisure time might indicate both a rise in material wealth and an enhancement of personal agency and autonomy. Such adjustments suggest both enhanced functioning and increased capacities in low-income rural areas, where time poverty and livelihood instability frequently limit options.

6 Conclusion

In this study, the short- and long-run impacts of an unconditional cash transfer program implemented in the state of Telangana on time-use patterns among rural agricultural households are estimated. The analysis shows that household behaviour has clear temporal dynamics. Immediately after the implementation of the UCT (2019), the transfers lead to decrease in time spent on ESNA and NSNA activities, and an increase in time spent on SNA and SC activities. However, as households absorbed the transfer as a reliable source of income, this tendency eventually reversed in the long-run (2024), suggesting a gradual shift in the distribution of labour and leisure time. These results correspond with standard labour-leisure theory, which holds that income effects mostly define long-term behavioural responses, whereas substitution effects or liquidity-driven adjustments shape initial behavioural responses.

Thus, the findings raise an important question often debated in the literature: do cash transfers undermine participation in paid work, or do they instead reflect improved welfare that enables a reallocation of time toward leisure? In this context, the study finds that in the long-run, the cash transfer program enhances the welfare of the individual as observed through the increase in time spent on leisure, which is a proxy to assess welfare. While some interpretations suggest that unconditional transfers may reduce labour supply incentives, an alternative view — supported by standard labour–leisure trade-off theory — is that individuals, having become relatively wealthier, exercise greater agency over their time-use. In this context, the observed shift away from paid work in the long-run need not imply reduced productivity, but rather a welfare-enhancing rebalancing of time between market and non-market activities.

The findings from this study highlight the significance of incorporating time-use analysis in the assessment of social security programs such as cash transfer programs. The obtained results assert that unconditional cash transfers have the potential to affect not only consumption but also time allocations, which is an important component of wellbeing. Such multifaceted effects should be taken into consideration by policymakers while designing and scaling up of these cash transfer programs. To better understand behavioural mechanisms, future research should include structural models. It could also examine how time-use varies by gender, caste, or kind of livelihood etc., particularly in rural and informal economies.

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A Additional Tables

Table A.1: Determinants of treatment status (Probit model estimates)

Variables	**UCT_2019** (1)	**UCT_2024** (2)
Gender: Female	-0.043	0.041
	(0.048)	(0.045)
Marital status: Married	0.167**	0.095
	(0.068)	(0.065)
1. Hindu	-0.393*	0.156
	(0.228)	(0.138)
1. Muslim	-0.611***	-0.644***
	(0.278)	(0.224)
Farmer: Medium and above	-0.188***	-0.261***
	(0.052)	(0.050)
Age	-0.004	-0.003
	(0.002)	(0.002)
log(MPCE)	0.475***	0.502***
	(0.049)	(0.053)
Proportion of Children	-0.492***	-0.462***
	(0.153)	(0.149)
Proportion of Elderly	-1.474***	-0.835***
	(0.248)	(0.165)
Years of Education	-0.054***	-0.037***
	(0.005)	(0.005)
Constant	-3.721***	-4.755***
	(0.501)	(0.516)
Observations	3,427	3,834

Note: (1) Standard errors in parentheses.
(2) $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.2: Correlation Matrix of Residuals and Test of Independence (2019)

	SNA	**ESNA**	**NSNA**	**SC**
SNA	1.0000			
ESNA	-0.4590	1.0000		
NSNA	-0.6549	-0.0918	1.0000	
SC	-0.4177	-0.1555	-0.0552	1.0000
Breusch–Pagan Test of Independence				
$\chi^2(6) = 3259.414$				p-value = 0.0000

Note: The significant p-value indicates residuals are not independent across equations.

Table A.3: Correlation Matrix of Residuals and Test of Independence (2024)

	SNA	**ESNA**	**NSNA**	**SC**
SNA	1.0000			
ESNA	-0.4760	1.0000		
NSNA	-0.6847	-0.0781	1.0000	
SC	-0.3658	-0.1163	-0.0865	1.0000
Breusch–Pagan Test of Independence				
$\chi^2(6) = 3259.414$				p-value = 0.0000

Note: The significant p-value indicates residuals are not independent across equations.

Table A.4: Descriptive Statistics, 2019 and 2024

Variable	**Nature of Variable**	**2019 Mean (SD)**	**2024 Mean (SD)**
Gender			
Male	Discrete	0.573 (0.495)	0.590 (0.492)
Female	Discrete	0.427 (0.495)	0.410 (0.492)
Age	Continuous	38.81 (11.02)	40.15 (10.62)
Marital Status			
Unmarried and others	Discrete	0.157 (0.363)	0.143 (0.351)
Married	Discrete	0.843 (0.363)	0.857 (0.351)
Religion			
Hindu	Discrete	0.973 (0.161)	0.956 (0.204)
Muslim	Discrete	0.020 (0.139)	0.021 (0.143)
Farmer Category			
Marginal & Small	Discrete	0.730 (0.444)	0.726 (0.446)
Medium & Above	Discrete	0.270 (0.444)	0.274 (0.446)
Log MPCE	Continuous	8.91 (0.478)	9.31 (0.419)
Education (years)	Continuous	4.84 (4.80)	5.77 (4.77)
Proportion of Children	Continuous	0.100 (0.155)	0.085 (0.147)
Proportion of Elderly	Continuous	0.036 (0.094)	0.077 (0.133)
Cooking Energy			
Clean Fuels	Discrete	0.704 (0.456)	0.727 (0.445)
Biomass Fuels	Discrete	0.296 (0.456)	0.273 (0.445)
Lighting Energy			
Electricity	Discrete	0.970 (0.170)	0.996 (0.061)
Other Sources	Discrete	0.030 (0.170)	0.004 (0.061)
Sweeping Floor			
Manual	Discrete	0.995 (0.068)	0.987 (0.115)
Other Sources	Discrete	0.005 (0.068)	0.013 (0.115)
Washing Clothes			
Manual	Discrete	0.995 (0.073)	0.975 (0.156)
Other Sources	Discrete	0.005 (0.073)	0.025 (0.156)

Table A.5: Estimates for different categories of TU using SURE Framework - ATE (2019)

Variables	**SNA**	**ESNA**	**NSNA**	**SC**
	(1)	(2)	(3)	(4)
Treatment	30.12***	-20.12***	-22.07***	12.08***
	(6.092)	(3.860)	(4.451)	(3.472)
Gender: Female	-118.00***	232.10***	-77.43***	-36.69***
	(6.234)	(4.087)	(4.502)	(3.346)
Age	0.28	-1.27***	0.63***	0.36**
	(0.320)	(0.202)	(0.238)	(0.177)
Marital status: Married	-2.08	47.57***	-23.92***	-21.57***
	(8.797)	(5.857)	(6.531)	(4.992)
1.Hindu	-50.55	27.41	17.60	5.54
	(31.620)	(21.970)	(16.670)	(22.310)
1.Muslim	-20.26	30.62	15.69	-26.04
	(36.870)	(24.350)	(21.590)	(24.390)
Farmer: Medium and above	-2.72	2.70	-	-
	(3.923)	(3.923)	-	-
log(MPCE)	23.29***	-3.79	7.28	-26.78***
	(6.339)	(3.786)	(4.887)	(3.714)
Education years	-3.13***	1.15***	1.70***	0.28
	(0.687)	(0.444)	(0.514)	(0.383)
Proportion of Children	-33.79*	59.32***	-68.07***	42.54***
	(19.240)	(12.880)	(13.740)	(10.480)
Proportion of Elderly	7.77	26.48	-35.02	0.78
	(31.450)	(18.290)	(23.470)	(19.180)
2.Cooking energy (1=clean fuels; 2=biomass fuels)	-	-14.31***	-	14.34***
	-	(3.231)	-	(3.230)
1.Lighting fuel (1=electricity; 0=other sources)	-	-2.80	-	2.80
	-	(6.755)	-	(6.756)
1.Sweeping floor (1=manual; 0=other sources)	-	0.05	-	-
	-	(0.055)	-	-
1.Washing clothes (1=manual; 0=other sources)	-	-0.02	-	-
	-	(0.076)	-	-
Constant	253.80***	58.97	193.90***	933.20***
	(64.860)	(40.450)	(47.350)	(40.250)
Observations		3,405		
R-squared	0.117	0.562	0.121	0.073

Note: (1) Robust standard errors in parentheses.
(2) $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.6: Estimates for Different Categories of TU using SURE Framework - ATE (2024)

Variables	**SNA** (1)	**ESNA** (2)	**NSNA** (3)	**SC** (4)
Treatment	-33.18***	0.11	38.25***	-5.20*
	(5.471)	(3.260)	(4.254)	(2.851)
Gender: Female	-108.30***	237.70***	-84.04***	-45.34***
	(5.569)	(3.639)	(4.123)	(2.740)
Age	0.53*	-1.94***	0.78***	0.63***
	(0.287)	(0.187)	(0.226)	(0.147)
Marital Status: Married	0.28	60.95***	-39.47***	-21.76***
	(8.271)	(5.161)	(6.671)	(4.096)
1.Hindu	-3.53	-16.82	35.57***	-15.23**
	(19.610)	(16.280)	(12.460)	(7.238)
1.Muslim	-17.49	-46.09**	58.43***	5.12
	(26.050)	(17.960)	(20.060)	(13.150)
Farmer: Medium and above	-2.39	2.31	-	-
	(3.356)	(3.356)	-	-
log(MPCE)	8.61	-12.50***	9.53*	-5.62*
	(6.424)	(4.154)	(5.067)	(3.064)
Education Years	-2.55***	1.68***	1.19**	-0.31
	(0.637)	(0.371)	(0.508)	(0.333)
Proportion of Children	51.69***	21.07**	-67.76***	-5.03
	(17.110)	(10.420)	(13.150)	(8.677)
Proportion of Elderly	11.36	-7.44	-4.90	0.98
	(20.260)	(11.580)	(15.860)	(9.898)
2.Cooking energy (1 = clean fuels; 2 = biomass fuels)	-	4.36	-	-4.38
	-	(2.796)	-	(2.795)
1.Lighting fuel (1 = electricity; 0 = other sources)	-	3.45	-	-3.75
	-	(16.680)	-	(16.560)
1.Sweeping floor (1 = manual; 0 = other sources)	-	-0.10	-	-
	-	(0.106)	-	-
1.Washing clothes (1 = manual; 0 = other sources)	-	0.18**	-	-
	-	(0.081)	-	-
Constant	354.60***	186.50***	126.90**	772.00***
	(62.620)	(43.900)	(50.000)	(33.940)
Observations		3,806		
R-squared	0.105	0.613	0.146	0.086

Note: (1) Robust standard errors in parentheses.
(2) $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.7: Estimates for Time-Use Categories using GSEM Framework - ATT (2019)

Variables	**SNA** (1)	**ESNA** (2)	**NSNA** (3)	**Self-care** (4)
Treatment	30.87***	-18.00***	-22.86***	10.02***
	(6.199)	(4.013)	(4.503)	(3.533)
Gender: Female	-123.8***	233.8***	-72.06***	-37.98***
	(6.663)	(4.260)	(4.827)	(3.521)
Age	0.0483	-1.441***	0.914***	0.481**
	(0.348)	(0.217)	(0.250)	(0.194)
Marital Status: Married	-7.261	56.83***	-26.54***	-23.01***
	(9.722)	(6.566)	(6.847)	(5.583)
1.Hindu	-40.44	38.98	10.05	-7.945
	(34.22)	(23.93)	(20.72)	(24.31)
1.Muslim	-20.60	40.47	16.58	-35.91
	(40.98)	(26.97)	(25.78)	(26.84)
Farmer: Medium and above	-1.740	1.615	-	-
	(4.402)	(4.404)	-	-
log(MPCE)	29.64***	-6.686	9.805*	-32.34***
	(7.163)	(4.448)	(5.434)	(4.088)
Education Years	-3.906***	1.743***	1.703***	0.460
	(0.751)	(0.468)	(0.536)	(0.423)
Proportion of Children	-36.31*	52.37***	-55.67***	39.48***
	(20.98)	(13.93)	(14.75)	(10.90)
Proportion of Elderly	-21.13	39.82*	-34.45	15.69
	(38.60)	(21.95)	(27.05)	(21.80)
2.Cooking energy (1 = clean; 2 = biomass)	-	-12.97***	-	13.20***
	-	(3.584)	-	(3.581)
1.Lighting fuel (1 = electricity; 0 = other sources)	-	-2.539	-	2.704
	-	(7.915)	-	(7.923)
1.Sweeping floor (1 = manual; 0 = other sources)	-	3.241***	-	-
	-	(0.931)	-	-
1.Washing clothes (1 = manual; 0 = other sources)	-	0.369	-	-
	-	(0.598)	-	-
Constant	209.8***	55.97	169.4***	996.6***
	(73.15)	(47.34)	(54.35)	(44.54)
Observations		3,405		

Note: (1) Robust standard errors in parentheses.
(2) $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
(3) The estimates from the GSEM model are non-convergent.

Table A.8: Estimates for Time-Use Categories using GSEM Framework - ATT (2024)

VARIABLES	(1) SNA	(2) ESNA	(3) NSNA	(4) Self-Care
Treatment	-33.30***	2.17	37.26***	-6.06**
	(5.555)	(3.407)	(4.252)	(3.006)
Gender: Female	-112.10***	232.70***	-77.31***	-43.20***
	(5.912)	(3.717)	(4.451)	(2.996)
Age	0.55*	-2.14***	0.85***	0.74***
	(0.317)	(0.204)	(0.248)	(0.162)
Marital Status: Married	2.10	63.59***	-43.67***	-22.03***
	(9.085)	(5.647)	(7.529)	(4.282)
1.Hindu	7.06	-19.71	24.60*	-11.58
	(19.610)	(15.530)	(14.850)	(8.043)
1.Muslim	-17.91	-23.69	52.40*	-10.47
	(37.150)	(19.780)	(29.960)	(15.220)
Farmer: Medium and above	-8.94**	8.59**	-	-
	(3.904)	(3.879)	-	-
log(MPCE)	17.90***	-12.18*	3.03	-7.82
	(6.882)	(7.249)	(15.180)	(8.700)
Education Years	-2.61***	1.56***	1.28**	-0.23
	(0.693)	(0.405)	(0.532)	(0.348)
Proportion of Children	47.29**	24.50**	-70.16***	-1.92
	(18.410)	(11.210)	(13.990)	(9.703)
Proportion of Elderly	12.10	-9.96	-0.81	-1.52
	(23.130)	(13.040)	(17.960)	(11.650)
Cooking Energy (1 = clean; 2 = biomass)	-	4.81	-	-4.65
	-	(3.280)	-	(3.259)
Lighting Fuel (1 = electricity; 0 = other)	-	23.40	-	-19.56
	-	(19.730)	-	(18.520)
Sweeping Floor (1 = manual; 0 = other)	-	0.69*	-	-
	-	(0.368)	-	-
Washing Clothes (1 = manual; 0 = other)	-	1.60***	-	-
	-	(0.480)	-	-
Constant	260.0***	168.8***	197.2	800.1***
	(66.720)	(63.520)	(151.500)	(98.790)
Observations	3,806	3,806	3,806	3,806

Note: (1) Robust standard errors in parentheses.
(2) $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
(3) The estimates from the GSEM model are non-convergent.

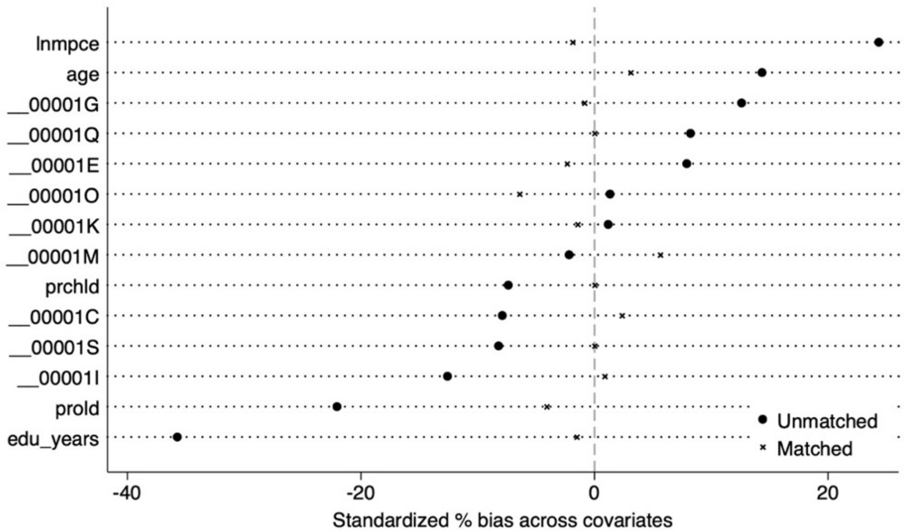

Figure A.1: Standardised Bias across Covariates based on TUS 2019

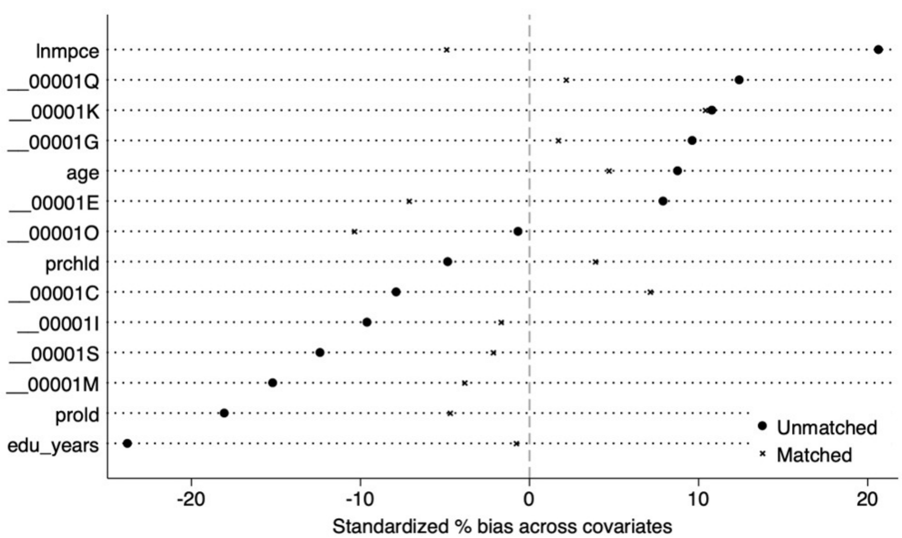

Figure A.2: Standardised Bias across Covariates based on TUS 2024

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