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The Impact of Public Employment on Child Labour and School Attendance:

Evidence from a Social Protection Programme in Andhra Pradesh and Telangana, India

by

Ida Lindström – ida-lindstrom@outlook.com

Abstract: To address child labour, research discusses the potential of social protection programmes. This thesis therefore examines the unresolved impact on child labour and children's school attendance of its household members' participation in the public employment programme MGNREGS in Andhra Pradesh and Telangana, India. By applying the combined difference-in-differences propensity score matching method, it is, however, found that beneficiary children between 11 and 16 years old engage more in paid work when its household members participate in MGNREGS. This applies in particular to beneficiary girls when female household members participate in the programme. Whilst MGNREGS is not found to be an effective tool for reducing the incidence of paid child labour among children in the concerned age range and states, no conclusions can be drawn about the programme's impact on unpaid child labour and school attendance. Lastly, it is found that the amount of leisure reduces for beneficiary boys when male household members participate in the programme. Overall, with regard to the research objective, it can be relevant to build additional safety nets into the programme and prioritize its combination with other social protection programmes.

Key words: Public Employment Programme, Child Labour, School Attendance, Difference-in-Differences, Propensity Score Matching

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1 Introduction

According to the latest estimates presented in the report from the International Labour Organization (ILO) (2018), 152 million children aged 5-17 are engaged in child labour worldwide. The majority of this work (69 %) concerns unpaid family work within the family farm, enterprise and household. Although the occurrence of child labour has declined by a third since 2000, it remains a global challenge, affecting children’s short-term and long-term opportunities in life. Besides often interfering with education, it is further discussed in the report how early employment undermines children’s mental and physical health. As such, child labour risks reinforcing intergenerational transmissions of poverty. This, together with its potentially negative impact on the economic development of national economies, makes the eradication of child labour a policy objective of many developing countries.

ILO (2018) further presents Asia and the Pacific as the region with the second largest concentration of child labour in the world, of which India is a central contributor in this regard. More specifically, with 10.1 million children employed, representing close to 7 % of the world total, India alone faces critical challenges. Through the enactment of the Right to Education Act in 2009 and the Child Labour Amendment (Prohibition and Regulation) Act in 2016, the Government of India has taken legislative actions to reduce the incidence of child labour (ILO, 2021). Nevertheless, for these types of regulations to be effective, they need to be supported by other measures. With the well-established link between poverty, income shocks and child labour, a growing amount of research points to the importance of social protection, which through its often-provided financial support can mitigate households’ economic vulnerability (ILO, 2018).

Among the instruments of social protection are public employment programmes, of which one of the world’s largest schemes of this kind can be found in India. The so-called Mahatma Gandhi National Rural Employment Guarantee Scheme (hereafter, MGNREGS) was initiated in 2006 and involved 55 million households in 2019–2020 (ILO, 2020). With the intention to support households during lean agricultural seasons, the programme aims to provide rural households with at least 100 days of guaranteed paid work per year (Government of India, 2013). Whilst this type of programme is not intended to address child labour, the household's temporary increase in income from employment may affect the child's time allocation. Whereas there is extensive evidence that other forms of social protection such as conditional cash transfers can reduce the incidence of child labour, it remains an open question as whether public employment programmes such as MGNREGS can serve as effective tools for this purpose (ILO, 2018). Given the extent of child labour in India, the country's undertaken measures to prevent its occurrence, including the programme's extensive coverage, it is considered important to investigate this matter in further detail.

1.1 Research Problem

Previous research examining the effect of MGNREGS on child labour presents different conclusions. This is in part attributable to differently adopted definitions of child labour where the existing literature tends to analyse only certain parts of the child's undertaken activities, such as paid market work. Child labour is, however, a complex phenomenon. One common definition of the term, presented by ILO (2018), concerns work that is physically, mentally, socially or morally harmful to the development of the child. Consequently, work that interferes with school attendance is also included in the term. Whereas the literature often analyses activities of economic character, there are therefore a number of additional forms under which children can be engaged in work. The most central activity, and as indicated above, is unpaid family work such as farming and household chores. By not including unpaid activities in the analysis, the conclusions can be misleading on how children, and especially girls, allocate their time and can thus give rise to biased responses from public policy (Dammert, de Hoop, Mvukiyehe & Rosati, 2017; Edmonds & Thévenon, 2019; Lambon-Quayefio, 2021).

Only a few studies have examined the impact of MGNREGS based on this broader definition of child labour. These include the work by Islam and Sivasankaran (2014), Shah and Steinberg (2015) and Sheahan, Liu, Narayanan and Barrett (2020). Similarly, they investigate the impact of household participation in MGNREGS on the child's full time allocation, but with conflicting findings. Furthermore, although not considered in these works, there are indications that the results can vary depending on whether the participant is the mother or the father of the child (Afridi, Mukhopadhyay & Sahoo, 2016). This suggests that in addition to the various kinds of paid and unpaid work performed by the child, it is important to consider the gender of the household’s MGNREGS-participant. Therefore, given the complexity of the child labour phenomenon where the majority of the children are employed within the own family unit, this thesis will contribute to the existing literature in three ways. Besides examining the effect of MGNREGS on child labour based on a broader definition of the term, the analysis will be disaggregated by gender of the household’s programme participant. This will be done using the longitudinal dataset Young Lives, which contains information about the child’s daily time allocation from 2006 to 2016. Whilst the dataset has been widely used in previous research, including in the child labour literature, it has not been used for this research objective before.

1.2 Aim and Scope

The aim of this thesis is thus to examine the impact of MGNREGS on child labour in accordance with the suggested broader definition of the term. Therefore, paid work outside the household, unpaid household work, schooling but also leisure will be examined.

While MGNREGS has national coverage, the implementation of the programme relies on the local governments of the individual states. As a result, there is a variation in the supply of employment with uneven outcomes across regions (Thapa, 2014), thus motivating the need to analyse individual states over a general impact evaluation for the country as a whole. The state of choice is the former Andhra Pradesh, which was divided into the two states Andhra Pradesh and Telangana in 2014 (Andhra Pradesh Reorganisation Act, 2014), and stems from three reasons. Besides the rich availability of data, Andhra Pradesh and Telangana are one of the states with the largest coverage of the programme in India (approximately 4 million and 2.5 million households in 2019-2020, respectively) (Ministry of Rural Development, n.d.*a*). In addition, despite the introduction of a number of local legislative initiatives (Saharia, 2013), the prevalence of child labour remains high in this region according to the latest Census data (Government of India, 2011). Given the local variations and the relevance of Andhra Pradesh and Telangana based on the purpose of the thesis, the regional choice is considered appropriate. Nevertheless, the findings may be relevant also for other parts of India as well as for other countries that aim to develop public employment programmes of this kind.

Therefore, the thesis asks the following research question:

What is the impact on child labour and children's school attendance of its household's *participation in MGNREGS in Andhra Pradesh and Telangana?*

As introduced, to gain a fuller understanding of the potential impacts of the programme in this regard, the analysis will consider hours per typical weekday spent on paid work outside the household, unpaid household tasks, referring to activities such as farming and other family business, unpaid household chores, schooling and leisure. Moreover, the following sub-question is formulated:

1. Do the results differ, and if so, how, depending on the gender of the beneficiary child including if the household programme participant is female or male?

Relying on the difference-in-differences propensity score matching method it is found that beneficiary children, and particularly girls when female household members participate in the programme, on average increase their time spent on paid work of its household members' participation in MGNREGS compared to the control group. Consequently, the programme is not found to be an effective tool for the purpose of reducing the amount of paid child labour among children in the examined age range and states. However, it remains inconclusive how the programme affects unpaid child labour including school attendance among beneficiary children. Lastly, beneficiary boys are found to significantly reduce their time spent on leisure when male household members participate in the programme.

1.3 Outline of the Thesis

The outline of the thesis is structured as follows: section 2 reviews previous research and theory followed by a formulation of the theoretical expectations and hypotheses. Section 3 describes the data and the methodological approach, after which section 4 presents the empirical analysis consisting of the main results, sensitivity analysis and discussion. Lastly, section 5 concludes.

2 Previous Research and Theory

The following section is divided into two parts. First, previous research will be explored. The section therefore begins by presenting MGNREGS, its targeting process, objectives, and determinants, after which the determinants of child labour are discussed. Thereafter, previous findings on the effect of public employment programmes, and particularly MGNREGS, on child labour are examined. Together, this forms the basis for the second part of the chapter in which the theoretical expectations and the hypotheses are presented.

2.1 Previous Research

2.1.1 Mahatma Gandhi National Rural Employment Guarantee Scheme (*MGNREGS*)

Social protection corresponds to policies and programmes that aim to reduce poverty and vulnerability across the life cycle. Through its three classifications – social assistance, social insurance and labour market programmes – it provides support for individuals of different ages and needs in the form of, for example, child and family benefits, health protection and employment support (ILO, 2017). Social protection was globally recognized as an important development instrument in the late 1990s (Merrien, 2013), and its increasingly central role in policy-making is evident also in India. MGNREGS was enacted by the Indian Parliament in 2005 and came into force in February 2006. The programme, which covers all districts in the country with the exception of districts with 100 % urban population, was implemented in three phases. Initially, the programme was made available in the country's 200 most backward districts selected on the basis of, among others, the population of Scheduled Tribes and Scheduled Castes, and were expanded to include a further 130 districts in 2007. The remaining districts were included in the final phase in 2008 (Government of India, 2013).

In line with the general feature of public employment programmes, MGNREGS provides employment for a targeted group of the population. More specifically, as further presented in the report from the Government of India (2013), the programme serves to provide a minimum of 100 days of guaranteed paid work each year per rural household whose adult household members voluntarily apply for performing unskilled work. In other words, to be eligible for work within the programme, it is specified that the applicant must reside in a rural area and exceed 18 years of age. Given this geographic requirement including that MGNREGS is based on a rights-based and self-selecting design, a central target group of the programme corresponds to the socially disadvantaged groups of society. In particular, the report emphasises women, who must make up at least one third of the participants in the programme, including Scheduled Tribes and Scheduled Castes. Given that agriculture is a primary source of income for rural households in India (Chand & Srivastava, 2014; Reddy, Reddy, Nagaraj & Bantilan, 2014), the programme aims to protect and strengthen the livelihoods during lean agricultural seasons whilst empowering the marginalised groups of society in the eligible areas. Furthermore, given the type of work that is performed under the programme – local and small-scale infrastructure projects – the act aims to create, among others, durable assets, higher land productivity including improved water security and flood management in rural India (Government of India, 2013).

As further explained in the report, work is to be provided by the local authorities within 15 days of application to a set wage. If this is not met, the wage-seeker is legally entitled to receive unemployment allowance. However, although MGNREGS strives to be a bottom-up and demand-driven programme, Thapa (2014) discusses how its scope and success still largely depends on the state's capacity to, among others, provide employment. By extension, this can affect its participation rates. With an overall uncertainty as to whether work will be guaranteed, research has found that people can be discouraged from demanding work under the programme (Datta & Singh, 2016; Himanshu, Mukhopadhyay & Sharan, 2015). This is further supported by Narayanan, Das, Liu, and Barrett (2017) whose results further suggest that this relationship can be amplified in times of crisis such as drought shocks. Besides this determinant, factors such as gender of the participant, including occupation, caste, educational status, and housing quality of the household are shown to influence the enrolment rates at both national level and in the former Andhra Pradesh (Jha, Gaiha & Pandey, 2010; Shariff, 2009).

2.1.2 Child Labour

The child labour literature is vast and broadly contains two categories of determinants, economic and non-economic factors. Whereas the former mainly concerns the income level of households, other factors such as land ownership, imperfect capital markets and economic shocks can influence households' decisions about child labour participation. Non-economic factors relate to for example parental level of education and preferences, distribution of power in the household, gender and age of the child, household composition, including proximity to school and urban areas.

Economic Factors

A substantial body of literature supports the view of poverty as the key determinant of child labour. An important contribution in this regard was made by Basu and Van (1998). Presenting the so-called *luxury axiom*, the authors argue that children's leisure time corresponds to a luxury good in the household's consumption. As such, child labour is relied upon only when parents cannot provide with an above subsistence living standard in its absence. This hypothesis has since then been discussed and supported by empirical evidence from various researchers in the field (Basu, 1999; Edmonds, 2005; Edmonds & Pavcnik, 2005; Edmonds & Schady, 2012; Ray, 2000) with empirical evidence provided also for India (see for example Bhukuth & Ballet, 2006; Skyt Nielsen & Dubey, 2002). The view that child labour primarily involves poorer households was later challenged by Bhalotra and Heady in 2003. In contrast, the authors present the *wealth paradox*, emerging from imperfect labour and land markets, and conclude that the likelihood of work increases for children in land-rich households. As a result of these findings, Basu with colleagues re-examined their previous theoretical framework in 2010. Based on data from Northern India, the authors suggest the possibility of an inverted-U relationship between child labour and land holdings where the income effect dominates after reaching a certain amount of household wealth (Basu, Das & Dutta, 2010).

Child labour can also emerge as a result of imperfect credit markets, and this for mainly two reasons. By hindering the possibility to borrow against future incomes, household investments in education become less effective (Baland & Robinson, 2000; Ranjan, 2001). In addition, poorer households risk being more vulnerable to economic shocks such as crop failure, resulting in child labour as a coping strategy. The latter relationship is covered by extensive empirical support. Whereas Beegle, Dehejia and Gatti (2006) and Bandara, Dehejia and Lavie-Rouse

(2015) provide evidence for African countries, Duryea, Lam and Levison (2007) reach similar conclusions for Brazil. Looking at the former Andhra Pradesh specifically, Krutikova (2009) finds that children in employment increases with income shocks such as natural disaster and crop failure. Similarly, as a result of rain shocks, Shah and Steinberg (2017) show how transitory earning opportunities in India cause temporarily higher levels of child labour. Given that the majority of the world's children work in agriculture, including that it corresponds to a primary source of income among rural households in India, these results may not be surprising (Chand & Srivastava, 2014; ILO, 2018; Reddy et al., 2014).

Non-Economic Factors

In accordance with the above discussions, poverty is mentioned as a central driving force behind child labour. However, as households gain more resources and as suggested by the *luxury axiom*, pass a given subsistence level, other non-economic factors become important. Among these are parental level of education. Given that parents know the long-term value of schooling, Webbink, Smits and de Jong (2010) conclude that higher levels of education among parents is associated with lower levels of child labour measured by household chores and family business work. Covering 16 African and Asian countries, their analysis indicates that this is especially true for the mother's education, where children with more educated mothers work less. This is also supported by Self and Grabowski (2009) for the Indian states Uttar Pradesh and Bihar. Along similar lines, Krutikova (2009) suggests that a higher level of education for the household head reduces both paid and unpaid child labour in the former Andhra Pradesh.

Furthermore, as the allocation of family resources is often decided by the parents in the household, parental preferences are believed to be closely related to child labour participation. Most typically, the literature assumes that parents act altruistically towards their children (see for example Basu & Van, 1998; Bhalotra, 2004), an assumption that is supported empirically. For one, research suggests that parents with higher educational expectations for their children is associated with a lower probability of work (Gahlaut, 2011). Similarly, using household survey data from rural India, Sakamoto (2006) concludes that parents with greater concern for the welfare of their children are more reluctant towards involving their children in economic activities. However, the results show diverging preferences between the mother and the father. For male-dominated households, children are found to be more likely to be engaged in labour, suggesting that bargaining power in the household is an additional determinant of child labour. The relevance of bargaining power to explain child labour is supported by various researchers in the field (see for example Afoakwah, Deng & Onur, 2018; Emerson & Souza, 2007; Huisman & Smits, 2009; Ngenzebuke, 2016). Using educational level for adult women and men in the household as a proxy for bargaining power, Krutikova (2009) provides empirical support for this also in the former Andhra Pradesh.

In addition to these factors, the child's activities can vary depending on its gender and age, including the composition of the household with regard to the presence of siblings and adults (Edmonds, 2006; Webbink, Smits & de Jong, 2010). Lastly, research indicates that access to school and proximity to urban areas affect the incidence of child labour (Fafchamps & Wahba, 2006; Sakamoto, 2006).

2.1.3 Public Employment Programmes, *MGNREGS* and Child Labour

To continue the progress against child labour, the above review shows the importance of developing policies that help mitigate the economic vulnerability of households. As previously discussed, this has begun to be recognized by a number of countries and where tools such as social protection has received increasing attention around the world (ILO, 2018; Merrien, 2013). However, the ways in which public employment programmes can affect child labour remains scarcely documented in the literature (Dammert et al., 2017).

To date, research exists on mainly four public employment programmes – Youth Cash for Work Programme in Sierra Leone, the Programme for Unemployed Male and Female Head of Households in Argentina, the Public Safety Net Programme in Ethiopia, and the Mahatma Gandhi National Rural Employment Guarantee Scheme in India (ILO, 2018). Based on the findings from the child labour literature, the existing theoretical framework distinguishes between two different effects: the income effect and the substitution effect. Based on the *luxury axiom* presented by Basu and Van (1998), a higher household income by participating in a public employment programme is expected to reduce the need for child labour through an income effect (Hoddinott, Giligan & Taffesse, 2009). By extension and in accordance with the literature on human capital investment, this can be reflected by an increase in school attendance (Behrman & Knowles, 1999). However, unlike other social protection schemes, and as discussed by Hoddinott, Giligan and Taffesse (2009), public employment programmes pose a labour requirement on the participating households. The intrahousehold division of labour between the household members can therefore be altered where the children are burdened with work previously undertaken by the participating adults. This therefore constitutes the substitution effect, suggesting that adult and child labour are substitutes (see Basu & Van, 1998 for further discussions about the *substitution axiom*). Hoddinott, Giligan and Taffesse (2009) further emphasize that the two effects do not necessarily need to be mutually exclusive. As the child's leisure time can be adjusted, it is possible to see a simultaneous increase in both components. Based on these by the literature potentially opposing effects on child labour, it remains an empirical question as to which effect will dominate.

The ambiguity in the effects can be reflected in, among others, the research conducted by Rosas and Sabarwal (2016). In their analysis of the short-term effects of the Youth Cash for Work Programme in Sierra Leone on child labour, it is suggested that the programme reduces school attendance while time spent on paid work does not increase among children between 6 and 14 years of age. This may possibly indicate that participation in the programme increases the need for household chores to be done by children through a substitution effect, although the publication does not discuss such a potential effect. Using a matching difference-in-differences approach, Juras (2014) reaches similar conclusions for the programme in Argentina, but where significant evidence is found also for a reduction in paid work. Like Rosas and Sabarwal (2016), no distinction is made between girls and boys, including that unpaid activities performed by the child are excluded from the analysis. A more detailed analysis of the effects of public work on child labour is offered by Hoddinott, Giligan and Taffesse (2009) in their examination of the Public Safety Net Programme in Ethiopia. Based on propensity score matching, their results indicate that boys experience a reduction in child labour driven by less responsibilities within both agricultural activities and household chores. On the contrary, time spent on domestic chores increases for girls.

Similarly, the impact of MGNREGS on the time allocation of beneficiary children remains contradictive. Among the studies that consider the entire time allocation of the child, Islam and Sivasankaran (2014) suggest that the income effect dominates for younger children between 6 and 9 years old in MGNREGS-participating households with an associated increase in school attendance. Being the only publication of the three that consider time spent on leisure, the researchers find a significant decrease of 0.197 days per week. Regarding beneficiary children between the ages of 10 and 14, the results are generally insignificant although the coefficients point to an increase in time spent on outside work, household tasks and chores with a reduction in leisure in line with the substitution effect. Similarly, the older children aged 15 to 17 are suggested to spend more time on household work and work outside the household through the substitution effect at the expense of time spent on schooling. More specifically, children in this age range are suggested to spend 0.131 days more working outside the household together with 0.194 days less in school in the last seven days compared to children of non-participating households. Separated by gender, the results are statistically significant for boys, whilst the coefficients for girls are similar in magnitude and direction but less precise. Similar conclusions are drawn by Shah and Steinberg (2015) where children aged 13–17 are suggested to experience a decrease in school attendance by 2.8 percentage points and an increase in productive work by 2.4 percentage points. The researchers thereto obtain significant gender differences. Whereas boys primarily substitute for paid work, girls engage in unpaid domestic work. For the younger children, however, the results are mixed.

In contrast to these findings, based on a matching difference-in-differences approach, Sheahan et al. (2020) find no within-household substitution of either paid or unpaid work towards the beneficiary children of the household. The used data does not allow the researchers to analyse potential impacts on schooling. Additionally, as the discussed works only consider household participation, it is currently unknown whether the conclusions will be affected when considering the gender of the MGNREGS-participant. The conclusions presented by Afridi, Mukhopadhyay and Sahoo (2016), who analyse the effect of MGNREGS on time spent on school, indicate that such a division is important to consider. According to their findings, a mother’s participation is associated with an increase in school attendance for both sexes, while the opposite effect applies if the father has an employment under the programme.

2.2 Theoretical Expectations and Hypotheses

According to the previous sub-section, it is thus *a priori* difficult to determine the effects of public employment programmes on child labour. Therefore, whilst the theoretical framework provides an indication of the possible impacts of public employment programmes on the child’s time allocation, empirical evidence is needed to facilitate the work of policy makers in responding to potential unintended consequences of the programmes. This equally applies to the case of India. Given the conflicting findings for MGNREGS, where the gender of the programme participant to date remains unconsidered, this thesis aims to provide further clarity in the matter.

Based on the theoretical framework including findings from previous research, the thesis is shaped around the following hypotheses:

1. Through the income effect, a higher household income obtained by household participation in MGNREGS is expected to reduce the beneficiary children's time spent on paid work.
2. Through the substitution effect, household participation in MGNREGS is expected to increase the beneficiary children's time spent on unpaid work consisting of household tasks and chores.
3. Household participation in MGNREGS is expected to reduce the beneficiary children's time spent on schooling and leisure.
4. Disaggregated on gender of the children whose household participates in MGNREGS: beneficiary girls are expected to increase the time spent on unpaid household chores with a decrease in schooling. Beneficiary boys are expected to increase the time spent on paid work with a decrease in schooling.
5. With regard to the gender of the household's MGNREGS-participant: female participation is expected to increase the beneficiary children's time spent on schooling whereas the opposite is expected to apply for male participation. These results are expected to apply for both beneficiary girls and boys in the household.

3 Data and Methodology

To investigate the above research question, and in accordance with previous research on the subject, a quantitative research design will be implemented. The following section is therefore divided into three sub-sections. First, the used dataset including the sampling and collection approach will be described in detail emphasising the relevance, representativity and reliability of the available data. Thereafter, descriptive statistics will be presented followed by the methodological approach.

3.1 Source Material

The analysis is based on the Young Lives longitudinal dataset, which is an international research project aimed at understanding the causes and consequences of childhood poverty. Whilst the project is core-funded by the Foreign, Commonwealth & Development Office (FCDO), it is coordinated by the Oxford Department of International Development (ODID) at the University of Oxford. Over a 15-year period, the study follows approximately 3 000 households in the former Andhra Pradesh with the first round starting in 2002. In total, there are five survey rounds (2002, 2006, 2009, 2013, 2016), which are all publicly available at the UK Data Service.

The study consists of a younger and older cohort of 2 011 and 1 008 children in the first round, respectively, and is considered by the producers to be a large enough sample to perform statistical analysis. The two cohorts, which were one and eight years old at the first survey round, were sampled in geographic clusters through a semi-purposive approach. Initially, 10 districts were selected based on a selection of criteria[1]. Within the chosen clusters, the individuals were selected randomly. In comparison to other longitudinal studies, the attrition rate is low for the Young Lives sample covering the former Andhra Pradesh (Young Lives, 2017). For the survey rounds used in this thesis, the attrition rate was 1.79 % for the younger cohort (2006, 2013) and 1.71 % for the older cohort (2006, 2009). Although the drop out has been partly non-random, Outes-Leon and Dercon (2008) conclude that it is unlikely that this will cause significant attrition bias. An overview of the structure of the Young Lives sample is presented in Table 1.

Table 1 Overview of the Structure of the Young Lives Sample

	Younger cohort					Older cohort				
	2002	**2006**	**2009**	**2013**	**2016**	**2002**	**2006**	**2009**	**2013**	**2016**
N	2 011	1 950	1 931	1 915	1 900	1 008	994	977	952	922
Mean age	1.00	5.36	7.95	11.98	15.00	7.98	12.32	14.94	19.00	22.00
Girls	930	903	897	885	876	517	510	499	487	474
Boys	1 081	1 047	1 034	1 030	1 024	491	484	478	465	448

Source: author's compilation based on the Young Lives dataset.

With regard to the aim of the research project, poorer households were over-sampled (Young Lives, 2017). This skewness is, however, considered relevant for this study as the primary target group of the programme corresponds to the poorer and marginalised groups of society (Government of India, 2013). Nevertheless, a broad group of children were included in order to ensure regional representation (Young Lives, 2017). Through a detailed assessment of the Young Lives sampling approach, Kumra (2008) compares the dataset to the nationally

[1] The 10 districts are West Godavari, Srikakulam, Kadapa and Anantapur in Andhra Pradesh and Karimnagar, Jayashankar, Nagarkurnool, Mahabubnagar, Jogulamba in Telangana. The 10th district corresponds to the state capital of Andhra Pradesh and Telangana, Hyderabad (Young Lives, 2017).

representative survey Demographic and Health Survey (DHS). Whilst it is not intended for the Young Lives dataset to be nationally representative, from a comparison of characteristics such as household wealth and assets, education, gender and ethnicity, the researcher concludes that the sample is representative of the children in Andhra Pradesh and Telangana. Consequently, it is stated that it serves as a valuable and appropriate instrument for conducting causal analysis (Kumra, 2008). This can be further supported through a simple comparison between the Young Lives sample and data for the former Andhra Pradesh collected through the National Sample Survey. Looking at monthly total per capita expenditure for the closest comparative years, it amounted to on average 803 Rs. in 2004/2005, 1736 Rs. in 2009/2010 and 2220 Rs. in 2011/2012 according to the reports published by the National Sample Survey Organisation (2006, 2011, 2015). Similarly, although generally slightly lower, the corresponding figure for the sample in this study is 857 Rs. in the second survey round, 1436 Rs. in the third survey round and 2193 Rs. in the fourth survey round.

All survey rounds consist of a child and a household questionnaire which are primarily answered by the child's primary caregiver. After the Young Lives children pass the age of 8, the child questionnaire is answered by the children themselves. The study collects detailed information about various demographic and household-level factors related to, among others, socio-economic status and expenditure patterns. On the individual level, questions concern parental background, including time-use, education and health status of the child. From round 2 in 2006, various questions concerning participation in MGNREGS are included in the household questionnaire. To provide further information about the local environment, each survey round includes a community questionnaire answered by the representative of the community (Young Lives, 2011). Due to the rich availability of data, there is no need for additional data sources to be incorporated in the analysis. Through all five rounds, the questionnaires were administered in the local language, thus preventing misunderstandings that language barriers may cause.

Lastly, it should be noted that all work performed by children is not necessarily harmful and should be considered as child labour. Rather, certain types of work can be regarded as positive for their personal development (ILO, 2018). Due to data limitations, however, it is not possible to distinguish the specific types of work including the conditions under which the work is performed. This constitutes a recurring limitation in the current child labour literature (Lambon-Quayefio, 2021). In line with similar research in the field and in order to capture part of the definition of the term, school attendance is also included in the analysis. Whilst being aware of this limitation in the interpretation of the results, the dataset has been used in a variety of professional social science research, including to examine various child labour issues (see for example Young Lives, 2021).

3.2 Descriptive Statistics

Table 2 presents baseline descriptive statistics on relevant household characteristics for the untreated (non-participating) and treated (participating) households in 2006. Overall, the observable attributes are relatively unbalanced between the two groups. In particular, it is shown that participating households in MGNREGS on average have considerably lower monthly expenditures and socio-economic status measured through a wealth index and where relatively more households belong to the Scheduled Tribes and Scheduled Castes. Whereas there are no considerable differences in household size, 42.8 % of the treated households have experienced income shocks since the previous survey round in 2002 compared to 21.3 % of the households in the untreated group. In addition, as shown in the table, on average 38.8 % of the participating households are self-employed in agriculture compared to 15.5 % of the non-participating households. Similarly, the treated households reside to a greater extent in rural areas and where the parents of the household have a relatively lower level of education compared to the non-participating households. Although an evaluation of the programme's targeting efficiency is not an objective of the thesis, an initial analysis of the sampled MGNREGS-participants thus indicates a functioning targeting mechanism, reaching the more economically and socially vulnerable groups of society. These results are further supported by t-tests of selected baseline characteristics of the untreated and treated households. The results are presented in Table A.1 in Appendix A. Note that each variable will be presented in detail in section 3.3.4.

Table 2 Baseline Descriptive Statistics (2006) – Household Characteristics

	Untreated				Treated			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Household characteristics								
Total per cap. expenditure (Rs.)	1038.224	715.485	219.583	8723.959	625.637	399.761	130.917	4456.833
Ethnicity								
Scheduled Tribes	8.1%	0.273	0	1	23.6%	0.425	0	1
Scheduled Caste	10.1%	0.302	0	1	15.3%	0.361	0	1
Backward Caste	44.5%	0.497	0	1	52.2%	0.500	0	1
Other	37.3%	0.484	0	1	8.8%	0.283	0	1
Wealth index	0.591	0.191	0.094	0.946	0.364	0.160	0.009	0.926
Income shock	21.3%	0.409	0	1	42.8%	0.495	0	1
Household size	5.374	2.205	3	23	5.379	2.012	2	28
HH. occupation								
Self-empl. non-agri.	28.3%	0.450	0	1	9.6%	0.295	0	1
Self-empl. agri.	15.5%	0.362	0	1	38.8%	0.488	0	1
Regular wage empl.	49.4%	0.500	0	1	46.2%	0.499	0	1
Unempl. / HH. dependent	6.9%	0.253	0	1	5.4%	0.227	0	1
Mother's education (in years)	5.649	4.623	0	15	1.879	3.015	0	12
Father's education (in years)	7.643	4.845	0	15	3.196	3.953	0	15
Rural site (=1)	49.6%	0.500	0	1	99.4%	0.080	0	1
Time to school (in minutes)	12.389	10.877	0	90	12.037	15.629	0	180
Child's sex (girl=1)	47.9%	0.500	0	1	47.1%	0.500	0	1
Child's age	7.610	3.236	4.5	13.167	7.528	3.195	4.667	12.917
Number of observations		800				626		

Source: author's calculations based on the Young Lives dataset.

Turning to the outcome variables of interest, Table 3 displays post-programme descriptive statistics. The means presented in the table suggest that whilst none of the children in the two treatment groups spend a considerable amount of time on paid work, children of treated households spend slightly more time on those activities compared to children of non-participating MGNREGS-households. Instead, the children, regardless of treatment status, are suggested to spend relatively more time on unpaid work. Compared to children of untreated households, the children of treated households seem to spend on average 0.108 hours more per day on unpaid household tasks, referring to activities such as farming and other family business, and slightly more time performing unpaid household chores. With regard to the latter, they are suggested to spend on average 1.222 hours per day. Thus, the above-presented international statistics from ILO (2018), suggesting that the majority of the work is performed within the own family unit, is supported also by this sample. Furthermore, although children of both treatment states are suggested to have a high school attendance, children of treated households spend slightly less time on schooling compared to the control group. This equally applies to the hours spent on leisure per day. As shown in the table, no more than 12 hours per day is spent on any of the listed activities.

Table 3 Post-Programme Descriptive Statistics (2009/2013) – Outcome Variables of Interest

	Untreated				Treated			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Outcomes of interest (h/day)								
Paid work	0.003	0.050	0	1	0.024	0.381	0	8
Household tasks	0.020	0.199	0	4	0.128	0.527	0	7
Household chores	0.981	0.977	0	8	1.222	1.096	0	10
Schooling	8.425	1.159	0	12	8.102	1.186	0	12
Leisure	3.668	1.338	1	11	3.629	1.446	0	12
Number of observations		800				626		

Source: author's calculations based on the Young Lives dataset.

As presented in Table A.2 in Appendix A, the differences in means are statistically significant for all outcomes except for paid work and leisure according to two-sampled t-tests. Nevertheless, these estimates must be viewed with caution. If treatment state had been assigned randomly, the differences in means would provide unbiased estimates of programme impacts. However, given the pre-existing differences in observable characteristics shown in Table 2 and Table A.1, this can give rise to highly misleading comparisons (Rosenbaum & Rubin, 1983). Consequently, more sophisticated methods are needed in order to estimate the causal impact on child labour and children's school attendance of its household members' participation in MGNREGS.

3.3 Methodological Approach

Selection bias corresponds to the fundamental issue of impact evaluations and arises due to the inability to observe the outcome of the treatment group in the absence of treatment. To obtain the non-treatment outcome, one can only observe the parallel result of the control group. However, as discussed above, to only compare before and after differences in means of the two groups will most likely provide biased estimates. To construct credible counterfactuals in the absence of experimental data, quasi-experimental methods have become widely accepted in empirical research within the social sciences. For example, and in line with previous research on the subject, the combination of the difference-in-differences method and propensity score matching is an applied econometric method, for its ability to correct for selection bias and identify the average treatment effect on the treated (ATT) (Abadie, 2005). Given the non-experimental design of MGNREGS, this combined identification strategy becomes relevant also in this thesis. To properly motivate this reasoning, the difference-in-differences method and propensity score matching will first be explained separately.

3.3.1 Difference-in-Differences (DID) Method

Lechner (2011) describes the framework of difference-in-differences (DID) as follows. The outcome of interest for individual i at time t corresponds to $Y^D(i,t)$ where t = 0 in the pre-programme period and t = 1 in the post-programme period for the population observed. As indicated, part of the population is employed under MGNREGS between these two periods. More specifically, we denote D = 1 for the individuals who participated in the programme; D = 0 otherwise. Whereas the former group is commonly referred to as *treated*, the latter group is called *untreated* (or *controls*). Depending on the treatment status, the potential outcomes of interest for each group and time are thus defined Y^0 and Y^1 of which only one outcome is observed. Note that the individuals only are employed after the pre-programme period. Thus, $D = 0$ for all i when t = 0. The DID method therefore estimates the ATT as follows,

$$ATT^{DID} = E[Y^1(i,1) - Y^0(i,0) \mid D = 1] - E[Y^0(i,1) - Y^0(i,0) \mid D = 0] \qquad (1)$$

As suggested, the DID estimate corresponds to the difference of the mean outcomes of programme participation before and after the intervention minus the corresponding mean outcome difference of the control group for the same period. Under this approach, characteristics that are time-invariant within each group (within parentheses) and time-varying but constant across the treatment and control group (outside parentheses) are controlled for. Therefore, by subtracting the two differences, this method removes the selection bias caused by time-invariant unobservable and observable factors. By extension, this implies that the time series of mean outcomes in the treatment and control group should follow a common trend in absence of treatment. This corresponds to the key identifying assumption of the method and is known as the parallel trend assumption. In other words, conditional on observable characteristics X, the following equality should hold:

$$E[Y^0(i,1) - Y^0(i,0) \mid X, D = 1] = E[Y^0(i,1) - Y^0(i,0) \mid X, D = 0] \qquad (2)$$

where $Y^0(i,1)$ corresponds to the potential outcome concerning child labour and school attendance in absence of public employment in the post-programme period for individual i and

$Y^0(i, 0)$ refers to the potential outcome in absence of public employment in the pre-programme period for individual i.

Putting it in further context, given that this assumption holds, the impact on child labour and children's school attendance of its household members' participation in MGNREGS is estimated through the following basic DID equation:

$$y_{it} = \beta_0 + \beta_1(treat_{it}) + \beta_2(time_{it}) + \beta_3(treat_{it} \times time_{it}) + \beta_4 X_{it} + \varepsilon_{it} \qquad (3)$$

where y_{it} denotes the dependent variables hours per typical weekday spent on paid work, unpaid household tasks, unpaid household chores, schooling or leisure for child *i* at time *t*. The variables $treat_{it}$ and $time_{it}$ are dummy variables that equal one if the household members have public employment under MGNREGS and if the observation is in the post-programme period, respectively. Similarly, the interaction term, $treat_{it} \times time_{it}$, is formulated as a dummy variable and equals one for the individuals who have public employment in the post-programme period. In other words, β_3 corresponds to the coefficient of the independent variables in this thesis and, in accordance with the research objective, will concern three different formulations of participation in MGNREGS: (1) household participation, (2) female household participation, and (3) male household participation. X_{it} is a vector of observable control variables, introduced in Table 2, and which will be discussed in detail in section 3.3.4.

However, if the pre-treatment characteristics, which are thought to influence the outcome variables in this study, are unbalanced between the two treatment groups, the parallel trend assumption will be too stringent and thus give biased DID estimates (Abadie, 2005). As shown in Table 2, this is suggested to be the case in the context of MGNREGS and is further commonly justified on two grounds in the literature – the programmes non-random placement including its self-selecting nature (see for example Sheahan et al., 2020; Varshney, Goel & Meenakshi, 2018). Therefore, in order to construct a credible control group, propensity score matching is introduced.

3.3.2 Propensity Score Matching (PSM) Method

In accordance with the explanations provided by Caliendo and Kopeinig (2008), propensity score matching (PSM) is built on the following principles. The PSM method addresses selection bias by constructing an artificial control group that resembles the MGNREGS-participants as close as possible. More specifically, based on a vector of observable characteristics, the method computes a propensity score defined as the probability of being employed under the programme. In formal terms, the propensity score can be written as, $P(D = 1 \mid X) = P(X)$. The propensity score is then used to match similar treated and untreated individuals. Therefore, by creating "statistical twins", the incorporation of the method enables the parallel trend assumption discussed above to become more plausible.

The method, which was first introduced by Rosenbaum and Rubin (1983), relies on two identifying assumptions. The so-called Conditional Independence Assumption (CIA) (also known as unconfoundedness or selection on observables) implies that conditional on observable characteristics X, all of which can be observed by the researcher and are unaffected by treatment, the potential outcomes of the treated and control group are independent of treatment assignment. Formally, the assumption can be written as,

$$Y^0, Y^1 \perp D \mid X \tag{4}$$

where $\perp$ denotes independence. Given that the CIA holds, the assumption can equally be written as,

$$Y^0, Y^1 \perp D \mid P(X) \tag{5}$$

stating that the potential outcomes are independent of treatment status conditional on the propensity score. By controlling for the propensity score $P(X)$, the treatment can then be regarded as randomly assigned.

The second assumption is known as the Common Support Condition, and states that, given the same observable characteristics X, the probability of being employed under the programme, and equivalently in the control group, lies between 0 and 1,

$$0 < P(D = 1 \mid X) < 1 \tag{6}$$

As such, the treatment status D cannot be perfectly predicted. By ensuring an overlap in the characteristics of the two groups, the assumption is also called the overlap condition.

Given that the two assumptions hold, the PSM method estimates the ATT as[2],

$$ATT^{PSM} = E_{P(X)\mid D=1}\{E[Y^1 \mid D = 1, P(X)] - E[Y^0 \mid D = 0, P(X)]\} \qquad (7)$$

Expressed differently and in context, the PSM estimator corresponds to the mean difference in outcomes concerning child labour and school attendance over the region of common support when household members participate in MGNREGS. By being weighted by the appropriate propensity scores, the PSM approach enables the elimination of selection bias caused by disparities in observable characteristics X between the programme participants and the non-programme participants.

It should be noted, however, that household members' decision to self-select into MGNREGS need not only stem from observable factors but also from unobservable ones. Similarly, as previously discussed, the child labour literature puts forward unobservable determinants such as parental preferences for understanding children's time allocation. Since these characteristics cannot be isolated from the impact of treatment merely by matching, it causes the CIA assumption to be violated with an associated estimation bias. Therefore, in order to allow selection on unobservables whilst constructing a credible control group, Caliendo and Kopeinig (2008) discusses how the PSM method can be combined with the DID method[3] – an estimation strategy that also can be identified in existing research on MGNREGS.

---

[2] Note that the assumptions are weakened when estimating the ATT,

Conditional Independence Assumption: $Y^0 \perp D \mid X$

Common Support Condition: $P(D = 1 \mid X) < 1$

[3] Instrumental variables estimation corresponds to another identification strategy that PSM can be combined with (Caliendo & Kopeinig, 2008).

3.3.3 Difference-in-Differences Propensity Score Matching (DID-PSM) Method

The difference-in-differences propensity score matching (DID-PSM) method was developed by Heckman, Ichimura and Todd (1997), and is, as suggested by its name, based on the combination of the DID and PSM method. Therefore, provided that the unobservable differences in outcomes between MGNREGS-participants and non-participants are time-invariant, the CIA assumption can be relaxed and thus remove potential bias by combining PSM with the conventional DID method. Furthermore, in the words of Smith and Todd (2005), by reducing the heterogeneity in observable factors through matching including not imposing the linear functional form restriction in estimating the outcome variables, the DID-PSM estimator is considered superior to the conventional DID method.

Just as the DID-PSM approach combines the strengths of the two methods, it relies on the remaining identifying assumptions of both techniques: the parallel trend assumption (2) and the common support condition (6). When the two assumptions hold, the ATT can be estimated as,

$$ATT^{DID-PSM} = \frac{1}{N_{D=1}} \sum_{i \in D=1 \cap S} \left[\left(Y^1(i,1) - Y^0(i,0) \right) - \sum_{j \in D=0 \cap S} w_{ij} \left(Y^0(j,1) - Y^0(j,0) \right) \right] \quad (8)$$

Where S refers to the area of common covariate support, and w_{ij} is the weighting factor that determines the weight a "statistical twin" is assigned when constructing the control group (Caliendo & Kopeinig, 2008).

In particular, the DID-PSM method has been applied in analyses of labour market interventions but has come to be applied in a variety of contexts over the years (Nolan, 2008). For example, it can be identified in impact evaluations of social protection programmes against various outcome variables, including child labour (see for example Juras, 2014; Sheahan et al., 2020; Varshney, Goel & Meenakshi, 2018). To provide reliable estimates of programme impact through the use of this combined method, Heckman, Ichimura and Todd (1997) argue that (1) treated and untreated individuals should have access to the same markets, (2) information about treated and untreated individuals should be collected from the same data source, and (3) the used data includes relevant covariates that can identify programme participation as well as outcomes. Given the previous sections, each criterion can be argued to be satisfied in this research.

3.3.4 Constructing the *MGNREGS* Control Group

DID-PSM is implemented through a sequence of steps. First, one needs to estimate the propensity score based on a set of chosen variables, choose a matching algorithm and model. Before performing the empirical analysis, it is thereafter important to assess the matching quality and the identifying assumptions. As discussed, the CIA needs to be met for a reliable matching, thus requiring that the outcomes are independent of treatment status conditional on the propensity score. Therefore, the choice of variables X must credibly meet this condition, implying that variables that affect both the decision to participate in the programme and the time allocation of children should be included (Caliendo & Kopeinig, 2008). Therefore, in order to construct a credible control group, the eligibility requirements and target groups of the programme as discussed in section 2.1.1 are replicated to the extent possible whilst simultaneously considering the determinants of child labour.

First, being a densely populated urban district, the state capital of Andhra Pradesh and Telangana, Hyderabad, is not covered by the programme. Therefore, Hyderabad is excluded from the analysis, which also corresponds to the only district in the dataset that is not a part of MGNREGS (Ministry of Rural Development, n.d.*b*). In line with the eligibility criteria, it is also ensured that the participating household members are above the age of 18. Furthermore, common to both selection into the programme and the incidence of child labour are various welfare factors including income shocks. Therefore, household-level variables capturing monthly total per capita expenditure, caste, a wealth index[4] and occurrence of income shocks such as crop failure, drought and rain are included. Household size is also considered.

[4] The Young Lives wealth index captures the socio-economic status of households and is constructed from three equally weighted indices: (1) housing quality, (2) access to services, and (3) ownership of consumer durables. See Appendix B for a detailed description.

As outlined in section 2, occupation and years of education are other central determinants and are thus included. Similar to previous findings and approaches within this field of research, occupation captures that of the household head whereas level of education concerns the mother and the father in the household (see for example Uppal, 2009). The latter choice is further supported by the findings of Kurosaki, Ito, Fuwa, Kubo and Sawada (2006) who in an empirical analysis of the former Andhra Pradesh suggest that parents' level of education is a more central determinant of child labour compared to the educational status of other household members. Geographically and in accordance with the child labour literature, it is indicated whether the residential area of the household is rural or urban, including access to school measured by travel time to school in minutes. Regarding individual characteristics, the gender and age of the child are considered. Lastly, in order to control for district-level time-variant effects of demand and supply shocks, policy changes, including the rollout schedule of MGNREGS, district-year fixed effects are included in the model[5]. A detailed listing of the covariates used for matching are shown in Table B.1 in Appendix B.

As mentioned, it is important that only covariates that are unaffected by treatment are included in the analysis. This can be ensured by matching on the pre-treatment characteristics (Caliendo & Kopeinig, 2008). As questions about children's time allocation were not included in the survey in 2002, the second survey round in 2006 is established as the baseline period. With regard to the rollout schedule of MGNREGS, some households in the dataset had already benefitted from the programme at this point and are therefore excluded from the sample. When establishing the post-treatment sample, other factors must be considered. Given the purpose of analysing the impact of MGNREGS on child labour and school attendance, careful consideration must be given to the ages of the children in the sample. In order to create a representative age range whilst ensuring that the children are not yet expected to be in the labour

[5] As done by Islam and Sivasankaran (2014) and Sheahan et al. (2020).

market, two survey rounds were pooled, namely the third survey round (2009) and the fourth survey round (2013) for the older and younger cohort, respectively. As a result, the sample consists of children between the ages of 4.5 and 13 at the baseline period (mean age: 7.5), and 11 to 16 years old after treatment (mean age: 13). As the questionnaires do not consider the accumulated length of household participation in the programme, this does not result in loss of information.

Based on this choice of variables, a matching algorithm is now to be selected. There are several types of matching algorithms, which through different approaches contrast the outcomes of the treated individuals with the corresponding outcomes of the control group members. Among the propensity score matching estimators are nearest neighbour matching, caliper and radius matching, stratification and interval matching, including kernel and local linear matching (Caliendo & Kopeinig, 2008). The choice of matching algorithm largely depends on the data structure and can be particularly important for small samples. Whereas there is little formal guidance in the choice of optimal method, it is suggested to consider the unmatched distribution of propensity scores between the two treatment groups (Bryson, Dorsett & Purdon, 2002; Heckman, Ichimura & Todd, 1997). The distribution of the propensity scores for non-MGNREGS and MGNREGS-participants prior to matching is displayed in Figures 1.1-1.3 below. Based on the words of Bryson, Dorsett and Purdon (2002), as some treated individuals have several close neighbours while the opposite holds for other treated individuals in the sample, the commonly used non-parametric kernel matching estimator is suitable for this thesis.

To construct the counterfactual outcome, the kernel matching algorithm calculates weighted averages of almost all individuals in the control group. Depending on the choice of kernel function, the weights depend on the distance between the observation of each control group member to that of the participant for which the counterfactual is estimated, with usually a higher weight given to the comparators that provide a better match. By using nearly all available information, the kernel approach can achieve a lower variance in the estimations. Simultaneously, there is a risk of including poor matches in the analysis, making it of significant importance that the common support condition is satisfied. The application of kernel matching requires two choices: the choice of kernel function and bandwidth parameter (Caliendo & Kopeinig, 2008). Given that the former has proven to be less important in applied research (DiNardo & Tobias, 2001), the popular Epanechnikov kernel function is applied. By restricting the analysis to only use the information within a specific bandwidth of the estimated propensity score, this function can avoid poor matches (Heckman, Ichimura & Todd, 1997). The relatively more important choice according to the literature, bandwidth, exhibits a bias-variance trade-off. Whilst a higher bandwidth yields a smoother estimated density function with a decreasing variance, it can smooth away underlying features, leading to a biased estimate (Caliendo & Kopeinig, 2008). To obtain an appropriate bias-variance compromise, the user-written command *kmatch* is used for estimating the econometric specifications in this study for its feature to select a data-driven automatic bandwidth (Jann, 2017). The model choice, which is considered less critical for cases of binary treatments, is a probit function (Caliendo & Kopeinig, 2008). Standard errors are bootstrapped with 1000 replications[6].

3.3.5 Assessment of the Matching Quality and the Identifying Assumptions

For the regressions to be reliable, the matching needs to be of good quality and support the underlying identifying assumptions. With regard to the matching quality, the propensity score estimations need to balance the covariates (Augurzky & Schmidt, 2001). According to Rosenbaum and Rubin (1985), one suitable indicator for assessing the matching quality is to analyse the standardized difference in means before and after matching. Consequently, this is a common assessment approach in evaluation studies (Caliendo & Kopeinig, 2008; Zhang, Kim, Lonjon & Zhu, 2018). The respective means of the pre-treatment covariates with their associated standardized mean difference before and after matching are displayed in Tables 4.1-4.3. Whereas Table 4.1 concerns household participation as a whole, Tables 4.2 and 4.3 correspond to female and male household participation, respectively.

[6] For nearest neighbour matching, Abadie and Imbens (2008) show that bootstrapping can yield inconsistent results for one-to-one matching. For kernel matching, however, there are no indications on that bootstrapping would be inappropriate (Jann, 2017).

Table 4.1 Comparison of Covariates Before and After Matching at the Baseline Period – Household Participation

	Unmatched			Matched		
Covariates	Treated	Untreated	StdDif	Treated	Untreated	StdDif
Total per cap. expenditure (Rs.)	625.636	1038.224	-0.712	636.985	680.698	-0.075
Ethnicity						
Base level: Scheduled Tribes						
Scheduled Caste	0.153	0.101	0.157	0.155	0.171	-0.048
Backward Caste	0.522	0.445	0.155	0.532	0.585	-0.105
Other	0.088	0.372	-0.718	0.090	0.084	0.016
Wealth index	0.364	0.591	-1.283	0.372	0.352	0.114
Income shock	0.428	0.212	0.475	0.421	0.432	-0.024
Household size	5.379	5.374	0.002	5.359	5.161	0.094
HH. occupation						
Base level: Self-empl. non-agri.						
Self-empl. agri.	0.388	0.155	0.543	0.371	0.339	0.074
Regular wage empl.	0.462	0.494	-0.064	0.474	0.491	-0.033
Unempl. / HH. dependent	0.054	0.069	-0.060	0.055	0.069	-0.060
Mother's education (in years)	1.879	5.649	-0.966	1.932	1.659	0.070
Father's education (in years)	3.196	7.643	-1.006	3.311	3.178	0.030
Rural site (=1)	0.994	0.496	1.388	0.993	0.986	0.020
Time to school (in minutes)	12.037	12.389	-0.026	11.882	12.674	-0.059
Child's sex (girl=1)	0.471	0.479	-0.015	0.478	0.499	-0.042
Child's age	7.528	7.610	-0.026	7.523	7.384	0.043

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Standard errors are bootstrapped with 1000 replications. District-year fixed effects included. Source: author's calculations based on the Young Lives dataset.

Table 4.2 Comparison of Covariates Before and After Matching at the Baseline Period – Female Household Participation

	Unmatched			Matched		
Covariates	Treated	Untreated	StdDif	Treated	Untreated	StdDif
Total per cap. expenditure (Rs.)	608.784	1018.624	-0.721	619.993	669.090	-0.086
Ethnicity						
Base level: Scheduled Tribes						
Scheduled Caste	0.151	0.106	0.134	0.155	0.169	-0.041
Backward Caste	0.528	0.447	0.164	0.540	0.543	-0.007
Other	0.078	0.358	-0.719	0.082	0.083	-0.002
Wealth index	0.358	0.578	-1.244	0.368	0.359	0.054
Income shock	0.427	0.229	0.431	0.411	0.455	-0.095
Household size	5.381	5.373	0.004	5.389	5.185	0.097
HH. occupation						
Base level: Self-empl. non-agri.						
Self-empl. agri.	0.390	0.171	0.501	0.374	0.351	0.052
Regular wage empl.	0.472	0.485	-0.027	0.482	0.490	-0.015
Unempl. / HH. dependent	0.055	0.067	-0.050	0.056	0.068	-0.051
Mother's education (in years)	1.790	5.427	-0.939	1.832	1.631	0.052
Father's education (in years)	3.089	7.383	-0.972	3.215	3.153	0.014
Rural site (=1)	0.993	0.534	1.283	0.993	0.994	-0.003
Time to school (in minutes)	11.662	12.606	-0.071	11.809	11.309	0.038
Child's sex (girl=1)	0.468	0.480	-0.025	0.475	0.530	-0.111
Child's age	7.315	7.742	-0.134	7.376	7.155	0.069

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Standard errors are bootstrapped with 1000 replications. District-year fixed effects included. Source: author's calculations based on the Young Lives dataset.

Table 4.3 Comparison of Covariates Before and After Matching at the Baseline Period – Male Household Participation

	Unmatched			Matched		
Covariates	Treated	Untreated	StdDif	Treated	Untreated	StdDif
Total per cap. expenditure (Rs.)	607.672	968.410	-0.646	633.057	650.580	-0.031
Ethnicity						
Base level: Scheduled Tribes						
Scheduled Caste	0.157	0.110	0.139	0.169	0.185	-0.047
Backward Caste	0.480	0.479	0.002	0.516	0.530	-0.028
Other	0.086	0.319	-0.605	0.093	0.084	0.022
Wealth index	0.346	0.556	-1.163	0.365	0.361	0.021
Income shock	0.448	0.244	0.437	0.428	0.459	-0.066
Household size	5.436	5.349	0.042	5.399	5.325	0.035
HH. occupation						
Base level: Self-empl. non-agri.						
Self-empl. agri.	0.434	0.178	0.577	0.391	0.405	-0.031
Regular wage empl.	0.443	0.496	-0.106	0.477	0.432	0.090
Unempl. / HH. dependent	0.039	0.073	-0.150	0.042	0.049	-0.032
Mother's education (in years)	1.643	5.043	-0.892	1.731	1.633	0.026
Father's education (in years)	2.832	6.967	-0.943	2.988	3.025	-0.008
Rural site (=1)	0.993	0.590	1.142	0.993	0.993	-0.000
Time to school (in minutes)	11.668	12.487	-0.060	11.856	12.890	-0.076
Child's sex (girl=1)	0.482	0.473	0.018	0.479	0.482	-0.006
Child's age	7.363	7.668	-0.096	7.444	7.438	0.002

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Standard errors are bootstrapped with 1000 replications. District-year fixed effects included. Source: author's calculations based on the Young Lives dataset.

Compared to after the matching procedure, and as shown in Tables 4.1-4.3, the means of the covariates between the treated and untreated individuals are considerably different before matching. According to the statistical literature, an absolute standardized difference in means less than or equal to 0.25 after matching generally indicates well-balanced covariates (Rubin, 2001; Stuart, 2010). A smaller threshold is applied by Normand, Landrum, Guadagnoli, Ayanian, Ryan, Cleary and McNeil (2001) and others and correspond to 0.1 (see Austin, 2009; Mamdani, Sykora, Li, Normand, Streiner, Austin, Rochon & Anderson, 2005). As the absolute standardized mean differences of (nearly) all matched covariates are less than (0.1) 0.25, the treatment and control group can be considered balanced. The same outputs are graphically represented in Figures C.1.1-C.1.3 in Appendix C. In addition to the standardized difference in means, the variance ratio is a common statistical measure for balance assessment. As graphically shown in Figures C.1.1-C.1.3 in Appendix C, the variance ratios for the covariates are close to 1, or at least between 0.5 and 2. Thus, additional support is provided for a satisfactory matching in this regard (Rubin, 2001; Stuart, 2010).

As outlined in section 3.3.3, the DID-PSM method relies on the common support condition and the parallel trend assumption. To analyse the former, a common approach in applied research is a visual comparison of the density distribution of the propensity scores in the treated and control group. More specifically, to make inferences about treatment effects, there needs to first be a sufficient overlap in the propensity scores across the two groups prior to matching. Second, after matching, the distribution (balance) of the scores should appear similar (Caliendo & Kopeinig, 2008). In the words of Lechner (2008), given that a potential violation of the assumption can be identified through such an approach, it is not needed to perform a more complicated analysis. Figures 1.1-1.3 present the areas of common support before and after matching for the three formulations of programme participation. As shown, there is a satisfactory area of common support before matching, resulting in 25 households (27 for female household participation; 31 for male household participation) being excluded due to off-support. This is further depicted in Figures C.2.1-C.2.3 and C.3.1-C.3.3 in Appendix C, which display box plots of the areas of common support and cumulative distribution plots before and after matching, respectively. With a relatively small proportion of lost observations, it is proposed that this causes few problems, especially regarding the representativeness of the results (Bryson, Dorsett & Purdon, 2002). Nevertheless, the sensitivity of the estimated effects will be further examined in sub-section 4.2. After matching, the propensity scores appear to be balanced. This is shown in Figures 1.1-1.3, including in the box plots of distributions of propensity score displayed in Figures C.4.1-C.4.3 in Appendix C. Together, therefore, the visual comparisons provide empirical support for the common support condition.

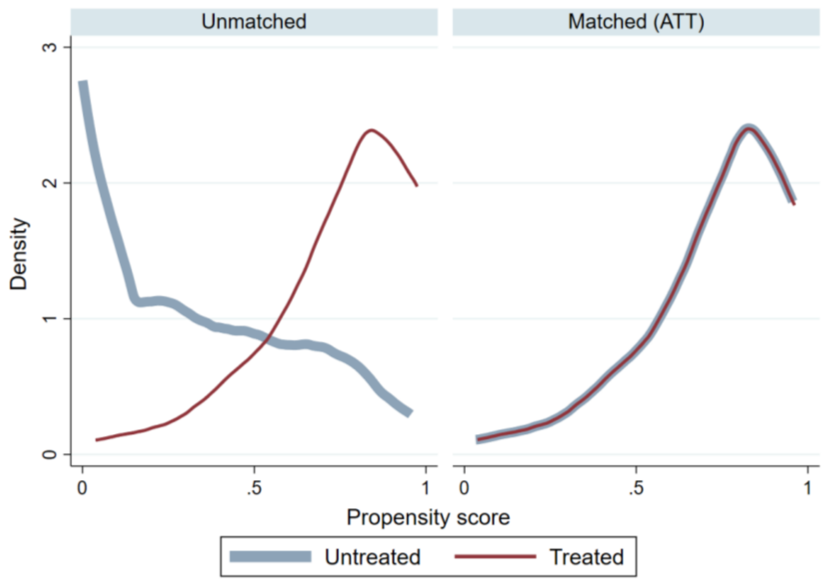

Figure 1.1 Area of Common Support and Kernel Density Plot Before and After Matching – Household Participation

Source: author’s calculations based on the Young Lives dataset.

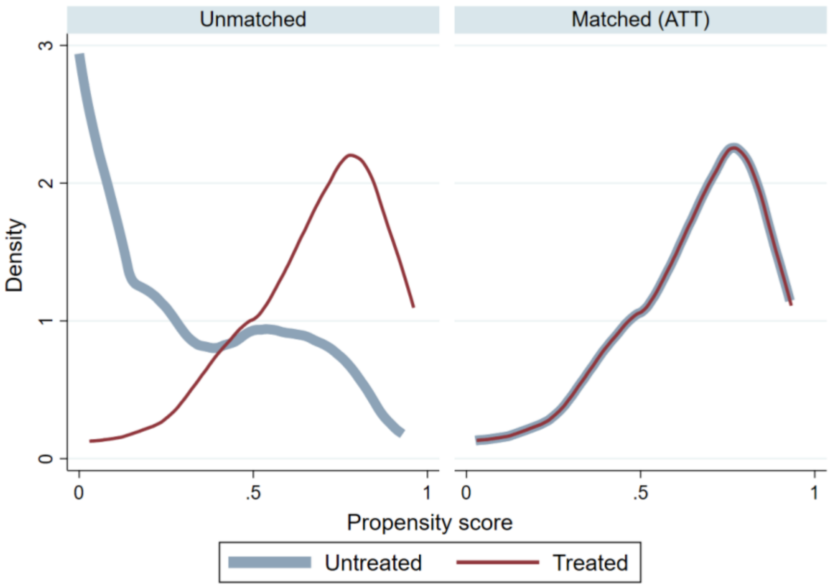

Figure 1.2 Area of Common Support and Kernel Density Plot Before and After Matching – Female Household Participation

Source: author's calculations based on the Young Lives dataset.

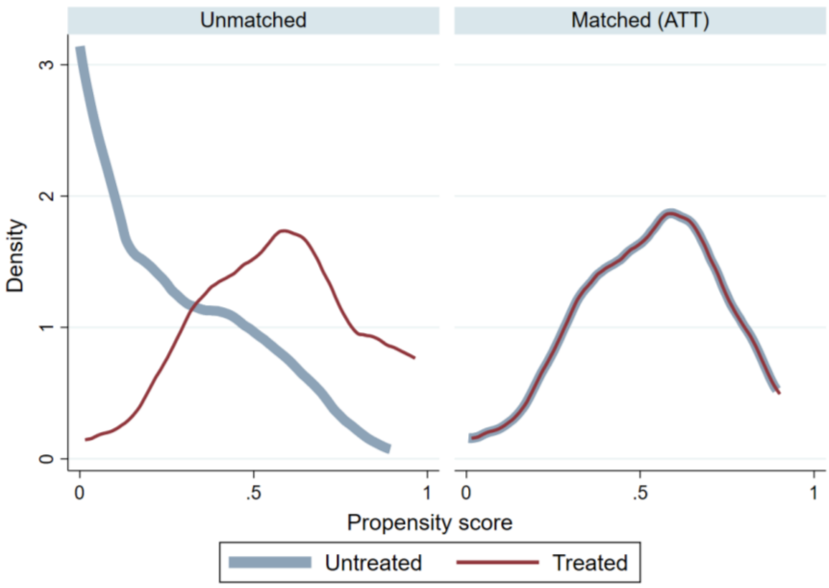

Figure 1.3 Area of Common Support and Kernel Density Plot Before and After Matching – Male Household Participation

Source: author's calculations based on the Young Lives dataset.

As previously discussed, the parallel trend assumption implies that the time series of outcomes in the treatment and control group should follow a common trend in the absence of treatment. Due to the impossibility of observing the outcome of the same individual and time period in both treatment states, the assumption is often visually inspected by comparing the trends of the two groups for a minimum of two pre-treatment periods (Angrist & Pischke, 2015). In this thesis, the assumption could thus be analysed by comparing the trend for MGNREGS-participants and non-MGNREGS participants between 2002 and 2006. Unfortunately, the producers of the Young Lives dataset did not include questions about children's time allocation in 2002. As such, the assumption cannot be visually tested in this case. Nevertheless, and as was displayed in Tables 4.1-4.3 above, the inclusion of PSM ensures that the individuals in the sample have similar pre-treatment characteristics. Thereto, the analysis controls for relevant observable determinants in accordance with the literature on MGNREGS and child labour whilst allowing for selection on time-invariant unobservables. Whereas this makes it reasonable to believe that the assumption is satisfied, when interpreting the results, it should yet carefully be kept in mind that the assumption has not been formally inspected.

Lastly, it is important to emphasize that the matching approach is not a 'magic bullet' that will solve evaluation problems entirely. Although the discussions above indicate that the underlying identifying assumptions – due to rich availability of data including an understanding of the institutional set-up of MGNREGS – are credibly met, there can still be observable characteristics that cannot be controlled for. Similarly, selection bias caused by time-variant unobservable factors cannot be removed by the DID method. Together, this violates the CIA assumption. In this regard, however, and in accordance with the reasoning of Sheahan et al. (2020), it is likely that the discussed supply-driven nature of the programme dampens self-selection. Nevertheless, this cannot eliminate the presence of selection bias entirely. Thereto, it is not possible to rule out issues of reversed causality. Lastly, as the analysis is based on longitudinal data, and where the third and fourth survey rounds are merged, individuals risk being compared across different macroeconomic conditions. Although the above analysis indicates a successful matching with satisfied assumptions and where the data is representative for Andhra Pradesh and Telangana, the external validity of the results can thus be weakened. This should carefully be kept in mind when interpreting the results.

4 Empirical Analysis

The following chapter presents the empirical analysis. After the results have been presented, the robustness of the results will be checked in sub-section 4.2. Thereafter, the main findings will be discussed in light of the existing body of literature in sub-section 4.3.

4.1 Results

In accordance with the research question, the following results present the estimated impact on child labour and children's school attendance of its household's, including female and male household members', participation in MGNREGS in Andhra Pradesh and Telangana. By extension, the point estimates concern hours per typical weekday spent on paid work outside the household, unpaid household tasks referring to activities such as farming and other family business, unpaid household chores, schooling and leisure. The results of the first formulation of programme participation – household participation – are displayed in Table 5. As can be seen in each panel of the table, the first and second row report the differences between the treated and control group at the baseline and post-treatment period, respectively. The row of interest corresponds to the third row, displaying the DID-PSM estimators for the outcome variables of interest.

Panel A reports the estimations of the pooled sample, thus referring to beneficiary children of the entire sample. According to the results, household participation in MGNREGS is associated with a statistically significant increase in time spent on paid work among the beneficiary children. Being statistically significant at the 10 percent level, the estimator suggests that beneficiary children spend on average 2 minutes more on paid work outside the household per day compared to the control group[7]. Therefore, it results in the first hypothesis being rejected. By extension, this contradicts the discussed income effect when analysing the impact of MGNREGS on paid child labour in Andhra Pradesh and Telangana. Rather, the estimate indicates that beneficiary children substitute, or possibly complement, the outside work undertaken by adult household members. In contrast, the point estimates for household tasks and chores are statistically insignificant. Thus, the data provides no statistical evidence on how household MGNREGS-participation on average affects time spent on unpaid work among beneficiary children in Andhra Pradesh and Telangana. Similarly, no conclusions can be drawn about the impact of household participation in MGNREGS on time spent on schooling and leisure among beneficiary children compared to the control group. The second and third hypothesis, suggesting an increase in unpaid child labour and a decrease in schooling and leisure, can therefore not be statistically confirmed although the sign of the point estimates, with the exception of household chores, are in line with the theoretical expectations.

Panel B and Panel C in Table 5 report the effects disaggregated on girls and boys, respectively. It should be noted that when the treatment groups are separated by gender, two new individual matching estimations and consequently control groups are created. Therefore, the results and the number of matched observations of the two sub-samples do not necessarily together equal the corresponding results for the pooled sample in Panel A. As can be seen in the table, none of the results are statistically significant at the standard significance levels for any of the sexes. Consequently, no conclusions can be drawn about the average impact on girls' and boys' time spent on paid and unpaid work, including schooling and leisure of its household's participation in MGNREGS in Andhra Pradesh and Telangana compared to the control group. By extension, the fourth hypothesis cannot be statistically accepted, although the sign of the coefficients of the concerned outcome variables for both sexes are in line with the theoretical expectations.

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[7] 0.033 h/day x 60 min/h = 1.98 min/day.

Table 5 The Impact on Children's Time Allocation of its Household's Participation in MGNREGS

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.008	-0.004	0.028	0.090	0.076
	(0.011)	(0.040)	(0.083)	(0.194)	(0.255)
Post-treatment					
Difference (T-C)	0.025	-0.001	-0.029	-0.034	0.041
	(0.017)	(0.056)	(0.108)	(0.146)	(0.161)
DID-PSM	**0.033***	0.003	-0.057	-0.124	-0.035
	(0.020)	(0.066)	(0.133)	(0.216)	(0.286)
Observations	1426	1426	1426	1426	1426
Matched observations	601	601	601	601	601
Panel B: Girls					
Baseline					
Difference (T-C)	-0.001	0.010	0.148	0.317	-0.348
	(0.009)	(0.009)	(0.127)	(0.360)	(0.422)
Post-treatment					
Difference (T-C)	0.049	-0.016	0.203	0.043	-0.011
	(0.040)	(0.056)	(0.188)	(0.178)	(0.202)
DID-PSM	0.050	-0.027	0.054	-0.275	0.337
	(0.041)	(0.057)	(0.213)	(0.316)	(0.409)
Observations	1426	1426	1426	1426	1426
Matched observations	286	286	286	286	286
Panel C: Boys					
Baseline					
Difference (T-C)	-0.005	0.049	-0.069	0.039	0.396
	(0.014)	(0.073)	(0.124)	(0.335)	(0.353)
Post-treatment					
Difference (T-C)	0.003	0.060	-0.138	-0.132	-0.128
	(0.004)	(0.129)	(0.155)	(0.248)	(0.274)
DID-PSM	0.008	0.011	-0.068	-0.171	-0.524
	(0.014)	(0.151)	(0.198)	(0.362)	(0.387)
Observations	1426	1426	1426	1426	1426
Matched observations	323	323	323	323	323

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.005, Panel B: 0.011, Panel C: 0.012. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Table 6 reports the results when the household's MGNREGS-participants are female. As in Table 5 Panel A, there is a statistically significant impact on time spent on paid work among beneficiary children when the household participant in MGNREGS is female. More specifically, it is suggested that beneficiary children spend on average 2.7 minutes more per day on paid work compared to the control group (significant at the 5 percent level). Consequently, it challenges a dominance of the income effect in Andhra Pradesh and Telangana. Similar to the results in Table 5, no conclusions can be drawn as to whether beneficiary children substitute for unpaid household work when females in the household participate in MGNREGS compared to the control group. Similarly, the point estimate for schooling is statistically insignificant. Hypothesis 5, suggesting a positive association between beneficiary children's school attendance and female household programme participation, can therefore not be confirmed although the sign of the point estimate is in accordance with the theoretical expectations.

Panel B and Panel C in Table 6 report the effects disaggregated on girls and boys, respectively. It is important to keep in mind that by dividing the sample between both female and male programme participants, and the gender of the beneficiary children, the sample size decreases. Therefore, the interpretation of the results in Panel B and Panel C should be done cautiously with estimation points that should be regarded as trends rather than precise estimates. According to the estimates in Panel B and Panel C, it is found that especially girls in Andhra Pradesh and Telangana substitute, or possibly complement, the paid work undertaken by adult household members. With a point estimate of 0.090, the results suggest that beneficiary girls spend on average 5.4 minutes more per day on paid work when females in the household participate in MGNREGS compared to the control group (significant at the 5 percent level). The corresponding estimate for boys is both statistically insignificant and marginal. As in the pooled sample in Panel A, none of the results for the remaining outcome variables of interest for girls and boys are statistically significant at the standard significance levels. Being aware of that the point estimates for schooling are not statistically confirmed, it is, however, interesting to note that the coefficient in Panel C is negative, thus contradicting the expectation according to hypothesis 5.

Table 6 The Impact on Children's Time Allocation of its Female Household Members' Participation in MGNREGS

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.017*	0.002	0.061	0.010	-0.118
	(0.010)	(0.035)	(0.079)	(0.187)	(0.237)
Post-treatment					
Difference (T-C)	0.028	-0.021	0.007	0.090	-0.100
	(0.020)	(0.052)	(0.100)	(0.127)	(0.150)
DID-PSM	**0.045****	-0.023	-0.055	0.079	0.018
	(0.023)	(0.062)	(0.119)	(0.206)	(0.261)
Observations	1426	1426	1426	1426	1426
Matched observations	535	535	535	535	535
Panel B: Girls					
Baseline					
Difference (T-C)	-0.035*	0.012	-0.007	0.044	0.084
	(0.021)	(0.010)	(0.121)	(0.277)	(0.355)
Post-treatment					
Difference (T-C)	0.055	-0.012	0.087	0.048	-0.091
	(0.042)	(0.053)	(0.188)	(0.144)	(0.189)
DID-PSM	**0.090****	-0.024	0.094	0.005	-0.175
	(0.047)	(0.054)	(0.208)	(0.274)	(0.376)
Observations	1426	1426	1426	1426	1426
Matched observations	256	256	256	256	256
Panel C: Boys					
Baseline					
Difference (T-C)	-0.007	-0.010	-0.016	0.062	-0.092
	(0.009)	(0.063)	(0.102)	(0.300)	(0.328)
Post-treatment					
Difference (T-C)	0.004	0.010	-0.145	-0.036	-0.180
	(0.004)	(0.090)	(0.135)	(0.221)	(0.241)
DID-PSM	0.010	0.020	-0.129	-0.100	-0.089
	(0.009)	(0.109)	(0.161)	(0.338)	(0.368)
Observations	1426	1426	1426	1426	1426
Matched observations	284	284	284	284	284

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.004, Panel B: 0.010, Panel C: 0.012. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Finally, Table 7 reports the results when the household's MGNREGS-participants are male. Similarly, there is a statistically significant impact on time spent on paid work among beneficiary children when the household participant in MGNREGS is male. As in the case with female participants, it is suggested that beneficiary children spend on average 2.6 minutes more per day on paid work compared to the control group (significant at the 10 percent level). As such, the study finds no notable gender differences with regard to the impact of gender of the adult participant on time spent on paid work among beneficiary children in Andhra Pradesh and Telangana. As for the other two formulations of programme participation, the other outcome variables are statistically insignificant at the standard significance levels for the pooled sample. As such, it cannot be concluded whether beneficiary children on average substitute to unpaid household work when males in the household participate in MGNREGS in Andhra Pradesh and Telangana nor how their time spent on schooling and leisure is affected compared to the control group. Nevertheless, in contrast to what was expected in hypothesis 5, the coefficient for schooling points to the opposite direction.

Panel B and Panel C in Table 7 report the effects disaggregated on girls and boys, respectively. In contrast to when the household participant in MGNREGS is female, the estimation for paid work is no longer statistically significant for beneficiary girls. According to these results, female participants seem to be the driving force behind girls' increasing time spent on paid work in Andhra Pradesh and Telangana. In line with Table 5 and Table 6 Panel B, the remaining outcome variables for girls are statistically insignificant. Notably, although statistically insignificant, the estimation point for schooling for girls is positive also when males in the household are employed under the programme, thus contradicting hypothesis 5. Regarding the outcomes for beneficiary boys, the outcome variables concerning paid and unpaid work including schooling are statistically insignificant at the standard significance levels. Nevertheless, in contrast to what was expected in hypothesis 5, the estimation point for schooling is positive when the male household members participate in MGNREGS compared to the control group. Interestingly, there is a significant impact on time spent on leisure among beneficiary boys of male household participation in MGNREGS. More specifically, being significant at the 5 percent level, the results suggest a reduction of on average 39 minutes per day in leisure among beneficiary boys whose male household members participate in the programme compared to the control group.

Table 7 The Impact on Children's Time Allocation of its Male Household Members' Participation in MGNREGS

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.013	0.032	-0.004	-0.052	0.134
	(0.010)	(0.034)	(0.071)	(0.168)	(0.209)
Post-treatment					
Difference (T-C)	0.031	0.075*	-0.007	0.031	-0.076
	(0.025)	(0.041)	(0.086)	(0.105)	(0.128)
DID-PSM	**0.044***	0.044	-0.003	0.083	-0.210
	(0.026)	(0.051)	(0.106)	(0.182)	(0.231)
Observations	1426	1426	1426	1426	1426
Matched observations	409	409	409	409	409
Panel B: Girls					
Baseline					
Difference (T-C)	-0.012	0.015	0.041	-0.041	0.152
	(0.023)	(0.012)	(0.119)	(0.260)	(0.358)
Post-treatment					
Difference (T-C)	0.071	0.079*	-0.007	0.106	-0.077
	(0.050)	(0.043)	(0.127)	(0.143)	(0.175)
DID-PSM	0.083	0.064	-0.048	0.147	-0.230
	(0.055)	(0.045)	(0.150)	(0.251)	(0.355)
Observations	1426	1426	1426	1426	1426
Matched observations	198	198	198	198	198
Panel C: Boys					
Baseline					
Difference (T-C)	-0.006	0.047	-0.012	-0.230	0.492*
	(0.008)	(0.051)	(0.085)	(0.225)	(0.282)
Post-treatment					
Difference (T-C)	-0.004	0.094	-0.137	-0.103	-0.159
	(0.005)	(0.066)	(0.102)	(0.145)	(0.194)
DID-PSM	0.002	0.047	-0.125	0.126	**-0.651****
	(0.010)	(0.081)	(0.129)	(0.267)	(0.330)
Observations	1426	1426	1426	1426	1426
Matched observations	213	213	213	213	213

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.009, Panel B: 0.018, Panel C: 0.034. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

To summarize, regardless of formulation of programme participation, it is found that beneficiary children in Andhra Pradesh and Telangana on average increase their time spent on paid work of its household members' participation in MGNREGS compared to the control group. Furthermore, female household participants are found to increase the amount of paid work amongst beneficiary girls. Whilst this contradicts the income effect, it remains inconclusive whether children, both girls and boys, also substitute for unpaid work previously undertaken by the participating adults in the household. Similarly, it cannot be concluded how children's, both girls' and boys', school attendance is affected including if the outcome would change depending on if the MGNREGS-participant is female or male. Lastly, a notable gender difference concerns time spent on leisure where beneficiary boys are found to experience a significant reduction when male household members participate in the programme.

Finally, it is important to put the results in context. On the individual level, the increased time spent on paid work per day among beneficiary children is only marginal. However, when considering for example the result in Table 5 Panel A, household employment in MGNREGS results in approximately a total of 20 hours more spent on paid work per day when considering the total impact on the 601 matched beneficiary children. Given that approximately 6.5 million households participated in the programme in Andhra Pradesh and Telangana in 2019-2020, this gives an indication on the extent to which programme participation yet can affect the aggregate levels of paid child labour in the two states. This also applies to the suggested changes in time spent on leisure among beneficiary boys.

4.2 Sensitivity Analysis

To check for the robustness of the main results, adjustments are done with regard to both the methodological approach and the econometric specifications. First, as displayed in Figures 1.1-1.3, the density in the tails of the distribution of propensity scores are thin. To avoid potential evaluation bias through poor matches, Lechner (2002) suggests excluding the observations with a propensity score below 0.1 and above 0.9, thus restricting the region of common support to the middle area. The results are reported in Tables D.1.1-D.1.3 in Appendix D. The point estimates for paid work for the pooled sample (Panel A) including beneficiary girls (Panel B) and boys (Panel C) when analysing the impact of household and female household participation do not change significantly compared to the previous findings (see Tables D.1.1-D.1.2).

However, when restricting the common support region for male household participation (Table D.1.3), the coefficient for paid work for the pooled sample is no longer statistically significant. The size of the coefficient is, however, relatively unchanged. The estimate for leisure for beneficiary boys when males participate in the programme is similar to the original methodological specification and corresponds to an estimated reduction of on average 38 minutes per day compared to the control group (significant at the 10 percent level).

Second, instead of relying on a data-driven automatic bandwidth selection, the bandwidth is set to 0.06. This is by the literature viewed as the average optimal bandwidth (Heckman, Ichimura & Todd, 1997). As is reported in Tables D.2.1-D.2.3 in Appendix D, the results do not change significantly, thus lending support to the estimations of the original methodological specification.

Lastly, as previously discussed, the household composition with regard to the presence of siblings and adults can affect the incidence of child labour (see section 2.1.2). To avoid potential multicollinearity, the control variable for household size is replaced by the following four control variables: the number of children between the ages of 0-5, 6-12 and 13-17, including the number of adult household members above the age of 18. The results are displayed in Tables D.3.1-D.3.3 in Appendix D and are found to not change significantly compared to the overall findings of the original econometric specifications. Surprisingly, however, and compared to Table 5 Panel C, the point estimate for leisure in Table D.3.1 Panel C is now statistically significant at the 10 percent level. When controlling for household composition, beneficiary boys are suggested to experience a reduction of on average 41 minutes per day in leisure when the household participates in the programme in Andhra Pradesh and Telangana compared to the control group. The point estimate has changed slightly in size compared to the result in Table 5 Panel C and is now more in line with the results for boys when analysing the impact of male household members' participation in MGNREGS.

Overall, the similarities of the impact estimates produced by the different methodological and econometric specifications lend confidence to the main results concerning paid work and leisure.

4.3 Discussion

Based on the above-presented results, several interesting similarities and differences can be identified in light of the current research frontier. First and foremost, the theoretical framework suggests that public employment for example can reduce paid child labour through an income effect. This has later been supported by several researchers in the field regarding other public employment programmes (see for example Hoddinott, Giligan & Taffesse, 2009; Juras, 2014; Rosas & Sabarwal, 2016), as well as for MGNREGS. Based on this, the results for paid work presented in this thesis can initially seem contradictive. However, once careful consideration is given to the characteristics of the households and children in the sample, the outcome for paid work can be viewed as consistent with current child labour literature including previous findings on the impact of MGNREGS on paid child labour.

First, it is relevant to consider the income levels of the participating households in the sample. As explained, the income effect states that a higher household income by participating in a public employment programme reduces the need for child labour. Given the significantly positive impact of household participation in MGNREGS on paid child labour, this may simply indicate that the households do not reduce this need through employment. Whereas this cannot be examined directly through the used data, it is possible to assess whether such reasoning is reasonable by making a comparison of the monthly per capita expenditure level of the participating households in the sample with national data. According to the Young Lives dataset, the average monthly per capita expenditure of the participating households was 1050 Rs. in the third survey round in 2009 and 1531 Rs. in the fourth survey round in 2013 (not reported). In contrast, and as presented in sub-section 3.1, the corresponding level in the former Andhra Pradesh was on average 1736 Rs. in 2009/2010 and 2220 Rs. in 2011/2012 according to the National Sample Survey. Whilst deviating income levels are expected given the programme's targeting process, the relatively significantly lower income levels among participating households after employment may provide an explanation as to why the income effect does not dominate when households in Andhra Pradesh and Telangana participate in the programme. Based on the same reasoning, this may provide support for the *luxury axiom*. Alternatively, these findings might be in line with the above-discussed inverted-U relationship between child labour and household wealth presented by Basu, Das and Dutta (2010). In order to reach more clarity in these matters, it could be meaningful for future researchers to analyse the relationship between for example received wages, income levels and child labour rather than household participation formulated as a binary treatment variable. Given the research objective of this research, it is important to note that these discussion points do not allow any conclusions to be drawn about the overall welfare impact of this anti-poverty programme.

Second, it should be noted that the children in the sample of the thesis are 11 to 16 years old after treatment. Similarly, the work by Islam and Sivasankaran (2014) including Shah and Steinberg (2015) focus in part on children over the age of 12. As was presented in section 2.1.3, whereas the income effect dominates for the younger children, both publications find a significantly positive impact of household participation in MGNREGS on paid work among beneficiary children within this age range through the substitution effect. In view of these findings, the results of this thesis strengthen the conclusion that older children of programme participating households substitute into paid labour. Whilst several reasons have been put forward as to why this is the case in rural India, they are commonly based on the expectation that older children are more productive and therefore substitutable for adult labour than younger household members. Keeping this in mind, several researchers have concluded that MGNREGS causes an increase in private sector wages in the states in which the programme is implemented, including in the former Andhra Pradesh (Berg, Bhattacharyya, Durgam & Ramachandra, 2012; Imbert & Papp, 2015). With the thereby increased opportunity cost of schooling, older children are found to be more likely to respond to the increased wages in the rural economy by increasing their labour supply compared to the younger children (Islam & Sivasankaran, 2014; Shah & Steinberg, 2015). Furthermore, the implementation of MGNREGS in, among others, the former Andhra Pradesh, has been shown to be correlated with a substantial fall in time spent on private sector work by rural adults (Imbert & Papp, 2015). Besides responding to higher wages, it is therefore discussed whether the implementation of the programme can open up job opportunities in the private sector for children as adults now spend relatively more time on public work. Thus, although it is not tested directly, Islam and Sivasankaran (2014) and Shah and Steinberg (2015) discuss the increased job availability as an additional reason as to why older children substitute into paid labour. Overall, these findings demonstrate the value of also analysing the differential effects on child labour and school attendance by different age groups of children. This was not possible due to available data, but nevertheless constitutes a limitation of this research.

Together, these discussed results point to the importance of paying careful consideration to the characteristics of the target groups, as well as potential spill-over effects when designing public employment programmes of this kind. Given the research objective and that MGNREGS is not found to reduce the incidence of paid child labour among older children in Andhra Pradesh and Telangana, in order to further support India's efforts to combat the prevalence of child labour, it can therefore be necessary to build additional safety nets into MGNREGS. How these should be designed, however, lies beyond the scope of this thesis. Additionally, if the programme's labour market effects cause children to substitute toward paid work, complementary social programmes such as for example conditional cash transfers can be important to continue prioritizing[8]. This may also be of relevance for other Indian states including other public employment programmes that operate in a similar environment (for further discussions, see for example Islam & Sivasankaran, 2014; Shah & Steinberg, 2015). Although a reduced incidence of child labour is not an objective of MGNREGS, given the country's previously undertaken measures against its occurrence including the programme's extensive coverage these findings are nevertheless believed to be of interest for policy makers in India.

Disaggregated on gender of the children, and in light of the current body of literature, it remains unclear why girls are the drivers for the increased engagement in paid work outside the household. Whilst, for example, Das and Mukherjee (2019) find a significantly positive association between MGNREGS and paid work among primarily girls, current evidence rather emphasizes that boys substitute into market work in rural India (see Islam & Sivasankaran, 2014; Shah & Steinberg, 2015). Based on the same reasoning, it is unclear why this increase is caused by female household programme participation. Other unexpected findings concern unpaid child labour and school attendance. In contrast to the previous research discussed with

[8] Beyond the, in the introduction, discussed evidence that for example conditional cash transfers can reduce the incidence of child labour, Alik-Lagrange and Ravallion (2015) show that, compared to net workfare earnings, a basic-income guarantee dominates in terms of the impact on poverty for a given budgetary outlay.

the exception of the work of Sheahan et al. (2020), the results throughout suggest insignificant effects of MGNREGS on these activities. To reconcile these overall ambiguities, whilst they could be due to factors such as the use of for example a relatively small sample size or (un)observable time-variant factors that are not controlled for, further research is needed. This further applies to whether and how more careful consideration should be paid to the gender of the MGNREGS-participant when designing a programme of this kind.

As a final point, the significantly negative association between public employment under MGNREGS and leisure among beneficiary boys supports the possibility for children to adjust their leisure in line with either or both the income and substitution effects as suggested by Hoddinott, Giligan and Taffesse (2009) and discussed in section 2.1.3. Although it cannot be confirmed what the freed time is adjusted in favour of, it adds further understanding on how public employment can affect the time allocation of children and is thus suggested to be included in future research with a similar research objective.

5 Conclusion

To conclude, among the countries in the Asia and Pacific region, India faces critical challenges in combating the prevalence of child labour. Although the country has taken legislative actions in this regard, research emphasizes the need to support them with further measures. With the well-established link between poverty, income shocks and child labour, a growing amount of research points to the importance of social protection. Given that it remains unresolved as whether the Indian public employment programme MGNREGS can serve as an effective tool for this purpose, this study investigates this matter in further detail. More specifically, using the longitudinal dataset Young Lives, this thesis examines the impact on child labour and children's school attendance of its household's participation in MGNREGS in the states Andhra Pradesh and Telangana. Given the complex aspects of child labour and compared to previous research, the analysis adopts a broad definition of the term and therefore concerns children's time spent on paid work outside the household, unpaid household tasks referring to activities such as farming and other family business, unpaid household chores, schooling and leisure. In light of this research objective, it is further examined whether the results differ, and if so, how, depending on the gender of the beneficiary child including if the household programme participant is female or male.

By applying the combined DID-PSM method it is found that beneficiary children between 11 and 16 years old engage more in paid work when its household participates in MGNREGS. This equally applies when the household's MGNREGS-participant is either female or male. Whereas there is no evidence of gender differentials with regard to the MGNREGS-participant in these cases, the results change when the analysis is disaggregated on the gender of the beneficiary children. Here, it is found that only girls increase their time spent on paid work which is driven by the female household MGNREGS-participants in Andhra Pradesh and Telangana. Although the increases in paid work are marginal on the individual level, corresponding to an increase between approximately 2-5 minutes per day, they can yet contribute with a significant aggregate effect in Andhra Pradesh and Telangana with an associated impact on their work against the occurrence of paid child labour. As such, MGNREGS is not found to be an effective tool for reducing the incidence of paid child labour among children in this age range in the examined states. As it remains inconclusive whether children, both girls and boys, substitute for unpaid work previously undertaken by the participating adults in the household, no statements can be made regarding the programmes potential to affect unpaid child labour. Similarly, it cannot be concluded how children's, both girls' and boys', school attendance is affected in these states including if the outcome changes depending on if the MGNREGS-participant is female or male. There are, however, other notable gender differences. According to the main results, beneficiary boys are found to reduce their time spent on leisure when male household members participate in the programme in Andhra Pradesh and Telangana.

Although the results are plausible for several discussed reasons, they give rise to important points that should be considered for future research. First and foremost, the above discussions demonstrate the importance of analysing the differential effects on child labour and school attendance by different age groups of children whilst also considering potential changes in time spent on leisure. Furthermore, by analysing the relationship between for example received wages, income levels and child labour rather than household participation formulated as a binary treatment variable, future research can potentially provide further understanding on the relationship between participation in MGNREGS and child labour and school attendance. By, among others, incorporating these points, empirical evidence could potentially be provided for some of the inconclusive findings in this thesis whilst providing the research frontier with further evidence on whether and how the gender of the MGNREGS-participant should receive further focus when designing a programme of this kind.

Together, the main findings including discussions in this study point to the importance for policy makers to pay close attention to the characteristics of the target groups in the programme, as well as potential spill-over effects when implementing MGNREGS. Given this thesis focus on child labour and school attendance, it can therefore be relevant to build additional safety nets into the programme including prioritizing its combination with other social protection programmes. Although a reduced incidence of child labour is not an objective of the programme, given the country's previously undertaken measures in this regard including the programme's extensive coverage this is nevertheless believed to be of interest for relevant governmental bodies in Andhra Pradesh and Telangana, and possibly also in other Indian states.

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Appendix A

Table A.1 Baseline Two-Sample T-test for Difference in Means (2006) – Household Characteristics

	Untreated		Treated		Difference	
	Mean	Std. Err.	Mean	Std. Err.	Value	| T-stat |
Household characteristics						
Total per cap. expenditure (Rs.)	1038.224	25.296	625.637	15.978	**412.587**	12.934***
Wealth index	0.591	0.007	0.364	0.006	**0.227**	23.796***
Income shock	21.3%	0.014	42.8%	0.020	**-21.5%**	8.998***
Household size	5.374	0.078	5.379	0.080	-0.005	0.043
Mother's education (in years)	5.649	0.163	1.879	0.120	**3.770**	17.672***
Father's education (in years)	7.643	0.171	3.196	0.160	**4.447**	18.618***
Rural site (=1)	49.6%	0.018	99.4%	0.003	**-49.8%**	24.628***
Time to school (in minutes)	12.389	0.385	12.037	0.625	0.352	0.501
Child's sex (girl=1)	47.9%	0.018	47.1%	0.020	0.8%	0.281
Child's age	7.610	0.114	7.528	0.128	0.082	0.481
Number of observations	800		626			

*** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Table A.2 Post-Programme Two-Sample T-test for Difference in Means (2009/2013) – Outcome Variables of Interest

	Untreated		Treated		Difference	
	Mean	Std. Err.	Mean	Std. Err.	Value	| T-stat |
Outcomes of interest (h/day)						
Paid work	0.003	0.002	0.024	0.015	-0.021	1.577
Household tasks	0.020	0.007	0.128	0.021	**-0.108**	5.318***
Household chores	0.981	0.035	1.222	0.044	**-0.241**	4.378***
Schooling	8.425	0.041	8.102	0.047	**0.323**	5.165***
Leisure	3.668	0.047	3.629	0.058	0.039	0.515
Number of observations	800		626			

*** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Appendix B

Wealth Index

The Young Lives wealth index is constructed from three equally weighted indices, of which each index is computed as a simple average of the indicators listed below (Briones, 2017):

(1) Housing quality index (hq) – simple average of quality of walls, roof, and floor, including household density computed as a rescaled value of rooms to household size ratio.

(2) Access to services index (sv) – simple average of access to electricity, safe drinking water, sanitation facility, and fuel for cooking.

(3) Consumer durables index (cd) – simple average of the household's ownership of common household items.

$$wi_{it} = \frac{hq_{it} + sv_{it} + cd_{it}}{3}$$

Table B.1 List of Baseline Covariates

Variable name	Variable	Unit
Total per cap. expenditure (Rs.)	Monthly total consumption per capita, current rupees.	Continuous
Ethnicity	Scheduled Tribes, Scheduled Caste, Backward Caste, or Other (Hindu, Muslim, Buddhist, Christian).	Categorical
Wealth index	See Appendix B.	Continuous, between 0 and 1.
Income shock	If the household has experienced at least one of the following shocks since previous round: drought, flooding, erosion, frost, crop failure, or natural disaster.	Dummy
Household size	The size of the household.	Continuous
HH. occupation	Occupation of the household head: self-employment outside agriculture, self-employment within agriculture, regular wage employment, or unemployed/household dependent.	Categorical
Mother's education (in years)	Mother's education in years.	Continuous
Father's education (in years)	Father's education in years.	Continuous
Rural site (=1)	Household area of residence (rural/urban).	Dummy
Time to school (in minutes)	Travel time to school (in minutes).	Continuous
Child's sex (girl=1)	Sex of the child.	Dummy
Child's age	Age of the child.	Continuous

Appendix C

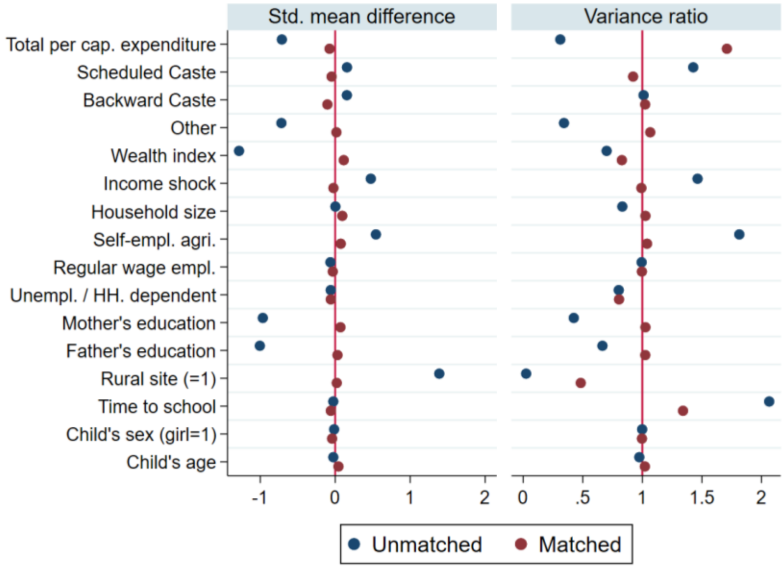

Figure C.1.1 Comparison of Standard Mean Difference and Variance Ratio Before and After Matching – Household Participation

Source: author's calculations based on the Young Lives dataset.

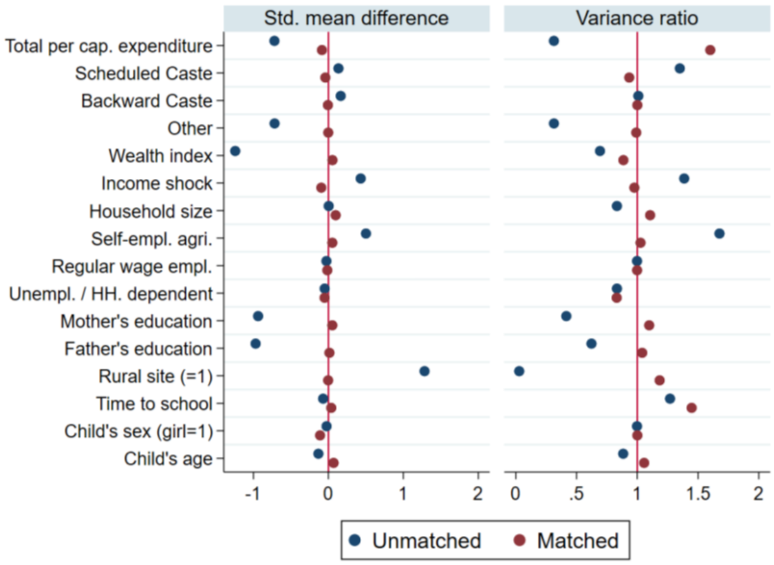

Figure C.1.2 Comparison of Standard Mean Difference and Variance Ratio Before and After Matching – Female Household Participation

Source: author's calculations based on the Young Lives dataset.

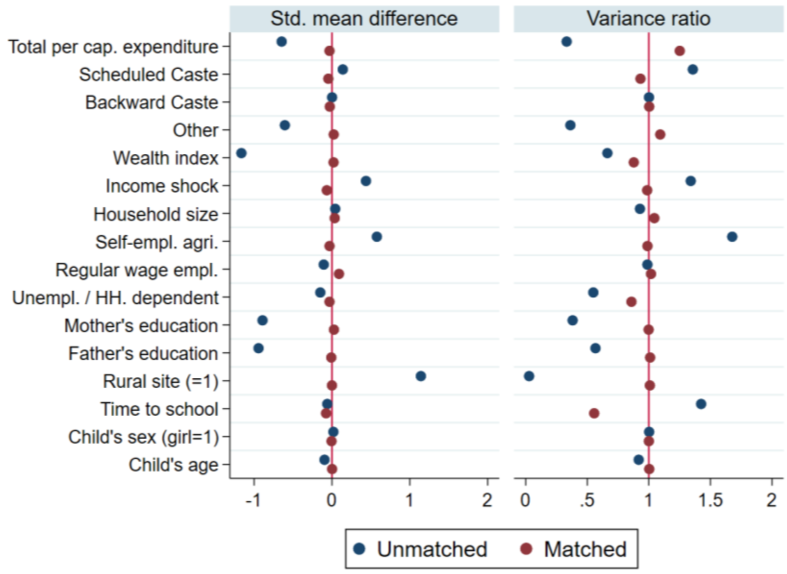

Figure C.1.3 Comparison of Standard Mean Difference and Variance Ratio Before and After Matching – Male Household Participation

Source: author's calculations based on the Young Lives dataset.

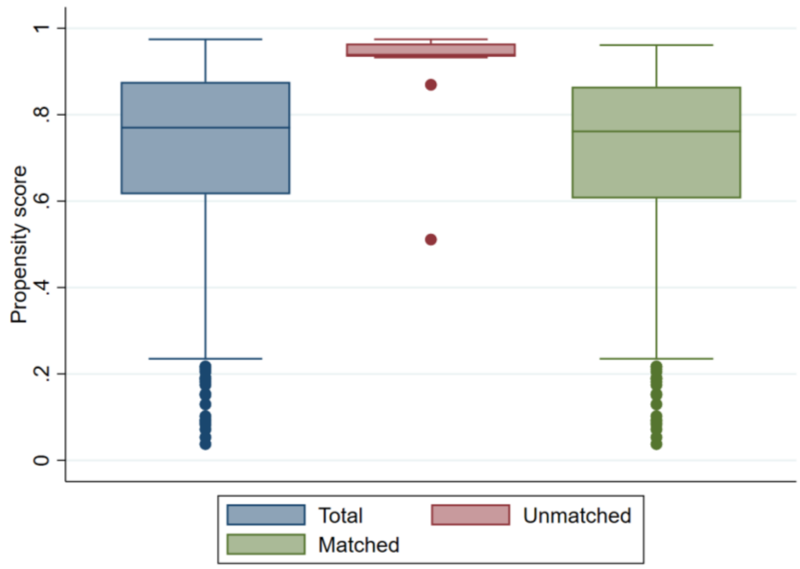

Figure C.2.1 Box Plot of Area of Common Support Before and After Matching – Household Participation

Source: author's calculations based on the Young Lives dataset.

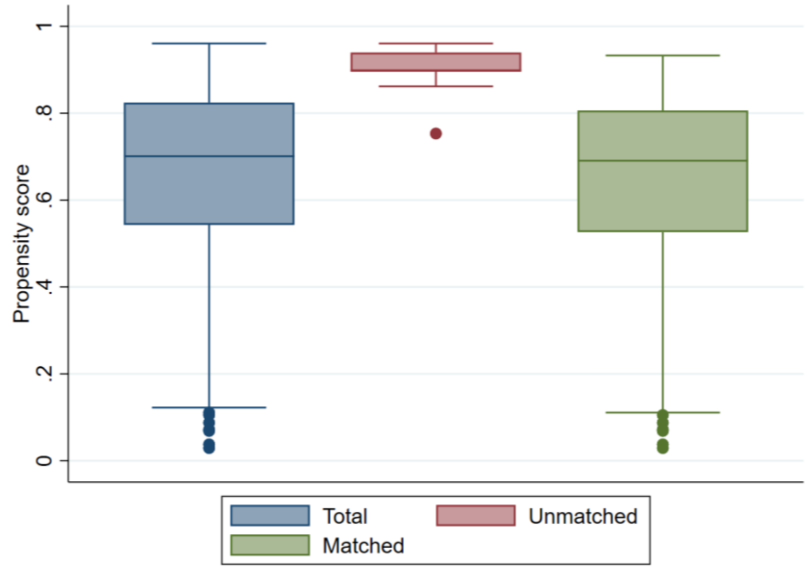

Figure C.2.2 Box Plot of Area of Common Support Before and After Matching – Female Household Participation

Source: author's calculations based on the Young Lives dataset.

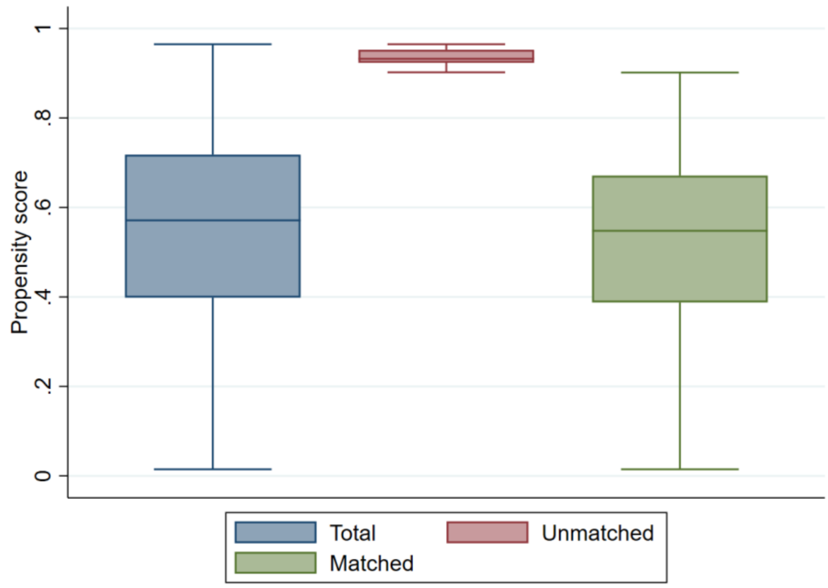

Figure C.2.3 Box Plot of Area of Common Support Before and After Matching – Male Household Participation

Source: author's calculations based on the Young Lives dataset.

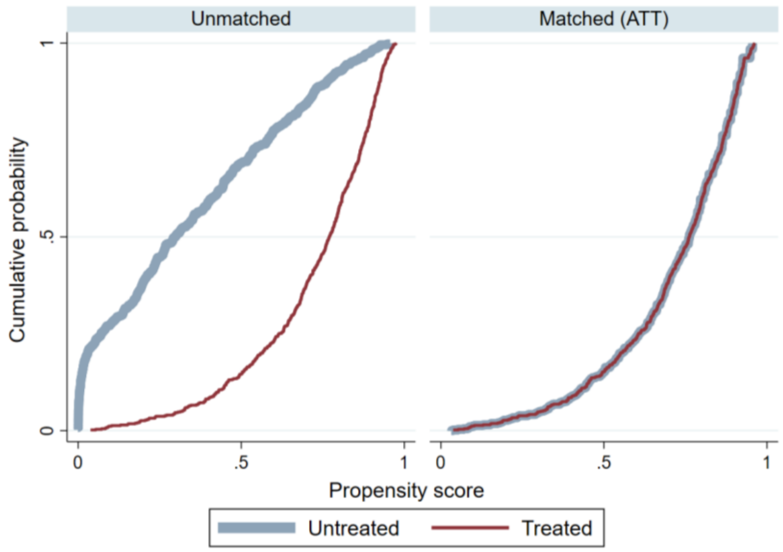

Figure C.3.1 Cumulative Distribution Plot Before and After Matching – Household Participation

Source: author's calculations based on the Young Lives dataset.

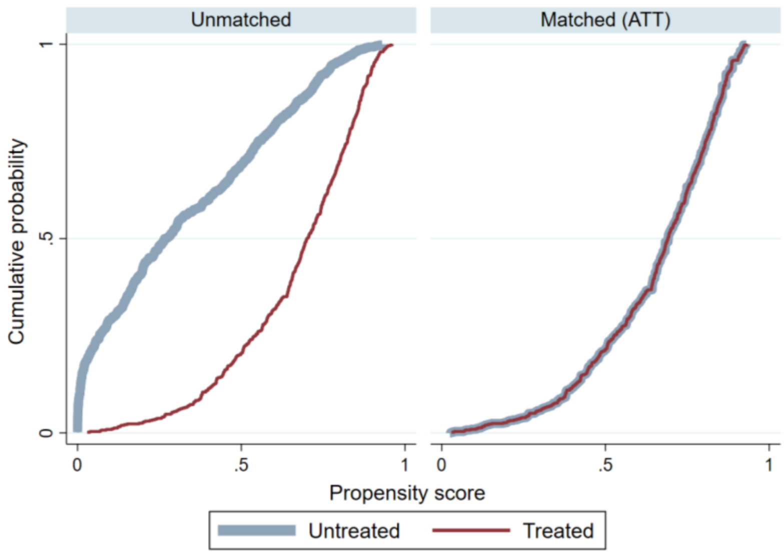

Figure C.3.2 Cumulative Distribution Plot Before and After Matching – Female Household Participation

Source: author's calculations based on the Young Lives dataset.

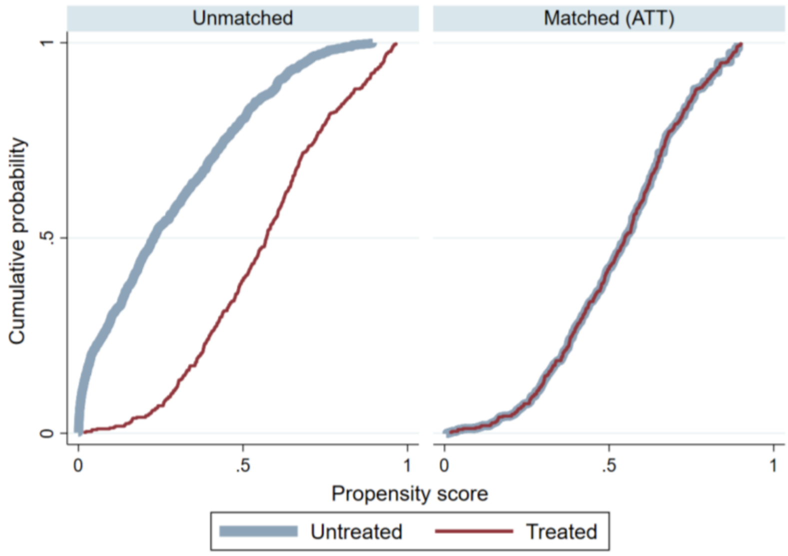

Figure C.3.3 Cumulative Distribution Plot Before and After Matching – Male Household Participation

Source: author's calculations based on the Young Lives dataset.

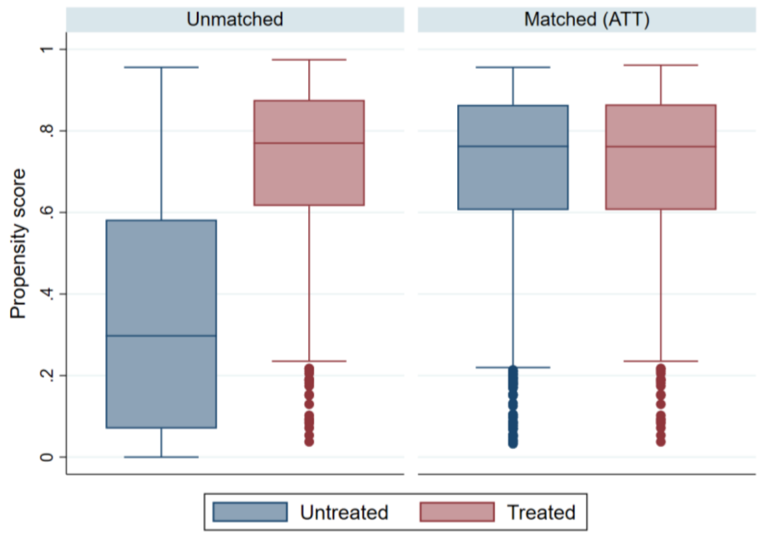

Figure C.4.1 Distribution of Propensity Score Before and After Matching – Household Participation

Source: author's calculations based on the Young Lives dataset.

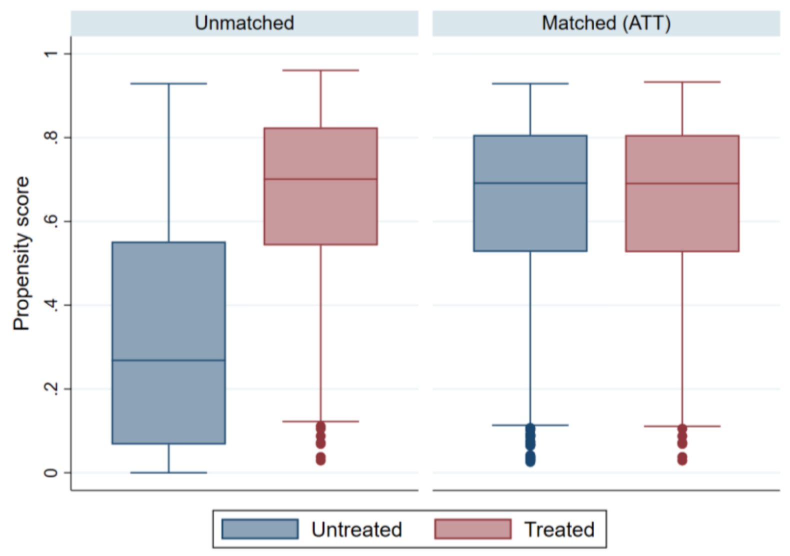

Figure C.4.2 Distribution of Propensity Score Before and After Matching – Female Household Participation

Source: author's calculations based on the Young Lives dataset.

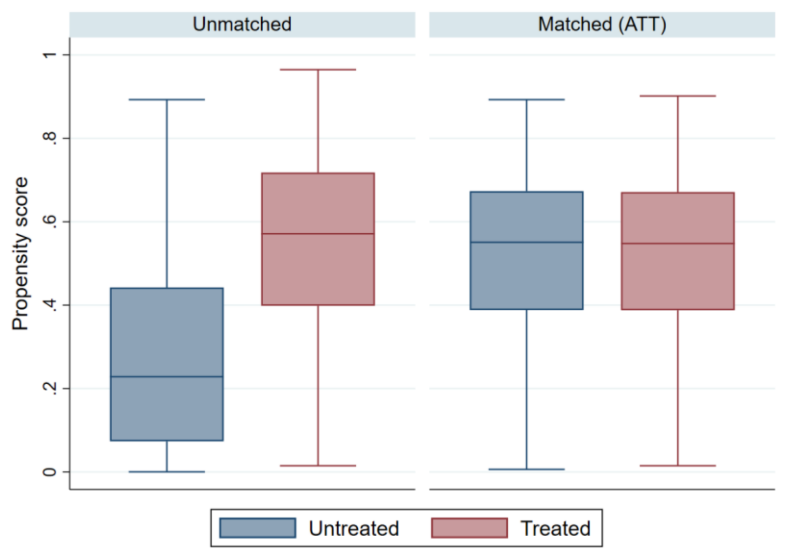

Figure C.4.3 Distribution of Propensity Score Before and After Matching – Male Household Participation

Source: author's calculations based on the Young Lives dataset.

Appendix D

Table D.1.1 The Impact on Children's Time Allocation of its Household's Participation in MGNREGS – Restricted Area of Common Support

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.010	-0.008	-0.009	0.354*	-0.124
	(0.012)	(0.047)	(0.098)	(0.206)	(0.280)
Post-treatment					
Difference (T-C)	0.030	-0.022	-0.061	0.054	-0.086
	(0.021)	(0.060)	(0.119)	(0.153)	(0.173)
DID-PSM	**0.041***	-0.014	-0.052	-0.300	0.038
	(0.024)	(0.075)	(0.152)	(0.231)	(0.313)
Observations	1426	1426	1426	1426	1426
Matched observations	498	498	498	498	498
Panel B: Girls					
Baseline					
Difference (T-C)	-0.007	0.009	0.031	0.477	-0.829*
	(0.011)	(0.010)	(0.157)	(0.342)	(0.448)
Post-treatment					
Difference (T-C)	0.063	-0.018	0.098	0.043	-0.104
	(0.053)	(0.058)	(0.211)	(0.159)	(0.209)
DID-PSM	0.070	-0.027	0.066	-0.434	0.725
	(0.053)	(0.059)	(0.252)	(0.348)	(0.454)
Observations	1426	1426	1426	1426	1426
Matched observations	222	222	222	222	222
Panel C: Boys					
Baseline					
Difference (T-C)	-0.006	0.026	-0.035	-0.135	0.138
	(0.017)	(0.094)	(0.122)	(0.318)	(0.396)
Post-treatment					
Difference (T-C)	0.004	0.095	-0.245	0.008	-0.336
	(0.004)	(0.098)	(0.152)	(0.271)	(0.288)
DID-PSM	0.010	0.069	-0.209	0.143	-0.473
	(0.017)	(0.138)	(0.193)	(0.358)	(0.440)
Observations	1426	1426	1426	1426	1426
Matched observations	249	249	249	249	249

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.005, Panel B: 0.010, Panel C: 0.012. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Table D.1.2 The Impact on Children's Time Allocation of its Female Household Members' Participation in MGNREGS – Restricted Area of Common Support

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.018*	0.003	0.067	0.135	-0.220
	(0.010)	(0.039)	(0.082)	(0.187)	(0.240)
Post-treatment					
Difference (T-C)	0.030	-0.034	0.036	0.112	-0.112
	(0.021)	(0.052)	(0.109)	(0.132)	(0.161)
DID-PSM	**0.047****	-0.037	-0.031	-0.023	0.108
	(0.024)	(0.063)	(0.130)	(0.208)	(0.270)
Observations	1426	1426	1426	1426	1426
Matched observations	506	506	506	506	506
Panel B: Girls					
Baseline					
Difference (T-C)	-0.040**	0.013	-0.032	0.075	-0.008
	(0.020)	(0.011)	(0.133)	(0.289)	(0.379)
Post-treatment					
Difference (T-C)	0.059	-0.029	0.048	0.075	-0.160
	(0.046)	(0.054)	(0.187)	(0.142)	(0.193)
DID-PSM	**0.099****	-0.041	0.080	0.001	-0.152
	(0.050)	(0.056)	(0.207)	(0.290)	(0.409)
Observations	1426	1426	1426	1426	1426
Matched observations	238	238	238	238	238
Panel C: Boys					
Baseline					
Difference (T-C)	-0.007	-0.009	0.052	0.014	-0.178
	(0.011)	(0.077)	(0.115)	(0.297)	(0.394)
Post-treatment					
Difference (T-C)	0.004	0.012	-0.056	-0.149	-0.208
	(0.005)	(0.102)	(0.140)	(0.219)	(0.263)
DID-PSM	0.011	0.021	-0.108	-0.163	-0.029
	(0.012)	(0.124)	(0.173)	(0.342)	(0.437)
Observations	1426	1426	1426	1426	1426
Matched observations	250	250	250	250	250

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.004, Panel B: 0.009, Panel C: 0.008. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Table D.1.3 The Impact on Children's Time Allocation of its Male Household Members' Participation in MGNREGS – Restricted Area of Common Support

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.013	0.005	-0.035	0.046	0.095
	(0.010)	(0.037)	(0.079)	(0.190)	(0.235)
Post-treatment					
Difference (T-C)	0.033	0.064	-0.006	0.060	-0.113
	(0.028)	(0.046)	(0.094)	(0.116)	(0.139)
DID-PSM	0.046	0.059	0.029	0.014	-0.208
	(0.030)	(0.057)	(0.111)	(0.216)	(0.260)
Observations	1426	1426	1426	1426	1426
Matched observations	376	376	376	376	376
Panel B: Girls					
Baseline					
Difference (T-C)	-0.012	0.017	-0.068	0.161	-0.182
	(0.019)	(0.013)	(0.135)	(0.277)	(0.368)
Post-treatment					
Difference (T-C)	0.077	0.085*	-0.019	0.262*	-0.293
	(0.058)	(0.047)	(0.144)	(0.151)	(0.192)
DID-PSM	0.090	0.069	0.049	0.101	-0.111
	(0.060)	(0.049)	(0.181)	(0.278)	(0.405)
Observations	1426	1426	1426	1426	1426
Matched observations	181	181	181	181	181
Panel C: Boys					
Baseline					
Difference (T-C)	-0.006	0.054	-0.032	-0.260	0.487
	(0.010)	(0.059)	(0.097)	(0.250)	(0.302)
Post-treatment					
Difference (T-C)	-0.006	0.073	-0.159	-0.080	-0.145
	(0.007)	(0.077)	(0.115)	(0.171)	(0.215)
DID-PSM	0.001	0.019	-0.127	0.179	**-0.632***
	(0.012)	(0.092)	(0.147)	(0.287)	(0.347)
Observations	1426	1426	1426	1426	1426
Matched observations	195	195	195	195	195

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.005, Panel B: 0.011, Panel C: 0.016. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Table D.2.1 The Impact on Children's Time Allocation of its Household's Participation in MGNREGS – Bandwidth 0.06

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.008	-0.004	0.026	0.057	0.018
	(0.010)	(0.032)	(0.068)	(0.193)	(0.227)
Post-treatment					
Difference (T-C)	0.024	0.024	0.013	-0.016	-0.050
	(0.015)	(0.053)	(0.103)	(0.142)	(0.151)
DID-PSM	**0.032***	0.028	-0.013	-0.073	-0.068
	(0.018)	(0.060)	(0.118)	(0.204)	(0.254)
Observations	1426	1426	1426	1426	1426
Matched observations	626	626	626	626	626
Panel B: Girls					
Baseline					
Difference (T-C)	0.003	0.010	0.169*	0.327	-0.366
	(0.007)	(0.008)	(0.100)	(0.364)	(0.420)
Post-treatment					
Difference (T-C)	0.047	-0.011	0.132	0.054	0.023
	(0.032)	(0.054)	(0.156)	(0.181)	(0.190)
DID-PSM	0.044	0.001	-0.036	-0.273	0.389
	(0.032)	(0.055)	(0.173)	(0.300)	(0.396)
Observations	1426	1426	1426	1426	1426
Matched observations	295	295	295	295	295
Panel C: Boys					
Baseline					
Difference (T-C)	-0.009	0.022	-0.085	-0.045	0.361
	(0.013)	(0.064)	(0.121)	(0.378)	(0.318)
Post-treatment					
Difference (T-C)	0.003	-0.020	-0.126	-0.095	-0.052
	(0.003)	(0.138)	(0.162)	(0.241)	(0.260)
DID-PSM	0.012	-0.043	-0.041	-0.050	-0.414
	(0.013)	(0.152)	(0.198)	(0.394)	(0.368)
Observations	1426	1426	1426	1426	1426
Matched observations	331	331	331	331	331

Notes: Epanechnikov kernel function with a bandwidth equal to 0.06, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.06, Panel B: 0.06, Panel C: 0.06. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Table D.2.2 The Impact on Children's Time Allocation of its Female Household Members' Participation in MGNREGS – Bandwidth 0.06

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.012	0.004	0.066	0.081	-0.026
	(0.010)	(0.028)	(0.060)	(0.169)	(0.200)
Post-treatment					
Difference (T-C)	0.027	-0.013	0.003	0.107	-0.156
	(0.017)	(0.050)	(0.091)	(0.131)	(0.145)
DID-PSM	**0.039****	-0.017	-0.063	0.026	-0.130
	(0.019)	(0.055)	(0.102)	(0.187)	(0.230)
Observations	1426	1426	1426	1426	1426
Matched observations	562	562	562	562	562
Panel B: Girls					
Baseline					
Difference (T-C)	-0.022	0.011	-0.081	0.081	0.037
	(0.022)	(0.008)	(0.088)	(0.256)	(0.339)
Post-treatment					
Difference (T-C)	0.053	-0.018	0.090	0.075	-0.080
	(0.035)	(0.052)	(0.162)	(0.133)	(0.161)
DID-PSM	**0.076***	-0.030	0.009	-0.006	-0.117
	(0.041)	(0.053)	(0.176)	(0.238)	(0.352)
Observations	1426	1426	1426	1426	1426
Matched observations	263	263	263	263	263
Panel C: Boys					
Baseline					
Difference (T-C)	-0.004	0.007	0.013	0.163	-0.057
	(0.006)	(0.049)	(0.089)	(0.295)	(0.304)
Post-treatment					
Difference (T-C)	0.004	0.001	-0.185	0.023	-0.158
	(0.003)	(0.082)	(0.141)	(0.239)	(0.251)
DID-PSM	0.007	-0.007	-0.198	-0.140	-0.101
	(0.007)	(0.098)	(0.149)	(0.348)	(0.362)
Observations	1426	1426	1426	1426	1426
Matched observations	299	299	299	299	299

Notes: Epanechnikov kernel function with a bandwidth equal to 0.06, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.06, Panel B: 0.06, Panel C: 0.06. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Table D.2.3 The Impact on Children's Time Allocation of its Male Household Members' Participation in MGNREGS – Bandwidth 0.06

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.012	0.033	-0.014	-0.046	0.178
	(0.016)	(0.029)	(0.061)	(0.177)	(0.267)
Post-treatment					
Difference (T-C)	0.030	0.072**	-0.071	-0.024	-0.045
	(0.021)	(0.035)	(0.079)	(0.098)	(0.120)
DID-PSM	**0.042***	0.039	-0.056	0.022	-0.223
	(0.026)	(0.044)	(0.086)	(0.179)	(0.284)
Observations	1426	1426	1426	1426	1426
Matched observations	434	434	434	434	434
Panel B: Girls					
Baseline					
Difference (T-C)	-0.028	0.014	0.053	-0.181	0.455
	(0.033)	(0.011)	(0.105)	(0.270)	(0.392)
Post-treatment					
Difference (T-C)	0.066	0.069	0.005	-0.026	0.068
	(0.048)	(0.043)	(0.124)	(0.167)	(0.163)
DID-PSM	0.094	0.055	-0.048	0.155	-0.387
	(0.059)	(0.044)	(0.140)	(0.227)	(0.378)
Observations	1426	1426	1426	1426	1426
Matched observations	212	212	212	212	212
Panel C: Boys					
Baseline					
Difference (T-C)	-0.006	0.043	-0.008	-0.232	0.589**
	(0.007)	(0.053)	(0.080)	(0.227)	(0.284)
Post-treatment					
Difference (T-C)	-0.004	0.086	-0.095	-0.093	-0.187
	(0.005)	(0.065)	(0.098)	(0.139)	(0.187)
DID-PSM	0.002	0.043	-0.086	0.140	**-0.776****
	(0.008)	(0.082)	(0.123)	(0.268)	(0.330)
Observations	1426	1426	1426	1426	1426
Matched observations	218	218	218	218	218

Notes: Epanechnikov kernel function with a bandwidth equal to 0.06, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.06, Panel B: 0.06, Panel C: 0.06. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Table D.3.1 The Impact on Children's Time Allocation of its Household's Participation in MGNREGS – Household Composition

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.012	-0.010	0.071	0.096	0.002
	(0.011)	(0.039)	(0.083)	(0.198)	(0.250)
Post-treatment					
Difference (T-C)	0.025	0.039	0.055	0.051	-0.177
	(0.018)	(0.052)	(0.109)	(0.139)	(0.157)
DID-PSM	**0.038***	0.049	-0.016	-0.045	-0.179
	(0.021)	(0.063)	(0.127)	(0.211)	(0.278)
Observations	1426	1426	1426	1426	1426
Matched observations	597	597	597	597	597
Panel B: Girls					
Baseline					
Difference (T-C)	0.005	0.011	0.159	0.280	-0.374
	(0.009)	(0.009)	(0.126)	(0.380)	(0.442)
Post-treatment					
Difference (T-C)	0.049	0.026	0.206	-0.048	-0.012
	(0.034)	(0.056)	(0.171)	(0.178)	(0.194)
DID-PSM	0.044	0.015	0.047	-0.328	0.361
	(0.035)	(0.057)	(0.202)	(0.336)	(0.432)
Observations	1426	1426	1426	1426	1426
Matched observations	285	285	285	285	285
Panel C: Boys					
Baseline					
Difference (T-C)	-0.004	0.004	-0.105	-0.129	0.586*
	(0.016)	(0.073)	(0.114)	(0.350)	(0.339)
Post-treatment					
Difference (T-C)	0.003	-0.044	-0.038	-0.089	-0.097
	(0.003)	(0.118)	(0.153)	(0.240)	(0.277)
DID-PSM	0.007	-0.049	0.068	0.040	**-0.683***
	(0.016)	(0.140)	(0.189)	(0.359)	(0.384)
Observations	1426	1426	1426	1426	1426
Matched observations	312	312	312	312	312

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Household size is replaced with control variables for household composition. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.006, Panel B: 0.015, Panel C: 0.014. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Table D.3.2 The Impact on Children's Time Allocation of its Female Household Members' Participation in MGNREGS – Household Composition

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.013	-0.009	0.065	0.232	-0.218
	(0.011)	(0.036)	(0.075)	(0.180)	(0.233)
Post-treatment					
Difference (T-C)	0.028	-0.014	-0.006	0.102	-0.109
	(0.019)	(0.051)	(0.103)	(0.134)	(0.152)
DID-PSM	**0.040***	-0.005	-0.070	-0.130	0.109
	(0.022)	(0.059)	(0.122)	(0.208)	(0.263)
Observations	1426	1426	1426	1426	1426
Matched observations	542	542	542	542	542
Panel B: Girls					
Baseline					
Difference (T-C)	-0.033*	0.012	0.068	-0.026	0.081
	(0.019)	(0.010)	(0.124)	(0.282)	(0.350)
Post-treatment					
Difference (T-C)	0.055	-0.028	0.039	0.079	-0.103
	(0.046)	(0.053)	(0.186)	(0.144)	(0.189)
DID-PSM	**0.089***	-0.040	-0.029	0.106	-0.184
	(0.049)	(0.054)	(0.209)	(0.275)	(0.380)
Observations	1426	1426	1426	1426	1426
Matched observations	253	253	253	253	253
Panel C: Boys					
Baseline					
Difference (T-C)	-0.001	0.038	0.007	0.111	-0.123
	(0.009)	(0.060)	(0.095)	(0.299)	(0.345)
Post-treatment					
Difference (T-C)	0.003	0.050	-0.114	-0.016	-0.161
	(0.004)	(0.086)	(0.133)	(0.211)	(0.238)
DID-PSM	0.005	0.012	-0.121	-0.127	-0.038
	(0.009)	(0.105)	(0.150)	(0.339)	(0.380)
Observations	1426	1426	1426	1426	1426
Matched observations	294	294	294	294	294

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Household size is replaced with control variables for household composition. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.005, Panel B: 0.009, Panel C: 0.012. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.

Table D.3.3 The Impact on Children's Time Allocation of its Male Household Members' Participation in MGNREGS – Household Composition

	(1) Paid work	(2) Household tasks	(3) Household chores	(4) Schooling	(5) Leisure
Panel A: Pooled Sample					
Baseline					
Difference (T-C)	-0.015	0.015	0.056	-0.026	0.095
	(0.012)	(0.033)	(0.062)	(0.171)	(0.225)
Post-treatment					
Difference (T-C)	0.033	0.076**	-0.006	0.020	-0.106
	(0.024)	(0.038)	(0.082)	(0.100)	(0.122)
DID-PSM	**0.048***	0.060	-0.062	0.046	-0.201
	(0.026)	(0.049)	(0.096)	(0.181)	(0.244)
Observations	1426	1426	1426	1426	1426
Matched observations	401	401	401	401	401
Panel B: Girls					
Baseline					
Difference (T-C)	-0.021	0.015	0.056	-0.131	0.305
	(0.023)	(0.012)	(0.117)	(0.267)	(0.345)
Post-treatment					
Difference (T-C)	0.070	0.070	0.075	0.014	-0.043
	(0.051)	(0.045)	(0.129)	(0.154)	(0.173)
DID-PSM	0.091	0.055	0.019	0.146	-0.348
	(0.056)	(0.046)	(0.158)	(0.261)	(0.354)
Observations	1426	1426	1426	1426	1426
Matched observations	201	201	201	201	201
Panel C: Boys					
Baseline					
Difference (T-C)	-0.009	0.034	-0.024	-0.161	0.495
	(0.009)	(0.057)	(0.081)	(0.242)	(0.302)
Post-treatment					
Difference (T-C)	-0.005	0.085	-0.092	-0.106	-0.171
	(0.007)	(0.062)	(0.108)	(0.141)	(0.180)
DID-PSM	0.004	0.051	-0.068	0.056	**-0.666****
	(0.012)	(0.083)	(0.129)	(0.274)	(0.329)
Observations	1426	1426	1426	1426	1426
Matched observations	208	208	208	208	208

Notes: Epanechnikov kernel function with data-driven automatic bandwidth, probit model. Includes the covariates listed in Table B.1 with district-year fixed effects. Household size is replaced with control variables for household composition. Bootstrapped standard errors with 1000 replications in parantheses. Bandwidth Panel A: 0.013, Panel B: 0.021, Panel C: 0.028. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculations based on the Young Lives dataset.