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Can unconditional in-kind transfers keep children out of work and in school? Evidence from Indonesia*

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Abstract

The International Labour Organisation estimates that 152 million children are engaging in child labour globally which creates a need for evidence based policies and interventions to eliminate it. Particularly, there is limited evidence about the effect of in-kind transfers on child labour, impeding policy development. We address this evidence gap by examining the impacts of an unconditional in-kind transfer, a subsidised rice program, on child labour as well as schooling, using household survey data from Indonesia. To identify the causal effect we employ coarsened exact matching with difference-in-differences estimator. The results indicate that the program is effective in increasing the probability of schooling for girls though it does not have a significant impact on the probability of working as a child. However, as an unconditional in-kind transfer, its ability to increase schooling for girls, especially of those who are not currently attending school, provides an important policy implication on how a food subsidy program can indirectly influence child wellbeing.

JEL classification: J82; I21; I38

Keywords: Child labour; Schooling; Food subsidy; Raskin; Indonesia; Coarsened exact matching

1 Introduction

The International Labour Organisation estimates that 152 million children are in child labour globally, accounting for almost one in every ten children worldwide. Nearly half of these children (73 million) are engaged in hazardous work leading to adverse consequences on their wellbeing. Child labour also constitutes the violation of children's right to education, as 32 percent of those in child labour are out of school and are completely deprived of education (ILO, 2017). These figures reveal that eliminating child labour remains formidable, and thus, calls for evidence on the impact of policy interventions relevant to child labour and schooling (ILO, 2017). Since child labour is mainly driven by household vulnerabilities

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connected with poverty, risks and shocks (Basu & Hoang, 1998; Edmonds, 2007; Jafarey & Lahiri, 2005; ILO, 2013; ILO, 2017), social protection programs are deemed as a potential mechanism in addressing it (ILO, 2017). There are various social protection tools that ensure income security and welfare of poor households. From a child labour perspective, instruments such as cash and in-kind transfer programs, public employment programs, social health protection and unemployment protection are stated to be most relevant (ILO, 2013), even though the explicit objective of implementing those is not to reduce child labour.

This paper examines the impact of an 'unconditional' in-kind transfer - a food subsidy - on the labour supply and schooling of children. To this end, we consider one of the largest subsidised food programs known as 'Raskin' (or rice for the poor) that is currently in operation in Indonesia. By relying on a rich data source, Indonesia Family Life Survey (IFLS), we seek to answer two specific questions: (1) Does the food subsidy program provide sufficient incentive for the households to reduce the supply of child labour? (2) Does it induce an increase in schooling of children and, if so, is this at the expense of their leisure time? The main identification issue arises from selection bias due to non random distribution of the subsidy and unobserved heterogeneity. To address this, we implement coarsened exact matching (CEM) with the difference-in-differences (DiD) estimator.

This study makes several contributions to the growing literature on policy interventions in improving the welfare of children. First, it adds to the evidence on the effectiveness of social protection instruments on child labour and schooling, with reference to a subsidised food program in a less developed country. There is a plethora of studies that have examined the impact of cash transfers - both conditional and unconditional[1]- on child labour and schooling in various country contexts.[2] Nevertheless, much less is known with regard to the impact of other social protection instruments on child labour outcomes, impeding policy development (de Hoop & Rosati, 2013; Edmonds, 2007; ILO, 2013; ILO, 2017).[3] Particularly, when considering in-kind transfers, a small number of studies have only looked at the impact of 'conditional' in-kind transfers such as school vouchers and food for education programs, on child labour and schooling.[4] However, the limited evidence on such interventions is also inconclusive (ILO, 2013). Unconditional in-kind transfers could be a potential source for eradicating child labour due to two reasons: (1) Food based social assistance programs have a significant influence on households by easing their budget constraints (Alderman et al., 2018; ILO, 2013), (2) food and nutrition programs lead to considerable

[1]Both conditional and unconditional cash transfers provide households with an income transfer, to address issues and vulnerabilities associated with poverty. However, in contrast to unconditional cash transfers, conditional cash transfers are given on a certain condition that the individuals receiving the transfer should fulfil specific requirements. For instance, maintaining regular attendance in school or ensuring regular health checkups (de Hoop and Rosati, 2014a; ILO, 2013).

[2]See Covarrubias, Davis & Winters (2012); de Janvry et al. (2006); Edmonds & Schady (2012); Gee (2010); Levy & Ohis (2007); Skoufias et al. (2001) among many others. For a systematic review of cash transfers on child labour, see de Hoop and Rosati (2014).

[3]There are few studies that have examined the effects of social protection tools other than cash transfers on child labour and schooling. For instance, Guarcello et al. (2010) and Thirumurthy et al. (2008) have examined the impact of social health protection on child labour. Edmonds (2006) and de Carvalho Filho (2012) provide evidence on the effect of income security in old age (a pension scheme) on child labour and schooling.

[4]See Angrist et al. (2002); de Hoop & Rosati (2014b); Kazianga et al. (2009) and Ravallion & Wodon (2000). Cheung and Berlin (2015) and Meng and Ryan (2010) study the impact of food for education programs on schooling outcomes only.

labour supply effects in both developed and developing countries (Currie & Gahvari, 2008).[5] Therefore, to the best of our knowledge, this is the first paper that seeks to examine the effect of an unconditional food subsidy on the labour supply and schooling of children.

Second, though the Raskin program was introduced in 1998, its impact on child labour does not appear to have been studied (Gupta & Huang, 2018; US Department of Labour's Bureau of International Labour Affairs, 2015). Raskin was initially implemented as an emergency food security program, however, at present it has become the largest social protection program in Indonesia. Given the magnitude of the program it is interesting to examine to what extent such a well-established program could address vulnerabilities associated with poverty. To the best of our knowledge, this is the first evaluation of, specifically, the Raskin program at the microeconomic level which particularly looks at child wellbeing with regard to child labour and schooling.

The results reveal that the subsidised rice program in Indonesia is effective in increasing the probability of schooling for girls, though there is no impact on the supply of child labour of both, boys and girls. Specifically, it is found that the Raskin program increases the likelihood of schooling for girls who are neither schooling nor working, by approximately 2.5 per cent. Given the fact that there is limited time to be allocated between labour supply, schooling and leisure, it is also found that Raskin causes girls to forgo their leisure time for increased schooling.

The rest of the paper is organised as follows. Section 2 provides a brief background on child labour, education and Indonesia's Raskin program. Section 3 describes the data source and the variables used in the study. Section 4 outlines the methodology. Section 5 presents the main results while Section 6 describes the impact on child leisure time and provides robustness checks. The concluding remarks and policy implications are given in Section 7.

2 Background

2.1 Global estimates of child labour and education

The term child labour refers to work that has negative consequences on the wellbeing of children in terms of physical, social, psychological or educational development (Dayıoğlu, 2013; Edmonds, 2015) and thus, leading to a deprivation of their fundamental rights. There are two international conventions, namely; International Labour Organisation (ILO) Minimum Age Convention No 138 and ILO Worst Forms of Child Labour Convention No. 182 that form the basis of defining the concept of child labour. Based on these two conventions, ILO defines 'child labour' as "all children under 15 years of age who are economically active excluding (i) those who are under five years old and (ii) those between 12 to 14

[5] According to Alderman et al. (2018), though there is an increased provision of cash transfers, food and vouchers assistance (which are generally unconditional transfers) is still a predominant method in developing countries. Based on administrative data from programs in 108 countries, food assistance programs cover 20.4 percent of the population in those settings. In contrast, the coverage of unconditional and conditional cash transfers is 7 and 3.1 percent respectively.

years old and spend less than 14 hours a week on their jobs, unless their activities or occupations are hazardous by nature or circumstance. Added to this are 15 to 17 years old children in the worst forms of child labour" (ILO, 2002, p. 32).[6] However, despite this standard definition, different countries tend to define child labour in various forms. This is because the extent to which 'child labour' differs from 'light work' depends on factors such as age, type of work, duration of work as well as rules and regulations implemented by individual countries (IPEC, 2004).[7]

According to recent estimates, there is a total of 152 million children aged 5 to 17 years in child labour worldwide (ILO, 2017). In terms of age profile, 48 per cent of these child workers are in the age category of 5 to 11 years whereas 28 per cent are aged 12 to 14 years. Further, the boys are at a higher risk of child labour and the gender gap increases with age. More specifically, as reported by the ILO (2017) the percentage of male child workers accounts for 58 per cent meaning there are 24 million more boys than girls in child labour. However, it is believed that such noticeable gender gap may be as a result of underreporting of work activities by girls. This is because, much of the household chores performed by girls as a form of work are not explicitly considered in estimating child labour.

Child labour is predominantly seen in the regions of Africa, Asia and Pacific which together host nine out of every ten children in child labour (ILO, 2017). Since most of the African and Asian countries are agriculture oriented, agricultural sector accounts for 71 per cent of total child workers whereas the industrial and services sectors account for 12 and 17 per cent respectively.

One of the related issues of child labour is that it inevitably hinders the education of children in terms of low enrolment as well as performance. According to the International Labour Organisation (2017), 32 per cent of those children between 5 to 14 years who are in child labour are completely deprived of education. Though the remaining majority of children attend school while working, empirical studies have shown that these children also perform poorly in school leading to low educational attainment (Edmonds, 2008; Emerson et al., 2017). Thus, to address this serious issue of child labour and low schooling, as evident by the above statistics, the Sustainable Development Goals do in fact include a renewed global commitment to end child labour in all its forms by 2025 (ILO, 2017).

2.2 Child labour and education in Indonesia

With more than 250 million people, Indonesia is the fourth most populous nation in the world. As one of the largest economies in Southeast Asia, Indonesia has experienced a decline in economic growth since 2012, owing to the end of the export boom. In 2017, the country was ranked 127th among all the

[6] Worst forms of child labour include both hazardous work and unconditional worst forms of labour. Hazardous work is defined either as (i) work which exposes children to physical, psychological or sexual abuse; (ii) work underground, under water, at dangerous heights or in confined spaces; (iii) work with dangerous machinery, equipment and tools, or which involves the manual handling or transport of heavy loads, (iv) work in an unhealthy environments; or (v) work under particularly difficult conditions such as work for long hours or during the night. Unconditional work forms of labour includes all forms of slavery, child prostitution and trafficking of children. (ILO, 2002)

[7] The term 'light work' is not deemed 'child labour'. According to ILO (2002), light work should (i) not be harmful to a child's health and development and (ii) not prejudice attendance at school and participation in vocational training.

countries in the world in terms of its GDP per capita (in purchasing power parity) which was $12,400 (CIA, 2018).[8] Indonesia struggles with many problems such as poverty (where almost 11 per cent of its population are below the poverty line), unemployment, inequality and corruption. However, as a country with a predominantly young population,[9] these problems affect the children most. According to UNICEF (2013), Indonesia has a high incidence of child labour, child marriages, sexual exploitation and lack of birth registration which inevitably lead to adverse impact on child wellbeing.

Education is compulsory for Indonesian children aged seven to fifteen years. As a result, the country has made a significant progress in ensuring more than 95 per cent of children aged between 7 to 12 years are attending primary or junior secondary school. Despite high enrolment rates, many children do not complete all levels of formal education; 1 in 10 children do not transit from primary to junior secondary level and almost 1 in 5 children who complete junior secondary do not continue into the final years of their education (UNICEF, 2016).[10] Low transitions from primary to secondary school is mainly seen among children from poor families and rural areas. Specifically, junior secondary aged children in rural areas are 1.5 times less likely to attend school compared to those in urban areas. Moreover, children from the poorest households are four times more likely to be out of school than those in the richest. According to BAPPENAS and UNICEF (2017), around 1.8 million children of lower secondary school age were out of school in 2015. At senior secondary level, over five million children aged 16 to 18 were out of school. One of the main reasons for high drop-outs rates is poverty forcing the children to engage in some form of child labour while depriving them of their right to education.

When we particularly look at the issue of child labour, the statistics reveal that it is, in fact, a considerable problem in Indonesia. According to the 2009 Labour Force Survey (SAKERNAS), across Indonesia, 7.7 per cent of boys and 6.0 per cent of girls aged 5 to 17 years were engaged in harmful child labour, making a total of 6.9 per cent of children (BAPPENAS & UNICEF, 2017). Furthermore, it is also reported that close to half of child labourers aged 5 to 14 years worked in hazardous conditions (BAPPENAS & UNICEF, 2017)[11]. The problem of child labour is mainly seen in rural areas with 12.5 percent of children aged 10 to 17 years working, compared to that of 5.9 percent in urban areas (as cited in US Department of Labour's Bureau of International Labour Affairs, 2015). In line with the global trends of child labour, the highest number of children aged between 10 to 14 years are employed in the agricultural sector which accounts for 62 percent, whereas the industrial and services sector consist of 12 percent and 26 percent respectively.

Though most of the working children attend school, it certainly limits the time available for education hindering their ability to reach the potential. Based on the 2015 Programme for International Student

[8] As cited in Central Intelligence Agency (24 November 2018) Retrieved from https://www.cia.gov/library/publications/resources/the-world-factbook/geos/id.html.

[9] Almost one third of Indonesian population (84 million) accounts for children under the age of 18 years.

[10] As cited in UNICEF Indonesia (10 November 2018) Retrieved from https://www.unicef.org/indonesia/education.html

[11] These child labour figures are low estimates as the 2009 Indonesia Child Labour Survey did not collect information on all types of hazardous work or all of the worst forms of child labour (BAPPENAS & UNICEF, 2017).

Assessment (PISA), less than a third of 15-year-old students in Indonesia achieved at least minimum proficiency in mathematics and 44 per cent in reading (BAPPENAS & UNICEF, 2017). Therefore, as a developing country, eliminating child labour while increasing educational attainment is crucial for the country's sustainable economic growth and development.

2.3 The Raskin Program

In order to address the problem of poverty as well as issues arising out of it, there are several social protection programs that are implemented by the government of Indonesia. 'Raskin' (or rice for the poor) is one of the cross-sectoral national programs intended to alleviate poverty and provide social protection which is funded by the central government. Raskin was first introduced in 1998, as an emergency food security program in the form of subsidised rice assistance prioritised to poor and vulnerable households.[12] However, at present, it has become a permanent nation-wide social protection program targeted at the poorest 40 per cent of the households in Indonesia with the largest government budget allocation (Banerjee et al., 2016; Trimmer et al., 2018; World Bank, 2012).

The targeted households are selected based on a proxy-means test which is updated every three years. In addition to the income of the household, factors such as number of toddlers and school-age children in the household, whether the household head is a female and the physical condition of the house are also considered in determining the eligibility for the program.[13] However, there is no specific selection criterion for the program as it has changed several times based on the data sources used (Trimmer et al., 2018). In general there is little control by the central government in monitoring and determining the eligibility, since the local officials have substantial authority over the implementation of the program at the local level (Banerjee et al., 2016; World Bank, 2012). As a result Raskin has been criticised for considerable 'leakages' where eligible households receive only a third of the intended subsidy (see Banerjee et al., 2016; Trimmer et al., 2018).

The rationale of the program is to reduce the burden of household expenditure on food. In poor households the food expenditure constitutes the largest share of its total expenditure which can range from 45 to 77 percent (Banerjee & Duflo, 2011). As rice is considered to be the staple food in Indonesia, an increase in price of rice can adversely affect the purchasing power of the poor. This is because rice accounts for almost a quarter of the average monthly expenditure in poor households, contributing around 34 per cent and 26 per cent to the official rural and urban poverty budgets, respectively (Sumarto & Widyanti, 2008; Trimmer et al., 2018). Hence, by providing a certain quantity of rice at a subsidised price could lead to ease the budget constraints of poor households vulnerable to child labour (ILO, 2013).

[12] Initially this program was named as Operasi Pasar Khusus (OPK) meaning Special Market Operation. The government changed its name to 'Raskin' (rice for poor families) in 2002. In 2016, it was again renamed as Rastra (literally prosperous rice).

[13] As cited in Rastra - Rice for Family Welfare (25 July 2018) Retrieved from http://raskin.bangda.kemendagri.go.id /tentang-raskin/tujuan-raskin.html.

This program allows the beneficiary households to purchase up to a maximum of 15 kilograms of medium quality rice per month - about half of a typical household's monthly rice consumption - at a subsidised rate of one-fifth of the market price (Banerjee et al., 2016). To put these numbers into perspective, the intended subsidy value of the allocation of 15 kilograms of rice accounts for about five percent of the monthly consumption expenditure of those households who are below the poverty line. Further, it is also shown that ensuring accurate targeting of the program could reduce poverty by about 1.2 per cent or 2.69 people (The State Ministry of National Development Planning - Indonesia, 2013).[14] Raskin also benefits the children of poor households. According to the 2015 SUSENAS, 43 per cent of children were living in households receiving subsidised rice (BAPPENAS & UNICEF, 2017). As a food subsidy Raskin improves the nutrition status of children. This, in turn, could lead to important implications on reducing child labour and increasing schooling.

3 Data

3.1 Indonesia Family Life Survey (IFLS)

The data source that we use for the empirical analysis is the Indonesia Family Life Survey (IFLS). The IFLS is an ongoing longitudinal survey which is administered by the RAND organisation. Currently, there are five waves covering years 1993 (IFLS 1), 1997/98 (IFLS 2 and IFLS2+), 2000 (IFLS 3), 2007 (IFLS 4) and 2014 (IFLS 5). The IFLS consists of several unique features. First, it is one of the few large-scale population-based surveys in operation for more than 20 years, especially in the context of a developing country. Second, in terms of representation, the first wave of survey sample represented about 83 percent of the Indonesian population living in 13 of the country's 26 provinces at that time (Strauss et al., 2009). In IFLS1, data were collected from over 22,000 individuals in 7,224 households. By 2014, the numbers had increased to 50,000 individuals from 17,000 households. Third, there is over 85 per cent re-contact rate in each wave leading to high quality of data with relatively low attrition (Strauss et al., 2016). Finally, IFLS is a multipurpose survey which collects information at the individual, household and community level. Therefore, it includes data on a range of topics such as demographics, household consumption patterns, labour market outcomes, health outcomes, schooling, migration, receipt of social transfers etc. which facilitate the conduct of extensive research with regard to various aspects.

[14] As cited in Rastra - Rice for Family Welfare (25 July 2018) Retrieved from http://raskin.bangda.kemendagri.go.id /tentang-raskin/tujuan-raskin.html.

3.2 Sample and Variable Definitions

For this study, we use data from the 1997, 2000, 2007 and 2014 waves of the IFLS.[15] Our sample is restricted to children between the age of 5 to 14 years old, as child labour is defined as children aged 5 to 14 years who are economically active. The term 'economically active' refers to the participation in the production of economic goods and services, meaning it can be either for wages or as unpaid work performed as part of family business (Edmonds, 2007). Therefore, the supply of labour for household activities and chores are not considered as child labour.[16]

In our study, there are two main outcome variables of interest - child labour and schooling. The data in relation to these is extracted from the child module of the IFLS, which is administered to children below 15 years old.[17] Constructed as binary variables, child labour takes on a value of 1 if the child has ever worked and 0 otherwise.[18] Similarly, schooling takes on a value of 1 if the child is currently in school and 0 otherwise. The treatment variable used in this study is a dummy variable which is assigned a value of 1 if the household has ever bought subsidised rice from Raskin program during the past year and 0 otherwise.

As a rich data set IFLS allows us to control for a set of socio demographic characteristics that are well established in the literature. Specifically, we include child's age, religion, parental characteristics such as parent's age, marital status, occupation and educational attainment as control variables. Furthermore, we also include variables on the household's demographics such as household size, dependency ratio, the gender of the household head and ownership of assets. Standard indicators such as access to electricity, water, proper sanitation and source of fuel are included as housing characteristics. The monthly per capita expenditure, which is constructed by adding both food and non-food expenditure, is used to proxy for household income. Moreover, we also consider regional heterogeneity by including a dummy variable for urban area as well as provincial dummy variables in our estimation. A complete list of variables used in this study is presented in Table A1.

As the Raskin program began in 1998, there is one pre-exposure period:1997 and three potential post exposure periods of 2000, 2007 and 2014. However, since there is a seven-year gap between the subsequent waves after year 2000, the use of panel data leads to a loss of significant number of observations. This is because children who are eight years or older in 2000 are excluded from the child modules in 2007 and 2014 waves as they would be above 15 years of age. Therefore, we use pooled cross section data to maximise the number of observations. Accordingly, our sample consists of 28,287 children (Girls - 13827

[15]We do not use data from the first wave IFLS1 (1993) due to the differences in the format of the questions and the considerable number of missing observations in relation to parental information.

[16]The child' s participation in household chores are provided only in 2007(IFLS 4) and 2014 (IFLS 5) waves.

[17]This means the respondent is usually a child below 15 years old. Sometimes the questions are answered by an older sibling or another household member such as mother, aunt or grandmother who deemed the most knowledgeable source of information for the child.

[18]From year 2000 onwards, the child module contains seperate questions on the child's work status for the last month, week and ever as well as type of work. However, to ensure consistency of the child labour measure across different waves we have used the ever worked participation.

and Boys - 14460) between the age of 5 to 14 years from 11,277 households. After excluding observations with missing responses, 18,288 observations remained in the sample.[19] As per empirical evidence, gender differences play a significant role in determining child work (Edmonds, 2007) which is also applicable in the context of Indonesia (De Silva & Sumarto, 2015; Suryahadi et al., 2005). Hence, we consider girls and boys separately in our study. Tables A2 and A3 in Appendix presents the the summary statistics of girls and boys respectively. Approximately, six percent of girls and seven per cent of boys are engaged in work which corresponds to the actual percentage of child labour in Indonesia. In line with previous studies, the proportion of girls in child labour is less compared to that of boys and the opposite is true for schooling. On average 82 percent of children (both girls and boys) are currently attending school. The average age is 9.5 years. Half of the children are from a rural household. Around 20 per cent of the children are in poverty as reflected by the household characteristics such as poor sanitation and use of nearby river, land or sea as the toilet.

To understand the context in terms of those who receive Raskin and those who do not, we derive the descriptive statistics by the control and treatment assignment. Tables A2 and A3 in Appendix also report the mean values across groups and the results of t-tests on the difference of means. When considering the mean values of the dependent variable of child labour, it is evident that there is a significant difference between the control and treatment groups in both girls and boys samples. As anticipated, the households that receive Raskin have a higher proportion of children involved in child labour. However, the percentage of children attending school is also high in the treatment groups, though the difference is not statistically significant for boys. Furthermore, as expected, there are also significant differences across the control and treatment groups especially in terms of household and parent characteristics. This is because as Raskin is targeted at the poorest households, the two groups are likely to differ in variables that capture the aspects of poverty. In general, the households that receive Raskin are poorer and less educated. Such significant differences in the two groups may imply that there is non-random selection into treatment and thus, the control group may not act as a perfect counterfactual to the treatment group.

4 Methodology

4.1 Coarsened Exact Matching

To estimate the effect of receiving Raskin on child labour supply and schooling it is important to establish a causal relationship between the treatment and the outcome variables. However, given that this study is based on non-experimental data it is important to address the problem of selection bias, as the variables that determine the receipt of the subsidy would also determine the outcome variables. In other words,

[19] A significant number of missing information are in relation to parental characteristics.

the households that are meant to receive Raskin are, in fact, the poor households with high probability of child work and low schooling. This means that the treated and the control groups differ in terms of other covariates. Therefore, the outcomes of those who receive the subsidy and those who do not would differ even in the absence of the subsidy resulting in selection bias (Caliendo & Kopeining, 2008, Heckman et al., 1998).

Previous studies on program evaluation have relied on techniques such as randomised controlled trial (RCT), difference-in-differences (DiD), regression discontinuity design (RDD), matching or a combination of aforesaid methods to deal with sample selection bias arising from non random assignment of the treatment and unobserved heterogeneity. In this study we use a matching technique combined with difference-in-differences (matched DiD) to estimate the treatment effect. We select matching as the identification strategy for two reasons. First, the Raskin program does not have any clear assignment rules such as an eligibility score (Trimmer et al., 2018) that explain why some households received the rice subsidy and others did not. Second, the availability of a rich data source that contains data on both households that received Raskin and that did not, enables us to estimate a control group that has as similar as possible characteristics as the treatment group (Gertler et al., 2011).

There are several types of matching methods that are widely applied in the empirical literature. These methods differ primarily on the technique that is used to find at least one control unit for each of the treated units that is similar on the covariates. However, the major limitation of using the common matching methods, such as, propensity score and Mahalanobis matching, is that they do not necessarily guarantee a reduction of imbalance (i.e. differences between the treated and control groups) in a given data set. For instance, the application of propensity score matching leads only to an improvement of balance on some covariates while decreasing the balance on other covariates (Iacus et al., 2012). Moreover, these methods depend on a set of unverifiable assumptions about the data generating process and despite such assumptions its properties only hold on average across samples. The use of these techniques, therefore, can increase both model dependence and imbalance (Iacus et al., 2012); meaning that they are ad-hoc and inefficient (Blackwell et al. 2009).

As a solution for these problems Iacus, King and Porro (2012) propose a matching method known as coarsened exact matching (CEM), which is derived from exact matching theory. CEM can be applied in sample data with minimum assumptions about the data generating process. The only assumption it makes about the data is the standard ignorability assumption of non-experimental studies; which implies that the treatment assignment is independent of the potential outcomes given the covariates;[20]

$$D_i \perp \{Y_i(0), Y_i(1)\} \,|X \tag{1}$$

CEM belongs to the class of monotonic imbalance bounding (IMB) matching methods. Hence, in

[20]This is also referred to as the unconfoundedness assumption by Imbens (2004). According to Cameron and Trivedi (2005), this assumption implies that there is no omitted variable bias once $\mathbf{x}$ is included in the regression leading to unconfoundedness.

contrast to other matching methods, CEM balances between the control and treatment groups chosen ex ante; and adjusting the imbalance on one covariate does not affect the balance of any other (Blackwell et al. 2009). In fact, CEM has the ability to reduce imbalance, model dependence, estimation error, bias, variance and mean squared error. Further, according to Blackwell et al. (2009), CEM also possesses a number of beneficial properties. First, CEM meets the congruence principle meaning both the data space and the analysis space is similar. Second, CEM automatically restricts the matched data to areas of common empirical support. Finally, CEM is computationally very efficient, even for large datasets. Therefore, contrary to previous empirical literature on child labour, we use CEM to deal explicitly with the treatment selection bias owing to its desirable features.[21]

4.2 Matched Difference-in-differences

The presence of data in relation to before and after intervention allows us to combine the coarsened exact matching with the difference-in-differences (DiD) technique. Following Ravallion (2007), panel data are not necessary for calculating DiD. This is because the double-difference estimator which provides the mean treatment effect on the treated for period one can be derived as follows;[22]

$$DID = E\left(Y_1^T - Y_0^C | T_1 = 1\right) - E\left(Y_1^C - Y_0^C | T_1 = 0\right) \tag{2}$$

It is apparent that what is required is the set of four means that make up DiD; where the means need not be calculated for the same sample over time. Therefore, by using pooled data over both time periods and across treatment status, the treatment effect can be identified by the following regression;

$$Y_{it} = \alpha + \gamma T_{i1} + \delta t + \beta T_{i1} t + \eta \mathbf{X}_{it}^{'} + \varepsilon_i \qquad (t = 0, 1;\ i = 1, ..., n) \tag{3}$$

where Y_{it} is the outcome measure for the ith individual observed at two time periods, t = 0,1; T_{i1} is the treatment status in period one, with $T_{i1} = 1$ if the individual receives the program (is 'treated') and $T_{i1} = 0$ otherwise; $\mathbf{X}_{it}$ is a vector of covariates. The regression coefficient β on the interaction effect between the treatment dummy variable (T_{i1}) and time (t) identifies the DiD impact.

Combining coarsened exact matching with DiD, allows us to offset any limitations of matching as an identification strategy and thereby to increase the robustness of the estimated counterfactual (Gertler et al., 2011). Since matching is simply a data-preprocessing technique, it is required to use a parametric model to estimate the casual effect. According to Ho et al. (2007), applying a matching method to the data before analysis reduces model dependence.

[21] See Iacus et al. (2012); Stata implementation of the algorithm is described in Blackwell et al. (2009)
[22] See Ravallion (2007) for detailed derivation.

4.3 Empirical Model

The parents' decision to send the child either to work or school is a joint decision as both would be competing for child's time. Moreover, given that child labour and schooling are denoted as binary variables, we use a bivariate probit model to estimate the effect of Raskin on the likelihood of child labour supply and school attendance, conditional on a set of individual and household characteristics. A bivariate probit model explicitly considers the existence of possible correlation between the unobserved factors of the two probit regressions by capturing any interrelation between working and schooling.

Incorporating equation (3), the bivariate DiD model under the latent variable framework is derived as follows;

$$y^*_{1it} = \alpha_1 + \delta_1 yrAfter_{1it} + \beta_1 yrAfter * Raskin_{1it} + \eta_{\mathbf{1}} \mathbf{X}'_{1it} + u_{1it} \tag{4}$$

$$y^*_{2it} = \alpha_2 + \delta_2 yrAfter_{2it} + \beta_2 yrAfter * Raskin_{2it} + \eta_2 X'_{2it} + u_{2it} \tag{5}$$

where the observed outcomes are stated as;

$$y_{1it} = \{ \begin{array}{ll} 1, & \text{if } y^*_{1it} > 0 \\ 0, & otherwise \end{array} \tag{6}$$

$$y_{2it} = \{ \begin{array}{ll} 1, & \text{if } y^*_{2it} > 0 \\ 0, & otherwise \end{array} \tag{7}$$

where y_{1it} =1 if the child has ever worked in year t and 0 otherwise; $y_{2it} = 1$ if the child is currently in school in year t and 0 if not;[23] $yrAfter_{it}$ is an indicator variable for the period after Raskin was introduced. This takes on a value of 1 for years 2000, 2007 and 2014 and 0 for the year 1997. Our variable of interest is $yrAfter * Raskin_{it}$ which equals 1 if the child i lives in a household that receives Raskin in year t and 0 otherwise. $\mathbf{X}_{1it}$ and $\mathbf{X}_{2it}$ are vectors of individual, parent and household covariates that affect the child's labour supply (y_{1it}) and schooling decision (y_{2it}), respectively. u_{1it} and u_{2it} are the error terms with a bivariate normal distribution with $Cov\left[u_{1it}, u_{2it}|X_{1it}, X_{2it}\right]=\rho$

In the event where $\rho = 0$, the model collapses into two separate probit models for y_{1it} and y_{2it}. If ρ is significant we can conclude that there is a correlation between the unobserved factors affecting both working and schooling. In such case the results of the univariate probit model would be inefficient and biased.

5 Empirical Results

We begin our empirical analysis with coarsened exact matching (CEM). The first step of CEM is to select the control variables to be included in matching. In view of Heckman et al. (1998), all variables that can affect both treatment assignment and outcome should be included in the matching process so as to satisfy

[23] y^*_{1it} and y^*_{2it} represent the latent variables of desire to work and attend school respectively.

the assumption of strong ignorability. In this study, we match the treated and the control households based on the observable household characteristics that act as proxies for household's poverty level and thus leads to treatment assignment. This is because, as a food subsidy, Raskin is targeted at the poorest households which is determined by the level of household's income and welfare. Therefore, based on a probit estimation we identify the significant covariates that determine Raskin and, hence, mimic the rules of eligibility into the program.[24] Accordingly, the covariates that are used for the coarsening process are, residence (urban or rural), dependency ratio, the gender of the household head, per capita expenditure, ownership of business, whether the household purchases water, uses firewood for cooking and uses the nearby river, land or sea as the toilet.

The matching outcomes are summarised in Table A4 in Appendix. When considering the sample of girls, of the 5974 households that receive Raskin, 5060 households or 85 percent are matched, whereas 914 households or 15 percent are not matched; the former were matched to 6110 out of 7853 households that do not receive Raskin. A similar outcome is also apparent for the sub-sample of boys.

The quality of the matching outcomes is diagnosed by an assessment of covariate balance. Tables A5 and A6 in Appendix report the results for both pre- and post-matching of the two subsamples. According to Table A5, the overall multivariate imbalance decreases substantially from 0.63 to 0.51. There is also a significant reduction in the univariate imbalance for each of the covariates. Further, the post-match mean differences between treated and control groups are almost negligible. This suggests that CEM has produced a reasonable match. Likewise, the post covariate balance for the sample of boys also indicates a good match.

It is important to note that with coarsening, there would be some imbalance remaining in the matched data. According to Blackwell et al. (2009), such imbalance can be controlled via a statistical model. Therefore, we use a bivariate probit model on the matched data to estimate the causal effect of Raskin on child labour and schooling. The weights generated by the CEM process are also included in the model, so as to equalise the number of treated and control units within each stratum (Iacus et al., forthcoming).

Table 1 reports the main regression results of the bivariate probit model for girls and boys separately.[25] The correlation coefficient between the error terms - rho (ρ) is significantly different from zero for both groups at 1% level. This confirms the importance of employing the bivariate probit model as the estimations derived from a univariate model would be inefficient. As expected, its sign suggests that there is a negative correlation between the unobserved factors affecting the probability of working and attending school. In Table 1, the estimated coefficient of yrAfter*Raskin is the treatment effect of receiving Raskin on the probability of working as a child or attending school. It is evident that this coefficient has a positive impact on schooling for girls which is significant at 5% level while no impact on child labour is observed. When considering boys, Raskin has no impact on either work or school as none

[24] Results are available upon request.

[25] The reported results are with robust standard errors clustered at both household and province levels. Clustering at municipalities and subdistricts levels also provide quantitatively similar results.

of the coefficients are statistically significant at conventional levels.

Table 1: Effect of Raskin on child labour and schooling for girls and boys: Bivariate probit estimates with CEM

	Girls		Boys	
Variables	(1)	(2)	(3)	(4)
	Work	School	Work	School
yrAfter	1.128***	-0.970***	1.194***	-0.687***
	(0.229)	(0.163)	(0.152)	(0.143)
yrAfter*Raskin	-0.085	0.153**	0.020	-0.042
	(0.076)	(0.075)	(0.068)	(0.071)
Constant	-5.875***	-16.835***	-4.656***	-15.484***
	(1.010)	(0.940)	(0.883)	(0.883)
Rho	**-0.170*** **		**-0.164*** **	
	(0.064)		**(0.049)**	
Number of observations	8,825		9,563	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include the full set of control variables as given in Appendix Table A1, year and province fixed effects as well as the corresponding weights generated by CEM. Please see Appendix Table A7 for comprehensive results.

Tables 2 and 3 present the average marginal effects of the estimated coefficients. Given that we use a bivariate probit model, there are four observed joint outcomes of work and school. Specifically, with regard to treatment effect, it is possible to identify the impact of receiving Raskin on the probability of; (1) working only, (2) schooling only, (3) both working and schooling (4) neither working or schooling. According to Table 2, receiving Raskin increases the probability of schooling for girls by 2.5 percent. Notably, this increase comes from the group of girls who are neither working nor schooling. This is because Raskin decreases the probability of idling among girls by 1.6 percent which corresponds with the increase in probability of schooling.

Furthermore, in line with existing empirical studies, Tables 2 and 3 also reveal that the variables such as the age of the child, dependency ratio, the ownership of a business and the use of firewood for cooking which act as a proxy for poverty are all significant determinants of child labour and schooling for both girls and boys with the expected signs. Interestingly, maternal characteristics have a significant impact on the working and schooling decisions of girls. If the mother is employed in a paid occupation it is more likely to increase the probability of work and decrease the probability of schooling for girls, suggesting that such households are more vulnerable to poverty. The marginal effects indicate that the probability of schooling for girls decreases by 1.6 percent if the mother is employed in a paid occupation. Further, the level of maternal education also increases the probability of schooling for girls by approximately six percent while reducing the likelihood of work by about 0.5 percent.

According to Table 3, the decision whether to send a boy child to work or school is mainly determined

Table 2: Average Marginal Effects of the Bivariate Probit Model: Girls

Variables	(1) Work only (work = 1 school = 0)	(2) School only (work = 0 school = 1)	(3) Both work & school (work = 1 school = 1)	(4) Idle (work = 0 school = 0)
yrAfter	0.012***	-0.165***	0.062***	0.092***
	(0.002)	(0.017)	(0.008)	(0.015)
yrAfter*Raskin	-0.002*	0.025**	-0.007	-0.016*
	(0.001)	(0.011)	(0.007)	(0.009)
Child age	0.008***	0.064***	0.011***	-0.083***
	(0.001)	(0.003)	(0.001)	(0.002)
Dependency ratio	0.003***	-0.027***	0.016***	0.009
	(0.001)	(0.010)	(0.006)	(0.007)
Own business	0.009***	-0.071***	0.057***	0.006
	(0.002)	(0.010)	(0.007)	(0.007)
Cook firewood	0.003***	-0.035***	0.013	0.018*
	(0.001)	(0.012)	(0.008)	(0.009)
Mother- paid occupation	0.002**	-0.016*	0.020***	-0.006
	(0.001)	(0.010)	(0.006)	(0.007)
Mother completed junior education	-0.005***	0.060***	-0.020	-0.034**
	(0.002)	(0.022)	(0.013)	(0.017)
Mother completed tertiary education	-0.005***	0.058**	-0.036***	-0.017
	(0.002)	(0.024)	(0.011)	(0.021)
Father completed tertiary education	-0.005***	0.059**	-0.031**	-0.023
	(0.002)	(0.026)	(0.014)	(0.021)
Predicted probability of outcome	0.0070	0.7723	0.0571	0.1636

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. Marginal effects represent the percentage change in probability of an outcome given a unitary increase in a continuous variable or change from 0 to 1 for binary variables. All estimations include year and province fixed effects as well as the corresponding weights generated by CEM. Please see Appendix Table A8 for comprehensive results.

by the wealth and assets of the household. A ten percent increase in the assets per capita increases the probability of schooling for boys by nine percent while reducing the likelihood of work by one percent. Moreover, if the household has its own farmland, then boys are more likely to be employed and therefore less likely to go to school. This provides evidence that boys tend to engage more in field work compared to girls. Similar to girls, level of parental education also has a significant impact on the labour supply and schooling of boys. As anticipated, an increase in the level of parent's education reduces the likelihood of work by approximately 0.6 percent while increasing the probability of schooling by five to six per cent.

As a goodness-of-fit measure we report the comparison of the sample means of actual work-school outcomes versus the predicted probabilities after bivariate probit model. In view of Appendix Table A10, it is apparent that the estimated model performs well such that the predicted probabilities are almost similar to that of actual sample means.

Table 3: Average Marginal Effects of the Bivariate Probit Model: Boys

Variables	(1) Work only (work = 1 school = 0)	(2) School only (work = 0 school = 1)	(3) Both work & school (work = 1 school = 1)	(4) Idle (work = 0 school = 0)
yrAfter	0.014***	-0.153***	0.074***	0.065***
	(0.002)	(0.016)	(0.007)	(0.014)
yrAfter*Raskin	0.001	-0.007	0.002	0.005
	(0.001)	(0.011)	(0.007)	(0.008)
Child age	0.009***	0.064***	0.014***	-0.087***
	(0.001)	(0.002)	(0.001)	(0.002)
Dependency ratio	0.002**	-0.020**	0.008	0.009
	(0.001)	(0.009)	(0.006)	(0.006)
Assets per capita (ln)	-0.001**	0.009***	-0.004*	-0.004
	(0.000)	(0.003)	(0.002)	(0.002)
Own business	0.005***	-0.043***	0.039***	-0.001
	(0.001)	(0.010)	(0.007)	(0.007)
Own farm land	0.003**	-0.025**	0.029***	-0.007
	(0.001)	(0.011)	(0.007)	(0.008)
Cook firewood	0.004***	-0.034***	0.008	0.022**
	(0.001)	(0.012)	(0.008)	(0.009)
Mother completed junior school	-0.005***	0.054**	0.007	-0.056***
	(0.002)	(0.021)	(0.016)	(0.013)
Mother completed tertiary education	-0.004**	0.051*	-0.003	-0.043***
	(0.002)	(0.028)	(0.023)	(0.016)
Father completed senior school	-0.006***	0.064***	-0.035***	-0.022
	(0.002)	(0.022)	(0.014)	(0.017)
Father completed tertiary education	-0.006***	0.054**	-0.045***	-0.003
	(0.002)	(0.023)	(0.011)	(0.020)
Predicted probability of outcome	0.0081	0.7572	0.0640	0.1701

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. Marginal effects represent the percentage change in probability of an outcome given a unitary increase in a continuous variable or change from 0 to 1 for binary variables. All estimations include year and province fixed effects as well as the corresponding weights generated by CEM. Please see Appendix Table A9 for comprehensive results.

6 Discussion

6.1 Impact on the Child's Leisure Time

According to the theoretical literature (see Ersado, 2005; Ravallion & Wodon, 2000), child's limited time is allocated between school attendance, child's labour supply and leisure. This means an increase in either schooling, labour supply or both should inevitably lead to a reduction in child's leisure. Since Raskin increases the probability of schooling for girls, we examine whether this increase occurs at the expense of the child's leisure hours using the following DID specification;

$$L_{it} = \alpha_0 + \delta yrAfter_{it} + \beta yrAfter * Raskin_{it} + \eta \mathbf{X}_{it}^{'} + \varepsilon_i \quad (8)$$

where L_{it} denotes the leisure time of child i at year t calculated as total number of hours per week minus the time spent for work and schooling activities per week, $yrAfter_{it}$ is an indicator variable for the period after Raskin was introduced. This takes on a value of 1 for years 2000, 2007 and 2014 and

0 for the year 1997. $yrAfter * Raskin_{it}$ represents a binary variable equal to 1 if the child i lives in a household that receives Raskin in year t and 0 otherwise and $\mathbf{X}_{it}$ represents the vector of same individual, household and parental characteristics used in the bivariate probit specification.

The above equation (8) is estimated using Ordinary Least Squares (OLS) with the corresponding weights generated by CEM. Columns 1 and 2 of Table A11 in Appendix report the estimation results for girls and boys respectively. Consistent with the bivariate probit results, Raskin does not appear to have a significant impact on leisure time of boys at the conventional levels. Nevertheless, for girls, there is a significant negative effect on their leisure time. These results assure the finding that due to the receipt of Raskin girls are more likely to attend school, which certainly leads to a reduction in time that they have for their leisure activities. One plausible justification for this would be that the productivity of schooling depends on the nutrition status of the child (Adelman et al., 2008). In other words, the availability of more food makes schooling productive such that individuals cut back on leisure, especially if leisure means resting due to tiredness or low energy.

6.2 Robustness Checks

One of the key identification assumptions of matching is that both treatment and control units are similar in terms of any unobservable variables that could affect both the probability of participating in the program and the outcomes of interest (Gertler et al., 2011). Though it is argued that selection on observables could also account for such unobservables to a certain extent, it is important to examine the nature of bias that could be induced by the presence of any unobservables. By following Datt and Uhe (2018), we estimate our bivariate probit model, assuming that some of the observed covariates are unobserved, and thereby the magnitude of bias on the treatment effect.

We derive two seperate estimations of which we exclude household and parent characteristics respectively. Appendix Table A12 reports the results.[26] It is evident that in both estimations the treatment effect on schooling is smaller compared to the original treatment effect based on the full set of covariates (see columns 2, 4 and 6). This suggests that selection on unobservables related to either household or parent characteristics is inducing a positive bias. Therefore, it can be inferred that in the event that there are any unobservables, the direction of bias is likely to be positive implying larger treatment effect on schooling than the estimated effect. Furthermore, if there are still other unobservables (such as bribery, corruption or favouritism) that may produce a negative bias, it would have to be sufficiently strong to reverse the estimated positive impact of Raskin on schooling (Datt and Uhe, 2018).

[26]These estimations are derived only for girls since the treatment effects of boys are found to be insignificant.

6.3 Interpretation and Comparison with related literature

Our results clearly show that Raskin is effective in increasing schooling for girls. However, its minimum or no effect on reducing child labour and increasing schooling particularly of boys may be counter-intuitive at first. As an unconditional in-kind transfer, it is expected that the monetary benefit derived from it would generate an income effect leading to an increase in schooling as well as a reduction in the supply of child labour. Nevertheless, in view of limited empirical evidence on conditional in-kind transfers, our results are not contradictory. Specifically, studies such as de Hoop and Rosati (2014b), Kazianga et al. (2009) and Ravallion and Wodon (2000) all show that even an in-kind transfer such as food for education programs that are conditioned on school attendance are also effective only in increasing schooling while having a minimum or no impact in reducing children's overall involvement in child labour activities. Therefore, given that Raskin is an unconditional transfer, its ability to increase schooling for girls specifically of those who are not currently attending school, by approximately 2.5 per cent provides a useful policy insight on how food subsidies can indirectly influence the wellbeing of children.

The finding that Raskin has a significant impact on increasing the probability of schooling for only girls but not for boys merits further discussion. Compared to girls, boys generally have higher participation in market work meaning lower likelihood of attending school. This is also observable in our sample (see Appendix Tables A2 and A3). Especially, in developing countries, girls are nearly 30 percent less likely to participate in paid market work, as they are mainly engaged in household chores (Edmonds, 2007). Since household activities are not considered as child labour by definition, being a boy increases the probability of a child being involved in labour activities and thereby reduces schooling, which is also true in the context of Indonesia (De Silva & Sumarto, 2015; Suryahadi et al., 2005). This provides a justification as to why Raskin only leads to an increase in schooling for girls, as the opportunity cost of sending a boy child to school may be higher for a poor household in terms of lost income.

On a different note, the ability of Raskin to increase schooling for girls is beneficial due to two reasons. First, girls have significantly higher returns to schooling which is approximately one to two per cent higher than that of boys in Indonesia (Deolalikar, 1993; Dumauli, 2015 and Purnastuti et al., 2015). Second, by increased participation in school, girls would have better chance for education, health and safety leading to other positive outcomes such as a reduction in child marriages and sexual exploitation (World Bank, 2017). According to BAPPENAS & UNICEF (2017), Indonesia has a high incidence of child marriages and sexual exploitation where one in ten women (12 per cent) aged 20 to 24 years was married or in union before the age of 18 in 2015. At least 30 per cent of the females below the age of 18 are engaged in or forced into sex work (UNICEF, 2013). Therefore, by inducing girls to attend school, Raskin may also have an indirect effect on eliminating such harmful practices. In fact, Baryshnikova et al. (2018) show that Raskin significantly reduces the likelihood of child marriages in Indonesia, which complements with our findings.

The limited effect of the Raskin program on the supply of child labour and schooling may be due to several reasons. First, the benefit of the subsidy which accounts for about five percent of the monthly consumption expenditure of poor households, may not be sufficient to keep children out of the labour market. Particularly, to achieve greater impacts on child labour, the income transfers should be of sufficiently sizeable value (Datt & Uhe, 2018). However, in view of Banerjee and Duflo (2011), the poor usually do not do what is in their best interest even if they could afford to do so. This means rather than utilising the income effect that they receive from the rice subsidy to forgo the income earned from child labour, they may spend it on less important things such as festivals and family events. Second, the limited effect of the Raskin program can also be attributed to the behavioural constraints of the poor such as small inconveniences (Banerjee & Duflo, 2011) that restrict them to gain the full benefit of the subsidy. Specifically, around two to three percent of those who are eligible to receive Raskin have refused the receipt of the subsidy at least once in a given year due to reasons such as inability to go on the allocated day, lack of time or long distance to the distribution centre. Third, there may also be issues of accurate targeting of the program leading to both inclusion and exclusion errors.[27] It is stated that redistribution programs in less developed countries often "leak" due to various reasons such as targeting method used, take up problems, corruption and bribes (Banerjee et al., 2016; Currie & Gahvari, 2008; Trimmer et al., 2018). According to Banerjee et al. (2016), though the government of Indonesia spends over US$ 1.5 billion a year on the Raskin program, less than half of the rice was actually reaching the intended households. Therefore, this study also underscores the importance of accurate targeting of government social protection programs so as to achieve the ultimate goal of poverty reduction.

7 Conclusion and Policy Implications

Child labour continues to be a problem of the developing world, where nine out of every ten children in child labour are in the regions of Africa, Asia and Pacific. Therefore, there is a compelling need for evidence based interventions on child labour to inform policy responses. Since child labour is strongly related with and determined by poverty, social protection programs are a potential source of mitigation. Though there is ample evidence on the impact of cash transfers on child labour, evidence on the effect of other social protection tools particularly in-kind transfers is limited. This paper addresses this empirical gap by examining the impacts of an unconditional in-kind transfer - a subsidised food program on child work as well as schooling. To this end, we consider the Raskin program, which is the largest subsidised rice program in Indonesia.

The results of this study show, that in general, a food subsidy is not effective in reducing the labour supply of children - both girls and boys. However, the program has a strong effect in inducing girls who

[27] An exclusion error occurs when a potentially eligible person or household does not participate in a program.

are neither schooling nor working to attend school. Specifically, a subsidy on a staple food like rice can lead to an increase in the probability of schooling for girls by 2.5 per cent. Further, it is also found that, because of increased schooling, there is a reduction in leisure time for girls.

In line with previous studies on conditional in-kind transfers and child labour, our results are not contradictory. In fact, as an unconditional in-kind transfer, the ability of a food subsidy to increase schooling of girls in a developing country provides an important policy implication on how social protection tools can indirectly influence the wellbeing of children.

The minimum effect of the subsidy on child labour may be due to several reasons. Among them the size of the subsidy as well as targeting issues leading to considerable leakages are prominent. Therefore, the findings of our study indicate that to reap the maximum benefits of pro-poor programs such as subsidised food programs, it is vital to design such programs in a manner that maximises its reach and intensity. This would inevitably have a considerable impact on the welfare of poor households and thereby ensure child wellbeing.

Appendix

Table A1: Variable Description

Variable	Description
Child-working	=1 if the child has ever worked
Child-schooling	=1 if the child is still in school
Raskin	=1 if the household has ever bought rice from Raskin (during the past year)
Child Characteristics	
Child-age	Age of the child
Child-age2	Age of the child squared
Child-religion-Islam	=1 if the child's religion is Islam
Household Characteristics	
HH size	The number of members in the household
Dependency ratio	The ratio of the number of household members aged below 14 and above 65 years to the number of working members aged 15 - 64 years
HHH-female	=1 if the household head is a female
Urban	=1 if the household is in an urban area
Own business	=1 if the household has its own farm business
Own farm land	=1 if the household has its own farm land
Per capita expenditure (PCE) (ln)	Logarithm of monthly per capita expenditure
Assets per capita (ln)	Logarithm of household assets per capita
Electricity	=1 if the household has access to electricity
Water	=1 if the household purchases water
Toilet-river/land/sea	=1 if the household does not have proper toilet facilities
Cook-firewood	=1 if the household uses firewood as the main source of energy for cooking
Poor sanitation	=1 if the household has poor sanitation
Parent Characteristics	
Mother-age	Age of the mother
Father-age	Age of the father
Mother-married	=1 if the mother is married
Mother-paid occupation	=1 if the mother is occupied in a paid occupation
Father-paid occupation	=1 if the father is occupied in a paid occupation
Mother completed elementary school	=1 if the mother has completed elementary school
Mother completed junior school	=1 if the mother has completed junior school
Mother completed senior school	=1 if the mother has completed senior school
Mother completed tertiary education	=1 if the mother has completed tertiary education
Father completed elementary school	=1 if the father has completed elementary school
Father completed junior school	=1 if the father has completed junior school
Father completed senior school	=1 if the father has completed senior school
Father completed tertiary education	=1 if the father has completed tertiary education
Mother completed the highest level of education	=1 if the mother has completed the highest level of education
Father completed the highest level of education	=1 if the father has completed the highest level of education
Provincial Dummies	Seperate indicator variables for each of the following provinces: North Sumarta, West Sumarta, South Sumarta, Lampung, Jakarta, West Java, Central Java, Yogyakarta, East Java, Bali, West Nusa Tenggara, South Sulawesi and South Kalimantan

Table A2: Summary Statistics: Girls

Variables	Full Sample		Control Group Raskin = 0		Treatment Group Raskin = 1		Mean Difference
	Mean	SD	Mean	SD	Mean	SD	
Child-working	0.06	0.25	0.04	0.21	0.09	0.29	-0.05***
Child-still in school	0.83	0.38	0.82	0.38	0.84	0.37	-0.01**
Child Characteristics							
Child-age	9.46	2.88	9.47	2.90	9.46	2.86	0.01
Child-religion-Islam	0.90	0.30	0.89	0.32	0.93	0.26	-0.04***
Household Characteristics							
HH size	5.21	1.88	5.28	1.94	5.12	1.80	0.16***
Dependency ratio	1.08	0.68	1.06	0.67	1.09	0.69	-0.03**
HHH-female	0.12	0.33	0.11	0.32	0.14	0.34	-0.02***
Urban	0.49	0.50	0.55	0.50	0.40	0.49	0.14***
Own business	0.43	0.49	0.42	0.49	0.43	0.49	0.00
Own farm land	0.32	0.47	0.30	0.46	0.35	0.48	-0.05***
Per capita expenditure (PCE) (ln)	12.55	1.21	12.46	1.40	12.67	0.87	-0.22***
Assets per capita (ln)	15.31	1.93	15.32	2.11	15.29	1.65	0.03
Electricity	0.93	0.26	0.91	0.28	0.94	0.23	-0.03***
Water	0.28	0.45	0.32	0.47	0.24	0.43	0.08***
Toilet-river/land/sea	0.21	0.41	0.18	0.39	0.24	0.43	-0.06***
Cook-firewood	0.36	0.48	0.31	0.46	0.42	0.49	-0.12***
Poor sanitation	0.22	0.41	0.20	0.40	0.24	0.42	-0.03***
Parent Characteristics							
Mother-age	36.18	6.95	36.27	6.78	36.06	7.16	0.21
Father-age	40.87	8.09	40.84	7.75	40.91	8.52	-0.07
Mother-married	0.97	0.17	0.98	0.15	0.96	0.20	0.02***
Mother-paid occupation	0.42	0.49	0.40	0.49	0.45	0.50	-0.05***
Father-paid occupation	0.87	0.33	0.89	0.32	0.85	0.35	0.04***
Mother completed elementary school	0.45	0.50	0.39	0.49	0.52	0.50	-0.13***
Mother completed junior school	0.18	0.39	0.16	0.37	0.22	0.41	-0.06***
Mother completed senior school	0.21	0.41	0.26	0.44	0.15	0.36	0.11***
Mother completed tertiary education	0.07	0.25	0.10	0.31	0.02	0.14	0.08***
Father completed elementary school	0.43	0.49	0.37	0.48	0.51	0.50	-0.14***
Father completed junior school	0.16	0.37	0.14	0.34	0.19	0.39	-0.05***
Father completed senior school	0.26	0.44	0.31	0.46	0.19	0.39	0.12***
Father completed tertiary education	0.09	0.28	0.13	0.33	0.03	0.17	0.10***
Mother completed the highest level of education	0.63	0.48	0.64	0.48	0.61	0.49	0.04***
Father completed the highest level of education	0.62	0.49	0.65	0.48	0.57	0.50	0.08***

Notes: Mean difference is the difference of means between the control and treatment groups for each of the variables. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Summary Statistics: Boys

Variables	Full Sample		Control Group Raskin = 0		Treatment Group Raskin = 1		Mean Difference
	Mean	SD	Mean	SD	Mean	SD	
Child-working	0.07	0.26	0.06	0.23	0.10	0.30	-0.04***
Child-still in school	0.82	0.39	0.81	0.39	0.82	0.38	-0.01
Child Characteristics							
Child-age	9.44	2.87	9.42	2.89	9.47	2.84	-0.05
Child-religion-Islam	0.90	0.30	0.88	0.33	0.93	0.26	-0.05***
Household Characteristics							
HH size	5.21	1.86	5.25	1.87	5.14	1.84	0.12***
Dependency ratio	1.09	0.69	1.10	0.67	1.07	0.71	0.02**
HHH-female	0.12	0.33	0.10	0.31	0.15	0.36	-0.05***
Urban	0.50	0.50	0.56	0.50	0.41	0.49	0.15***
Own business	0.42	0.49	0.42	0.49	0.42	0.49	-0.01
Own farm land	0.30	0.46	0.29	0.45	0.33	0.47	-0.04***
Per capita expenditure (PCE) (ln)	12.57	1.21	12.48	1.41	12.68	0.87	-0.20***
Assets per capita (ln)	15.26	1.94	15.27	2.13	15.26	1.65	0.01
Electricity	0.93	0.26	0.91	0.28	0.95	0.23	-0.03***
Water	0.28	0.45	0.32	0.47	0.23	0.42	0.09***
Toilet-river/land/sea	0.21	0.40	0.19	0.39	0.23	0.42	-0.04***
Cook-firewood	0.36	0.48	0.31	0.46	0.42	0.49	-0.12***
Poor sanitation	0.22	0.42	0.20	0.40	0.25	0.43	-0.04***
Parent Characteristics							
Mother-age	36.29	6.81	36.23	6.49	36.38	7.22	-0.15
Father-age	41.04	8.02	40.95	7.61	41.16	8.54	-0.21
Mother-married	0.97	0.18	0.98	0.15	0.95	0.21	0.03***
Mother-paid occupation	0.41	0.49	0.39	0.49	0.46	0.50	-0.07***
Father-paid occupation	0.87	0.34	0.88	0.32	0.85	0.36	0.04***
Mother completed elementary school	0.44	0.50	0.38	0.48	0.53	0.50	-0.15***
Mother completed junior school	0.19	0.39	0.17	0.37	0.22	0.42	-0.05***
Mother completed senior school	0.21	0.41	0.26	0.44	0.14	0.35	0.12***
Mother completed tertiary education	0.07	0.26	0.11	0.31	0.02	0.14	0.09***
Father completed elementary school	0.41	0.49	0.35	0.48	0.49	0.50	-0.14***
Father completed junior school	0.17	0.37	0.15	0.36	0.19	0.39	-0.04***
Father completed senior school	0.26	0.44	0.30	0.46	0.21	0.41	0.09***
Father completed tertiary education	0.09	0.29	0.14	0.34	0.03	0.18	0.10***
Mother completed the highest level of education	0.63	0.48	0.64	0.48	0.61	0.49	0.03***
Father completed the highest level of education	0.63	0.48	0.65	0.48	0.60	0.49	0.06***

Notes: Mean difference is the difference of means between the control and treatment groups for each of the variables. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Coarsened Exact Matching Summary

	Girls		Boys	
	Control (Raskin = 0)	Treatment (Raskin = 1)	Control (Raskin = 0)	Treatment (Raskin = 1)
All	7853	5974	8309	6151
Matched	6110	5060	6501	5251
Unmatched	1743	914	1808	900

Table A5: Covariate Balance - Girls

Pre-match multivariate L1 distance: 0.6345

	Pre-match univariate imbalance		Sample Mean	
	L1	Mean Difference	Control (Raskin=0)	Treatment (Raskin = 1)
Urban	0.141	-0.141	0.549	0.405
Dependency ratio	0.039	0.025	1.063	1.092
HHH female	0.026	0.026	0.113	0.137
Per capita expenditure (ln)	0.322	0.223	12.457	12.673
Own business	0.004	0.004	0.425	0.429
Water	0.082	-0.082	0.320	0.237
Cook firewood	0.112	0.112	0.307	0.423
Toilet-River/land/sea	0.053	0.053	0.183	0.239

Post-match multivariate L1 distance: 0.5126

	Post-match univariate imbalance		Sample Mean	
	L1	Mean Difference	Control (Raskin=0)	Treatment (Raskin = 1)
Urban	0.000	0.000	0.413	0.413
Dependency ratio	0.022	-0.002	0.994	0.992
HHH female	0.000	0.000	0.090	0.090
Per capita expenditure (ln)	0.057	0.009	12.661	12.669
Own business	0.000	0.000	0.420	0.420
Water	0.000	0.000	0.219	0.219
Cook firewood	0.000	0.000	0.393	0.393
Toilet-River/land/sea	0.000	0.000	0.199	0.199

Table A6: Covariate Balance - Boys

Pre-match multivariate L1 distance: 0.6406

	Pre-match univariate imbalance		Sample Mean	
	L1	Mean Difference	Control (Raskin=0)	Treatment (Raskin = 1)
Urban	0.149	-0.149	0.560	0.411
Dependency ratio	0.060	-0.023	1.096	1.073
HHH female	0.044	0.044	0.105	0.151
Per capita expenditure (ln)	0.313	0.201	12.481	12.679
Own business	0.007	0.007	0.417	0.423
Water	0.095	-0.095	0.325	0.231
Cook firewood	0.114	0.114	0.308	0.424
Toilet-river/land/sea	0.037	0.037	0.189	0.228

Post-match multivariate L1 distance: 0.5114

	Post-match univariate imbalance		Sample Mean	
	L1	Mean Difference	Control (Raskin=0)	Treatment (Raskin = 1)
Urban	0.000	0.000	0.418	0.418
Dependency ratio	0.034	0.002	0.970	0.973
HHH female	0.000	0.000	0.092	0.092
Per capita expenditure (ln)	0.064	0.002	12.689	12.691
Own business	0.000	0.000	0.417	0.417
Water	0.000	0.000	0.219	0.219
Cook firewood	0.000	0.000	0.402	0.402
Toilet-river/land/sea	0.000	0.000	0.190	0.190

Table A7: **Estimated Bivariate Probit Model for Girls and Boys**

Variables	Girls		Boys	
	(1)	(2)	(3)	(4)
	Work	School	Work	School
yrAfter	1.128***	-0.970***	1.194***	-0.687***
	(0.229)	(0.163)	(0.152)	(0.143)
yrAfter*Raskin	-0.085	0.153**	0.020	-0.042
	(0.076)	(0.075)	(0.068)	(0.071)
Child age	0.254***	3.078***	0.180*	2.932***
	(0.096)	(0.093)	(0.094)	(0.087)
Child age2	-0.003	-0.150***	0.001	-0.141***
	(0.005)	(0.005)	(0.004)	(0.004)
Religion Islam	-0.301**	-0.204	-0.375***	-0.086
	(0.129)	(0.142)	(0.140)	(0.128)
Urban	-0.129*	0.046	-0.099	0.079
	(0.076)	(0.069)	(0.070)	(0.070)
HH size	0.015	0.020	-0.015	-0.006
	(0.019)	(0.021)	(0.018)	(0.018)
Dependency ratio	0.178***	-0.096	0.088	-0.090
	(0.062)	(0.059)	(0.057)	(0.055)
HHH - female	0.043	0.004	0.112	-0.063
	(0.160)	(0.137)	(0.156)	(0.139)
Assets per capita (ln)	0.039	0.071***	-0.044*	0.037*
	(0.029)	(0.023)	(0.022)	(0.021)
Per capita expenditure (PCE) (ln)	0.048	0.185***	0.065	0.195***
	(0.062)	(0.062)	(0.058)	(0.062)
Own business	0.610***	-0.118*	0.369***	-0.035
	(0.070)	(0.067)	(0.065)	(0.057)
Own farm land	0.021	0.117	0.266***	0.031
	(0.073)	(0.076)	(0.067)	(0.068)
Electricity	-0.067	0.331**	-0.108	0.273**
	(0.148)	(0.154)	(0.130)	(0.118)
Water	-0.052	0.014	-0.061	-0.046
	(0.076)	(0.064)	(0.077)	(0.069)
Cook firewood	0.154*	-0.177**	0.102	-0.204***
	(0.082)	(0.082)	(0.075)	(0.077)
Toilet - river/land/sea	0.105	-0.112	0.061	-0.074
	(0.099)	(0.103)	(0.090)	(0.082)
Poor sanitation	0.165**	0.036	0.098	0.043
	(0.080)	(0.082)	(0.071)	(0.072)
Mother-age	-0.002	-0.001	-0.000	-0.001
	(0.008)	(0.009)	(0.007)	(0.007)
Father age	-0.002	0.001	0.011*	0.002
	(0.006)	(0.008)	(0.006)	(0.006)
Mother married	-0.002	0.442*	-0.141	-0.268
	(0.210)	(0.229)	(0.206)	(0.216)
Mother- paid occupation	0.210***	0.029	0.086	-0.026
	(0.069)	(0.063)	(0.063)	(0.059)
Father - paid occupation	-0.012	-0.153*	0.191**	0.035
	(0.091)	(0.087)	(0.082)	(0.082)
Mother completed elementary school	-0.156	0.247*	0.064	0.322***
	(0.124)	(0.137)	(0.124)	(0.112)
Mother completed junior school	-0.265*	0.341**	0.015	0.519***
	(0.160)	(0.165)	(0.148)	(0.134)
Mother completed senior school	-0.321*	0.275*	0.065	0.353**
	(0.173)	(0.161)	(0.162)	(0.138)
Mother completed tertiary education	-0.525**	0.192	-0.067	0.415**
	(0.215)	(0.193)	(0.220)	(0.167)

Father completed elementary school	-0.187	0.189	-0.280**	0.113
	(0.154)	(0.157)	(0.133)	(0.132)
Father completed junior school	-0.133	0.422**	-0.233	0.127
	(0.180)	(0.171)	(0.147)	(0.150)
Father completed senior school	-0.222	0.350**	-0.396**	0.231
	(0.184)	(0.173)	(0.159)	(0.152)
Father completed tertiary education	-0.424*	0.247	-0.573***	0.069
	(0.237)	(0.198)	(0.194)	(0.174)
Mother completed highest level of edu.	-0.057	0.095	-0.125*	0.138**
	(0.076)	(0.076)	(0.073)	(0.069)
Father completed highest level of edu.	0.032	0.179**	0.018	0.134**
	(0.077)	(0.074)	(0.073)	(0.067)
Constant	-5.875***	-16.835***	-4.656***	-15.484***
	(1.010)	(0.940)	(0.883)	(0.883)
Rho	-0.170***		-0.164***	
	(0.064)		(0.049)	
Number of observations	8,825		9,563	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. All estimations include year and province fixed effects as well as the corresponding weights generated by CEM.

Table A8: Average Marginal Effects of the Bivariate Probit Model - Girls

Variables	(1) Work only (work = 1 school = 0)	(2) School only (work = 0 school = 1)	(3) Both work & school (work = 1 school = 1)	(4) Idle (work = 0 school = 0)
yrAfter	0.012***	-0.165***	0.062***	0.092***
	(0.002)	(0.017)	(0.008)	(0.015)
yrAfter*Raskin	-0.002*	0.025**	-0.007	-0.016*
	(0.001)	(0.011)	(0.007)	(0.009)
Child age	0.008***	0.064***	0.011***	-0.083***
	(0.001)	(0.003)	(0.001)	(0.002)
Religion Islam	-0.001	0.011	-0.034**	0.025*
	(0.002)	(0.022)	(0.016)	(0.014)
Urban	-0.002*	0.017	-0.011*	-0.004
	(0.001)	(0.011)	(0.007)	(0.008)
HH size	-0.000	0.001	0.002	-0.002
	(0.000)	(0.003)	(0.002)	(0.002)
Dependency ratio	0.003***	-0.027***	0.016***	0.009
	(0.001)	(0.010)	(0.006)	(0.007)
HHH - female	0.000	-0.004	0.004	-0.001
	(0.002)	(0.019)	(0.016)	(0.016)
Assets per capita (ln)	-0.000	0.004	0.004	-0.008***
	(0.000)	(0.004)	(0.003)	(0.003)
Per capita expenditure (PCE) (ln)	-0.001	0.016*	0.006	-0.021***
	(0.001)	(0.009)	(0.006)	(0.007)
Own business	0.009***	-0.071***	0.057***	0.006
	(0.002)	(0.010)	(0.007)	(0.007)
Own farm land	-0.001	0.011	0.003	-0.013
	(0.001)	(0.011)	(0.007)	(0.008)
Electricity	-0.004	0.046*	-0.003	-0.038**
	(0.003)	(0.025)	(0.014)	(0.019)
Water	-0.001	0.006	-0.005	-0.001
	(0.001)	(0.010)	(0.007)	(0.007)
Cook firewood	0.003***	-0.035***	0.013	0.018*
	(0.001)	(0.012)	(0.008)	(0.009)
Toilet - river/land/sea	0.002	-0.023	0.009	0.011
	(0.002)	(0.016)	(0.010)	(0.012)
Poor sanitation	0.002	-0.012	0.017**	-0.006
	(0.001)	(0.013)	(0.008)	(0.009)
Mother-age	-0.000	0.000	-0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.001)
Father age	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)
Mother married	-0.005	0.055	0.005	-0.054*
	(0.005)	(0.037)	(0.018)	(0.031)
Mother- paid occupation	0.002**	-0.016*	0.020***	-0.006
	(0.001)	(0.010)	(0.006)	(0.007)
Father - paid occupation	0.001	-0.016	-0.002	0.017*
	(0.001)	(0.013)	(0.009)	(0.009)
Mother completed elementary school	-0.004*	0.042**	-0.012	-0.026*
	(0.002)	(0.021)	(0.011)	(0.015)
Mother completed junior school	-0.005***	0.060***	-0.020	-0.034**
	(0.002)	(0.022)	(0.013)	(0.017)
Mother completed senior school	-0.005**	0.057**	-0.025*	-0.027
	(0.002)	(0.022)	(0.013)	(0.017)
Mother completed tertiary education	-0.005***	0.058**	-0.036***	-0.017
	(0.002)	(0.024)	(0.011)	(0.021)
Father completed elementary school	-0.004	0.038	-0.015	-0.019
	(0.003)	(0.025)	(0.014)	(0.017)

Father completed junior school	-0.005**	0.057**	-0.009	-0.044**
	(0.002)	(0.025)	(0.015)	(0.017)
Father completed senior school	-0.005**	0.057**	-0.017	-0.036**
	(0.002)	(0.026)	(0.015)	(0.018)
Father completed tertiary education	-0.005***	0.059**	-0.031**	-0.023
	(0.002)	(0.026)	(0.014)	(0.021)
Mother completed the highest level of education	-0.002	0.016	-0.004	-0.010
	(0.001)	(0.011)	(0.007)	(0.009)
Father completed the highest level of education	-0.001	0.017	0.005	-0.020**
	(0.001)	(0.011)	(0.007)	(0.008)
Predicted probability of outcome	0.0070	0.7723	0.0571	0.1636

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses, clustered at household and province levels. Marginal effects represent the percentage change in probability of an outcome given a unitary increase in a continuous variable or change from 0 to 1 for binary variables. All estimations include year and province fixed effects as well as the corresponding weights generated by CEM.

Table A9: Average Marginal Effects of the Bivariate Probit Model - Boys

Variables	(1) Work only (work = 1 school = 0)	(2) School only (work = 0 school = 1)	(3) Both work & school (work = 1 school = 1)	(4) Idle (work = 0 school = 0)
yrAfter	0.014***	-0.153***	0.074***	0.065***
	(0.002)	(0.016)	(0.007)	(0.014)
yrAfter*Raskin	0.001	-0.007	0.002	0.005
	(0.001)	(0.011)	(0.007)	(0.008)
Child age	0.009***	0.064***	0.014***	-0.087***
	(0.001)	(0.002)	(0.001)	(0.002)
Religion Islam	-0.004	0.036	-0.047**	0.015
	(0.003)	(0.024)	(0.020)	(0.014)
Urban	-0.002*	0.019*	-0.009	-0.008
	(0.001)	(0.011)	(0.007)	(0.008)
HH size	-0.000	0.001	-0.002	0.001
	(0.000)	(0.003)	(0.002)	(0.002)
Dependency ratio	0.002**	-0.020**	0.008	0.009
	(0.001)	(0.009)	(0.006)	(0.006)
HHH - female	0.002	-0.020	0.011	0.006
	(0.003)	(0.023)	(0.018)	(0.017)
Assets per capita (ln)	-0.001**	0.009***	-0.004*	-0.004
	(0.000)	(0.003)	(0.002)	(0.002)
Per capita expenditure (PCE) (ln)	-0.001	0.016	0.009	-0.023***
	(0.001)	(0.010)	(0.006)	(0.007)
Own business	0.005***	-0.043***	0.039***	-0.001
	(0.001)	(0.010)	(0.007)	(0.007)
Own farm land	0.003**	-0.025**	0.029***	-0.007
	(0.001)	(0.011)	(0.007)	(0.008)
Electricity	-0.005*	0.045**	-0.008	-0.032**
	(0.003)	(0.021)	(0.015)	(0.015)
Water	-0.000	0.001	-0.007	0.006
	(0.001)	(0.011)	(0.008)	(0.008)
Cook firewood	0.004***	-0.034***	0.008	0.022**
	(0.001)	(0.012)	(0.008)	(0.009)
Toilet - river/land/sea	0.002	-0.015	0.006	0.008
	(0.002)	(0.014)	(0.010)	(0.010)
Poor sanitation	0.001	-0.006	0.011	-0.006
	(0.001)	(0.012)	(0.008)	(0.008)
Mother-age	0.000	-0.000	-0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.001)
Father age	0.000	-0.001	0.001*	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)
Mother married	0.001	-0.013	-0.019	0.031
	(0.003)	(0.035)	(0.025)	(0.022)
Mother- paid occupation	0.001	-0.012	0.009	0.002
	(0.001)	(0.009)	(0.007)	(0.007)
Father - paid occupation	0.002	-0.014	0.019**	-0.006
	(0.001)	(0.012)	(0.007)	(0.010)
Mother completed elementary school	-0.003	0.031*	0.010	-0.038***
	(0.002)	(0.019)	(0.013)	(0.013)
Mother completed junior school	-0.005***	0.054**	0.007	-0.056***
	(0.002)	(0.021)	(0.016)	(0.013)
Mother completed senior school	-0.003	0.031	0.011	-0.039***
	(0.002)	(0.024)	(0.018)	(0.014)
Mother completed tertiary education	-0.004**	0.051*	-0.003	-0.043***
	(0.002)	(0.028)	(0.023)	(0.016)
Father completed elementary school	-0.005**	0.042**	-0.028**	-0.009
	(0.003)	(0.021)	(0.014)	(0.015)

Father completed junior school	-0.004*	0.037*	-0.021	-0.012
	(0.002)	(0.021)	(0.013)	(0.017)
Father completed senior school	-0.006***	0.064***	-0.035***	-0.022
	(0.002)	(0.022)	(0.014)	(0.017)
Father completed tertiary education	-0.006***	0.054**	-0.045***	-0.003
	(0.002)	(0.023)	(0.011)	(0.020)
Mother completed the highest level of education	-0.003**	0.029**	-0.012	-0.014*
	(0.001)	(0.011)	(0.008)	(0.008)
Father completed the highest level of education	-0.001	0.014	0.003	-0.016**
	(0.001)	(0.011)	(0.008)	(0.008)
Predicted probability of outcome	0.0081	0.7572	0.0640	0.1701

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses, clustered at household and province levels. Marginal effects represent the percentage change in probability of an outcome given a unitary increase in a continuous variable or change from 0 to 1 for binary variables. All estimations include year and province fixed effects as well as the corresponding weights generated by CEM.

Table A10: Actual and Predicted Probabilities

Girls				
	Work only (work = 1 school = 0)	School only (work = 0 school = 1)	Both work & school (work = 1 school = 1)	Idle (work = 0 school = 0)
Sample Mean	0.0099	0.7759	0.0547	0.1595
Predicted Probability	0.0070	0.7723	0.0571	0.1636
Number of observations	137	10729	756	2205

Boys				
	Work only (work = 1 school = 0)	School only (work = 0 school = 1)	Both work & school (work = 1 school = 1)	Idle (work = 0 school = 0)
Sample Mean	0.0128	0.7567	0.0615	0.1690
Predicted Probability	0.0081	0.7572	0.0640	0.1701
Number of observations	185	10942	889	2444

Note: Predicted probability represents the predictive margins of a given outcome.

Table A11: Regression on Leisure hours

Variables	Girls	Boys
	Leisure hours	Leisure hours
yrAfter	16.097***	12.278***
	(0.839)	(0.747)
yrAfter*Raskin	-0.847**	-0.074
	(0.418)	(0.381)
Child age	-12.012***	-11.782***
	(0.409)	(0.384)
Child age2	0.507***	0.482***
	(0.022)	(0.021)
Religion Islam	0.215	3.473***
	(0.799)	(0.848)
Urban	-0.599	-0.859**
	(0.421)	(0.390)
HH size	0.080	0.137
	(0.105)	(0.101)
Dependency ratio	-0.133	-0.601*
	(0.331)	(0.314)
HHH - female	0.676	-0.427
	(0.887)	(0.734)
Assets per capita (ln)	-0.127	-0.138
	(0.133)	(0.119)
Per capita expenditure (PCE) (ln)	-1.197***	-0.716**
	(0.332)	(0.332)
Own business	0.061	0.508
	(0.341)	(0.324)
Own farm land	-0.236	-0.877**
	(0.435)	(0.395)
Electricity	-2.325**	-0.908
	(0.984)	(0.840)
Water	0.718*	0.291
	(0.367)	(0.387)
Cook firewood	0.487	0.806*
	(0.452)	(0.429)
Toilet - river/land/sea	1.142*	1.032**
	(0.586)	(0.487)
Poor sanitation	0.107	0.228
	(0.453)	(0.419)
Mother-age	-0.014	-0.057
	(0.043)	(0.038)
Father age	-0.009	0.005
	(0.036)	(0.034)
Mother married	-1.796	-1.157
	(1.295)	(1.289)
Mother- paid occupation	-0.357	-0.075
	(0.356)	(0.340)
Father - paid occupation	0.524	-1.044**
	(0.515)	(0.468)
Mother completed elementary school	0.206	-1.134
	(1.053)	(0.896)
Mother completed junior school	-0.123	-2.151**
	(1.148)	(0.966)
Mother completed senior school	-0.002	-1.825*
	(1.203)	(1.017)
Mother completed tertiary education	-0.944	-2.419**
	(1.391)	(1.182)
Father completed elementary school	-1.233	-1.993*
	(0.822)	(1.106)

Father completed junior school	-1.858*	-2.014*
	(0.989)	(1.146)
Father completed senior school	-2.121**	-2.408**
	(0.976)	(1.169)
Father completed tertiary education	-2.780**	-1.734
	(1.082)	(1.270)
Mother completed highest level of edu.	-0.626	-0.570
	(0.408)	(0.393)
Father completed highest level of edu.	-0.783*	0.184
	(0.406)	(0.391)
Constant	220.966***	217.707***
	(4.771)	(4.716)
Number of observations	8,825	9,563
R-squared	0.441	0.431

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$ Robust standard errors in parentheses, clustered at household and province levels. All estimations include year and province fixed effects as well as the corresponding weights generated by CEM.

Table A12: Robustness Check: Treating some observables as unobservable

	Estimation 1		Estimation 2		Original Estimation	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Work	School	Work	School	Work	School
yrAfter	1.150***	-0.477***	1.122***	-0.948***	1.128***	-0.970***
	(0.198)	(0.111)	(0.228)	(0.162)	(0.229)	(0.163)
yrAfter*raskin	-0.094	0.133*	-0.036	0.142*	-0.085	0.153**
	(0.077)	(0.078)	(0.075)	(0.073)	(0.076)	(0.075)
Constant	-4.338***	-13.358***	-5.521***	-16.476***	-5.875***	-16.835***
	(0.624)	(0.567)	(0.977)	(0.889)	(1.010)	(0.940)
Child Characteristics	Yes		Yes		Yes	
Household Characteristics	No		Yes		Yes	
Parent Characteristics	Yes		No		Yes	
Year Fixed Effects	Yes		Yes		Yes	
Provincial Fixed Effects	Yes		Yes		Yes	
Rho	-0.184***		-0.181***		-0.170***	
	(0.063)		(0.069)		(0.064)	
Number of observations	8,909		8,825		8,825	

Notes: *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors in parentheses, clustered at household and province levels. All estimations include the corresponding weights generated by CEM.

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