EDUCATION TRANSFERS, EXPENDITURES AND CHILD LABOUR SUPPLY IN INDONESIA:

AN EVALUATION OF IMPACTS AND FLYPAPER EFFECTS

SUDARNO SUMARTO AND INDUNIL DE SILVA

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Education Transfers, Expenditures and Child Labour Supply in Indonesia:

An Evaluation of Impacts and Flypaper Effects

Sudarno Sumarto and Indunil De Silva[1]

December 2013

Abstract

In this paper we investigate how the receipt of educational transfers, scholarships and related assistance programmes affects the labour supply of children and the marginal spending behaviour of households on children's educational goods. We use a nationally representative household survey of unusual scope and richness from Indonesia. We found strong evidence of educational cash transfers and related assistance programmes significantly decreasing the time spent by children on income-generating activities in Indonesia. Households receiving educational transfers, scholarships and assistance were also found to spend more at the margin on voluntary educational goods. These results were stronger on children living in poor families. The findings of this study lend support to the growing view in the literature that educational transfers, scholarships and related assistance can actually have a positive impact on economic development by increasing the level of investment in human capital. Our results are particularly relevant for understanding the role of cash transfers and education assistance in middle-income countries, where enrolment rates are already at satisfactory levels, but the challenge is to keep post-primary students in school. Finally, the principle message that emerges from the study is: there are quantitatively non-negligible, average gains from educational transfers and support programmes on household education spending and child labour, especially for the poor.

Key Words: Cash transfers, child labour, education expenditure, flypaper effect.

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1. Introduction

Government transfers and subsidies that aim to address the issues of poverty, child labour and low educational attainment, especially among women and children, have generated substantial interest among researchers and policy makers. Educational transfers and subsidies have become particularly popular policy tools, as they can deliver the initial stimulus to move an economy to a relatively more desirable equilibrium in the presence of poverty traps, externalities and multiple equilibria (Banerjee 2003 and Galor and Zeira 1993). As market-oriented, demand-side interventions that combat poverty and child labour, educational cash transfers, school voucher programmes and subsidised education schemes complement traditional supply-side policies, such as general subsidies or investments in schools, hospitals, and social services. Furthermore, they generate positive externalities and higher equity in educational expenditures, leading to higher levels of welfare and yielding concave returns for the policy makers (Das 2004).

Both conditional and Unconditional Cash Transfers (UCTs) have been rigorously evaluated worldwide. Conditional transfer programmes such as Progresa (now referred to as Oportunidades) in Mexico, Bolsa Escola (now called Bolsa Familia) in Brazil, and Red de Proteccion Social in Nicaragua, have been showed to foster investment in human capital, increase the use of health resources, and successfully combat poverty and vulnerability (J. Behrman et.al 2005; Bourguignon et.al 2003). A vast amount of literature indicates that both conditional and Unconditional Cash Transfers (UCTs) have successfully increased school attendance and reduced the child labour supply (ECLAC, 2006; Fizbein and Schady, 2009; Behrman et al. 2005; Schady & Araujo 2008). However, recent impact evaluation studies have also shown that in some instances interventions that encourage schooling and aim to reduce child labour have had unintended consequences and have actually increased the probability of children engaging in work (Cigno and Rosati, 2005; Edmonds, 2007). Therefore, as government transfers and subsidies are becoming increasingly more popular in developing countries, the aim of this paper is to investigate the effect of educational transfers on school attendance and child labour, and to find to what extent the intended beneficiaries of public transfer programmes actually benefit from them. In particular, the study intends to investigate whether government transfers to a specific household member have an intra-household 'flypaper effect', meaning that they "stick" to that specific member who receives it, such as a poor student, child, etc., or as the theory of altruism (Becker, 1974, 1981) implies, they generate no or insignificant gains to the recipient of the transfer since households redistribute the extra income from an individual welfare scheme among all the members.

In this paper, we first analyse the decisions to attend school and to work. Because the school and work decisions are closely related, they are treated as simultaneous decisions which will be analysed in the context of a bivariate Probit model. We begin by assessing the effect of child labour on schooling and how various individual and household characteristics affect the chances that a child will attend school and/or participate in other activities that may interfere with schooling. Next, we investigate how the receipt of educational transfers, scholarships and related assistance affects the labour supply of children in Indonesia.

Finally, we test for the first time in Indonesia whether an intra-household flypaper effect exists for child-targeted transfers. We investigate the impact of Indonesia's education cash transfer programme for poor students (BSM, *Bantuan Siswa Miskin)* on both household and child-level voluntary education expenditures. For most households in Indonesia that received the education cash transfer for poor students, parents had more money for all expenditures, including expenditures on voluntary educational goods and other, non-educational goods. The existence of IFE in these households would indicate that parents voluntarily spend the extra money from the transfer on education or education-related goods and services for the child receiving the transfer.

We will utilise a rich dataset that contains child-specific education expenditures, Indonesia Social and Economic Survey (Susenas) – 2009. It is a nationwide survey conducted to collect information on social and economics indices, which functions as a main source of monitoring social and economic progress in society. Susenas has been conducted on an annual basis since 1963. Since 1992, in addition to a basic social and economic questionnaire (core), a more specialised questionnaire was introduced (module). The core questionnaire contains basic information about household and individual characteristics including health, death, education/literacy, employment, fertility and family planning, housing, and household expenditure. There are three modules of Susenas and each module is added in a three-year cycle. In 2009, the module's topic was social life, culture, and education. Unlike previous Susenas, the same sample was used for both core and module questionnaires. It consisted of 291,753 households and was designed to be representative at national, province and district/city levels. The Susenas 2009-July survey contains an education cost data module containing various expenditure categories for each school-enrolled child. It will enable us to examine if the education cash transfer increased voluntary education expenditure and whether the fly-paper effect exists within households.

2. Schooling, Child Labour and Education Programmes: Review of the International Evidence

Recent studies have shown that the high costs of education and limited access to schooling are the main factors behind low school enrolment and increasing child labour. Policies that reduce the price of education and increase access to schooling have thus been proposed to reduce child labour. Among them are unconditional assistance programmes, such as the cash transfer programme in Ecuador (Bono de Desarollo Humano), the old age pension programme in South Africa, or the child support grants, also in South Africa. They have been found to in general reduce child labour, increase school enrolment, reduce drop-out rates and improve health and nutrition in children (Edmonds and Schady 2009; Edmonds 2006; Case, Hosegood, and Lund 2005; Duflo 2003). Their close relatives, conditional transfer programmes such as Progresa (now referred to as Oportunidades) in Mexico, Bolsa Escola (now called Bolsa Familia) in Brazil, and Red de Proteccion Social in Nicaragua, have been shown to have wider development effects, fostering investment in human capital, increasing the use of health resources, and successfully combating poverty and vulnerability (J. Behrman et.al 2005; Bourguignon et.al 2003).

Latin American examples compellingly show that unconditional cash transfers can assist poor households in meeting the prohibitive cost of children's education, also that they can contribute to retaining children in school and limiting child labour supply. Theoretically, as Ravallion and Wodon (2000) suggest, this link can be demonstrated through an experiment that creates an exogenous decrease in the price of schooling, which would allow us to see the impact of the price of education on child labour supply. The wage rate for child labour can be appropriately used as a component of the price of labour. But unfortunately, since the wage rate is also the price of leisure, disentangling the own price effect from the cross-price effect is tricky using wage data. The effects of school price (i.e. as measured by presence of a school in the region, distance or travel time to school, expenditures on schooling, etc.) on child labour are thus mixed, primarily due to indicators that poorly capture the school price (Grootaert and Patrinos, 1998).

Empirically, however, it has been shown that there is a trade-off between children's education and work. Studies in Brazil revealed that child labour tends to drive children away from both school and leisure. Most children who work in Brazil also attend school, but their lower share is enrolled and more regularly attends classes than the share of children who are not working. School-aged children who work are also less likely to do their homework or attend after-school tutorials. There thus appears to be some reduction in quantity of schooling for children who engage in child labour (World Bank 2001).

Moreover, child labour can impede the children's ability to acquire or retain material at school, as it often subjects them to physical and emotional strains. In rural areas, working children are often employed in heavy manual labour and exposed to unsafe working conditions. Children who work on sisal (jute) or sugarcane plantations often suffer injuries from long knives and machetes used for cutting, piling, and hauling the crops. In urban areas, child workers may engage in other arduous activities, such as street vending or garbage collection, or illegal ones, like selling drugs or prostitution (Cardoso and Souza 2003). At the same time, there are rewards to work, especially when the skills learnt at the workplace enhance the returns from schooling.

It is generally agreed that the cause of child labour is parental poverty (Basu, 2003). Basu and Van (1998) argue further that the past household models discounted an important economic element in the child labour analysis: a labour market where children are potential workers will be prone to multiple equilibria. Basu (2003) explains why this insight is important: "Consider a poor country, where wages are very low and all children are for that very reason made to work. Now assume, for the sake of argument, that child labour is banned. The firms that are using child labour will be forced to seek adults to fill those gaps. Hence the wage rate of adult labour will rise. Now, it is entirely possible that if the wages were high to start with, then the parents would not have sent the children out to work anyway. Hence, even if the law is now revoked, wages will be high, children will not work and this will sustain the high wage. In other words, this economy had multiple equilibria and hence the law works simply as a mechanism for deflecting the economy from the inferior equilibrium, where wages are low and children work, to the superior equilibrium, where wages are high and there is no child labour."

In poor households, especially in developing countries, the decision to send children to work is quite common, as children are usually a valuable economic resource for poor parents. Cain (1977) found that children in a Bangladeshi village were economically active from the age of six, and that boys were net producers by the age of 15. According to Mendelievich (1979), Cain and Mozumder (1980) and Grootaert and Kanbur (1995), child labour is an integral part of the household's risk management strategy. Poor households with little savings, little access to credit and a limited asset base face harsh repercussions from job losses and other shocks on the households' income, and hedge against these risks by sending children to work. Jacoby and Skoufias (1997) confirm these findings, having found that child labour helps smooth the incomes of poor rural Indian families who have little access to credit.

Despite the well-established links between education, child labour and cash transfers that support education, partly due to data limitations few previous studies have examined the impact of an education cash transfer on child-specific expenditures (even Shi 2008, examines a school fee exemption and subsidy). According to Rosenzweig (1986), when the household head acts as the ultimate decision-making unit, the impact of a child-targeted transfer will depend on the allocation of resources among family members by the household head. For example, if one child in a family receives a free meal in school, their parents might reallocate away some food at home to other members of the family, such as their siblings. Similarly, Jacoby (2002) states that if parental altruism is operative in a Beckerian (1974, 1981) household model, an infra-marginal transfer to one child should not affect the consumption of that child, holding household resources constant.

Relatively little attention has also been paid to whether cash transfers that support education have fly-paper effects. Even the existing studies on intra-household flypaper effects are mostly nutrition-related, with the exception of Shi (2008). For example, Jacoby (2002) examines the impact of a school-feeding programme on child caloric intake in the Philippines. He finds no re-allocation of calories away from the child within the household in response to the feeding programme. The total daily calorie intake of the recipient child rises by almost one to one with the school meal calories. Similarly, Afridi (2005) analyses the impact of a school feeding programme on daily caloric consumption of children in India and investigates factors that affect the magnitude of the reallocation of resources. The study finds that the nutrient intake of programme participants increased by 49 to 100 percent per child. Finally, Shi (2008) studies the existence of resource reallocation within households after a child receives a subsidy for covering the schooling fees in rural China. The study concludes that the reductions in educational fees generated by the subsidies were matched by increased voluntary educational spending on the children receiving these reductions, providing strong evidence of an intra-household flypaper effect.

3. Schooling, Child Labour and Education Programmes: Review of the Evidence from Indonesia

Almost all educational indicators in Indonesia have improved very remarkably over the past 40 years (Suharti 2013). Net enrolment rates for both primary and junior secondary schools experienced significant increases during this period of time. The net primary school enrolment rate has increased from 72 percent in 1975 and then reached nearly universal coverage by 2009. The net enrolment rate for junior secondary education also rose from 18 percent in the 1970s to about 70 percent in recent years. Achievements in early childhood education (ECD) are also notable. Currently, 50 percent of four- to six year-olds have received some type of early learning or education (up from 25 percent a decade earlier). The improvements in school enrolment rates have edged Indonesia closer to other countries in the Asia-Pacific region in terms of educational attainment, resulting in a higher than usual senior secondary enrolment rate for its level of GDP per capita. For example, Indonesia's enrolment rates profile have paralleled that of China, with higher than expected secondary education enrolment rates for its level of income, but still behind in higher education.

Indonesia is also one of the few countries in the world that increased public expenditure on education by over 60 percent during the last five-year period. The Government of Indonesia introduced a constitutionally mandated allocation of (a minimum of) 20 percent of government spending to education (hereafter "the 20 percent rule") in 2003. This decision led to an enormous increase in funds allocated for education, making it the largest government expenditure after fuel subsidies (World Bank 2013).

However, in the backdrop of inspiring outcomes, the benefits of the new education policy are still not satisfactory. For example, a study conducted by Arza Del Granado, Fengler et al. (2007) found the existence of a wide gap between the educational attainment of poor and rich groups at the junior and senior secondary levels. Children from poor families are 20 percent less likely to be enrolled in junior secondary than children from wealthier families. Additionally, Suryadarma (2006) found that children living in rural areas have less access to junior secondary education. Jones (2003) conducted qualitative interviews in several provinces in Indonesia and found several reasons behind the disparities in access to schooling across Indonesia. Firstly, children from poor families were found to have difficulties in paying for transportation costs associated with schooling. Secondly, the relatively low importance given to education by parents in some parts of the country caused children not to attend school. Hardjono (2004) investigated the influence of poverty on school drop-outs in two provinces in Indonesia, Bali and West Nusa Tenggara. Most importantly, the study found that non-continuation to junior secondary school in both provinces was due to the inability to pay, particularly for transportation costs, and the inadequate capacity and facilities in the junior secondary schools. The study found also that cultural factors also play an important role in educational attainment. One of the primary reasons for the very high primary school completion rates among Balinese children is the culture of prioritising education in Bali. This was in contrast to a relatively higher rate of children who did not finish primary school in West Nusa Tenggara, as a result of a low regard for education among the parents there. Similarly, the Madurese tribe in Pontianak traditionally arrange for their daughters to be married as soon as they finish primary school.

Poverty combined with the low educational level of families drives Indonesian children into child labour. It is estimated that there are some four million children engaged in child labour in Indonesia, while nearly two-thirds of out-of-school children engage in some productive activity. One quarter of out-of-school children in the age group 10-14 years have less than four years of education, implying that they will grow up to be functionally illiterate adults. These estimates highlight the importance of expanding educational support programmes and accelerating their implementation.

According to Priyambada, Suryahadi and Sumarto (2002), schooling and part-time work often go together in Indonesia. They observed a declining trend in child labour, which later come to a halt as a result of the 1990s crisis, and found that children attend school and engage in work at the same time. The study also found that students from severely poor families search for employment to finance their own education. Encouragingly, some of the most recent figures have shown that overall children's employment declined during the period from 2007 to 2010 from 4.9 percent to 3.7 percent for the narrower 10-14 year-old child population (UCW-ILO, UNICEF, and WB 2012).

Child employment also remains an important policy concern in Indonesia because as many as half of the children who work are exposed to hazardous conditions in the workplace. Many of them are engaged in the worst forms of child labour, such as agriculture and domestic service. Children who work in agriculture, on rubber, palm oil and tobacco farms, often carry heavy loads, use pesticides and work long hours. They may be exposed to extreme weather, sharp objects, falls from tall heights and respiratory problems. Children, primarily girls aged 12 to 15, also work as domestic servants. They often work long hours, sometimes without days of rest or holidays, and may be at risk of mental, physical and sexual abuse (USDOL 2011).

The prevalence of child work varies greatly by location and the level of education of the head of household. The incidence of child labour is much higher in rural districts in comparison to cities. It was in the rural areas, however, that Indonesia experienced the largest decline in child labour during the last decade. The falling trends in rural areas mirror the declining dominance of the agricultural sector.

Child labour incidence has also been found to fall with the level of education of the household head. Male children living in households where the head has not finished primary education have a six times higher probability to work than in households where the head has a university degree. Child work incidence in general has been decreasing for all the household-head levels of education in Indonesia (Kis-Katos and Sparrow 2009).

Since the 1998 economic crisis, the government of Indonesia, in partnership with several development organisations, has been rolling out social assistance programmes to address the financial difficulties and other constraints that parents and children face with respect to schooling. Broadly, these education-related government social assistance programmes include a school operational assistance programme, a scholarship programme for students from poor families, and school construction and rehabilitation schemes. The fourth amendment of the Indonesian Constitution also stipulated that the budget for education should be at least 20 percent of the total State budget. In recent years, there has been a small but growing literature on the evaluation of education assistance programmes in Indonesia, especially focusing on school enrolment and dropout rates. Cameron (2009) evaluates the role played by Indonesia's social safety net scholarships programme in reducing school dropout rates during the Asian financial crisis, with the assumption that many households would find it difficult to keep their children in school, which caused the dropout rates to be high. He found scholarships to be effective in reducing dropping out from lower secondary school, the level of schooling at which students were historically most at risk of dropping out. Sparrow (2007) investigated the impact of the Indonesian scholarship programme, which was implemented in 1998 to preserve access to education for the poor during the economic crisis. The study found that the programme increased school enrolment, especially for primary school aged children from poor rural households. The paper concludes that the scholarships had assisted households in smoothing consumption during the crisis period.

In this study, we seek to examine the effects of the Cash Transfer for the Poor Students Programme/Bantuan Siswa Miskin (BSM) that was introduced in 2008 and covers all education levels from Elementary school level to University. The key objectives of the programme are to remove barriers that marginalised students face in participating in education, assist poor students in gaining appropriate access to education services, prevent dropping out from school, help meet the educational needs of at-risk children and support the Government's Nine Years Compulsory Education programme. The programme provides cash transfers to cover educational costs (such as books, school transportation and uniforms) for students from poor households, who are selected by school administrators. It is fully financed by the Central Government and does not require any contributions or cost sharing on the part of students as beneficiaries, local governments or schools. At present, the programme covers eight million students across the country, ranging from primary school to tertiary education level.

4. Analytical and Conceptual Framework

We first develop the theoretical model behind the schooling and labour supply decision of children, assuming the "unitary model" of the household, where the head of the household is the decision maker. Our model follows Ravallion et al. (2000) and Rosati et al. (2003), where the utility function of the representative household in our model is given by:

$$U = U(C, H, S: X)$$

where household consumption is C, H is the child's leisure, S is child's school attendance and X is a vector of exogenous household child, household and demographic characteristics that parameterise the utility function.

The time constraint that maximises utility can be expressed as:

$$T = H + S + L$$

where the household head allocated the child's total time-T, between leisure –H, school attendance-S, and child's labour supply-L By equating adult exogenous household income-Y and output from household production with the cost of production and household consumption, the household budget constraint can be stated as:

$$P_c C + P_s S \leq Y + WL$$

The household utility maximisation problem can be thus formally stated as:

$$\max_{C,H,S} U(C, H, S: X)$$

$$s.t. \quad \begin{matrix} P_c C + P_s S \leq Y + WL \\ T = H + S + L \end{matrix}$$

where P_c, P_s and W are price of consumption, schooling and child labour. We assume household income, adult labour supply and leisure to be exogenous. Thus, when parents become unemployed, it is not because of their choice but due to external market conditions. Solving the above model yields several important inferences. Comparative statics properties of the model show that an increase in parent's income/returns to labour will lead to an increase in the probability of the child attending school and reduces the numbers of hours the child works. Similarly, when there are high returns to child labour (increased work opportunities, higher wages), both schooling and leisure will fall, and the supply of labour will rise. Employing this framework it can be shown how child labour can be a function of not only income and wealth but also of parent's occupation, characteristics and preferences.

Next, we evaluate the impact education cash transfers and related assistance on child labour and educational expenditure. We start with the hypothesis that the education cash transfer is fully fungible. Since households have their own preferences on spending, the notion of the cash transfer being targeted at students becomes inconsistent with the concept of the transfer being fully fungible. Households have the tendency to cut their own planned spending when the transfer is less than they would have intended to spend. Under this scenario, one should not see on average a differential impact on transfer recipients versus non-transfer recipients. But at the same time there is empirical evidence of flypaper effects where individually targeted transfers (such as child-specific transfers) had increasing and positive effects on these individuals/children's outcomes. Finally with the possibility that expected outcomes to being ambiguous from a theoretical perspective, the impact of the educational cash transfer can be presented under the framework of maximising household utility. The household utility maximising problem can be represented as:

$$\max_{X,E}\{U(X,E,a_1,a_2)\}$$

$$S.t. \quad P_x X + P_E E \leq I$$

The household maximises its utility over two sets of goods: consumption of voluntary educational goods-E and a vector of all other goods-X. We assume that both X and E are normal goods and $U(X,E)$ satisfy the conditions $(1)\ U_X > 0, U_E > 0, (2)\ U_{XX} < 0, U_{EE} < 0, (3) U_{XE} > 0$. Income is denoted by I and P_x represents the price of the composite good/other goods, and P_E is the price of voluntary educational goods. The parameters a_1 and a_2 represents household preferences for voluntary educational goods and the composite good, which are determined by individual and household characteristics such as age, gender, education, demographic compositions, etc. Assuming an interior optimum and combining the first-order conditions, we can derive an equation:

$$\frac{\partial U(X,E,a_1,a_2)/\partial X}{\partial U(X,E,a_1,a_2)/\partial E} = \frac{P_x}{P_E} = P$$

Equation (…) is the relative price of the composite good that yields the usual utility maximisation condition, which states that the household will equate the marginal rate of substitution between X and E to the ratio of the prices of the two goods. Optimal demand functions for X and E can be expressed as:

$$X^* = X(I, a_1, a_2, \mathrm{P})$$

$$E^* = E(I, a_1, a_2, \mathrm{P})$$

The consumption of voluntary educational goods-E will be a function that is increasing in income, preferences and the relative price of the composite good.

Subsequently, the educational cash transfer can be introduced by re-writing a new budget constraint that maximises U as:

$$S.t. \quad P_x X + P_E E \leq I + \mathrm{T}$$

The new optimal demand functions with the cash transfer can be written as:

$$X^* = X(I, a_1, a_2, \mathrm{P}, \mathrm{T})$$

$$E^* = E(I, a_1, a_2, \mathrm{P}, \mathrm{T})$$

It is evident that the cash transfer will not alter the relative price of education and will only induce an income effect.

5. Empirical Strategy and Data

We begin with the econometric specification of the child's decision to attend school or to work. The decision for a child to attend school, supply labour, or both, is a time allocation decision. Thus the decision whether a child works or attends school is a joint one as the child, or its parents, would have to choose between both activities. We use a bivariate Probit model that explicitly takes this interdependency into account and tests the likelihood of children working and going to school, taking into consideration varied individual and household characteristics. The model permits for the existence of possible correlated disturbances between two Probit equations. It also allows us to test whether the joint estimation has additional explanatory power compared to using univariate Probit estimation for each decision.

The general structure of the bivariate Probit specification can be expressed as:

$$y_1^* = \boldsymbol{X_1'\beta_1} + \varepsilon_1$$

$$y_2^* = \boldsymbol{X_2'\beta_2} + \varepsilon_2,$$

where the observability criteria for the two binary outcomes can be stated as:

$$y_1 = \begin{cases} 1\ if\ y_1^* > 0 \\ 0, otherwise \end{cases}$$

$$y_2 = \begin{cases} 1\ if\ y_2^* > 0 \\ 0, otherwise' \end{cases}$$

where in turn $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ are vectors of individual and household covariates that effect the child's schooling and labour supply decision respectively. ε_1 and ε_2 are error terms to have a bivariate normal distribution with $Cov[\varepsilon_1, \varepsilon_2 | \boldsymbol{X_1}, \boldsymbol{X_2}\ ]$=$\rho$

The joint probabilities that enter into the likelihood function can be expressed as:

$$\mathbb{P}_{ij} = Pr(y_1 = i, y_2 = j\ |\boldsymbol{X_1}, \boldsymbol{X_2}\ ) = \Phi(\mathbb{p}\boldsymbol{X_1'\beta_1}, \mathbb{q}\boldsymbol{X_2'\beta_2};\ \mathbb{p}, \mathbb{q}, \rho),$$

where $\mathbb{p} = \begin{cases} 1\ if\ y_1 = 1 \\ -1\ if\ y_1 = 0 \end{cases}$ and $\mathbb{q} == \begin{cases} 1\ if\ y_2 = 1 \\ -1\ if\ y_2 = 0 \end{cases}$

The log-likelihood for the bivariate Probit is then given by:

$$\ell(\theta) = \sum_{y_1=1,y_2=0} \ln \Phi_{10}(\theta) + \sum_{y_1=1,y_2=1} \ln \Phi_{11}(\theta) + \sum_{y_1=0,y_2=1} \ln \Phi_{01}(\theta) + \sum_{y_1=0,y_2=0} \ln \Phi_{00}(\theta),$$

Where $\Phi_{ij}(\cdot)$ is the joint probability that y_1 assumes a value of i and y_2 takes a value of j, for I,j=0,1 and θ is the parameter vector consisting of $\boldsymbol{\beta_1}, \boldsymbol{\beta_2}$ **and** ρ. Maximum likelihood estimates are obtained by simultaneously setting to zero the derivative of the log likelihood function with respect to the parameters of interest. The estimated regression coefficients will be converted into marginal effects with the same vector of covariates being included in the two equations for the system to be identified.
Subsequently, we employ the quasi-experimental propensity score methodology to estimate the impact of education transfers and related assistance on child's labour supply and educational expenditure.

We will utilise a rich dataset that contains individual-specific education expenditures, enabling us to examine if the education cash transfer increased voluntary education expenditure and whether the fly-paper effect exists within the household. In this study, we accept the existence of the intra-household fly-paper only if there is a statistically significant increase or positive impact on the voluntary education expenditure of a child receiving education cash transfer. We take into account only voluntary education expenditures at the child-level when seeking for the intra-household flypaper effect. However, for the sake of robustness and to gauge the general impact of the programme, we separately estimate treatment effects at the household-level.

The basic problem in any treatment evaluation begins with the inference of a causal relationship between the treatment and outcome. In a canonical single treatment setting, one can observe $\left(Y_i,\ X_{i,}\ D_i\right),\ i \ldots, N$ and the impact on Y from a hypothetical change in D while holding X constant. Such inference is the key feature of a potential outcome model, where the outcome variable of the treated state is compared to the outcome variable of the untreated state. However, it is impossible to simultaneously observe both states for any given individual. Thus, the problem is akin to one of missing data, which can be solved by techniques of casual inference carried out in terms of counterfactuals. The counterfactual question is: `what would have happened to children who received the education transfer if they had not received the transfer'. First, assume the setup of a randomised treatment assignment, where no one is included in the treatment group because the benefits of the treatment to that individual would be large, and no one is excluded because the expected benefit is small. Let the vector of observables be $(Y_i,\ X_{i,}\ D_i),\ i \ldots, N$. Where Y is the scalar-value outcome variable, X is a vector of observables, and D a binary indicator of treatment (D takes the value of 1 if the child receives the transfer, 0 otherwise). In the potential outcome framework, one can define Δ as the difference between the outcome in the treated and untreated states as:

$$\Delta = Y_1 - Y_0$$

It is important to note that Δ is not directly observable, since an individual cannot be observed in both states. The two key evaluation parameters that will be used in this study will be the average treatment effect on the treated (ATT), defined as (in sample analogues):

$$\mathrm{ATT} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N_T}} [\Delta_\mathrm{i} | \mathrm{D_i} = 1]$$

Where $\mathrm{N_T} = \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{D_i}$. ATT is the mean effect of those who actually participate in the programme. The treatment evaluation problem can be easily understood by writing the ATT as

$$ATT = E(\Delta | D = 1) = E(Y_1 | D = 1) - E(Y_0 | D = 1)$$

From the above equation, the problem of selection bias is straightforward, since the second term on the right side- $E(Y_0|D = 1)$, the counterfactual mean of the treated, is not observable. If the condition $E(Y_1|D = 1) = E(Y_0|D = 1)$ holds, one can use the non-participants in the cash transfer programme as the comparison group. But with non-experimental data this condition will not hold, since the components that determine the receiving the transfer also determines the outcome variable of interest. Thus, the outcomes of the transfer recipients would differ even in the absence of receiving the transfer, leading to a selection bias. It may be the case that selection bias can be fully accounted for by observables characteristics (such as age, skill differences, etc.). In this case, simply including the relevant variables in the outcome equation can eliminate selection bias. But in practice, unobservable characteristics effecting participation can also influence outcomes. ATT can be thus expressed as:

$$E[Y_1 | D = 1] - E[Y_0 | D = 0] = ATT + E[Y_0 | D = 1] - E[Y_0 | D = 0]$$

The difference between the left hand side of the equation and the ATT is the self-selection bias. The true parameter ATT is only identified if

$$E[Y_0|D = 1] - E[Y_0|D = 0] = 0$$

In this paper, we adopt the quasi-experimental propensity score matching method (PSM) that deals explicitly with treatment selection bias and addresses the key evaluation problem of $E[Y_0|D = 1]$ being unobservable.

The essential idea of propensity score matching (PSM) is to match participants and non-participants on their observable characteristics. The mean effect of treatment (participation) can be estimated as the average difference in outcomes between the treated and non-treated. When the counterfactual mean for the treated- $E[Y_0|D = 1]$, is not observed, one has to invoke `identifying assumptions' to estimate the casual effect of a programme on the outcome. The first identification assumption in propensity score matching is referred to as the conditional independent assumption (CIA), and is expressed as:

$$Y_{0,}Y_1 \perp D|X$$

It states that outcomes are independent of programme participation, after controlling for the variation in outcomes induced by differences in X. The second assumption identification assumption is referred to as the overlap or matching assumption, written as

$$0 < Pr[D = 1|X] < 1$$

This assumption implies that for each value of X there is both treated and untreated individuals. In other words, for each participant there is another non-participant with a similar X. A practical constraint that exists in matching is that when the number of covariates X_i increases, the chances of finding a match reduces. However, Rosenbaum and Rubin (1983) showed that matching on the propensity score $P(X)$- the probability of participating in a programme, could achieve consistent estimates of the treatment effect the same way as matching on all covariates. Essentially, the proposition Rosenbaum and Rubin (1983) can be stated as: Let $P(X_i)$ be the probability of unit i having been assigned to treatment, defined as $P(X_i) \equiv \Pr(D_i = 1|\, X_i) = E(D_i|X_i)$. Assume that $0 < P(X_i) < 1$, for all X_i and $\Pr(D_1, D_2\, , D_N\, |\, X_1, X_2, \dots X_N) = \prod_{i=1,\dots N} P(X_i)^{D_i}\, (1 - P(X_i)^{1-D_i}$ for the N units in the sample. Then, $\{(Y_{i1}, Y_{i0}) \perp D_i\}\,|\, X_i \Rightarrow \{(Y_{i1}, Y_{i0}) \perp D_i\}\, P(X_i)$. *Corollary:* If $\{(Y_{i1}, Y_{i0}) \perp D_i\}\,|\, X$ and the assumptions of the above proposition hold, then

$\Delta|_{D=1} = E\{E(Y_i|D_i = 0, P(X_i))|D_i = 1\}$. The proposition implies that observations with the same propensity score have the same distribution of the full vector of covariates X_i. The propensity score will be estimated by a Probit model: $\Pr(D = 1|X = x) = \Phi(X'\beta)$.

After estimating the propensity score, the next decision to be made concerns the common support region(s). Enforcing the common support region ensures that any combination of characteristics observed in the participation group can also be observed among non-participants. The approach referred to as the `minima and maxima' condition will be used in all estimations in this paper. The basic idea of this condition is to delete all participants, whose propensity score is smaller than the minimum and higher than the maximum in the non-participants. Therefore participants who fall outside the common support region will be discarded and for these individuals the treatment effect will not be estimated. When the proportion of lost individuals is small, this poses few problems. However, if there is a significant reduction in the sample size, then there are doubts about whether the estimated effect on the remaining individuals can be viewed as a representative of the full sample.

Having enforced the common support region, the next step is to choose the matching algorithm. The general formula for the matching estimator is given by:

$$B_M = \frac{1}{N_T} \sum_{i \in \{d=1\}} \left[Y_{i1} - \sum_j w(i,j) Y_{j0} \right]$$

Where B_M denoted the matching estimator for the bias, $0 < w(i,j) \leq 1$ is the set of treated individuals and j is an element of the set of matched comparison units. $W(i,j)$ represents a weighting function that depends on the specific matching estimator. Results will be presented for four matching algorithms: nearest-neighbor matching, caliper matching, radius matching and kernel matching. The nearest neighbour matching method assigns a weight equal to one, $W(i,j) = 1$, and takes each transfer recipient in turn and identifies the non-recipient with the closest propensity score. The nearest neighbor method will be implemented with replacement, so that a non-recipient can be used more than once as a match. A variant of the nearest neighbour matching is calliper matching. The calliper matching method chooses the nearest neighbour within a calliper of width δ, so that $\{j: |P(X_i) - P(X_j)| < \delta\}$ where $P(X)$ is the propensity score. Therefore calliper matching imposes a form of quality control on the match by setting a tolerance level on the maximum propensity score distance. Dehejia and Wahba (2002) introduced a variant of calliper matching which is referred to as radius matching. In radius matching the idea is to use not only the nearest neighbour within each calliper but all of the comparison members (non-participants) within the calliper. The final matching algorithm that will be used in the study is referred to as kernel matching. Kernel matching uses all the non-participants for each participant in the matching process. The kernel is a function that weights the contribution of each non-participant, so that more importance is attached to those non-participants providing a better match. The Gaussian and the Epanechnikov will be used as weighting functions with kernel matching.

The final step in propensity score matching is to assess the matching quality. Three measures will be used to judge the performance of the match: standardised bias and the t-Test. The standardised bias for each covariate as suggested by Rosenbaum and Rubin (1985) is defined as the percentage of the square root of the average sample variances in both groups, and is expressed as:

$$SB_{before} = 100 \cdot \frac{\bar{X}_1 - \bar{X}_0}{\sqrt{0.5 \cdot (V_1(X) + V_1(X))}}$$

$$SB_{before} = 100 \cdot \frac{\bar{X}_{1M} - \bar{X}_{0M}}{\sqrt{0.5 \cdot (V_{1M}(X) + V_{1M}(X))}}$$

Where $X_1(V_1)$ is the mean (variance) in the treatment group before matching and $X_0(V_0)$ the analogue for the comparison group. $X_{1M}(V_{1M})$ and $X_{0M}(V_{0M})$ are the corresponding values for the matched samples.

For all child-level educational expenditure analysis, we use children of the age of 6 to 18 years. We only consider children who regularly participate in the labour market as child workers. It is assumed that these children supply labour to either earn a living for themselves or to supplement household incomes. Children engaged in housekeeping activities and performing household chores – such as cleaning, cooking, or washing – are thus not regarded to be child labour in this study. Being consistent with other previous studies on child labour and in accordance with the law, children aged less than fifteen years who participate in the labour market will be considered as supplying labour. Since all work related questions were asked only for individuals above the age of ten years, our sub-sample for child labour supply will be for all children between the ages of ten to 14 years. The treatment variable for children receiving any educational assistance will be a binary variable (yes=1 and no=0) generated from the survey question of "Receive scholarship/educational assistance in the past year?"

6. Empirical Results

Table 4 gives the estimated results from the bivariate Probit regressions. The first column of estimates gives the parameters that affect the work decision, whereas the second gives the estimates of the parameters that affect the schooling decision. The correlation coefficient-ρ, is significantly negative in the estimations. This means that there is a negative relationship between attending school and working. This could imply that there are some unidentified factors that increase the probability of attending school and at the same time decrease the probability of working. Schooling and child labour are thus activities that children, or their parents, have to choose between.

According to Table 4, the probability of working increases with the child's age. The age variable captures the effect of the absolute value of the labour of a child of a given age. Thus this could be interpreted as an indication of the fact that the accumulated human capital (in case of children) increases potential wages and therefore the probability of working. Virtually all empirical work on child labour has indicated that the age and gender of the child are important determinants of their educational and work activities. Being a male child increases the probability of a child being involved in labour activities, which is also evident from Table 4.

We assumed that parents' ages would also have an impact on child activities. According to Table 4, the higher the household head's age, the higher the educational attainment of the child and the lower the likelihood for the child to work. Younger parents are likely to be at a more financially constrained point in their life and may have less capacity to cover school expenses, thus having a greater need for their children's labour. There is ample empirical evidence in the literature that the education level of the parent decreases the probability of their children working and increases the probability of schooling. Parental education can potentially influence the allocation of children's time, mainly through income and preferences.

Since both market work and household work are common in developing countries, we use proxies to capture both these types of activities. We use household's heads in agriculture to capture market work, since usually most children work close to home, so that it is local labour market conditions that will determine the demand for their labour. Similarly, we proxy the demand for domestic work by using housing facilities, such as poor access to water and sanitation conditions. The absence of such services might substantially increase the domestic burden workload for children without, or without directly, affecting the decision to send a child to school, once the wealth of the household has been controlled for. Our findings indicate that children in agricultural households have a higher probability of working and less likelihood of attending school. Similarly, children living in houses with poor sanitation are also more likely to work and less likely to attend school.

The nature of the household head's occupation also matters: if the parents are unemployed or employed irregularly, a child's labour may be considered as a substitute for their labour or hired labour, thus decreasing the chances of that child attending school. Furthermore, a father's employment in the informal sector, as opposed to the formal one, raises the probability that the child will also work in the informal sector. Being consistent with this expectation, our results show that when the household head works in the informal sector, the probability of children to supply labour is also higher.

Subsequently, we examine the effects of household composition on children's work and schooling via the household dependency ratio. Our findings indicate that children are more likely to engage in work and not attend school in households with high dependency ratios. The probability of children working was also found to be higher in rural areas than in urban areas, which is a global and general characteristic of child labour. Table 4 also confirms the Basu and Vans (1998) luxury axiom that poverty drives child labour. Usually, the joint probability of working and not going to school drops sharply with household wealth. Children in poor households were found to have a higher probability of working and a lower likelihood of attending school. This result is generally consistent with theoretical literature, which mentions poverty as one of the main factors explaining child labour.

Table 5. Binary Propensity Score Model, $Pr(D=1|X=x)=\Phi(X'\beta)$ presents the results for the individual samples of analysis stratified by expenditure quintiles: bottom 20th percentile, 20th-40th percentile, 40th-60th percentile, 60th-80th percentile, top 20th percentile. Estimates are for the Probit regression where the binary outcome takes a value one if the child is receiving any type of an educational transfer or assistantship. The results are generally unsurprising and reveal a number of significant covariates of programme participation. It is important to note that the standard regression based method and propensity score matching differs significantly with regard to the choice of control variables. In a standard regression, preference is usually given to variables that one can argue are exogenous to outcomes, but in propensity score

matching the primary interest is in covariates (not good predictors) and thus including variables even when they are poor predictors. Analytic results and simulations of Rubin and Thomas (1996) suggests that variables with weak predictive ability for outcomes can still help minimise bias in estimating casual effects with propensity score matching. In essence, the main purpose of the propensity score estimation is not to predict selection into treatment but to balance covariates and get closer to the observationally identical non-participant.

Next, the common support region was examined by plotting a histogram of the propensity score. The common support is the region where the propensity score has a positive density for both treated and non-treated units. Figures 1 gives the frequency distribution of the propensity scores based on Table 5. Binary Propensity Score Model, $\Pr(D=1|X=x)=\Phi(X'\beta)$ for the children receiving (treated) and not receiving (untreated) any educational assistantship. All other histograms reveal that there is a substantial region of overlap, and that a severe common support problem does not exist. It is evident from Figure 1. Overlap and Distribution of Propensity Scores that any combination of characteristics observed in the treatment groups can be observed among the control groups among all estimated quintiles. In all quintiles, the probability mass in the treated group is located to the same side of that of the non-treated group. Since the main purpose is not on the Probit probability estimations but to match households, it is encouraging to see that a large fraction of households from both groups (treated and untreated) gets an estimated probability in the same range. The upshot of Figure 1. Overlap and Distribution of Propensity Scores is that there is sufficient common support that provides strong evidence for causal inference.

Results on covariate balancing are presented in the Appendix. Each cell reports the average standardised bias of the different covariates after matching. It is evident that the differences between the households in the treated and untreated groups are quite small after matching, and that matching has removed any bias that had existed for almost all covariates. A t-test of equality of means in the two samples of participants and nonparticipants indicates that there is no systematic pattern of significant differences between the covariates in the treatment and non-treated groups after conditioning on the propensity score. The exact number of individuals lost due to common support requirement is also negligible in Table 6. Individuals lost due to common support requirement (%).

Table 7. Binary Treatment Effects of Educational Assistance on Child Education Spending reports the estimated mean impacts of educational transfers on children's voluntary educational spending. The estimates of the average treatment effect on the treated (ATT) are

obtained via propensity score matching, using four matching algorithms and imposing the 'minima and maxima' common support. The results for the mean impact indicate that receiving educational transfers and assistance significantly increases education spending for the bottom three quintiles, though the magnitude varies by matching method.

For all quintile groups, children receiving educational assistance or transfers spend more at the margin on education than what they would have spent without any educational support. For example, Table 7. Binary Treatment Effects of Educational Assistance on Child Education Spending shows that children receiving educational assistance spend between 10% and 14% more at the margin on voluntary educational goods. In other words, when controlling for the level of expenditure, households receiving educational assistance and transfers spend more of their additional increments to expenditure on education.

These large marginal increases in 'child-specific' education spending arising from educational transfers and scholarships thus confirm the existence of an intra-household fly-paper-effect. However, these gains are not visible for the children in the 80^{th}-100^{th} percentile, implying that even if children in the richest quintile actually received some additional educational support, their households' voluntary educational spending for them would not increase.

Thus, a careful selection of only the poor and vulnerable households becomes a vital component in the design and success of any educational support programme. The poorest and vulnerable children should be given special priority in selection, and need to be regularly assessed to maintain the focus on the poor and low-income programme participants.

Table 8 presents the results of the impact of educational transfers, scholarships and assistance on the probability of children to work. The estimates represent the marginal effects of a child receiving educational assistance on the probability of being in the labour force. It is evident from the results that the education cash transfers and assistance given to children were large enough to reduce the amount of time spent working, especially among the poor. For instance, receiving education transfers and assistance reduces the probability of children working in the poorest households by one to three percentage points. The results again confirm that benefits are heavily skewed to the poor - the two lowest quintiles of the participating children receive the largest share of education assistance benefits.

The additional financial support from education transfers and assistance seem to reduce the pressure for children to work and will in turn allow spending more time on school-related activities. Our results are consistent with previous research, which has shown that transfer programmes rolled out to reduce child labour and increase schooling and homework time are all changes which may improve educational achievement (Maluccio, 2009; Skoufias ad Parker, 2001). We also find no significant impact of transfers on voluntary educational spending for the children in the upper part of the welfare distribution. These results are not surprising, as the transfers and assistance were too small of an incentive to have any positive effects on school enrolment for students at the upper part of the welfare distribution.

7. Conclusion and Policy Implications

This paper has used a large, nationally representative household survey from Indonesia to analyse how the receipt of educational transfers, scholarships and related assistance affects the child labour supply and households' spending behaviour on children's education and related goods and services.

Several key findings emerged from the study. We found strong evidence of a reduction in the labour supply of children at the bottom of the welfare distribution (lowest 20 percent) due to Indonesia's education cash transfers and related assistance. Households receiving educational transfers, scholarships and assistance were also found to spend more at the margin on voluntary educational goods. At the mean, households receiving educational transfers, scholarships and assistance spend 10% to 14% more on their children's voluntary educational goods at the margin than what they would have without any additional educational support.

These large marginal increases in education spending at the child-level arising from educational transfers and scholarships thus confirm the existence of an intra-household fly-paper-effect. Educational transfers, scholarships and assistance have been associated with increased voluntary educational spending on the child receiving such support, with little re-allocation taking place within the household, providing strong evidence of benefits sticking to children. If education transfers and assistance are viewed as transitory and uncertain stream of income and support, then our findings are consistent with the permanent income hypothesis, which generally finds that the marginal propensity to invest the transitory income (transfers, subsidies, remittances, etc.) is higher than that for permanent income, such as salaries (Paxson,1992).

Thus it becomes evident that a well-targeted and administered educational assistance programme that lowers the price of schooling can be successful in inducing children to spend less time on work, especially among the poor. Since the benefits of education transfers and support programmes are mostly concentrated among the poor and vulnerable, it is important to identify and select only the poor and vulnerable households for any targeted education support intervention. Our results are particularly relevant in the context of understanding the role of cash transfers and educational assistance in middle-income countries, where school enrolment rates are already at satisfactory levels, but the challenge is to keep the students in school at post-primary educational institutions. A relatively higher marginal propensity to invest in education among transfer- and assistance- receiving households in Indonesia will undoubtedly be beneficial in augmenting human capital in the country.

In summary, our findings suggest that educational transfers, scholarships and assistance are successful in increasing household investments in education as well as in reducing children's labour supply by providing an incentive to forgo the labour income. Our results suggest that transfer schemes in Indonesia could be further improved and redesigned to increase the children's educational spending and time spent in school. For example, larger transfers, incentives for school completion and payments that vary with the geographic remoteness of the household could be considered to improve BSM. A special emphasis could be given to rural areas, and a condition could be set that the children in the households receiving the educational transfers must attend school and are not allowed to work at all. Improving the schools themselves could probably also reduce children's labour supply and encourage them to spend more time in school. Improved targeting, combined with the expansion of programme's coverage and sharper geographical targeting, and an increasing in the real value of the transfer, are thus the most plausible policies that can enhance the impact of transfers on children's educational achievements.

The findings of this study lend support to the growing view in the literature that educational transfers, scholarships and related assistance can actually have a positive impact on economic development by increasing the level of investment in human capital. The principle message that emerges from the study is that there are quantitatively non-negligible average gains from educational transfers and support programmes on household education spending and child labour, especially for the poor.

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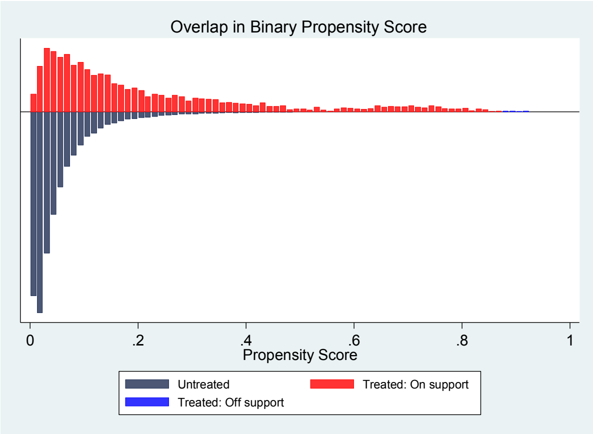
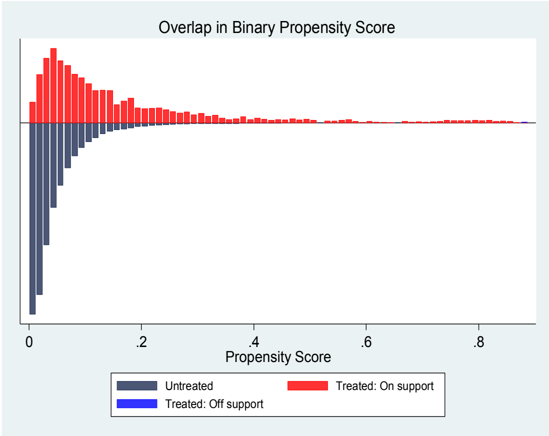
Figure 1. Overlap and Distribution of Propensity Scores: Overlap and Distribution of Propensity Scores

Quintile-1



Quintile-2



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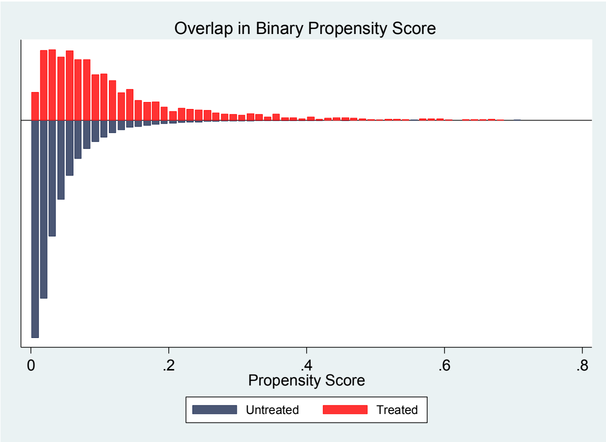

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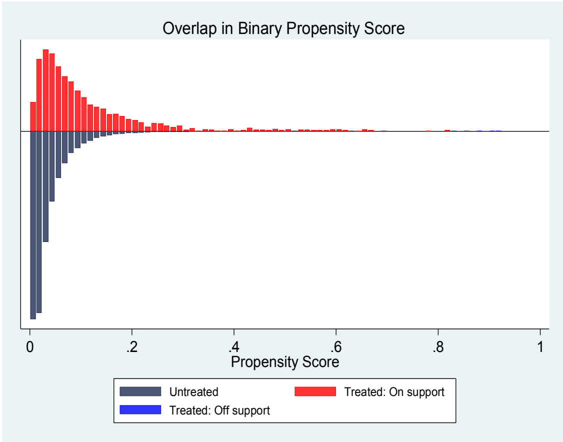


Quintile-5

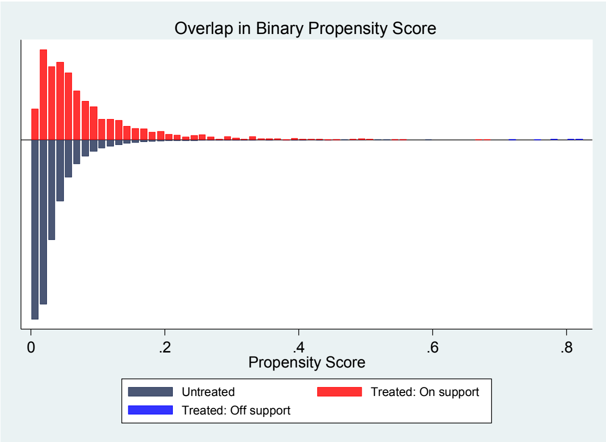
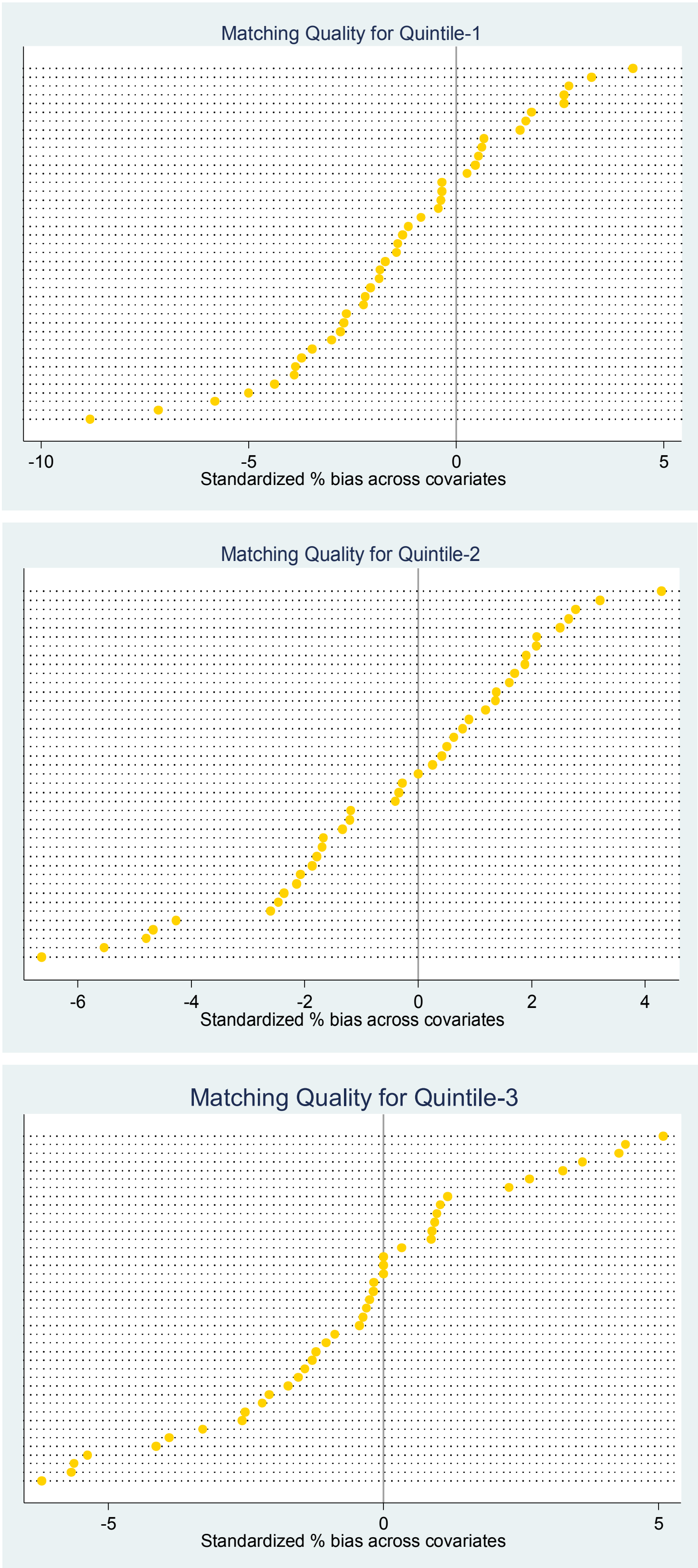
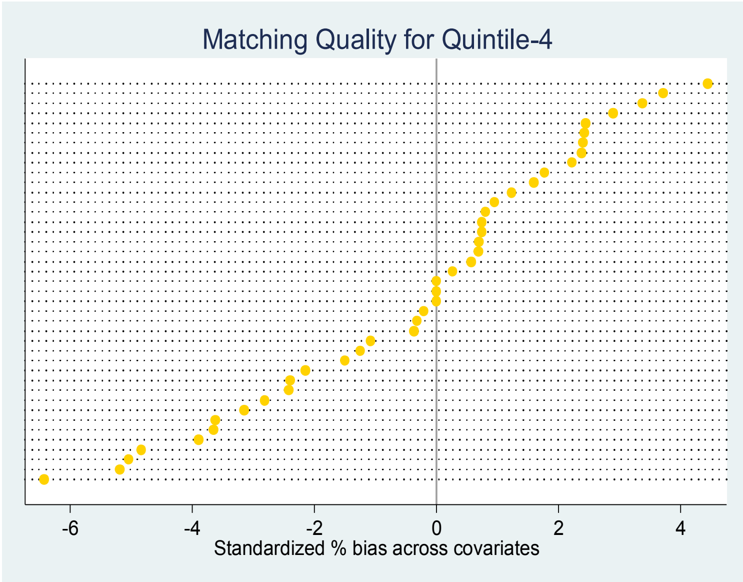


Figure 2: Matching Quality – –Standardised Bias Reductio




Matching Quality for Quintile-4
-6
-4
-2
0
2
4
Standardized % bias across covariates

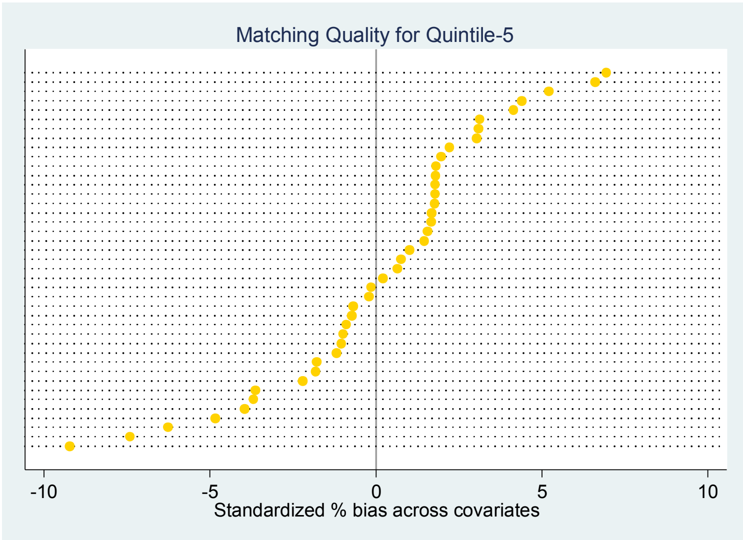

Matching Quality for Quintile-5
-10
-5
0
5
10
Standardized % bias across covariates

Table 1: Education of Children Age 7-18

		All	Male	Female	Java	Off Java	Urban	Rural
2007	Not/neverenrolle	1.45	1.54	1.37	1.45	0.7	0.61	1.89
	Enrolled	84.8	84.44	85.2	84.8	84.39	88.99	82.66
	DropAout	13.74	14.03	13.43	13.74	14.92	10.4	15.45
2009	Not/neverenrolle	1.58	1.68	1.48	0.6	1.9	0.5	2.1
	Enrolled	85.29	84.82	85.88	84.8	85.5	88.8	83.58
	DropAout	13.13	13.5	12.72	14.6	12.6	10.7	14.32
2011	Not/neverenrolle	2.25	2.31	2.19	0.89	2.74	0.62	3.31
	Enrolled	87.06	86.22	87.96	87.87	86.77	90.59	84.79
	DropAout	10.69	11.48	9.85	11.25	10.49	8.79	11.91

Table 2: Reason for Not Enrolling in School

	2007		2009		2011	
	Age7-12	Age7-18	Age7-12	Age7-18	Age7-12	Age7-18
No money	35.3	52.48	35.3	51.12	32.26	43.58
Have to work	1.63	7.38	2.6	9.7	1.51	10.18

Table 3: Highest Diploma Obtained

		Male	Female	Age 7-18	Java	Off Java
2007	None	29.85	31.39	55.64	26.76	35.25
	Elementary	27.4	29.35	24.46	30.4	27.47
	JuniorHigh	15.93	14.93	14.86	15.08	15.6
	SeniorHigh	12.89	11.43	1.6	11.13	12.63
	Vocational	5.13	3.69	0.42	5.67	3.89
2009	None	31.3	32.6	55.2	28.4	33.4
	Elementary	26.5	27.8	24.1	28.6	26.5
	JuniorHigh	15.6	14.9	15.3	14.9	15.4
	SeniorHigh	13.5	12	1.8	11.3	-
	Vocational	5.13	3.62	0.55	6.09	3.67
2011	None	30.39	31.89	55.84	27.45	32.73
	Elementary	26.65	27.78	24.92	28.43	26.66
	JuniorHigh	15.3	14.89	15.47	14.95	15.17
	SeniorHigh	13.05	11.31	0.51	11.23	12.62
	Vocational	5.4	3.87	0.38	6.08	4.03

Table 4: Child Labour Supply and School Attendance – Bivariate Probit Regressions

VARIABLES	(1) Working Equation Marginal Effect (dy/dx)	(2) School Equation Marginal Effect (dy/dx)
Age of Child	0.0208***	-0.0248***
	(0.0004)	(0.0005)
Male Child	0.0209***	-0.0103***
	(0.0012)	(0.0013)
Household Head Age	-0.0002***	0.0002***
	(0.0001)	(0.0001)
Household Head Female	0.0225***	-0.0102***
	(0.0026)	(0.0025)
Household Head - SD Education	-0.0181***	0.0269***
	(0.0013)	(0.0013)
Household Head - SMP Education	-0.0090***	0.0376***
	(0.0017)	(0.0014)
Household Head - SMA Education	-0.0107***	0.0459***
	(0.0017)	(0.0013)
Household Head in Informal Sector	0.0275***	-0.0089***
	(0.0014)	(0.0016)
Household Head in Agriculture	0.0174***	-0.0123***
	(0.0015)	(0.0017)
Rural	0.0298***	-0.0058***
	(0.0014)	(0.0017)
House with Poor Sanitation	0.0299***	-0.0367***
	(0.0016)	(0.0018)
Household Dependency Ratio	0.0148***	-0.0045***
	(0.0008)	(0.0009)
Poor Household	0.0034**	-0.0433***
	(0.0015)	(0.0021)
Observations	117,561	117,561
Rho	-0.5606	
Wald chi-sqr(26)	8572.32	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The general structure of the bivariate Probit specification can be expressed as:

$y_1^* = \boldsymbol{X'_1\beta_1} + \varepsilon_1$ and $y_2^* = \boldsymbol{X'_2\beta_2} + \varepsilon_2$. Where the observability criteria for the two binary outcomes can be stated as:
$y_1 = \begin{cases} 1\ if\ y_1^* > 0 \\ 0, otherwise \end{cases}, y_2 = \begin{cases} 1\ if\ y_2^* > 0 \\ 0, otherwise \end{cases}$

Table 5. Binary Propensity Score Model, $\Pr(D = 1|X = x) = \Phi(X'\beta)$

	Quintile -1	Quintile2	Quintile - 3	Quintile - 4	Quintile - 5
female	0.032	0.070***	0.045*	0.121***	0.094***
	(0.023)	(0.025)	(0.027)	(0.028)	(0.032)
age	0.041***	0.046***	0.049***	0.039***	0.042***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Urban	0.038	0.062	0.018	-0.007	-0.143***
	(0.042)	(0.038)	(0.036)	(0.037)	(0.037)
Age-HHH	-0.001	0.001	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Female-HHH	0.238***	0.225***	0.278***	0.219***	0.268***
	(0.045)	(0.045)	(0.047)	(0.047)	(0.050)
Share male age 0-6	0.183	-0.042	0.468***	-0.153	0.067
	(0.160)	(0.164)	(0.170)	(0.182)	(0.197)
Share female age 0-6	0.032	0.063	0.021	-0.002	0.100
	(0.162)	(0.168)	(0.176)	(0.188)	(0.202)
Share males age 6-17	-0.075	0.090	-0.118	0.102	-0.000
	(0.137)	(0.129)	(0.128)	(0.131)	(0.125)
Share females age 6-17	0.060	0.129	0.021	-0.075	0.017
	(0.138)	(0.134)	(0.131)	(0.134)	(0.136)
Share females age 18-64	0.032	0.120	0.040	0.043	-0.218
	(0.172)	(0.164)	(0.158)	(0.153)	(0.148)
Share males age 65+	0.222	0.406	0.453*	0.363	0.421
	(0.279)	(0.269)	(0.269)	(0.269)	(0.292)
Share females age 65+	0.102	-0.236	0.271	0.150	-0.296
	(0.249)	(0.242)	(0.231)	(0.239)	(0.275)
HHH in Agri	-0.003	0.035	0.010	0.018	0.132***
	(0.032)	(0.033)	(0.032)	(0.034)	(0.038)
HHH in mining	-0.147	0.075	0.042	0.186**	0.126
	(0.092)	(0.090)	(0.083)	(0.082)	(0.086)
HHH in elec/gas/water	-0.064	-0.003	-0.046	-0.483*	0.076
	(0.254)	(0.250)	(0.240)	(0.287)	(0.129)
HHH in construction	-0.022	0.206***	0.130***	0.143***	-0.008
	(0.054)	(0.049)	(0.049)	(0.049)	(0.061)
HHH in trade/restaurent	-0.025	-0.030	-0.075*	-0.004	0.036
	(0.052)	(0.047)	(0.041)	(0.037)	(0.036)
HHH edu-sd	0.008	-0.042	-0.039	-0.044	0.062
	(0.028)	(0.030)	(0.031)	(0.033)	(0.038)
HHH edy-smp	-0.033	-0.015	-0.012	-0.068*	0.000
	(0.039)	(0.039)	(0.039)	(0.039)	(0.042)
HHH edu-sma	-0.054	-0.086**	-0.044	-0.088**	-0.019

Table 5 (Cont.): Binary Propensity Score Model, $\Pr(D = 1|X = x) = \Phi(X'\beta)$

	Quintile -1	Quintile2	Quintile - 3	Quintile - 4	Quintile - 5
House-own	-0.037	-0.024	-0.118***	-0.198***	-0.096*
	(0.046)	(0.045)	(0.045)	(0.044)	(0.055)
House-lease/rent	0.027	0.207***	-0.015	-0.029	-0.032
	(0.073)	(0.066)	(0.064)	(0.063)	(0.072)
House-freelease	-0.102	-0.091	-0.224**	-0.214**	-0.070
	(0.088)	(0.091)	(0.102)	(0.096)	(0.113)
House-official	-0.230	-0.246	-0.241*	-0.490***	-0.084
	(0.191)	(0.164)	(0.129)	(0.118)	(0.084)
Floor-not soil	-0.011	0.026	-0.133***	-0.059	0.005
	(0.037)	(0.040)	(0.044)	(0.056)	(0.074)
Wall-concrete	-0.134***	-0.221***	-0.094*	-0.069	-0.148*
	(0.044)	(0.046)	(0.051)	(0.063)	(0.077)
Wall-wood	-0.008	-0.117**	-0.011	0.001	-0.045
	(0.042)	(0.048)	(0.052)	(0.065)	(0.081)
Roof-concrete/tile	-0.038	-0.199***	-0.078	-0.152**	-0.028
	(0.064)	(0.065)	(0.071)	(0.071)	(0.079)
Roof-iron sheet	-0.061	-0.218***	-0.058	-0.103*	0.013
	(0.040)	(0.044)	(0.051)	(0.053)	(0.067)
Roof-asbestos	-0.141*	-0.205**	-0.073	-0.131*	-0.055
	(0.086)	(0.084)	(0.086)	(0.080)	(0.092)
Water-branded recycled	0.060	-0.015	0.023	-0.120*	-0.087
	(0.090)	(0.080)	(0.073)	(0.068)	(0.061)
Water piped meter	-0.042	0.040	0.126**	-0.033	-0.005
	(0.058)	(0.054)	(0.052)	(0.053)	(0.052)
Water-terrestial/pump	0.084*	-0.081*	-0.024	-0.044	-0.004
	(0.049)	(0.047)	(0.046)	(0.045)	(0.053)
Water-protected/well	-0.006	-0.041	-0.017	-0.109***	0.022
	(0.031)	(0.032)	(0.034)	(0.036)	(0.045)
Water drinking-buy	-0.003	-0.101**	-0.090**	-0.096**	0.043
	(0.047)	(0.047)	(0.046)	(0.044)	(0.042)
Electricity-PLN	-0.023	0.053	-0.068	-0.085	0.082
	(0.039)	(0.045)	(0.048)	(0.057)	(0.086)
Electricity-non PLN	0.016	0.084	-0.006	-0.053	0.034
	(0.054)	(0.061)	(0.063)	(0.068)	(0.095)
Electricity-parafin/petro	-0.152*	-0.184	-0.024	0.039	-0.181
	(0.088)	(0.114)	(0.106)	(0.127)	(0.213)
Toilet-tank/septic	-0.113***	-0.070*	-0.097**	-0.023	-0.124*
	(0.040)	(0.041)	(0.044)	(0.050)	(0.066)
Toilet-river/lake/sea	-0.102**	0.012	0.008	0.024	0.042
	(0.041)	(0.042)	(0.048)	(0.056)	(0.076)
Toilet-pithole	-0.105***	0.008	-0.047	0.020	-0.015
	(0.040)	(0.042)	(0.047)	(0.054)	(0.072)
Constant	-2.249***	-1.994***	-1.610***	-1.395***	-5.575***
	(0.440)	(0.299)	(0.324)	(0.310)	(0.197)
Observations	44,137	45,222	44,953	45,445	44,067
Pseudo R-Squared	0.20	0.17	0.19	0.17	0.18

Table 6: Individuals lost due to common support requirement (%)

	Matching Algorithm	Quintile - 1	Quintile - 2	Quintile - 3	Quintile - 4	Quintile -
Total Voluntary Expenditure	NN	0.000	0.000	0.000	0.000	0.000
	5-NN	0.000	0.000	0.000	0.000	0.000
	NN (caliper): δ=0.001	0.000	0.254	0.084	0.114	0.059
	Radius: δ=0.001	0.000	0.254	0.084	0.114	0.059
	Kernel					
	Epanechnikov (bw=0.06)	0.000	0.000	0.000	0.000	0.000
	Gaussian (bw=0.1)	0.000	0.000	0.000	0.000	0.000
Books and Stationary	NN	0.000	0.000	0.000	0.000	0.000
	5-NN	0.000	0.000	0.000	0.000	0.000
	NN (caliper): δ=0.001	0.378	0.229	0.102	0.086	0.049
	Radius: δ=0.001	0.378	0.229	0.102	0.086	0.049
	Kernel					
	Epanechnikov (bw=0.06)	0.000	0.000	0.000	0.000	0.000
	Gaussian (bw=0.1)	0.000	0.000	0.000	0.000	0.000
Other Support Material	Matching Algorithm					
	NN	0.000	0.000	0.000	0.000	0.000
	5-NN	0.000	0.000	0.000	0.000	0.000
	NN (caliper): δ=0.001	0.022	0.036	0.089	0.092	0.063
	Radius: δ=0.001	0.022	0.036	0.089	0.092	0.063
	Kernel					
	Epanechnikov (bw=0.06)	0.000	0.000	0.000	0.000	0.000
	Gaussian (bw=0.1)	0.000	0.000	0.000	0.000	0.000
Tutoring/Courses	Matching Algorithm					
	NN	0.000	0.000	0.000	0.000	0.000
	5-NN	0.000	0.000	0.000	0.000	0.000
	NN (caliper): δ=0.001	0.642	0.295	0.272	0.241	0.045
	Radius: δ=0.001	0.642	0.295	0.272	0.241	0.045
	Kernel					
	Epanechnikov (bw=0.06)	0.000	0.000	0.000	0.000	0.000
	Gaussian (bw=0.1)	0.000	0.000	0.000	0.000	0.000

Table 7: Binary Treatment Effects of Educational Assistance on Child Education Spending

	Matching Algorithm	ATT: Quintile - 1	ATT: Quintile - 2	ATT: Quintile - 3	ATT: Quintile - 4	ATT: Quintile - 5
Total Voluntary Expenditure	NN	0.106	0.097	0.141	0.046	0.048
		(0.030)***	(0.036)***	(0.040)***	(0.044)	(0.053)
	5-NN	0.092	0.045	0.093	0.036	0.055
		(0.024)***	(0.025)**	(0.031)***	(0.034)	(0.041)
	NN (caliper): δ=0.001	0.100	0.077	0.139	0.032	0.037
		(0.030)***	(0.035)**	(0.040)***	(0.044)	(0.054)
	Radius: δ=0.001	0.086	0.017	0.075	0.029	0.047
		(0.023)***	(0.026)	(0.029)***	(0.031)	(0.038)
	Kernel					
	Epanechnikov (bw=0.06)	0.086	0.055	0.084	0.036	0.032
		(0.022)***	(0.026)**	(0.028)***	(0.031)	(0.037)
	Gaussian (bw=0.1)	0.100	0.067	0.088	0.026	0.025
		(0.021)***	(0.024)**	(0.027)***	(0.030)	(0.036)
Books and Stationary	NN	0.110	0.120	0.086	0.030	0.090
		(0.043)***	(0.049)**	(0.054)	(0.057)	(0.066)
	5-NN	0.102	0.072	0.075	0.014	0.032
		(0.034)***	(0.038)**	(0.041)*	(0.045)	(0.051)
	NN (caliper): δ=0.001	0.093	0.104	0.065	0.027	0.071
		(0.043)**	(0.048)***	(0.054)	(0.058)	(0.067)
	Radius: δ=0.001	0.080	0.028	0.068	-0.010	0.019
		(0.032)**	(0.035)	(0.039)*	(0.042)	(0.048)
	Kernel					
	Epanechnikov (bw=0.06)	0.101	0.046	0.092	-0.012	-0.023
		(0.032)***	(0.035)	(0.038)**	(0.041)	(0.046)
	Gaussian (bw=0.1)	0.101	0.061	0.076	-0.037	-0.095
		(0.030)***	(0 .033)**	(0.036)**	(0.040)	(0.076)
Other Support Material	NN	0.058	0.077	0.001	0.092	0.132
		(0.028)**	(0.035)**	(0.041)	(0.044)**	(0.054)**
	5-NN	0.048	0.029	0.040	0.041	0.107
		(0.022)**	(0.027)	(0.032)	(0.034)	(0.042)**
	NN (caliper): δ=0.001	0.059	0.079	-0.002	0.084	0.123
		(0.028)**	(.035)**	(0.041)	(0.044)*	(0.054)**
	Radius: δ=0.001	0.035	0.014	0.029	0.046	0.090
		(0.021)**	-0.025	(0.030)	(0.032)	(0.040)**
	Kernel					
	Epanechnikov (bw=0.06)	0.039	0.023	0.054	0.052	0.103
		(0.020)*	(0.024)	(0.029)*	(0.031)*	(0.040)**
	Gaussian (bw=0.1)	0.052	0.044	0.084	0.068	0.100
		(0 .020)**	(0.024)*	(0.028)***	(0.030)**	(0.058)**
Tutoring/Courses	NN	0.062	0.0620	0.058	0.059	0.052
		(0.031)**	(0.034)*	(0.060)	(0.066)	(0.158)
	5-NN	0.029	0.026	0.061	0.016	0.006
		(0.027)	(0.033)	(0.048)	(0.052)	(0.124)
	NN (caliper): δ=0.001	0.075	0.0560	0.050	0.075	0.064
		(0.032)**	(0.039)	(0.061)	(0.063)	(0.158)
	Radius: δ=0.001	0.023	0.006	0.047	0.002	0.074
		(0.026)	(0.032)	(0.047)	(0.050)	(0.115)
	Kernel					
	Epanechnikov (bw=0.06)	0.019	0.000	0.067	-0.008	0.019
		(0.024)	(0.030)	(0.045)	(0.050)	(0.112)
	Gaussian (bw=0.1)	0.021	0.007	0.088	-0.021	0.049
		(0.023)	(0.029)	(0.043)**	(0.047)	(0.110)

Table 8: Binary Treatment Marginal Effects of Educational Assistance on Child Labour Supply

Matching Algorithm	ATT: Quintile - 1	ATT: Quintile - 2	ATT: Quintile - 3	ATT: Quintile - 4	ATT: Quintile - 5
NN	-0.032	-0.0238**	-0.0037	-0.0073	0.0039
	(0.010)***	(0.01)	(0.011)	(0 .0122)	(0.012)
5-NN	-0.013	-0.004	-0.001	0.007	0.010
	(0.007)**	(0.009)	(0.008)	(0 .0093)	(0.0095)
NN (caliper): δ=0.001	-0.021	-0.014	-0.006	-0.007	0 .0013
	(0.009)**	(0.011)	(0.011)	(0.012)	(0.012)
Radius: δ=0.001	-0.010	0.003	0 .0017	-0.001	0.011
	(0.01)	(0.008)	(0.008)	(0 .0090)	(0.009)
Kernel					
Epanechnikov (bw=0.06)	-0.011	0.001	0 .0066	0.007	0.012
	(0.007)*	(0.009)	(0.008)	(0.009)	(0.009)
Gaussian (bw=0.1)	-0.006	0.005	0 .0067	0.010	0.017
	(0.007)	(0.008)	(0 .0075)	(0 .0084)	(0.009)

Appendix

Matching Quality Indicators for Quintile - 1

Variable	Treated	Control	%bias	t	p>t
female	0.50	0.48	4.30	1.68	0.09
age	11.40	11.67	-8.80	-3.38	0.00
Urban	0.20	0.20	-1.70	-0.67	0.51
Age-HHH	44.50	45.10	-5.80	-2.28	0.02
Female-HHH	0.12	0.13	-3.50	-1.25	0.21
Share male age 0-6	0.07	0.06	2.60	1.01	0.31
Share female age 0-6	0.06	0.06	1.80	0.71	0.48
Share males age 6-17	0.21	0.21	-0.40	-0.15	0.88
Share females age 6-17	0.20	0.20	3.30	1.28	0.20
Share females age 18-64	0.23	0.23	-7.20	-2.64	0.01
Share males age 65+	0.01	0.01	-2.70	-1.04	0.30
Share females age 65+	0.01	0.02	-1.10	-0.44	0.66
HHH in Agri	0.64	0.64	0.50	0.21	0.83
HHH in mining	0.01	0.01	0.30	0.12	0.91
HHH in elec/gas/water	0.00	0.00	-0.80	-0.33	0.74
HHH in construction	0.05	0.05	1.70	0.69	0.49
HHH in trade/restaurent	0.06	0.07	-3.70	-1.43	0.15
HHH edu-sd	0.37	0.37	-1.40	-0.55	0.58
HHH edu-smp	0.14	0.14	-1.30	-0.51	0.61
HHH edu-sma	0.11	0.10	1.50	0.62	0.54
House-own	0.85	0.86	-2.80	-1.13	0.26
House-lease/rent	0.04	0.04	2.60	1.02	0.31
House-freelease	0.02	0.02	0.60	0.26	0.80
House-official	0.00	0.01	-4.40	-1.68	0.09
Floor-not soil	0.79	0.79	-1.90	-0.72	0.47
Wall-concrete	0.31	0.33	-3.90	-1.55	0.12
Wall-wood	0.48	0.47	2.70	1.07	0.29
Roof-concrete/tile	0.25	0.25	-0.40	-0.18	0.86
Roof-iron sheet	0.51	0.52	-2.10	-0.81	0.42
Roof-asbestos	0.02	0.03	-2.20	-0.88	0.38
Water-branded recycled	0.03	0.03	-1.80	-0.66	0.51
Water piped meter	0.09	0.08	0.70	0.27	0.79
Water-terrestial/pump	0.09	0.09	-0.30	-0.14	0.89
Water-protected/well	0.26	0.27	-1.40	-0.57	0.57
Water drinking-buy	0.14	0.14	0.50	0.18	0.85
Electricity-PLN	0.57	0.58	-3.00	-1.16	0.25
Electricity-non PLN	0.09	0.09	-0.40	-0.13	0.90
Electricity-parafin/petro	0.02	0.03	-3.90	-1.48	0.14
Toilet-tank/septic	0.29	0.30	-2.70	-1.06	0.29
Toilet-river/lake/sea	0.21	0.22	-2.20	-0.90	0.37
Toilet-pithole	0.24	0.26	-5.00	-1.96	0.05

Matching Quality Indicators for Quintile – 2

Variable	Treated	Control	%bias	t	p>t
female	0.52	0.53	-1.30	-0.48	0.63
age	11.86	11.93	-2.10	-0.75	0.45
Urban	0.27	0.28	-1.70	-0.59	0.55
Age-HHH	44.99	44.95	0.40	0.15	0.88
Female-HHH	0.12	0.14	-5.50	-1.77	0.08
Share male age 0-6	0.05	0.05	-1.20	-0.43	0.67
Share female age 0-6	0.04	0.04	-1.80	-0.63	0.53
Share males age 6-17	0.21	0.21	0.80	0.28	0.78
Share females age 6-17	0.21	0.21	-1.20	-0.42	0.67
Share females age 18-64	0.24	0.24	1.90	0.64	0.52
Share males age 65+	0.01	0.01	2.50	0.88	0.38
Share females age 65+	0.01	0.02	-4.30	-1.45	0.15
HHH in Agri	0.57	0.55	2.80	0.99	0.32
HHH in mining	0.02	0.02	-0.30	-0.10	0.92
HHH in elec/gas/water	0.00	0.00	0.00	0.00	1.00
HHH in construction	0.09	0.08	1.90	0.65	0.52
HHH in trade/restaurent	0.08	0.09	-2.40	-0.85	0.39
HHH edu-sd	0.35	0.37	-4.70	-1.67	0.10
HHH edu-smp	0.16	0.16	1.70	0.61	0.54
HHH edu-sma	0.14	0.13	2.10	0.78	0.44
House-own	0.83	0.82	2.10	0.73	0.46
House-lease/rent	0.07	0.07	-0.30	-0.11	0.91
House-freelease	0.02	0.02	0.50	0.19	0.85
House-official	0.01	0.00	4.30	2.07	0.04
Floor-not soil	0.85	0.85	1.40	0.47	0.64
Wall-concrete	0.40	0.41	-2.50	-0.88	0.38
Wall-wood	0.46	0.45	1.20	0.42	0.67
Roof-concrete/tile	0.29	0.29	0.30	0.09	0.93
Roof-iron sheet	0.51	0.53	-4.80	-1.71	0.09
Roof-asbestos	0.03	0.03	2.70	1.00	0.32
Water-branded recycled	0.04	0.04	1.40	0.49	0.63
Water piped meter	0.13	0.14	-2.60	-0.91	0.36
Water-terrestial/pump	0.10	0.09	0.90	0.33	0.74
Water-protected/well	0.28	0.29	-2.10	-0.75	0.46
Water drinking-buy	0.19	0.19	-0.40	-0.14	0.89
Electricity-PLN	0.71	0.71	0.60	0.22	0.83
Electricity-non PLN	0.07	0.07	3.20	1.16	0.25
Electricity-parafin/petro	0.01	0.02	-6.60	-2.32	0.02
Toilet-tank/septic	0.35	0.36	-1.90	-0.67	0.50
Toilet-river/lake/sea	0.22	0.21	1.60	0.58	0.56
Toilet-pithole	0.24	0.24	-1.70	-0.59	0.56

Matching Quality Indicators for Quintile – 3

Variable	Treated	Control	%bias	t	p>t
female	0.52	0.51	1.00	0.34	0.74
age	12.22	12.35	-4.10	-1.38	0.17
Urban	0.33	0.34	-2.20	-0.72	0.47
Age-HHH	45.21	45.12	0.90	0.28	0.78
Female-HHH	0.13	0.14	-1.20	-0.36	0.72
Share male age 0-6	0.04	0.04	-1.40	-0.45	0.65
Share female age 0-6	0.03	0.04	-1.30	-0.43	0.67
Share males age 6-17	0.20	0.20	-0.40	-0.12	0.91
Share females age 6-17	0.20	0.20	1.20	0.37	0.71
Share females age 18-64	0.26	0.26	-0.30	-0.09	0.93
Share males age 65+	0.01	0.01	-0.40	-0.13	0.89
Share females age 65+	0.02	0.02	-2.10	-0.61	0.55
HHH in Agri	0.46	0.46	0.00	0.00	1.00
HHH in mining	0.02	0.03	-1.60	-0.49	0.63
HHH in elec/gas/water	0.00	0.00	-0.90	-0.28	0.78
HHH in construction	0.08	0.08	-0.20	-0.06	0.96
HHH in trade/restaurent	0.11	0.10	2.60	0.91	0.36
HHH edu-sd	0.33	0.34	-3.30	-1.07	0.28
HHH edu-smp	0.16	0.16	0.90	0.29	0.77
HHH edu-sma	0.19	0.19	0.90	0.31	0.76
House-own	0.81	0.81	1.00	0.31	0.76
House-lease/rent	0.07	0.07	-1.70	-0.55	0.58
House-freelease	0.02	0.02	0.30	0.11	0.91
House-official	0.01	0.01	0.00	0.00	1.00
Floor-not soil	0.87	0.87	0.00	0.00	1.00
Wall-concrete	0.50	0.50	-0.20	-0.06	0.95
Wall-wood	0.39	0.40	-2.50	-0.82	0.41
Roof-concrete/tile	0.33	0.31	3.30	1.09	0.28
Roof-iron sheet	0.52	0.55	-6.20	-2.03	0.04
Roof-asbestos	0.04	0.04	2.30	0.77	0.44
Water-branded recycled	0.06	0.07	-5.70	-1.80	0.07
Water piped meter	0.16	0.16	-0.30	-0.08	0.93
Water-terrestial/pump	0.12	0.10	4.30	1.48	0.14
Water-protected/well	0.29	0.28	3.60	1.19	0.23
Water drinking-buy	0.23	0.25	-5.60	-1.83	0.07
Electricity-PLN	0.77	0.78	-2.60	-0.81	0.42
Electricity-non PLN	0.08	0.07	5.10	1.68	0.09
Electricity-parafin/petro	0.02	0.02	-3.90	-1.16	0.25
Toilet-tank/septic	0.45	0.48	-5.40	-1.75	0.08
Toilet-river/lake/sea	0.20	0.18	4.40	1.45	0.15
Toilet-pithole	0.21	0.22	-1.00	-0.34	0.74

Matching Quality Indicators for Quintile – 4

Variable	Treated	Control	%bias	t	p>t
female	0.52	0.52	-0.30	-0.10	0.92
age	12.39	12.48	-2.80	-0.88	0.38
Urban	0.38	0.39	-1.10	-0.33	0.74
Age-HHH	45.70	45.58	1.20	0.37	0.71
Female-HHH	0.13	0.15	-6.40	-1.74	0.08
Share male age 0-6	0.03	0.03	2.90	0.93	0.35
Share female age 0-6	0.03	0.03	2.40	0.76	0.45
Share males age 6-17	0.20	0.20	-1.20	-0.38	0.71
Share females age 6-17	0.20	0.20	0.60	0.17	0.86
Share females age 18-64	0.27	0.27	-4.80	-1.39	0.17
Share males age 65+	0.01	0.01	-3.90	-1.06	0.29
Share females age 65+	0.02	0.01	2.20	0.64	0.52
HHH in Agri	0.39	0.37	4.40	1.37	0.17
HHH in mining	0.03	0.03	0.00	0.00	1.00
HHH in elec/gas/water	0.00	0.00	0.00	0.00	1.00
HHH in construction	0.08	0.08	-0.20	-0.06	0.95
HHH in trade/restaurent	0.14	0.13	0.70	0.24	0.81
HHH edu-sd	0.31	0.29	2.40	0.74	0.46
HHH edu-smp	0.16	0.17	-2.40	-0.75	0.45
HHH edu-sma	0.23	0.25	-3.60	-1.14	0.25
House-own	0.80	0.80	1.60	0.49	0.63
House-lease/rent	0.08	0.08	0.80	0.24	0.81
House-freelease	0.02	0.02	-1.50	-0.46	0.64
House-official	0.01	0.01	0.00	0.00	1.00
Floor-not soil	0.92	0.93	-3.10	-0.95	0.35
Wall-concrete	0.57	0.58	-2.10	-0.66	0.51
Wall-wood	0.36	0.35	1.80	0.54	0.59
Roof-concrete/tile	0.33	0.32	2.40	0.76	0.45
Roof-iron sheet	0.52	0.53	-2.40	-0.75	0.46
Roof-asbestos	0.06	0.06	0.70	0.21	0.84
Water-branded recycled	0.08	0.08	-0.40	-0.12	0.91
Water piped meter	0.18	0.18	0.30	0.08	0.93
Water-terrestial/pump	0.14	0.13	3.70	1.18	0.24
Water-protected/well	0.25	0.27	-5.00	-1.55	0.12
Water drinking-buy	0.27	0.27	0.70	0.22	0.83
Electricity-PLN	0.81	0.83	-5.20	-1.56	0.12
Electricity-non PLN	0.09	0.09	1.00	0.29	0.77
Electricity-parafin/petro	0.01	0.01	3.40	1.03	0.30
Toilet-tank/septic	0.54	0.53	0.70	0.23	0.82
Toilet-river/lake/sea	0.16	0.17	-3.70	-1.09	0.28
Toilet-pithole	0.20	0.19	2.40	0.73	0.46

Matching Quality Indicators for Quintile – 5

Variable	Treated	Control	%bias	t	p>t
female	0.54	0.56	-3.70	-1.04	0.30
age	12.84	13.15	-9.20	-2.66	0.01
Urban	0.49	0.50	-1.80	-0.50	0.62
Age-HHH	45.45	45.27	1.80	0.49	0.63
Female-HHH	0.13	0.13	-0.20	-0.05	0.96
Share male age 0-6	0.03	0.03	1.60	0.45	0.65
Share female age 0-6	0.03	0.03	-1.00	-0.28	0.78
Share males age 6-17	0.19	0.18	3.00	0.83	0.40
Share females age 6-17	0.20	0.21	-0.70	-0.18	0.85
Share females age 18-64	0.28	0.28	-1.80	-0.48	0.63
Share males age 65+	0.01	0.01	0.70	0.19	0.85
Share females age 65+	0.01	0.01	0.20	0.05	0.96
HHH in Agri	0.26	0.29	-6.30	-1.64	0.10
HHH in mining	0.03	0.03	-1.20	-0.32	0.75
HHH in elec/gas/water	0.01	0.01	2.00	0.58	0.56
HHH in construction	0.05	0.04	1.80	0.53	0.60
HHH in trade/restaurent	0.17	0.16	1.70	0.48	0.63
HHH edu-sd	0.22	0.21	1.80	0.48	0.63
HHH edu-smp	0.14	0.14	1.50	0.41	0.68
HHH edu-sma	0.31	0.30	3.10	0.89	0.37
House-own	0.81	0.80	1.80	0.50	0.62
House-lease/rent	0.07	0.08	-3.60	-1.00	0.32
House-freelease	0.02	0.01	1.00	0.29	0.77
House-official	0.04	0.04	0.60	0.19	0.85
Floor-not soil	0.96	0.95	4.40	1.11	0.27
Wall-concrete	0.69	0.69	-0.10	-0.04	0.97
Wall-wood	0.27	0.27	-1.00	-0.28	0.78
Roof-concrete/tile	0.37	0.36	2.20	0.63	0.53
Roof-iron sheet	0.53	0.53	-0.90	-0.25	0.80
Roof-asbestos	0.05	0.06	-4.00	-1.09	0.28
Water-branded recycled	0.17	0.16	1.80	0.53	0.60
Water piped meter	0.28	0.26	3.10	0.88	0.38
Water-terrestial/pump	0.13	0.12	1.70	0.49	0.63
Water-protected/well	0.21	0.22	-2.20	-0.61	0.54
Water drinking-buy	0.47	0.45	5.20	1.47	0.14
Electricity-PLN	0.88	0.86	6.60	1.72	0.09
Electricity-non PLN	0.08	0.08	-0.70	-0.20	0.85
Electricity-parafin/petro	0.00	0.01	-4.80	-1.22	0.22
Toilet-tank/septic	0.66	0.69	-7.40	-2.01	0.04
Toilet-river/lake/sea	0.11	0.09	7.00	1.87	0.06
Toilet-pithole	0.18	0.17	4.10	1.12	0.26

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