How do educational transfers affect child labour supply and expenditures? Evidence from Indonesia of impact and flypaper effects.

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Education Transfers, Expenditures and Child Labour Supply: Evidence of Impact and Flypaper Effects in Indonesia

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Abstract

This paper utilises a large nationally representative household survey of unusual scope and richness from Indonesia to analyse 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 found strong evidence of educational cash transfers and related assistance programmes significantly decreasing the time spent by children in 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 for children living in poor families. Our results are particularly relevant for understanding the role of cash transfers and educational assistance in middle income countries where enrolment rates are already at satisfactory levels, but the challenge is to keep the students in school at post-primary levels.

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

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1. Introduction

The use of government transfers and subsidies to address the challenges posed by poverty, child labour and low levels of educational attainment among the more vulnerable sections of the population, namely, women and children, has generated substantial interest in both research and public policy forums. Educational transfers and subsidies in particular 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; Galor and Zeira 1993). Additionally, along with school voucher programmes and certain subsidised education schemes, educational cash transfer programmes have now become part of a growing policy emphasis on the use of market-oriented demand-side interventions to combat poverty and child labour. They complement traditional supply-side instruments, such as general subsidies or investments in schools, hospitals, and other providers of social services. Ultimately, positive externalities and higher equity in educational expenditures generated through these transfers and subsidies will lead to higher levels of welfare and will yield concave returns for the social planner (Das 2004).

Both conditional and unconditional Cash Transfers (CCTs and UCTs) have been rigorously evaluated worldwide, covering a wide range of programmes including non-contributory pension schemes, education transfers, disability benefits, child allowance, and income support. 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 proved evidence in fostering investment in human capital, increasing the use of health resources, and being successful in combating poverty and vulnerability (Behrman et.al 2005; Bourguignon et.al 2003). Unconditional programme evaluations 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, have concluded that all of these programmes in general help to reduce child labour, increase school enrolment and reduce drop-out rates, and improve health and nutrition outcomes in children (Edmonds and Schady 2009; Edmonds 2006; Case, Hosegood, and Lund 2005; Duflo 2003).

A plethora of evidence now exists on whether there is a trade-off between common forms of work and schooling, especially within the context of social assistance and schooling incentives. Child labour has a tendency to decline with household prosperity and the availability of schools and small incentives, such as providing children with a meal in school or giving parents subsidies, transfers and scholarships. The vast amount of literature that exists evaluating impacts indicates that many transfer programmes have successfully increased school attendance and reduced 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 to encourage schooling and reduce child labour have had unintended consequences (Cigno and Rosati, 2005; Edmonds, 2007).

In fact, some policies and programmes that have been implemented to increase schooling have actually increased the probability of children engaging in work. Thus, it is important to note that the empirical evidence on the causal effects of schooling, child labour and education assistance programmes can sometimes be ambiguous, and may have many different policy implications.

One of the objectives of this study is to test for intra-household flypaper effects (IFE) by examining the impact of an education cash transfer on child-level education expenditures in Indonesia. Education transfers are designed to improve child schooling and raise educational spending. The ability of such programmes to have a positive impact on individual children depends on how households choose to allocate the transfer among their members; interventions that target specific individuals in a household may become futile by reallocations of the resource away from the child. On the other hand, when transfers are not reallocated away from the intended beneficiary, this phenomenon is referred to as the intra-household 'flypaper effect' because the transfer 'sticks' to the child (like flies stick on flypaper).

Notwithstanding the large recent literature on the impacts of various social protection and transfer programmes on household welfare outcomes such as school enrolment and child labour, relatively little attention has been paid to studying the effect of such transfers on household expenditure patterns and their flypaper effects. Even the existing studies on intra-household flypaper effects are mostly on nutrition related outcomes, 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 reallocation of calories away from the child within the household in response to the feeding programme. The total daily calorie intake of the child rises almost one for one with the school meal calories. Afridi (2005) analyses the impact of a school feeding programme on daily caloric consumption of children in India and investigates factors which affect the magnitude of the reallocation of resources. The study finds that nutrient intake of programme participants increased by 49 to 100 percent. Shi (2008) studies the existence of reallocation of resources inside the household after a child receives a subsidy intended to cover the school fees in rural China. The study concludes that educational fee reductions were matched by increased voluntary educational spending on the same children receiving fee reductions, providing strong evidence of an intra-household flypaper effect.

Therefore as government transfers and subsidies are becoming increasingly popular in developing countries, one critical policy question that arises and needs to be investigated is to what extent the intended beneficiaries of such public transfer programmes actually benefit from these policy initiatives. It is vital to investigate whether government transfers to a specific household member, such as to a poor student, "stick" to that specific student, child, etc. Or, as the theory of altruism within the household (Becker, 1974, 1981) implies, where households pool their income and redistribute it among the members, intra-household resource reallocation in response to an individual welfare scheme may nullify any expected gains to the recipient of the transfer.

In this paper we first analyse the decisions to attend school and to work. Because 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 attempting to ascertain the effect of child labour on schooling and to determine how various individual and household characteristics affect the chances that a child will go to school and/or participate in other activities which may interfere with schooling. Next, we investigate how the receipt of educational transfers, scholarships and related assistance affect the labour supply of children in Indonesia.

Finally, we test, for the first time, whether an intra-household flypaper effect exists for child-targeted transfers by investigating the impact of Indonesia's education cash transfer programme for poor students on both household and child-level voluntary education expenditures. For most households in Indonesia, with 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. If the IFE exists, we would expect parents to spend the extra money especially on the voluntary education expenditure of the child receiving the transfer. We will utilize a rich dataset that contains child-specific education expenditures, enabling us to examine if the education cash transfer increased voluntary education expenditure and whether the flypaper effect existed within the household.

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

Almost all educational indicators have improved remarkably over the past 40 years in Indonesia (Suharti 2013). Both net enrolment rates for primary and junior secondary schools experienced significant increases during this period of time. The net primary school enrolment rate increased from 72 percent in 1975, reaching 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 4 to 6 year olds have attained some type of early learning or education (up from 25 percent a decade earlier). The improvements in school enrolment rates have brought Indonesia nearer to its neighbours, resulting in a higher than expected senior secondary enrolment rate for its level of GDP per capita. As an example, Indonesia's enrolment rates profile has paralleled that of China, with higher than expected secondary education enrolment rates for its level of income, but it is still behind in higher education. Indonesia is also one of the few countries in the world that was able to increase public expenditure on education by over 60 percent during the last five-year period. A constitutionally mandated allocation of (a minimum of) 20 percent of government spending towards education (hereafter "the 20 percent rule") was introduced by the government of Indonesia in 2003. This requirement led to an enormous increase in resources for education, making education the largest type of government expenditure after fuel subsidies (World Bank 2013).

However, against the backdrop of education as a whole showing inspiring outcomes, the distribution of the benefits of education policy in some respects still do not appear satisfactory. For example, a study conducted by Arza Del Granado, et al. (2007) found the existence of a wide gap between poor and rich groups at the junior and senior secondary school levels. Children from poor families are 20 percent less likely to be enrolled in junior secondary education than children from wealthier families. 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 schooling opportunity across Indonesia. Firstly, children from poor families were found to have difficulties in paying for transportation costs associated with schooling. Secondly, in some parts of the country relatively low recognition among parents regarding the importance of education were also a reason for children not attending school. Finally, cultural factors also play an important role in some instances; for example, the Madurese tribe in Pontianak traditionally arrange their daughters to be married as soon as they finish primary school. Hardjono (2004) investigated the influence of poverty on school dropouts in two provinces in Indonesia: Bali and West Nusa Tenggara. The study found that one of the primary reasons for the very high primary school completion rates among Balinese children is the culture of prioritising education among the Balinese. This was in contrast to a relatively higher percentage of children not finishing primary school in West Nusa Tenggara, as a result of the low regard for education among parents. Most importantly, Hardjono's study found that non-continuation into 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.

Since the 1998 economic crisis, the government of Indonesia in partnership with several development organisations has been implementing educational assistance and transfer programmes at several points in time, in order to address the financial difficulties and various other constraints faced by parents and children with respect to schooling. In recent years, there has been a small but growing literature evaluating education assistance programmes in Indonesia, especially investigating the effects on school enrolment and drop-out 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 at that time many households would have found it difficult to keep their children in school and thus drop-out rates would be high. The study found scholarships to be effective in reducing drop-outs at the level of schooling at which students were historically most at risk of dropping out, which is lower secondary school. Sparrow (2007) investigated the impact of an Indonesian scholarship programme implemented in 1998 to preserve access to education for the poor during the economic crisis. The study found the programme to have increased school enrolment, especially for primary school-aged children from poor rural households. Sparrow's paper also concludes that the scholarships 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) which was introduced in 2008 and covers all education levels from elementary school to university. The key objectives of the programme are to remove barriers preventing marginalised students from participating in education, to assist poor students in gaining appropriate access to education services, to prevent school drop-outs, to help in meeting the educational needs of at-risk children, as well as to support the Government's Nine Years Compulsory Education programme. The BSM programme provides cash transfers to cover associated 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, nor from local governments or the schools themselves.

During the initial 2008-2009 period, targeting for the BSM programme lacked clarity in the selection of beneficiaries. The number of beneficiaries was determined by the availability of funds received by provincial authorities from the Ministry of Education, and the selection of beneficiaries was often left to local education offices or headmasters of the schools. At the national level, there was an understanding that the scholarship needed to prioritise children whose families were in the conditional cash transfer programme (PKH programme, described below) as these families were very poor. Disbursement of the transfer was done at the beginning of the academic year (usually in the months of July or August).

In 2009, the BSM programme budget of IDR 1.6 trillion covered 3.6 million students. At present, the programme covers 8 million students across the country, ranging from primary school to tertiary education level. In 2009, the unit cost per scholarship ranged between IDR360,000 to IDR720,000 depending on the level and type of school the student was attending. Poor students enrolled in madrasah (Islamic) schools received a higher amount than those in regular schools. To put these numbers into perspective, average household per student spending on primary education was IDR 362,000 per year in 2009. In contrast, average household per student spending on junior secondary education was IDR 653,000 in 2009, while household spending on senior secondary education was IDR 1,438,000. Thus, for the poorest households the scholarships are quite significant contributions to monthly income and cover a large part of the expenditures on education.

3. Analytical and Conceptual Framework

We first develop the theoretical model behind our schooling and labour supply decision of children and assume 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 the child's school attendance and X is the vector of exogenous child, household and demographic characteristics which 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 cost of production and household consumption, the household budget constraint can be stated as:

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

Where P_c, P_s and W are price of consumption, schooling and child labour.

The household utility maximisation problem can be formally stated as:

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

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

The educational cash transfer (M) can be introduced by simply re-writing a new budget constraint that maximizes U as:

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

We assume household income-Y, 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 first-order conditions of the model yields several outcomes. 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 that a child attends school and reduces the numbers of hours worked. Similarly, when there are high returns to child labour (increased work opportunities, higher wages), schooling and leisure will fall and the supply of labour will rise. Employing this framework shows how child labour can be a function not only of income and wealth but also of parents' occupation, characteristics and preferences. It is also evident that household consumption-*C* (which includes consumption of voluntary educational goods) will increase with income, and that a cash transfer will not alter relative prices and will only induce an income effect.

4. Empirical Strategy

We begin with the econometric specification for 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 both activities would be competing for the child's time. We use a bivariate Probit model that explicitly takes this interdependency into account and test the likelihood of children working and going to school, conditional on varying individual and household characteristics. A bivariate Probit model allows for the existence of possible correlated disturbance between two Probit equations. It also allows us to test whether the joint estimation has additional explanatory power compared to using an univariate Probit estimation for each decision (Ersado 2002).

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

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

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

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 $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ are vectors of individual and household covariates that affect 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:

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

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.

Next, 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 which contains individual-specific education expenditures, enabling us to examine if the education cash transfer increased voluntary education expenditure and whether the flypaper effect existed within the household. In this study, we accept the existence of the intra-household flypaper effect only if there is a statistically significant increase or positive impact on the voluntary education expenditure of a child receiving an education cash transfer.

The basic problem in treatment evaluation begins with the inference of a causal relationship between the treatment and outcome. In a canonical single treatment setting, one can observe $(Y_i,\ X_{i,}\ D_i)$, $i \ldots, N$ 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 observe both states for any given individual simultaneously. 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'.

Firstly, we 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. The thinking behind random assignment is that by randomising treatment assignment, the group attributes for the different treatments will be roughly equivalent and therefore any effect observed between treatment groups can be linked to the treatment effect and is not a characteristic of the individuals in the group. Following Caliendo et.al. (2005), 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 where:

$$\Delta = Y_1 - Y_0$$

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 state (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 immediately 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 $E(Y_0|D = 1) = E(Y_0|D = 0)$ holds, one can use the nonparticipants as the comparison group. But with non-experimental data this condition will not hold, since the components which determine the receiving of the transfer also determines the outcome variable of interest (Caliendo et.al. (2005)). 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, gender, etc.). In this case, selection bias can be eliminated simply by including the relevant variables in the outcome equation. But in practice, unobservable characteristics affecting participation can also influence outcomes, expressing the ATT 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) which 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 causal 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 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 are both treated and untreated individuals. In other words, for each participant there is another non-participant with a similar X. A practical constraint which 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 with matching on the propensity score $P(X)$, the probability of participating in a programme could achieve consistent estimates of the treatment effect in the same way as matching on all covariates[2].

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 criterion for minima and maxima comparison is to delete all observations whose propensity score is smaller than the minimum and larger than the maximum in the opposite group. Having

[2] The proposition by 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 $\Pr(D_1, D_2\, , D_N \,|\, X_1, X_2, \ldots X_N) = \prod_{i=1,\ldots N} P(X_i)^{D_i} (1 - P(X_i)^{1-D_i}$ 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: $\Pr(D = 1|X = x) = \Phi(X'\beta)$.

enforced the common support region, the final 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 $0 < w(i,j) \leq 1$ is the weight given to comparison unit j in the construction of the 'counterfactual' for treated unit i. Results will be presented for four matching algorithms: nearest-neighbour 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-neighbour 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 caliper matching. The caliper matching method chooses the nearest-neighbour within a caliper of width δ, so that $\{j: |P(X_i) - P(X_j)| < \delta\}$ where $P(X)$ is the propensity score. Therefore, caliper 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 caliper matching which is referred to as radius matching. In radius matching the idea is to use not only the nearest-neighbour within each caliper but all of the comparison members (non-participants) within the caliper. 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. For the sake of comparison and to assess the sensitivity of the estimates to the choice of the matching algorithm, we will present results for all four matching methods.

5. Data

This study employs the Indonesia Social and Economic Survey (Susenas) from July2009. Susenas is a nationwide survey conducted to collect information on social and economics indices. It 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 includes an education cost data module containing various expenditure categories for each school-enrolled child. Descriptive statistics for all key variables are given in the Appendix.

For all child-level educational expenditure analysis, we use children from the ages 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 either to earn a living for themselves or to supplement household incomes. Children engaged in housekeeping activities and who perform household chores – such as cleaning, cooking, or washing – are thus not regarded as child labour in this study. Consistent with previous studies on child labour and in accordance with the law, children below 15 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 10 years, our sub-sample for child labour supply will be for all children between the ages of 10 to 14 years. The treatment variable for children to receive 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?". Thus for both the child labour supply and school attendance, bivariate probit regressions and ATT treatment effects of educational assistance on child labour estimates will be based on the sub-sample of all children between the ages of 10 to 14 years. The full sample of children aged 6-18 will used for ATT treatment effects of educational assistance on child education spending.

The Susenas survey collects information on a broad range of topics including demographic characteristics, household income and expenditure, literacy and education, household amenities and employment. Demographic characteristics that include both the individual and household head's age, gender, marital status and the number of males and females in different age categories within the household were used in the analysis. The dependency ratio was calculated as the ratio of the number of individuals aged below 14 and above 65 to the number of working household members aged 15-64. Employment characteristics of the household head used in the analysis included the employment sector, such as agriculture, industry, services, etc. Information on housing characteristics comprised standard indicators such as ownership, roofing, wall and floor conditions, type and access to water, electricity and sanitation. Finally, we measure poverty, identifying poor households by employing the provincial poverty lines for rural and urban areas, which were constructed by the Indonesian Central Bureau of Statistics. After adjusting for spatial price differences, the official national poverty line was estimated at IDR. 224,602 for the July 2009 Susenas.

6. Empirical Results

We first present the results of the decisions to attend school and to work. Because the school and work decisions are closely related, they are treated as simultaneous decisions which were analysed in the context of a bivariate Probit model. We begin by attempting to ascertain the effect of child labour on schooling and to determine how various individual and household characteristics affect the chances that a child will go to school and/or participate in other activities which may interfere with schooling. Next, we present the impact of the educational cash transfer on education expenditure and on the labour supply of children in Indonesia.

Table 1 gives the estimated results from the bivariate Probit regressions. Proxies for the demand for market and domestic work were included in the bivariate 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 be interpreted to imply the existence of some unobserved factors that increase the probability of attending school decrease the probability of working. Schooling and child labour are thus competing activities. According to Table 1, the probability of working increases with a child's age. The age variable catches the effect of the absolute returns to (?) the labour of a child of a given age. This could be interpreted as an indication of the fact that the accumulated human capital 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. Also evident from Table 1 is how being a male child increases the probability of a child being involved in labour activities.

We assumed that parents' ages would also have an impact on child activities. According to Table 1, the household head's age has a decreasing effect on their children's labour supply and an increasing effect on schooling. Younger parents are likely to be at a more monetary-constrained point in their lifecycle and may have less capacity to meet school expenses, and have a greater need for their children's labour. Results also suggest that higher levels of education of the household head decrease the probability of a child working while at the same time increasing school attendance. There is ample empirical evidence in the literature that the education of the parents decreases the probability of a child 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 is common in developing countries, we use proxies that capture both these types of activities. We use household heads being in agriculture to capture market work, since usually most children work close to home, which means 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 workload for children with or without directly affecting the parents' 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 are less likely to attend school. Similarly, children living in houses with poor sanitation are also more likely to work and not attend school.

The nature of the household heads' occupation also matters: if the parents are unemployed or in irregular employment, a child's labour may be considered a substitute for their labour or for hired labour, thus decreasing the chances of attending school. Furthermore, the effect of the father being in the informal sector as opposed to being a formal employee is important because it raises the probability that the child will also be an unpaid family worker. Consistent with this expectation, our results show that when the household head is in the informal sector, the probability of children supplying labour is also higher.

We examine the effects of household composition on children's work and schooling via the household dependency ratio. Findings indicate that children are more likely to engage in work and not attend school with higher dependency ratios within the household. The probability of children working was also found to be more in rural areas than in urban areas, which is a global and general characteristic of child labour. Table 1 also confirms Basu and Vans' (1998) luxury axiom that poverty drives child labour. Usually, the joint probability of working and not going to school drops off sharply with household wealth. Children in poor households were found to have a higher probability of working and lower school attendance. This result is generally consistent with the theoretical literature which concludes that poverty is one of the main hypotheses explaining child labour.

The Appendix presents the results for propensity to receive an educational assistantship for the individual samples stratified by expenditure quintiles: bottom 20^{th} percentile, 20^{th}-40^{th} percentile, 40^{th}-60^{th} percentile, 60^{th}-80^{th} percentile, top 20^{th} 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 differ significantly with regard to the choice of control variables. In a standard regression, preference is usually given to variables which one can argue are exogenous to outcomes, but in propensity score matching the primary interest is in covariates (not good predictors), thus including variables even when they are poor predictors. Analytic results and simulations by Rubin and Thomas (1996) suggest that variables with weak predictive ability for outcomes can still help minimise bias in estimating causal effects with propensity score matching. In essence, the main purpose of the propensity score estimation is not to predict selection for treatment but to balance covariates and get closer to the observationally identical non-participant.

Table 1: 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

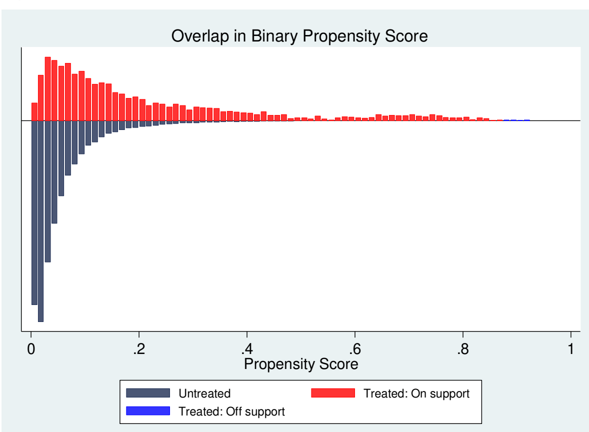
*** p<0.01, ** p<0.05, * p<0.1

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: $y_1 = \begin{cases} 1\ if\ y_1^* > 0 \\ 0, otherwise \end{cases}$, $y_2 = \begin{cases} 1\ if\ y_2^* > 0 \\ 0, otherwise \end{cases}$.

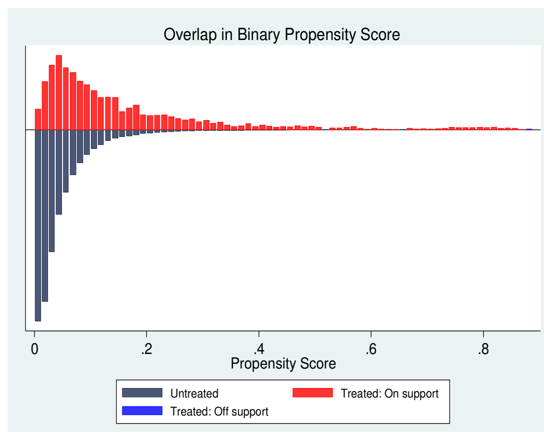
Next, the common support region was examined by plotting a histogram of the propensity score. The common support is the region where the propensity score has a positive density for both treated and non-treated units. On average, observations lost due to common support were around 0.05% for each quintile. Figure 1 gives the frequency distribution of the propensity scores based on Probit regression estimates reported in the Appendix 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 a severe common support problem does not exist. It is evident from Figure 1 that any combination of characteristics observed in the treatment groups can also be observed among the control groups in all estimated quintiles. In all quintiles, the probability mass in the treated group is located on (?) the same side as that of the non-treated group. Since the main purpose is not to identify 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 of the same range. The upshot of Figure 1 is that there is sufficient common support to provide strong evidence for causal inference.[3]

Figure 1: Overlap and Distribution of Propensity Scores

Quintile-1

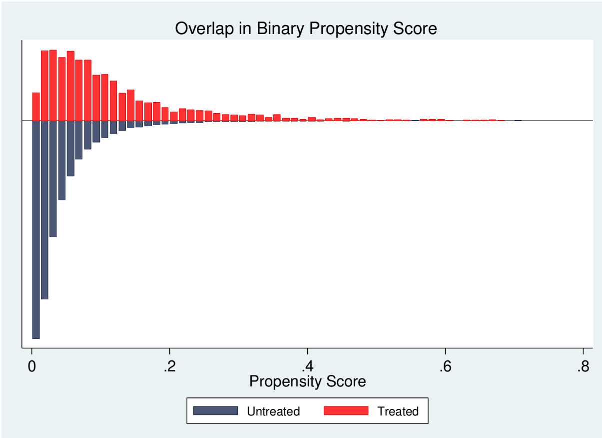


Quintile-2

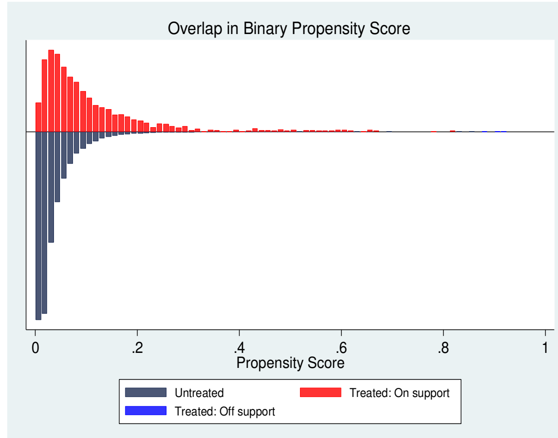


[3] We also performed tests on covariate balancing. It was found that the differences between the households between the treated and untreated groups are quite small after matching, and that matching removed any bias that existed for almost all covariates. A t-test of equality of means in the two samples of participants and non-participants revealed that there is no systematic pattern of significant differences between the covariates in the treated and non-treated groups after conditioning on the propensity score. The test results and the exact number of individuals lost due to common support requirement are available upon request from the authors.

Quintile-3



Quintile-4



Quintile-5

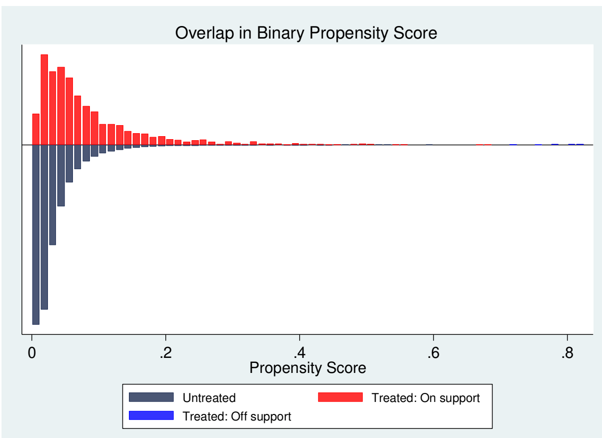


Table 2 reports the estimated mean impacts on children's voluntary educational spending. The estimates of the average treatment effect on the treated (ATT) are obtained via propensity score matching, using four matching algorithms and imposing the 'minima and maxima' common support. The results for the mean impact indicate that receiving educational transfers and assistance significantly increases education spending for the bottom three quintiles, although the magnitude varies by matching method. For all quintile groups, children receiving educational assistance or transfers spend more at the margin on education than they would have spent without any educational support. For example, the nearest neighbour matching algorithm in Table 2 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 on expenditure on education. These large marginal increases in 'child-specific' education spending arising from educational transfers and scholarships are thus confirmatory evidence of the existence of an intra-household flypaper effect.

However, these gains are not visible for the children in the 80^{th}-100^{th} percentile, implying that even without receiving any additional educational support there would be no difference in voluntary educational spending for children in the richest quintile. Thus, selection of only the poor and vulnerable households becomes a pre-requisite and vital component in the design and success of any educational support programme. The poorest and most vulnerable children should be given special priority in selection and need to be regularly assessed to maintain the focus on poor and low-income programme participants. From the standpoint of the economy at large, these educational assistance-inspired additional expenditures on children's voluntary educational goods represent significant productive investment having critical second- and third-round effects on health, total factor productivity, etc.

Table 2: 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)
	<u>Kernel</u>					
	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)
	<u>Kernel</u>					
	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)**
	<u>Kernel</u>					
	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)
	<u>Kernel</u>					
	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 3: 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)

Table 3 presents the results of the impact of educational transfers, scholarships and assistance on the probability of children working. 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 generous enough to reduce the amount of time spent outside school working, especially for the poor. Results based on Table 3 clearly show that receiving educational transfers and assistance have a significant negative impact on children's work for the poorest. For instance, receiving education transfers and assistance reduces the probability of children working in the poorest households by one to three percentage points. These results again confirm that benefits are heavily skewed towards the poor - the two lowest quintiles of the participating children receive the largest share of education assistance benefits.

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

6. Conclusion and Policy Implications

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

Several key findings emerged from the study. We found strong effects on the reduction in the labour supply of children at the bottom of the welfare distribution 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 they would have spent without any additional educational support.

These large marginal increases in education spending at the child-level arising from educational transfers and scholarships are thus confirmatory evidence for the existence of an intra-household flypaper effect. Educational transfers, scholarships and assistance have been associated with increased voluntary educational spending on the same child receiving the 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 streams of income and support, then our findings are consistent with the permanent income hypothesis, which generally finds that the marginal propensity to invest out of transitory income (transfers, subsidies, remittances, etc.) is higher than that for permanent income such as salaries (Paxson,1992).

It is evident that well-targeted and well-administered educational assistance programmes which lower the price of schooling can be successful in inducing children to spend less time on work, especially for the poor in Indonesia. Since the beneficial impacts of education transfers and support programmes are mostly concentrated among the poor and vulnerable, this highlights the benefits from identifying and selecting only poor and vulnerable households in any targeted education support intervention. Our results are particularly relevant for understanding the role of cash transfers and educational assistance in middle-income countries where enrolment rates are already at satisfactory levels, but the challenge is to keep the students in school at post-primary levels. Relatively higher marginal propensity to invest in educational goods among educational transfer and assistance- receiving households in Indonesia will no doubt be beneficial in augmenting human capital in the country at large.

In sum, our findings suggest that educational transfers, scholarships and assistance are successful in increasing household investments in educational goods and simultaneously reducing children's labour supply by providing an effective incentive to forgo the labour income. Our results suggest that transfer schemes in Indonesia could be further improved and redesigned to increase and influence children's educational spending and time spent in school; for example, larger transfers, incentives for completion and payments which vary with the spatial remoteness of the household could be considered. According to De Silva (2014), districts with low levels of school enrolment rates in Indonesia are characterised by high levels of poverty and low economic growth and output. Suryadarma (2006) found that children living in rural areas have less access to junior secondary education. Households living in remote, poor and backward regions in terms of economic performance (such as Papua, Kalimantan and Sulawesi) need special priority in the allocation of education scholarships. Allocation of government funds for the education transfer programme needs to disproportionately target lagging regions with severe poverty and low economic output. Thus, raising the quota of scholarships and provision of additional fiscal transfers to local government education budgets – with due consideration of spatial remoteness, regional disparities and economic backwardness – needs to be considered an important policy priority.

A special emphasis could be placed on rural areas, with the condition that children in the households receiving the educational transfers must attend school and are not allowed to work at all. Improved targeting combined in particular with expansion of coverage and sharper geographical targeting of the programme, plus increasing the real value of the transfer, are possibly the most feasible policies for enhancing impacts on the educational achievements of children.

The findings of this study lend support to the growing view in the literature that educational transfers, scholarships and related assistance can have a positive impact on economic development by increasing the level of investment in human capital. Finally, 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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Appendix – Descriptive Statistics

	Obs	Mean	Std. Dev.	Min	Max
Receive education transfer	248101	0.04	0.19	0.00	1.00
Total education expenditure (IDR)	248101	359548	346781	2000	20700000
Expenditure on books and stationary (IDR)	248101	67137	104054	1500	4500000
Expenditure-other support material (IDR)	248101	26900	62561	3000	3600000
Expenditure on tutoring (IDR)	248101	23089	104964	3500	5000000
Child-working	117561	0.07	0.25	0.00	1.00
Child-inschool	117561	0.92	0.26	0.00	1.00
Informal-HHH	117561	0.65	0.48	0.00	1.00
Poor sanitation	117561	0.26	0.44	0.00	1.00
Dependency Ratio	117561	1.05	0.71	0.09	9.00
Poor household	117561	0.19	0.39	0.00	1.00
Child-female	248101	0.49	0.50	0.00	1.00
Child-age	248101	11.28	3.36	6.00	18.00
Urban	248101	0.35	0.48	0.00	1.00
Age-Household Head (HHH)	248101	44.50	10.08	10.00	98.00
Female-HHH	248101	0.08	0.27	0.00	1.00
Share male age 0-6	248101	0.04	0.09	0.00	0.57
Share female age 0-6	248101	0.04	0.08	0.00	0.60
Share males age 6-17	248101	0.21	0.16	0.00	1.00
Share females age 6-17	248101	0.20	0.16	0.00	1.00
Share females age 18-64	248101	0.25	0.10	0.00	1.00
Share males age 65+	248101	0.01	0.04	0.00	0.67
Share females age 65+	248101	0.01	0.05	0.00	0.67
HHH in Agri	248101	0.45	0.50	0.00	1.00
HHH in mining	248101	0.02	0.14	0.00	1.00
HHH in elec/gas/water	248101	0.00	0.07	0.00	1.00
HHH in construction	248101	0.06	0.24	0.00	1.00
HHH in trade/restaurent	248101	0.12	0.33	0.00	1.00
HHH edu-sd	248101	0.31	0.46	0.00	1.00
HHH edy-smp	248101	0.16	0.37	0.00	1.00
HHH edu-sma	248101	0.23	0.42	0.00	1.00

Appendix – Descriptive Statistics (cont.)

	Obs	Mean	Std. Dev.	Min	Max
House-own	248101	0.83	0.38	0	1
House-lease/rent	248101	0.06	0.23	0	1
House-freelease	248101	0.02	0.15	0	1
House-official	248101	0.02	0.13	0	1
Floor-not soil	248101	0.90	0.30	0	1
Wall-concrete	248101	0.55	0.50	0	1
Wall-wood	248101	0.36	0.48	0	1
Roof-concrete/tile	248101	0.36	0.48	0	1
Roof-iron sheet	248101	0.49	0.50	0	1
Roof-asbestos	248101	0.04	0.20	0	1
Water-branded recycled	248101	0.09	0.28	0	1
Water piped meter	248101	0.16	0.37	0	1
Water-terrestial/pump	248101	0.12	0.33	0	1
Water-protected/well	248101	0.27	0.45	0	1
Water drinking-buy	248101	0.28	0.45	0	1
Electricity-PLN	248101	0.79	0.41	0	1
Electricity-non PLN	248101	0.08	0.26	0	1
Electricity-parafin/petro	248101	0.02	0.12	0	1
Toilet-tank/septic	248101	0.50	0.50	0	1
Toilet-river/lake/sea	248101	0.18	0.38	0	1
Toilet-pithole	248101	0.20	0.40	0	1

Appendix: 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

Appendix: **(Cont.): Binary Propensity Score Model,** $\mathbf{Pr}(\boldsymbol{D}=\mathbf{1}|\boldsymbol{X}=\boldsymbol{x})=\boldsymbol{\Phi}(\boldsymbol{X}'\boldsymbol{\beta})$

	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

Note: District dummies were included in all estimations but not reported.