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Impacts of Indonesian Bantuan Siswa Miskin (BSM) on Senior Secondary Child Schooling and Working

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Abstract

Educational inequality is one of the most prevalent problems faced by developing countries. The group that faces the biggest gap in terms of access to education is adolescents aged 16-18 years. This paper analyses a sample of 16-18 year olds to investigate the impact of the Indonesian's Conditional Cash Transfer, Bantuan Siswa Miskin (BSM), on recipients and their non-recipient siblings. The findings suggest that the BSM increases the schooling of the recipients. However, there is no significant impact on the non-recipient siblings' schooling. Further, the program succeeds in significantly reducing the incidence of child labour for recipient and non-recipient girls, with no such impact evident for boys.

Keywords: Child schooling; Child working; Conditional cash transfer; Bantuan Siswa Miskin; Indonesia; Coarsened exact matching

JEL Codes: J82 · I21 · I38

1. Introduction

Child labour and inequality in educational opportunities remain chronic problems in many developing countries where poverty is prevalent. While education has been recognised as one sector of human capital that must be improved to break the chain of poverty in households, poverty itself curtails individual's ability to achieve higher education lev-

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els (Pohan et al., 2013). Further, poor and out-of-school children are more likely to work in order to help their parents finance basic household needs. These children are exposed to dangers in the working environment such as physical or sexual abuse, harmful chemical exposure, and long hours of work (Bima and Marlina, 2017). Such problems are most severe for the children in the high school age cohort (16-18 years of age) as higher education level is usually associated with higher costs (Suharyo and Widyanti, 2006).

The major cause of difficulty for the poor in accessing education is financial constraints. Bank (2012) found that poor families spend approximately 20 percent of their total expenditure for out of pocket costs, including uniforms and transportation. Furthermore, for the poor, the opportunity cost of attending school is significant: they would forego potential income if they were to attend school instead of working. Therefore, the cost of education for the poor is doubly expensive. Thus, Conditional Cash Transfer (CCT) programs have been proposed as a means to improve school participation and reduce the prevalence of child labour.

In this paper we study the effect of the Indonesian national CCT program, *Bantuan Siswa Miskin* (BSM), on the school enrollment and labour force participation of children aged 16-18 years, the cohort that is most likely to be out-of-school. Specifically, using longitudinal data from Indonesian Family Life Survey (IFLS), we employ the Difference-in-Differences (DiD) estimator on a pre-matched sample to answer the following questions: (1) Does BSM affect the schooling and working of recipient children? (2) Does program participation affect the schooling and labour choices of non-recipient siblings? As BSM is a natural experiment, the program participation assignment is non-random. To address the problems of selection bias, we pre-process the sample using Coarsened Exact Matching (CEM) methodology by Iacus et al. (2012).

Indonesia provides a unique case with its educational CCT program, *Bantuan Siswa Miskin* (BSM). Unlike most CCT programs in other countries, which are implemented only in a subset of areas usually chosen based on some poverty indicators, the BSM is implemented nationally in all districts and cities of Indonesia. Further, the BSM has a wide range of targeted school levels, from elementary to senior secondary school, while, most programs in other countries have less coverage. For example, in the Nicaragua

RPS and Honduras PRAF, eligible children are younger children, who are initially more likely to enrol in school (Galiani and McEwan, 2013; Maluccio and Flores, 2005). Some programs target older cohorts that are less likely to attend school, such as Cambodia Education Sector Support Project Scholarship Program (CSP) and Colombian Conditional Subsidies for School Attendance. These two programs target children who had completed fifth and sixth grade respectively (Barrera-Osorio et al., 2011; Ferreira et al., 2017). However, the scope of these programs is limited. The CSP Program is only implemented in 100 schools, which are located in areas with a high poverty rate, out of about 800 middle schools operated in Cambodia. Meanwhile, the Colombian experiment analysed by Barrera-Osorio et al. (2011) only ran in two out of twelve localities in Bogota, Colombia.

This paper differs from the existing literature related to the impacts of CCTs on child's schooling and working in the following ways. First, we focus on the cohort that is most unlikely to attend school and most likely to participate in labour force: the cohort of 16-18 year olds, normally in senior secondary school level. Most existing papers study the effect of CCTs on younger children's enrollment, usually in primary or middle school (Behrman et al. (2005); Cardoso and De Souza (2009); Ferro et al. (2010); Galiani and McEwan (2013); Maluccio and Flores (2005)). One randomized control study in Mexico by Schultz (2004) looks at the effect of Progresa on children's schooling for those aged 6-18 years old. However, Progresa was only available to children in third to ninth grade and implemented only in two-thirds (314 out of 495) of the localities.

Second, this study also investigates the impact of BSM on senior secondary school children who did not receive the subsidy while their siblings did. This topic has not been fully explored in the literature. The findings of studies regarding children of younger age that do look at CCT spillover effects on siblings remain ambiguous. In an intention-to-treat framework, Lincove and Parker (2015) find that, besides providing a positive effect for eligible children of 7-13 years of age, Nicaraguan Red de Proteccion Social (RPS) also benefited ineligible older brothers, increasing schooling and leading to fewer hours worked. By contrast, Ferreira et al. (2017) show that the CCT in one area of Cambodia (CESSP scholarship program) has no effect on the untreated children's participation in schooling and working. Meanwhile, the Colombia experiment by Barrera-Osorio et al. (2011) shows that CCTs might exhibit negative effects on the non-treated siblings.

Third, the IFLS dataset enables us to avoid bias from the effect of other scholarships received by the BSM recipients. To do this, we control for whether the children receive school benefits from any other source, as there is no requirement that BSM recipients must not receive any other school subsidies.

In terms of methodology, our paper differs from the literature by addressing the non-random assignment with a pre-processing technique. Commonly, studies using data from a non-randomized experiment employ the Propensity Score Matching (PSM) approach to match observations with a similar covariates' distribution (Stuart, 2010). However, the PSM approach does not guarantee to reduce the imbalance between the treatment and control groups (Iacus et al., 2012). To address this problem, we use Coarsened Exact Matching (CEM) by Iacus et al. (2012). CEM is used to mimic ideal exact matching to match a non-treated unit that has exactly similar covariate values with a treated unit, by coarsening the covariates. Further, unlike other similar studies that usually use univariate Probit or Logit models, we apply a bivariate Probit model as in Baryshnikova and Jayawardana (2019). Since both decisions, going to school and working, have time as a constraint, there might be a correlation between the unobserved factors affecting both variables. Thus, the bivariate Probit model is used to obtain an unbiased estimator of the BSM effect on the decision of children to go to school or/and to work. Lastly, as we do not know the exact assignment rules for BSM, there exists some model uncertainty. We employ Bayesian Model Averaging (BMA) as a robustness check. The BMA approach addresses this problem by calculating a posterior distribution over coefficients and models (Montgomery and Nyhan, 2010).

The results reveal that receiving BSM is associated with a rise in the probability of schooling for both boys and girls, aged 16-18 years, with treated girls benefiting more than treated boys. Besides increasing schooling enrollment, the BSM also negatively affects the likelihood of girls going into work, though there is no such impact for boys. As a result, the rise in the probability of schooling for girls (21.6 percentage points) is substantially larger than that for boys (11 percentage points). Regarding untreated siblings, the estimation results show that the presence of treated siblings produces improvement only in the labour outcomes of untreated girls aged 16-18 years. If a non-treated girl has a treated sibling in the household, the probability of the girl going into work decreases by 8.4 percentage points. In contrast, there is no such impact for untreated boys. Further, there is no evidence to support the notion that the BSM benefit received by treated siblings imposes effects on the schooling of untreated siblings, for either boys or girls.

The rest of this study is organised as follows. Section 2 provides background on the educational CCT programs, children's schooling and working in Indonesia, and the Indonesian BSM program. Section 3 discusses the data, sample, and variables used for the analysis, followed by the methodology in Section 4. Section 5 presents the main results and robustness checks. Finally, Section 6 provides a summary and conclusion for the study.

2. Background

2.1. *Impacts of Educational CCT Programs*

In developing countries, Conditional Cash Transfer (CCT) has become a widespread approach to alleviating severe poverty and its negative impact on child schooling and working (de Hoop and Rosati, 2014). The growing literature linking educational CCT programs with improving child schooling and working outcomes has consistently found that educational CCT programs across developing countries succeed in improving schooling outcomes. These programs have increased attendance rates, enrolment rates, and continuation rates, while decreasing dropout rates and repetition rates (Attanasio et al., 2010; Behrman et al., 2005; Cardoso and De Souza, 2009; Glewwe and Olinto, 2004; Maluccio and Flores, 2005; Schultz, 2004; Skoufias and Parker, 2001). However, to date there has been no study specifically examining the impact of the Indonesian educational CCT program, Bantuan Siswa Miskin (BSM) on school attendance or enrolment rates. Though there exist several studies regarding the BSM, these mainly discuss the impact on school achievements through examination scores (Purba, 2018; Yulianti, 2015).

Although CCT programs are often not specifically designed to solve the child labour issue, it is expected that increases in schooling lead to a decrease in working. Many scholars have found that CCT programs in developing countries have lowered the participation of the treated children in the labour force, measured either by the probability of engaging in work or by the number of hours the child spent in work (Attanasio et al., 2010; Behrman et al., 2005; Cardoso and De Souza, 2009; Ferro et al., 2010; Galiani and McEwan, 2013; Maluccio and Flores, 2005; Skoufias and Parker, 2001). However, there is also evidence from Honduras' CCT program (PRAF II) that the subsidy only reduced the child labour incidence by 0.5 percent, and so is insignificant (Glewwe and Olinto, 2004). Considering literature relating to the Indonesia, De Silva and Sumarto (2015) showed that educational cash transfers and assistance programs have significantly reduced the number of hours spent on income-generating activities by children in Indonesia. However, that study examines all Indonesian cash transfers and assistance programs as a whole, instead of focusing specifically on the BSM.

While the effects of the program on the treated children's wellbeing have been well explored, the potential impacts of CCT on siblings remain undetermined. Studies investigating this topic for younger children have produced mixed results. Lincove and Parker (2015), using the data from the Nicaraguan Red de Proteccion Social (RPS) program, found that, besides providing a positive effect for eligible children of 7-13 years of age, the RPS also benefited ineligible older brothers, increasing schooling and leading to fewer hours worked. By contrast, an experiment in Colombia conducted by Barrera-Osorio et al. (2011) revealed that the CCT program might impose a negative effect on the schooling of non-recipient children whose sibling received the program benefit. The experiment found that the educational participation rate of untreated children whose sibling was treated by the program tended to be lower, compared to that of untreated children whose siblings were also not treated. Meanwhile, evidence from Cambodia suggested that untreated children's participation in schooling and working was unaffected by that country's CESSP Scholarship Program (Ferreira et al., 2017).

There are three potential effects of CCT on families as presented in the theoretical model by Ferreira et al. (2017). Firstly, the conditionality of the CCT could decrease schooling costs only for the eligible children, which is called a substitution effect. Secondly, the transfer could impose an income effect that positively affects all siblings. Thirdly, there is the possibility that, in order to send their eligible children to school, parents may substitute the labour of the eligible children for the ineligible children. This displacement effect would favour the eligible children, but negatively affect the ineligible siblings who are forced into substituting the labour. Summarising these three effects, the CCT is expected to positively affect the eligible children, but have ambiguous effects for ineligible siblings. The ultimate effect on ineligible siblings depends on the magnitude of the income and displacement effects. With this in mind, this study aims to contribute to the topic of the effect of CCT programs on untreated siblings.

2.2. *Child Schooling and Working in Indonesia*

Indonesia is a country with a large youth population. More than one-third of Indonesia's population, approximately 85 million individuals, are children, and these children have a crucial role in the country's sustainable growth and development. However, children in Indonesia face many challenges. UNICEF (n.d.a) has reported that many Indonesian children suffer from poverty and inequity, hunger and disease, violence, and climate change, and these problems have inevitable adverse impacts on children's wellbeing, including on their education.

In order to improve education throughout Indonesia, since 1994 the government has launched multiple programs to develop the compulsory 9-year basic education system. Accordingly, access to primary and junior secondary schooling has rapidly increased, with the net enrolment rate for primary school reaching 97.58 percent by 2018. This achievement is beyond even the target of the government's Medium-Term Development Plan (*RPJMN*) 2019, which is 94.8 percent. However, the same success has not been repeated for the senior secondary level. According to BPS (2018), over the same period, less than 61 percent of children aged 16-18 years are enrolled in senior high school. There is a significant gap in enrolments between children living in urban and rural areas, with an enrolment rate of 64.65 percent and 55.93 percent, respectively. This rate is even worse for the 20 percent of poorest households, in which the net senior secondary enrolment rate only reached 47.53 percent. Therefore, in 2010 the Indonesian government initiated a 12-year compulsory education program to replace the previous 9-year compulsory education system (Priyono and Febriany, 2013). This initiative aims to provide education equality for youth aged 16 to 18 years.

The high number of children out of school is inevitably associated with other problems, including the high incidence of child labour. According to the 2016 National Social-Economic Survey (*Susenas*), more than 4.5 million school-aged children are out of school. Around 1 million children are out of primary and junior secondary school, and another 3.6 million children are out of senior secondary schooling. From those numbers of out-of-school children, approximately half are involved in the labour force. These working children are exposed to at least 14 serious hazards, ranging from working with dangerous objects to being engaged in unhealthy environments (UNICEF, n.d.b).

Moreover, there is also a group of children who attend school while also participating in some form of work. In 2018, about 7 of 100 students aged between 10-24 years old had performed work during the previous week. From a sample of children aged 16-18 years old, 8.58 percent who were enrolled in senior secondary school also participated in working activities (BPS, 2018). There was no significant gap between urban and rural areas. Meanwhile, in regards to gender, the percentage of working students was higher for boys (7.93 percent) than girls (6.06 percent). By school level, the incidence of working students was relatively high for senior secondary school students, at around 8.58 percent. Though these students still do manage to attend school, their time for education is limited as they are also forced to split it between working hours. Consequently, they have less time to study and do homework outside of school hours, and so their school performance tends to be lower compared to those who do not work (Priyambada et al., 2005). Given the low school enrolment rate and high participation in the labour force of children 16-18 years in Indonesia, we focus on examining this group of children.

2.3. *The Indonesian BSM Program*

Recognising the importance of education and the financial difficulties of the poor, governments in developing countries, including Indonesia, have over the last decade developed numerous programs to increase the ability of the poor to access education. The 1997-1998 financial crisis was a starting point for the Indonesian government to allocate more funds to finance the education sector (Kharisma, 2013). Various subsidy programs were launched to fund the 9-year (and later 12-year) education program, to ensure all children, including those from poor families, are able to access basic education, as mandated by Education Law Number 20. The Indonesian government effort started with reducing school fees by providing a grant for primary school and junior secondary school through the *Bantuan Operasional Sekolah* (BOS) program. However, this program could not cover out-of-pocket education costs, which represent a significant cost for the poor. Accordingly, the Indonesia government subsequently launched the *Bantuan Siswa Miskin* (BSM) program, a conditional cash transfer for poor students, which assists them in financing education support costs.

The BSM was created for enrolled students from poor households at all school levels, from primary school to senior high school. While the transfer for secular school students is managed by the *Kementerian Pendidikan dan Kebudayaan* (Ministry of Education and Culture - MoEC), the transfer for students at religious schools is managed by the *Kementerian Agama* (Ministry of Religious Affairs- MoRA). According to Bank (2012), in its first year, 2008, the BSM was distributed to about 3 million students overall. This number increased in 2010 to almost 6 million beneficiary students. The increase was even larger after targeting improvements in 2011. In 2012, in total, about 7.7 million students received the transfer, and this figure continued to increase to approximately 11.2 million in 2014 (Larasati and Howel, 2014).

As the BSM is aimed at children from poor and vulnerable households, the program's target identification system has a vital role in its effectiveness. It has been reported, however, that the BSM has crucial issues with targeting that have led to both exclusion and inclusion errors (Bank, 2012). In the beginning years of the BSM, recipient nomination was performed by schools and school committees. As a result, the children who had a close relationship to the school head or committee were likely to receive the benefit, even if they did not come from a poor family. Moreover, there was no mechanism by which households could register their children as potential recipients.

Given those facts, in 2011, household characteristics data were integrated from various sources into a unified database (BDT). All social safety net programs in Indonesia, including the BSM, could then use this database to determine targeted families (TNP2K, n.d.). As a result, the coverage of poor children improved from only 3-4 percent of the poorest households in 2009 to 42 percent in 2013, and then to 60 percent in 2014 (Larasati and Howel, 2014). However, this percentage implies that an exclusion error still exists, caused by deficiencies in the implementation of the new mechanism, such as incomplete information for school-aged children, the long chain that exists in data compilation from schools to their related Ministry, and the late distribution of the BSM card.

Besides these targeting problems, existing studies have also raised concern over the amount and delivery timing of the BSM benefit (Abbas et al., 2014; Larasati and Howel, 2014; Bank, 2012). It has been reported that the amount of BSM subsidy only covers about one-third of out-of-pocket education costs. This problem could increase incentives for poor parents to still send their children to the labour force, even despite receiving the subsidy. Further, delivery of the benefit not being at the beginning of the school year, which is when the fund is most needed, could also hamper the efficiency of the program. Regarding these issues, it is important to examine whether the BSM program actually is functioning to significantly increase school participation and simultaneously reduce the incidence of child working.

3. Data

This paper employs data from the Indonesia Family Life Survey (IFLS). The IFLS is a longitudinal survey in Indonesia that has been conducted for five waves: IFLS1 (1993), IFLS2 and IFLS2+(1997/1998), IFLS3 (2000), IFLS4 (2007), and IFLS5 (2014). The advantage of using this data is that it has a complete section on education and employment history for individuals aged 15 years and above, including information on whether or not the individual received benefits from the BSM program. At the same time, it also provides information at the household and community levels. This extensive information enables us to relate a child to their parents and community allowing us to control for the socioeconomic background of individuals.

As this study aims to examine the impact of the BSM program that commenced in 2008, we use waves IFLS4 and IFLS5. The IFLS4 (2007) provides information from the pre-treatment period, whereas the IFLS5 (2014) covers the post-treatment period. The sample used in this analysis is restricted to children aged 16 to 18 years old, as we focus on the effects of the BSM for children who would normally be enrolled in senior secondary school.

We construct two binary variables for our two main outcomes, schooling and working. The variable $attend_school$ takes on a value of 1 if the child is currently attending school, while the variable $working$ takes on a value of 1 if the child worked during the past week. The term 'working' here refers to the definition used by (de Hoop and Rosati, 2014), meaning work in economic activities. In other words, an individual is considered to be working if he/she participates in the production of goods or services, either by working for pay or by contributing to a family business without pay. Thus, doing household chores is not included in the definition of working.

In order to understand the effect of the BSM on the beneficiary children, we use a treatment variable, denoted by *BSMind*, which is a dummy variable that is equal to 1 if the child received the BSM benefit during the previous school year. Additionally, to study the spillover effect on the non-receipient siblings, we use the treatment variable *BSMsib*, which is equal to 1 if the child has any siblings who received the BSM benefit during the previous year. For the latter purpose, the sub-sample analysed only consists of children who are not exposed to the BSM program themselves.

Furthermore, to control for the socioeconomic background of children, we construct variables that are extensively used in the previous literature. For child characteristics, we include the child's age, gender, and whether they receive any school assistance besides BSM. We also include household demographic characteristics, such as living area (urban), asset ownership, and the number of school-aged children living in the household. Due to poor income data, we use the share of food expenditure as a proxy for household income. We assume that the bigger the share of food expenditure, the poorer the household, as most of the income in the household is spent on food, instead of on investing in human capital. Ownership of transfer cards and letters of poor status, both identification documents issued by the Indonesian government to low income earners, are also included as indicators of poverty. Moreover, we also consider dwelling conditions that could indicate poverty in the household, including access to electricity, proper toilet facilities, the source of energy for cooking, and proper sanitation. Finally, as parents' education level and occupation have been known to affect children's wellbeing, we also include those characteristics in our study. A variable list used in the analysis, along with their definitions, is presented in Table 1.

Accordingly, our sample consists of 3,225 children aged 16-18 years, in which there are 1485 boys and 1,530 girls. That said, the sub-sample for spillover effects to siblings has slightly fewer observations, as we exclude the children receiving the BSM benefit, which are 239 children, or about 11 percent of 2,169 observations from the year 2014. Tables 2 and 3 present the summary statistics for the sample and sub-sample, respectively. From the data in both tables, it is apparent that boys are more likely than girls to attend school and to go into work. These statistics suggest that a child's gender plays a significant role in determining the child's schooling and working, as noted by Baryshnikova and Jayawardana (2019). Thus, we also analyse boys and girls separately in this study.

Descriptive statistics by the control and treatment group are presented in Tables 4 and 5 to get a better understanding of who receives the BSM and who does not. Reviewing the mean values of the outcome variables across the groups, we know that the treatment group has a higher percentage of children attending school for both genders. Similarly, as expected, the percentage of children participating in the labour force is lower in the treatment group, although the difference is not significant in all of the cohorts.

The fact that the BSM program is focused on poor children leads to an expectation that the household and parent characteristics between the two groups will be different significantly, especially those that indicate poverty. Generally, it is true for parent characteristics that the treatment group has significantly less-educated parents.

Nevertheless, we do not see much significant difference in variables representing household characteristics between the two groups. The result of a t-test on the difference of means suggests that a significant difference exists only for the ownership of transfer cards, ownership of letters of poor status, and number of school-aged children. Although generally the treatment group is more likely to have a higher share of food expenditure, poor sanitation, and a toilet nearby a river, land or sea, the differences are not significant compared to the control group. Interestingly, it seems that the children who do not receive the BSM tend to live in a household with less access to electricity, and with firewood being used for cooking. It is evident that there remain issues with the accuracy of the program's targeting system, as found by the existing literature (Larasati and Howel, 2014; Bank, 2012). This inaccurate targeting leads to both inclusion errors, in which the non-poor receive the subsidy, and exclusion errors, in which the poor do not receive the subsidy.

4. Empirical Strategy

4.1. *Matching*

Analysis using observations from a natural experiment often needs specific techniques to obtain an unbiased estimator. In contrast to a true experiment, a natural experiment, which often occurs because of new government policy, does not choose its treatment and control groups randomly. In our case, the BSM program is focused on poor children, which means the observational data we use incorporates covariate imbalance between the BSM recipient children and the non-recipients. Therefore, we first match the observations to find at least one control unit for each treated unit that has identical characteristics. This matching process aims to reduce the imbalance in covariates across the groups (Stuart, 2010).

The most commonly used matching method is propensity score matching (PSM). As its name suggests, this method utilises propensity score, allowing us to construct matched sets of observations with similar covariates distribution without the requirement for an exact match on all individual variables (Stuart, 2010). However, the use of the PSM method does not necessarily reduce the imbalance of the data set. While the method improves the balance in some covariates, it decreases the balance in other covariates. Furthermore, the properties only hold by imposing a set of unverifiable assumptions about the process of data generation (Iacus et al., 2012). Therefore, according to King and Nielsen (2019), the use of a PSM approach increases imbalance, inefficiency, model dependence, research discretion, and statistical bias at some points.

In order to counter those problems, we employ another matching method, Coarsened Exact Matching (CEM), which was introduced by Iacus et al. (2012). This approach implements the exact matching method, a matching technique used to find a non-treated unit that has exactly identical covariate values with a treated unit, by coarsening the covariates. Unlike the PSM, the use of the CEM approach guarantees a reduction in the imbalance between the matched treated and control groups. Besides this, the application of the CEM requires only minimal assumptions about the data generation process. Given these benefits, Iacus et al. (2012) claim that the CEM has a strong ability in reducing imbalance, model dependence, estimation error, bias, variance, and other criteria, compared to the other widely used matching methods. Thus, this study utilises the CEM technique to match the treatment and control groups of our observational data. The weight resulting from this technique then is incorporated in the bivariate DiD Probit model discussed in the next sections.

4.2. *Bivariate Probit Model*

The observations we use for analysis are collected for two groups for two periods. The first group is the treatment group that receives treatment in one period, whereas the second group is the control group that does not receive the treatment during both periods. We use the combination of coarsened exact matching (CEM) and difference-in-difference (DiD) approach to estimate the treatment effect on the treated group. Use of DiD removes estimation bias resulting both from permanent differences between the groups, and from differences caused by time trends that is not related to the treatment (Li et al., 2012).

Both children's schooling and working variables are denoted by binary variables; we thus use a Probit model to examine the impacts of the BSM program. However, child participation in school and the labour force participation may be interdependent. The decision to go to school or work could not be separated, since both schooling and working would take most of the child's time. As a result, there may be a correlation between the unobserved factors affecting both variables that could lead to biased estimation if we use a standard univariate Probit model. To address this issue, a bivariate Probit model is utilised to obtain estimation of the BSM effects of the likelihood of a child attending school and working, given the same set of independent variables and correlation between the error terms.

To answer our main question of the effect of the BSM program on beneficiary children, the bivariate DiD Probit model is represented as follows:

$$S^*_{1it} = \alpha_1 + \beta_1 yrAfter_{1it} + \gamma_1 (yrAfter * BSMind)_{1it} + \delta_1 X'_{1it} + e_{1it} \tag{1}$$

$$W^*_{2it} = \alpha_2 + \beta_2 yrAfter_{2it} + \gamma_2 (yrAfter * BSMind)_{2it} + \delta_2 X'_{2it} + e_{2it} \tag{2}$$

Where S^*_{1it} and W^*_{2it} be unobserved variables, and the observed outcomes are denoted as:

$$S_{1it} = \begin{cases} 1, & if \quad S^*_{1it}>0 \\ 0, & otherwise \end{cases} \tag{3}$$

$$W_{2it} = \begin{cases} 1, & if \quad W^*_{2it}>0 \\ 0, & otherwise \end{cases} \tag{4}$$

where S_{1it}=1 if the child i worked for pay, or worked at the family-owned business during the past week in year t and 0 otherwise; W_{2it}=1 if the child i is currently attending school in year t and 0 otherwise; $yrAfter_{it}$=1 if the year is 2014 and 0 if the year is 2007; and the variable of interest, $(yrAfter * BSMind)_{it}$=1 if the child i receives the BSM benefit in year t and 0 otherwise. The vectors X_{1it} and X_{2it} respectively denote a number of individual, household, and parent factors that are likely affecting the child's schooling and working. e_{1it} and e_{2it} are the error terms, which are assumed to be bivariate normally distributed with mean zero, unit variance and correlation coefficient ρ.

A significant ρ (rho) indicates that a correlation between the unobserved components in both a child's schooling and working exists. Thus, the bivariate probit model should be used in this case, as the univariate probit model would result in biased estimation. However, if the ρ (rho) is 0, the model should be separated into two univariate probit models.

Furthermore, in order to answer our second question of the spillover effects of the BSM on siblings, we use the same empirical strategy as used for the main question, except for the treatment variable and the sample. For this analysis we only include the subsample of children aged 16-18 years who do not receive the BSM benefit. Then, the bivariate DiD model to estimate the effects on siblings are derived as follows:

$$S_{3it}^{*} = \alpha_3 + \beta_3 yrAfter_{3it} + \gamma_3 (yrAfter * BSMsib)_{3it} + \delta_3 X_{3it}' + e_{3it} \tag{5}$$

$$W_{4it}^{*} = \alpha_4 + \beta_4 yrAfter_{4it} + \gamma_4 (yrAfter * BSMsib)_{4it} + \delta_4 X_{4it}' + e_{4it} \tag{6}$$

Let S_{3it}^{*} and W_{4it}^{*} are unobserved variables, the observed outcomes are denoted as:

$$S_{3it} = \begin{cases} 1, & if \quad S_{3it}^{*}>0 \\ 0, & otherwise \end{cases} \tag{7}$$

$$W_{4it} = \begin{cases} 1, & if \quad W_{4it}^{*}>0 \\ 0, & otherwise \end{cases} \tag{8}$$

where S_{3it}=1 if the sibling worked for pay or worked at the family-owned business during the past week in year t and 0 otherwise; W_{4it}=1 if the sibling is currently attending school in year t and 0 otherwise; $yrAfter_{it}$=1 if the year is 2014 and 0 if the year is 2007; and the variable of interest, $(yrAfter{*}BSMsib)_{it}$=1 if in the household there is a minimum of 1 child, but not the individual i, who receives the BSM benefit in year t and 0 otherwise. Similar with Equations 1 and 2, the vectors X_{3it} and X_{4it} denote a number of control variables and e_{3it} and e_{4it} are the error terms with $Cov[e_{3it}, e_{4it}|X_{3it}, X_{4it}] = \rho$.

5. Results

5.1. *Effects on BSM Recipients*

We begin with the results from Coarsened Exact Matching (CEM). Firstly, we match the treatment and control groups based on the observable household characteristics. The BSM is targeted at children from poor households, but we do not know the exact rule used for assignment of the BSM. Therefore, we identify the significant household characteristics determining BSM recipients based on the OLS regression results (Table 6). According to the estimation, the covariates used for the matching process are the share of food expenditure, ownership of transfer cards, ownership of letters of poor status, and the access to proper toilet facilities.

The matching quality is assessed by the covariate imbalance reduction. Table 7 reports the covariate imbalances for the pre- and post-match of the total sample, and the girls and boys sub-samples separately. As seen in the table, the multivariate and univariate imbalances for each of the covariates reduce substantially in all samples. All the mean differences between the treatment and control groups in the post-match decrease to nearly zero and become insignificant, suggesting a reasonable match.

The regression results of the bivariate DiD probit model are reported in Table 8. The correlation coefficient, ρ, between the error terms is significant for all regressions. This indicates that estimation using a univariate model would be inefficient, and, thus, the bivariate model should be used. Considering the bivariate model estimation, the BSM has a substantially positive impact on schooling for children aged 16-18 years. The estimated coefficient of our treatment variable, $yrAfter * BSMind$, is positive and significant at 1 percent significance level for all samples and subsamples. Moreover, the results suggest that the program lowers the probability of girls working, albeit only at a 10 percent significance level (Table 8 Column 7). However, the BSM program does not have a significant impact on children's working for boys. This indicates that the amount of the BSM benefit may not be sufficient to replace the opportunity cost from sending the boys to the labour force, as has been shown by Bank (2012) and Larasati and Howel (2014).

To quantify the impact of each of the independent variables on schooling and working outcomes, we analyse the marginal effects of the estimated coefficient. Table 9 reports four joint outcomes of schooling and working: school only, work only, both work and school, and neither work nor school (idle). Overall, receiving the BSM subsidy increases the probability of schooling by 14.7 percentage points among children aged 16-18 years (Table 9). Most of this increase is likely to come from the group who are not engaged in either school or work, as the BSM reduces the probability of idling by 9.2 percentage points. Further, the increase in probability of schooling is associated with a decrease in probability of 'work only', and an increase in probability of both, schooling and working. Those movements occur because of the group of children who previously were only working and who, after the BSM intervention, are attending school while still continuing to work.

When considering separate regressions by gender, the directions of the BSM impacts on the four joint outcomes are similar to those in the full sample regressions. However, it seems that girls overall are more favoured than boys. As mentioned above, besides increasing schooling outcomes, the BSM also negatively affects the likelihood of a girl going into work. Meanwhile, however, there is no such impact on working for boys. As a result, the girls who receive the BSM benefit are more likely to focus on school only rather than doing both, school and work, whereas the beneficiary boys still have a high tendency to do both, school and work. Moreover, the increase in the probability of schooling for girls is substantially larger than that for boys, at 21.6 and 11 percentage points, respectively. Further, the likelihood of both, working and schooling, for boys increases by 8 percentage points, which is higher than the increase for girls (only 3.2 percentage points).

Moreover, the estimation results show that some control variables also significantly affect children's schooling and working. First, besides the child's gender, other school assistance has a highly significant effect on participation in school and work. All three regressions suggest that the children who receive school assistance besides the BSM are more likely to attend school only, and less likely to participate in the labour force only. Acting as proxies for poverty, household characteristics, such as the number of school-aged children, living areas (urban), the share of food expenditure, ownership of farmland, and access to electricity, have a significant impact on schooling and working decisions with expected signs.

Next, as expected, the full sample regressions reveal that parents' education (both father's and mother's) impact positively on schooling participation and negatively on working participation. For the girls' and boys' subsamples, the effect of mother's education is stronger than that of the father's education. Further, interestingly, if the household has its own business, the boys are more likely to participate in generating-income activities and, thus, are less likely to attend school. Meanwhile, the ownership of a business has no impact on the decision whether girls go to school or work. This indicates that boys have a higher tendency to participate in the family business, compared to girls.

5.2. ***Effects on BSM Recipients' Siblings***

Analysis for BSM spillover effects on siblings is restricted to the sub-sample of children who do not receive the BSM benefit. Some of those children have a sibling that is treated by the BSM, and this group is categorised as a treatment group for the sibling analysis. Meanwhile, the control group consists of the children whose sibling(s) are also not treated by the BSM. Thus, the treatment variable for this spillover analysis is $BSMsib$. Similar to the above analysis, we use an OLS estimation to determine variables that mimic the rules of BSM assignment. Accordingly, the variables we used for the CEM process are the number of school-aged children, ownership of transfer cards, ownership of letters of poor status, and energy used for cooking. The matching summaries of pre- and post-match covariate balances are reported in Table 10.

Next, as in the previous analysis, the weight produced by the CEM is incorporated in the bivariate probit model. The estimation results from this empirical model are presented in Table 11. The full sample regression reveals that the presence of a treated sibling reduces the likelihood of going into work for a non-treated child aged 16-18 years of age. However, this effect seems to only apply for girls, and there is no such effect for boys. In other words, there is no presence of a displacement effect for both boys and girls. Instead, the income effect dominates, albeit only existing for the untreated girls. Further, the estimated coefficient of $yrAfter * BSMsib$ reveals that the effect on child schooling is absent in this model for neither boys nor girls aged 16-18 years. This implies that, although an income effect dominates for girls, its size is still not sufficient to send untreated girls to school.

The marginal effects of the estimated coefficients are reported in Table 12. As the presence of treated siblings does not affect either schooling or working decisions for boys, the marginal effects also indicate that there is no effect on the four joint outcomes for boys. Meanwhile, if a non-treated girl has a treated sibling in the household, the probability of the girl going into work only decreases by 8.4 percentage points. Similarly, the likelihood of the girl going to both school and work also reduces by 6.6 percentage points. Nevertheless, the probability of idling for girls increases by 9.7 percentage points, as the decrease in working is not accompanied by an increase in schooling. In other words, for the group of girls who previously have worked only, after their sibling receives the BSM treatment, they no longer go to work but also do not go to school (i.e. they are idling).

Looking at the effects of the socioeconomic characteristics, the results of this sibling model are qualitatively similar to those of the individual model (the BSM-recipent analysis). Receiving other school assistance increases the likelihood of school only and decreases the likelihood of work only for both boys and girls. Moreover, household characteristics, including the number of children of school-age, share of food expenditure, and access to electricity, significantly affect the schooling and working in all three regressions of this model with the expected signs. Unlike in the individual model, though, the effect of the child's father's education is as strong as the effect of mother's education for both boys and girls. Interestingly, the ownership of transfer cards that indicates the poverty of the household only affects the outcomes for girls. Lastly, as seen in the individual model, boys who live in a household owning a business are less likely to participate in school and are more likely to participate in work activities.

5.3. *Robustness checks*

As we do not know the exact rules for assigning the BSM recipients, there exists model uncertainty. To address this problem, we using Bayesian Model Averaging (BMA) approach to determine the covariates used for the matching process. The BMA approach calculates posterior distributions over coefficients and models (Montgomery and Nyhan, 2010) which tell us how likely each of the variables is to be included in the model.

Table 13 presents the estimation results of the BMA approach in determining covariates affecting the first treatment variable, BSMind. As suggested by De Luca and Magnus (2011), an auxiliary regressor that is robustly correlated with the outcome of its coefficient has t ratio with an absolute value greater than one, or approximately corresponds to a posterior inclusion probability (pip) greater than 0.5. In our regression, the variables that satisfy this guideline are the ownership of transfer cards, ownership of the letter of poor status, and share of food expenditure. Meanwhile, the toilet facilities variables that we used previously are excluded. After identification of the three robust regressors, these regressors are used in the CEM process. The matching covariate balances with covariates determined by BMA technique indicate a reasonably good match (Table 14).

Next, we weigh the bivariate probit estimation that includes the new weights generated by the CEM. Table 15 indicates that the treatment effects resulting from the new estimation have similar signs and significance levels with those of the original estimation, albeit with a slightly different magnitude.

We do the same robustness check using the BMA approach for the siblings model. Table 16 indicates that the posterior inclusion probability is greater than 0.5 for four regressors: the number of school-aged children, ownership of transfer cards, ownership of letters of poor status, and the energy source used for cooking. These variables are the same as the ones we used in the original matching process. This indicates that the CEM results in the previous section for the siblings model are robust.

6. Conclusion

Educational inequality is one of the most prevalent problems faced by developing countries. Children from the poorest families often cannot achieve high levels of education due to financial difficulties. The group that faces the biggest gap in terms of access to education is adolescents aged 16-18 years. For example, in 2018, the net enrolment rate of children aged 16-18 years in Indonesia into senior secondary school was less than 70 percent. This low enrolment rate is also strongly related to the high incidence of child labour. More than half of children who are out of school participate in the labour force. Besides this, even when poor children manage to attend school, many still tend to also work in order to generate income to cover their education costs.

This study fills the literature gap by examining the impact of the Indonesian *Bantuan Siswa Miskin* (BSM) program, launched in 2008, on schooling and working of the 16-18 year olds. In addition, this study also fills an empirical gap by examining the spillover effects of this CCT program on untreated secondary school age siblings.

Using the Indonesian Family Life Survey (IFLS), our analysis utilises a bivariate DiD Probit model that incorporates weights generated by Coarsened Exact Matching (CEM). The results reveal that the BSM program is effective in increasing the participation of children in schooling for both boys and girls. However, the program succeeds in reducing the probability of working only for girls. As a result, the BSM program increases the probability of girls attending school by 21.6 percentage points, which is far above the increase for boys of 11 percentage points. In contrast, the probability of boy recipients of the BSM engaging in both work and school increases by 8 percentage points, whereas that for girls increases only by 3.2 percentage points. This implies that girls who are treated by the BSM are more likely to focus on school only, whereas treated boys still have a relatively high tendency to work while also attending school.

Analysis of the impact of the BSM on untreated siblings suggests that only girls benefit from the presence of treated siblings. The regression results reveal that the presence of a treated sibling reduces the likelihood that the non-recipient girls aged 16-18 years old will engage in work. Meanwhile, there is neither a rise nor a fall in the probability of non-recipient boys' engagement with work. These results indicate that the

BSM program does not impose a displacement effect on either girls or boys. Instead, an income effect exists, but only for untreated girls. Further, we find that in both the girls and boys sub-samples, there was not enough evidence to support the notion that the presence of treated siblings affects the schooling probability of untreated siblings. This implies that, although an income effect exists for the female siblings, the size of the effect is not significant enough to send the untreated girls to school.

Overall, based on these findings, the BSM program can be considered effective in increasing the school participation rate of the treated children. It also seems that the program does not impose a negative effect such as a displacement effect, on the untreated siblings. However, the benefit amount of this program is not likely to offset the opportunity cost of sending male children, either the treated or untreated, to the labour force.

Disclosure statement

No potential conflict of interest was reported by the authors.

References

Abbas, Hafid, Daniel Moulton, I Made Sumertajaya, Premono Koekoeh, M. Nur Aidi, Suratno, Mansyur, GN Wibawa, and Alvian Sroyer (2014) "Penaksiran cepat untuk transfer tunai program bantuan siswa miskin (Quick Understanding of Cash Transfer for Poor Students)," report.

Attanasio, Orazio, Emla Fitzsimons, Ana Gomez, MarthaÂăIsabel GutiÃľrrez, Costas Meghir, and Alice Mesnard (2010) "Children's schooling and work in the presence of a conditional cash transfer program in rural Colombia," *Economic Development and Cultural Change*, Vol. 58, No. 2, pp. 181–210, DOI: 10.1086/648188.

Bank, The World (2012) "Bantuan siswa miskin: Cash transfers for poor students," report, The World Bank.

Barrera-Osorio, Felipe, Marianne Bertrand, Leigh L. Linden, and Francisco Perez-Calle (2011) "Improving the design of conditional transfer programs: Evidence from a randomized education experiment in Colombia," *American Economic Journal: Applied Economics*, Vol. 3, No. 2, pp. 167–195, URL: https://pubs.aeaweb.org/doi/pdfplus/10.1257/app.3.2.167, DOI: 10.1257/app.3.2.167.

Baryshnikova, Nadezhda V. and Danusha Jayawardana (2019) "Can unconditional in-kind transfers keep children out of work and in school? Evidence from Indonesia," *School of Economics Working Papers 2019-01*, URL: https://ideas.repec.org/p/adl/wpaper/2019-01.html.

Behrman, JereÂăR, Piyali Sengupta, and Petra Todd (2005) "Progressing through PROGRESA: An impact assessment of a school subsidy experiment in Rural Mexico," *Economic Development and Cultural Change*, Vol. 54, No. 1, pp. 237–275, DOI: 10.1086/431263.

Bima, Luhur and Cecilia Marlina (2017) "The 2013 update of multidimensional child poverty in Indonesia," *SMERU Working Paper*, URL: https://smeru.or.id/en/content/2013-update-multidimensional-child-poverty-indonesia.

BPS (2018) "Potret pendidikan Indonesia: Statistik pendidikan 2018 (Profile of Indonesian education: Education Statistics 2018)," report, Badan Pusat Statistik (BPS) Indonesia.

Cardoso, E. and A.P.F. De Souza (2009) *The impact of cash transfers on child labor and school enrollment in Brazil*, pp. 133–146, DOI: 10.1057/9780230620100.

De Luca, Giuseppe and Jan R. Magnus (2011) "Bayesian model averaging and weighted-average least squares: equivariance, stability, and numerical issues," *The Stata Journal*, Vol. 11, No. 4, p. 518, DOI: 10.1177/1536867X1201100402.

De Silva, Indunil and Sudarno Sumarto (2015) "How do educational transfers affect child labour supply and expenditures? Evidence from Indonesia of impact and flypaper effects," *Oxford Development Studies*, Vol. 43, No. 4, pp. 1–25, DOI: 10.1080/13600818.2015.1032232.

Ferreira, F. H. G., D. Filmer, and N. Schady (2017) "Own and sibling effects of conditional cash transfer programs: Theory and evidence from Cambodia," *Research on Economic Inequality*, Vol. 25, pp. 259–298, DOI: 10.1108/S1049-258520170000025008.

Ferro, A. R., A. L. Kassouf, and D. Levison (2010) "The impact of conditional cash transfer programs on household work decisions in Brazil," *Research in Labor Economics*, Vol. 31, pp. 193–218, DOI: 10.1108/S0147-9121(2010)0000031010.

Galiani, Sebastian and Patrick J. McEwan (2013) "The heterogeneous impact of conditional cash transfers," *Journal of Public Economics*, Vol. 103, pp. 85–96, DOI: 10.1016/j.jpubeco.2013.04.004.

Glewwe, Paul and Pedro Olinto (2004) "Evaluating of the impact of conditional cash transfers on schooling: An experimental analysis of Honduras' PRAF program," URL: http://web.worldbank.org/archive/website01404/WEB/IMAGES/GLEWWEOL.PDF.

de Hoop, Jacobus and Furio C. Rosati (2014) "Cash transfers and child labor," *World Bank Research Observer*, Vol. 29, No. 2, pp. 202–234, DOI: 10.1093/wbro/lku003.

Iacus, Stefano M., Gary King, and Giuseppe Porro (2012) "Causal inference without balance checking: Coarsened exact matching," *Political Analysis*, Vol. 20, No. 1, pp. 1–24, DOI: 10.1093/pan/mpr013.

Kharisma, Bayu (2013) "Dampak program bantuan operasional sekolah (BOS) terhadap tingkat putus sekolah di Indonesia: Analisis DID (BOS impacts on school drop-out rate in Indonesia: DID Analysis)," *Jurnal Ekonomi Kuantitatif Terapan*, Vol. 6, No. 1, URL: https://ojs.unud.ac.id/index.php/jekt/article/view/4508.

King, Gary and Richard Nielsen (2019) "Why propensity scores should not be used for matching," *Political Analysis*, pp. 1–20, DOI: 10.1017/pan.2019.11.

Larasati, Dyah and Fiona Howel (2014) "Bantuan siswa miskin (BSM): Indonesian cash transfer programme for poor students," *International Policy Centre for Inclusive Growth*, URL: https://ipcig.org/pub/bah/PRB46BA_BSM_Indonesian_Cash_Transfer_Programme_for_Poor_Students.pdf.

Li, Haojie, Daniel J. Graham, and Arnab Majumdar (2012) "The effects of congestion charging on road traffic casualties: A causal analysis using difference-in-difference estimation," *Accident Analysis and Prevention*, Vol. 49, pp. 366–377, DOI: 10.1016/j.aap.2012.02.013.

Lincove, Jane Arnold and Adam Parker (2015) "The influence of conditional cash transfers on eligible children and their siblings," *Education Economics*, Vol. 24, No. 4, pp. 1–22, DOI: 10.1080/09645292.2015.1019431.

Maluccio, John and Rafael Flores (2005) "Impact evaluation of a conditional cash transfer program," *IDEAS Working Paper Series from RePEc*, URL: https://ideas.repec.org/p/fpr/resrep/141.html.

Montgomery, Jacob M. and Brendan Nyhan (2010) "Bayesian model averaging: Theoretical developments and practical applications," *Political Analysis*, Vol. 18, No. 2, pp. 245–270, DOI: 10.1093/pan/mpq001.

Pohan, Masniaritta, Jeffrey D. Vitale, Brian Adam, Arthur Stoecker, and Keith Willett (2013) "How education breaks the cycle of poverty: An inter-regional study of Indonesian households," URL: https://shareok.org/bitstream/handle/11244/10981/Pohan_okstate_0664D_12713.pdf?sequence=1.

Priyambada, Agus, Asep Suryahadi, and Sudarno Sumarto (2005) "What happened to child labor in Indonesia during the economic crisis : The trade-off between school and work," *IDEAS Working Paper Series from RePEc*, URL: http://ideas.repec.org/p/eab/laborw/22535.html.

Priyono, Edy and Vita Febriany (2013) "General senior secondary education financing in Indonesia," report.

Purba, Rosinta Hotmaida Febrianti (2018) "Impact evaluation of Indonesia conditional cash transfer program (BSM) on student achievement," *European Journal of Economics and Business Studies*, Vol. 4, No. 1, pp. 98–109, URL: https://ideas.repec.org/a/eur/ejesjr/225.html.

Schultz, T. Paul (2004) "School subsidies for the poor: evaluating the Mexican PROGRESA poverty program," *Journal of Development Economics*, Vol. 74, No. 1, pp. 199–250, DOI: 10.1016/j.jdeveco.2003.12.009.

Skoufias, Emmanuel and Susan Wendy Parker (2001) "Conditional cash transfers and their impact on child work and schooling: Evidence from the PROGRESA program in Mexico," *EconomÃŋa*, Vol. 2, No. 1, pp. 45–86, URL: https://www.jstor.org/stable/20065413?seq=1.

Stuart, Ea (2010) "Matching methods for causal inference: A review and a look forward," *Statistical Science*, Vol. 25, No. 1, pp. 1–21, DOI: 10.1214/09-STS313.

Suharyo, Widjajanti I. and Wenefrida Widyanti (2006) "The school operational assistance (BOS) program and the poor's access to basic education."

TNP2K (n.d.) "Data Indicator: Unified Database," URL: http://tnp2k.go.id/data-and-indicator/unified-database.

UNICEF (n.d.a) "The children: The big picture," URL: https://www.unicef.org/indonesia/children.html.

——— (n.d.b) "The children: The school years," URL: https://www.unicef.org/indonesia/children_26446.html.

Yulianti, Nina Restyana (2015) *The functioning and effect of a cash transfer program in Indonesia* Thesis, URL: https://www.semanticscholar.org/paper/The-Functioning-and-Effect-of-a-Cash-Transfer-in-Yulianti/45c8231b6dfd7acaaa302cbadf4fae33cba1f411.

Tables

Table 1.: Variable Description

Variable (1)	**Description** (2)
attend_school	=1 if the child is currently attending school
working	=1 if the child worked for pay or worked at family-owned business during the past week
BSMind	=1 if the child received assistance for school costs from the BSM program during the previous school year
BSMsib	=1 if the child had any siblings receiving assistance for school costs from BSM program during the previous school year
Child Characteristics	
age	age of the child
age_square	age of the child squared
female	=1 if the child is a female
other_school_assistance	=1 if the child received assistance for school costs from any sources beside the BSM during the previous school year
number_of_children	the number of children aged 7 to 18 in the household
Household Characteristics	
urban	=1 if the household is located in an urban area
share_xfood	the proportion of food expenditure to total expenditure of the household
own_farm_land	=1 if the household owns farm land
own_business	=1 if the household owns a business
transfer_cards	=1 if the household has a transfer card
letter_of_poor	=1 if the household has a letter of poor status
electricity	=1 if the household has access to electricity
toilet_river_land_sea	=1 if the household does not have a proper toilet
cook_firewood	=1 if the household uses firewood as an energy source for cooking
poor_sanitation	=1 if the household does not have proper sanitation
Parents Characteristics	
father_low_edu	=1 if the father has completed elementary or junior secondary school
father_med_edu	=1 if the father has completed senior secondary school
father_high_edu	=1 if the father has completed tertiary school
father_paid	=1 if the father works for pay
mother_low_edu	=1 if the mother has completed elementary or junior secondary school
mother_med_edu	=1 if the mother has completed senior secondary school
mother_high_edu	=1 if the mother has completed tertiary school
mother_paid	=1 if the mother works for pay
Province Dummies	Variables for each of the following provinces: North Sumatra, West Sumatra, Lampung, DKI Jakarta, West Java, Central Java, Yogyakarta, East Java, Bali, West Nusa Tenggara, South Kalimantan, and South Sulawesi

Table 2.: Summary Statistics - BSM Recipients

Variables	Boys+Girls		Boys		Girls	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
(1)	(2)	(3)	(4)	(5)	(6)	(7)
attend_school	0.592	(0.492)	0.610	(0.488)	0.575	(0.495)
working	0.313	(0.464)	0.386	(0.487)	0.244	(0.43)
BSMind	0.057	(0.231)	0.053	(0.224)	0.060	(0.238)
age	16.994	(0.82)	16.984	(0.822)	17.003	(0.818)
female	0.519	(0.5)	0.000	(0)	1.000	(0)
other_school_asisstance	0.179	(0.384)	0.187	(0.39)	0.172	(0.377)
number_of_children	2.084	(1.091)	2.099	(1.077)	2.070	(1.103)
urban	0.521	(0.5)	0.522	(0.5)	0.520	(0.5)
share_xfood	0.505	(0.171)	0.514	(0.171)	0.497	(0.17)
own_farm_land	0.282	(0.45)	0.292	(0.455)	0.272	(0.445)
own_business	0.394	(0.489)	0.400	(0.49)	0.389	(0.488)
transfer_cards	0.233	(0.423)	0.251	(0.434)	0.216	(0.412)
letter_of_poor	0.231	(0.421)	0.227	(0.419)	0.235	(0.424)
electricity	0.977	(0.15)	0.976	(0.152)	0.977	(0.148)
toilet_river_land_sea	0.121	(0.327)	0.121	(0.327)	0.121	(0.327)
cook_firewood	0.290	(0.454)	0.298	(0.458)	0.282	(0.45)
poor_sanitation	0.205	(0.403)	0.217	(0.412)	0.193	(0.395)
father_low_edu	0.465	(0.499)	0.485	(0.5)	0.446	(0.497)
father_med_edu	0.184	(0.388)	0.188	(0.391)	0.181	(0.385)
father_high_edu	0.077	(0.267)	0.078	(0.269)	0.076	(0.265)
father_paid	0.623	(0.485)	0.657	(0.475)	0.592	(0.492)
mother_low_edu	0.540	(0.498)	0.564	(0.496)	0.518	(0.5)
mother_med_edu	0.145	(0.353)	0.149	(0.356)	0.142	(0.349)
mother_high_edu	0.050	(0.219)	0.052	(0.222)	0.049	(0.216)
mother_paid	0.357	(0.479)	0.371	(0.483)	0.344	(0.475)
Obs	4208		2026		2182	

Table 3.: Summary Statistics - BSM Recipients' Siblings

Variables	Boys+Girls		Boys		Girls	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
(1)	(2)	(3)	(4)	(5)	(6)	(7)
attend_school	0.579	(0.494)	0.600	(0.49)	0.560	(0.497)
working	0.315	(0.464)	0.386	(0.487)	0.248	(0.432)
BSMsib	0.044	(0.205)	0.048	(0.215)	0.040	(0.196)
age	17.002	(0.821)	16.998	(0.821)	17.005	(0.82)
female	0.517	(0.5)	0.000	(0)	1.000	(0)
other_school_asisstance	0.174	(0.379)	0.184	(0.388)	0.163	(0.37)
number_of_children	2.064	(1.078)	2.081	(1.069)	2.049	(1.087)
urban	0.520	(0.5)	0.521	(0.5)	0.518	(0.5)
share_xfood	0.507	(0.172)	0.517	(0.172)	0.499	(0.172)
own_farm_land	0.281	(0.449)	0.294	(0.456)	0.269	(0.443)
own_business	0.395	(0.489)	0.400	(0.49)	0.389	(0.488)
transfer_cards	0.223	(0.416)	0.243	(0.429)	0.204	(0.403)
letter_of_poor	0.213	(0.41)	0.211	(0.408)	0.216	(0.411)
electricity	0.976	(0.154)	0.975	(0.156)	0.977	(0.151)
toilet_river_land_sea	0.123	(0.329)	0.122	(0.327)	0.124	(0.33)
cook_firewood	0.289	(0.453)	0.297	(0.457)	0.281	(0.45)
poor_sanitation	0.206	(0.404)	0.219	(0.414)	0.194	(0.395)
father_low_edu	0.459	(0.498)	0.479	(0.5)	0.440	(0.496)
father_med_edu	0.185	(0.388)	0.189	(0.391)	0.182	(0.386)
father_high_edu	0.081	(0.273)	0.083	(0.276)	0.079	(0.27)
father_paid	0.625	(0.484)	0.657	(0.475)	0.596	(0.491)
mother_low_edu	0.536	(0.499)	0.560	(0.496)	0.514	(0.5)
mother_med_edu	0.145	(0.352)	0.151	(0.358)	0.139	(0.346)
mother_high_edu	0.051	(0.221)	0.053	(0.223)	0.050	(0.219)
mother_paid	0.356	(0.479)	0.371	(0.483)	0.341	(0.474)
Obs	3969		1919		2050	

Table 4.: Summary Statistics Based on Group - BSM Recipients

Variables	Boys+Girls					Boys					Girls				
	Control		Treatment		Diff	Control		Treatment		Diff	Control		Treatment		Diff
	Mean	SD	Mean	SD		Mean	SD	Mean	SD		Mean	SD	Mean	SD	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
attend_school	0.579	(0.494)	0.799	(0.401)	-0.220***	0.600	(0.49)	0.785	(0.413)	-0.185***	0.560	(0.497)	0.811	(0.393)	-0.251***
working	0.315	(0.464)	0.276	(0.448)	0.039	0.386	(0.487)	0.383	(0.488)	0.003	0.248	(0.432)	0.189	(0.393)	0.058
BSMsib	0.044	(0.205)	0.276	(0.448)	-0.232***	0.048	(0.215)	0.243	(0.431)	-0.195***	0.040	(0.196)	0.303	(0.461)	-0.263***
age	17.002	(0.821)	16.858	(0.797)	0.144**	16.998	(0.821)	16.720	(0.799)	0.279***	17.005	(0.82)	16.970	(0.781)	0.036
female	0.517	(0.5)	0.552	(0.498)	-0.036	0.000	(0)	0.000	(0)	0.000	1.000	(0)	1.000	(0)	0.000
other_school_asisstance	0.174	(0.379)	0.272	(0.446)	-0.098***	0.184	(0.388)	0.234	(0.425)	-0.049	0.163	(0.37)	0.303	(0.461)	-0.140***
number_of_children	2.064	(1.078)	2.364	(1.218)	-0.300***	2.081	(1.069)	2.374	(1.17)	-0.293*	2.049	(1.087)	2.356	(1.261)	-0.308**
urban	0.520	(0.5)	0.548	(0.499)	-0.029	0.521	(0.5)	0.542	(0.501)	-0.021	0.518	(0.5)	0.553	(0.499)	-0.035
share_xfood	0.507	(0.172)	0.479	(0.146)	0.028**	0.517	(0.172)	0.478	(0.152)	0.039*	0.499	(0.172)	0.480	(0.141)	0.018
own_farm_land	0.281	(0.449)	0.297	(0.458)	-0.016	0.294	(0.456)	0.271	(0.447)	0.023	0.269	(0.443)	0.318	(0.468)	-0.050
own_business	0.395	(0.489)	0.389	(0.489)	0.006	0.400	(0.49)	0.402	(0.493)	-0.002	0.389	(0.488)	0.379	(0.487)	0.011
transfer_cards	0.223	(0.416)	0.410	(0.493)	-0.187***	0.243	(0.429)	0.402	(0.493)	-0.159**	0.204	(0.403)	0.417	(0.495)	-0.213***
letter_of_poor	0.213	(0.41)	0.523	(0.501)	-0.310***	0.211	(0.408)	0.514	(0.502)	-0.303***	0.216	(0.411)	0.530	(0.501)	-0.315***
electricity	0.976	(0.154)	0.996	(0.065)	-0.020***	0.975	(0.156)	1.000	(0)	-0.025***	0.977	(0.151)	0.992	(0.087)	-0.016
toilet_river_land_sea	0.123	(0.329)	0.092	(0.29)	0.031	0.122	(0.327)	0.112	(0.317)	0.010	0.124	(0.33)	0.076	(0.266)	0.049*
cook_firewood	0.289	(0.453)	0.310	(0.463)	-0.021	0.297	(0.457)	0.327	(0.471)	-0.030	0.281	(0.45)	0.295	(0.458)	-0.014
poor_sanitation	0.206	(0.404)	0.184	(0.388)	0.022	0.219	(0.414)	0.178	(0.384)	0.041	0.194	(0.395)	0.189	(0.393)	0.004
father_low_edu	0.459	(0.498)	0.569	(0.496)	-0.110***	0.479	(0.5)	0.598	(0.493)	-0.119*	0.440	(0.496)	0.545	(0.5)	-0.106*
father_med_edu	0.185	(0.388)	0.167	(0.374)	0.018	0.189	(0.391)	0.178	(0.384)	0.011	0.182	(0.386)	0.159	(0.367)	0.023
father_high_edu	0.081	(0.273)	0.017	(0.129)	0.064***	0.083	(0.276)	0.000	(0)	0.083***	0.079	(0.27)	0.030	(0.172)	0.049**
father_paid	0.625	(0.484)	0.586	(0.494)	0.040	0.657	(0.475)	0.654	(0.478)	0.003	0.596	(0.491)	0.530	(0.501)	0.065
mother_low_edu	0.536	(0.499)	0.603	(0.49)	-0.066*	0.560	(0.496)	0.626	(0.486)	-0.066	0.514	(0.5)	0.583	(0.495)	-0.070
mother_med_edu	0.145	(0.352)	0.155	(0.362)	-0.010	0.151	(0.358)	0.112	(0.317)	0.039	0.139	(0.346)	0.189	(0.393)	-0.050
mother_high_edu	0.051	(0.221)	0.033	(0.18)	0.018	0.053	(0.223)	0.037	(0.191)	0.015	0.050	(0.219)	0.030	(0.172)	0.020
mother_paid	0.356	(0.479)	0.381	(0.487)	-0.025	0.371	(0.483)	0.383	(0.488)	-0.013	0.341	(0.474)	0.379	(0.487)	-0.037
Obs	3969		239		4208	1919		107		2026	2050		132		2182

Note: $^{*}p < 10\%,^{**} p < 5\%,^{***} p < 1\%$.

Table 5.: Summary Statistics Based on Group - BSM Recipients' Siblings

	Boys+Girls					Boys					Girls				
Variables	Control		Treatment		Diff	Control		Treatment		Diff	Control		Treatment		Diff
	Mean	SD	Mean	SD		Mean	SD	Mean	SD		Mean	SD	Mean	SD	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
attend_school	0.582	(0.493)	0.520	(0.501)	0.062	0.605	(0.489)	0.505	(0.503)	0.100	0.560	(0.496)	0.537	(0.502)	0.024
working	0.312	(0.463)	0.371	(0.485)	-0.059	0.378	(0.485)	0.538	(0.501)	-0.159**	0.251	(0.433)	0.183	(0.389)	0.068
BSMsib	0.000	(0)	1.000	(0)	-1.000	0.000	(0)	1.000	(0)	-1.000	0.000	(0)	1.000	(0)	-1.000
age	17.005	(0.82)	16.943	(0.842)	0.062	16.998	(0.82)	17.000	(0.847)	-0.002	17.011	(0.819)	16.878	(0.837)	0.133
female	0.519	(0.5)	0.469	(0.5)	0.050	0.000	(0)	0.000	(0)	0.000	1.000	(0)	1.000	(0)	0.000
other_school_asisstance	0.170	(0.375)	0.257	(0.438)	-0.087*	0.179	(0.383)	0.301	(0.461)	-0.123*	0.162	(0.368)	0.207	(0.408)	-0.046
number_of_children	2.002	(1.037)	3.189	(1.205)	-1.186***	2.016	(1.025)	3.140	(1.212)	-1.123***	1.990	(1.047)	3.244	(1.202)	-1.254***
urban	0.516	(0.5)	0.594	(0.492)	-0.078*	0.520	(0.5)	0.538	(0.501)	-0.017	0.512	(0.5)	0.659	(0.477)	-0.146**
share_xfood	0.507	(0.173)	0.517	(0.156)	-0.010	0.516	(0.173)	0.529	(0.165)	-0.013	0.498	(0.174)	0.502	(0.145)	-0.004
own_farm_land	0.282	(0.45)	0.251	(0.435)	0.031	0.293	(0.455)	0.301	(0.461)	-0.008	0.272	(0.445)	0.195	(0.399)	0.077
own_business	0.391	(0.488)	0.457	(0.5)	-0.066	0.402	(0.491)	0.366	(0.484)	0.037	0.381	(0.486)	0.561	(0.499)	-0.180**
transfer_cards	0.208	(0.406)	0.531	(0.5)	-0.323***	0.224	(0.417)	0.613	(0.49)	-0.389***	0.194	(0.395)	0.439	(0.499)	-0.245***
letter_of_poor	0.202	(0.401)	0.463	(0.5)	-0.261***	0.198	(0.398)	0.462	(0.501)	-0.265***	0.205	(0.404)	0.463	(0.502)	-0.258***
electricity	0.975	(0.156)	0.994	(0.076)	-0.019**	0.974	(0.158)	0.989	(0.104)	-0.015	0.976	(0.155)	1.000	(0)	-0.024***
toilet_river_land_sea	0.123	(0.328)	0.131	(0.339)	-0.009	0.123	(0.329)	0.097	(0.297)	0.027	0.122	(0.328)	0.171	(0.379)	-0.048
cook_firewood	0.290	(0.454)	0.251	(0.435)	0.039	0.298	(0.457)	0.280	(0.451)	0.018	0.284	(0.451)	0.220	(0.416)	0.064
poor_sanitation	0.205	(0.404)	0.229	(0.421)	-0.024	0.219	(0.413)	0.226	(0.42)	-0.007	0.192	(0.394)	0.232	(0.425)	-0.040
father_low_edu	0.452	(0.498)	0.606	(0.49)	-0.154***	0.474	(0.499)	0.570	(0.498)	-0.096	0.431	(0.495)	0.646	(0.481)	-0.215***
father_med_edu	0.187	(0.39)	0.154	(0.362)	0.032	0.192	(0.394)	0.129	(0.337)	0.063	0.182	(0.386)	0.183	(0.389)	-0.001
father_high_edu	0.084	(0.278)	0.011	(0.107)	0.073***	0.087	(0.281)	0.011	(0.104)	0.076***	0.082	(0.274)	0.012	(0.11)	0.070***
father_paid	0.625	(0.484)	0.629	(0.485)	-0.003	0.661	(0.473)	0.581	(0.496)	0.080	0.592	(0.492)	0.683	(0.468)	-0.091
mother_low_edu	0.532	(0.499)	0.629	(0.485)	-0.097*	0.558	(0.497)	0.602	(0.492)	-0.044	0.508	(0.5)	0.659	(0.477)	-0.151**
mother_med_edu	0.147	(0.354)	0.109	(0.312)	0.038	0.152	(0.359)	0.129	(0.337)	0.023	0.141	(0.348)	0.085	(0.281)	0.056
mother_high_edu	0.054	(0.225)	0.006	(0.076)	0.048***	0.055	(0.228)	0.011	(0.104)	0.044***	0.052	(0.223)	0.000	(0)	0.052***
mother_paid	0.355	(0.479)	0.360	(0.481)	-0.005	0.374	(0.484)	0.301	(0.461)	0.073	0.338	(0.473)	0.427	(0.498)	-0.089
Obs	3794		175		3969	1826		93		1919	1968		82		2050

Note: $^{*}p < 10\%,^{**} p < 5\%,^{***} p < 1\%$.

Table 6.: OLS Estimation Results of BSM Recipients Determinants

BSMind (1)	Coef (2)	Std. Error (3)
hhsize	0.001	(0.001)
numbchildren	0.005	(0.004)
age	-0.009	(0.003)***
female	0.015	(0.007)**
urban	-0.008	(0.008)
share_xfood	-0.091	(0.023)***
share_xmedical	-0.135	(0.068)**
transfer_cards	0.058	(0.009)***
letter_of_poor	0.077	(0.009)***
OtherSchAssist	0.004	(0.009)
father_low_edu	0.017	(0.009)*
father_med_edu	-0.001	(0.011)
father_high_edu	-0.030	(0.015)*
electricity	0.038	(0.028)
water	-0.004	(0.008)
toilet_river_land_sea	-0.028	(0.012)**
cook_firewood	-0.008	(0.009)
Obs	4727	

Note: $^{*}p < 10\%$, $^{**}p < 5\%$, $^{***}p < 1\%$.

Table 7.: Covariate Balances - BSM Recipients

	Boys+Girls				Boys				Girls			
	Pre-match multivariate L1 distance: 0.41918403				Pre-match multivariate L1 distance: 0.47401765				Pre-match multivariate L1 distance: 0.45827749			
Variables	Pre- match uni-variate imbalance		Sample Mean		Pre-match uni-variate imbalance		Sample Mean		Pre-match uni-variate imbalance		Sample Mean	
	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
number_of _children	0.158	-0.028**	0.507	0.479	0.170	-0.039*	0.517	0.478	0.167	-0.018	0.499	0.480
transfer_cards	0.181	0.181***	0.223	0.410	0.155	0.155**	0.243	0.402	0.205	0.205***	0.204	0.417
letter_of_poor	0.297	0.297***	0.213	0.523	0.299	0.299***	0.211	0.514	0.296	0.296***	0.216	0.530
toilet_river land_sea	0.036	-0.036	0.123	0.092	0.008	-0.008	0.122	0.112	0.059	-0.059*	0.124	0.076

	Boys+Girls				Boys				Girls			
	Post-match multivariate L1 distance: 0.20737664				Post-match multivariate L1 distance: 0.26023437				Post-match multivariate L1 distance: 0.20458734			
Variables	Post-match uni-variate imbalance		Sample Mean		Post-match uni-variate imbalance		Sample Mean		Post-match uni-variate imbalance		Sample mean	
	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
number_of _children	0.102	-0.001	0.483	0.482	0.137	-0.002	0.493	0.491	0.111	0.001	0.479	0.480
transfer_cards	0	0	0.405	0.405	0	0	0.373	0.373	0	0	0.417	0.417
letter_of_poor	0	0	0.519	0.519	0	0	0.490	0.490	0	0	0.530	0.530
toilet_river land_sea	0	0	0.084	0.084	0	0	0.088	0.088	0	0	0.076	0.076

Note: $^{*}p < 10\%, ^{**}p < 5\%, ^{***}p < 1\%$.

Table 8.: Estimated Bivariate Probit Model - BSM Recipients

Variables	Boys+Girls		Boys		Girls	
	School	Work	School	Work	School	Work
(1)	(2)	(3)	(4)	(5)	(6)	(7)
yrAFTER	-0.351***	0.164	-0.379***	0.179	-0.324**	0.105
	(0.090)	(0.153)	(0.126)	(0.125)	(0.129)	(0.153)
yrAFTER_BSMind	0.689***	-0.182	0.647***	-0.046	0.849***	-0.246*
	(0.107)	(0.129)	(0.160)	(0.193)	(0.146)	(0.139)
age	2.785	-0.374	3.386	-0.640	1.327	0.725
	(1.823)	(3.066)	(3.994)	(4.047)	(3.545)	(4.078)
age_square	-0.099*	0.021	-0.116	0.029	-0.056	-0.012
	(0.054)	(0.090)	(0.118)	(0.119)	(0.104)	(0.121)
female	-0.044	-0.452***	-	-	-	-
	(0.073)	(0.069)				
other_school_assistance	0.585***	-0.192**	0.765***	-0.238	0.458***	-0.224**
	(0.130)	(0.079)	(0.144)	(0.170)	(0.149)	(0.099)
number_of_children	-0.064**	0.077***	-0.091***	0.143***	0.017	-0.015
	(0.025)	(0.024)	(0.031)	(0.045)	(0.041)	(0.034)
urban	0.142	-0.117	0.025	-0.228**	0.183	0.160
	(0.109)	(0.080)	(0.109)	(0.099)	(0.189)	(0.098)
share_xfood	-1.790***	0.952***	-1.822***	0.720**	-1.217**	1.389***
	(0.355)	(0.237)	(0.257)	(0.298)	(0.549)	(0.362)
own_farm_land	0.270***	0.146	0.447***	0.015	0.165	0.266*
	(0.071)	(0.106)	(0.112)	(0.163)	(0.146)	(0.158)
own_business	-0.021	0.211***	-0.186**	0.315***	0.162	0.006
	(0.056)	(0.071)	(0.094)	(0.108)	(0.144)	(0.095)
transfer_cards	-0.117*	0.152***	-0.133	0.088	-0.232	0.082
	(0.067)	(0.036)	(0.098)	(0.127)	(0.147)	(0.155)
letter_of_poor	0.110	-0.002	0.019	0.125	0.293***	-0.186
	(0.090)	(0.070)	(0.095)	(0.080)	(0.101)	(0.140)
electricity	0.371**	-0.840***	0.663**	-1.250***	0.839**	-1.436***
	(0.185)	(0.166)	(0.302)	(0.475)	(0.425)	(0.307)
toilet_river_land_sea	-0.152	0.249	-0.040	0.182	-0.407	0.397
	(0.139)	(0.190)	(0.207)	(0.221)	(0.298)	(0.351)
cook_firewood	-0.126	-0.035	-0.398***	0.190*	0.012	-0.236
	(0.081)	(0.053)	(0.140)	(0.112)	(0.113)	(0.154)
poor_sanitation	-0.015	-0.140*	0.204*	-0.173	-0.354***	-0.046
	(0.089)	(0.075)	(0.117)	(0.123)	(0.089)	(0.146)
father_low_edu	0.025	-0.159*	-0.210	0.096	-0.138	-0.264**
	(0.065)	(0.090)	(0.132)	(0.121)	(0.139)	(0.129)
father_med_edu	0.351***	-0.181**	-0.176	0.121	0.227	-0.252
	(0.119)	(0.074)	(0.164)	(0.153)	(0.281)	(0.179)
father_high_edu	0.456***	-0.711***	0.072	-0.387**	0.307	-0.799**
	(0.158)	(0.187)	(0.233)	(0.157)	(0.277)	(0.331)
father_paid	0.026	0.092	0.087	-0.024	0.233**	0.002
	(0.079)	(0.111)	(0.124)	(0.188)	(0.107)	(0.126)

continued from previous page

Variables	Boys+Girls		Boys		Girls	
	School	Work	School	Work	School	Work
(1)	(2)	(3)	(4)	(5)	(6)	(7)
mother_low_edu	0.205**	0.089	0.302**	-0.065	0.249*	0.181
	(0.095)	(0.063)	(0.145)	(0.142)	(0.147)	(0.142)
mother_med_edu	0.389***	-0.040	0.343*	-0.204	0.530***	0.084
	(0.149)	(0.088)	(0.199)	(0.164)	(0.137)	(0.229)
mother_high_edu	1.219***	-0.201	1.329***	-0.492	1.654***	-0.540
	(0.197)	(0.238)	(0.250)	(0.326)	(0.332)	(0.414)
mother_paid	-0.049	0.093	-0.142	0.051	0.039	0.094
	(0.091)	(0.065)	(0.119)	(0.115)	(0.086)	(0.138)
Constant	-18.102	-0.042	-23.073	2.368	-6.630	-8.986
	(15.510)	(26.051)	(34.049)	(34.757)	(29.872)	(34.504)
Province Dummies	Yes		Yes		Yes	
Observations	3,225		1,485		1,530	
Artrho	-0.745***		-0.861***		-0.801***	
	(0.056)		(0.069)		(0.072)	
Rho	-0.632		-0.697		-0.665	

Note: Standard errors are reported in the parenthesis.

$^{*}p < 10\%$,$^{**}\ p < 5\%$,$^{***}\ p < 1\%$.

All estimations include the corresponding weights generated by the CEM.

Table 9.: Average Marginal Effects of the Bivariate Probit Model - BSM Recipients

	Boys+Girls				Boys				Girls			
Variables	School only (school=1 work=0)	Work only (school=0 work=1)	Both (school=1 work=1)	Idle (school=0 work=0)	School only (school=1 work=0)	Work only (school=0 work=1)	Both (school=1 work=1)	Idle (school=0 work=0)	School only (school=1 work=0)	Work only (school=0 work=1)	Both (school=1 work=1)	Idle (school=0 work=0)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
yrAFTER	-0.092***	0.061**	-0.010	0.041*	-0.094**	0.078**	-0.018	0.033**	-0.084*	0.040	-0.011	0.055***
	(0.035)	(0.028)	(0.022)	(0.022)	(0.040)	(0.032)	(0.017)	(0.015)	(0.044)	(0.034)	(0.009)	(0.016)
yrAFTER_BSMind	0.147***	-0.095***	0.040**	-0.092***	0.110**	-0.095**	0.080**	-0.094***	0.216***	-0.099***	0.032***	-0.148***
	(0.038)	(0.020)	(0.020)	(0.011)	(0.054)	(0.043)	(0.033)	(0.027)	(0.043)	(0.031)	(0.010)	(0.021)
age	0.598	-0.347	0.230	-0.481	0.651	-0.557	0.341	-0.436	0.224	0.036	0.163	-0.423
	(0.719)	(0.607)	(0.407)	(0.439)	(1.346)	(1.088)	(0.439)	(0.341)	(0.935)	(0.765)	(0.458)	(1.008)
age_square	-0.022	0.014	-0.007	0.016	-0.024	0.020	-0.010	0.014	-0.011	0.002	-0.005	0.015
	(0.021)	(0.018)	(0.012)	(0.013)	(0.040)	(0.032)	(0.013)	(0.010)	(0.028)	(0.023)	(0.013)	(0.030)
female	0.061***	-0.069***	-0.074***	0.082***	-	-	-	-	-	-	-	-
	(0.017)	(0.013)	(0.014)	(0.019)								
other_school_assistance	0.140***	-0.089***	0.030***	-0.081***	0.165***	-0.139***	0.059**	-0.085***	0.126***	-0.069***	0.008	-0.064**
	(0.033)	(0.021)	(0.010)	(0.016)	(0.049)	(0.039)	(0.024)	(0.019)	(0.039)	(0.023)	(0.010)	(0.029)
number_of_children	-0.024***	0.019***	0.005	0.000	-0.042***	0.033***	0.015*	-0.007	0.005	-0.004	-0.000	-0.001
	(0.007)	(0.005)	(0.004)	(0.005)	(0.011)	(0.008)	(0.008)	(0.007)	(0.011)	(0.007)	(0.004)	(0.009)
urban	0.045*	-0.033*	-0.003	-0.009	0.048*	-0.037*	-0.040*	0.029	0.025	0.015	0.029**	-0.069*
	(0.026)	(0.019)	(0.015)	(0.022)	(0.026)	(0.021)	(0.023)	(0.021)	(0.045)	(0.023)	(0.014)	(0.040)
share_xfood	-0.493***	0.336***	-0.039	0.196***	-0.423***	0.354***	-0.112*	0.180***	-0.415***	0.321***	0.060	0.035
	(0.087)	(0.061)	(0.041)	(0.066)	(0.078)	(0.063)	(0.059)	(0.051)	(0.131)	(0.072)	(0.052)	(0.134)
own_farm_land	0.025	-0.007	0.054***	-0.072***	0.067	-0.059	0.064***	-0.072***	0.010	0.035	0.038***	-0.083***
	(0.023)	(0.018)	(0.020)	(0.019)	(0.046)	(0.037)	(0.023)	(0.016)	(0.046)	(0.034)	(0.012)	(0.021)
own_business	-0.037**	0.036***	0.030***	-0.030**	-0.090***	0.071***	0.035**	-0.017	0.036	-0.010	0.012	-0.038
	(0.017)	(0.014)	(0.011)	(0.014)	(0.033)	(0.027)	(0.014)	(0.011)	(0.029)	(0.014)	(0.017)	(0.044)
transfer_cards	-0.046***	0.037***	0.011	-0.002	-0.038	0.031	-0.001	0.008	-0.061	0.030	-0.007	0.038*
	(0.015)	(0.010)	(0.008)	(0.013)	(0.034)	(0.027)	(0.021)	(0.017)	(0.046)	(0.035)	(0.010)	(0.022)
letter_of_poor	0.022	-0.012	0.011	-0.021	-0.021	0.015	0.027	-0.021	0.085**	-0.052*	0.001	-0.034**
	(0.025)	(0.018)	(0.010)	(0.015)	(0.023)	(0.018)	(0.019)	(0.018)	(0.036)	(0.030)	(0.010)	(0.016)
electricity	0.211***	-0.189***	-0.098**	0.076**	0.344***	-0.272***	-0.149	0.078	0.335***	-0.304***	-0.090**	0.059
	(0.039)	(0.043)	(0.047)	(0.031)	(0.105)	(0.082)	(0.098)	(0.083)	(0.107)	(0.060)	(0.039)	(0.100)
toilet_river_land_sea	-0.068	0.058	0.023	-0.012	-0.041	0.032	0.030	-0.020	-0.132	0.096	0.013	0.023
	(0.055)	(0.048)	(0.018)	(0.014)	(0.072)	(0.059)	(0.023)	(0.017)	(0.102)	(0.079)	(0.018)	(0.021)

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Variables	Boys+Girls School only (school=1 work=0)	Boys+Girls Work only (school=0 work=1)	Boys+Girls Both (school=1 work=1)	Boys+Girls Idle (school=0 work=0)	Boys School only (school=1 work=0)	Boys Work only (school=0 work=1)	Boys Both (school=1 work=1)	Boys Idle (school=0 work=0)	Girls School only (school=1 work=0)	Girls Work only (school=0 work=1)	Girls Both (school=1 work=1)	Girls Idle (school=0 work=0)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
cook_firewood	-0.020	0.007	-0.018**	0.031*	-0.099**	0.082**	-0.018	0.035**	0.027	-0.041	-0.023	0.038
	(0.021)	(0.014)	(0.009)	(0.016)	(0.040)	(0.032)	(0.016)	(0.016)	(0.034)	(0.029)	(0.015)	(0.031)
poor_sanitation	0.017	-0.021	-0.022***	0.025*	0.065*	-0.053*	-0.005	-0.007	-0.075***	0.016	-0.028*	0.087***
	(0.026)	(0.019)	(0.008)	(0.014)	(0.037)	(0.029)	(0.021)	(0.018)	(0.027)	(0.026)	(0.017)	(0.032)
father_low_edu	0.029	-0.028	-0.021	0.020	-0.051	0.043	-0.010	0.019	-0.004	-0.036	-0.036***	0.076***
	(0.021)	(0.017)	(0.013)	(0.016)	(0.036)	(0.029)	(0.025)	(0.023)	(0.040)	(0.028)	(0.011)	(0.026)
father_med_edu	0.095***	-0.062***	0.007	-0.040*	-0.051	0.042	-0.001	0.010	0.077	-0.059	-0.010	-0.008
	(0.026)	(0.015)	(0.016)	(0.024)	(0.048)	(0.039)	(0.026)	(0.024)	(0.077)	(0.047)	(0.012)	(0.043)
father_high_edu	0.184***	-0.129***	-0.055***	0.001	0.086	-0.066	-0.064**	0.045	0.151*	-0.158**	-0.061*	0.068
	(0.046)	(0.024)	(0.016)	(0.029)	(0.059)	(0.049)	(0.027)	(0.028)	(0.078)	(0.065)	(0.032)	(0.067)
father_paid	-0.009	0.012	0.016	-0.020	0.018	-0.015	0.007	-0.010	0.052	-0.015	0.016**	-0.053***
	(0.030)	(0.024)	(0.012)	(0.013)	(0.048)	(0.038)	(0.032)	(0.026)	(0.035)	(0.028)	(0.008)	(0.011)
mother_low_edu	0.027	-0.006	0.034***	-0.055***	0.060	-0.051	0.029*	-0.038***	0.037	0.014	0.035***	-0.087***
	(0.023)	(0.015)	(0.012)	(0.020)	(0.047)	(0.038)	(0.017)	(0.015)	(0.042)	(0.031)	(0.013)	(0.029)
mother_med_edu	0.077**	-0.048**	0.035*	-0.065***	0.093*	-0.076*	0.008	-0.024	0.110**	-0.021	0.044**	-0.134***
	(0.034)	(0.023)	(0.018)	(0.023)	(0.054)	(0.044)	(0.030)	(0.029)	(0.046)	(0.044)	(0.022)	(0.039)
mother_high_edu	0.203***	-0.144***	0.084	-0.143***	0.302***	-0.254***	0.088	-0.136**	0.427***	-0.204***	0.056	-0.279***
	(0.059)	(0.021)	(0.060)	(0.017)	(0.077)	(0.060)	(0.068)	(0.058)	(0.093)	(0.076)	(0.048)	(0.107)
mother_paid	-0.024	0.020	0.009	-0.005	-0.032	0.027	-0.010	0.015	-0.001	0.014	0.012	-0.025
	(0.026)	(0.019)	(0.007)	(0.012)	(0.038)	(0.031)	(0.015)	(0.013)	(0.027)	(0.026)	(0.014)	(0.026)
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,225	3,225	3,225	3,225	1,485	1,485	1,485	1,485	1,530	1,530	1,530	1,530

Note: Standard errors are reported in the parenthesis.

$^{*}p < 10\%,^{**}p < 5\%,^{***}p < 1\%$.

All estimations include the corresponding weights generated by the CEM.

Table 10.: Covariate Balances - BSM Recipients' Siblings

	Boys+Girls				Boys				Girls			
	Pre-match multivariate L1 distance: 0.55829197				Pre-match multivariate L1 distance: 0.60196091				Pre-match multivariate L1 distance: 0.56014013			
Variables	Pre- match univariate imbalance		Sample Mean		Pre-match univariate imbalance		Sample Mean		Pre-match univariate imbalance		Sample Mean	
	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
number_of _children	0.404	1.185***	2.002	3.189	0.372	1.123***	2.016	3.140	0.440	1.253***	1.990	3.244
transfer_cards	0.317	0.317***	0.208	0.531	0.382	0.382***	0.224	0.613	0.240	0.240***	0.194	0.439
letter_of_poor	0.245	0.245***	0.202	0.463	0.253	0.253***	0.198	0.462	0.239	0.239***	0.205	0.463
cook_firewood	0.039	-0.039	0.290	0.251	0.018	-0.018	0.298	0.280	0.065	-0.065	0.284	0.220

	Boys+Girls				Boys				Girls			
	Post-match multivariate L1 distance: 4.692e-15				Post-match multivariate L1 distance: 1.398e-15				Post-match multivariate L1 distance: 3.244e-16			
Variables	Post-match univariate imbalance		Sample Mean		Post-match univariate imbalance		Sample Mean		Post-match univariate imbalance		Sample mean	
	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
number_of _children	0	0	3.071	3.071	0	0	2.954	2.954	0	0	3.052	3.052
transfer_cards	0	0	0.541	0.541	0	0	0.609	0.609	0	0	0.429	0.429
letter_of_poor	0	0	0.459	0.459	0	0	0.483	0.483	0	0	0.442	0.442
cook_firewood	0	0	0.259	0.259	0	0	0.299	0.299	0	0	0.234	0.234

Note: $^{*}p < 10\%$,** $p < 5\%$,*** $p < 1\%$.

Table 11.: Estimated Bivariate Probit Model - BSM Recipients' Siblings

Variables	Boys+Girls		Boys		Girls	
	School	Work	School	Work	School	Work
(1)	(2)	(3)	(4)	(5)	(6)	(7)
yrAFTER	-0.309***	0.209	-0.532***	0.349	0.012	-0.073
	(0.119)	(0.171)	(0.160)	(0.212)	(0.174)	(0.205)
yrAFTER_BSMsib	0.107	-0.221**	0.207	0.011	-0.048	-0.508***
	(0.136)	(0.110)	(0.225)	(0.152)	(0.160)	(0.196)
age	-1.434	4.552	-3.526	9.267	-4.103	-2.627
	(3.299)	(3.666)	(4.647)	(5.814)	(2.959)	(2.838)
age_square	0.026	-0.125	0.086	-0.265	0.102	0.087
	(0.096)	(0.106)	(0.137)	(0.170)	(0.086)	(0.083)
female	-0.012	-0.330***	-	-	-	-
	(0.116)	(0.110)				
other_school_assistance	0.795***	-0.192**	0.945***	-0.430***	0.735***	-0.209
	(0.160)	(0.092)	(0.156)	(0.145)	(0.261)	(0.211)
number_of_children	-0.174***	0.156**	-0.264**	0.215**	-0.164	0.192*
	(0.059)	(0.075)	(0.106)	(0.085)	(0.128)	(0.113)
urban	0.223	-0.117	0.186	-0.224	0.240	-0.013
	(0.141)	(0.127)	(0.166)	(0.193)	(0.207)	(0.158)
share_xfood	-1.741***	0.893***	-2.313***	0.693*	-1.430**	1.053***
	(0.431)	(0.261)	(0.498)	(0.386)	(0.587)	(0.301)
own_farm_land	0.215*	0.267	0.366***	0.223	-0.006	0.453**
	(0.112)	(0.181)	(0.098)	(0.246)	(0.218)	(0.206)
own_business	-0.002	0.139	-0.133	0.236**	0.068	0.168
	(0.099)	(0.086)	(0.090)	(0.114)	(0.158)	(0.124)
transfer_cards	-0.241***	0.268***	-0.114	0.108	-0.278***	0.394***
	(0.081)	(0.082)	(0.145)	(0.113)	(0.103)	(0.149)
letter_of_poor	0.047	-0.008	0.050	0.027	-0.118	-0.021
	(0.158)	(0.118)	(0.158)	(0.071)	(0.184)	(0.177)
electricity	0.735***	-0.833***	0.508*	-0.621***	1.749***	-0.874***
	(0.249)	(0.160)	(0.264)	(0.221)	(0.670)	(0.294)
toilet_river_land_sea	-0.249	0.335**	-0.070	0.371***	-0.186	0.149
	(0.197)	(0.139)	(0.205)	(0.126)	(0.318)	(0.243)
cook_firewood	-0.008	-0.095	-0.240**	0.147	0.134	-0.389**
	(0.119)	(0.104)	(0.116)	(0.111)	(0.151)	(0.170)
poor_sanitation	0.003	-0.207*	0.408***	-0.459***	-0.168	-0.108
	(0.100)	(0.117)	(0.125)	(0.139)	(0.114)	(0.154)
father_low_edu	-0.082	-0.133	-0.243	-0.127	0.041	-0.394**
	(0.097)	(0.128)	(0.214)	(0.201)	(0.252)	(0.187)
father_med_edu	0.205*	-0.225	-0.077	-0.270	0.278	-0.142
	(0.119)	(0.140)	(0.255)	(0.311)	(0.231)	(0.214)
father_high_edu	0.611***	-0.982***	0.353	-0.917***	0.760*	-1.388***
	(0.165)	(0.175)	(0.375)	(0.303)	(0.397)	(0.399)
father_paid	0.048	0.085	0.254*	0.103	-0.008	0.178
	(0.076)	(0.131)	(0.134)	(0.237)	(0.167)	(0.117)

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Variables	Boys+Girls		Boys		Girls	
	School	Work	School	Work	School	Work
(1)	(2)	(3)	(4)	(5)	(6)	(7)
mother_low_edu	0.411***	-0.037	0.429**	-0.247	0.449**	0.196
	(0.087)	(0.120)	(0.211)	(0.196)	(0.205)	(0.244)
mother_med_edu	0.499***	-0.103	0.368	-0.357	0.509*	0.030
	(0.168)	(0.151)	(0.282)	(0.247)	(0.284)	(0.367)
mother_high_edu	1.250***	-0.195	1.396**	-0.355	1.147	-0.575
	(0.393)	(0.289)	(0.596)	(0.428)	(0.709)	(0.429)
mother_paid	-0.120	0.198*	0.051	0.123	-0.235	0.236*
	(0.097)	(0.105)	(0.131)	(0.160)	(0.149)	(0.133)
Constant	17.110	-41.173	36.310	-81.391	38.788	18.860
	(28.144)	(31.374)	(39.501)	(49.813)	(24.803)	(24.352)
Province Dummies	Yes		Yes		Yes	
Observations	2,067		1,011		999	
Artrho	-0.728***		-0.875***		-0.684***	
	(0.075)		(0.094)		(0.129)	
Rho	-0.622		-0.704			

Note: Standard errors are reported in the parenthesis.

$^{*}p < 10\%, ^{**}p < 5\%, ^{***}p < 1\%$.

All estimations include the corresponding weights generated by the CEM.

Table 12.: Average Marginal Effects of the Bivariate Probit Model - BSM Recipients' Siblings

Variables	Boys+Girls				Boys				Girls			
	School only (school=1 work=0)	Work only (school=0 work=1)	Both (school=1 work=1)	Idle (school=0 work=0)	School only (school=1 work=0)	Work only (school=0 work=1)	Both (school=1 work=1)	Idle (school=0 work=0)	School only (school=1 work=0)	Work only (school=0 work=1)	Both (school=1 work=1)	Idle (school=0 work=0)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
yrAFTER	-0.084**	0.072*	-0.004	0.016	-0.133***	0.129**	-0.014	0.019	0.011	-0.014	-0.008	0.010
	(0.040)	(0.040)	(0.019)	(0.025)	(0.050)	(0.052)	(0.024)	(0.028)	(0.048)	(0.044)	(0.024)	(0.039)
yrAFTER_BSMsib	0.050	-0.052*	-0.019	0.021	0.029	-0.025	0.028	-0.033	0.053	-0.084**	-0.066**	0.097**
	(0.034)	(0.028)	(0.015)	(0.027)	(0.050)	(0.048)	(0.026)	(0.030)	(0.039)	(0.037)	(0.027)	(0.045)
age	-0.897	1.011	0.482	-0.596	-1.972	2.049	0.991*	-1.069*	-0.456	-0.088	-0.688*	1.232*
	(1.044)	(0.996)	(0.296)	(0.392)	(1.487)	(1.515)	(0.523)	(0.588)	(0.688)	(0.571)	(0.417)	(0.700)
age_square	0.022	-0.026	-0.015*	0.019*	0.054	-0.057	-0.030**	0.033*	0.009	0.006	0.020	-0.034*
	(0.030)	(0.029)	(0.009)	(0.011)	(0.044)	(0.044)	(0.015)	(0.017)	(0.020)	(0.017)	(0.012)	(0.020)
female	0.045	-0.061**	-0.048***	0.064**	-	-	-	-	-	-	-	-
	(0.028)	(0.026)	(0.018)	(0.026)								
other_school_assistance	0.167***	-0.130***	0.068***	-0.105***	0.207***	-0.196***	0.055***	-0.066***	0.165***	-0.102**	0.040	-0.103*
	(0.032)	(0.026)	(0.022)	(0.023)	(0.036)	(0.037)	(0.019)	(0.023)	(0.056)	(0.044)	(0.032)	(0.058)
number_of_children	-0.053***	0.048**	0.003	0.002	-0.073***	0.071***	-0.001	0.002	-0.055*	0.048*	0.009	-0.002
	(0.019)	(0.019)	(0.008)	(0.011)	(0.027)	(0.026)	(0.009)	(0.010)	(0.031)	(0.027)	(0.014)	(0.024)
urban	0.057*	-0.047	0.008	-0.018	0.063	-0.063	-0.011	0.011	0.047	-0.024	0.020	-0.043
	(0.031)	(0.029)	(0.024)	(0.035)	(0.044)	(0.044)	(0.031)	(0.034)	(0.048)	(0.037)	(0.023)	(0.041)
share_xfood	-0.437***	0.360***	-0.067*	0.145***	-0.452***	0.419***	-0.191***	0.224***	-0.400***	0.310***	0.001	0.088
	(0.103)	(0.088)	(0.035)	(0.055)	(0.105)	(0.107)	(0.065)	(0.071)	(0.121)	(0.078)	(0.061)	(0.122)
own_farm_land	-0.005	0.021	0.068***	-0.084***	0.019	-0.009	0.082***	-0.093***	-0.057	0.079*	0.055**	-0.077*
	(0.043)	(0.041)	(0.025)	(0.024)	(0.051)	(0.053)	(0.028)	(0.031)	(0.055)	(0.045)	(0.027)	(0.043)
own_business	-0.020	0.026	0.019	-0.025	-0.057**	0.058**	0.020	-0.021	-0.008	0.023	0.027	-0.042
	(0.025)	(0.023)	(0.013)	(0.019)	(0.027)	(0.027)	(0.016)	(0.018)	(0.037)	(0.029)	(0.018)	(0.032)
transfer_cards	-0.082***	0.077***	0.011	-0.006	-0.034	0.033	0.002	-0.002	-0.101***	0.093***	0.023	-0.016
	(0.022)	(0.021)	(0.011)	(0.016)	(0.034)	(0.033)	(0.018)	(0.021)	(0.028)	(0.029)	(0.020)	(0.030)
letter_of_poor	0.010	-0.007	0.004	-0.007	0.003	-0.002	0.011	-0.012	-0.020	0.007	-0.013	0.026
	(0.040)	(0.035)	(0.016)	(0.024)	(0.031)	(0.029)	(0.018)	(0.020)	(0.051)	(0.043)	(0.017)	(0.029)
electricity	0.223***	-0.261***	-0.017	0.055***	0.172***	-0.172***	-0.031	0.031	0.438***	-0.307***	0.049	-0.180
	(0.043)	(0.062)	(0.022)	(0.017)	(0.052)	(0.051)	(0.051)	(0.056)	(0.148)	(0.089)	(0.057)	(0.120)
toilet_river_land_sea	-0.092*	0.095*	0.019	-0.022	-0.068	0.073*	0.049**	-0.053**	-0.053	0.042	0.002	0.010
	(0.050)	(0.049)	(0.018)	(0.023)	(0.043)	(0.041)	(0.024)	(0.027)	(0.087)	(0.068)	(0.016)	(0.033)

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Variables	Boys+Girls				Boys				Girls			
	School only (school=1 work=0)	Work only (school=0 work=1)	Both (school=1 work=1)	Idle (school=0 work=0)	School only (school=1 work=0)	Work only (school=0 work=1)	Both (school=1 work=1)	Idle (school=0 work=0)	School only (school=1 work=0)	Work only (school=0 work=1)	Both (school=1 work=1)	Idle (school=0 work=0)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
cook_firewood	0.012	-0.017	-0.014	0.020	-0.059**	0.056**	-0.008	0.010	0.073	-0.079**	-0.036**	0.042
	(0.032)	(0.028)	(0.013)	(0.021)	(0.028)	(0.028)	(0.019)	(0.021)	(0.046)	(0.039)	(0.017)	(0.026)
poor_sanitation	0.028	-0.039	-0.027*	0.038	0.132***	-0.132***	-0.019	0.018	-0.019	-0.004	-0.028**	0.051**
	(0.027)	(0.026)	(0.016)	(0.027)	(0.037)	(0.036)	(0.017)	(0.019)	(0.038)	(0.035)	(0.014)	(0.020)
father_low_edu	0.004	-0.016	-0.028	0.040	-0.016	0.010	-0.051	0.058	0.056	-0.072*	-0.045	0.060
	(0.027)	(0.028)	(0.019)	(0.027)	(0.047)	(0.047)	(0.039)	(0.043)	(0.054)	(0.043)	(0.030)	(0.051)
father_med_edu	0.069***	-0.063**	-0.010	0.004	0.031	-0.037	-0.052	0.058	0.070	-0.049	0.007	-0.028
	(0.027)	(0.025)	(0.025)	(0.037)	(0.067)	(0.068)	(0.053)	(0.059)	(0.045)	(0.037)	(0.037)	(0.063)
father_high_edu	0.240***	-0.207***	-0.065***	0.032	0.196**	-0.203**	-0.098**	0.105*	0.314***	-0.308***	-0.102*	0.096
	(0.043)	(0.025)	(0.015)	(0.040)	(0.088)	(0.086)	(0.050)	(0.056)	(0.091)	(0.086)	(0.054)	(0.085)
father_paid	-0.003	0.011	0.017	-0.025	0.022	-0.015	0.049	-0.055	-0.023	0.032	0.021*	-0.029
	(0.025)	(0.028)	(0.018)	(0.026)	(0.048)	(0.049)	(0.035)	(0.038)	(0.042)	(0.033)	(0.012)	(0.024)
mother_low_edu	0.079***	-0.052*	0.040***	-0.067***	0.102*	-0.098*	0.017	-0.021	0.061	-0.006	0.064**	-0.119**
	(0.026)	(0.029)	(0.015)	(0.024)	(0.054)	(0.053)	(0.028)	(0.030)	(0.055)	(0.051)	(0.031)	(0.050)
mother_med_edu	0.102**	-0.076**	0.043	-0.068**	0.110	-0.109	-0.008	0.007	0.093	-0.040	0.049	-0.102**
	(0.045)	(0.036)	(0.028)	(0.028)	(0.071)	(0.069)	(0.036)	(0.039)	(0.091)	(0.084)	(0.033)	(0.047)
mother_high_edu	0.205***	-0.181***	0.118	-0.143***	0.263**	-0.242**	0.125	-0.146	0.288**	-0.202***	0.032	-0.118
	(0.070)	(0.045)	(0.099)	(0.040)	(0.112)	(0.109)	(0.098)	(0.111)	(0.116)	(0.068)	(0.103)	(0.186)
mother_paid	-0.049*	0.051*	0.015*	-0.016	-0.012	0.014	0.026*	-0.029*	-0.073*	0.062*	0.008	0.004
	(0.030)	(0.029)	(0.008)	(0.010)	(0.042)	(0.042)	(0.015)	(0.016)	(0.040)	(0.033)	(0.013)	(0.022)
Province Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,067	2,067	2,067	2,067	1,011	1,011	1,011	1,011	999	999	999	999

Note: Standard errors are reported in the parenthesis.

$^{*}p < 10\%, ^{**}p < 5\%, ^{***}p < 1\%$.

All estimations include the corresponding weights generated by the CEM.

Table 13.: Bayesian Model Averaging Summary - BSM Recipients

BSMind (1)	Coef. (2)	Std. Err. (3)	t (4)	pip (5)
age	-0.001	(0.024)	-0.03	0.15
age_square	0.000	(0.001)	-0.11	0.16
female	0.000	(0.002)	0.13	0.03
other_school_assistance	0.002	(0.007)	0.28	0.09
number_of_children	0.003	(0.005)	0.63	0.32
urban	0.000	(0.002)	-0.09	0.02
share_xfood	-0.073	(0.037)	-1.95	0.86***
own_farm_land	0.000	(0.003)	0.14	0.03
own_business	0.000	(0.001)	-0.06	0.02
transfer_cards	0.045	(0.011)	4.23	1.00***
letter_of_poor	0.087	(0.01)	8.86	1.00***
electricity	0.003	(0.015)	0.23	0.07
toilet_river_land_sea	-0.004	(0.011)	-0.36	0.14
cook_firewood	0.000	(0.001)	0.03	0.02
poor_sanitation	0.000	(0.003)	-0.13	0.03
Observations	3570			

Note: Standard errors are reported in the parenthesis,$^{***}pip > 0.5$.

Table 14.: Covariate Balances with BMA - BSM Recipients

	Boys+Girls				Boys				Girls			
	Pre-match multivariate L1 distance: 0.38299786				Pre-match multivariate L1 distance: 0.41732353				Pre-match multivariate L1 distance: 0.42329134			
Variables	Pre- match univariate imbalance		Sample Mean		Pre-match univariate imbalance		Sample Mean		Pre-match univariate imbalance		Sample Mean	
	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
number_of _children	0.158	-0.028**	0.507	0.479	0.17	-0.039*	0.517	0.478	0.167	-0.018	0.499	0.480
transfer_cards	0.181	0.181***	0.223	0.41	0.155	0.155**	0.243	0.402	0.205	0.205***	0.204	0.417
letter_of_poor	0.297	0.297***	0.213	0.523	0.299	0.299***	0.211	0.514	0.296	0.296***	0.216	0.530

	Boys+Girls				Boys				Girls			
	Post-match multivariate L1 distance: 0.17996524				Post-match multivariate L1 distance: 0.2128569				Post-match multivariate L1 distance: 0.19527003			
Variables	Post- match univariate imbalance		Sample Mean		Post-match univariate imbalance		Sample Mean		Post-match univariate imbalance		Sample Mean	
	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment	L1	Mean Diff	Control	Treatment
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
number_of _children	0.106	-0.001	0.480	0.479	0.157	-0.003	0.486	0.484	0.111	0.001	0.479	0.480
transfer_cards	0	0	0.410	0.410	0	0	0.390	0.390	0	0	0.417	0.417
letter_of_poor	0	0	0.523	0.523	0	0	0.505	0.505	0	0	0.530	0.530

Note: $^{*}p < 10\%,^{**} p < 5\%,^{***} p < 1\%$.

Table 15.: Estimated Bivariate Probit Model - BSM Recipients (Robustness Checks: Using BMA to Determine CEM Covariates)

Variables	Boys+Girls		Boys		Girls	
	School	Work	School	Work	School	Work
(1)	(2)	(3)	(4)	(5)	(6)	(7)
yrAFTER	-0.362***	0.174	-0.390***	0.120	-0.301***	0.105
	(0.083)	(0.128)	(0.126)	(0.146)	(0.101)	(0.140)
yrAFTER_BSMind	0.712***	-0.190	0.677***	-0.034	0.811***	-0.239*
	(0.111)	(0.139)	(0.175)	(0.174)	(0.138)	(0.145)
age	2.788	0.763	4.251	0.598	0.230	0.880
	(1.777)	(2.627)	(3.458)	(3.684)	(3.561)	(3.784)
age_square	-0.099*	-0.013	-0.142	-0.008	-0.024	-0.017
	(0.053)	(0.077)	(0.102)	(0.108)	(0.105)	(0.112)
female	-0.025	-0.454***	-	-	-	-
	(0.073)	(0.065)				
other_school_assistance	0.553***	-0.203**	0.763***	-0.174	0.487***	-0.252***
	(0.139)	(0.080)	(0.128)	(0.157)	(0.158)	(0.096)
number_of_children	-0.043*	0.088***	-0.094***	0.148***	0.003	-0.000
	(0.024)	(0.020)	(0.030)	(0.036)	(0.037)	(0.033)
urban	0.107	-0.103	-0.009	-0.267**	0.201	0.160*
	(0.126)	(0.087)	(0.100)	(0.116)	(0.197)	(0.090)
share_xfood	-1.650***	0.925***	-1.610***	0.869***	-1.063**	1.306***
	(0.398)	(0.233)	(0.246)	(0.258)	(0.525)	(0.376)
own_farm_land	0.252***	0.149	0.393***	0.062	0.179	0.252*
	(0.088)	(0.118)	(0.091)	(0.162)	(0.151)	(0.142)
own_business	-0.016	0.194***	-0.255***	0.266***	0.225	-0.017
	(0.059)	(0.068)	(0.081)	(0.091)	(0.148)	(0.084)
transfer_cards	-0.140**	0.147***	-0.139	0.083	-0.212	0.104
	(0.069)	(0.035)	(0.086)	(0.093)	(0.131)	(0.130)
letter_of_poor	0.121	-0.022	0.049	0.104	0.263***	-0.164
	(0.080)	(0.070)	(0.091)	(0.075)	(0.085)	(0.122)
electricity	0.359**	-0.766***	0.477*	-1.160***	0.729	-1.178***
	(0.182)	(0.132)	(0.249)	(0.351)	(0.469)	(0.254)
toilet_river_land_sea	-0.158	0.195	-0.259**	0.202*	-0.233	0.173
	(0.138)	(0.143)	(0.107)	(0.120)	(0.200)	(0.195)
cook_firewood	-0.222***	-0.008	-0.424***	0.213**	-0.052	-0.175
	(0.083)	(0.054)	(0.141)	(0.105)	(0.104)	(0.140)
poor_sanitation	0.017	-0.137*	0.117	-0.145	-0.383***	-0.054
	(0.090)	(0.077)	(0.097)	(0.127)	(0.088)	(0.118)
father_low_edu	0.023	-0.169**	-0.151	-0.003	-0.087	-0.227**
	(0.065)	(0.085)	(0.149)	(0.111)	(0.122)	(0.108)
father_med_edu	0.352***	-0.183***	-0.084	0.084	0.270	-0.226
	(0.121)	(0.068)	(0.141)	(0.130)	(0.262)	(0.149)
father_high_edu	0.440***	-0.712***	0.171	-0.453***	0.370	-0.750**
	(0.148)	(0.179)	(0.245)	(0.144)	(0.273)	(0.306)
father_paid	0.025	0.106	0.029	0.014	0.170**	0.025
	(0.077)	(0.113)	(0.135)	(0.175)	(0.085)	(0.139)

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Variables	Boys+Girls		Boys		Girls	
	School	Work	School	Work	School	Work
(1)	(2)	(3)	(4)	(5)	(6)	(7)
mother_low_edu	0.183**	0.068	0.244**	-0.136	0.272*	0.189
	(0.093)	(0.055)	(0.114)	(0.149)	(0.147)	(0.130)
mother_med_edu	0.392***	-0.087	0.263	-0.219	0.589***	0.042
	(0.144)	(0.092)	(0.165)	(0.202)	(0.142)	(0.217)
mother_high_edu	1.291***	-0.253	1.282***	-0.518	1.662***	-0.566
	(0.183)	(0.238)	(0.236)	(0.344)	(0.348)	(0.403)
mother_paid	-0.027	0.123*	-0.165	0.091	-0.040	0.153
	(0.101)	(0.064)	(0.119)	(0.131)	(0.096)	(0.116)
Constant	-18.270	-9.645	-29.967	-7.965	2.612	-10.615
	(15.074)	(22.343)	(29.520)	(31.542)	(30.093)	(32.080)
Province Dummies	Yes		Yes		Yes	
Observations	3,402		1,592		1,657	
Artrho	-0.729***		-0.829***		-0.731***	
	(0.053)		(0.075)		(0.074)	
Rho	-0.623		-0.680		-0.624	

Note: Standard errors are reported in the parenthesis.

$^{*}p < 10\%$,** $p < 5\%$,*** $p < 1\%$.

All estimations include the corresponding weights generated by the CEM.

Table 16.: Bayesian Model Averaging Summary - BSM Recipients' Siblings

BSMsib (1)	Coef. (2)	Std. Err. (3)	t (4)	pip (5)
age	0.000	(0.01)	-0.02	0.02
age_square	0.000	(0.00)	0.02	0.02
female	0.000	(0.002)	-0.12	0.03
other_school_assistance	0.003	(0.008)	0.38	0.15
number_of_children	0.046	(0.003)	13.41	1***
urban	0.000	(0.001)	0.02	0.02
share_xfood	0.000	(0.005)	-0.1	0.02
own_farm_land	0.000	(0.001)	-0.05	0.02
own_business	0.000	(0.001)	0.01	0.02
transfer_cards	0.071	(0.009)	7.55	1***
letter_of_poor	0.039	(0.009)	4.16	1***
electricity	0.020	(0.034)	0.59	0.3
toilet_river_land_sea	-0.001	(0.005)	-0.18	0.05
cook_firewood	-0.023	(0.013)	-1.7	0.81***
poor_sanitation	0.000	(0.001)	-0.03	0.02
Observations	3335			

Note: Standard errors are reported in the parenthesis,$^{***}pip > 0.5$.