Impact Evaluation of Indonesia Conditional Cash Transfer Program (BSM) on Student Achievement

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Abstract

One of the Indonesia's Government efforts to improve the quality of education, particularly at the primary and secondary level, is the provision of BSM. This program launched under TNP2K due to the lack of significant BOS program in overcoming the number of drop out students due to parenting difficulties in meeting other educational needs such as uniforms, shoes, transportation costs and other education expenses not covered by BOS funds. However, the implementation of BSM has drawn a lot of criticism, especially regarding budget management and in terms of targeting, thus potentially hampering the achievement of BSM policy objectives. At the same time, there are inclusive errors and depending on the level of education, 50 to 70 percent of beneficiaries are ineligible. Whereas the budget for BSM program is proportional and in 2017 reaches Rp. 416.1 trillion or 27.4 percent of total APBN expenditure. Using the data from the 5th Indonesian Family Life Survey (IFLS) wave 5th, this study analyses the impact of BSM delivery on student achievement as measured by the final school exam scores. The method of analysis used is Propensity Score Matching, so the average treatment effect of BSM policy can be obtained. Despite the low targeting performance, the analysis shows that the program has a positive effect. Analysis shows Students who receive BSM program assistance get a higher test score of 5.6 percent than students who do not receive the program. Based on the analysis, the paper concludes that the program should be maintained and targeting efficiency needs to be improved as the program has a meaningful effect for low-income households in terms of increasing student achievement.

Keywords: BSM, cash transfer, PSM, student score, subsidy program.

Introduction

People center development places humans as the subject of development (Korten, 1984). In terms of investment, Becker in Sulistyaningrum (2016) indicates that education has a positive relationship with economic growth, namely through human capital investments (human capital) future income will increase. Based on the findings of the World Bank, the rate of return on investment in education shows a higher figure than physical investment, which is 15.3 percent versus 9.1 percent (Fattah, 2009). Human capital in the form of education and health will increase the potential of individual income, and will affect the economy through a number of externalities (DE Silva & Sumarto, 2015). Becker and Amartya Sen suggest that educational investments are means of addressing the problem of poverty and democratic growth. Through educational investment, a person's standard of living will increase, thus equipping individuals with the ability to access jobs to generate income. The role of education is also seen in the macro level. Augmented Solow-Swan model incorporates the role of education as a production factor that capable to explaining the variation in real per capita income between countries (DE Silva & Sumarto, 2015).

The awareness related to importance of education is used as a means to eradicate poverty from 9% to 10% (Bappenas, 2013). Various government poverty alleviation programs have suppressed poverty year after year. One way to alleviate poverty is through the Anti Poverty Program whose benefits are targeted specifically to the poor. The Anti Poverty Program in Indonesia is part of the Social Safety Net (SSN) introduced in 1998 (Daly & Fane, 2002).

The Conditional Cash Transfer program has been widely introduced in Latin America and some countries around the world as a social policy tool for reducing poverty. Distribution of cash assistance to poor households based on the requirements of beneficiaries in education and health. The program is also a kind of support to meet SDG's goals to eradicate poverty and improve the education and health sector.

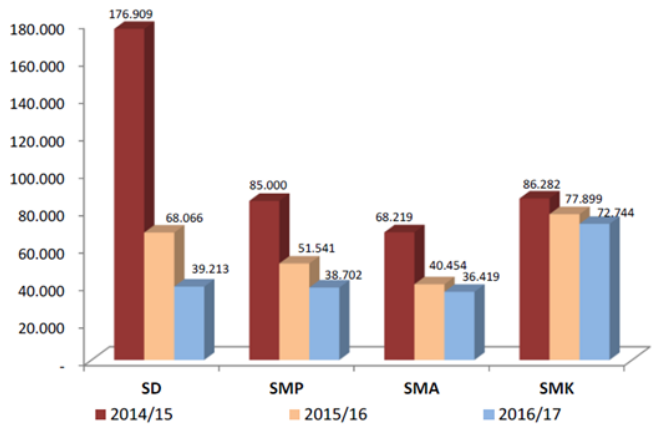
Table 1 Poverty Reduction Program Scheme

No	Program Name	Social Protection Program		
		Volume	Target Amount	Period of Implementation
1	Rice Subsidy (Raskin)	15 Kg per poor household every month	15.5 million poor households	1998-Present
2	Family Hope Program (PKH)	1.4 Million Rupiah (IDR) cash transfer per household every year	2.4 million very poor households	2007-Present
3	Poor Student Assistance (BSM)	Cash transfer Primarly School: IDR 380 thousand/year, Junior High School: IDR 450 thousand/year, Senior High School: IDR 750 thousand/year.	8.7 million students	2008–Present
4	Temporary Direct Assistance (BLSM)	IDR 150,000 cash aid per poor and vulnerable household	15.5 million households.	2013 (4 months duration)

Source: Poverty Reduction Acceleration Team (TNP2K)

The target of BSM is 25 percent of the poorest households categorized by per capita expenditure level. The program focuses on children in school age, which is between 7 and 18 years old. The BSM program was launched under TNP2K due to the lack of significance of BOS program in overcoming the number of drop out students and increasing the number of student participation in school participation as shown in Graph 1. It is caused by the difficulty of parents/family in fulfilling other education needs such as uniform, , shoes, transportation costs and other education expenses not covered by BOS funds (TNP2K, 2012). The TNP2K poverty reduction program like BSM has been regarded as a success. However, how this success is achieved is much less clear (Ashcroft, 2015). This is because the impact evaluation system does not always exist to catch it.

Graph 1 The Growth of Dropouts Students by Education Level 2014-2017



- SD: Primarly School
- SMP: Junior High School
- SMA: Senior High School
- SMK: vocational secondary school

Source: Ministry of Education and Culture, 2017

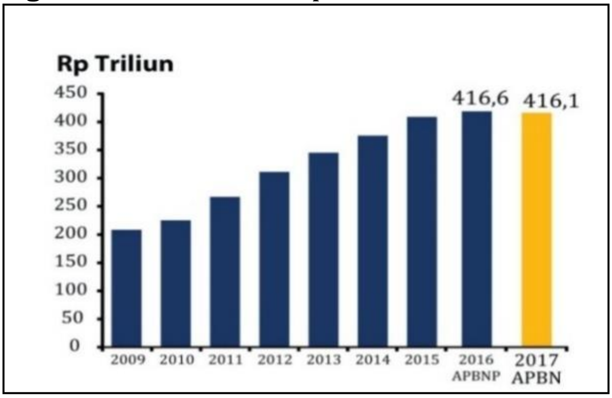
Government Intervention

The role of strategic education in the economy is to encourage every country to provide a certain quality education services to its citizens. Government presence is necessary because education services cannot be fully provided by market mechanisms. Through several policy programs such as BOS, BSM, and PKH known as Conditional Cash Transfer. Government intervention is needed to ensure that all residents have access to affordable and quality of education services. In almost every country, this government obligation is contained in the basic constitution. In practice, governments in some countries, especially in developing countries have prioritized budget allocations for education. In some developing countries, the government designed an educational subsidy program to ensure that children have access to education services, such as PROGRESA (Programa de Educacion, Salud y Aliimentacion) in Mexico, PRAF (Programa de Asignacion Familiar) in Honduras, PETI (Programa de Erradicacao do Trabalho Infantil) in Brazil, FA (Familias en Accion) in Colombia, in Indonesia there are BOS (Sulistyaningrum, 2016) and BSM (Yulianti, 2015).

From the budget side, the proportion of the The Indonesian Budget (APBN) for education is at least 20 percent. Because it is proportional, the amount of education budget will follow the amount of APBN expenditure allocation. In APBN 2017, education budget is allocated IDR 416.1 trillion or 27.4 percent of total APBN expenditure. Figure 2 shows the graph of the development of the education budget during 2009 - 2017 with an increasing trend.

Based on data from the Ministry of Finance of Indonesia, the target of the 2017 education budget is allocated for school rehabilitation, professional allowances, Smart Indonesia Card, Bidik Misi assistance, and School Operational Assistance (BOS), and Poor Student Assistance (BSM). BSM funds in APBN 2017 of Rp. 45.2 trillion or about 11 percent of the total education budget. This shows that the BSM program is crucial and is expected to have a positive impact on the quantity and quality of education services throughout Indonesia.

Figure 2 Government Expenditure Trends in the Education Sector



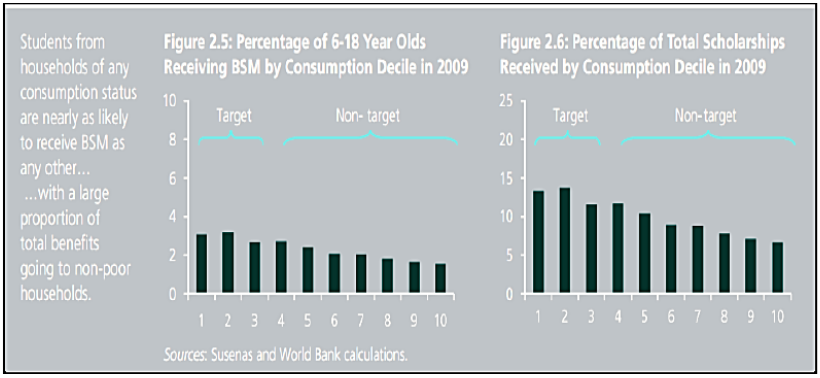
Source: Ministry of Finance Indonesia

Compliers and Non-Compliers Issues

During the first year of operation, BSM coverage reached 3.6 million students. The number increased to 8 million by 2013 and covers 33 provinces in Indonesia. Unfortunately, the World Bank (2012a) found that there was a misnomer in the first year of BSM implementation. The problem is that BSM was also accepted by non-target students in 2009 as shown in Figure 1, which is larger than the targeted students. Figure 1 also shows that the percentage of beneficiaries receiving the program (decile 1 - decile 3) is only 40 percent of those who should receive it. The budget is only able to absorb less than 15 percent of the poorest people. The World

Bank (2012a) argues that BSM is 'ineffective in identifying students' as beneficiaries of the program. The reasons are lack of program socialization, limited program monitoring and the need to prove the database used in targeting.

Figure 1 Percentage of Children Aged 6-18 Years Receiving BSM (Based on Desile Consumption)



Source: World Bank 2012a : 46.

A study conducted by Rand Corporation (2013) also found that BSM programs were less successful due to lack of regulatory and monitoring provisions, time issues, and limited coverage due to government budget (Baker & Siemens, 2013). Although BSM operates in all provinces and its budget is the third largest among the social safety net programs in Indonesia, it only covers 2.3 percent of children among the 6-18-year age group (World Bank, 2014). In short, this condition indicates that BSM has problems with targeting effectiveness, therefore, is still unable to help all the poor in terms of educational cost constraints.

In its development, many critics addressed to BSM implementation. World Bank (2015) writes that the BSM budget has not been effective in improving the quality of education, partly because of the low participation of school committees in determining the BSM budget allocation. This raises the question of the effectiveness of the disbursement of BSM funds. To test the effectiveness, one of the methods that can be used is to see the impact of BSM on improving students' learning achievement with national final examination scores as the proxy.

This study aims to evaluate the impact of BSM on the final national examination scores. There are two contributions from this study. First, this research would like to see the impact of BSM on student achievement. Previous research with the Indonesian case (Yulianti, 2015) only looked at the impact of BSM on the drop-out rate of students, and Widnyani & Sukadana (2017) at CCT allocations by poor families. Secondly, this study also controls several other government policy programs as explanatory variables, such as School Operational Assistance and Family Hope Program allegedly influencing student achievement. Previous research related to BOS with Indonesian case (Sulistyaningrum, 2016) has not controlled other education programs.

Literature Review

Education Subsidy Program Benefits

Murnane & Ganimian (2014) discussed the evaluation of the impact of educational programs in 33 low- to middle-income countries. There are four conclusions given. *First*, reducing school costs and providing alternatives to traditional public schools, improving attendance and student achievement, although not improving performance. *Second*, providing information on the quality of schools and the benefits of schooling generally improves student outcomes and achievements. *Third*, better resources do not improve performance unless there is an effort to change the student learning experience in school. *Fourth*, 'good' incentives for teachers can improve teacher performance and improve student achievement.

Supply and Demand Approach

Government subsidy programs in increasing enrollment can be differentiated into supply approach and demand approach. Supply approach for example by building schools, increasing school resources by increasing teacher salaries, providing training, reducing class size, and more. Supply approach can increase enrollment in some cases but not specifically increase the enrollment of poor students and can expand the gap of educational attainment of poor and wealthy children (Schultz, 2001). The result of evaluation of PRAF program in Honduras found that demand approach increase enrollment while supply approach does not (Glewwe & Olinto, 2004). Demand approach provides administratively targeted subsidies for the poor in the community so it is expected to reduce the gap enrollment between poor and non-poor. The demand approach has been shown to reduce inequality in education and incomes in Mexico and other Latin American countries (Schultz, 2001).

Impact Evaluation of Education Subsidy Programs in Various Countries

Fiszbein & Schady (2009: 128-129) provides a summary of studies conducted by the World Bank in estimating the impact of CCT (conditional cash transfer) on enrollment and school attendance. Almost every evaluation shows a positive effect of CCT on enrollment, although the effect is sometimes found among some age groups and not in other groups.

Table 1 presents some of the results of impact evaluation studies in various countries. Based on time series data of national level of Bangladesh, enrollment level of male middle school is higher than female student. Beginning in the early 1990s education subsidies for female students were introduced in Bangladesh and lowered the level of inequality of male and female enrollment. S. Khandker, Pitt, & Fuwa (2010) evaluated the impact of the subsidy program and found that there was a significant impact on the enrollment of high school girls. Endogenous issues arise from the time of program introduction. The FE conditional logit model is used to eliminate village-level heterogeneity that may affect factors from outcomes, individual school enrollment, and program introduction times. The available data is sufficient to estimate the marginal effect but not to identify the average effect. Samples are broken down into ages 11-18 and 13-18 years, for both men and women. The age is a risky age for drop out students.

The FA Program in Columbia covers aspects of health, nutrition, and education. This program was implemented in 2001. Attanasio, Fitzsimons, & Gomez (2005) evaluated the impact of the FA on education. In the field of education, the FA provides monthly subsidies to eligible mothers. Terms of subsidies are welfare under a certain cut-off, have children aged 7-17 years, and live in the treatment area. The impact of subsidy was measured by comparing enrollment rates between individuals in the treatment area and control areas. Enrollment prior to the enactment of the FA Program was analysed to see if there was any difference between treatment and control areas, due to the anticipated effects and/ or different fundamentals across regions. The impact estimation is done by linear regression parametric method. The results obtained from the procedure are not different from the regression method. Linear regression is chosen because of its parametric foundation. Based on the impact evaluation, the FA program effectively increased the enrollment rate in the 14-17 year age group, both in rural and urban areas.

Maluccio & Flores (2004) evaluated the impact of the RPS program in Nicaragua. The RPS program provides additional income for households to increase food expenditure, reduce primary school drop-out rates, and improve health care and nutrition for under-fives. Household and individual-level data are taken before and after the RPS program is implemented. This allows the calculation of the average program impact with double-difference method. In the educational aspect, the average effect on the enrollment of children aged 7-13 years showed significant results for follow-up in 2001 and 2002. Prior to the RPS program, enrollment rates in the treatment and control groups showed almost the same number, around 70%. During follow-up in 2001 and 2002, enrollment in the treatment group reached 90% while in the control group 75.1% and 79.2%.

The PROGRESA in Mexico provides a wide range of assistance to families belonging to the extreme-poor category and targeting mainly rural communities. The goal is to improve standards of living, health and nutrition, and increase educational opportunities for children. In determining households that are included in the poor enough category to obtain subsidies, household household well-being indexes are calculated based on the 1997 census, from information on household consumption, assets, and income. The success of the randomization design is evident from the insignificant value of enrollment differences from the treatment and control group prior to the start of the program. The difference-in-difference estimator showed that the PRORESA program increased enrollment by 0.66 years at the baseline level of 6.80 year old school (Schultz, 2001).

Table 2 Study on the Impact Evaluation of Education Subsidy Programs in Several Countries

Program	Variable	Method	Result	References
Country: Bangladesh Program: female school stipend program	Y:enrollment	Fixed Effect coditional logit: school/village level Two data set: cross section of Household and School panel data	Based on cross section data of households, the program improves secondary education for women. Based on school panel data: the program has a significant impact on the enrollment rate of women	(S. Khandker et al., 2010)
Country: Columbia Program: FA (Familias en Accion),	Y:enrollment	Linear Regression	The FA program effectively improves enrollment rates in children ages 14-17 Men get a positive effect better than women.	(Attanasio et al., 2005)
Country: Mexico Program: PROGRESA	Y:enrollment	Randomized design, Double-difference estimator	Enrollment increased by 0.66 years at the baseline level of 6.80 years of schooling	(Schultz, 2001)
Country: UK Program: Means-tested grants for children aged 16-18 years	Y: drop-out proportions	Matching Method on Panel Data	Full-time participation rate increased by 7% a year later.	(Dearden, Emmerson, Frayne, & Meghir, 2000)
Country: Honduras Program: PRAF II Two interventions were analyzed: Demand intervention & supply side incentive	Y:*enrollment* children aged 6-13 years	Econometrics	Demand side intervention increases 1-2% enrollment rate, reduces dropout 2-3%, increases school attendance by 0.8% / month. No effect on child labor force. Based on the simulation, in the long run, demand intervention	(Glewwe & Olinto, 2004)

Program	Variable	Method	Result	References
			increases the years of schooling 0.7% for children aged 14 years. Supply side intervention has no impact.	

Poor Student Assistance (BSM) in Indonesia

The Indonesia Government in 2001 reduced the fuel subsidy and allocated it for subsidies in education, health and infrastructure. There are two education subsidy programs that lasted for 4 years until the year 2004 namely; 1) BKM is a cash transfer for elementary, junior and senior high school students; and 2) BKS or grants for schools.

In 2005, BKM and BKS were changed to BOS. All poor students get priority to receive BOS. These poor students are not required to pay tuition, while the other students still pay tuition but not as high as the school cost prior to the BOS program. Since 2009, BOS has been allocated for poor and non-poor students. However, due to the increasing number of dropouts every year, the government issued BSM programs. It is expected that all students would not only be free from the burden of paying school operational costs, but also poor students get additional assistance for transportation and school uniforms. Furthermore, the Indonesian government adds nominal assistance with the aim of improving the quality of basic education, not merely fulfilling the previous objective of the compulsory 9-year study.

Not many studies evaluate the impact of BSM programs. Yulianti (2015) evaluated the impact and function of CCT in overcoming the number of dropouts, using a descriptive analysis approach showed negative results and significantly reduced the number of students who dropped out of school. Sulistyaningrum (2016) evaluated the impact of BOS program on elementary school exam scores. Using the Propensity Score Matching (PSM) and Near Neighbour (NN) matching algorithms, it was concluded that the BOS program was able to increase student value. The data used is IFLS 4 (2007). Student exam scores are measured at the age of 11 years or when students are in 6th grade. Trials are held simultaneously at the national level by MOEC. In general, parental education is positively correlated with student test scores.

Data, Variables, and Analysis Methods

This study uses secondary data sourced from Indonesia Family Life Survey (IFLS). IFLS was the first longitudinal survey conducted in Indonesia in 1993, 2000, 2007, 2014. IFLS's initial sample represented 83 percent of Indonesia's population, living in 13 provinces from 26 provinces (Strauss, Witoelar, & Sikoki, 2016). IFLS data contains information on various aspects of household life and individuals. The data used in this study focuses on children's education, which comes from book 5 and book 3A. IFLS data contains information on the status of whether or not the IFLS-sponsored child receives BSM education assistance at school. In addition, in the IFLS there were also questions about the value of the National Exam (UN), so that information can be obtained on the outcome variables of this study. In order to evaluate the impact of BSM, information on the characteristics of children, families, and schools can all be obtained from IFLS.

The dependent variable in this study is the value of UN/EBTANAS students, while the treatment variable is dummy whether students receive BSM or not. To estimate the probability of students obtaining BSM, several explanatory variables are used, such as sex, location (village/town), size of household, parental education level, household expenditure, electricity ownership, farmland ownership, home ownership status, schools (public/ private), cigarette expenditures, health expenditures, and education expenditures.

Theoretically, the most appropriate method of impact evaluation is the randomisation of comparing actual and counterfactual results (Rubin 1977). However, this method cannot be done if data collection is done after the program runs. One method for evaluating non-random impacts is the Propensity Score Matching (PSM) to overcome the selection bias problem in the determination of programming through the matching process (Rosenbaum & Rubin, 1983). The PSM method designs a control group based on the probability of respondents participating in the program, using observed characteristics. Participating respondents were compared with non-participating respondents. In this approach, there is no need to match each treated unit (Heckman, 1997) to the untreated unit which has the exact same value for all observed control characteristics. Instead, for each unit in the treatment group and in the non-participation group, the probability will be calculated that the units listed in the program are based on the observed characteristic value, called the propensity score. Angrist. and Pischke (2008) show the following PSM equations:

$$\boldsymbol{Y = \alpha + \beta T_i + \gamma A_i + \mu_i}$$

Here Y is the result of the student's score. α is the intercept, β Ti is the causal effect of the BSM programming, γA_i is the effect of the control variable.

The average treatment effect of the program is calculated by comparing the average outcome (outcome) between the participating respondents and the non-participating respondents. The validity of the PSM model depends on two assumptions; 1). conditional independence, 2). There is sufficient common support between participating and non-participating respondents (S. Khandker et al., 2010; Abadie & Imbens, 2006; Dahejia & Wahaba, 1999).

The assumption of conditional independence states that with certain explanatory variables not influenced by the presence or absence of treatment, the potential outcome is independent of the treatment decision. If Y_i^T represents the outcomes for participants and Y_i^C represents outcomes for non-participants, conditional independence can be written.

$$\left(Y_i^T, Y_i^C\right) \ldots . T_i \mid X_i$$

For estimated treatment of treated, the above assumptions can be relaxed to:

$$\left(Y_i^C\right) \ldots . T_i \mid X_i$$

The common support assumption emphasizes that the observations included in the treatment have similar comparative observations based on the distribution of the propensity score. This condition can be written in the equation:

$$(0 < P(T_i = 1 \mid X_i) < 1)$$

The effectiveness of the PSM method also depends on the number of samples and the comparison between the number of participants and non-participants so that a representative support can be obtained. For estimation of treatment of treated, these assumptions can be relaxed to:

$$(P(T_i = 1 \mid X_i) < 1)$$

If these two assumptions are met, we can calculate the Treatment of Treated (TOT) with the following equation:

$$TOT_{PSM} = E_{P(X)|\,T=1}\{E[Y^T \mid T = 1, P(X)] - E\,(Y^C \mid T = 0, P(X)]\}$$

Systematically, the following PSM steps (Khandker, Koolwal, & Samad, 2010) are:

Estimate the program participation model by using a number of covariates (explanatory variables) that are suspected to have an effect on the program's participation.

Determine the shared common support area that represents the distribution of the propensity score between the participating and nonparticipant groups, and perform the balancing test.

Match participants and non-participants using several techniques; nearest-neighbor matching, caliper or radius matching, stratification or interval matching, kernel and local linear matching, difference in difference matching.

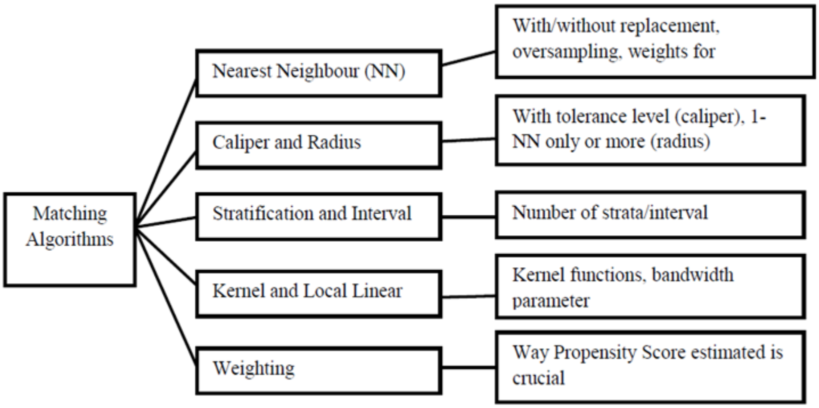
In addition, according to Marco Caliendo & Kopenig (2005), the implementation steps of PSM are as follows:

Estimated Propensity Score

There are two steps to do estimation of propensity score that is choosing model specification and variable selection. The choice of variables should be based on previous findings as well as relevant economic theory.

Choosing a Matching Algorithm

Five different matching algorithms according to M. Caliendo & Kopeinig (2005): Nearest Neighbors (NN), Caliper and Radius, Stratification and Interval, Kernel and Local Linear and Weighting (Figure 2), and this paper will use NN matching algorithms. There is no superior method among all matching methods. This is due to the trade-off between bias and variance that will affect the estimated value of ATT (Caliendo and Kopeinig, 2008).



Testing overlaps or common support

This stage is an important part in matching estimation (Sulistyaningrum, 2016) for ensuring matching between the treated group and the control group.

Test the Matching Quality

Tests that can be performed include standardized bias, t test before and after matching and F joint equality of means test on sample matched. If there is no difference (receiving H0), it means that the sample used has good matching quality. If the match quality is poor or there is still a difference, it's better to repeat the same steps until the matching quality is satisfactory.

Sensitivity Analysis

Sensitivity analysis was conducted to see the presence of hidden bias due to unmeasured variables in treated and untreated groups. The Wilcoxon marked rank test can be used to perform to perform sensitivity analysis.

Results and Discussion

Table 3 Samples of Beneficiaries and Non BSM Program Receivers

Beneficiaries	Non BSM Program
205	1.252

Source : Indonesia Family Life Survey (IFLS) Database

Table 3 shows that there were 205 students who received the last one year program and 1,252 students did not receive. To determine household treatment and control, a matching process is done by including all household characteristics variable that has been determined by TNP2K as the condition of program beneficiaries.

The variables used in the PSM must meet the Conditional Independent Assumption (CIA) in which the outcome variable must be independent of the conditional treatment of the propensity score (Caliendo & Kopeinig, 2005). The model meets the CIA if the outcomes to be administered from the treatment group are not influenced by other variables other than treatment variables, meaning the outcome of the intervention is not the influence of other factors outside the intervention. The probability score match is a solution to the problem of dimensions and can be estimated using probit or logit models. Since most statistical literature tends to use probit, this study also uses probit models to obtain predictive propensity scores (Dehejia & Wahba, 1998). The probability of obtaining BSM is determined by various individual characteristics as in table 4 above. In column 1 (table 4), internet access variables, mobile ownership, estimated number of students in the classroom, length of trip to school, household expenditure logs for food in a month is significant.

Table 4 BSM Probit Model

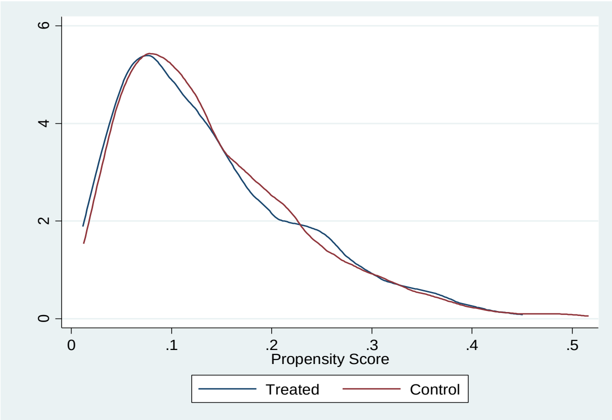
bsm	Parameter Estimation	
	Coefficient (1)	Std. Err (2)
Man	-.0428243	.0886154
Age	.0636282	.0540174
Internet	-.2231214**	.1013334
Phone	-.2347335**	.100796
Transportation	.0042593	.0048241
Class_size	-.0088417**	.004373
public	.1461131	.1394117
jumlah_art	.047976	.0304487
Yearsof_schooling	-.0414357***	.011099
Lnfood	-.2225261***	.0843454
Urban	.1273698	.0957205
lnavgsmok14	.0047508	.0231115
lneduc_exp14	-.0656882	.0421147
_Cons	2.48459**	1.31741

Note: dependent variable is BSM where 1 for receiver, 0 other

*Significant at 10%, **significant at 5%, ***significant at 1%

This study used Near Neighbor Matching, because the data distribution did not differ significantly in the treated group and control group as shown in Figure 2. The distribution of treated group had higher propensity score than the control group.

Figure 2 Propensity Score Distribution and Common Support



Sianesi (2006) states that common support should be checked, requiring that there be treated group units and control groups that have similarity values of propensity matching after matching when the density values of the treatment group and the control group occur overlap (intersection). The common support area represents the similarity of characteristics between the two groups based on the similarity of the distribution of its propensity values. Table 5 confirms that common support is met because there is an overlap propensity score between treated and control groups.

Table 5 Characteristics of Explanatory Variables (Average)

	Non-BSM	BSM	Difference	(p-value)
Total Final Exams (UAN) Value	15.33	15.04	0.29	0.09
Average Final Exams (UAN) Value	7.66	7.52	0.14	0.09
Final Exams (UAN): Mathematics	7.50	7.31	0.20	0.10
Final Exams (UAN): Bahasa	7.82	7.71	0.11	0.00
dummy student gender	0.49	0.48	0.01	0.24
Student age	13.15	13.17	-0.02	0.27
dummy using internet or not	0.69	0.50	0.19	0.00
dummy using mobile phone or not	0.74	0.56	0.17	0.00
Approximate length of trip to school	10.52	11.46	-0.94	0.00
Estimated number of students in the class	30.53	27.90	2.63	0.00
Dummy public or private SD type	0.86	0.90	-0.05	0.00
Amount of Household member	4.72	4.97	-0.24	0.00
Head of household education	8.82	6.40	2.41	0.00

log Household expenses for food	14.44	14.22	0.22	0.00
dummy urban or rural	0.61	0.54	0.07	0.00
lnavg_smoking14	9.29	9.30	-0.01	0.89
lneduc_exp14	12.97	12.51	0.46	0.00

Estimates are conducted to analyse how far the impact of the BSM program affect student attainment. Figure 3 shows the results of the Average Treatment Effects on the Treated (ATET) of the BSM program as a whole. From the estimation results using NN Matching the author found that the BSM program was able to increase the average score of BSM recipient students by 5.6 percent greater than the students who did not receive the program at the level of significance of 10 percent.

Figure 3 BSM Effect on Student Score Average (New Method)

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Treatment-effects estimation                Number of obs      =      1,395
Estimator      : propensity-score matching  Matches: requested =          1
Outcome model  : matching                                  min =          1
Treatment model: probit                                    max =          2
```

skor_rata	Coef.	AI Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
ATET						
ban_bsm (1 vs 0)	.2154923	.1181986	1.82	0.068	-.0161727	.4471573

Source: processed using STATA

Cash transfer programs can have a positive effect on student achievement (Sulistyaningrum, 2016). As in other developing countries, cash transfers such as BSM are indeed able to decrease not only drop-out rates, and allow improvements in achievement of poor students.

Figure 3 ATT Estimation with NN Matching

ATT estimation with Nearest Neighbor Matching method
(random draw version)
Analytical standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
195	167	0.452	0.254	1.778

Note: the numbers of treated and controls refer to actual nearest neighbour matches

Discussion and Conclusion

This study as a whole, indicates that estimated using PSM, BSM program managed to improve student achievement test results. BSM program has a positive and significant impact on the average score of children. Students receiving program assistance received a higher test score of 5.6 percent. As a program of assistance to poor students, BSM helps students gain access to education, especially basic education, because the government can ensure direct use of subsidies for students, although it is difficult to properly monitor the use of aid funds. As Widnyani & Sukadana (2017) finds in evaluating the use of CCT funds in the form of BLSM by households, the increase in family income due to CCT increases household consumption of cigarettes. Thus, further research can evaluate the allocation of the use of BSM funds by individuals so that it is known whether the aid program is being used properly.

Researcher are aware of the limitations of the preparation of this paper, such as; 1) the impact evaluation of matching methods makes it possible to overcome the bias through statistical techniques and form a comparison group although there is no counterfactual data, but the bias is not completely eliminated. Nevertheless, the matching method is considered to be the best alternative after RCT (Almunawaroh, 2016); 2) there is possibility of causality by the use of household expenditure variable, education expenditure, food expenditure and cigarette expenditure. Thus, it is necessary to conduct further study to form a more comprehensive construct related to the effectiveness of the BSM program.

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Appendix

Abbreviation

PSM	Propensity Score Matching
BAPPENAS	Indonesian Ministry of National Development Planning (Badan Perencanaan dan Pembangunan Nasional)
BDT	Integrated Database
BSM	Poor Student Assistance (Bantuan Siswa Miskin)
BOS	School Operational Assistance (Bantuan Operasional Siswa)
BKM	Special Assistance for Student (Bantuan Khusus Murid)
BKS	Special Assistance for School (Bantuan Khusus Sekolah)
CCT	Conditional Cash Transfer
BLT	Direct Cash Assistance (Bantuan Langsung Tunai)
BPS	Central Bureau of Statistics (Badan Pusat Statistik)
GDP	Gross Domestic Product

JAMKESMAS	Indonesian National Health Insurance (Jaminan Kesehatan Masyarakat)
JPS	Social Safety Net (Jaringan Pengaman Sosia)l
KPS	Social Protection Cards (Kartu Perlindungan Sosial)
LPG	Liquid Petroleum Gas
PKH	Family Hope Program (Program Keluarga Harapan)
PPLS	Social Protection Program Data Collection
RASKIN	Rice for the Poor (Beras Miskin)
SKTM	Certificate of inability/Poor (Surat Keterangan Miskin)
TNP2K	National Team for Accelerating Poverty Reduction (Tim Nasional Percepatan Penanggulangan Kemiskinan)