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Program Keluarga Harapan and Senior Secondary Out-of-School Rates

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ABSTRACT

Research Originality: The novelty of this study lies in its use of a combined approach of probit analysis and propensity score matching to evaluate the impact of the *Program Keluarga Harapan* (PKH) on reducing out-of-school rates at the senior high school level, specifically before and after the COVID-19 pandemic.

Research Objectives: The study aims to empirically assess the effectiveness of PKH in enhancing educational outcomes to break the cycle of poverty.

Research Methods: The study also utilizes recent data from 2019 and 2022, reflecting the increased financial support of up to IDR 10 million per family per year. The analysis was conducted in two stages: first, on the overall sample of students from eastern Indonesia and other regions, and second, on a subsample of students in eastern Indonesia.

Empirical Results: The results indicate that PKH was more effective in 2022, with a 2.3% reduction in the overall sample and a 1.4% reduction in the eastern Indonesian subsample in preventing students from dropping out of school compared to 2019.

Implications: The study suggests that PKH can effectively support educational participation and reduce out-of-school rates, supplementing primary programs like PIP (*Program Indonesia Pintar*).

Keywords:

education; *program keluarga harapan* (PKH); out-of-school children rate; marginal effect; propensity score matching

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INTRODUCTION

Goal 4 of the Sustainable Development Goals (SDGs) emphasizes universal access to equitable and quality primary and secondary education, ensuring all children have equal opportunities to learn and succeed in their educational pursuits. To achieve this goal, every child must complete their education without dropping out. Due to the global consensus in agreement with Goal 4, the out-of-school rate of school-age children is expected to decrease. However, according to data from the United Nations Educational, Scientific and Cultural Organization (UNESCO), education remains in a state of emergency, as indicated by the high non-attendance rate in recent years. In 2022, UNESCO reported that 244 million children were out of school worldwide.

Indonesia also needs more out-of-school children. Data from the Central Bureau of Statistics' Education Statistics show that the number of out-of-school children in Indonesia remains relatively high, with the country experiencing an increase in 2022, especially at the senior high school level. The prevalence of out-of-school children at the senior high school level 2022 increased to 22.52% from 21.47% in 2021. This figure surpasses those of primary and junior high school levels. In other words, the proportion of 16 to 18-year-olds in Indonesia who do not complete their senior high school education is approximately 22 per 100 children.

The Central Bureau of Statistics' Education Statistics data also show that eastern Indonesia, known as *Kawasan Timur Indonesia*, is primarily responsible for the rise in the number of children not attending senior high school or its equivalent. This uptick in out-of-school children occurred despite a boost in the education budget from 2019 to 2022. Data from the Ministry of Finance show that from 2019 to 2022, the education budget increased from IDR 460.3 trillion in 2019 to IDR 473.7 trillion in 2020, IDR 479.6 trillion in 2021, and IDR 574.9 trillion in 2022.

There is a positive correlation between education level and the out-of-school rate, and this relationship shows an increasing trend; essentially, the higher the education level, the higher the out-of-school rate. Although children may complete primary school, secondary education is usually a burden for people experiencing poverty due to additional costs and educational facilities far from where they live (Baird et al., 2013). This data indicates that children in senior high school require more money than those in primary or junior high school. The increased costs associated with schooling directly impact the educational opportunities available to individuals within a household. When a family suffers economic hardships, it inevitably disrupts some aspects of their lives, including educational opportunities.

The widening disparity in access to higher levels of education among economic groups is reflected in the poor's notably low school enrollment rate compared to the non-poor, resulting in the increasing out-of-school rate. Children from low-income families still face the challenge of completing 12 years of primary education. In their study, Granado et al. (2007) find a wide gap between the educational attainment of poor and rich groups at the junior and senior secondary school levels, with children from low-

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income families being 20% less likely to attend junior secondary school compared to children from wealthy families. In addition, Suryadarma (2006) found that children living in rural areas have lower access to junior secondary school education. Other studies find that poverty is closely associated with children dropping out of school. Adelman and Szekely (2017) find a negative correlation between school enrollment in Central America and factors such as poverty, unemployment of the head of the household, and children being the primary breadwinners. In line with the previous two studies, Takahashi (2011) also finds that children living in neighborhoods that are more affluent and have a high proportion of children enrolled in school are more likely to attend school.

To overcome Indonesia's high out-of-school rates, the national government must play an active role in ensuring that the entire population has equal access to education for the entire population. One solution is to alleviate poverty, thus giving low-income families better access to higher education. The Indonesian government has implemented various fiscal policies to address this problem because productive government spending and direct contact with the public interest will stimulate the economy (Fiscal Policy Agency, 2012). One government intervention is cash transfer programs. The additional income provided by cash transfer programs, both conditional and unconditional, allows households to increase investment in education. By reducing the relative price of education, conditional cash transfers for school enrollment can increase investment in education and reduce child labor when households are not credit-constrained (de Hoop & Rosati, 2014).

One such cash assistance program is the *program Keluarga Harapan* (PKH), implemented in 2007. The PKH is a conditional cash transfer (CCT) program that alleviates poverty. This program was initially implemented in Mexico and Brazil and has since been widely adopted by other countries as a social assistance strategy (Rawlings & Rubio, 2005). In Indonesia, the PKH budget, which has prerequisites for its disbursement, including the fulfillment of educational aspects such as school attendance, increased from IDR 32.65 trillion (10 million KPM) in 2019 to IDR 37.4 trillion (10 million KPM) in 2020. The budget slightly decreased in 2021 to IDR 28.7 trillion (10 million KPM) and remained the same in 2022 at IDR 28.7 trillion (10 million KPM) (Ministry of Social Affairs, 2019). Although the PKH budget decreased from 2019 to 2021 before stabilizing in 2022, the number of out-of-school children increased in 2022.

The PKH policy assumes that increasing children's school enrollment will reduce out-of-school rates because school-age children from beneficiary families must enroll and maintain a certain level of school attendance to receive the CCT. In this case, the increase in parents' income from PKH assistance, accompanied by the prerequisite of school enrollment and attendance of children, is expected to increase school enrollment. This view is supported by Hartarto and Wardani (2023), who state that from a policy perspective, the program can change parents' aspirations for their children to get higher education. By addressing the education issue, the hope is that children from low-income households can escape the poverty they may have inherited from their parents. Therefore, the cash transfer program is vital in advancing children'schildren's education and welfare (Hidayatina & Ozzane, 2019).

CCT programs have attracted the attention of researchers who want to evaluate government policies that explicitly and implicitly affect educational outcomes. Baird et al. (2013) evaluate 75 studies on cash transfers and find that CCT and unconditional cash transfer (UCT) programs significantly affect school enrollment. They determined that children from households in the CCT group have a greater chance of being enrolled in school than those from households in the UCT group, with no statistically significant difference found between the groups. Galiani and McEwan (2013) and Saavedra andGarcía (2012) also find that CCT programs effectively increase school enrollment and attendance. In line with previous studies, Glewwe and Kassouf (2012), Janvry et al. (2012), Edmonds and Schady (2012), and Brauw and Hoddinott (2011) find that CCT programs can increase school enrollment and reduce dropout rates.

In Indonesia, several studies examine the effect of the PKH on educational outcomes. Yulianti et al. (2015) determine that implementing the PKH effectively reduced school dropout rates. However, it is different from previous research by Alatas et al. (2011), who found that the PKH can increase the duration of school attendance for PKH-beneficiary children. However, it does not increase children's participation in the education system or retain them in it. Likewise, Lee and Hwang (2016) found that the PKH did not significantly increase school enrollment. Furthermore, the financial returns of PKH children attending school are lower than those of non-PKH children in the short and medium term. However, in the long term, the economic returns are greater than those of non-PKH children.

The PKH can also influence educational attainment. Several studies have shown that the PKH can improve beneficiary children'schildren's attendance rates and academic achievement (Cahyadi et al., 2020; Wasim et al., 2019). Thus, the literature shows that cash transfers have varying impacts on educational outcomes in different countries. In Indonesia, research on the PKH and academic outcomes is limited. The impact of the PKH on educational outcomes has yet to be examined using the probit analysis method coupled with the propensity score matching (PSM) method. The PSM method can minimize the potential bias in standard regression methods, thereby increasing the accuracy of research results. Therefore, the novelty of this research comes from the research method and the use of educational outcomes (out-of-school rates) as a measure of the impact of the PKH. This study also uses relatively recent data from 2019 and 2022, which is sufficient to evaluate the effectiveness of the PKH more than a decade since the program's implementation in 2007. MicroSave Consulting (2019), in the Operational Assessment and Impact Evaluation Report of the PKH, the amount of assistance has been increased to a maximum of IDR 10 million per family per year with a non-flat scheme so that the amount of assistance varies depending on the conditions of beneficiaries, referred as *Keluarga Penerima Manfaat* (KPM).

As the PKH includes an educational participation conditionality in its disbursement, this study empirically examines and analyzes the program's impact on educational output in Indonesia. From a policy perspective, this study aims to determine two things: (1) whether there is indeed a relationship between participation in the PKH and the out-of-

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school rate at the senior high school level and (2) whether PKH assistance has the potential to reduce the out-of-school rate at the senior high school level, especially in eastern Indonesia. The results of this study can guide decision-makers in formulating policies to strengthen social protection programs that are beneficial for children's education.

METHODS

This study uses individual-level data sourced from *Survei Sosial Ekonomi Nasional* (SUSENAS) and Basic Education data. For analysis, this study uses the PSM method to determine the impact of the PKH on school out-of-school rates by comparing individuals in households that receive PKH assistance as a treatment group with individuals in households that do not receive PKH assistance as a comparison (control). This study employs PSM combined with difference-in-differences, based on research from Hartarto and Wardani (2023). A probit regression, which considers the PSM model's weight, is later conducted to analyze data. This study employs a probit regression, a type of logistic regression, as it is designed for binary outcomes with a dependent variable that can take on two values: 0 and 1. The binary nature of values 0 and 1 can reflect probability. This study examines the probability of children in a household not attending or dropping out of school.

The PSM method was introduced by Rosenbaum and Rubin in 1983. Propensity refers to the probability of receiving a treatment (or both). This method of analysis uses propensity scores to match treated and untreated individuals. Propensity score refers to the probability of an individual not receiving treatment when the individual has received treatment. Propensity scores are estimated and used to reduce the impact of potential confounders. The quantitative approach determines the impact of a policy or program by examining the treatment group. This is done by calculating the average value of the treatment effect, otherwise called the average treatment effect on the treated (ATT). The formula for ATT is as follows:

$$ATT = (Y_1 - Y_0 \mid D = 1) = E(Y_1 \mid D = 1) - E(Y_0 \mid D = 0)$$

where Y_1 is the dependent variable (PKH) after treatment, Y_0 is the dependent variable when not getting treatment, D=1 is the treatment group, and D=0 is the control group.

When comparing what would have happened if the group had not received the treatment (counterfactual), it may be challenging to determine the expected value for the treatment group using the formula above. In this case, the expected value is PKH or E(Y0|D=1) because the treatment group has already received it. Experts recognize that even when regression adjustments are applied, bias from potential confounding can cause problems in concluding observational studies. When evaluating impact using only conventional analytical tools, adjustments for bias must be accounted for and are difficult to carry out (Hullsiek & Louis, 2002).

To overcome this problem, it is essential to use an analysis method that can effectively reduce bias by appropriately adjusting the covariates in both groups. To minimize bias, there must be a comparison group that does not receive the treatment (also known as the control group) with the same characteristics as the treatment group. PSM can effectively reduce bias, thus improving the accuracy of estimating a program's impact on outcomes (Hullsiek & Louis, 2002). PSM is advantageous over regression-based methods because it is a non-parametric approach that avoids specifying the relationship between characteristics and outcomes. Another advantage of this method is that it focuses on issues of common support, thus ensuring that comparisons of incidences of non-attendance between individuals receiving and not receiving PKH assistance are only made if both groups of individuals share the same characteristics.

This study PSM as its multivariate analysis method to assess the impact of the PKH on the educational outcome of dropping out of school. The logistic regression analysis results determine that the covariate variables included in the matching stage significantly impact PKH enrollment. These covariates in the PSM model will be excluded from the observations if the logistic regression analysis results show no impact on the main independent variable, PKH enrollment.

First, we calculate the propensity scores for the treatment group (recipients of PKH assistance) and the control group (non-recipients of PKH assistance) by performing a logistic regression on the covariates. This regression analysis is conducted to assess the impact of confounding variables on PKH enrollment among individual households in Indonesia, both before and after matching. It matches the propensity score of each respondent in the treatment group with the closest control group score. After obtaining the logistic regression analysis results on the covariate variables, the covariate variables that do not significantly affect the main independent variable (PKH enrollment) can be eliminated. The covariate variables that significantly affect PKH enrollment will be used to test the impact of the PKH on school out-of-school rates through the PSM method.

Next, we match the covariate variables. This matching ensures that the covariate variables in the study are matched between the treatment group (recipients of PKH) and the control group (non-recipients of PKH). Following research by Hartarto and Wardani (2023), we first determine the most appropriate matching algorithm among several. Matching algorithms vary in the allocation of weights to adjust the relative distance between treated and untreated individuals when matched. Thus, the choice of a matching algorithm can significantly affect the accuracy of the estimation results (Hartarto & Wardani, 2023). We use matching algorithms such as nearest neighbor, caliper, radius, and kernel to assess the robustness of the estimation results.

The matching analysis generates the ATT value, which shows the average value of the outcome variable, namely the incidence of not attending school, after matching. The difference in out-of-school rates before and after matching will be compared with out-of-school rates before and after matching with the PKH enrollment variable as the main independent variable. There is a successful matching process if propensity score overlap between treatment and control groups. This stage aims to strengthen the interpretation and assess whether the matching in the PSM method is appropriate by looking at the distribution between the treatment and control groups. The last step tests the matching quality by comparing the distribution of covariate X before and after matching. The

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standardized difference calculation is used for each covariate X before and after matching. The percentage of bias reduction can determine the accuracy of the matching result.

PSM is used to create identical comparison groups by considering the propensity score of a variable or set of variables. In this method, the caliper is used to ensure balance between the matched groups. The caliper determines the maximum tolerance of difference in propensity score between two individuals in the comparison group. When nearest neighbor, caliper, radius, and kernel algorithms are employed to find matches, a caliper value is required to limit the maximum difference allowed between matching propensity pairs. The method to determine the caliper value may differ based on the preference and characteristics of the data used.

This study also conducts a probit regression to ensure the robustness of the model. The probit regression in this study uses the weight of the best algorithm among the four algorithms to reduce bias in the PSM method of each sample group. In their studies, Hidayanti and Ozzane (2019) and Yulianti (2015) also use probit regressions to analyze educational assistance on educational outcomes. Our data sample consists of individuals aged 16 to 21 at the senior high school or equivalent education level. In addition to estimating the parameter β, this study also estimates the marginal effect, namely, if β changes, how does it affect the probability of not attending school (Yi = 1) or attending school (Yi = 0)? The empirical model in this study is conducted at the senior high school education level based on the research model of Yulianti (2015).

The probit model improves for several reasons after PSM weights are applied. First, there is the reduction of selection bias. PSM helps to balance the distribution of covariate characteristics between the treatment and control groups; thus, the estimation results of the probit model become more valid and unbiased by the initial differences that exist before treatment. Second, using PSM weights, each observation in the probit model is assigned a weight based on how representative it is in the context of treatment or control. The weight can improve the treatment effect estimation by prioritizing more representative observations, thus improving the accuracy and reliability of the probit model estimation results. Third, PSM helps ensure that the study results are more generalizable to a broader population, as they reflect a more balanced and representative population. These factors enhance the probit model's effectiveness in capturing the causal relationship between the treatment and the observed outcome.

This study employs the incidence of not attending school as its dependent variable and PKH enrollment as its independent variable. The control variables are gender, age, education of the household head, number of household members, per capita expenditure, PIP, BPNT (*Bantuan Pangan Non Tunai*), school availability, urban or rural status, and the teacher–student ratio at the senior high school level. In this study, senior high school refers to senior general secondary school (SMA) and senior vocational secondary school (SMK) in Indonesia. This study assesses how the PKH affects the likelihood of non-attendance of school for those aged 16 to 21 at the senior secondary level by analyzing it as a function of PKH and control variables (X).

This study uses two sample sets: the full sample individual dataset and the subsample individual dataset. The full sample individual dataset includes individuals aged 16 to 21 at the senior high school level of education. This dataset includes recipients and non-recipients of PKH benefits. This dataset also includes individuals who are from eastern Indonesia and those who are not from eastern Indonesia. We use this dataset to analyze and answer the first research question of whether PKH assistance can reduce the incidence of not attending school among senior high school-aged children.

The second dataset takes the individuals from eastern Indonesia as the subsample. Eastern Indonesia includes the islands of Kalimantan, Sulawesi, Maluku, Nusa Tenggara, and Papua as defined by Presidential Regulation No. 2 of 2015 on the National Medium-Term Development Plan 2015-2019, Book I of the National Development Agenda, which states that western Indonesia includes Sumatra, Java, and Bali, while all other regions are considered eastern Indonesia. This subsample dataset consists of individuals from eastern Indonesia who are at the senior high school education level and are categorized into two groups: those who receive PKH benefits and those who do not. We use this dataset to analyze and answer the second research question of whether PKH assistance has the potential to reduce out-of-school rates in eastern Indonesia.

RESULTS AND DISCUSSION

The PSM analysis of the impact of PKH enrollment on the out-of-school rate at the senior high school level indicates that there is a difference in the out-of-school rate between individuals who receive PKH assistance and those who do not, but it is in the wrong direction. After matching the observed covariates, we find that PKH enrollment significantly reduces the out-of-school rate at the senior high school level, especially in the full sample in 2019 and the full sample and subsample in 2022. Table 1 reports the results from the PSM and common support analyses.

Table 1. Tabulation of PSM Results

Years (ATT)	Nearest neighbor		Caliper		Radius		Kernel	
	Diff (S.E.)	T-stat	Diff (S.E.)	T-stat	Diff (S.E.)	T-stat	Diff (S.E.)	T-stat
2019 (full sample)	−0.033*** (0.006)	5.36	−0.030*** (0.005)	5.48	−0.030*** (0.004)	6.60	−0.029*** (0.004)	6.67
2019 (subsample)	−0.009 (0.009)	0.98	−0.002 (0.008)	0.31	−0.005 (0.007)	0.79	−0.005 (0.006)	0.79
2022 (full sample)	−0.027*** (0.005)	4.94	−0.030*** (0.005)	6.24	−0.035*** (0.004)	8.52	−0.034*** (0.004)	8.69
2022 (subsample)	−0.015* (0.008)	1.84	−0.019** (0.007)	2.51	−0.022*** (0.006)	3.47	−0.024*** (0.006)	3.86

For the full sample for 2019, the nearest neighbor, caliper, and kernel matching algorithms in the PSM process allow all covariates to get a matching pair or total common

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support of 106,893, consisting of 85,441 individuals who did not receive PKH assistance and 21,452 individuals who did. All covariates are on support, meaning no respondents are discarded (off support), in the matching process except for in the radius algorithm, where 15 individuals are off support but not significant. In the 2019 subsample, the nearest neighbor, caliper, and kernel matching algorithms in the PSM process allow all covariates to get a matching pair or total common support of 45,082, consisting of 35,837 individuals who did not receive PKH assistance and 9,245 individuals who did. All covariates are on support except for in the radius algorithm, where 167 individuals are off support but not significant.

Table 2. The Common Support

Full sample 2019
(a)

Common Support	NN		Caliper		Radius		Kernel	
	On Support	Off Support	On Support	Off Support	On Support	Off Support	On Support	Off Support
Treatment	21,452	0	21,452	0	21,437	15	21,452	0
Control	85,441	0	85,441	0	85,441	0	85,441	0
Total	106,893	0	106,893	0	106,878	15	106,893	0

Subsample 2019
(b)

Common Support	NN		Caliper		Radius		Kernel	
	On Support	Off Support	On Support	Off Support	On Support	Off Support	On Support	Off Support
Treatment	9,245	0	9,245	0	9,078	167	9,245	0
Control	35,837	0	35,837	0	35,837	0	35,837	0
Total	45,082	0	45,082	0	44,915	167	45,082	0

Full sample 2022
(c)

Common Support	NN		Caliper		Radius		Kernel	
	On Support	Off Support	On Support	Off Support	On Support	Off Support	On Support	Off Support
Treatment	27,935	0	27,934	1	27,910	25	27,934	1
Control	84,469	0	84,469	0	84,469	0	84,469	0
Total	112,404	0	112,403	1	112,379	25	112,403	1

Subsample 2022
(d)

Common Support	NN		Caliper		Radius		Kernel	
	On Support	Off Support	On Support	Off Support	On Support	Off Support	On Support	Off Support
Treatment	12,617	0	12,617	0	12,520	97	12,617	0
Control	34,355	0	34,355	0	34,355	0	34,355	0
Total	46,972	0	46,972	0	46,875	97	46,972	0

In the full sample for 2022, the nearest neighbor matching algorithm in the PSM process allows all covariates to get a matching pair or total common support of 112,404, consisting of 84,469 individuals who did not receive PKH assistance and 27,935 individuals who did. Most covariates are on support. However, in the caliper, radius, and kernel algorithms 1, 25, and 1 individual(s), respectively, are off support but not significant. In the 2022 subsample, the nearest neighbor, caliper, and kernel matching algorithms in the PSM process allow all covariates to get a matching pair or total common support of 46,972, consisting of 34,355 individuals who did not receive PKH assistance and 12,617 individuals who did. All covariates are on support except for in the radius algorithm, where 97 individuals are off support; however, this number is not significant.

Table 3 Matching Quality Test

Full sample 2019
(a)

Algorithm	Before Matching (%)		After Matching (%)		Reduction in Bias (%)	
	MeanBias	MedBias	MeanBias	MedBias	MeanBias	MedBias
Nearest neighbor	35.4	25.9	5.0	5.9	85.9	77.2
Caliper	35.4	25.9	5.2	5.9	85.3	77.2
Radius	35.4	25.9	5.5	5.9	84.5	77.2
Kernel	35.4	25.9	5.7	6.1	83.9	76.4

Subsample 2019
(b)

Algorithm	Before Matching (%)		After Matching (%)		Reduction in Bias (%)	
	MeanBias	MedBias	MeanBias	MedBias	MeanBias	MedBias
Nearest neighbor	36.1	34.6	3.9	4.3	89.2	87.6
Caliper	36.1	34.6	3.6	4.4	90.0	87.3
Radius	36.1	34.6	3.7	4	89.8	88.4
Kernel	36.1	34.6	3.2	3.5	91.1	89.9

Full sample 2022
(c)

Algorithm	Before Matching (%)		After Matching (%)		Reduction in Bias (%)	
	MeanBias	MedBias	MeanBias	MedBias	MeanBias	MedBias
Nearest neighbor	31.6	17.4	2.3	2.3	92.7	86.8
Caliper	31.6	17.4	2.2	1.7	93.0	90.2
Radius	31.6	17.4	2.4	1.4	92.4	92.0
Kernel	31.6	17.4	2.3	1.4	92.7	92.0

Subsample 2022
(d)

Algorithm	Before Matching (%)		After Matching (%)		Reduction in Bias (%)	
	MeanBias	MedBias	MeanBias	MedBias	MeanBias	MedBias
Nearest neighbor	32.5	16.8	2.2	1.4	93.2	91.7
Caliper	32.5	16.8	2.2	1.2	93.2	92.9
Radius	32.5	16.8	1.9	1.4	94.2	91.7
Kernel	32.5	16.8	2.1	1.8	93.5	89.3

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Therefore, the PSM results for the four algorithms in the four sample groups exceed the satisfactory threshold. After obtaining the results of the four algorithms and sample groups, a quality matching test is conducted. This test is based on the results of bias reduction in the analysis conducted by matching propensity scores. Table 3 outlines the details of the bias reduction of each algorithm based on the results of the four matching algorithms.

In the 2019 full sample, the nearest neighbor algorithm has the highest bias reduction, with a decrease of 85.9% in mean bias and 77.2% in median (med) bias. However, in the 2019 subsample, the kernel algorithm has the largest bias reduction, with a decrease of 91.1% in mean bias and 89.9% in median bias. In the full sample for 2022, the kernel algorithm also produced the highest bias reduction of 92.7% in mean bias and 92% in median bias. In the 2022 subsample, the radius algorithm produced the largest decrease in bias, with a decline of 94.2% in mean bias and 91.7% in median bias.

Based on the matching results in Table 3, the algorithm that produces the highest bias reduction compared to other algorithms, the weights in the algorithm, will be used in probit logistic regression to ensure the robustness of the model. Table 4 reports the estimation results measuring the effect of the PKH on out-of-school rates. The findings on the full sample show that the PKH is negatively associated with the probability of individuals not attending senior high school with a statistically significant relationship. In other words, the PKH effectively reduces the probability of children leaving secondary school.

The estimation results show that children from households that received PKH assistance had a 1.9% lower probability of not attending senior high school than those from families that did not receive PKH assistance at the senior high school level in 2019. In the eastern Indonesian subsample, the PKH is positively associated with a 0.2% increased risk of individuals not attending senior high school. However, this relationship is not statistically significant, implying that the PKH failed to reduce the probability of children not attending senior high school in eastern Indonesia in 2019. A comparison of the results from the full sample with those from the subsample in eastern Indonesia show that the PKH has a more pronounced impact in reducing the probability of a student dropping out of school in the overall sample.

Table 4 also shows that for the full sample in 2022, the PKH is statistically negatively associated with the probability of individuals discontinuing their education at the senior high school level, and this relationship is statistically significant. Therefore, the PKH has a moderately effective impact in reducing the out-of-school rate at the senior high school level. The estimation results show that children from households receiving PKH assistance have a 2.3% lower probability of not attending senior high school than those from families not receiving PKH assistance at the senior high school level.

Table 4. Probit Estimation Results

Variable	Full Sample Marginal Effect in 2019	Subsample Marginal Effect in 2019	Full Sample Marginal Effect in 2022	Subsample Marginal Effect in 2022
PKH	−0.019***	0.002	−0.023***	−0.014**
	(0.005)	(0.005)	(0.003)	(0.006)
PIP	−0.308***	−0.305***	−0.284***	−0.265***
	(0.007)	(0.009)	(0.008)	(0.015)
BPNT	0.042***	0.045***	0.033***	0.034***
	(0.006)	(0.010)	(0.003)	(0.006)
Gender	0.020***	0.021***	0.022***	0.021***
	(0.005)	(0.005)	(0.003)	(0.006)
Educational degree	−0.058***	−0.057***	−0.058***	−0.058***
	(0.001)	(0.001)	(0.000)	(0.001)
Expenditure per capita	−0.019***	−0.014***	−0.045***	−0.022***
	(0.005)	(0.005)	(0.004)	(0.006)
Age of the household head	−0.001***	−0.001***	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Education of the household head	−0.010***	−0.009***	−0.001***	−0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
The number of household members	0.001	0.001	−0.003***	−0.001
	(0.002)	(0.001)	(0.001)	(0.002)
Urban and rural areas	−0.023***	−0.012*	−0.034***	−0.038***
	(0.005)	(0.007)	(0.004)	(0.007)
The number of high schools / vocational schools	0.025***	0.013***	0.018***	−0.001
	(0.003)	(0.004)	(0.002)	(0.004)
Student to teacher ratio of senior high school	0.045***	0.011	0.065***	0.038***
	(0.011)	(0.012)	(0.009)	(0.013)
Eastern Indonesia	−0.010*		0.007*	
	(0.005)		(0.004)	

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

The findings from the analysis of the eastern Indonesia subsample in Table 4 show that the PKH lowers the probability of children not attending senior high school by 1.4%. This relationship is statistically significant at the 5% level, which means that the impact of the PKH on reducing the out-of-school rates for senior high schools in eastern Indonesia is effective but still lower than the overall sample in the same year. A comparison of the results from the full sample with those from the subsample of students in eastern Indonesia shows that the PKH has a more substantial and more effective influence in reducing the probability of dropping out of school in the full sample at the 1% significance level.

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The results of this study contradict those from previous studies that indicate CCT programs such as PKH do not significantly impact educational outcomes such as school enrollment and non-enrollment rates (Alatas et al. 2011; Lee & Hwang 2016). In their studies, Alatas et al. (2011) and Lee and Hwang (2016) conclude that the PKH does not increase school enrollment rates; in the context of these studies, school participation rate, dropout rate, and out-of-school rate are interrelated educational outcomes. A high rate of school enrollment will reduce the number of children who drop out of school and contribute to reducing the number of children who are not in school. The reverse is true as well. In this study, we show that the PKH policy was quite effective in reducing the out-of-school rate. The difference in results could be due to previous studies having only evaluated the PKH in its early period of adoption and not using PSM for analysis. The use of PSM in this study minimized potential bias, thus resulting in more precise conclusions.

A comparison of the results of the full sample and subsample probit in Table 4 shows that in 2022, the PKH has a greater effect in reducing the likelihood of children dropping out at senior high school level with a magnitude of 2.3% and 1.4%, respectively. However, when compared to the magnitude from other studies based on relatively similar programs in Latin America, these results are still relatively low. Research on CCT programs in Latin America shows significant reductions in out-of-school children are prevalent in case studies of programs such as Progresa/Oportunidades in Mexico and Bolsa Familia in Brazil. Schultz (2004) shows that Progresa/Oportunidades significantly increased school enrollment and reduced dropout rates among children from low-income families. Schultz notes that school enrollment rates increased by approximately 8%–10% for children of secondary school age. Bolsa Familia in Brazil has shown similar results. Glewwe and Kassouf (2012) find that Bolsa Familia contributed significantly to increasing school enrollment and reducing dropout rates. The program increased enrollment by approximately 5.5% in grades 1–4 and 6.5% in grades 5–8.

Bolsa Familia targets eligible beneficiaries of its services with high accuracy. This is achieved through geographic and means-testing mechanisms under the unified family registry (Cadastro Único), with 73% of transfers going to the poorest quintile and accumulated to 94% to the first and second poorest quintile. This achievement ranks Bolsa Familia first in targeting accuracy among other transfer programs in Latin American countries and among the top six transfer programs in developing countries (Lindert et al., 2007). A similar program in Mexico, Prospera (formerly Oportunidades and Progresa), also has an effective compliance, or commitment, verification mechanism where verification is done through reports from schools. Fiszbein et al. (2009) reveal that the compliance verification process, conducted every two months, starts with the education service provider or school responsible for filling in the compliance information form. The form is then returned to the coordinating agency at the state level and forwarded to the coordinating agency at the national level. There is a specific agency responsible for listing the beneficiaries and the amount to be paid each period.

The low impact of the PKH in Indonesia on the number of out-of-school children, especially at the high school/vocational level, compared to the achievements in Latin American countries may be due to several factors. Coverage and targeting limitations may reduce the effectiveness of the PKH in Indonesia. These limitations can make assistance unavailable to families who need it. If the program is not well-targeted or does not cover all children who are vulnerable to dropping out of school, then the impact on the number of out-of-school children will be less than optimal. Yulianti et al. (2015) assert that one of the main problems found in implementing social protection programs is related to targeting recipients. Targeting is necessary because the available funds are limited; however, it is difficult to accurately identify target households (Yulianti et al., 2015). There are two types of mis-targeting: inclusion errors and exclusion errors. In addition, weak supervision means that there is no feedback to increase programs' effectiveness. The commitment verification process is crucial to ensure the effectiveness of the PKH as it relates to the fulfillment of KPM obligations. PKH facilitators collect data on beneficiary compliance with health and education conditions by visiting local health centers or schools (MicroSave Consulting, 2019). However, the manual nature of the process creates the potential for human error.

CONCLUSION

Based on the results of the probit logistic regression analysis using the weights from the best algorithm in the PSM analysis, the findings from the overall sample estimation show that the PKH can significantly reduce the probability of children not attending senior high school/vocational school education in the overall sample in both 2019 and 2022. In 2022, the PKH significantly reduced the probability of children not attending high school in the subsample, while in 2019, it failed to do so in eastern Indonesia. In 2019, the overall sample showed a significant negative relationship between the PKH and out-of-school rates, while this was not observed in the smaller subsample. However, in 2022, the PKH had a stronger and more significant impact on reducing out-of-school rates in both the overall sample and the subsample, with the overall sample showing a higher level of statistical significance. The 2022 estimates indicate that the PKH was more effective in decreasing the likelihood of children not attending senior high school than in 2019.

It is crucial to maintain the education requirement of the PKH to encourage education participation and reduce the number of out-of-school children. Improving the quality of the PKH's monitoring and evaluation methods is also critical to maintain the program's relevancy. The national government should work with local governments, particularly provinces, to ensure data accuracy and build an integrated database. Digitalization of verification through mobile applications is necessary to reduce human error. The PKH also needs to expand its coverage to reach more students in need and improve the standard of education services, especially in eastern Indonesia. Data integration between the central and lower-level governments is essential to minimize targeting errors.

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