

Analysis of the Impact of PIP Education Subsidies on School Participation in Central Java Province in 2023

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Abstract

Education is an important factor in human development and long-term economic growth through improving human resource quality. However, low school enrollment, particularly among disadvantaged groups, remains a challenge requiring appropriate policy intervention. Through the Program Indonesia Pintar, the Indonesian government provides educational subsidies to increase access and school participation for students from low-income families. This study aims to analyze the impact of PIP on school participation among children aged 6–21 years in Central Java Province in 2023. The study uses secondary data from the March 2023 National Socio-Economic Survey Core Module with a sample of 22,286 individuals. The analysis applies Propensity Score Matching to address selection bias between PIP recipients and non-recipients. The analysis includes propensity score estimation using logistic regression, common support testing, covariate balance testing, and estimation of the Average Treatment Effect on the Treated. The covariates include home ownership status, floor quality, sanitation, access to adequate drinking water, household size, gender, and age. The results show that the matching process successfully balanced the characteristics of recipient and non-recipient groups. The ATET estimation produces a coefficient of 0.0375, significant at the 5 percent level, indicating that PIP recipients have a 3.75 percent higher probability of school participation than non-recipients. These findings demonstrate that PIP is effective in improving school participation and should be strengthened as a policy instrument to promote equal access to education, particularly for disadvantaged children.

Keywords: Program Indonesia Pintar, School Participation, Propensity Score Matching, Educational Subsidy, Central Java.

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1. Introduction

Education is one of the sectors that plays a crucial role in improving the quality of human resources and driving a country's development [1]. Through education, people can acquire knowledge, skills, and better opportunities to improve their standard of living. Therefore, the level of education in a society is often used as an indicator of development success. In a global context, the importance of education is reflected in the fourth Sustainable Development Goal (SDG), which aims to ensure inclusive, equitable, and quality education and promote lifelong learning opportunities for all [2].

In Indonesia, the commitment to educational development is enshrined in the Preamble to the 1945 Constitution, which affirms the state's goal of enlightening the nation. This commitment is reinforced by Article 31 of the 1945 Constitution, which guarantees every citizen's right to education and requires the government to allocate at least 20 percent of the State Budget (APBN) and Regional Budget (APBD) to education [3]. The government continues to develop various education policies and programs to improve access to and the quality of education for the entire population.

Nevertheless, ensuring equitable access to education remains a challenge for Indonesia. Differences in household socioeconomic conditions mean that not all

children have equal opportunities to access education. Families with higher levels of well-being generally have greater capacity to meet their children's educational needs, including both school fees and other supporting costs. Conversely, economic constraints often hinder the continuity of a child's education and can even increase the risk of dropping out [4] [5]. This situation indicates that economic factors remain one of the key determinants of school enrollment [6].

As part of its commitment to expanding access to education, the Indonesian government launched the Assistance for Poor Students (BSM) program in 2008, which was later expanded into the Indonesia Pintar Program (PIP) in 2015. Legally, the Indonesia Pintar Program is designed to help cover the personal educational expenses of students from poor or near-poor families [7]. Through this program, the government seeks to ensure that economic constraints do not prevent school-age children from completing their primary and secondary education [4].

In practice, the Indonesia Pintar Program has reached millions of students throughout Indonesia. The program is expected to improve access to education, sustain school operations, and reduce dropout rates [8]. Nevertheless, there are still a number of school-age children who have not fully participated in the formal education system. This situation indicates that the effectiveness of educational assistance programs still needs to be evaluated, particularly in measuring the

extent to which the program actually impacts school participation.

Previous research conducted by Mulyani, Ridwan, and Nazer showed that school participation is influenced by various factors, including household economic conditions, region of residence, per capita expenditure, and receipt of social assistance [8]. The study also found that participation in the Indonesia Pintar Program has a significant effect on increasing school enrollment. However, differences in the socioeconomic characteristics of communities across regions allow for variations in the program's impact, necessitating studies focused on more specific areas.

Central Java Province is one of the provinces with a large population and diverse socioeconomic characteristics. Differences in community welfare levels, demographic conditions, and access to educational facilities across regions have the potential to influence school enrollment rates as well as the effectiveness of the Indonesia Pintar (PIP) Program. The actual challenges regarding school participation in this region are reflected in the trends of the School Participation Rate (APS) for Central Java Province for the 2019–2023 period (percent), as shown in Figure 1.

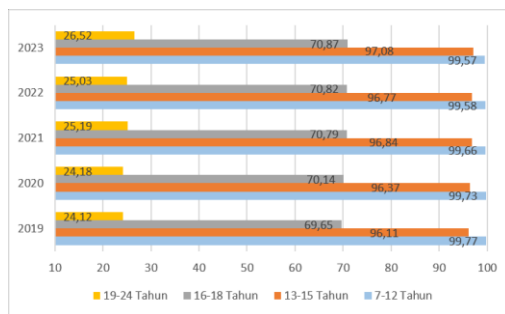


Figure 1. School Participation Rate (APS) in Central Java Province, 2019–2023 (Percent)

Based on data from the Central Statistics Agency (BPS) presented in Figure 1 above, there is a striking disparity in participation rates among age groups in Central Java Province [9]. The School Enrollment Rate (SER) for the elementary school age group (7–12 years) shows excellent performance, remaining stable at nearly 100%. The 13–15 age group also remains at a relatively stable and consistent level, hovering around 96%. Structural barriers begin to become apparent among the productive adolescent age group (16–18 years), which has experienced a drastic decline and has stagnated at 70% [5]. The sharpest decline occurred among the higher education age group (19–24 years), which has remained low, ranging from 24% to 26%. The pattern of declining participation, which widens as children get older, indicates the presence of economic constraints that burden families when their children must advance to higher levels of education. This situation underscores the urgency of conducting an in-depth evaluation of the effectiveness of the Indonesia Pintar Program (PIP) in Central Java Province using a representative statistical database [10].

Given these conditions, this study aims to analyze the

socioeconomic characteristics of households that are and are not recipients of the Indonesia Pintar Program in Central Java Province in 2023, identify the factors influencing households' chances of receiving assistance, and measure the program's impact on school enrollment. The results of this study are expected to serve as evaluation material and input for the government in improving the effectiveness of the Indonesia Pintar Program as an instrument for equalizing access to education and increasing school participation in Central Java Province [11].

2. Research Method

This study utilises secondary data from the March 2023 National Socio-Economic Survey (Susenas) Education Module, conducted by the Central Statistics Agency (BPS) [12]. The scope of the study is limited to Central Java Province, with the unit of analysis being children aged 6–21 years, in accordance with the target group of the Indonesia Pintar Programme (PIP) as stipulated in Ministry of Education and Culture Regulation No. 10 of 2020 concerning the Indonesia Pintar Programme [7]. Individual data (kor23_ind) and household data (kor_rt) were merged using the household identification variable (URUT), then filtered by region and age. Observations with missing values for the PIP recipient status and sanitation variables were excluded from the sample, resulting in a final sample of 22,286 observations. All data processing was carried out using Stata 17 MP software.

This study utilises three groups of variables: outcome variables (school attendance), treatment variables (PIP recipient status), and matching covariates [20]. The selection of covariates was based on the theoretical consideration that household socio-economic conditions influence both the probability of PIP receipt and school participation [4] [5]. Variables such as the head of household's education level, which were used in previous studies by Yosefina and Prasetyo as well as Utami and Wicaksono, were not available in the Susenas individual data files used [5] [6]. Therefore, this study uses proxies for household physical conditions and well-being, namely home ownership, floor quality, sanitation, and drinking water sources. The full operational definitions are presented in Table 1.

Table 1. Operational Definitions of Variables

Variable	Name	Name	Operational Definition	Scale	Outcome
Outcome	status_sch	School Participation	Given a value of 1 if the child aged 6–21 years is currently in school; 0 if not yet in school or has never been to school or is no longer in school.	Dummy	–
	PIP	Recipient of PIP	Given a value of 1 if the child receives the Indonesia Smart Program (PIP/KIP); 0 if not receiving.	Dummy	–
Matching Covariates	ramah_milik	Home Ownership	Given a value of 1 if the house is owned by the family; 0 if rented/leased/other. Reflects household assets.	Dummy	–
	lantai_layak	Floor Quality	Given a value of 1 if the main floor is marble/granite/tiles/vinyl (decent); 0 if earth/bamboo/wood. Proxy for physical condition of the house.	Dummy	–
	sanitasi_layak	Adequate Sanitation	Given a value of 1 if the toilet facility is a private or shared toilet (adequate); 0 if not adequate.	Dummy	–
	air_layak	Adequate Drinking Water	Given a value of 1 if the source of drinking water is adequate (packaged/pipes/well/protected well); 0 if not adequate.	Dummy	–
Household Characteristics	jumlah_art	Number of Household Members	Total number of people living in one household. The greater the number of household members, the higher the household expenditure burden.	Continuous	–
Child Characteristics	jenis_kelamin	Child Gender	Given a value of 1 if the child is female; 0 if male. Used because gender affects school participation.	Dummy	–
	umur	Child Age	Age of the child in years (6–21 years). Used as a proxy to control for differences in education level.	Continuous	–

To identify the causal impact of the PIP on school attendance, this study employs the Propensity Score Matching (PSM) method. The choice of this method is based on the observational, non-experimental nature of the data, wherein PIP recipients were not selected at random but were targeted at poor households whose characteristics systematically differ from those of non-recipients a situation that has the potential to introduce selection bias. Previous research on the impact of the PIP in Indonesia [4] has demonstrated that PSM is effective in addressing selection bias in the context of Conditional Cash Transfer (CCT) programmes, whilst studies relying solely on ordinary logistic regression [5] [6] were unable to produce estimates of causal impact.

PSM works by matching each treatment unit with a control unit that has the most similar propensity score. The propensity score is defined as the conditional probability of receiving the PIP based on observed covariates (X): $p(X) = \Pr(\text{PIP} = 1 \mid X)$... (1). The key assumption underpinning PSM is the Conditional Independence Assumption (CIA): once conditioned on X , PIP receipt status is independent of the counterfactual outcome $Y(0)$. This assumption is satisfied if all relevant and observed confounding factors have been included as covariates in the model.

The propensity score is estimated using a logistic (logit) regression model with PIP receipt status as the dependent variable and seven covariates as independent variables: $\log[p(X)/(1-p(X))] = \beta_0 + \beta_1 \cdot \text{home_ownership} + \beta_2 \cdot \text{adequate_flooring} + \beta_3 \cdot \text{adequate_sanitation} + \beta_4 \cdot \text{adequate_water_supply} + \beta_5 \cdot \text{number_of_children} + \beta_6 \cdot \text{gender} + \beta_7 \cdot \text{age}$... (2). The estimated propensity scores were then used as the basis for matching between units during the matching stage. The complete results of the logit model estimation are presented in the Results and Discussion section.

This study utilised the 1-to-1 nearest neighbour matching algorithm via the 'teffects psmatch' command in Stata 17, whereby each treatment unit was matched with a single control unit having the closest propensity score. The sample prior to matching comprised 22,286 observations (4,658 treatment units and 17,628 control units). Following the matching process, 4,486 pairs were identified that met the common support criterion, resulting in a total matched sample of 8,972 observations.

The quality of the matching was evaluated using a covariate balance test via the 'tebalance summarize' command in Stata 17. The indicators used were the standardised difference and the variance ratio, each calculated before (raw) and after (matched) the matching process. Covariates are considered balanced if the standardised difference after matching, $|d|$, is less than 0.10 and the variance ratio falls within the range 0.5–2.0. The results of the balance test are presented in the Results and Discussion section.

The parameter estimated is the Average Treatment Effect on the Treated (ATET), which is the average impact of receiving PIP on participation in special

schools within the PIP recipient group: $\text{ATET} = E[Y(1) - Y(0) \mid \text{PIP} = 1]$... (3). where $Y(1)$ and $Y(0)$ are, respectively, school participation with and without PIP in the recipient group. As $Y(0)$ cannot be observed directly, its value is estimated from the outcomes of matched control units. The estimation is carried out using the Abadie–Imbens robust standard error in the 'teffects psmatch' command. The use of ATET, rather than the Average Treatment Effect (ATE), is consistent with the study's objective of measuring the specific impact of the PIP on the group that actually received the assistance [4].

3. Result and Discussion

The sample in this study consisted of 22,286 school-aged children (ages 6–21) in Central Java Province, drawn from the March 2023 SUSENAS data. Of this total, 4,486 children were recorded as recipients of the Indonesia Pintar Program (PIP), while 17,800 children did not receive PIP. Next Descriptive Statistics Table on Table 2.

Table 2. Descriptive Statistics Table

Variable	Non-PIP (N = 17,800)	PIP (N = 4,486)
Home Ownership	89.40	87.87
Adequate Flooring	75.96	65.20
Adequate Sanitation	81.80	79.09
Adequate Drinking Water	80.15	77.42
Household Size	4.30	4.36
Child's Sex	48.54	49.58
Child's Age	13.70	11.93

Table 2 presents a comparison of characteristics between the two groups. In general, the PIP recipient group tends to come from households with poorer housing conditions compared to the non-recipient group. The proportion of households with adequate flooring among PIP recipients was only 65.20%, lower than that of non-recipients, which reached 75.96%. There is a significant difference of about 10 percentage points, indicating that PIP recipient children do, on average, come from households with limited economic conditions.

A similar pattern is observed for the variables of adequate sanitation and access to safe drinking water, although the gap is not as large as that for adequate flooring. The PIP recipient group has a proportion of adequate sanitation at 79.09% compared to 81.80% among non-recipients, and access to safe drinking water at 77.42% compared to 80.15%. Homeownership rates were also slightly lower among the PIP recipient group, at 87.87% (PIP) versus 89.40% (non-PIP). Overall, this housing profile is consistent with the characteristics of low-income households targeted by the PIP program.

A striking difference is also evident in the age variable. The average age of children in the PIP recipient group is 11.93 years, which is nearly two years younger than the non-recipient group, whose average is 13.70 years. This indicates that the age distribution between the two groups is uneven. Other variables, such as gender, the number of domestic workers, and home ownership,

show smaller differences between the groups.

The existence of systematic differences in characteristics between the PIP recipient and non-recipient groups means that a direct comparison of school participation (without matching) cannot be immediately interpreted as a causal effect of the PIP. The PSM method is used to address this imbalance. The propensity score can simply be understood as the probability that a child is a PIP recipient based on observable household characteristics. The higher the propensity score, the greater the likelihood that the child will be categorized as a PIP recipient. This value will later be used as the basis for matching, in which PIP recipient children will be paired with non-recipient children whose propensity scores are most similar, ensuring that the resulting comparison is comparable.

The propensity score is estimated using a logistic regression model with PIP recipient status as the dependent variable (1 = recipient, 0 = non-recipient) and seven covariates: home ownership, floor quality, adequate sanitation, adequate drinking water, number of household members, gender, and age. These seven variables were selected because, in theory, they reflect household economic conditions relevant to the PIP selection mechanism. The estimation results are presented in the following Table 3.

Table 3. Propensity Score Estimation Table (Logit Model)

Variabel	Koefisien	Std.Error	z	p-value
Home Ownership	-0.155	0.053	-2.91	0.004
Adequate Flooring	-0.526	0.036	14.35	0.000
Adequate Sanitation	-0.115	0.044	-2.59	0.010
Adequate Water Supply	-0.081	0.043	-1.88	0.061
Number of Domestic Workers	0.016	0.014	1.17	0.243
Gender	0.043	0.034	1.27	0.206
Age	-0.099	0.004	23.81	0.000
Constant	0.468	0.109	4.28	0.000
Obs	22.286			
Pseudo R	0.0378			
LR chi ² (7)	847.06			0.000

Overall, the logit model is statistically significant with an LR chi-squared(7) value of 847.06 ($p < 0.001$). This means that the seven variables collectively explain the differences in PIP acceptance status. Nevertheless, the Pseudo R² value of 0.0378 indicates that this model explains a relatively small proportion of the variation. This is considered reasonable, given that PIP eligibility in practice is also influenced by administrative factors and demographic data not recorded in SUSENAS such as whether a child is enrolled in a school that submits PIP data, or whether the family actively registers for the program.

In terms of coefficient significance, several findings indicate that the variables adequate housing, adequate flooring, and adequate sanitation all have a negative effect on the probability of receiving PIP and are statistically significant. This is consistent with the logic behind PIP targeting, whereby households with poorer housing conditions tend to be the program's target. The "adequate flooring" variable has the largest

coefficient, at -0.526 with a p-value of 0.001; this indicates that the condition of a household's flooring is one of the strongest characteristics in distinguishing between PIP recipients and non-recipients.

These findings are consistent with research that utilised binary logistic regression analysis on household survey data from developing countries and found that the physical characteristics of housing and asset ownership were significantly and negatively correlated with the probability of a household being classified as poor [13]. A similar pattern is reflected in the PIP targeting mechanism, where the condition of flooring, sanitation and overall housing adequacy serve as valid proxies for poverty; households with poorer housing conditions were found to have a higher probability of becoming programme beneficiaries.

Age also has a significant negative effect, with a coefficient of -0.099 and a p-value of 0.001, meaning that the older the child, the less likely they are to receive PIP in this sample. This may reflect drop-out rates among older children as well as a reduction in programme coverage. On the other hand, the variables for access to safe drinking water, the number of ARTs, and gender were not statistically significant; however, they were retained due to their theoretical relevance as proxies for household economic conditions.

Once the propensity scores for each child in the sample had been successfully estimated, the next step was to carry out the matching process. The method used was 1:1 nearest neighbour matching, whereby each child receiving PIP was matched with one child not receiving PIP whose propensity score was closest. If there were two children with very similar profiles and comparable backgrounds, but one was a PIP recipient and the other was not, then the difference in school attendance between the two could be more convincingly attributed to the effect of PIP.

From a total of 22,286 observations and samples, the matching process yielded 8,972 matched pairs of observations used in the subsequent analysis. A total of 4,486 PIP recipients (treated) and 4,486 non-recipients (control) were successfully matched. Before examining the estimated effects, it is important to consider whether the distribution of propensity scores between the PIP recipient and non-recipient groups has sufficient overlap; this condition is referred to as 'common support', i.e. the range of propensity scores where both groups are equally represented. If there is insufficient overlap, the matching process cannot be carried out validly as there are no comparable matches. Next Density Plot/Overlap Plot on Figure 2.

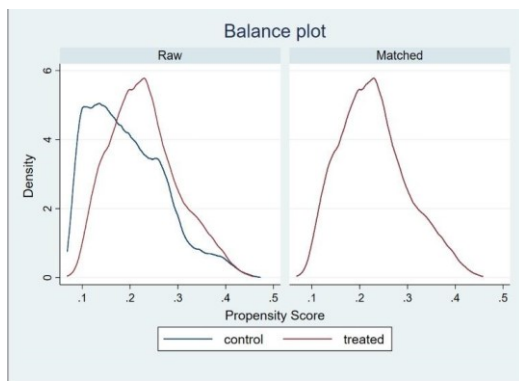


Figure 2. Density Plot/Overlap Plot

Based on the balance plot in Figure 1, the propensity score distributions of the PIP recipient (treated) and non-recipient (control) groups show substantial overlap, particularly in the range from 0.1 to 0.4. This confirms that the common support assumption is met, meaning that for every child receiving PIP, there is at least one non-recipient child with a sufficiently similar profile to serve as a matching pair. In the right-hand panel (matched), the two distributions appear close together and overlapping, indicating that the matching process has successfully selected more comparable pairs.

To demonstrate the success of the matching more systematically, a covariate balance test was conducted, comparing the distributions of each variable between the treated and control groups before and after matching, using the standardised difference measure. According to Rubin (2001), matching is considered to have produced good balance if the absolute value of the standardised difference is below the threshold of 0.25 and the variance ratio falls within the range of 0.5 to 2.0 [14]. Some of Austin's research literature applies stricter criteria, with a threshold for the standardised difference set below 0.1 [15]. Next Covariate Balance Test on Table 4.

Table 4. Covariate Balance Test

Variabel	Standardized differences			Variance ratio	
	Raw	Matched		Raw	Matched
Home Ownership	-	0.004	Home Ownership	-	-0.048
Adequate Flooring	0.048	-0.011	Adequate Flooring	-	-0.237
Adequate Sanitation	0.237	-0.011	Adequate Sanitation	-	-0.068
Adequate Water Supply	0.068	0.006	Adequate Water Supply	-	-0.066
Number of Domestic Workers	0.066	0.057	Number of Domestic Workers	0.048	0.048
Gender	0.020	0.007	Gender	0.020	0.020
Age	-	0.013	Age	-	-0.454
	0.454				

Based on the results of the balance test, it can be seen that all covariate variables showed a significant reduction in standardised difference following matching, approaching zero. Prior to matching, several variables exhibited considerable differences in characteristics, particularly the age variable (-0.455)

and the 'floor_suitable' variable. However, after matching, the standardised difference for the 'general' variable fell to 0.013 and that for 'floor condition' to 0.011; the overall range for all variables was between 0.011 and 0.057, indicating that the matching process successfully reduced the selection bias that had previously existed between the treatment and control groups.

Furthermore, the variance ratio values after matching ranged from 0.985 to 1.152, which is close to one. These values indicate that the variation in characteristics between the treatment and control groups was relatively balanced after matching [15]. The number of observations after matching showed that all 4,486 households receiving PIP successfully obtained suitable comparison pairs from the control group. It can therefore be concluded that the matching process successfully produced a good balance of characteristics between the two groups.

These results are consistent with the criteria set out by Rubin, who states that a variance ratio between 0.5 and 2.0 indicates adequate balance between the treatment and control groups [14]. As all variance ratio values in this study fall well within this range and are close to one, the assumption of covariate balance can be considered to have been met. This is in line with Stuart, who emphasises that the success of the matching process is characterised by the similarity in the distribution of covariates between the treatment and control groups, thereby enabling a more reliable comparison between the groups, much like a randomised experiment [16]. Next Table of ATET Estimation Results on Table 5.

Table 5. Table of ATET Estimation Results

Product	Koefisien	AI Robust Std.Err.	z	p-value	95%CI
ATET PIP (1 vs 0)	0.0375	0.0032	11.67	0.000	[0.0312,0.0438]

Having confirmed that the characteristics between the treatment and control groups are balanced, the impact of the Indonesia Pintar Programme was estimated using the Average Treatment Effect on the Treated (ATET) method. The estimation results show that the ATET coefficient is 0.0375 with a standard error of 0.0032. The z-statistic obtained is 11.67, with a p-value of 0.000. In substance, an ATET coefficient of 0.0375 can be interpreted to mean that receiving a subsidy from the Indonesia Pintar Programme (PIP) increases the probability of school attendance among recipients by approximately 3.75 per cent compared with households that do not receive the programme. As the p-value is smaller than the 5 per cent significance level, the null hypothesis (H_0) is rejected. Consequently, the Indonesia Pintar Programme has been shown to have a significant impact on educational attainment. Furthermore, the 95 per cent confidence interval ranges from 0.0312 to 0.0438, which does not include zero; therefore, the programme's effect can be considered statistically significant.

The results of this study indicate that the Indonesia Pintar Programme has been implemented in line with

the policy objectives set by the government, namely to expand access to education. The Indonesia Pintar Programme has made a tangible contribution to improving access to education and reducing dropout rates amongst pupils from poor families [17]. In other words, the Indonesia Pintar Programme has been shown to be effective in increasing school attendance amongst programme beneficiaries after socio-economic factors influencing the likelihood of receiving assistance were controlled for using the Propensity Score Matching method. This finding is consistent with the research by Ulfa and Rezki, who found that the Indonesia Pintar Programme (PIP) has a positive impact on school attendance in Indonesia [4]. The results of this study are also consistent with those of Haryono and Rumayya, who used the Propensity Score Matching method on 2022 Susenas data and found that PIP recipients had a lower risk of dropping out of school compared to non-recipients across all levels of education, particularly at lower secondary and upper secondary levels [18]. The consistency of these findings suggests that educational assistance through the PIP plays a role in reducing the economic barriers faced by poor households, thereby increasing children's chances of remaining in school and completing their education.

Although the Indonesia Pintar Programme (PIP) has been shown to have a positive and significant impact on educational attainment, the magnitude of the effect is relatively small, at 3.75 per cent. These results indicate that educational attainment is influenced not only by the educational assistance provided through the PIP but also by various other factors, such as household economic conditions; consequently, the success of improving educational attainment does not depend solely on educational assistance but also requires support from various social, economic and environmental aspects so that the programme's benefits can be felt more fully. These findings are supported by research by Dewa and Prasetyo, which examined the factors influencing school participation among 16–18-year-olds (upper secondary school or equivalent) in West Java Province [5].

These findings are consistent with research by Ivan, who evaluated the implementation of the Indonesia Pintar Programme (PIP) and the School Operational Assistance (BOS) scheme in Indonesia. The study showed that an increase in the Gross Enrolment Rate (GER) and Net Enrolment Rate (NER), as well as a reduction in the number of out-of-school children (OOS), cannot be fully achieved through educational assistance programmes alone. These results indicate that the effectiveness of educational programmes is also influenced by the accuracy of beneficiary targeting, oversight of programme implementation, and various other socio-economic factors [19].

Furthermore, research by Utami and Wicaksono also found that household socio-economic conditions are one of the key determinants of school participation in Indonesia [6]. Consequently, the effectiveness of the

Indonesia Pintar Programme's implementation needs to be continuously improved by enhancing the accuracy of beneficiary targeting, monitoring the distribution of aid, and fostering synergy with other education and social protection programmes. It is hoped that these efforts will strengthen the programme's impact in improving educational participation and sustainability for those in need. In the long term, improved access to and participation in education through the Indonesia Pintar Programme is expected to contribute to enhancing the quality of human resources, labour productivity, community income, and sustainable economic well-being.

4. Conclusion

Based on the results of an analysis using the Propensity Score Matching (PSM) method, it was found that the variables of home ownership, floor condition, adequate sanitation, and age had a significant effect on the probability of being accepted into the Indonesia Pintar Program (PIP). Furthermore, the balance test results indicate that the matching process successfully balanced the characteristics between the PIP recipient and non-recipient groups, and the Average Treatment Effect on the Treated coefficient indicates that the Indonesia Pintar Program (PIP) has a positive and significant effect on educational status, with a coefficient value of 0.0375. These findings indicate that PIP recipients have a higher educational status compared to the non-recipient group after characteristic matching. Nevertheless, the magnitude of the effect is still relatively limited, suggesting that educational status is influenced not only by educational assistance but also by various other social and economic factors. Therefore, the government needs to improve the targeting of recipients and strengthen the synergy between the PIP and other social assistance programs and education policies so that the benefits provided can be optimized. In addition, improving the PIP distribution mechanism must be a top priority, given the ongoing issues with misallocation where some funds are channeled to ineligible students while eligible students are not reached by the program. For future research, it is recommended to include a wider variety of socioeconomic variables or to use panel data so that other factors influencing educational status can be analyzed more comprehensively.

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