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# The Impact of Microcredit on Child Education and Child Labor in Indonesian Microenterprise Households

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## Abstract

*Microcredit is a financial instrument designed to improve well-being and reduced poverty rate. It also provides non-economic opportunities particularly in child education. This research aims to analyze the impact of microcredit participation from both formal and informal source on education and child labor in Indonesian Micro-Enterprise Households. This study utilizes data from the Indonesia Family Life Survey 5th wave in 2014/2015 and employs Propensity Score Matching model. The result shows that formal microcredit significantly raises school participation while reducing school gap. However informal microcredit does not show similar benefits on child education. The effect of child labor both from formal and informal microcredit remain inconclusive, highlight the need for further research that account for potential confounding factors. This finding suggests policymakers to prioritize access to formal microcredit especially for micro-enterprise households.*

**Key words :** Child Education, Child Labor, Micro-enterprise, Microcredit, Propensity Score Matching

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## INTRODUCTION

The accumulation of human capital, particularly through the expansion of educational opportunity is widely recognized as a significant contributor to economic growth (Kandulu et al., 2020; Mankiw et al., 1992; Pelinescu, 2015). This strategy has been demonstrably effective in boosting productivity, leading to increased individual and national incomes and reduced poverty rates (Doan et al., 2014).

Maldonado & González-Vega (2008) highlights significant challenges to promoting educational attainment. They identify that parental motivation, income limitations and competing demands on a child's time as a significant factor impacting the demand for child education. Furthermore, Menon (2010) emphasizes that parents encounter a trade-off between investing in their child's education or utilizing them as a child labor.

Child labor is a complex social and economic phenomenon, encompasses any economic activity within the labor market that detrimentally impacts children's well-being. This includes work that is harmful or dangerous to children, or that interferes with their education by denying them to attend school, forcing to leave school prematurely, or requiring them to combine school attendance with excessively long and heavy work (ILO, 2021). Statistics Indonesia (BPS, 2022) reported that both number and proportion of child labor as defined by Law Number 13 of 2003 concerning Manpower, showed significant variation from 2017 to 2021. Notably, the year 2020 witnessed the highest percentage, attributable to the covid-19 pandemic, as shown in the figure 1 below:

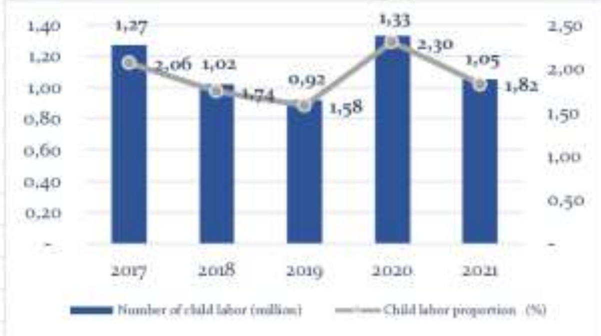


**Figure 1.** Number and proportion of child labor aged 5-17 in Indonesia

*Source:* Statistic Indonesia (2022), processed

Engaging in child labor carries detrimental long-term consequences, potentially diminishing both individual and national well-being in the future (Tang & Zhao, 2023). Furthermore, these children are likely to perpetuate the cycle of poverty by replicating their parents' economic struggles due to the limitations imposed by inadequate education and skill development, which cripple their future earning potential.

Expanding access to credit for households emerges as a promising strategy to both enhance educational attainment and mitigate child labor. This approach aligns with Baland & Robinson (2000) proposition that child labor stems not only from poverty but also from constrained financial resources. However, traditional formal credit often imposes significant barriers to entry for impoverished households due to stringent collateral requirement. Consequently, informal credit sources, despite their potential exploitation, become attractive due to their streamlined processes. In this context, microcredit emerges as a viable solution, bridging the gap between informal and formal lending by offering small collateral-free loans.

However, the impact of microcredit on education and child labor remains a subject of debate among policymakers due to the considerable variability and even contradictory findings presented by researchers. Several empirical studies reveal a positive association between microcredit access and education outcomes. This link has been established by diverse studies, including those by Agyapong et al. (2017); Becchetti & Conzo (2014); Kandulu et al. (2020); Thai (2018); Wydick (1999); You & Annim (2014). However, some studies suggest that microcredit utilized for business expansion might increase labor demand Islam & Choe (2013); Mehta (2020); Pham & Nguyen (2019); Shimamura & Lastarria-Cornhiel (2010).

Moreover, the source of microcredit needs further investigation due to its potential for differential impact on education. Doan et al. (2014) investigated the impact of microcredit on children's education in Vietnam with diverse statistical methods, revealed small and short terms loan fail to improve the poor's child schooling. In addition, formal credit participation significantly increases school enrollment and reduced school gap, while informal credit, adversely affected child schooling. This finding aligns with You & Annim (2014) study in rural China, identified a positive long-term effect of formal microcredit on educational achievement. By addressing educational barriers and empowering families, microcredit offers a promising strategy for disrupting the poverty cycle and fostering long term positive change.

However, Phan et al. (2023) conducted their research in Vietnam employing Poisson model. Their findings suggest that access to microcredit, regardless of whether it originated from formal or informal sources, exerts a negative impact on children's educational investment. Notably, the negative impact associated with formal microcredit was found to be relatively smaller than that associated with informal microcredit. This disparity is attributed to the distinct and longer repayment periods. Conversely, informal microcredit typically entails higher interest rates, smaller loan amounts, and shorter repayment periods.

Shen & Hannum (2021) introduced the concept of incorporating credit limit as an indicator of a family's socioeconomic status and its subsequent impact on children's education opportunities. This broader concept of credit limit encompasses both formal and informal credit channels associated with a family's economic and social capital. This ultimately influences income and wealth. Access to credit, even at basic level, can empower parents to meet educational expenses and keep their children enrolled in school. Moreover, it can potentially facilitate access to higher-quality educational opportunities. However, Kondratjeva & Chen (2018) present contrasting findings, suggest that children from families with access to credit, regardless of its sources, tend to experience lower educational attainment compare to their counterparts from non-borrowing families. Interestingly, they observe an inverse relationship between paternal credit access and boys' education, and between maternal access and girls' education. In contrast, they report a positive association between informal credit and both boys' education and child labor, particularly when mothers are the borrowers. A similar positive association, albeit statistically insignificant, is seen for girls regarding school and child labor. These findings imply a possible, imperfect substitution relationship between education and child labor. This implies that reduced schooling does not always directly translate to increased child labor, and vice versa, meaning increased child labor does not always result in reduced schooling.

Due to inconsistencies of prior research finding and limited research on this topic within the Indonesian context, this study aims to investigate the impact of both formal and informal microcredit access on child education and child labor within micro-enterprise households. This study will employ three key dependent variables such as school participation, school gap and child labor participation. By providing empirical evidence, this research seeks to expand the existing knowledge base on the crucial topic. Furthermore, this research aims to inform policymakers with valuable insight, and implement effective policies that not only optimize micro-enterprise performance but also prioritize the protection and well-being of children, particularly their access to quality education.

## RESEARCH METHODS

This study utilizes data from the fifth wave of Indonesia Family Life Survey (IFLS 5), conducted in 2014/2015, to analyze the impact of microcredit. This study compares outcomes between households participating in formal and/or informal microcredit as a treatment group with households without access to credit. The study focuses on children between ages of 5 and 14, including both biological and non-biological children, living in households that operate non-farm micro-enterprises.

To address of limitation of IFLS5 in explicitly identifying the loan source of respondents, this study will employ a combined approach utilizing from BH01 (which assesses household access to loan sources) and BH10 (which capture the amount of loan received). This combined approach will allow us to differentiate between households with formal and informal loans using criteria established in the Ministerial regulation of Finance Number 12/PMK.06/2005 concerning Microcredit regulation as follow: 1) Microcredit refers to a type of credit provided for working capital and investment, 2) Distributed by Financial Institution such as Commercial Banks, Rural Credit Banks, Pawn Shops, Cooperatives, Baitul Maal wat Tamwil (BMT), and other financial institutions adhering to sharia/profit-sharing principles, 3) Targeted productive business activities, both individual and groups, 4) Maximum financing amount is IDR. 50 million.

This study uses the following criteria for child labor based on ILO-UNICEF National criteria such as: 1) Children aged 5-12 who work more than one hour per week and children aged 13-14 who work more than 15 hours per week, 2) Two type of activities include wage employment and participation in the household enterprise (farm and non-farm business). This study defines micro-enterprises based on criteria established in law Number 20 of 2008 on Micro, Small, and Medium Enterprises as Net-worth (excluding land and building) up to IDR. 50 million. This study additionally considers the World Bank's employment criteria, which define micro-enterprise as having a maximum of 10 employees.

**Table 1.** List of Variables Used in the Research

| Variables | Description |
|---|---|
| **Dependent Variables** | |
| *school participation* | Dummy Variable<br>1. Attending school<br>0. Not attending school |

| **Variables** | **Description** |
|---|---|
| *school_gap* | Deviation of expected grade based on age from current grade |
| *child Labor* | *Dummy variable*<br>1. Child labor<br>0. Otherwise |
| ***Treatment* Variable** | |
| *treatment_cformal* | *Dummy variable*<br>1. Households with formal microcredit<br>0. Households without credit |
| *treatment_cinformal* | *Dummy variable*<br>1. Households with informal microcredit<br>0. Households without credit |
| **Control Variables** | |
| **Child Characteristics** | |
| *Age* | Children age |
| *Female* | *Dummy variable*<br>1. Female<br>0. Male |
| **Household Characteristics** | |
| *f_educ* | Father educations |
| *m_educ* | Mother educations |
| *dependency_ratio* | (Number of children aged 0-14) + (Number of adults aged more than 64)/ (number of working-age population (15-64 years) |
| *Ln_omzet* | Natural logarithm of total households-enterprise revenue |
| *ln_expsch* | Natural logarithm of total expenditure for school |
| *dummy_saving* | Dummy saving<br>1. Having a saving, certificate or deposit<br>0. Otherwise |
| *sktm* | Having poor certificates (Surat Keterangan Tidak Mampu (SKTM)) |
| **Ragion Characteristic** | |
| *rural* | Dummy variable<br>1. Rural<br>0. Otherwise |

*Source :* IFLS 5

This study will employ quantitative analysis to investigate the relationship between variables through econometric modeling. To address selection bias, this study employe Propensity Score Matching (PSM) as implemented in previous studies by Kandulu et al., (2020); Doan et al., (2014). Specifically, this study will utilize Average Treatment Effect on the Treated (ATT) to examine the average treatment effect of microcredit participation (formal and/or informal) on child education and child labor participation among credit-receiving households compared to non-credit-receiving households, which can be expressed as follows:

$$ATT = E(Y(1)|D = 1) - (Y(0)|D = 0)\ldots(1)$$

Where (Y (1) | D=1) is an outcome from treatment group-credit receiving households (formal or informal microcredit) and (Y (1) |D=0) is an outcome from control group-non-credit receiving households.

Logistic regression will be employed to estimate the probability of having formal or informal microcredit, which can be expressed as follows:

$$P(T = 1|X) = \frac{\exp(\beta_0 + \beta_1 X + \beta_2 M + \beta_3 N)}{1 + \exp(\beta_0 + \beta_1 X + \beta_2 M + \beta_3 N)} \quad (2)$$

To estimate the treatment effect, this study will use Psmatch2 on STATA. This study will employ two matching algorithms: Nearest Neighbor (NN-3), which matches each subject in the treatment group with three nearest neighbors from control groups, combined with a Caliper (0,2) to address potential poor matches due to large score differences between treatment and control groups (Austin, 2011). Furthermore, Kernel matching will also be utilized because it uses a Kernel function to weight observations, thereby enhancing robustness to outlier in the matching process. This approach is similar to that used in studies of Haryanto et al. (2023), Wonde et al. (2022). To assess the sensitivity of our findings to unobserved biases, we will conduct a Rosenbaum bound sensitivity analysis.

## RESULTS AND DISCUSSION

The first part of results discussion will present summary statistic for each variable used in this study. Sample 1 focuses on households participating in formal microcredit and sample 2 focuses on households participating in informal microcredit sources as shown in table 2 below.

Table 2 summarizes the summary statistics for dependent variables and covariates for both the treatment and control groups. The number of observations for each variable differes between treatment and control groups, with the treatment group exhibits a smaller number compared to its control counterpart.

Households with formal microcredit in the sample 1, the treatment group shows a slightly higher school participation rate (94,7 percent) compared to the control group (94,4 percent). Additionally, children in the treatment group experienced a lower school gap (7,1 percent). However child labor variable shows an opposing trend, where the treatment group has a higher percentage (8,7 percent) compared to the control group.

Households with informal microcredit in the sample 2, the treatment group shows a higher school participation rate (95,1 percent) compared to the control group (94,4 percent). Similarly, both the school gap and child labor percentages were higher in the treatment group compared to the control group.

**Table 2.** Summary Statistics

| Variable | Sample 1 (Formal Microcredit) | | | | | | Sampel 2 (Informal Microcredit) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Treatment Group* | | | *Control Group* | | | *Treatment Group* | | | *Control Group* | | |
| | Obs | *Mean* | SE | Obs | *Mean* | SE | Obs | *Mean* | SE | Obs | *Mean* | SE |
| *school Participation* | 636 | 0,947 | 0,225 | 1.890 | 0,944 | 0,230 | 405 | 0,951 | 0,217 | 1.890 | 0,944 | 0,230 |

| Variable | Sample 1 (Formal Microcredit) | | | | | | Sampel 2 (Informal Microcredit) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Treatment Group* | | | *Control Group* | | | *Treatment Group* | | | *Control Group* | | |
| | Obs | *Mean* | SE | Obs | *Mean* | SE | Obs | *Mean* | SE | Obs | *Mean* | SE |
| *school_gap* | 715 | 0,071 | 0,398 | 2.101 | 0,099 | 0,490 | 441 | 0,109 | 0,454 | 2.101 | 0,099 | 0,490 |
| *child_labor* | 722 | 0,087 | 0,282 | 2.209 | 0,073 | 0,260 | 448 | 0,098 | 0,298 | 2.209 | 0,073 | 0,260 |
| *age* | 733 | 9,246 | 2,832 | 2.479 | 9,457 | 2,811 | 462 | 9,667 | 2,832 | 2.479 | 9,457 | 2,811 |
| *female* | 733 | 0,488 | 0,500 | 2.479 | 0,479 | 0,500 | 462 | 0,489 | 0,500 | 2.479 | 0,479 | 0,500 |
| *f_educ* | 629 | 9,711 | 3,931 | 1.793 | 9,366 | 4,170 | 377 | 9,467 | 3,609 | 1.793 | 9,366 | 4,170 |
| *m_educ* | 699 | 9,227 | 3,726 | 1.989 | 9,176 | 4,059 | 424 | 8,724 | 3,588 | 1.989 | 9,176 | 4,059 |
| *dependency_ratio* | 733 | 76,448 | 42,269 | 2.479 | 80,382 | 52,890 | 462 | 85,087 | 52,863 | 2.479 | 80,382 | 52,890 |
| *ln_omzet* | 733 | 0,175 | 1,677 | 2.281 | 0,265 | 2,004 | 462 | 0,292 | 2,107 | 2.181 | 0,265 | 2,004 |
| *ln_expsch* | 710 | 15,310 | 0,949 | 2.143 | 15,250 | 0,998 | 454 | 15,285 | 0,958 | 2.143 | 15,250 | 0,998 |
| *dummy_saving* | 733 | 0,424 | 0,495 | 2.179 | 0,365 | 0,481 | 462 | 0,3636 | 0,482 | 2.179 | 0,365 | 0,481 |
| *sktm* | 733 | 0,321 | 0,467 | 2.181 | 0,238 | 0,426 | 462 | 0,325 | 0,469 | 2.181 | 0,238 | 0,426 |
| *rural* | 733 | 0,3192 | 0,466 | 2.479 | 0,360 | 0,480 | 462 | 0,320 | 0,467 | 2.479 | 0,360 | 0,480 |

Source : IFLS 5 (Data Processed)

There are several stages involved in conducting an analysis using Propensity Score Matching (PSM). The first stage is to estimate the propensity score. This study utilizes logistic regression to estimate the propensity score as shown in the table 3.

**Table 3.** Logistic Regression

| *Variable* | Sample 1 (Formal Microcredit) | | Sampel 2 (Informal Microcredit) | |
|---|---|---|---|---|
| | *Coefficient* | *SE* | *Coefficient* | *SE* |
| *age* | -0,0175 | 0,0179 | 0,0244 | 0,0216 |
| *female* | 0,0163 | 0,0969 | 0,0794 | 0,1174 |
| *f_educ* | 0,0292 | 0,0160 | 0,0402** | 0,0192 |
| *m_educ* | -0,0154 | 0,0164 | -0,064*** | 0,0199 |
| *dependency_ratio* | -0,0023** | 0,0010 | 0,0014 | 0,0011 |
| *ln_omzet* | -0,0247 | 0,0302 | 0,0214 | 0,0288 |
| *ln_expsch* | 0,0927* | 0,0523 | 0,0461 | 0,0634 |
| *dummy_saving* | 0,2844*** | 0,1028 | 0,1585 | 0,1261 |
| *sktm* | 0,4691*** | 0,1074 | 0,2487* | 0,1310 |
| *rural* | -0,0505 | 0,1063 | -0,1664 | 0,1294 |
| *_cons* | -2,4661*** | 0,7821 | -2,4945*** | 0,9484 |
| *obs* | 2246 | | 2.012 | |

****significant level 1%, ** significant level 5%, *significant level 10%*

*Source :* IFLS 5 (Data Processed)

Table 3 presents the result of logistic regression for both samples. Sample 1, four out of the ten independent variables significatly influence the dependent variable at significant level 10 percent or less. The estimates indicate that the probability of having formal microcredit increases significantly with saving and ownership of SKTM. School expenditure also has a positive and statistically significant effect, while higher dependency ratio has a negative effect on the probability of having formal microcredit. Similarly, in the sample 2, three out of the ten independent variables significantly influenced the dependent variable. The probability of having informal microcredit increase significantly with ownership of SKTM and higher father's education. However, a higher mother's education level is negatively associated with the probability of having informal microcredit. Domingue et al. (2009) highlight the importance of including all independent variables in the propensity score estimations, even those that do not appear to significantly impact treatment assignment. This practice helps to mitigates the risk of omitted variable bias, which can arise when relevant variables are excluded from the model, potentially leading to inaccurate estimates. While the number of independent variables with significantly significant effects on the dependent variable is relatively modest, the balancing score results obtained using the "pscore" command on STATA are satisfactory. This allows the inclusion of all independent variables in the subsequent analysis.

In the following stage of PSM analysis, we will conduct a matching quality check. This is typically accomplished by examining two key aspects: mean bias and common support.

The mean bias test was employed to assess whether the matching process successfully reduced bias. The results of mean bias after matching for two matching algorithms are presented in the table 4 and 5. Caliendo and Kopeinig (2008) observed that in many studies, the mean bias typically falls within the range of 3 to 5 percent (although no strict threshold exists).

Table 4 and 5 show a significant reduction in mean bias for both NN (3) with Caliper (0,2) and Kernel Matching Algorithms. Additionally, the mean bias for all three dependent variables generally decreased after matching in both samples. Furthermore, p-values after matching were insignificant for all samples in both tables. These results imply an absence of a statistically significant difference between the treatment and control groups after matching, suggesting the effectiveness of matching process.

**Table 4.** Covariate Balance After Matching in the Sample 2 (Informal Microcredit)

| *Variable* | *School Participation* | | | | *School Gap* | | | | *Child Labor* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Mean* | | *% bias* | *P-value* | *Mean* | | *% bias* | *P-value* | *Mean* | | *% bias* | *P-value* |
| | *Treatment* | *Control* | | | *Treatment* | *Control* | | | *Treatment* | *Control* | | |
| **NN (3) with Caliper (0,2) Matching** | | | | | | | | | | | | |
| age | 9,72 | 9,72 | -0,3 | 0,96 | 9,23 | 9,23 | -0,20 | 0,97 | 9,23 | 9,24 | -0,20 | 0,97 |
| female | 0,48 | 0,49 | -1,2 | 0,85 | 0,48 | 0,49 | -1,10 | 0,85 | 0,48 | 0,49 | -1,10 | 0,85 |
| f_educ | 9,60 | 9,58 | 0,50 | 0,94 | 9,71 | 9,73 | -0,4 | 0,95 | 9,70 | 9,71 | -0,30 | 0,96 |
| m_educ | 9,14 | 9,16 | -0,6 | 0,92 | 9,28 | 9,34 | -1,50 | 0,80 | 9,28 | 9,33 | -1,40 | 0,81 |
| dependency_ratio | 75,66 | 75,34 | 0,70 | 0,91 | 76,80 | 76,97 | -0,4 | 0,95 | 76,84 | 76,98 | -0,30 | 0,96 |
| ln_omzet | 0,18 | 0,18 | -0,1 | 0,99 | 0,16 | 0,15 | 0,50 | 0,92 | 0,16 | 0,15 | 0,50 | 0,92 |
| ln_expsch | 15,33 | 15,31 | 1,50 | 0,81 | 15,32 | 15,31 | 1,20 | 0,84 | 15,32 | 15,31 | 1,20 | 0,84 |
| dummy_saving | 0,42 | 0,41 | 2,10 | 0,74 | 0,43 | 0,42 | 2,00 | 0,73 | 0,43 | 0,42 | 2,10 | 0,72 |
| sktm | 0,34 | 0,31 | 6,20 | 0,33 | 0,33 | 0,31 | 5,80 | 0,34 | 0,33 | 0,31 | 5,70 | 0,34 |
| rural | 0,32 | 0,33 | -1,6 | 0,80 | 0,32 | 0,33 | -1,00 | 0,86 | 0,32 | 0,32 | -1,00 | 0,86 |
| **Mean Bias** | | **1,5** | | | | **1,4** | | | | **1,4** | | |
| **Kernel Matching** | | | | | | | | | | | | |
| age | 9,72 | 9,69 | 0,90 | 0,88 | 9,23 | 9,28 | -1,90 | 0,74 | 9,23 | 9,20 | 1,00 | 0,86 |
| female | 0,48 | 0,46 | 4,70 | 0,45 | 0,48 | 0,50 | -3,60 | 0,54 | 0,48 | 0,48 | 0,70 | 0,91 |
| f_educ | 9,60 | 9,69 | -2,2 | 0,72 | 9,71 | 9,73 | -0,50 | 0,94 | 9,70 | 9,48 | 5,50 | 0,34 |
| m_educ | 9,14 | 9,16 | -0,6 | 0,92 | 9,28 | 9,17 | 2,70 | 0,65 | 9,28 | 9,04 | 6,10 | 0,29 |
| dependency_ratio | 75,66 | 74,80 | 1,80 | 0,75 | 76,80 | 76,02 | 1,70 | 0,77 | 76,84 | 75,10 | 3,70 | 0,49 |
| ln_omzet | 0,18 | 0,15 | 1,60 | 0,78 | 0,16 | 0,13 | 2,00 | 0,70 | 0,16 | 0,15 | 0,60 | 0,91 |
| ln_expsch | 15,33 | 15,33 | -0,4 | 0,94 | 15,32 | 15,34 | -2,20 | 0,70 | 15,32 | 15,31 | 0,90 | 0,87 |
| dummy_saving | 0,42 | 0,41 | 1,20 | 0,85 | 0,43 | 0,44 | -2,20 | 0,71 | 0,43 | 0,41 | 4,70 | 0,42 |
| sktm | 0,34 | 0,34 | 1,30 | 0,85 | 0,33 | 0,31 | 4,00 | 0,51 | 0,33 | 0,34 | -2,70 | 0,65 |
| rural | 0,32 | 0,35 | -6,3 | 0,31 | 0,32 | 0,33 | -2,60 | 0,65 | 0,32 | 0,32 | -0,4 | 0,95 |
| **Mean Bias** | | **2,1** | | | | **2,3** | | | | **2,6** | | |

*Source :* IFLS 5 (Data Processed)

**Table 5.** Covariate Balance After Matching in the Sample 1 (Formal Microcredit)

| *Variable* | *School Participation* | | | | *School Gap* | | | | *Child Labor* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Mean* | | *%* | *P-* | *Mean* | | *%* | *P-* | *Mean* | | *%* | *P-value* |
| | *Treatment* | *Control* | *bias* | *value* | *Treatment* | *Control* | *bias* | *value* | *Treatment* | *Control* | *bias* | |
| **NN (3) with Caliper (0,2) Matching** | | | | | | | | | | | | |
| age | 9,98 | 9,93 | 1,90 | 0,81 | 9,59 | 9,51 | 2,7 | 0,71 | 9,60 | 9,52 | 2,9 | 0,70 |
| female | 0,49 | 0,49 | 0,4 | 0,96 | 0,50 | 0,49 | 0,9 | 0,91 | 0,50 | 0,49 | 0,9 | 0,90 |
| f_educ | 9,49 | 9,46 | 0,7 | 0,93 | 9,47 | 9,44 | 0,9 | 0,91 | 9,47 | 9,44 | 0,9 | 0,91 |
| m_educ | 8,58 | 8,72 | -3,7 | 0,64 | 8,71 | 8,87 | -4,2 | 0,58 | 8,71 | 8,87 | -4,2 | 0,57 |
| dependency_ratio | 84,07 | 83,62 | 0,9 | 0,91 | 83,92 | 83,46 | 0,9 | 0,91 | 84,01 | 83,57 | 0,9 | 0,91 |
| ln_omzet | 0,35 | 0,29 | 2,8 | 0,73 | 0,32 | 0,28 | 2,2 | 0,78 | 0,32 | 0,27 | 2,2 | 0,78 |
| ln_expsch | 15,31 | 15,30 | 0,9 | 0,91 | 15,28 | 15,27 | 1,00 | 0,90 | 15,28 | 15,27 | 1,10 | 0,88 |
| dummy_saving | 0,39 | 0,38 | 1,50 | 0,84 | 0,39 | 0,39 | 1,30 | 0,86 | 0,39 | 0,39 | 1,30 | 0,87 |
| sktm | 0,32 | 0,30 | 5,7 | 0,48 | 0,31 | 0,28 | 5,6 | 0,47 | 0,31 | 0,28 | 5,3 | 0,49 |
| rural | 0,31 | 0,32 | -2,6 | 0,74 | 0,32 | 0,33 | -2,5 | 0,74 | 0,31 | 0,33 | -2,5 | 0,74 |
| **Mean Bias** | | **2,1** | | | | **2,2** | | | | **2,2** | | |
| **Kernel Matching** | | | | | | | | | | | | |
| age | 9,98 | 10,03 | -2.1 | 0,79 | 9,59 | 9,68 | -3,4 | 0,64 | 9,60 | 9,72 | -4,1 | 0,58 |
| female | 0,49 | 0,47 | 4.1 | 0,60 | 0,50 | 0,49 | 2,0 | 0,78 | 0,50 | 0,48 | 2,6 | 0,73 |
| f_educ | 9,49 | 9,54 | -1.5 | 0,85 | 9,47 | 9,38 | 2,3 | 0,76 | 9,47 | 9,36 | 2,8 | 0,70 |
| m_educ | 8,58 | 8,55 | 0.8 | 0,92 | 8,71 | 8,63 | 2,3 | 0,76 | 8,71 | 8,56 | 4,0 | 0,59 |
| dependency_ratio | 84,07 | 82,81 | 2.4 | 0,76 | 83,92 | 82,91 | 2,0 | 0,79 | 84,01 | 82,62 | 2,7 | 0,72 |
| ln_omzet | 0,35 | 0,38 | -1.5 | 0,86 | 0,32 | 0,27 | 2,2 | 0,77 | 0,32 | 0,26 | 2,6 | 0,73 |
| ln_expsch | 15,31 | 15,33 | -1.9 | 0,81 | 15,28 | 15,26 | 2,0 | 0,79 | 15,28 | 15,30 | -1,6 | 0,84 |
| dummy_saving | 0,39 | 0,39 | 1.1 | 0,89 | 0,39 | 0,40 | -1,7 | 0,82 | 0,39 | 0,37 | 5,2 | 0,49 |
| sktm | 0,32 | 0,31 | 2.9 | 0,72 | 0,31 | 0,31 | -1,0 | 0,89 | 0,31 | 0,33 | -4,6 | 0,56 |
| rural | 0,31 | 0,32 | -1.3 | 0,87 | 0,32 | 0,33 | -3,9 | 0,60 | 0,31 | 0,35 | -7,8 | 0,29 |
| **Mean Bias** | | **2,0** | | | | **2,3** | | | | **3,8** | | |

*Source :* IFLS 5 (Data Processed)

The second way to assess the quality of matching is to verify the presence of common support or overlap between the treatment and the control group (Kahndhaker et al., 2010). In this study, verification was accomplished by employing twoway kdensity command on STATA to generate pre- and post-matching graphs for each utilized dependent variable as shown in the figure 2 and 3.

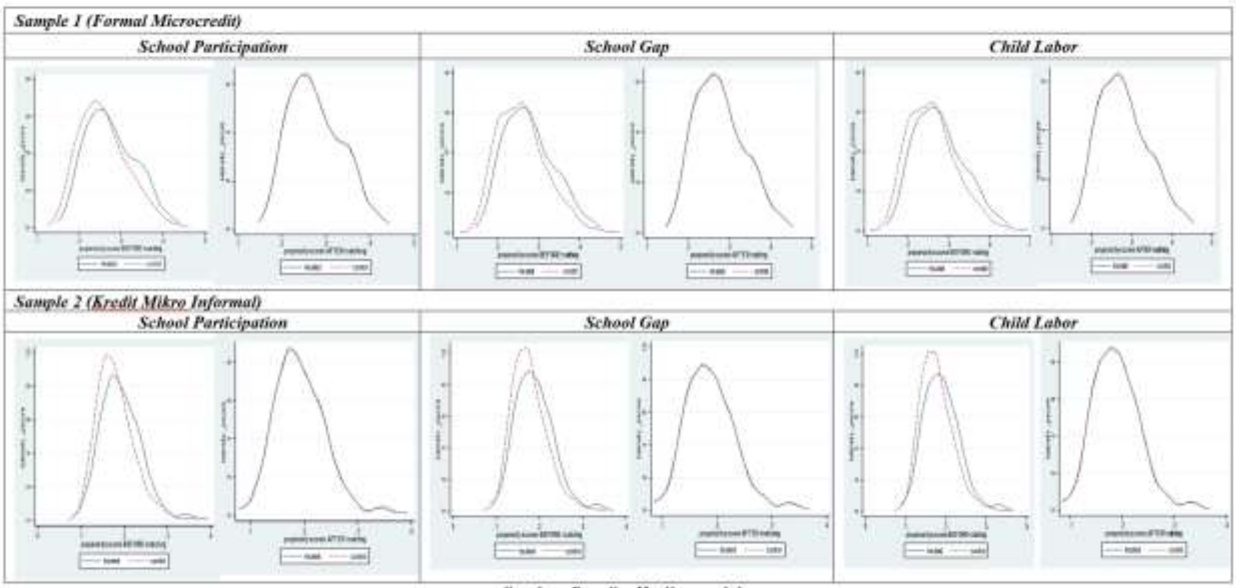


**Figure 2.** Propensity score distribution and common support NN (3) with Caliper (0,2)

*Source :* IFLS 5 (Data Processed)

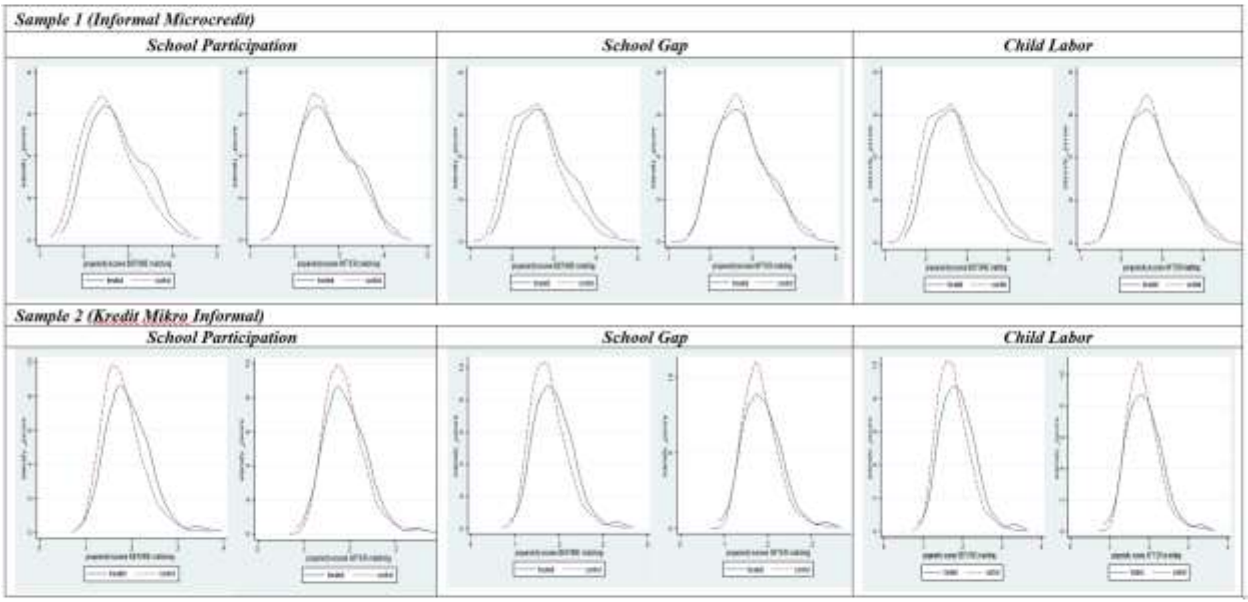


**Figure 3.** Propensity score distribution and common support using Kernel Matching
*Source :* IFLS 5 (Data Processed)

Figure 2 and 3 illustrate the pre- and post-matching conditions employing different matching algorithms. Following the matching process, an overlap was observed between the treatment and control groups for both samples, regardless of the algorithm employed. This overlap suggests successful matching on the propensity score, implying each treatment variable now has a comparable counterfactual (control group) with similar characteristics.

The estimation results of the impact of microcredit from two different source (formal and informal) on the education and child labor on micro-enterprise households are presented in the table 6 below.

**Table 6.** ATT Estimation

| *Outcome* | *Formal Microcredit* | | *Informal Microcredit* | |
|---|---|---|---|---|
| | *NN (3) Caliper (0.2)* | *Kernel* | *NN (3) Caliper (0.2)* | *Kernel* |
| *School Participation* | 0,0209* (0,0114) | 0,0163* (0,0094) | 0,0061 (0.0143) | 0,0050 (0,0122) |
| *School Gap* | -0,0388** (0,0189) | -0,0281** (0,0143) | -0,0102 (0,0271) | -0,0164 (0,0221) |
| *Child Labor* | 0,0174 ( 0,0150) | 0,0125 (0,0135) | 0,0213 (0,0188) | 0,0089 (0,0167) |

***significant at alpha 1%, **significant at alpha 5%, *significant at alpha 10%
*Source :* IFLS 5 (Data Processed)

According to the ATT estimation in table 6, for sample 1 using both NN (3) with Caliper (0,2) dan Kernel matching algorithms, indicate that formal microcredit significantly increases the probability of children's school participation by 1,63 to 2,09 percent and reduces the probability of school gap by 2,81 to 3,88 percent compared to those non-credit recipient households. This finding aligns with previous studies by Doan et al. (2014); Kandulu et al. (2020); Wydick (1999); You & Annim (2014), highlight that microcredit utilized for productive activities, such as business venture, can generally generate income, leading to increased investment in children's education.

Unlike the positive impact on education, the coefficient for child labor was not statistically significant using either matching algorithm. However, the positive coefficient for child labor variable warrants further investigation. Kandulu et al. (2020) stated that school participation and child labor are not mutually exclusive. Additionally, Kondratjeva & Chen (2018) highlight that low school attendance is not always associated with high child labor rates.

Meanwhile, for sample 2, the ATT estimation results obtained using both NN (3) with Caliper (0,2) and Kernel Matching, show no statistically significant difference in the probability of school participation, school gap or child labor between households with informal microcredit and those without. This finding is supported by the insignificant effect observed in the estimated results.

The final step in PSM analysis involves conducting a sensitivity analysis. This examines the potential influence of unobserved variables, which may affect the outcome but remain unmeasured in the analysis, on the estimated treatment effects. Hidden bias can arise when the probability of receiving the treatment differs among observed individuals due to these unobserved variables (Caliendo & Kopeinig, 2005). As noted by Rosenbaum (2005) in Caliendo & Kopeinig (2008), a study is considered sensitive to such hidden bias if the gamma value is close to 1 and the p-value is not statistically significant at the 5% levels.

Table 7 and 8 present the sensitivity test results for sample 1 and sample 2, respectively using NN (3) with Caliper (0.2) and Kernel Matching. In the table 7, using NN (3) with Caliper (0.2) matching, sensitivity results show that for variables school participation and school gap indicates sensitivity to hidden bias at gamma value range from 2,8 to 3,0 for school participation and 2,2 to 3,0 for school gap (p-value > 0,05). In the Kernel matching test shows significant p-value (p-value < 0,05) up to gamma 3 for both dependent variables, suggesting no sensitivity to hidden bias or suggests minimal influence from unobserved factors on these estimations. In contrast, the child labor variable in the sample 1 exhibits sensitivity in both test (at low gamma, p-value > 0,05). This suggest that unobserved factors may be influencing the results, and the positive impact observed might not be solely attributed to formal microcredit.

For sample 2, using NN (3) with Caliper (0.2) matching, sensitivity results show that for variables school participation and school gap indicates sensitivity to hidden bias at gamma value range from 1,7 to 3,0 with p-value < 0.05. Meanwhile, Kernel Matching test show significant p-value (p-value < 0,05) up to gamma 3, indicating no sensitivity to hidden bias. On the other hand, the child labor variable show sensitivity in both test (p-value > 0,05 at low gamma), suggesting potential influence form unobserved factors (sanglestsawai, 2015 in Nardjo & Adjasi, 2020).

**Table 7.** Rosenbaum Sensitivity Analysis for Sample 1 (Formal Microcredit)

| *Gamma* | NN (3) dengan *Caliper (0.2) Matching* | | | *Kernel Matching* | | |
|---|---|---|---|---|---|---|
| | *School Participation* | *School Gap* | *Child Labor* | *School Participation* | *School Gap* | *Child Labor* |
| | *Significance level* | *Significance level* | *Significance level* | *Significance level* | *Significance level* | *Significance level* |

| | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0,0000 | 0,0000 | 0,000 | 0,000 | 0,9997 | 0,9997 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 1.1 | 0,0000 | 0,0000 | 0,000 | 0,000 | 1,0000 | 0,9980 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 1.2 | 0,0000 | 0,0000 | 0,000 | 0,000 | 1,0000 | 0,9904 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 1.3 | 0,0000 | 0,0000 | 0,000 | 0,000 | 1,0000 | 0,9679 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 1.4 | 0,0000 | 0,0000 | 0,000 | 0,000 | 1,0000 | 0,9194 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 1.5 | 0,0000 | 0,0000 | 0,000 | 0,000 | 1,0000 | 0,8373 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 1.6 | 0,0001 | 0,0000 | 0,000 | 0,001 | 1,0000 | 0,7238 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 1.7 | 0,0002 | 0,0000 | 0,000 | 0,003 | 1,0000 | 0,5905 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 1.8 | 0,0005 | 0,0000 | 0,000 | 0,007 | 1,0000 | 0,4540 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 1.9 | 0,0011 | 0,0000 | 0,000 | 0,013 | 1,0000 | 0,3296 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 2 | 0,0021 | 0,0000 | 0,000 | 0,024 | 1,0000 | 0,2265 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 2.1 | 0,0039 | 0,0000 | 0,000 | 0,040 | 1,0000 | 0,1480 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 2.2 | 0,0066 | 0,0000 | 0,000 | 0,063 | 1,0000 | 0,0923 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 2.3 | 0,0106 | 0,0000 | 0,000 | 0,093 | 1,0000 | 0,0552 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 2.4 | 0,0162 | 0,0000 | 0,000 | 0,131 | 1,0000 | 0,0318 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 2.5 | 0,0238 | 0,0000 | 0,000 | 0,176 | 1,0000 | 0,0177 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 2.6 | 0,0337 | 0,0000 | 0,000 | 0,227 | 1,0000 | 0,0095 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 2.7 | 0,0460 | 0,0000 | 0,000 | 0,283 | 1,0000 | 0,0050 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 2.8 | 0,0610 | 0,0000 | 0,000 | 0,343 | 1,0000 | 0,0026 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 2.9 | 0,0788 | 0,0000 | 0,000 | 0,404 | 1,0000 | 0,0013 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |
| 3 | 0,0995 | 0,0000 | 0,000 | 0,466 | 1,0000 | 0,0006 | 0,000 | 0,000 | 0,000 | 0,000 | 1,000 | 1,000 |

*Source :* IFLS 5 (Data Processed)

**Table 7.** Rosenbaum Sensitivity Analysis for Sample 2 (Informal Microcredit)

| **Gamma** | **NN (3) dengan *Caliper (0.2) Matching*** | | | | | | ***Kernel Matching*** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***School Participation*** | | ***School Gap*** | | ***Child Labor*** | | ***School Gap*** | | **School Gap** | | **Child Labor** | |
| | *Significance level* | | *Significance level* | | *Significance level* | | *Significance level* | | *Significance level* | | *Significance level* | |
| | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* |
| 1 | 0,0003 | 0,0003 | 0,000 | 0,000 | 0,9943 | 0,9943 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 1.1 | 0,0009 | 0,0001 | 0,000 | 0,000 | 0,9987 | 0,9805 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 1.2 | 0,0024 | 0,0000 | 0,000 | 0,001 | 0,9997 | 0,9497 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 1.3 | 0,0055 | 0,0000 | 0,000 | 0,003 | 0,9999 | 0,8954 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 1.4 | 0,0110 | 0,0000 | 0,000 | 0,006 | 1,0000 | 0,8160 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 1.5 | 0,0198 | 0,0000 | 0,000 | 0,013 | 1,0000 | 0,7157 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 1.6 | 0,0328 | 0,0000 | 0,000 | 0,024 | 1,0000 | 0,6033 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 1.7 | 0,0504 | 0,0000 | 0,000 | 0,040 | 1,0000 | 0,4891 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 1.8 | 0,0732 | 0,0000 | 0,000 | 0,063 | 1,0000 | 0,3821 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 1.9 | 0,1010 | 0,0000 | 0,000 | 0,093 | 1,0000 | 0,2884 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 2 | 0,1337 | 0,0000 | 0,000 | 0,130 | 1,0000 | 0,2109 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 2.1 | 0,1707 | 0,0000 | 0,000 | 0,173 | 1,0000 | 0,1498 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 2.2 | 0,2115 | 0,0000 | 0,000 | 0,221 | 1,0000 | 0,1037 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 2.3 | 0,2552 | 0,0000 | 0,000 | 0,273 | 1,0000 | 0,0701 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 2.4 | 0,3010 | 0,0000 | 0,000 | 0,329 | 1,0000 | 0,0464 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 2.5 | 0,3480 | 0,0000 | 0,000 | 0,386 | 1,0000 | 0,0301 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 1,0000 |
| 2.6 | 0,3955 | 0,0000 | 0,000 | 0,443 | 1,0000 | 0,0192 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 0,9999 |
| 2.7 | 0,4426 | 0,0000 | 0,000 | 0,499 | 1,0000 | 0,0121 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 0,9998 |
| 2.8 | 0,4888 | 0,0000 | 0,000 | 0,553 | 1,0000 | 0,0075 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 0,9995 |
| 2.9 | 0,5335 | 0,0000 | 0,000 | 0,604 | 1,0000 | 0,0046 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 0,9990 |
| 3 | 0,5763 | 0,0000 | 0,000 | 0,652 | 1,0000 | 0,0028 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 1,0000 | 0,9979 |

| Gamma | NN (3) dengan *Caliper (0.2) Matching* | | | | | | *Kernel Matching* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***School Participation*** | | ***School Gap*** | | ***Child Labor*** | | ***School Gap*** | | **School Gap** | | **Child Labor** | |
| | *Significance level* | | *Significance level* | | *Significance level* | | *Significance level* | | *Significance level* | | *Significance level* | |
| | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* | *Upper bound* | *Lower bound* |

*Source :* IFLS 5 (Data Processed)

## CONCLUSION

This study aims to analyze impact of microcredit both from both formal and informal source on education and child labor in Indonesian micro-enterprise households.

The result of the study using Propensity Score Matching are in line with previous research by Doan et al. (2014); Kandulu et al. (2020); You & Annim (2014). The analysis reveals a positive and significant impact of formal microcredit participation on educational attainment, evidenced by a significant increase in the probability of school participation and decrease in the probability of school gap.

Furthermore, the sensitivity test results show that both sample 1 and sample 2, using two independent variables of school participation and school gap, are not sensitive to hidden bias. Therefore, it can be concluded that the research result is robust to unobserved bias.

Moreover, microcredit form both formal and informal sources exhibited no significant impact on child labor in either sample. The sensitivity test suggest that unobserved factors may be influencing these results. This limits out ability to draw definitive conclusions about the impact of microcredit on child labor.

This study reveals that the households participating in formal microcredit are more likely to send their children to school compared to those without access to credit. However, participation in informal microcredit does not appear to have a significant impact on children's education attainment. Meanwhile, the impact of both formal and informal microcredit on child labor cannot be determined due to the model's sensitivity to hidden bias.

This finding contributes to a better understanding of the impact of microcredit on education and child labor among micro-enterprise households in Indonesia. Based on the results, author recommends that policymakers to prioritize expanding access to formal microcredit.

Given the limited research on the impact of microcredit on education and child labor in Indonesia context, future research exploring these limitations holds significant promise for strengthening the understanding of microcredit's impact. Recommendation for future research include employing alternative research methodologies that can effectively address the challenge of unobserved factors. This might entail combining propensity score matching with fixed effects or instrumental variables. Additionally, extending the study period or employing panel data could further strengthen the analysis in the future research.

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