Effects of Cash Transfers on Child Labor Across Parental Working Sectors: Evidence From Indonesia

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Abstract

This study examines whether the effect of conditional cash transfers on child labor varies by the household head's working sector and occupation type. Using the March 2023 Indonesian National Socio-Economic Survey, we analyze 180,515 children aged 10–17 in households with an employed head. We estimate the effect of Program Keluarga Harapan (PKH) using a recursive bivariate probit, weighted to the population and clustered at the primary sampling unit. We test the exclusion restrictions directly and use inverse-probability-weighted regression adjustment and propensity-score matching as robustness checks. In the preferred specification, the estimated reduction in child labor is 3.2 percentage points and is not statistically significant (p = .101). Both robustness estimators agree in sign and place the reduction below half a percentage point. We find no statistical evidence that the effect on child labor differs by the household head's working sector, occupation type, or the child's sex. Among PKH recipients, additional receipt of Program Indonesia Pintar, an education-specific transfer conditional on school enrollment, is associated with a 4.1-percentage-point higher probability of school attendance (p = .009). Overall, the design and combination of transfers may matter more than cash receipt alone.

Keywords

Cash transfers; child labor; Indonesia; recursive bivariate probit

Introduction

Even though a number of steps have been taken to tackle child labor, including legislative initiatives introduced since the late 1990s and the Roadmap Towards a Child Labour-Free Indonesia, which was launched in 2015, Indonesia has still not reached its goal of eliminating child labor by 2022. About 1.01 million children were still involved in child labor in 2023, a figure that has remained relatively unchanged since 2018 (BPS-Statistics Indonesia, 2024). Although normative and procedural regulations might in principle ban child labor, especially in the formal sector, they do not adequately take into account the supply-side factors that influence household behavior, in particular among low-income families. This is important because poverty remains a major cause of child labor (Sandra et al., 2020). Children from low-income households may therefore continue to work in the informal sector, where regulatory supervision is limited (Fotoniata & Moutos, 2013). The fact that Indonesia's poverty rate has remained fairly stable at about 10% in recent years means that eliminating child labor is still a major policy issue.

A widely used supply-side measure to address child labor is the provision of cash transfers. By easing the financial constraints that households face, cash assistance can reduce the need for children to engage in income-earning activities. Conditional cash transfers (CCTs) are especially pertinent because they increase household income while encouraging investment in children's education. The conditions linked to these transfers can result in greater school attendance and make education more appealing than alternative choices. The cash payments can offset the resources lost when children spend more time in school. CCTs can therefore have an impact on child labor both by increasing household income and by changing the relative cost of schooling (de Hoop & Rosati, 2014).

In Indonesia, the Program Keluarga Harapan (PKH) is the nation's primary CCT program. It provides cash assistance to poor and vulnerable families on the condition that they meet requirements in education, health, and social welfare. By combining household-level income support with education-related conditions, PKH is relevant to how children divide their time between school and work (Utami et al., 2024). The program itself, however, is not primarily intended to terminate child labor; any impact on child labor is thus a result of the program's income support and education conditions, not an explicit aim. Another cash transfer program that affects children's time allocation is the Program Indonesia Pintar (PIP). PIP offers financial help to poor and vulnerable school-age children to enable them to participate in education. By alleviating the financial difficulties associated with attending school, this assistance could influence how children allocate their time between school and work (Wahyudi et al., 2026). The program therefore provides another example of how financial support for education can affect children's engagement in work.

Evidence on the effect of cash transfers on child labor remains inconclusive. Some reviews and various evaluations indicate a reduction (de Hoop & Rosati, 2014; Del Carpio et al., 2016; Gee, 2010; Parker & Todd, 2017), while others show that there is no significant impact on work participation (Cepaluni et al., 2022; Lee & Hwang, 2016; Utami et al., 2024). A further group observes improvements in schooling without a corresponding decrease in work (Attanasio et al., 2010; Wardani et al., 2022). A possible reason for this is that the transfer may lead to a reduction in the number of hours worked and promote better school attendance because of the requirements attached to it, even though it does not necessarily remove the possibility of children working, since it usually does not require them to completely stop taking part in

labor. This situation is particularly clear in poor households in rural areas, where the opportunity cost of attending school is often greater than the transfer amount, and the expected benefits of education are seen as low (Krauss, 2017).

Del Carpio et al. (2016) offered a thoughtful framework explaining how household decisions about child labor are influenced by family characteristics, child characteristics, and work-specific dynamics. The study emphasizes that some types of work, like schooling, can be skill-forming. As a result, households may compare the future returns from schooling with those from work. For instance, children in families running their own businesses might be more inclined to join in child labor if they believe such work helps build skills similar to those gained through school. When the anticipated future earnings from education are lower than the immediate and potential gains from skill-forming labor, or when the opportunity cost of schooling outweighs the value of the household transfer, financial transfers alone may not be enough to stop child labor.

Even though there are these findings, the empirical literature has not fully looked at the kind of child labor carried out by children according to the working sector and occupation of their parents within this approach, particularly in Indonesia. For instance, Hidayatina (2018) found that PKH reduced child working hours in both economic activities and in household chores. However, this study was limited in geographical scope and did not account for parental employment circumstances. De Silva and Sumarto (2015), by contrast, pointed out that Bantuan Siswa Miskin (BSM), educational support transfers for the poor, can lead to positive spillover effects provided the amounts are sufficient, or parents distribute them in a beneficial manner.

On the other hand, Hudang et al. (2024) observed that recipients usually use the transfers for other essential needs, such as food, since recipients are likely to come from deprived families, and this may weaken the program's impact on children's education by reducing the time children spend working. Furthermore, the conditionality of the program might harm the children even more, as they could end up having to balance school and work because of the improper use of the transfers. Households are more likely to keep children in school when the expected future returns from education exceed its current costs (Hartarto et al., 2021; Krauss, 2017; Lee & Hwang, 2016).

It is conceivable that earlier research on cash transfers and child labor in Indonesia has still not fully examined the various characteristics which might affect a family's decision to send their children to work, especially the sectors in which parents are employed and their specific occupations (De Silva & Sumarto, 2015; Hartarto et al., 2021; Hidayatina, 2018; Hudang et al., 2024; Jayawardana et al., 2021; Utami et al., 2024; Wahyudi et al., 2026) (as shown in Table 2). Nevertheless, Utami et al. (2024) stated that it is important to examine household-level characteristics that have received little attention and might influence the impact of cash transfers on child labor.

Therefore, this study examines the previously underexplored area by investigating the effect of the CCT on child labor, with a focus on three aspects: first, the impact across different parental working sectors and occupational types, which may represent underexplored dimensions of the CCT's relationship to child labor; second, since the PKH program was not designed to eliminate child labor, whether other education-related cash transfers, such as the PIP, should also be introduced; and third, how the transfers are used within the family.

Theoretical framework and literature review

Theoretical framework

The study is based on the theoretical framework developed by Del Carpio et al. (2016). It shows household decision-making as involving a trade-off between child labor and schooling. Every household is assumed to experience two separate periods: the present and the future. The model consists of three cases which demonstrate how different reactions to CCT might fare. For convenience, Table 1 gives a summary of the symbols used in the three cases and their meaning within the framework.

Table 1: Notation Used in the Theoretical Framework

Symbol	Meaning
s	Time allocated to schooling
l	Time allocated to physical/non-skilled child labor
h	Time allocated to skilled/skill-forming child labor
p_s	Cost of schooling before transfer
p_T	Effective schooling cost after transfer
T	Cash transfer received by household
L	Productive assets complementing physical labor
H	Productive assets complementing skilled labor
f_i	the child's productivity in each type of labor (physical or skilled)
R_s	Future return to schooling
R_h	Future return to skilled child labor
ϕ	Share of child's future income accruing to household
ρ	Time-preference parameter or degree of patience to postpone child labor

In Case 1, the child's time is allocated between schooling (s) and labor (l), subject to $s + l = 1$. The household income function for child labor is:

$$Y_1 = Lf_l \ln l - p_s s - ml \quad (1)$$

Equation (1) represents the household's income function in the first period. Household present income increases with the additional time allocation of child labor (l), the children's productivity (f_l), and asset complements to child labor such as land or machines (L). On the other hand, the time allocation of schooling, given the cost of schooling ($p_s s$) and the adverse effect of child labor (ml) will reduce the current household income. In the second period, when the children become adults, the household's income function will be:

$$Y_2 = \phi R_s s, \quad (2)$$

The future income in a household is determined by the part of the future return from schooling that is passed on to the household.

The household's lifetime objective is to maximize income in both periods, and the family's optimal function will be $\max_{l} Y_1 + \rho Y_2$ limited by the child's time allocation. The maximization function will be:

$$\max_{l} Y = Lf_l \ ln \ l - p_s(1 - l) - ml + \ \rho\phi R_s(1 - l) \tag{3}$$

where ρ is the time-preference parameter, representing the household's degree of patience to postpone current consumption for future income. Hence, the first-order condition will be:

$$\frac{\partial Y}{\partial l} = Lf_l \ \frac{1}{l} + p_s - m - \rho\phi R_s = 0 \tag{4}$$

Solving for the household's optimal allocation of the child's time to labor gives

$$l^* = \frac{Lf_l}{\rho\phi R - p_s + m} \tag{5}$$

This expression shows that the optimal amount of child labor depends on children's productivity, household productive assets, the effective cost of schooling, the cost of child labor, and the expected return to schooling. The CCT is assumed to reduce the net effective cost of schooling. Note that $p_T = p_s - \alpha T, \alpha > 0$, where α represents the extent to which the transfer offsets school-related costs. Substituting p_T into Equation 6 gives the optimal child-labor allocation as a function of the transfer

$$l^* = \frac{Lf_l}{\rho\phi R - p_s + \alpha T + m} \tag{6}$$

The comparative static with respect to the CCT is therefore

$$\frac{\partial l^*}{\partial T} = -\frac{\alpha Lf_l}{(\rho\phi R - p_s + \alpha T + m)^2} < 0 \tag{7}$$

As a result, when the conditional cash transfer increases, the household reduces the amount of time it allocates to child labor.

In Case 2, child labor is divided into two categories: physical labor (for example, farm work) and skilled labor (for example, commerce or services), and the time constraint for children is $s + l + h = 1$. Each kind of labor requires complementary assets: L (such as land and tools) for physical labor and H (such as business or service assets) for skilled labor. The objective function is then:

$$\max_{lh} Y = Lf_l \ ln \ l + Hf_h \ ln \ h - p_T(1 - l - h) - m(l + h) + \ \rho\phi R_s(1 - l - h) \tag{8}$$

The relative allocation between the two types of labor is expressed as:

$$\frac{l}{h} = \frac{Lf_l}{Hf_h} \tag{9}$$

This ratio shows that the balance between physical and skilled child labor depends jointly on the types of household assets and on child-specific abilities. For instance, children living in a household that owns a business (H) that complements their skills might be involved in labor, especially girls (low f_l, probably high in f_h).

For Case 3, the model treats the h type of child labor as skill-forming activities, which also yield future returns, like schooling. Hence, the expected return for the second period, considering both schooling and skill-forming labor, is denoted as $Y_2 = \phi(R_s + \phi R_h)$. Hence, the optimal function will be:

$$\max_{lh} Y = Lf_l \ln l + Hf_h \ln h - p_T(1 - l - h) - m(l + h) + \rho\phi R_s(1 - l - h) + \rho\phi R_h \quad (10).$$

This case shows that households may allocate children's time to skill-forming labor when the future return of such labor, R_h, is relatively higher than the future return of schooling, R_h.

In summary, the three cases provide a sequential framework for understanding the effect of CCT on child labor through various scenarios. Case 1 establishes that reducing the net effective cost of schooling through CCT will simply increase time allocation to schooling and reduce child labor. Case 2 distinguishes child labor into two types (physical and skilled) and identifies the productive assets that complement both. Case 3 recognizes that skilled child labor may generate future returns R_h. Hence, schooling and skill-forming labor might become competing forms of human-capital investment. Thus, the reduction in child labor following a reduction in p_s through CCT may vary by household type. The effect is plausibly smaller in households with greater H and higher R_h.

Based on the theoretical framework mentioned above, we propose two hypotheses for empirical testing. The first is that conditional cash transfers reduce child labor by decreasing the effective cost of schooling and making schooling more attractive relative to other options (H1). The second is that the impact of conditional cash transfers on child labor differs by the working sector and occupation type of the household head, due to variations in the productive environment and the potential value of children's labor (H2).

Literature review

The study of child labor goes back to Becker and Lewis (1973), who viewed child work as being included in the household's strategy for maximizing utility. Basu and Van (1998) developed this view by introducing the "luxury axiom", which states that child labor mainly occurs in households that cannot afford to give up the income their children earn. Hence, the less income the parents have, the more likely they are to get their children to work; on the other hand, if the parents' income is adequate, they are less likely to have their children work. Later research built on this concept by demonstrating that an income shock can change the level of child labor. For example, Edmonds and Schady (2012) discovered that even small amounts of aid given to low-income families result in a substantial decrease in child labor, while other studies found that families suffering from economic drought tend to get their children involved in work as a way of coping (Beegle et al., 2009; Khanam & Ross, 2011; Krauss, 2017). According to this view, when households face less tight budget constraints, parents prefer to have their children go to school or engage in leisure rather than work. Budget constraints can be eased through cash transfers or by gaining access to credit. As a result, the need for children to work will be reduced (Bandara et al., 2015).

The so-called luxury axiom idea was later questioned by Bhalotra (2003), who put forward what is known as the wealth paradox. It was observed that even among wealthier households, children may still be made to work, especially among those with access to business-related or productive assets such as land. This indicates that the decisions regarding child labor are influenced by complex household circumstances beyond simple economic limitations

(Krauss, 2017). These circumstances vary according to the children's characteristics such as their age and gender (de Hoop & Rosati, 2014; Islam & Hoque, 2022; Khanam & Ross, 2011); family features including the parents' education, age and gender, the number of people in the family and the dependency ratio (Attanasio et al., 2010; Del Carpio et al., 2016; Khanam & Ross, 2011; Krauss, 2017; Wardani et al., 2022); and community-level factors such as the social attitude towards child labor that is common in a given area (Adonteng-Kissi, 2023) and the expected return on a child's education, which is likely to differ from one area to another (Krauss, 2017; Lee & Hwang, 2016).

In Indonesia, the research into child labor, in particular the effects of cash transfers, also showed variation. Hidayatina (2018) discovered that PKH led to a significant decrease in both economic and domestic child labor as well as in the number of hours children spent working. Although the results differed by gender and place (rural or urban), the effects were always greater for economic activities. On the other hand, Utami et al. (2024) found, using propensity score matching, no statistically significant effect of PKH on child labor, regardless of whether the children were involved in paid or unpaid work. Wardani et al. (2022) examined BSM and concluded that although the transfers did not reduce child labor, they did significantly improve school attendance, particularly among older children.

Wahyudi et al. (2026) found that both PIP and PKH were linked to a reduction in exclusive child labor. However, PIP had a stronger and more consistent relationship with shifting children towards exclusive schooling. Conversely, PKH showed a stronger association with continuing dual activities of attending school and working. Jayawardana et al. (2021) investigated how in-kind transfers (rice subsidies) reduce child labor participation, particularly among boys.

As seen in Table 2, other Indonesian studies examined the mechanisms responsible for these effects. Lee and Hwang (2016) found that PKH helps to reduce the opportunity cost of schooling, but maintained that the level of the transfer was not high enough in the short term; in order to make schooling more attractive than child labor in the short term, the transfers would have to increase by as much as 400%. De Silva and Sumarto (2015) noted that BSM not only reduced the supply of child labor but also produced 'flypaper effects', that is, transfers were deliberately spent on the children's educational expenses. On the other hand, Hudang et al. (2024) found that although PKH increased food consumption expenditure, its impact on children's educational attainment was negative. Furthermore, other studies have shown that PKH increased parents' aspirations regarding their children's educational attainment (Hartarto & Wardani, 2023; Hartarto et al., 2021).

Table 2: Prior Indonesian CCT and Child-Labor Studies

Author (year)	Data	Method	Key finding
De Silva & Sumarto (2015)	Susenas 2009	Propensity score matching; marginal-spending (flypaper) analysis	Educational transfers reduce child labor, particularly among children from poor families. Recipient households also increase spending on educational goods.
Lee & Hwang (2016)	IFLS plus Indonesian	Ex-post review plus rate-of-	PKH does not significantly reduce child labor or increase enrolment. The transfer appears

Author (year)	Data	Method	Key finding
	government statistics	return / cost–benefit comparison (short, medium, long term)	insufficient to offset the opportunity cost of child labor in the short and medium term.
Hidayatina (2018)	IFLS 2014 (Java only)	Bivariate probit with endogenous dummy	PKH reduces child labor participation and working hours, although the effects vary by gender and area of residence.
Hartarto et al. (2021)	Primary: interviews from 30 subdistricts in Yogyakarta province	Qualitative case study (COM-B Model)	PKH influences parents' educational aspirations for their children, suggesting a behavioral mechanism that may affect the schooling–child labor decision beyond the direct income effect
Jayawardana et al. (2021)	IFLS 1997–2014	Coarsened exact matching with difference-in-differences	The rice subsidy lowers the probability of working for boys, especially those combining work and school, but has no significant effect on the probability of schooling.
Wardani et al. (2022)	IFLS; recipients and their non-recipient siblings	Matched difference-in-differences	BSM increases schooling among recipients, particularly at the senior-secondary level, but does not significantly reduce their likelihood of child labor
Hartarto & Wardani (2023)	IFLS 2007 and 2014	Propensity score matching combined with difference-in-differences	PKH increases parents' educational aspirations for their children, suggesting an aspirational pathway through which the program may influence the schooling–child labor decision
Hudang et al. (2024)	IFLS 2007 and 2014	Difference-in-differences	PKH increases food consumption expenditure but does not significantly improve children's educational attainment. The findings provide limited evidence that the transfer reduces child labor through increased investment in children.
Utami et al. (2024)	IFLS 2014	Propensity score matching	PKH has no statistically significant impact on child labor under any matching technique: receiving the CCT does not necessarily stop poor households from sending children to work.
Wahyudi et al. (2026)	Susenas 2023	Multinomial logit	PIP is associated with lower child labor and greater exclusive school participation, particularly among urban and poorer households. PKH is also associated with lower child labor, although recipients are more likely to combine schooling and child labor

Indonesian literature has already looked at a number of aspects of heterogeneity, such as gender, geographic location, and household characteristics, as shown in Table 2. However, the studies referred to do not systematically examine the working sector and occupational

type of the head of household as dimensions of heterogeneity, as had been mentioned earlier in the introduction.

Data and methods

Data source and survey design

The study uses the 2023 edition of the Indonesian National Socio-Economic Survey (Survei Sosial Ekonomi Nasional [Susenas]), conducted by BPS-Statistics Indonesia (2023a, 2023b). We acquired the data from BPS-Statistics Indonesia's official microdata web service by purchasing the relevant microdata files, which include detailed information on demographic and socio-economic characteristics, labor-force participation, education, housing and expenditure, and participation in social programs.

The sampling method employed by Susenas is stratified multistage sampling, involving the selection of households in several stages within each primary sampling unit (PSU) and sampling stratum. In our analysis, we use the household sampling weights supplied by BPS-Statistics Indonesia to account for unequal probabilities of selection and ensure that the estimates are representative of the population. Because children are part of households, and households are selected within PSUs, we cluster standard errors at the PSU level to account for correlation within each PSU. As the 2023 public-use data do not contain the identifiers for the sampling strata, it is not possible for us to explicitly replicate the stratification element in the variance estimation.

The sample initially includes 189,254 children aged 10–17. We then exclude 8,739 children living in households where the head is unemployed because the working sector and occupation type variables are used in the heterogeneity analysis. The final sample comprises 180,515 children in 136,755 households, distributed across 33,986 PSUs.

Variables

The dataset uses two indicators of child activity as its dependent variables. The first of these is work, which refers to a child having taken part in some form of economic activity with the aim of earning income or helping to contribute to household income for at least one hour over the previous week. The second is school attendance, which means the child attended either formal or informal school at the primary, secondary, or tertiary level. The key independent variable in this study is participation in PKH, which is quantified as binary: 1 if children participate in PKH and 0 if they do not. A second independent variable, used in a separate model for additional analysis, is participation in PIP; this is also recorded as binary.

The control variables comprise a range of child characteristics such as age and gender; attributes of the household head such as their age, gender, level of education, and whether or not they have internet access; the area of residence of the household, including the working sectors and occupational types; household factors such as the location of residence (rural or urban), per capita expenditure, the ratio of food to non-food expenditure, and the dependency ratio; and municipal features such as regional economic growth and the quality of the educational facilities.

The working sector is categorized into three groups —agriculture, industry, and services— based on the children's household heads' primary activities, as indicated in the 26-industrial origins categorization of Statistics Indonesia. Occupational types are classified into four categories according to the household heads' employment status: business owner (operates their own enterprise, including self-employed, assisted by unpaid workers, and those assisted by paid workers), regular worker (a paid employee with a regular working routine), freelancer (an independent worker without a formal contract or fixed working schedule), and unpaid family worker (a person who helps in a family business without receiving any financial payment).

Empirical methods

The study aims to examine whether the effect of CCT on child labor varies across household heads' working sectors and occupation types. Two key conditions need to be recognized. First, targeting PKH beneficiaries relies on a proxy means test, which may not capture the full multidimensional determinants of the household and therefore risks both inclusion and exclusion errors in beneficiary selection (Syamsulhakim & Khadijah, 2021). Second, the cross-sectional data used raise endogeneity concerns about the relationship between the treatment and the outcomes. Specifically, the same unobserved characteristics that influence household eligibility for PKH may also directly affect the likelihood of children engaging in work. For example, relatively low-income families may be more likely to participate in the program and may also influence children's activities, such as working or schooling. We employ a Recursive Bivariate Probit (RBP) model, which estimates the treatment effect jointly with the error correlation (ρ); its recursive structure imposes rather than tests the direction of causality, so the causal reading rests on joint normality and on the exclusion restrictions (Filippini et al., 2018). The RBP model employed is depicted as:

$$CT_{ij}^{*} = a_1 + \beta_{1i}' X_i + \partial Z_{1i} + \varepsilon_{1i} \quad (11)$$

$$W_{ij}^{*} = a_2 + \delta CT_{ij} + \beta_{2i}' X_i + \varepsilon_{2i} \quad (12)$$

$$CT_{ij} = 1 \text{ if } CT_{ij}^{*} > 0, W_{ij} = 1 \text{ if } W_{ij}^{*} > 0$$

$CT_{ij} = 1$ if child i in activity j is participating in the program and 0 if otherwise. $W_{ij} = 1$ if child i is involved in activity j and 0 if otherwise. X_i are observed independent variables that influence the participation in the program and the children's activities; see Table 3 for the full variable lists. and Z_1 represent the vector influencing program participation that is not included in Equation 12 (the candidates are: land ownership, economic growth, and the quality of education facilities). Both ε_1 and ε_2 represent unobserved error terms associated with program participation and children's work activities, respectively. The correlation between these error terms is expressed as $\rho = \text{corr}(\varepsilon_1, \varepsilon_2)$. A Wald test is used to determine whether this correlation differs significantly from zero. The coefficient δ represents the effect of program participation on children's activities.

After estimating the RBP model on the full sample, we first examine the exclusion restriction. Next, we analyze heterogeneity in subsamples based on the child's gender, the household head's working sector, and occupation type. Because these subsamples do not overlap, we use a Wald test to check if treatment effects are equal across the different moderator categories.

We only use Holm-adjusted pairwise comparisons if the main test shows a significant difference.

We also looked at whether combining PKH and PIP is more effective. For this, we create three separate groups: non-recipients, households that receive only PKH, and those that receive both. We compare each treatment to the group that does not receive any transfers. To check the robustness of our results, we use propensity score matching (PSM) and inverse-probability-weighted regression adjustment (IPWRA). We also examine how beneficiary households spend the transfers by looking at intra-household expenditures. All data management, analysis, and estimation were done using Stata.

Results and discussion

Descriptive statistics

Table 3 lists the variables used in the analysis. These are grouped into categories: child activities, transfer receipt, child characteristics, household head characteristics, household characteristics, and municipal characteristics.

Table 3: Descriptive Statistics and Mean Differences Between Beneficiaries and Non-Beneficiaries

Variable	Mean	SD	Diff: by PKH	SE
Activities				
School	0.904	0.295	−0.015***	(0.0032)
Work	0.032	0.176	0.012***	(0.0017)
Cash Transfers				
PKH	0.237	0.425	—	
PIP	0.176	0.381	0.239***	(0.0047)
PKH and PIP (dual)	0.085	0.279	0.359***	(0.0045)
Child characteristics				
Child age	13.447	2.330	0.241***	(0.0192)
Child male	0.508	0.500	−0.001	(0.0045)
Child education	1.828	0.807	0.050***	(0.0068)
HH head characteristics				
HH head age	46.250	8.524	1.558***	(0.0974)
HH head male	0.939	0.239	−0.015***	(0.0030)
HH head education	2.100	1.066	−0.613***	(0.0109)
HH head type of work				
Business owner	0.477	0.499	0.040***	(0.0057)
Worker	0.395	0.489	−0.125***	(0.0055)
Freelance	0.119	0.323	0.082***	(0.0044)
Unpaid/family worker	0.009	0.097	0.003***	(0.0010)
HH head working sectors				
Agriculture	0.342	0.474	0.168***	(0.0056)
Industry	0.245	0.430	0.019***	(0.0052)
Service	0.412	0.492	−0.187***	(0.0056)
HH head has access to Internet	0.693	0.461	−0.247***	(0.0055)
HH head has Bank account	0.570	0.495	−0.146***	(0.0057)

Variable	Mean	SD	Diff: by PKH	SE
Household characteristics				
Live in urban area	0.564	0.496	−0.165***	(0.0063)
Log per capita expenditure	13.865	0.595	−0.360***	(0.0061)
Food/non-food expenditure	1.479	0.768	0.324***	(0.0093)
Dependency ratio	0.336	0.188	−0.003	(0.0020)
Land owning	0.720	0.449	−0.012**	(0.0054)
Municipal characteristics				
Economic growth	4.549	2.058	−0.240***	(0.0186)
Quality of education facilities	0.824	0.164	−0.023***	(0.0019)

Note: Number of observations: 180,515

The descriptive statistics show that 90.4% of children aged 10 to 17 in households with an employed head attend school, and 3.2% are economically active. Some children do both: 1.2% both go to school and work, so 37.7% of working children are also enrolled in school. Another 7.6% neither attend school nor work. Around 23.7% of children receive PKH benefits, 17.6% get PIP, and 8.5% receive both.

Comparing beneficiaries and non-beneficiaries shows that children who receive CCT are more disadvantaged. They are more likely to work (+0.012) and less likely to attend school (−0.015). Children in PKH households are generally older (+0.241) and have slightly higher educational attainment (+0.050). Their household heads are older (+1.558) but have much lower education levels (−0.613) and are slightly less likely to be male. PKH households are more likely to have heads who are business owners (+0.040), freelance workers (+0.082), or unpaid family workers (+0.003), and less likely to have regular workers (−0.125). By sector, PKH household heads are more likely to work in agriculture (+0.168), only slightly more likely to work in industry (+0.019), and less likely to work in services (−0.187). PKH recipients are poorer, with lower per capita spending (−0.360), less access to banking (−0.146) and the internet (−0.247), and are less likely to live in urban areas (−0.165). Food absorbs a larger share of their budget (+0.324 in the food-to-non-food ratio), a standard indicator of greater welfare need. They are also slightly less likely to own land (−0.012). PKH households are far more likely to receive PIP as well (+0.239), and 8.5% of children receive both transfers. This means the scheme targets low-income households and the selection is not random. At the municipal level, beneficiaries live in areas with slower economic growth (−0.240) and worse educational facilities (−0.023).

Table 4 shows how children's activities are distributed across the household head's sector and occupation and, for working children, across their own. Child labor is concentrated in family production: 55.6% of working children live in agricultural households and 63.8% in business-owning households, while 55.7% of working children are themselves unpaid family workers, rising to 63.8% among girls. Half of working boys are in agriculture (50.2%), while half of working girls are in services (50.7%). Children work predominantly within family enterprises rather than in an external labor market.

Table 4: The Distribution of Children's Activities by the Head of Household's Working Sector and Occupation Type

Children's activities	HH head's working sector			HH head's occupation type				*N*
	Agri.	Ind.	Serv.	Owner	Reg.	Free.	Unpaid	
Not working	33.52	24.77	41.71	47.22	40.02	11.84	0.93	172,651
Working	55.58	17.70	26.73	63.75	22.52	12.23	1.51	7,864
Child's own sector/occupation								
Working children	45.09	17.18	37.72	7.61	25.83	10.91	55.65	7,864
Boys	50.17	18.40	31.44	8.09	25.62	14.60	51.69	5,161
Girls	34.66	14.69	50.66	6.63	26.24	3.33	63.79	2,703

These findings are broadly consistent with our theoretical framework. Productive assets in each area support both child labor and children's productivity. Family-owned businesses make it easier to include child labor as part of informal skill development, while family work in agriculture often involves assets like land that complement child labor. Boys are more involved in agriculture, while girls are more active in services. These setups also mean lower hiring costs, less need for supervision, and less risk from the outside labor market, making child labor more practical within the household (Adonteng-Kissi, 2023; Basu et al., 2010; Bhalotra, 2003).

Recursive Bivariate Probit Results

Decisions to work and attend school are interrelated, and participation in the transfer is not random, so we estimate a recursive bivariate probit that allows the two errors to be correlated. Using the three candidate exclusion variables of Z_1 as described in the Methods section, that correlation is substantial (ρ = 0.47; Wald $\chi^2(1)$ = 14.41, p < .001), indicating potential endogeneity of PKH participation.

We check the exclusion restrictions by looking at the candidates' direct effects on the outcomes. With regard to child labor, neither land ownership nor district economic growth has any detectable direct effect together ($\chi^2(2)$ = 0.71, p = .702); in contrast, education-facility quality does have such an effect ($\chi^2(1)$ = 40.61, p < .001) and is therefore kept as a control variable instead of being treated as an exclusion. Land ownership and district economic growth remain jointly significant in the participation equation ($\chi^2(2)$ = 14.09, p < .001).

Table 5 gives the ATET estimates based on different identifying assumptions. When all three of the candidates for exclusion are included in Z_1, the estimated decrease in child labor is −0.070 (p = .005), but this estimate is based on an invalid education-facility exclusion. If that exclusion is removed, the estimate in the preferred specification becomes −0.032 (p = .101), which is similar to the figure obtained in the case of no exclusion (−0.033, p = .090). Accordingly, the negative association is not statistically different from zero under the preferred identification. The estimate for schooling stays at about −0.12 in all the specifications, but it is regarded as a conditional association since the exclusion restrictions are not jointly valid for that outcome.

Table 5: Exclusion Tests, Sensitivity to the Identifying Assumption, and ATET

	Child labor		Schooling	
Panel A. Direct effect in the outcome equation	**Coef.**	***p***	**Coef.**	***p***
Land ownership	−0.018	.504	0.060	.003
District economic growth	0.002	.618	0.001	.692
Education-facility provision	−0.426	< .001	0.230	< .001
Joint test, land + growth	$\chi^2(2) = 0.71$	.702	$\chi^2(2) = 9.02$	.011
Test, education-facility provision	$\chi^2(1) = 40.61$	< .001	$\chi^2(1) = 22.50$	< .001
Panel B. ATET by identifying assumption	**ATET**	***p***	**ATET**	***p***
(A) Land, growth, facilities excluded	−0.070 (0.025)	.005	−0.120 (0.012)	< .001
(B) Growth, facilities excluded	−0.074 (0.024)	.002	−0.120 (0.012)	< .001
(C) No exclusion (x = z)	−0.033 (0.020)	.090	−0.120 (0.012)	< .001
(D) Land, growth excluded [preferred]	−0.032 (0.019)	.101	−0.121 (0.012)	< .001

Note: Panel A reports coefficients with all candidate variables included in both equations and corresponding Wald tests (z^2 for single restrictions). Panel B reports average treatment effects on the treated (ATETs) under alternative exclusion restrictions. Standard errors appear in parentheses.

Table 6 reports marginal effects on the covariates under the preferred specification (D). The results are broadly consistent with expected patterns. Older children and boys have higher joint probabilities of work and PKH participation but lower joint probabilities of schooling and PKH participation, whereas higher child education is associated with the opposite pattern. Several household characteristics also show substantial associations with children's activities. Higher per-capita expenditure, urban residence, and internet access are associated with lower work and schooling, while associations with household head characteristics vary across outcomes.

Table 6: Marginal Effects on the Covariates

Panel A. Marginal effects on covariates	**Work, PKH (1,1)**	**School, PKH (1,1)**
Child characteristics		
Child age	0.0059*** (0.0002)	−0.0166*** (0.0004)
Child male	0.0054*** (0.0004)	−0.0044*** (0.0006)
Child education level	−0.0081*** (0.0004)	0.0268*** (0.0007)
Household head characteristics		
Age	−0.0001*** (0.0000)	0.0005** (0.0002)
Male	−0.0053*** (0.0008)	−0.0159** (0.0069)
Education level	−0.0031*** (0.0002)	−0.0403*** (0.0018)
Regular worker (base: business owner)	−0.0033*** (0.0005)	−0.0010 (0.0042)
Freelancer	−0.0010 (0.0007)	0.0454*** (0.0059)
Unpaid / family worker	0.0034 (0.0028)	0.0223 (0.0165)
Industry (base: agriculture)	−0.0010 (0.0006)	0.0155*** (0.0051)
Service	−0.0027*** (0.0005)	−0.0231*** (0.0046)
Has internet access	−0.0047*** (0.0005)	−0.0587*** (0.0042)
Has bank account	0.0004 (0.0005)	0.0193*** (0.0038)
Household and municipal characteristics		
Lives in urban area	−0.0035*** (0.0005)	−0.0317*** (0.0041)
Log per capita expenditure	−0.0047*** (0.0005)	−0.1238*** (0.0038)

Panel A. Marginal effects on covariates	Work, PKH (1,1)	School, PKH (1,1)
Food/non-food expenditure ratio	0.0026*** (0.0003)	0.0120*** (0.0025)
Dependency ratio	0.0021* (0.0012)	−0.0669*** (0.0091)
Education-facility index	−0.0067*** (0.0012)	0.0399*** (0.0105)
Participation equation only		
Land ownership	−0.0004** (0.0002)	−0.0141*** (0.0038)
District economic growth	−0.0000** (0.0000)	−0.0012** (0.0006)

*Note: Significance levels: *** p < .01; ** p < .05; * p < .10*

Two results are worth focusing on. Firstly, the district education-facility quality variable is linked to less child labor (−0.0067) and more schooling (+0.0399). Because the index directly affects both outcomes, it also does not satisfy the exclusion restriction required for an excluded instrument.

Secondly, there is a negative total association between the household head's level of education and schooling (−0.0403), which at first sight is surprising. When we decomposed this effect, we found a small positive direct component (+0.0015) but a much larger negative indirect component via participation in the PKH program (−0.0418), which drives the negative total effect. Therefore, the negative total association does not indicate a negative direct relationship between the parents' education and schooling; instead, it is due to the indirect pathway through program participation. In the case of child labor, the corresponding total effect (−0.0031) comprises a negative direct effect (−0.0018) and a slightly smaller negative indirect effect through participation in the PKH program (−0.0013).

Heterogeneity by working sector and occupation type

Since the overall treatment effect is not precisely estimated, the subgroup estimates are regarded as exploratory. Tests of equality across the k categories of each moderator are carried out using a Wald statistic with $k-1$ restrictions, because the estimates are based on separate subsamples. Pairwise contrasts are only examined after a significant omnibus test has been obtained (see Table 7).

Table 7: Average Treatment Effects on Each Child's Activities by Household Head Working Sector, Occupation Type, Child's Sex, and Within Family-Production Settings

Subgroup	ATET, labor	ATET, schooling	*N*	Equality test
Overall	**−0.032 (0.019)**	**−0.121 (0.012)**	**180,515**	**Labor: $\chi^2(2) = 0.37$, $p = .831$; schooling: $\chi^2(1) = 0.04$, $p = .836$**
Working sector				
Agriculture	−0.026 (0.018)	NC	79,839	
Industry	−0.036 (0.015)	−0.120 (0.023)	35,659	
Service	−0.047 (0.034)	−0.114 (0.020)	65,017	
Occupation type				Labor: $\chi^2(3) = 2.44$, $p = .486$; schooling: $\chi^2(2) = 9.37$, $p = .009$
Business owner	−0.047 (0.028)	−0.134 (0.017)	99,687	
Regular worker	−0.014 (0.017)	−0.085 (0.018)	63,000	
Freelancer	0.027 (0.052)	NC	15,879	

Subgroup	ATET, labor	ATET, schooling	*N*	Equality test
Unpaid / family worker	0.018 (0.045)	0.368 (0.208)	1,949	
Child's sex				Labor: $\chi^2(1) = 0.47$, $p = .494$; schooling: $\chi^2(1) = 2.11$, $p = .146$
Boys	−0.092 (0.114)	−0.138 (0.018)	93,568	
Girls	−0.013 (0.014)	−0.104 (0.015)	86,947	
Child's sex, within family-production settings				
Boys, agriculture	−0.025 (0.119)	NC	41,536	Labor: $\chi^2(1) = 0.00$, $p = .973$; schooling: NC
Girls, agriculture	−0.020 (0.007)	NC	38,303	
Boys, business owner	−0.049 (0.120)	−0.140 (0.028)	51,757	Labor: $\chi^2(1) = 0.01$, $p = .915$; schooling: $\chi^2(1) = 0.25$, $p = .615$
Girls, business owner	−0.036 (0.025)	−0.123 (0.019)	47,930	

Note: Standard errors in parentheses. "NC" indicates non-convergence. Equality tests are Wald statistics on k−1 restrictions across independent subsamples; degrees of freedom are reduced where a cell did not converge.

As depicted in Table 7, for child labor, the tests provide no evidence of treatment-effect heterogeneity according to the working sector ($\chi^2(2) = 0.37$, $p = .831$), occupation type ($\chi^2(3) = 2.44$, $p = .486$), or the sex of the child ($\chi^2(1) = 0.47$, $p = .494$). The same holds for schooling by child sex (χ^2 (1) = 2.11, $p = .146$). Additionally, within family-production settings, gender differences are not supported either for agricultural households ($p = .973$) or for business-owning households ($p = .915$). All contrasts were computed for both outcomes; individual contrasts are discussed only where the omnibus test rejects, but their aggregate outcome is reported either way.

For schooling, the occupation-type equality test is rejected (χ^2 (2) = 9.37, $p = .009$). However, the test covers only three of four occupation categories because one subgroup model does not converge, and no pairwise contrast survives Holm correction. We therefore treat this result as suggestive rather than evidence of systematic treatment-effect heterogeneity. By contrast, equality by child sex cannot be rejected ($\chi^2(1) = 2.11$, $p = .146$). Within family-production settings, the agricultural subgroup estimates by child sex are limited by non-convergence. Given the absence of a valid exclusion restriction for this outcome, these results should be interpreted cautiously.

Robustness checks and analysis of dual PKH and PIP recipients

We re-estimate under selection on observables, using IPWRA as the primary comparator and PSM as a secondary check (see Table 8). IPWRA utilizes probability weights and a cluster-robust variance estimator, so it is estimated using the same approach as RBP. Reweighting achieves close balance: 44,955 treated and 135,560 control observations are reweighted to 88,670 and 91,845, respectively, with complete common support and no treated observation off support.

Table 8: Treatment Effects Under Alternative Identifying Assumptions

Estimator	Child labor		Schooling		
	ATET	*p*	ATET	*p*	
RBP, preferred	−0.032 (0.019)	.101	−0.121 (0.012)	< .001	Joint normality of the two errors; land and growth affect participation only
IPWRA, weighted + clustered	−0.004 (0.002)	.028	0.033 (0.003)	< .001	Selection on observables; consistent if either the treatment or the outcome model is correct
PSM, nearest-neighbour (1-NN)	−0.003 (0.002)	.138	0.042 (0.003)	< .001	Selection on observables; common support, and a correctly specified propensity score

Note: Standard errors in parentheses. The recursive bivariate probit and IPWRA are weighted by the Susenas household weight and clustered at the primary sampling unit; nearest-neighbor matching admits neither.

For child labor, the estimators agree in direction: −0.032 under RBP (p = .101), −0.004 under IPWRA (p = .028), and −0.003 under PSM (p = .138), though the magnitude is substantially smaller under selection on observables. For schooling, the estimates differ in sign: −0.121 under RBP (p < .001), compared with +0.033 under IPWRA and +0.042 under PSM (both p < .001). This difference may reflect the identification assumptions. IPWRA and PSM rely on selection on observables and set the correlation between the treatment and outcome disturbances to zero, whereas RBP estimates this correlation. For the schooling outcome, the correlation (ρ) is large and positive (0.530), reflecting favorable unobserved selection into participation and pushing the estimated treatment effect downward.

Because no credible excluded set survives the exclusion tests, the data do not identify this parameter for schooling. Estimates that do not rest on joint normality point the same way: +0.033 under IPWRA and +0.042 under matching. The same caution applies that neither selection on observables nor the exclusion restriction required to identify the disturbance correlation can be established from the data. We therefore report the direction but do not nominate a preferred magnitude.

We next examined whether PKH is more effective when combined with PIP. Table 9 defines four mutually exclusive groups: 119,785 households receiving neither transfer, 29,652 receiving PKH only, 15,303 receiving both PKH and PIP, and 15,775 receiving PIP only. Each contrast is estimated using the combined sample of the two groups being compared and evaluated for the treated group. For PKH participation, we model it using household characteristics. For PIP participation, including dual recipients of PIP and PKH, the equation also includes the child's age, sex, and education level. The direct contrast, which examines the effect of adding PIP among PKH recipients, uses PKH-only households as the comparison group and provides the relevant test of complementarity.

Table 9: Treatment Effects of PKH and PIP Combinations

Contrast	Child labor		Schooling		N (sample/ treated)
	ATET	*p*	ATET	*p*	
Overall PKH,	−0.032 (0.019)	.101	−0.121 (0.012)	< .001	180,515 / 44,955
PKH only vs. non-recipients	−0.029 (0.034)	.394	−0.160 (0.013)	< .001	149,437 / 29,652
PKH + PIP vs. non-recipients	−0.081 (0.027)	.003	0.022 (0.019)	.246	135,088 / 15,303
Adding PIP among PKH recipients	**−0.021 (0.016)**	**.185**	**0.041 (0.016)**	**.009**	**44,955/15,303**

Note: Standard errors in parentheses; all estimates weighted and clustered at the primary sampling unit.

For child labor, the comparison between PKH + PIP recipients and non-recipients shows a reduction of −0.081 (p = .003), while PKH-only recipients versus non-recipients show a change of −0.029 (p = .394). The direct comparison between PKH + PIP and PKH alone is −0.021 (p = .185), indicating no significant evidence that adding PIP decreases child labor beyond PKH alone. For schooling, the direct contrast is +0.041 (p = .009), suggesting that adding PIP to PKH increases school attendance by 4.1 percentage points. Participation is treated as endogenous, and land ownership and district growth remain the excluded variables. However, their validity was only tested for PKH, and land ownership does not meet that test for schooling outcomes. Therefore, this result should be viewed as aligned with the design of the two transfer programs rather than as a definitive causal effect.

The reported use of PKH transfers provides additional context for these findings. In the PKH utilization module, 75.2% of recipient households report spending part of the transfer on food and 65.7% on education. Education is the only one of the seven recorded uses that is reported less frequently by households in which the child mainly works than by those in which the child mainly attends school, by 6.5 percentage points; all the other uses, including food and housing, are more common among households in which the child is working (see Table 10). This aligns with the marginal-spending effect found by De Silva and Sumarto (2015) for educational transfers in Indonesia, although our data record reported use rather than marginal expenditure, so the comparison is only indicative.

Table 10: Reported Use of the PKH Transfer by Child's Main Activity

Reported use of the transfer	All PKH households	Child mainly schooling	Child mainly working	Difference (working − schooling)
Food	75.2	75.2	78.6	3.52 (1.57)**
Education	**65.7**	**67.4**	**59.5**	**−6.46 (1.85)*** **
Housing	24.3	24.3	29.2	5.12 (1.82)***
Medicine and health	10.7	10.6	12.7	2.06 (1.16)*
Debt repayment	6.3	6.3	7.2	0.95 (1.01)
Expectant mothers	1.7	1.8	2.3	0.64 (0.57)
Other uses	1.3	1.3	2.4	1.18 (0.49)**

*Note: Percentages of recipient households reporting each use; categories are not mutually exclusive and all seven recorded uses are shown. The final column is the design-adjusted difference between households whose child mainly works and those whose child mainly attends school, with standard errors in parentheses, clustered at the primary sampling unit. *** $p < .01$, ** $p < .05$.*

Additional evidence from Indonesia aligns with this pattern: Hudang et al. (2024) reported that PKH boosts food expenditure but has limited, statistically insignificant effects on children's education. Similarly, Cahyadi et al. (2020) found no statistically distinguishable consumption effects over six years and reject any increases above about 10% of per capita consumption.

Discussion

The question of whether cash transfers reduce child labor in Indonesia remains contested. Hidayatina (2018) and De Silva and Sumarto (2015) reported reductions, while Lee and Hwang (2016) and Utami et al. (2024) find no effect. Our estimates align more with the latter and suggest the disagreement may be partly due to methodological differences. All specifications yield negative estimates, but once the exclusion restrictions are tested, the reduction is no longer distinguishable from zero, and the matching estimates place it below 0.5%. Hidayatina (2018) used the same estimator, partly identified through local school availability. We tested this restriction instead of assuming it, finding that quality of district education-facility provision influences both outcomes directly. When we moved it into the outcome equation, the significance of the labor reduction disappears. Our contribution is not a different sign but evidence that the estimated effect is sensitive to the identifying assumption.

The fact that child labor consists largely of unpaid work in family businesses can help to explain why its effect on the labor margin is so limited. In such cases, removing a child means giving up household production rather than losing wages. Cahyadi et al. (2020) estimate an experimental reduction of 4.4 percentage points, but only for wage work, excluding household work. A transfer could reduce wage work without removing children from family production, and how outcomes are defined might help explain the difference.

The clearest positive association concerns school attendance. We found that among households already receiving PKH, additional receipt of PIP is associated with higher school attendance without reducing child labor. This result is similar to that of Wardani et al. (2022), who evaluate educational cash transfers and find that they raise the probability of schooling while leaving the recipient's probability of working unchanged. Likewise, Wahyudi et al. (2026), analyzing the 2023 Susenas data, also associate PIP with exclusive schooling, while PKH is connected with children who both work and go to school. It therefore seems that the policy emphasis should lie in how the various programs complement one another rather than in the amount of individual transfers. Nonetheless, the identification in our model is quite fragile: the estimate can be obtained even in the absence of an excluded instrument, and in that case identification depends on joint normality, which cannot be tested using the data.

Hypothesis 1 (H1), which predicts that conditional cash transfers reduce child labor, is not supported when the exclusion restrictions are tested: the estimate is negative across all specifications but not statistically distinguishable from zero in the preferred model. Similarly, Hypothesis 2 (H2) — that the effect varies with the household head's working sector — is also not supported: equality cannot be rejected on any moderator, and no pairwise contrast survives correction for multiple testing. Neither result refutes the hypotheses; both remain unsupported by these data.

Limitations

The principal limitations concern identification, program exposure, and heterogeneity. The RBP relies on the assumption of joint normality and on the exclusion of variables in the participation equation. However, our tests indicate that the quality of district education facilities does not hold with respect to child labor and land ownership for schooling. Although two candidate exclusion variables were not rejected by the tests for child labor, their estimates are still very close to those from the no-exclusion specification, which suggests that identification depends mainly on the functional form.

Furthermore, the estimates for schooling do not change across different specifications and have the opposite sign to those of the matching estimators; we therefore regard them as conditional associations rather than as causal effects. Second, the PIP complementarity finding also warrants similar caution: since PIP is paid out through schools to enrolled children, receipt is inherently linked to schooling, and the exclusions used in the contrast have been tested only for PKH and land ownership, and fail for the schooling outcome. Hence, the result is compatible with the way the program is designed rather than providing evidence of a causal complementarity effect. Moreover, since only self-reported receipt is available and there are no figures on the amount of transfers or the duration of exposure, an analysis of treatment intensity is not possible. Also, the household head's working sector and occupation type are not randomly distributed and may be endogenous, and the RBP does not account for selection into these characteristics; therefore, the subgroup estimates should be seen as reflecting differences among observable household types rather than causal moderation effects.

Apart from these problems relating to identification, the cross-sectional design places limitations on our understanding of the dynamics of the program. Since the length of exposure is not observed, households that received PKH for one year and those that received it for ten years are treated as identical in this case. Moreover, both the way the data are measured and the sampling method introduce further restrictions. The stratum identifiers are not available in the publicly available 2023 Susenas data, which means that it is not possible to reproduce the stratification; since stratification usually reduces sampling variance, our standard errors are therefore conservative. Lastly, the data do not include measures of activity for children under the age of ten. Since the welfare deciles are updated infrequently, the information on program receipt in 2023 may be based on household circumstances recorded at an earlier date.

Conclusion

This study investigates whether conditional cash transfers affect child labor differently depending on household productive structures. The findings offer a narrower answer: after testing the necessary assumptions instead of presuming them, PKH is not associated with a statistically distinguishable reduction in child labor. Under selection on observables, the effect is statistically significant but small—about one-tenth of the rate children would otherwise face. We also find no consistent evidence of heterogeneity across household head's employment sector or occupation type. The more discernible response is on schooling: PKH recipients receiving additional PIP are 4.1 percentage points more likely to attend school, though this is not definitively causal. Overall, the results imply that the challenge is not just the transfer amount; in contexts where children contribute to family production, cash may not offset the opportunity cost of pulling them from work. Conversely, education-focused aid

seems to promote schooling more directly. Therefore, to reduce child labor and boost school attendance, program integration may be more important than transfer size alone, making the combination of PKH and PIP a key consideration for practical evaluation.

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References

Adonteng-Kissi, O. (2023). Parental perceptions of the nature of child labour in rural and urban Ghana: Cultural versus economic necessity. *Child Care in Practice*, *29*(2), 118–138. https://doi.org/10.1080/13575279.2020.1868407

Attanasio, O., Fitzsimons, E., Gomez, A., Gutiérrez, M. I., Meghir, C., & Mesnard, A. (2010). Children's schooling and work in the presence of a conditional cash transfer program in rural Colombia. *Economic Development and Cultural Change*, *58*(2), 181–210. https://doi.org/10.1086/648188

Bandara, A., Dehejia, R., & Lavie-Rouse, S. (2015). The impact of income and non-income shocks on child labor: Evidence from a panel survey of Tanzania. *World Development*, *67*, 218–237. https://doi.org/10.1016/j.worlddev.2014.10.019

Basu, K., Das, S., & Dutta, B. (2010). Child labor and household wealth: Theory and empirical evidence of an inverted-U. *Journal of Development Economics*, *91*(1), 8–14. https://doi.org/10.1016/j.jdeveco.2009.01.006

Basu, K., & Van, P. H. (1998). The economics of child labor. *American Economic Review*, *88*(3), 412–427. https://www.jstor.org/stable/116842

Becker, G. S., & Lewis, H. G. (1973). On the interaction between the quantity and quality of children. *Journal of Political Economy*, *81*(2), S279–S288. https://doi.org/10.1086/260166

Beegle, K., Dehejia, R., & Gatti, R. (2009). Why should we care about child labor? The education, labor market, and health consequences of child labor. *Journal of Human Resources*, *44*(4), 871–889. https://doi.org/10.3368/jhr.44.4.871

Bhalotra, S. (2003). Child farm labor: The wealth paradox. *The World Bank Economic Review*, *17*(2), 197–227. https://doi.org/10.1093/wber/lhg017

BPS-Statistics Indonesia. (2023a). *Survei Sosial Ekonomi Nasional 2023 Maret (KOR)* [March 2023 National Socioeconomic Survey (Core)] [Data set]. SILASTIK. https://silastik.bps.go.id/v3/index.php/mikrodata/detail/ZnZSZms4aStzN2JUSVY1QklqZ08rdz09

BPS-Statistics Indonesia. (2023b). *Survei Sosial Ekonomi Nasional 2023 Maret (Modul Konsumsi dan Pengeluaran)* [March 2023 National Socioeconomic Survey (Consumption and Expenditure Module)] [Data set]. SILASTIK. https://silastik.bps.go.id/v3/index.php/mikrodata/detail/U1BGcE5sYzFvamI2SGw0YmVUYUlDZz09

BPS-Statistics Indonesia. (2024, April 30). *Indikator Pekerjaan Layak di Indonesia 2023* [Decent Work Indicators in Indonesia 2023]. https://www.bps.go.id/id/publication/2024/04/30/8fe6c4f34d5f1b9953903873/decent-work-indicators-in-indonesia-2023.html

Cahyadi, N., Hanna, R., Olken, B. A., Prima, R. A., Satriawan, E., & Syamsulhakim, E. (2020). Cumulative impacts of conditional cash transfer programs: Experimental evidence from Indonesia. *American Economic Journal: Economic Policy*, *12*(4), 88–110. https://doi.org/10.1257/pol.20190245

Cepaluni, G., Chewning, T. K., Driscoll, A., & Faganello, M. A. (2022). Conditional cash transfers and child labor. *World Development*, *152*, Article 105768. https://doi.org/10.1016/j.worlddev.2021.105768

de Hoop, J., & Rosati, F. C. (2014). Cash transfers and child labor. *The World Bank Research Observer*, *29*(2), 202–234. https://doi.org/10.1093/wbro/lku003

De Silva, I., & Sumarto, S. (2015). How do educational transfers affect child labour supply and expenditures? Evidence from Indonesia of impact and flypaper effects. *Oxford Development Studies*, *43*(4), 483–507. https://doi.org/10.1080/13600818.2015.1032232

Del Carpio, X. V., Loayza, N. V., & Wada, T. (2016). The impact of conditional cash transfers on the amount and type of child labor. *World Development*, *80*, 33–47. https://doi.org/10.1016/j.worlddev.2015.11.013

Edmonds, E. V., & Schady, N. (2012). Poverty alleviation and child labor. *American Economic Journal: Economic Policy*, *4*(4), 100–124. https://doi.org/10.1257/pol.4.4.100

Filippini, M., Greene, W. H., Kumar, N., & Martinez-Cruz, A. L. (2018). A note on the different interpretation of the correlation parameters in the bivariate probit and the recursive bivariate probit. *Economics Letters*, *167*, 104–107. https://doi.org/10.1016/j.econlet.2018.03.018

Fotoniata, E., & Moutos, T. (2013). Product quality, informality, and child labor. *Review of Development Economics*, *17*(2), 268–283. https://doi.org/10.1111/rode.12031

Gee, K. A. (2010). Reducing child labour through conditional cash transfers: Evidence from Nicaragua's *Red de Protección Social*. *Development Policy Review*, *28*(6), 711–732. https://doi.org/10.1111/j.1467-7679.2010.00506.x

Hartarto, R. B., & Wardani, D. T. K. (2023). Does conditional cash transfer change educational aspirations? Evidence from Indonesia. *International Journal of Social Economics*, *50*(1), 148–161. https://doi.org/10.1108/IJSE-11-2021-0671

Hartarto, R. B., Wardani, D. T. K., & Azizurrohman, M. (2021). A qualitative study of conditional cash transfer and education aspirations: Evidence from Yogyakarta. *Journal of Social Service Research*, *47*(6), 776–785. https://doi.org/10.1080/01488376.2021.1918314

Hidayatina, A. (2018). The effects of the cash transfer programme for poor students on child's work participation: Evidence from Java (Indonesia). *Journal of Indonesian Social Sciences and Humanities*, *8*(1), 41–58. https://doi.org/10.14203/jissh.v8i1.93

Hudang, A. K., Hariyanto, T., & Handoyo, R. D. (2024). Does conditional cash transfer deliver? The Indonesian evidence on PKH. *Business: Theory and Practice*, *25*(2), 447–457. https://doi.org/10.3846/btp.2024.13865

Islam, R., & Hoque, M. M. (2022). Trade-off between schooling and labor for children: Understanding the determinative factors among rural households in Bangladesh. *Frontiers in Sociology*, *7*, Article 839231. https://doi.org/10.3389/fsoc.2022.839231

Jayawardana, D., Baryshnikova, N. V., & Pham, N. T. A. (2021). Can unconditional in-kind transfers keep children out of work and in school? Evidence from Indonesia. *The B.E. Journal of Economic Analysis & Policy*, *21*(3), 1035–1065. https://doi.org/10.1515/bejeap-2020-0442

Khanam, R., & Ross, R. (2011). Is child work a deterrent to school attendance and school attainment? *International Journal of Social Economics*, *38*(8), 692–713. https://doi.org/10.1108/03068291111143901

Krauss, A. (2017). Understanding child labour beyond the standard economic assumption of monetary poverty. *Cambridge Journal of Economics*, *41*(2), 545–574. https://doi.org/10.1093/cje/bew019

Lee, K. W., & Hwang, M. (2016). Conditional cash transfer against child labor: Indonesia Program Keluarga Harapan. *Asia Pacific Education Review*, *17*(3), 391–401. https://doi.org/10.1007/s12564-016-9436-7

Parker, S. W., & Todd, P. E. (2017). Conditional cash transfers: The case of Progresa/Oportunidades. *Journal of Economic Literature*, *55*(3), 866–915. https://doi.org/10.1257/jel.20151233

Sandra, H., Majid, M. S. A., Dawood, T. C., & Hamid, A. (2020). What causes children to work in Indonesia? *The Journal of Asian Finance, Economics and Business*, *7*(11), 585–593. https://doi.org/10.13106/jafeb.2020.vol7.no11.585

Syamsulhakim, E., & Khadijah, N. (2021, December 23). *Graduating from a conditional cash transfer program in Indonesia: Results of a household survey of prosperous-independent graduates of the Family Hope Program (PKH) in 2020*. World Bank. https://doi.org/10.1596/36784

Utami, R. T., Hartarto, R. B., Tri Wibowo, W., & Iskandar, M. L. (2024). Ending child labour: Does conditional cash transfer matter? Evidence from Indonesia. *International Journal of Social Economics*, *51*(9), 1195–1208. https://doi.org/10.1108/IJSE-07-2023-0580

Wahyudi, S. T., Basofi, A., Susilo, S., & Badriyah, N. (2026). The differential impact of educational cash transfers on child labor and schooling: Insight from Indonesia. *Cogent Education*, *13*(1), Article 2698884. https://doi.org/10.1080/2331186X.2026.2698884

Wardani, A. N., Baryshnikova, N. V., & Jayawardana, D. (2022). Do secondary school children stay in school and out of the labour market in the presence of an educational cash transfer? *Education Economics*, *30*(6), 612–623. https://doi.org/10.1080/09645292.2022.2027874