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Impact of *Program Keluarga Harapan* on Child Labor During Covid-19

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Abstract

This research examines the impact of the *Program Keluarga Harapan* (PKH), a conditional cash transfer program, on child labor in Indonesia. The study focuses on the periods before and during the COVID-19 pandemic, using data from the National Socioeconomic Survey (Susenas) from March 2019 to 2021. The study specifically looks at children aged 10-17 from economically vulnerable families living in urban and rural areas. The research employs the Propensity Score Matching (PSM) technique to determine the impact of PKH on child labor participation as a response to economic shocks and school closures during the pandemic. The findings indicate that while PKH provides financial assistance to families, it has not significantly reduced child labor during the pandemic or before. Despite an increase in the amount of aid and changes to monthly distributions during the pandemic, the proportion of working children has increased, especially in urban areas, where child labour rates have significantly risen compared to rural areas. This research emphasizes the need for comprehensive policy strategies to reduce reliance on child labor as a coping strategy during crises.

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INTRODUCTION

Child labor has long been a global issue, profoundly affecting human capital development due to its negative impacts on children's health and education (Hamenoo et al., 2018; Schult & Strauss, 2008). Illnesses often afflict children, leading to frequent absences from school. Additionally, their academic performance typically lags behind that of peers who solely focus on their studies, as work commitments diminish their study time. These issues harm children's immediate well-being and future income potential (Fitz & League, 2021; Posso, 2017). Thus, child labor is a social problem with substantial economic implications for national growth and development.

The Covid-19 pandemic has exacerbated the prevalence of child labor due to increased economic vulnerability and poverty resulting from global lockdowns (ILO & UNICEF, 2022). School closures have endangered the most vulnerable children, increasing the likelihood that they will never return to education and possibly leading to further child labor or underage marriages (UNICEF, 2021). In 2020, the global number of child laborers reached 160 million, marking an increase of 8.4 million from four years earlier (ILO & UNICEF, 2022). Figure 1 shows that in Indonesia, the pandemic significantly escalated child labor, with figures rising from 920,000 in 2019 to 1.33 million in 2020. Though the numbers declined in 2021, they remained above pre-pandemic levels.

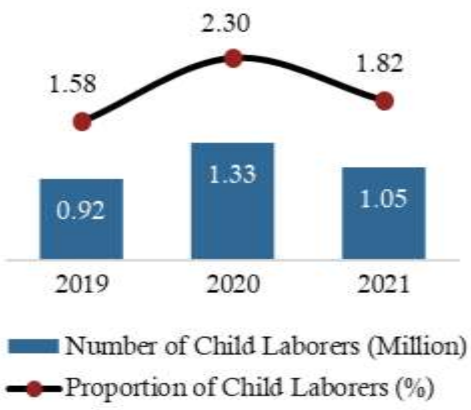

Figure 1. Child Labor in Indonesia
Source: BPS-Statistics Indonesia, 2022

The pandemic has presented policymakers with significant social and economic challenges, requiring decisions that balance health risks with economic impacts. While essential for controlling virus spread, mobility restrictions have induced severe economic shocks worldwide, affecting income and livelihoods (Aragie et al., 2021; Baldwin & Di Mauro, 2020). In response to these economic shocks, many low-income households face difficult decisions, such as prioritizing child labor over education for survival (Bandara et al., 2015; Malik et al., 2022). Impoverished parents often view children as economic assets, leading to child labor as a coping mechanism to mitigate economic downturns (Bandara et al., 2015; Grootaert & Kanbur, 1995; Ravallion & Wodon, 2000).

In response to these challenges, the Indonesian government has enhanced its ongoing conditional cash transfer (CCT) program, *Program Keluarga Harapan* (PKH), initially launched in 2007. This program aims to alleviate poverty and promote human capital development by offering financial assistance to underprivileged families, thus breaking the cycle of poverty across generations (Ministry of Social Affairs, 2022). Theoretically, the CCT program can reduce child labor either by substituting child wages (income effect) or by replacing the time children spend at work with time spent in school (substitution effect) (Cepaluni et al., 2022). During the pandemic, the government increased PKH benefits, raising the aid per component by 25% and transitioning from quarterly to monthly distributions (Ministry of Finance, 2021).

Despite their intended purpose, global studies on the impact of cash transfer (CCT) programs on child labor yield varied findings. De Hoop & Rosati (2014) analyzed 23 impact evaluations and found that CCT programs that reduce household vulnerability generally reduce child labor. Similarly, Dammert et al. (2018) reviewed five evaluations of CCT programs and concluded that these programs typically decrease the incidence of child labor and help mitigate the impacts of economic shocks that may compel children to work. Del Carpio et al. (2016) further confirmed that a CCT program in Nicaragua effectively reduced the number of child workers, especially in the agricultural sector.

Conversely, other studies lack sufficient evidence to assert that CCT programs can consistently reduce child labor, particularly in response to shocks. Cepaluni et al. (2022), Fitz & League (2021), and Pais et al. (2017) found that the *Bolsa Familia* in Brazil has not significantly reduced child labor. The program struggles to compensate for exogenous shocks, such as twin births (Cepaluni et al., 2022).. While *Bolsa Familia* can mitigate some of these effects, it does not adequately address the needs of boys and older children (Fitz & League, 2021). Similarly, research on the *Progresa* in Mexico indicated that it fails to prevent an increase in child labor as a response to economic downturns and health crises affecting the head of the household (De Janvry et al., 2006).

In the Indonesian context, evaluations of the PKH's impact on child labor also show varied results. Initial findings from a 2007 baseline survey by Sparrow et al. (2008) found no significant differences in child labor incidents between treatment and control groups. Two years later, Alatas et al. (2011) reported that PKH had not significantly reduced child labor. However, six years after implementation, Cahyadi et al. (2020) documented a 4.4% point reduction in the proportion of children engaged in paid work. According to Dammert et al. (2018), differences in the definition of child labor, the context of implementation, and policy instruments can lead to varied outcomes regarding child labor.

Given the diverse findings and the crucial role of CCTs during economic crises, this research aims to bridge critical gaps in the current understanding of how CCT programs, particularly Indonesia's PKH, impact child labor during the Covid-19 pandemic. By comparing pre-pandemic data in 2019 and pandemic data in 2021 across rural and urban contexts, this study assesses whether PKH is an effective safety net against child labor under crisis conditions. Focused on Indonesia's socioeconomic context, this study seeks to provide actionable insights to optimize CCT interventions. Examining the dynamics of economic agent behavior concerning this crisis can help better understand how government interventions can influence outcomes if similar crises occur (Baria, 2020).

The impact of CCT on child labor can be explained by the "unitary model" of household decision-making. This model posits that households aim to maximize utility across consumption, education, and leisure, considering all income sources and schooling costs (Dammert et al., 2018). Assuming household income, adult labor, and leisure are exogenous, an increase in adult household income raises the likelihood of school attendance and reduces child labor. Similarly, high returns on child labor (such as increased job opportunities and higher wages) decrease school and leisure time while increasing the labor supply (De Silva & Sumarto, 2015). In this context, PKH serves as supplementary income, potentially alleviating school costs and reducing child labor by relieving economic pressures on families (Edmonds & Schady, 2012; Hidayatina & Garces-Ozanne, 2019).

As a targeted poverty alleviation program, PKH is designed for households meeting specific eligibility criteria rather than selected randomly, which introduces potential selection bias issues. To mitigate this bias, Becker & Ichino (2002) recommend employing Propensity Score Matching (PSM), which compares outcomes between treatment and control groups that are similar across key characteristics. As Caliendo & Kopeinig (2008) suggested, matching is a practical approach to address this selection bias.

Therefore, this study adopts the PSM method. PSM constructs a statistical comparison group based on a probability model of program participation using observable characteristics (Khandker et al., 2010) and subsequently matches the propensity scores of treatment subjects with those in the control group. This approach ensures that the comparison between treatment and control groups meets the necessary assumptions for estimating the counterfactual (Gertler et al., 2016).

Previous studies using the PSM method, such as those by Fitz & League (2021) and Pais et al. (2017), have evaluated Brazil's conditional cash transfer program, *Bolsa Familia*. Employing a PSM model can resolve the issue of significant differences between the treatment and control samples, which could otherwise affect the results (Pais et al., 2017). The strengths of this approach lie in its ability to control for program selection and improve comparisons across households based on observable characteristics (Fitz & League, 2021). Their results indicate that Bolsa Familia has not been able to reduce the incidence of child labor. Shocks, such as high rainfall, increased the likelihood of paid child labor, and Bolsa Familia failed to curb the increase in child labor among boys and older children (Fitz & League, 2021).

RESEARCH METHODS

This study utilizes data from the National Socioeconomic Survey (Susenas) for March 2019 and 2021 to investigate child labor dynamics in Indonesia. The analysis includes rural and urban settings to explore the phenomenon of child labor across distinct regional categories due to differences in its prevalence, the significant variation in the proportion of PKH recipients, and potential differences in the effects of the Covid-19 pandemic. The urban component focuses on "Kelurahan," an administrative term in Indonesia for urban villages, the smallest government administration units within cities.

Table 1. Operational Variabel

Variable	Unit	Description
(1)	(2)	(3)
Child Labor	1= Child Labor 0= Not a child labor	A dummy variable, valued at one for children engaged in work and zero for those not engaged. Child labor includes children aged 10-12 years who worked during the previous week, children aged 13-14 years who worked over 14 hours in the past week, and children aged 15-17 years who worked over 40 hours in the past week.
PKH	1= Received PKH 0= Did not receive PKH	A dummy variable that records whether the child benefits from the Program Keluarga Harapan (PKH), assigned a value of one for recipients and zero for non-recipients.
Child Age	years	The age of the child in years.
Social Assistance PIP	1= Received PIP 0= Did not receive PIP	A dummy variable that records whether the child benefits from the Program Indonesia Pintar (PIP), assigned a value of one for recipients and zero for non-recipients.
Head of Household Education Level	1= Elementary school or below 0= Junior high school or above	A dummy variable, set to one for those with elementary education or less, and zero for junior high school or higher.
Head of Household Field of Business	1= Agriculture, Livestock and Fisheries 0= Other	A dummy variable with a value of one if the head of household works in the agriculture, livestock, or fisheries field of business, and zero for other sectors.
Head of Household Employment Status	1= Family worker/unpaid/not working 0= Working/ Having business	A dummy variable, valued at one for unemployed or unpaid family workers, and zero for employed or self-employed individuals.
House Ownership	1=Not owning a house 0=Owning a house	A dummy variable, set to one for non-owners (including renters and those in provided housing) and zero for owners.

Source: BPS-Statistics Indonesia, 2022 (Processed)

These urban villages are analogous to "Desa," or rural, found within districts known as "Kabupaten." Both cities and districts operate at equivalent governmental levels, differentiated by population size and economic activities.

The analysis focuses on children aged 10-17 years who are currently in school and unmarried. The age range complies with Law No. 13 of 2003 concerning Employment, with the lower limit set to align with Susenas data coverage. The study specifically targets children from poor households, defined as those with per capita spending below the poverty line, reflecting BPS-Statistics Indonesia's concept of poverty. This sample selection, inspired by the research of Pais et al. (2017), aims to include households experiencing similar levels of economic vulnerability as those benefiting from the PKH.

In this study, as detailed in Table 1, the dependent variable is child labor, defined according to the conceptual framework provided by ILO-UNICEF Indonesia under Law No. 13 of 2003 concerning Employment. The independent variable is participation in the PKH, which categorizes children into treatment and control groups for PSM analysis. The treatment group comprises PKH beneficiaries, while the control group includes similar children from non-beneficiary households. Several covariates are also utilized in developing the propensity score for the study, including the child's age, participation in Program Indonesia Pintar (PIP) aimed at ensuring equitable access to quality education across all educational levels (Caniago et al., 2021), educational attainment of the household head, field of business of the household head, household head's employment status, and ownership status of housing.

The Propensity Score Matching (PSM) method is employed for analysis and is particularly recommended for studies where randomization is impractical (Jalan & Ravallion, 2003). PSM estimates the likelihood of treatment based on control variables and matches subjects based on these propensity scores, helping to simulate a randomized experiment environment (Becker & Ichino, 2002; Gertler et al., 2016). Jalan & Ravallion (2003) and Gertler et al. (2016) outline the stages in the application of PSM as follows:

As depicted in Figure 2, PSM analysis involves several key steps: Determine control variables that influence the incidence of child labor and participation in the PKH. Second, estimating the propensity score, which is the probability of PKH participation. This score will match the treatment group with the control group. Third step is verifying common support to ensure that the distribution of propensity scores between the treatment and control groups has sufficient overlap, allowing for effective matching. Fourth step is conducting matching analysis by applying the nearest neighbour matching method to pair the treatment group with the control group based on the closest propensity scores. The last step is calculating the average treatment effect on the treated (ATT), which represents the impact of PKH on the incidence of child labor.

ATT explicitly focuses on the impact of the intervention on subjects who align with the program's intended target group (Caliendo & Kopeinig, 2008). In general, the ATT estimate is formulated as follows:

$$ATT = E(Y_i^T | S_i = 1, X_i = x) - E(Y_h^C | S_h = 0, X_h = x) \quad \ldots\ldots (1)$$

Where ATT stands for the average treatment effect on the treated. Y_i^T represents the average outcome of the treatment group for the i-th observation and Y_h^C indicates the average outcome of the control group for the h-th observation. $S_i = 1$ refers to the treatment group, and $S_h = 0$ signifies the control group.

The primary aim of applying the PSM method in this study is to mitigate selection bias. Selection bias occurs when the estimated impact of a study deviates from the actual impact due to how participants are selected. This bias is prevalent when the comparison group does not satisfy the required criteria (Gertler et al., 2016). The PKH program, a poverty alleviation initiative designed for poor households based on specific, non-random criteria, is particularly prone to selection bias. Matching is an effective strategy to counteract this issue (Caliendo & Kopeinig, 2008). PSM also reduces potential high-dimensional matching problems into a single-dimensional issue (Rosenbaum & Rubin, 1983), ensuring the treatment and control groups are as comparable as possible.

According to Khandker et al. (2010, the validity of PSM depends on two conditions. First, conditional independence, that is, factors that are not observed, do not affect participation. Second is large common support or overlapping propensity scores across the entire treatment and control sample. The advantages and disadvantages of PSM depend on the extent to which observed characteristics drive program participation.

This study hypothesizes that the *Program Keluarga Harapan* (PKH) influences child labor before and during the Covid-19 pandemic in rural and urban Indonesia, suggesting that children in PKH beneficiary households are less likely to work than non-recipient households. The ATT value provides a focused estimate of this impact (Caliendo & Kopeinig, 2008). However, using repeated cross-section data for ATT estimation can risk inconsistent results if the composition of treatment and control groups changes over time. Nonetheless, as Blundell and Costa Dias (2000) in Aerts & Schmidt (2008) noted, a clear trade-off exists between available information and the restrictions needed for a reliable estimator. If there are no significant policy changes between the studied years and the dataset is large, ATT estimation with repeated cross-section data remains variable.

RESULTS AND DISCUSSION

According to Figure 3, based on the geographic classification of the children's residence, the prevalence of child labor in rural areas consistently surpasses that in urban areas over two observed periods. During the Covid-19 pandemic, child labor in rural areas increased from 1.47% to 1.94%. Conversely, urban areas witnessed a more pronounced rise, with child labor escalating by almost 700% from 0.15% to 1.24%, reducing the disparity between rural and urban child labor rates.

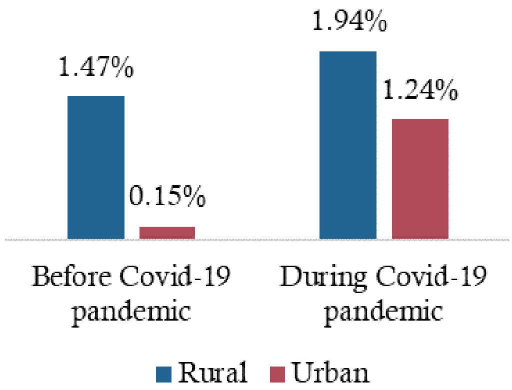

Figure 3. The Prevalence of Child Labor
Source: BPS-Statistics Indonesia, (2022)

In response to the pandemic, on March 31, 2020, the government enacted the Government Regulation in Lieu of Law (Perppu) Number 1 of 2020 and introduced Stimulus Package III. This policy included additional budget allocations for 2020 aimed at enhancing health services and social protection measures. Among these measures, the benefits under the PKH were increased by 25% per component, with distribution frequencies changing from quarterly to monthly (Ministry of Finance, 2021).

Before the pandemic, out of 16,926 analyzed units (covering both rural and urban settings), 39.21% (6,636 units) were beneficiaries of PKH. During the pandemic, the number increased to 8,351 out of 20,597 units, or 40.54%. Notably, PKH beneficiaries were predominantly from rural areas, making up 75% of recipients, about three times the proportion of urban beneficiaries at 25%. Tables 2 and 3 provide descriptive statistics of rural and urban variables, segmented by PKH participation status before and during the pandemic.

Child-related characteristics include age and participation in the PIP, head of household-related characteristics cover educational attainment, sector of employment, and job status, while household characteristics focus on home ownership. These variables are integral to the Proxy Mean Test of the Integrated Database (BDT) 2015 for identifying beneficiaries of poverty alleviation programs such as PKH (The National Team for the Acceleration of Poverty Reduction, 2015).

Table 2. Descriptive Statistics of Main Variables (Rural)

Variable	Before the Covid-19 Pandemic				During the Covid-19 Pandemic			
	PKH Recipient	Non-PKH Recipient	Total	p-value	PKH Recipient	Non-PKH Recipient	Total	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Child Age (*years*)	12.97	12.82	12.88	0.0002 ***	13.13	12.90	12.99	0.0000 ***
Social Assistance PIP *1= Received PIP* *0= Did not receive PIP*	0.5181	0.1768	0.3119	0.0000 ***	0.3977	0.1421	0.2485	0.0000 ***
Head of Household Education Level *1= Elementary school or below* *0= Junior high school or above*	0.7690	0.6439	0.6934	0.0000 ***	0.7423	0.6388	0.6818	0.0000 ***
Head of Household Field of Business *1= Agriculture, Livestock and Fisheries* *0= Other*	0.7227	0.6909	0.7035	0.0001 ***	0.7658	0.7349	0.7478	0.0000 ***
Head of Household Employment Status *1= Family worker/unpaid/not working* *0= Working/ Having business*	0.1394	0.1156	0.1250	0.0001 ***	0.1408	0.1120	0.1240	0.0000 ***
House Ownership *1=Not owning a house* *0=Owning a house*	0.0693	0.0809	0.0763	0.0157 **	0.0579	0.0804	0.0710	0.0000 **
Child Labor *1=Child labor* *0=Not a child labor*	0.0130	0.0159	0.0147	0.1868	0.0165	0.0214	0.0194	0.0295 **

Note: Total observations before the pandemic included 5,078 PKH recipients and 7,751 non recipients. During the pandemic, the figures were 6,251 recipients and 8,767 non-recipients. All reported values are averages. P_value was determined using an independent t-test. ***,** indicated statistical significance at 1% and 5%

Source: BPS-Statistics Indonesia, 2022 (Processed).

As indicated in Table 2, significant differences were observed in 2019, before the pandemic, across various characteristics between rural PKH recipients and non-recipients. Both groups' children averaged around 13 years of age. A higher proportion of children receiving PKH also benefited from the PIP (51.81%) compared to non-recipients (17.68%). Most household heads in both categories generally had only elementary education, with 76.90% PKH recipients and 64.39% non-recipients. The primary employment sectors were agriculture, livestock, and fisheries, involving 72.27% of PKH recipients and 69.09% of non-recipients. Employment types were mostly paid work or entrepreneurship, with 86.06% of recipients and 88.44% of non-recipients falling into these categories. House ownership was also high among both groups, with 93.07% of recipients and 91.91% of non-recipients owning their residences. The incidence of child labor was 1.30% among PKH recipients and 1.59% among non-recipients, with no statistically significant difference in the average number of child laborers between the two groups.

During the pandemic, there remained notable differences in the characteristics of children receiving PKH benefits in rural areas. The average age of PKH recipient children ranged between 13 and 14 years, while non-recipient children were typically between 12 and 13 years old. The% of PKH recipient children receiving PIP support was 39.77%, compared to just 14.21% among non-recipients. From the head of household perspective, the highest educational attainment was predominantly elementary school or equivalent, with 74.23% of recipients and 63.88% of non-recipients. Most household heads continued to work in the primary sectors of agriculture, livestock, and fisheries, with 76.58% of recipients and 73.49% of non-recipients employed in these fields. The employment status largely comprised paid workers or entrepreneurs, with 85.9% of recipients and 88.80% of non-recipients. Homeownership remained prevalent, with 94.21% of recipient households and 91.96% of non-recipient households owning their properties. During this period, 1.65% of PKH recipient children were engaged in child labor, compared to a significantly higher rate of 2.14% among non-recipients (see Table 2).

For urban children in 2019, as detailed in Table 3, PKH recipient and non-recipient children had an average age of around 13 years. A greater proportion of PKH recipient children also benefited from PIP assistance (58.15%) compared to non-recipients (15.64%). Most urban head of household PKH recipients had completed at most elementary education (65.15%), while the proportion for non-recipients was 48.96%. The business sectors significantly differed from rural areas, with only about 25% of urban head of household PKH recipients working in agriculture, livestock, and fisheries, compared to 20.80% of non-recipients. The predominant employment types were paid work or entrepreneurship, at approximately 74% for both groups. House ownership was lower than in rural areas, with 74.07% of PKH recipients and 73.22% of non-recipients owning their houses. The incidence of child labor among PKH recipient children during this pre-pandemic period was significantly lower than in rural areas, with 0.19% for PKH recipients and 0.12% for non-recipients. The average number of child laborers in both groups was not significantly different.

Table 3. Descriptive Statistics of Main Variables (Urban)

Variable	Before the Covid-19 Pandemic				During the Covid-19 Pandemic			
	PKH Recipient	Non-PKH Recipient	Total	p-value	PKH Recipient	Non-PKH Recipient	Total	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Child Age *(years)*	13.11	12.99	13.03	0.0882 *	13.24	12.94	13.06	0.0000 ***
Social Assistance PIP *1= Received PIP* *0= Did not receive PIP*	0.5815	0.1564	0.3180	0.0000 ***	0.4819	0.1337	0.2647	0.0000 ***
Head of Household Education Level *1= Elementary school or below* *0= Junior high school or above*	0.6515	0.4896	0.5511	0.0000 ***	0.5838	0.4067	0.4734	0.0000 ***
Head of Household Field of Business *1= Agriculture, Livestock and Fisheries* *0= Other*	0.2490	0.2080	0.2236	0.0022 ***	0.2595	0.1949	0.2192	0.0000 ***
Head of Household Employment Status *1= Family worker/unpaid/not working* *0= Working/ Having business*	0.2548	0.2529	0.2536	0.8888	0.2581	0.2325	0.2422	0.0309 **
House Ownership *1=Not owning a house* *0=Owning a house*	0.2593	0.2678	0.2646	0.5487	0.2586	0.3435	0.3115	0.0000 **
Child Labor *1=Child labor* *0=Not a child labor*	0.0019	0.0012	0.0015	0.5456	0.0152	0.0106	0.0124	0.1318

Note: Total observations before the pandemic was 1,558 PKH recipients and 2,539 non-recipients. During the pandemic, the figures changed to 2,100 PKH recipients and 3,479 non-recipients. All reported values are averages. P_value was determined using an independent t-test. ***,**,* indicated statistical significance at 1%, 5% and 10%.

Source: BPS-Statistics Indonesia, 2022 (Processed)

In 2021, the average age of PKH recipient and non-recipient children in urban areas remained around 13 years. PKH recipients who also received PIP support amounted to 48.19%, while for non-recipient children, only 13.37%. Most urban head of household PKH recipients had completed at most elementary education (58.38%), while the proportion for non-recipients was 40.67%. About 26% of household heads from the PKH recipient group worked in the agriculture, livestock, and fisheries sectors, while for the non-recipient group, the percentage was smaller, at 19.49%. The predominant employment types remained as paid workers or entrepreneurs, with percentages of 74.19% for PKH recipients and 76.75% for non-recipients. Homeownership was also high, with 74.14% of PKH recipients and 65.65% of non-recipients owning their homes. During the pandemic, the% of child laborers in urban areas increased sharply. The increase in the PKH recipient child group was almost 800%, to 1.52%.

Meanwhile, the increase was more than 900% in the non-recipient child group, to 1.06% (see Table 3). However, the average number of child laborers in both groups during this pandemic period was not statistically significantly different. The sharp increase in the percentage of child laborers in urban areas has reduced the gap between the percentages of child laborers in rural and urban areas.

The first step in analyzing the impact of PKH on the child labor phenomenon during the period before and during the Covid-19 pandemic using the PSM method is to calculate the estimated propensity score value. The propensity score is the probability of a subject entering the treatment group based on certain covariate characteristics (Becker & Ichino, 2002). Tables 4 and 5 show the estimated propensity score results for both categories of areas using logistic regression. The estimation results show that the probability of participation in PKH aligns with the program's targeting variables, as the Proxy Mean Test indicates. This is highlighted by the significant impact of these variables, most of which affect the likelihood of PKH participation.

Table 4. Propensity Score Estimation for PKH Participation in Rural Areas

Variable	Before the Covid-19 Pandemic			During the Covid-19 Pandemic		
	Coefficient	Standard Error	Odds Rasio	Coefficient	Standard Error	Odds Rasio
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Child Age (*years*)	0.05 ***	0.01	1.06	0.05 ***	0.01	1.06
Social Assistance PIP *1= Received PIP* *0= Did not receive PIP*	1.61 ***	0.04	4.99	1.39 ***	0.04	4.00
Head of Household Education Level *1= Elementary school or below* *0= Junior high school or above*	0.52 ***	0.04	1.68	0.43 ***	0.04	1.53
Head of Household Field of Business *1= Agriculture, Livestock and Fisheries* *0= Other*	0.13 ***	0.05	1.14	0.19 ***	0.04	1.21
Head of Household Employment Status *1= Family worker/unpaid/not working* *0= Working/ Having business*	0.16 **	0.06	1.17	0.26 ***	0.06	1.30
House Ownership *1=Not owning a house* *0=Owning a house*	-0.15 **	0.08	0.86	-0.33 ***	0.07	0.72

Note: ***,** indicated statistical significance at 1% and 5%
Source: BPS-Statistics Indonesia, 2022 (Processed)

As indicated in Table 4 for rural areas, both before and during the COVID-19 pandemic, factors such as age and child participation in PIP explain household participation in the PKH program. Moreover, household head characteristics such as education level, field of business, job status and ownership status of the building also significantly predict program participation, with all covariates showing consistent relationships across both periods.

Table 5. Propensity Score Estimation for PKH Participation in Urban Areas

Variable	Before the Covid-19 Pandemic			During the Covid-19 Pandemic		
	Coefficient	Standard Error	Odds Rasio	Coefficient	Standar Eror	Odds Rasio
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Child Age (*years*)	0.05 ***	0.02	1.05	0.07 ***	0.01	1.08
Social Assistance PIP *1= Received PIP* *0= Did not receive PIP*	1.99 ***	0.08	7.31	1.80 ***	0.07	6.04
Head of Household Education Level *1= Elementary school or below* *0= Junior high school or above*	0.53 ***	0.08	1.69	0.61 ***	0.06	1.84
Head of Household Field of Business *1= Agriculture, Livestock and Fisheries* *0= Other*	-0.03 *	0.09	0.97	0.21 ***	0.07	1.23
Head of Household Employment Status *1= Family worker/unpaid/not working* *0= Working/ Having business*	0.16	0.08	1.17	0.07	0.07	1.08
House Ownership *1=Not owning a house* *0=Owning a house*	0.11	0.08	1.12	-0.21 ***	0.07	0.81

Note: ***,* indicated statistical significance at 1% and 10%
Source: BPS-Statistics Indonesia, 2022 (Processed).

In urban areas, detailed in Table 5, age and child participation in PIP continue to predict household participation in the PKH program before and during the COVID-19 pandemic. The household head's education level and business type also significantly influence participation. Interestingly, while job status did not affect participation before the pandemic, it became a factor during the pandemic. Furthermore, building ownership emerged as a significant predictor during the pandemic period, contrasting its negligible impact before the pandemic.

After estimating the propensity score for each unit of analysis, the subsequent step involves evaluating the common support to determine if there is an overlap in the propensity score distributions between the treatment group (PKH recipient children) and the control group (non-PKH recipient children). This overlap is crucial for enabling the matching process. Insufficient common support compromises the efficacy of the PSM method, as it restricts the comparison of data between the two groups (Gertler et al., 2016). Figure 4 illustrates that the distributions of the treatment and control groups significantly overlap, demonstrating robust common support across all used covariates, thus allowing the matching analysis to proceed.

This study employs the nearest neighbor with ties matching technique. This approach yields the ATT, representing the mean difference in outcomes between the treatment and control groups within the common support region. This difference is interpreted as the effect of the PKH program on child labor. However, before interpreting the result of the matching analysis, it is crucial to confirm whether the balancing property assumption is satisfied. PSM analysis is effective when the treatment and control groups are balanced, implying that the groups have similar propensity scores based on similar covariate variables (Khandker et al., 2010).

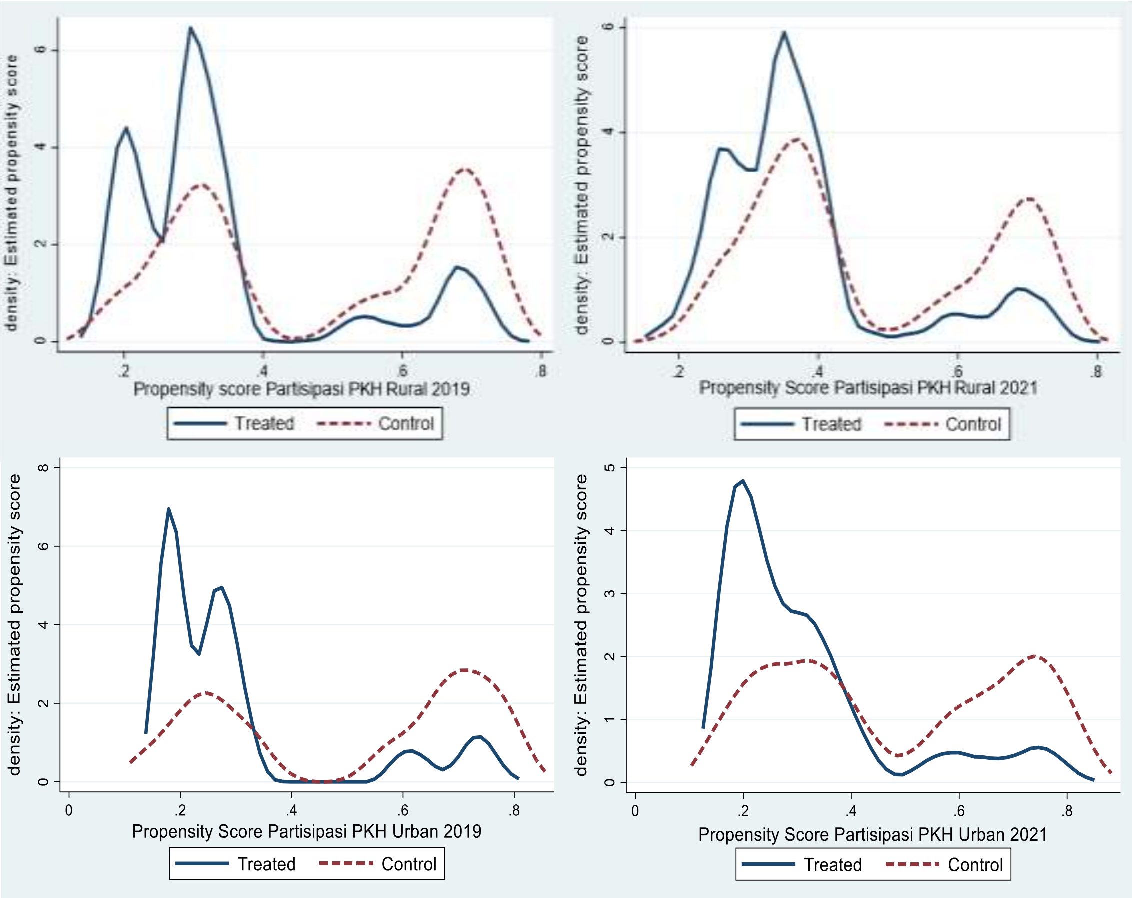

Figure 4. Propensity Score Distribution and Common Support Areas
Source: BPS-Statistics Indonesia, 2022 (Processed).

A common indicator used in many evaluation studies for the balancing test is the standardized bias (SB) before and after matching (Caliendo & Kopeinig, 2008). Table 6 indicates that prior to matching, there was a significant imbalance, as evidenced by large standardized biases in the covariate variables. However, after matching, there is a marked reduction in standardized bias, approaching zero in both periods analyzed. This indicates the elimination of significant differences in the average covariates between the two groups post-matching. The matching process has thus successfully maintained the balance of covariate variable distributions in the treatment and control groups throughout the pre-pandemic and during the COVID-19 pandemic periods. Consequently, the assumption of subject randomization in the study is fulfilled, allowing for the analysis of the cause-effect relationship (counterfactual) between the treatment and dependent variables (Becker & Ichino, 2002; Gertler et al., 2016).

Table 6. Balancing Test

Variable	Sample	Rural						Urban					
		Before the Covid-19 Pandemic			During the Covid-19 Pandemic			Before the Covid-19 Pandemic			During the Covid-19 Pandemic		
		%bias	t-test	p>|t|	%bias	t-test	p>|t|	%bias	t-test	p>|t|	%bias	t-test	p>|t|
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Child Age	Unmatched	6.8	3.79	0.000	10.5	6.32	0.000	5.5	1.71	0.088	13.3	4.84	0.000
	Matched	0.0	0.01	0.989	0.1	0.06	0.951	-1.4	-0.40	0.690	-0.4	-0.14	0.891
Social Assistance PIP	Unmatched	76.8	43.75	0.000	60.1	37.35	0.000	98.1	31.64	0.000	81.4	30.91	0.000
	Matched	0.0	0.00	1.000	0.0	0.00	1.000	0.0	0.00	1.000	0.0	0.00	1.000
Head of Household Education Level	Unmatched	27.7	15.16	0.000	22.5	13.51	0.000	33.1	10.24	0.000	36.0	13.03	0.000
	Matched	0.0	0.00	1.000	-0.2	-0.12	0.902	-0.1	-0.04	0.970	-0.2	-0.06	0.950
Head of Household Field of Business	Unmatched	7.0	3.86	0.000	7.1	4.30	0.000	9.8	3.07	0.002	15.5	5.67	0.000
	Matched	0.0	0.00	1.000	-0.1	-0.06	0.949	2.0	0.54	0.587	1.5	0.46	0.645
Head of Household Employment Status	Unmatched	7.1	3.99	0.000	8.7	5.28	0.000	0.4	0.14	0.889	5.9	2.16	0.031
	Matched	0.7	0.34	0.730	1.0	0.52	0.605	0.6	0.16	0.869	4.0	1.29	0.198
House Ownership	Unmatched	-4.4	-2.42	0.016	-8.9	-5.30	0.016	-1.9	-0.60	0.549	-18.6	-6.66	0.000
	Matched	1.0	0.51	0.608	0.6	0.35	0.729	1.0	0.29	0.774	1.4	0.46	0.646

Source: BPS-Statistics Indonesia, 2022 (Processed).

Table 7 illustrates the prevalence of child labor before and during the pandemic, showing that rural areas had higher rates compared to urban regions, a trend consistent with global patterns where rural areas typically exhibit approximately three times higher child labor rates than urban areas, as reported ILO and UNICEF (2021). However, during the pandemic, the rural-urban disparity in child labor diminished. The PSM analysis conducted across both rural and urban areas found insufficient evidence to suggest a significant impact of the PKH program on child labor, both pre-pandemic and during the Covid-19 crisis.

Table 7. Impact of PKH on Child Labor

Areas	Before the Covid-19 Pandemic					During the Covid-19 Pandemic				
	Treated	Control	ATT	S.E.	t-stat	Treated	Control	ATT	S.E.	t-stat
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Rural	1.30	1.40	-0.10	0.0026	-0.38	1.65	1.86	-0.21	0.0026	-0.82
Urban	0.19	0.09	0.10	0.0017	0.59	1.53	1.21	0.31	0.0041	0.77
Total	1.04	1.12	-0.08	0.0020	-0.40	1.62	1.65	-0.03	0.0022	-0.14

Source: BPS-Statistics Indonesia, 2022 (Processed).

In rural areas before the pandemic, the ATT value was -0.10, indicating that PKH-recipient children had a 0.1% point the lower likelihood of engaging in child labor compared to non-PKH-recipient children. However, this result lacked statistical significance, with the t-test value falling below the threshold of $t(0.05;\infty)=1.96$. Thus, it cannot be concluded that PKH participation significantly influenced child labor incidence before the pandemic. During the pandemic period, child labor rates increased in both the treatment and control groups, indicating that economic shocks prompted poor households to resort to child labor as a coping mechanism (Bandara et al., 2015). Despite the negative ATT value of -0.21 during this period, signifying a 0.21% point in the lower likelihood of child labor among PKH recipient children, statistical significance was not achieved. The negative ATT coefficients in both periods suggest that increased household income from PKH assistance may reduce the likelihood of children engaging in labor. However, the positive effect of PKH on child labor reduction was not statistically significant.

In urban areas, a contrasting trend emerged during the pandemic. Despite child labor rates surging in both the treatment and control groups, rising from 0.19% and 0.09% to 1.53% and 1.21%, respectively, children receiving PKH were unexpectedly more inclined to participate in child labor in both periods. However, it is important to note that this increase was not statistically significant. This deviation from the hypothesized direction of the relationship highlights the intricate nature of social protection's effectiveness in mitigating child labor, as emphasized by Dammert et al. (2018).

Households benefiting from PKH may invest the additional income in productive assets, particularly amid the pandemic when many families face reduced income and working hours. This creates opportunities for children to engage in productive household activities directly. Additionally, school closures implemented as part of virus containment measures have consequences for children. During these periods, the time allocated for schooling diminishes significantly while the time available for work increases. This aligns with findings from a study in Sierra Leone, West Africa, where school closures during the Ebola crisis corresponded directly with heightened child labor rates (Save the Children et al., 2015).

CONCLUSION

This research sheds light on the dynamics of child labor in Indonesia during the Covid-19 pandemic, particularly examining the role of the *Program Keluarga Harapan* (PKH), a conditional cash transfer program. This study contributes to the literature on the efficacy of social protection programs in crises, employing the Propensity Score Matching method. The findings highlight the persistence and complexity of child labor issues, emphasizing geographical disparities and the significant surge in child labor during the pandemic, especially in urban areas. Although the PKH program shows potential, its impact on reducing child labor is constrained, particularly during periods of severe economic shock.

The results emphasize the critical need for policymakers to acknowledge the multifaceted nature of child labor when designing interventions. Enhancing existing programs could involve greater flexibility to adapt to sudden economic shifts, such as modifying benefits and coverage. Rural-urban dynamics should be considered because urban children are more vulnerable during crises. Moreover, targeted support for educational engagement during emergencies is essential, particularly in regions facing challenges with remote learning due to infrastructure limitations. Additionally, there should be a consideration for implementing specific anti-child labor conditions, as the time children spend at school and work does not fully coincide. Therefore, mere school attendance requirements may not effectively reduce child labor.

This study's limitation lies in its focus on the post-implementation period of the PKH policy without analyzing initial or baseline conditions. This restricts the analysis to a specific timeframe. Additionally, the use of PSM depends heavily on the covariates selected, influencing the results based on the similarity between treatment and control groups using these covariates and only considering observable variables, not non-observable ones. Future research should include baseline conditions before policy implementation or employ longitudinal data to gain deeper insights into the impacts over time. Further exploration of suitable analytical methods is recommended to enhance understanding of PKH's effects on child labor.

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