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Quality of School Service Delivery, Human Capital, and Child Labor: Empirical Evidence from Indonesia

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ABSTRACT

The contribution of this research is analyzing the effect of the quality of primary and secondary school service delivery on child labor practices, taking Indonesia as a case study. It is a non-trivial issue for a country like Indonesia, which achieved significant economic progress, but still faced the topic of child labor. The research used data of approximately 55,000 children sampled in the 2018 Indonesian Labor Force Survey (Sakernas), and primary and secondary school accreditation data of Indonesia. Regarding a probit regression model, this paper found that better quality of school service delivery reduces the chance of child labor. Robust to alternate specifications, the findings of this study confirm the hypothesis that quality of school service delivery influences the decision of Indonesian households to send their children to work. It is also found that the education level of the household head decreases the chance of child labor. The implication of this result is, improvement in the quality of school service delivery can serve as an important tool to eliminate child labor. For policy, the government should direct more technical support, and resources to increase the quality of school service delivery, especially in rural and disadvantaged areas. In addition to fulfilling the UN Sustainable Development Goals (SDGs) target 8.7 on eliminating child labor, this policy is aligned with achieving SDGs target number 10; reducing inequality within a country.

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1. Introduction

The International Labor Organization (ILO) reports that 152 million children (9.6% of all children worldwide) work as child laborers globally (ILO, 2017). Among these, 72 million perform jobs that abuse them physically, sexually, or mentally or involve hazardous equipment, substances, processes, places, and hours (Dennis, 1999). Numerous studies indicated detrimental effects. Child labor impedes academic achievement and dropout rates (Tang et al., 2018), and its adverse effect on learning is worse than performing household chores (Zabaleta, 2011). Child labor affects children's health (Nelson and Quiton, 2018) and earnings during adulthood by inhibiting cognitive development (Chakraborty and Chakraborty, 2018; Hidayatina and Garces-Ozanne, 2019).

Terminating child labor by 2030 is goal 8.7 of 17 Sustainable Development Goals (SDGs) promulgated by the United Nations in 2015 (UNODC, 2020). Although the number of child workers globally has declined by 94 million since 2000, the pace of reduction has slowed by two-thirds since 2014 (ILO, 2019).

The world's largest number of child labor prevails in the Asia-Pacific (Suka Society, 2010). A member of the G20 since 2008, Indonesia is the world's fourth-most populous country, the third-largest Asia-Pacific nation by population, and the largest country in Southeast Asia (Central Intelligence Agency, 2020). According to ILO, however, in 2018, approximately 2.9 million Indonesian children were involved in child labor, which accounts for about 4% of the nation's children and a percentage mirrored throughout the Asia-Pacific (United Nations, 2019).

In 2017, Indonesia's government vowed to eliminate child labor by 2022 by boosting school enrollments. According to data from UNESCO, Indonesia's high school enrollment rate improved from 69.5% in 2011 to 80% in 2017, and enrollments in primary and lower-secondary school were 100% and 95%, respectively, in 2017. Indonesia's pupil-teacher ratio declined from 20 in 2004 to 16 in 2017. Nonetheless, educational outcomes remain unimpressive. The literacy rate of Indonesia is substantially lower than other Southeast Asian countries (Dilas, 2019). Furthermore, 55% of Indonesian children who completed schooling were functionally illiterate compared to 14% in Vietnam and 20% in the OECD (World Bank, 2018). The World Bank (2018) defines “functionally illiterate” as those who lack skills to enter the labor market (e.g., ability to read but inability to comprehend content of a text).

It seems unlikely for Indonesia to eradicate child labor by 2022 (Freedom United, 2018; US Department of Labor, 2018; Villadiego, 2018); it needs new strategies to expedite its elimination. One strategy has been to improve the quality of primary and secondary schools nationwide. Toward that end, Indonesia adopted accreditation standards in 2005 to demonstrate schools meet governmental standards (Maba, 2017; Pijano, 2010). Figure 1 illustrates that in 2018, 74% of Indonesia's schools were accredited A (excellent) or B (good); however, that percentage ranges from 93% in economically developed Java and Bali to 45% in rural Papua, West Papua, West Sulawesi, Southeast Sulawesi, and Central Kalimantan. Accreditation indicates school quality (Eaton, 2006), and it is uneven in Indonesia.

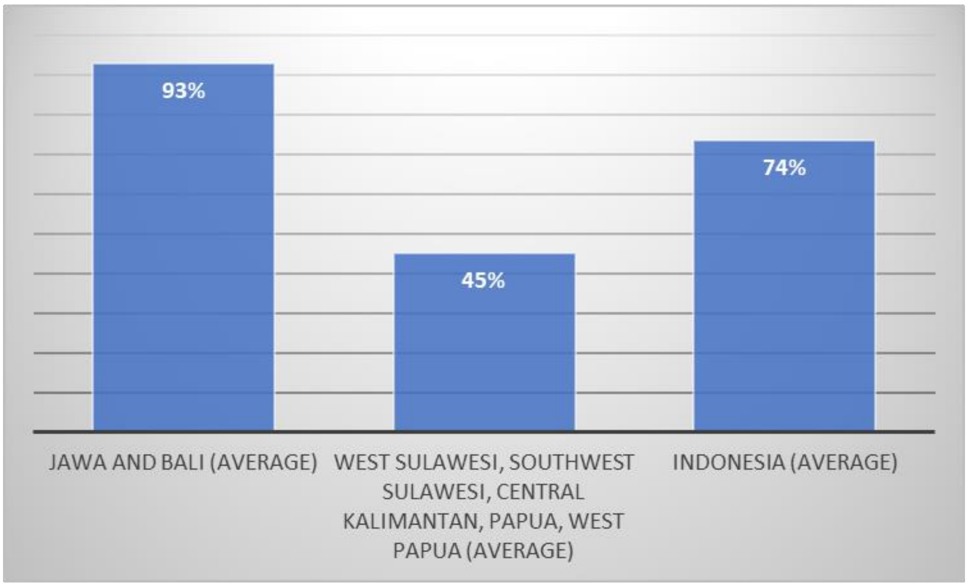

Figure 1. Percent of Schools with A ("excellent") and B ("good") Accreditation Grade in 2018
Source: Data source from BANSM (Table A1 in Appendix).

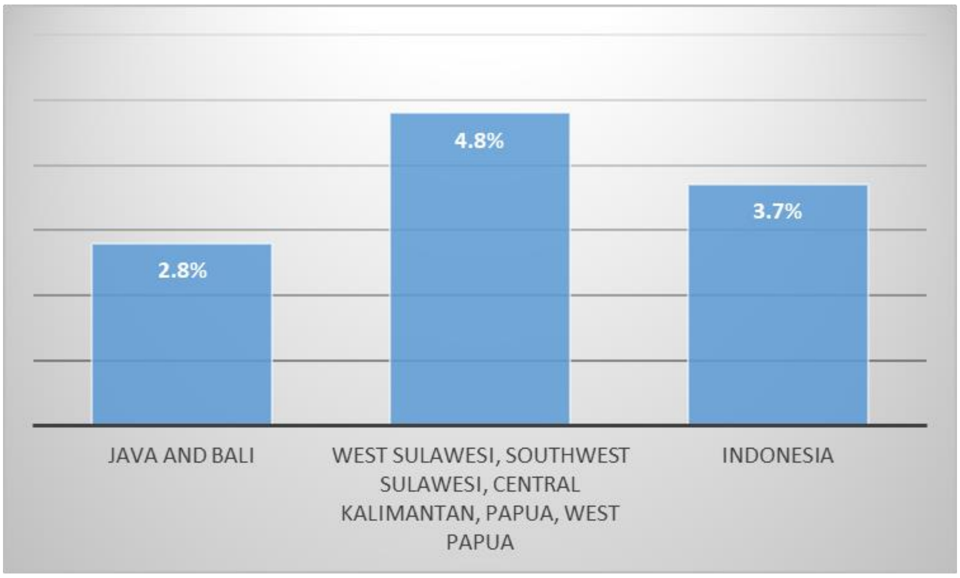

Figure 2. Percent of Child Labor Based on 2018 Sakernas Data
Source: Data Source BPS (Table A1 in Appendix).

Moreover, child labor is centered in provinces with lower percentages of A- and B-accredited schools, averaging 2.8% in Java and Bali versus 4.8% in Papua, West Papua, West Sulawesi, Southeast Sulawesi and Central Kalimantan (Figure 2).
Household heads primarily decide whether children will be put to work (Lima et al., 2015), and their personal characteristics often underpin that decision (Shafiq, 2007). Lower quality schools lead to lower returns from education (Purnastuti et al., 2015). Given that the quality of schools is questionable, the returns from schooling is low;

therefore parents (or heads of household) might prefer to send children to work for income instead of school (Ersado, 2005).

There exists no extant literature on the relationship between quality of school service delivery and child labor, particularly in Indonesia. The current study addresses this scholarly gap by empirically investigating the relationship of BANSM accreditation (a proxy for school quality) with child labor in Indonesia and expanding the analysis to include related demographic factors. The paper is structured as follows. Section 2 reviews the literature. Section 3 provides the empirical framework. Section 4 presents findings discussed in Section 5. Lastly, Section 6 concludes the study with recommendations.

2. Literature Review

Numerous studies show that the prevalence of child labor positively influences demographic characteristics, such as female heads of household (Chiwaula, 2010), the number of household members (Togunde and Richardson, 2006; Chong and Yanez-Pagans, 2019), agricultural employment (Fafchamps and Wahba, 2006; Kumar, 2013), and location in rural areas (Webbink et al., 2015; Chong and Yanez-Pagans, 2019). Characteristics, such as the education of the household head (Cummings, 2016), age (Ersado, 2005; Alcaraz et al., 2012), and biological relation to children in the household (Hedges et al., 2019) negatively related with child labor. While poverty was found to motivate participation in child labor (Abdullahi and Noor, 2017).

Furthermore, children's characteristics influence the likelihood of what UN SDGs label “enforced labor.” Boys are more likely to be child workers than girls (Webbink et al., 2015; Afriyie et al., 2019). Although Abou's (2014) findings are mixed, Alcaraz et al. (2012) found that older children are more vulnerable. Children enrolled in school are less prone to enforced labor (Zabaleta, 2011; Hidayatina and Garces-Ozanne, 2019; Quattri and Watkins, 2019; Can Tang et al., 2020; Lu, 2020).

Considering previous studies, we hypothesize that the quality of available schools’ influences strongly with the prevalence of child labor in Indonesia. This is done because household heads decide whether children work (Lima et al., 2015). They reason that lesser-quality schools deliver lower returns from education (Purnastuti et al., 2015) and send children to work instead of school (Ersado, 2005).

The foremost indicator of quality among Indonesia's primary and secondary schools is certification by the independent National Accreditation Agency (BANSM) (Maba, 2017), which determine the degree to which schools meet National Education Standards (SNP) (Amriani et al., 2018). BANSM assigns rankings of excellent (A), good (B), fair (C), and poor/unaccredited (TT) as an indicator of educational outcomes (Eaton, 2006), and schools must post their ratings to display to the public (Haryati, 2014). This study introduces BANSM accreditation as a new parameter in the literature. BANSM criteria, which is an important consideration for the statistical analysis, disregard a school's socio-economic surroundings (Maba, 2017). Therefore, ratings preclude reverse causality, which is the prevalence of child labor influences the accreditation assigned.

3. Method

The data were gathered for 55,000 children and their households from the August 2018 Indonesian National Labor Force Survey (Sakernas) by the Indonesian Statistics Agency (BPS). Sakernas collects data only for children aged 11-14. Because data exclude younger children, the results may understate the prevalence of child labor in Indonesia, which is defined per ILO convention 138 (ILO, 2020).

The BANSM accreditations were collected for 54,007 primary and secondary schools across Indonesia in 2018 and culled 510 districts for schools accredited A (excellent) or B (good).

The data were analyzed using a probit framework, which regresses binary dependent variables (Hidayatina and Garces-Ozanne, 2019; Dawood et al., 2019). The dependent variable—child labor (*Z*)—is a dummy variable coded 1 if the surveyed child does paid work and 0 otherwise.

Twelve regressors were employed for the analysis. This study's distinguishing parameter, *SAcc*, denotes the percentage of schools accredited A or B in a district. The other eleven variables in the study are consistent with previous empirical studies. *Rel* is a dummy variable coded 1 for household heads who are biological parents of the resident children and 0 otherwise. *OcHH* is a dummy coded 1 for household heads who work in agricultural sector and 0 otherwise. *Loc* is a dummy variable coded 1(0) for households in urban (rural) areas. *EduHH* is the number of years the household head attended school, and *AgeHH* is their age in years. *GenHH* is the gender of the household head (1 if male, 0 if female). *NHM* is the number of household members. *Gen* is a gender dummy coded 1 for male and 0 for female children. *Age* denotes children's ages. *Schpart* is a dummy coded 1 if the child attends school and 0 otherwise. In addition, *poverty* is the percentage of households living below the poverty line in surveyed districts. The model is as follows:

$$Z = \beta_0 + \beta_1 SAcc_i + \beta_2 Rel_i + \beta_3 OcHH_i + \beta_4 Loc_i + \beta_5 EduHH_i + \beta_6 AgeHH_i + \beta_7 GenHH_i + \beta_8 NHM_i + \beta_9 Gen_i + \beta_{10} Age_i + \beta_{11} Schpart_i + \beta_{12} Poverty_i + \varepsilon_i \quad (1)$$

The analysis performs several robustness checks of the results. Two variables denote measures of socio-economic welfare in each district as robustness checks: economic growth (*GRDP*), and human development index (*HDI*). The reason for employing economic growth for robustness check of the results is that it is a measure economic welfare. On the other hand, poverty is viewed as a measure economic deprivation

(Berthoud and Bryan, 2011). In economics literature, economic growth is not uncommon to be coupled with poverty (for example see Cruz and Ahmed, 2018), or even contested (Dauda, 2017). While the motivation for employing Human Development index (HDI) for robustness check of the estimation is that HDI is an alternative and comprehensive measure of welfare to growth (Seth and Villar, 2014). In the literature, HDI is not uncommon combined with poverty (Tran et al., 2017), and even with economic growth in analysis (Hasan, 2021). In addition, the regression is distinguished between rural and urban. Other than serving as additional robustness check, this differentiation provides further insight of the results. Finally, data of children age group 11 to 17 is regressed with the rural and urban regression, as additional robustness checks. The reason for employing this alternative age group is to test the results using instead the ILO Convention 182 which define the age group in performing child labor as 5 to 17 years old (ILO, 1999), while the Sakernas Survey collects data only for respondents starting from age 11 years old (BPS, 2019).

4. Results

In Table 1 column 2, the coefficient for school quality (*SAcc*) is negative and statistically significant; indicating that quality of school service delivery decreases the prevalence of child labor. This result confirms our hypothesis per Lima et al. (2015) that household heads are less inclined to send children to work if local schools are of higher quality.

In addition, the absolute value of *SAcc* in Table 1 column 2 is second only to school attendance (*Schpart*) as an indicator of child labor. This finding is consistent with that of Hidayatina and Garces-Ozanne (2019), Quattri and Watkins (2019), Can Tang et al. (2020), and Lu (2020).

This result is robust to several alternative specifications. The first alternative specification replaces *poverty* with economic growth (*GRDP*). In Table 1 column 5, *GRDP* positively and significantly influences child labor, a finding that accords with Kambhampati and Rajan (2006). In line with the baseline specification, school quality (*SAcc*) negatively and significantly influences child labor and is second statistically only to school participation (*Schpart*).

The second robustness check combines welfare variables *poverty* and *GRDP*. Table1 column 8 reveals that school quality (*SAcsc*) negatively and significantly influences child labor and ranks second statistically only to school participation (*Schpart*).

The third alternative specification (Table 1 column 11) indicates that *HDI* has no statistically significant relationship with child labor and that school quality (*SAcc*) negatively and significantly influences it. *SAcc* ranks second only to school participation (*Schpart*) in relation to child labor.

The fourth alternative specification combines socio-economic welfare variables *poverty, GRDP and HDI*. Table 1 column 14 reveals that school quality (*SAcsc*) negatively and significantly influences child labor and ranks second statistically only to school participation (*Schpart*).

Following Arabsheibani and Abang Ali (2016), squaring children's ages (*AgeSq*) as a robustness check preserved results of the currect study (Table 2 column 2). School quality (*SAcc*) retains a negative and significant relationship with child labor, second only to school participation (*Schpart*). These results hold under alternate specifications for *GRDP*, and *HDI* (Table 2 columns 5–14).

The fifth robustness check specification is splitting the sample between rural and urban. Table 3 reveals that school quality (*SAcsc*) negatively and significantly influences child labor and ranks second statistically only to school participation (*Schpart*) in both urban and rural areas. However, the magnitude of the absolute value of the coefficient for school quality (*SAcsc*) is 66 percent higher in urban than in rural areas (Table 3 columns 2 and 5). This signifies that the disincentive for child labor due to better school quality is lower in rural than in urban areas. The reason for the stark difference in the results is that the quality of schools in rural areas lower are than in urban areas to begin with. This is shown by a test of the means of school quality between rural an urban by regressing school quality (*SAcsc*) with dummy variable distinguishing rural and urban (*Loc*). The result of the test of the means is as follows.

$$SAcc_i = 0.692 + 0.125Loc_i \qquad (2)$$

prob (0.000) (0.000)

The test of the means shows that the coefficient of the difference in school quality between rural and urban (*Loc*) is positive and significant, implying that school quality are higher in urban than in rural areas. The result implies that improving school quality in rural areas is imperative in order to eliminate child labor.

The final robustness check is employing data of children aged 11 to 17 as per the ILO Convention 182. Table 3 columns 8 and 11 reveals that school quality (*SAcsc*) negatively and significantly influences child labor and ranks second statistically only to school participation (*Schpart*). It also shows that the magnitude of the absolute value of the coefficient for school quality (*SAcsc*) is higher in urban than in rural areas. Employing this alternative age group also improves the fit of the model as shown by the higher values for the McFadden R-squared.

Tables 1, 2, and 3 show a negative coefficient for the household head's biological relation to household children (*Rel*). A non-biological child is more likely to be a child worker than a biological child, as indicated in Serra (2009), Novella (2018), and Hedges et al. (2019).

Prevalence of child labor strongly influences agricultural households (*OcHH*) and households in rural areas (*Loc*) (Tables 1 and 2). The former result supports Kumar

(2013) and Tang et al. (2016) and the latter supports Tang et al. (2018) and Chong and Yanez-Pagans (2019).

Household heads education (*EduHH*) negatively and significantly influences child labor, a result that confirms Susanli et al. (2016) and Cummings (2016).

Table 1 suggests an inverse relationship between child labor and older household heads (*AgeHH*), consistent with the findings of Alcaraz et al. (2012) and Arabsheibani and Abang Ali, 2016). These results persist under robustness checks for all model specifications (Tables 1 to 3).

Table 1. Estimation Results and Robustness Checks

Variable	Coef	S.E.	prob	Coef	S.E.	prob	Coef	S.E.	prob	Coef	S.E.	prob	Coef	S.E.	prob
SAcc	-0.279	0.059	0.000	-0.307	0.052	0.000	-0.276	0.059	0.000	-0.346	0.062	0.000	-0.319	0.063	0.000
Rel	0.012	0.035	0.725	0.014	0.035	0.676	0.014	0.035	0.686	0.013	0.035	0.702	0.015	0.035	0.672
OcHH	0.069	0.024	0.004	0.072	0.024	0.002	0.070	0.024	0.003	0.072	0.024	0.002	0.072	0.024	0.002
Loc	-0.169	0.024	0.000	-0.175	0.024	0.000	-0.173	0.024	0.000	-0.176	0.025	0.000	-0.181	0.025	0.000
EduHH	-0.007	0.002	0.003	-0.007	0.002	0.002	-0.007	0.002	0.003	-0.007	0.002	0.002	-0.008	0.002	0.001
AgeHH	-0.003	0.001	0.004	-0.003	0.001	0.004	-0.003	0.001	0.004	-0.003	0.001	0.003	-0.004	0.001	0.003
GenHH	-0.191	0.033	0.000	-0.191	0.033	0.000	-0.190	0.033	0.000	-0.192	0.033	0.000	-0.189	0.033	0.000
NHM	0.018	0.006	0.003	0.018	0.006	0.003	0.018	0.006	0.004	0.018	0.006	0.003	0.017	0.006	0.007
Gen	-0.010	0.020	0.638	-0.010	0.020	0.616	-0.010	0.020	0.615	-0.010	0.020	0.637	-0.010	0.020	0.612
Age	-0.098	0.009	0.000	-0.098	0.009	0.000	-0.098	0.009	0.000	-0.098	0.009	0.000	-0.098	0.009	0.000
Schpart	-1.226	0.038	0.000	-1.224	0.038	0.000	-1.223	0.038	0.000	-1.230	0.038	0.000	-1.229	0.038	0.000
Poverty	0.001	0.002	0.377				0.002	0.002	0.289				0.004	0.002	0.047
GRDP				0.025	0.007	0.001	0.026	0.007	0.001				0.025	0.007	0.001
HDI										0.003	0.002	0.237	0.005	0.003	0.053
Constant	1.095	0.158	0.000	1.001	0.157	0.000	0.953	0.163	0.000	1.004	0.187	0.000	0.638	0.230	0.006
HL-Test:	14.98	prob	0.060	14.33	prob	0.074	11.16	prob	0.193	9.06	prob	0.337	8.839	8.839	0.356
AIC:			0.304			0.304			0.304			0.304			
Observations:			55772			55772			55772			55772			
McFadden R-squared			0.076			0.076			0.076			0.076			0.077
LR statistic			1384.9			1395.9			1397.1			1385.5			1400.8
Prob.			0.000			0.000			0.000			0.000			0.000

Source: Research finding.

Table 2. Estimation Results and Robustness Checks

Variable	**Coef**	**S.E.**	**prob**	**Coef**	**S.E.**	**prob**	**Coef**	**S.E.**	**prob**	**Coef**	**S.E.**	**prob**	**Coef**	**S.E.**	**prob**
SAcc	-0.278	0.059	0.000	-0.306	0.052	0.000	-0.275	0.059	0.000	-0.345	0.062	0.000	-0.318	0.063	0.000
Rel	0.012	0.035	0.725	0.014	0.035	0.677	0.014	0.035	0.686	0.013	0.035	0.703	0.015	0.035	0.672
OcHH	0.069	0.024	0.004	0.072	0.024	0.002	0.070	0.024	0.003	0.073	0.024	0.002	0.072	0.024	0.002
Loc	-0.169	0.024	0.000	-0.175	0.024	0.000	-0.173	0.024	0.000	-0.176	0.025	0.000	-0.180	0.025	0.000
EduHH	-0.007	0.002	0.004	-0.007	0.002	0.003	-0.007	0.002	0.003	-0.007	0.002	0.002	-0.008	0.002	0.001
AgeHH	-0.003	0.001	0.004	-0.003	0.001	0.004	-0.003	0.001	0.004	-0.003	0.001	0.003	-0.004	0.001	0.003
GenHH	-0.191	0.033	0.000	-0.192	0.033	0.000	-0.191	0.033	0.000	-0.192	0.033	0.000	-0.189	0.033	0.000
NHM	0.018	0.006	0.003	0.018	0.006	0.003	0.018	0.006	0.004	0.018	0.006	0.003	0.017	0.006	0.007
Gen	-0.009	0.020	0.650	-0.010	0.020	0.627	-0.010	0.020	0.626	-0.009	0.020	0.649	-0.010	0.020	0.623
Age	0.346	0.255	0.175	0.343	0.255	0.179	0.344	0.255	0.178	0.344	0.255	0.177	0.343	0.255	0.178
AgeSq	-0.018	0.010	0.081	-0.018	0.010	0.084	-0.018	0.010	0.083	-0.018	0.010	0.082	-0.018	0.010	0.084
Schpart	-1.229	0.038	0.000	-1.227	0.038	0.000	-1.226	0.038	0.000	-1.234	0.038	0.000	-1.232	0.039	0.000
Poverty	0.001	0.002	0.375				0.002	0.002	0.287				0.004	0.002	0.046
GRDP				0.025	0.007	0.001	0.026	0.007	0.001				0.025	0.007	0.001
HDI										0.002	0.002	0.240	0.005	0.003	0.053
Constant	-1.645	1.580	0.298	-1.721	1.580	0.276	-1.774	1.581	0.262	-1.726	1.583	0.276	-2.083	1.589	0.190
HL-Test:	14.844	prob	**0.062**	12.783	prob	**0.120**	11.995	prob	**0.151**	8.736	prob	**0.365**	8.226	prob	**0.412**
AIC:			0.304			0.304			0.304			0.304			0.304
Observations:			55772			55772			55772			55772			55772
McFadden R-squared			0.076			0.076			0.077			0.076			0.077
LR statistic			1387			1399			1400			1389			1389
Prob.			0.000			0.000			0.000			0.000			0.000

Source: Research finding.

Table 3. Estimation Results and Robustness Checks

Variable	Age 11 to 14 urban			Age 11 to 14 rural			Age 11 to 17 urban			Age 11 to 17 rural		
	Coef	**S.E.**	**prob**	**Coef**	**S.E.**	**prob**	**Coef**	**S.E.**	**prob**	**Coef**	**S.E.**	**prob**
SAcc	-0.469	0.120	0.000	-0.283	0.074	0.000	-0.389	0.097	0.000	-0.213	0.064	0.001
Rel	0.083	0.062	0.182	-0.011	0.042	0.672	-0.137	0.040	0.001	0.000	0.034	0.999
OcHH				0.072	0.027	0.002				0.018	0.023	0.420
Loc												
EduHH	-0.019	0.004	0.000	-0.003	0.003	0.001	-0.011	0.003	0.000	-0.006	0.003	0.011
AgeHH	-0.008	0.002	0.000	-0.002	0.001	0.003	-0.009	0.002	0.000	-0.003	0.001	0.007
GenHH	-0.121	0.058	0.038	-0.228	0.041	0.000	-0.070	0.043	0.108	-0.188	0.034	0.000
NHM	0.015	0.011	0.166	0.018	0.008	0.007	0.012	0.008	0.139	0.023	0.006	0.000
Gen	-0.087	0.036	0.016	0.026	0.025	0.612	0.002	0.028	0.934	0.120	0.022	0.000
Age	-0.089	0.016	0.000	-0.102	0.011	0.000	-0.086	0.008	0.000	-0.153	0.006	0.000
Schpart	-1.334	0.072	0.000	-1.208	0.046	0.000	-1.734	0.039	0.000	-1.467	0.030	0.000
Poverty	0.001	0.004	0.764	0.007	0.002	0.047	-0.001	0.003	0.715	0.003	0.002	0.089
GRDP	0.030	0.013	0.025	0.027	0.009	0.001	0.023	0.010	0.029	0.022	0.008	0.003
HDI	-0.007	0.004	0.105	0.013	0.003	0.053	-0.003	0.003	0.445	0.015	0.003	0.000
Constant	1.654	0.394	0.000	-0.016	0.292	0.006	1.741	0.280	0.000	0.688	0.232	0.003
HL-Test	7.19	prob	0.517	15.44	prob	0.051	25.74	Prob	0.001	62.51	Prob	0.000
AIC			0.223			0.363			0.208			0.304
Observations			23976			31796			42471			52435
McFadden R-squared			0.078			0.066			0.219			0.149
LR statistic			452.8			814.4			2469			2783
Prob.			0.000			0.000			0.000			0.000

Source: Research finding.

In Tables 1, 2, and 3, the coefficient for *GenHH* is negative, consistent with Chiwaula (2010) and Cummings (2016). Child labor influences more strongly with households headed by women.

The prevalence of child labor is higher in larger households (*NHM*). This finding accords with Nengroo and Bhat (2017) and Chong and Yanez-Pagans (2019). However, relationships for children's gender (*Gen*) is statistically significant for girls in urban areas but is significant for boys in rural areas. Both results withstand robustness checks in all model specifications (Tables 1, 2, and 3).

5. Discussion

Consistent with the research intention, the analysis found that the quality of primary and secondary schools influences lesser prevalence of child labor in Indonesia, a conclusion robust to alternative model specifications. Because households primarily determine whether children work (Lima et al., 2015), results imply that the chance of households sending their children to work reduce as the quality of improves.

One explanation for that conclusion is households believe quality schools portend increased returns from education. Purnastuti et al. (2015) found that lower school quality is related with lower returns from schooling. Furthermore, Carter et al., (2017) found that the returns from primary and secondary education influenced child labor. Indonesia mandates that schools post their accreditation publicly (Haryati, 2014). In light of information of higher returns from schooling, households substituted child labor for other activities, such as school. Studies show that better schools positively related to more schooling (Hanushek et al., 2008; Pop-Eleches and Urquiola, 2013) and more schooling influences less child labor (Zabaleta, 2011; Hidayatina and Garces-Ozanne, 2019; Quattri and Watkins, 2019; Can Tang et al., 2020; Lu, 2020).

The aforementioned result implies that improving the quality of primary and secondary schools reduces child labor. As a policy matter, Indonesia's central and district governments and all stakeholders should intensify efforts to improve the quality of primary and secondary schools nationwide, especially in rural and underprivileged areas. Such policies would accentuate efforts to eliminate child labor and achieve SDGs.

Although findings in the literature are mixed, we find that non-biological children are more likely to be child workers. Zabaleta's corroborating argument (2011) relates child labor to educational outcomes, and Sinha et al. (2016) found that educational outcomes of non-biological children are below those of biological offspring. Indonesian regulations concerning fostering and adoption need to minimize prospects of children being exploited and assure their access to quality education.

Confirming extant literature, the current study found that children in agricultural households are at greater risk of becoming child workers than children in nonagricultural households. Agriculture is the largest employer of child labor (Carter et al., 2017). Children in rural areas are more at risk than children in urban areas since agricultural households are rural. This is attributable to the lack of good quality educational facilities, which are further difficult to access in rural than urban areas (Werner et al., 2019). In addition, better transportation infrastructure in urban areas facilitates sending children to school rather than work (Webbink et al., 2015). Expanding non-farm livelihoods in rural areas promises a positive impact on schooling (Janssens et al., 2019) and consequently child labor, but with a caveat. Lakdawala (2018) found that expanding microcredit in rural areas stimulated rural entrepreneurship; however Bhuiya et al. (2019) demonstrated an increase in child labor to the detriment of schooling. Given these findings, rural development policies need to coordinate farm productivity, non-farm economic opportunities, and efforts to minimize child employment in rural areas.

Child labor is less evident when household heads are well educated or older. Alcaraz et al. (2012) attribute that to the higher earnings potential of education and lessened need to send children to work. Emerson and Souza (2003) argue that well-educated household heads understand the detriments of child labor and the benefits of education for children’s futures. Moreover, households with older heads might include more employable adults, reducing the need for children to work (Priyambada et al., 2005). Although the percentage of households headed by children in the Sakernas survey is small (0.28%), they are vulnerable to hardship and child labor (Gubwe et al., 2015). Therefore, Indonesia's government needs to assure the needs and schooling of child households, likely via public transfers.

Child labor is more prevalent in poor households, households headed by women, and large households. These findings relate to poverty in developing economies (Todaro and Smith, 2012), greater joblessness among women in rural and urban areas (Yao, 2017), and the burdens of larger families that adults cannot satisfy (Priyambada et al., 2005). To alleviate this problem, Indonesia's government needs targeted job-creation or entrepreneurship programs that minimize child labor as an offshoot. Additionally, it should provide public transfers to supplement incomes of these households.

6. Conclusion

Using Sakernas data and probit models, this study found that higher-quality schools (as proxied by accreditation rankings) positively and strongly related with lower prevalence of child labor among 55,000 children in 510 Indonesian school districts in 2018. Robust to several alternate model specifications, this result confirms our research hypothesis and implies that improving the quality of primary and secondary schools can diminish child labor. Moreover, improving school quality complements school participation in the effort to eliminate child labor. Indonesia's government should intensify efforts to increase the quality of primary and secondary schools nationwide, and prioritize schools in rural areas. In particular, it should direct more effort, technical support, and resources to improve school quality, especially among locals and demographic cohorts identified in the current analysis. These and related policies could accelerate the elimination of child labor and meet the UN's SDG target 8.7. They would further fulfill SDGs target number 10 to reduce intra-country inequality.

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Appendix

Table A1. Percentage of Schools with Accreditation Grade A or B and child labor in 2018 by Province

Province	Accreditation Grade				% of A and B Accreditation	Percent of Child Labor
	A	B	C	Poor		
DI Yogyakarta	1,441	603	30	5	98%	2.5%
Bali	1,099	845	45	2	98%	4.8%
DKI Jakarta	1,804	753	66	14	97%	1.7%
West Java	6,825	9,250	616	49	96%	2.7%
Central Java	7,654	10,424	977	41	95%	2.7%
Banten	1,167	2,586	810	96	81%	2.5%
East Java	6,223	15,014	3,244	197	86%	2.9%
Java and Bali (Average)					**93%**	**2.8%**
Bangka Belitung	309	392	63	23	89%	5.1%
West Sumatera	869	1,733	446	42	84%	3.5%
West Nusa Tenggara	756	1598	403	58	84%	6.1%
East Kalimantan	666	692	308	10	81%	2.8%
Gorontalo	278	589	154	56	81%	5.6%
North Sumatera	1,537	4,968	1,676	53	79%	5.9%
South Kalimantan	497	1,581	500	70	78%	3.3%
Aceh	583	1,593	581	95	76%	2.2%
South Sulawesi	234	1,137	454	11	75%	6.1%
North Sulawesi	355	970	410	50	74%	1.9%
Riau	846	984	476	165	74%	2.5%
South Sumatera	811	2,120	1,094	119	71%	2.5%
Lampung	368	2,412	1,133	95	69%	2.9%
Riau Islands	120	268	155	35	67%	2.1%
Central Sulawesi	317	1,237	657	137	66%	5.6%
Bengkulu	337	641	457	89	64%	2.9%
East Nusa Tenggara	164	874	515	65	64%	5.6%
West Kalimantan	320	952	615	131	63%	3.5%
North Maluku	217	843	569	67	63%	2.4%
Jambi	297	1,623	1,077	80	62%	3.5%
North Kalimantan	78	222	160	43	60%	3.0%
Maluku	191	639	457	106	60%	2.9%
Southeast Sulawesi	291	1,029	1,025	362	49%	6.3%
Central Kalimantan	188	627	732	161	48%	4.3%

West Papua	125	295	473	37	45%	3.1%
Papua	103	385	488	144	44%	4.8%
West Sulawesi	70	413	547	169	40%	5.5%
West Sulawesi, Southeast Sulawesi, Central Kalimantan, West Papua, Papua (average)					**45%**	**4.8%**
Indonesia (average)					**74%**	**3.7%**

Source: BANSM and BPS.