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Children's Resilience to Not Working Before and During the Pandemic in Rural Indonesia

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Abstract

Children are an asset to a country and a resource that will further national and international development goals. Children who work will be threatened by their health, safety, education, and development. In the last 10 years, BPS has recorded the percentage of child labor fluctuating with the latest record in 2021 at 2.63 percent. The high percentage makes the phenomenon of child labor still a global concern to be addressed as contained in the Sustainable Development Goals. Therefore, the purpose of this study is to determine the determinants of children's resilience not to work in rural areas during the observation period before and during the COVID-19 pandemic. This study uses a three-level survival analysis method by utilizing Sakernas data for August 2019-2020 and data from the BPS website. The results of this study obtained that the percentage of children aged 15-17 years who worked increased during the pandemic by 5.62 percent to 18.88 percent in rural areas. The variables of child gender, child education, child status at individual level; household head gender, household head occupation sector, and household poverty status at household level; and percentage of poor population at districts level significantly affect the resilience of children aged 15-17 not to work in the period before and during the COVID-19 pandemic.

Keywords: multilevel survival, child labor, rural areas, covid-19.

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1. Introduction

The issue of child labor has become one of the world's concerns. Children are the generation and resources that will continue national and international development goals, and their health, safety, education, and development are threatened if they are not properly cared for. Law No. 20/1999 on the ratification of International Labor Organization (ILO) Convention No. 138 Concerning Minimum Age for Admission to Employment discusses the elimination of child labor and the limitation of the minimum age for admission to employment. The Indonesian government itself regulates in Law No. 13 Article 68 of 2013 regarding the prohibition of child labor with a minimum age limit for children working in jobs that endanger the safety, or morals of children must not be less than 18 (eighteen) years old while for light work it must not be less than 16 (sixteen) years old. The phenomenon of child labor can cause physical deformation and long-term health problems to deprive children of their rights, especially in terms of education. In addition, the poverty of a country will continue to be maintained, workers' wages will become lower and lower their labor costs and make many investors use child labor because of their low production costs (International Labor Organization, 2004).

Efforts to solve the problem of child labor are also outlined in the Sustainable Development Goals (SDGs) target 8.7 to secure the prohibition and elimination of the worst forms of child labor, including the recruitment and use of child soldiers, and by 2025 end child labor in all its forms (Kementerian PPN/Bappenas, 2020). In the RPJMN 2020-2024, the Indonesian government mentioned in one of the development agendas to create quality and competitive human resources, namely healthy and intelligent, adaptive, innovative, skilled, and characterized human resources. To achieve this goal, human development policies are directed, among others, by improving the quality of children, women, and youth (Kementrian PPN/Bappenas, 2020). Improving the quality of children can be done in various ways, one of which is through improving education. Many child laborers tend to be exploited in their work and find it difficult to get decent work because they are not guaranteed to have 12 years of compulsory education (Pahlevi & Dokhi, 2021).

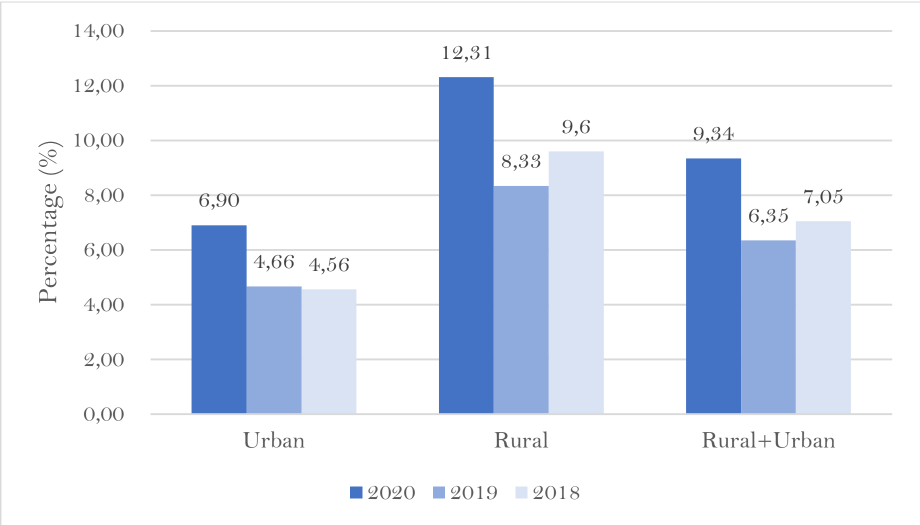


Figure 1. Percentage of Children 10-17 Years of Age Working by Type of Region 2018-2020
Source: (Kementerian Perempuan dan Pemberdayaan Anak, 2021)

Based on figure 2, the percentage of child labor still fluctuates from 2018 and there is a gap between regions of residence. The percentage of children aged 10-17 years who work is more in rural areas, reaching 12.31 percent, while in urban areas the percentage is only 6.90 percent (Kementerian Perempuan dan Pemberdayaan Anak, 2021). According to ILO & UNICEF (2021), rural areas have fewer educational facilities or adequate schools. As a result, the motivation for children to be motivated by school is low and parents see school activities as less important than work. There are several things that cause working children to dominate rural areas which are grouped into two factors, namely push factors and pull factors. The push factor is the low understanding of the rural community regarding the issue of child labor in terms of conceptual, rules, and also risks and the lack of public facilities provided for children so that children's free time in rural areas is mostly used to help parents' work. While the pull factors include the high demand for labor in rural areas due to the large number of companies operating in rural areas, there are quite a number of irregular jobs found in rural areas so that adults tend to work in cities and villages experience labor shortages. In addition, there is limited technology and innovation in rural jobs where many companies do not have semi-automatic or automatic tools, so everything is done manually. Therefore, when the need for workers is very high and the number of adults is limited, children will enter the labor market (Hermanus et al., 2019).

Several studies on child labor have been conducted previously such as by Sari & Wardana (2021) who found that the variables that have a significant effect on the status of exploitation of child labor at the individual level are gender, the sector of work of child laborers, and the sector of work of the head of the household. Meanwhile, poverty level and average years of schooling have a significant effect on the status of exploitation of child labor at the regional level. Then, in Sari & Krismanti (2022), it was found that at the individual level, the status of child labor is influenced by age, work sector, and working hours of children; at the household level, it is influenced by the gender of the household head, education of the household head, classification of residence, and welfare level; and at the regional level, it is influenced by district poverty. In terms of individual and household factors, the education level of the child and the head of household are significant to the child labor decision. In addition, poverty is a driving factor for child labor (Nugraha et al., 2022).

Child labor is not enough to analyze with regression by looking at the working status because it is also important to look at the time or age when the child first worked so that a survival analysis is used which will examine how the child's resilience does not start working. Working children are a social problem that is not only influenced by individual child factors but also by the different characteristics of an environment. These differences are related to contextual factors in each region at the district level and at lower levels such as households because these levels have a variety of characteristics from various aspects. In addition, fixed effects at the regional level can also control for unobservable factors that may cause biased results. Data that has a hierarchical structure cannot be analyzed only with the survival method but needs to use a method that is able to accommodate the hierarchical data with multilevel. Variables at the district level are used because lower levels have not been able to be obtained. This study will aim to identify the characteristics of working children and analyze the determinant variables of children's resilience to not working before and during the pandemic in Indonesia by focusing the analysis on rural areas using multilevel survival analysis using the district level and household level in 2019-2020.

2. Methodology

2.1. Theoretical Basis

Children are defined in many laws and regulations such as in Law of the Republic of Indonesia No. 39 of 1999 concerning Human Rights article 1 paragraph 5 defines "a child is every human being under the age of 18 (eighteen) years and not married, including children who are still in the womb if it is in their interest". The 1945 Constitution regulates human rights, including the rights of children as outlined in the Convention on the Rights of the Child as set out in Presidential Decree No 36 of 1990, namely: Right to Name and Citizenship, Right to Nationality, Right to Equality and Non-Discrimination, Right to Protection, Right to Education, Right to Play, Right to Recreation, Right to Food, Right to Health, dan Right to Participate in Development.

The Central Bureau of Statistics (BPS) differentiates the definition between working children and child labor. BPS distinguishes between working children and child laborers. Working children are children who do work for more than one hour during a seven-day period. The work can be paid or unpaid, for the market or not, permanent or part-time, and legal or illegal. Child labor, on the other hand, is a child who engages in work that is detrimental to their well-being and hinders their education, development, and future. The concept of child labor is differentiated through age groups and working hours, namely: 1) all working children aged 10-12 years regardless of their working hours, 2) children aged 13-14 years who work more than 15 hours per week, and 3) working children aged 15-17 years who work more than 40 hours per week. The concept of child labor categorized by working hours is used because there is still no special survey of child labor, so the concept of "child labor" still uses the approach of working hours in a week regardless of the conditions mentioned earlier (Kementerian Perempuan dan Pemberdayaan Anak, 2021).

Gender plays an important role in determining whether boys or girls are likely to be employed and the type of work they do (International Labor Organization, 2004). Then, in Magdalena et al. (2021) also explained that children's chances of working from households with male household heads are smaller than children whose households are headed by women. In human capital theory, people with higher education will also earn higher income (Borjas, 2013). Household head occupation sector is also a determining factor in the phenomenon of working children where children have a greater chance of becoming child laborers if they come from households where the head of the household does not work or works but in the informal sector (Ardana et al., 2016). Khausik Basu's theory states two important assumptions in the case of child labor. First, households with high enough income will not send their children to work. Second, substitution between child and adult workers where when all unskilled adults work there will continue to be a demand for labor so that many poor families will encourage their children to work (Todaro & Smith, 2015). The size of a household also affects where the economic burden in a household will increase when the number of household members increases (Pahlevi & Dokhi, 2021).

2.2. Data and Scope of Research

This study uses data sourced from the August 2019-2020 National Labor Force Survey (Sakernas) micro data and the Central Statistics Agency website (https://bps.go.id/). The locus of this research covers all regions of Indonesia by specializing in rural areas. Respondents in this study are children of the population aged 15-17 years who work in households in rural areas in 2019 and 2020. The eligible sample obtained was 69,711 samples after sample selection by excluding the head of the household, domestic helpers, drivers/gardeners, and people who were not related to the head of the household. The dependent variable in this study is the age at which the child first worked. A child who is already working at the time of enumeration will be declared as an event observer. Meanwhile, a child who is not working at the time of enumeration is declared as a censored observation.

The type of censoring used is type I right censoring, meaning that observations can enter the study at the same time during the observation period and the study period is fixed from the beginning. The explanatory variables, which are the variables that determine the response variable and whose values are determined freely in this study, include the sex of the child, the child's education, and the child's status at the individual level; the sex of the household head, the education of the household head, the employment sector of the household head, the household size, and the poverty status of the household as the household level, as well as the percentage of poor people, and the average years of schooling at the district level obtained from the BPS website. Other explanatory variables can be seen in Table 1.

Table 1. Operational definition of research variables

Notation	Variable Name	Categories
(1)	(2)	(3)
T	Child's Age at First Employment	Numeric (years)
Status	Observed Status	0: Not working (censored) 1: Working (event)
	Individual Level	
X_{111}	Child's Gender	0: Girls (ref) 1: Boys
X_{112}	Child Education	0: Not yet in or dropped out of school(ref) 1: School
X_{113}	Child Status	0: Other than children (ref) 1: Children
	Household Level	
Y_{11}	Sex of Household Head	0: Female (ref) 1: Male
Y_{12}	Household Head Education	0: Elementary school or below (ref) 1: Junior high School and above

Notation	Variable Name	Categories
Y_{13}	Household Head Occupation Sector	0: Others (ref) 1: Formal
Y_{14}	Household Size	0: > 4 people (ref) 1: ≤ 4 people
Y_{15}	Household Poverty Status	0: Poor (ref) 1: Not poor
District Level		
Z_1	Percentage of Poor Population (Po)	Numeric (percentage)
Z_2	Average Years of School	Numeric (years)

Description: (ref) reference category

2.3. Analysis Method

This study uses descriptive analysis and inferential analysis methods. Descriptive analysis is used to see how the general description of the phenomenon of children working in rural areas throughout Indonesia as well as the pattern of the relationship between individual variables, households and districts on the response variable presented in the form of tables, diagrams, and Kaplan-meier survival curves to see differences in the resilience of children aged 15-17 not to start working on each individual and household factor. Kaplan-Meier survival curve is one of the nonparametric methods used in estimating the survival function or hazard function. The Kaplan-meier estimator is also called the product limit estimator which utilizes the product limit formula to calculate the survival probability estimate. The Kaplan-Meier survival curve can only be used for descriptive analysis and cannot show the magnitude of the influence of the independent variable on the dependent variable. In addition, log-rank testing was also conducted to statistically prove differences in survival curves between categories of the factor by calculating the difference between the observed and expected variable categories.

Inferential analysis was used to identify variables that significantly influenced the resilience of children aged 15-17 not to start working in rural areas. The inference analysis used in this study is a three-level survival analysis with random intercept using the Accelerated Failure Time (AFT) model. When a response variable is in the form of time, one of the analysis methods that can be used to see the relationship between response variables and independent variables is survival analysis. Meanwhile, when the data used has a multilevel structure, multilevel analysis should be used.

The data in this study has a multilevel structure consisting of individual level, household level, and district level. In multilevel analysis, there are two models, namely the random intercept model and the random slope model. The random intercept model has a different intercept value in each sample unit/group, but the value of the slope is always the same in each sample unit/group. Meanwhile, the random slope model has a different slope value for each sample unit/group (Harlan, 2017). In this study, a random intercept model is used so that the effect of the independent variables on the response variable in each district is assumed to be the same. The following is a survival model with a three-level lognormal and log-logistic distribution with random intercept without interaction is as follows:

$$t = \left[\frac{1}{S(t)} - 1\right]^{1/p} \times \exp\,(\beta_{000} + \beta_{00r}Z_{rk} + \textstyle\sum_{q=1}^{Q} \beta_{0qk}Y_{qjk} + \sum_{p=1}^{P} \beta_{pjk}X_{pijk} + u_{0j} \; + v_{00k} + e_{ijk} \quad (1)$$

$$t = \exp\,(\sigma z) \times \exp\,(\beta_{000} + \beta_{00r}Z_{rk} + \textstyle\sum_{q=1}^{Q} \beta_{0qk}Y_{qjk} + \sum_{p=1}^{P} \beta_{pjk}X_{pijk} + u_{0jk} + v_{00} \; + e_{ijk} \quad (2)$$

Description:

t : acceleration factor function
$S(t)$: survival probability
β_{000} : fixed intercept
β_{p00} : fixed slope of the p-th explanatory variable at the individual level (level 1)
X_{pijk} : p-th explanatory variable of the i-th individual in the j-th household in the k-th district at level 1
β_{0q0} : fixed slope of the q-th explanatory variable at the household level (level 2)
Y_{qjk} : q-th explanatory variable on the j-th household in the k-th district at level 2
β_{00} : fixed slope of the r-th explanatory variable at the districts level (level 3)
Z_{rk} : r-th explanatory variable in the k-th district at level 3
u_{0jk} : random effect of the j-th household in the k-th district
v_{00} : random effect of the k-th district
e_{ijk} : residuals of the i-th individual in the j-th household in the k-th district

The stages of three-level survival analysis carried out in this study are as follows (Hox, 2018):

a. Selection of parametric distribution by AIC null model

Parametric distribution selection is done by comparing the Akaike's Information Criterion (AIC) values of the exponential, weibull, log-logistic, and lognormal distributions in the null model (model without independent variables). The AIC statistic is calculated as: -2 log likelihood + 2p (where p is the number of parameters in the model) (Kleinbaum & Klein, 2012). The distribution with the smallest AIC value is selected as a suitable distribution to continue the analysis. Then, the selection of independent variables using the best distribution is carried out by forming all possible combinations of models of the independent variables used. Furthermore, from all possible models, it is selected again based on the AIC value .

b. Random effect significance testing

Random effect significance testing is done by testing the likelihood ratio test. This test aims to determine whether the model with random effect is better than the model without random effect with the following hypothesis.

$H_0 : \sigma_{\mu 0}^2 = 0$ (random effect is not significant)
$H_a : \sigma_{\mu 0}^2 > 0$ (random effect is significant)
The test statistics used are as follows.

$$LR = -2ln\left(\frac{likelihood\ model\ survival\ \text{tanpa}\ random\ effect}{likelihood\ model\ survival\ \text{dengan}\ random\ effect}\right) \sim \chi^2_{(1)} \quad (3)$$

Using α = 0.05, if LR > χ2 or p - $value$ < 0.05 then Ho will be rejected and the conclusion obtained is that at the 5 percent significance level, there is enough evidence that the random effect is significant so that the two-level survival model is better used than the one-level survival model.

c. Simultaneous parameter significance testing
Simultaneous parameter testing aims to determine whether the independent variables jointly affect the length of time (age) of children aged 15-17 years to first work with the following research hypothesis.

$H_0 : \beta_{\text{p}0} = \cdots = \beta_{0q0} = \cdots = \beta_{00\text{r}} = 0$ (No independent variable has a significant effect on the dependent variable)

H_0 : At least one $\beta_{pqr} \neq 0$ (At least one independent variable that has a significant effect on the dependent variable)

The test statistics used are as follows.

$$G = -2ln\left(\frac{L_0}{L_1}\right) \sim \chi^2_{(v)} \quad (4)$$

where L_0 is the null model likelihood and L_1 is the conditional model likelihood.

By using α = 0.05, the decision will be to reject H_0 if the value of the test statistic $G > \chi^2_{0,05(v)}$ or p-value <0.05 where v is the number of $p + q + r$. When H_0 is rejected, the conclusion that can be drawn is that there is sufficient evidence that there is at least one independent variable that significantly affects survival time at the 5 percent significance level.

d. Partial parameter significance testing
Partial parameter testing aims to determine whether the independent variables partially affect the length of time (age) of children aged 15-17 years to first work. Partial parameter significance testing uses the Wald test (Hox, 2018) with the following research hypothesis.

Level 1:
$H_0 : \beta_{p00} = 0$ (the p-th level 1 independent variable does not significantly affect the dependent variable)
$H_a : \beta_{p00} \neq 0$ (the p-th level 1 independent variable does significantly affect the dependent variable)
Level 2:
$H_0 : \beta_{0q0} = 0$ (the q-th level 2 independent variable does not significantly affect the dependent variable)

H_a : $\beta_{0q0} \neq 0$ (the q-th level 2 independent variable does significantly affect the dependent variable)

Level 3:

H_0 : $\beta_{00r} = 0$ (the r-th level 3 independent variable does not significantly affect the dependent variable)

H_a : $\beta_{00r} \neq 0$ (the r-th level 3 independent variable does significantly affect the dependent variable)

The test statistics used are as follows.

Level 1:

$$W = \frac{\widehat{\beta_{p00}}}{\widehat{se}(\widehat{\beta_{p00}})} \sim N(0,1) \tag{5}$$

Level 2:

$$W = \frac{\widehat{\beta_{0q0}}}{\widehat{se}(\widehat{\beta_{0q0}})} \sim N(0,1) \tag{6}$$

Level 3:

$$W = \frac{\widehat{\beta_{00r}}}{\widehat{se}(\widehat{\beta_{00r}})} \sim N(0,1) \tag{7}$$

where:

$\widehat{\beta_{p00}}$: the p-th level 1 parameter estimation

$\widehat{se}(\widehat{\beta_{p00}})$: estimated standard error for β_{p00}

$\widehat{\beta_{0q0}}$: the q-th level 2 parameter estimation

$\widehat{se}(\widehat{\beta_{0q0}})$: estimated standard error for β_{0q0}

$\widehat{\beta_{00r}}$: the r-th level 3 parameter estimation

$\widehat{se}(\widehat{\beta_{00r}})$: estimated standard error for β_{00r}.

At α=0.05, the decision is to reject H_0 if the test statistic $W > Z_{\frac{0.05}{2}}$ or p-value <0.05. When H_0 is rejected, the conclusion that can be drawn is that there is sufficient evidence that the independent variable significantly affects survival time at the 5 percent significance level.

e. Calculation of the intraclass correlation coefficient (ICC) value

The ICC value is used to see the magnitude of variation in the age of children aged 15-17 years to first work between districts/cities in rural areas throughout Indonesia. The ICC value can be calculated with the following equation (Hox, 2018)

$$\hat{\rho} = \frac{\sigma_{\mu 0}^2}{\sigma_{\mu 0}^2 + \sigma_e^2} \tag{8}$$

Description:

σ_e^2 : variance at the lower level $\left(\frac{\pi^2}{3} = 3.29\right)$

$\sigma_{\mu 0}^2$: variance at higher level

Sorra & Dyer (2010) stated that ICC above 0.05 or five percent is able to show the variation between groups so that multilevel analysis is needed. The value of $\sigma^2_{\mu 0}$ is obtained from $\widehat{var}(\mu_{0j})$ which shows random effects between groups.

3. Results and Discussions

Based on the results of data processing, it was found that 13.26 percent of children aged 15-17 years worked before the COVID-19 pandemic in rural areas and during the pandemic the percentage of working children increased by 5.62 percent to 18.88 percent. Meanwhile, the average working age of children aged 15-17 years before and during the COVID-19 pandemic in rural areas was 14 years and 13 years, respectively.

Table 2. Percentage of children aged 15-17 working by individual and household factors

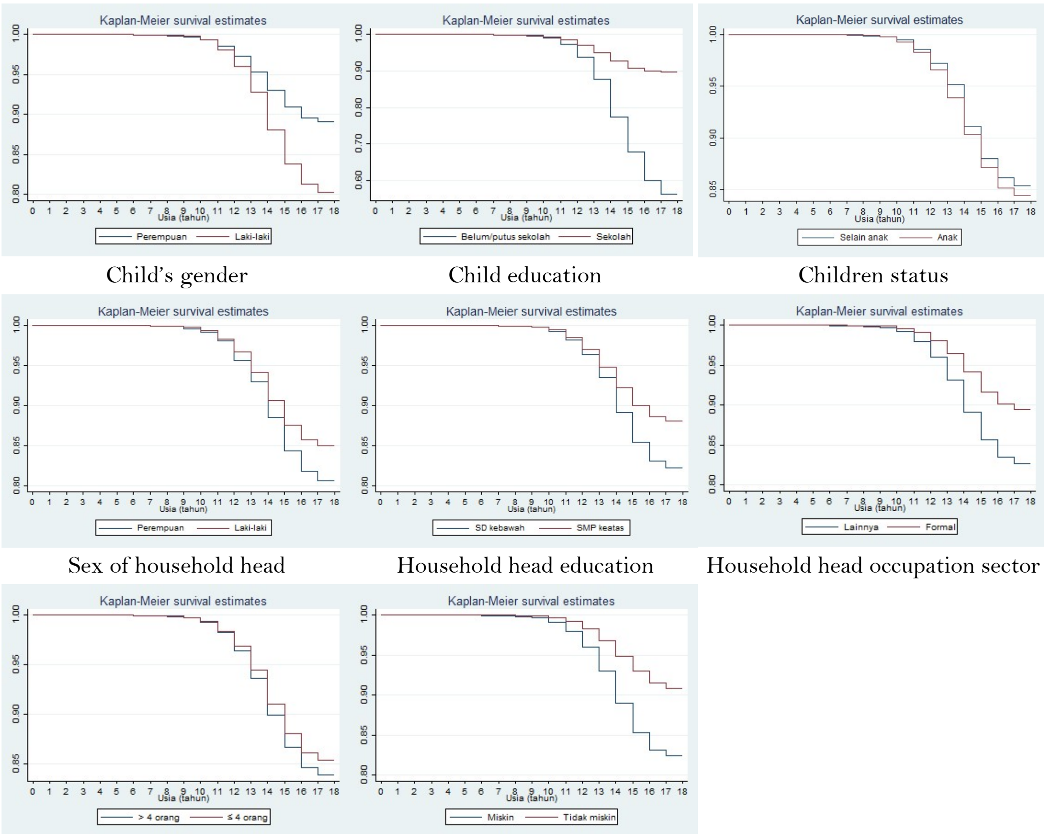
Variable Name	Category	Percentage (%)	
		Pre-Pandemic	Pandemic
(1)	(2)	(3)	(4)
Child's Gender	0: Girls (ref)	33,91	39,27
	1: Boys	66,09	60,73
Child Education	0: Not yet in or dropped out of school (ref)	46,87	30,70
	1: School	53,13	69,30
Child Status	0: Other than children (ref)	9,49	8,44
	1: Children	90,51	91,56
Sex of Household Head	0: Female (ref)	12,93	13,64
	1: Male	87,07	86,36
Household Head Education	0: Elementary school or below (ref)	70,76	63,01
	1: Junior High School and above	29,24	36,99
Household Head Occupation Sector	0: Others (ref)	80,84	82,77
	1: Formal	19,16	17,23
Household Size	0: > 4 people (ref)	49,01	47,37
	1: ≤ 4 people	50,99	52,63
Household Poverty Status	0: Poor (ref)	82,29	85,15
	1: Not poor	17,71	14,85

Table 2. Percentage of children aged 15-17 working by individual and household factors (cont)

Source: Sakernas Agustus 2019-2020 (processed)

Table 2 shows that children aged 15-17 years are predominantly boys, are currently attending school and have the status of as a child in their household. From household characteristics, children aged 15-17 years mostly come from male-headed households, have at most elementary school education, work outside the formal sector, from small families from households with at most 4 members and belong to poor households. This statement applies to the two data periods before and during the COVID-19 pandemic.

The Kaplan-Meier survival curves in Figure 3 show the estimated survival time curves for age at first employment for each individual level variable. The curve of a category that is at the bottom indicates that the category is faster to become a working child than the comparison category. Based on Figure 3, it is known that the category of children aged 15-17 years who are prone to enter the labor market sooner is in the category of boys, neither out of school nor dropping out of school, female head of household, head of household education less than senior high school, working in the informal sector, belonging to a large family (ART > 4 people) or belonging to a poor household. Meanwhile, the Kaplan-Meier curves on the child status variable are quite close, meaning that there is no difference in the duration of job search on this variable. These results are in line with the results of the log-rank test conducted on each independent variable.



Child's gender | Child education | Children status

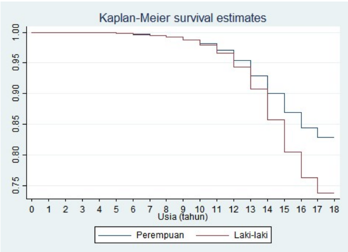
Sex of household head | Household head education | Household head occupation sector

Household size | Household poverty status

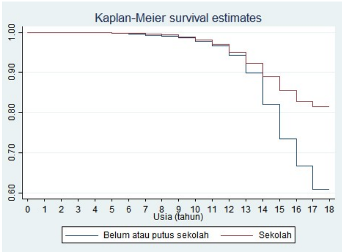
Figure 2. Kaplan-meier survival curve based on individual level variables at pre-pandemic period

Source: Sakernas Agustus 2019 (processed)

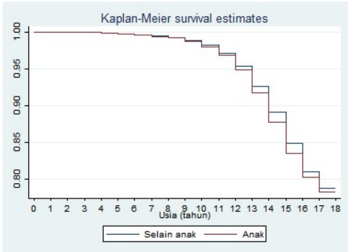
The Kaplan-Meier survival curve in Figure 4 also shows the estimated survival time curve of children's age at first employment based on each individual level variable in the period during the pandemic. Based on Figure 4, it is known that the category of children aged 15-17 years who are prone to entering the labor market earlier is in the category of boys, neither out of school nor dropping out of school, female head of household, head of household education less than high school, working in the informal sector, belonging to a large family (ART > 4 people) or belonging to a poor household. Meanwhile, the Kaplan-Meier curves on the child status variable are quite close, meaning that there is no difference in the duration of job search on this variable. These results are in line with the results of log-rank testing conducted on each independent variable and the results in the analysis of the period before the COVID-19 pandemic.



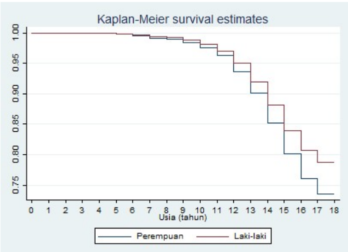
Child’s gender



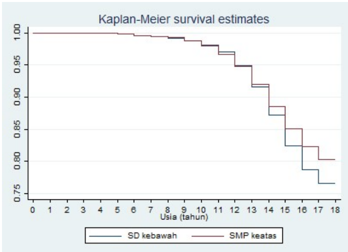
Child education



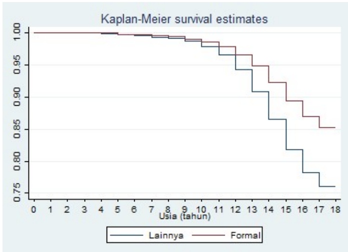
Children status



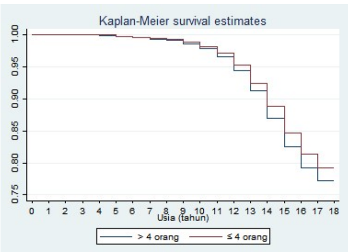
Sex of household head



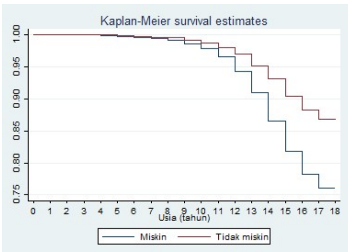
Household head education



Household head occupation sector



Household size



Household poverty status

Figure 3. Kaplan-meier survival curve based on individual level variables at pre-pandemic period

Source: Sakernas Agustus 2020 (processed)

Based on the modeling results on the null model, the lognormal distribution has the smallest AIC value on the data for the period before the COVID-19 pandemic and the log-logistic distribution has the smallest AIC value on the data for the period during the COVID-19 pandemic.

Therefore, these two distributions were chosen to explain the age resilience of children not to start working.

Table 3. AIC value based on parametric distribution

Distribution	AIC	
	Pre-pandemic	Pandemic
(1)	(2)	(3)
Exponential	59.525,73	82.678,31
Weibull	206.320,4	245.900,6
Lognormal	51.298,05	71.260,75
Log-logistik	51.449,47	71.168,64

Source: Sakernas Agustus 2019-2020 (processed)

Followed by this test is used to determine whether the multilevel model is better applied in forming the model. The statistical value of the Likelihood Ratio test (LR) on the data for the period before and during the COVID-19 pandemic is 1574.23 and 2010.63, respectively, with the resulting p-value both being <0.0001. The resulting decision is to reject Ho so that it can be concluded that with a significance level of 5 percent it can be concluded that the random effect is significant so that the three-level survival model is better than the one-level survival model for modeling the age survival of children not to start working.

By using the simultaneous test, the significance of the independent variables together will be known. The following is the G test statistic obtained by calculating the G statistic with a value of 3197.504 which is greater than the value of $\chi^2 = 18.307$ so that the resulting decision is to reject Ho. With a significance level of 5 percent, it can be concluded that there is at least one explanatory variable that affects the age at first employment of children 15-17 years old in the pre-pandemic period. Meanwhile, in the period during the pandemic, the G test statistic of 4079.642 is greater than the value of $\chi^2 = 18.307$ so that the resulting decision is to reject H_o. With a significance level of 5 percent, it can be concluded that there is at least one explanatory variable that affects the age of first employment of children 15-17 years old. In the partial test, variables are said to have a significant effect if the value of the W test statistic is greater than the value of $Z = 1.96$ or the resulting p-value is less than $\alpha = 0.05$. The test results are available in Table 7 and it can be seen that with a significance level of 5 percent, the variables of child gender, child education, child status, gender of household head, employment sector of household head, household poverty status, and percentage of poor people significantly affect the resilience of children aged 15-17 not to work in the period before and during the COVID-19 pandemic (see Table 4).

Table 4. Percentage of children aged 15-17 working by individual and household factors

Variable	Pre-Pandemic Period			Pandemic Period		
	$\hat{\beta}$	$\hat{\gamma}$	p-value	$\hat{\beta}$	$\hat{\gamma}$	p-value
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	3,1597	23,563	<0,001	3,1097	22,414	<0,001*
logs	-1,1097	0,3297	<0,001	-1,6664	1,1889	<0,001*
Var (cons) districts	0,0071	1,0071		0,0036	1,0036	
Var (cons) households	0,0797	1,0830		0,0747	1,0776	
Individual Level						
Child's gender (ref : Girls)						
1: Boys (X_{111})	-0,1236	0,8837	<0,001*	-0,1099	0,8959	<0,001*
Child education (ref : Not yet in or dropped out of school)						
1: School (X_{112})	0,3879	1,4738	<0,001*	0,1990	1,2202	<0,001*
Child status (ref : Other than children)						
1: Children (X_{113})	-0,0506	0,9506	<0,001*	-0,0409	0,9599	<0,001*
Household Level						
Sex of Household head (ref : Female)						
1: Male (Y_{11})	0,0517	1,0531	<0,001*	0,0544	1,0559	<0,001*
Household head education (ref : Elementary school or below)						
1: Junior high school and above (Y_{12})	0,0086		0,273	-0,0099		0,147
Household head occupation sector (ref : Others)						
1: Formal (Y_{13})	0,0491	1,0503	<0,001*	0,0806	1,0839	<0,001*
Household size (ref : > 4 people)						
1: ≤ 4 people (Y_{14})	0,0068		0,357	0,0119		0,067
Household poverty status (ref : Poor)						
1: Not poor (Y_{15})	0,0935	1,0980	<0,001*	0,1076	11,1136	<0,001*
District Level						
Percentage of Poor Population	-0,0050	0,9950	<0,001*	-0,0032	0,9968	<0,001*
Average Years of School	-0,0043		0,284	0,0002		0,961

Source: Sakernas Agustus 2019-2020 (processed)

Description: * significant at 5% test level

Evaluation of the effect of independent variables on resilience time can be done through the interpretation of the acceleration factor value for each independent variable in the best model. An acceleration factor ($\hat{\gamma}$) value of more than one indicates that in categorical variables, the resilience of children aged 15-17 years not to start working until the age of 18 years for a particular category is longer than that of the reference category. Based on the information in Table 4, the following is an interpretation of each independent variable that affects the resilience of children aged 15-17 years not to work before and during the COVID-19 pandemic in rural areas.

3.1. Child Gender

Based on Table 4, the acceleration factor value of the child gender variable in the pre-pandemic data is 0.8837. This means that boys aged 15-17 years in rural areas started working 11.63 percent earlier than girls. From the data for the period during the pandemic, the acceleration factor value of the child gender variable is 0.8959. This means that boys aged 15-17 years in rural areas started working 10.41 percent earlier than girls. This result is in line with Dinak & Arcana (2022) that boys have lower resilience compared to girls. In addition, research by Magdalena et al. (2021) also found that boys would be more likely to work than girls. As is known in social patriarchy, Indonesian society places the value of boys higher than girls so that if children must work. Other studies have also proven that a child with a male sex has a significant impact and has a greater likelihood of working than a girl so that whatever theory is adopted in society, it is seen that men remain the foundation of family expectations in terms of economics, including for underage men (Teguh et al., 2019).

3.2. Child Education

Based on Table 4, the acceleration factor value of the child education variable in the pre-pandemic data is 1.4738. This means that children aged 15-17 years who go to school in rural areas start working 47.38 percent later than children who have not or have dropped out of school in rural areas. From the data for the period during the pandemic, the acceleration factor value of the child education variable is 1.2202. This means that children aged 15-17 years who go to school in rural areas start working 22.02 percent later than children who have not attended or dropped out of school in rural areas. These results are in line with Dinak & Arcana (2022) that children who have not graduated from elementary school have lower resilience compared to children who have at least graduated from basic education. Research Satriawan (2021) also found that most child laborers working in the informal sector were still in school. Another study conducted by Magdalena et al. (2021) where children are less likely to participate in the labor market as their education increases and when children with low education levels grow up, they become untrained adults.

3.3. Child Status

Based on Table 4, the acceleration factor value of the child status variable in the pre-pandemic data is 0.9506. This means that children aged 15-17 years in their households have the status of a child 4.94 percent earlier than those with status other than child. From the data for the period during the pandemic, the acceleration factor value of child status variable is 0.9599. This means that children aged 15-17 years in their households have the status of a child 4.01 percent earlier than those with status other than child. Other research conducted by Webbink et al. (2013) where they may take over or inherit the company, work experience on the family farm or own business may also be important for biological children.

3.4. Household Head Gender

Based on Table 4, the acceleration factor value of the household head gender in the pre-pandemic data is 1.0531. This means that children aged 15-17 years with male household heads in rural areas start working 5.31 percent later than children of female household heads in rural areas, assuming other variables are constant. From the data for the period during the pandemic, the acceleration factor value of the household head gender variable is 1.0559. This means that children aged 15-17 years with male household heads in rural areas start working 5.59 percent later than children aged 15-17 years with female household heads in rural areas. This result is in line with research conducted by Siddiqi (2013) who found that the gender of the head of household determines the effect on the decision to send children to work.

3.5. Household Head Occupation Sector

Based on Table 4, the acceleration factor value of the household head occupation sector variable is 1.0503, which means that children aged 15-17 years old from household heads who work in the formal sector in rural areas start working 5.03 percent slower than children from household heads who work in the informal sector or do not work. From the data for the period during the pandemic, the acceleration factor value of the variable number of ART is 1.0839, meaning that children aged 15-17 years who work in the formal sector in rural areas start working 8.39 percent slower than children of household heads who work in the informal sector or do not work. This result is in line with research conducted by Dinak & Arcana (2022) that children of household heads who work in the formal sector have higher resilience compared to children of household heads who work in the informal sector or do not work.

3.6. Household Poverty Status

Based on Table 4, the acceleration factor value of the household poverty status variable in the pre-pandemic data is 1.0980. This means that children aged 15-17 years from poor households in rural areas work 9.80 percent slower than children from non-poor households. From the data for the period during the pandemic, the acceleration factor value of the variable number of ART is 1.1136. This means that children aged 15-17 years from poor households in rural areas work 11.36 percent slower than children from non-poor households. This result is in line with Dinak & Arcana (2022) that children who come from poor status ≤ quintile2 have lower resilience compared to children who come from poor status > quintile2. Research by Siddiqi (2013) states that household income is influential in determining children's decision to work in Lahore. This is also in line with the assumption that households with a high enough income to indicate welfare status will not send their children to work (Todaro & Smith, 2015).

3.7. Percentage of Poor Population

Based on Table 4, the acceleration factor value of the variable percentage of the poor population in the pre-pandemic data is 0.9950. This means that for every one percent increase in the poor population in a province, children aged 15-17 years in rural areas in the district will be 0.50 percent slower to start working. the value of the acceleration factor variable for the percentage of poor people in the pre-pandemic data is 0.9968. This means that for every one percent increase in the poor population in a province, children aged 15-17 years in rural areas in the district will be 0.32 percent slower to start working. This result is in line with the research of Sari & Krismanti (2022) and Sari & Wardana (2021) where at the district level, which can represent the level of the wider community and regional characteristics, the poor population variable is a significant variable affecting the exploitation of working children.

Finally, we calculate the ICC value by using the second level and third-level error variance estimates. At pre-pandemic period, 0.21 percent of the variation in children's age at starting work was due to differences in characteristics in each district in rural areas throughout Indonesia and 2.36 percent of the variation in children's age at starting work was due to differences in characteristics in each district in rural areas throughout Indonesia. During the pandemic, 0.11 percent of the variation in children's age at starting work was due to differences in characteristics in each district in rural areas throughout Indonesia and 2.22 percent of the variation in children's age at starting work was due to differences in characteristics in each district in rural areas throughout Indonesia. Although the ICC value in both periods is small, it is in accordance with the statement that the greater the coverage of the second level group, the magnitude of the ICC will decrease where in Hox (2018) it is also written that there are findings of household level ICC ranging from 0.0 - 0.3.

4. Conclusion

The characteristics of children aged 15-17 years who work in rural areas in the pre-pandemic and pandemic periods are more likely to be boys, currently attending school and status in the household as children. From household characteristics, children aged 15-17 years mostly come from male-headed households, have the highest primary education, work outside the formal sector, from small families from households with a maximum number of 4 members and belong to poor households. The variables that influence the resilience of children aged 15-17 not to work before and during the pandemic in rural areas are: child gender, child education, child status at the individual level; gender and occupation sector of the household head, and household poverty status variable at the household level; and percentage of poor population at the contextual level. Child education has the greatest influence on the resilience of children aged 15-17 years not to work compared to other variables.

Sakernas in August is the source of data to be processed in this study. Sakernas is a special survey that collects data on employment with two data collection periods, namely February and August. Sakernas in August can only estimate data up to the district level, so the use of Sakernas data is a limitation in this study which focuses on rural areas. Although it specifically discusses the labor sector, the available information on child labor is still minimal, making some variables a little difficult to obtain. The ILO defines child labor with an age range of 5-17 years. Meanwhile, Sakernas respondents are limited to the population aged 15 years and above, so this study only analyzes respondents aged 15-17 years, focusing on the age of the child when they first started working.

Recommendations that can be given to the government in an effort to overcome the problem of child labor, among others, by evaluate the implementation of the 12-year compulsory education program that has been in effect so that it can further reduce the increasing participation of working children in rural areas. The government can also provide educational opportunities for households with unstable economic conditions through scholarships or other assistance such as KJP or KIP. Then, increase in cash or non-cash transfers will help households fulfill needs that are not met by their earned income. And last, the need for strict enforcement of the applicable legal sanctions in Article 181 paragraph (1) of Law No. 13 Year 2003 for business actors who employ children. Suggestions for future research to use primary data to add variables such as the reasons why children work, the birth order of children, and other variables that cannot be captured in this study.

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