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The Non-Linear Relationship Between Land Ownership and Child Labor

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Abstract

This study examines the relationship between household land ownership and the number of hours children spend working. This assumption is based on previous research suggesting that children from households with large landholdings are more likely to be engaged in child labor than those from land-poor households. This phenomenon arises from the fact that land is a crucial asset for agricultural households, often requiring family members, including children, to participate in farm-related activities. This study employs a random effects method using panel data from the Indonesia Family Life Survey (IFLS) for the years 2000, 2007, and 2014. The findings reveal a distinct pattern, particularly in the Indonesian context, where land size exhibits a non-linear relationship with children's working hours. As land ownership increases, children's working hours tend to decrease; however, beyond a certain threshold, children's working hours begin to rise with increasing land size. Heterogeneity analysis further indicates that non-food farmland has a greater impact on the increase in children's working hours. This may be due to the higher demand for additional labor in larger-scale agricultural production, which often relies on family members for support.

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INTRODUCTION

The issue of child labor has become a significant topic in socioeconomic research due to its profound impact on children's well-being and future prospects. This problem not only restricts children's access to proper education but also hinders their physical, mental, and emotional development (Bar & Basu, 2009; Candrawati & Auwalin, 2024; Giri & Singh, 2016; Nicolella & Kassouf, 2018; Oryoie et al., 2017). In developing countries, economic factors often serve as the primary motivation for families to rely on children as an additional source of income (Kharisma et al., 2022). Consequently, several researchers have hypothesized a link between child labor and poverty.

This hypothesis is grounded in the child labor theory proposed by Basu & Van (1998), which highlights a critical observation: most families prefer not to send their children to work, and those that do so typically face severe economic constraints. This assertion is difficult to refute, as the majority of child laborers are found in developing and impoverished countries (Ajefu & Massacky, 2023; Basu & Dimova, 2024). Furthermore, child labor is often associated with declining school enrollment rates and lower academic performance. If this trend persists, it may lead to stagnation or even a decline in the quality of human capital (Burrone & Giannelli, 2020; De Hoop et al., 2019; Dumas, 2020; Utama & Handayani, 2020).

Beyond poverty, land ownership also influences a family's decision to involve children in labor (Basu et al., 2010; Dumas, 2013). Households with limited land resources often struggle to meet basic needs, which may compel them to rely on child labor as a means of economic survival. However, the relationship between land ownership and child labor participation remains insufficiently explored. In rural areas, particularly those dependent on agriculture, land serves as the primary source of income. Nonetheless, due to small landholdings, many families have little choice but to engage their children in labor to sustain their livelihoods.

Further research on the relationship between land size and its implications for children's decision to work is essential for understanding how land limitations create significant economic pressures that ultimately affect children (Basu et al., 2010; Dumas, 2013). The connection between land ownership and child labor also raises important considerations, as highlighted in the findings of Hailu and Girma (2022). Specifically, if household asset ownership, such as land, continues to increase due to the intensification of child labor, there may be a threshold at which, once household wealth reaches a sufficient level, families cease to involve their children in labor, even if they possess a large amount of land. This concept could serve as a theoretical foundation for this study, necessitating further empirical exploration to address the question posed by Basu et al. (2010). As household land ownership increases, does child labor initially rise and then decline, following an inverted U-shaped curve, or does it follow a U-shaped pattern? This question also highlights a limitation of the current study, which assumes that the land market is less flexible than the labor market.

Building on these findings, this study posits that poverty is the primary cause of child labor. However, beyond this prevailing consensus, some researchers challenge this mainstream perspective. For instance, Brown et al. (2012) argue that the incidence of child labor is influenced by per capita income. Additionally, some scholars emphasize the role of non-economic factors in child labor, particularly those unrelated to poverty, such as parental attitudes and labor market flexibility. Research conducted by Cockburn and Dostie (2007) and Ali (2019) provides evidence that the demand for child labor varies across households, depending on the composition of household assets and the demographic characteristics of the region.

The assumption that labor markets in developing countries are imperfect is widely recognized (Hindman, 2014). In other words, poor households that might otherwise send their children to work as a means of escaping extreme poverty may be unable to do so due to limited access to nearby labor markets (Dumas, 2020). This assumption is supported by several studies, which suggest that many parents are reluctant to send their children to work in distant locations that are difficult to reach (Foster & Rosenzweig, 1994; Jayaraj & Subramanian, 2007).

In this context, if a household seeks to increase its income and achieve a certain level of wealth through land ownership, it is inevitable that its members, including children, may be encouraged to work. This is because new economic opportunities emerge that were previously unavailable due to a lack of ideal employment options. This phenomenon can be understood as a consequence of labor market imperfections. Several studies by Ahmad et al. (2020), Aminu et al. (2022), Edmonds (2002) and Hailu & Girma (2022), further support this notion, indicating that in countries such as Vietnam, Pakistan, Ethiopia, and Nigeria, households possessing assets such as land, livestock, and family-owned businesses are more likely to involve their children in labor.

In the context of agricultural households, at least two main objectives shape decision-making: meeting household consumption needs and maximizing profits from agricultural activities. Consequently, household consumption and production decisions are interdependent. This interdependence suggests that child labor may serve as a substitute for adult labor in agricultural production. Additionally, household assets—such as land, livestock, and technology can significantly influence decisions regarding the use of child labor.

This study adopts the empirical model of longitudinal panels proposed by Bar and Basu (2009). In agricultural households, it is assumed that there are *n* households ($i = 1,2,3, \dots, n$). For each household i at period t, individuals are classified into two groups: child workers ℓ_{ct} and adult workers (or parents) within the household ℓ_{at}, and external workers who are unrelated to the family ℓ_{et}. The period t refers to the annual time frame for each household. In the initial period, children can either attend school or not. If the child chooses to attend school, they will receive higher wages (wages for skilled labor) as they grow older. Conversely, if the child does not attend school, their future wages will be lower, denoted as $w_n < w_s$, where w_n represents the wages of unskilled labor and w_s represents the wages of skilled labor.

$$w_{it} = f(\ell_{it}) \quad \text{..} (1)$$

It can be explained that wages depend on resources sold or rented by households in the form of labor, both adult individuals and children. Meanwhile, the condition of an adult individual working as a farmer is derived from his past as a child laborer in the previous period:

$$\ell_{at} = \delta \ell_{ct-1} \quad \text{..} (2)$$

Where δ represents the survival rate of an individual in a household, the above equation suggests that experiencing child labor in the agricultural sector increases the likelihood of continuing to work in the same sector as an adult. However, this outcome is strongly influenced by the number of household assets, particularly in rural communities, where agricultural land constitutes the primary asset.

Adopting the model proposed by Bar & Basu (2009), this study employs the Cobb-Douglas agricultural production function to examine the relationship between child labor and the extent of land ownership by households, as expressed in the following equation:

$$y_t = f(k_t, \ell_{at} + \ell_{ct} + \ell_{et}) \quad \text{..........................} (3)$$

The amount of land owned by households is assumed to be $k_t \geq 0$ and labor using the equation $\ell_t = \ell_{at} + \ell_{ct} + \ell_{et}$ so that the land and labor factors can produce output in the form of y_t by:

$$y_t = k_t^{\alpha}(\ell_{at} + \ell_{ct} + \ell_{et})^{\beta} \quad \text{...........................} (4)$$

Assuming constant returns to scale, each unit of labor—whether provided by children or adults contributes proportionally to household income. This implies that the increased productivity of former child laborers as adults does not significantly impact the overall efficiency of the sector. This assumption is critical for understanding how historical decisions regarding child labor influence workforce structure and the long-term productivity of the sector.

As previously discussed, when households operate in an imperfect labor market, they face constraints in hiring external workers. As a result, they tend to rely on internal labor resources—primarily children—to assist in cultivating agricultural land. This dynamic leads to the following equation:

$$y_t = k_t^{\alpha}(\ell_{ct+1} + \ell_{ct})^{\beta} \quad (5)$$

From equation (5), it is necessary to prove Young's theorem to find the relationship between land and workers with the restriction of $\alpha + \beta = 1,\ 0 < \alpha < 1,\ 0 < \beta < 1$ with the property of increasing but diminishing. Then marginal productivity is lowered through labor and land will be obtained as follows:

$$f_{kt} = \frac{\partial y_t}{\partial k_t} = \alpha k_t^{\alpha-1}(\ell_{ct+1} + \ell_{ct})^{\beta} > 0 \quad (6)$$

$$f_{\ell t} = \frac{\partial y_t}{\partial \ell_t} = \beta k_t^{\alpha}(\ell_{ct+1} + \ell_{ct})^{\beta-1} > 0 \quad (7)$$

$$f_{kt\ell t} = \frac{\partial^2 y_t}{\partial k_t . \partial \ell_t} = \alpha\beta k_t^{\alpha-1}(\ell_{ct+1} + \ell_{ct})^{\beta-1} > 0 \quad (8)$$

$$f_{\ell tkt} = \frac{\partial^2 y_t}{\partial \ell_t \partial k_t} = \alpha\beta k_t^{\alpha-1}(\ell_{ct+1} + \ell_{ct})^{\beta-1} > 0 \quad (9)$$

From the derivation of Young's theorem, it can be said that $f_{kt\ell t} = f_{\ell tkt}$. While the second-order condition of equation (5) will get a negative value as follows:

$$f_{ktkt} = \frac{\partial y_t^2}{\partial^2 k_t} = \alpha(\alpha - 1)k_t^{\alpha-2}(\ell_{ct+1} + \ell_{ct})^{\beta} < 0 \quad (10)$$

$$f_{\ell t\ell t} = \frac{\partial y_t^2}{\partial^2 \ell_t} = \beta(\beta - 1)k_t^{\alpha}(\ell_{ct+1} + \ell_{ct})^{\beta-2} < 0 \quad (11)$$

From equation (6) to equation (9) shows marginal productivity of labor (MPL) and marginal productivity of capital (MPK). Meanwhile, equations (10) and (11) affirm the findings of Basu et al. (2010) that the impact of capital and labor on output has the property of increasing but diminishing (see Figure 1), meaning that at a certain threshold, if households feel that they already have capital in the form of sufficient land size, they will stop using child labor and switch to recruiting external workers.

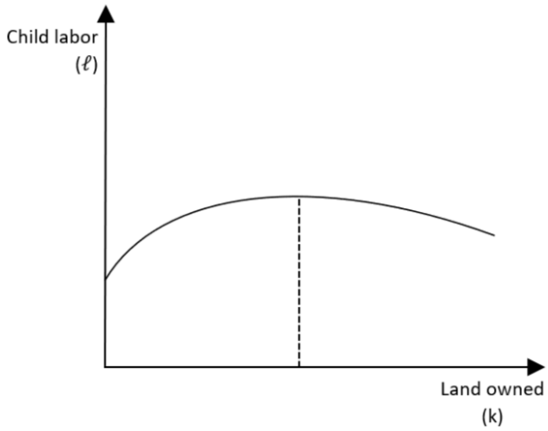

Figure 1. Inverted U-shaped relationship between land size and children's working hours
Source: IFLS Data Processed, 2025

The growing concern over the urgent need to address child labor highlights the importance of conducting a comprehensive analysis to better understand its underlying causes. Therefore, the preceding discussion warrants careful consideration. This study builds on the theoretical frameworks established by previous research, which develop rigorous models to examine this issue. It aims to advance empirical analysis by leveraging the most recent datasets from various countries, utilizing both cross-sectional and longitudinal panel data.

Unlike prior studies, this research employs longitudinal data to analyze the impact of land size on child labor, specifically focusing on children's working hours. While similar studies by Basu et al. (2010) and Dumas (2013) have examined this relationship in Pakistan and Ghana, no research has yet investigated the link between land size and children's working hours in Indonesia. This study hypothesizes that an exogenous increase in the land area owned by agricultural households may influence the prevalence of child labor in different ways, depending on the extent of land ownership. However, beyond a certain threshold, further increases in land area could lead to a shift in child labor prevalence, diverging from prior trends and potentially forming either an inverted U-shaped or U-shaped relationship.

RESEARCH METHODS

This study utilizes survey data from three waves of the Indonesia Family Life Survey (IFLS), specifically waves 3, 4, and 5. The primary independent variable is the area of agricultural land owned by households, which was recorded only in wave 3 of the IFLS in 2000. This limitation arises because the first two waves of the IFLS primarily focused on health, education, and basic economic conditions (Aribowo & Yudhistira, 2021; Strauss et al., 2016; Thomas et al., 2001). Using panel data from 2000 to 2014, this study specifically examines agricultural households in Indonesia and their decisions regarding child labor. The IFLS was chosen for its robust characteristics, including a baseline survey attrition rate of 16.33% by wave 5. Moreover, it is the only available longitudinal dataset at the household level in Indonesia (Dartanto et al., 2020, 2023; Moeis et al., 2020).

In terms of econometric models, this study employs a random effects panel data model, as it provides more efficient estimations than the fixed effects model. The random effects model retains variations between individuals, whereas the fixed effects model eliminates unobserved individual heterogeneity, which may reduce the amount of available information and affect estimation efficiency (Choi et al., 2023; Kaddoura & Westerlund, 2023; Pacifico, 2023). Additionally, the random effects model utilizes both within-individual and between-individual variations in panel data, whereas the fixed effects model relies solely on within-individual variations. To assess whether the random effects model is appropriate, a Hausman test is conducted. This test compares the estimates from both models, with the null hypothesis stating that the random effects model is more efficient (Teixeira & Queirós, 2016; Wooldridge, 2002).

The dependent variable in this study is the prevalence of child labor, constructed using the number of child working hours. This is determined by combining individual and household information based on classification codes in the IFLS survey. Child labor is defined as work performed by children aged 4 to 14 years, following the classification used by Kharisma et al. (2022), which also relies on IFLS data. Given this study's focus on agricultural households, household dynamics are analyzed by identifying households with child labor in 2000 and tracking them in 2007 and 2014 based on consistent classification codes.

For the independent variable, this study considers land area, defined as the total agricultural land owned by the household, including both food and non-food farmland. To control for additional factors, several covariates are included based on Basu et al. (2010), such as the number of children, the number of adult males, the number of adult females, the years of schooling for adult males and females, and the average age of working children within the household. Basu et al. (2010) suggested that the relationship between land size and child labor prevalence is non-linear. Accordingly, the models used in this study are specified as follows:

$$Child_{it} = \beta_0 + \beta_1 Land_{it} + \beta_2 Land_{it}^2 + \beta_3 \boldsymbol{X}'_{it}\boldsymbol{\gamma} + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (12)$$

Where $Child_{it}$ is a dependent variable represented by the number of children's working hours in the household, $Land_{it}$ is an independent variable measured by the area of land owned by the household, $Land_{it}^2$ is used to see the effect of the U curve on the dynamics of children's working hours when the land reaches a certain threshold. Whereas $\boldsymbol{X}'_{it}$ represents the control variable, $\boldsymbol{\gamma}$ is the coefficient vector and ε_{it} is the error term.

Table 1. Variable and Data

Variables	Description	Data Sources	Notes/Data Processing
$Child_{it}$	Children working hours per week	IFLS wave 3,4,5	It indicates the number of hours children work per week in hours and is derived from relevant IFLS variables that record child labor in formal/informal sectors.
$Land_{it}$	Land ownership by households	IFLS wave 3,4,5	It represents the land size owned by the household in hectares or square meters.
$Land\_square_{it}$	Land ownership by households square	IFLS wave 3,4,5	Land size squared from Landit for analyzing non-linear relationships.
$Total\_Children_{it}$	Number of children in the households	IFLS wave 3,4,5	The number of children in a household living with their parents.
$Total\_Males_{it}$	Number of adult males in the households	IFLS wave 3,4,5	The number of adult males in a household.
$Total\_Females_{it}$	Number of adult females in the households	IFLS wave 3,4,5	The number of adult females in a household.
Yos_Father_{it}	Years of schooling father	IFLS wave 3,4,5	The number of years of education completed by the father in the household.
Yos_Mother_{it}	Years of schooling mother	IFLS wave 3,4,5	The number of years of education completed by the mother in the household.
$Total\_Daughter_{it}$	Number of daughters in the households	IFLS wave 3,4,5	The number of daughters in a household.
$Total\_Boys_{it}$	Number of boys in the households	IFLS wave 3,4,5	The number of boys in a household.
$Age\_Children_{it}$	Average year of children in the households	IFLS wave 3,4,5	It is calculated by summing the ages of all children in the household and dividing by the total number of children.

Source: IFLS Data Processed, 2025

In the additional model, this study breaks down the independent variables into two, namely the area of food agricultural land and the area of non-food agricultural land. The goal is to expand or deepen the understanding of the relationship between existing variables by adding new dimensions (Deininger & Jin, 2006; Kapetanios et al., 2021). The area of food and non-food agricultural land usually has different characteristics and dynamics. Food agriculture refers to land used for crops that directly support food security (rice, corn, sweet potatoes, sugarcane, and the like), while non-food agriculture refers to land used for industrial or commercial crops (oil palm, rubber, tobacco, and timber needs). Additional models in this study are:

$$Child_{it} = \beta_0 + \beta_1 LandFood_{it} + \beta_2 LandFood_{it}^2 + \beta_3 \boldsymbol{X}'_{it}\boldsymbol{\gamma} + \varepsilon_{it} \quad \text{......... (13)}$$

$$Child_{it} = \beta_0 + \beta_1 LandnonFood_{it} + \beta_2 LandnonFood_{it}^2 + \beta_3 \boldsymbol{X}'_{it}\boldsymbol{\gamma} + \varepsilon_{it} \quad \text{.. (14)}$$

Beyond the primary models, this study also examines the impact of gender on the dependent variables through a heterogeneity analysis (Barkowski et al., 2020). Gender roles often influence the amount of time children spend working, suggesting that the relationship between factors such as land size or land size growth may differ between boys and girls. For

Table 2. Descriptive Statistics

Variables	Observation	Mean	Std. Deviation	Minimum	Maximum
$Child_{it}$	1275	4.8298	11.4144	0	119
$Land_{it}$	1275	6.0485	57.6455	0	1600
$Land\_square_{it}$	1275	3356.98	73782	0	2560000
$Total\_Children_{it}$	1275	1.8101	.84146	1	6
$Total\_Males_{it}$	1275	3.8164	2.5734	0	13
$Total\_Females_{it}$	1275	.68784	1.7133	0	10
Yos_Father_{it}	1275	6.2188	4.9598	0	22
Yos_Mother_{it}	1275	5.3356	4.5059	0	22
$Total\_Daughter_{it}$	1275	.88784	.78992	0	5
$Total\_Boys_{it}$	1275	.92235	.81456	0	4
$Avg\_AgeChildren_{it}$	1275	6.9529	2.9353	4	14

Source: IFLS Data Processed, 2025

instance, boys may be more likely to engage in agricultural or physically demanding tasks, whereas girls may assume greater household responsibilities. By conducting a gender-specific analysis, this study seeks to identify variations in the factors affecting children's working hours based on gender.

RESULTS AND DISCUSSION

The descriptive statistics presented in Table 2 provide an overview of the distribution of key variables in a sample drawn from the IFLS panel data, comprising 1,275 observations across waves 3, 4, and 5. The average number of working hours for children in households is 4.83, with a standard deviation of 11.41, indicating substantial variability in child labor across households. The minimum value for this variable is 0, while the maximum reaches 119, suggesting that certain households report significantly higher child working hours compared to the average. This variability may indicate the presence of outliers, which could influence the results of subsequent analyses. Therefore, conducting a heterogeneity analysis is essential to ensure the robustness of the research model (Gujarati et al., 2015).

In contrast, the independent variable—household land ownership—has an average value of 6.05, with a standard deviation of 57.65, reflecting considerable disparities in landholding sizes. The substantial variability in land ownership suggests that while some households possess minimal land, others hold significantly larger areas. These disparities may have important implications for household economic resilience, potentially influencing the prevalence of child labor, particularly in terms of children's working hours (Dumas, 2020).

Household demographic characteristics are also reflected in variables such as the number of children and the distribution of male and female members within the household. The average number of children per household is 1.81, with a standard deviation of 0.84, indicating that most households have a number of children close to the mean.

Regarding parental education, the average years of schooling completed by fathers and mothers are 6.21 and 5.33 years, respectively, with standard deviations of 4.96 and 4.51. Notably, the data suggest that, on average, mothers attain slightly higher levels of education than fathers. Specifically, mothers are more likely to have completed elementary school, whereas fathers, on average, did not complete elementary education. Parental education is included as a control variable in this study, as it is closely associated with household welfare and social mobility (Becker, 2019; Becker et al., 2018) This underscores the significant role of parental education in shaping household decisions regarding child labor (Blåka & Jacobsen, 2024).

The average age of children per household is 6.95 years, with a standard deviation of 2.93. Overall, these descriptive statistics offer valuable insights into the socioeconomic characteristics of households in the sample, serving as a foundation for subsequent employment economics research (World Bank, 2022).

Figure 2 illustrates the relationship between the number of household members and the extent of land ownership. In this study, land ownership is considered a key indicator of household welfare, particularly in developing countries like Indonesia, where it is strongly linked to the agrarian sector. The graph reveals a correlation between household size (ART) and land ownership, showing that land holdings tend to increase as the number of household members grows—up to a certain point—after which they begin to decline. This pattern aligns with agrarian economic theory, which posits that larger households generally have greater access to land to meet their subsistence needs (Deininger & Jin, 2006). However, beyond a certain threshold—approximately 7 to 8 household members—the amount of land owned begins to decrease.

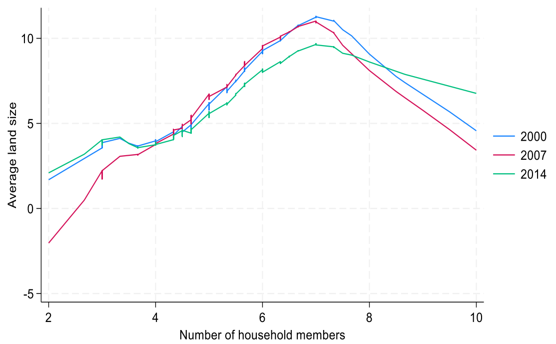

Figure 2. The relationship between the number of household members and land size
Source: IFLS Data Processed, 2025

This phenomenon can be attributed to land fragmentation resulting from inheritance systems, which leads to smaller land holdings per individual (Holden et al., 2013). Additionally, external factors—such as urbanization, shifts in agrarian policies, and the expansion of industrial activities—contribute to dynamic changes in land ownership, often beyond the control of individual households. These factors can result in the gradual reduction of agricultural land (Adamie, 2021; Rigg et al., 2016).

Between 2000 and 2007, land ownership patterns remained relatively stable. However, by 2014, a divergence became apparent, with larger households experiencing a decline in land holdings compared to previous years. Government interventions, such as land redistribution programs and land certification initiatives, may have influenced these trends. A study by the World Bank. Boretti & Rosa (2019) highlights that agrarian reforms and land legalization significantly impact land distribution patterns, particularly for low-income households.

Figure 3 illustrates the relationship between children's average age and their average working hours across three different periods: 2000, 2007, and 2014. The data reveal a clear pattern in which working hours increase as children grow older, with a notable rise beyond a certain age. During early childhood (approximately ages 4–10), working hours remain relatively stable with minor fluctuations. This finding aligns with the research of Edmonds and Pavcnik (2005), which suggests that children in this age group are primarily engaged in light household chores or minor economic activities within the household, such as cooking, caring for younger siblings, and cleaning.

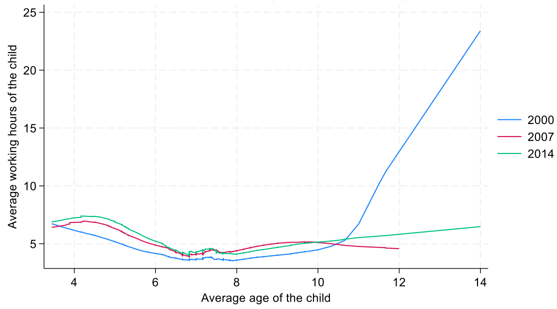

Figure 3. The relationship between the average age of children and working hours
Source: IFLS Data Processed, 2025

However, following the age of 10, there is a gradual increase in children's working hours, particularly in 2000 and 2007. The sharp rise in working hours around the age of 14 in 2000 indicates a period of more intense child labor, which may be attributed to increasing economic pressures within households, especially as the number of children rises. For impoverished households, it is assumed that limited resources may force them to rely on additional income, often at the expense of child labor.

In contrast, the years 2007 and 2014 showed a slight correction, with children working fewer hours in certain age groups. This shift can be attributed to policy interventions, including poverty alleviation programs, increased access to education, and the enforcement of child protection regulations, which have been gradually implemented by the International Labor Organization (ILO) and related institutions such as the Ministry of Manpower (ILO, 2013). Notably, a sharp increase in children's working hours occurred in the 12–14 year age group. This trend aligns with the findings of Basu and Van (1998), who argued that economic factors are the primary drivers of child labor, with households under economic stress more likely to rely on children to supplement family income. Additionally, the observed differences in trends across the years may reflect broader structural changes in the economy, such as the transition from an agricultural to an industrial and service-based economy, which can alter the patterns of children's employment (Dumas, 2013)

Table 3. Empirical Estimation Results (Baseline Model)

Dependent variable: children working hours	**All Crops**	
	FE	**RE**
$Land_{it}$	-0.00871**	-0.0119***
	(-2.09)	(-3.68)
$Land\_Square_{it}$	0.00000642**	0.00000772***
	(2.36)	(3.77)
$Total\_Children_{it}$	2.397***	3.007***
	(4.60)	(6.55)
$Total\_Males_{it}$	-0.413	-0.424**
	(-1.44)	(-2.11)
$Total\_Females_{it}$	-0.353	-0.229
	(-0.54)	(-0.81)
Yos_Father_{it}	0.0732	-0.00222
	(0.56)	(-0.03)
Yos_Mother_{it}	0.180	-0.00262
	(1.10)	(-0.03)
$Total\_Daughter_{it}$ **x** $Age\_Children_{it}$	0.359***	0.253***
	(3.93)	(3.22)
Constant	-0.936	0.0557
	(-0.55)	(0.05)
Observation	1275	1275
R-Square	0.069	0.065
Hausman	(p-value=0.3489)	(p-value=0.3489)

Note: Numbers in parentheses are t-statistics. The *, **, and *** signs refer to the level of significance, 10%, 5%, and 1%, respectively.

Source: IFLS Data Processed, 2025

The empirical results indicate that household land ownership influences children's working hours in a non-linear pattern. To determine the appropriate model, a Hausman test was conducted to compare the fixed effects and random effects models. With a p-value of 0.3489, the random effects model was selected, as it better accounts for variability between households by incorporating it as part of the error term. Additionally, the random effects model is more suitable for analyses involving larger sample sizes and greater variability in household characteristics.

In the initial stages, an increase in land size is associated with a reduction in children's working hours, suggesting that households with larger productive assets experience improved economic conditions and are less reliant on child labor. However, beyond a certain threshold of land ownership, children's working hours tend to increase. This suggests that households with moderate landholdings may face limitations in terms of adult labor or access to agricultural technology, prompting the involvement of children in agricultural activities to support production processes.These findings support the hypothesis that households with larger landholdings are less likely to involve children in agricultural work, as they have greater access to adult labor or other resources that can substitute for child labor (Ravallion, 2005). Conversely, Dumas (2007) suggests that farming households with small landholdings are more reliant on child labor due to limited capital to hire external workers, while households with very large landholdings may also involve their children to meet additional labor demands. This finding contrasts with Basu et al. (2010), who found that an increase in land size was associated with a rise in children's working hours. The discrepancy between these findings underscores the complexity of the relationship between land size and children's working hours, highlighting the influence of various contextual factors such as land ownership structure, land type, and the characteristics of agricultural households. According to Basu et al. (2010), land is a fundamental element in most agrarian economic models, often considered a hereditary asset or inheritance.

As previously discussed, the inflexible nature of land suggests that if it were a flexible asset, it could be relocated at the owner's discretion and adjusted according to labor demands. However, given the assumption that land is inherited and preserved as part of agrarian culture, this rigidity contributes to market imperfections. In the Solow-Swan model, production factors consist of two key elements: capital and labor, with land classified as capital. If land is considered a stationary factor, it does not interfere with efficiency, as its owner functions as an entrepreneur who employs other resources effectively (Romer, 2012). Bhalotra and Heady (2003) identified this phenomenon as the "wealth paradox," highlighting that while land is the most important asset in agrarian societies, many poor households lack land ownership. This challenges the prevailing assumption that child labor is confined solely to impoverished households (Basu & Van, 1998).

Beyond land ownership, the number of children in a household is positively correlated with children's working hours. Larger households, which typically face greater economic burdens, are more likely to involve their children in work. Conversely, the presence of adult males in the household tends to reduce children's working hours, though the effect is relatively modest. In contrast, the number of adult females does not significantly influence children's working hours, potentially reflecting traditional gender roles within the household. These findings support the hypothesis proposed by Bhalotra and Heady (2003), which suggests that a greater presence of adult males in the household can decrease reliance on child labor.

Parental education, however, did not show a significant impact on children's working hours, suggesting that educational attainment does not directly influence the decision to involve children in agricultural labor. While existing literature indicates that higher education levels can reduce reliance on child labor (Dumas, 2020) in the agricultural sector, economic pressures and labor demands often outweigh educational considerations. These findings align with research demonstrating that economic factors, such as land ownership and the need to enhance agricultural productivity, are more influential in determining children's participation in agricultural work (Dumas, 2020).

Interestingly, the interaction between the number of girls and the average age of children reveals that older girls tend to work longer hours than boys. This finding is consistent with previous studies indicating that in economically disadvantaged households, girls are often more engaged in both domestic and agricultural labor compared to boys. These results align with household economics theory, which posits that households with more children have stronger incentives to rely on child labor to meet economic needs (Edmonds & Pavcnik, 2005).

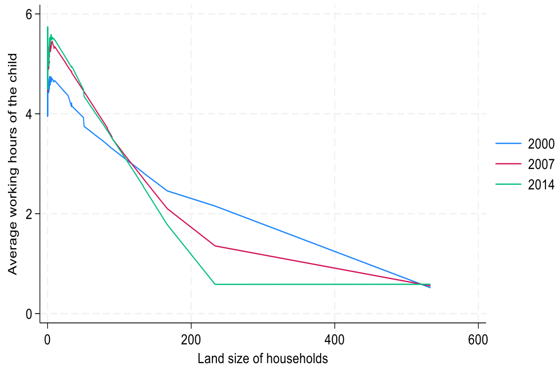

Figure 4. Non-linear relationship between land size and children's working hours.
Source: IFLS Data Processed, 2025

Figure 4 further illustrates the non-linear relationship between land size and children's working hours. In general, as household land size increases, children's working hours decrease. This finding aligns with family economic theory, which posits that households with larger assets (e.g., land) tend to have greater economic resources, reducing their dependence on child labor (Basu & Van, 1998). In 2000, the graph indicates that children from households with smaller landholdings had higher working hours compared to subsequent years. This may reflect the more challenging economic conditions of that period, which necessitated child labor as a means of supporting household income. However, in 2007, there was a decline in children's working hours, possibly due to policy changes or economic improvements that reduced reliance on child labor. This trend became even more pronounced in 2014, with children in households owning larger land plots working less frequently. This decline may be attributed to economic development, agricultural modernization, and improved access to education, allowing children to prioritize schooling over work.

These findings are consistent with previous research, which suggests that asset ownership—particularly land—plays a crucial role in reducing child labor by providing households with more stable economic resources (Edmonds & Pavcnik, 2005). Additionally, the decline in children's working hours in recent years may be linked to stronger child protection policies and the expansion of basic education (Ahmad et al., 2020; Inder et al., 2017). These trends suggest that policies aimed at increasing access to land and other productive assets for low-income families could be an effective strategy for reducing child labor dependency. Furthermore, broader educational interventions and social assistance programs could reinforce this decline, ensuring better access to education and improved long-term outcomes for children. Thus, asset ownership, coupled with appropriate policy support, plays a critical role in addressing child labor issues and enhancing children's overall well-being.

In the heterogeneity analysis, this study categorizes land size based on its use in food and non-food agriculture. Statistically, the relationship between land size and children's working hours differs between these two agricultural sectors. In food agriculture, an increase in land size does not exhibit a significant non-linear effect on children's working hours, indicating that additional land does not necessarily alter child labor participation. In contrast, in the non-food agriculture sector, a significant non-linear relationship emerges, suggesting that beyond a certain threshold, an increase in land size can lead to higher child labor participation. This may be because non-food agriculture, such as plantations or horticulture, requires a larger labor force compared to food agriculture, which tends to be more capital-intensive.

Other factors influencing both sectors include household size and the number of girls in the household, both of which are positively associated with children's working hours. A higher number of children in a household increases the likelihood of child labor as families seek additional economic support. Meanwhile, the presence of more boys in a household tends to reduce overall child labor, possibly because boys are more likely to find employment outside the agricultural sector.

Overall, the differing patterns between food and non-food agriculture suggest that while land tenure in non-food agriculture is more responsive to reducing children's working hours, it also exhibits a non-linear pattern where land expansion may increase labor needs beyond a certain scale. This can be explained by economies of scale in food agriculture, where households with larger landholdings are more likely to adopt mechanization or hire additional labor (Dumas, 2020). Conversely, in the non-food agricultural sector, households with large landholdings tend to rely more on child labor, likely due to the greater labor demands associated with large-scale production, often requiring family members' involvement in agricultural work (Basu et al., 2010).

Table 4. Results of Empirical Analysis on Types of Food and Non-Food Crop

Dependent variable: children working hours	**Food Crop**		**Non-Food Crop**	
	FE	**RE**	**FE**	**RE**
$Land_{it}$	-0.000910	-0.00354	-0.0166***	-0.0203***
	(-0.10)	(-0.34)	(-2.71)	(-6.17)
$Land\_Square_{it}$	-0.000000503	0.000000378	0.0000113***	0.0000129***
	(-0.03)	(0.02)	(2.88)	(6.14)
$Total\_Children_{it}$	2.398***	3.011***	2.399***	3.006***
	(4.58)	(6.55)	(4.60)	(6.55)
$Total\_Males_{it}$	-0.421	-0.431**	-0.423	-0.431**
	(-1.45)	(-2.14)	(-1.48)	(-2.15)
$Total\_Females_{it}$	-0.352	-0.230	-0.357	-0.234
	(-0.54)	(-0.81)	(-0.55)	(-0.83)
Yos_Father_{it}	0.0733	-0.00369	0.0662	-0.00343
	(0.56)	(-0.05)	(0.51)	(-0.04)
Yos_Mother_{it}	0.191	0.00148	0.183	0.000146
	(1.17)	(0.02)	(1.13)	(0.00)
*$Total\_Daughter_{it}$ **x***	0.356***	0.252***	0.360***	0.255***
$Age\_Children_{it}$	(3.90)	(3.20)	(3.94)	(3.24)
Constant	-0.986	0.0380	-0.883	0.0623
	(-0.58)	(0.03)	(-0.52)	(0.05)
Observation	1275	1275	1275	1275
R-Square	0.068	0.064	0.069	0.065
Hausman	(p-value=0.3357)		(p-value=0.3556)	

Note: Numbers in parentheses are t-statistics. The *, **, and *** signs refer to the level of significance, 10%, 5%, and 1%, respectively.

Source: IFLS Data Processed, 2025

In the second heterogeneity or sub sample analysis that differentiated the two sample groups between boys and girls, it was seen that there was a significant influence of land size on children's working hours in both groups. For boys, the larger the land owned by the family, the fewer working hours are done. This significant coefficient suggests that greater land ownership reduces dependence on boy labor, which is associated with the ability of households to add to more stable resources. Similar results were found in girls, albeit with slightly smaller effects. The decline in working hours for girls with larger land sizes suggests that policies that improve family welfare, such as providing wider access to land, have the potential to reduce the exploitation of girls' labor, which is often more affected by household economic demands.

Table 5. Sub-Sample Analysis

Dependent variable: children working hours	Boys		Girls	
	FE	RE	FE	RE
Land$_{it}$	-0.00610**	-0.00709***	-0.00447*	-0.00543***
	(-2.09)	(-4.13)	(-1.82)	(-2.80)
Land_Square$_{it}$	0.00000375**	0.00000390***	0.00000268*	0.00000266**
	(1.98)	(3.52)	(1.71)	(2.06)
Constant	2.369***	2.468***	2.503***	2.599***
	(209.92)	(10.79)	(257.23)	(10.67)
Observation	1275	1275	1275	1275
R-square	0.001			

Note: Numbers in parentheses are t-statistics. The *, **, and *** signs refer to the level of significance, 10%, 5%, and 1%, respectively.
Source: IFLS Data Processed, 2025

However, when looking at the non-linear effect of land size on children's working hours, there are indications that at a certain point, the larger the land owned, can increase children's working hours, although the impact is relatively small. In boys, this effect is slightly greater compared to girls. This phenomenon can be explained by the characteristics of the non-food agricultural sector or seasonal jobs that require more labor when the land scale is getting larger. While generally increasing land size reduces reliance on child labor, there are certain situations where families with larger land sizes need more labor to run their farm operations, so children may be more involved in the work.

Overall, these findings highlight the importance of incorporating gender dynamics into policies aimed at reducing child labor. While increasing land size is associated with a significant decline in working hours for both boys and girls, the differences in gender impact suggest that boys are more likely to engage in labor outside the household, often in more physically demanding roles. Policies that focus solely on improving land access without considering gender-specific employment patterns in the agricultural sector may be less effective if they fail to account for the distinct ways in which boys and girls contribute to household economic activities.

Therefore, policies that support reducing dependence on child labor need to integrate a more holistic approach that takes into account gender factors, as well as specific agricultural sectors to ensure long-term success in reducing child labor exploitation. This effect may be due to greater production demands on households with large land holdings, which encourages children to stay employed on farms as part of the family labor strategy (Dumas, 2020). The results of this robustness test corroborate the main finding that land ownership has a significant influence in determining children's involvement in agricultural work, but with different effects between boys and girls. These results are also consistent with previous research that shows that gender plays an important role in child labor decisions in the context of agriculture, where boys are more likely to be involved in physical work in the field, while girls are more involved in household chores or agricultural activities that are not as heavy as boys (Inder et al., 2017).

The results of this sub-sample analysis make an important contribution to the literature on child labor in the agricultural sector, especially in developing countries. Some of the key implications are supported by previous research. First, this study reinforces the finding that economic factors and family assets, such as land ownership, have different impacts on the involvement of boys and girls in child labor (Kharisma et al., 2022). Second, the non-linear relationship found in this study suggests that increasing land ownership initially reduces children's involvement in agricultural work, but at some point may increase their working hours as part of the expansion of agricultural production. Third, these findings also support the hypothesis that households with wider land ownership are more likely to rely on child labor when resources to recruit adult labor are limited.

CONCLUSION

This study demonstrates a significant non-linear relationship between land ownership and children's working hours. In the initial stages, an increase in land size reduces children's working hours, suggesting that additional productive assets improve household economic conditions, thereby decreasing reliance on child labor. However, beyond a certain threshold, further increases in land size lead to a slight rise in children's working hours, forming a U-shaped curve.

Heterogeneity analysis reveals distinct patterns between agri-food and non-food agricultural sectors. In the agri-food sector, land size does not exhibit a significant non-linear relationship with children's working hours. Conversely, in the non-food agricultural sector, a significant non-linear pattern emerges, likely due to greater labor demands associated with larger landholdings, necessitating increased child labor. These findings diverge from Basu et al. (2010). This study reveals that the non-linear pattern that occurs is in the form of a U-curve instead of an Inverted U. The distinction in land size is suspected to be an important reason for the difference in non-linear curves which also means that each agrarian country may have a different context in looking at the influence of land size on children's working hours.

Although this study is a pioneer in replicating the theory of child labor by Basu and Van (1998) in the context of the influence of land size on children's working hours in the agricultural sector in Indonesia, researchers realize that there are still some limitations. First, this study uses past IFLS data with a span of seven years. The seven-year interval is considered too long, making it quite difficult to capture the causes of dynamic changes in land ownership by households, which can be a strong justification for this study. Second, this study is limited to using variable control in the form of child and parent characteristics. Further research can facilitate other controls or determinants that answer in detail the issue of child labor and land size in Indonesia, such as agrarian reform policies in the form of agricultural sector incentives, land certification policies, and assistance that encourages the productivity of agricultural households that are considered to influence household decisions involving child labor. Third, although the random effect results show consistency, there is still a suspicion that there is still outlier data, especially on independent variables. Therefore, further research can use the censoring method to control outlier variables so that they can get more robust estimates.

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