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Research article

Nonfarm Participation and Household Educational Investment: Evidence in Rural Indonesia

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ABSTRACT

Participating in nonfarm employment as a diversification strategy increases the probability of farm households becoming less vulnerable to income shocks and improves rural household welfare. This study aims to fill the research gap about the impact of nonfarm participation on rural household educational investment using nationally representative data for Indonesia. Using topographical characteristics in each district as the instrumental variable (IV). This study reveals that participating in nonfarm employment significantly contributes to enhancing household educational expenditure in rural farming households. The OLS specification without controls yields a negative and insignificant coefficient for nonfarm participation. With household and district controls, the estimate becomes positive but remains small at 0.11 percentage points. The IV estimate is larger at 3.39 percentage points, indicating possible downward bias in the OLS results, likely related to unobserved factors that jointly affect nonfarm participation and educational spending with negative bias. There is substantial heterogeneity in the impacts of nonfarm participation across subsamples. The role of nonfarming is relatively higher in male-headed households and in households that run their own farm business assisted by temporary or unpaid workers. Nonfarm employment plays an essential role and is more prominent in eastern Indonesia. Income diversification to nonfarm sectors can potentially increase educational investment, particularly in relatively lagging regions, thereby reducing inequality in rural education.

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1. INTRODUCTION

Agricultural households in rural regions, particularly within impoverished and developing nations, remain highly vulnerable to income shocks precipitated by climate change, crop price volatility, and disease outbreaks. Natural disasters such as droughts and floods, which significantly impact crop yields, can induce severe adverse income shocks for farmers (Ahmed, 2024; Chuang, 2019; Hussain et al., 2020; Mishra et al., 2015; and Wahdat et al., 2021). These negative shocks jeopardize financial stability and overall well-being, often leaving long-lasting effects that necessitate robust recovery and resilience strategies. In response, farm households may adopt consumption-smoothing strategies by adjusting their spending patterns across both food and non-food categories. To mitigate such risks, households in both developed and developing countries frequently diversify their income by seeking employment in non-farm sectors. This diversification strategy increases the probability that a household will become less vulnerable to shocks (Adzawla et al., 2020; Chuang, 2019; and Dimova et al., 2015). While several studies have documented the positive influence of non-farm employment on household well-being and food security, significant gaps remain in understanding its specific effects across different expenditure categories (Owusu et al., 2011; Rahman & Mishra, 2020; and Tesfaye & Nayak, 2022).

This study extends the existing literature by specifically examining the relationship between non-farm employment and educational expenditure, an area where empirical evidence remains sparse.

Education serves as a critical investment in human capital, empowering individuals to escape poverty traps and secure long-term welfare. However, educational spending is particularly sensitive to income fluctuations in rural developing countries. Cameron & Worswick (2001) show that Indonesian farming families lacking access to credit or alternative employment often reduce educational spending when faced with income declines. Furthermore, livelihood diversification shapes parental investment through variations in income stability and future aspirations, suggesting that non-farm and purely agricultural households may follow distinct educational investment patterns.

Education serves as a critical investment in human capital, empowering individuals to break the cycle of poverty and secure long-term welfare. In the context of rural areas within developing nations, household income remains a primary determinant of educational investment (Addai, 2022; Kumari & Ramana Murthy, 2022; Ogundari & Abdulai, 2014; and Tilak, 2002). When families lack the financial capacity to fund their children's schooling, they risk becoming ensnared in a persistent poverty trap (Barham et al., 1995; and Laborda & Sotelsek, 2020). Furthermore, educational spending patterns vary significantly across different livelihood types. Livelihood diversification influences parental investment decisions by altering income stability, access to resources and services, and future aspirations (Hedges et al., 2016). Empirical evidence of greater intergenerational persistence among non-farm households compared to agricultural ones further suggests that these distinct economic groups follow unique educational investment trajectories (Emran et al., 2020). Ultimately, parents with higher and more stable income streams possess greater resources to allocate toward their children's overall well-being and educational opportunities.

Previous studies on the link between non-farm participation and household outcomes have produced heterogeneous results. While maternal non-farm entrepreneurship has been found to increase children's secondary schooling in rural Ghana, evidence from China indicates that non-farm participation, while increasing leisure and food consumption, may have no significant effect on educational spending (Janssens et al., 2019; and Ma et al., 2022). These contrasting findings likely reflect differences in local labor market conditions, household priorities, and methodological approaches. In settings where non-farm activities yield substantial and stable income, households possess greater capacity and incentives to invest in schooling; however, where gains are modest, such earnings may not translate into higher educational investment. These factors underscore that the impact of non-farm participation is highly context-dependent and potentially confounded by unobserved household characteristics.

Indonesia serves as a compelling locus for this study, as over half of the nation's poor population (51.33%) relies primarily on the agricultural sector for income. Rural Indonesia is currently undergoing structural economic shifts, requiring small farmers to manage both agricultural and non-agricultural enterprises. This study focuses on rural areas because educational attainment there lags significantly behind urban centers. In rural Indonesia, while 74.17% of those who enter senior high school complete their studies, only 53.85% of the overall rural population actually reaches that educational level. This high dropout rate highlights a critical challenge for educational equity and development. Furthermore, average monthly per capita expenditure on education in rural areas is only 2.20%, compared to 3.59% in urban areas (BPS-Statistics Indonesia, 2021).

This paper aims to examine whether participation in nonfarm activities among agricultural households in rural Indonesia affects educational investment. The objectives are to estimate the effect of nonfarm participation on household educational spending, to address endogeneity in participation decisions using an instrumental-variable approach, and to assess whether the estimated effects vary across different household groups. This study contributes in three ways. First, it uses nationally representative data from rural Indonesia, where a substantial share of poor households depend primarily on agriculture and children's educational attainment remains low. Second, it focuses on household educational spending on children, a decision that has important implications for policies aimed at improving human capital and rural development, which has received limited attention in prior quantitative studies. Third, by employing an IV approach, the study isolates the causal effect of nonfarm participation on educational investment, addressing potential endogeneity due to unobserved household characteristics. In doing so, this research provides new evidence that helps reconcile mixed findings in the literature and offers insights relevant for educational and rural

development policy in Indonesia. The remainder of this paper is structured as follows: Section 2 describes the research methods; Section 3 presents the results and discussion, including descriptive statistics, effect estimations, robustness checks, and heterogeneity analysis; and Section 4 concludes.

2. RESEARCH METHODS

2.1. Data

This study utilizes pooled cross-sectional data spanning 2019 to 2021, sourced from the National Socioeconomic Survey (SUSENAS). The analytic sample is restricted to rural households with school-age children (5 to 18 years) whose household heads are primarily employed in the agricultural sector. This selection criterion yields 80,663 eligible samples distributed across 470 districts, drawn from an initial pool of approximately 900,000 observations. Topographical data, specifically regarding village terrain (slopes, peaks, valleys, and flat areas), is integrated from the 2018 Village Potential Data Collection (PODES). Additional control variables are gathered from SUSENAS, PODES, the Ministry of Finance, and the Ministry of Higher Education, Science, and Technology. The dependent variable is defined as the proportion of household expenditure allocated to education, serving as a proxy for educational investment and reflecting household priorities relative to other basic needs. The primary variable of interest is a binary indicator for non-farm employment participation, assigned a value of 1 if at least one household member is engaged in the non-agricultural sector and 0 otherwise. To account for potential confounders, the model incorporates household-level controls, including income, size, and the age, sex, and education of the household head, alongside district-level educational expenditures.

2.2. Model Specification

The baseline analysis employs Ordinary Least Squares (OLS) to estimate the impact of non-farm participation on educational spending. In the model equation (1), notation of h, r, and t denote household, region, and year respectively. The parameter (β) of interest is expected to be positive, suggesting that the presence of non-farm income may bolster investment in children's education. X is a vector of control variables, which are household and district characteristics. Year fixed effects (FE) are included to mitigate time-varying unobserved heterogeneity. However, the OLS estimates may suffer from endogeneity bias, as unobserved dimensions jointly correlate with both non-farm participation and educational investment decisions.

$$Share_educexp_{h,t} = \alpha + \beta Nonfarm_{h,t} + \gamma X_{h,t} + \gamma_t + \varepsilon_{h,t} \quad (1)$$

Equation (1) has potential bias because of the endogeneity issue. Households participating in non-farm activities are potentially selected along unobserved dimensions that are jointly correlated with education investment. Given the potential endogeneity of nonfarm participation with respect to educational expenditure due to unobserved household and community characteristics, we implement an instrumental variable two-stage least squares (IV-2SLS) estimation strategy. This study applies the IV method using topographical characteristics in districts. Using data from PODES, topographical characteristics in each village were explained by three types, such as slope/peak, valley, and flat areas. The instrument defines as percentage of villages with flat areas to total villages in each district. The topographic characteristics of an area are expected to affect the probability of farming households participating in nonfarm employment. Areas with challenging topography, such as rugged terrain or steep slopes, may have limited infrastructure and transportation options, making it more difficult for farm households to access nonfarm employment opportunities in more accessible areas (Fang et al., 2012; and Tran et al., 2016). Areas chosen to be developed by infrastructure, such as electricity, are mainly because of their flatter gradient (Dinkelman, 2011). Residents will respond to the existence of access to electricity to diversify their jobs apart from farming by doing business in the microenterprise.

As the exogeneity, topography should not be directly affected by other variables in the model, particularly those related to the outcome variable or the decision to participate in nonfarm employment, because of the natural process. The other concern of the IV strategy is the exclusion restriction assumption. This assumption requires that any effect of the instrument on the outcome variable is exclusively through its potential effect on exposure. Considering that some geographical characteristics influence nonfarm participation of farming households in their surrounding areas, it is expected that the more accessible an area is, the more people work in nonfarm jobs, which will enhance their entry into nonfarm jobs.

We also argue that there is no correlation between the percentage of villages with flat areas and household expenditure on education. The correlation exists only through its effect on participation in nonfarm employment. Although flat areas may offer better infrastructure or school accessibility, these factors are not the main determinants of educational spending in rural agricultural settings. Such expenditure is primarily shaped by household income, parental preferences, and district-level education policies rather than by local terrain. Any link between flat terrain and educational expenditure in rural farm household are mainly driven by improved access to nonfarm work, leading to increased household income and strengthening both the capacity and the preference for investing in children's education.

The first-stage regression test is conducted to determine the instrument's strength. It checks whether the percentage of villages with flat areas correlates with the endogenous variable but not with the error in the equations. Percent flat is the instrument that has to be significantly correlated with household nonfarm participation and not correlated with unobserved factors. The validity of IV estimates relies on a first-stage F-statistic exceeding the conventional threshold of 10, indicating a sufficiently strong instrument (Stock & Yogo, 2005). Coefficient α_1 in equation (2) is the first-stage effect of the instrumental variable and is expected to be positive and statistically significant. The parameter of interest in equation (3), β_1 measures the effect of agricultural households' livelihood strategy on children's educational investment.

$$nonfarm_{h,t} = \alpha_0 + \alpha_1 percent_flat_{h,t-1} + \alpha_2 X_{h,t} + \gamma_t + \varepsilon_{h,t} \quad (2)$$

$$prop_educ_{h,t} = \beta_0 + \beta_1 \widehat{nonfarm}_{h,t} + \beta_2 X_{h,t} + \gamma_t \quad (3)$$

For post-regression analysis, we perform a robustness check using Kinky-Least Squares (KLS) as proposed by Kripfganz & Kiviet (2021). This method provides instrument-free inference by placing bounds on the potential correlation between the endogenous regressor and the error term. KLS inference allows for sensitivity checks and is considered as a complement to instrument-based procedures. This approach places bounds on the correlation of the endogenous regressor with the error term (ρ). Hence, it does not rely on having an IV for the nonfarm or satisfying the exclusion restriction. This method corrects for OLS bias based on a grid of possible endogeneity correlations, but requires expert judgment to define the acceptable degree of endogeneity. Sun et al. (2023) use a broad interval of -0.75 to 0.75 as their reference grid, and we draw on this benchmark but restrict the range to the portion that is empirically plausible in our setting, given the expected sign of endogeneity.

Another robustness check for a coefficient stability test is by estimating the IV model using another instrument, the nonfarm networks. This instrument is commonly used for nonfarm participation (Bui & Hoang, 2021; Hoang et al., 2014; Ma et al., 2023; and Ma et al., 2022). We further test coefficient stability by employing non-farm networks, measured as the district-level participation rate from the previous year, as an alternative instrument. This instrument relies on the premise that relation-based knowledge sharing encourages agricultural households to enter the non-farm labor market. We assess impact heterogeneity by disaggregating the sample by the gender of the household head, farm job categories, and regional location (East versus West Indonesia). These subsample analyses account for variations in economic vulnerability and regional challenges, such as disparate infrastructure development, to provide more nuanced empirical evidence for rural policy formulation.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics and Exploration

Approximately 31.61% of the study sample consists of households participating in non-farm employment, defined as agricultural households where at least one member is engaged in the non-agricultural sector. Table 1 reports the summary statistics reveal significant differences in educational expenditure and socioeconomic characteristics between diversified and purely agricultural households. Households participating in the non-farm sector report relatively higher total incomes, measured via the expenditure approach, compared to their purely agricultural counterparts.

Table 1. Summary Statistics of Selected Variables between the Two Groups

Variables	Farm household with nonfarm (n=25,496)		Farm household without nonfarm (n=55,167)	
	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)
Annual household expenditure on education (IDR)	1,121,545	1,335,427	968,753	1,365,221
Annual household expenditure on education- per student (IDR)	761,488	933,263	642,206	868,009
Proportion of expenditure on education	0.0257	0.0249	0.0276	0.0277
Age of household head	51.374	11.157	45.622	10.986
Sex of household head (1=male)	0.9178	0.2746	0.8954	0.3060
Education level of household head				
No schooling/ incomplete in primary	0.2945	0.4558	0.3219	0.4672
Primary school	0.3950	0.4889	0.3760	0.4844
Junior high school	0.1399	0.3469	0.1462	0.3533
Senior high school	0.1526	0.3596	0.1426	0.3497
College	0.0180	0.1329	0.0133	0.1146
Household size	5.0321	1.6256	4.2979	1.4299
Number of students	1.2514	0.9347	1.3163	0.9688
Presence of senior high school student in household	0.2138	0.4099	0.1869	0.3899
Total annual expenditure (million rupiahs)	45.952	27.904	36.708	22.755
Local government expenditure on education- per student (million IDR)	9.1780	10.460	9.0482	8.4916

Furthermore, annual educational spending, both total and per-student, is higher in households with diversified income streams. This trend is corroborated by the higher mean presence of senior high school students in non-farm participating households.

3.2. Causal Impact of Non-farm Participation on Education

To establish a causal relationship, we instrument non-farm participation using topographical characteristics. The first stage regressions for the IV estimates in Table 2 suggest that topography has a positive influence on the likelihood of household members engaging in nonfarm work. Controlling for household characteristics lowers the estimate, but it remains significant. Each increase of 10 percentage points in villages with plain areas will increase households' probability of nonfarm participation by 6.64%, evaluated at the mean level. The weak identification test by Kleibergen-Paap Wald (KPW) F-statistics is high and above the common thresholds.

Monotonicity is another key assumption, implying that the instrument affects the endogenous regressor in only one direction. Although untestable, this assumption is consistent with empirical findings on rural economic participation. Because infrastructure provision is less costly in flat areas, such locations are more likely to receive connectivity improvements that enhance access to nonfarm opportunities. Asher & Novosad (2020) show that better rural connectivity is associated with higher nonfarm employment, while Dinkelman (2011) demonstrates that flatter areas face lower infrastructure costs and that expanded electrification increases employment and microenterprise activity, both forms of nonfarm work.

Table 2. First Stage Regression of Endogenous Variable: Household Nonfarm Participation

	Nonfarm participation (1=at least one household member work in nonfarm sector)	
	No control	All controls included
	(1)	(2)
District topographical characteristic (% of villages with flat area)	0.0024*** (0.0004)	0.0021*** (0.0004)
Year FE	Yes	Yes
KPW F-statistics	45.07	33.60
Observations	80 663	80 663

Notes: All controls include household controls and local government education expenditure. Robust standard errors in parentheses. Significant coefficients are indicated by *** p<0.01, ** p<0.05, *p<0.1

Consistent with this, Figure 1 shows a positive predicted relationship between flat topography and our measures of nonfarm participation, supporting the relevance of the monotonicity assumption.

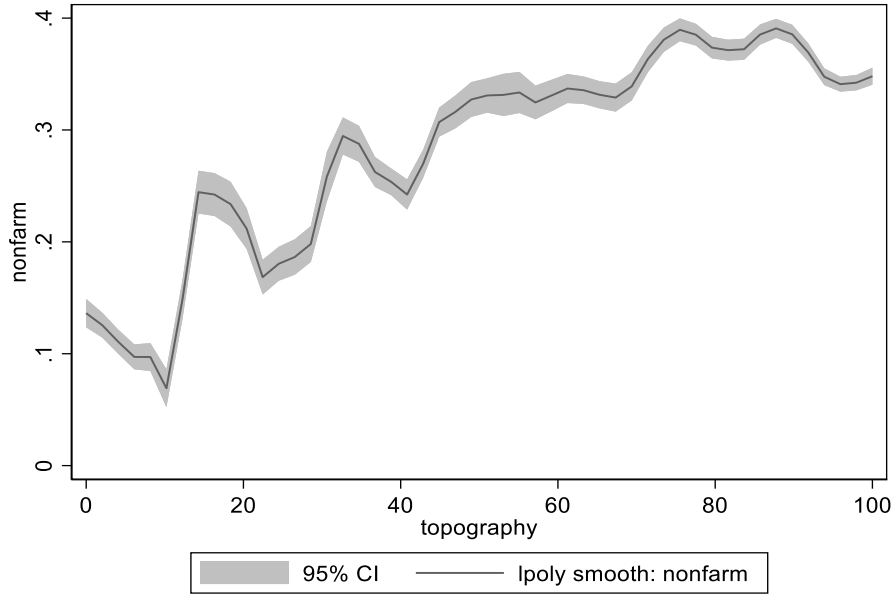


Figure 1. Percentage Village with Flat Area in District and Dummy Household Nonfarm Participation

The summarized impact of non-farm participation on educational investment is presented in Table 3. Farm households with employment diversification to the nonfarm sector have increased the proportion of expenditure on education. While baseline OLS models without controls produce negative coefficients due to negative selection along unobserved dimensions, the inclusion of household and district-level controls, such as local government education spending, substantially mitigates this bias. The negative coefficient arises because households are negatively selected along unobserved dimensions that are positively correlated with education investment. After we include a set of household controls along with district-level characteristics such as local government spending on education per student, the confounding influence of these factors is substantially reduced. Moreover, the magnitude becomes higher in the IV estimate, reflecting further reduction of downward bias as the IV isolates the exogenous variation in access to nonfarm opportunities rather than those of negative selection or distress.

This study reveals that the nonfarm participation significantly increases the proportion of household expenditure on children's education by approximately 3.39 percentage points. Given that the mean proportion of expenditure on education is 2.76%, this corresponds to an increase of 122.83% in improving household expenditure on education. These findings align with existing literature suggesting that non-farm activities bolster household capacity to cover schooling costs that agricultural income alone may not sufficiently support. For example, studies by Jenkins et al. (2019) and Janssens et al. (2019) similarly find positive associations between non-farm engagement and educational outcomes.

Table 3. Results of Nonfarm Participation Effect on Household Expenditure on Education

Dep. variable: Proportion of expenditure on education to total expenditure				
Variables	**OLS Model**		**IV Model**	
	(1)	**(2)**	**(3)**	**(4)**
Nonfarm (1= Household participating in nonfarm employment; 0=others)	-0.0019**	0.0011***	0.0353***	0.0339***
	(0.0008)	(0.0004)	(0.0096)	(0.0086)
Age head of household		0.0002***		-0.0001
		(0.0000)		(0.0001)
Sex head of household		-0.0022***		-0.0013*
		(0.0005)		(0.0007)
Education head of household:				
Primary school		0.0019***		0.0000
		(0.0005)		(0.0005)
Junior high school		0.0035***		0.0009
		(0.0006)		(0.0007)
Senior high school		0.0039***		0.0008
		(0.0006)		(0.0009)
College		0.0013		-0.0024*
		(0.0009)		(0.0013)
Household size		-0.0039***		-0.0062***
		(0.0001)		(0.0007)
Beneficiaries:				
PKH		0.0026***		0.0027***
		(0.0006)		(0.0007)
PIP		0.0018***		0.0013**
		(0.0006)		(0.0006)
Number of students		0.0129***		0.0156***
		(0.0004)		(0.0008)
Dummy of secondary high student		0.0157***		0.0149***
		(0.0006)		(0.0007)
Ln annual expenditure		-0.0039***		-0.0081***
		(0.0006)		(0.0014)
Ln local government expenditure on education- per student		-0.0001		-0.0000
		(0.0011)		(0.0008)
Constant	0.0273***	0.0839***	0.0149***	0.1666***
	(0.0009)	(0.0222)	(0.0035)	(0.0295)
Year FE	Yes	Yes	Yes	Yes
Household Controls	No	Yes	No	Yes
Observations	80,663	80,663	80,663	80,663

Note: Robust standard errors in parentheses. Significant coefficients are indicated by *** p<0.01, ** p<0.05, *p<0.1

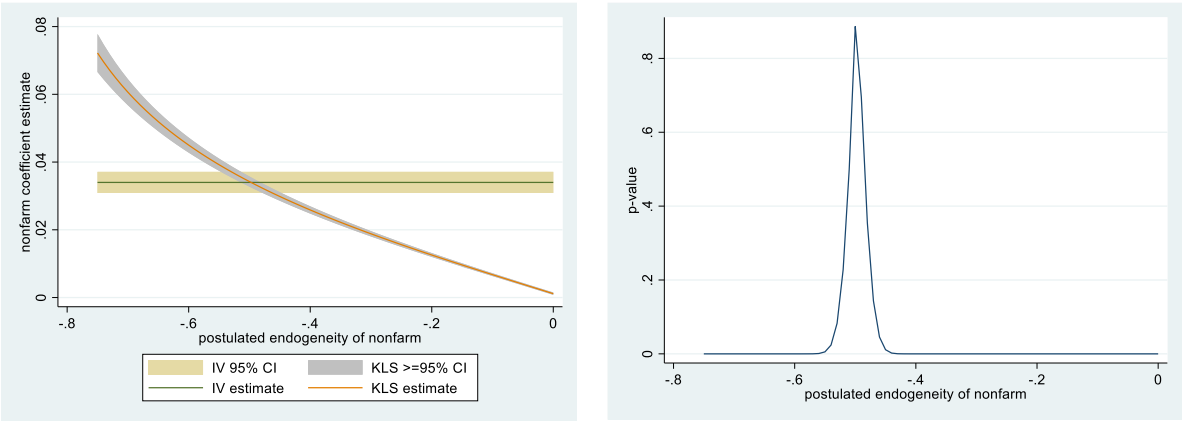
Conversely, our results contrast with those of Ma et al. (2022) in China, who found insignificant effects on education spending; this discrepancy likely reflects our specific focus on rural farm households with school-aged children. By focusing specifically on rural farm households with school-aged children, our study addresses this gap and provides direct evidence of the positive impact of diversification of income on educational spending.

3.3. Robustness Check

To verify the validity of our IV estimates, we employ the Kinky-Least Squares (KLS) method proposed by Kripfganz and Kiviet (2021). KLS provides an analytical correction that accounts for all possible values of endogeneity correlations in OLS. The downward bias in our OLS estimates suggests a negative correlation between nonfarm participation and the error term, leading us to set the KLS analysis postulated endogeneity range for nonfarm participation from -0.75 to zero. The KLS sensitivity analysis confirms that the estimated effect remains positive and statistically significant across a broad range of postulated endogeneity values.

The left panel (a) shows that the estimated effect of non-farm participation on the share of educational expenditure remains positive and statistically significant over a wide range of

postulated endogeneity values. The estimate converges to zero only under extreme negative correlation between non-farm participation and the regression error term, a magnitude substantially larger than what is typically observed in comparable settings.



(a) (b)

Figure 2. KLS Robustness Analysis for Nonfarm Participation

The right panel (b) corroborates this result by showing that the null of no effect is rejected for nearly all plausible values of the endogeneity parameter, except within a narrow interval characterized by strong negative selection. Taken together, these findings suggest that the positive IV estimate is robust to moderate violations of the exclusion restriction and that unobserved selection would need to be both negative and implausibly large to overturn the main conclusions.

Table 4. Second stage nonfarm participation impact on household expenditure on education using nonfarm network as the instrument

	Proportion of expenditure on education to total expenditure	
	(1)	**(2)**
Nonfarm (1= Household participating in nonfarm employment; 0=Others)	0.0497***	0.0408***
	(0.0054)	(0.0065)
KPW F-statistics	235.301	140.505
Year FE	Yes	Yes
Household Controls	No	Yes
Observations	80 663	80 663

Notes: Robust standard errors in parentheses. Significant coefficients are indicated by ***p<0.01, **p<0.05, *p<0.1

We also checked our sensitivity parameter using a different instrument, nonfarm networks in the district from the previous year. Table 4 also suggests a similar result, we utilize district-level non-farm networks from the previous year as an alternative instrument, which yields similar results and confirms that participation increases educational expenditure shares in agricultural households. We expect the instrument to be strong and valid because the F test is greater than a common threshold, holds the monotonicity assumption, and is relevant to the variable of interest.

3.4. Heterogeneous Effect

To consider the heterogeneity in the impacts of nonfarm participation across subsamples, first, we estimate each gender of the head of household. The estimation shows that the effect is higher in male-headed households relative to the mean household expenditure on education (Table 5). The second heterogeneity analysis is based on the working status of the household head. In this study, the eligible sample is an agricultural household defined by a household head who works in the agricultural sector.

Table 5. Heterogeneous Effect of Nonfarm Participation by Sex of Household's Head

	Proportion of expenditure on education	
	Male-headed household	**Female-headed household**
	(1)	(2)
Nonfarm (1= Household participating in nonfarm employment; 0=Others)	0.0346***	0.0375***
	(0.0085)	(0.0133)
KPW F-statistics	29.221	61.649
Year FE	Yes	Yes
Household Controls	Yes	Yes
Observations	72 798	7 865

Notes: All controls include household controls and local government education expenditure per student. The robust standard errors in parentheses. Significant coefficients are indicated by *** p<0.01, ** p<0.05, *p<0.1

The household head's working status reflects their role in the sector, either as a farm owner/manager or an employee. Differences in status may reflect differences in implications and outcomes. We divided the sample into six groups, from self-employed to casual employees or unpaid family workers.

Table 6. Heterogeneous Effect of Nonfarm Participation by Household's Head Working Status

	Proportion of expenditure on education					
	Self-employed	**Employer assisted by temporary**	**Employer assisted by permanent workers**	**Employee**	**Casual employee**	**Family/ Unpaid worker**
	(1)	(2)	(3)	(4)	(5)	(6)
Nonfarm (1= Household participating in nonfarm employment; 0=Others)	0.051***	0.037***	-0.019	-0.264	0.110	0.031***
	(0.019)	(0.010)	(0.056)	(3.544)	(0.114)	(0.008)
KPW F-statistics	7.591	33.973	0.899	0.006	0.948	28.53
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22 700	42 004	2 654	3 564	8 370	1 371

Notes: All controls include household controls and district controls (government education expenditure and number of school). Robust standard errors in parentheses. Significant coefficients are indicated by *** p<0.01, ** p<0.05, *p<0.1

The results in Table 6 show that the positive effect of nonfarm participation is concentrated in informal-farm households. The effect is significant for self-employed farmers and most prominently for employers assisted by temporary or unpaid workers, supported by KPW F-Statistics in Table 6 show common thresholds. In contrast, statistically insignificant coefficient parameters may be because the instrument is not working well in predicting nonfarm household status in some subsamples. Consequently, the estimates for these subsamples cannot be interpreted causally.

Table 7. Heterogeneous Effect of Nonfarm Participation by region

	Proportion of expenditure on education	
	East	**West**
	(1)	(2)
Nonfarm (1= Household participating in nonfarm employment; 0=others)	0.0342***	-0.2199
	(0.0098)	(0.2544)
KPW F-statistics	28.390	0.798
Year FE	Yes	Yes
Household controls	Yes	Yes
Observations	39 977	40 686

Notes: All controls include household controls and local government education expenditure per student. Robust standard errors in parentheses. Significant coefficients are indicated by *** p<0.01, ** p<0.05, *p<0.1.

Another heterogeneity test is by different regions, eastern and western Indonesia. The western group consists of Sumatra, Java, Bali, and Kalimantan, while the eastern consists of Sulawesi, Nusa Tenggara Island, Maluku Island, and Papua. We replicate the IV regression with full control and present it in Table 7. The result indicates that the impact is significant in the east region. This can be considered as input for the government that the importance of nonfarm businesses is to encourage household investment in education in the lagging region.

3.5. Discussion

Our empirical results demonstrate that participation in non-farm employment significantly increases household investment in human capital by elevating educational expenditures. Initially, the impact was estimated using a baseline model both with and without control variables. In the baseline specification that omitted covariates, the impact appeared negatively significant. However, upon the inclusion of several variables influencing educational outcomes, the effect increased substantially and shifted to a positive significance. To address potential omitted variable bias and unobserved confounders, we employed an instrumental variable (IV) approach. The IV estimation yielded a positively significant impact with a notably higher coefficient value, suggesting a negative bias in the baseline OLS model. This bias likely arises from an omitted confounder that is positively correlated with educational expenditure but negatively correlated with non-farm participation.

We expect that the unobserved variable bias in our study may come from specific household characteristics. Parents' aspirations to send their children to a higher level of education can occur in agricultural households, which may face labor frictions in diversifying their income in the nonfarm sector. If there are limited members in a household, parents choose to send their children to school without involving them in work to expect a higher number of children's future labor market prospects. Furthermore, agricultural households with older cohorts tend to find it challenging to move out of agriculture, for example, because of a lack of education and skills. Porzio et al. (2022) show that human capital influences structural transformation. The principal driver of the aggregate labor reallocation away from the agricultural sector was the entry of new cohorts into the labor market, rather than movements across sectors by established members of the workforce. Such cohort-driven dynamics help explain why some households invest heavily in education despite being unable to diversify into nonfarm work, thereby generating the pattern of negative selection that biases OLS downward. We find that the positive and significant effect of nonfarm participation is concentrated among informal farm households. Nonfarm income plays a vital role in facilitating human capital investment for these households, which typically face constraints in accessing formal credit and experience income fluctuations from farming. This effect could stem from the necessity of supplementing farm income to cover educational costs or from the belief that education enhances opportunities for more secure and stable livelihoods beyond agriculture. We exclude the regional or main islands' fixed effect in the model because of variation of the instrument is significant across islands, therefore reducing the power of the instrument. As a result of the heterogeneity analysis, the instrument is strong enough to increase the probability of nonfarm participation, particularly in the eastern area. The result shows that the significant effect of nonfarm participation in the eastern region suggests that income diversification in the lagging region still has become a substantial effort to enhance investment in human capital.

The Local Average Treatment Effect (LATE) identified by our IV strategy captures the impact on households whose nonfarm participation is shaped by topographical accessibility. In such areas, modest improvements in land accessibility substantially affect households' ability to participate in nonfarm activities, which explains why the LATE is more prominent in the eastern region. Figure 3 illustrates that districts in Eastern Indonesia have more slopes, peaks, or valleys, making the eastern highlands comparatively challenging to reach. Consistent with this, descriptive statistics indicate that the proportion of rural farm households engaged in nonfarm activities is markedly lower in the East (25.37%) than in the West (37.74%), aligning with the presence of more binding access frictions in the eastern region. This characterization implies that the estimated effect should not be interpreted as an average effect for all rural households, but rather as a causal impact for topography-constrained households whose labor allocation decisions are shaped by geographic barriers.

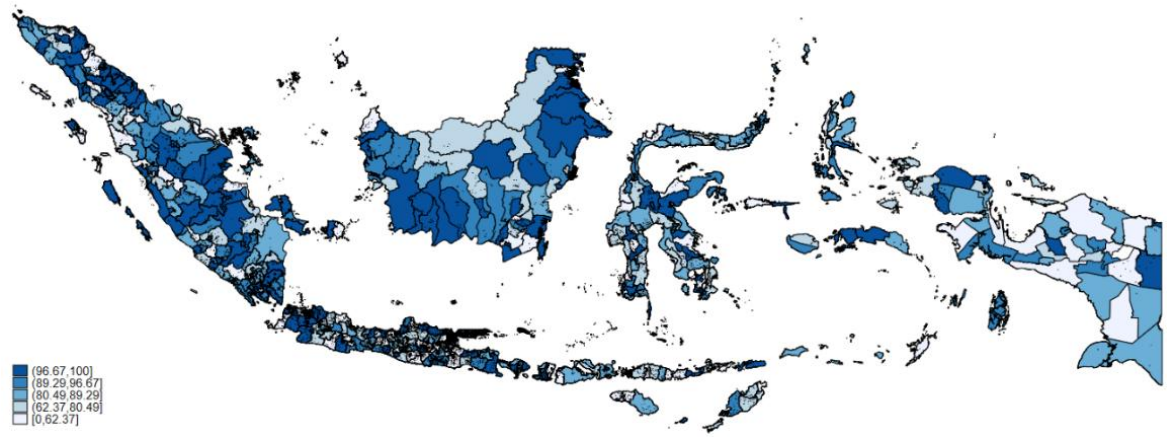


Figure 3. Percentage of Village with Flat Area in District

Accordingly, policy interventions should focus on reducing terrain-related barriers that limit their ability to participate in nonfarm activities. Enhancing rural infrastructure, such as improving road quality, bridge construction, and strengthening local transport networks, positively facilitates nonfarm participation (Do et al., 2019; Lei et al., 2019; Mahmud & Sawada, 2018; and Nkegbe et al., 2022). Evidence from rural Indonesia similarly indicates that infrastructure improvements are associated with higher participation rates in nonfarm sectors (Gibson & Olivia, 2010; and Kamaludin & Qibthiyyah, 2022). Additionally, to ease access constraints, Yuliani & Nasrudin (2024) show that strengthening household liquidity through predictable cash transfers can also promote nonfarm participation by relaxing short-term financial barriers that often limit rural households' ability to start or sustain nonfarm activities. Beyond infrastructure and income stabilization through cash transfers, policies could further strengthen households' capacity for educational investment by easing credit constraints and improving skill formation, for instance, through school subsidy programs, microcredit for rural families, or vocational training, which together can enhance human capital accumulation and promote inclusive structural transformation in lagging regions.

This study has several limitations that should be acknowledged. The available SUSENAS data do not include household income or nonfarm-specific earnings, preventing empirical separation of potential mechanisms such as income enhancement and risk smoothing. As a result, the estimated effect should be interpreted as the overall causal impact of nonfarm participation on educational expenditure rather than evidence for a specific transmission channel. Future research with richer data, including detailed income modules or panel information, would be needed to identify the relative importance of these mechanisms.

4. CONCLUSIONS

This study provides an empirical assessment of the impact of non-farm employment participation on the educational investment of rural farm households. Our findings demonstrate that participation in the non-farm sector exerts a substantial positive influence on household educational expenditure. Specifically, the transition into non-farm employment is associated with a 3.39 percentage point increase in educational spending, representing a 122.83% increase relative to the mean level. The results of the heterogeneity analysis indicate that the impact is more pronounced among male-headed households and households operating farm enterprises. Furthermore, regional disaggregation reveals that this positive effect is particularly significant in Eastern Indonesia, a relatively lagging region characterized by distinct developmental challenges. These findings are robust across alternative definitions of non-farm participation and various estimation strategies. Collectively, the results suggest that policies aimed at promoting non-farm opportunities—such as improving rural infrastructure and reducing structural barriers to entry—can serve as a potent mechanism for enhancing human capital investment in rural children.

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