International Journal of Social Science Research and Review

http://ijssrr.com
editor@ijssrr.com
Volume 9, Issue 3
March, 2026
Pages: 355-361

Do Natural Resource Rents Enhance Labor Productivity? Evidence from Vietnam

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http://dx.doi.org/10.47814/ijssrr.v9i3.3288

Abstract

This study examines the effects of economic growth, human capital, and natural resource rents on labor productivity in Vietnam over the period 1991–2021. Using time-series data from the World Development Indicators and the Penn World Table, the study employs a threshold regression model in which human capital is used as the threshold variable to capture non-linear relationships. The results indicate that economic growth has a consistently positive and statistically significant impact on labor productivity across all regimes. In contrast, human capital effect positively only after surpassing a certain threshold; at low and medium levels, its effect on labor productivity is negative. Based on these findings, the study shows policy implications that emphasize improving the quality of human capital through better education, skills development, and technological absorption, while gradually reducing reliance on natural resource exploitation as a key driver of economic growth.

Keywords: *Human Capital; Labor Productivity; Natural Resource Rents; Nonlinear Effects; Threshold Regression*

1. Introduction

Labor productivity is defined as gross domestic product (GDP) per worker (Mohamed Fathy & Amira Abdelmoez, 2022). It is a important economic metric that is intimately linked to economic growth, competitiveness, and people's quality of life (Laut et al., 2023). In many developing countries, labor productivity remains substantially lower than in developed economies, which is a key factor driving the discrepancy in per capita income between these groups of countries (Mohamed Fathy & Amira Abdelmoez, 2022). Investment in education and healthcare plays a vital role in enhancing labor productivity in both the short and long run, as it changes workers' skills, health, and the productive potential of future generations (Baharin et al., 2020; Kraay, 2019).

Human capital, including workers' skills, knowledge, personal characteristics, and health, plays important factors in improving labor productivity (Saha et al., 2025). Investment in education helps workers develop job skills, critical thinking, and the ability to adapt to new technologies, and each additional year of schooling may increase average wages (McGivney & Winthrop, 2016). In addition, close working relationships among skilled workers leads to knowledge spillovers, which improve productivity at both firm and national levels (Laut et al., 2023). Countries with higher human capital levels often experience faster economic growth and higher per capita income (Saha et al., 2025) A stable and growing economy provides financial resources for governments and households to reinvest in education and healthcare, which improves population quality and creates a positive development cycle (He, 2024). Health and education help workers adapt more quickly to new technologies (Arshad & Malik, 2015). Investment in R&D and human capital contributes to higher total factor productivity (TFP) (Nguyen Thi My Linh, 2020). The share of highly skilled and qualified workers has a stronger effect on productivity than the capital ratio(Afrooz et al., 2010). The relationship between resource exploitation and labor productivity is often viewed from a sustainability perspective. Studies show that countries whose economies rely too heavily on unstable resources, such as natural resource rents or cheap labor, often face difficulties in achieving long-term sustainable development (Nguyen Hoang Le et al., 2019). A strong focus on raw resource extraction is often linked to outdated technologies, which can trap countries in a cycle of low productivity and weak incentives for innovation (Nguyen Hoang Le et al., 2019).

In the digital age and with the rapid rise of AI in the labor market (Liu et al., 2023), traditional education systems may no longer provide all the skills needed, which calls for further research on the ability of human capital to absorb new technologies (McGivney & Winthrop, 2016; Prathyusha, 2025). Human capital shows long-term investment in education, training, and health to improve workforce capacity, thereby directly raising labor productivity, increasing income, and serving as a key driver of sustainable economic growth (Nguyen Ba Ngoc, 2008). Therefore, studying the links between human capital, natural resource rents, economic growth, and labor productivity is important for Vietnam's development policies.

2. *Methodology*

2.1. Data

This study uses annual time-series data covering the period 1991–2021, collected from the World Development Indicators (WDI) of the World Bank and the Penn World Table 11.0, resulting in 31 observations. This sample size satisfies the minimum requirements for time-series regression analysis, as suggested by (Tabachnick et al., 2013) and (Manh Hong Pham et al., 2022).

The study includes four variables: LP (labor productivity), GDP per person employed at constant PPP prices (2021); GDP_PC (GDP per capita) at constant prices; NRR (natural resource rent as a share of GDP); and HC (human capital), measured by the Human Capital Index from the Penn World Table.

Table 2.1 reports the descriptive statistics for the variables based on 31 observations. On average, labor productivity was about US$12,003 per worker, GDP per capita was approximately US$1,816, and natural resource rent accounted for 7.09% of GDP. Human capital showed low variation over time, suggesting a relatively stable improvement during the study period.

Table 2.1: Descriptive statistics of variables

Indicators	LP	GDP (constant 2021 PPP $)	NRR (% of GDP)	HC
Mean	12002.92	1815.61	7.09	2.211
Median	11423.15	1699.68	7.30	2.231
Standard Deviation	4780.36	817.00	3.21	0.312
Kurtosis	-0.52	-0.93	-0.56	-1.491
Skewness	0.61	0.47	0.23	-0.130
Range	16666.48	2644.47	12.11	0.943
Minimum	5415.95	713.75	1.81	1.722
Maximum	31	31	31	31

2.2. Threshold Regression Model

The threshold regression model was first introduced by (Tong, 1983) in studies on nonlinear time series. This approach was developed by (Chan & Tong, 1986). (Hansen, 1999, 2000a) further developed the method by establishing its theoretical framework for non-dynamic panel data and proposing a way to construct confidence intervals using the likelihood ratio statistic. Subsequent developments include the PSTR model proposed by (González et al., 2005) and the theory of multiple threshold variables developed by (Chong & Yan, 2014).

The advantages of this method are its ability to model heterogeneity and sudden turning points in economic data, allowing the coefficients to vary across observed regimes with high accuracy (Hansen, 2000b). One drawback, though, is that the null hypothesis does not specify the threshold parameter. However, a limitation arises when the threshold parameter is not identified under the null hypothesis, which leads to non-standard distributions and requires computationally demanding bootstrap procedures (Rothfelder & Boldea, 2022).

Threshold regression (Hansen, 2000b) is based on the assumption that the effects of explanatory variables on the dependent variable are not constant but vary across different levels of a threshold variable. In this study, human capital (HC) is chosen as the threshold variable to reflect differences in the relationships among variables across levels of human capital development.

The econometric model of the threshold regression approach is specified as follows:

$$y_t = \begin{cases} \alpha_1 + \beta_1' x_t + \varepsilon_t, \text{ if } q_t \leq \gamma \\ \alpha_2 + \beta_2' x_t + \varepsilon_t, \quad \text{ if } q_t > \gamma \end{cases}$$

Where: y_t : is the dependent variable; x_t : is the independent variable; q_t : is the threshold variable; and γ: denotes the threshold value.

The empirical model in this study is specified as follows:
The threshold variable is HC:

$$\ln LP_t = \begin{cases} \alpha_1 + \beta_{11}\ln GDPPC_t + \beta_{12} NRR_t + \beta_{13} HC_t + \varepsilon_t, \text{ nếu } HC_t \leq \gamma_1 \\ \alpha_2 + \beta_{21}\ln GDPPC_t + \beta_{22} NRR_t + \beta_{23} HC_t + \varepsilon_t, \text{ nếu } \gamma_1 < HC_t \leq \gamma_2 \\ \alpha_3 + \beta_{31}\ln GDPPC_t + \beta_{32} NRR_t + \beta_{33} HC_t + \varepsilon_t, \text{ nếu } HC_t > \gamma_2 \end{cases}$$

In threshold regression, threshold values are endogenously estimated from the data. The optimal threshold Hansen (2000b) is obtained by minimizing the model's sum of squared residuals $\hat{\gamma}$.

$$\hat{\gamma} = \operatorname{argmin} S_n(\gamma), \gamma \in \left[\underline{\gamma}, \overline{\gamma}\right]$$

3. *Results and Discussion*

3.1. Threshold Regression Results

The threshold regression results show that the effects of economic growth, natural resource rents, and human capital on labor productivity depend on the threshold levels of human capital (HC). Economic growth (lnGDPPC) has a positive and statistically significant effect in all regimes. At low and medium levels of human capital (HC < 2.5861), the effect of HC is negative, while when the highest threshold is exceeded (HC ≥ 2.5861), the effect of HC becomes positive and statistically significant. Natural resource rents (NRR) generally have a negative effect but are only weakly statistically significant at higher levels of human capital. Diagnostic tests indicate that the model does not violate the basic econometric assumptions, confirming the reliability of the estimated results.

Table 3.4: Threshold Regression Results with Human Capital (HC) as the Threshold Variable

R-squared	0.9999
Adjusted R-squared	0.9998
Log-likelihood	123.4121
Akaike Information Criterion (AIC)	-7.1879
Durbin–Watson statistic	2.0357

Threshold Value	Variable	Coefficient	Std. Error	Prob.
HC < 1.8458	lnGDPPC	2.3897	0.1045	0.0000
	NRR	-0.0008	0.0027	0.7725
	HC	-4.1199	0.3875	0.0000
1.8458 ≤ HC < 2.4208	lnGDPPC	1.5440	0.0050	0.0000
	NRR	-0.0013	0.0008	0.0966
	HC	-0.9498	0.0190	0.0000
2.4208 ≤ HC < 2.5861	lnGDPPC	2.0477	0.1392	0.0000
	NRR	-0.0031	0.0026	0.2621
	HC	-2.5252	0.4283	0.0000
HC ≥ 2.5861	lnGDPPC	1.0332	0.0497	0.0000
	NRR	-0.0113	0.0059	0.0703
	HC	0.6168	0.1511	0.0006

Diagnostic tests

Test	F-Statistic	Prob.
Breusch–Godfrey autocorrelation test (LM test)	2.7180	0.0946
Breusch–Pagan–Godfrey heteroskedasticity test	0.5234	0.8724

The Bai–Perron test results show that three human capital thresholds are statistically significant at the 5% level, as the Scaled F-statistics are greater than the critical values in the first three tests, confirming that the model with three HC thresholds is optimal. This indicates that the relationship between the explanatory variables and labor productivity is nonlinear. Therefore, applying a threshold regression model is appropriate for this study.

Table 3.5. Bai–Perron Multiple Threshold Test Results
Threshold variable: Human Capital (HC)
Sample: 1991–2021; Number of observations: 31

Threshold test	F-statistic	Scaled F-statistic	Critical value(5%)	Decision
0 vs. 1	12.3173	36.952	13.98	Reject H_0
1 vs. 2	20.0226	60.0678	15.72	Reject H_0
2 vs. 3	12.6979	38.0936	16.83	Reject H_0
3 vs. 4	3.8067	11.42	17.61	Fail to reject H_0

Estimated threshold values (HC): 1.8458; 2.4208; 2.5861

3.2. Discussion

Economic growth is widely viewed as a key factor that opens the way for sustained increases in productive capacity, which in turn promotes labor productivity(Osiobe, 2019). This view is further supported by the argument that investment-driven growth and productivity improvement through technological change are two inseparable processes (Riedel, 2007).

The results of this study are consistent with the findings of (Chatzimichael & Tzouvelekas, 2014) who examined 121 countries and showed that improvements in human capital contribute about 19.5% to labor productivity growth. (Frank, 1996) also points out that highly skilled labor has a positive effect on labor productivity in manufacturing industries in the EU. However, the magnitude of this effect may vary by gender and type of activity. For example, in Pakistan, male education significantly increases income in non-farm activities but does not have a clear impact on direct productivity in crop production (Fafchamps & Quisumbing, 1998). In Vietnam, empirical evidence for the period 1996–2017 shows that the contribution of human capital to labor productivity growth is about 14% (Nguyen Thi Dong & Le Thi Van Hue, 2019). Investment in higher education and the attraction of high-quality foreign direct investment are considered key solutions for achieving future economic breakthroughs (Nguyen Tan Vinh, 2019).

The results of this study also indicate that natural resource rents constrain labor productivity, which is supported by empirical evidence from oil-exporting countries. Research by Mehrara shows that in 11 oil-exporting countries, oil revenues help increase spending on education but reduce the actual quality of the education system as enrollment expands, resulting in education failing to generate positive long-run effects on productivity and GDP (Osiobe, 2019). In addition, negative environmental factors arising from resource extraction are shown by (Zivin & Neidell, 2013) to cause biological effects that reduce health, thereby directly constraining human labor productivity.

4. Conclusion and Policy Implications

Using a threshold regression model, this study shows that the effects of economic growth, human capital, and natural resource rents on labor productivity in Vietnam (1991–2021) are nonlinear and depend on human capital thresholds.

The results show that human capital does not automatically increase labor productivity, as its effect is negative at low and medium levels due to limitations in education quality, skills, and technology absorption. Its effect becomes positive and statistically significant only when human capital reaches the highest threshold. In addition, labor productivity is often constrained by natural resource rents, particularly in regimes with higher levels of human capital, while economic growth consistently has a positive effect across all regimes.

Policy implications. Based on these findings, Vietnam should shift its development strategy from quantity expansion to improving the quality of human capital through stronger higher education, skills training, and enhanced capacity for technological adoption. At the same time, dependence on natural resource rents should be gradually reduced, and closer linkages should be strengthened between human capital investment, technological innovation, and structural transformation to enhance labor productivity.

Limitations and future research. This study is limited by the use of national-level time-series data and the exclusion of institutional and innovation factors. Future research could employ panel data, dynamic threshold models, and indicators of institutional quality and innovation to better explain how human capital is transformed into labor productivity.

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