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Linking Social Investment in Education and Health to Labor Productivity: The Case of Vietnam

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Abstract

This study aims to evaluate the impact of investment in the education and healthcare sectors on labor productivity in Vietnam from 2000 to 2023. Grounded in human capital theory and the endogenous growth model, this study employs the Autoregressive Distributed Lag approach to examine both the short- and long-run relationships among key macroeconomic variables, including investment in education, investment in healthcare, foreign direct investment, and labor productivity. The empirical findings reveal that in the long run, investment in both education and healthcare exerts a positive influence on labor productivity. Specifically, investment in education is statistically significant at the 5% level, whereas healthcare investment is significant at the 10% level. Conversely, foreign direct investment does not exhibit a statistically significant effect on labor productivity in the long term. In the short run, education investment continues to show a positive and significant impact, whereas the effects of healthcare investment and foreign direct investment are positive, but not statistically robust. The error correction coefficient is negative and statistically significant, indicating a relatively rapid adjustment speed of 74.18% per year toward long-run equilibrium. The diagnostic tests confirmed the validity and reliability of the model. This study highlights the critical role of education and healthcare in enhancing labor productivity and recommends that the government prioritize strategic budget allocation and improve the efficiency of public investment to foster sustainable economic growth.

Keywords: *Education, Healthcare, Labor Productivity, ARDL, Human Capital.*

JEL Classigcation Code: I15; I25; J24; O40; F21.

Introduction

Labor productivity is a core determinant of economic growth and national competitiveness, particularly in the context of deepening globalization. In modern economic research, labor productivity not only reflects the efficiency of labor resource utilization, but also serves as a comprehensive measure of key input factors such as human capital, technology, and institutional quality. Among these, investment in education and healthcare is widely recognized as a critical pillar for enhancing the quality of human capital, thereby positively influencing labor productivity. In the case of Vietnam, a country undergoing a significant transition from an agriculture-based economy to one driven by industrialization and modernization, examining the impact of education and healthcare on labor productivity is not only theoretically relevant but also holds substantial practical value in shaping sustainable development policies.

Human capital theory, developed by economists such as Becker (1964) and Schultz (1961), provides a crucial theoretical foundation for understanding the relationship between investment in education, healthcare, and labor productivity. According to Becker (1964), education and

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training are forms of investment aimed at enhancing workers' skills, knowledge, and competencies, thereby increasing productivity and income. Similarly, Schultz (1961) emphasized that health, an inseparable component of human capital, plays a decisive role in maintaining and optimizing work performance. Healthy workers are able to work longer, less likely to be absent, and maintain higher levels of concentration than those in poor health. These two factors formed a causal chain. Education improves the capacity to absorb and apply new technologies and foster innovation, while healthcare ensures the physical and mental well-being necessary to translate knowledge into an effective labor output.

The endogenous growth models proposed by Lucas (1988) and Romer (1990) further reinforce the argument that investment in human capital is a primary driver of labor productivity and long-term economic growth. Unlike Solow's (1956) neoclassical growth model, which treats technology as an exogenous factor, the endogenous growth theory emphasizes the critical role of public policies, particularly government expenditure on education and healthcare, in generating a virtuous cycle among knowledge, health, and productivity. This perspective is especially relevant for developing countries, such as Vietnam, where limited financial resources necessitate strategic prioritization in investment allocation.

Furthermore, recent empirical studies have demonstrated a strong link between education, healthcare, and labor productivity. For instance, Gupta and Sharma (2023), using data from 15 developing countries, found that increased public spending on basic healthcare significantly enhanced average labor productivity. Similarly, Kim and Park (2024), through multivariate regression analysis of Korean data, showed that investment in technical education and vocational training substantially improves workers' technological adaptability, leading to higher productivity compared to those who only completed general education. Another study by Adebayo et al. (2023) in Africa revealed that the combination of improved mental health services and enhanced quality of higher education can boost labor performance, particularly in sectors requiring creative and cognitive skills.

Vietnam has made notable improvements in labor productivity in recent years; however, significant limitations remain when compared to other countries in the region. According to the General Statistics Office (GSO, 2023), the average annual growth rate of labor productivity in Vietnam over the past decade has reached approximately 4–5%, which is higher than the global average. Nevertheless, in absolute terms, Vietnam's labor productivity remains substantially lower than that of other ASEAN nations. For example, Vietnam's productivity is only approximately 20–25% in Singapore, 30% in Malaysia, and 50% in Thailand.

The relatively poor quality of human resources is one of the main reasons for low productivity. Although the proportion of trained workers has increased over time, the majority still lack specialized training or necessary skills to meet the demands of a digital and industrialized economy. This issue is particularly evident in labor-intensive sectors, such as textiles, footwear, and agricultural processing, where workers typically perform simple tasks and have limited access to advanced technologies.

In addition, the limited effectiveness of capital and technology utilization hampers productivity growth. Despite attracting substantial foreign direct investment (FDI), Vietnam has not fully realized the expected benefits in terms of technology transfer and workforce upskilling from the FDI sector. Most domestic enterprises continue to operate with outdated technologies, resulting in persistently low labor productivity.

In addition, factors such as working conditions, wage policies, workers' health, and the overall business environment exert a significant influence on labor productivity. To address these challenges, Vietnam must adopt long-term strategies focused on improving the quality of education and healthcare, promoting technological adoption, and enhancing workplace environments to foster sustainable productivity growth.

These issues underscore the need for an in-depth empirical study of how investment in education and healthcare impacts labor productivity in Vietnam. Such research is essential to inform strategic policy directions aimed at achieving sustainable future development in the coming period.

Literature Review

Education has long been considered a critical factor in promoting economic growth and enhancing labor productivity. Numerous studies have explored this relationship, yielding both consistent and divergent results, depending on the national context, level of analysis, and research methodology.

Al-Tal (1990), for instance, examined the impact of education on economic growth in Jordan during 1971–1988. The findings indicate that primary and lower-secondary education have a positive effect, whereas upper-secondary and tertiary education have a negative impact. This was attributed to rising unemployment among graduates due to the limited capacity of the labor market to absorb them. Similarly, Al-Zoubi and Al-Tal (2004) emphasized the importance of human capital investment in driving economic growth. Both studies highlight the critical role of basic education and suggest improving its quality to optimize its contribution to development.

At a broader level, Bergeaud et al. (2018), using data from 17 OECD countries between 1890 and 2013, demonstrated that educational attainment significantly influenced productivity growth, more so than physical capital. Hanushek (2013), based on research across more than 40 countries, concluded that, while developing nations have improved access to education, the gap in education quality and cognitive skills remains. Thus, quality of education is deemed a key determinant of long-term growth outcomes. Similarly, Jozičić and Škare (2016), in a study of Croatia, affirmed that the effectiveness of the education system matters more than the sheer volume of investment. Meanwhile, Priatna (2020) found that education and training positively affect labor productivity in the public sector, one of the few studies that assess education's impact at the micro level by specific sector.

Zhao (2019) presented an alternative perspective in the context of China, where the expansion of higher education was found to potentially exert a negative impact on labor productivity due to inefficient allocation of resources. In contrast, Delalibera and Ferreira (2019) highlighted that lower secondary education plays a critical role in boosting long-term productivity. This finding is supported by Krasniqi and Topxhiu (2016), who emphasized the importance of investing in education during adolescence. More recently, Belchik (2022) addressed the role of artificial intelligence in enhancing labor productivity, suggesting that higher education should focus on innovation and technology to meet rising productivity demands.

Despite the differences in methodology and context, most studies converge on the view that education plays a vital role in enhancing productivity and promoting economic growth. However, significant divergences remain in terms of geographic focus, sectoral analysis, and whether studies emphasize the quantity or quality of education. Some findings also indicate negative effects resulting from inefficiencies in education delivery or mismatches between skills and labor market needs. A key takeaway is that the quality of education is more crucial than quantity and that effective investment in foundational levels of education, such as lower-secondary education, can have substantial long-term effects on productivity.

Beyond education, healthcare and health status are essential components of human capital that directly influence labor productivity. Although research in this domain is abundant, findings are often mixed.

Knapp (2007), using height as a proxy for health in Italy and Denmark, found a positive correlation between health and labor productivity. Cole and Neumayer (2006) analyzed data from 52 developed and developing countries and concluded that poor health reduces total factor productivity. Bhargava et al. (2001), Using data from 125 countries, Bhargava et al. (2001) confirmed a positive correlation between adult survival rates (a proxy for health) and Gross Domestic Product (GDP). Dormont et al. (2008), studying the U.S., Japan, and OECD countries between 1970 and 2002, found that healthcare expenditure positively affects productivity, with predictive models suggesting a strong future increase in health spending. Similarly, Peykarjou (2011), in a study of OIC countries, reported a positive association between life expectancy and economic growth, while higher fertility rates were found to have a negative impact.

However, not all studies found a positive impact. In Pakistan, Bukhari and Butt (2007) argued that healthcare expenditure has no significant effect on labor productivity. Umoru and Yaqub (2013) concluded that while health status is positively associated with productivity, its relationship with GDP remains unclear. Eneji et al. (2013) suggested that public healthcare spending in Nigeria accounts for up to 53% of the variation in labor productivity. Wei et al. (2018) discovered that the impact of healthcare spending varied by region in China, was positive in urban areas, and negative in agricultural sectors. Mohammadzadeh et al. (2019) found clear evidence of a positive long-run relationship between healthcare expenditures and productivity in Iran. Similarly, Raghupathi and Raghupathi (2020) confirmed a strong positive association between public healthcare spending and productivity in the United States.

In summary, studies conducted in developed countries, such as the U.S., Japan, and Europe, tend to confirm the significantly positive effect of healthcare expenditure and health status on labor productivity. In contrast, findings from some developing countries such as Pakistan and Nigeria are inconsistent, indicating the potential influence of mediating factors such as healthcare infrastructure, the efficiency of public spending, and the broader policy environment.

The literature review also reveals that most existing studies focus on the individual effects of education or healthcare on economic growth or labor productivity. However, few studies have integrated both education and healthcare into a unified model to assess their combined impact on productivity. Moreover, the mixed findings across countries underscore the need for further empirical evidence to clarify the role of investment in education and healthcare in enhancing labor productivity, an essential requirement for the sustainable development of emerging economies such as Vietnam.

Based on the aforementioned literature review, this study proposes the following research model for Vietnam.

$$LBD_t = \beta_0 + \beta_1 EDU_t + \beta_2 MED_t + \beta_3 FDI_t + \varepsilon_t \quad (1$$

Where LBP denotes labor productivity, EDU represents total social investment in education and training, MED refers to total social investment in healthcare, and FDI indicates foreign direct investment. The dataset covers the period 2000–2023. The variable descriptions are presented in Table 1.

Acronyms	**Description**	**Sources**
LBD	Annual growth rate of output per worker (%)	International Labour Organization https://ilostat.ilo.org/data/#
EDU	Total Social Investment in Education and Training (% of GDP)	Vietnam Statistical Yearbook
MED	Total Social Investment in Medical (% of GDP)	
FDI	Foreign direct investment, net inflows (% of GDP)	https://databank.worldbank.org/source/world-development-indicators#indicators#

Table 1. Description of Variables

Source: author's compilation.

Model (1) was developed based on recent related studies, including those by Magableh et al. (2022), Ullah et al. (2019), and Yilmaz (2022). Specifically,

Magableh et al. (2022) analyzed the impact of education on labor productivity in Jordan during the period 1984–2018 by employing the Autoregressive Distributed Lag (ARDL) model to examine both short- and long-run relationships. The primary objective of this study was to identify the role of education as a component of human capital in promoting labor productivity growth, particularly in Jordan, which faces numerous challenges such as high unemployment, limited public spending on education, and pressures from refugee inflows. The research model included independent variables such as the capital-to-labor ratio, foreign direct investment, and an education index, with labor productivity, measured as real income per worker, serving as the dependent variable.

The study found that in the long run, all independent variables had a positive and statistically significant impact on labor productivity. However, in the short term, the education index exhibited a negative and statistically significant effect. This short-run negative effect was attributed to a mismatch between the quality and orientation of education and the actual needs of the labor market, resulting in high unemployment, even among the educated workforce. The study emphasized that while investment in education positively influences labor productivity in the long term, structural reforms and better alignment between the education system and labor market demands are essential to mitigate short-run inefficiencies. Accordingly, the authors recommend improving the quality of education, increasing vocational training opportunities, and enhancing public spending in the education sector.

Ullah et al. (2019) examined the impact of health status on labor productivity in Pakistan over the period 1980–2010 by employing the ARDL approach to assess both short- and long-run relationships among macroeconomic variables. The primary objective of this study is to determine the role of health capital, an essential component of human capital, in improving labor productivity. The dependent variable used in the model was GDP per employed person, representing labor productivity. The independent variables included life expectancy (as a proxy for health status), public expenditure on education (as a percentage of GDP, representing education capital), the consumer price index (reflecting inflation), and foreign direct investment (as a proxy for technology transfer).

The empirical results indicate that, in the long run, health status has a positive and statistically significant effect on labor productivity. Education expenditure also showed a positive impact, whereas FDI exerted a positive but statistically insignificant influence. In the short term, the effect of health on productivity was not statistically significant, whereas education continued to demonstrate a modest positive influence.

Based on these findings, the study recommends that the Pakistani government increase investment in both healthcare and education to enhance labor productivity, and at the same time, improve the absorptive capacity for technology transfer from FDI to promote sustainable economic growth.

Yilmaz (2022) investigated the long-run relationship between per capita healthcare expenditure and labor productivity in 35 OECD countries during 2000–2015, using panel data and advanced quantitative methods such as cointegration tests, Granger causality analysis, and the Augmented Mean Group estimator. In this study, labor productivity was measured by GDP per employed person, while the primary independent variable was per capita healthcare spending, representing investment in healthcare.

The findings confirm the existence of a long-run cointegrating relationship between healthcare expenditure and labor productivity, indicating that the two variables move together in a stable long-term pattern. Long-run regression estimates show that a 1% increase in per capita healthcare expenditure leads to an average increase of 0.0754% in labor productivity. This result demonstrates the statistically significant and positive impact of healthcare investment on labor productivity at the 1% significance level. Moreover, the Granger causality test revealed a bidirectional causal relationship between healthcare spending and labor productivity. This implies that increased healthcare investment improves workers' health, thereby enhancing productivity, whereas higher productivity levels generate greater income, enabling governments and households to invest more in healthcare. This study provides strong empirical evidence that investment in healthcare is a key driver of productivity growth in developed economies. Simultaneously, improved labor productivity contributes to expanding healthcare resources, thereby creating a sustainable development cycle.

Additionally, regarding the role of FDI in labor productivity, a recent study by Saha (2024) evaluated the effect of FDI on labor productivity and the moderating role of productive capacity. Using data from 88 countries between 2000 and 2018, the study found that FDI initially had a negative impact on labor productivity; however, once a country reached a certain threshold of productive capacity, the effect of FDI became positive. These findings highlight that FDI does not directly enhance productivity unless it is accompanied by sufficient domestic productive capacity. This study is the first to identify the threshold level at which FDI impacts shift, providing evidence that strengthening productive capacity is essential for maximizing the benefits of FDI on labor productivity. These results have important policy implications, recommending that countries focus on enhancing their productive capabilities to fully leverage foreign investment for productivity growth.

Methodology

ARDL model was selected because of its flexibility in capturing both long- and short-run relationships among time-series variables, an essential feature in macroeconomic research. Unlike traditional regression techniques, ARDL does not require all variables to be integrated in the same order as long as none of them are integrated of order two I(2). This makes ARDL a powerful tool for analyzing macroeconomic data, which often exhibit volatility and nonstationary trends over time.

Originally developed by Im et al. (2003), the ARDL model has been widely applied in empirical studies that examine national macroeconomic indicators. One of its key advantages is its ability to test for cointegration among variables without requiring them to be integrated in the same order. This feature is particularly valuable in Vietnam, where macroeconomic data often display mixed integration properties.

Additionally, ARDL is an unrestricted dynamic model in which the dependent variable is expressed as a function of its own lags and the lags of the explanatory variables. This structure allows the model to reflect the influence of past values on present and future outcomes, making it highly effective for analyzing economic shocks. Consequently, many researchers have adopted ARDL in macroeconomic studies because of its ability to provide reliable estimates for both short- and long-run relationships.

Overall, ARDL offers several significant advantages: it avoids issues related to the order of integration by allowing for variables that are I(0) or I(1) (but not I(2)); it is suitable for both large and small samples, unlike other methods that require large datasets for reliable estimation, and can yield unbiased estimates even when some explanatory variables are endogenous, thus offering better control over endogeneity bias (Adom et al., 2018). The Bounds testing procedure within the ARDL framework enables the identification of long-run equilibrium relationships through an Error Correction Model (ECM), which provides estimates for short- and long-run coefficients as well as the speed of adjustment toward equilibrium.

The ARDL quantitative analysis procedure is conducted in the following steps: first, the optimal lag length is determined using information criteria such as the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ) to select the most appropriate lag structure for the model.

Second, the stationarity of the variables is tested using the Augmented Dickey-Fuller (ADF) or Phillips-Perron (PP) unit root tests to ensure that none of the variables are integrated of order two I(2) and that the model contains a mix of I(0) and I(1) series.

Third, the cointegration relationship is tested using the bounds-testing approach to assess the existence of a long-run equilibrium among the variables. If the calculated F-statistic exceeds the upper-bound critical value (I(1)), evidence of a long-run relationship is confirmed.

Once cointegration is established and the optimal lag lengths are selected, the ARDL model is estimated to analyze both long-run and short-run dynamics.

Finally, the short-run effects of the explanatory variables are computed using an Error Correction Model (ECM), derived from the ARDL framework, following the methodology proposed by Engle and Granger (1987). The ECM not only captures short-term adjustments but also includes an error correction term that indicates the speed of adjustment to the long-run equilibrium after a shock.

Based on Equation (1), the ARDL regression model employed in this study was as follows:

$$\mathrm{DLBD_t} = \beta_0 + \sum_{i=>1} \beta_1 \mathrm{DLBD_{t-i}} + \sum_i \beta_2 \mathrm{DEDU_{t-i}} + \sum_i \beta_3 \mathrm{DMED_{t-i}} + \sum_i \beta_4 \mathrm{DFDI_{t-i}} + \lambda_1 \mathrm{LBD_{t-1}} + \lambda_2 \mathrm{EDU_{t-1}} + \lambda_3 \mathrm{MED_{t-1}} + \lambda_4 \mathrm{FDI_{t-1}} + \varepsilon_{it}$$

The model for assessing long-term impact is defined:

$$\mathrm{LBD_t} = \beta_0 + \lambda_1 \mathrm{LBD_{t-1}} + \lambda_2 \mathrm{EDU_{t-1}} + \lambda_3 \mathrm{MED_{t-1}} + \lambda_4 \mathrm{FDI_{t-1}} + \varepsilon_{1t}$$

And the model for assessing short-term impact is specified:

$$\mathrm{DLDB_t} = \beta_0 + \sum_{i=>1} \beta_1 \mathrm{DLBD_{t-i}} + \sum_i \beta_2 \mathrm{DEDU_{t-i}} + \sum_i \beta_3 \mathrm{DMED_{t-i}} + \sum_i \beta_4 \mathrm{DFDI_{t-i}} + \varepsilon_{2t}$$

The Error Correction Model (ECM) is evaluated based on the following specification:

$$\mathrm{DLBD_t} = \beta_0 + \sum_{i=>1} \beta_1 \mathrm{DLBD_{t-i}} + \sum_i \beta_2 \mathrm{DEDU_{t-i}} + \sum_i \beta_3 \mathrm{DMED_{t-i}} + \sum_i \beta_4 \mathrm{DFDI_{t-i}} + \psi \mathrm{ECM_{t-i}} + \varepsilon_{2t} \quad (5)$$

The Error Correction Model (ECM) is designed to capture short-run dynamics while accounting for long-run equilibrium relationships among variables. Coefficient ψ represents the speed of adjustment toward the long-run equilibrium following a deviation. If ψ is negative and statistically significant, it indicates the presence of a self-correcting mechanism whereby the dependent variable adjusts back to its long-run equilibrium level after a shock.

Regression Results

	LBP	EDU	MED	FDI
Mean	4.537375	0.983219	0.590299	4.838462
Median	4.732000	1.022190	0.588687	4.305017
Maximum	8.035000	1.377574	0.791968	9.663039
Minimum	1.994000	0.556310	0.465257	3.390404
Std. Dev.	1.447488	0.279664	0.088351	1.546602
Skewness	0.091014	-0.146342	0.336030	2.025834
Kurtosis	2.921561	1.607482	2.339085	6.322852
Jarque-Bera	0.239287	2.024772	0.888473	27.45736
Probability	0.980548	0.363351	0.641314	0.120001
Sum	108.8970	23.59726	14.16717	116.1231
Sum Sq. Dev.	48.19012	1.798877	0.179534	55.01550
Observations	24	24	24	24

Table 2. Descriptive Statistics of Variables

Source: Calculated by the author using Eviews

Table 2 presents descriptive statistics of the key economic variables, highlighting important characteristics of each indicator. Labor productivity (LBP) recorded an average growth rate of 4.54%, ranging from 1.99% to 8.04%, and followed an approximately normal distribution (Jarque-Bera: 0.98), indicating relatively stable productivity growth.

Education investment (EDU) averaged 0.98% of the GDP, fluctuating between 0.56% and 1.38%. However, the distribution is slightly left-skewed and platykurtic, suggesting that educational spending remains low and inconsistent. Healthcare investment (MED) averaged 0.59% of GDP, with a narrow range of 0.47% to 0.79%, and exhibited the lowest standard deviation among all variables. While this reflects stability, the investment level is significantly below international benchmarks and the distribution is slightly right-skewed.

FDI accounted for an average of 4.84% of GDP, with a wide range from 3.39% to 9.66%, indicating that FDI plays an important role in the economy but is highly volatile, with several periods of sharp increases.

In comparative terms, FDI and LBP exhibit a greater influence on the economy, whereas EDU and MED reflect relatively limited social investment, which should be enhanced to support sustainable development. These statistics offer a clear picture of resource allocation and the variability of key economic drivers, thereby providing valuable insights for policy formulation.

	LBP	EDU	MED	FDI
LBP	1.00000	0.35327	-0.13228	-0.39265
EDU	0.35327	1.00000	0.58723	0.18687
MED	-0.13228	0.58723	1.00000	-0.04502
FDI	-0.39265	0.18687	-0.04502	1.00000
Source: Calculated by the author using Eviews				

Table 3. Correlation Coefficients of Variables

Table 3 indicates the correlation coefficients among LBP, EDU, MED, and FDI. The results indicate a positive correlation between labor productivity and educational investment, suggesting that higher educational investment may support productivity growth, although the strength of this relationship is modest. In contrast, LBP is negatively correlated with both healthcare investment (MED) and FDI, with the correlation between LBP and FDI being notably negative. This may imply that increasing FDI does not necessarily lead to improved labor productivity, potentially because FDI is concentrated in sectors that do not generate high value-added labor.

There is a strong positive correlation between EDU and MED, indicating that investments in education and healthcare often go hand-in-hand, reflecting a coordinated approach to social development policy. EDU also shows a weak positive correlation with FDI, implying that better education may help attract FDI, although this relationship is not particularly strong. By contrast, MED and FDI are weakly and negatively correlated, suggesting that increased healthcare investment does not necessarily coincide with higher FDI inflows.

Overall, the correlation coefficients revealed a complex interplay between the variables. EDU appears to have a positive influence on both LBP and MED, while FDI does not demonstrate a clear positive impact on productivity or social investment, warranting further investigation of the structure and effectiveness of FDI.

According to Mukaka (2012), applying the empirical rule for interpreting the correlation strength, the independent variables in the model exhibit moderate intercorrelation, with all coefficients below 0.70. This ensures the absence of multicollinearity and satisfies one of the key conditions for a reliable model estimation.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-49.65398	NA	0.001249	4.665564	4.863041	4.715229
1	-22.34322	42.74727*	0.000480*	3.682020*	4.669406*	3.930344*

Table 4. Optimal Lag Selection

Source: Calculated by the author using EViews

Table 4 demonstrates the results of optimal lag selection for the ARDL model based on several information criteria, including the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ), with lag lengths of 0 and 1 under consideration. The results indicate that a lag length of one is optimal, as it is favored by the majority of the criteria. Specifically, the values for lag 1—LR (42.74727), FPE (0.000480), AIC (3.682020), SC (4.669406), and HQ (3.930344)— were all superior and marked with an asterisk (*), indicating the best fit.

By contrast, at lag 0, the corresponding values are LogL (–49.65398), FPE (0.001249), AIC (4.665564), SC (4.863041), and HQ (4.715229), which are all less favorable than lag 1. The log-likelihood value at lag 1 (–22.34322) was significantly higher than that at lag 0, further confirming that the model with lag 1 had a better fit to the data.

Criteria such as AIC, SC, and HQ, which are commonly used to balance the model goodness-of-fit against complexity, consistently support the selection of lag 1. This reinforces the choice of Lag 1 as the optimal lag structure for the subsequent model estimation.

Variables	ADF		PP	
	No Trend	Trend	No Trend	Trend
I(0)				
LBP	-3.009253**	-3.275906*	-3.040432**	-3.363631*
EDU	-0.351086	-5.746227	-1.184066	-4.159215**
MED	-3.148873**	-4.472514***	-3.207123**	-4.506563***
FDI	-3.339791	-3.249715	-2.369327	-2.316363
I(1)				
LBP	-5.206732***	-5.075127***	-8.055881***	-8.362599***
EDU	-10.69268***	-10.45665***	-10.35181***	-10.17224***
MED	-7.775305***	-7.848955***	-9.387748***	-10.47306***
FDI	-3.944985***	-3.885097**	-3.269164**	-3.185081**

Table 5. Stationarity Test Results of Variables

Note: The symbols ***, **, and * indicate that the series is stationary at the significance levels of 1%, 5%, and 10%, respectively. Source: Calculated by the author using Eviews

Table 5 exposes the unit root test results for the variables LBP, EDU, MED, and FDI using both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) methods, conducted at both level I(0) and first difference I(1). At level, LBP and MED are stationary under both tests at the 1%, 5%, and 10% significance levels, with test statistics of –3.009253 and –3.148873 (ADF) and –3.40432 and –3.20712 (PP), respectively. In contrast, EDU is stationary only when a trend is included (ADF: –5.746227; PP: –4.159215), while FDI is non-stationary in both intercept-only and trend-included cases (ADF: –3.339791; PP: –2.369327).

At the first difference, I(1), all variables become stationary at the 1% significance level, with very low test statistics, such as LBP (ADF: –5.206732; PP: –8.055881), EDU (ADF: –10.69268; PP: –10.35181), MED (ADF: –7.775305; PP: –9.387748), and FDI (ADF: –3.944985; PP: –3.269164).

These results indicate that the variables are integrated in mixed order: LBP and MED are stationary at level I(0), whereas EDU and FDI are stationary only at the first difference I(1). Therefore, the ARDL estimation method is appropriate for this study because it allows for variables of mixed integration orders (I(0) and I(1)) and enables the examination of both short- and long-run relationships within the model.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	5.810224	10%	2.72	3.77
K	3	5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61

Table 6. Bound Test Results

Source: Calculated by the author using Eviews

Table 6 displays the results of the F-bounds test used to examine the existence of a long-run relationship among the variables, with the null hypothesis stating that no level relationship exists. The computed F-statistic is 5.810224, with k =3 (corresponding to three independent variables). This value is compared against critical bounds at various significance levels for both I(0) and I(1) cases. At the 10% significance level, the critical values are 2.72 (I(0)) and 3.77 (I(1)); at 5%, they are 3.23 and 4.35; at 2.5%, they are 3.69 and 4.89; and at 1%, the bounds are 4.29 and 5.61.

Because the F-statistic of 5.810224 exceeds the upper bound (I(1)) at the 1% level (5.61), the null hypothesis of no long-run relationship is strongly rejected. This provides robust evidence for the existence of a long-run cointegrating relationship among the variables LBP, EDU, MED, and FDI within the ARDL framework.

These findings are consistent with the unit root test results in Table 5, which confirm mixed integration orders (I(0) and I(1)), further validating the suitability of the ARDL approach. Consequently, the Bounds test confirms the presence of cointegration, justifying further analysis of both short- and long-run dynamics using ARDL methodology to gain deeper insights into the relationships among the variables.

Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
The dependent variable: LBP. Long-Term Estimation Results				
EDU	4.349760	1.988813	-2.187113	0.0430

MED	13.54912	7.406250	1.829417	0.0849
FDI	-0.236724	0.232119	-1.019839	0.3221
The dependent variable: D(LBP). Short-Term Estimation Results				
C	1.311865	2.742109	0.478414	0.6385
LBP(-1)	-0.741775	0.183099	-4.051225	0.1008
EDU	3.226541	1.439449	-2.241510	0.0386
MED(-1)	10.05039	5.073948	1.980783	0.1640
FDI	0.175596	0.174565	-1.005902	0.0286
D(MED)	2.754949	4.011472	0.686768	0.5015
CointEq(-1)*	-0.741775	0.152765	-4.855669	0.0001

Table 7. Estimation Results

Source: Calculated by the author using Eviews

Long-run regression results: Investment in education and training has a positive and statistically significant impact on labor productivity growth, with a coefficient of 4.349760 and a p-value of 0.0430 ($p < 0.05$). This indicates that educational investment positively contributes to labor productivity in the long term. Healthcare investment also showed a positive coefficient (13.54912) and was statistically significant at the 10% level ($p = 0.0849$), suggesting a potential positive effect of healthcare spending on productivity growth. In contrast, FDI has a negative coefficient (–0.236724) and is not statistically significant ($p = 0.3221$), implying that FDI does not have a clear long-run impact on labor productivity in the Vietnamese context.

Short-run regression results: Investment in education and training continues to have a positive and statistically significant impact on labor productivity in the short run, with a coefficient of 3.226541 and a p-value of 0.0386. This reinforces the finding that educational investment is beneficial in both the short and long terms. Healthcare investment also has a positive short-run effect (coefficient: 10.05039), but is not statistically significant ($p = 0.1640$), indicating that the evidence is insufficient to confirm a robust short-term impact. On the other hand, FDI has a positive and statistically significant short-run effect on labor productivity (coefficient: 0.175596, $p = 0.0286$), indicating that FDI contributes positively to short-term productivity growth. The error correction term CointEq(–1) is negative (–0.741775) and highly statistically significant ($p = 0.0001$), confirming the presence of a stable long-run equilibrium relationship. This value implies that approximately 74.18% of the deviations from the long-run equilibrium in labor productivity are corrected within each period, reflecting a relatively fast adjustment process toward equilibrium.

No	**Test**	**P-Value**	**Results**
1	Normality test	0.6644	The residuals follow a normal distribution.

No	Test	P-Value	Results
2	Breusch-Godfrey Serial Correlation LM Test	0.2913	No autocorrelation
3	Heteroskedasticity Test: Breusch-Pagan-Godfrey	0.5027	No heteroskedasticity
4	Ramsey Reset Test	0.7312	No need for additional variables

Table 8. Diagnostic Test Results

Source: Calculated by the author using Eviews

Table 8 reports the results of post-estimation diagnostic tests for the ARDL model, including four key tests to assess the model's validity. First, the Normality Test yields a p-value of 0.6644, which is greater than 0.05, indicating that the residuals follow a normal distribution, satisfying one of the fundamental assumptions of classical regression. Second, the Breusch-Godfrey Serial Correlation LM Test shows a p-value of 0.2913, also above 0.05, suggesting that there is no serial correlation in the residuals, thereby confirming the independence of errors. Third, the Heteroskedasticity Test (Breusch-Pagan-Godfrey) provides a p-value of 0.5027, which exceeds the 0.05 threshold, indicating the absence of heteroskedasticity and confirming that the variance of residuals is constant (homoscedastic). Lastly, the Ramsey RESET Test returns a p-value of 0.7312, again higher than 0.05, implying that no omitted variables are present and that the functional form of the model is correctly specified. Overall, these diagnostic tests confirm that the ARDL model is well-specified and does not violate the key classical regression assumptions, thereby ensuring that the estimated relationships among the variables can be interpreted with confidence.

Variables	Coefficient Variances	Centered VIF
LBP(-1)	0.033525	1.161215
EDU	2.072015	2.437427
MED	16.09190	2.026669
MED(-1)	10.43124	1.225575
FDI	0.030473	1.194627

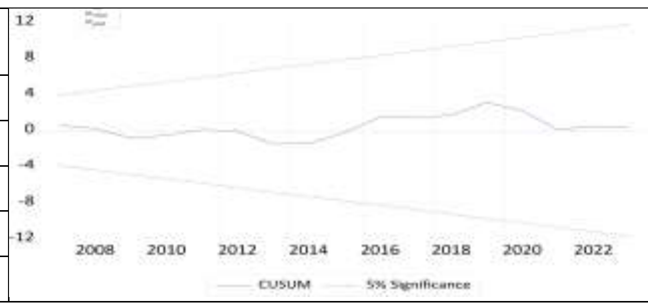

Table 9. Variance Inflation Factor (VIF) and CUSUM Test Results

Source: Calculated by the author using Eviews

Table 9 shows the results of the Variance Inflation Factor (VIF) and CUSUM test to assess the robustness and structural stability of the ARDL model. Regarding VIF, all variables exhibit low-centered VIF values, ranging from 1.194627 (FDI) to 2.437427 (EDU), all well below the commonly accepted threshold of 10. Hair et al. (2006) indicate that the model estimating long-run effects does not suffer from multicollinearity among the independent variables (LBP(-1), EDU, MED, MED(-1), and FDI). Specifically, the variance values for the variables were LBP(-1): 0.033525, EDU: 2.072015, MED: 16.09190, MED(-1): 10.43124, and FDI: 0.030473, with corresponding VIF values of 1.61215, 2.437427, 2.026669, 1.225575, and 1.194627, respectively. These results confirm that there was no serious collinearity problem in the model. In the CUSUM test, the plotted CUSUM line (blue) remained within the 5% significance bounds (orange lines) throughout the study period. This indicates that the ARDL model is structurally stable with no significant parameter shifts over time. Overall, the VIF and CUSUM test results confirm that the model is free from multicollinearity and is structurally stable, ensuring the reliability of the ARDL regression findings.

Conclusion and Policy Implications

Conclusion

This study employs the ARDL model to examine the effects of investment in education, healthcare, and FDI on labor productivity in Vietnam. The results indicate that in the long run, both education and healthcare investment have positive impacts on labor productivity. Specifically, educational investment is statistically significant at the 5% level, confirming its crucial role in enhancing workforce performance. This aligns with previous findings from Hanushek (2013), Jozičić and Škare (2016), and Magableh et al. (2022), which emphasize the decisive role of education quality in long-term growth.

Likewise, healthcare investment demonstrates a positive long-term impact, consistent with the findings of Yilmaz (2022) and Dormont et al. (2008), underscoring the importance of workers' health in improving productivity. However, FDI does not show statistical significance in the long run, suggesting that Vietnam is yet to fully leverage technology transfer from FDI inflows, a concern also highlighted by Saha (2024), who argues that domestic productive capacity is a prerequisite for FDI to yield positive outcomes.

In the short run, educational investment continues to exert a statistically significant and positive influence on labor productivity, reinforcing the importance of sustained investment in this sector. In contrast, healthcare investment, although positively signed, lacks statistical significance, potentially due to time lags in effect or unequal efficiency across regions, which is consistent with Wei et al. (2018) in the Chinese context. Notably, FDI has a positive and statistically significant impact in the short run, indicating that foreign capital provides immediate benefits to labor markets and technological advancement, although such effects may not persist over time.

The estimated error correction term indicates a speed of adjustment of 74.18% per period, suggesting a strong and rapid return to the long-run equilibrium after deviations. Overall, the findings confirm that investment in education and healthcare forms a solid foundation for enhancing labor productivity and emphasizes the need for policies to improve both the quality and effectiveness of FDI utilization.

Policy Implications

Based on the above findings, the following policy recommendations are proposed for the Vietnamese government to promote labor productivity growth:

Increased investment in education and training. Given the significant and positive impact of education on labor productivity in both the short and long terms, the government should prioritize education spending, especially in technical training, digital skills, and innovation-driven programs.

Enhancing healthcare investment for long-term efficiency. Although the current effect of healthcare spending is not statistically strong, its positive direction suggests that long-term strategies are required to improve service quality. A healthy workforce is critical to sustaining productivity and economic growth.

Reassess FDI attraction strategies to improve the impact. As FDI has a positive effect only in the short term and lacks long-term significance, the government should target high-quality FDI, particularly in high-tech sectors, knowledge transfer, and workforce upskilling.

Promote macroeconomic stability and adaptive policy frameworks. As the error correction speed indicates rapid equilibrium restoration, the government must closely monitor economic shocks and adopt flexible macroeconomic policies to maintain sustainable productivity growth.

Integrating fiscal policy with enterprise development. A favorable business environment should be fostered through tax incentives, financial support, and innovation encouragement, enabling firms to invest in workforce development and technological improvements.

In summary, the government should prioritize investment in education and healthcare, enhance the quality of FDI, maintain macroeconomic stability, and support a sustainable business ecosystem to maximize labor productivity in both the short and long term.

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