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Impact of Health on Labour Productivity in Morocco: Insights from Dynamic ARDL and KRLS Techniques

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Abstract:

This study examines the impact of health, as measured by life expectancy (LE), on labour productivity, measured by GDP per capita (GDPC), in Morocco from 1990 to 2021. Utilizing a dynamic Autoregressive Distributed Lag (DYNARDL) model, along with the Kernel-Based Regularized Least Squares (KRLS) method, we assess the counterfactual impact of life expectancy while holding other variables constant. Our findings indicate that life expectancy has a significant and positive effect on labour productivity in both the short and long term. Specifically, a 1% increase in LE leads to a 6% increase in GDPC in the long run, while in the short run, this effect is even more pronounced, with a 1% change in LE resulting in a 14% variation in GDPC. These results highlight the critical role of health improvements in enhancing economic productivity in developing economies, aligning closely with the Sustainable Development Goals (SDGs), particularly Goal 3 - Good Health and Well-being and Goal 8 - Decent Work and Economic Growth. Additionally, DYNARDL simulations suggest that a projected 10% increase in life expectancy could initially accelerate labour productivity, although this acceleration rate diminishes over time, eventually stabilizing. These findings underscore the importance of sustained health investments to achieve not only long-term economic growth in Morocco but also broader SDG targets, such as reducing inequalities and fostering sustainable, inclusive economic development.

Keywords: health, life expectancy, labour productivity, developing economy, dynamic ARDL, KRLS, Morocco.

JEL Classification: I15; E24; J24; C54.

Introduction

Theories on economic growth suggest that capital accumulation and technological advancement are crucial for a country's development. Physical and human capital are the most important in determining the economic growth of a country.

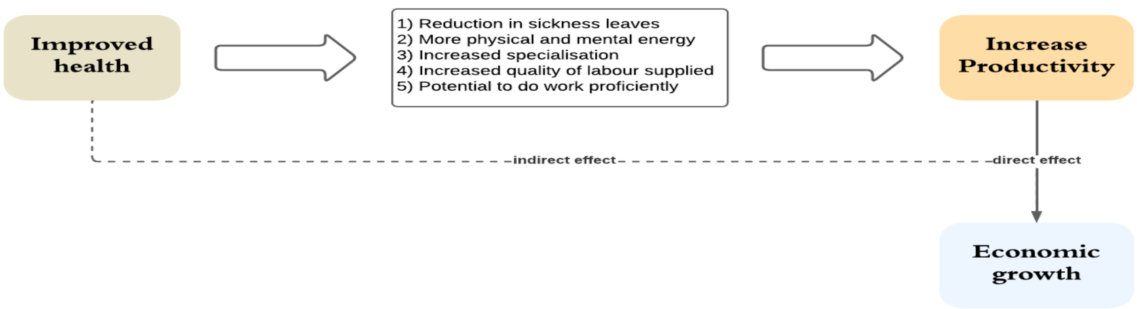
In human capital theory, health is recognized as a critical aspect of individuals', nations' development and economic well-being worldwide. African countries have taken a series of reforms to boost investment in health and meet the Sustainable Development Goals (SDGs).

Furthermore, the contributions of health to human capital development and economic simulation draw attention to the involvement of governments in improving this sector, especially in developing countries (Wu et al., 2021; Beylik et al., 2022). Considering the importance of economic growth, governments try to invest more and more in human capital, in particular in the health and education sectors, which leads to an increase in productivity and positively affects the economic outlook (Lucas, 1988; Mankiw et al., 1992; Arrow et al., 1995).

In many developing countries, inadequate health conditions have the potential to impede economic growth and hinder progress in development (Schultz, 2005). Insufficient healthcare and social security in these countries result in significant welfare losses due to illness, preventing individuals from working and supporting their dependents. At the aggregate level, productivity and economic development can be affected negatively by poor health and high disease burden. So, improved health can increase the economic output by 4%, as explained by Bloom et al. (2004).

Also, improving health can promote economic growth by (1) reducing losses in productivity due to workers being ill, (2) enabling the use of natural resources that were previously inaccessible because of disease, (3) raising school enrolment, which in turn enhances learning, and (4) freeing up resources that would otherwise have been spent on treating diseases. (Lea, 1993). The research literature consistently demonstrates a positive link between health and economic growth, mediated by productivity. (Barro, 1991; Levine & Renelt, 1992; Bhargava et al., 2001; Bloom et al., 2004) This connection, although not direct, signifies that improvements in health conditions contribute to increased economic growth, primarily through enhanced productivity (Figure 1).

Figure 1: Nexus between health, labour productivity and economic growth



Source: developed by the authors

The Moroccan government has implemented several social programs and increased healthcare spending to enhance social welfare and promote social inclusion in the economy, such as building new hospitals, increasing the number of doctors and nurses in training, and opening the market to private investment. According to the National Population and Family

Health Survey ((NPFH, 2018)), key health indicators in Morocco have significantly improved. For instance, life expectancy at birth has remarkably increased, from 47 years in 1967 to 74.8 years in 2013. Also, the infant mortality rates have experienced a substantial decline, dropping from 113.6 in 1967 to 28.8 per thousand live births in 2013. Similarly, maternal mortality has significantly decreased, from 359 in 1981 to 112 per hundred thousand live births in 2013 (NPFH, 2018).

Nevertheless, the current healthcare system in Morocco faces substantial resource deficits, especially in human resources. Despite an increased budget in recent years, investment in health has remained relatively low, hovering between 4% and 6% of the GDP from 2000 to 2019. The COVID-19 crisis has not only exposed the weaknesses of this system but has also emphasized the insufficiencies in social protection mechanisms.

In this context, the Moroccan government initiated a national project to generalize social protection to all citizens in 2021. Moreover, they allocated $2.4 billion to the healthcare system in 2022. This project comprises four primary objectives: Firstly, they intend to make basic compulsory health insurance available to everyone in 2022. Secondly, their objective is to universalize family allowances by 2024. In 2025, they plan to extend pension scheme membership to all employees currently without pension coverage. Finally, they will universalize job loss indemnity by 2025.

Given the above, the present study examines the relationship between labour productivity and health in the long and short run in Morocco from 1990 to 2021 using a dynamic ARDL approach.

The paper is structured as follows: After introduction, Section 1 provides a literature review of health-labour productivity; Section 2 presents the data and the empirical model; Section 3 outlines the methodology such as ARDL, DYNARDL, and KRLSS models; Section 4 covers the results and discussion, and last Section concludes the paper.

1. Literature Review

Many variables, such as human capital (Abdelgany & Saleh, 2023), trade, financial development, innovation, industrialization (Samargandi, 2018), capital deepening, institutional quality, technology, agriculture (% GPD), and inflation (Dua & Garg, 2019), determine labour productivity. Numerous studies have explored the link between health and labour productivity at the micro and macro levels. This literature review aims to summarize key findings and insights from previous studies.

Knapp (2007) examined the link between health and labour productivity using adult height as a health measure. The study utilized the Cochrane-Orcutt regression methodology, and the results indicated a strong positive correlation between height and labour productivity in Italy and Denmark. Bhargava et al. (2001) examined the correlation between GDP and adult survival rate across developing and developed countries. Utilizing a panel model, the authors found a strong positive correlation between adult survival rate and GDP. Cole & Neumayer (2006) used a Two-Stage Least Squares regression (2SLS) model on panel data from 52 countries between 1965 and 1995. They found that poor health and inflation negatively affect productivity in both developed and developing countries.

On the other hand, Raghupathi & Raghupathi (2020) added other variables, such as income and labour productivity, to explain the link between health and economic performance. They find a positive effect of health expenditures on labour productivity, income, and GPD through a Visual Analytics Method.

Similarly, Dormont et al. (2008) also examined this relation for USA, Japan, and 30 OECD countries by employing various regression models such as Pooled Panel Regression, one and two fixed effect regressions. The results showed a positive correlation between health expenditures and productivity. However, this correlation reports mixed results.

In the same way, Haider & Butt, (2006) employed VAR and ECM models to analyse the correlation between these variables in Pakistan. The empirical results indicated a negative impact of health expenditure on GDP and no significant association between them. Umoru & Yaqub, (2013) used a GMM method to investigate the relationship between labour productivity and health in Nigeria from 1975 to 2010. Their research revealed a positive correlation between these two variables, with education and technology also positively influencing productivity. Kedir (2009) utilized household panel data from Ethiopia between 1994 and 2000 to estimate a relationship between health indicators (indicated by height and Body Mass Index) and wages (as a measure of productivity/growth). The study revealed that education, height, and Body Mass Index positively and significantly impact productivity.

Many studies attempt to determine the relationship between health and labour productivity by estimating their elasticities. The following Table 1 displays these studies that include measures of health and labour productivity:

Table 1: Elasticities between health and labour productivity

Study	Productivity measures	Health measures	Countries and time period	Model and econometric methods	Elasticities
Baharin et al. (2020)	Gross Domestic Product (GDP) per worker	Life expectation	Indonesia (1981–2014)	Log-log model ARDL approach	0.34 – 0.35
Rivera & Currais, (1999)	Gross Domestic Product per worker	Health expenditure as a % of GDP	24 OECD countries (1960–90)	Log-log model OLS estimation and instrumental variables	0.21–0.22
Bhargava et al. (2001)	GDP per capita growth	Adult survival rate	Panel of countries (1965–90)	Panel model static random effects models	0.192-0.333
Barro & Lee (1994)	GDP growth rate per capita	Life expectancy	1965-1975 1975-1985	SUR with country random effects	0.58
Saha (2013)	TFP growth	Life expectancy	India 1961-2008	Growth accounting method to estimate TFP growth and OLS	0.0019
Ullah et al. (2019)	GDP per person employed	Life expectancy	Pakistan 1980 - 2010	ARDL approach	0.0945
Aghion et al. (2010)	GDP per capita	Life expectancy	OECD countries 1960-2000	OLS Estimates	0.43- 0.91

Source: developed by the authors

2. Data and Empirical Model

The study's main objective is to investigate health's impact on labour productivity in Morocco using data from 1990 to 2021. The following model is written as:

$$GDPC_t = f(CPI_t, FDI_t, LE_t, EDUC_t) \quad (1)$$

In our model, GDPC represents GDP per capita, obtained by dividing GDP by the total population and expressed as GDP per hour worked, times the number of hours worked per person. It serves as a proxy for labour productivity (OECD, 2014). Life expectancy at birth (LE) measures health, while CPI reflects the effect of inflation. EDUC refers to expenditure in the education sector, and the current model also considers foreign direct investment (FDI) as a proxy for technology transfer, significantly affecting productivity.

In the Table 2, we presented a definition of each variable, along with their respective data sources and periods.

Table 2: The definition of each variable

Symbol	Description	Unit	Source
$\mathbf{GDPC_t}$	GDP per capita	dollar/person	World Bank Open Data (2023)
$\mathbf{CPI_t}$	Inflation rate	%	World Bank Open Data (2023)
$\mathbf{FDI_t}$	Foreign direct investment	dollar	UNCTADstat, (2023)
$\mathbf{LE_t}$	Life expectancy at birth	years	World Bank Open Data (2023)
$\mathbf{EDUC_t}$	The government's total public expenditure in the education sector	Current LCU	MENARADATA

Source: developed by the authors.

The model mentioned above can be written as follows:

$$ln(GDPC_t) = \alpha_0 + \alpha_1 \ln(CPI_t) + \alpha_2 \ln(FDI_t) + \alpha_3 \ln(LE_t) + \alpha_4 \ln(EDUC_t) + \varepsilon_t \quad (2)$$

where: ε_t – error, α_0 is the constant term, α_1, α_2, α_3, α4, α_4 are the coefficients (elasticities).

All the variables are used in log form. Using a log-log econometric model has several advantages. The coefficients represent elasticities, which show the percentage changes in the dependent variable associated with a 1% change in the independent variable. Percentage changes are more meaningful than absolute changes. By taking the variables' natural logarithm, the data's scale is normalized, which helps mitigate the impact of outliers and heteroskedasticity. This leads to more robust estimates and can improve the data's statistical properties, such as reducing heteroskedasticity, stabilizing variance, and improving the normality assumption of the error term. Table 3 and Table 4 presents summary statistics and correlation between the variables, while Figure 2 displays the plots of these variables.

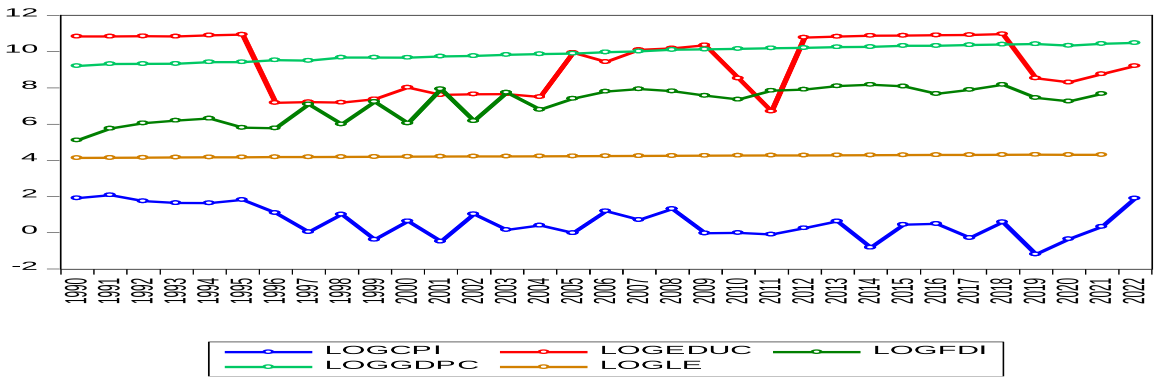
Based on the summary statistics, it is evident that all variables follow a normal distribution as the Jarque-Bera (JB) probability is higher than 1% and 5%.

Table 3: Statistics summary

	LOGGDPC	LOGCPI	LOGEDUC	LOGFDI	LOGLE
Mean	9.911971	0.547482	9.367051	7.131051	4.231398
Median	9.933239	0.467588	10.02497	7.430500	4.232884
Maximum	10.43749	2.077711	10.97767	8.177797	4.307707
Minimum	9.215419	-1.192749	6.706862	5.105945	4.134334
Std. Dev.	0.385649	0.836116	1.552731	0.901991	0.054258
Skewness	-0.254468	0.089200	-0.323911	-0.635911	-0.162344
Kurtosis	1.724120	2.271346	1.420406	2.017654	1.782345
Jarque-Bera	2.515849	0.750351	3.886390	3.443381	2.117476
Probability	0.284243	0.687169	0.143246	0.178764	0.346893
Sum	317.1831	17.51942	299.7456	228.1936	135.4048
Sum Sq. Dev.	4.610486	21.67177	74.74019	25.22124	0.091261
Observations	32	32	32	32	32

Source: developed by the authors

Figure 2: Plot of variables



Source: developed by the authors.

Table 4: Correlation matrix

	LOGGDPC	LOGEDUC	LOGCPI	LOGFDI	LOGLE
LOGGDPC	1.0000				
LOGEDUC	0.0643	1.0000			
LOGCPI	-0.6685	0.3644	1.0000		
LOGFDI	0.8325	0.0803	-0.6706	1.0000	
LOGLE	0.9958	0.0711	-0.6823	0.8216	1.0000

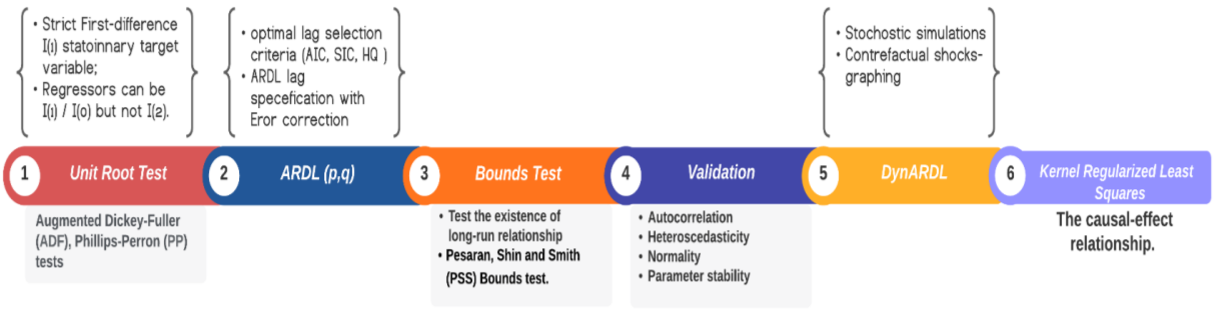
Source: developed by the authors.

3. Methodology: ARDL and DYNARDL Approach

Figure 3 below shows six stages for modelling the impact of health (measured by Life expectancy) on labour productivity (measured by GDP per capita) in Morocco. In the first step, we use ADF and PP tests to check stationarity and identify the integration order. In the second step, we estimated the ARDL model when all variables integrate into I(0) and I(1) to specify short- and long-run associations between variables. In the third step, we employed the

Pesaran, Shin, and Smith Bounds (PSS) test to ascertain the existence of long-term cointegration. We employ stability tests to validate our ARDL model during the fourth step. In the fifth step, we perform DYNARDL simulations. In the sixth step, we use a type of machine learning called kernel-based regularized least squares (KRLS) to find causal associations among the variables.

Figure 3: Modelling steps



Source: developed by the authors.

ARDL Model

Numerous cointegration techniques exist for analysing the long-term relationship between macroeconomic variables. (Granger, 1981; Engle & Granger, 1987; Johansen & Juselius, 1990; Johansen, 1995)

We analysed the impact of health on labour productivity in Morocco using data from 1990-2021 by employing the cointegration technique developed by Pesaran & Shin (1995) and Pesaran et al. (2001). Using this technique offers numerous advantages compared to traditional methods. Initially, this approach is appropriate for a limited number of observations. The present study covers 32 yearly observations (Table 3), making it a better fit for this case. In contrast, traditional cointegration methods need a substantial sample size and are not applicable to a small sample (Narayan & Narayan, 2005). Furthermore, the traditional methods require solving a large number of equations, whereas this approach is easy to use and interpret. The ARDL model used in this study can be represented by equation (3).

$$\begin{aligned}\Delta\, lnGDPC_t &= \alpha_0 + \sum_{i=1}^{p} \tau_i \Delta \ln(GDPC_{t-1}) + \sum_{i=1}^{p} \beta_i \Delta \ln(CPI_{t-1}) + \sum_{i=1}^{p} \theta_i \Delta \ln(FDI_{t-1}) \\ &+ \sum_{i=1}^{p} \vartheta_i \Delta \ln(LE_{t-1}) + \sum_{i=1}^{p} \delta_i \Delta \ln(EDUC_{t-1}) + \gamma_{GDPC} \ln(GDPC_{t-1}) \\ &+ \gamma_{CPI} \ln\,(CPI_{t-1}) + \gamma_{FDI} \ln\,(FDI_{t-1}) + \gamma_{LE} \ln\,(LE_{t-1}) + \gamma_{EDUC} \ln\,(EDUC_{t-1}) \\ &+ \varepsilon_t \end{aligned} \tag{3}$$

where: τ_i , β_i, θ_i, ϑ_i, δ_i refer to constant intercepts, γ_{GDPC}, γ_{CPI}, γ_{FDI}, γ_{LE}, γ_{EDUC} are the long-run coefficients, and ε_t is the error term.

Equation 3 tests for the long run level relationship.

$H_0: \gamma_{GDPC} = \gamma_{CPI} = \gamma_{FDI} = \gamma_{LE} = \gamma_{EDUC} = 0$: no long run relationship

$H_1: \gamma_{GDPC} \neq \gamma_{CPI} \neq \gamma_{FDI} \neq \gamma_{LE} \neq \gamma_{EDUC} \neq 0$: long run relationship exists.

If H_0 is rejected, we can infer that cointegration exists. Equation 4.1 estimates long-run coefficients, whereas equation 4.2 estimates short-run coefficients for cointegrated variables. ((Pesaran et al., 2001))

$$\boldsymbol{l}nGDPC_t = \alpha_0 + \sum_{i=1}^{p} \delta_{GDPC} \ln(GDPC_{t-1}) + \sum_{i=1}^{p} \delta_{CPI} \ln(CPI_{t-1}) + \sum_{i=1}^{p} \delta_{FDI} \ln(FDI_{t-1}) + \sum_{i=1}^{p} \delta_{FDI} \ln(FDI_{t-1}) + \sum_{i=1}^{p} \delta_{LE} \ln(LE_{t-1}) + \varepsilon_{0t} \tag{4.1}$$

$$\Delta\, lnGDPC_t = \alpha_1 + \sum_{i=1}^{p} \tau_{1i} \Delta \ln(GDPC_{t-1}) + \sum_{i=1}^{p} \beta_{1i} \Delta \ln(CPI_{t-1}) + \sum_{i=1}^{p} \theta_{1i} \Delta \ln(FDI_{t-1}) + \sum_{i=1}^{p} \vartheta_{1i} \Delta \ln(LE_{t-1}) + \sum_{i=1}^{p} \delta_{1i} \Delta \ln(EDUC_{t-1}) + \gamma_{ECM} \mathrm{ECM_{t-1}} + \varepsilon_{1t} \tag{4.2}$$

where: ECM is the error correction term, while Δ representing the first difference operator.

Equation 4.1 provides long-term coefficients for level variables at the optimal lag p. Equation 4.2 estimates short-term coefficients by employing an ECM model. γ_{ECM} in 4.2 represents the speed of adjustment to equilibrium position in response to shocks. It is expected to have a negative value and be statistically significant. The ECM lagged by one period describes the speed of adjustment to equilibrium from the previous shock.

Equation 4.2 coefficients demonstrate the short-run effect of independent variable on $\Delta\, lnGDPC_t$, and equation 4.3 illustrates ECM's recovery speed from deviation.

$$ECM_t = lnGDPC_t - \alpha_0 - \sum_{i=1}^{p} \delta_{GDPC} \ln(GDPC_{t-1}) - \sum_{i=1}^{p} \delta_{CPI} \ln(CPI_{t-1}) - \sum_{i=1}^{p} \delta_{FDI} \ln(FDI_{t-1}) - \sum_{i=1}^{p} \delta_{FDI} \ln(FDI_{t-1}) - \sum_{i=1}^{p} \delta_{LE} \ln(LE_{t-1}) \tag{4.3}$$

DYNARDL Simulations

In this study, we perform dynamic AutoRegressive Distributed Lag (DYNARDL) model (Jordan & Philips, 2018), to assess the counterfactual impact of one factor. In contrast, all other variables are held constant while examining the dependent variable.

DYNARDL simulations necessitate that the dependent variable exhibits first-difference stationarity. Furthermore, independent variables may be integrated at either I(0) or I(1), but they should not exceed I(1). The model simulation can evaluate the impact of changes on the independent variables (positive or negative) since the data is dynamic. (Sarkodie & Owusu, 2020). Equation 5 displays the DYNARDL model, which is an ECM version of the ARDL model.

$$\Delta\, lnGDPC_t = \alpha_0 + \sum_{i=1}^{p} \tau_i \Delta \ln(GDPC_{t-1}) + \sum_{i=1}^{p} \beta_i \Delta \ln(CPI_{t-1}) + \sum_{i=1}^{p} \theta_i \Delta \ln(FDI_{t-1}) + \sum_{i=1}^{p} \vartheta_i \Delta \ln(LE_{t-1}) + \sum_{i=1}^{p} \delta_i \Delta \ln(EDUC_{t-1}) + \gamma_{GDPC} \ln(GDPC_{t-1}) + \gamma_{CPI} \ln(CPI_{t-1}) + \gamma_{FDI} \ln(FDI_{t-1}) + \gamma_{LE} \ln(LE_{t-1}) + \gamma_{EDUC} \ln(EDUC_{t-1}) + \gamma_{ECM} \mathrm{ECM_{t-1}} \tag{5}$$

KRLS Model

The Kernel-Based Regularized Least Squares (KRLS) model is a very effective machine-learning method that may be used for both regression and classification applications. It combines the advantages of kernel approaches, which enable the capture of complex non-linear relationships in data, with the straightforwardness and effectiveness of regularized linear models. (Hainmueller & Hazlett, 2014; Ferwerda et al., 2017).

4. Results and Discussions

4.1 Order of integration: Unit Root Tests

Phillips-Perron (1989) and Augmented Dickey & Fuller (1981) tests are implemented to verify the parameters' characteristics and determine the order of integration. The ADF test examines the constancy of the mean of the time series, while the PP test examines the constancy of the variance of the time series, addressing heteroscedasticity and serial correlation issues.

Table 5: The results of the ADF and PP tests

Variable	Level PP	Δ PP	Level ADF	Δ ADF	Remark
LOGGDPC	-2.152423	-11.52782***	-1.388822	-9.183367***	$I(1)$
LOGCPI	-2.687864***	-11.26542***	-2.875527***	-10.12893***	$I(0)$
LOGEDUC	-2.650378	-6.464982***	-2.623542	-6.058650***	$I(1)$
LOGFDI	-5.766054***	-57.09996***	-5.846054***	-15.34605	$I(0)$
LOGLE	-2.537540	-2.966161**	- 1.949327	0.841406	$I(1)$

Note: The level and first-difference of the Phillips-Perron unit root test are denoted by Level PP and Δ PP. The level and first-difference of the augmented-Dickey Fuller unit root test are denoted by Level ADF and Δ ADF. The null hypothesis of no unit root is rejected at a significance level of 1% when the symbol *** is used, and at a significance level of 5% when the symbol ** is used.

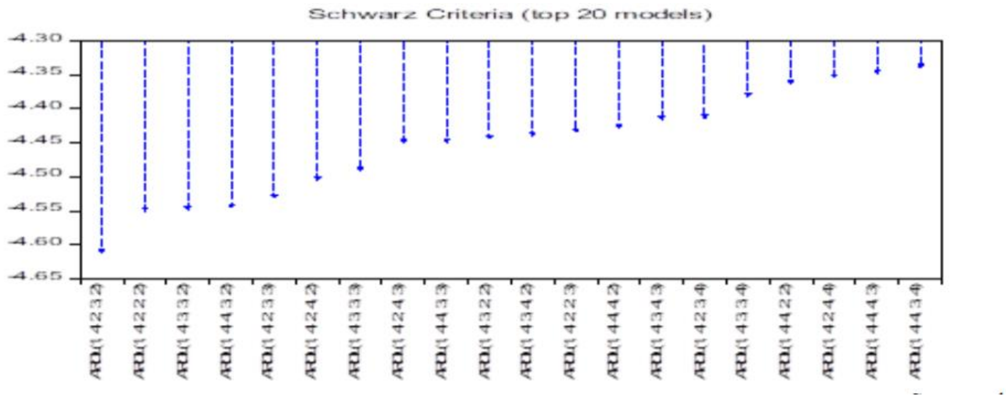
Source: developed by the authors

According to tests results, we can estimate the ARDL and DYNARDL models in our study, due to the integration of LOGGPDC at I(1) and the integration of independent parameters at I(0) and I(1).

4.2 Estimation of ARDL Model

To estimate the ARDL model accurately, choosing the most suitable lag is crucial. This selection is guided by several criteria. In our case, we selected Schwarz's Bayesian Information Criterion (SBIC) for model selection. According to Figure 4, the selected model is ARDL (1,4,3,2), and the estimation results are summarized in the Table 7 and Table 8.

Figure 4: Model selection method: Schwarz criterion (SIC)



Source: developed by the authors.

Co-integration

The results of the Bounds test for co-integration between variables are presented in Table 6. The results suggest that the F-statistic, which was calculated as 17.40374 for equation 3, exceeds the critical values at 1%, 5%, and 10%. Consequently, the null hypothesis is rejected. This conclusion suggests a long-term relationship between health and labour productivity in Morocco.

Table 6: Pesaran, Shin, and Smith Bounds Testing F-Bounds Test

Test Statistic	Value	Signif.	$I(0)$	$I(1)$
Finite Sample: n=30				
F-statistic	17.40374	10%	2.525	3.56
N (*)	4	5%	3.058	4.223
Actual Sample Size	28	1%	4.28	5.84

Note:(*) N denotes the number of independent variables.
Source: developed by the authors.

Short-Run and Long-Run models

We can now estimate both the long-run and short-run model after confirming the existence of a co-integration relationship. A short-term equation among the variables is estimated in Table 7.

Table 7: Short-run estimation equation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D (LOGCPI)	0.014483	0.004544	3.187258	0.0086***
D (LOGCPI (-1))	-0.077183	0.008315	-9.282560	0.0000***
D (LOGCPI(-2))	-0.047279	0.006168	-7.665283	0.0000***
D (LOGCPI (-3))	-0.023295	0.004422	-5.267822	0.0003***
D (LOGEDUC)	-0.013051	0.002115	-6.170386	0.0001***
D (LOGEDUC (-1))	0.013010	0.002489	5.227162	0.0003***
D(LOGFDI)	0.036537	0.005654	6.461979	0.0000***
D (LOGFDI (-1))	-0.082892	0.012355	-6.709318	0.0000***
D (LOGFDI (-2))	-0.018065	0.007512	-2.404733	0.0349**
D(LOGLE)	11.00218	1.488735	7.390290	0.0000***
D (LOGLE (-1))	-8.817026	1.428757	-6.171116	0.0001***

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CointEq (-1) *	-1.393840	0.113097	-12.32425	0.0000***
R^2 Adjusted R^2 DW	0.999252 0.998163 2.559210	F-statistic Prob(F-statistic)	918.1559*** 0.000000	

Source: developed by the authors

After assessing short-term elasticity, the next step is to examine the findings regarding long-term elasticity. The results for long-term elasticity are displayed in Table 8 below.

Table 8: Long-run estimation equation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOGCPI	0.079790	0.008158	9.780946	0.0000***
LOGEDUC	-0.023860	0.002266	-10.52861	0.0000***
LOGFDI	0.134022	0.008863	15.12114	0.0000***
LOGLE	6.225698	0.169847	36.65480	0.0000***
C	-17.19862	0.662465	-25.96157	0.0000***

Source: developed by the authors

The results from the short and long-run estimation equations effectively capture fluctuations in labour productivity (GDP per capita). Each independent variable significantly impacts labour productivity in Morocco, as shown by their statistically significant coefficients. The model explained a substantial portion, evident through high R-squared (99,92%) and adjusted R-squared (99,81%) values. The Durbin-Watson (DW) statistic is around 2.56, indicating no significant autocorrelation order 1 in the model's residuals.

Diagnostic Tests

Tables 9, Table 10, Table 11 and Table 12 describe diagnostic tests for the ARDL model. These tables display the number of tests without problems related to autocorrelation, heteroskedasticity, misspecification, and normality. Notably, all probabilities exceeding 5% indicate that there are no problems in our model.

The number of recursive residual cumulative (CUSUM) and square cumulative of the residual recursive (CUSUMSQ) tests (Figure 5) also show that there is no misspecification evidence and expected instability.

Table 9: Breusch-Godfrey LM test

Lags(p)	F	df	Prob > F	Decision
1	1.463880	1,10	0.2541	No serial correlation
2	0.702876	2,9	0.5204	
3	0.478179	3,8	0.7063	
4	1.714818	4,7	0.2502	

Table 10: Heteroskedasticity Test: White

Lags(p)	Value	df	Prob	Decision
F-statistic	1.335564	16,11	0.3182	No heteroscedasticity
Obs*R-squared	18.48473	16	0.2963	
Scaled explained SS	3.175158	16	0.9998	

Table 11: Ramsey test

	Value	df	Probability	Decision
t-statistic	0.986075	10	0.3474	No misspecification
F-statistic	0.972345	(1, 10)	0.3474	

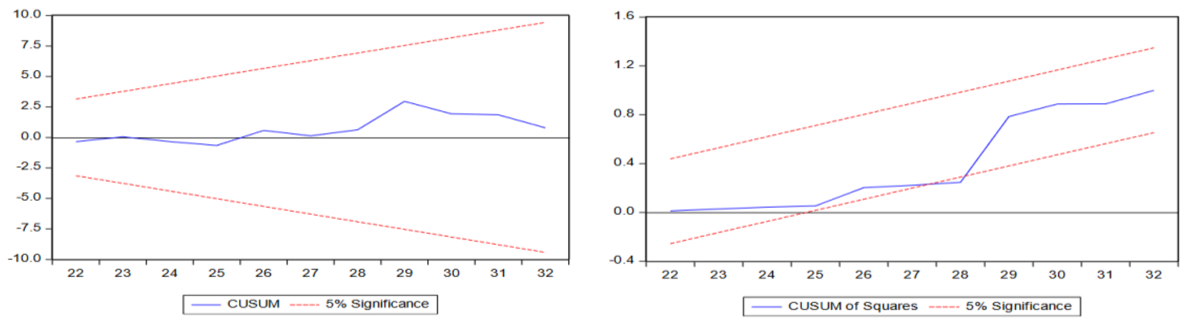
Source: developed by the authors

Table 12: Skewness/Kurtosis and Jarque-Berra tests for normality.

Variable	Kurtosis	Skewness	Jarque-Berra	Prob > chi2	Decision
Residuals	3.225937	0.075954	0.086478	0.957683	Normal

Source: developed by the authors

Figure 5: CUSUM CUSUMQ test for stability



Source: developed by the authors

4.3 DYNARDL Simulations

As a precondition for estimating the DYNARDL simulations, several residual tests were performed to address issues such as serial correlation, heteroscedasticity, and deviations from normality. In contrast, all tests (tables 9-12) confirmed the validity of the estimated DYNARDL.

The DYNARDL simulations provide a visual representation of how changes in the actual regressor affect the dependent variable while keeping other explanatory variables constant. FDI, education expenditures, life expectancy, and inflation are variables that have an anticipated impact on GDPC in Morocco, with fluctuations expected to be about 10%. Figure 6 illustrates the impact of each dependent variable on GDPC, with a 10% change (+/-). The average prediction is indicated by dots, which are calculated using DYNARDL. The empirical estimation is presented in Table 13.

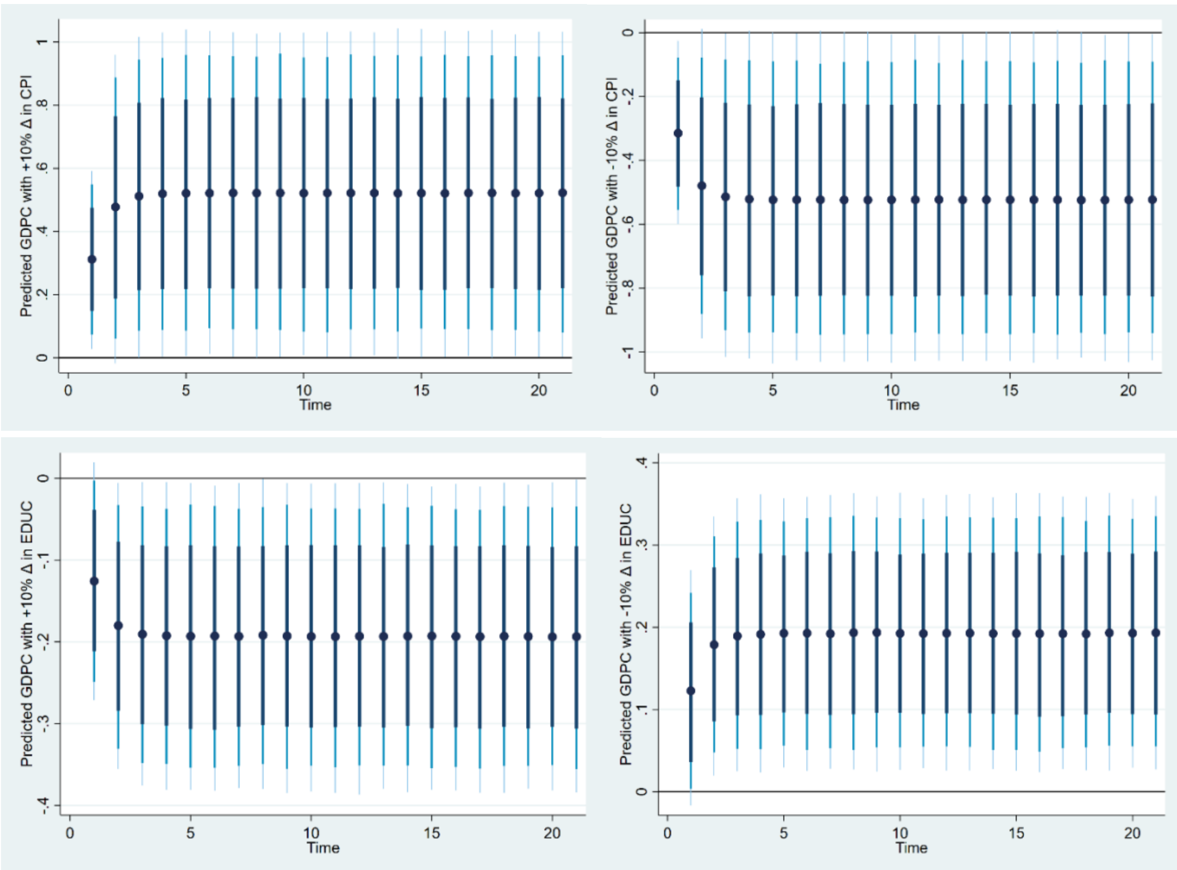
Table 13: The dynamic ARDL estimation – Part A + Part B

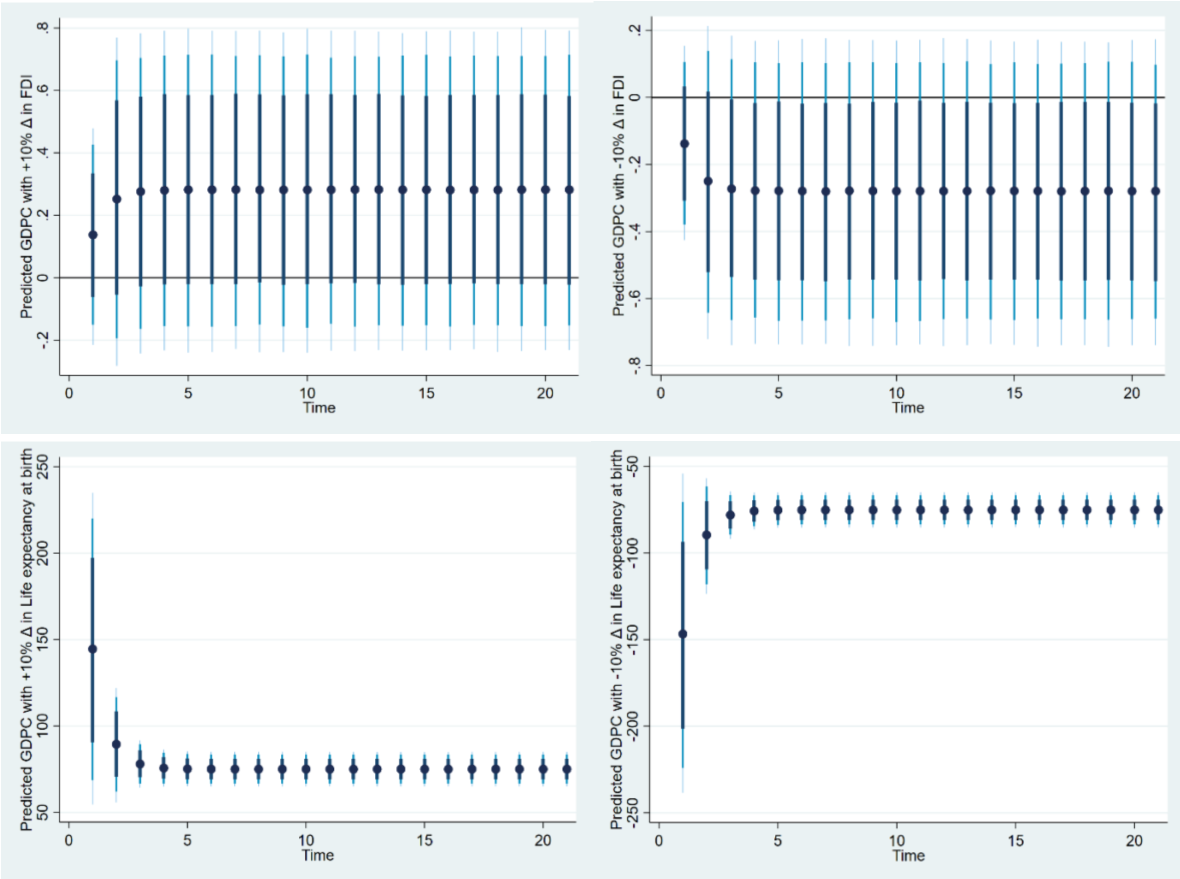
Source	Sum Square	df	MS
Model	0.045018256	9	0.005002028
Residual	0.020786664	21	0.000989841
Total	0.06580492	30	0.002193497
R-squared	= 0.6841	No of observations	= 31
F(9, 21)	=5.05	Prob > F	= 0.0011
Adj R-squared	=0.5487	Root MSE	= 0.03146

Part B						
	Coefficient	Std. **errs**.	t	P>t	[95% conf.	interval]
$\boldsymbol{ECM_{t-1}}$	-0.7932369	0.1959619	-4.05	0.001**	-1.200762	-0.3857119
Long-run						
LOGCPI	0.041244	0.0235596	1.75	0.095	-0.0077509	0.0902389
LOGFDI	0.0224003	0.0260585	0.86	0.400	-0.0317913	0.0765919
LOGEDUC	-0.015395	0.0070338	-2.19	0.040**	-0.0300227	-0.0007674
LOGLE	5.963339	1.323808	4.50	0.000***	3.210329	8.716349
Short-run						
D LOGCPI	0.0312697	0.0137672	2.27	0.034**	0.0026393	0.0599002
D_LOGEDUC	-0.0124915	0.0059526	-2.10	0.048**	-0.0248705	-0.0001124
D LOGFDI	0.0137931	0.0155843	0.89	0.386	-0.0186161	0.0462024
D_LOGLE	14.53531	4.664893	3.12	0.005**	4.834131	24.23648
C	-17.4486	3.832033	-4.55	0.000***	-25.41775	-9.479452

Note: *** statistical significance at 1% significance level. ** significance at 5 % significance level.
Source: developed by the authors (Stata output)

Figure 6: Impact of a 10% (+/-) change in each dependent variable on labour productivity, with dots showing the average forecast value





Note: The dark blue to light blue line denotes the 75%, 90%, and 95% confidence intervals.
Source: developed by the authors (Stata output)

4.4 KRLSS Technique Estimation

To improve the outcomes of this study, we implemented a machine learning approach known as Kernelized Regularized Least Squares (KRLS) to investigate and determine the relationships between the variables. Table 14 shows that the general model estimated using the KRLSS method has a predictive value of 0.9953, indicating that the model's explanatory variables account for 99.53% of the variation in GDPC (labour productivity). This high value suggests that the model effectively captures the factors influencing labour productivity.

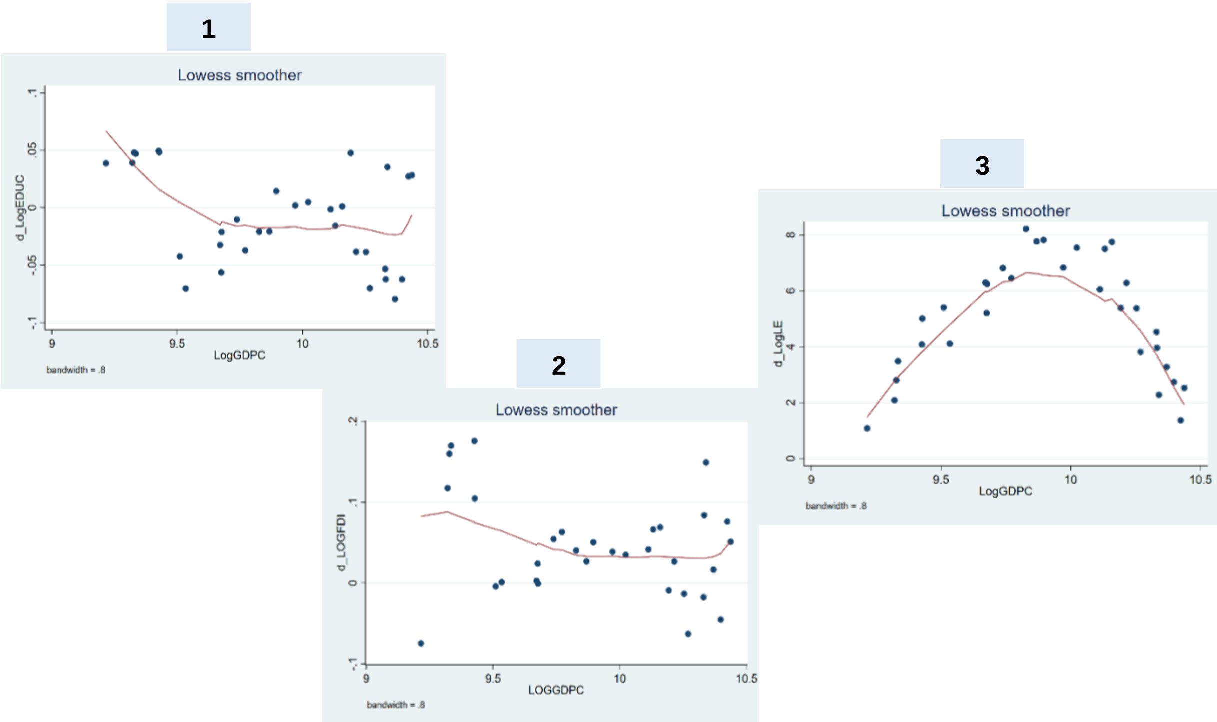
Table 14: Pointwise derivatives using KRLS

LOGGDPC	Avg.	SE	t	P>|t|	P25	P50	P75
LOGCPI	0.011138	.010811	1.030	0.312	-0.025415	0.012983	0.044597
LOGFDI	0.044351	.013446	3.299	0.003***	0.000273	0.039562	0.072624
LOGEDUC	-0.009453	.004313	-2.192	0.037**	-0.040529	-0.013005	0.03192
LOGLE	5.00122	.189119	26.445	0.000***	3.37717	5.28924	6.63267
R^2	0.9953	Lambda	0.06902	Obs.	32		
Tolerance	0.032	Looloss	0.5376	Eff. Df.	17.28		

Note: *** statistical significance at 1% significance level. ** significance at 5 % significance level.
Source: developed by the authors (Stata output)

The study also investigates the long-term effects of changes in life expectancy, education expenditures, and foreign direct investment (FDI) on labour productivity. This is done by analysing the pointwise derivative, as shown in Figure 7.

Figure 7: Plot of Pointwise marginal effect: (1) of FDI; (2) of EDUC; (3) of LE



Source: developed by the authors (Stata output)

4.5 Discussion of Results

Our analysis reveals that health measured by Life expectancy (LE) has a significant and positive effect on labour productivity measured by GDP per capita (GDPC) in both the short and long term. This result corroborates the findings of Ullah et al. (2019) and Mehmood et al. (2022) for developing economies. Looking at the relationship between health and labour productivity in the ARDL, DYNARDL, and KRLSS models, we find that LE has a bigger effect on GDPC than other dependent variables over both time periods.

Indeed, the coefficient for LE is approximately 6%, indicating that a 1% increase in LE results in a 6% increase in GDPC in the long run. In the short run, this coefficient is around 14%, suggesting that a 1% change in LE leads to a 14% variation in GDPC. These findings underscore the critical role of health improvements in driving economic productivity in Morocco.

The study also reveals that foreign direct investment (FDI) has a positive effect on Morocco's GDPC, with the coefficient indicating that a 1% rise in FDI leads to a 0.04% increase in labour productivity. These results are consistent with the literature, including the study by (Saucedo et al., 2020).

The CPI's impact on GDPC in Morocco reveals a positive effect of approximately 0.07%. However, in the DYNARDL and KRLSS models, this impact is not statistically significant at the 5% level, likely due to the small sample size.

Therefore, education expenditure (EDUC) shows a negative correlation with labour productivity (GDPC). This result aligns with the study of Magableh et al. (2022) in Jordan. The coefficient -0.023860 indicates that a 1% change in EDUC causes a -0.023% variation in GDPC in the long run.

The speed of adjustment term parameter represents the annual rate of correction of an 80% distortion until the reinstatement of the long-term equilibrium route. Therefore, a temporary disruption in the determining factors may take around 8 years to re-establish the long-term equilibrium condition. The average pairwise marginal effect of FDI, EDUC, and LE are 0.04%, -0.01%, and 5%, respectively. Except for inflation, the probability value of every parameter at a 1% and 5% significance level indicates evidence of a causal effect correlation.

Figure 7 illustrates the analysis of the marginal effect of health (LE) on labour productivity (GDPC) in Morocco, which shows that improvements in health conditions increase production up to a certain point before showing diminishing marginal returns.

Additionally, Figure 6 displays the parameter charts of the DYNARDL simulations. We use the DYNARDL simulations to assess the marginal returns of health (LE) on labour productivity (GDPC) by introducing counterfactual shocks. The calculation included the yearly average increase rate of life expectancy, which is around 10%. Figure 6 demonstrates that a projected 10% increase in the health shock (LE) might lead to a progressively higher acceleration of labour productivity (GDPC) during the first year. However, this acceleration rate decreases with time, eventually stabilizing in the subsequent period. Moreover, there is a forecasted decrease in worker productivity from 150 to 90 for the first term, followed by a further decline to 70 for subsequent decades.

Conclusion

This paper concluded that Health (LE) is revealed to have significantly and positively affected labour productivity (GDPC). Indeed, the impact of LE on GDPC is higher than the other dependent variables such as FDI, CPI and EDUC in the short and long run in Morocco. The elasticity between LE and GDPC is around 6%.

This suggests that improvements in health outcomes can have a substantial impact on the overall productivity of the labour force in Morocco. The findings of this study highlight the importance of investing in healthcare infrastructure and programs to not only improve the population's well-being but also boost economic growth and development. Additionally, the results indicate that policies aimed at promoting better health outcomes can lead to significant gains in labour productivity and overall economic performance in the country.

In the same context, a 10% shock in health (LE) might lead to a progressively higher acceleration of labour productivity (GDPC) during the first year. However, this acceleration rate decreases with time, eventually stabilizing in the subsequent period. Moreover, there is a forecasted decrease in worker productivity from 150 to 90 for the first term, followed by a further decline to 70 for subsequent decades.

Credit Authorship Contribution Statement

Conceptualization, N. E.L. and R. R.; methodology, N. E.L. and R. R.; software, N. E.L. and R. R.; validation, N. E.L. and R. R.; formal analysis, N. E.L. and R. R.; investigation, N. E.L. and R. R.; resources, N. E.L. and R. R.; data curation, N. E.L. and R. R.; writing-original draft preparation, N. E.L. and R. R.; writing-review and editing, N. E.L. and R. R. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

Abdelgany, M., & Saleh, A. (2023). Human Capital and Labour Productivity: Empirical Evidence from Developing Countries. *International Journal of Economics Finance and Management Sciences*, 10, 173–184. https://doi.org/10.11648/j.ijefm.20221004.13

Aghion, P., Howitt, P., & Murtin, F. (2010). The Relationship Between Health and Growth: When Lucas Meets Nelson-Phelps (Working Paper 15813). *National Bureau of Economic Research.* https://doi.org/10.3386/w15813

Arrow, K., Bolin, B., Costanza, R., Dasgupta, P., Folke, C., Holling, C. S., Jansson, B.-O., Levin, S., Mäler, K.-G., Perrings, C., & Pimentel, D. (1995). Economic growth, carrying capacity, and the environment. *Ecological Economics*, 15(2), 91–95. https://doi.org/10.1016/0921-8009(95)00059-3

Baharin, R., Syah Aji, R. H., Yussof, I., & Mohd Saukani, N. (2020). Impact of Human Resource Investment on Labour Productivity in Indonesia. *Iranian Journal of Management Studies*, 13(1), 139–164. https://doi.org/10.22059/ijms.2019.280284.673616

Barro, R. J. (1991). Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics*, 106(2), 407–443. https://doi.org/10.2307/2937943

Barro, R. J., & Lee, J.-W. (1994). Sources of economic growth. *Carnegie-Rochester Conference Series on Public Policy*, 40, 1–46. https://doi.org/10.1016/0167-2231(94)90002-7

Beylik, U., Cirakli, U., Cetin, M., Ecevit, E., & Senol, O. (2022). The relationship between health expenditure indicators and economic growth in OECD countries: A Driscoll-Kraay approach. *Frontiers in Public Health*, 10, 1050550. https://doi.org/10.3389/fpubh.2022.1050550

Bhargava, A., Jamison, D. T., Lau, L. J., & Murray, C. J. (2001). Modeling the effects of health on economic growth. *Journal of Health Economics*, 20(3), 423–440. https://doi.org/10.1016/s0167-6296(01)00073-x

Bloom, D. E., Canning, D., & Sevilla, J. (2004). The Effect of Health on Economic Growth: A Production Function Approach. *World Development*, 32(1), 1–13. https://doi.org/10.1016/j.worlddev.2003.07.002

Cole, M., & Neumayer, E. (2006). The impact of poor health on total factor productivity. *Journal of Development Studies*, 42(6), 918–938.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica*, 49(4), 1057–1072. https://doi.org/10.2307/1912517

Dormont, B., Oliveira Martins, J., Pelgrin, F., & Suhrcke, M. (2008). Health Expenditures, Longevity and Growth (SSRN Scholarly Paper 1130315). https://doi.org/10.2139/ssrn.1130315

Dua, P., & Garg, N. K. (2019). Determinants of labour productivity: Comparison between developing and developed countries of Asia-Pacific. *Pacific Economic Review*, 24(5), 686–704. https://doi.org/10.1111/1468-0106.12294

Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica*, 55(2), 251–276. https://doi.org/10.2307/1913236

Ferwerda, J., Hainmueller, J., & Hazlett, C. J. (2017). Kernel-Based Regularized Least Squares in R (KRLS) and Stata (KRLS). *Journal of Statistical Software*, 79, 1–26. https://doi.org/10.18637/jss.v079.i03

Granger, C. W. J. (1981). Some properties of time series data and their use in econometric model specification. Journal of Econometrics, 16(1), 121–130. https://doi.org/10.1016/0304-4076(81)90079-8

Haider, A., & Butt, M. S. (2006). The Direction of Causality between Health Spending and GDP: The Case of Pakistan. *MPRA Paper*, Article 23379. https://ideas.repec.org//p/pra/mprapa/23379.html

Hainmueller, J., & Hazlett, C. (2014). Kernel Regularized Least Squares: Reducing Misspecification Bias with a Flexible and Interpretable Machine Learning Approach. *Political Analysis*, 22(2), 143–168.

Johansen, S. (1995). A Statistical Analysis of Cointegration for I(2) Variables. *Econometric Theory*, 11(1), 25–59.

Johansen, S., & Juselius, K. (1990). Maximum Likelihood Estimation and Inference on Cointegration—With Applications to the Demand for Money. *Oxford Bulletin of Economics and Statistics*, 52(2), 169–210. https://doi.org/10.1111/j.1468-0084.1990.mp52002003.x

Jordan, S., & Philips, A. Q. (2018). The R Journal: Dynamic Simulation and Testing for Single-Equation Cointegrating and Stationary Autoregressive Distributed Lag Models. *The R Journal*, 10(2), 469–488. https://doi.org/10.32614/RJ-2018-076

Kedir, A. M. (2009). Health and Productivity: Panel Data Evidence from Ethiopia. *African Development Review*, 21(1), 59–72. https://doi.org/10.1111/j.1467-8268.2009.00203.x

Knapp, D. (2007). *The Influence of Health on Labour Productivity: An Analysis of European Conscription Data* [Thesis, The Ohio State University]. https://kb.osu.edu/handle/1811/25245

Lea, R. A. (1993). World Development Report 1993: Investing in Health. Forum for Development Studies, 20(1), 114–117. https://doi.org/10.1080/08039410.1993.9665939

Levine, R., & Renelt, D. (1992). A Sensitivity Analysis of Cross-Country Growth Regressions. *The American Economic Review*, 82(4), 942–963.

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22(1), 3–42. https://doi.org/10.1016/0304-3932(88)90168-7

Magableh, S., Alalawneh, M., & Alqalawi, U. (2022). An empirical study on the effect of education on labour productivity. *Journal of Governance and Regulation,* 11(2, Special Issue), 301–308. https://doi.org/10.22495/jgrv11i2siart9

Mankiw, Romer, D., & Weil, D. (1992). A Contribution to the Empirics of Economic Growth. *Quarterly Journal of Economics*, 107(May), 407–437.

Mehmood, A., Siddique, H. M. A., & Ali, A. (2022). Impact of Health on Worker Productivity: Evidence from South Asia. *Bulletin of Business and Economics*, 11(2), Article 2.

Narayan, S., & Narayan, P. K. (2005). An empirical analysis of Fiji's import demand function. *Journal of Economic Studies*, 32(2), 158–168. https://doi.org/10.1108/01443580510600931

NPFH. (2018). Morocco National Survey on Population and Family Health 2017-2018. https://www.sante.gov.ma/Publications/Etudes_enquete/Documents/2019/03/Rapport%20pr%C3%A9liminaire_ENPSF-2018.pdf

OECD. (2014). GDP per capita and productivity growth. Organisation for Economic Co-operation and Development. https://www.oecd-ilibrary.org/employment/data/oecd-productivity-statistics/gdp-per-capita-and-productivity-growth_data-00685-en

Perron, P. (1989). The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis. *Econometrica*, 57(6), 1361–1401. https://doi.org/10.2307/1913712

Pesaran, M. H., & Shin, Y. (1995). An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis. *Cambridge Working Papers in Economics,* Article 9514. https://ideas.repec.org//p/cam/camdae/9514.html

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics,* 16(3), 289–326. https://doi.org/10.1002/jae.616

Raghupathi, V., & Raghupathi, W. (2020). Healthcare Expenditure and Economic Performance: Insights from the United States Data. *Frontiers in Public Health*, 8. https://www.frontiersin.org/articles/10.3389/fpubh.2020.00156

Rivera, B., & Currais, L. (1999). Economic growth and health: Direct impact or reverse causation? *Applied Economics Letters,* 6(11), 761–764. https://doi.org/10.1080/135048599352367

Saha, S. (2013). Impact of Health on Productivity Growth in India. https://www.semanticscholar.org/paper/Impact-of-Health-on-Productivity-Growth-in-India-Saha/bc54b71843ce3db5d57ee5c7aa15a8c511c92bc1

Samargandi, N. (2018). Determinants of Labour Productivity in MENA Countries. *Emerging Markets Finance and Trade,* 54(5), 1063–1081. https://doi.org/10.1080/1540496X.2017.1418658

Sarkodie, S. A., & Owusu, P. A. (2020). How to apply the novel dynamic ARDL simulations (DYNARDL) and Kernel-based regularized least squares (KRLS). *MethodsX*, 7, 101160. https://doi.org/10.1016/j.mex.2020.101160

Saucedo, E., Ozuna, T., & Zamora, H. (2020). The effect of FDI on low and high-skilled employment and wages in Mexico: A study for the manufacture and service sectors. *Journal for Labour Market Research,* 54(1), 9. https://doi.org/10.1186/s12651-020-00273-x

Schultz, T. P. (2005). Productive Benefits of Health: Evidence from Low-Income Countries.

Ullah, S., Malik, M. N., & ul Hassan, M. (2019). Impact of Health on Labour Productivity: Empirical Evidence from Pakistan. *European Online Journal of Natural and Social Sciences,* 8(1), Article 1.

Umoru, D., & Yaqub, J. (2013). Labour Productivity and Health Capital in Nigeria: The Empirical Evidence. https://www.semanticscholar.org/paper/Labour-Productivity-and-Health-Capital-in-Nigeria%3A-Umoru-Yaqub/5dcdc3ad657f9fb1b992612af05c2103500af851

UNCTADstat. (2023). [Dataset]. https://unctadstat.unctad.org/wds/ReportFolders/reportFolders.aspx

World Bank Open Data. (2023). [Dataset]. https://data.worldbank.org

Wu, C.-F., Chang, T., Wang, C.-M., Wu, T.-P., Lin, M.-C., & Huang, S.-C. (2021). Measuring the Impact of Health on Economic Growth Using Pooling Data in Regions of Asia: Evidence from a Quantile-On-Quantile Analysis. *Frontiers in Public Health,* 9. https://www.frontiersin.org/articles/10.3389/fpubh.2021.689610