JPEPFM Journal of Public Economy and Public Financial Management

Journal of Public Economy and Public Financial Management
Cilt/Volume: 5
Sayı/Issue: 2
Ekim/October 2025

Makale İlk Gönderim Tarihi/Received (First): 28.07.2025

Makale Kabul Tarihi /Accepted: 30.08.2025

Citation / Atıf: Biçer, İ. & Konca, M. (2025). The Impact of Economic Growth, Physician Density, and Student-Teacher Ratio on Life Expectancy at Birth: Evidence from Belgium. *Journal of Public Economy and Public Financial Management*, 5(2), 126-141. https://doi.org/10.71284/jpepfm.202522.

RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

THE IMPACT OF ECONOMIC GROWTH, PHYSICIAN DENSITY, AND STUDENT-TEACHER RATIO ON LIFE EXPECTANCY AT BIRTH: EVIDENCE FROM BELGIUM

İsmail BİÇER[1]

Murat KONCA[2]

Abstract

Life expectancy at birth (LEAB) denotes the average number of years a newborn is anticipated to live, assuming current conditions persist throughout their lifetime. This study investigates the influence of economic growth, the number of physicians per 1,000 inhabitants, and the student–teacher ratio on LEAB in Belgium. Initially, the analysis utilizes data spanning from 1970 to 2017 and applies the Autoregressive Distributed Lag (ARDL) bounds testing approach. To validate the robustness of the ARDL findings, the study further employs Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegrating Regression (CCR) techniques. These additional methods enhance the reliability of the results. The ARDL analysis reveals no statistically significant relationship between LEAB and either economic growth or the student–teacher ratio in both the short and long run. However, a positive and significant association is observed between LEAB and the number of physicians per 1,000 individuals. Consistent with these findings, FMOLS, DOLS, and CCR estimations also indicate a positive and statistically significant relationship between LEAB and physician density. Furthermore, these methods identify a negative and significant correlation between LEAB and the student–teacher ratio. In conclusion, policies aimed at reducing income inequality and ensuring equitable access to healthcare and education services for all segments of society can play a vital role in improving life expectancy outcomes.

Keywords: Life Expectancy, Physician Density, Economic Growth, Student–Teacher Ratio, ARDL

***JEL Codes**:* I10, I15

[1] Lecturer Ph.D, Pamukkale University, Çivril Atasay Kamer Vocational School, Health Institutions Management, ismailbiceer@gmail.com, ORCID: 0000-0003-1878-0546

[2] Asst. Prof., Çankırı Karatekin University, Faculty of Health Sciences, Department of Health Management, konca71@gmail.com, ORCID: 0000-0002-6830-8090

1. INTRODUCTION

Life expectancy at birth (LEAB) refers to the estimated average lifespan of a newborn, under the assumption that prevailing mortality rates remain unchanged throughout their life. This metric is widely recognized as a fundamental indicator for assessing a country's or region's socioeconomic development. Despite global improvements in LEAB over the last two centuries (Münz, 2012), considerable disparities persist between developed and developing countries (Bilas et al., 2014). These differences are largely attributed to variations in socio-economic, socio-cultural, and environmental conditions, which play a crucial role in shaping life expectancy (Sufian, 2013).

Since the early 1990s, Belgium has implemented measures to improve both LEAB and the overall quality of life for its citizens. In this context, Belgium's federal and regional governments have introduced various reforms in areas such as tobacco control, cancer screening, road accident prevention, the promotion of healthier eating habits and physical activity, air quality improvement, and enhanced access to healthcare services (Maertens de Noordhout et al., 2018). Furthermore, the Organization for Economic Co-operation and Development (OECD) has identified multiple challenges within the Belgian healthcare system. These include disparities in access to health and medical services, underinvestment in preventive care, the growing prevalence of specific risk factors, and inefficiencies in the allocation and utilization of clinical resources (Pearson, 2017). In line with the measures taken and the reforms implemented, LEAB in Belgium showed a steady increase for many years until 2020, except for a slight decline observed in 2012 and 2015. However, due to the excess mortality caused by SARS-CoV-2 (COVID-19), Belgium's LEAB decreased to 80.8 years in 2020 and continued to decline to 79.6 years in 2022. Belgium's 2022 LEAB approached the European Union (EU)-14 average of 79.7 years (EU-14 are countries who were members of the EU before 2004). In 2023, LEAB was recorded as 83.2 years in the Flemish Region, 82.2 years in the Brussels-Capital Region, and 80.6 years in the Walloon Region. In 2023, LEAB increased across all regions, surpassing the 2019 levels. In 2023, LEAB in Belgium reached 80.18 years, surpassing the 2019 pre-COVID level and marking the highest recorded level to date (Sciensano, 2024).

As observed, LEAB has been increasing across countries in recent years. Analyzing the factors influencing these increases can provide valuable insights into health status and contribute to further improvements in this key indicator (Sasanipour, 2024). Within this framework, the study aimed to explore how economic growth, physician density (per 1,000 inhabitants), and the student–teacher ratio influence life expectancy at birth (LEAB) in Belgium.

2. LITERATURE REVIEW

In the literature, there is a wide variety of studies aimed at identifying the factors influencing LEAB. Various categories of potential factors influencing LEAB have been identified. These encompass healthcare spending, health financing strategies, medical care components, health behaviors and public health measures, social determinants, social spending, and additional external influences, each classified into distinct types (Roffia et al., 2023).

One of the key determinants of life expectancy at birth (LEAB) is income growth, commonly represented by gross domestic product (GDP) per capita, which serves as a widely accepted proxy for income levels. As income rises, higher levels of well-being enable individuals to maintain a better quality of life and improved health conditions. Increased financial resources allow for better access to healthcare services, improved living conditions, and healthier lifestyles, all of which contribute to higher LEAB.

According to endogenous growth theory, human capital is a fundamental driver of economic growth (Taban & Kar, 2006). Within this framework, health is regarded as a critical component of human capital, significantly contributing to economic performance. A considerable body of research has examined the relationship between economic growth and life expectancy at birth (LEAB), employing diverse methodological and econometric approaches.

Mayer (2001), using Granger causality analysis with data covering the years 1950 to 1990, identified a positive effect of life expectancy at birth (LEAB) on economic growth. Similarly, Bloom et al. (2001) conducted a panel data analysis for 104 countries spanning the period 1960–1990 and reported a positive association between LEAB and economic growth. Consistent with these results, Husain (2012) utilized the two-stage least squares (2SLS) method on data from 59 countries between 1980 and 2004 and also found that LEAB positively affects economic growth. In the case of Türkiye, Avcı and Çalışkan (2024) employed the Autoregressive Distributed Lag (ARDL) bounds testing approach on data from 1960 to 2014 and revealed a positive relationship between LEAB and gross domestic product (GDP). Expanding the analysis to a broader sample, Sultana et al. (2022) used the System Generalized Method of Moments (GMM) technique on data from 93 developing and 48 developed countries for the period 1980–2008. Their findings indicated a positive effect of LEAB on economic growth in developing countries, while a negative effect was observed in developed countries. However, some studies have found no statistically significant relationship between the two variables. Acemoglu and Johnson (2007) reported no meaningful relationship between LEAB and economic growth, and Bowser (2010) reached a similar conclusion. To help account for the divergence in these findings, Preston (1975) introduced the “Preston Curve,” which illustrates a positive relationship between GDP per capita and LEAB in low- and middle-income countries. The curve suggests that as income rises, health outcomes such as mortality rates and LEAB improve, although this relationship tends to weaken in high-income countries. The Preston Curve illustrates that in low-income countries, an increase in per capita income leads to significant improvements in health outcomes and an extension of LEAB. As economic development progresses in these countries, access to healthcare services, sanitation, nutrition, and overall living conditions improve, resulting in a notable decline in mortality rates. This marks a critical turning point for developing countries, as higher economic growth directly contributes to better public health and longer LEAB. However, the Preston Curve highlights that in high-income countries, this relationship becomes more limited. This is because these countries have already reached a point where health infrastructure is well-developed, and living conditions are high in these countries. At this stage, LEAB continues to increase, but at a slower rate. In other words, while mortality rates in high-income countries reaches very low levels, the incremental gains in LEAB diminishes as per capita income continues to rise.

Another key factor influencing a country’s LEAB is the number of physicians per 1,000 people. An increase in the number of physicians in a country enhances access to healthcare services and improves the likelihood of early disease diagnosis. A higher physician density contributes to a more efficient healthcare system, facilitates the expansion of preventive healthcare services, and aids in the better management of chronic diseases. Furthermore, countries with a higher number of physicians per 1,000 people tend to have greater investments in healthcare infrastructure and medical technology. These factors, when combined, contribute to an increase in average LEAB. Numerous studies have provided empirical evidence supporting this relationship, demonstrating that a well-developed healthcare system with sufficient medical personnel leads to better health outcomes and longer LEAB. In a study conducted by Teker et al. (2012), the factors influencing LEAB for men and women in Turkey between 1975 and 2009 were analyzed. The study's findings revealed that the number of physicians has a significant impact on LEAB, demonstrating that greater access to healthcare professionals contributes to increased LEAB. In a study conducted by Park and Nam (2019), data from 34 OECD member countries covering the period between 1994 and 2012 were analyzed using a fixed-effects panel data analysis. The results indicated that the number of physicians per 1,000 people has a positive and significant impact on LEAB, reinforcing the idea that greater access to healthcare professionals contributes to improved public health and increased LEAB. Similarly, Delavari et al. (2019), in their study on Iran, identified a statistically significant and positive relationship between the number of physicians per 10,000 individuals and life expectancy at birth (LEAB). Consistent with these findings, Balan and Jaba (2011) reported a comparable positive association in Romania, demonstrating that higher physician density is linked to increased LEAB. These findings further support the idea that greater availability of healthcare professionals contributes to improved LEAB.

Education can also be counted among the factors influencing LEAB. According to various studies in the literature, the average years of education have a positive and significant impact on LEAB (Bilas et al., 2014; Ali & Ahmad, 2014; Sede & Ohemeng, 2015). As education levels increase, individuals become more health-conscious, leading to better health behaviors, improved disease prevention, and greater utilization of healthcare services, all of which contribute to longer LEAB. A review of the literature reveals that no study has directly measured the impact of the number of students per teacher on LEAB. However, the student-to-teacher ratio can influence the quality of education in a country. Teachers with fewer students can provide more individual attention and support, leading to higher educational quality. Countries with lower student-to-teacher ratios tend to be wealthier and more developed, which often correlates with better healthcare services and improved living conditions. As a result, these factors may contribute to higher LEAB, even though the direct impact of the student-to-teacher ratio on LEAB has not been explicitly studied. In a study conducted by Daşdemir (2008), it was found that increases in the average years of education and decreases in the student-to-teacher ratio positively impact economic growth. Similarly, Avcı (2019) found that a decline in the student-to-teacher ratio in vocational and technical secondary education contributes to an increase in GDP. Although no direct relationship has been established between the student-to-teacher ratio and LEAB, it is expected that countries with strong income and education levels also tend to have higher LEAB. This suggests that improvements in education quality and economic development indirectly contribute to longer LEAB.

3. RESEARCH

This study analyzes data from Belgium covering the years 1970 to 2017 by applying the Autoregressive Distributed Lag (ARDL) bounds testing method. The dependent variable is life expectancy at birth (LEAB), expressed in years. The independent variables include the economic growth rate (Growth), the number of physicians per 1,000 people (Physician), and the pupil–teacher ratio (Ptr), representing the number of students per teacher. To ensure a distribution closer to normality and to address potential heteroscedasticity, the natural logarithms (Ln) of all variables were taken prior to estimation.

The analysis commenced with the assessment of the stationarity properties of the variables through the Augmented Dickey-Fuller (ADF) test, a widely used unit root test in empirical time series research. Following this, the optimal lag length was selected using a Vector Autoregressive (VAR) model, which is commonly applied to capture the dynamic interactions among time series variables. In the next step, the Autoregressive Distributed Lag (ARDL) bounds testing approach was implemented to examine the existence of a long-run cointegration relationship among the variables. The ARDL method, frequently combined with the bounds testing procedure, is suitable for identifying long-term equilibrium relationships. Once cointegration was confirmed, an Error Correction Model (ECM) was estimated to capture the short-run dynamics of the system.

To verify the robustness of the ARDL results, additional cointegration estimation techniques were employed, including Fully Modified Ordinary Least Squares (FMOLS), which estimates long-run coefficients; Dynamic Ordinary Least Squares (DOLS), which accounts for autocorrelation and endogeneity by including leads and lags of the differenced regressors; and Canonical Cointegrating Regression (CCR), which corrects for both autocorrelation and endogeneity to produce efficient estimates in non-stationary contexts. These complementary methods served to reinforce the reliability of the study's findings. All results were evaluated at the 5% significance level, and the analyses were conducted using EViews 13 software. As the research relied entirely on secondary data, ethical approval was not required. The econometric procedures used in the study are detailed in the following sections.

3.1. Augmented Dickey-Fuller

Studies with time series should control if there is spurious regression and also if the effects of temporary shocks are not persistent. In this context, it is crucial to first eliminate unit roots and ensure stationary in the series. The stationary property of a series is defined by the constancy of its mean and variance over time, as well as the equality of covariance values between two periods. Ensuring the stationary of the series contributes to producing accurate and reliable analytical results (Gujarati, 2016).

The Augmented Dickey-Fuller (ADF) test, developed by Dickey and Fuller (1981), is employed to determine whether a time series contains a unit root, particularly in cases where autocorrelation is present in the error terms. This method enhances the original Dickey-Fuller test by including lagged values of the dependent variable’s differences, thereby correcting for serial correlation in the residuals. The ADF test assesses the following hypotheses:

H_0: The series has a unit root (i.e., it is non-stationary).

H_1: The series is stationary.

The null hypothesis of the Augmented Dickey-Fuller (ADF) test posits that the time series is non-stationary, implying the presence of a unit root. Conversely, the alternative hypothesis suggests that the series is stationary. To perform the test, the following regression equations—originally proposed by Dickey and Fuller (1981)—are estimated to account for different deterministic components:

$$\Delta X_t = \beta_0 + \beta_1 X_{t-1} + \sum_{i=1}^{k} \lambda_i \, \Delta X_{t-i} + \mathrm{u}_t \tag{1}$$

$$\Delta X_t = \beta_0 + \beta_1 X_{t-1} + \beta_2 trend \sum_{i=1}^{k} \lambda_i \, \Delta X_{t-i} + \mathrm{u}_t \tag{2}$$

In the equations, X represents the series under consideration, Δ denotes the difference operator, k refers to the lags of the dependent variable added to the equation, β and λ are the parameters, the trend represents the linear time trend, and u_t denotes the error term.

3.2. Vector Autoregressive

The appropriate lag length for the series within the ARDL bounds testing framework was determined through Vector Autoregressive (VAR) analysis. The VAR model, originally introduced by Sims (1980), is widely utilized to capture the dynamic interactions among multiple time series variables and to inform lag selection in econometric modeling. Opposing the distinction between endogenous and exogenous variables, Sims argued that every variable in an econometric model could influence other variables while also being influenced by them, thus developing the VAR model. The primary objective of employing the Vector Autoregressive (VAR) model is not limited to detecting unidirectional causality between variables; rather, it also facilitates the examination of both forward and backward dynamic linkages among them (Kearney & Monadjemi, 1990). A conventional two-variable VAR model can be specified as follows:

$$y_t = a_1 + \sum_{i=1}^{p} \mathrm{b}_{1i} \, y_{t-i} + \sum_{i=1}^{p} \mathrm{b}_{2i} \, x_{t-i} \, \mathrm{v}_{1t} \tag{3}$$

$$x_t = c_1 + \sum_{i=1}^{p} \mathrm{d}_{1i} \, y_{t-i} + \sum_{i=1}^{p} \mathrm{d}_{2i} \, x_{t-i} \, \mathrm{v}_{2t} \tag{4}$$

In the given model, p signifies the lag order, and v refers to the random error terms, which are assumed to have a mean of zero, no autocorrelation with their lagged values, constant variance, and to follow a normal distribution. The assumption in the VAR framework that error terms are uncorrelated with their own lags does not constrain the model, as extending the lag length of the variables can resolve potential autocorrelation issues. If, at any point, the error terms are correlated—meaning their correlation deviates from zero—a shift in one error term can influence the others. Furthermore, the error terms in the VAR model are assumed to be uncorrelated with all explanatory variables on the right-hand side of the equations. Since these equations include only lagged values of the endogenous variables as regressors, the issue of simultaneity does not arise. Consequently, each equation in the system can be consistently estimated using the standard Ordinary Least Squares (OLS) method (Özgen & Güloğlu, 2004).

Determining the optimal lag length is a fundamental step in producing reliable estimations within the Vector Autoregressive (VAR) framework. This selection is typically guided by statistical criteria—such as the Likelihood Ratio (LR) test, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SC), and Hannan-Quinn Criterion (HQ)—with the aim of identifying the lag structure that best captures the underlying data dynamics while minimizing model misspecification.

3.3. Autoregressive Distributed Lag (ARDL)

To analyze both long-run and short-run dynamics among the variables under investigation, various econometric methods are employed. Among these, the Autoregressive Distributed Lag (ARDL) bounds testing approach—initially introduced by Pesaran and Shin (1995) and subsequently extended by Pesaran, Shin, and Smith (2001)—is particularly noteworthy for its flexibility and effectiveness in small sample contexts. A key advantage of the ARDL method is its flexibility in application, as it can be used regardless of whether the variables are level stationary or stationary at their first difference. This feature removes the necessity of determining the integration order of variables before conducting the bounds test. Nonetheless, the ARDL framework is not suitable for variables that are integrated at the second difference level (Çağlayan, 2006), making it essential to perform unit root tests beforehand. Additionally, the ARDL approach stands out for providing more reliable results in studies with small sample sizes (Narayan & Smyth, 2005). Furthermore, this method offers the advantage of distinguishing between short-term and long-term analyses. The ARDL bounds testing model is represented as follows:

$$Y_t = \alpha + \sum_{i=1}^{p} \lambda_i\, Y_{t-i} + \sum_{j=1}^{q_1} \delta_{1j}\, X_{1,t-i} + \sum_{j=1}^{q_2} \delta_{2j}\, X_{2,t-i} + \cdots + \sum_{j=1}^{q_k} \delta_{kj}\, X_{k,t-i} + \varepsilon_t \qquad (5)$$

In the ARDL model specification, Y_t represents the dependent variable, while $X_{i,t}$ (for i=1,2,…,k) denotes the set of explanatory variables. The parameter p signifies the lag order of the dependent variable, and q_i indicates the lag length associated with each independent variable. The constant term is denoted by α, λ_i corresponds to the coefficients of the lagged dependent variable, δ_{ij} captures the coefficients of the lagged explanatory variables, and ε_t represents the stochastic error term. After determining the appropriate lag structure, the ARDL bounds testing approach utilizes the F-statistic to evaluate the presence of a long-run cointegration relationship among the variables.

H_0: $\beta_1=\beta_2=\beta_3=\beta_4=0$ (There is no cointegration)

The validity of the cointegration relationship is evaluated using the F-test, as proposed by Narayan (2005). If the calculated F-statistic exceeds the upper bound of the critical values, this provides evidence in favor of a long-run cointegration relationship among the variables, leading to the rejection of the null hypothesis (H_0). Conversely, if the F-statistic falls below the lower bound, the null hypothesis of no cointegration cannot be rejected. In cases where the F-statistic lies between the lower and upper bounds, the test results are considered inconclusive.

3.4. Error Correction Model

Once a long-term relationship among the series has been established, the next step is to assess the existence and direction of causality between them. Granger (1988) emphasized that conventional Granger causality tests are not appropriate when variables are cointegrated. In such cases, it is more suitable to apply causality analysis through an Error Correction Model (ECM). The ECM was specifically developed to address this issue, enabling researchers to separate long-run equilibrium relationships from short-run dynamics and to better understand short-term adjustments among variables. In general, the ECM:

$$\Delta Y_t = \alpha + \sum_{i=1}^{p} \beta_i\, \Delta Y_{t-i} + \sum_{j=1}^{q} \gamma_j\, \Delta X_{t-i} + \lambda EC_{t-1} + \varepsilon_t \qquad (6)$$

In the model, ΔY_t represents the difference of the dependent variable (short-term change); ΔX_t represents the difference of the independent variables; $ECT_{(-1)}$ represents the one lag of error correction term (ECT represents the cointegration relationship); λ is the error correction coefficient; and ε_t is the error term. The error correction term EC_{t-1} measures the deviation from the long-term equilibrium, and if the system deviates from the long-term equilibrium, the error correction mechanism ensures the return to equilibrium. For the ECM model to function properly, it is important that the coefficient of $ECT_{(-1)}$ takes values between 0 and -1 and is statistically significant.

3.4. Robustness Tests

In the current research, FMOLS, DOLS, and CCR cointegration estimation methods were used to evaluate how consistent the results obtained from the ARDL model were across different methods.

FMOLS is an econometric method used to estimate long-term cointegration relationships. It was developed by Phillips and Hansen (1990) and has been particularly used to correct issues such as autocorrelation and heteroskedasticity in time series data. FMOLS is an improved version of the classical OLS regression. The basic regression model is as follows:

$$Y_t = \alpha + \beta X_t + u_t \tag{7}$$

In the above model, Y_t represents the dependent variable, X_t is the vector of independent variables, and u_t denotes the error term. The FMOLS method provides more reliable estimates by correcting the distortions caused by autocorrelation and non-stationary series in this standard regression.

DOLS, developed by Stock and Watson (1993), is a regression method used to estimate long-term relationships in cointegrated series. Like FMOLS, DOLS corrects for autoregressive dependence and issues of changing variance, making the long-term coefficients more reliable. The DOLS model estimates the long-term relationship between the dependent variable $Y_t$and the independent variable X_t by adding the differences and lagged values of the independent variables to the model, thereby correcting for autocorrelation and distortions. The general DOLS regression model can be written as follows:

$$Y_t = \alpha + \beta X_t + \sum_{i=-q}^{q} \gamma_j \, \Delta X_{t-i} + \varepsilon_t \tag{8}$$

In the above model, Y_t represents the dependent variable, X_t is the independent variable, ΔX_{t-i} refers to the differences and lagged values of the independent variable, β denotes the long-term coefficients, γ_j represents the short-term correction coefficients, and ε_t is the error term. The DOLS method corrects the distortions that arise in the classical OLS method by including the lagged and lead differences of the independent variable in the model.

CCR, developed by Park (1992), is a regression method used for cointegrated time series. Like FMOLS and DOLS, the CCR method corrects the issues of autocorrelation and changing variance in long-term predictions. The CCR method applies transformations to the error term to correct the distortions of the classical OLS regression. The general CCR regression model can be written as follows:

$$Y_t = \alpha + \beta X_t + u_t \tag{9}$$

In the above model, Y_t represents the dependent variable, X_t is the vector of independent variables, and u_t denotes the error term. The CCR method ensures the consistency of the long-term coefficients by restructuring the error terms compared to the classical OLS regression.

3.5. Findings and Discussion

The first findings obtained within the scope of the study were descriptive statistics and these statistics were shown in Table 1. According to Table 1, mean Leab, Growth, Physician, and Ptr were found to be 76.42368±3.184928, 4.230614±1.890568, 2.771812±0.579590, and 15.35117±3.186174, respectively.

Table 1. Descriptive statistics

	Leab	**Growth**$^{+}$	**Physician**	**Ptr**
Mean	76.42368	4.230614	2.771812	15.35117
Maximum	81.49268	8.348702	3.740000	19.76149
Minimum	70.97195	0.001058	1.500000	11.03429
Standard Deviation	3.184928	1.890568	0.579590	3.186174
Observations	48	48	48	48

$^{+}$ Since these variables recorded negative values in certain years, and taking the natural logarithm of a negative number is not possible, a constant was added to all Gdpgrwth values to transform the smallest negative value into a very small

The stationarity properties of the variables utilized in the analysis were examined using the Augmented Dickey-Fuller (ADF) test, a widely adopted unit root test in the empirical economics literature (see Table 2). The test results revealed that the dependent variable was integrated of order one [I(1)] under both the intercept-only and the intercept-and-trend specifications, thereby confirming the suitability of the ARDL bounds testing approach for the model. As for the independent variables, LnGrowth was found to be stationary at level [I(0)] in both model specifications. LnPhysician exhibited first-difference stationarity [I(1)] under the intercept-and-trend model, while LnPtr was level stationary [I(0)]. Under the intercept-only specification, however, both LnPhysician and LnPtr were found to be integrated of order one [I(1)].

Table 2. Unit Root Test Results

	Augmented Dickey-Fuller (ADF) Test			
	At Level (t-Statistic)		At First Difference (t-Statistic)	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
LnLeab	-1.84	-2.00	11.90**	-7.88**
LnGrowth	-7.48**	-7.39**	-7.98**	-7.98**
LnPhysician	-2.43	-1.42	-6.41**	7.22**
LnPtr	0.47	-4.61**	-7.83**	-7.74**

** denotes significant at %1; * denotes significant at %5

The optimal lag length was determined using the Vector Autoregressive (VAR) model, and the results indicated that a lag length of one was the most appropriate for the study (see Table 3). Accordingly, the maximum lag length was set to one based on the selection criteria derived from the VAR model.

Table 3. VAR Results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	89.09285	NA	2.46e-07	-3.867857	-3.705658	-3.807706
1	258.9208	301.0586*	2.27e-10*	-10.86003*	-10.04904*	-10.55928*
2	274.4958	24.77855	2.36e-10	-10.84072	-9.380928	-10.29936
3	282.0905	10.70163	3.63e-10	-10.45866	-8.350073	-9.676695
4	288.1844	7.478800	6.27e-10	-10.00838	-7.250997	-8.985810

*Represents the lag length determined by each selection criterion; LR refers to the sequential modified Likelihood Ratio test statistic (applied at the 5% significance level); FPE stands for Final Prediction Error; AIC denotes the Akaike Information Criterion; SC is the Schwarz Information Criterion; and HQ indicates the Hannan-Quinn Information Criterion.

Table 4 presents the bounds testing results, and it is seen that the value of F-statistic (7.256256) was greater than the upper limits for both 5% (5.07) and 1% (6.36) significance levels in I(1). These results revealed that there was a cointegration relationship among the study variables, namely, the study variables were found to be cointegrated.

Table 4. Bounds Test Results

Test Statistic	Value	k
F-statistic	7.256256	3
Critical Value Bounds		
Significance	I(0) Bound	I(1) Bound
5%	4.01	5.07
1%	5.17	6.36

The ARDL (1, 0, 0, 0) model was identified as the best-fitting model in the study, and the long-run results for this model are presented in Table 5. According to the long-run findings, LnGrowth, LnPhysician, and LnPtr had a positive impact on LnLeab. However, only LnPhysician was found to have a statistically significant effect in the long run ($p<0.05$).

Table 5. Long-Run Results

Dependent Variable: LnLeab				
Selected Model: ARDL(1, 0, 0, 0)				
Variable	**Coefficient**	**Standard error**	**t-Statistic**	**p value**
LnGrowth	0.000242	0.000294	0.823925	0.4147
LnPhysician	0.013149	0.002391	5.500093	0.0001**
LnPtr	0.003987	0.006485	0.614832	0.5421
C	4.243974	0.019505	217.588426	0.0001**
@TREND	0.002881	0.000107	26.955478	0.0001**

** donates significant at %1; * donates significant at %5

The results of the Error Correction Model (ECM) are presented in Table 6. In the short run, similar to the long-run estimates, LnGrowth, LnPhysician, and LnPtr were found to have a positive effect on LnLEAB. However, among these variables, only LnPhysician exhibited a statistically significant impact at the 5% significance level ($p < 0.05$). The lagged error correction term (ECTt-1) was negative, statistically significant, and fell within the expected range of –1 and 0. Specifically, the coefficient indicated that approximately 87% of the short-run disequilibrium is corrected in each period, suggesting a relatively rapid adjustment toward long-run equilibrium.

Table 6. Short-Run Results

Variable	Coefficient	Standard error	t-Statistic	p value
D(LnGrowth)	0.000212	0.000252	0.841782	0.4048
D(LnPhysician)	0.011543	0.003073	3.755714	0.0005**
D(LnPtr)	0.003500	0.005639	0.620634	0.5383
D(@TREND())	0.002529	0.000464	5.447200	0.0001**
C	3.72542	0.633521	5.87925	0.0001**
ECT (-1)	-0.877816	0.160943	-5.454194	0.0001**

** donates significant at %1; * donates significant at %5

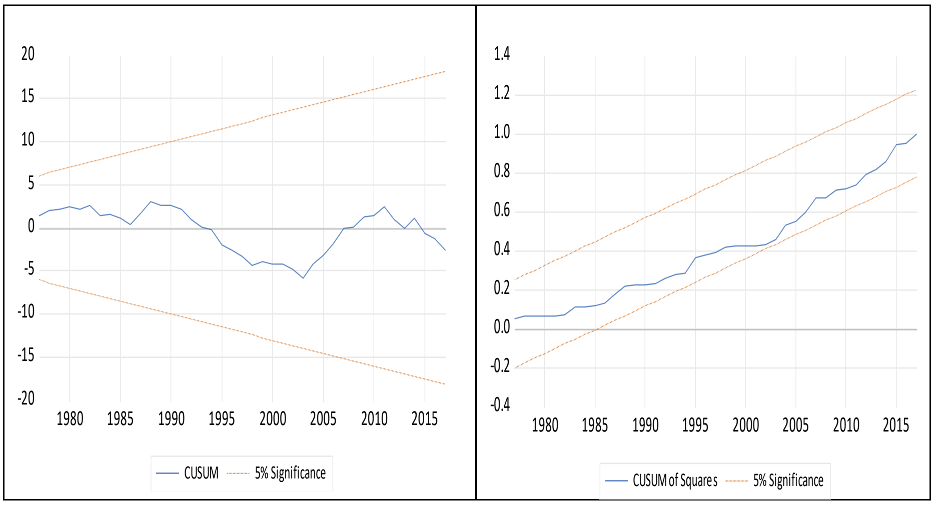
Diagnostic tests related to the ARDL bounds testing model of the study were carried out and the results were shown in Table 7. According to Table 7, the study model was distributed normally, did not have any problems regarding heteroskedasticity and serial correlation, and was correctly specified.

Table 7. Diagnostic tests

	p value	Result
Jarque-Bera Normality Test	0.554	Normal distribution.
Heteroskedasticity Test: Breusch-Pagan-Godfrey	0.103	No heteroskedasticity.
Breusch-Godfrey Serial Correlation LM Test	0.339	No Serial Correlation.
Ramsey RESET Test	0.329	Model was correctly specified.

The stability of the estimated model was evaluated using the Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMSQ) tests, with the corresponding plots presented in Figure 1. As illustrated, the trajectories of both test statistics remained within the 5% critical boundaries throughout the sample period, indicating that the model's coefficients were stable over time. These results confirm the structural stability of the model and support the reliability of the estimated relationships.

Figure 1. CUSUM and CUSUM of Squares



To ensure the robustness and consistency of the findings obtained through the ARDL bounds testing approach, the study additionally employed alternative cointegration estimation techniques, namely Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegrating Regression (CCR). The outcomes of these additional estimations are displayed in Table 8. According to these results, the effect of LnGrowth on LnLeab was found to be insignificant across all three regression models ($p>0.05$), whereas the effects of the other variables were statistically significant ($p<0.05$). Specifically, LnPhysician had a significant positive impact on LnLeab, while LnPtr exhibited a significant negative effect (Table 8).

Table 8. Results of Robustness Tests

Dependent Variable: LnLeab			
	FMOLS	**DOLS**	**CCR**
LnGrowth	(0.001100)	(0.002452)	(0.001157)
LnPhysician	(0.032598) **	(0.028547) *	(0.033381) **
LnPtr	(-0.172785) **	(-0.171174) **	(-0.172829) **
C	(4.770967) **	(4.769441) **	(4.770162) **

** donates significant at %1; * donates significant at %5

4. CONCLUSION AND DISCUSSION

This study aimed to investigate the impact of economic growth, physician density (per 1,000 population), and the pupil–teacher ratio on life expectancy at birth in the context of Belgium.

The findings of the study indicated a positive relationship between life expectancy at birth (LEAB) and gross domestic product (GDP) in both the short and long run. However, this association was not found to be statistically significant. The existing literature on the nexus between LEAB and economic growth presents mixed evidence, with prior studies reporting divergent outcomes depending on the country context, time period, and methodological approach. Some studies found a positive relationship (Mayer, 2001; Husain, 2012), while others reported a negative relationship in developed countries (Sultana et al., 2022), and some found no relationship at all (Acemoglu & Johnson, 2007; Bowser, 2010). As outlined in the literature section to emphasize the variation in findings across studies, Preston (1975) introduced the concept of the "Preston Curve," which illustrates a positive correlation between GDP per capita and average life expectancy in low- and middle-income countries. However, the curve also indicates that this relationship tends to diminish in high-income countries. This is because, in high-income countries, health infrastructure is already well-developed, and living conditions have reached a high level. At this stage, life expectancy continues to increase, but at a slower pace. In other words, in high-income countries, death rates drop to very low levels, but as income per capita increases, the increase in life expectancy becomes more limited. Additionally, it is important to consider how much of the income generated from economic growth is directed towards the healthcare sector. If economic growth does not benefit large segments of society due to unequal income distribution, it may not have a strong impact on life expectancy. Furthermore, short-term economic fluctuations, financial crises, or underlying structural factors may weaken or obscure the relationship between economic growth and life expectancy, rendering it statistically insignificant. In this regard, the findings of the present study are considered consistent with the broader literature and offer a meaningful contribution by highlighting the complex and context-dependent nature of this relationship.

Another finding of the study revealed a positive association between life expectancy at birth (LEAB) and the pupil–teacher ratio in both the short- and long-run analyses. However, this relationship was not statistically significant. Notably, the existing literature appears to lack studies that directly examine the relationship between LEAB and the pupil–teacher ratio, suggesting a gap that this study partially addresses. While previous research suggests a positive relationship between educational attainment and life expectancy at birth (Bilas et al., 2014; Ali and Ahmad, 2014; Sede and Ohemeng, 2015), the expected relationship between the pupil-teacher ratio and life expectancy at birth is negative. This is because the pupil-teacher ratio in a country can affect the quality of education. Teachers with fewer students can devote more time to their students, provide individual support, and thus, the quality of education may improve. A high pupil-teacher ratio indicates that class sizes are large, and the educational resources available per student may be limited. This can make it difficult for individuals to gain adequate education and health awareness from an early age. When the quality of education is low, individuals may lack the necessary knowledge to become aware of health issues, develop healthy living habits, and protect themselves from diseases. Additionally, a low level of education can increase the likelihood of individuals working in lower-income jobs, which may limit their access to healthcare services. When these factors combine, a high pupil-teacher ratio can lead to a deterioration of health indicators in the general population, and thus, a decrease in life expectancy. According to the robustness tests conducted at the end of the study, the increase in the pupil-teacher ratio has a statistically significant negative effect on life expectancy at birth according to the FMOLS, DOLS, and CCR methods. In this context, it is believed that the findings obtained are significant in terms of their contribution to the literature.

Another key finding of the study demonstrated a positive and statistically significant relationship between life expectancy at birth (LEAB) and the number of physicians per 1,000 people in both the short- and long-term analyses. In other words, an increase in physician density was associated with improvements in LEAB, underscoring the critical role of access to healthcare services in enhancing population health outcomes. In many studies in the literature, it has been found that the number of physicians has a positive and significant impact on LEAB (Balan and Jaba, 2011; Teker et al., 2012; Park and Nam, 2019; Delavari et al., 2019). The results of this study align with the existing literature. The link between the number of physicians and life expectancy at birth is primarily due to the essential role that access to healthcare services plays in determining life expectancy. A higher number of physicians enhances individuals' access to medical care, allowing for earlier disease detection, more effective treatment, and broader application of preventive healthcare measures. In particular, a high number of physicians in the management of infectious and chronic diseases can reduce mortality rates and increase life expectancy. Additionally, advancements in the healthcare system can raise individuals' general health awareness and improve the quality of healthcare services, contributing to a healthier life for the entire population. Based on the robustness checks performed at the conclusion of the study, the number of physicians was found to have a statistically significant positive impact on life expectancy at birth across the FMOLS, DOLS, and CCR estimation methods. These findings support the reliability and consistency of the results obtained from the ARDL model.

Conclusion

In developed countries, factors influencing life expectancy have become increasingly diverse, encompassing variables such as income levels, educational attainment, healthcare expenditures, the size and capacity of the healthcare workforce, inflation, and rising healthcare costs. Beyond economic development, elements such as a country's geographical location, cultural norms, lifestyle behaviors, and dietary habits are also recognized as important contributors to longevity across all development contexts. In the study, the number of physicians per 1,000 people was identified as the most influential variable on life expectancy at birth in Belgium. This result has been confirmed through various robustness tests. In Belgium, having a long-life expectancy is directly related to the number of physicians. The conditions in which people live affect their health status and contribute to disparities between socio-economic groups. Socio-economic inequalities in health can be found in all countries around the world, including the most developed ones. To create a sustainable and efficient healthcare sector and, as a result, achieve desired health outcomes such as longer life expectancy, collaborations between the healthcare sector and other sectors in the country should be increased. To gain a more comprehensive understanding of the interplay between education, economic growth, and life expectancy at birth in Belgium, it is essential to consider regional disparities. Enhancing social support programs targeting low-income populations may help mitigate these inequalities. Moreover, policies aimed at reducing income inequality and ensuring equitable access to healthcare and educational services across all segments of society could play a pivotal role in improving life expectancy outcomes.

When developing strategies to increase life expectancy, it is important for health administrators to consider the impact of physician density and take measures to improve access to healthcare services, especially in disadvantaged regions. Increasing the number of physicians alone is not sufficient; ensuring a balanced regional distribution is also crucial for reducing health inequalities. In addition, structuring healthcare services to include not only curative but also preventive care can help improve the overall level of public health. In this context, administrators should adopt data-driven decision-making processes to develop effective and targeted health policies.

Ethical Statement and Author Contributions	
Yazat katkı Oranı: 1. Yazar: %50 2. Yazar: %50	***Contribution Rate*** 1. Author: %50 2. Author: %50
Çıkar Çatışması: Çıkar çatışması beyan edilmemiştir	***Conflicts of Interest:*** No conflict of interest declared.
Etik Kurul İzni: Etik kurul izni gerektirmemektedir	***Ethics Committee Permission*** This study does not require ethics committee approval.
Teşekkür	***Acknowledgements***

REFERENCES

Acemoglu, D., & Johnson, S. (2007). Disease and development: the effect of life expectancy on economic growth. *Journal of political Economy*, *115*(6), 925-985.

Ali, A., & Ahmad, K. (2014). The impact of socio-economic factors on life expectancy for sultanate of Oman: An empirical analysis.

Avci, H. C. (2019). Sağlığın iktisadi büyümeye etkisi: Türkiye için üretim fonksiyonu yaklaşımı.

Avcı, H. C., & Çalışkan, Z. (2024). The effect of health on economic growth: A production function approach for Turkey. *Panoeconomicus*, *71*(3), 373-393.

Balan, C., & Jaba, E. (2011). Statistical Analysis of The Determinants of Life Expectancy in Romania. *Romanian Journal of Regional Science*, *5*(2).

Bilas, V., Franc, S., & Bošnjak, M. (2014). Determinant factors of life expectancy at birth in the European Union countries. *Collegium antropologicum*, *38*(1), 1-9.

Bloom, D. E., Canning, D., & Sevilla, J. P. (2001). The effect of health on economic growth: theory and evidence.

Bowser, D. (2010). The effect of life expectancy on economic growth in the United States. In *Population Association of America Conference* (pp. 1-58).

Çağlayan, E. (2006). Enflasyon, faiz oranı ve büyümenin yurtiçi tasarruflar üzerindeki etkileri. *Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi*, *21*(1), 423-438.

Daşdemir, A. M. (2008). AB Üyesi Ülkelerde Beşeri Sermaye ve Ekonomik Büyüme İlişkisi: Panel Veri Analizi (Yüksek Lisans Tezi). *İzmir: Dokuz Eylül Üniversitesi Sosyal Bilimler Enstitüsü*.

Delavari, S., Zandian, H., Rezaei, S., Moradinazar, M., Delavari, S., Saber, A., & Fallah, R. (2016). Life expectancy and its socioeconomic determinants in Iran. *Electronic physician*, *8*(10), 3062.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: journal of the Econometric Society*, 1057-1072.

Granger, C. W. (1988). Some recent development in a concept of causality. *Journal of econometrics*, *39*(1-2), 199-211.

Gujarati, D. N. (2016). Örneklerle Ekonometri, Çeviren: N. *Bolatoğlu, BB101 Yayınları, Ankara*.

Husain, M. J. (2012). Alternative estimates of the effect of the increase of life expectancy on economic growth. *Economics Bulletin*, *32*(4), 3025-3035.

Kearney, C., & Monadjemi, M. (1990). Fiscal policy and current account performance: International evidence on the twin deficits. *Journal of Macroeconomics*, *12*(2), 197-219.

Maertens de Noordhout, C., Van Oyen, H., Speybroeck, N., & Devleesschauwer, B. (2018). Changes in health in Belgium, 1990–2016: a benchmarking analysis based on the global burden of disease 2016 study. *BMC public health*, *18*, 1-13.

Mayer, D. (2001). The long-term impact of health on economic growth in Latin America. *World development*, *29*(6), 1025-1033.

Münz, R. (2012). Demographic trend in the world. *Collection of Papers*.

Narayan, P. K. (2005). The saving and investment nexus for China: evidence from cointegration tests. *Applied economics*, *37*(17), 1979-1990.

Özgen, F. B., & Güloglu, B. (2004). Türkiye'de iç borçların iktisadi etkilerinin VAR tekniğiyle analizi.

Park, J. Y. (1992). Canonical cointegrating regressions. *Econometrica: Journal of the Econometric Society*, 119-143.

Park, M. B., & Nam, E. W. (2019). National level social determinants of health and outcomes: Longitudinal analysis of 27 industrialized countries. *Sage Open*, *9*(2), 2158244019854496.

Pearson, M. (2017). *Performance of the belgium health system in international comparison*. Available address:https://www.health.belgium.be/sites/default/files/uploads/fields/fpshealth_theme_file/presentation_mark_pearson_belgium_health_system_performance_final.pdf

Pesaran, M. H., & Shin, Y. (1995). *An autoregressive distributed lag modelling approach to cointegration analysis* (Vol. 9514, pp. 371-413). Cambridge, UK: Department of Applied Economics, University of Cambridge.

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.

Phillips, P. C., & Hansen, B. E. (1990). Statistical inference in instrumental variables regression with I (1) processes. *The review of economic studies*, *57*(1), 99-125.

Preston, S. H. (1975). The changing relation between mortality and level of economic development. *Population studies*, *29*(2), 231-248.

Roffia, P., Bucciol, A., & Hashlamoun, S. (2023). Determinants of life expectancy at birth: a longitudinal study on OECD countries. *International Journal of Health Economics and Management*, *23*(2), 189-212.

Sasanipour, M. (2024). Disparities in Life Expectancy at Birth: A Comparative Study of Iran and MENA Region Countries. *Journal of Population Association of Iran*, *18*(36), 405-443.

Sciensano. (2024). *Life expectancy and quality of life: life expectancy, health status report*, 15 Jul 2024, Brussels, Belgium, https://www.healthybelgium.be/en/health-status/life-expectancy-and-quality-of-life/life-expectancy

Sede, P. I., & Ohemeng, W. (2015). Socio-economic determinants of life expectancy in Nigeria (1980–2011). *Health economics review*, *5*, 1-11.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 1-48.

Stock, J. H., & Watson, M. W. (1993). A simple estimator of cointegrating vectors in higher order integrated systems. *Econometrica: journal of the Econometric Society*, 783-820.

Sufian, A. J. M. (2013). Life expectancy and its socioeconomic determinants-a discriminant analysis of national level data.

Sultana, T., Dey, S. R., & Tareque, M. (2022). Exploring the linkage between human capital and economic growth: A look at 141 developing and developed countries. *Economic Systems*, *46*(3), 101017.

Taban, S., & Kar, M., (2006). Beşerî sermaye ve ekonomik büyüme: Nedensellik analizi, 1969-2001. *Sosyal Bilimler Dergisi*, 1.

Teker, D., Teker, S., & Sönmez, M. (2012). Ekonomik değişkenlerin kadın ve erkeğin yaşam süresine etkisi. *İşletme Araştırmaları Dergisi*, *4*(3), 118-126.