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How vulnerable employment and public health quality shape labour productivity: A comparative study of European economies

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Abstract. The relationship between health indicators and labour productivity has been gaining increasing importance as European economies have come to navigate ageing populations, health-related absenteeism, and evolving employment structures. This study investigates how absenteeism, vulnerable employment, and Disability-Adjusted Life Years (DALYs) affect GDP per person employed across 21 European countries from 2000 to 2021. Employing a robust methodological framework – including Two-Way Fixed Effects, Feasible Generalized Least Squares, and Linear Mixed Models – the analysis accounted for heteroscedasticity, unobserved heterogeneity, and the panel structure of the data. The Linear Mixed

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Model was identified as the most reliable for interpreting outcomes based on model comparison criteria. The findings indicate that a 1% increase in absenteeism is associated with a 0.064% decrease in GDP per person employed. DALYs among older workers (aged 50–69) reduce productivity by 0.657% per 1% increase, while DALYs among younger workers (aged 15–49) show a marginally positive effect of 0.132%. Vulnerable employment has a marginally positive impact of 0.089% per 1% increase. In contrast, a 1% rise in the share of wage and salaried workers contributes to a 2.383% increase in productivity. These findings underscore the importance of strengthening health systems for ageing workers, reducing employment vulnerability, and promoting stable, formal job opportunities to support long-term economic performance.

Keywords: labour productivity, health indicators, absenteeism, vulnerable employment, Disability-Adjusted Life Years (DALYs), European countries, panel data analysis

JEL Classification: I15, J21, J24, J81, O52, C23

1. INTRODUCTION

The COVID-19 pandemic has had lasting effects on global health and employment. Long-term health issues are known to have an impact on labour productivity and workforce participation. Understanding this relationship is crucial for designing policies supporting health recovery and economic productivity. A study by the Brookings Institution estimated that, as of August 2022, between 2 to 4 million Americans of working age were unable to work as a result of long COVID. This represents a substantial portion of the labour force and highlights the significant impact of long-term COVID-19 restrictions on employment (Bach, 2022). Among long COVID patients admitted to specialised clinics in the UK, 23.5% reduced their working hours, and 28.2% were no longer engaged in paid work. This reduction in workforce participation and productivity underscores the economic burden of long-term COVID-19 on both individuals and the broader economy (Kwon et al., 2024).

Many countries are confronted with the challenge of an ageing population, which leads to a shrinking labour force and increased healthcare demands. Investigating how health interventions can prolong workforce participation is essential for maintaining economic productivity. Projections indicate that the overall labour force participation rate in the United States is expected to decline to 60.1% by 2031, primarily due to an ageing population (Dubina et al., 2022).

The rise in conditions such as stress, anxiety, and burnout has increasingly impacted both workplace efficiency and employee performance. Exploring this dimension helps businesses and policymakers create supportive environments that enhance productivity and well-being. A recent survey by APA (2023) discovered that 77% of the labour force was informed that they were facing work-related stress, and 57% indicated they had felt burnt out due to work-related stress. According to the World Health Organization, depression and anxiety disorders result in an annual global economic loss of about US$1 trillion due to reduced productivity, with approximately 12 billion workdays forfeited each year because of these mental health challenges (WHO, 2024).

The shift toward remote and hybrid work models has transformed the connection between well-being, employment, and productivity. Flexible work arrangements can boost mental health; however, they may also create challenges by merging professional and personal boundaries, which can affect performance.

Working remotely often enhances productivity due to fewer interruptions and the ability to design a customised workspace. Moreover, it provides employees with more independence, enabling better task and time management. This increased control can improve job satisfaction and lower stress. However, work and home life overlap may introduce distinct stressors and emotional difficulties (Positive Reset Mental Health Clinic Eatontown, NJ, 2025).

Labour productivity plays a crucial role in driving economic expansion and maintaining competitiveness. Recognising the impact of employee well-being on productivity enables companies to enhance performance and assists governments in shaping effective labour policies. According to the International Labour Organization, productivity growth is directly associated with economic development, competitiveness, and overall living standards. Rather than shifts between sectors, improvements within individual industries are the primary catalyst for economic progress. Hollingshead (2019) found that employees with poor dietary habits are 66% more likely to experience productivity declines, while those unable to exercise during the workday face a 96% higher likelihood of decreased productivity. These insights emphasise the strong link between workforce health and productivity, highlighting the importance of fostering healthier lifestyles in the workplace.

With rising healthcare costs, governments and employers increasingly focus on preventive health measures to reduce absenteeism and healthcare expenditures. This makes the relationship between health and productivity more economically significant. The Australian Prevention Partnership Centre (n.d.) highlights that prevention lowers healthcare costs and reduces economic losses associated with premature death and prolonged ill health. By investing in preventive strategies, economies can alleviate the financial burdens of chronic diseases and enhance workforce productivity.

Automation and digital transformation reshape job roles, requiring workers to be adaptable and continuously upskill. Maintaining good physical and mental health is critical for sustaining productivity in this dynamic environment.

Investigating the correlation between health, employment, and labour productivity is critical for creating sustainable economies and improving individual well-being. With evolving challenges such as post-pandemic health effects, ageing populations, and the mental health crisis, this topic is more relevant than ever. Insights from this research can guide policymakers, employers, and healthcare providers in developing strategies that enhance both workforce health and economic performance.

2. LITERATURE REVIEW

The complex relationship between health, employment, and labour productivity is central to economic and public health research. Existing literature emphasises that good health enhances labour productivity, reduces absenteeism, and increases workforce participation, while poor health negatively impacts productivity and economic growth.

Several studies highlight the socio-economic factors influencing this relationship. Kačerauskas and Valantinaitė (2023) explore the money-happiness nexus in Lithuania, while Stehlíková et al. (2023) observe how health system quality affected COVID-19 mortality rates in EU countries. Vysochyna et al. (2023) examine how the COVID-19 epidemic has altered the influence of healthcare spending on sustainable economic growth. The influence of work-family disbalances on emotional exhaustion is noted by Tutar et al. (2024), with self-efficacy and stress perception as mediators. Borissov (2024) emphasises that proactive organisational measures can enhance employee resilience and reduce turnover.

Human capital is identified as an essential cause of economic growth. Jarząbek and Stolarska-Szeląg (2024) highlight that university education improves employment prospects for disabled persons. Bhatti and Alnehabi (2023) note that HR practices such as training and performance appraisals positively impact productivity. Djamal et al. (2023) observe that while human capital positively influences GDP in the short term, this factor's longstanding impact is less pronounced than the labour force and physical capital. Davidov (2024) states that employees with secondary and junior engineering education emphasised good working conditions more than those with academic degrees.

Generational differences also shape labour market dynamics. Trifan and Pantea (2024) emphasise Millennials' and Generation Z's flexibility and meaningful work preferences. Kuzior et al. (2023) and Wolf (2023) advocate for continuous professional development, while Maró et al. (2024) and Karahan et al. (2023) propose measures to address generational transitions in agriculture in Hungary, Turkey, and Japan.

Socioeconomic policies further influence labour productivity. Yurchyk et al. (2023) demonstrate a GDP multiplier effect of social protection expenditures in Ukraine. Badea et al. (2024) propose a framework to enhance occupational safety and health for workers with disabilities, while Kaddouri and Benelbar (2024) highlight foreign investment's role in enhancing productivity and technology transfer. Meanwhile, Taubayev et al. (2024) stress the importance of education and labour safety in minimising economic losses. Family well-being improves with balanced time allocation and equitable domestic responsibility sharing, as noted by Hong et al. (2024). Yehorova and Drozd (2024) emphasise reducing absenteeism, unemployment, and mortality to strengthen macroeconomic freedoms.

Demographic shifts, particularly ageing populations, present challenges to labour productivity. Ngoc et al. (2024) observe a negative correlation between healthcare investments and economic growth, though this is mitigated by human capital development. Saari et al. (2024) emphasise balancing technological efficiency with empathetic eldercare, while Benchea and Ilie (2023) advocate for digital literacy and soft skills to ensure success in the digital age. Wiłkość-Dębczyńska et al. (2024) explore how neurofeedback training impacts cognitive abilities in older individuals, including those diagnosed with mild cognitive impairment and early-stage dementia. Psychological health is progressively recognised as a serious reason influencing labour productivity. Yu (2025) states that employee training and development investments are crucial in maximising the benefits of digital transformation. A skilled workforce adapts more readily to new technologies and drives innovation, leading to superior ESG outcomes.

The importance of mental health is underscored by Mureşan et al. (2023), who find that stress negatively affects happiness. The COVID-19 contagion accelerated remote and hybrid work models, with Adams-Harmon et al. (2024) and Mujtaba and Lawrence (2024) highlighting the benefits of flexible employment arrangements for employee well-being and talent retention.

Financial literacy is another crucial factor. Johnson and Kasztelnik (2024) define financial socialisation as acquiring financial knowledge and behaviours shaped by family dynamics, culture, and socioeconomic conditions. Empathetic leadership and ethical decision-making are essential for managing human capital risks and promoting employee well-being (Mendez, 2024; Clay, 2024). Kuzior et al. (2022a) explore the intricate connections between Ukraine's health insurance systems, household income, and public health funding. Meanwhile, Kuzior et al. (2022b) highlight that initiatives supporting affordable mortgage lending and increased public investment in housing development can substantially improve public health by enhancing living conditions.

Technological readiness is essential for global competitiveness. Istudor et al. (2024) emphasise the need for comprehensive skill development and talent retention in AI integration. Mishchuk et al. (2024) note that resilient economies attract skilled migrants, while Kuděj et al. (2023) identify workforce adaptability as critical for SMEs' success. Lukić (2023) highlights the importance of strategic working capital management in Serbia's trade industry. Androniceanu and Georgescu (2023) found a positive correlation between digital competencies and human development indicators in Romania. Bagh et al. (2023) and Filemon et al. (2024) highlight the negative impact of capital and labour market distortions on corporate valuation and long-term growth. Li et al. (2024) found that comprehensive human resource strategies enhance employee creativity, with social and human capital as key mediators.

Environmental factors, such as wind turbine noise, also affect productivity, as Pleban et al. (2024) and Pleban and Radosz (2023) noted. Moreover, the pandemic disrupted healthcare services, as evidenced by Amusa (2024), with significant declines in patient visits and staff furloughs.

The literature demonstrates that health, employment, and labour productivity are interconnected, with human capital being a fundamental economic growth base. The evolving labour market, shaped by demographic shifts, technological advancements, and flexible work models, underscores the need to prioritise employee well-being and adaptability.

This research aims to analyse the interconnection between health indicators and labour productivity, specifically GDP per person employed, across 21 countries over the period from 2000 to 2021. The study investigates how factors such as absenteeism due to illness, vulnerable employment, Disability-Adjusted Life Years (DALYs) across different age groups, and the share of wage and salaried workers impact labour productivity. The objective is to provide insights that can inform policymakers and businesses on strategies to enhance workforce productivity while considering health-related challenges.

The following hypotheses guide the research:

H1: Absenteeism from work due to illness negatively affects GDP per person employed.

H2: Higher levels of vulnerable employment are associated with lower GDP per person employed.

H3: An increase in Disability-Adjusted Life Years (DALYs) among individuals aged 15-49 negatively impacts GDP per person employed.

H4: An increase in DALYs among individuals aged 50-69 negatively impacts GDP per person employed.

3. METHODOLOGY

Data Sources

This study investigates the relationship between GDP per person employed and various labour and health indicators across 21 countries from 2000 to 2021. The data sources for each variable are presented in Table 1.

Table 1

Variables and their sources.

Variables	Description	Source
Predicted variable		
y1	GDP per person employed (constant 2021 PPP $)	World Bank (n.d.)
Predictors		
x1	Absenteeism from work due to illness, days per employee per year	WHO ER (n.d.)
x2	Vulnerable employment, total (% of total employment) (modelled ILO estimate)	World Bank (n.d.)
x3	Disability-Adjusted Life Years (15-49 years) Rate	IHME (n.d.)
x4	Disability-Adjusted Life Years (50-69 years) Rate	IHME (n.d.)
Control variable		
x5	Wage and salaried workers, total (% of total employment) (modelled ILO estimate)	World Bank (n.d.)

Source: own compilation

Indicators like Absenteeism from work due to illness and Disability-Adjusted Life Years (DALYs) serve as critical proxies for evaluating the performance and effectiveness of a country's health system. The indicator Absenteeism from Work Due to Illness (Days per Employee per Year) reflects the number of workdays lost due to health-related issues. It is a direct measure of the workforce's health and its effect on productivity. High absenteeism rates may indicate inadequate healthcare services, delayed treatment, or poor preventive care, which prolongs recovery and keeps individuals out of work. Frequent absenteeism often reflects the prevalence of chronic diseases and poor health management within the population. Lost workdays directly reduce economic output and increase business costs, making this indicator crucial for assessing public health and economic performance. DALYs measure the overall burden of disease by accounting for both years of life failed due to early mortality and years existing with disability. They provide a comprehensive assessment of population health. High DALY rates indicate a more significant burden of disease, reflecting both mortality and morbidity that affect labour productivity and economic growth. Lower DALY rates suggest a more effective healthcare system capable of preventing and managing diseases, thus minimising their long-term impact on individuals' work capacity. By analysing DALYs for different age groups (e.g., 15-49 and 50-69 years), researchers can assess how health challenges affect different segments of the workforce, highlighting age-specific healthcare needs.

Including Vulnerable Employment and Wage and Salaried Workers as independent variables enhances the model's explanatory power. Thus, the indicator Vulnerable Employment (% of Total Employment) reflects the share of workers in insecure, informal jobs with limited benefits and job security. Higher rates of vulnerable employment often correlate with lower productivity due to unstable working conditions, lack of training, and reduced motivation. The metric Wage and Salaried Workers (% of Total Employment) represents the proportion of the workforce in stable, formal employment. Wage and salaried workers generally enjoy better working conditions, higher job satisfaction, and greater access to healthcare and social protections, all of which contribute to improved productivity.

Sample Description

The dataset includes panel data for 21 countries: Austria (22 observation), Croatia (18), Czechia (22), Denmark (18), Estonia (22), France (19), Germany (22), Hungary (22), Lithuania (22), Luxembourg (22), Malta (16), Netherlands (22), Norway (22), Poland (22), Romania (22), Slovakia (22), Slovenia (22), Spain (22), Sweden (22), Ukraine (22), and United Kingdom (22). The panel is unbalanced, with each country observed between 7 and 22 years, resulting in a total of 390 observations.

The choosing to sample only European countries is explained by the following reasons:

- European countries share similar socio-economic and political frameworks due to their geographic proximity, cultural similarities, and economic integration within the European Union. This homogeneity reduces confounding variables and allows for more reliable health and productivity indicator comparisons.
- Europe has one of the world's most ageing populations, leading to workforce challenges and rising healthcare costs. Analysing the relationship between health and productivity in this context is critical for understanding how demographic shifts affect economic performance.
- European countries generally have comprehensive, standardised, and publicly accessible health and labour productivity data from organisations such as Eurostat, the World Bank, and the World Health Organization (WHO). Using this high-quality data ensures the study's robustness and credibility.
- Many European countries have similar or harmonised labour regulations, social welfare systems, and healthcare policies, which help isolate the effects of health indicators on productivity without excessive policy-related variability. This facilitates the identification of more generalised patterns and trends.
- Limiting the study to European countries ensures manageable data collection and analysis while still covering a diverse range of economies, from highly industrialised nations like Germany and France

to emerging economies like Romania and Croatia. This diversity allows the study to capture a broad spectrum of labour market dynamics while maintaining regional coherence.

Data Transformation and Statistical Tests

- Given the significant difference in AIC and BIC values, the logarithmic form of variables was used to improve model fit.
- The Shapiro-Wilk test assessed normality, indicating that none of the variables follow a normal distribution.
- The Breusch-Pagan test identified heteroscedasticity, leading to using Feasible Generalized Least Squares (FGLS) and Linear Mixed Models (LMM) to address this issue.

Econometric Models

- The Two-Way Fixed Effects Model accounts for both country-specific and time-specific unobserved heterogeneity, which was conducted using the plm() function in R with the "within" estimator. Fixed effects were preferred over random ones, as the Hausman test indicated.
- Feasible Generalized Least Squares (FGLS) addressed heteroscedasticity and provided more efficient estimates, which were conducted using the "lm()" function in R with weighted adjustments.
- Linear Mixed Model (LMM) incorporated both fixed effects (predictors) and random effects (country-specific intercepts) and was conducted using the "Elmer ()" function in R, with REML estimation.

Model Selection

- The Two-Way Fixed Effects Model is chosen for causal interpretation due to its consistency and control of unobserved heterogeneity.
- The FGLS model is addressing heteroscedasticity.
- The Linear Mixed Model is selected for predictive analysis due to its flexibility in handling individual-specific variability.

Software and Tools

All statistical analyses were performed using R Studio.

4. EMPIRICAL RESULTS AND DISCUSSION

Descriptive measures like mean, median, standard deviation, range, and skewness offer a clear overview of the dataset's characteristics. They help understand each variable's central tendencies, variability, and distribution, offering context before diving into complex analyses. By presenting summary statistics, the data's reliability and validity are demonstrated. For instance, extreme outliers or unusually high variability can be identified, which may affect model performance and interpretation. Table 2 presented summary statistics for variables like GDP per person employed (y1), absenteeism (x1), and DALYs (x3, x4). These statistics were essential for justifying logarithmic transformations due to high skewness and supporting decisions like employing Feasible Generalized Least Squares (FGLS) to address heteroscedasticity.

Table 2

Summary statistics

	id	year	x1	x2	x3	x4	x5	y1
Number of observations	390	390	390	390	390	390	390	390
Mean	10,27	11,42	11,61	10,99	5363,09	22551,4	85,41	105887
Standard Deviation	5,88	6,17	4,39	5,93	1881,42	8840,79	5,85	52386,6
Median	10	11	11,48	10,49	4919,36	18935,3	85,5	98213,1
Trimmed Mean	10,13	11,41	11,39	10,09	5041,33	21478,2	86,03	97096,4
Median Absolute Deviation	7,41	7,41	4,08	4,75	1140,76	7174,97	4,75	35337,3
Minimum	1	1	1,33	3,97	3027,46	10602,5	53,91	24980,7
Maximum	21	22	27	45,01	14165,4	52140,7	95,19	316456
Range	20	21	25,67	41,05	11138	41538,2	41,28	291476
Skewness	0,16	0,01	0,59	2,52	1,78	0,96	-1,9	2,14
Kurtosis	-1,08	-1,15	0,69	9,16	3,41	0,21	6,34	5,2
Standard Error	0,30	0,31	0,22	0,30	95,27	447,67	0,30	2652,7

Source: Authors' calculations in R studio.

The Shapiro-Wilk normality test is used in research to evaluate if a dataset follows a normal distribution. It is preferred for several reasons, particularly in econometric and statistical modelling contexts. Many statistical methods, including regression models, assume that residuals or variables are normally distributed. The Shapiro-Wilk test helps verify this assumption. Violations can affect the accuracy of parameter estimates, confidence intervals, and hypothesis tests. The test results (Table 3) showed that variables are not normally distributed. This justified using logarithmic transformations to reduce skewness and improve model fit.

Table 3

Results of the Shapiro-Wilk normality test for variables

Variables	**Shapiro-Wilk normality test**	
	W	p-value
y1	0.76978	< 0.0001
x1	0.9767	< 0.0001
x2	0.77013	< 0.0001
x3	0.81902	< 0.0001
x4	0.89041	< 0.0001
x5	0.8538	< 0.0001

Source: Authors' calculations in R studio.

Figures A1-A6 in Appendix A present the histograms of variables y1 and x1-x5. That supports the preference for logarithmic transformations of the variables.

AIC (Akaike Information Criterion) is used to compare models: the lower the AIC value, the better the model balances accuracy and complexity. BIC (Bayesian Information Criterion) compares models and selects the most suitable one, considering the number of parameters and sample size. As with AIC, a lower BIC value indicates a better model. The outputs of AIC and BIC calculations are presented in Table 4.

Table 4

The results of the Akaike Information Criterion and Bayesian Information Criterion

Model	df (degrees of freedom)	AIC	BIC
Model_nominal	7	9364.4043	9392.16730
Model_log	7	-111.0294	-83.26641

Source: Authors' calculations in R studio.

AIC (Akaike Information Criterion) is used to compare models – the lower the AIC value, the better the model in terms of balancing accuracy and complexity. Model_log has a significantly lower AIC (-111.0294 compared to 9364.4043), indicating that it is substantially better in quality compared to model_nominal. The difference in AIC values is so significant that it demonstrates the clear superiority of the logarithmic model.

Model_log has a significantly lower BIC (-83.26641 compared to 9392.16730), indicating a much better fit to the data. The difference in BIC values between the two models is vast, demonstrating the clear superiority of the logarithmic model.

The Thumb rule states that if the difference in BIC exceeds 10, it indicates that one model is significantly better than the other. In this case, the difference is over 9000, a strong argument for model_log.

That means that the log form of variables should be used in models.

The Lagrange Multiplier test, also called the Breusch-Pagan LM test, evaluates whether random effects are suitable compared to a pooled OLS model in panel data analysis. Given the very small p-value (< 0.05), the null hypothesis of no panel effects is rejected, indicating significant cross-country differences and rendering the pooled OLS model unsuitable. The Hausman Test determines whether a Fixed Effects (FE) or Random Effects (RE) model is more appropriate by examining whether entity-specific effects correlate with the regressors. With a p-value of 0.0385 below 0.05, the null hypothesis is rejected, confirming that country-specific effects are correlated with the regressors. Consequently, the RE model is inconsistent, making the FE model the preferred choice for this panel data analysis.

The Two-Way FE (Within) Model is preferred because it accounts for entity-specific and time-specific unobserved heterogeneity, addresses endogeneity issues, and yields more reliable estimates for panel data, especially in scenarios with unbalanced data and potential omitted variable bias. This makes it more robust and interpretable than one-way fixed or random effects models.

In this case, the panel type is the unbalanced panel with 21 entities, spanning between 7 to 22 time periods, totalling 390 observations.

The predictor x5 (Wage and salaried workers (% of total employment)) is highly significant, p-value<0.0001. That means a 1% increase in the proportion of wage and salaried workers is associated with a 2.276% increase in GDP per person employed. This firm's positive effect suggests that formal, stable employment is crucial in enhancing labour productivity, likely due to better working conditions, job security, and human capital development.

The model accounts for approximately 26% of the variation in GDP per person employed, incorporating both individual and time-fixed effects. The Studentized Breusch-Pagan test, applied to the two-way fixed effects panel model, yielded a test statistic of 60.338 with five degrees of freedom and a p-value of < 0.0001. Since the p-value is well below the 0.05 threshold, the null hypothesis of homoscedasticity is rejected. This indicates that the residuals exhibit heteroscedasticity, which violates a key assumption of linear regression and may result in inefficient estimates and biased standard errors.

Table 5

Two-way fixed effects (within) panel model outputs.

Two-way effects Within Model Call: plm(formula = log(y1) ~ log(x1) + log(x2) + log(x3) + log(x4) + log(x5), data = pdata, effect = "twoways", model = "within") Unbalanced Panel: n = 21, T = 7-22, N = 390				
Residuals				
Min.	1st Qu.	Median	3rd Qu.	Max.
-0.23790257	-0.03002629	-0.00042264	0.03168788	0.20191101
Coefficients				
Variables	Estimate	Std. Error	t-value	Pr(>|t|)
Log(x1)	-0.012448	0.020529	-0.6064	0.544673
Log(x2)	0.154108	0.048712	3.1636	0.001697**
Log(x3)	-0.222122	0.077073	2.8820	0.004201**
Log(x4)	0.143598	0.093128	-1.5419	0.124010
Log(x5)	2.276375	0.263155	8.6503	< 0.0001***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Total Sum of Squares: 1.771 Residual Sum of Squares: 1.311 R-Squared: 0.25973 Adj. R-Squared: 0.16046 F-statistic: 24.0694 on 5 and 343 DF, p-value: < 0.0001				

Source: Authors' calculations in R studio.

The regression in Table 6 is part of the Breusch-Pagan test for heteroscedasticity, where the predicted variable is the squared or log of residuals from the primary model.

Table 6

Regression where the predicted variable is the log of residuals from the primary model output.

Call: lm(formula = log_residuals ~ log(x1) + log(x2) + log(x3) + log(x4) + log(x5), data = pdata)				
Residuals				
Min.	1st Qu.	Median	3rd Qu.	Max.
-9.7131	-1.1181	0.4299	1.5929	4.5015
Coefficients				
Variables	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	4.1562	18.5742	0.224	0.82306
Log(x1)	0.7717	0.3104	2.486	0.01333*
Log(x2)	-0.8280	0.6390	-1.296	0.19586
Log(x3)	5.2915	1.0120	5.229	<0.0001***
Log(x4)	-2.6133	0.8579	-3.046	0.00248**
Log(x5)	-6.9057	3.7288	-1.852	0.06479.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Residual standard error: 2.363 on 384 degrees of freedom Multiple R-squared: 0.1166, Adjusted R-squared: 0.1051 F-statistic: 10.14 on 5 and 384 DF, p-value: <0.0001				

Source: Authors' calculations in R studio.

The whole F-test is highly significant (p<0.0001), indicating that at least one of the predictors influences the variance of residuals. Key contributors to heteroscedasticity are the following: log(x1) (Absenteeism) and log(x3) (DALYs for 15-49 years) with positive impact (increase Variability) and log(x4) (DALYs for 50-69 years) and log(x5) (Wage and salaried workers) with negative impact (reduce variability).

The Breusch-Pagan test confirms heteroscedasticity in the panel data. Predictors like absenteeism and younger-age health issues increase variance, while older-age health impacts and formal employment reduce variability.

The better way to address this issue is to explore Feasible Generalized Least Squares (FGLS) if the heteroscedasticity is clustered by countries or time.

Table 7

The Feasible Generalized Least Squares model outputs.

Call: lm(formula = log_residuals ~ log(x1) + log(x2) + log(x3) + log(x4) + log(x5), data = pdata)				
Residuals				
Min.	1st Qu.	Median	3rd Qu.	Max.
-9.7131	-1.1181	0.4299	1.5929	4.5015
Coefficients				
Variables	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	4.1562	18.5742	0.224	0.82306
Log(x1)	0.7717	0.3104	2.486	0.01333*
Log(x2)	-0.8280	0.6390	-1.296	0.19586
Log(x3)	5.2915	1.0120	5.229	<0.0001***
Log(x4)	-2.6133	0.8579	-3.046	0.00248**
Log(x5)	-6.9057	3.7288	-1.852	0.06479.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Residual standard error: 2.363 on 384 degrees of freedom Multiple R-squared: 0.1166, Adjusted R-squared: 0.1051 F-statistic: 10.14 on 5 and 384 DF, p-value: <0.0001				

Source: Authors' calculations in R studio.

The residual standard error (8.694) is smaller than the two-way fixed effects (within) the panel model, indicating improved efficiency. The model explains the 71.82% variation in GDP per person employed. Adjusted R-squared = 0.7146, which is not much smaller than R-squared. The f-statistic (195.8) is highly significant with a p-value<0.0001.

Log (x1) is significant at 0.1% level, p-value<0.0001. That means a 1% growth in absenteeism is correlated with a 0.096% growth in GDP per person employed. Interestingly, the sign is now positive compared to previous models, suggesting that after accounting for heteroscedasticity, absenteeism may be correlated with productivity in unexpected ways (perhaps due to industry-specific effects). log(x2) is significant at 0.1%, p<0.0001. This could be interpreted in the following way – a 1% rise in vulnerable employment is linked with a 0.623% reduction in GDP per person employed. This aligns with the expected negative relationship, as vulnerable employment typically reflects lower productivity. log (x3) is not significant (p-value=0.7087). log(x4) is significant at 0.1%, p<0.0001. This means that a 1% increase in DALYs for older workers is associated with a 0.673% decrease in GDP per person employed. This supports the idea that poor health in older workers negatively impacts productivity. Log (x5) is significant at a 1% level (p=0.00228), which means a 1% raise in the share of wage and salaried workers is associated with a 1.498% decrease in GDP per person employed, counterintuitive compared to previous models. This could indicate that other structural factors might influence this relationship after correcting for heteroscedasticity or that the weight adjustments have altered the variable's impact.

The R2 of 71.82% is significantly higher than the 25.97% observed in the two-way fixed effects model, implying that addressing heteroscedasticity via FGLS led to more efficient and accurate estimates. The sign of log(x1) flipped from negative to positive, and log(x5) flipped from positive to negative. These shifts highlight how heteroscedasticity may have previously biased estimates.

To address limitations in FGLS, particularly its inability to account for unobserved individual heterogeneity across countries, it is recommended to build a Linear Mixed Model (LMM) after the FGLS model. Unlike FGLS, the LMM includes random effects, allowing it to model country-specific variability and provide more flexible, reliable estimates – especially with unbalanced panel data. The LMM incorporates both fixed effects (predictors that are the same across all individuals) and random effects (individual-specific intercepts). In this model, the variable id acts as the random effect, capturing unobserved heterogeneity across individuals.

The advantages of LMM are the following:

- Accounts for individual-specific heterogeneity using random intercepts.
- Allows for inferences beyond the sample by modelling random effects.
- Provides efficient estimates even with unbalanced data.

Table 8

The outputs from the Linear Mixed Model.

Linear mixed model fit by REML ['lmerMod'] Formula: log(y1) ~ log(x1) + log(x2) + log(x3) + log(x4) + log(x5) + (1 | id) Data: pdata REML criterion at convergence: -839.7				
Residuals				
Min.	1st Qu.	Median	3rd Qu.	Max.
-5.3623	-0.4432	-0.0484	0.5243	3.4089

Random effects:			
Groups	Name	Variance	Std.Dev.
id	(Intercept)	0.074935	0.27374
Residual		0.004795	0.06925
Number of obs: 390, groups: id, 21			

Coefficients				
Variables	Estimate	Std. Error	t-value	Significance
(Intercept)	6.22123	1.46581	4.244	*** Significant
log(x1)	-0.06434	0.02088	-3.082	** Significant
log(x2)	0.08855	0.05241	1.689	* Marginally Significant
log(x3)	0.13163	0.07893	1.668	* Marginally Significant
log(x4)	-0.65657	0.07120	-9.222	** Significant
log(x5)	2.38345	0.28653	8.318	** Significant

Correlation of Fixed Effects					
	(Intr)	lg(x1)	lg(x2)	lg(x3)	lg(x4)
log(x1)	-0.025				
log(x2)	-0.821	0.134			
log(x3)	-0.045	-0.111	-0.092		
log(x4)	-0.126	0.016	0.128	-0.895	
log(x5)	-0.977	0.027	0.822	0.034	0.049

Source: Authors' calculations in R studio.

High correlations between predictors may indicate potential multicollinearity, but since LMMs are robust to some degree of correlation, this may not be critical:

Intercept and log(x5) (−0.977) – very high, but expected since both influence the baseline level of GDP;

log(x2) and log(x5) (0.822) indicate potential collinearity between vulnerable employment and wage workers.

Residuals range from -5.36 to 3.413.413.41, with a relatively small interquartile range (IQR: -0.443 to 0.524), indicating a good fit. REML Criterion (-839.7) is used for comparing nested models.

The standard deviation of the random intercepts across individuals is 0.27374, indicating moderate heterogeneity in baseline GDP per person employed. The residual standard deviation is 0.06925, suggesting a relatively low level of unexplained variation after accounting for both fixed and random effects. Since the random intercept variance is larger than the residual variance, individual-specific effects account for a significant part of the deviation in the outcome.

Table 9 compares LMM with Two-Way FE and FGLS models. Table 9 compares the three models presented and gives the base for choosing the best model considering different criteria (R2, heteroscedasticity correction, model flexibility, etc.). Four of the five criteria indicate that the best choice is LMM (REML), so the explanation of the influence of variables should be based on it.

Table 9

Comparison of LMM with Two-Way FE and FGLS models.

Criteria	**Two-Way FE**	**FGLS**	**LMM (REML)**	**Best Choice**
R2	0.2597	0.7182	Not directly available	FGLS (Highest R2)
Fixed Effects consistency	Consistent	Potential Bias	Consistent	TWFE or LMM
Random Effects	None	None	Random Intercepts	LMM
Heteroscedasticity Correction	No	Corrected	Random Effects Reduce Bias	FGLS or LMM
Model flexibility	Limited	Limited	Flexible (Random Effects)	LMM

Source: Authors' calculations in R studio.

In LMM, the Intercept is significant, which means the expected log GDP per person employed is 6.22 when all predictors are zero. A 1% growth in absenteeism is linked with a 0.064% reduction in GDP per person employed, significant at the 1% level. A 1% growth in vulnerable employment is linked with a 0.088% increase in GDP per person employed, but only marginally significant. A 1% increase in DALYs for younger workers is correlated with a 0.132% growth of GDP per person employed, which is also only marginally significant. A 1% increase in DALYs for older workers is related to a 0.657% decrease in GDP per person employed; it is significant at a high level (0.1%). A 1% rise in the portion of wage and salaried workers is associated with a 2.38% increase in GDP per person employed, which is also highly significant.

The absenteeism might be associated with a positive impact on GDP per person employed, which can seem counterintuitive, but several economic and organisational factors could lead to this outcome:

- Absenteeism may allow overworked employees to recover from stress or burnout, improving their performance upon returning. Rested employees are more productive, creative, and efficient, enhancing worker output. For example, adequate rest reduces errors and improves decision-making, especially in cognitive and creative tasks. The study by Akerlof and Yellen (1990) discusses the correlation between employee morale, force, and productivity, implying that strategic absenteeism might improve overall efficiency by preventing burnout
- If employees with lower productivity are more likely to be absent, the average productivity of those who remain at work increases. Since GDP per person employed is calculated as a total output divided by the number of workers present, the absence of less productive workers raises the average output per worker. The research by Pfeifer (2010) indicates that absenteeism may selectively reduce the presence of less productive workers, temporarily increasing average productivity.

- High absenteeism may lead companies to streamline processes and optimise their workforce to maintain productivity with fewer employees. Leaner operations often result in higher productivity per worker. Companies might adopt automation or process improvements to compensate for frequent absences, increasing long-term productivity (Autor et al., 2003).
- In economies with advanced technology and flexible labour markets, temporary absenteeism may have minimal impact on output, preserving or even raising productivity metrics. For instance, in highly automated industries, absenteeism might not reduce overall production, thus increasing GDP per person employed. This study by Bloom et al. (2015) found that remote work improved efforts and job satisfaction outputs, suggesting that certain forms of absenteeism (like remote work) might increase productivity per worker.
- The positive correlation may be short-lived. Prolonged or widespread absenteeism typically reduces productivity and negatively impacts GDP in the long run. The effect is more likely in jobs with flexible schedules or team-based tasks. Absenteeism usually lowers productivity in roles where individual presence is critical (e.g., healthcare, manufacturing). Absenteeism due to illness or burnout may have different effects than strategic absences (e.g., taking time off to prevent burnout).

Since the Hausman Test rejected the Random Effects model assumption, the LMM is a valid alternative because it models random intercepts while still controlling for correlations in predictors. Unlike FGLS, which assumes no correlation with entity effects, the LMM allows for entity-specific variability without introducing bias.

As a result, for causal interpretation, the Two-Way Fixed Effects Model (since the Hausman Test rejected RE assumptions) for predictive performance and flexibility – the Linear Mixed Model, since it captures individual heterogeneity while providing more efficient estimates than FE models. FGLS is less appropriate because of the potential correlation between entity effects and regressors.

Based on model comparison criteria, the Linear Mixed Model (LMM) using REML estimation emerged as the most robust analytical framework and formed the basis of this discussion. The findings revealed that absenteeism had a statistically significant negative effect on GDP per person employed, contradicting Hypothesis H1, which anticipated a negative relationship. Hypothesis H2, predicting that vulnerable employment reduces productivity, received only marginal support, as the LMM showed a weakly positive but borderline significant effect. Hypothesis H3, expecting a negative impact of DALYs among individuals aged 15–49, was not supported; instead, a marginally significant positive relationship suggested potential resilience among younger workers. Hypothesis H4 was strongly supported, with DALYs in the 50–69 age group demonstrating a significant negative impact on productivity. Notably, the share of wage and salaried workers had the strongest positive association with GDP per person employed, underscoring the importance of formal and stable employment. Overall, the results indicate that health issues among older workers and precarious employment structures are detrimental to productivity, while younger workers may maintain performance levels despite health burdens. These insights support targeted policy interventions focused on strengthening health support for ageing workers and fostering secure employment conditions to sustain economic performance.

5. DISCUSSION

This study examined the influence of health-related and employment indicators on labour productivity – measured by GDP per person employed – across 21 European countries from 2000 to 2021. Drawing on the Linear Mixed Model, which was determined to be the most appropriate method based on model comparison criteria, the discussion highlights key findings in relation to the existing literature.

The analysis revealed that absenteeism due to illness (x1) had a statistically significant negative association with productivity in the LMM. This supports the widely accepted view in the literature that poor health reduces economic output. Hollingshead (2019) identified a clear link between poor employee health and diminished workplace performance, while Pfeifer (2010) suggested that selective absenteeism might temporarily raise average productivity. However, the significant negative coefficient in the LMM aligns more closely with traditional interpretations and reinforces the need for adequate health interventions to reduce work absences.

Vulnerable employment (x2) displayed a marginally positive relationship with GDP per person employed in the LMM, offering limited support for Hypothesis H2. Although this finding is somewhat unexpected, it could reflect a productivity boost in economies with high informal employment due to lower labour costs or flexible job structures. Nevertheless, this must be interpreted cautiously, as Bhatti and Alnehabi (2023) stress that stable employment and structured HR practices are key drivers of sustained productivity gains. The weak significance in the LMM also suggests that any benefits from vulnerable employment are likely short-term or sector-specific.

In contrast to expectations, DALYs among younger individuals aged 15–49 (x3) had a marginally positive and near-significant relationship with productivity. While this contradicts Hypothesis H3, it may reflect the resilience of younger workers or adaptive labour market responses, such as task redistribution or flexible work arrangements. This echoes Borissov's (2024) argument that younger cohorts often maintain performance even under health-related pressures. However, as the effect was only marginally significant, further investigation is warranted to understand whether this reflects a broader pattern or specific regional dynamics.

For older workers (x4), the study found a substantial negative impact of DALYs on productivity, supporting Hypothesis H4. This result is consistent with the findings of Stehlíková et al. (2023) and Wiłkość-Dębczyńska et al. (2024), who emphasised the productivity costs associated with ageing populations and chronic health burdens. The robust negative association underscores the urgency of addressing health challenges older workforce segments face to prevent long-term economic strain.

Finally, the proportion of wage and salaried workers (x5) exhibited a highly significant and positive effect on productivity in the LMM, reaffirming the economic importance of formal, secure employment. This result aligns with the broader literature, including Djamal et al. (2023), who stressed the role of stable job structures and human capital investment in enhancing labour output. The finding also reinforces the need for labour policies that strengthen access to formal employment and improve job quality.

The LMM-based findings highlight the nuanced and age-sensitive relationship between health and productivity. While younger workers may demonstrate resilience despite health challenges, poor health among older workers significantly hampers productivity. Vulnerable employment may offer temporary economic advantages but lacks the long-term benefits of stable, salaried positions. These insights suggest that policymakers should prioritise healthcare investment for ageing workers, reduce informal employment, and promote stable, well-supported job opportunities to maintain economic growth. Future research should further explore sectoral effects, longitudinal dynamics, and the potential mediating role of institutional and healthcare systems in shaping these outcomes.

6. CONCLUSION

Understanding the relationship between health indicators and labour productivity is increasingly relevant as economies face challenges from ageing populations, health-related absenteeism, and evolving employment structures. This study aimed to assess how absenteeism, vulnerable employment, and DALYs among different age groups impact GDP per person employed in 21 European countries from 2000 to

2021. Using a robust methodology that included Two-Way Fixed Effects, Feasible Generalized Least Squares, and Linear Mixed Models, the analysis accounted for heteroscedasticity, unobserved heterogeneity, and panel data structure to ensure reliable results.

The main findings revealed complex yet insightful relationships between health indicators, employment structures, and labour productivity. Based on the Linear Mixed Model – identified as the most suitable model – the results show that absenteeism had a statistically significant negative impact on GDP per person employed, challenging the notion that short-term absences might enhance average productivity. Vulnerable employment demonstrated a marginally positive, though weak, association with productivity, suggesting that any perceived gains from informal or insecure work are likely unsustainable. DALYs among younger workers (aged 15–49) showed a marginally significant positive correlation with productivity, potentially indicating resilience or compensatory mechanisms within this demographic. In contrast, DALYs among older workers (50–69) strongly and significantly negatively affected productivity, highlighting the economic costs of declining health in ageing labour forces. Finally, the share of wage and salaried workers had the most robust positive effect on productivity, reaffirming the critical role of stable, formal employment in driving economic performance. These results underscore the need for targeted labour and health policies that reduce vulnerability, support ageing workers, and expand access to formal employment as key strategies to sustain long-term productivity growth.

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APPENDIX A.

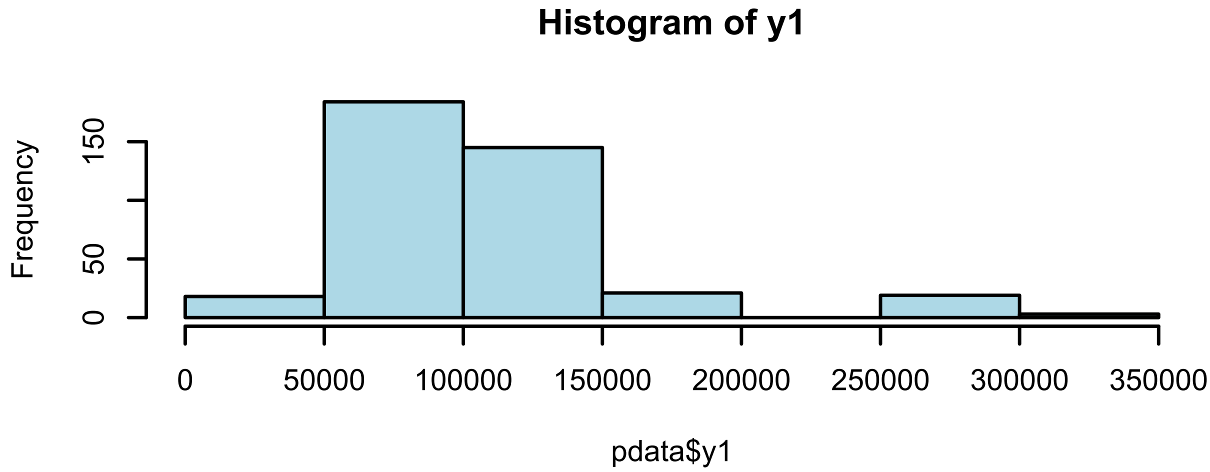

Figure A1. Histogram of the y1 (GDP per person employed (constant 2021 PPP $)).
Source: Authors' calculations in R studio.

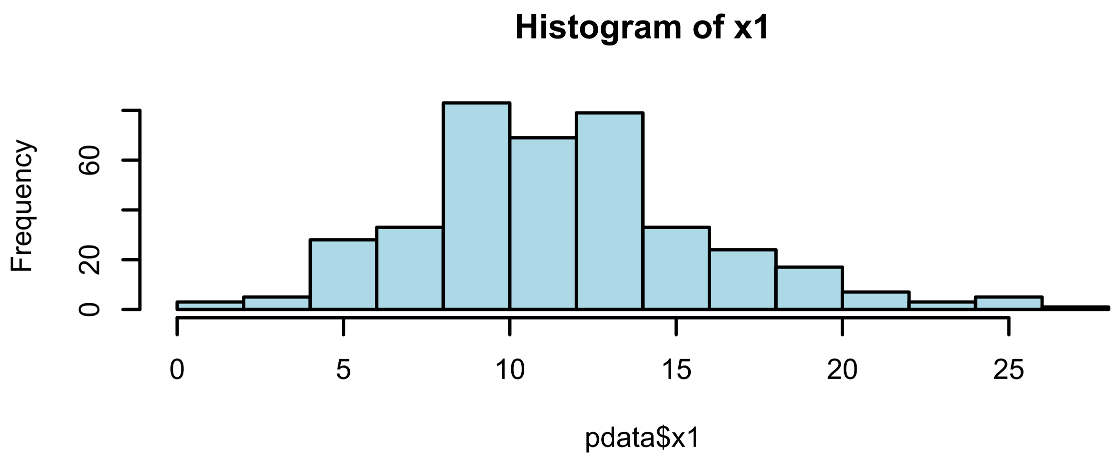

Figure A2. Histogram of the x1 (Absenteeism from work due to illness, days per employee per year).
Source: Authors' calculations in R studio

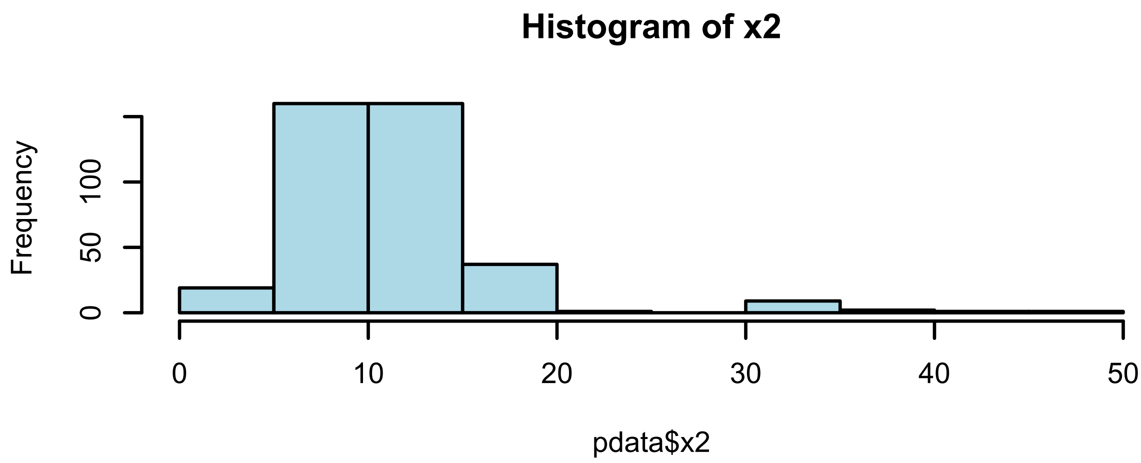

Figure A3. Histogram of the x2 (Vulnerable employment, total (% of total employment) (modelled ILO estimate).
Source: Authors' calculations in R studio

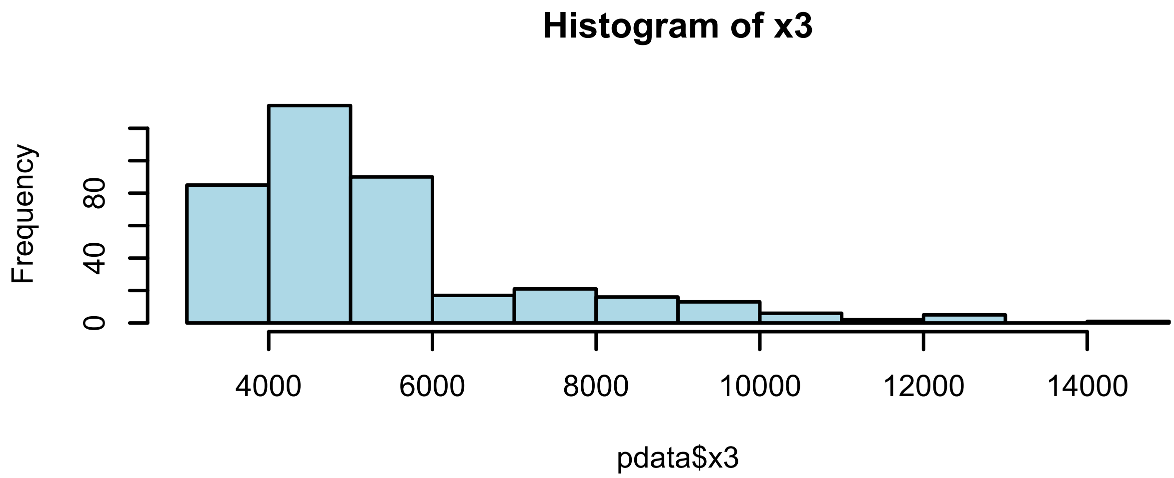

Figure A4. Histogram of the x3 (Disability-Adjusted Life Years (15-49 years), rate).
Source: Authors' calculations in R studio

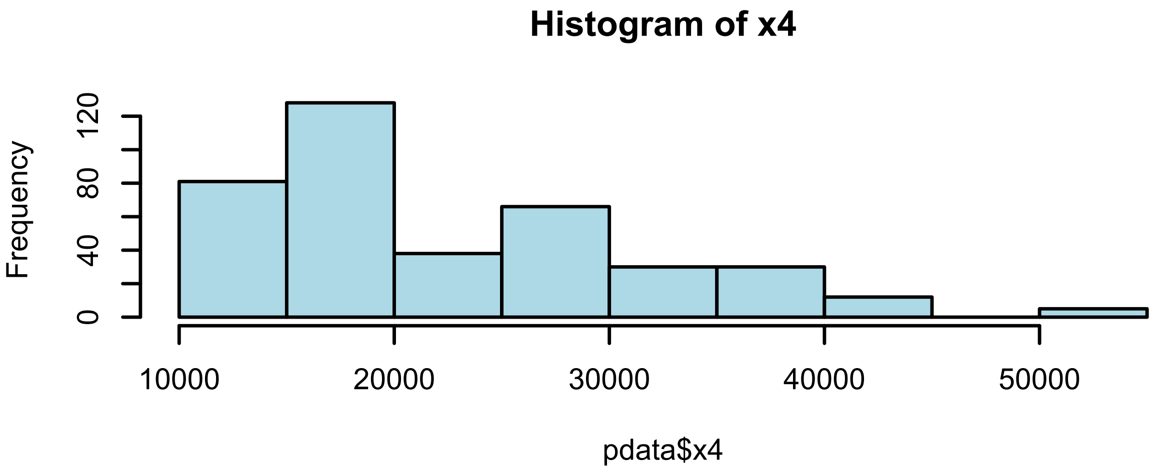

Figure A5. Histogram of the x4 (Disability-Adjusted Life Years (50-69 years), rate).
Source: Authors' calculations in R studio

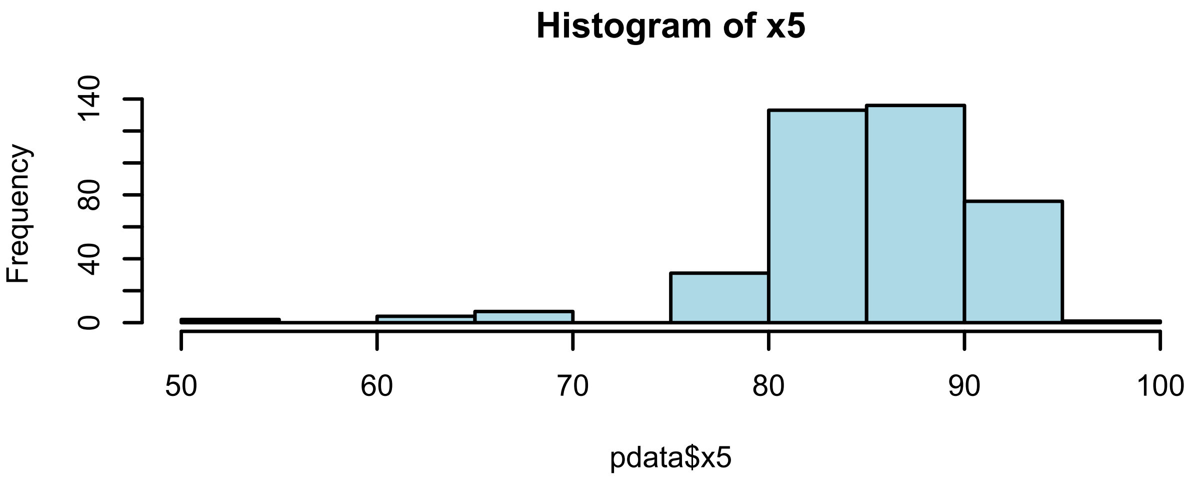

Figure A6. Histogram of the x5 (Wage and salaried workers, total (% of total employment) (modelled ILO estimate)).
Source: Authors' calculations in R studio