# IMPACT OF AGEING AND TECHNOLOGICAL PROGRESS ON LABOUR PRODUCTIVITY

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# IMPACT OF AGEING AND TECHNOLOGICAL PROGRESS ON LABOUR PRODUCTIVITY

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**Abstract**
This paper analyses determinants of labour productivity observed on a country level for fifteen selected OECD countries observed in the period from 2012 to 2019. It simultaneously studies the effect of ageing and technological progress on labour productivity and provides insight into characteristics that are shared between countries with high levels of labour productivity. Year-level data have been collected from OECD and UNCTAD, and two different methodologies (panel data and cluster analysis) have been used. Results on the impact of selected explanatory variables on labour productivity vary depending on the methodology used. The ageing of society undoubtedly has a positive impact, while the results of panel data analysis indicate a statistically insignificant effect of employment protection and investment in human capital. On the other hand, the cluster analysis results suggest that countries with higher levels of employment protection belong to a group of countries with higher levels of labour productivity. Similar results are obtained regarding investment in human capital, i.e. the level of public expenditure on education. The most significant difference in obtained results is related to technology, i.e. frontier technology readiness index, since the results of panel analysis suggest a negative, and K-means cluster a positive effect on labour productivity.

Keywords**:** labour productivity, ageing, technological progress, OECD countries

*JEL classification*: C33, C38, J24

## INTRODUCTION

Ageing of society and technological progress as ongoing forces have various sociological and economic repercussions. At the same time, economic goals observed on a firm or a country level do not change much over decades and, in most cases, are under strong pressure to decrease inputs and increase output. In that sense, the issue of labour productivity is the focus of this research. Labour productivity can be observed on an individual (employee), firm or country level. Regardless of the perspective on productivity, it has its specific determinants. Consequently, a vast literature on labour productivity explores different aspects and views of this subject (e.g. Bjuggren 2018; Brookes, James, and Rizov 2018; Delalibera and Ferreira 2019; Hernæs et al. 2023; Lee and Shin 2021; etc.). However, this paper is focused on productivity analysed on a country level, and even though there are similar studies that analyse determinants of labour productivity on a country level (e.g. Andriulis, Butkus, and Matuzevičiūtė 2022;

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Neycheva 2010; Park, Shin, and Kikkawa 2021; etc.), this study takes into consideration both ageing and technological progress, along with other variables, which distinguishes it from other research on the subject. In that sense, this paper aims to answer the following research questions:

- What determines labour productivity, and what is the nature of the impact of respective explanatory variables?
- Which characteristics are shared between countries with high levels of labour productivity?

Obtaining answers to these questions adds to the field since this paper uses explanatory variables, such as a portion of the elderly population and the frontier technology readiness index, which are rarely used in similar research, and to the author's best knowledge, have never been used simultaneously. Consequently, providing different perspectives on the issue, along with possible theoretical benefits, results in insights valuable to policymakers and other stakeholders interested in labour productivity. Namely, the analysis is performed on fifteen OECD countries, and two different methodologies have been used to detect which variables should be more in the focus of policymakers while creating an economic environment and incentives that increase labour productivity. Additionally, obtained results can benefit researchers in the field since they further deepen the problem of increasing labour productivity in a situation where significant variables do not have a uniform effect. This provides new knowledge on the theme, as well as guidance for future research on the subject.

The remainder of the paper is structured in the following way. A brief literature overview focused on selected determinants of labour productivity is given in the second chapter. Data description is provided in the third chapter and is followed by the research methodology. Results and discussion are given in the fifth chapter, followed by the conclusion.

## 2. A BRIEF LITERATURE OVERVIEW

As stated, labour productivity can be observed from different perspectives ranging from an individual level, where personal traits play a significant role, to a country level with significantly different explanatory variables. In that sense, while observing labour productivity on a country level, it is evident that **employment protection** has often been used as an explanatory variable in various studies. However, no unified conclusion exists on its impact (cf. Brookes, James, and Rizov 2018). On one side, stricter employment protection increases adjustment costs making firing someone more complex and expensive. In other words, more rigid employment protection might negatively affect labour productivity since it can lead to a suboptimal situation in which an employer retains the same employment level even though it would be more in line with the current business situation to decrease it or replace existing employees with those that are more suitable for a respective job position. On the other side, increased job security might stimulate workers to acquire more firm-specific skills, resulting in increased human capital and, consequently, higher labour productivity (Belot, Boone, and van Ours 2007). However, Bjuggren (2018) states that this impact might depend on a firm size since his results on firm-level data in Sweden indicate that increased labour market flexibility increases labour productivity. Brookes, James, and Rizov (2018) expand this variability of possible impact, stating, based on an extensive literature overview, that it can vary depending on different sectors and types of organisations and across countries.

Further, regarding labour productivity, it is necessary to reflect on **technology** and the country's readiness to use and adopt frontier technologies. Namely, pressure to decrease inputs usage, increase productivity and finally increase profits forces companies to invest in productivity growth. Consequently, labour productivity on a country level is becoming increasingly influenced by technological progress since, as Stiglitz (2014) stated, labour-augmenting technologies reduce direct and indirect turnover costs. However, when it comes to labour-productivity growth, it can be decomposed into "technological change (shifts in the world production frontier), technological catch-up (movements toward or away from the frontier) and capital accumulation (movement along the frontier)" (Kumar, and Russell 2002). This issue becomes even more important if we observe it from the perspective of the ongoing fourth, i.e., the fifth industry revolution (Santhi, and Muthuswamy 2023), especially with artificial intelligence (AI) technology rapidly changing how we perceive jobs and activities. Therefore, along with the numerous positive advantages that frontier technologies might have on productivity (Fanoro, Božanić, and Sinha 2021), it is necessary to consider the country's characteristics while drawing conclusions on their overall impact. In other words, even though technological progress is expected to most likely benefit productivity observed on a company level, its effect on a country level might be adverse (Lau et al. 2023).

Closely connected to the issue of technological development and the country's readiness to use and adopt frontier technologies is the issue of **human capital**. Lau et al. 2023) present an excellent theoretical overview of the importance of human capital in stimulating economic growth, emphasising that the nexus between them is mixed. This is especially important considering different overall education levels between countries and consequently different correlations with technology, e.g. prevailing unskilled human capital is likely to encourage imitation or spreading of the remaining technology while skilled human capital will more likely innovate and lead technological change (Lau et al. 2023). While observing education on a country level, the issue of public expenditures arises. In that sense, public expenditures on education are often used as a proxy for investment in human capital, and a positive impact on labour productivity is expected. However, it seems that, while analysing the connection between the effects of education on growth via its impact on labour productivity, there is a threshold level of human capital beyond which further increase in human capital will not lead to productivity improvements (Neycheva 2010). There is another dimension to the impact of public expenditure on labour productivity as well. Namely, reallocating expenses between education levels seems to matter, indicating that a stronger effect will result from early childhood or lower levels of education (Delalibera, and Ferreira 2019) compared to investment in tertiary education (Lau et al. 2023).

Along with technological progress, the **ageing** of the population, especially in developed countries, affects their economies by decreasing the working population ratio and burdening government pension funds and health systems. However, the influence of age can vary across individuals, occupations and industries (Hernæs et al. 2023) and can change over the years because of: a) public health policies that increase the average life expectancy and b) automatisation, i.e. robotisation process that helps the elderly to continue contributing to the economy (Park, Shin, and Kikkawa 2021). Hence, studies on the impact of ageing on productivity and growth are not uniform regarding their conclusions. In that sense, Andriulis, Butkus, and Matuzevičiūtė (2022) provide an excellent overview of studies on this issue whose results vary from positive, over unconfirmed, to negative impact.

## 3. DATA DESCRIPTION

Fifteen OECD countries (list available in Table 5) have been analysed in the period from 2012 to 2019. Year-level data have been collected from OECD and UNCTAD, and the definition of each used variable is presented in Table 1, while their descriptive statistics are presented in Table 2.

**Table 1.** Description of variables

| Variable (code) | Definition | Source |
|---|---|---|
| **PROD** | Labour productivity; GDP per hour worked; USD, current prices, current PPPs | OECD |
| **POP65** | Population 65 years old and over; % of the total population | OECD |
| **Eprot** | Strictness of employment protection – collective dismissals; index; synthetic indicator; range 0 to 6 | OECD |
| **EDUC** | Total public expenditure on education as a percentage of total government expenditure; % | OECD |
| **TECH** | Frontier technology readiness index; range 0 to 1 | UNCTAD |

Source: Author based on information retrieved from OECD, UNCTAD and World Bank.

Labour productivity (PROD) is the focus of this research and is measured by the level of GDP per hour worked (as in Cui et al. 2019; Vertakova, Maltseva, and Shulgina 2019, etc.), expressed in current purchasing power parities since multiple countries with different currencies and different employment levels form the sample. The impact of ageing (POP65), measured by the portion of the elderly population, is expected to affect labour productivity positively. Namely, countries with a higher portion of the population that is 65 and older have restricted access to the input of labour and consequently are forced to optimise available resources. Strictness of employment protection (Eprot) can have both positive and negative impact on labour productivity. Namely, stricter protection is more beneficial to employees and can enable them to be more productive because of more favourable working conditions, especially in the sense that higher employment protection results in higher financial stability for employees and their family members, motivating them to gain firm-specific knowledge (Višić 2018). On the other hand, a more flexible labour market with a lower level of employee protection enables employers to adjust the level of employment to the current needs of their business, resulting in higher productivity. Higher public expenditure on education (EDUC) is expected to result in higher productivity levels. Namely, this impact is indirect and affects both employers and employees that should, via received education, increase their productivity. However, this positive effect is expected solely under the assumption that public expenditure on education is used to increase the quality of the received education in respective countries. Countries with higher readiness to use and adopt frontier technologies (TECH) are expected to have higher labour productivity. In other words, frontier technologies are expected to increase productivity since they are supposed to enable more efficient use of all inputs.

**Table 2.** Descriptive statistics (2012-2019)

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **PROD** | 120 | 53,258 | 16,847 | 23,4 | 94,2 |
| **POP65** | 120 | 17,062 | 2,641 | 9,8 | 21,5 |
| **Eprot** | 120 | 2,569 | 1,099 | 0 | 3,63 |
| **EDUC** | 120 | 12,553 | 2,949 | 9 | 21,4 |
| **TECH** | 120 | 0,803 | 0,122 | 0,512 | 1 |

Source: Author's calculations.

## 4. METHODOLOGY

Two different methodologies have been used to analyse labour productivity. In order to answer the first research question, a balanced panel data on selected OECD countries in the period from 2012 to 2019 have been analysed via three models. Since the second research question is directed towards detecting which characteristics are shared between countries with high levels of labour productivity, data for 2019 have been analysed using the clustering method.

The first segment of the empirical analysis has been performed using static panel data analysis. The following Pooled Ordinary Least Squares (POLS) model has been formed:

$$PROD_{it}=\beta_0 + \beta_1\ POP65_{it}+\beta_2\ Eprot_{it} + \beta_3\ EDUC_{it} + \beta_4\ TECH_{it} + u_{it};\quad i=1,\dots n,\ t=1,\dots T \qquad (1)$$

Where $PROD_{it}$ is the outcome variable for observation unit *i* (country) in year *t*, and *n* is the total number of observation units. Parameter $\beta_o$ is a constant term, while other $\beta$ parameters are related to each of the four explanatory variables. Further, the error term $u_{it}$ is assumed to be independent and identically distributed by observation unit and time. However, due to the nature of the panel data containing observations of the same unit that are dependent over the years, POLS parameter estimates are biased and inconsistent. Therefore, the fixed effect model (FE) that assumes the correlation between the observation unit error term and explanatory variables has been formed. Since FE estimators are unsuitable for analysing the effect of time-invariant variables, the random effect model (RE) has also been formed. These three models and the results of respective tests to choose the most appropriate among them (FE model) are presented in Table 3. The overall F-test has been used to choose between POLS and FE model, the Breusch-Pagan test to choose between POLS and RE model, while the Hausman test has been used to select between FE and RE model. Statistical package Stata 13 has been used to perform the analysis.

With the aim of answering the second research question, a K-means clustering, as a form of unsupervised learning algorithm, has been used. In order to perform the analysis, this method requires selecting the number of clusters prior to the analysis. Consequently, considering studies with similar logic (Trpeski, and Cvetanoska 2019; Višić 2018; Haynes, and Haynes 2016, etc.), the analysis is set to be performed with three cluster groups. A dependent variable and four previously mentioned explanatory variables have been used in K-means clustering, performed on data for all observed countries in the year 2019. IBM Statistics SPSS 23 has been used for the clustering method.

## 5. RESULTS AND DISCUSSION

As previously stated, according to obtained results of tests necessary to choose between the POLS and FE model (overall F-test), Poled and RE model (Breusch-Pagan test) and the FE and RE model (Hausman test), the FE model is the most appropriate model with the use of respective data. In that sense, according to the results presented in Table 3, it is evident that, as expected and in line with findings in Lee, Kwak, and Song (2020), the ageing process positively impacts labour productivity. Acemoglu and Restrepo (2017) offer an additional explanation stating that there is no negative effect on economic growth (correlated to labour productivity) because technology adjusts and undo this potential negative effect of ageing.

However, according to obtained results, the impact of the country's readiness to use and adopt frontier technologies seems to influence productivity negatively. These results are unexpected but can be explained considering the analysed period. Namely, frontier technologies, among other segments, include AI and blockchain, and the analysis covered the period until 2019. Hence, it is possible that the real impact of these technologies is yet to come (Santhi, and Muthuswamy 2023; Fanoro, Božanić, and Sinha 2021; Muro, and Andes 2015). In other words, in times of transition to more complex technologies, a certain number of workers, especially low-skilled, lose their jobs (Graetz and Michaels 2018), consequently decreasing productivity on a country level since they haven't transitioned to the more complex job position.

According to obtained results of the FE model, the strictness of employment protection does not affect labour productivity. Scarpetta, and Tressel (2004) got similar results indicating no significant effect of labour market regulation, but they used a multifactor productivity variable. A possible explanation might result from the dual nature of this variable, where opposing effects are related to the same variable. Namely, it can increase and decrease productivity, depending on the stronger effect. In other words, stricter employment protection increases productivity because of the positive impact it has on employees, but at the same time, it can decrease productivity due to negative impact related to the effect on employers forcing them to operate away from the optimum when it comes to needing input level.

Total public expenditure on education also seems not to affect labour productivity. Even though the positive impact of higher quality education that should result from higher public expenditure on education is theoretically undeniable, its impact on productivity is not direct and includes a certain time lag. Further, most of the sample consists of countries with highly developed educational systems, where increasing expenditure in that field would not significantly affect the quality of education and, indirectly, labour productivity. In that sense, here obtained results are understandable and in line with the logic presented in Lau et al. (2023).

**Table 3.** POLS, FE and RE estimates (2012-2019)

| **Variables Dependent variable: PROD** | **Model POLS** | **Model FE** | **Model RE** |
|---|---|---|---|
| **POP65** | 0.8688274 | 4.719*** | 4.580*** |
| | (0.577) | (0.345) | (0.351) |
| **Eprot** | 5.861*** | -4.140 | -0.587 |
| | (1.320) | (5.960) | (2.659) |
| **EDUC** | 1.998*** | 0.095 | 0.321 |
| | (0.447) | (0.385) | (0.396) |
| **TECH** | 84.636*** | -35.562*** | -19.290* |
| | (9.689) | (11.466) | (11.258) |
| **Constant** | -69.641*** | 10.733 | -11.918 |
| | (11.064) | (19.515) | (12.810) |
| Observations | 120 | 120 | 120 |
| R-squared | 0.644 | 0.670 | 0.662 |
| POLS vs FE (F-test and Prob > F) | | 111.92 (0.000) | |
| POLS vs RE (chibar2 and Prob > chibar2 – BP test) | | | 261.47 (0.000) |
| Hausman test (chibar2 and Prob > chibar2) | | 26.69 (0.000) | |

Notes: ***, **, * denote significance at the 1%, 5%, and 10% significance level. Robust standard errors are in parenthesis. POLS vs FE - The overall F-test for 14 individual differences (F-test that all $\alpha_i$=0) shows that there are significant differences between individuals and that the FE model is more appropriate (F test that all u_i=0: F(14, 101) = 111.92). The Breusch-Pagan test (BP) has been used to test for the presence of random effects, i.e. to choose between the POLS and RE model; since there are random effects, RE is preferred over POLS. The Hausman test rejects the null hypothesis that the coefficients for the years are jointly equal to zero (Prob > F is 0.000), which confirms that the FE model should be used instead of the RE model.

As stated, the second research question has been analysed using K-means cluster analysis. Obtained results are presented in Table 4, showing the final cluster centres revealing that clusters are not uniform, and in Table 5, indicating the Euclidean distance between each case, i.e. country, as measures of similarity.

**Table 4.** Final Cluster Centers (2019)

| | Cluster | | |
|---|---|---|---|
| | **1** | **2** | **3** |
| **PROD** | 52,36 | 80,91 | 28,14 |
| **POP65** | 17,98 | 19,58 | 11,80 |
| **Eprot** | 2,55 | 3,10 | 0,00 |
| **EDUC** | 11,65 | 12,55 | 21,23 |
| **TECH** | ,78 | ,88 | ,57 |

**Table 5.** Cluster membership (2019)

| Case/Country | Cluster | Distance |
|---|---|---|
| Australia | 1 | 9,024 |
| Austria | 2 | 3,957 |
| Chile | 3 | 0,000 |
| Czech Republic | 1 | 4,110 |
| Estonia | 1 | 6,288 |
| France | 2 | 3,788 |
| Germany | 2 | 4,746 |
| New Zealand | 1 | 5,877 |
| Norway | 2 | 12,601 |
| Poland | 1 | 6,956 |
| Slovak Republic | 1 | 8,602 |
| Slovenia | 1 | 2,150 |
| Spain | 1 | 7,530 |
| Sweden | 2 | 3,748 |
| United Kingdom | 1 | 13,036 |

It is evident that cluster 2, with the highest level of labour productivity, also has the highest portion of the elderly population, and these results are completely in line with those obtained in the FE model. However, this cluster also has the highest level of employment protection (in line with the findings of Storm and Naastepad 2007) and the highest frontier technology readiness index. These results confirm that, when it comes to the impact of a country's readiness to use and adopt frontier technologies on labour productivity, newer data are more likely to confirm the expected positive effect. Presented logic related to frontier technologies is confirmed with results on the same variable obtained for cluster 3, a cluster with the lowest level of the respective index. Further, Chile is the only member of cluster 3, and the fact that it has the lowest level of gross national income (GNI) per capita among observed countries (The World Bank

2023), makes it reasonable that it has the highest percentage of total public expenditure on education since it needs to catch up highly developed countries. This explains the results obtained from panel data analysis, where this effect appeared insignificant. However, regarding employment protection, its impact on labour productivity seems to be positive according to the results of a K-means cluster since the cluster with the highest labour productivity had the highest level of protection. However, one should be careful before making strong conclusions about the impact of these two variables (Eprot and EDUC) on labour productivity since the sample consists of countries that are not homogenous in terms of the level of economic development and strength. Additionally, type of education might play a significant role as well. Namely, as Krueger and Kumar (2004) indicate, countries that provide 'general' rather than 'skill-specific' education grow faster in times of rapid technological change.

## CONCLUSION

This paper has aimed to analyse labour productivity observed on a country level for fifteen selected OECD countries. Two different methodologies (panel data and cluster analysis) have been used, and all obtained results are grounded in theory. However, results on the impact of selected explanatory variables on labour productivity are different, i.e. vary depending on the methodology used. Namely, the ageing of society, measured by the percentage of the elderly population, undoubtedly has a positive impact. However, the results of panel data analysis (FE model) indicate a statistically insignificant effect of employment protection and investment in human capital, measured by the portion of total public expenditure on education. On the other hand, the cluster analysis results suggest that countries with higher levels of employment protection belong to a group of countries with higher levels of labour productivity. The same logic applies to the investment in human capital, with the necessary remark on evident differences between countries in terms of their development since Chile, as the poorest country (measured by GNI per capita), is the only country belonging to the cluster with the highest level of public expenditure on education. The most significant difference in obtained results is related to technology, i.e. frontier technology readiness index, since the results of the FE model suggest a negative, and K-means cluster a positive effect on labour productivity. Along with previously presented explanations for each variable, differences in obtained results are most likely the result of simultaneous effects of ageing and technological change that affect countries differently and at different points in time. Obtained results indicate that while forming labour protection policies, policymakers should balance between two opposing effects for employers and employees at the same time while taking into consideration country-specific characteristics. Namely, along with the possible dual impact of this variable, labour productivity is also under the influence of the process of ageing and technological progress. In that sense, technological progress might diminish the possible negative effects of ageing. Still, at the same time, it may create additional problems regarding labour productivity since it may decrease labour demand as a result of advanced in used technology. The education level is closely related to decreased demand for labour. Consequently, along with adjusting the level of expenses for education, policymakers should adjust which type and level of education to support more to create an optimal labour supply, i.e. future employees that will be able to cope with the economic consequences of fast technological progress accompanied with the ageing of the society.

The presented analysis has its shortcomings. The newest available data on the frontier technology readiness index are (at this point) those related to 2019, while data on robot density on a country level over the years are not publicly available, and data on the usage of AI are yet to be collected. Therefore, the impact of frontier technologies on labour productivity might not be captured at its full strength. Additionally, its impact might be evident with a certain time lag. Further, the issue of employment protection could be observed from a wider perspective, i.e. as a segment of *flexicurity policies* in EU member states that, along with employment protection legislation, including lifelong learning programs, active and passive labour market policies (for more insight in the issue c.f. Dolenc and Laporšek 2013). In that sense, a more detailed analysis would provide valuable insight to policymakers indicating which activities produce the desired effect. Additionally, since the balanced panel model has been used, the sample size has been reduced to only fifteen countries. Consequently, future research on the theme will be directed towards including additional explanatory variables and expanding the sample to observe developing and developed countries separately. In that sense, more precise policy recommendations, especially in the context of labour protection and public expenditure on different levels of education, will be grounded in country-specific situations.

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