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Exploring the relationship between R&D investment and the labour market outcomes in the OECD countries

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Abstract

This paper examines the relationship between labour market outcomes, labour market policies and investment in R&D in OECD countries from 2011 to 2021. Firstly, the relationships between labour market variables and R&D investment variables were estimated using Pearson correlation. Subsequently, predictive models were developed using eight algorithms to assess their performance in explaining labour market outcomes. K-fold cross-validation was employed to average results over multiple train/test splits. Initial findings indicate that R&D investment was positively associated with the employment rate and labour force participation rate, and negatively associated with the unemployment rate. Furthermore, public spending on active labour market policies showed a significant association with R&D investment variables. Additionally, findings based on the performance of predictive models revealed that data on R&D investment and labour market outcomes exhibit complex interactions best captured by ensemble techniques – Random Forest and Gradient Boosting. Regardless of the model used, the strictness of employment protection for temporary contracts consistently emerged as an important predictor for all labour market outcomes. Moreover, indicators

Keywords

- Industry 4.0
- innovation
- labour market
- labour market institutions
- OECD countries
- research and development

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related to R&D investment demonstrated relatively strong predictive power, suggesting a meaningful contribution of such investment to employment outcomes. Innovation-related measures also emerged as relevant factors influencing labour market outcomes in OECD countries.

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Introduction

The recent advances in technology make governments become increasingly aware of the importance of using the digital economy for innovation, social and economic growth and social prosperity. Innovations and new technologies within the digital economy can enhance goods and services and address policy challenges across various sectors, including labour market, education, health, the environment, public governance and transport, as well as influencing employment, productivity and overall well-being. What is more, innovations are essential for future job creation, economic growth and competitiveness. Even though, innovations and new technologies create opportunities for firms, employees and society to engage in economic activities, these technologies may also displace workers in some occupations, increasing existing gaps in labour markets, resulting in greater inequality and new digital divides (OECD, 2016).

These innovations are primarily driven by investments in research and development, which are a key factor in driving technological progress and contributing to increased prosperity, improved labour productivity, and more (Diebolt & Hippe, 2019; Sun et al., 2016). Investments in research and development also play an important role in promoting innovation within the economy, as the availability of funds for research and development determines entrepreneurs' and communities' access to new technologies and innovations (Schmidt et al., 2016). Recent economic advances, known as Industry 4.0 or the fourth industrial revolution, have led to many fundamental changes in the labour market. New technologies and innovations continuously reshape labour markets, impacting labour demand and supply, wages, work environments and workplace structures (Acemoglu & Restrepo, 2020; Flores et al., 2019; Pereira & Romero, 2017; Schroeder et al., 2017). Given the development of new digital technologies, a thorough understanding of labour markets changes remains crucial for policymakers, employers, employees and society at large. This necessitates the development of customised labour market institutions and policies (Goos et al., 2019).

This paper examines the relationship between labour market outcomes, labour market policies and investments in research and development in OECD countries from 2011 to 2021. Given that both labour market performance and R&D investment are shaped by the broader economic context, it is important to consider the socio-economic conditions prevailing during the analysed period. Generally, the socio-economic situation of OECD countries varied between 2011 and 2021. In 2011, OECD countries recorded real GDP growth of 2.1%, although some countries experienced negative economic growth, including Greece (–9.9%). By 2021, the economic situation had improved significantly, with the average growth rate for the OECD reaching 6.3%, and all OECD countries recording positive growth. This represented a marked improvement compared to the previous year, in which almost all OECD countries experienced negative growth due to the COVID-19 pandemic (OECD, 2025c). Regarding GDP per capita growth, it was 1.4% in 2011 and increased to 5.8% in 2021 in OECD countries. However, in 2020, OECD members on average reported –4.3% GDP per capita growth due to the COVID-19 pandemic (World Bank, 2025a). Inflation (CPI) in OECD countries was 3% in 2011, with most countries recording higher inflation than the OECD average. By 2021, inflation in OECD countries had risen to 4%, mainly due to the COVID-19 pandemic (OECD, 2025a). Government expenditure on education in OECD countries remained at 5.1% of GDP in both 2011 and 2021. For most years of the analysed period, government spending on education was below 5% on average among OECD members. However, substantial differences exist between countries. In 2021, Scandinavian countries allocated the highest share of GDP to education (around 7%), while countries such as Ireland, Turkey and Greece devoted the least (World Bank, 2025b). Furthermore, by the end of the analysed period, OECD countries were recovering from the effects of the COVID-19 pandemic. Importantly, this period was also marked by a growing prevalence of working from home and increased flexibility in employment arrangements across OECD countries (OECD, 2021).

Therefore, combining data on labour market characteristics across OECD countries with data on investment in research and development allowed for an assessment of the relationships between employment rates, unemployment rates and labour force participation rates with R&D investment variables in these countries. Firstly, the relationships between labour market variables and R&D investment variables were estimated using Pearson correlation. Subsequently, predictive models were developed using eight algorithms to assess their performance in explaining labour market outcomes. The importance of individual variables, measured in terms of predictive power, was also evaluated within the best-performing models. K-fold cross-validation was employed to average results over multiple train/test splits, providing more reliable and less biased estimates of model performance.

This study contributes to the literature by assessing the relationships between labour market outcomes, labour market policies and investments in research and development financed from different sources. Furthermore, this paper discusses the benefits and challenges of new technologies and innovations for labour market participants. It also highlights the importance of investments in research and development and innovation for socio-economic growth and job creation in the evolving labour market.

The paper is structured as follows. The next section provides a literature review on the labour market in the face of new technologies and R&D investments. This is followed by the methodology section, which outlines the time and geographical scope, methods used and the selection of variables. The third section presents and discusses the results of the empirical analysis. Finally, the paper concludes with a summary of limitations and suggestions for future research.

1. The labour market in the face of new technologies and R&D investments: an overview

The growing focus on Industry 4.0 has raised numerous inquiries regarding the significance and impact of these changes on labour markets. Previous studies suggest that the influence of the fourth industrial revolution is expected to have a more positive effect on labour markets in developed countries due to their competitive advantage and higher wage rates (Nafchi & Mohelská, 2018). However, the risk of job automation and associated technological unemployment may still manifest in developed labour markets. For instance, an analysis by Acemoglu & Restrepo (2020) indicates a negative impact of industrial robots on wages and labour demand in the USA, along with a positive impact on productivity. Furthermore, an analysis by Frey and Osborne (2017) reveals that about 47% of employment in the USA is at risk of computerisation in the next decade or two. In contrast, Klenert et al. (2023) indicate that industrial robots do not reduce the share of low-skill employment, which contrasts with the popular view that robots reduce employment. However, they demonstrate that countries and sectors with relatively high levels of automation are more resilient to the decline in manufacturing, especially in terms of employment. The literature also indicates that the main solutions for reducing technological unemployment include reducing the working week, rethinking higher education, creating minimum income guarantees and reforming tax systems (Lima et al., 2021).

Another challenge of Industry 4.0 is the labour market polarisation, as middle-skilled jobs involving routine tasks are at a high risk of being replaced by automation (Sumer, 2018). Additionally, the development of new technologies has led to the rapid transformation of workers' tasks. On the one hand, there will be an increased demand for employees who perform innovative and creative tasks (Flores et al., 2019). On the other hand, routine tasks will be partially or entirely replaced by robots and machines (Sumer, 2018).

Moreover, benefits and challenges in the labour market related to recent technological changes mean that labour market institutions, including labour market policies still play a crucial role in the digital economy. Previous studies (e.g. Fernández-Macías, 2015; Fernández-Macías & Hurley, 2017) indicate that the majority of structural employment changes across European countries result from country-specific institutions and policies that mediate the consequences of technological changes in labour markets. For instance, in Germany, employment polarisation began as wage compression markedly declined since the millennium. This change is probably linked to both the reduced influence of trade unions and the "Hartz" labour market reforms (Dustmann et al., 2014). This suggests that labour market institutions play a crucial mediating role in how technological advancements affect the labour market. In addition, Rendall and Weiss (2016) state that labour market polarisation in Germany was slower due to the apprenticeship system and the fact that firms had lower incentives to replace these skilled workers compared to countries with less structured training programs. Consequently, labour market institutions that provide workers with broad protections or relatively high benefits may be more inclined to invest in training to equip workers with digital skills, helping them adapt to the technological change.

Therefore, technological progress and emerging new technologies pose numerous challenges for the labour market. On the one hand, new technologies may result in some employees losing their jobs or needing to change careers in response to the broad impact of digitalisation and technological advancements. On the other hand, the recent advance in technology requires that workers adapt their skills to the evolving labour market, where digitalisation and new technologies play a crucial role. Therefore, it is essential to provide training and appropriate education, as well as implement organisational management strategies to meet the new market requirements (Arntz et al., 2016; Ing et al., 2019; Maresova et al., 2018; Ninan et al., 2019; Petrillo et al., 2018; Sumer, 2018). These changes may require organisations and governments to invest in infrastructure and training to fully capitalise on the opportunities arising from Industry 4.0 advancements. Investments in research and development play a fundamental role in preparing the labour market for the challenges associated with digitalisation and technological progress. Thus, both governments and organisations will play a fundamental role in educating the workforce while their engagement in efforts on investments in research and development, innovations and developing the digital economy will influence labour market outcomes as well (Burgess & Connell 2020; Ing et al., 2019; Schroeder et al., 2017).

Investment in research and development is a key driver of technological progress, stimulating education, labour productivity and contributing to higher levels of GDP per capita (Diebolt & Hippe, 2019; Sun et al., 2016). Moreover, investments in research and development play a significant role in fostering innovation in the economy, as the availability of R&D funding largely determines entrepreneurs' and communities' access to innovations (Schmidt et al., 2016). Furthermore, considering the ageing population in highly developed countries and the resulting decline in the labour force, both R&D and innovation investments are crucial for ensuring future growth. It is also emphasised that R&D and innovation investments are necessary not only from economic and social perspectives but also from an environmental one (Steeman et al., 2024).

Government financial support for research and development is crucial for sustaining and ensuring socio-economic progress, as well as fostering innovation, particularly when private initiatives alone are not sufficient. Businesses are also key players in financing research and development and, consequently, in driving innovation. However, companies' willingness to invest depends largely on economic opportunities, including the overall economic situation in a given country. The COVID-19 pandemic has demonstrated that, especially during periods of economic downturn, government support may be necessary to address social and economic challenges, particularly those related to the labour market (OECD, 2024b, 2024f). Importantly, the development of a knowledge-based economy can be stimulated not only by government and business investments in R&D but also by investments made by higher education institutions. These institutions play a crucial role in fostering innovation through scientific research and human capital development. Strengthening the mutual links between higher education institutions and enterprises is also essential (Hunady et al., 2019). Given these implications, as well as recent changes resulting from the increasing role of new technologies and digitalisation in the labour market, and the significant role of R&D investments in implementing new technologies and innovations – including those in the labour market – it is worth conducting an empirical assessment of the relationship between labour market outcomes, labour market policies and investments in research and development.

2. Methodology

This paper empirically assesses the relationship between labour market outcomes, labour market policies and investments in research and development in OECD countries. The empirical analysis includes countries that belong to the

Organisation for Economic Co-Operation and Development in the years 2011–2021. Based on the literature review, the following research questions have been formulated:

- What were the level and growth rate of R&D expenditure in OECD countries from 2011 to 2021?
- Are investments in research and development (financed by the government, business and higher education) related to labour market outcomes and policies?

The research methodology consists of five steps. Firstly, data on labour market and investment in research and development in the OECD countries were collected and the database was created. Next, the descriptive statistics of the used variables were calculated. In the next step, the relationships between labour market variables and investment in research and development variables in the OECD countries were estimated using the Pearson correlation. After that, we built predictive models to assess their performance in explaining labour market outcomes, including the employment rate, unemployment rate and labour force participation rate in OECD countries. In order to build the models, we chose 8 algorithms:

- Linear Regression – fits a straight line by minimising squared errors;
- Ridge – extend linear regression with L2 regularisation to control overfitting;
- Lasso – extend linear regression with L1 regularisation to control overfitting;
- Decision Tree – recursively splits data into homogeneous regions;
- Random Forest – averages predictions over many bootstrapped trees;
- Gradient Boosting – sequentially builds trees to correct prior errors;
- K-Nearest Neighbors (KNeighbors) – predicts by averaging nearby training points;
- Support Vector Regression (SVR) – fits a margin-maximising regression function within an ε-insensitive tube.

We also estimated the importance of variables (in terms of predictive power) within the best-performing models. The independent variables included: LMP, ALMP, PLMP, TRAINING, Strictness_temporary, Trade_Union, Strictness_regular, B_GERD, GOV_GERD, GERD_PC, GERD_GROWTH, HERD, Share_patent, Start-up, ICT_invest, Top_doc, and VC_invest (see Table 1). It should be emphasised that, in the case of missing individual values, zeros were imputed to avoid deleting entire records from the dataset. In order to have more reliable and less biased estimations of models we used k-fold cross-validation, which averages results over multiple train/test splits. All calculations were conducted using STATA and Python. Finally, the results were presented and discussed with the previous research.

The factors included in the study were chosen to capture the nature of labour market dynamics and research and development and innovation-related factors from both theoretical considerations and empirical relevance. Investment in research and development is key to innovation in the digital economy (OECD, 2018, 2024b). Additionally, research and development are also among the most important factors in preparing an economy to face the challenges of the fourth industrial revolution, particularly in the context of the labour market (Anbumozhi et al., 2020; ILO, 2019). R&D includes basic research (aimed at building new knowledge with no specific practical purpose), applied research (creating new knowledge with a specific

Table 1. Description and sources of used variables

Variable	Description	Source
Labour market variables		
UNEMPL	Unemployment rate (% of total labour force)	OECD (2024g)
EMPL	Employment rate (% of total working age population)	OECD (2024a)
LABOUR	Labour force participation rate (% of total 25-64 years old)	OECD (2024c)
LMP	Public spending on labour markets (% of GDP)	OECD (2024e)
ALMP	Public spending on active labour market (% of GDP)	
PLMP	Public spending on passive labour market (% of GDP)	
TRAINING	Public spending on training (% of GDP)	
Strictness_regular	Strictness of employment protection, individual dismissals (regular contracts)	OECD.Stat (2025a)
Strictness_temporary	Strictness of employment protection (temporary contracts)	
Trade_Union	Trade union density (% of employees)	OECD.Stat (2025b)
Investment in research and development variables		
GERD_PC	Gross domestic spending on R&D per capita (current PPP $)	OECD (2024d)
GERD_GROWTH	Compound annual growth rate of gross domestic spending on R&D (constant prices)	
GOV_GERD	Government-financed GERD (as a percentage of GDP)	
B_GERD	Business-financed GERD (as a percentage of GDP)	
HERD	Higher education expenditure on R&D (as a percentage of GDP)	
Share_patent	Share of countries in “triadic” patent families	
ICT_invest	ICT investment (total; as a share of GDP)	OECD (2025b)
VC_invest	Venture capital investment in the ICT sector (as a share of GDP)	
Start-up	Share of start-up firms (up to 2 years old) in the business population (Information industries (ISIC 26+58-63))	
Top_doc	Top 10% most-cited documents in computer science (as a share of the top 10% ranked documents in all fields)	

Source: own elaboration.

application) and experimental development (to create new products or processes) (OECD, 2015). Moreover, considering the importance of information industries in overall business R&D spending, these sectors may be key beneficiaries from public spending on R&D. Additionally, government support for business R&D aims to encourage businesses to invest in developing new knowledge that transforms industries and markets and results in benefits to society, as well as is commonly justified as a strategy to address various market and institutional failures (OECD, 2018).

Based on these circumstances, the empirical analysis includes the following measures: gross domestic spending on R&D; government-financed spending on R&D; business-financed spending on R&D; higher education spending on R&D, gross domestic spending on R&D per capita (current PPP $) and annual growth rate of gross domestic spending on R&D. Additionally, ICT investment (total; as a share of GDP), Venture capital investment in the ICT sector (as a share of GDP), Share of start-up firms (up to 2 years old) in the business population (Information industries (ISIC 26+58-63), share of countries in "triadic" patent families, and Top 10% most-cited documents in computer science (as a share of the top 10% ranked documents in all fields) were also involved in the empirical analysis. The empirical analysis also includes the following labour market variables: employment rate, unemployment rate, labour force participation rate and public spending on labour market policies (Table 1)[3].

3. Results and discussion

Table 2 provides an overview of the descriptive statistics on labour market characteristics, investment in R&D and innovation in OECD countries from 2011 to 2021. The average employment rate over the analysed period was 68.45%, while the unemployment rate and labour force participation rate were 7.7% and 75.36%, respectively. However, the standard deviation of the unemployment rate, at 4.47%, indicates significant variability in unemployment rates across different countries. Furthermore, on average, during this period, OECD countries allocated 1.47% of GDP to labour market policies. Notably, they allocated more to passive labour market policies (0.89% of GDP) than to active labour market policies (0.57% of GDP). This was likely due to the challenges in the labour market related to the COVID-19 pandemic. Moreover, the descriptive statistics on investment in

[3] However, some variables were included only in the predictive models due to the fact that correlation analysis explores only linear relationships while predictive models may also capture non-linear relationships and complex interactions between variables.

R&D indicate that the average gross domestic spending on R&D per capita was 958.92$, with a standard deviation of 577.9$, suggesting significant variability. Considering government, business and higher education spending on R&D, the data show that the business enterprise sector allocated, on average, 1.1% of GDP, while the government allocated 0.59%, and the higher education sector allocated 0.47% of GDP. As the data presented in the table indicate, most R&D work in OECD countries is conducted by higher education and enterprises, which is why the role of the state is crucial in this regard. In particular, public policies supporting innovation play a key role in directing enterprises' investment efforts toward the most pressing socio-economic areas (OECD, 2024b).

Table 2. Descriptive statistics of used variables

Variable	Min	Q_1	Q_2	Mean	Q_3	Max	Standard deviation	Countries	Observations
UNEMPL	2.02	4.84	6.59	7.70	8.80	27.83	4.47	32	352
EMPL	48.48	64.37	69.08	68.45	73.37	80.48	6.45	32	352
LABOUR	62.05	71.39	75.48	75.36	79.17	89.20	5.59	32	352
LMP	0.24	0.66	1.18	1.47	2.15	4.80	0.97	31	335
ALMP	0.08	0.24	0.49	0.57	0.76	4.14	0.48	31	336
PLMP	0.12	0.37	0.62	0.89	1.35	3.36	0.67	31	336
TRAINING	0.00	0.04	0.08	0.13	0.16	0.64	0.14	30	338
Strictness_regular	0.09	1.64	2.33	2.15	2.55	4.13	0.73	25	276
Strictness_temporary	0.21	1.58	2.13	2.08	2.54	3.83	0.83	25	275
Trade_Union	4.50	13.20	17.85	26.12	32.55	69.60	18.46	21	237
GERD_PC	71.41	442.15	894.47	958.92	1388.98	2551.96	577.90	30	340
GERD_GROWTH	–30.53	0.56	3.22	3.81	6.76	56.60	7.62	29	321
GOV_GERD	0.12	0.46	0.55	0.59	0.74	1.12	0.22	28	313
B_GERD	0.09	0.58	0.80	1.10	1.64	3.75	0.76	28	314
HERD	0.11	0.33	0.43	0.47	0.43	1.04	0.20	31	341
Share_patent	0.00	0.04	0.51	2.81	1.54	35.56	6.91	32	320
ICT_invest	0.73	1.82	2.45	2.60	3.23	8.69	1.06	31	310
VC_invest	0.00	0.02	0.03	0.09	0.07	2.27	0.23	31	336
Start-up	8.50	24.80	30.20	30.10	35.05	60.30	8.46	29	248
Top_doc	2.45	6.23	7.91	8.50	9.50	27.40	3.61	32	352

Note: the table involves values of the indicators in the years 2011–2021.

Source: own calculations based on the data collected from the sources listed in Table 1.

Figure 1 shows compound annual growth rate of gross domestic spending on R&D (GERD_GROWTH) in the OECD countries from 2011 to 2021. The countries exhibited variation in terms of the growth rate of government expenditure on R&D. In 2011, the highest GERD growth rate was observed in European countries, such as Estonia, Lithuania, Latvia and the Czech Republic (56.6%, 22.2%, 21.2% and 18.5%, respectively). However, in 2011, some OECD countries recorded a negative growth rate, specifically Portugal, Spain, Ireland and Italy (–6.7%, –2.8%, –1.5%, and –0.7%, respectively). Interestingly, in 2021, the annual GERD growth rate showed reduced diversity, and the differences among countries were less pronounced. The highest GERD growth rate in 2021 was observed in Hungary, Poland (10.5%, respectively), and in Portugal (9.9%). In contrast, negative growth rates in 2021 were observed in Chile (–8.1%), Canada (–2.0%) and Denmark (–0.7%).

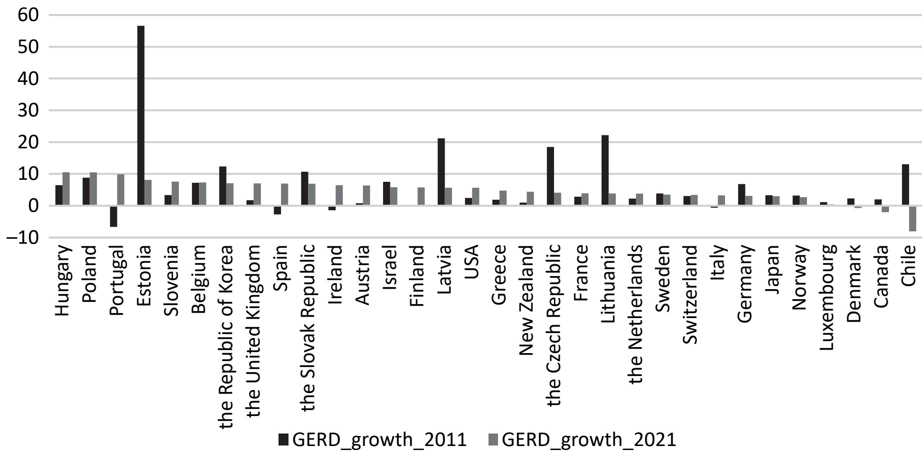

Figure 1. GERD growth rate in OECD countries

Note: due to insufficient data, the values of the indicator in Slovenia and Switzerland in 2011 were replaced by the values for 2012; the value of the indicator in the Netherlands in 2011 was replaced by the value for 2014; and the values of the indicator in Chile and Ireland in 2021 were replaced by the values for 2020.

Source: own elaboration based on: (OECD, 2024d).

Table 3 presents the correlation between labour market variables and R&D investment variables. First, R&D investment variables were positively associated with the employment rate and labour force participation rate in OECD countries, and negatively associated with the unemployment rate. Furthermore, a positive and statistically significant association was found between R&D investment variables and labour market policies (both overall and active policies). However, this relationship was statistically significant only for higher education spending on R&D. Moreover, a positive and statistically significant correlation was observed between higher education and government-financed R&D spending and public spending on training. In contrast, the correlation between R&D investment variables and passive labour market policy was not statistically significant.

Table 3. Correlation between labour market variables and R&D investment variables

	LMP	ALMP	PLMP	TRAINING	UNEMPL	EMPL	LABOUR	GERD_PC	GOV_GERD	B_GERD
ALMP	0.68*									
PLMP	–0.34	–0.07								
TRAINING	0.67*	0.61*	–0.18							
UNEMPL	0.22*	–0.04	0.35*	0.05						
EMPL	–0.02	0.20*	–0.19*	0.08	–0.72*					
LABOUR	0.23*	0.27*	0.13*	0.13*	–0.44*	0.88*				
GERD_PC	0.13	0.24	–0.00	0.30	–0.49*	0.50*	0.38*			
GOV_GERD	0.23	0.37	0.18	0.43*	–0.28*	0.35*	0.28*	0.70*		
B_GERD	0.02	0.30	–0.01	0.18	–0.44*	0.35*	0.19*	0.84*	0.70*	
HERD	0.50*	0.67*	–0.05	0.52*	–0.05	0.36*	0.26	0.50*	0.67*	0.41*

Note: * Significant at level 10%; ** Significant at level 5%; ***Significant at level 1%. Due to space limitations, the figures are restricted to presenting only relatively strong correlations (i.e. > 0.5).

Source: own calculations based on: (OECD, 2024a, 2024c, 2024d, 2024e, 2024g).

Figure 2 presents the correlation between labour market policy (LMP) and higher education spending on R&D. The findings show that countries with relatively high R&D investment also tend to have high levels of public spending on labour market policies (e.g. Denmark, Austria, Finland, the Netherlands and Sweden).

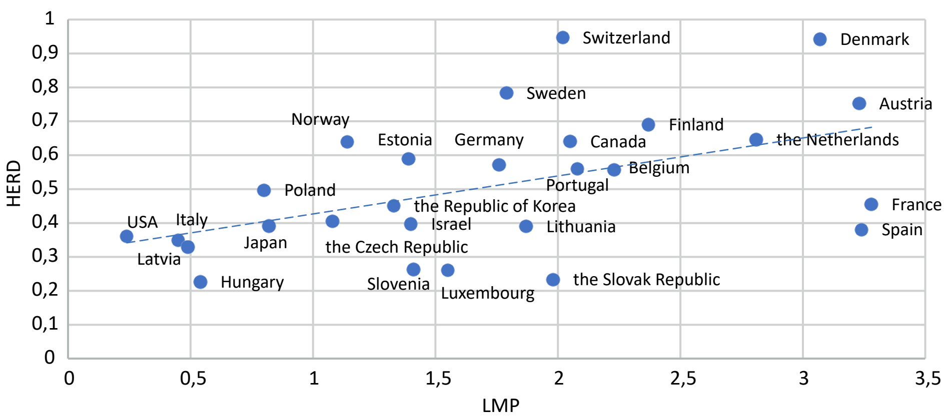

Figure 2. Correlations between LMP and HERD (0.50*)

Note: * Significant at level 10%; ** Significant at level 5%; ***Significant at level 1%. The values of correlation and their significance were shown in parentheses. Figures 2–4 show the results for 30 OECD countries in 2021 (due to insufficient data the following countries were excluded: Australia, Chile, Colombia, Costa Rica, the United Kingdom, Iceland, Mexico, Turkey).

Source: own calculations based on: (OECD, 2024d, 2024e).

This implies that both elements are important for economic prosperity. Given that investments in research and development lead to significant economic and social changes, implementing such changes may also require broad-based political and socio-economic initiatives, including labour market institutions (Sheehan & Wyckoff, 2003). The results further indicate that most Central and Eastern European countries tend to have lower R&D expenditure compared to other OECD countries.

A positive and statistically significant relationship was observed between public spending on labour market policy (LMP) and gross domestic expenditure on R&D (GOV_GERD) (Table 3, Figure 3). Furthermore, the results indicate a positive relationship between public spending on training and higher education expenditure on R&D. Figure 4 examines the bivariate associations between public spending on training and higher education expenditure on R&D. This relationship provides some indication that training may enhance the skills and competencies of employees, enabling them to engage more in innovative activities. This result is also consistent with the study by Ninan et al. (2019), who indicate that training must be provided to adapt employees' skills to the requirements of the new labour market.

Moreover, as employees become more involved in technology-driven processes and better equipped to contribute to R&D initiatives, this may lead to an increase in R&D spending. Additionally, this may be related to collaborative efforts in fostering education and technological development, thereby stimulating research and development activities. Furthermore, public spending on labour market policies supports the growth of employees' skills and competencies, resulting in higher human capital. This increased human capital also fosters a greater potential for re-

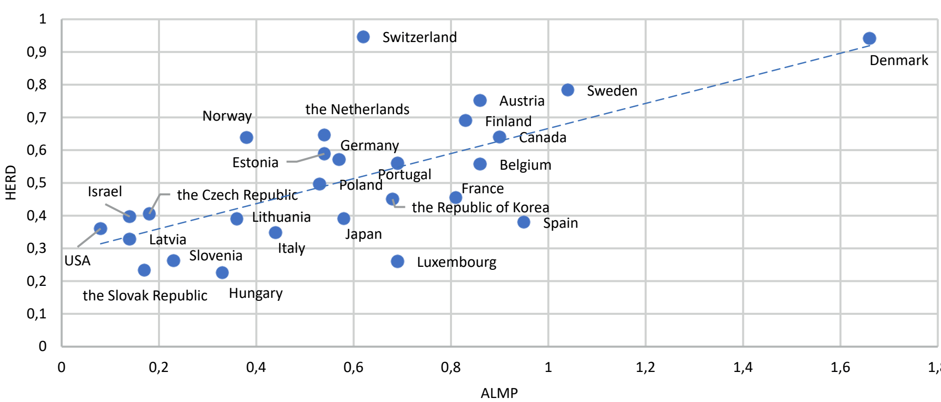

Figure 3. Correlations between ALMP and HERD (0.67*)

Note: as in Figure 2.

Source: own calculations based on: (OECD, 2024d, 2024e).

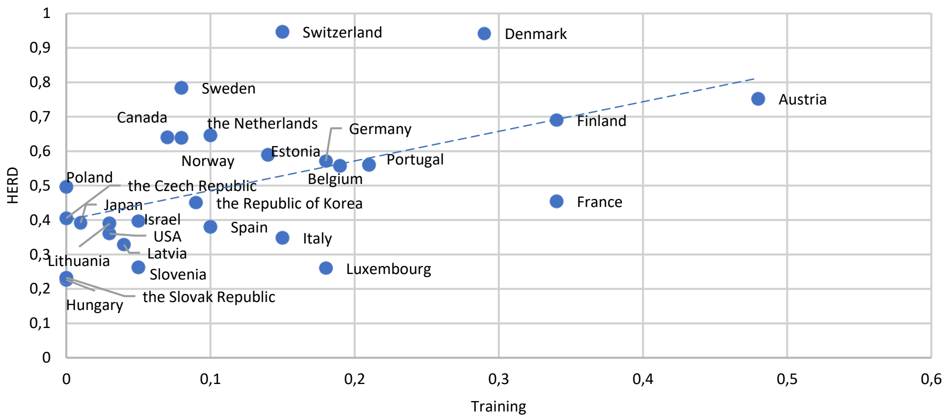

Figure 4. Correlations between TRAINING and HERD (0.52*)

Note: as in Figure 2.

Source: own calculations based on: (OECD, 2024d, 2024e).

search and developmental activities in educational institutions, and in the overall economy. Active labour market policies aimed at improving employment and supporting the development of workers' skills and knowledge can also increase the potential for research in educational institutions. What is more, this may also result from the conditions accompanying cooperation between educational institutions.

Overall, the correlation values for labour market outcomes and investment in research and development indicate a positive relationship between the employment rate and labour force participation rate and investment in R&D in the OECD countries (Table 3, Figure 5). Conversely, the results indicate a negative relationship between the unemployment rate and investment in R&D in each country. While these findings are not surprising, they establish significant connections between these indicators. Firstly, labour market outcomes remained better in developed countries, which were also more technologically advanced. Additionally, a developed and stable economic environment may encourage educational institutions to increase their efforts in science and technology. Furthermore, higher employment (or lower unemployment) may lead to a greater demand for research and development to support employees in the evolving digital labour markets.

In the next step of our analysis, predictive models for employment rate, unemployment rate and labour force participation rate were estimated. Tables 4, 5 and 6 present the performance of the predictive models for employment rate, unemployment rate and labour force participation rate, respectively. Using 5-fold cross-validation, Random Forest and Gradient Boosting achieved the highest predictive performance among all models tested. Specifically, these models demonstrated relatively high R^2 values for the each of three considered dependent variables:

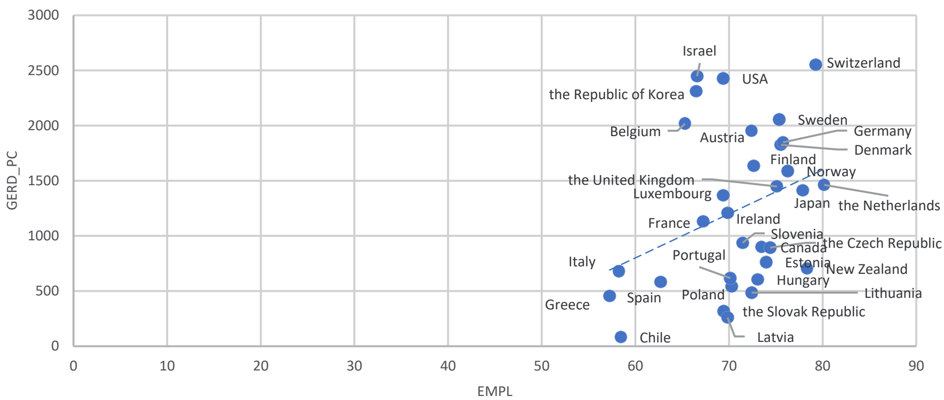

Figure 5. Correlations between GERD_PC and EMPL (0.50*)

Note: * Significant at level 10%; ** Significant at level 5%; ***Significant at level 1%. Figure 5 presents the results for 32 OECD countries (due to insufficient data the following countries were excluded: Australia, Colombia, Costa Rica, the United Kingdom, Iceland, Mexico, Turkey).

Source: own calculations based on: (OECD, 2024a, 2024d).

- 0.76 for employment rate;
- 0.82 for labour force participation rate;
- 0.75 and 0.77 for unemployment rate.

These models also produced relatively low error rates: mean absolute error (MAE) ranged from 1.39 to 2.17, while root mean square error (RMSE) ranged from 2.07 to 3.72 for all Random Forest and Gradient Boosting models.

Furthermore, the Random Forest and Gradient Boosting models exhibits relatively high stability, as indicated by low values of standard deviation of the R^2. This indicates that the models' performance was stable and reliable, as well as consistent across different data splits. In contrast, other models (e.g. K-Nearest Neighbors algorithm (KNeighbors) or Support Vector Regression (SVR)) showed lower predictive performance. Their explanatory power was significantly weaker, with R^2 values ranging from 0.05 to 0.23; they also exhibited higher prediction errors (e.g. MAE ranging from 4.85 to 2.52). Thus, the data exhibit complex interactions that are most effectively captured by ensemble techniques such as Random Forest and Gradient Boosting. Therefore, in the next step, we focus on these two models to explore the predictive power of the independent variables for the dependent variables.

Figure 6 presents the influence of individual variables on the prediction of the employment rate (EMPL variable), labour force participation rate (LABOUR variable), and unemployment rate (UNEMPL variable) in Random Forest and Gradient Boosting models. Firstly, regardless of the model used, the strictness of employment protection for temporary contracts (Strictness_temporary variable) emerged

Table 4. Performance of predictive models (dependent variable: EMPL)

Model	R^2	MAE	RMSE	MSE	Standardized *R*-squared
LinearRegression	0.43	3.58	4.72	22.86	0.11
Ridge	0.47	3.54	4.58	21.37	0.07
Lasso	0.29	4.29	5.3	28.83	0.05
DecisionTree	0.48	2.71	4.4	19.46	0.16
RandomForest	0.76	2.15	3.08	9.74	0.06
GradientBoosting	0.76	2.17	3.01	9.17	0.06
KNeighbors	0.15	4.57	5.71	32.78	0.16
SVR	0.14	4.85	5.86	35.19	0.04

Source: own calculations in Python based on the results of 5-fold cross-validation of the models on the dataset, which contained data from: (OECD, 2024a, 2024c, 2024d, 2024e, 2024g, 2025b; OECD.Stat, 2025a, 2025b).

Table 5. Performance of predictive models (dependent variable: LABOUR)

Model	R^2	MAE	RMSE	MSE	Standardized *R*-squared
LinearRegression	0.53	2.99	3.77	14.36	0.11
Ridge	0.55	2.95	3.71	13.82	0.09
Lasso	0.43	3.47	4.19	17.58	0.06
DecisionTree	0.53	2.12	3.72	14.27	0.18
RandomForest	0.82	1.53	2.32	5.56	0.07
GradientBoosting	0.82	1.55	2.28	5.32	0.07
KNeighbors	0.14	4.06	5.13	26.44	0.04
SVR	0.05	4.41	5.39	29.24	0.03

Source: own calculations in Python based on: (OECD, 2024a, 2024c, 2024d, 2024e, 2024g, 2025b; OECD. Stat, 2025a, 2025b).

Table 6. Performance of predictive models (dependent variable: UNEMPL)

Model	R^2	MAE	RMSE	MSE	Standardized *R*-squared
LinearRegression	0.34	2.50	3.45	12.38	0.06
Ridge	0.36	2.47	3.41	12.18	0.07
Lasso	0.19	2.70	3.85	15.75	0.05
DecisionTree	0.67	1.47	2.36	5.62	0.08
RandomForest	0.75	1.40	2.11	4.68	0.03
GradientBoosting	0.77	1.39	2.07	4.61	0.04
KNeighbors	0.23	2.52	3.67	14.04	0.20
SVR	0.13	2.68	4.02	17.48	0.08

Source: own calculations in Python based on the results of 5-fold cross-validation of the models on the dataset, which contained data from: (OECD, 2024a, 2024c, 2024d, 2024e, 2024g, 2025b; OECD.Stat, 2025a, 2025b).

as an important predictor for both the employment rate and the labour force participation rate. In addition, this variable was also a significant predictor for the unemployment rate. These results indicate a significant and strong association between labour market flexibility and labour market outcomes. Thus, the findings suggest that legal employment protection – particularly regarding temporary contracts, plays a crucial role in shaping labour market outcomes in OECD countries.

Furthermore, indicators related to investment in research and development, such as higher education expenditure on R&D, as a percentage of GDP (HERD variable) or gross domestic spending on R&D per capita (GERD_PC variable), also demonstrated relatively strong predictive power. These findings suggest that investment in research and development contributes meaningfully to employment outcomes in the analysed countries. Additionally, the results underline the importance of higher education and R&D investment for the functioning of labour markets in OECD countries.

The data presented in Figure 6 also show that public spending on passive labour market (% of GDP, PLMP variable) has relatively high predictive power for the unemployment rate. This relationship is not surprising, and highlights the role of such spending in mitigating the negative effects of unemployment, assuming it is balanced with active labour market policies. Finally, innovations-related measures, such as ICT investment (ICT_invest variable) and the share of the top 10% most-cited documents in computer science relative to all fields (Top_doc variable) also emerged as the relevant factors influencing the employment rate, la-

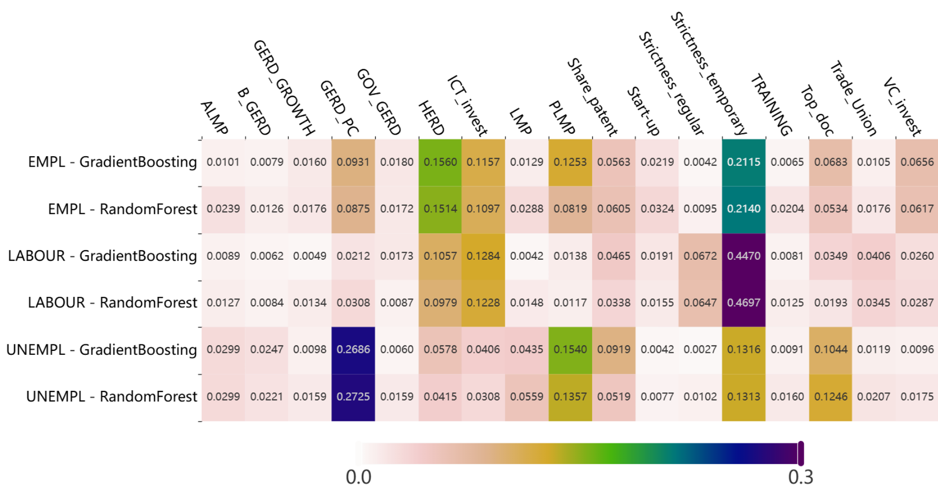

Figure 6. Ranking of variables by predictive importance

Note: interactive version is available at https://data.lewoniewski.info/oecd/.

Source: own calculations in Python based on the results of 5-fold cross-validation of the models on the dataset, which contained data from: (OECD, 2024a, 2024c, 2024d, 2024e, 2024g).

bour force participation rate, and in the case of Top_doc, the unemployment rate in the OECD countries. Therefore, factors that promote and support the development of digital innovations, as well as those that advance knowledge on innovation, are important predictors of labour-market outcomes in OECD countries. In conclusion, the findings underline a robust set of factors across all models, supporting the stability of our results.

Conclusions

In conclusion, the growth rate of gross domestic spending on R&D rate in 2011 was significantly higher in individual countries (when the term “Industry 4.0” was coined) compared to the growth rate in 2021. Undoubtedly, the origins of this phenomenon can be attributed to the crisis caused by the COVID-19 pandemic. Despite this, the GERD growth rate remained positive in most OECD countries. The findings indicate that investment in research and development was positively associated with the employment rate and labour force participation rate in OECD countries, while it was negatively related to the unemployment rate. Moreover, public spending on active labour market policies was found to be significantly correlated with R&D investment variables. Conversely, the relationship between R&D investment variables and passive labour market policies was not statistically significant.

The findings also reveal that OECD countries with relatively high R&D investment tend to have high levels of public spending on labour market policies. This highlights the fact that although investments in research and development bring many positive changes to socio-economic life, they also require extensive institutional changes. The results indicate a positive relationship between public spending on training and higher education expenditure on R&D. This suggests that training may enhance employees’ skills and competencies, enabling them to participate more actively in innovative activities. This finding is also consistent with the previous studies, which emphasise that training must be provided to adapt employees’ skills to the changing labour market requirements.

Furthermore, based on the performance of the predictive models using 5-fold cross-validation, Random Forest and Gradient Boosting achieved the highest predictive accuracy among all models tested for employment rate, unemployment rate and labour force participation rate, respectively. The Random Forest and Gradient Boosting models also exhibits relatively high stability, as indicated by low values of standard deviation of the R^2. These findings show that the data on the R&D investment and the labour market in the OECD countries exhibit complex interactions that are most effectively captured by ensemble techniques such as Random Forest and Gradient Boosting. Regardless of the model used, the strictness of employment protection for temporary contracts emerged as an important predictor for both the employment rate and the labour force participation rate. In addition, this variable was also a significant predictor for the unemployment rate. These findings indicate a significant and strong relationship between labour market flexibility and labour market outcomes. Furthermore, indicators related to investment in research and development also demonstrated relatively strong predictive power, suggesting that investment in research and development contributes meaningfully to employment outcomes in the analysed countries. Moreover, public spending on passive labour market has relatively high predictive power for the unemployment rate, highlighting the role of such spending in mitigating the negative effects of unemployment. Finally, innovations-related measures also emerged as the relevant factors influencing the labour market outcomes in the OECD countries.

This research contributes to the existing knowledge from both theoretical and practical perspectives. First, it examines the relationships between labour market outcomes, labour market institutions, as well as investments in research and development financed from different sources. Specifically, it discusses the significance of R&D expenditure by the government, business sector and higher education. Moreover, it explores the benefits and challenges of new technologies and innovations for labour market participants. Finally, the implications of this study may be relevant for supporting the benefits and addressing the challenges in the labour market resulting from technological progress through appropriate investments in research and development. Despite these contributions, this study has certain limitations. It was constrained by limited access to up-to-date data sources for labour market policies. However, the data were collected carefully from official international databases. Additionally, the study is limited to OECD countries for which statistical data were available, and is based on a static approach to inputs and outcomes. Furthermore, conducting a cluster analysis in order to group OECD countries in terms of labour market outcomes and reveal potential differences in studied relationships could be considered for further studies. In addition, the present study could be extended to include non-OECD countries, and examining investments in research and development may reveal their effects on the labour market over a longer time horizon.

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