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Employment Dynamics and Economic Performance: Divergent Impacts in the EU-27 Regions

Evangelos Rasvanis[1]

[1] Department of Economics, University of Macedonia, Thessaloniki, Greece

Correspondence: Evangelos Rasvanis, Department of Economics, University of Macedonia, 156 Egnatia Street, Thessaloniki, 54636, Greece. E-mail: rasvanis/at/uom.edu.gr

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Abstract

The labour market is a key driver of regional economic outcomes, with factors such as unemployment, labour productivity and workforce composition shaping prosperity. High unemployment often reflects inefficiencies in resource allocation, leading to reduced productivity and consumer spending, while investments in human capital and productivity drive innovation, competitiveness, and growth. This study analyses the impact of labour market conditions and demographics on economic performance across EU-27 regions over two decades. Using quantile regression models, the research highlights the varying effects of workforce dynamics across regions at different stages of development. The findings reveal that unemployment disproportionately impacts low- and middle-income regions, while investments in lifelong learning yield significant returns in less developed regions. Labour productivity is a key driver, with employment in science and technology sectors particularly influential in wealthier regions. Additionally, demographic factors such as population density and changes in population size play significant roles in shaping economic outcomes. The study highlights the need for region-specific policies that address disparities, promote education and innovation in less developed areas, and balance wage growth with productivity in wealthier regions to foster sustainable growth and EU-wide convergence.

Keywords: Unemployment, labour productivity, lifelong education, demographic factors, economic performance, EU-27 regions

1. Introduction

Economic disparities across the European Union (EU) remain a persistent challenge, with unemployment rates in less-developed regions often double those of wealthier areas (Eurostat, 2023). Such inequities emphasise the need to comprehend the causal factors underlying regional economic performance. Okun's (1962) seminal work in the United States laid the foundation for labour economics by identifying a significant negative correlation between unemployment and Gross National Product (GNP). This pioneering study has inspired decades of research on employment dynamics and their implications for economic growth (e.g. Arifi et al., 2023). Okun's findings highlighted employment as central to economic activity, linking labour force participation to income and productivity.

Demographic factors, such as population size and age structure, significantly influence labour markets and workforce composition. Understanding these interdependencies is vital for fostering sustainable economic growth, reducing inequality, and enhancing social welfare. The study of labour force and economic performance within European countries has drawn significant attention in recent years, particularly in the wake of economic disruptions, such as the Eurozone debt crisis and the global financial crisis (e.g., Marelli & Signorelli, 2010). These events have highlighted the interaction between macroeconomic variables and employment, underlining the importance of understanding both linear and asymmetric effects for policy-making and economic stability.

A rich body of literature has established foundational determinants of employment and economic performance at the national level. The positive correlation between Gross Domestic Product (GDP) per capita and employment is well-documented (Andrei et al., 2009; Chiang et al., 2015), as is the significant influence of compensation of employees on labour market conditions (Autor et al., 2008). Demographic changes also pose significant challenges, affecting both labour supply and demand, as well as labour productivity (Lisenkova et al., 2010). In addition, investment in human capital through education and the promotion of innovation are recognised as drivers of sustainable economic growth, job creation, and competitiveness (Visvizi et al., 2018; Zeng & Zhang, 2022).

However, regional disparities persist. Economic downturns, for example, tend to exacerbate unemployment and economic challenges in less developed regions, with some regions and sectors being unevenly affected (Bloom, 2009; Reinhart & Rogoff, 2010). EU policies aimed at promoting economic and social cohesion have had uneven results, often revealing inefficiencies in planning and implementation (Crescenzi et al., 2017). Furthermore, emerging challenges posed by climate change and energy market uncertainties are exerting a growing impact on the macroeconomic stability and labour markets of European regions, leading to unpredictable outcomes (Andersson et al., 2020; Rodriguez-Pose & Bartalucci, 2023).

Although national-level analyses of employment and economic performance are abundant, regional-level studies remain limited, often failing to capture the local differences and heterogeneity that drive disparities. This paper addresses this gap by focusing on how employment dynamics, such as working hours, wages, and the share of employees in high-value-added sectors, shape economic growth across EU-27 regions over the past two decades. This study has three primary objectives: first, to examine the relationship between employment dynamics and economic performance in these regions; second, to explore how demographic characteristics, in conjunction with labour market conditions, shape regional economies; and third, to identify nonlinear relationships and varying effects of labour market determinants across regions at different stages of economic development, considering different initial conditions and growth trajectories, using a quantile regression approach.

The next section will present a review of relevant literature, followed by the description of the methodology used to achieve the research objectives. Subsequently, the research findings will be analysed and discussed. Finally, the paper will conclude by drawing implications for policies that could promote more equitable development among EU-27 regions.

2. Related Literature

The economic performance of regions within the EU-27 member states exhibits significant disparities. Gross domestic product (GDP) and especially gross domestic product per capita, which are the most common indicators for measuring the economic growth of a country or region, are influenced by a range of different factors. Factors such as labour market dynamics (Dimova & Nordman, 2014), demographic shifts (Sundqvist, 2023), and innovation capacities (Crescenzi et al., 2020) all play critical roles in shaping regional economic outcomes and divergent trajectories between regions. For instance, regions like Oberbayern in Germany or Ile-de-France in France, known for their skilled workforce, strong research and development (R&D) capabilities and favourable business environments are more likely to experience higher levels of economic prosperity and growth compared to regions like Extremadura in Spain or Dytiki Makedonia in Greece, which faces challenges such as lower industrial activity and high unemployment rates (Eurostat, 2023).

2.1 Labour Market Dynamics and Economic Growth

Unemployment remains a critical variable in assessing regional economic growth. High unemployment rates mean that a region or a country does not use its labour resources efficiently and are usually symptoms of underlying economic problems, such as inadequate demand for labour, mismatches between skills and job opportunities or structural economic weaknesses related to labour market institutions (Heimberger et al., 2017; Hjazeen et al., 2021). Regions grappling with high unemployment often face significant social and economic challenges, including increased poverty rates (Ayala et al., 2017) and reduced consumer spending (Ganong & Noel, 2019), which further impedes economic performance. Moreover, within the framework of the Cobb-Douglas production function, unemployment signifies underutilised labour, directly reducing effective labour input and, consequently, limiting aggregate productivity and economic growth (Hajkova et al., 2007). Although these insights highlight the critical role of labour in economic growth, they often lack details on how variations in unemployment's impact may be influenced by regional policies.

Educational attainment as well as lifelong learning and continuous training are also crucial determinants of regional economic performance, due to their contribution to improving the efficiency and specialisation of human resources, thus affecting the labour market (Jenkins et al., 2003). Regions that emphasise lifelong learning and skills development are better equipped to adapt to the changing demands of the global economy. This continuous investment in human capital is closely linked to higher levels of employment in science and technology sectors. Regions with a greater proportion of their workforce engaged in these high value-added sectors tend to experience faster economic growth and higher GDP levels (Teixeira & Queirós, 2016). This is because employment in these sectors directly contributes to innovation, technological progress and overall economic competitiveness of regions (Porter, 2003).

As labour is a fundamental factor of production, improvements in labour productivity are crucial for enhancing economic performance. Increased labour productivity −achieved through skill development, technological

advancements, or optimised processes− enables each unit of labour to generate more output, directly contributing to regional and national economic growth. This efficiency supports the production of more goods and services with the same labour input, thereby boosting GDP and overall economic outcomes (Romer, 1990). Conversely, regions with strong economic performance can drive labour productivity improvements through increased investments in technology, education, and infrastructure, enhancing workers' efficiency and skills (Acemoglu, 2002). Such regions are more likely to experience sustainable economic growth, lower unemployment rates, and higher standards of living. Regions with lower productivity, on the other hand, may struggle to keep pace, leading to stagnation or decline. While these positive feedback loops can drive economic growth, they may also exacerbate regional disparities, a topic that warrants further investigation.

Recent years have seen much discussion on how working hours affect productivity. Countries like Japan and Iceland have even experimented with a four-day working week. Studies on the relationship between working hours and productivity emphasise that various elements, such as fatigue and employee commitment, can influence this dynamic. Collewet and Sauermann (2017) identified that increased working hours lead to diminishing returns, especially for less experienced workers, where fatigue significantly reduces productivity. Similarly, Okazaki et al. (2019) found that while working hours alone are not strongly associated with productivity, high levels of work engagement can sustain or even enhance productivity despite longer hours. Pencavel (2014) further supports this, demonstrating that productivity increases with working hours up to a certain threshold, beyond which it plateaus and may decline due to fatigue. These studies indicate that while extended working hours may initially increase productivity, maintaining high performance requires a balance of working hours alongside strategies to mitigate fatigue and enhance employee engagement.

Wages are another factor that can play an important role in affecting labour productivity (Kumar et al., 2012). Higher wages can lead to productivity growth through various channels. First, better compensation can boost workers' motivation, encouraging greater effort and commitment to tasks. This is often referred to as the 'efficiency wage' theory, where employers pay higher than market wages to boost productivity and reduce turnover (Shapiro & Stiglitz, 1986). Second, higher wages can attract more skilled and competent workers, increasing the overall quality of the workforce. Third, higher wages may allow workers better access to education, healthcare and nutrition, which can enhance their physical and mental capacity to perform their work effectively (Cutler & Lleras-Muney, 2006). On the contrary, low wages can cause worker discontent and lower output. Nevertheless, this relationship can vary depending on factors such as the industry, the economic context and the specific structure of wage systems.

Sectors related to science and technology, such as the ICT sector, significantly contribute to the economic growth of nations (Jalava & Pohjola, 2002). These sectors foster innovation, increase productivity, and create high-value jobs. By developing new technologies and digital solutions, they enhance efficiency, optimise operations, and open up new markets. Moreover, they bolster other sectors, creating a ripple effect that strengthens both regional and national competitiveness (Coccia, 2019; Jalava & Pohjola, 2002). However, while the literature highlights the transformative potential of high value-added sectors, it often underexamines regional disparities in access to resources required for their development, which may exacerbate inequalities. The focus on these sectors as growth drivers also tends to overlook trade-offs, such as labour displacement or dependence on specific industries. Systems-theoretic approaches, including evolutionary, neo-Schumpeterian, and complex systems dynamics, offer valuable perspectives on the broader socio-economic roles of science and technology (Aghion et al., 2009). Yet, these frameworks predominantly emphasise macro-level trends, often neglecting region-specific challenges and local labour market adaptability. Employees in high value-added sectors remain crucial, as their skills and creativity drive innovation and regional economic health (Bayarçelik & Taşel, 2012).

2.2 The Role of Demographic Factors

A critical demographic factor affecting both the workforce and economic performance is the age dependency ratio. Regions with a higher proportion of non-working age people compared to the working-age population face unique economic challenges. These challenges often appear in the form of increased fiscal pressure on social services and a reduced workforce capable of supporting economic growth (Cruz & Ahmed, 2018). High dependency ratios can place substantial pressure on the workforce, as fewer workers are available to support a larger dependent population. This can potentially lead to labour shortages and greater stress on social welfare systems. As a result, more resources may be allocated to healthcare and pensions for the elderly (Harper, 2010), which could limit investment in sectors that drive economic productivity.

Another demographic aspect that can affect the labour force of a region and its economic growth is the positive or negative change in its population. This can come either from natural population growth (i.e. an increase in births)

or due to a positive balance in migration. Empirical studies at the national level show the existence of dynamic interdependence in the path of economic growth and population change between countries (e.g., Brida et al., 2024).

Finally, population density is another important factor related to labour market that affects regional economic development. High population density can foster agglomeration economies by enabling closer proximity between firms and workers, which enhances productivity through mechanisms such as knowledge spillovers, access to a large pool of skilled labour, better labour market matching and shared infrastructure (Duranton & Puga, 2020). Nevertheless, excessive density can also lead to congestion, higher living costs, and heightened levels of air and noise pollution, potentially outweighing the benefits of agglomeration (Krugman, 1998). As a result, the impact of population density on economic output varies significantly depending on how regions manage these challenges.

3. Methodology

3.1 Data and Variables

Secondary data from 237 NUTS-2 (version 2021) regions of the EU-27 for the period 2003-2022, derived from Eurostat's regional database (2023) and the annual regional database of the European Commission ARDECO (2024), were employed to investigate the employment dynamics impact on the economic performance of EU-27 regions. Eurostat and ARDECO were chosen for their reliability and extensive coverage, offering a robust basis for analysing EU economic trends. The five overseas regions of France[1] were not included in the sample, due to the existence of several missing values in most variables. This time frame encompasses a period of significant economic and social changes in the EU, including the financial crisis of 2008 and the subsequent recovery, as well as the COVID-19 pandemic and the exit of the United Kingdom (Brexit) from the EU. These events posed unique challenges, such as economic disruptions, lockdowns, restrictions, and trade uncertainties, which significantly affected businesses and labour markets within the EU-27 regions.

To support the investigation of employment characteristics on regional economic growth, the dataset included key economic performance indicators, such as *GDP per capita* as percentage of EU-27 average and the percentage change in *Gross Value Added* (GVA) of a region compared to the previous period (year), both derived from Eurostat database. The percentage change in GVA serves as a secondary dependent variable in this study, utilised to check the robustness of the results with GDP per capita, which is used as primary dependent variable. GVA is a core metric that captures the economic output produced within a region and its percentage change offers an important measure of short-term economic performance, provided a differentiated perspective on the dynamics of regional economic development. This variable helps assess not only the absolute growth of an economy but also its relative performance over time. By employing the percentage change in GVA, this study is able to capture the effects of employment and other socio-economic factors on regional economic acceleration or deceleration, which is valuable in understanding regional disparities. This dual consideration of both GDP per capita and percentage change in GVA provides a holistic perspective of regional economic health, highlighting which EU-27 regions are catching up, stagnating, or falling behind over time.

The dataset also included employment and labour market condition variables, such as the unemployment rate (Eurostat), participation rate in education and training (Eurostat) among individuals ageing from 25 to 64 years (economically active population), real labour productivity per hour worked (ARDECO), hours worked per employed person (ARDECO), and real compensation per hours worked, measured in constant 2015 prices (ARDECO). By incorporating the last two variables, the study aims to provide a deeper understanding of the relationship between hours worked, compensation, and their impact on regional economic performance, beyond their immediate effects on labour productivity. Finally, it examines the impact of the percentage of the labour force employed in science and technology sectors (Eurostat) on the economic performance of EU-27 regions. These variables were selected based on their demonstrated importance in the literature and their ability to capture the diverse factors affecting regional economic development.

Apart from the above variables, the study controlled for regional demographic characteristics that directly affect the labour market. These controls include age dependency ratio (Eurostat), population density (Eurostat), which serves as a proxy for agglomeration economies and in particular for urbanisation economies (Rasvanis & Tselios, 2024), and total annual population change (ARDECO), which is the sum of natural change (births minus deaths) plus net migration, and reflects labour supply, as well as consumer demand, thereby affecting regional economic performance. Furthermore, the study controlled for research and development (R&D) expenditure (Eurostat), calculated as percentage of GDP in purchasing power standards (PPS) (Eurostat), a critical factor driving long-term economic growth, particularly in developed regions (Gumus & Celikay, 2015; Sylwester, 2001). Regions that allocate substantial resources to R&D tend to be at the forefront of innovation and technological progress, both of which are indispensable for sustaining competitiveness in the global marketplace (Crescenzi et al., 2020). The

association between innovation and economic performance is reinforced by the positive effect that R&D expenditure has on overall productivity and the development of new products and services (Camagni & Capello, 2017).

For the analysis of the data, a quantile regression model was selected as the primary method following the descriptive statistics. In addition, a multicollinearity test was implemented to ensure the robustness of the regression results. Unlike traditional mean regression models, which focus only on the average effects, quantile regression enables the examination of the impact of variables across different points (quantiles) within the distribution (Waldmann, 2018). This approach is particularly suited to the objectives of this study, as it reveals how employment dynamics influence economic performance differently across regions, uncovering insights that would be obscured by averages. Moreover, quantile regression provides reliable estimates even when error terms deviate from a normal distribution, and is less affected by outliers. By capturing the variability of effects across regions, it serves as a valuable tool for understanding the heterogeneous impacts of employment on regional economic outcomes. This flexibility is crucial for informed policymaking, as it helps identify regions with divergent economic behaviours and labour market responses.

To address missing at random (MAR) data in some independent variables, Multiple Imputation (MI) was employed. This technique involved creating multiple complete datasets by imputing missing values. The Appendix provides an overview of missing data percentages for each variable, justifying the use of MI for reliable results. Each imputed dataset was analysed using Ordinary Least Squares (OLS) regression, and the results were then combined to produce a single, overall inference (Rubin, 1987). This approach ensured robust analysis and preserved the reliability of estimates despite incomplete data. Labour productivity was log-transformed to reduce the variation in the data, ensuring a more stable and interpretable relationship with economic outcomes.

3.2 Econometric Specification

Figure 1 illustrates the flow of the methodology followed.

Figure 1. Methodological framework

To explore whether employment dynamics affect economic performance of each EU-27 regions and how they affect each one, the following baseline econometric specification was used:

$$Q_T(y_{it}/x_{it}, z_{it}) = \alpha_i + \delta_i + \beta(\tau)x_{it} + \gamma(\tau)z_{it} + \varepsilon_{it}(\tau) \quad (1)$$

where $Q_T(y_{it}/x_{it}, z_{it})$ represents the conditional quantile of the dependent variable y_{it} (economic performance of region i at time t) at quantile τ; α_i stands for the fixed effects per region that capture the time-invariant characteristics that are unique to each region, and δ_i represents time fixed effects that take into account macroeconomic shocks or trends common to all regions in the same period. x_{it} is a vector of variables related to employment dynamics, z_{it} is a vector of control variables, while $\beta(\tau)$ and $\gamma(\tau)$ are vectors of quantile-specific coefficients, reflecting the impact of the labour market variables and control variables respectively, at different points of the conditional distribution of the dependent variable, and $\varepsilon_{it}(\tau)$ is the quantile-specific error term, which is assumed to satisfy the standard quantile regression assumptions.

By applying the variables, already mentioned in subsection 3.1, in Equation 1, we end up with the following equation:

$$\begin{aligned} Q\tau(y_{it}) = {} & \zeta_i + \eta_i + \theta_1(\tau)UnemploymentRate_{it} \\ & + \theta_2(\tau)Education\&Training_{it} + \theta_3(\tau)LabourProductivity_{it} + \theta_4(\tau)HoursWorkedpc_{it} \\ & + \theta_5(\tau)Compensation_{it} + \theta_6(\tau)Employment\_Sience\&Technology_{it} \\ & + \lambda_1(\tau)AgeDependencyRatio_{it} + \lambda_2(\tau)PopulationChange_{it} \\ & + \lambda_3(\tau)PopulationDensity_{it} + \lambda_4(\tau)R\&D\_Expenditure_{it} + \omega_{it}(\tau), \end{aligned} \quad (2)$$

where $Q\tau(y_{it})$ is the τ-th quantile of the dependent variable y_{it}, which is the economic performance of region i at time t, measured in two ways: a) by GDP per capita in PPS and b) by the percentage change in regional GVA. ζ_i and η_i represent the region-specific fixed effects and time fixed effects respectively. The variables $UnemplemploymentRate_{it}$, $Education\&Training_{it}$, $LabourProductivity_{it}$, $HoursWorkedpe_{it}$, $Compensation_{it}$, and $Employment\_Sience\&Technology_{it}$ represent, respectively, the unemployment rate,

the percentage of people aged 25–64 participating in education and training, real labour productivity per hour worked, hours worked per employed person, average income per hour worked, and the employment rate in science and technology sectors for region *i* during year *t*.

The model also controls for demographic factors. More specifically, it controls for the impact of age dependency ratio, total population change and population density on the economic performance of region *i* in year *t* through the variables $AgeDependencyRatio_{it}$, $PopulationChange_{it}$, and $PopulationDensity_{it}$ respectively. Finaly, the influence of R&D expenditure as percentage of GDP of the region *i* during year *t* is controlled through the variable $R\&D\_Expenditure_{it}$. $\theta_1(\tau)$, $\theta_2(\tau)$,…, $\theta_6(\tau)$ are the quantile-specific coefficients for the variables related to employment dynamics, while $\lambda_1(\tau)$, $\lambda_2(\tau)$, …, $\lambda_4(\tau)$ are the quantile-specific coefficients for the control variables, and $\omega_{it}(\tau)$ is the quantile-specific error term.

4. Analysis

4.1 Descriptive Statistics

The descriptive statistics for NUTS 2 regions of the EU-27, as shown in Table 1, reveal marked differences in their economic, demographic and employment-related indicators.

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
GDP per capita	4740	96.10	37.77	21	286
GVA	4740	1.58	3.95	-23.4	68
Unemployment Rate	4740	8.78	5.40	1.30	37.30
Education &Training	4740	9.24	6.62	0.50	38.10
Labour Productivity	4740	3,224.61	1,937.64	54	14,915
Hours Worked pe	4740	16,775.89	2,203.64	12,780	24,080
Compensation	4740	207.06	105.84	22	472
Employment_Science & Technology	4740	29.13	8.32	10.50	66.10
Age Dependency Ratio	4740	66.09	7.14	45	91
Population Change	4740	16.41	85.71	-631	642
Population Density	4740	345.40	817.01	3.30	7660
R&D expenditure	4740	1.52	1.11	0.55	11.20

In particular, GDP per capita in percentage of the EU-27 average ranges widely, from a minimum value of 21 to a maximum of 286 percent, reflecting significant economic differentiation between regions. Its standard deviation further highlights the disparity in economic well-being. Annual changes in GVA show an average growth rate of 1.6 percent, with a high standard deviation and variations between -23.4 percent and 68 percent, indicating also extreme fluctuations in economic output among EU-27 regions.

Moving on to employment-related variables, the unemployment rate averages 8.78 percent, which is notably higher than the world average value of 6.1 percent for the same time period, according to World Bank data (2024). Unemployment rates across EU-27 regions vary significantly, ranging from 1.3 percent to 37.3 percent. Participation in education and training (for those aged 25-64) averages 9.24 percent, with considerable variation, reflecting diverse educational policies and training opportunities across regions. Real labour productivity per hour worked averages 3,244.61 €, which is an impressive figure compared to many other regions in the world. This suggests that the value generated in EU-27 regions is significantly high, which is probably due to advanced technologies, developed infrastructure and a highly skilled workforce. Hours worked annually per employed person varies between 12,780 and 24,080, with an average of about 16,776 hours. Real compensation per hour worked, averages 207.06 €, suggesting high remuneration levels consistent with high productivity. This compensation is considerably higher than in developing regions and competitive with other advanced economies. In addition, 29.13 percent of the EU-27 labour force works in science and technology sectors, with significant variation (10.5 to 66.1 percent). Regions with high percentages are more innovative, while those with lower percentages are likely to be dependent on traditional sectors such as agriculture, suggesting inequalities in technological development.

Figure 2 provides an initial insight into how the main variables vary across different regional income categories.

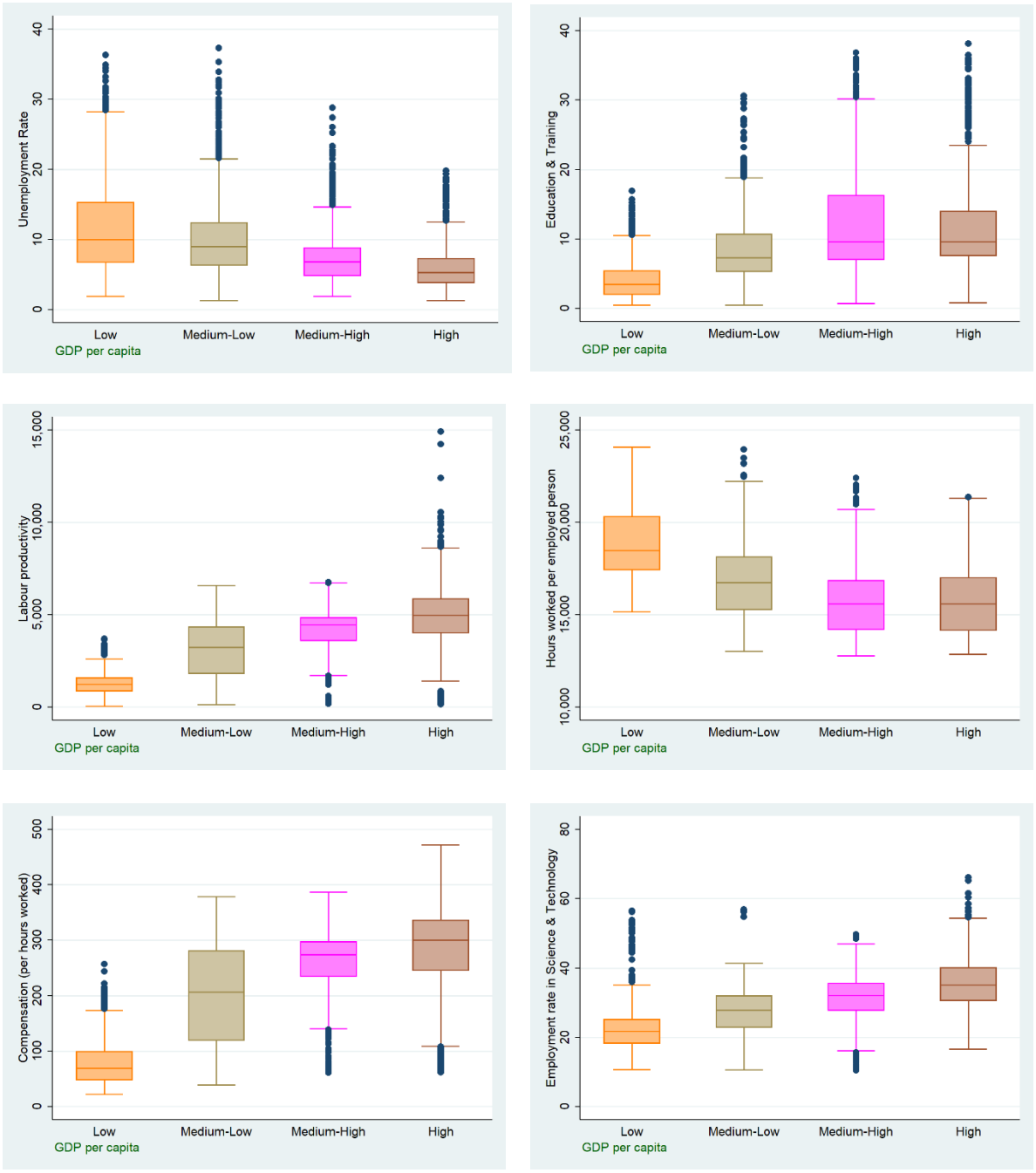

Figure 2. Boxplots of employment-related variables across GDP per capita categories in EU regions

Regions with higher GDP per capita generally exhibit higher compensation, labour productivity, and employment rate in science and technology sectors, while unemployment rates decrease, highlighting positive correlations between these factors and economic prosperity by regional income category.

As for control variables, the EU-27 regions exhibit an age dependency ratio averaging 66.09, meaning that around 66 of every 100 people are in the 0-19 or 65+ age ranges, representing a dependent population. This places a burden on the working-age population to support those economically inactive. Population density varies widely, from 3.3 to 7,660 persons per square kilometer, highlighting strong demographic and geographical diversity. Finally, R&D expenditure as percentage of GDP in the EU-27 regions averages 1.52 percent. The values range from 0.55 € to 11.20 percent, indicating large disparities in R&D investment across regions.

4.2 Impact of Employment Dynamics on GDP per Capita

Table 2 presents how the main and control variables of the model impact GDP per capita at four percentiles: the 25th (p25), 50th (p50), 75th (p75), and 90th (p90) percentiles.

Table 2. Quantile regression results on the impact of employment dynamics on GDP per capita

Dependent Variable is ***GDP per capita***	p25	p50	p75	p90
Unemployment Rate	-1.08564***	-1.03029***	-1.28743***	-1.29502
	(0.079)	(0.077)	(0.082)	(0.114)
Education &Training	0.42688***	0.12890**	0.23399***	0.17644*
	(0.069)	(0.066)	(0.071)	(0.074)
Labour Productivity (log)	2.42130***	2.50722***	2.32908***	1.99647***
	(0.474)	(0.459)	(0.489)	(0.683)
Hours Worked pe	0.00202***	0.00392***	0.00582***	0.00742***
	(0.001)	(0.001)	(0.001)	(0.001)
Compensation	0.21593***	0.26497***	0.29555***	0.30465***
	(0.007)	(0.007)	(0.007)	(0.010)
Employment_Science & Technology	0.17448**	0.39467***	0.37780***	1.00553***
	(0.068)	(0.066)	(0.070)	(0.098)
Controls				
Age Dependency Ratio	-1.06537***	-1.27401***	-1.46823***	-1.67696***
	(0.056)	(0.054)	(0.058)	(0.081)
Population Change	0.02054***	0.02341***	0.02161***	0.02327***
	(0.005)	(0.005)	(0.005)	(0.007)
Population Density	0.00335***	0.00829***	0.01677***	0.01598***
	(0.001)	(0.001)	(0.001)	(0.001)
R&D expenditure	2.63285***	1.99944	1.58736	0.13398
	(0.445)	(0.431)	(0.459)	(0.641)
Constant	51.090***	28.27234***	15.99966**	0.52141
	(7.128)	(6.902)	(7.356)	(10.264)
Observations	4,740	4,740	4,740	4,740
Pseudo R^2	0.5231	0.5220	0.5271	0.5469

*Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.10*

The results reflect the different effects of these variables on the distribution of GDP per capita, which gives us insights into how the relationship between these variables and GDP per capita changes at different levels of economic performance. Unemployment rate has a significantly negative relationship with GDP per capita across most percentiles, suggesting that regions with higher unemployment rates are more adversely affected. Economically less developed as well as above-average income areas may find that high unemployment deepens their struggles, reducing productivity and wealth creation. Policymakers in these regions could address high unemployment by implementing targeted job creation initiatives to foster economic resilience. For higher-income regions (90th percentile), unemployment seems not to affect economic growth, probably due to the fact that economic strength may mitigate this impact. The participation rate in education and training shows a statistically significant positive association with GDP per capita in all regions, but this effect is stronger in less developed ones, as illustrated in Figure 3. This suggests that in less developed regions, where education and skills levels may be lower, even modest increases in participation can have a significant impact. A small investment in human capital development can lead to substantial improvements in workforce skills and productivity, ultimately boosting the economy in these regions.

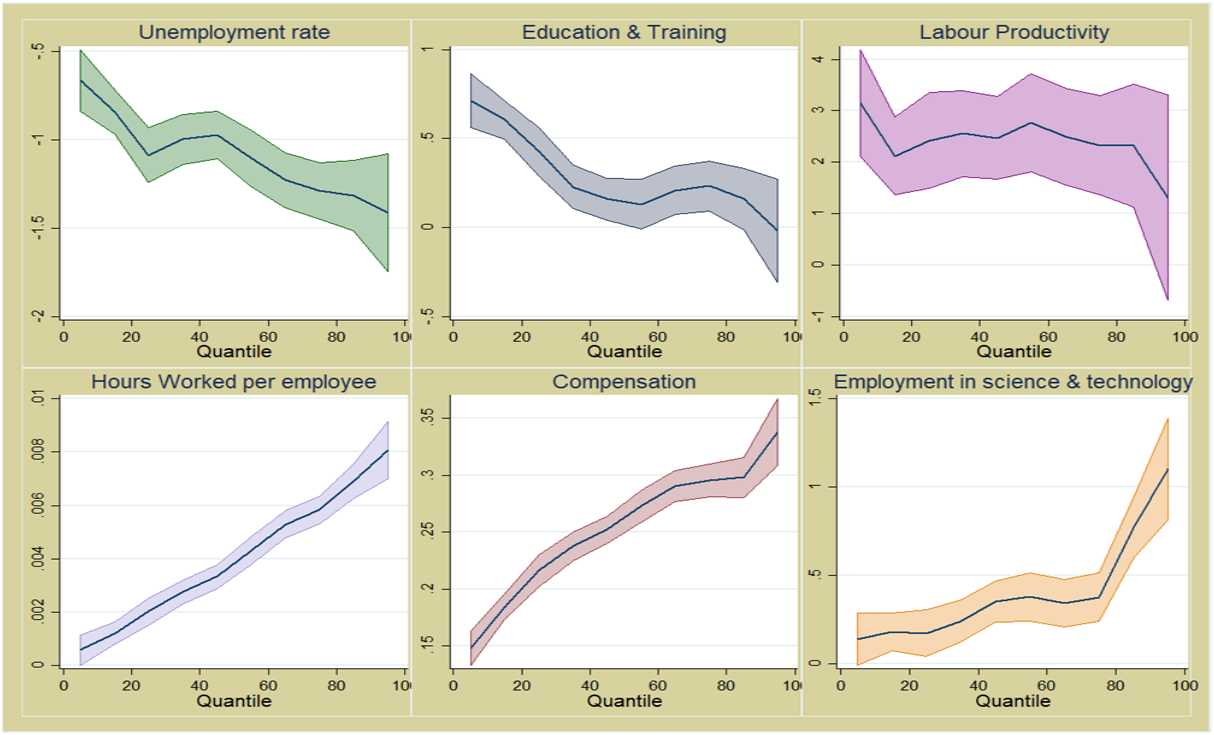

Figure 3. Quantile regression coefficients

Labour productivity consistently boosts GDP per capita across all regions, with the strongest effects observed in low- and middle-income regions. This highlights the potential for productivity improvements to reduce income disparities and stimulate growth. Similarly, hours worked per employed person positively impact GDP per capita across all levels, with a stronger effect in developed regions, where additional work hours generate greater economic output due to higher baseline productivity.

Real compensation per hour worked positively impacts GDP per capita across all regions. Regions where workers receive higher wages, often wealthier or more developed regions, experience greater economic activity and improved living standards, which translate into higher GDP per capita. Even in lower-income regions, wage increases can stimulate consumption and investment, driving economic growth.

The percentage of the labour force employed in science and technology sectors positively influences GDP per capita with a particularly strong effect at the 90th percentile. This highlights the critical role of high-tech industries in driving advanced economies. To maximise returns, policymakers should focus on promoting science and technology sectors, particularly in high-income areas where infrastructure and networks enhance their impact.

As for the control variables, higher age dependency ratio negatively impacts GDP per capita, especially in wealthier regions, by straining the working population. Population growth and density, on the other hand, positively influence GDP per capita. Population growth expands the labour force and consumer base, while population density promotes efficient resource use, infrastructure development, and innovation, leading to agglomeration economies that boost productivity and economic activity. The final control variable, R&D expenditure, significantly boosts GDP per capita in lower-income regions, with its impact decreasing as regional income levels rise. This indicates that R&D investments yield higher returns in less developed regions, where innovation capacity is lower, while wealthier regions experience diminishing marginal benefits due to their already advanced technological infrastructure.

4.3 Impact of Employment Dynamics on GVA

Table 3 presents quantile regression results on the effects of key and control variables on GVA.

Table 3. Quantile regression results on employment dynamics and GVA change

*Dependent Variable is **GVA** (Pct change on previous period)*	p25	p50	p75	p90
Unemployment Rate	-0.10870***	-0.09595***	-0.09257***	-0.11095***
	(0.014)	(0.010)	(0.013)	(0.021)
Education &Training	0.02759**	0.02084**	0.02028*	0.01630
	(0.012)	(0.009)	(0.011)	(0.018)
Labour Productivity (log)	0.11313	0.09089	0.14582* (0.077)	0.08925
	(0.086)	(0.063)		(0.124)
Hours Worked pe	0.00018***	0.00011***	0.00003	0.00014**
	(0.01)	(0.001)	(0.001)	(0.001)
Compensation	-0.00504***	-0.00956***	-0.01415***	-0.01449***
	(0.001)	(0.001)	(0.001)	(0.002)
Employment_Science & Technology	0.05120***	0.03559***	0.04131***	0.05273***
	(0.012)	(0.009)	(0.011)	(0.018)
Controls				
Age Dependency Ratio	-0.01890*	-0.00393	0.00437	0.02260
	(0.010)	(0.008)	(0.010)	(0.015)
Population Change	0.00714***	0.00592***	0.00444***	0.00327***
	(0.001)	(0.001)	(0.001)	(0.001)
Population Density	-0.00021**	0.00014**	0.00016**	0.00004
	(0.001)	(0.001)	(0.001)	(0.001)
R&D expenditure	0.07097	0.16048*** (0.059)	0.19251***	0.07883
	(0.080)		(0.072)	(0.117)
Constant	-2.59066**	0.78889	3.51845***	2.87030
	(1.288)	(0.952)	(1.150)	(1.867)
Observations	4,740	4,740	4,740	4,740
Pseudo R^2	0.0454	0.0554	0.0754	0.0806

*Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.10*

Employment dynamics influence GVA similarly to GDP per capita but with notable differences. Unemployment rate negatively affects GVA across all regions, with slightly more pronounced effects at the lower (p25) and upper (p90) percentiles. This suggests that the adverse effects of unemployment on output are significant in both less developed and high performing economies, albeit for different reasons. In vulnerable regions it reflects structural weaknesses, while in advanced ones it may be related to high reliance on skilled labour.

Participation rates in education and training impact GVA, similarly to GDP per capita, even with differences across developed and less developed regions. In less developed regions, these investments drive output improvements by addressing skill gaps. However, in more developed regions, the impact of these investments diminishes, becoming statistically insignificant in the most advanced ones.

Interestingly, while labour productivity has a significant positive effect on GDP per capita, it does not have the same impact on GVA, where its effect is not statistically significant except at the 75th percentile, where it is significant at the 0.10 level. This difference may be due to the nature of the indicator (i.e., GVA), as it represents the overall economic output of a region, encompassing both labour and capital contributions across a broad range of sectors, including those with less direct responsiveness to labour productivity improvements (Acemoglu & Dell, 2010), such as services or industries with lower labour elasticity.

The relationship between hours worked per employed person and GVA is more complex than with GDP per capita. While hours worked has a small but positive effect on GDP per employed person across all percentiles, it only significantly impacts GVA at the 25th, 50th, and 90th percentiles, with the strongest effect observed at the lowest percentile. This suggests that in less productive industries, common in lower percentiles, additional hours have a greater impact on output.

While real compensation exhibits a positive correlation with GDP per capita, this is contrasted by its negative relationship with GVA. This suggests that wage increases, if not accompanied by corresponding productivity gains,

may negatively impact overall output. Therefore, policies should focus on aligning wage growth with productivity improvements, particularly in more developed regions.

Employment in science and technology sectors significantly boosts both GVA and GDP per capita, highlighting the role of high-tech industries in regional growth. This impact is strongest in wealthier regions, where advanced infrastructure and economies of scale amplify returns. While middle-income regions may see smaller initial benefits, fostering science and technology employment remains crucial for long-term growth.

Control variables reveal notable differences in their effects on GDP per capita and GVA. The age dependency ratio negatively affects GDP per capita across all income categories due to the economic burden of non-working populations, but it has no statistically significant effect on GVA except in regions within the lowest percentile. This suggests that age structure influences income levels rather than overall output as measured by GVA. Total population change similarly affects both indicators, but in the case of percentage change of GVA its impact decreases in more developed regions. Population density also shows differences: while it boosts GDP per capita, particularly in more developed regions due to urbanisation, it positively influences GVA only in middle- and upper-middle-income areas, where agglomeration benefits, such as labour pooling and specialised networks, support economic output. Although R&D expenditure significantly boosts GDP per capita only in lower income regions, its effect on GVA is statistically significant at the median and upper-middle percentile, suggesting that R&D contributes more effectively to economic output in regions with moderate economic development, where established structures may better leverage innovation.

5. Discussion

The role of the unemployment rate in economic performance, as demonstrated by the results of this study, aligns with traditional economic theory (Okun, 1962), which asserts that higher unemployment typically correlates with lower economic performance. Nevertheless, at the highest income levels, this relationship is not statistically significant, suggesting that wealthier economies may be less sensitive to unemployment fluctuations. This is consistent with empirical studies suggesting that developed economies may have stronger mechanisms, such as effective regulatory and governance systems (Bartolucci et al., 2018), to mitigate unemployment impacts. Notably, this finding complements the observations of Heimberger et al. (2017), who identify structural unemployment as a growth constraint, by highlighting how the impact of unemployment varies across income levels, amplifying disparities in less-developed regions. Similarly, lifelong education and training investments show a positive relationship with both GDP per capita and GVA, in line with prior research highlighting education's critical role in economic performance. Blundell et al. (1999) emphasise how a skilled workforce accelerates growth, while Idrees and Siddiqi (2013) demonstrate that such investments are particularly effective in developing regions, where they drive productivity gains. This study further finds that education significantly boosts GDP per capita and GVA, particularly in lower-income regions. These findings highlight the importance of human capital development for reducing regional economic disparities within the EU and contribute to the ongoing discussion on economic convergence.

Labour productivity strongly impacts GDP per capita, especially in less developed regions, where improved efficiency boosts economic performance. This supports Acemoglu and Dell's (2010) argument that productivity improvements are essential for economic development, particularly in emerging or developing economies. Additionally, hours worked positively affects GDP per capita, with stronger impacts in high-income regions due to greater hourly productivity. However, its effect on GVA is less consistent, reflecting diminishing returns as extended hours reduce productivity, especially among less experienced workers (Collewet & Sauermann, 2017). Real compensation per hour worked also boosts GDP per capita by increasing purchasing power and productivity, particularly in lower-income regions (Kumar et al., 2012). Yet, higher wages negatively affect GVA, highlighting the need to balance wage growth with productivity for sustainable output (Keynes, 1936).

Finally, the proportion of the labour force employed in science and technology sectors significantly boosts economic performance, supporting theories on technology as a key growth driver (Coccia, 2019; Romer, 1990). The stronger impact in developed regions reflects their superior infrastructure and capacity for innovation (Acemoglu & Robinson, 2012). These findings advance regional economics by highlighting innovation-led employment's role in sustaining economic performance and the uneven capacity to leverage technological advancements, challenging assumptions of uniform benefits across regions.

Control variables such as the age dependency ratio negatively affect GDP per capita, particularly in high-income regions, indicating demographic pressures on productivity. This aligns with previous studies at the country level, which emphasise the economic strain of aging populations on growth potential and fiscal sustainability (e.g., Bloom et al., 2010). In contrast, the impact on GVA is non-significant, suggesting that age dependency may not

directly affect value-added growth in the same way it affects GDP per capita. Population change and density positively affect GDP per capita across all percentiles, supporting Liu et al.'s (2024) findings on urbanisation and economic growth. However, the effect of population change on GVA diminishes at higher percentiles, indicating a reduced role in driving value-added growth in mature economies, consistent with Brida et al. (2024). Interestingly, this study's findings on the effect of R&D expenditure on GDP per capita and GVA differ from those of Gumus and Celikay (2015) at the country level, who report that R&D expenditure positively affects all countries in the long run, with lower impacts in less developed countries in the short term. This divergence highlights the importance of considering income heterogeneity when analysing the economic impact of R&D at regional and national levels.

Despite these contributions, the study is not without limitations. First, its reliance on secondary data sources may introduce potential inconsistencies. Second, the focus on EU-27 regions may limit the generalizability of the findings to other contexts. Future research could address these limitations by exploring similar dynamics in non-European regions and utilising primary data for further validation.

6. Conclusions

This paper examines the relationship between labour market dynamics and economic performance across EU-27 regions over the past two decades. By employing quantile regression techniques, the study analyses how factors such as unemployment, lifelong education and training, labour productivity, and demographic characteristics affect economic outcomes, measured through GDP per capita and GVA.

Key findings indicate that unemployment has a greater negative impact on low- and middle-income regions, reflecting their heightened vulnerability to labour market inefficiencies. Participation in lifelong education and training demonstrates divergent effects: it fosters greater productivity and economic expansion in less developed regions but yields comparatively fewer benefits in more advanced regions. Labour productivity is a key factor for growth in all regions, highlighting its importance in shaping economic results. The influence of hours worked per employed person on per capita income is weakly positive, and this impact grows as regions become more economically developed. Wage increases are generally beneficial for GDP per capita, particularly in wealthier regions, though an imbalance between wage growth and productivity can negatively affect GVA. Finally, employment in science and technology sectors is a significant driver of economic growth, with the strongest effects in highly developed regions.

The findings highlight the importance of tailored strategies to address regional disparities. In less developed regions, investments in education, training, and innovation systems are critical for boosting labour productivity and economic growth. Addressing structural unemployment through targeted initiatives can further enhance resilience. In wealthier regions, the focus should be on balancing wage growth with productivity improvements and fostering innovation-driven industries to ensure long-term stability and competitiveness. Overall, the study highlights the necessity of region-specific economic policies to address disparities and promote balanced, sustainable growth, and achieve the long-awaited convergence across the EU-27 regions.

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Notes

Note 1. The five French overseas regions that excluded from the dataset are: Guadeloupe, Martinique, Guyane, La Réunion, and Mayotte.

Appendix

Percentage of missing values for key variables included in the analysis

Variable	Unemployment rate	Participation rate in Education & Training	Age dependency ratio	Population density
% of missing values	4.7	4.6	2	3.5