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DISSERTATION IN ECONOMICS & FINANCE

TITLE: Is technology after our jobs? An economic analysis on the impact of technological innovation on employment: evidence from Europe

Acknowledgements

I hereby certify that this dissertation, which is approximately 11,479 words in length, has been composed by me, that it is the record of work carried out by me and that it has not been submitted in any previous application for a degree. This project was conducted by me at the University of St Andrews from September 2022 to August 2023 towards fulfilment of the requirements of the University of St Andrews for the degree of Msc Finance and Economics under the supervision of Dr Nikolay Chernyshev.

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Abstract

The question of whether technological advancements will result in widespread unemployment is currently one of the most fervently debated topics in the realm of economics. Even though schools of thought vary considerably about whether technology will inevitably lead to job destruction, innovation, a critical driver of economic growth, has diverse implications for employment across different countries and economic structures. Nevertheless, existing literature has primarily explored these implications at the microeconomic and firm levels, often overlooking the broader macroeconomic aspects. This study aims to bridge this gap by undertaking a cross-country analysis, examining the interaction between innovation and employment across European countries over the period 2007-2019. The findings from this study reveal a positive and statistically significant association between technological innovation and employment growth. Specifically, countries whose industries are more engaged in innovative activities experience higher rates of job creation. This empirical evidence supports the notion that technological innovation acts as a key driver of employment, contrary to the widespread concern that innovation may lead to job displacement. In light of these findings, this study advocates for targeted policy measures and investment efforts to stimulate innovation at the European level further. As the results suggest, these efforts could play a pivotal role in promoting economic prosperity throughout Europe by harnessing the potential of technological innovation to generate sustainable employment opportunities.

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1

Introduction

The issue of unemployment has been a longstanding and complex challenge in Europe that demands innovative and effective solutions to foster economic expansion and support the creation of job opportunities. Policymakers across Europe have increasingly turned to technological innovation as a lever to stimulate employment and enhance competitiveness in the global market (Commission et al., 2023). Nations across the world are increasingly investing in research and development (R&D), technological advancements, and entrepreneurial activities to foster innovation and stay ahead in the race for economic prosperity. According to the "European Innovation Scoreboard 2023," investment in R&D and the implementation of new technologies have been recognized as key drivers in creating high-skilled jobs and improving economic resilience. The European Commission's Horizon 2023 program further underscores this emphasis, allocating substantial funding towards research and innovation with the aim of addressing societal challenges. Among its ambitious objectives is the generation of 300,000 employment opportunities by 2040, with a notable 40% of these jobs being categorised as highly skilled (Commission et al., 2021). Nevertheless, while innovation offers numerous benefits, it also raises complex questions regarding labour market dynamics, skills mismatches, and the potential displacement of certain job categories.

Economic theory outlines that technological advancement inherently enhances labour productivity by optimising the efficiency of work processes. This optimisation enables a reduced workforce to generate an equivalent level of output, thereby effectuating what economic literature describes as ”labour-saving.” This phenomenon reflects the ability of technology to replace or augment human effort, leading to a shift in labour demand. The neo-Schumpeterian view of ”creative destruction” believe that modern economies are moving into a new era driven mostly by technologies. The implementation of new technologies has the potential to generate new employment prospects while concurrently phasing out outdated occupations. However, the specifics of where jobs are created or destroyed depends on what the technology does and their speed of adoption (Fagerberg and Mowery, 2006). Additionally, there’s a notable disparity in the sectors impacted by job losses and those witnessing new job growth, potentially resulting in skill discrepancies and misalignments. While the widespread unemployment crisis attributed to technological advancements hasn’t been evident since the first industrial revolution, the intricate and multifaceted relationship between technological innovation and employment remains a subject of heated debate among economists and the general public. The focus often turns to the immediate effect of innovation on the labour market and its potential permanent effects. On the one hand, the predominant fear, deeply rooted in Ricardo’s concept of the ’machinery question’, is that automation and technological advances could lead to mass unemployment. These ideas are captured by the labour-saving or displacement effect whereby workers are replaced by technology, particularly in industries that rely heavily on manual or repetitive labour, such as manufacturing, leading to job losses. From this perspective, innovation has the potential to create unemployment and increase income inequality for those individuals who are unable to adapt to new technology. Indeed, recent studies indicate that technological progress affects more than just employment, extending to other economic indicators, such as wages. A study conducted by Acemoglu and Restrepo (2022) in the US and published by the National Bureau of Economic Research (NBER) reveals that automation has contributed significantly to the rise in wage inequality in the US over the last 40 years. On the other hand, classical economists have long been optimistic about the labour-friendly nature of technological innovation. On the other hand, the Compensation Theory provides a counter-narrative to the concerns regarding job losses due to automation and innovation. It postulates that while new technologies may render certain roles obsolete, there is a concurrent emergence of new sectors and job opportunities, effectively compensating for these losses. This equilibrium is achieved through various mechanisms. However, for these compensatory effects to materialise optimally, an adaptable workforce, policy interventions, and continuous educational endeavours are crucial.

This dissertation aims to investigate the impact of technological innovation on employment within a European context by analyzing a sample of 20 countries (Germany, Spain, Poland, Sweden, Ireland, Hungary, Norway, Italy, Czech Republic, Luxembourg, Netherlands, Portugal, Austria, Denmark, France, the UK, Estonia, Slovenia and Latvia) over the period 2007-2019. A random sampling method was employed to ensure the representativeness and generalizability of the study's findings. The study is organised as follows. In Section 1, I present the theoretical background surrounding the role of technology in macroeconomic theory and the impact of technological innovation on employment, followed by a discussion of empirical evidence at both aggregate and sectoral levels. Methodology and data are presented in Sections 3 and 4. Sections 5 and 6 offer empirical findings. Lastly, Section 6 presents a discussion of the limitations of this study, while Section 7 offers the conclusion.

2

Theory

2.1 The Role of Technology in Macroeconomic Theory

Economic theory acknowledges technology's pivotal role in driving productivity and fueling economic growth. The approach of the neoclassical growth models is to employ a tool known as the aggregate production function (APF), which relates the input factors of capital accumulation K(t), labour augmenting technological progress A(t), and labour L(t) to output Y(t). Mathematically, it takes the form:

$$Y(t) = F[K(t), A(t)L(t)] \tag{1}$$

At any point, a country's economy has some capital, labour and technological progress, which are combined to produce output Romer (2019). Technological progress is a broad term that, in the context of the Solow model developed by Nobel laureate Robert Solow represents everything from advancements in knowledge, methods and production processes which ultimately lead to enrichments in production capabilities. It is important to highlight that technological progress A(t) and labour L(t) mix in a multiplicative way. A(t)L(t) is defined as the effectiveness of labour, and A(t) is known as labour augmenting. As firms adopt technological advancements, they can achieve greater productivity with the same amount of inputs, boosting production capabilities and generating higher living standards. If economic growth were only characterised by an increase in capital accumulation and labour, then a county's living standards would eventually stop rising because of diminishing returns on capital. The neoclassical growth model's critical assumption states that it is only through technological progress that any economy can ultimately avoid economic stagnation and enjoy sustained growth. Indeed, the positive effects of technological change on productivity and economic growth have been widely researched and documented theoretically and empirically (See Mairesse and Sassenou, 1991; Ortega-Argilés et al., 2009. However, if long-term economic growth stems from technological progress, it may be worth asking whether the labour market is too subject to the influence of innovation and in what way.

2.2 Theoretical Background

Technological unemployment refers to a scenario wherein the speed of labour-saving technological innovation outstrips the rate at which we can generate new employment opportunities, as described by Keynes (2010). It also represents a situation wherein individuals are unemployed and seeking jobs due to the adoption of advanced operational processes and organizational strategies that reduce the need for human labour (Klimczuk-Kochanska and Klimczuk, 2015). Fundamentally, technological, automation, and mechanization developments diminish the necessity for human involvement across various professional fields. The basic economic premise is that for technological improvements to garner a larger portion of the market, they need to demonstrate higher efficiency and productivity compared to the currently employed workforce. When technological advancements and innovation allow firms to produce the same level of output using fewer labour inputs, this phenomenon is formally referred to as labour-saving technological change. The implementation of new technologies can lead to a decrease in demand for certain jobs, resulting in job displacement and potentially permanent adverse effects on the job market. This is especially true in sectors or industries that heavily rely on technological and automation processes (See Zimmermann, 1991; Feldmann, 2013). Therefore, a central concern is whether the swift technological advancements will displace jobs at a quicker rate than we can conceive new roles that utilise human skills. The debate and concern arising from the expansion of technological innovation and the subsequent impact on employment can be traced back to Keynes (2010) essay ‘Economic Possibilities for our Grandchildren’ published in 1930. In his essay, J. M. Keynes cautioned about the potential for ’technological unemployment’. A crucial aspect of this concern hinges on the pace of technological transformation and whether it will exceed the capacity of the workforce to adjust and, where needed, acquire new skills for emerging job roles. It is important to note that employment evolution due to technological advancements is not a novel phenomenon. Since the Industrial Revolution, the widespread substitution of labour with machinery and new technology has sparked debates among economists and policymakers regarding its economic and social consequences. Classical economists began to suggest the existence of market forces that would counteract the transitory negative effect of innovation on employment and its long-term job-creating effect. These forces act as mitigating forces, ensuring that while certain jobs may be disrupted or displaced by technology, new opportunities and industries emerge, leading to overall economic growth and improved employment prospects. As a result, while a segment of the economic sphere cautions about the potentially permanent implications of pervasive technological integration, the other sphere emphasises the dynamic nature of the labour market and the capacity of innovation to generate net positive effects on the economy and society as a whole. These latter ideas constitute the foundation of what Marx later defined as the compensation theory. This theory reflects a general optimism among classical economists about markets’ self-regulating and self-adjusting nature. They believed that any short-term disruptions caused by technological progress would be offset in the long term by new opportunities and economic growth. Jean-Baptiste Say is a notable proponent of this line of thought; he expressed great confidence in the market’s ability to adjust and argued that the efficiencies brought by technological advancements and increased productivity could be reinvested into the economy, creating new industries and jobs. So while certain jobs might disappear due to technological change, new ones would take their place. This line of reasoning aligns with Say’s Law in the sense that economic production (in this case, driven by technological innovation) can spur economic demand (for new types of goods and services, which require new types of jobs). Thomas Malthus supported this view by emphasising the positive effects arising from the strong demand dynamics in England at the time. Nevertheless, despite the optimism of classical economists, the English working classes experienced significant impoverishment due to job losses and deskilling caused by mechanization (Pianta, 2009). The negative perception of machines among workers resulted in the formation of trade unions and anti-technology Luddite movements (Hobsbawm, 1952). However, classical economists also acknowledged workers' concerns and the important role played by policymakers. In the late eighteenth century, James Steuart highlighted the challenge of reabsorbing the unemployment caused by rapid mechanization, suggesting a role for government intervention to ensure policies are in place to support those whose jobs are displaced in the short term while also suggesting retraining and education programs to help them adapt to the changing job market. A prominent supporter of the compensation mechanism theory was classical economist David Ricardo, who explored the implications of technological progress and the introduction of machinery on the economy and labour in his seminal essay "On Machinery," published in 1821 as part of "On the Principles of Political Economy and Taxation". Ricardo acknowledges the potential for increased productivity and economic growth resulting from labour-saving machinery. However, he also acknowledged workers' concerns about machinery's impact. He raises concerns about the short-term adverse effects on workers, such as unemployment and declining wages, particularly for those engaged in tasks easily mechanised. Despite the transitory negative effect on workers, Ricardo believed the economy could offset negative employment effects. In the long run, the benefits of technological advancements would prevail, leading to improved societal welfare (Ricardo, 2015).

2.3 Empirical evidence at the aggregate level

The assessment of the impact of technological innovation on employment has been approached and evaluated through various levels of analysis, each carrying benefits and constraints: macro, sectoral, and firm analysis. Starting with macroeconomic studies, Sinclair (1981) investigated the potential impact of technological progress on job destruction using a macroeconomic IS/LM approach to US data. The author concluded that although certain tasks previously performed by humans can be automated, thus reducing the need for human labour, the existence of a positive compensation mechanism whereby new industries and occupations may emerge, thus creating new opportunities. It is crucial to note that the compensation mechanism only becomes apparent if demand elasticity and the elasticity of factor substitution are sufficiently high (Piva and Vivarelli, 2017). Similarly, in the UK, Layard and Nickell (1985) suggested that structural factors, such as changes in the demand for labour, have crucial consequences on employment. The authors outlined that the initial job displacement caused by technological change can be offset only by an adequately high elasticity of the demand for labour. Based on data from nine OECD countries over the period 1960-90, Pini (1995) finds that technological progress negatively affects employment. Nevertheless, the authors also mentioned the existence of other equally important compensation effects in terms of the export dynamics, which directly and indirectly stem from the innovation process.Vivarelli (1995) applied a 3SLS regression to data from Italy and the US over the period 1960-88. The authors argued that the compensation mechanism, characterised by a decrease in prices, was observed in both countries. Similarly, Simonetti (2000) extended the 3SLS model to data from the US, Italy, France and Japan over the period 1965-1993. The authors argue that compensation mechanisms via a decrease in prices and an increase in income are prevalent (particularly in France and Italy). More recent studies on the aggregate level support the existence of a compensation mechanism. Feldmann (2013) analysed data from 21 industrial countries over the period 1985-2009. Instead of relying on R&D expenditure as a measure of innovation, the author utilised triadic patents in their study, which differs from the majority of previous research. However, he found evidence of the existence of a compensation mechanism via prices and wages. He found that technological change caused significant job displacement over a 3-year period. However, this effect tends to disappear in the long run. Similar evidence emerges from studies on the impact of technological innovation on unemployment. Sokhanvar (2020) examined panel data from five European countries to evaluate how changes in R&D intensity impact both short-term and long-term unemployment rates. Results show that a given increase in R&D expenditure significantly impacts the rate of unemployment in the short run. The authors argue that the short-run increase in unemployment is likely a direct consequence of technological change "due to the possible mismatch between the skills required by the newly created tasks (jobs) and the skills of the existing pool of workers". In the long run, however, an increase in R&D expenditure likely leads to lower levels of unemployment. Lydeka and Karaliute (2021) analysed data from 28 European countries over the period 1992-2016 to assess the impact of technological change on unemployment. According to the authors, there are instances where technological innovation has an impact on unemployment. Some of the presented estimations from the study suggest a statistically significant and positive effect of product innovation (measured by expenditure on R&D) on unemployment. However, no statistically significant evidence was found about the impact of process innovation (as measured by the number of patent applications) on unemployment.

2.4 Empirical evidence at the firm and sectoral level

Sectoral and firm-level analysis has recently become more prominent thanks to the wider availability of data. It is interesting to observe that, with a few exceptions, studies conducted at the firm level consistently demonstrate that technological innovation has a beneficial impact on employment. For example, Reenen (1997) investigated firm-level panel data of 598 firms in the UK and found that technological innovation was associated with higher firm-level employment. Similarly, Blanchflower and Burgess (1998) investigated and compared the effect of innovation in Britain in 1990 and Australia in 1989-90. They found that the introduction of new technologies led to an increase in labour by around 2.5% in Britain and 1.5% in Australia (per annum basis). Similar results are observable in studies covering firms in continental Europe. For example, in France, Greenan and Guellec (2000) analysed a sample of 15,186 French firms over the period 1986–90 and found that innovative firms and sectors generate jobs to a greater degree than others over the medium run. Furthermore, they found that process innovation leads to higher job creation than product innovation at the firm level. On the other hand, when looking at individual sectors, it becomes clear that the opposite is actually true. The authors attribute this to the substitution effect, which is emphasized in the theory of creative destruction. Similarly, (Smolny (1998); Smolny (2002)) examined a large sample of panel data of manufacturing firms from West Germany and found that innovative firms generated more employment than their non-innovative counterparts. In Italy, Vivarelli (2005) found a positive relationship between innovation and employment based on a dataset of 575 Italian manufacturing firms over the period 1992-97. However, a few studies performed at the firm level find a negative or inconclusive positive relationship between innovation and employment. Based on 8220 manufacturing firms over the period 1981-85, Vivarelli et al. (1996) found an overall negative impact of technology on employment in Italian manufacturing firms caused by the dominant role of process innovation in firms' innovative activities. Conversely, jobs were increased in sectors with higher product innovation. Brouwer et al. (1993) investigated the influence of innovation on growth rates of employment in 859 Dutch manufacturing firms over the period 1983-88 and found the impact of product innovation to be positive. However, the overall impact of innovation, measured as total R&D expenditure, was found to be negative. Finally, Klette and Førre (1998) analysed a large dataset covering more than 80% of manufacturing employment in Norway over the period 1982–92, suggesting no distinct relationship between innovation, measured by R&D investments, and job creation. With a few exceptions, most studies conducted at the firm level find comparable evidence of the positive effect of technological innovation on jobs. However, studies performed at the sectoral level showcase diverse effects on employment.Antonucci and Pianta (2002) expanded on a previous study by analyzing data from eight European countries taken from the Community Innovation Survey between 1994-96. They discovered that technological change had a detrimental effect on employment across European manufacturing industries. According to a study by Tomás (2002), data from the Spanish economy from the mid-1980s to late-1990s showed a general trend towards a decrease in the number of workers employed in technology-intensive sectors. Similarly, Klette and Førre (1998) found evidence in their sectoral analysis that R&D intensive sectors in Norway experienced a decline in employment compared to the rest of the manufacturing sector. Studies have shown that innovation has a negative impact on employment in Europe, affecting not just the manufacturing industry but other sectors as well, including the service sector. For example, according to Savona (2002), innovation activities in the Italian service sector have a negative impact on overall employment. The impact on jobs is more pronounced in less qualified jobs, and the labour-displacing effect is especially prevalent in these cases. However, there is a considerable amount of literature that supports the idea that product innovation is labour-friendly. For example, Greenan and Guellec (2000) analysed 18 industries within the French manufacturing sector and found that innovation-intensive industries generated more jobs than less innovative industries. While the authors' findings suggest that process innovation has a greater impact at the firm level, they argue that product innovation is more influential at the sectoral level. Companies that prioritize process innovation often generate more job opportunities, but this comes with a cost for other firms. Consequently, the effect of process innovation on employment is unfavourable for the entire industry. Conversely, product innovation has a more positive impact on employment throughout the manufacturing sector. A study by Bogliacino and Pianta (2010) analyzed data from eight European countries from 1994 to 2004 to explore the relationship between innovation and employment in manufacturing and service industries. Based on empirical evidence, the authors find that product innovation positively impacts job growth. This study provides support for the idea that "employment growth is sustained by the entry of new firms and by the introduction of new products that expand sales", in accordance with the Schumpeterian perspective. Similarly, a study conducted by Coad and Rao (2011) on US high-tech manufacturing industries from 1963 to 2002 revealed that innovation (measured in terms of both R&D expenditure and patents) led to job growth. Bogliacino and Vivarelli (2012) analyzed data from 25 manufacturing and service sectors across 16 European countries between 1996-2005. They discovered that R&D expenditure, which measures product innovation, has a positive impact on job creation and is conducive to a labour-friendly nature. The study conducted by Buerger et al. (2012) explores how the growth rate of patents, research and development (R&D), and employment are related using panel data from Germany over the time frame 1999-2005. The data indicates that more patents lead to employment growth in the medical and optical equipment and electronics industries. This, however, does not apply to the chemicals and transport equipment industries. Based on about 20,000 firms operating in the manufacturing and service sectors from France, Germany, Spain and the UK over the period 1998–2000, Harrison et al. (2014) find that job displacement often occurs with process innovation. However, compensation effects are prevalent, and job growth is linked to product innovation.

3

Models and Estimation Methods

This section explains the methods used to measure innovation and examines different econometric methodologies and models used to study the relationship between innovation and employment. This study uses three models to provide an in-depth analysis of the impact of innovation on employment at the aggregate level. Firstly, I will utilise a country-specific fixed-effect panel regression to control for individual characteristics that remain constant over time within each country. This model will allow isolating innovation's unique effects on employment dynamics while considering cross-sectional variations across countries. Furthermore, I aim to explore potential variations in the impact of innovation on employment across different income groups. For this purpose, the second model will divide countries based on their GDP per capita, enabling to gauge how innovation affects employment differently in different income brackets. Lastly, the third model allows for two forms of non-linearity captured by the quadratic terms $tbrd\_l1sq$ and $agesq$.

3.1 Model 1: Country-Specific Fixed Effect Panel Regression

The initial model employed in this study entails a basic country-specific fixed effect panel regression. Such a model allows us to control for individual country-level characteristics and account for unobserved heterogeneity across the analysed nations. Mathematically, this model takes the form:

$$\begin{aligned} emp_i = &\alpha_i + \beta_1 tbrd\_l1_i + \beta_2 cpi\_l1_i + \beta_3 gfcf\_l1_i + \beta_4 gdpg\_l1_i \\ &+ \beta_5 edupub\_l1_i + \beta_6 taxsl\_l1_i + \beta_7 popg\_l1_i \\ &+ \beta_8 empprot\_l1_i + \beta_9 indgovsup\_l1_i + \beta_{10} age_i \\ &+ \alpha_i + u_i \end{aligned} \tag{1}$$

Where *emp* is the aggregate employment level in the country i; *tbrd* represents the total business enterprise research & development (R&D) conducted in country i (as a proxy for innovation); *tpf* indicates the number of triadic patent family; *cpi* is the inflation rate; *gfcf* is the gross fixed capital formation is a proxy for capital; *gdpg* is the GDP growth; *edupub* is the government expenditure on total education; *taxsl* is the implied subsidy rate on R&D expenditure on large firms in a loss-making scenario; *popg* is the population growth; *empprot* indicates the strictness of employment protection – individual and collective dismissals (regular contracts); *indgovsup* is the indirect government support through R&D tax incentives expressed in real terms, and *age* is the average age of the labour force. Section 4 provides a comprehensive explanation of how the variable was calculated. Lastly, α_i are country-fixed effects, capturing unobserved heterogeneity that might be constant across time within each country and u_i is the error term.

3.2 Model 2: Fixed Effects Model Segmented by GDP per Capita

In an attempt to discern the impact of innovation on employment across European countries, Model 3 groups countries into three categories according to their Gross Domestic Product per capita, adjusted for Purchasing Power Parity (PPP): high-income, upper-middle-income, and lower-middle-income. The "Fixed Effects Model Segmented by GDP per Capita" aims to ascertain the impact of innovation on employment across economies of varying income levels. By integrating country-specific fixed effects, the model allows for the examination of how innovation influences job creation and employment rates in different income economies. In the process of creating the subgroups, a strategic division of the sample into three distinct subgroups was employed to ensure homogeneity across income categories. It is important to note that, according to the World Bank classification [1], all countries within the sample fall into the high-income income brackets. By adhering strictly to this categorization, there emerges an inherent risk of establishing unbalanced subgroups, with high-income countries predominantly constituting the bulk of the dataset. I deviated from the traditional World Bank division to circumvent this issue and ensure that each subgroup captured a representative spectrum of the data.

1. Category 1 (High GDP per capita): Countries with a GDP per capita above $\$50,000$;
2. Category 2 (Upper-middle GDP per capita): Countries with a GDP per capita between $\$35,000$ and $\$50,000$;
3. Category 3 (Lower-middle GDP per capita): Countries with a GDP per capita below $\$35,000$.

Mathematically, the model takes the same form as the one utilised in Section 3.1

[1] For further details on the World Bank's country classifications by income level for 2022-2023, it is recommended to consult OECD (2023*b*)

$$
\begin{aligned}
emp_i = & \alpha_i + \beta_1 tbrd\_l1_i + \beta_2 cpi\_l1_i + \beta_3 gfcf\_l1_i + \beta_4 gdpg\_l1_i \\
& + \beta_5 edupub\_l1_i + \beta_6 taxsl\_l1_i + \beta_7 popg\_l1_i \\
& + \beta_8 empprot\_l1_i + \beta_9 indgovsup\_l1_i + \beta_{10} age_i \\
& + \alpha_i + u_i
\end{aligned} \tag{2}
$$

Economic theory does indeed explore different perspectives on how innovation impacts employment across countries with different income levels. This is because the context - including income levels and factors like institutional frameworks, educational systems, infrastructure, and so forth - can significantly influence how innovation translates into employment outcomes. The skill-biased technological change theory posits that technological innovation tends to increase the demand for skilled labour while reducing the demand for unskilled labour. This effect can be more pronounced in high-income countries, where technological innovation is more prevalent. For instance, Katz and Autor (1999) discuss the rise in the relative wages of highly educated workers in the United States and argues that this reflects an increase in the relative demand for skilled workers due to skill-biased technological change. Furthermore, there also appear to be strong correlations between industry-level indicators of technological change (computer investments, the growth of employee computer use, R&D expenditures, utilisation of scientists and engineers, changes in capital intensity measures) and the within-industry growth in the relative employment (See Berndt et al., 1992; Berman et al., 1994; Autor et al., 1998 Machin and Reenen, 1998). On the other hand, lower-income countries, which might rely more on less skilled labour, could see a less immediate impact on employment from technological innovation. Similarly, the technology gap theory suggests that differences in the ability to adopt and implement new technologies can create a gap between countries. Fagerberg (1987) found a strong correlation between economic development (measured by GDP per capita) and technological development (measured through R&D and patent statistics). In a similar vein, Vivarelli (2014) argues that only developed countries that enjoy a sufficient level of endogenous R&D and innovation capabilities would be able to fully develop the growth and employment potentialities of the new technologies. Logically, high-income countries might be better positioned to capitalize on technological innovation due to better infrastructure, highly skilled labour availability, and more capital availability. For instance, Sampson (2023) argues that countries with higher R&D efficiency are richer and have a comparative advantage in more innovation-dependent industries. In contrast, lower-income countries may face challenges in these areas, which could limit the employment benefits they gain from technological innovation. Finally, past literature emphasizes that a country's structural factors, such as shifts in the labour market demand, can have significant impacts on employment. Additionally, they note that the initial job displacement caused by technological advancements can only be counteracted by a sufficiently high level of elasticity in the labour market demand (See Piva and Vivarelli, 2017; Layard and Nickell, 1985). Therefore, the structure and flexibility of labour markets and the overall institutional framework of a nation can affect how innovation impacts employment. The primary reason is that labour market flexibility allows for quicker and smoother adaptation to changes introduced by Innovation. In economies where labour markets are more flexible and there is a strong institutional framework supporting innovation (often the case in high-income countries), technological advances might lead to more significant job creation. In contrast, innovation might not translate effectively into employment growth in countries with rigid labour markets and weaker institutional support. However, it is important to note that all countries used in this study are members of the OECD and classified as high-income economies according to the World Bank classifications. It should be noted that this study did not include any low-income countries; therefore, the observed differences may be less remarkable. Nevertheless, the European countries included in this study vary significantly regarding their economic development and strengths. Furthermore, the economies range from very large to much smaller. Therefore, significant differences in economic influence, global presence, and domestic industry dynamics among these countries may influence how innovation affects employment.

3.3 Model 3: Non-Linear Fixed Effects Model

This model includes two forms of non-linearity: the quadratic term for $tbrd\_l1$ and age.

$$
\begin{aligned}
emp_i = & \alpha_i + \beta_1 tbrd\_l1_i + \beta_2 tbrd\_l1sq_i + \beta_3 cpi\_l1_i + \beta_4 gfcf\_l1_i + \beta_5 gdpg\_l1_i \\
& + \beta_6 edupub\_l1_i + \beta_7 taxsl\_l1_i + \beta_8 popg\_l1_i \\
& + \beta_9 empprot\_l1_i + \beta_{10} indgovsup\_l1_i + \beta_{11} age\_l1_i \\
& + \beta_{12} age\_l1sq_i + \alpha_i + u_i
\end{aligned}
\tag{3}
$$

The first non-linearity concerns the introduction of the quadratic term $tbrd\_l1sq$ to capture the nonlinear relationship between total business R&D expenditure and employment, highlighting the potential diminishing marginal effects of R&D allocated by large firms on job creation. This term represents a critical acknowledgement of the dampening effects of R&D, wherein initial investments may lead to growth in employment, but subsequent expenditures yield diminishing returns. By including the quadratic term, the model attempts to test the possibility that not all increments in R&D expenditure will translate into proportional increases in employment. The second form of non-linearity captures the nonlinear effect of age on employment. Expanding upon the groundwork laid by Shah et al. (2022) on the investigation of the impact of R&D investment on employment growth in Japan, I constructed the final model designed to capture the non-linear relationship between age and employment in Europe. In formulating the econometric model, the authors took into account the impact of the ageing population and labour force in Japan. Europe has been confronted with analogous challenges stemming from its ageing population. Both regions have been grappling with the consequences of increasing life expectancies, declining birth rates, and a significant portion of their population approaching or already in the elderly category. These demographic shifts have profound implications for the labour market. Existing literature suggests that age has a nonlinear effect on the labour market (See Schwartz and Kleiner, 1999; Rosenzweig, 1976; De Lange et al., 2021). Following Shah et al. (2022) approach, I apply a quadratic effect to capture the aforementioned nonlinear effect. This is captured by the variable *agesq*.

4

Data

4.1 Sample overview

This study relies on a dataset covering 20 European countries (Germany, Spain, Poland, Sweden, Ireland, Hungary, Norway, Italy, Czech Republic, Luxembourg, the Netherlands, Portugal, Austria, Denmark, France, the UK, Slovakia, Estonia, Slovenia and Latvia) over the period 2007-2019 for a total of 260 observations. The primary source of data is the OECD database, from which I extracted data for employment, total business enterprise R&D, triadic patent family, CPI, GFCF, implied tax subsidies for the loss-making scenarios, and employment protection. Data for GDP growth, total governmental spending on education, and population growth were extracted from the World Bank database. Finally, I calculated the values for indirect government support through R&D tax incentives in real terms and the average age of the labour force for each country. Table A1 summarises the variables utilised in this study and their respective acronyms.

4.2 Variables Description

In order to properly account for the impact of technological innovation, I have specifically selected two indicators: total business enterprise research and development (R&D) as the primary proxy for innovation and the trident patent family count as a general proxy for innovation to provide supporting evidence. Data representing total business enterprise R&D expenditures are adjusted to account for inflationary changes and are expressed in terms of 2015 constant prices. Consequently, the figures presented in this analysis are denominated in US Dollars millions, using 2015 as the reference year. Patent statistics can provide useful information but have some drawbacks. While patents do serve as an indicator of innovation, they may not always accurately capture the full scope of the inventive and innovative activity. For example, Griliches (1990) found that at the aggregate level, the absolute decline in inventive activity was largely caused by bureaucratic obstacles rather than economic or technological factors, thereby making it difficult to conclusively explain the causes of the relative decline in patenting activity relative to the growth in R&D expenditures. Additionally, certain firms may perceive the expense of obtaining a patent to be excessive and the process of filling a patent to be time-consuming and instead choose to safeguard their inventive ideas through alternative methods like secrecy or registering for a copyright [1]. Acknowledging that using patents as the sole metric for assessing innovation can lead to partial conclusions is important. The rationale behind this is that the mere fact of being patented does not always translate into innovation, and some sectors do not file for patents as frequently as others, making patent counts a poor metric to measure innovation in those specific industries [2].

The model includes important macroeconomic factors to account for any economic impact that could affect employment levels. These variables include GDP growth, inflation (CPI), gross fixed capital formation (GFCF), population growth and governmental spending on total education. The relationship between employment and GDP has been

[1] See Archibugi (1992) for more information about the use of patents as indicators of technological innovation

[2] See Arundel and Kabla (1998) for more information about the percentage of innovations being patented and the varying degree to which different sectors patent

thoroughly explored in both theoretical and empirical literature. The economic theory relies heavily on Okun's law to provide an explanation for the relationship between employment rates and GDP growth. This law posits that for every 1% increase in GDP growth, there is a corresponding decrease in unemployment rates by approximately 0.5%. Inflation is commonly measured through the Consumer Price Index (CPI), which keeps track of the average change in prices of a selected basket of goods and services consumed by households. Economic theory commonly explains the relationship between inflation and (un)employment by the Philips Curve, which assert a negative association between inflation and unemployment. However, this particular study places its focus on employment rather than unemployment, and as such, a positive relationship between the two is anticipated. Gross fixed capital formation (GFCF) serves as a measure of capital and plays a significant role in domestic investment and economic growth. The interplay between labour and capital is a nuanced one. The presence of capital can have both complementary and substitution effects on the demand for labour. In the case of a complementary effect, both additional capital and workers are required to meet the demand. However, in the case of a substitution effect, the demand for labour decreases as more capital is needed instead (Luca Marcolin, 2016). Several studies have employed the use of GFCF, or Gross Fixed Capital Formation, to observe the effects of investment on employment levels (Van Roy et al., 2018; Piva and Vivarelli, 2018).

This study also attempts to include variables to account for policy interventions. Government policies can play a critical role in shaping the way innovation affects employment. Policy measures like spending on education, employment protection and tax incentives on R&D can all contribute to promoting innovation and ultimately affect employment outcomes. The variable *edupub* represents the amount of investment allocated by the government on all aspects of education within a specific country. This includes expenditures related to primary, secondary, and higher education. A well-educated and skilled workforce is more likely to engage in innovative activities, as they possess the necessary knowledge and capabilities to create and implement new ideas and technologies. Nevertheless, it is important to note that the relationship between government spending on education and innovation is not linear and can be influenced by other factors. The variable *empprot* has been included to capture the degree of flexibility in labour market regulations. Specifically, this indicator evaluates the strictness of regulations on the individual and collective dismissal of workers on regular contracts. Finally, this study incorporates three indicators that can be used to assess the level of support for innovation and subsequent employment outcomes. The first indicator is indirect government support through R&D tax incentives. Businesses can receive tax incentives for conducting R&D. These incentives can come in the form of allowances, credits, or other favourable tax treatment for R&D spending. Based on the OECD Science, Technology and Industry Scoreboard 2017, 25 out of 37 countries increased their government support for business research and development (R&D) expenditure as a percentage of their GDP from 2006 to 2015. R&D tax incentives made up almost 50% of the government support for business R&D in the OECD area in 2015, which was an increase from one-third in 2006. Additionally, in 2017, 30 OECD countries provided favourable tax treatment for business R&D expenditures, compared to 16 OECD countries in 2000 (OECD, 2017). It is clear that R&D tax incentives have become a major tool for promoting business R&D as governments worldwide increasingly rely on tax incentives to promote business R&D to encourage innovation. The values for indirect government support through R&D tax incentives (*indgovsup*) were calculated by taking the values for indirect government support through R&D tax incentives as a percentage of business enterprise R&D (BERD) for each country and multiplying by 2015 PPP constant prices. This approach allows to account for both the percentage allocation of R&D and adjustment for changes in purchasing power over time. Lastly, this study employs implied tax subsidies for the loss-making scenarios. This variable indicates the estimated value of tax subsidies received by each firm. This measure reflects the fiscal benefits provided by the government to support research, development, and innovation. Similarly to indirect government support through R&D tax incentives, the implied tax subsidy helps evaluate policy effectiveness. As seen above, government introduce R&D tax incentives as a policy tool to stimulate innovation. Firms that receive tax benefits for their R&D expenditures are more likely to allocate resources towards research and development projects. By including this variable in the analysis, we can assess how variations in R&D tax incentives on loss-making scenarios influence firms' decisions to invest in innovation, which can subsequently affect employment levels. For the variable *age* it was essential to obtain data regarding the mean age of the labour force for each country over the period 2007-2019. However, as this data was not readily accessible, I utilised the following approach to determine the average age of the labour force: First, I downloaded the employment rate by age group: people aged 15 to 24, aged 25 to 54, and aged 55 to 64.[3] For each group, I calculated the midpoint or average age. Then I multiplied the midpoint of each age group by the corresponding percentage of the employed population. However, since the percentage of the employed population is measured as a percentage in the same age group and not the overall working population, this required a further step. The results from the multiplication were summed together for each year. Finally, I divided this sum by the total percentage of the employed population, which is the sum of the percentages for all age groups. It's important to note that this is an estimation and assumes that the age distribution within each group is uniform, which is unlikely to be completely accurate. The real-world distribution might be skewed towards each group's younger or older end. However, in the absence of more detailed data, this method provides a rough estimate of the average age of the labour force in each country over the years 2007-2019.

All variables, except for age, have been lagged by one period for several reasons. The utilization of the one-period lagged approach addresses potential endogeneity concerns. By introducing time lags, we establish temporal precedence, affirming that innovation precedes employment changes. Firms often take time to adjust their employment decisions in response to changes in innovation. This approach acknowledges that the effects of innovation on employment might not be immediate and could take some time to materialise, as firms might take time to implement innovation advancements and adapt their workforce accordingly. Finally, it is worth noting that while this study made an effort to incorporate important factors that impact employment in the econometric models, these

[3]Refer to OECD (2023*a*) to access comprehensive information regarding the calculation methodology of these indicators.

models may still be subject to omitted variable bias as certain variables were not included due to lack of data availability and avoid making the models overly complex. This decision was made in order to maintain simplicity and avoid overwhelming complexity in the models.

5

Empirical Analysis

5.1 Data properties and descriptive statistics

Table A2 provides an overview of the descriptive statistics for the variables used in the econometrics models listed in Section 3. All macroeconomic variables listed are expressed in percentage terms. $tbrd\_l1$ is expressed in million US dollars constant prices with 2015 being taken as the reference year. $indgovsup\_l1$ is too expressed in real terms. Table A4 reports the results for the Pairwise correlation matrix for all variables used in the model. A strong positive correlation exists between the lagged value of total business enterprise R&D and patent counts. A strong correlation between business R&D spending and the number of patents in Europe could suggest that firms innovating within the national boundaries predominantly choose patents as a means to protect their inventions and intellectual property resulting from R&D efforts. However, while a strong correlation between R&D spending and patents may imply that R&D efforts contribute to the creation of patents, other factors and external influences could also play a role. In the following analysis, patents will be incorporated exclusively in Model 1 for the purpose of conducting a robustness check. Subsequent to this, due to the observed high degree of collinearity between patents and R&D expenditure, the variable representing patent counts will be excluded from further analyses. This decision is taken to mitigate the issues associated with multicollinearity, which could potentially distort the estimated coefficients and undermine the reliability of the model. Aside from the two innovation measures—patents and R&D

expenditure—the correlation analyses conducted among the various independent variables under consideration do not manifest any substantial concerns. Thus, the exclusion of patents is targeted to enhance the robustness and interpretability of the results while maintaining a focus on the primary research objectives.

5.2 Aggregate analysis

In the country-specific FE model, each country is assigned a specific fixed effect (dummy variable) to control for country-specific unobserved heterogeneity. This means that the model accounts for any country-specific factors that influence employment but are not directly observed in the data. Therefore, the coefficient reflects the average impact of lagged R&D investment on employment across all countries in the dataset. If this coefficient is positive (negative), it suggests that, on average, an increase in R&D investment from the previous period is associated with an increase (decrease) in employment levels across countries.

Table 1 reports the country-specific FE panel regression results for the three models. The first model incorporates both innovation measure - R&D and patents; the second model excludes patents from the regression due to high degree of collinearity witnessed in the correlation matrix whereas the third model will serve as robustness check to verify the reliability of patent count as a measure for innovation. The lagged variable for total business enterprise R&D ($tbrd\_l1$) emerges as strongly statistically significant with a positive coefficient in both models. This suggests that a one million dollar increase in business R&D investment in the previous period is associated with a .0001 increase in employment levels across countries, ceteris paribus. In other words, the positive sign might indicate that investments in R&D can spur job creation in the short run. The small coefficient of total business enterprise R&D ($tbrd\_l1$) suggests that, in this model, the impact of business R&D on job creation is relatively small. A similar positive relationship was observed in a state-level analysis conducted in the United States, as reported by Krousie (2018). In this study, a positive coefficient of 0.0001 was found, although it is important to note that the dependent variable in this analysis was unemployment,

Table 1: Country-specific Fixed Effect Regression Models

Variables	(1)	(2)	(3)
tbrd_l1	0.000136**	0.000121**	
	(0.000061)	(0.000050)	
tpf_l1	0.000881		-0.001729
	(0.001930)		(0.001592)
cpi_l1	-0.4339***	-0.4344***	-0.4244***
	(0.107)	(0.107)	(0.108)
gfcf_l1	0.03326	0.03368	0.03394
	(0.02225)	(0.02218)	(0.02251)
gdpg_l1	0.2655***	0.2633***	0.2678***
	(0.06964)	(0.06933)	(0.07035)
edupub_l1	-0.7928**	-0.7966**	-0.7475*
	(0.3375)	(0.3366)	(0.3394)
taxsl_l1	12.1005***	12.2585***	12.9889***
	(4.1044)	(4.0807)	(4.1091)
popg_l1	1.8137***	1.8469***	2.2737***
	(0.5925)	(0.5867)	(0.5569)
empprot_l1	-4.3342***	-4.3608***	-4.4771***
	(1.4780)	(1.4736)	(1.4530)
indgovsup_l1	-2.36e-06	-1.92e-06	-5.66e-09
	(3.78e-06)	(3.65e-06)	(2.31e-06)
age	0.1983	0.2227	0.4688
	(0.3691)	(0.3644)	(0.3290)
Constant	75.25***	74.80***	66.4***
	(16.00)	(15.94)	(14.68)
Observations	209	209	211
R-squared	0.904	0.903	0.899
Adj. R-squared	0.887	0.888	0.884
RMSE	2.086	2.081	2.111
F-test	55.54***	57.70***	56.14***

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
1: FE regression with tbrd_l1 and tpf_l1, 2: FE regression with tbrd_l1 only, 3: FE regression with tpf_l1 only.

rather than employment. However, this does not necessarily mean that R&D has a negligible role in job creation in general. The relationship between R&D and employment can be quite complex and could be indirect. The Neo-Schumpeterian view of innovation argues that R&D might lead to new products, services, or more efficient processes, which could boost a company's productivity and competitiveness (Malerba, 2004). This could potentially lead to increased revenues and, in turn, more employment opportunities over the longer term. Furthermore, the knowledge spillover theory suggests that R&D doesn't only benefit the firm or industry where it's conducted. Instead, knowledge and innovations can "spill over" to other firms or sectors, potentially leading to wider economic and employment gains (Griliches, 1992). However, the impact of patents filed in the previous period (tpf_l1) is not statistically significant, indicating that employment levels are not significantly influenced by increased patents in the previous period. These results are not surprising. Although not all R&D activities may directly translate into job creation, especially in the short term, business R&D better links the creation and development of innovative activities to employment. R&D conducted by businesses is often more market-oriented and focused on commercial viability. It is driven by the need to stay competitive, respond to customer demands, and seize market opportunities. As a result, innovations arising from business R&D are more likely to have practical applications and real-world impacts on employment. As a result of this increased demand, businesses may have to expand their production capacity, which can create jobs in manufacturing, research, development, and related support functions. Investing in R&D can give businesses a competitive edge. By innovating, they can stand out from competitors and gain more customers, potentially increasing market share. This may require expanding and hiring more employees to keep up with demand. Results seem to reinforce the idea that a higher number of patents does not inherently translate into job growth in the countries observed in the analysis. Some patents may be incremental improvements or extensions of existing technologies rather than breakthrough innovations. Companies often file defensive patents to protect their existing products or technologies from potential infringement claims by others. These patents may not represent active efforts to create new innovations but are taken as precautionary measures. Similarly, many innovations do not rely on patents for protection or may be kept as trade secrets. Therefore, not all innovations are captured in patent databases. Overall results from the other independent variables do not seem to vary greatly across the three models. Regarding economic indicators, lagged inflation captured by the consumer price index (cpi_l1) shows a statistically significant negative effect on employment. Contrary to what economic theory suggests, higher inflation in the previous period is associated with lower employment levels within individual countries when controlling for country-specific factors. Similar studies encountered a common problem when conducting identify-specific FE regression, suggesting that when inflation is repeated across all identities, it may not accurately reflect the true effect (See Shah et al., 2022). Conversely, GDP growth exhibits a positive and strong statistically significant relationship with workers' demand. Interestingly, lagged gross fixed capital formation displays a positive coefficient, albeit insignificant. Lastly, an increase in population leads to a higher demand for labour. Examining the policy intervention variables results in some interesting findings. The coefficient for $edupub\_l1$ is negative and statistically significant considering country-specific fixed effects. The coefficient for $taxsl\_l1$ is positive and statistically significant at the highest significance level, suggesting that increases in the implied tax rate variable would, on average, correspond to increases in employment, holding other factors constant. The logic could be that these subsidies enhance companies' post-tax profitability by reducing the marginal cost of supply. This would enable them to invest more in their operations, potentially leading to increased hiring. On the other hand, employment protection ($empprot\_l1$) shows a negative relationship with employment. This relationship may appear counterintuitive. However, from an economic perspective, these protection measures can also create disincentives for employers to hire new workers. While employment protection measures aim to safeguard workers' job security, it is important to consider the potential unintended consequences. In some cases, strict regulations may create a climate of caution among employers, who may be hesitant to hire due to concerns about the potential costs and challenges associated with terminating employees' contracts if necessary. Furthermore, the uncertainty arising from the potential inability to adjust workforce size according to future economic changes could lead employers to hold back on hiring. Reduced labour market flexibility can act as a hiring deterrent if stringent legislation makes workforce adjustments difficult. As a result, there may be a short-term reduction in employment opportunities. Lastly, the coefficients for lagged indirect government support and the average age of the labour force are negative but not statistically significant. In the final stage of the analysis, a model was constructed to conduct robustness checks on the hypothesised positive relationship between technological innovation and employment. This step was undertaken to ensure the validity and reliability of the findings, by testing and confirming the observed positive impact of technological innovation on employment levels. Such a model introduces business R&D expenditure as a share of GDP. This metric standardizes R&D expenditures relative to the size of the economy. To quantify the relative significance of business Research and Development (R&D) expenditures within the context of the overall economy, we define the share of business R&D in real terms relative to the Gross Domestic Product (GDP), also expressed in real terms. Data for the GDP in constant price terms were obtained by the World Bank database. To obtain the Share of business R&D, the following steps were taken: The dataset provided by the World Bank represents the Real Gross Domestic Product (GDP) of a given country and is measured in constant US price terms with 2015 taken as the reference year. To standardise this measure, I converted the Real GDP into millions of US dollars by simply dividing the resultant figure by one million. Then I divided data for business R&D by GDP expressed in US million. Lastly, I multiplied the share of business R&D by 100, thereby translating the fraction into a percentage format that allows for straightforward interpretation and comparison. Formally, let *R&D* represent the business R&D expenditure, measured in constant price terms (US million), and let *GDP* represent the real GDP, both expressed in the same monetary units. The formula to calculate the share of business R&D in real terms relative to GDP is represented as follows:

$$\text{Share of Business Enterprise R\&D} = \left(\frac{R\&D}{GDP}\right) \times 100$$

This yields Share of Business Enterprise R&D as a percentage, representing the proportion of GDP, that is accounted for by business R&D expenditures.

The coefficient associated with the lagged variable "sharerd_l1" is estimated at 2.819934, which is statistically significant at the 1% level. This result implies that a 1% increase in the share of R&D expenditures, lagged by one period, is associated with an average increase in employment by 2.819934. However, the magnitude of the standard error suggests that there is a notable degree of variability associated with this estimate, which

Table 2: Fixed Effects Model Regression -Share of business R&D

Variables	Coefficient
sharerd_l1	2.819934***
	(0.6754845)
cpi_l1	-0.3506738***
	(0.1058548)
gfcf_l1	0.0155919
	(0.0218823)
gdpg_l1	0.2596304***
	(0.067096)
edupub_l1	-0.928244**
	(0.3286728)
taxsl_l1	6.585003
	(4.177724)
popg_l1	2.230387***
	(0.5333995)
empprot_l1	-4.921221***
	(1.438234)
indgovsup_l1	0.00000105
	(0.00000327)
age	-0.1716782
	(0.3692358)
Constant	87.16184***
	(15.64745)
Observations	209
R-squared	0.909
Adjusted R-squared	0.894
F-test	61.72***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

necessitates a cautious interpretation of the result. Particularly, in situations where a coefficient of a regression model is excessively large, and the standard errors are notably high, it might be prudent to standardise the predictor variable. First and foremost, standardization, which involves rescaling the variables to have a mean of zero and a standard deviation of one, enhances the interpretability of the model. The coefficients are not directly comparable when predictor variables are measured on different scales. Standardizing the predictors facilitates a direct comparison since each coefficient then represents the change in the dependent variable per one standard deviation change in the predictor. Formally, let X be the original variable, Z be the standardized variable (or z-score), μ_X be the mean of X, and σ_X be the standard deviation of X. The formula to standardize variable

X is given as:

$$Z = \frac{X - \mu_X}{\sigma_X}$$

The standardized variable Z will have a mean of 0 and a standard deviation of 1. In the case of a regression model with dependent variable Y and a predictor X, and the original coefficient of X in the model is β, the standardised coefficient β_S can be computed as follows:

$$\beta_S = \beta \cdot \frac{\sigma_X}{\sigma_Y}$$

Where β_S is the standardized coefficient; β is the original coefficient of the variable X; σ_X is the standard deviation of the predictor variable X; σ_Y is the standard deviation of the dependent variable Y. The standardized coefficient β indicates the change in the dependent variable Y (in terms of its standard deviations) that is associated with a one standard deviation change in the predictor variable X. In this specific case, for the variable *sharebrd_l*1 with an original coefficient of 2.819934 and $\sigma_Y = 6.116009$ (the standard deviation of *emp*), the formula becomes:

$$\beta_{\text{sharebrd\_l1}} = 2.819934 \cdot \frac{1}{6.116009}$$

This is equivalent to:

$$\beta_{\text{sharebrd\_l1}} = \frac{2.819934}{6.116009}$$

Which yields:

$$\beta_{sharebrdl1} \approx 0.461$$

Therefore, for a one standard deviation increase in *sharebrd_l*1, employment is predicted to increase by approximately 0.461 standard deviations. This model supports the evidence from the previous models that a positive association exists between in innovation and growth in employment. To summarise, evidence was found to substantiate the positive relationship between business (R&D) expenditures and job growth at the aggregate level. The findings reveal that increased investments in R&D activities lead to a subsequent expansion in employment levels in Europe. In the following subsection, this study attempts to investigate whether these results differ across different income levels.

5.3 Impact of innovation on employment by GDP per capita

The model explored in Section 5.2 is extended to explore whether the impact of innovation on employment exhibits variation across different income levels. To this end, I have categorized the studied countries into three distinct groups founded on their Gross Domestic Product (GDP) per capita (PPP current prices). These categories – lower-middle, higher-middle, and high GDP per capita – offer a stratified perspective on the economies, facilitating an examination of the differential impacts of innovation on employment in economies that vary in their levels of income per inhabitant. The three regressions show a positive relationship between total business R&D and employment for upper- and lower-middle GDP per capita countries. The relationship is statistically significant and stronger for these two categories compared to high GDP per capita countries. These results suggest that employment growth is prevalent in the lower and higher middle-income bracket and that investment in R&D has been found to lead to more rapid growth in labour in lower-income countries as compared to their higher-income counterparts.

This phenomenon can be attributed to several factors. First, the catch-up effect allows these countries to benefit quickly from technological advancements, bridging the existing knowledge and technology gaps (Verspagen, 1991). The generally lower starting point in technological development means that even modest investments can lead to significant relative improvements. Additionally, the structure of the economy in these nations often emphasizes labour-intensive industries and government policies may be aligned to support R&D as part of broader developmental strategies. In light of the specific industry profiles of these countries, innovation plays a decisive role in influencing the rapid growth in labour demand, particularly within the manufacturing sector. Research by Piatkowski (2013) highlights that innovation in Polish manufacturing, especially in automotive and machinery, has been a central factor in driving both productivity and employment growth. Similarly, Slovakia, one of the world's largest per capita car producers, has seen its automotive industry flourish due to a constant infusion of new technologies, which according to Pavlínek (2015), not only increased production efficiency but also led to an expansion in employment. According to Inzelt (2004), a primary objective for Hungary has been to

Table 3: Fixed Effects Model Segmented by GDP per Capita

Variables	(1)	(2)	(3)
tbrd_l1	−.0000182	.0001359***	.0011796***
	(.0001965)	(.0000148)	(.000252)
cpi_l1	.1116313	−.3617389***	−.490829***
	(.1468194)	(.1090923)	(.1304491)
gfcf_l1	−.0033836	−.0409216	.0115117
	(.0165728)	(.0667188)	(.0386104)
gdpg_l1	.080759	.2160919	.4309842***
	(.0527119)	(.1276394)	(.1246139)
edupub_l1	−.7532089**	.0142762	−.6651103
	(.3208672)	(.494639)	(.5315567)
taxsl_l1	30.66269**	−10.81377	4.196675
	(12.54472)	(8.871284)	(4.463797)
popg_l1	2.214749**	−.0196815	6.266213***
	(.9012227)	(.2329719)	(1.078309)
empprot_l1	18.07844**	.8781908	−4.197858**
	(6.294263)	(1.781192)	(1.888768)
indgovsup_l1	$6.28e-07$	$9.76e-06$***	−.0000889**
	(.0000165)	($1.71e-06$)	(.0000434)
age	−.4333861	−.5559877**	1.985295**
	(.4714337)	(.2180567)	(.6772264)
Constant	44.05194	83.42646***	−5.039057
	(23.9569)	(12.08598)	(32.28671)
Observations	63	41	95
R-squared	0.961	0.997	0.879
Adj R-squared	0.9488	0.996	0.850
F-test	77.55***	711.34***	30.55***

*** p<0.01, ** p<0.05, * p<0.1
1: High-income countries, 2: Higher-middle countries, 3: Lower-middle countries.

ignite corporate interest in R&D activities. The country has aimed to facilitate the transfer of technology, foster the growth of small and medium-sized enterprises (SMEs) that are dedicated to new technologies, maintain and enhance R&D capabilities, and incentivize participation in international networks. Lastly, the ICT sector in Estonia is characterized by rapid innovation and is a key driver for employment, especially for skilled workers. According to a report redacted by the European Commission (2023), Estonia excels in terms of the proportion of Information and Communication Technologies (ICT) specialists in its workforce and boasts the leading percentage of ICT graduates (8.4%) among European Union member states in the EU. This reflects a broader trend wherein countries with significant ICT and software services sectors, like Estonia and Latvia, are seeing labour market transformations driven by innovation in these fields. Countries in the higher-middle bracket exhibited a smaller yet positive and statistically significant growth trajectory. These two groups share some similarities in terms of leading industries. For instance, in Germany, Italy, and France, key sectors such as automotive manufacturing, pharmaceuticals, machinery and equipment, and information technology services form a substantial part of the economies. These industries are characterized by high innovation, often driven by substantial investments in R&D. Therefore, companies operating in these industries tend to invest heavily in R&D, thus fostering innovation that can lead to the creation of new products or processes and, consequently, the need for additional skilled labour (Berger and Frey, 2016; Lucchese and Pianta, 2012). Therefore, in these countries, innovation is a driver of competitiveness and a significant factor in labour market dynamics, creating demand for a skilled and adaptable workforce to complement and implement new technologies. In the analysis of high-income European countries, including Austria, Sweden, Ireland, Norway, Luxembourg, and the Netherlands, it is observed that the countries included in the high GDP per capita income group display a negative and not statistically significant coefficient. In the high GDP and lower-middle-GDP countries, lagged inflation is negatively correlated with employment and is statistically significant. Lagged Gross Fixed Capital Formation ($gfcf\_l1$) does not significantly affect employment in any country category. Lagged GDP growth, $gdpg\_l1$, exhibits a positive and statistically significant effect on employment in lower-middle GDP per capita countries. However, this positive and significant relationship is not observed in high-GDP and upper-middle-GDP per capita countries. In these latter groups, the coefficient for lagged GDP growth fails to reach statistical significance. Public Education Expenditure ($edupub\_l1$): In high-GDP and lower-middle-GDP countries, public education expenditure negatively correlates with employment but is only statistically significant for the high GDP category. In upper-middle GDP countries, the correlation is positive but not statistically significant. Lagged implied tax subsidy on a loss-making scenario ($taxsl\_l1$) impact on employment is positive and statistically significant for high-GDP countries. Lagged population growth positively affects employment in high-GDP and lower-middle-GDP countries, and this effect is statistically significant. However, in upper-middle GDP countries, the effect is negative and not statistically significant. Employment Protection has a positive and statistically significant impact on employment in high-GDP countries and a negative and statistically significant impact in lower-middle GDP countries. In upper-middle GDP countries, the effect is positive but not statistically significant. The impact of lagged indirect government support through R&D on employment is positive in high-GDP, negative in lower-middle GDP countries, and positive in upper-middle GDP countries. However, the effect is only statistically significant in higher-middle and lower-middle GDP countries.

5.4 Non-Linear Fixed Effects Model

The non-linear FE regression analysis presented reveals several interesting findings. Firstly, the coefficient for $tbrd\_l1$ is positive and statistically significant at the 1% confidence level. This indicates that the initial increase in business R&D spending is positively associated with employment. This result is consistent with the findings in Model 1 and reflects the initial increase in employment driven by R&D spending efforts.

Table 4: Non-Linear Fixed Effects Model Regression

Variables	Model 3
tbrd_l1	0.0010463***
	(0.000173)
tbrd_l1sq	-6.23e-09***
	(1.13e-09)
cpi_l1	-0.3536089**
	(0.1006283)
gfcf_l1	0.0362911
	(0.0205741)
gdpg_l1	0.2145946**
	(0.0648342)
edupub_l1	-0.8986733**
	(0.3129108)
taxsl_l1	9.565791*
	(3.8864)
popg_l1	1.685006***
	(.5499649)
empprot_l1	-5.909018***
	(1.480291)
indgovsup_l1	-0.0000188***
	(4.52e-06)
age	-21.08424***
	(8.015086)
agesq	0.2434701**
	(.095836)
Constant	533.1854**
	(165.8938)
Observations	209
R-squared	0.9182
Adjusted R-squared	0.9039
F-test	64.12***

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The coefficient for $tbrd\_l1sq$ is negative and significant at the 1% confidence level.

This negative coefficient indicates a diminishing return of R&D spending on employment. In other words, as firms increase their R&D spending, they may reach a saturation point where additional investments yield progressively smaller returns regarding innovation, productivity, and employment. Essentially, the most valuable gains are realized early on, indicating that while initial investments in R&D might stimulate employment, subsequent investments yield less value incrementally, and the additional impact on employment becomes smaller and eventually even negative. The positive sign for business R&D shows the initial benefit of R&D on employment, but the negative quadratic term illustrates how this benefit decreases as spending continues to rise. This reflects the complex relationship where R&D drives employment and innovation initially, but as the competitive landscape changes and the market becomes saturated with similar innovations, the return on investment for R&D (and consequently employment in R&D roles) diminishes. In the forthcoming analysis, a primary focus will be dedicated to calculating the inflection point of the examined curve. More formally, the inflection point in an inverted U-shaped relationship represents the point where the function changes concavity, or in other words, where a trend or pattern changes direction. For an inverted U-shape, this is the peak of the curve. For a quadratic function of the form:

$$y = ax^2 + bx + c$$

Where y is employment and x is the quadratic term for business R&D, and the coefficient a is negative (indicating the inverted U-shape), the inflection point can be found using the following formula:

$$x = -\frac{b}{2a}$$

Thus, the inflection point for the relationship between 'emp' and '$tbrd\_l1$' is approximately USD $81,137.89$ million. Given the negative coefficient of '$tbrd\_l1sq$', this point represents the peak of the inverted U-shaped curve. Beyond this point, increases in business R&D will lead to decreases in employment; before this point, increases in business

R&D‘ will lead to increases in employment. These results provide compelling evidence for a pattern where initial increases in business R&D have a job-creating effect, but further increases result in diminishing returns. The nonlinear relationship between total business R&D ($tbrd\_l1$) and employment, as indicated by the squared term ($tbrd\_l1sq$), aligns with existing literature and might be explained through several underlying economic phenomena. This view is consistent with the broader literature on innovation economics and aligns with the understanding that technological advancements in competitive markets often follow a path of initial rapid gains followed by a dampening effect. The research regarding returns on R&D is fundamentally rooted in the Schumpeterian theory, which posits that larger enterprises enjoy significant benefits in conducting R&D. This advantage can be attributed to the economies of scale, enabling larger entities to capitalize more effectively on the returns from R&D compared to smaller sized firms (Cohen and Levin, 1989; Cohen et al., 1987). However, the theory emphasises that for firms competing in a ”Schumpetarian” industry - that is, a market comprised of many competitors - an increase in competitive pressure may initially increase R&D efforts but can lead to a dampening effect on a firm's investment in R&D overtime. This is primarily due to the expectation that increased rivalry in innovation will result in more competition in the post-innovation market. This added competition from similar innovations is likely to reduce the marginal value of a company's R&D investment, thus lessening the firm's incentive to invest in research and development (Scott, 2009). The dampening effect on R&D investment might also affect employment. If firms perceive that additional investment in R&D brings diminishing returns, they may slow down or reduce their R&D efforts, decreasing worker demand. Autor et al. (1998) found that firms with higher R&D intensity tend to exhibit more sluggish growth in their labour force. Conversely, a study conducted by Amoroso (2015) delineates that firms with a higher focus on knowledge-intensive activities experience non-diminishing returns to labour, contrary to less knowledge-intensive firms where diminishing returns are observed. In this context, smaller firms generally encounter diminishing returns, whereas larger organizations tend to experience non-diminishing or even increasing returns to labour. Nevertheless, in the presented statistical analysis, the coefficients for variables age_l1 and age_l1sq illustrate the complex relationship between age and employment. The anticipated signs of the two coefficients age_l1 and age_l1sq, as posited by Shah et al. (2022), were not corroborated by the observed data as this regression analysis did not observe the anticipated inverted U-shaped relationship.

6

Limitation of the Study

The macroeconomic approach used in this study allows for a more holistic view of the impact of innovation on employment because it includes all the indirect effects through which innovation affects employment. However, while this approach is the most comprehensive, it suffers from a few drawbacks. Constructing a model that fully captures the overall effect of innovation on employment is complex due to several reasons. As indicated by Piva and Vivarelli (2017), determining a suitable proxy for measuring innovation on a national scale is a complex endeavour due to the multi-faceted nature of innovation. It's worth bearing in mind that relying solely on input indicators such as R&D expenditure and output indicators such as patent counts as indicators of technological progress can leave out important information that can't be easily quantified. For instance, these metrics may not reflect advancements in non-formalised research, tacit knowledge, design, and engineering (Feldmann, 2013; Antonucci and Pianta, 2002). Capturing the diverse aspects of innovation and their impact on employment requires a comprehensive understanding of these factors and their interplay. Secondly, the proxies of innovation used in this study – total business enterprise R&D expenditure and triadic patent family – measured at the aggregate level do not distinguish between product and process innovation. Another important shortcoming is associated with the dependent variable itself: employment. Employment is characterised by complex socio-economic dynamics and is influenced by a multitude of factors. Even the relationship between innovation and employment is influenced by a range of socio-economic factors, including government policies, education and skills, and social dynamics. These factors interact with innovation in complex ways, making it challenging to isolate the specific impact of innovation on employment. Measuring the relationship between innovation and employment at the aggregate level can be complex due to differences in sectors, countries, and regions within nations. For instance, innovation is likely not evenly distributed throughout a country but rather concentrated in more industrialized areas. While innovation can lead to job creation in some industries and regions, it can also result in job displacement or automation in others. The net effects of innovation on employment can differ based on regional factors, such as industrial characteristics, labour skill levels, institutional frameworks, type of innovation, labour market conditions, and socio-economic factors. Accounting for this heterogeneity adds complexity to constructing a comprehensive model.

Moreover, there is often a time lag between the introduction of new innovations and their impact on employment. The effects of technological progress on employment can unfold over an extended period, and the outcomes may not be immediate or easily predictable. Additionally, it is uncertain whether higher R&D spending or patent activity effectively translates into introducing and adopting new technology. The uncertainty surrounding the diffusion and adoption of innovations further complicates the construction of a predictive model. Given these complexities, constructing a model that captures the overall effect of innovation on employment requires a deep understanding of the specific contexts in which innovation occurs. It is an ongoing research and policy analysis area that continues to evolve as our understanding of innovation and employment dynamics improves. Lastly, this study focuses solely on high-income countries. While it enables a more targeted exploration of the technological unemployment issue in Europe, it inherently constrains the generalisability of the findings to broader global contexts. The exclusion of middle and low-income countries may overlook significant interactions and dependencies within the global economic system and could inadvertently introduce biases that neglect the diverse challenges faced by countries outside the high-income bracket. For instance, barriers related to infrastructure, education, and access to technology may alter the dynamics of how innovation affects employment in these contexts. By taking into account these unique factors, scholars can develop a more nuanced understanding of the interplay between innovation and employment. Such an approach not only contributes to the academic literature but also has the potential to inform more effective and context-sensitive policies, fostering sustainable development and inclusive growth in regions that may otherwise be left behind in global technological advancement.

7

Conclusion

In light of the investigation conducted in this paper, which focuses on the relationship between technological change and employment in Europe over the period 2007-2019, these findings contribute valuable insights into an enduring concern. Notably, the evidence from this study suggests the presence of a productivity effect, where technological innovation is associated with employment growth in the short term. Contrary to the displacement effect observed in previous studies, this analysis indicates a different dynamic in Europe. The results from our data depict that, within the European labour market, technological advances have, on average, led to labour creation rather than destruction. While these findings for the period from 2007 to 2019 show a positive relationship between technological innovation and employment growth, it is imperative to approach these results with caution. This study acknowledges its limitations and the possibility that as technological advancements, policy framework, and market conditions continue to evolve, the relationship between technological innovation and employment may also change. Therefore, although this study does not support the displacement of labour by technology, I posit that this relationship could potentially shift in the future. In anticipation of these future changes, policymakers, educators, and industry leaders across Europe should consider the potential for future shifts in this relationship and begin preparing the workforce accordingly. This might include investments in education and training programs that equip workers with the skills necessary to adapt to an increasingly automated and AI-driven landscape, or policies that encourage the development and adoption of technologies that augment, rather than replace, human capabilities. In conclusion, our study offers a comprehensive perspective on the complex relationship between technological innovation and employment in Europe, highlighting the positive employment growth associated with technological innovation in the period from 2007 to 2019. However, as technology continues to advance at an unprecedented rate, it is essential for policymakers to prepare for a range of possible future scenarios in the labour market.

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Appendix A

Table 1: List of Variables

Variable Type	Variable Name with Unit	Acronym
Dependent	Employment	emp
Independent	Total business enterprise R&D	*tbrd*
	Triadic patent family	*tpf*
	CPI	*cpi*
	GFCF	*gfcf*
	GDP growth	*gdpg*
	Government spending on education, total	*edupub*
	Implied tax subsidy rates on R&D expenditure (Loss-making)	*taxsl*
	Population growth	*popg*
	Employment protection	*empprot*
	Indirect government support through R&D tax incentives	*indgovsup*
	Average age of the population	*age*

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
emp	260	67.565	6.116009	54.825	79.7
tbrd_l1	229	10911.15	17255.43	55.724	98037.3
tpf_l1	240	653.8626	1186.845	.6667	5809.557
cpi_l1	240	1.867588	1.941373	-4.478103	15.40232
gfcf_l1	240	1.647244	10.07892	-37.19627	50.50742
gdpg_l1	240	1.66313	3.544436	-14.62906	24.37045
edupub_l1	234	5.232612	1.11613	3.39287	8.55955
taxsl_l1	240	.1135417	.1189791	-.03	.43
popg_l1	240	.3820167	.7268292	-2.081305	2.89096
empprot_l1	216	2.531696	.4522812	1.603741	3.559524
indgovsup_l1	231	71955.67	161113	0	805674.9
age	260	41.44099	1.482494	37.42934	44.58781

Table 3: Correlation Matrix

	emp	**tbrd_l1**	**tpf_l1**	**cpi_l1**	**gfcf_l1**	**gdpg_l1**	**edupub_l1**	**taxsl_l1**	**popg_l1**	**empprot_l1**	**indgovsup_l1**	**age**
emp	1.0000											
tbrd_l1	0.2051	1.0000										
tpf_l1	0.2313	0.9486	1.0000									
cpi_l1	-0.1207	-0.1066	-0.0968	1.0000								
gfcf_l1	0.2163	0.0067	-0.0139	0.0626	1.0000							
gdpg_l1	0.2087	-0.0421	-0.0682	-0.0048	0.7469	1.0000						
edupub_l1	0.4633	-0.0248	-0.0063	-0.0548	-0.1001	-0.1830	1.0000					
taxsl_l1	-0.1178	-0.0887	-0.1095	-0.1443	-0.0004	0.0031	-0.0638	1.0000				
popg_l1	0.2430	0.0248	-0.0154	-0.1149	0.0276	0.0594	0.1368	-0.0443	1.0000			
empprot_l1	-0.1346	0.0811	0.1311	-0.0264	-0.1392	-0.1279	-0.2781	0.0310	-0.1462	1.0000		
indgovsup_l1	-0.0230	0.3885	0.3542	-0.0919	0.0130	-0.0329	0.0039	0.4189	0.0632	0.0089	1.0000	
age	-0.3905	-0.0779	-0.1500	-0.0500	0.0040	-0.0020	-0.2757	0.0956	-0.2549	0.0901	-0.0545	1.0000

Appendix B

```
encode country, gen(country_code)
xtset country_code year
drop country
gen tbrd_l1 = l1.tbrd
gen tpf_l1 = l1.tpf
gen cpi_l1= l1.cpi
gen gfcf_l1 = l1.gfcf
gen gdpg_l1 = l1.gdpg
gen edupub_l1 = l1.edupub
gen taxsp_l1 = l1.taxsp
gen taxsl_l1 = l1.taxsl
gen popg_l1 = l1.popg
gen empprot_l1 = l1.empprot
gen indgovsup_l1 = l1.indgovsup

#Descriptive stats
sum emp tbrd_l1 tpf_l1 cpi_l1 gfcf_l1 gdpg_l1 edupub_l1
   taxsl_l1 popg_l1 empprot_l1 indgovsup_l1 age

#correlation matrix
pwcorr emp tbrd_l1 tpf_l1 cpi_l1 gfcf_l1 gdpg_l1 edupub_l1
   taxsl_l1 popg_l1 empprot_l1 indgovsup_l1 age
```

```
#model 1
reg emp  tbrd_l1 tpf_l1 cpi_l1 gfcf_l1 gdpg_l1 edupub_l1
   taxsl_l1 popg_l1 empprot_l1 indgovsup_l1 age i.country
reg emp  tbrd_l1 cpi_l1 gfcf_l1 gdpg_l1 edupub_l1  taxsl_l1
   popg_l1 empprot_l1 indgovsup_l1 age i.country
reg emp  tpf_l1 cpi_l1 gfcf_l1 gdpg_l1 edupub_l1  taxsl_l1
   popg_l1 empprot_l1 indgovsup_l1 age i.country
gen sharebrd_l1 = l1.sharebrd
reg emp  sharebrd_l1 cpi_l1 gfcf_l1 gdpg_l1 edupub_l1
   taxsl_l1 popg_l1 empprot_l1 indgovsup_l1 age i.country

#model 2
reg emp tbrd_l1 cpi_l1 gfcf_l1 gdpg_l1 edupub_l1 taxsl_l1
   popg_l1 empprot_l1 indgovsup_l1 age i.country

#model 3
gen tbrd_l1sq = tbrd_l1^2
gen agesq = age^2
reg emp  tbrd_l1 tbrd_l1sq cpi_l1 gfcf_l1 gdpg_l1 edupub_l1
   taxsl_l1 popg_l1 empprot_l1 indgovsup_l1 age agesq i.
   country
```