Czech University of Life Sciences Prague

Faculty of Economics and Management

Department of Economics

Fostering a Knowledge-Based Economy: Key Drivers for Growth

Tatia Zarkua

Supervisors: Prof.dr. Wim Heijman
Doc. ing. Irena Benešová, Ph.D

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Fostering a Knowledge-Based Economy: Key Drivers for Growth

Abstract

This study examines the critical role of knowledge-based economy (KBE) development in driving sustainable economic growth and competitive advantage in the global economy. It underscores the dynamic interplay between entrepreneurship, innovation, research and development (R&D) investment, regional development strategies, government funding, and agricultural innovation as key factors in this transformative economic paradigm.

The analysis begins by exploring the impact of entrepreneurship, revealing a significant positive relationship between the Global Entrepreneurship Index (GEI) and GDP per capita, indicating that countries with higher GEI experience greater economic development. A regional analysis of KBE in the EU-28 NUTS 2 regions is then presented, showing that regional GDP per capita is strongly associated with KBE development.

The study continues by examining the impact of R&D investment, demonstrating that government funding is crucial in stimulating the private sector. It also delves into the relationship between government funding and economic outcomes, illustrating that funding for R&D positively affects private R&D expenditure. Finally, agricultural innovation is analysed through the lens of R&D expenditure, which significantly influences total crop output.

These findings provide valuable insights for policymakers, offering a roadmap for fostering long-term economic development. By strategically investing in entrepreneurship, R&D, and innovation, especially at the regional level, governments can drive sustainable development and improve competitiveness in an increasingly knowledge-driven global economy.

Keywords: *knowledge-based economy, entrepreneurship, innovation, R&D investments, NUTS 2 regions, government funding, agricultural innovation*

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1. Introduction

This study explores several critical aspects of knowledge-based economic (KBE) development and its role in fostering sustainable economic growth and enhancing competitive advantage in the global economy. As modern economies increasingly depend on knowledge and innovation, understanding how these factors interweave with entrepreneurship, research and development (R&D), regional development strategies, government funding, and agricultural innovation becomes essential for shaping long-term economic success.

Entrepreneurship emerges as a pivotal catalyst for economic dynamism in the fast-evolving global economy. Countries encouraging entrepreneurial activity have experienced greater economic growth, as evidenced by the positive relationship between the Global Entrepreneurship Index (GEI) and GDP per capita. Beyond entrepreneurship, R&D investment and government funding are vital in stimulating technological advancement, particularly in sectors like agriculture, where innovation directly impacts productivity.

Regional development strategies have become increasingly focused on promoting KBE at a more localised level. By analysing EU-28 NUTS 2 regions, this study reveals how investments in knowledge-intensive sectors contribute significantly to regional GDP per capita (Windrum & Tomlinson, 1999).

The agricultural sector, a cornerstone for many economies, particularly in developing regions, is also transforming innovation. R&D expenditure in agriculture has been shown to positively impact crop productivity, highlighting the necessity for continuous innovation to address global challenges like food security and climate change.

This dissertation examines the intricate relationships between these key components and their implications for policymakers. The study is structured as follows: First, the role of entrepreneurship in promoting economic growth is explored, followed by an in-depth regional analysis of KBE development within the EU-28 NUTS 2 regions. Next, the impact of R&D investment and government funding on private-sector innovation is analyzed. Lastly, the effects of agricultural innovation on productivity are examined, offering a comprehensive understanding of how these factors collectively contribute to long-term economic growth (Gildemacher & Wongtschowski, 2015). A brief outline of the dissertation is provided below.

In Chapter 2, the conceptual framework is presented, laying the theoretical foundation for the study. This framework serves as the lens through which the key components of KBE are examined, delving into the intricate relationships between selected elements and their collective impact on economic performance.

Chapter 3 follows with a detailed literature review, highlighting the key academic debates and empirical findings that have shaped the current understanding of KBE. By examining previous studies on entrepreneurship, R&D, and agricultural innovation, this research is positioned within the broader academic discourse, identifying gaps that this dissertation seeks to address.

Chapter 4 introduces the methodology and data selection used to conduct the analysis. The chosen methods and dataset are crucial for ensuring the rigor and reliability of the findings. Quantitative techniques are employed to capture the multifaceted nature of KBE development and its effects on economic performance.

Chapter 5 presents the results and discussion, offering a thorough data analysis. The analysis demonstrates how entrepreneurship, R&D investment, and agricultural innovation contribute to economic growth, both individually and in combination. A nuanced understanding of the relative importance of these factors is provided, with particular attention to the role of government funding in shaping outcomes.

Finally, in Chapter 6, the dissertation concludes by summarizing the key findings and exploring the implications for policymakers and business leaders. The need for strategic investments in KBE factors to ensure sustained economic growth is emphasized, particularly in regions seeking to enhance global competitiveness.

By offering a comprehensive analysis across multiple levels national, regional, and sectoral this dissertation provides valuable insights for scholars, policymakers, and industry leaders seeking to foster sustainable economic development through knowledge and innovation. The knowledge-based economy is not just an academic concept; it is the future of global economic prosperity, and this study aims to chart the path forward.

2. Conceptual Framework

2.1. Background and Context

In the contemporary global economy, the development of a knowledge-based economy (KBE) has emerged as a pivotal driver of sustainable economic growth and competitive advantage. The increasing importance of knowledge as a catalyst for entrepreneurship, innovation, competitiveness, and societal well-being within KBEs is well-documented (Lackéus, 2015; Milán-García et al., 2019; Apostu et al., 2022). This transformative economic paradigm hinges on the intricate interplay between entrepreneurship, innovation, research and development (R&D) investment, regional development strategies, and government funding, all of which rely on a well-educated and knowledgeable population.

Knowledge, often described as one of the most potent forces for social change, equips individuals with the skills necessary to access better job opportunities and improve their quality of life.

Understanding its significance in economic development requires a comprehensive grasp of the concept itself a process where a country's historically low living standards gradually improve, leading to enhanced economic and social circumstances for its population. In this context, knowledge acts as a powerful catalyst for such improvements.

Entrepreneurship, a vital component of KBEs, catalyses innovation, fostering new technologies and business models that propel economies forward (Acs, 2010; Sardana, 2016). Concurrently, robust R&D investment is essential for sustaining steady innovations and technological advancements. Initiatives for regional development play a crucial role in distributing the benefits of economic development equally, thereby enhancing social cohesion and reducing regional disparities. Government funding, both direct and indirect, provides the financial support and policy framework necessary to nurture these elements, creating an enabling environment for sustained economic development.Hypothesis development and Research Questions

2.2. Hypothesis development and Research Questions

2.2.1. The Impact of Entrepreneurship on Economic Growth in Knowledge-Based Economies [1]

This study seeks to unravel the relationships among these factors, underscoring their collective importance in fostering a resilient and dynamic KBE (Premand et al., 2016).

Despite the transformative potential of KBEs, significant challenges persist. Many urban and rural areas, in both developed and developing countries, continue to face insufficient knowledge infrastructure and services (Barrett et al., 2019). Additionally, there is a substantial shortage of technical and soft skills across various industries. The expansion of a skilled workforce is essential for boosting productivity, innovation, and technological progress.

Historically, the prioritisation of knowledge has not been confined to developed countries but has also been evident in developing nations (Grisay & Mählck, 1991). Expanding knowledge opportunities leads to a more skilled and knowledgeable society, which in turn applies its expertise in the marketplace (Sagiyeva et al., 2018). Numerous studies have consistently shown that education significantly impacts overall economic development (Hanushek & Woessmann, 2007; Curs & Singell, 2010; Brewer & McEwan, 2010).

Countries that foster an environment conducive to entrepreneurship and provide adequate resources for developing innovative new products and services are better positioned to achieve economic growth. Empirical evidence suggests that entrepreneurship leads to more equitable wealth distribution and a reduction in social issues (Mamede & Davidsson, 2004). This topic primarily concerns the diffusion of new technologies and the stimulation of economic activity.

Entrepreneurship not only promotes dynamic equality in the economy but also drives competition among various economic and industrial sectors (Korez-Vide & Tominc, 2016). It has the potential to revolutionise national and regional economies by generating new markets, adapting to and innovating within existing industries, raising overall productivity, and creating employment opportunities. The economic benefits of entrepreneurship extend beyond

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individual entrepreneurs and investors (Baumol & Strom, 2007; Kim et al., 2022). In today's startup economy, creativity and adaptability matter more than control, making small, innovative firms crucial in seizing market opportunities created by rapid technological advancements.

As previously discussed, entrepreneurship has enhanced productivity and economic development, providing a foundation for wealth creation and global development. Conversely, the KBE is based on developing, distributing, and implementing knowledge to drive organisational policies, international enterprises, and economic growth (Benoît, 2006). Knowledge has long been recognised as a source of efficient manufacturing processes and a driving force behind scientific and innovative advancements.

An extensive body of economic literature has identified numerous factors influencing GDP per capita, encompassing both economic and non-economic determinants. These factors have been explored in various studies, both theoretical (Porter & Stern, 2001; Shane, 2003) and empirical (Stel, 2006; Van Praag & Versloot, 2007; Block et al., 2016). Additionally, economists consistently acknowledge the significance of entrepreneurship in determining a country's GDP per capita, independent of its level of development (Brown & Ulijin, 2004; Vasconcelos & Oliveira, 2018; Galindo-Martin et al., 2020).

However, a significant research gap persists in understanding the intricate relationship between entrepreneurship and its impact on GDP per capita. While several studies have explored how entrepreneurship affects GDP per capita, there is a conspicuous scarcity of comparative analyses in both developed and developing countries. This limitation poses a challenge to achieving the comprehensive understanding required for guiding policymakers, entrepreneurs, and businesses. Without this understanding, informed decision-making aimed at promoting entrepreneurial activities and fostering economic development is hindered.

Thus, this study seeks to address this research gap by meticulously examining the multifaceted interplay between the Global Entrepreneurship Index (GEI) and GDP per capita across diverse global contexts, encompassing both developed and developing economies. A comprehensive understanding of economic development necessitates examining not only the influence of entrepreneurship (measured by the GEI) but also other critical factors that contribute to the growth of a KBE. These factors may include R&D investment, government support for innovation, and regional development strategies. By analysing these multifaceted elements, this study aims to provide valuable insights for policymakers and entrepreneurs to foster economic development through a thriving KBE.

After thoroughly considering the factors outlined above, the objective of this study is to conduct an empirical analysis of the impact of entrepreneurship on GDP per capita in selected countries. Through an in-depth examination of these interconnections, the intention is to provide valuable insights into the key drivers of economic development (expressed as GDP per capita) and offer recommendations for policymakers and entrepreneurs alike.

To achieve the aim, the following working hypothesis was developed:

(H1): *Entrepreneurship positively and significantly impacts GDP per capita.*

Finally, this chapter has provided a solid theoretical groundwork for future research into the role of entrepreneurship in knowledge-based economic development. National economic strategy may be greatly enhanced by encouraging entrepreneurial ecosystems, as this research reveals by analysing the correlation between entrepreneurship and GDP per capita. According to the research, entrepreneurship helps achieve comprehensive and long-term economic development by promoting social stability, equitable distribution of income, and technical innovation.

2.2.2. Regional Growth in Knowledge-Based Economies

Furthermore, as the global economy undergoes a fundamental transformation, with knowledge emerging as a primary driver of growth (OECD, 1996), this shift is reflected in regional development. Entrepreneurial activities, innovation, and economic progress are increasingly rooted in knowledge (Cooke & Leydesdorff, 2006). Historically, competition between nations and regions centred on material resources. However, this dynamic has been replaced by a focus on intangible resources, such as access to cutting-edge scientific knowledge (Dyker & Radosevic, 2000; Qian, 2018). Today, knowledge is widely recognised as the engine of economic growth (Spiezia & Weiler, 2007). The future prosperity of nations and regions hinges on human capital and scientific research, which fuel innovation and propel a new economic paradigm (Drucker, 1998; Godin, 2006). This growing emphasis on KBEs has spurred significant research interest in their impact on economic development.

While the importance of KBEs for economic growth is well-established (OECD, 1996; Dyker & Radosevic, 2000; Qian, 2018), existing research primarily focusses on the national level. The relationship between KBE development and regional GDP growth within the European Union's NUTS 2 regions remains under investigated. Although prior studies demonstrate the broader KBE-economic development connection, a deeper understanding specific to EU regions is lacking (ADB, 2007; Zeibote et al., 2019).

This part of the study aims to bridge this gap in the literature by conducting an empirical analysis of the relationship between KBE variables and GDP growth in EU NUTS 2 regions. Our primary research question centres on whether the development of a KBE is associated with the value of regional GDP.

To investigate the linkages between features of the knowledge-based economy and economic growth, the following working hypothesis is tested:

(H2): *The value of a regional gross domestic product is positively associated with the development of a knowledge-based economy.*

(H3): *The value of a regional gross domestic product is not positively associated with the development of a knowledge-based economy.*

Building upon the recognition of KBEs as drivers of regional growth, the EU's ongoing efforts to strengthen the competitiveness of European economic players in the face of globalisation warrant further investigation (Pavitt, 1998). Key initiatives include investing in research and development, harmonising regulations across member states, and supporting the growth of the digital economy. These efforts aim to equip economic players with the necessary tools and resources to succeed in the competitive global market. Consequently, R&D policy has become a shared priority for the EU and its member states (Bruno et al., 2022).

2.2.3. The Role of R&D in EU Economic Growth

The global economy is transitioning towards a situation where knowledge and innovation are the primary drivers of national economic development (OECD, 1999; Bilbao-Osorio & Rodríguez-Pose & Fratesi, 2004; Švarc & Dabić, 2017). This shift, fuelled by globalisation and the technological revolution, fundamentally alters economic patterns worldwide (Urbancova, 2013). While recognising this trend, concerns exist regarding the underinvestment in R&D capabilities in some EU member states compared to others (Balaz, 2011; Maghe & Cincera, 2016).

Addressing these concerns and ensuring sustained economic development necessitates a re-evaluation of expenditure priorities within the EU, focussing on integrating R&D, innovation, and education (European Commission, 2023). Various R&D programs, such as Horizon 2020 and Horizon Europe, facilitate this integration by channelling funding, supporting collaboration, and empowering actors like universities and private enterprises to contribute to the EU's shared policy goals (Szarowská, 2017; European Commission, 2023).

The EU's recognition of R&D's critical role in driving economic development and competitiveness has led to significant resource allocation towards building a robust KBE (CoR, 2017). However, questions remain regarding the effectiveness of these investments in driving real GDP per capita in the EU (Szarowská, 2017).

This section of the study aims to fill this gap by investigating the relationship between public and private R&D spending and real GDP per capita in the EU-27. Specifically, it seeks to determine whether higher levels of R&D spending are associated with higher real GDP per capita in the EU-27 member states over the period 2011-2020. Therefore, the following working hypothesis is being tested:

(H4): *There is a positive and significant relationship between the level of R&D spending and the level of real GDP per capita in the EU-27 countries.*

In conclusion, this chapter has outlined the central role that R&D investment plays in fostering economic growth within the European Union. As the global economy increasingly relies on information and innovation, the EU's emphasis on R&D has become crucial for sustaining competitiveness, improving productivity, and fostering economic growth. Nonetheless, differences in R&D spending across EU member states provide obstacles to attaining fair development.

2.2.4. Public and Private R&D

While the prior hypothesis (H4) focused on the relationship between R&D spending and real GDP per capita in the EU-27, it is crucial to delve deeper into the rationale behind this investigation. KBEs are fundamentally driven by innovation and continuously generating new knowledge (World Bank, 2008). R&D serves as the engine that propels this knowledge creation, fostering technological advancements and developing novel solutions that address evolving needs (Mowery & Rosenberg, 1998; Alexander et al., 2000).

In today's dynamic global landscape, R&D is a cornerstone of economic progress and competitiveness (Mowery & Rosenberg, 1998; Alexander et al., 2000). Nations worldwide acknowledge its key role in fostering innovation, propelling economic development, and ensuring long-term sustainability (Bucar, 2013; Wang et al., 2023). R&D catalyses scientific and technological advancements, generating novel products and services that address evolving societal needs while supporting enterprise competitiveness (Freeman, 1987). Furthermore, it fuels knowledge creation across diverse fields, contributing to societies' intellectual and academic capital (Valavanidis & Vlachogianni, 2016). Therefore, R&D represents a strategic investment for nations seeking to maintain a competitive edge and achieve sustainable development (Caloghirou et al., 2004; Edquist, 2005).

Building on this foundation, it is essential to explore the distinct yet interconnected roles of the public and private sectors in shaping the R&D landscape. Traditionally, public entities invest in fundamental research, pushing the frontiers of knowledge, while private companies focus on applied research and development activities aimed at commercialising new technologies (Cohen & Levinthal, 1989). However, these roles are not mutually exclusive; collaboration between the sectors can yield significant breakthroughs and accelerate innovation (Etzkowitz & Leydesdorff, 2000). Understanding these interactions is crucial for fostering a thriving innovation and economic development environment.

Moreover, the relationship between public and private R&D is multifaceted, characterized by intricate dynamics of collaboration, competition, and coexistence. One key aspect is complementarity, where public investments stimulate and enhance private-sector innovation (Griliches, 1994). Governments provide grants, subsidies, and research partnerships, fostering a collaborative environment that drives innovation forward (Nelson, 1982).

However, the public-private R&D relationship faces challenges. The concept of "crowding out" raises concerns about excessive public funding potentially discouraging private investment (Guellec & Pottelsberghe, 2000). Effective policymaking requires balancing promoting public good and supporting the independence of the private sector. This balance ensures that public funding complements and supports private initiatives without stifling private investment (European Commission, 2006).

To illustrate these dynamics, a report by the European Policy Analysis Group highlights that despite similar levels of public R&D spending, the EU lags behind the US in innovation. This disparity can be attributed to the private sector, where US businesses invest nearly twice as much in R&D compared to their EU counterparts, often concentrating on high-tech industries, while the EU focuses on mid-tech sectors such as automotive. This "middle technology trap" significantly hinders growth and geopolitical influence.

In light of these challenges, the report proposes institutional reforms to address this gap, such as decentralising decision-making to increase efficiency. However, challenges remain, such as attracting top scientists to the European Innovation Council (EIC) board and achieving efficiency gains through budget-neutral approaches.

While numerous studies have explored the relationship between government funding and private R&D expenditure (Guellec & Pottelsberghe, 2000; European Commission, 2008), a crucial question remains: how does the effectiveness of this funding vary across countries or groups with different economic structures? This study delves into this complex relationship by examining government funding and R&D expenditure across the 33 OECD member countries between 2005 and 2019. To better understand the interplay between public and private R&D investments in diverse economic structures, we will classify the 33 OECD countries into different groups.

Consequently, this study focusses on whether government R&D funding affects private R&D expenditure. Based on the research objectives, the following working hypothesis has been formulated:

(H5): *Increased government funding for R&D positively affects private R&D expenditure.*

In conclusion, the investigation into the relationship between R&D spending and real GDP per capita within the EU-27 underscores the critical role of research and development in driving innovation and economic growth. The framework established in this analysis highlights the importance of both public and private sector investments in fostering a vibrant knowledge-based economy (KBE). By examining the distinct functions of these sectors, we recognize how public funding can stimulate private R&D efforts, enhancing overall innovation and competitiveness.

2.2.5. Agricultural Innovation and Economic Growth in the EU

In addition to exploring the broader dynamics of KBEs, this study also examines a critical sector where innovation can catalyse significant economic advancement: agriculture (Evenson & Gollin, 2003; OECD, 2019; Wang et al., 2019). Innovation has consistently driven progress throughout history, enhancing productivity, economic development, and living standards. The European Union (EU) has highlighted the importance of knowledge-driven development and agricultural innovation in various strategic documents, such as the 'European Green Deal', 'Farm to fork strategy', 'Horizon Europe', and 'Horizon 2020' (Pound & Conroy, 2017; European Commission, 2021). These documents outline the role of innovation in enhancing agricultural productivity while ensuring sustainability and environmental protection. These initiatives aim to foster a knowledge-based economy, where intellectual capabilities, technological advancements, and information are primary drivers of economic development (European Commission, 2021).

The reliance on intellectual capabilities, innovation, and information as key drivers of economic development characterizes a KBE. In agriculture, this means leveraging scientific research, advanced technologies, and data analytics to improve agricultural outputs and sustainability. The EU's policies and funding priorities, which emphasise the integration of knowledge and innovation across various sectors, including agriculture, reflect its commitment to fostering a KBE (OECD, 1997).

In the context of a KBE, one of the key pillars driving agricultural innovation is research and development (R&D) in agriculture. R&D and expenditure in this field facilitate the discovery of new agricultural techniques, crop varieties, and environmental practices that align with sustainable development goals. Numerous studies (Piesse & Thirtle, 2010; Alston & Pardey, 2013) have demonstrated that agriculture R&D is a crucial determinant of agricultural productivity. This aligns with endogenous growth theory, introduced by Romer in 1990, that suggests that internal elements like technological innovation, human capital, and knowledge spillovers drive economic growth. This theory is especially important for grasping how agricultural innovation may stimulate economic development within the EU's KBE. Innovation in agriculture, a crucial aspect of endogenous growth theory, increases productivity and fosters sustainability (Lundvall, 2007; Johnson & Lundvall, 2013).

To operationalise innovation, agricultural innovation systems (AIS) play a crucial role (Riaz et al., 2014; Barry & Czech, 2017). These systems consist of networks that include various actors, organisations, and individuals that cooperate in order to introduce existing or new products, processes, and organisational forms into social and economic contexts. The networks are organised into three primary categories: research and education; business and enterprises, which encompass farmers and their associations; and bridging institutions, including extension services, brokering agencies, and contractual arrangements. Another component includes the supporting policies and institutions, whether formal or informal, that influence the interactions, reflections, knowledge creation, sharing, and collaborative learning and adaptation to external changes among these actors, thereby shaping the "enabling environment" (Tropical Agriculture Platform, 2016).

Government policies and institutional structures are another significant factor encouraging or hindering agricultural innovation. For instance, the EU's Common Agricultural Policy (CAP) offers direct subsidies to farmers, facilitates rural development projects, and finances innovative efforts (European Commission, 2020).

The Triple Helix model, developed by Etzkowitz and Leydesdorff, offers a framework for understanding the dynamic interactions between universities, industry, and government in fostering innovation and economic development (Etzkowitz & Leydesdorff, 1998; Fidanoski et al., 2022). The model emphasises how these three spheres collaborate to create a knowledge-based society where innovation drives technological advancement and entrepreneurship. Traditionally viewed as centres of knowledge generation, universities now play a more active role in innovation through research, commercialisation, and entrepreneurial activities. The industry that applies and markets new technologies benefits from collaboration with universities, gaining access to cutting-edge research and talent. Governments act as facilitators, providing policy frameworks and funding mechanisms to promote research and innovation. The interplay between these sectors creates a synergy that accelerates economic growth and technological progress, making the Triple Helix model a key theoretical approach in innovation studies (Cai & Lattu, 2022). This collaborative model is particularly relevant in knowledge economies, where technological innovation is vital for maintaining competitiveness and fostering sustainable economic development.

Given the extensive array of agricultural innovations and economic advancements among the various EU member states, Germany, the Netherlands, and Denmark stand out as some of the most progressive nations in sustainable farming practices and advanced agricultural technology. Their success stems from a robust digital infrastructure, favourable policies, and substantial expenditures in research and development (OECD, 2023).

However, not all member states have achieved the same level of progress. Comparative studies suggest that countries with limited access to finance, inadequate infrastructure, and regulatory barriers face challenges in adopting new agricultural technologies. These barriers highlight the need for tailored policy interventions that address the specific needs and conditions of each country (Hall et al., 2005; European Parliament, 2019).

Upon examining agricultural innovation through a KBE and the crucial role of R&D in the agricultural sector, it's evident that despite notable advancements, there are still areas requiring additional investigation. This study aims to address some of the existing gaps in understanding how R&D expenditure in agriculture directly influences agricultural productivity, particularly in the context of varying economic and environmental conditions across different countries.

To address these gaps, this study aims to provide a comprehensive analysis of how agricultural innovation impacts economic development at the country level within the EU. By focussing on national-level impacts and integrating the concept of a knowledge-based economy, this research seeks to offer a nuanced understanding of the transformative potential of agricultural innovation. Addressing this research gap, the following questions emerge as central to our inquiry:

How does innovation in agriculture contribute to economic development in EU countries?

What key factors enable or hinder the integration of agricultural innovation within a knowledge-based economy at the country level?

To structure this exploration, the following working hypotheses are proposed:

(H6): *Innovation in agriculture positively influences agricultural productivity.*

While prior research has explored the relationship between agricultural productivity and factors like technological advancements and policy interventions, the novelty of this study lies in its focus on R&D expenditure as a critical driver of innovation in agriculture. Unlike studies that primarily emphasise broader technological innovations or external factors, this research specifically examines how R&D expenditures directly translate into measurable improvements in productivity. Moreover, the potential interactions between R&D and economic variables, such as emissions and trade, remain underexplored in the existing literature.

Previous studies also tend to overlook the differentiated effects that R&D expenditure might have in various contexts, particularly in relation to real factor income and subsidies (Špička et al., 2009). By addressing these gaps, this study offers a novel combination of control variables that provide fresh insights into the broader implications of agricultural innovation (OECD, 2023). Applying a KBE framework and evaluating control variables such as population density and CO2 emissions further enhance the understanding of how agricultural innovation can be made more effective.

This approach contributes to academic research and has important implications for policy discussions, filling a key gap in the literature on the role of R&D expenditure in boosting agricultural productivity.

In conclusion, this study offers significant insights into the dynamics of KBEs and their impact on economic development. The study provides a comprehensive understanding of the factors driving economic development by examining the relationship between entrepreneurship, R&D investment, regional development, government funding, and agricultural innovation. The findings can assist policymakers and government officials in several ways:

The study identifies key drivers of economic development, such as entrepreneurship and R&D investment, allowing policymakers to focus resources and efforts on these areas to maximise economic growth.

The insights from the study can guide the formulation of policies that promote entrepreneurship, innovation, and agricultural progress. For instance, the study highlights the importance of government funding in nurturing a conducive environment for KBEs, suggesting that targeted financial support and policy frameworks are crucial for sustained economic development.

By examining the relationship between KBE development and regional GDP growth within the EU's NUTS 2 regions, the study provides valuable data for tailoring regional development initiatives. This ensures that the benefits of economic growth are equitably distributed, reducing regional disparities and enhancing social cohesion.

The study underscores the importance of a well-educated and knowledgeable population in driving economic development. Policymakers can use these insights to prioritise investments in education and professional development programs, ensuring a steady supply of skilled workers to meet industry demands.

The research highlights the critical role of R&D in fostering technological advancements and economic progress. Policymakers can use these findings to justify increased investment in R&D and create policies that encourage collaboration between the public and private sectors.

By comparing the impact of entrepreneurship and R&D investment across developed and developing countries, the study provides a nuanced understanding of how different economic structures influence these relationships. This can help policymakers in developing countries adopt best practices from developed nations to enhance their own economic strategies.

In conclusion, KBEs have emerged as a robust driver of economic development and competitiveness. This intricate system relies on a well-educated population, a thriving entrepreneurial ecosystem, robust R&D investment, and strategic government funding. However, significant challenges remain, such as regional disparities in knowledge infrastructure and a shortage of skilled workers. Despite these challenges, KBEs offer immense potential for economic development.

By delving into the relationship between entrepreneurship, R&D investment, regional development strategies, government funding, and agricultural innovation, this study aims to investigate the influence of these factors on economic development across a diverse range of countries, encompassing both developed and developing economies. By comparatively analysing these country clusters, the research offers a more nuanced understanding of this intricate relationship and informs policymakers in developing countries seeking to leverage best practices for economic growth.

Additionally, while the importance of KBEs for economic growth is well-established, existing research primarily focusses on the national level. This study addresses this gap by investigating the relationship between KBE development and economic growth at a more granular level, specifically within the European Union's NUTS 2 regions (H2). By analysing data at this regional level, the study can provide insights into how KBE development impacts economic growth across geographically diverse areas within the EU.

Furthermore, the study delves into a critical aspect of R&D investment by examining how government funding for R&D affects private R&D expenditure across countries with different economic structures (H4). This research question moves beyond simply analysing the overall impact of R&D spending. By considering the economic structure of a country, the study aims to provide a more nuanced understanding of how government funding interacts with private sector investment in R&D (H5).

Finally, this study highlights the importance of agricultural innovation within the KBE framework. By analysing how innovation in agriculture impacts economic development across EU member states, the research offers insights into the transformative potential of agricultural advancements (H6). This aspect of the study provides valuable perspectives on how integrating agricultural innovation into a knowledge-based economy can drive sustainable economic progress.

To achieve the objectives mentioned above, this study will be structured as follows: First, a comprehensive literature review will explore existing knowledge on KBEs and their impact on economic development, as well as the critical factors identified in this study, including entrepreneurship, R&D investment, government funding, regional development strategies, and agricultural innovation. This review will thoroughly examine how these interconnected elements contribute to the growth of KBEs and economic development across diverse contexts.

Subsequently, the methodology section will detail the research design, data collection, and analysis techniques employed in the study. The findings of the investigation will then be presented and discussed in the results and discussion section. Finally, the conclusion section will summarise the key takeaways, limitations of the study, and recommendations for future research.

3. Literature Review

3.1. Entrepreneurship and Economic Development in a Knowledge-Based Economy (KBE)

In the contemporary global economy, entrepreneurship is increasingly recognized as a pivotal driver of GDP per capita growth and overall economic advancement. The intricate and dynamic relationship between entrepreneurship and GDP per capita has long intrigued scholars and policymakers, given its profound implications for economic development. This literature review critically synthesizes extensive research, offering a nuanced exploration of how entrepreneurial activities propel economic growth, with a particular focus on the multifaceted mechanisms underlying this complex interplay.

The concept of "entrepreneurship" has its roots in 1766 when French economist Richard Cantillon first introduced it in his seminal work "Essay on the Nature of Trade in General" (Long, 1983). Cantillon distinguished entrepreneurship from financial activities by associating it with trade and defining entrepreneurs as individuals who undertake all the risks of starting a business, making investments, covering expenditures, and anticipating returns (Van Praag, 1999).

Joseph Schumpeter, a towering figure in economic thought, further elevated the concept by positioning entrepreneurship as a central element in economic development (Śledzik, 2013). Schumpeter emphasised the critical connection between innovation and entrepreneurship, arguing that the entrepreneur's primary role is to combine production factors in novel ways, thereby driving innovation—the bedrock of economic development (Hagedoorn, 1996). He identified five key strategies through which entrepreneurs could stimulate economic advancement: the creation of new products, innovation in production and sales methods, the adoption of novel market strategies, the discovery of new resources, and the restructuring of industries (Kotsemir and Abroskin, 2013).

For Schumpeter, profitability hinged on innovation. He regarded innovation as a fundamental force behind competitiveness and economic development, describing it as a "process of industrial mutation that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one" (Śledzik, 2013;

Malerba and McKelvey, 2020). Despite the theoretical consensus on the role of innovation and entrepreneurship, there remains a notable gap in empirical validation, largely due to the challenges in quantifying these factors and modelling their impact.

Empirical studies consistently reveal a significant relationship between entrepreneurship, GDP per capita, and innovation (Galindo & Méndez, 2014). Research has demonstrated a positive correlation between entrepreneurial activity and innovation in developed economies (Block et al., 2016; Crudu, 2019; Loukil, 2019), suggesting that increased entrepreneurial activity catalyzes innovation (Van Stel et al., 2005; Crudu, 2019). Additionally, empirical evidence points to the substantial contribution of small- and medium-sized enterprises (SMEs) to job creation, which in turn positively impacts GDP per capita (Wong et al., 2005; Haltiwanger et al., 2013).

However, the impact of entrepreneurship on economic development is not universally positive. Some studies indicate that entrepreneurship can negatively affect real GDP, GDP per capita, and broader economic development (Carree et al., 2007). Explanations for this include the risks associated with start-up ventures, cultural factors such as uncertainty avoidance, and methodological issues in measuring the economic impact of new entrepreneurial activities (Wennekers et al., 2010; Cunningham & Link, 2014). Moreover, motivations for entrepreneurship vary significantly across countries; in developed nations, entrepreneurship is often driven by the desire for self-improvement, whereas in developing countries, it is frequently a necessity due to limited employment opportunities (Shane, 2009; Crudu, 2019).

Fast-growing entrepreneurs are widely regarded as key contributors to GDP formation, innovation, technological advancement, productivity growth, and employment (Bygrave & Zacharakis, 2011). Entrepreneurs are the vanguard of economic and social progress (Broughel & Thierer, 2019). The European Central Bank underscores innovation as a critical driver of economic progress (European Central Bank, 2017), while Porter and Stern (2001) assert that “Innovation—in the form of new products, processes, and ways of managing—is essential to economic development.”

In today’s rapidly evolving economy, the significance of innovation continues to expand (Courvisanos and Mackenzie, 2014). For entrepreneurs, innovation offers a pathway to market leadership and profitability. Beyond individual enterprises, innovation is vital for national economic development (Maradana et al., 2017). It reshapes industrial structures and profoundly influences competitiveness and economic development at both micro- and macroeconomic levels (Dedahanov et al., 2017).

Recent studies spotlight successful global cases of entrepreneurship, reinforcing the robust link between innovation and entrepreneurship in fostering economic development (Wennekers et al., 2010; Brem, 2011; Stoica et al., 2020). Nonetheless, the impact of entrepreneurship and innovation is context-dependent, varying with a country's level of development (Hong & Sullivan, 2013; Maradana et al., 2017; Almodóvar-González et al., 2020). Porter's 1990 assertion that "innovation is the only way to maintain a competitive advantage" resonates today, though empirical studies offer mixed results regarding the role of innovation and entrepreneurship in economic progress. Drucker (1998) later emphasised that innovation is indispensable to entrepreneurship, with innovative leaders inspiring others to meet company objectives and generate further innovative solutions.

Practitioners seeking to measure the impact of entrepreneurship on economic development face significant challenges, yet proxies such as the Global Entrepreneurship Index (GEI) from the World Bank offer valuable insights into entrepreneurial activity and innovation levels within economies. Despite its widespread use, there remains a gap in the literature linking GEI values directly to economic development metrics. This paper aims to address this gap by employing GDP per capita as a proxy for economic development across a diverse dataset of countries.

3.2. Regional Development and the Knowledge-Based Economy

The global economic landscape is experiencing a remarkable change as areas progressively transition from conventional industrial frameworks to knowledge-driven economies. This evolution underscores the crucial importance of knowledge, innovation, and technology in fostering regional economic growth and enhancing competitiveness. Regional development theories are placing greater importance on local knowledge systems, human capital, and innovation ecosystems as essential factors for fostering growth over the long term. This chapter of the literature review will explore the theoretical underpinnings of regional development within the context of a knowledge-based economy. It will examine the processes of knowledge creation and dissemination, the influence of policy frameworks, and the various opportunities and challenges that regions face in a world driven by knowledge.

The essence of endogenous growth theory is at the core of what defines a knowledge-based economy. This theory posits that economic growth primarily arises from internal factors such as innovation, knowledge accumulation, and human capital, rather than depending on external influences like technological advancements or investments in physical capital. Well-known economists such as Paul Romer and Robert Lucas have emphasised the significance of knowledge and human capital in grasping the dynamics of long-term growth. In contrast to conventional neoclassical growth models that viewed technological progress as an outside influence, endogenous growth theory recognises knowledge production and innovation as essential elements of the growth process. Romer (1990) notably contended that knowledge is non-rivalrous, enabling extensive utilisation without lack or exclusion, which complicates efforts to stop others from benefiting from newly created knowledge. The features of knowledge play a crucial role in driving continuous economic growth.

Examining it from a regional perspective, Michael Porter’s theory of competitive advantage sheds light on the role of knowledge and innovation clusters in fostering regional development. According to Porter (1998), regions that host innovation clusters comprising a concentrated mix of companies, universities, research institutions, and supportive organizations—tend to see increased productivity and innovation as a result of knowledge spillover and resource sharing. These clusters allow companies to tap into each other's expertise and foster collaboration, leading to enhanced knowledge creation and sharing. Porter's cluster theory plays an important role in grasping the spatial dynamics of KBEs.

The rise of Regional Innovation Systems (RIS) stands out as a key idea in the context of regional development in KBEs. A RIS is a network comprising institutions, firms, and individuals in a particular geographic region that work together to create, share, and apply knowledge. This system encompasses universities, public research organisations, private companies, and various stakeholders who play a role in developing and disseminating new technologies and innovations. The RIS concept is closely connected to knowledge spillovers, where innovation from one firm or institution positively impacts others in the same area, fostering economic growth. These spillovers happen via employee movement, casual idea sharing, and structured partnerships between companies and research organisations. Acs, Audretsch, and Feldman (1994) suggest that companies situated close to innovation hubs, like research universities or high-tech firms, tend to be more productive due to their ability to readily access and incorporate new knowledge. This creates a positive feedback loop of innovation, where knowledge is constantly shared and expanded upon, enhancing the ability to innovate and fostering economic growth in the region.

The significance of spatial proximity in KBEs cannot be emphasised enough. The proximity hypothesis posits that areas with a high density of companies, research institutions, and skilled individuals are more likely to promote knowledge sharing and collaborative efforts.

Understanding the vital importance of knowledge and innovation, governments and policymakers have crafted frameworks aimed at fostering and facilitating the shift towards a knowledge-driven economy. In the EU, promoting knowledge-driven growth is at the heart of regional development policy, especially through initiatives such as the Smart Specialisation Strategy (S3) and Horizon Europe.

The Smart Specialisation Strategy (S3), integral to the EU's Cohesion Policy, seeks to bridge regional gaps by fostering innovation and promoting knowledge-driven growth throughout the Union. The fundamental concept of smart specialisation is that regions ought to concentrate on their distinct strengths and competitive edges instead of imitating the successes of others. For example, a region that has a robust agricultural foundation could concentrate on agri-tech or biotechnology, whereas a region heavily invested in manufacturing might prioritise advanced manufacturing initiatives. This focused strategy enables regions to allocate resources effectively, boosting their competitiveness in the global market.

Horizon Europe is an EU initiative that supports research and innovation, fostering collaboration between academia, industry, and government. This initiative enhances regional innovation networks by backing projects that promote knowledge and technological advancements, encouraging cross-border collaborations to tackle regional disparities in innovation capacity. Horizon Europe enables less developed regions to tap into the knowledge and expertise of more advanced areas, fostering balanced growth throughout the Union.

In today's knowledge-driven economy, the importance of human capital for regional development cannot be overstated. Areas that boast a highly educated workforce are more likely to draw in high-tech industries, promote innovation, and stimulate economic growth. As a result, governments and regional authorities focus on enhancing access to quality education, offering ongoing training, and creating upskilling opportunities to equip workers for a knowledge-based economy. The European Education Area of the EU seeks to unify and improve education among its member states, guaranteeing that individuals possess the necessary skills to succeed in a knowledge-based economy. Investing in education enhances human capital, resulting in increased innovation and productivity. Furthermore, universities and research institutions are essential in nurturing the upcoming wave of innovators, who propel economic growth by developing new technologies and business models.

Continuous education and skill development are essential for ensuring that the workforce remains competitive in a changing economic landscape. As industries evolve and new technologies arise, ongoing skill enhancements enable workers to stay pertinent. Areas that prioritise lifelong learning programs are better equipped to adjust to economic shifts and sustain their global competitiveness.

While there are advantages, KBEs also come with their own set of challenges. A significant challenge we face is the gap in innovation across different regions. Regions that are well-developed and have access to capital, knowledge infrastructure, and skilled labour gain significant advantages in the knowledge economy. In contrast, less developed areas face challenges in competing, which intensifies regional disparities.

One more hurdle is attaining sustainable development in KBEs. Areas aiming for growth through innovation need to take into account the environmental and social consequences of their actions (Chen & Dahlman, 2005). The idea of green growth, advocating for the use of innovation to tackle environmental issues, has become increasingly popular. Areas that adopt green technologies, renewable energy, and sustainable practices are more likely to achieve lasting economic and environmental growth.

The shift towards a knowledge-driven economy has reshaped regional development approaches, highlighting the importance of innovation, human resources, and teamwork. Theoretical frameworks like endogenous growth theory and regional innovation systems offer valuable perspectives on how regions can harness knowledge to foster economic development. Initiatives such as smart specialisation and Horizon Europe highlight the critical need to promote knowledge-driven growth and tackle regional inequalities. Nonetheless, the knowledge economy brings forth challenges as well, such as the innovation divide and the necessity for sustainable development.

Regional development involves a variety of strategies aimed at promoting economic growth in both developed and developing regions. The OECD (2022) highlights that regional development aims to uplift economically disadvantaged areas, enabling them to optimise resources and enhance the quality of life for their residents. Economic disparities among regions are a natural occurrence, often showcasing a relationship of interdependence between more developed and less developed areas. This dynamic is shaped by factors like natural and human resources, technology, legislative frameworks, and the values held within each region.

Although it's common to compare regional development across different countries, these comparisons frequently fall short of providing valuable insights because of the significant disparities between small, sparsely populated areas and large, densely populated regions. Regional economic disparities occur when some areas within a country enjoy quicker growth and more favourable economic results compared to others. The uneven growth across regions showcases a geographical pattern of interdependence that exists between developed and developing areas. Various factors play a role in shaping regional development, with some impacting it directly while others do so in more subtle ways. Important elements consist of natural and human resources, technological progress, financial assets, knowledge, legislative and institutional structures, values, ethics, and dedication.

To provide regional data for the European community, Eurostat established the Nomenclature of Territorial Units for Statistics (NUTS) classification in the early 1970s. The NUTS system divides each Member State into three distinct regions, ranging from large to small locations: NUTS 1, 2, and 3 (Eurostat, 2022).

Research on the geographical distribution of the knowledge-based economy (KBE) in EU member states has highlighted growing disparities between metropolitan centers and peripheral regions (Leydesdorff & Fritsch, 2006; Kim et al., 2022). The knowledge base of regional economies varies significantly, as each region has its own foundation of scientific, technological, and entrepreneurial knowledge. Many countries are increasing direct investments in generating new knowledge to promote growth in their domestic and regional economies.

The promotion of regional economic development is increasingly recognized as an active process involving enterprises, public and private development agencies, and research institutions. Knowledge-based regional development emphasises the skills and potential of regional actors, such as enterprises, urban centers, tech hubs, and research and education institutions. These strong organizational cultures underscore the interdependence of public and private activities. Understanding the circumstances in which complex development processes occur, and the relevance of multi-level skills in regional development, requires adopting a network approach to knowledge-based regional development processes (Cooke et al., 2007).

Regional policy processes play an indispensable role. At the regional level, policymaking is a collective process involving negotiation and compromise among various players from different policy levels, including non-state actors, non-governmental organizations, and professional associations (Cooke and Leydesdorff, 2006; Godin, 2008; Viale et al., 2010).

The literature concludes that knowledge-based regional development is a collaborative endeavour involving multiple actors and actions. It requires well-connected networks composed of various players and interconnected skills distributed across the networks responsible for developing and implementing regional innovation strategies.

The review of the KBE's impact on regional development, particularly within the EU, underscores the critical role of knowledge, information, innovation, human capital, and R&D as drivers of growth. However, it also highlights the challenge of regional disparities in knowledge and economic development, with a widening gap between metropolitan centers and peripheral regions in the EU. The importance of a "network approach" and the multi-level nature of skills in regional development are emphasised. Additionally, the review points to the potential of universities, research institutions, and tech hubs to foster knowledge-based growth. Collaboration and knowledge exchange among regional actors are crucial for successful development strategies. This review lays the groundwork for further research on EU regional development within the context of the KBE.

R&D expenditure is widely recognized as a key driver of economic growth and technological advancement. A robust body of empirical research has established a positive correlation between R&D investments and economic development, underscoring the critical role of innovation in fostering prosperity. However, the nature and significance of this relationship vary depending on factors such as economic context, types of R&D investments, and policy measures implemented.

This literature review thus delves into two critical areas: the historical foundations of EU R&D policy and the role of R&D expenditure in EU policy. Through this examination, the aim is to contribute to a more nuanced understanding of this dynamic within the context of the EU's diverse economic structures and varied policy approaches.

3.3. Historical Foundations of EU R&D Policy

The European Union's commitment to R&D has a rich and evolving history, marked by ambitious goals, collaborative initiatives, and continuous adaptation. This section explores the key milestones in this journey, highlighting the ever-expanding role of R&D in the EU's economic and societal landscape.

From its inception, the EU recognized the necessity of standardized data collection and analysis to facilitate comparisons of R&D efforts across member states. This recognition led to the adoption of the Proposed Standard Practice for Surveys of Research and Development by the OECD in 1963, commonly known as the Frascati Manual—a document that remains a cornerstone for measuring various aspects of R&D (OECD, 2015).

The roots of EU R&D policy were sown in the 1950s with the establishment of the European Economic Community (EEC) (Mourlon-Druol, 2017). The initial focus was on stimulating economic growth and competitiveness through measures such as industrial cooperation, reducing trade barriers, and increasing R&D investment (Tsoukalis, 1997).

The 1960s witnessed a surge in activity, with expert working groups focusing on specific areas like computers and telecommunications. Although political challenges temporarily halted these efforts, the Hague Summit of 1969 marked a pivotal turning point (Werner, 1969). The establishment of the Scientific and Technological Co-operation (COST) committee facilitated cross-country collaboration on research projects, laying the groundwork for future initiatives (European Commission, 2023).

The turn of the millennium brought a renewed emphasis on innovation with the ambitious Lisbon Strategy (Rodriguez et al., 2010). This vision aimed to transform the EU into the world's leading knowledge-based economy, necessitating significant reforms in education, research infrastructure, and R&D investment (Tassey, 1997).

Since the 1980s, the Framework Programmes for Research and Technological Development have been instrumental in funding research projects, encouraging collaboration, and supporting the development of new technologies (Laredo, 1998). These programs remain a cornerstone of EU R&D policy, fostering partnerships and driving innovation across diverse fields.

In today's world, the relentless demand for innovation underscores the critical importance of R&D. The EU remains steadfast in its commitment to this mission, continually enhancing its R&D policy to promote collaboration, knowledge transfer, and the development of cutting-edge technologies.

Recent studies have expanded upon historical foundations to analyse the evolution of the EU's R&D policy. This analysis is especially pertinent given the contemporary knowledge economy's challenges, including digital transformation, environmental sustainability, and regional disparities. Research conducted over the past decade emphasizes the EU's capacity to adapt to emerging global forces, illustrating that its approach to R&D policy is both flexible and innovative.

One of the most influential developments in recent EU R&D policy is the introduction of Horizon 2020, followed by Horizon Europe. Horizon 2020 set ambitious targets to foster research and innovation across member states, emphasizing international collaboration. Research by Veugelers (2015) highlights that Horizon 2020 not only promoted technological advancement but also addressed societal challenges, integrating research efforts with broader EU goals like sustainability and digitalization.

One of the most significant advancements in recent EU R&D policy is its responsiveness to the ongoing digital transformation affecting various industries. The EU has proactively adapted its R&D strategies to address both the challenges and opportunities presented by the digital economy. The Digital Europe Programme (DEP), launched in conjunction with Horizon Europe, focuses on key areas such as the development of advanced digital skills, the enhancement of cybersecurity, and the establishment of artificial intelligence infrastructure (European Commission, 2020). By aligning R&D funding with these digital priorities, the EU is strategically positioning itself to maintain a competitive edge on the global stage in an increasingly digitalized landscape.

The Digital Europe Programme complements Horizon Europe by addressing the existing gaps in digital capabilities across member states. It underscores the critical importance of robust digital infrastructure in promoting fair growth (Bıçakcı, 2024).

Addressing environmental challenges through research and development (R&D) has become a central component of European Union policy, particularly under the framework of the European Green Deal. This initiative emphasizes the importance of sustainability, with the objective of achieving climate neutrality in the EU by 2050. A significant part of Horizon Europe's budget is allocated to green innovation, supporting initiatives that advance renewable energy, promote circular economies, and foster sustainable agriculture (European Commission, 2024).

In our increasingly interconnected world, cross-border collaboration plays a crucial role in advancing scientific research. Horizon Europe places a strong emphasis on open science, fostering international partnerships and promoting the dissemination of research findings. This collaboration is essential not only within the EU but also with global partners, ensuring that European research has a significant impact on addressing global challenges.

Another notable development in EU R&D strategy is the growing emphasis on small and medium-sized firms (SMEs) (OECD, 2017). The EU has established a number of financing structures, including the European Innovation Council (EIC), to encourage high-risk, high-reward initiatives, often driven by SMEs (European Commission, 2023). According to studies, agile innovation, which allows for the quick creation and implementation of new ideas, is made possible by SMEs.

Taken as a whole, EU new R&D initiatives show the countries will tackle modern problems by investing strategically in new technologies. The holistic approach of the EU to R&D policy in a dynamic global context is shown by Horizon Europe, digital and environmental programs, smart specialization, open science, and support for small and medium-sized enterprises (SMEs) (OECD, 2017). With these initiatives, the EU is setting the standard for economic development, regional equality, and global competitiveness by encouraging a knowledge-driven economy.

3.4. The Role of R&D Expenditure in EU Policy

Across the European Union, countries exhibit varying degrees of proficiency in generating, accessing, and deploying knowledge effectively. This diversity, shaped by institutional structures, influences how countries access and develop new technologies (Ramanayake, 2020). Effective policies for boosting competitiveness, innovation, and R&D must, therefore, account for these nuanced differences.

Scholars widely agree that successful R&D policies hinge on collaboration between governments, research institutions, industries, and enterprises (Chen & Yu, 2022; Glaziev & Schneider, 1993). This synergy is crucial for crafting effective policies and ensuring their successful implementation. Furthermore, academic research consistently points to technological progress as the primary driver of long-term economic development (Lorenz et al., 2005; Alsebai et al., 2022). To fully grasp the policies and strategies that influence the development and adoption of technology, it is essential to view them through the lens of a Knowledge-Based Economy (KBE). Within this framework, R&D functions as the engine for technological advancement. Given its economic significance, integrating R&D projects with other growth-oriented programs is vital for their success (Becker, 2015).

Effective policymaking thrives on cooperation, encompassing both policy formation and execution. Science policy, for instance, focuses on R&D investments and human capital development through education and training, while technology policy is concerned with creating the infrastructure that supports the development and deployment of new technologies (Nelson, 1993). Distinct from these, innovation policy aims to equip businesses with the capabilities to innovate (Fuest et al., 2024).

Currently, one of the EU's flagship R&D initiatives is Horizon 2020, the world's largest funding program for R&D (Kim & Yoo, 2019; European Commission, 2020). Launched in 2014, Horizon 2020 supports groundbreaking R&D projects with the potential to significantly impact society and the economy (European Commission, 2020). The program offers funding opportunities for R&D on a global scale, accommodating participants from basic research to applied projects, and encourages widespread participation from individuals and organizations worldwide.

Collaboration and partnerships among researchers, businesses, and stakeholders form a cornerstone of EU R&D policy. The EU actively promotes such collaborations through initiatives like the European Research Council (ERC) and the European Innovation Council (EIC). The ERC funds exceptional research across all scientific disciplines, while the EIC supports innovative start-ups and SMEs (European Commission, 2023; European Research Council, 2023).

Recognizing the importance of translating research findings into marketable solutions, the EU has launched initiatives such as the European Innovation Partnerships (EIPs). These partnerships bring together stakeholders across the innovation value chain to accelerate the commercialization of research discoveries, addressing specific challenges and opportunities related to research commercialization.

Beyond these initiatives, the EU provides R&D support through various funding mechanisms like the European Regional Development Fund (ERDF) and the European Social Fund (ESF) (European Commission, 2017; European Commission, 2023). These funds support R&D projects with the potential to create jobs, enhance competitiveness, and improve citizens' quality of life.

The EU's R&D policy is both comprehensive and ambitious, aiming to bolster innovation and competitiveness across the continent. Through its funding programs, the EU fosters collaboration, partnerships, and the commercialization of research, ultimately seeking to position Europe at the forefront of global innovation and technology (Pradhan et al., 2017).

In recent years, the European Union has made a significant step towards ensuring fair growth by committing to reducing regional gaps in research and development capacity. The European Commission's 2023 European Innovation Scoreboard shows that there are still significant differences between the western and eastern parts of the EU, as well as between the northern and southern areas. A number of studies (Navarro et al., 2021; González Cabral et al., 2023) have argued that the European Union's research and development policies should be adjusted to close these disparities. Support programs such as the Cohesion Fund and the European Regional Development Fund (ERDF) allow areas with lower R&D intensity to catch up and become more connected into the EU's innovation ecosystem (Rodriguez-Pose, 2020).

Additionally, open science and knowledge sharing have been heavily emphasised in recent EU R&D programs. Projects funded by Horizon Europe aim to increase research accessibility and openness via fostering partnerships between universities, businesses, and governments. This open scientific methodology is crucial for ensuring that inventions serve the wider society, rather than only benefiting certain companies or industries. Open science facilitates the integration of EU researchers into worldwide networks, hence enhancing the EU's capacity to address complex, transnational challenges (European Research Council, 2023).

In summary, EU R&D spending plans are becoming more complex, targeting not just economic development but also the reduction of regional imbalances, the promotion of sustainability, the advancement of digital transformation, and the encouragement of open research. This holistic strategy enables the EU to deal with many socio-economic issues, establishing it as a frontrunner in worldwide research and innovation.

3.5. Government R&D Funding in a Knowledge-Based Economy

In today's knowledge-based economy, R&D expenditure is a critical driver of economic growth, innovation, and global competitiveness. However, private firms may underinvest in R&D due to high upfront costs, long-term returns, and knowledge spillovers. Consequently, government funding plays an indispensable role in stimulating R&D activities.

Given the constraints of public resources, governments are under constant pressure to optimize the allocation of funds for maximum impact. This scrutiny extends to R&D expenditures a vital engine for long-term economic development, competitiveness, and job creation (OECD, 2009). However, the relationship between public and private R&D funding is complex and multifaceted.

Public and private R&D serve distinct, yet complementary, purposes. Public R&D aims to accelerate technological advancements and national productivity, often focusing on areas of long-term benefit or high risk that might not attract private investors (Arrow, 1962). In contrast, private R&D is driven by profit and market dominance, leading to a focus on innovations with clear commercial applications (Coccia, 2010).

Empirical studies suggest two primary effects of public R&D funding on private sector investment:

- **Complementary Effect**: Publicly funded R&D programs can act as a catalyst, encouraging private sector investment by providing crucial research infrastructure and de-risking early-stage research. This can incentivize private firms to invest further in development efforts (Mazzucato, 2021; Wang et al., 2021).
- **Crowding-Out Effect**: Conversely, excessive public R&D funding may inadvertently discourage private investment, a phenomenon known as the "crowding-out effect." Research by Guellec and De La Potterie (2003) indicates that large, established firms with strong R&D track records may disproportionately benefit from government grants or subsidies, potentially stifling innovation among smaller players.

While the crowding-out effect is a legitimate concern, it can be mitigated by knowledge spillovers from publicly funded research. These spillovers can benefit smaller firms lacking the resources to conduct their fundamental research (Alexander et al., 2000). Moreover, government funding can help level the playing field by providing smaller firms access to research infrastructure and expertise they would otherwise be unable to afford.

To optimize the effectiveness of public R&D funding and foster a thriving innovation ecosystem, governments must consider several key strategies:

- **Targeted Allocation**: Focus R&D investments on areas with the highest potential return on investment for economic and social development (OECD, 2015).
- **Impact Evaluation**: Develop robust methods to measure the effectiveness of R&D programs, ensuring that public resources are used efficiently (Mazzucato, 2021).
- **Fostering Collaboration**: Encourage collaboration between governments, research institutions, and private companies to accelerate innovation and knowledge transfer (Cunningham & Link, 2014).

Additionally, governments employ various funding mechanisms, such as direct grants, tax incentives, and public-private partnerships (PPPs), each with distinct advantages and limitations (OECD, 2011).

Competitive research grants, awarded through independent review processes, can support specific research projects aligned with national priorities (OECD, 2015). However, concerns about the efficiency and fairness of the grant selection process persist.

Tax incentives for R&D activities can broaden participation from private firms by reducing the financial burden of research investments (Crespi et al., 2016). Yet, their effectiveness may be limited if firms were already likely to undertake R&D regardless of the tax incentive, potentially leading to deadweight loss.

Public-private partnerships (PPPs) allow for pooling resources and expertise for large-scale R&D projects that may be too risky or expensive for individual actors (Mazzucato& Semieniuk, 2017; Vivona et al., 2023). However, managing fair risk-sharing, intellectual property rights, and maintaining project focus can be challenging (Cowan & Harison, 2001).

The optimal mix of funding mechanisms will depend on each KBE's specific objectives and context. However, a well-designed government R&D funding strategy can stimulate innovation, drive economic development, and foster long-term societal well-being within a knowledge-based economy.

Further, recent studies have shown that governments globally are increasingly acknowledging the significance of focused R&D investments in bolstering national and regional competitiveness, especially in sectors such as artificial intelligence, renewable energy, and biotechnology. Due to the lack of immediate economic value and the great potential for long-term gains in early-stage, high-risk ventures, academics argue that government-funded research and development is crucial.

Additionally, studies has shown that strategically placing public R&D funds may lead to significant economic gains, adding weight to the growing body of research that highlights the importance of innovation clusters. Research by Romero-Jordán et al. (2014) suggests that small businesses without the means to engage in independent research and development may benefit from clusters of comparable sectors that get financing from regional governments. The ability to tackle complicated technical problems and attain economies of scale in research and development investment depends on networking, information sharing, and cooperation, all of which are encouraged by regional clustering of innovation activities (Porter, 2003).

The significance of impact assessment in research and development policies is increasingly recognised. This methodology underscores the need of transcending conventional measures by integrating variables that signify social advantages, like environmental sustainability and enhancements in public health (OECD, 2019).

Finally, scholars like Autio et al. (2014) stress the need of developing dynamic capacities in enterprises that get funding from the government for R&D. Government investment, they say, should include tools that help businesses learn and adapt as well as resources that boost their ability to absorb new information. Public R&D expenditures provide long-term economic development and innovation when businesses develop these capacities, which allow them to better incorporate new information and innovate continuously.

To summerize, these observations highlight the complex role of government R&D spending in knowledge-driven economies (Tang et al., 2022). Effective R&D policies drive private sector investment and allow the development of new solutions to urgent social concerns. In the knowledge economy, well structured government financing policies that encourage knowledge spillovers, regional clusters, and impact-oriented assessments foster a resilient and sustainable innovation ecosystem.

3.6. Innovation in Agriculture

Innovation has consistently played a transformative role in agriculture, driving economic development and ensuring food security. In the European Union (EU), agricultural innovation is increasingly seen as a crucial factor in promoting economic development within the framework of a knowledge-based economy (KBE). A KBE emphasises the role of intellectual capabilities, technological advancements, and information over traditional physical resources. This literature review explores the intricate relationship between agricultural innovation and economic development within the EU, focusing on how the integration of a KBE framework can catalyse this process.

Agricultural innovation encompasses a wide range of activities, from the development of new crop varieties to the adoption of cutting-edge technologies such as precision farming and biotechnology. According to Fuglie (2012), innovation in agriculture is a primary driver of productivity growth, which in turn is essential for economic development. Innovations such as genetically modified organisms (GMOs), improved irrigation techniques, and advanced farming machinery have significantly increased agricultural output, reduced input costs, and enhanced environmental sustainability.

The EU has recognized the importance of innovation in agriculture through various policies and funding programs. The Common Agricultural Policy (CAP), for instance, has increasingly incorporated innovation as a key pillar, supporting the development and dissemination of new technologies to improve agricultural productivity and sustainability (European Commission, 2020). Additionally, the Horizon 2020 and Horizon Europe programs have provided substantial funding for research and innovation in agriculture, emphasizing the role of R&D in driving economic growth (European Commission, 2021).

The concept of a knowledge-based economy (KBE) is particularly relevant to the discussion of agricultural innovation in the EU. A KBE relies on the creation, dissemination, and application of knowledge to spur economic growth. As noted by Powell and Snellman (2004), a KBE is characterized by high levels of investment in education, research, and innovation, which are critical for advancing technological frontiers and enhancing productivity across sectors, including agriculture.

In the context of agriculture, a KBE framework involves leveraging scientific research, advanced technologies, and data analytics to improve agricultural practices. As stated by Alston (2010), the integration of knowledge-based strategies in agriculture can lead to significant improvements in crop yields, resource efficiency, and overall economic performance. This approach aligns with the EU's broader economic strategy, which seeks to position the region as a leader in innovation-driven economic growth.

Agricultural innovation has a direct impact on economic development by increasing productivity, creating jobs, and enhancing the competitiveness of the agricultural sector. According to Thirtle, Lin, and Piesse (2003), productivity growth in agriculture is one of the most effective ways to reduce poverty and stimulate economic development, particularly in rural areas. In the EU, where agriculture plays a vital role in the economy of many member states, innovation is crucial for maintaining competitiveness in the global market.

Empirical studies have shown that countries with higher levels of agricultural innovation tend to experience faster economic growth. Given the extensive array of agricultural innovations and economic advancements among the various EU member states, Germany, the Netherlands, and Denmark stand out as some of the most progressive nations in sustainable farming practices and advanced agricultural technology. Their success stems from a robust digital infrastructure, favourable policies, and substantial expenditures in research and development (OECD, 2023).

Despite the clear benefits of agricultural innovation, several barriers hinder its widespread adoption across the EU. These barriers include limited access to finance, inadequate infrastructure, and regulatory challenges. As noted by Knickel et al. (2009), small and medium-sized enterprises (SMEs) in the agricultural sector often struggle to secure the necessary funding to invest in new technologies, which limits their capacity to innovate.

Additionally, there are significant disparities in the levels of agricultural innovation and economic development across EU member states. Countries with advanced digital infrastructures and supportive policy environments, such as Germany and Sweden, are more successful in fostering agricultural innovation. In contrast, member states with less developed infrastructures and more stringent regulatory frameworks face greater challenges in integrating KBE principles into their agricultural sectors (OECD, 2023).

The literature suggests that government funding is essential in stimulating R&D expenditure within a KBE. While market failures justify government intervention, the potential for crowding-out effects, market distortions, and rent-seeking behaviour necessitates the careful design and implementation of funding programs. Optimizing the effectiveness of government R&D funding requires a focus on targeted allocation, robust impact evaluation, and fostering collaboration between public and private actors.

In exploring this relationship, scholars employ various methodologies, incorporating a range of measures to analyse the intricate dynamics between entrepreneurship, innovation, and economic development. One prominent measure utilized in our analysis is the Global Entrepreneurship Index (GEI), recognized for its comprehensive coverage of multiple dimensions of entrepreneurial activity and its extensive use in academic research (GEDI, 2019; Bonyadi & Sarreshtehdari, 2021; Inacio et al., 2021). Established in 2009, the GEDI Institute is a leading global research institution, and its GEI serves as a key evaluative tool, comparing entrepreneurial processes across more than 130 countries annually. The GEI assesses individual country performance at both national and global levels by examining the entrepreneurial beliefs, capabilities, and aspirations of local populations within their socioeconomic frameworks. This methodology enables the evaluation of regional ecosystem stability across 14 crucial pillars, offering valuable insights into the factors that drive entrepreneurial success.

By integrating data from the GEI with insights from the Global Competitiveness Index (GCI), this study seeks to provide a comprehensive analysis of the relationship between entrepreneurship and economic development on a global scale. In the face of intensifying global competitiveness challenges, the economic literature not only evaluates the economic well-being of individual countries but also delves into understanding the critical role of innovation in shaping competitiveness. Scholarly discourse on competitiveness presents diverse perspectives, encompassing varying definitions, development strategies, and impacts on economic development (Atkinson, 2013; Herman, 2018; Fyliuk et al., 2019; Reyes and Useche, 2019).

Michael Porter, a pioneering figure in this field, introduced the concept of "competitiveness" in his seminal work, *The Competitive Advantage of Nations* (Ketels, 2006). The OECD further defines competitiveness as the "ability of a country (region, location) to deliver the beyond-GDP goals for its citizens" (Aiginger et al., 2013). Since 1979, the World Economic Forum has contributed to this discourse through the Global Competitiveness Index, which measures countries' competitiveness by considering various factors, including stability, infrastructure, education, financial systems, market size, and innovation capabilities (WEF, 2020). The GCI facilitates competitiveness comparisons across countries and identifies the factors distinguishing more competitive nations. It categorizes countries into stages of development from least developed to innovation-driven economies—based on GDP per capita and a weighted average of 12 pillars.

This multifaceted approach enables a thorough exploration of how innovation, as measured by the GCI, significantly influences a country's competitiveness. By analysing specific GCI factors related to innovation, the study sheds light on what makes some countries more innovative and, consequently, more competitive. Recent analyses emphasise the significant competitiveness gaps between developed and developing countries, highlighting the ongoing challenges and opportunities for nations at different stages of economic development (WEF, 2015-2019).

Through this literature review, the study underscores the importance of methodological rigor and the integration of diverse measures, such as the GEI and GCI, to enhance our understanding of the dynamic interplay between entrepreneurship, innovation, and economic development on a global scale.

In conclusion, the literature consistently underscores the pivotal role of entrepreneurship, R&D investment, and government funding in driving economic development within a Knowledge-Based Economy (KBE). The intricate relationship between entrepreneurship and GDP per capita highlights that entrepreneurial activities particularly those fuelled by innovation are crucial for economic advancement. Innovation catalyses business growth and underpins national competitiveness in an increasingly knowledge-driven global economy.

The literature on agricultural innovation within the EU's KBE framework further demonstrates the transformative potential of integrating knowledge-based strategies into traditional sectors like agriculture. Such integration can lead to substantial improvements in productivity, sustainability, and overall economic performance. However, realizing these benefits requires overcoming barriers to innovation, especially in less developed member states. Ensuring that supportive policies and institutional frameworks are in place is essential for fostering widespread agricultural innovation.

Historical and contemporary perspectives, from Cantillon to Schumpeter, consistently position innovation as the cornerstone of economic development across various stages of national progress. This review also addresses regional development disparities within the EU, emphasizing the importance of a well-connected network of regional players to drive knowledge-based development. A network approach, coupled with robust regional policies, is vital for bridging the gap between regions, thereby promoting more balanced economic growth across the continent.

The historical foundations and current role of R&D expenditure within the EU's policy framework reflect a long-standing commitment to fostering innovation. Programs such as Horizon 2020 exemplify the EU's strategic approach to supporting groundbreaking research and development, underscoring the critical importance of collaboration between the public and private sectors.

Government funding remains a cornerstone in stimulating R&D activities, but it requires careful management to balance the complementary and crowding-out effects. Effective resource allocation, rigorous impact evaluation, and fostering collaboration are essential to ensuring that public investments in R&D yield maximum benefits. Recent studies underscore that innovation-driven growth necessitates a strategic and nuanced approach to government funding, leveraging both direct and indirect support mechanisms.

Contemporary literature continues to reinforce the significance of these elements in fostering knowledge-based economic development. Scholars such as Aghion et al. (2021) argue that sustained economic growth in advanced economies increasingly depends on innovation and the continuous accumulation of knowledge. Strategic government policies supporting R&D, education, and infrastructure are critical to maintaining competitiveness in a rapidly evolving global market. Furthermore, the concept of "innovation ecosystems," as highlighted by Gifford et al. (2020), underscores the importance of collaboration among entrepreneurs, universities, and government agencies to create environments conducive to technological advancement. This collaborative model not only enhances innovation capacity but also accelerates the diffusion of new technologies across industries and regions.

Ultimately, fostering knowledge-based economic development hinges on the synergistic interaction between entrepreneurship, R&D investment, and strategic government funding. This literature review illustrates how these elements collectively drive economic growth by enhancing innovation, productivity, and competitiveness. The historical and empirical evidence affirms that entrepreneurial activities, supported by robust R&D efforts and targeted government policies, are fundamental to achieving sustained economic development.

The central takeaway from this review is that a comprehensive and integrated approach leveraging the strengths of entrepreneurship, strategic R&D investments, effective government funding, and sector-specific innovation such as in agriculture is essential for fostering economic development within a knowledge-based economy. Policymakers and stakeholders must prioritize creating environments that support innovation, facilitate knowledge transfer, and ensure equitable regional development. By doing so, the EU can harness the full potential of its diverse economic landscape, driving sustained prosperity and competitiveness in the global market.

4. Methodology and Data sources

4.1. Methodological Framework and Data Selection: Analyzing the Impact of Entrepreneurship on Economic Development

In the initial stages of this research, an extensive literature review was undertaken to establish a robust foundation for understanding the current body of knowledge related to our research topic.

As previously outlined, as a first stage, this study aims to investigate the relationship between entrepreneurship and GDP per capita by leveraging data from the Global Entrepreneurship Index (GEI) and the Global Competitiveness Index (GCI) reports. The analysis encompasses a sample of 98 developed and developing countries (Table 1). The selection of these 98 countries was based on data availability for the variables pertinent to this study within the 2015–2019 World Economic Forum (WEF) reports. Additionally, the selection was narrowed to 98 countries due to consistent data availability across all variables used in our analysis, ensuring robustness and reliability in our findings.

The GEI was selected due to its comprehensive coverage of various aspects of entrepreneurial activity and its widespread use in academic research (GEDI, 2019; Bonyadi & Sarreshtehdari, 2021; Inacio et al., 2021). It evaluates entrepreneurial processes across more than 130 countries annually, offering insights into individual country performance on national and global scales. The GCI, meanwhile, provides a valuable framework for assessing the broader entrepreneurial environment through its analysis of local populations' entrepreneurial beliefs, capabilities, and aspirations within existing socioeconomic structures. This is facilitated by evaluating 14 key "pillars" of regional ecosystem stability. The "Methodology and Computation of the Global Competitiveness Index 2017–2018" was utilized to ensure a standardized and comprehensive approach that aligns with the study period. This methodology facilitates consistent cross-country comparisons and helps to measure the economic conditions that influence competitiveness and economic development.

Table 1. Selected 98 developed and developing countries

Albania	El Salvador	Latvia	Romania
Algeria	Estonia	Lithuania	Russian Federation
Argentina	Ethiopia	Luxembourg	Saudi Arabia
Australia	Finland	Madagascar	Serbia
Austria	France	Malawi	Singapore
Bahrain	Gambia, the	Malaysia	Slovak Republic
Bangladesh	Germany	Mali	Slovenia
Belgium	Ghana	Mauritania	South Africa
Botswana	Greece	Mexico	Spain
Brazil	Guatemala	Montenegro	Sri Lanka
Bulgaria	Honduras	Morocco	Sweden
Burundi	Hong Kong SAR	Mozambique	Switzerland
Cambodia	Hungary	Namibia	Tanzania
Cameroon	Iceland	Netherlands, the	Thailand
Canada	India	Nigeria	Trinidad and Tobago
Chad	Indonesia	Norway	Turkey
Chile	Ireland	Oman	Uganda
China	Israel	Pakistan	Ukraine
Colombia	Italy	Panama	United Arab Emirates
Costa Rica	Japan	Paraguay	United Kingdom
Croatia	Jordan	Peru	United States
Cyprus	Kazakhstan	Philippines	Vietnam
Czech Republic	Kenya	Poland	Zambia
Denmark	Korea, Republic of	Portugal	
Egypt	Kuwait	Qatar	

Source: The Global Competitiveness Report 2017–2018

However, the primary focus of our study is not merely on the descriptive aspects of GEI and GCI but instead on the causal relationship between entrepreneurship and GDP per capita. The core of our analysis involves testing this relationship using an Instrumental Variables (IV) approach, designed to address potential endogeneity concerns and confounding variables that may affect the estimation of this relationship.

The dependent variable in our study, GDP per capita (constant 2010 USD), is widely srecognised as a key indicator of economic development (Van Den Bergh, 2009; Cohen Kaminitz,2023; Bazaluk et al., 2024). While GDP per capita reflects the overall economic performance of a country, it is essential to emphasise that it does not directly measure entrepreneurial activity or innovation. Instead, GDP per capita is a proxy for the economic outcomes to which entrepreneurial activities contribute. The distinction lies in that GDP per capita captures the results of various economic processes, including those driven by entrepreneurship, rather than the entrepreneurial processes themselves.

The independent variables in our study, except for the GEI, include measures that capture various critical dimensions of a country's economic environment: infrastructure, health and primary education, higher education and training, market size, business sophistication, and innovation. These indicators, sourced from the "Methodology and Computation of the Global Competitiveness Index 2017–2018," were selected for their relevance in measuring the economic conditions that influence competitiveness. Although these variables are not components of the GEI, they are essential in explaining the broader economic context in which entrepreneurship operates. The GEI, which serves as a central variable in our analysis, evaluates the health and quality of entrepreneurship ecosystems across different countries. Additionally, while "Infrastructure," "Health and Primary Education," "Higher Education and Training," and "Business Sophistication" are indeed broad economic phenomena, in our study, they are rigorously operationalised into specific, quantifiable variables. This operationalisation, supported by a well-established methodology and empirical validation, ensures that these phenomena are accurately and reliably represented in our analysis, allowing for robust and meaningful conclusions about their impact on economic performance.

Table 2 explains the dependent and independent variables used in this research and their definitions.

Table 2. Description of the variables considered in the analysis

Variables	Definition	Source
	Dependent Variable	
GDP per capita (2015–2019)	GDP per capita is a fundamental economic indicator that measures the average income or standard of living of a country's population. It is calculated by dividing a nation's Gross Domestic Product (GDP) by its total population.	World Economic Forum; Foundations of descriptive and inferential statistics 2019; World Bank (WDI)
	Independent Variables	
Global Entrepreneurship Index (GEI)	A composite index measuring entrepreneurial attitudes, abilities, and aspirations at the country level.	The Global Entrepreneurship and Development Institute (GEDI Institute
Infrastructure	This variable assesses the quality of a country's infrastructure, including transportation, communication, energy, and public services, which are essential for economic functioning.	Methodology and Computation of the Global Competitiveness Index 2017–2018
Health and primary education	These variable measures the effectiveness of a country's health system and primary education. It includes population health indicators, the quality of primary education, and access to these services.	Methodology and Computation of the Global Competitiveness Index 2017–2018
Higher education and training	Higher education and training evaluate the quality and accessibility of tertiary education and workforce training, considering factors such as the relevance of education to workforce needs and the extent of staff training.	Methodology and Computation of the Global Competitiveness Index 2017–2018
Market size	Market size assesses the potential domestic demand within a country, considering factors like population size and purchasing power.	Methodology and Computation of the Global Competitiveness Index 2017–2018
Business sophistication	Business sophistication evaluates the innovation, efficiency, and technological readiness of a country's business sector, including the use of technology and market efficiency.	Methodology and Computation of the Global Competitiveness Index 2017–2018
Innovation	Innovation measures a country's capacity to generate new ideas, technologies, and products that contribute to economic development.	Methodology and Computation of the Global Competitiveness Index 2017–2018

While the GEI and GCI indicators focus on different aspects of economic performance GEI on entrepreneurial attitudes, abilities, and aspirations, and GCI on macroeconomic conditions that influence these entrepreneurial capacities—there is a potential for conceptual overlap. However, in this methodology, it is crucial to acknowledge the absence of overlap between selected variables within the panel dataset.

This non-overlapping nature arises from various factors, including changes in data collection methodologies and variations in variable definitions, temporal dynamics, the dynamic economic context, and potential policy and regulatory shifts. To navigate these complexities, a detailed examination of each variable for each year is conducted. This tailored analysis captures each variable's unique characteristics and contextual influences over time. Additionally, robustness checks are conducted to ensure the accuracy of the chosen methodology, even when dealing with non-overlapping variables.

Therefore, to prevent this analysis from suffering due to overlap and to test the hypothesis, a rigorous methodology was employed, beginning with a correlation analysis (Schreier & Scharf, 2010) to explore the associations between the dependent and independent variables.The calculation of the correlation coefficient is detailed below, where x represents the values of the independent variable, and y represents the values of the dependent variable. The formula applied is as follows:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x-\bar{x})(y-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x-\bar{x})^2} \cdot \sqrt{\sum_{i=1}^{n}(y-\bar{y})^2}} \tag{1}$$

Additionally, the dynamics of average GDP per capita (constant 2010 USD $) for the countries were analysed according to each stage of development considered in the analysis (Stage 1: Factor-driven, Transition from stage 1 to stage 2, Stage2: Efficiency-driven, Transition from stage 1 to stage 2, Stage3: Innovation-driven, Grand total average (Appendix 1, Table 32; Figure 4). This analysis illustrated the varying dynamics of economic growth across different stages of development, highlighting the critical role of innovation and efficiency in fostering sustained increases in GDP per capita.

Following this, an extensive analysis was conducted using cross-sectional linear regression models. To ensure an accurate estimation of regression coefficients, the Ordinary Least Squares (OLS) method was applied (Oksanen, 1991). This approach was designed to thoroughly investigate the complex relationship between entrepreneurship and GDP per capita across diverse economic contexts, encompassing both developed and developing countries.

Before proceeding to the cross-sectional analysis, a simple multiple linear regression model (Appendix 2, Table 33) was initially run without applying a log-log transformation. This preliminary model allowed for the examination of the direct, untransformed relationships between the independent variables and the dependent variable, offering a baseline understanding of the associations in their natural scales. By first analyzing these straightforward linear relationships, insights were gained into the raw effects of each predictor, which informed the subsequent decision to employ a log-log specification in the cross-sectional model. Therefore, for the cross-sectional analysis, a log-log OLS regression model (Wooldridge, 2010) was utilized to estimate the relationship between the independent variables and GDP per capita for each year within the study period. This model included 98 observations for each year, corresponding to the 98 countries in the sample. The log-log specification allowed for the interpretation of the estimated regression coefficients as elasticities.

The general equation for the cross-sectional OLS model with a log-log relationship between the dependent and independent variables presented below:

$$lny_i = \beta_0 + \sum_{i=1}^{n} \beta_i lnx_i + \sum_{j=1}^{m} \gamma_j + \varepsilon_i \tag{2}$$

The importance of considering all relevant instrumental variables that could impact the GEI was recognized. To this end, a comprehensive multicollinearity test was conducted on the independent variables. The results revealed significant multicollinearity, posing the risk of biased and inefficient estimates in an OLS framework (Atanlogun et al., 2014). Specifically, the high Variance Inflation Factors (VIFs) indicated that all variables, except GEI, exhibited very high VIFs and correspondingly low tolerance values. This finding made it necessary to adopt an alternative method. Consequently, the Two-Stage Least Squares (2SLS) approach was chosen (Greene, 2008), as it effectively addresses both multicollinearity and potential endogeneity issues.

Additionally, recognizing the potential for endogeneity or measurement errors—mainly since most of the independent variables, aside from GEI, are based on subjective survey data from business executives—the IV approach was adopted. The instruments were chosen based on their established relevance in previous studies and their theoretical significance in explaining GEI. An essential contribution of this analysis lies in the IV approach used to address endogeneity concerns. Specifically, external instruments that are both theoretically and empirically grounded were employed, ensuring they meet the relevance and exclusion restriction criteria. These instruments were selected because they strongly correlate with the endogenous regressors but are uncorrelated with the error term in the outcome equation, providing a credible identification strategy.

As the first step in the 2SLS method, GEI was regressed on four instrumental variables: infrastructure, health and primary education, higher education and training, and market size, all in log-log form. Innovation and business sophistication variables were excluded due to their lack of statistical significance. In contrast, the selected instruments produced highly significant p-values, confirming a strong correlation with GEI. However, after further analysis, it was found that excluding the higher education and training variable improved the Sargan over-identification test results. Based on this finding, higher education and training was omitted from the final list of instruments. This adjustment enhances the accuracy and reliability of the model, ensuring that the remaining instruments provide a stronger and more focused explanation of the relationship between GEI and economic outcomes.

Our approach offers a novel contribution by combining these specific instruments in the context of entrepreneurship and GDP per capita. While prior studies have used similar variables in different economic contexts, our research uniquely integrates these specific instruments and establishes their statistical association with the GEI. Each instrument was thoroughly tested to demonstrate its link to the GEI, setting this study apart from others.

The unique combination of these instruments within a panel IV 2SLS framework allowed us to control for endogeneity while addressing both country-specific and time-specific effects. This approach has not been explored in previous literature, adding significant value to our analysis. By applying this particular set of variables, which has never been tested together, this study offers new insights into the relationship between entrepreneurship and GDP per capita across 98 countries, enhancing the robustness and depth of the findings.

Moreover, a more focused and statistically robust model is provided by excluding innovation and business sophistication from the instrument set due to their lack of statistical significance in the first stage, thereby avoiding potential over-identification.This refined selection contributes to the novelty of our approach and offers a clearer understanding of the specific channels through which entrepreneurship affects economic growth.

Furthermore, the analysis was enhanced by employing a panel data approach, with 490 observations across 98 countries over five years. The panel specification allowed us to control for both time and country-specific effects, addressing unobserved heterogeneity and improving the robustness of our results.

$$lnx_1 = \theta_0 + \sum_{j=1}^{n} \theta_j lnz_j + v_i \quad \textbf{(3)}$$

$$lny_i = \beta_0 + \beta_1 \widehat{x_1} + \varepsilon_i \quad \textbf{(4)}$$

In equation (3), z_j – represents instrumental variables (infrastructure, health and primary education, and market size); θ_j – regression coefficients; v_i – error term. These instruments, backed by theoretical justification, contribute to the novelty of the instrumentalization, offering a more reliable approach to addressing potential biases arising from omitted variables and measurement errors.

Equation (4) contains fitted values of the dependent variable from equation (3). In this model specification, independent variables from the study dataset can be used as instruments. The estimated value of the coefficient $\beta 1$ is used to test the hypothesis.

The selected instruments were additionally validated through rigorous tests, including the Hausman, Sargan, and weak instruments tests. The Hausman test (Hausman, 1978) was used to determine whether the OLS or IV estimator provides more efficient and consistent results. The Sargan over-identification test evaluated whether the number of instruments was excessive. Furthermore, the weak instruments test determined whether the instruments were sufficiently strong. These tests were also valuable in identifying which variables should be used as regressors (in equation (4)) in the model and which should serve as instruments (regressors in equation (3)).

While the IV strategy has limitations, including potential concerns regarding unobserved confounding factors, threats to the exclusion restriction have been carefully considered. The combination of theoretical justification, empirical testing, and robustness checks, such as the Hausman test, Sargan test, and weak instruments test, demonstrates that the chosen instruments provide a reasonable approach to addressing potential endogeneity concerns.

Although there is always a risk of unobserved confounding factors, our approach is reasonable given the available data and theoretical considerations. Future research might explore alternative instruments or methods to strengthen the identification strategy further.

4.2. Methodological Framework and Data Selection: Regional Analysis of Knowledge-Based Economies: Insights from EU-28 NUTS 2 Regions

Building on the foundation established by the initial analysis of entrepreneurship and economic prosperity, the focus was turned to the European context. Specifically, the examination explored how knowledge-based economies contribute to GDP growth within the diverse regions of the EU-28. This focus on regional analysis allowed us to capture the intricate dynamics of economic development in different parts of Europe, offering a nuanced perspective that goes beyond national-level aggregates.

In selecting the dataset, consistency and reliability were prioritized, leading to a focus on the 2009-2012 timeframe. According to Eurostat (2022), this period provides the most consistent and reliable data across all EU-28 NUTS 2 regions, making it ideal for our analysis. Although this timeframe restricts the temporal scope of our study, it enhances the comparability of our findings, ensuring that our conclusions about the relationship between knowledge-based economies and GDP growth are both accurate and robust.

Our dataset included a variety of variables that serve as proxies for the development of a knowledge-based economy. These variables allowed us to conduct a panel data analysis across 225 regions initially. However, due to breaks in the time series, data from certain regions, including Ireland, Slovenia, and Lithuania, had to be excluded. This careful selection process ensured that our analysis remained focused on regions with complete and consistent data, thereby preserving the integrity of our empirical results.

To investigate the relationship between a knowledge-based economy and GDP growth, several key indicators were analyzed: gross domestic expenditure on R&D (GERD), R&D personnel and researchers, employment in knowledge-intensive jobs, patent applications, and student participation rates. These indicators provided a comprehensive overview of the factors driving economic development in the EU-28 NUTS 2 regions and their connection to the knowledge economy.

Our research aimed to uncover the linkages between features of the knowledge-based economy and economic growth by testing a central working hypothesis (H2 versus the alternative H3). A variety of proxies were employed to represent regional GDP and various aspects of a knowledge-based economy, using GDP per capita adjusted for purchasing power parity as the dependent variable. The robustness of our findings was ensured by testing both Fixed Effects (FE) and Random Effects (RE) models (Baltagi, 2010), with the Hausman test (Hausman, 1978) guiding our choice of model specification. In general form, the econometric specification of the FE model (equation 5) and RE model (equation 6) are as follows:

$$lny_i^t = \beta_0 + \sum_{j=1}^{n} \beta_j lnx_{ij}^t + \gamma_i + \delta_i + \tau_i + \varepsilon_t \qquad \textbf{(5)}$$

Where y_i^t – regional gross domestic product (PPS per inhabitant); x_{ij}^t – independent variables; γ_i – entity (region) specific fixed effects; δ_i – country-specific fixed; τ_i – time-specific fixed effects; β_0, β_j – regression coefficients; ε_t – error term.

$$lny_i^t = \beta_0 + \sum_{j=1}^{n} \beta_j lnx_{ij}^t + u_i + v_i + w_i + \varepsilon_t \qquad \textbf{(6)}$$

Where y_i^t – regional gross domestic product (PPS per inhabitant); x_{ij}^t – independent variables; u_i – entity (region) specific random effects; v_i – country-specific random effects; w_i – time-specific random effects; β_0, β_j – regression coefficients; ε_t – error term.

The econometric model used is designed to capture the effects of regional, country-specific, and time-specific factors on GDP growth. By including these dimensions, the unique contributions of knowledge-based economic activities to regional economic outcomes were isolated. This approach provided a detailed understanding of how knowledge-driven variables, such as innovation and human capital, influence economic growth across different European regions.

Table 3 provides descriptive statistics for the dataset, highlighting the study's key findings (Chattamvelli & Shanmugam, 2023). Additionally, this table provides an overview of the main trend and distribution of the selected variables, providing crucial insights into various aspects of the knowledge-based economy and GDP growth across various EU NUTS2 regions.

Table 3. Description of the variables considered in the analysis and results of descriptive statistics

Variable	Description	N	Min	Average	Std. dev.	Max
y_i^t	GDP per capita	860	25,970.8	13,417.1	3,213.1	88,646.2
x_1^t	Patent applications to EPO	786	19.2	27.0	0.1	202.0
x_2^t	R&D personnel	600	1.6	1.1	0.2	5.9
x_3^t	Gross Domestic Expenditure on Research & Development (GERD) by sector	762	975.7	1,792.5	1.8	18,393.1
x_4^t	Employment in high-technology sectors (high-technology manufacturing and knowledge-intensive high-technology services), in % of total.	852	3.4	1.8	0.5	10.1
x_5^t	Employment in the high-technology manufacturing sector, in % of total	621	1.3	0.9	0.2	5.8
x_6^t	Employment in medium high-technology manufacturing sector, in % of total	845	4.7	3.1	0.2	17.0
x_7^t	Employment in wholesale and retail trade; accommodation and food services activities; activities of households as employers, in % of total	894	19.7	4.6	9.9	41.0
x_8^t	Employment in total knowledge-intensive services sector, in % of total	896	37.3	8.4	14.2	59.9
x_9^t	Employment in knowledge-intensive high-technology services sector, in % of total	813	2.4	1.4	0.4	7.9
x_{10}^t	Employment in knowledge-intensive market services (expect financial intermediation and high-technology services) sector, in % of total	885	5.3	2.0	1.0	15.0
x_{11}^t	Employment in other knowledge-intensive sectors, in % of total	896	27.1	6.1	10.8	46.5
x_{12}^t	Employment in information and communication sector, in % of total	827	2.5	1.4	0.5	8.6
x_{13}^t	Employment in financial and insurance activities sector, in % of total	860	2.7	1.4	0.6	12.7
x_{14}^t	Employment in professional, scientific and technical activities sector, in % of total	881	4.4	1.9	0.8	12.9
x_{15}^t	Employment in education sector, in % of total	890	7.1	1.6	2.9	12.7
x_{16}^t	Employment in human health and social work activities sector, in % of total	896	10.5	4.4	3.2	25.5
x_{17}^t	Ratio of the proportion of students (ISCED 5-6) over the proportion of the population by NUTS 2 regions	736	0.9	0.5	0.1	4.1

Note: Data was sourced from Eurostat (2023), Autor's calculation

Notably, the total number of observations ranges from 600 to 896 due to incomplete data in certain years (Table 3). Therefore, the time series in our analysis was restricted to four years, highlighting the difficulties associated with conducting empirical research employing publicly available datasets. Due to various specifications (sets of independent variables), the number of observations utilized in estimating empirical models differs, and it is consistently stated for each model presented.

In addition to the primary analysis, further diagnostics were conducted to ensure the robustness of the results. A multicollinearity check was performed to assess the degree of correlation among the independent variables (Appendix 3, Table 34).

Moreover, an IV 2SLS model was employed to address potential endogeneity issues (Appendix 4, Table 35) (equation (3) and (4)). The use of instrumental variables allowed us to account for any bias arising from endogeneity, and the results from this model confirmed the validity of the original findings, with the key variables remaining significant and consistent in their impact on GDP per capita. These additional analyses reinforce the robustness and reliability of the study's conclusions.

In conclusion, our study's limited time series, driven by data availability constraints, highlights the importance of careful data selection in empirical research. A panel data approach with Fixed Effects (FE) or Random Effects (RE) models was utilized (Baltagi, 2010). While these models provide a robust framework for analysing regional variations, it's crucial to acknowledge limitations. The chosen knowledge-based economy proxies may not fully capture all aspects of such an economy. Further research could explore alternative proxies or even composite indices to achieve a more comprehensive picture. By acknowledging these limitations and considering alternative approaches in future studies, researchers can ensure the validity of their findings and advance our comprehension of the intricate relationship between a knowledge-based economy and GDP growth in the EU-28 NUTS2 regions (Fernández-Zubieta et al., 2010).

Following our investigation into the relationship between knowledge-based economies and GDP growth within the EU-28 NUTS 2 regions, the study progresses to a more focused objective: assessing the interconnections between Research and Development (R&D) expenditure and real GDP per capita within the European Union. This phase of the research is critical, as it seeks to quantify the impact of R&D investments on economic performance, providing insights that are particularly relevant in the context of the EU's innovation-driven policy agenda.

4.3. Methodological Framework and Data Selection: R&D expenditure and real GDP per capita within the European Union

To expand upon the basis of this study in this chapter, a significant step forward was taken by focusing on the interconnections between R&D expenditure and real GDP per capita within the EU-27. This objective is driven by the recognition that investment in research and development (R&D) is a critical component of economic growth, particularly in the context of knowledge-based economies.

To achieve this objective, a quantitative study was conducted using secondary data from Eurostat and other publicly accessible sources. To comprehensively assess the impact of R&D expenditure on real GDP per capita in the EU-27, a panel data analysis was conducted spanning ten years from 2011 to 2020. To investigate the influence of R&D expenditure on economic development within the EU-27 in the R&D policy context, a range of dependent and independent variables was utilized, as detailed in Table 4.

Real GDP per capita was chosen as the dependent variable, serving as a key indicator of economic prosperity and allowing for meaningful comparisons across countries and over time. Our analytical framework incorporated a range of independent variables that represent various dimensions of R&D activity, including gross domestic expenditure on R&D, the number of R&D personnel, and the rate of patent applications. These variables were carefully selected to reflect the multifaceted nature of R&D and its potential to drive economic growth.

Furthermore, Table 4 provides a comprehensive summary of the descriptive statistics, offering crucial insights into the distribution, central tendencies, and variability of each variable in the dataset (Chattamvelli and Shanmugam, 2023). This preliminary analysis establishes a solid foundation for understanding the underlying characteristics of the data, highlighting key trends, potential outliers, and the overall behaviour of the variables under consideration in this chapter. By presenting these statistical summaries, Table 4 enables a clearer interpretation of the relationships between selected variables, setting the stage for a more nuanced and informed panel data analysis.

Table 4. Description of the variables considered in the analysis

Variables	Description	Mean	Median	Standard deviation	Min	Max
Dependent						
Real GDP per capita	Real GDP per capita is a metric that measures the economic productivity per individual within a given economy while accounting for the effects of inflation. It represents the total value of products and services produced in a country during a particular period (typically one year) divided by the population.	25632.5	20275	167578	5320	84750
Independent						
GERD	Gross domestic expenditure on research and development (GERD) is a statistical measure of the total amount of money spent on research and development activities within a country's domestic economy.	425.4	296	311.3	40.1	1110.1
Number of Doctorate graduates	The number of individuals who have completed a doctoral degree program in a given time, typically a year.	3787.1	1899	5983	22	29303
Researchers by sector of performance	Researchers are professionals who are involved in the invention or production of new knowledge, services, methods, and systems, as well as managing projects.	79145.7	39190	111178	1258	667394
R&D personnel, by sectors of performance	R&D personnel consists of all employees working directly on R&D as well as those providing direct services to R&D, such as managers, administrative personnel, and office staff.	126198.8	58237	182055	2133	1037952
Percentage of Population by educational attainment level	Population by educational attainment level is an individual who completed the highest International Standard Classification of Education (ISCED) level programme.	27.4	28.1	7.3	12.9	42.8
National public funding to transnationally coordinated R&D	National public funding to transnational R&D refers to government contributions (central, regional, local) supporting transnational R&D producers and programs. It includes funding for transnational performers, Europe-wide programs, and bilateral or multilateral R&D initiatives between Member States, candidate countries, and EFTA countries.	5.4	3.7	4.5	0.1	23.2
Business enterprise expenditure on R&D	Business enterprise expenditure on R&D (BERD) represents the part of GERD incurred by Business enterprise sector entities. It is the measurement of intramural R&D expenditures in the business sector during a specific time period.	269.2	169.6	224.5	12.3	801.7
Government budget allocations for R&D (GBARD)	Government budget allocations for R&D (GBARD) are all allocations distributed to R&D by the federal, state, and local governments. Consequently, they refer to budget provisions and not actual expenditures.	137.9	115.7	89.3	18.5	370.2
Patent applications to the EPO by priority year	The number of exclusive rights awarded for an innovation, which is a product or procedure that offers a new way of doing something or a new technological solution to a problem.	86.6	30.19	99.6	0.8	350.4
Research and Innovation (R&I) projects Total cost per head	EU funded R&I projects total cost.	22.4	17.44	18.5	1.04	110.9

Note: Data was sourced from Eurostat (2023).

As in previous chapters, this section of the study begins with a correlation analysis to explore potential positive correlations between R&D expenditure and selected independent variables across the EU-27 (equation (1)). This initial step mirrors the earlier approach and provides a foundational understanding of the relationships within the dataset. By identifying basic correlations, a groundwork is established for more advanced statistical modeling. Building on this, multiple linear regression models were applied to rigorously investigate the hypothesized relationship between increased R&D investment and subsequent economic growth at the country level, enabling a deeper examination of the economic impact of R&D activities across the EU-27 (Soete et al., 2022).

Following the same methodology applied in previous chapters, Fixed Effects (FE) and Random Effects (RE) models were utilized on a balanced panel dataset (equations (5) and (6)) (Bell et al., 2019). These models were selected for their ability to capture both entity-specific and time-specific effects, which are crucial for understanding the nuanced impact of R&D expenditure across different countries and time periods. To estimate the regression coefficients, Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS) techniques were employed, particularly useful for addressing potential endogeneity issues.

To ensure coherence with previous chapters and enhance comprehension, a log-log linear regression model is utilized once again. This approach was chosen deliberately for its ability to interpret regression coefficients as elasticities as shown earlier in equation (2). In this model:y_i – is a dependent variable (Real GDP per capita); x_i – independent variables; γ_j – entities fixed or random effects; n – number of dependent variables; m – number of entities (countries); β_0, β_i – regression coefficients; ε_i – error term. This model provides valuable insights into the percentage change in real GDP per capita resulting from a one percent increase in R&D expenditure. This method offers a straightforward and intuitive understanding of the relationship between R&D investment and economic growth, making it an ideal choice for the analysis.

This section of the study also investigated the complex challenges posed by multicollinearity and endogeneity. Considering this empirical challenge, a deliberate and rigorous analytical approach was undertaken to enhance the methodological strength of the investigation. Therefore, the issue of collinearity was addressed by excluding some independent variables based on the VIF (Akinwande et al., 2015). At the same time, it is expected that patterns in the data used for inference will be equivalent to the patterns in the dataset used in this research, therefore the multicollinearity will have little impact on the output of the model. All of these factors will enable us to examine the impact of our factors on EU-27 countries in different stages of development.

The independent variables are derived from a survey covering various fields within a country, which may give rise to issues of endogeneity or measurement error. Taking advantage of the instrumental variables (IV) approach, specifically the two-stage least squares approach (Greene, 2008), can solve this issue. Using this approach, two models are estimated (equation (3) and equation (4)): Where z_j – instrumental variables; θ_j – regression coefficients; v_i – error term. Equation (4) contains fitted values of the dependent variable from equation (3). In this model specification, independent variables from the study dataset can be used as instruments. The estimated value of the coefficient $\beta 1$ is used to test the hypothesis.

The first stage of the model regressed the potentially endogenous variable (GERD) on a set of instruments (number of doctorate graduates, researchers by sector of performance, R&D personnel, by sectors of performance, percentage of population by educational attainment level, national public funding to transnationally coordinated R&D, business enterprise expenditure on R&D, government budget allocations for R&D (GBARD), patent applications, and research and innovation (R&I) projects total cost per head) in log-log form, and the second stage used the predicted values from the first stage to estimate the relationship between R&D expenditure and real GDP per capita. This method allowed us to isolate the exogenous variation in R&D expenditure and obtain unbiased estimates of its impact on economic growth.

By extending the research to explore the relationship between R&D expenditure and real GDP per capita within the EU-27, the scope of the analysis has been significantly broadened. This phase of the study reinforces the importance of R&D investment as a driver of economic growth and provides nuanced insights into how these investments play out across different stages of development within the EU. Our findings have important implications for policymakers, particularly in the context of the EU's ongoing efforts to foster innovation and economic resilience through targeted R&D policies.

Overall, this comprehensive analysis of R&D expenditure within the EU-27 contributes to a deeper understanding of the complex interplay between innovation, economic policy, and growth. It underscores the critical role of sustained investment in R&D as a cornerstone of economic development in the knowledge-driven economies of the 21st century.

4.4. Methodological Framework and Data Selection: Government policies and business R&D expenditure in OECD countries

Continuing from our previous stages, the next phase of our study adopted a multi-stage research design, allowing us to explore the nuanced interconnections between government policies and business R&D expenditure across a diverse set of OECD countries. This phase was crucial in providing a broader understanding of how different government interventions can influence private sector R&D investments, thereby contributing to overall economic growth.

The data was sourced from the OECD, encompassing a comprehensive panel dataset of 33 member countries over a 15-year period from 2005 to 2019. The chosen timeframe was deliberate, ensuring data comparability across nations while accounting for shifts in economic policies and global economic conditions. This period also provides a sufficiently broad window to analyse the evolution of government policies and their impact on business R&D expenditure, which is expressed in per capita terms to facilitate meaningful cross-country comparisons.

In this stage, dependent variable was Business Enterprise R&D Expenditure (BERD) per capita, measured in constant 2015 US dollars and adjusted for purchasing power parity (PPP). This variable reflects the level of private sector investment in R&D within each nation, clearly indicating the private sector's commitment to innovation and development. Our independent variables included government budget allocations for R&D, indirect government support through R&D tax incentives, Foreign Direct Investment (FDI) per capita, and R&D personnel per capita. These variables (Table 5) were selected for their relevance in capturing the multifaceted nature of government support for R&D and its potential to stimulate private sector investment.

The first step in our analytical process involved conducting descriptive statistics (Table 5) to gain a foundational understanding of the data distribution and characteristics of each variable. This analysis revealed significant variations in government support for R&D, particularly through indirect means such as tax incentives. The wide range observed in FDI engagement across countries further highlighted the disparities (-0.05889 min, 0.22437max) in how different nations attract and leverage foreign investment for R&D activities. These initial insights were critical in setting the stage for more detailed statistical analysis.

Table 5. Research Variables

Dependent Variable					
Variable	**Description**	**Mean**	**Median**	**Min**	**Max**
Business enterprise R&D expenditure (BERD) (per capita)	BERD captures the financial resources allocated by the business and private non-profit sector towards Research and Development (R&D) activities, expressed in constant 2015 US dollars and adjusted for purchasing power parity (PPP) to facilitate cross-country comparisons. Essentially, BERD (per capita) reflects the level of private sector investment in R&D within a nation.	0.00030	0.00007	0.00000	0.02646
Independent Variables					
Government budget allocations for R&D (per capita)	This variable is a quantitative measure of a government's commitment to research and development (R&D) activities within a nation. It reflects the financial resources, expressed as a per capita value, a government dedicates to support R&D endeavours.	0.00044	0.00035	0.00000	0.00155
Indirect government support through R&D tax incentives (per capita)	Indirect government support through R&D tax incentives means that the government encourages businesses to invest in research and development (R&D) activities by offering tax benefits, rather than directly giving them money.	0.38950	0.00001	0.00000	20.59946
Foreign Direct Investment (FDI) (per capita)	FDI refers to investment made by a resident of one economy into a business enterprise in another economy, establishing a lasting interest and exerting significant influence over the foreign business.	0.00313	0.00049	-0.05889	0.22437
R&D personnel (per capita)	R&D personnel are the people employed in Research and Development activities. They can encompass a wide range of roles depending on the specific industry and research focus.	0.00532	0.00558	0.00000	0.01124

Note: Data was sourced from OECD (2023) Authors' calculation

Following the descriptive analysis, a correlation analysis was conducted to assess the strength and direction of the linear relationships between the independent variables. Given the potential for multicollinearity, where independent variables are highly correlated and may distort regression results, Variance Inflation Factor (VIF) analysis was employed (Galvão & De Araújo, 2009). This step was essential in identifying and mitigating any multicollinearity issues, ensuring the robustness and reliability of our subsequent regression model.

Initially, both fixed-effects and random-effects models were considered, depending on the nature of the data and research question. However, during the regression analysis, the potential issue of multicollinearity was encountered, identified through correlation analysis. Highly correlated independent variables can lead to unreliable estimates and hinder model interpretability.

To address this issue and possible concerns about endogeneity, the instrumental variables (IV) approach was investigated, leveraging exogenous variables to obtain consistent coefficients in regression models. This approach involves estimating a two-stage least squares (2SLS) technique, a widely used IV estimation method. Using this approach, the same models as those in previous chapters were estimated: Where z_j – instrumental variables; θ_j – regression coefficients; v_i – error term. Equation (4) contains fitted values of the dependent variable from equation (3).

Despite these considerations, the multiple linear regression model was chosen as the primary approach in this study. While some correlations existed between the independent variables, they were not severe enough to significantly bias the estimates. This eliminated the need for complex instrumental variables (IV) or two-stage least squares (2SLS) techniques designed to address severe multicollinearity. To strengthen this assumption, a diagnostic test was conducted, including the Wu-Hausman test (Patrick, 2020), to assess the presence of endogeneity in regression models.

Although IV and 2SLS can account for more complex relationships, their estimation process can be intricate and may introduce additional uncertainties into the results. In our case, the multiple linear regression model provided a reliable framework for analysis without the potential drawbacks of more intricate methods. Additionally, multiple linear regression offers a balance of relative simplicity and robustness (Greene, 2003).

By implementing this multi-stage approach, the initial goal was to understand the data, identify potential issues like multicollinearity, and then employ appropriate techniques to obtain reliable estimates of the relationships between the variables of interest.

Limitations of this study include potential data gaps and variations in data quality across countries, given the inherent complexities of economic factors that may influence the relationship between government R&D funding and private R&D expenditure. Comparisons across different country groups were considered to strengthen the analysis and explore potential variations. These groups included all OECD countries in the sample, EU-15 countries, newly joined EU countries, other European countries not in the EU, and non-European OECD countries (Table 6).

Table 6. OECD country groups

All OECD countries in the sample	EU-15	Newly joined EU countries	Other European countries not in the EU, and non-European OECD countries
Australia	Austria	Czech Republic	Australia
Austria	Belgium	Estonia	Canada
Belgium	Denmark	Hungary	Iceland
Canada	Finland	Latvia	Japan
Czech Republic	France	Lithuania	Korea
Denmark	Germany	Poland	New Zealand
Estonia	Greece	Slovak Republic	Norway
Finland	Ireland	Slovenia	Switzerland
France	Italy		Türkiye
Germany	Luxembourg		United States
Greece	Netherlands		
Hungary	Portugal		
Iceland	Spain		
Ireland	Sweden		
Italy	United Kingdom		
Japan			
Korea			
Latvia			
Lithuania			
Luxembourg			
Netherlands			
New Zealand			
Norway			
Poland			
Portugal			
Slovak Republic			
Slovenia			
Spain			
Sweden			
Switzerland			
Türkiye			
United Kingdom			
United States			

Note: Data was sourced from OECD (2024)

By implementing this multi-stage approach, our study systematically investigated the relationships between government policies and business R&D expenditure across OECD countries. Therefore, the findings of this section will provide valuable insights into how different forms of government support whether through direct budget allocations, tax incentives, or other measures can effectively stimulate private sector investment in R&D. These insights are crucial for policymakers aiming to design interventions that promote innovation and economic growth in an increasingly competitive global landscape.

4.5. Methodological Framework and Data Selection: Innovation in Agriculture

Building on our previous analyses of R&D expenditure and its impact on economic growth, our study now focuses on exploring the relationship between agricultural innovation and economic development within the EU. This research phase is particularly relevant given agriculture's critical role in the economies of many EU member states and the increasing emphasis on innovation as a driver of sustainable agricultural practices and economic growth.

This section of the study employed a quantitative research design to investigate the relationship between agricultural innovation and economic development within the EU from 2000 to 2019. A cross-sectional analysis used secondary data from reputable sources such as Eurostat, the World Bank, and the European Commission.

Data collection focused on gathering variables reflecting agricultural innovation and economic development across EU member states (Table 7).

The dependent variable, agricultural productivity, is represented by Total crops output (€/ha). Agricultural innovation is measured using a composite index that includes indicators such as R&D expenditure in agriculture and the export value of agricultural products. These indicators will be aggregated to form an innovation score for each country. Therefore, the key independent variable is R&D expenditure in agriculture per hectare. To control for other factors influencing agricultural productivity, additional variables such as population density (inhabit/km^2), trade balance per hectare, CO_2 emissions per hectare, real factor income in agriculture per annual work unit (chain-linked volumes), and subsidies per hectare will be included in the model.

Table 7. Variables and expected effects

Variables	Variable Expected Effects	Source
Dependent		
Total crops output (per/ha)	Total Crops Output (per/ha) is expected to serve as a key indicator of agricultural productivity, reflecting the combined influence of innovation, economic conditions, and external factors.	Farm accountancy data network- European Commission, 2024
Independent		
R&D expenditure in agriculture (per ha)	As the main independent variable, a positive relationship is expected between R&D expenditure and total crops output. Increased investment in R&D should lead to improved technologies, farming practices, and innovations that boost productivity.	Eurostat, 2024
Control		
Population density (Ihab/km2)	Higher population density might positively affect productivity through improved infrastructure, market access, and labor availability. However, it could also lead to negative effects if it results in land overuse or environmental degradation. Therefore, a neutral to moderate positive relationship is expected, depending on the context of the country.	The World Bank, 2024
Trade Balance (per ha)	A positive trade balance in agriculture might signal higher exports and competitiveness, which could reflect greater productivity. Therefore, a positive relationship is expected between trade balance per hectare and agricultural productivity.	Farm accountancy data network-European Commission, 2024
Co2 Emissions (per ha)	This variable could negatively affect agricultural productivity if high emissions are associated with unsustainable farming practices. Conversely, emissions might reflect the intensity of agricultural activities, potentially linked to high-output farming techniques. The expected relationship could be context-specific, with higher emissions possibly indicating lower productivity in sustainable contexts.	The World Bank, 2024
Real factor income in agriculture (per annual work)	Higher real factor income suggests that the agricultural sector is generating more value relative to labor input, which should correlate with higher productivity. A positive relationship is expected between income and agricultural productivity.	Eurostat, 2024
Subsidies (per ha)	Agricultural subsidies are often aimed at increasing productivity by providing farmers with financial resources to invest in new technologies or inputs. Therefore, a positive relationship is expected between subsidies per hectare and productivity, although this could depend on the type and targeting of the subsidies.	Farm accountancy data network- European Commission, 2024

One of the analytical methods this study uses is multiple regression analysis in a log-log form (Greene, 2003). The Ordinary Least Squares (OLS) approach was employed to ensure an accurate estimate of regression coefficients (Oksanen, 1991). This approach was chosen due to its ability to capture the elasticity between the dependent and independent variables, thereby providing insights into the percentage change in economic development resulting from a one-percent change in agricultural innovation. The model also includes control variables to account for other factors that might influence economic development.

$$lny_i = \beta_0 + \sum_{j=1}^{n} \beta_j lnx_{ij} + \sum_{k=1}^{m} \gamma_k lnc_{ik} + \delta_i + \tau_i + \varepsilon_i \tag{7}$$

Where y_i – dependent variable (total crops output (€/ha)) for country i; x_{ij} – independent variables for country i with j indexing the different independent variables; c_{ik}- control variables country i with k indexing the different independent variables; β_0, β_i – regression coefficients; δ_i - entities fixed or random effects; n – number of independent variables; m – number of control variables; ε_i – error term.

This model specification allows for the interpretation of coefficients as elasticities, which is particularly useful in understanding the proportional impact of changes in agricultural innovation on economic development.

Before estimation, diagnostic tests were conducted to ensure the model's suitability. These tests include checking for multicollinearity using Variance Inflation Factor (VIF) analysis (Marcoulides & Raykov, 2009).

By using both random effects (RE) and fixed effects (FE) models, the analysis aimed to account for different potential sources of bias and test the consistency of the results (Bell et al., 2019). The choice of these models was further validated through the Hausman test (Hasman, 1978; Deutsch, 2012), which helped determine whether the random effects or fixed effects model is appropriate.

Additionally, to address potential endogeneity issues, instrumental variable (IV) techniques were considered. This approach involves estimating a two-stage least squares (2SLS) technique, a widely used IV estimation method. Therefore, as the first step in the 2SLS method, R&D expenditure in agriculture was regressed on four instrumental variables: population density, CO_2 emissions, real factor income, and subsidies. This approach allowed us to account for the influence of these external factors and mitigate potential endogeneity concerns, ensuring a more accurate assessment of the relationship between R&D expenditure and agricultural productivity. Based on these findings, CO_2 emissions were excluded from the final list of instruments, as it was found to be insignificant in the first stage. This adjustment improves the accuracy and reliability of the model, ensuring that the remaining instruments offer a stronger and more robust explanation of the relationships between the selected variables.

After estimating the models, in equation (3), z_j – represents instrumental variables (population density, real factor income in agriculture, CO2 emissions, and subsidies); θ_j – regression coefficients; ν_i – error term. These instruments, backed by theoretical justification, contribute to the novelty of the instrumentalization, offering a more reliable approach to addressing potential biases arising from omitted variables and measurement errors.

Equation (4) contains fitted values of the dependent variable from equation (2). In this model specification, independent variables from the study dataset can be used as instruments. The estimated value of the coefficient $\beta 1$ is used to test the hypothesis, evaluating whether (instrumented through z_j) has a substantial effect on y_i. Specifically, by estimating $\beta 1$, it was tested whether x_1 has a substantially affects on y_i . Significant results, indicated by the p-value, would confirm this relationship.

To strengthen the assumptions, diagnostic tests were conducted, including the weak instruments, Wu-Hausman, and Sargan tests (Patrick, 2020), to assess the presence of endogeneity in regression models.

While this study aims to provide robust insights into the relationship between agricultural innovation and economic development in the EU, several limitations must be acknowledged. The cross-sectional structure of the data restricts the capacity to determine a causal relationship. Additionally, the availability and quality of data across different countries may vary, potentially affecting the reliability of the findings. Despite these limitations, the study employs rigorous methods and comprehensive data sources to ensure the validity of the results.

In summary, this study employs a rigorous quantitative methodology to investigate the impact of agricultural innovation on economic development within the EU. By utilizing a log-log multiple regression model and robust statistical techniques, the study aims to provide empirical evidence supporting the hypothesis that higher agricultural innovation leads to greater economic development.

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5. Results and discussion

5.1. Overview of key findings: GEI and GDP per capita

This section presents the key findings of our research, offering a thorough analysis of the various models utilised to unravel the intricate relationships between the selected variables central to our study. Through a systematic examination of these models, the aim is to elucidate the dynamic interactions that shape the core outcomes of the investigation. This analytical approach not only underscores the complexity of the variables at play but also provides a deeper understanding of their individual and collective influence within the context of the research.

As outlined in the methodology section, our study first analysed 98 countries, representing a diverse mix of developed and developing economies, from 2015 to 2019. This expansive timeframe allowed us to capture various economic conditions and trajectories, providing a robust foundation for our analysis. The models employed were carefully designed to reflect the nuances and complexities inherent in this global cohort, offering insights that are both broad in scope and deep in detail.

By examining such a diverse set of countries, our study was able to explore the varied pathways through which entrepreneurship, innovation, infrastructure, and education contribute to economic development. This broad-based approach not only enhances the generalisability of our findings but also enables us to draw nuanced conclusions that are relevant across different economic contexts. The results presented in the following sections are a testament to the richness of the data and the methodological rigour applied in analysing these multifaceted relationships.

As the findings of this study are examined, it is important to underscore the intricate web of relationships uncovered among the key variables. The correlation matrix (Table 8) serves as a pivotal starting point, revealing notable connections illuminating how various factors influence GDP per capita and entrepreneurial indices across selected countries.

Table 8. Correlation matrix for the year 2015-2019

	GDP Per capita	GEI	Infrastructure	Health and Primary Education	High education and trainings	Market Size	Business Sophistication	Innovation
GDP Per capita	1	0,809***	0.068	0.059	0.078	0.035	0.06	0.116
GEI	0.809 ***	1	0.061	0.046	0.073	0.031	0.05	0.123
Infrastructure	0.068	0.061	1	0.978***	0.979***	0.954***	0.975***	0.954***
Health and Primary Education	0.059	0.046	0.978***	1	0.987***	0.949***	0.982***	0.953***
High education and trainings	0.078	0.073	0.979***	0.987***	1	0.948***	0.989***	0.968***
Market Size	0.035	0.031	0.954***	0949***	0.948***	1	0.962***	0.940***
Business Sophistication	0.06	0.05	0.975***	0.982***	0.989***	0.962***	1	0.962***
Innovation	0.116	0.123	0.954***	0.953***	0.968***	0.940***	0.962***	1

Significant codes: p < 0.1* , p < 0.05**, p < 0.01***

Note: Data was sourced from GEI Report 2015–2019; GCI Report 2015–2019; World Bank 2015–2019. Own calculations in R-studio

The matrix highlights the significant positive correlation between GDP per capita and the Global Entrepreneurship Index (GEI), which is particularly striking with a coefficient of 0.809. This strong relationship underscores the vital role that entrepreneurship plays in driving economic prosperity. It suggests that countries fostering a robust entrepreneurial environment tend to experience higher levels of economic development, a finding that aligns well with existing economic theories that emphasise the importance of innovation and enterprise as catalysts for growth.

Beyond this, the correlation matrix reveals other intriguing patterns. For instance, infrastructure, health and primary education, and higher education and training are not only closely linked with each other, exhibiting near-perfect correlations, but they also collectively contribute to the broader economic environment in which entrepreneurship flourishes. The interdependency among these variables might suggest that a country's success in fostering economic growth is not solely dependent on any single factor but rather on a well-coordinated development of multiple pillars, including education, infrastructure, and market sophistication.

Moreover, the relationships between business sophistication, market size, and innovation, all of which show strong correlations with each other, suggest that larger, more sophisticated markets are often more conducive to innovation. This reinforces the idea that economic development is a multifaceted process, where enhancing one aspect of the economy, such as market size, can have cascading effects that bolster other areas, like business sophistication and innovative capacity.

These correlations, while offering valuable insights, are just the beginning of a more detailed exploration. They set the stage for the subsequent regression analyses, where these relationships are further dissected to understand the specific impact of each variable on economic outcomes. Moving beyond simple correlations to more complex models provide a better understanding of the causal pathways that link entrepreneurship, infrastructure, education, and other critical factors to GDP per capita.

In summary, the correlation matrix provides a snapshot of the interconnectedness of the variables under study, revealing both expected and novel relationships that are essential for understanding the dynamics of economic development. These findings lay the groundwork for the deeper analyses that follow, where we aim to untangle these complex relationships and offer more nuanced insights into the mechanisms driving economic growth in different contexts.

Before advancing to a deeper analysis and subjecting our models to rigorous testing, it was essential to carefully consider the nature of the Global Entrepreneurship Index (GEI). The GEI, as highlighted by previous studies (GEDI, 2018; Szerb et al., 2018; Kremer, 2019), captures a broad spectrum of factors, encompassing both individual and institutional aspects of innovation—specifically product and process innovation. Given this dual nature, we recognised the potential for overlap and redundancy when including an independent variable specifically for innovation. Thus, to ensure the accuracy and reliability of our findings, we made the strategic decision to omit the independent variable "innovation" from our analysis. This decision allowed us to avoid potential multicollinearity and other statistical inaccuracies that could compromise the validity of our findings.

With this refinement in the model structure, the cross-sectional models for each year within the study period (2015-2019) were estimated. These models, represented in Table 9, were estimated log-log. This approach allows for a more straightforward interpretation of the coefficients as elasticities and enables us to better capture the proportional relationships between the variables under study. In a log-log model, the estimated coefficients can be interpreted as the percentage change in the dependent variable (GDP per capita) resulting from a one-percent change in the independent variables, providing us with a nuanced understanding of these relationships.

The results of these estimations revealed some noteworthy insights. Across all the countries included in our analysis, certain independent variables consistently showed a significant impact on GDP per capita. Notably, the GEI, infrastructure, and market size emerged as crucial drivers of economic growth, demonstrating statistically significant coefficients throughout the study period. These findings underscore the importance of a strong entrepreneurial ecosystem, robust infrastructure, and a sizable market in fostering economic prosperity.

However, not all variables demonstrated the same significance level across the board. Health and primary education, as well as higher education and training, were statistically insignificant throughout the entire period. This result is intriguing and suggests that the impact of educational variables on economic growth may not be uniform across all countries. The benefits of education may manifest differently depending on each country's specific economic, cultural, and institutional contexts. For instance, in some nations, the returns on investment in primary education may be lower due to high literacy and education levels, while in others, the quality of education may not yet be sufficient to drive significant economic gains.

As the data analysis delves deeper, it becomes evident that the dynamics of the coefficients exhibit notable fluctuations over time, reflecting the complex and evolving nature of economic development. Throughout the study period, subtle coefficient shifts are observed, particularly after 2017. These shifts provide valuable insights into the temporal influence of various factors on economic growth.

Specifically, the Global Entrepreneurship Index (GEI) estimates that as an independent variable, it consistently demonstrated a positive and highly significant impact on GDP per capita (measured in constant 2010 USD) across the entire sample of countries each year. This finding resonates with the conclusions drawn by other scholars in the field (Aparicio, 2017; Guerrero et al., 2020). However, an intriguing trend emerges: the ratio began to decline after 2016, hitting a low of 0.260 in 2017, before gradually rising again to 1.095 in 2019. This pattern suggests that the benefits of entrepreneurial activity on economic development do not manifest instantaneously but rather accumulate over time, reinforcing the necessity of long-term strategies that foster entrepreneurship.

The percentage change in the coefficient for infrastructure further underscores the temporal evolution of economic drivers. Between 2015 and 2017, the infrastructure coefficient remained positive and statistically significant, affirming its critical role in supporting economic growth during the early stages of development. Despite a decrease in 2018, where it fell to 0.509, it maintained its statistical significance, signalling that infrastructure investments continue to contribute meaningfully to economic progress, even as the economy matures. However, by 2019, the coefficients turned negative and statistically insignificant, perhaps indicating that the marginal returns on infrastructure investments diminish over time as other factors become more influential.

The analysis of health and primary education coefficients reveals a similar temporal shift. In the early years of the study, specifically from 2015 to 2017, these coefficients were negative and statistically insignificant, suggesting a limited direct impact on GDP per capita during that period. However, starting in 2018, the scenario began to change, with the ratio showing a marked increase of 67% by 2019. This rise indicates that health and primary education may be emerging as significant contributors to economic growth, particularly as countries enhance their investments in these areas.

When examining the role of higher education and training, the results reveal year-to-year variations, culminating in a significant peak in 2019, with a coefficient of 0.644—the highest observed in the entire study period. This trend could be interpreted as a growing recognition among countries of the critical importance of higher education and training in driving long-term economic prosperity. As a result, nations appear to be ramping up their investments in these sectors, anticipating a substantial positive impact on GDP per capita.

Market size, on the other hand, displayed an interesting trajectory. Except for 2019, it never exhibited a statistically significant impact on GDP per capita. Nonetheless, the ratio remained positive throughout the period, with a notable 26% increase in 2019 compared to 2018. This suggests that expanding market size may play an increasingly important role in economic growth, particularly as countries continue to integrate into the global economy and seek to enhance their market reach.

The analysis of business sophistication reveals a more volatile pattern. The coefficients for this variable began to grow steadily starting in 2017, yet experienced a sharp decline in 2019, eventually turning negative and statistically significant. This volatility may reflect the challenges and complexities associated with advancing business sophistication, particularly in a rapidly changing global economic environment. Nevertheless, it is posited that continued investments in this area are likely to yield long-term benefits, propelling selected countries towards sustained economic progress.

When synthesising these findings, it becomes clear that stimulating key sectors such as health and primary education, higher education and training, market size, and business sophistication is essential for achieving robust economic growth. The evidence suggests that countries that had invested more heavily in these areas from the outset would likely have realised faster improvements in GDP per capita. Ultimately, the analysis underscores the dual importance of both short-term and long-term investments in these critical sectors, as they collectively exert a significant influence on a nation's economic trajectory.

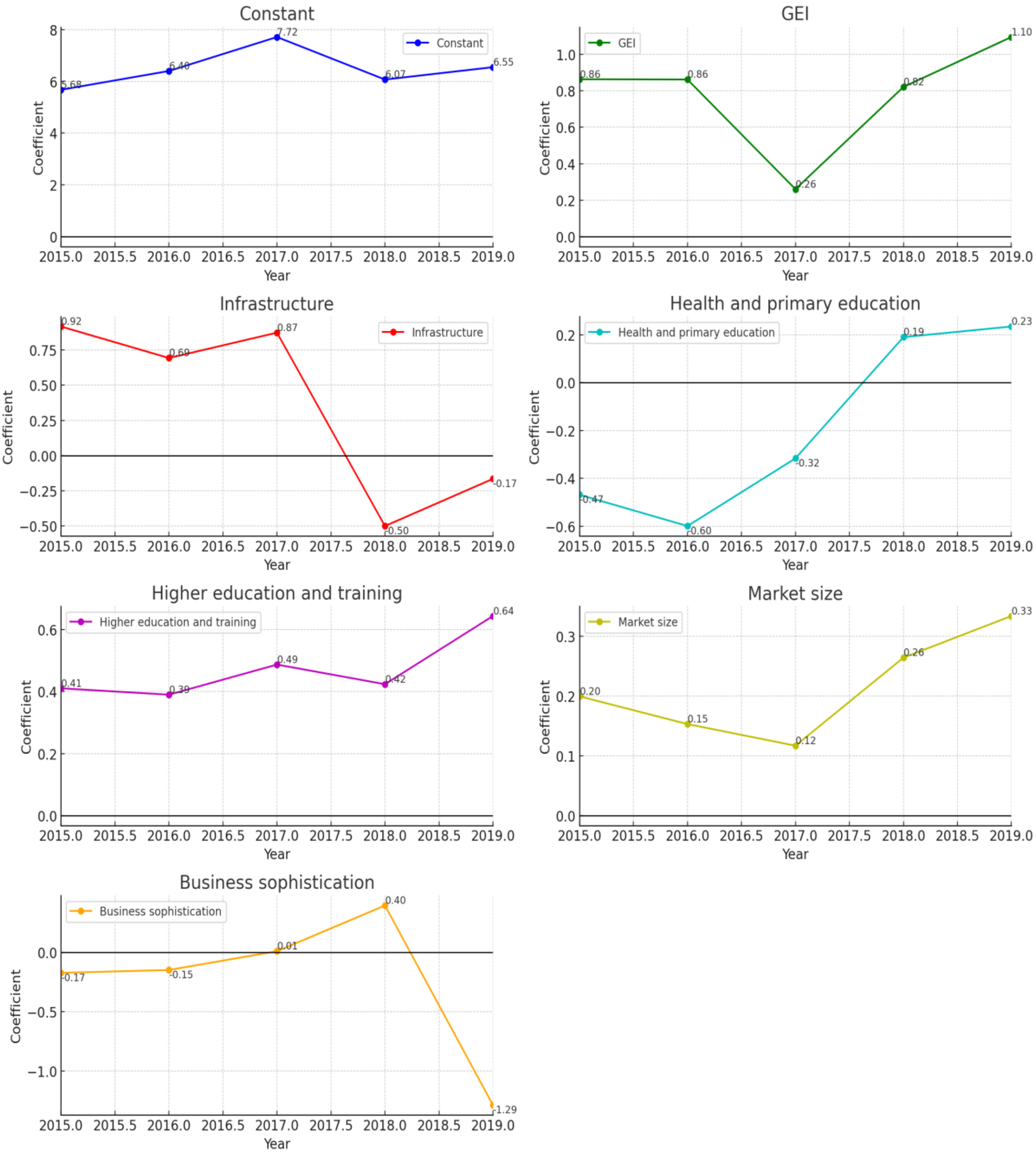
Table 9. Cross-sectional model (OLS) coefficient estimations, dependent variable: GDP per capita

	2015	2016	2017	2018	2019
	Constant				
Coefficient	5.67732	6.40475	7.71894	6.07401	6.55182
p-value	<0.0001***	<0.0001***	<0.0001***	<0.0001***	<0.0001***
	GEI				
Coefficient	0.863549	0.862178	0.259984	0.821288	1.0954
p-value	0.0012***	0.0006***	0.0827*	0.0003***	<0.0001***
	Infrastructure				
Coefficient	0.917319	0.69329	0.87359	−0.500908	−0.165489
p-value	0.0397**	<0.0001***	0.0469**	0.0018***	0.3832
	Health and primary education				
Coefficient	−0.468438	−0.599172	−0.316416	0.190103	0.234469
p-value	0.3751	0.1864	0.5545	0.7081	0.465
	Higher education and training				
Coefficient	0.410751	0.390164	0.487401	0.424038	0.644244
p-value	0.4266	0.3995	0.367	0.4238	0.118
	Market size				
Coefficient	0.19943	0.153022	0.116835	0.264169	0.333875
p-value	0.3049	0.3712	0.5522	0.1613	0.0515*
	Business sophistication				
Coefficient	−0.172075	−0.147765	0.0106365	0.396757	−1.28814
p-value	0.7801	0.7697	0.9868	0.5021	0.0125**
R-squared	0.922292	0.941605	0.917923	0.932145	0.930498
F (10, 87)	103.2579	140.2863	97.29865	119.5152	116.476
Adjusted R-squared	0.91336	0.934893	0.908489	0.924346	0.922509
P-value (F)	7.38E-44	3.20E-49	7.83E-43	2.11E-46	5.96E-46

Significant codes: $p < 0.1$* , $p < 0.05$**, $p < 0.01$***
Source: GEI Report 2015–2019; GCI Report 2015–2019; World Bank 2015–2019. Own calculations in R-studio

By illustrating the trends of selected variables on GDP per capita from 2015 to 2019, Figure 1 provides a more clear representation of the annual coefficients. A point on the trend line represents the estimated coefficient for each year, reflecting the relative impact of each indicator on GDP per capita over their respective time periods. This graphic displays variations in the intensity and direction of these correlations, allowing for a comparative analysis of how various economic variables impacted GDP per capita in each year of the selected time period.

Figure 1. Yearly Coefficient Trends of Economic Indicators on GDP Per Capita (2015–2019)



Source: GEI Report 2015–2019; GCI Report 2015–2019; World Bank 2015–2019. Own calculations

By refining the model to exclude potentially confounding variables and focusing on those with clear, consistent impacts, the goal was to provide a more accurate and context-sensitive analysis of the drivers of economic growth. The findings from Table 9 not only reinforce the importance of entrepreneurship, infrastructure, and market dynamics but also prompt a deeper exploration into the conditions under which education and health factors become significant. This nuanced approach allows us to understand the multifaceted nature of economic development better and provides valuable insights for tailoring policy interventions to the specific needs of different countries.

The Hausman test results served as a crucial turning point in our analysis, pointing to a significant difference between OLS estimates and consistent estimates raised concerns about the potential endogeneity of the model. This suggested that the entrepreneurship variable, as measured by GEI, may be influenced by GDP per capita in a way that could distort the true relationship between the two variables.

In response to this potential issue, the instrumental variables (IV) approach 2SLS was adopted, employing instrumental variables to address endogeneity concerns. This methodology proved superior to the previous models used in the study, offering a stronger explanatory framework and increased reliability in capturing the nuanced relationship between GEI and GDP per capita.

While the Sargan test raised some concerns about the validity of all instruments, the high F-statistic indicated that the instruments used in the model possessed sufficient explanatory power. This effectively mitigated concerns about instrument weakness. However, excluding the variable for higher education and training significantly improves the results of the Sargan over-identification test. Therefore, this variable was excluded from the list of instruments in the final model. This indicates that higher education is less associated with the GEI than other instruments. In other words, this suggests that health and primary education, infrastructure, and market size have a more significant link to the GEI and, by extension, to GDP per capita than higher education and training. It is also possible that these three instruments serve as prerequisites, while higher education only impacts the GEI in their presence. These aspects present interesting opportunities for further research. This finding is especially relevant for research that focuses on potential paths in which indicators of entrepreneurial activity impact economic development.

As a result of this methodological shift towards the IV 2SLS methodology, our analysis gained robustness, leading to a more convincing and academically grounded examination of the intricate relationship between entrepreneurship and GDP per capita. The outcomes from Model 2 (Table 10) further strengthened our confidence in the assertion that the IV 2SLS approach offers a more comprehensive and reliable means of unravelling the nuanced dynamics between these pivotal economic determinants.

Table 10. IV 2SLS model for the dependent variable GDP per capita (constant 2010 USD) (between estimator)

TSLS, using 490 observations				
Dependent variable: log of GDP per capita, in constant 2010 USD				
	Coefficient	**Std. error**	**t-ratio**	**p-value**
const	-1.62680	0.331827	- 4.903	<0.0001***
l_GEI	3.04050	0.0934421	32.54	<0.0001***
Mean dependent var	9.110937		S.D. dependent var	1.484236
Sum squared resid	289.5884		S.E. of regression	0.770337
R-squared	0.775729		Adjusted R-squared	0.775270
Chi-square (1)	1058.781		p-value	<0.0001***
Instruments	Infrastructure, health and primary education, and market size			
Hausman test				
Null hypothesis: OLS estimates are consistent				
Asymptotic test statistic: Chi-square (1) = 115.164, with p-value = <0.0001***				
Sargan over-identification test				
Null hypothesis: all instruments are valid				
Test statistic: LM = 1.68842 with p-value = P (Chi-square (3)> 1.68842) = 0.429897				
Weak instrument test - First-stage F-statistic (3, 486) = 155.189				

Significant codes: $p < 0.1$* , $p < 0.05$**, $p < 0.01$***
Source: GEI Report 2015–2019; GCI Report 2015–2019; World Bank 2015–2019. Own calculations in R-studio

This model shows a positive link between GEI and GDP per capita (constant 2010 USD). The coefficient equals approximately 3 (which means a 3% increase in GDP per capita when GEI increases by 1%). This model was estimated for all the selected countries. After conducting multiple analyses for selected countries and using all other variables instead of GEI as an independent variable, it was concluded that GDP per capita has a statistically significant relationship with GEI. In contrast, it does not exhibit such a relationship with any of the other examined variables. Models with other independent variables from the dataset (infrastructure, health and primary education, higher education and training, market size, and business sophistication) showed a significantly low level of R-squared and were excluded from the analysis. The fact that the effect of all other variables is already captured in GEI effectively explains our findings.

As part of the robustness checks, the addition of control variables was tested for the countries that demonstrated the highest errors after model fitting (Slovakia, India, and Hong Kong) and the baseline model (Table 12). As a result, the coefficient for GEI decreased to 2.47% (p-value < 0.0001). The direction of the effect stayed the same as in the baseline model, but the coefficients for control variables were not statistically significant. These findings confirm the outcomes of the baseline model while adding control variables with statistically insignificant coefficients. As a result, the baseline model was chosen as the main one.

Our analysis, which spans a diverse set of developed and developing countries, demonstrates that the relationship between GEI and GDP per capita holds consistently across different economic contexts. This is a critical insight, as it suggests that the impact of entrepreneurship on economic prosperity transcends national boundaries and developmental stages. The use of a pooled dataset allowed us to capture the variance between countries, providing a more holistic understanding of how improvements in entrepreneurial ecosystems contribute to economic outcomes on a global scale.

Interestingly, when GEI was replaced with other independent variables such as infrastructure, health and primary education, higher education and training, market size, and business sophistication, these variables failed to exhibit a statistically significant relationship with GDP per capita. Moreover, the models incorporating these variables yielded low R-squared values, indicating weak explanatory power. This contrast highlights GEI's unique and pivotal role as a composite measure of entrepreneurial activity. The fact that the influence of other variables appears to be subsumed within GEI underscores its comprehensive nature in capturing the multifaceted dimensions of entrepreneurship that drive economic growth.

The strength of the relationship between GEI and GDP per capita observed in our study aligns with and extends previous research findings. Other scholars have similarly documented the positive association between entrepreneurship and economic development (Aparicio, 2017; Doran et al., 2018; Guerrero et al., 2020). Our study builds on this existing literature by providing a more precise quantification of this relationship using the 2SLS method, thereby addressing potential endogeneity concerns that may have confounded earlier analyses.

However, it is crucial to acknowledge the distinction between correlation and causation. While our study confirms a strong association between GEI and GDP per capita, it does not definitively establish a causal link. The direction of influence—whether entrepreneurship drives economic growth or vice versa—remains an open question that warrants further investigation. This is a significant avenue for future research, which could employ longitudinal data or experimental designs to explore the causal mechanisms at play more rigorously.

Furthermore, the broader implications of our findings suggest that fostering entrepreneurial activities can serve as a critical foundation for enhancing a country's innovativeness and competitiveness. This interpretation is supported by hypotheses put forth by other scholars, who emphasise the role of entrepreneurship in catalysing economic dynamism and structural transformation (Naudé et al., 2011; Feki & Mnif, 2006; Farinha et al., 2018). The evidence from our study reinforces these views, suggesting that policies aimed at strengthening the entrepreneurial ecosystem through education, infrastructure, and market development might yield substantial economic dividends.

Following the initial results from the IV 2SLS model, a time trend was incorporated to account for any systematic temporal changes that could influence the outcome variable. By re-running the model with this adjustment, the aim was to enhance the accuracy and reliability of the estimates, ensuring that the observed relationships were not confounded by underlying time-based factors (Table 11). This model provides a more robust assessment of the impact of the independent variables, yielding results that better reflect their true effect on the dependent variable over the study period.

Table 11. Instrumental variable 2 stage-least-square model in log-log form. The model incorporates a time trend. Dependent variable GDP per capita

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-1.94476	0.33391	-5.824	1.04e-08 ***
log (GEI)	2.99831	0.08895	33.708	< 2e-16 ***
time_trend	0.15067	0.02376	6.340	5.24e-10 ***
Diagnostic tests				
	df1	df2	statistic	p-value
Weak instruments	3	485	160.376	<2e-16 ***
Wu-Hausman	1	486	116.978	<2e-16 ***
Sargan	2	NA	3.643	0.162
Instruments	Infrastructure, health and primary education, and market size			
Residual standard error	0.7357 on 487 degrees of freedom			
Multiple R-Squared	0.7461			
Adjusted R-squared	0.745			
Wald test	569 on 2 and 487 DF			
p-value	< 2.2e-16			

Significant codes: $p < 0.1$* , $p < 0.05$**, $p < 0.01$***
Source: GEI Report 2015–2019; GCI Report 2015–2019; World Bank 2015–2019. Own calculations in R-studio

The Global Entrepreneurship Index (GEI) coefficient suggests that a 1% increase in GEI correlates with approximately a 3% increase in GDP per capita. This is a considerable positive effect, demonstrating that entrepreneurial activity, as measured by GEI, has a strong and statistically significant impact on economic performance. The p-value for GEI is < 2e-16, representing a highly significant relationship. Thus, higher levels of entrepreneurship, as captured by GEI, are consistently associated with higher GDP per capita. This strong significance suggests that the increase in entrepreneurship leads directly to the rise in GDP per capita, and this relationship is unlikely to result from random variation.

The coefficient for the time trend variable (0.15067) reveals a positive time-related growth in GDP per capita, suggesting that GDP per capita increases by approximately 0.15% per year after controlling for the changes in entrepreneurship. This positive trend likely reflects other contributing factors to economic growth, such as technological advancements, population growth, or macroeconomic improvements not directly captured by GEI.

Diagnostic tests further strengthen these findings. The weak instruments test shows a statistic of 160.376 with a p-value < 2e-16, indicating that the instruments namely infrastructure, health and primary education, and market size are robust and effectively explain the endogenous variable, GEI. Additionally, the Sargan test results (p-value = 0.162) confirm that the instruments are valid, meaning they are not correlated with the error term, ensuring that the instruments used for GEI are appropriate and produce unbiased estimates.

The selection of 98 developed and developing countries contributes to the robustness and significance of these results. Developed and developing countries exhibit different levels of entrepreneurial activity, institutional support, and economic environments, and by including both, the model captures a wide spectrum of entrepreneurial ecosystems and their impacts on GDP per capita. In developing countries, entrepreneurship plays a critical role in driving economic growth due to their early stages of development. Small improvements in entrepreneurial activity, innovation, or ease of doing business can lead to significant GDP gains. On the other hand, in developed countries, entrepreneurship often drives high-tech innovation, productivity improvements, and advanced industries, contributing to economic growth despite already high levels of GDP per capita.

By incorporating both developed and developing countries, the results become more globally relevant. The significant relationship between entrepreneurship and GDP per capita suggests that this relationship holds across diverse economic contexts, underscoring the crucial role of entrepreneurship in fostering growth across different types of economies.

However, the fact that this analysis spans only five years (from 2015 to 2019) may also influence the observed positive and significant effect. Globally, the period from 2015 to 2019 was characterized by relative economic stability and recovery after the 2008 financial crisis, which created favourable conditions for entrepreneurship (Toarna & Cojanu, 2015). Many countries implemented pro-entrepreneurship policies during these years, such as promoting startups and fostering innovation, which may have amplified the positive impact of entrepreneurship on GDP per capita (OECD, 2020).

If the period were extended to include recessionary periods (e.g., during or after crises such as 2008 or 2020), the effect of entrepreneurship on GDP might not be as strongly positive. The limited time frame might capture only the early stages of entrepreneurial impacts, with a more noticeable effect during periods of stability. Additionally, the lag between entrepreneurial activity and its measurable impact on GDP per capita should be considered, as entrepreneurship may take several years to translate into economic growth. The analyzed five-year period may represent the initial stages of this process, while a longer time frame might reveal a more moderated effect once the early entrepreneurial impact is assimilated by the economy.

In summary, the results demonstrate a strong and statistically significant relationship between entrepreneurship and GDP per capita, with a positive time trend further contributing to economic growth. Including both developed and developing countries highlights the global relevance of entrepreneurship as a driver of economic performance. However, the relatively short time frame of five years and the specific period of global economic stability should be considered when interpreting the strength of these results. Longer-term studies may reveal more nuanced dynamics between entrepreneurship and GDP growth.

5.2. Overview of Key Findings: KBE and Regional Economic Performance

As this vital area of research continues to be explored, it becomes increasingly clear that entrepreneurship is not merely a consequence of economic prosperity but a driving force that can shape the future trajectory of nations.

Building upon the foundational analyses conducted earlier in this study, the next phase focusses on examining the hypotheses concerning the association between the development of a knowledge-based economy (KBE) and regional economic performance, specifically measured by gross domestic product (GDP) at the regional level.

To rigorously test the H2 and H3 hypotheses, both fixed effects (FE) and random effects (RE) regression analyses were employed. These models allow us to control for time-invariant and entity-specific factors that could potentially confound the relationship between our independent variables—measures of knowledge-based economy—and the dependent variable, regional GDP per capita.

In this stage of our analysis, the independent variables were expressed in their levels, making the interpretation of the coefficients less straightforward. To address this challenge and enhance the clarity of the results, the variables were transformed into their logarithmic forms, and the models were re-estimated in log-log form. This transformation allowed us to interpret the coefficient estimates as elasticities, providing more intuitive insights into the percentage change in GDP per capita resulting from a 1% change in the respective independent variable.

The estimates derived from the FE and RE models revealed several significant findings. Table 12 illustrates the findings of the FE model, which indicated that theGross Domestic Expenditure on Research and Development (GERD) emerged as a crucial driver of regional economic performance. The results demonstrated a positive and highly significant relationship between GERD and GDP per capita across the entire sample of regions for each year analysed. This finding aligns with the established literature on knowledge-based economies, which consistently highlights the pivotal role of R&D expenditure in fostering knowledge creation and, consequently, economic growth (Cameron, 2000; Miroshnychenko et al., 2020). This finding highlights the importance of expenditure in R&D for the selected regions. Several studies have addressed the significance of GERD; however, their analyses were conducted at the country level rather than the NUTS 2 region level (Veugelers & Mrak, 2009; Ejermo et al., 2011; Bak et al., 2022). It is reasonable to assume that such regional outcomes will have an impact on countries' overall outcomes.

R&D personnel is statistically significant for the FE (within) model only. According to the evidence presented in this chapter, the number of R&D personnel, the percentage of employment in education, and the ratio of the proportion of students over the proportion of the population have no significant influence on regional economic performance in the chosen areas. This partially contradicts studies highlighting the importance of human capital in knowledge economies (OECD, 1996; World Bank, 2022). It might be considered that the governments of the region's economies need to enhance investments in these sectors if they are to keep up with the advanced economies.

From Table 12, it can be seen that the employment in high-tech manufacturing and knowledge-intensive and high-technology services relationships are negative, though significant, and at a very low level of correlation for each model. Medium-tech manufacturing sectors are highly statistically significant for the FE and FE (within) models. Employment in the wholesale retail and trade sector is statistically significant for the FE (within) model only, while finance and insurance coefficients are statistically significant only for the FE and FE (within) models. Employment in the human health and social work activities sector has a positive and highly significant influence on GDP per capita (constant USD) at the level of the entire sample of countries for each year. This aligns with the understanding of KBEs as learning economies where a skilled workforce is essential (Sterlacchini, 2008). Additionally, this finding demonstrates how important health and social services are for the overall economic productivity of the EU (EC, 2014).

In the context of sectors that rely heavily on R&D and high technology, the model FE (reduced) offers insight into the correlation between sector-specific employment and economic results. Increasing R&D spending considerably improves the outcome variable, as shown in earlier models with a positive GERD coefficient of 0.530. This may be a reflection of the fact that investment in research encourages innovation and productivity in industries that prioritise technological progress. Higher employment in R&D corresponds with positive economic consequences, emphasising the role of skilled labour in encouraging sectors growth and innovation in NUTS 2 regions. This is further supported by R&D personnel, which has a positive correlation of 0.205.

Table 12. Random and fixed effects models

Dependent variable: log (GDP per_capita) panel linear				
	Model FE	Model RE	Model FE (within)	Model FE (reduced)
log(patents)	-0.007	0.002	-0.010	
	(0.023)	(0.003)	(0.009)	
log (GERD)	0.038	0.230***	0.050***	0.530
	(0.029)	(0.020)	(0.017)	
log(rd_personnel)	0.121	0.006	0.099**	0.205
	(0.075)	(0.027)	(0.039)	
log(high_tech_sectors)	0.177	0.095	0.081	
	(0.191)	(0.069)	(0.102)	
log(high_tech_man)	-0.145*	-0.046*	-0.082**	
	(0.073)	(0.027)	(0.040)	
log(med_tech_man)	0.077*	-0.007	0.061**	
	(0.042)	(0.030)	(0.024)	
log(wholesale_retail_trade)	0.111	-0.037	0.262***	
	(0.160)	(0.081)	(0.089)	
log(knowledge_intense_services)	0.374	0.675	0.028	
	(1.446)	(0.588)	(0.777)	
log(knowledge_intense_high_tech_services)	-0.428*	-0.157**	-0.274**	
	(0.251)	(0.072)	(0.126)	
log(knowledge_intense_market_services)	-0.153	0.037	-0.024	
	(0.281)	(0.105)	(0.149)	
log(knowledge_intense_other_serviees)	-0.965	-0.511	-0.569	
	(1.131)	(0.453)	(0.610)	
log(info_communication)	0.176	0.122**	0.163	-0.536
	(0.255)	(0.060)	(0.125)	
log(finance_and_insurance)	0.370***	-0.022	0.308***	
	(0.128)	(0.055)	(0.071)	
log(prof_scientifie_teeh_activities)	0.681***	0.114*	0.606***	
	(0.225)	(0.066)	(0.113)	
log(education)	0.050	-0.038	-0.039	
	(0.158)	(0.072)	(0.090)	
log(human_health_social_work)	1.052**	0.339**	0.992***	
	(0.158)	(0.072)	(0.084)	
log(proportion_students)	-0.005	-0.043	-0.016	
	(0.056)	(0.041)	(0.030)	
Constant	7.517***	6.925***		7.180
	(1.429)	(0.742)		
Observations	110	331	331	4
R2	0.919	0.960	0.899	1.000
Adjusted R2	0.904	0.958	0.893	
F Statistic	61.511***	654.784***	162.576***	
	(df =17; 92)		(df =17; 310)	

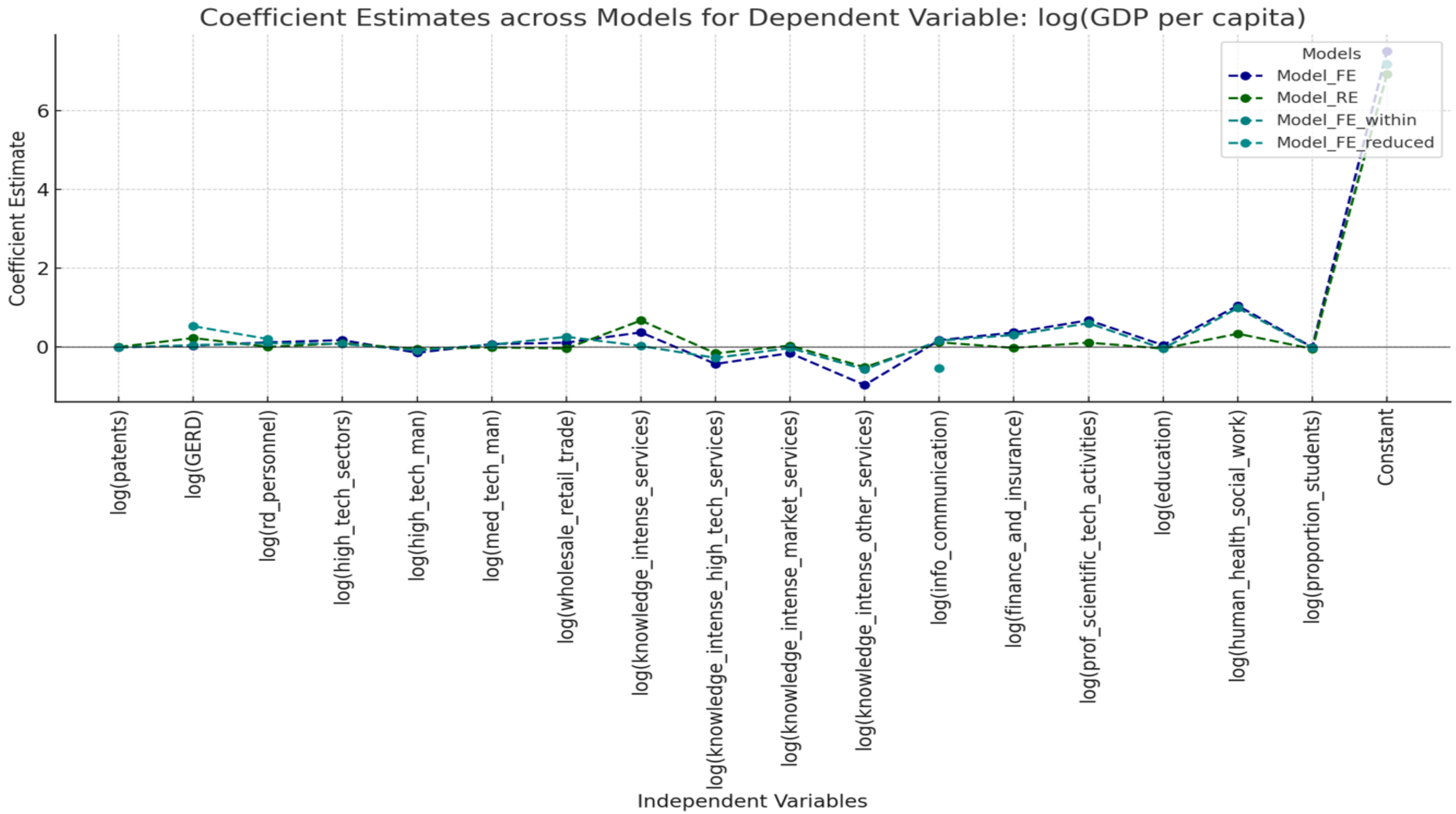
Significant codes: p < 0.1* , p < 0.05**, p < 0.01***
Source: Data was sourced from Eurostat (2022). Own calculations in R-studio

In contrast, employment in information and communication shows a negative coefficient (-0.536), indicating a potential adverse relationship between information and communication sector employment and the GDP per capita. Considering that investments and employment in information and communication are usually linked to increases in economic growth, this finding is rather interesting. The link between the two variables may be misleading because of the model's inherent complexity or because extensive use of information and communication does not always lead to the intended economic result. Concerns about overfitting arise from the model's perfect R^2 of 1, which indicates that it accounts for all variation in the dependent variable. This is particularly concerning considering the small sample size of 4 observations. The model may be too modified to this dataset, reducing its capacity to generalize, even if such a high R^2 seems optimal. In FE models, this is especially important since overfitting may occur with few observations, limiting the model's usefulness on larger datasets.

Overall, the model shows complicated dynamics in information and communication employment that need more study, but it also highlights the beneficial effects of R&D spending and employees in knowledge-intensive and high-tech industries in the selected regions. While these results add to our knowledge of the sector-specific employment and research investment drivers of economic success, they also show how important it is to interpret and validate these findings with caution when working with bigger datasets.

This figure 2 provides an insightful comparison of sectoral impacts on regional economic performance, emphasizing the importance of specific variables, such as R&D expenditure and knowledge-intensive sectors. By showing the stability across models, the figure aids in identifying which sectoral effects are most reliably associated with GDP per capita across the NUTS 2 regions.

Figure 2. Coefficient estimates across models



Source: Own calculations

As a next step, the analysis of the RE models (model RE, model RE (patents), model RE (students), model RE (patents, students)) was considered to determine whether it may help to extract more information from the data and distribute the variation in the model more effectively. These three models test the effect of the number of patents and the proportion of students in the population on regional GDP per capita. The table shows that various variables have a statistically significant effect on economic growth. Also, regional economic development seems increasingly dependent on GERD.

Table 13 demonstrated an interesting insight into the relationship between our variables. Similarly to previous models, GERD acts as a powerful driver, demonstrating a notably significant positive effect.

Model RE (patents) underscored the vital role of innovation—specifically, patent activity—as a key driver of economic growth. The positive and highly significant coefficient for the log of patents (0.205, $p<0.01$) unequivocally demonstrates that regions with higher levels of patent filings tend to enjoy higher GDP per capita. This finding resonates with the foundational theories of endogenous growth, where innovation, encapsulated through intellectual property like patents, is seen as a catalyst for economic expansion (Tekic et al., 2014). Among scholars, patents are recognized as an essential driver of economic development in a knowledge-based economy, and our findings match the results obtained by other experts (Tsakalerou, 2018).

Additionally, patents are more than mere legal protections; they symbolise the tangible outcomes of innovative processes (Thomson, 2013). The significant impact of patents on GDP per capita suggests that regions that actively engage in research and development (R&D) and successfully bring new ideas to the market are those that thrive economically. This model reinforces the argument that fostering a conducive environment for innovation through policies that support R&D, protect intellectual property, and incentivise commercialisation is critical for regional economic growth.

Table 13. Random effects model

	Model RE (patents)	Model RE (students)	Model RE (patents, students)	Model RE (reduced)
log(patents)	0.205***		0.203***	
	(0.011)		(0.013)	
log (GERD)				0.235***
				(0.014)
log(md_personnel)				
log(high_tech_sectors)				
log(high_tech_man)			-0.022*	
				(0.013)
log(med_tech_man)				
log(wholesale_retail_trade)				
log(knowledge_intense_services)				
log(knowledge_intense_high_tech_services)				
log(knowledge_intense_market_services)				
log(knowledge_intense_other_serviees)				
log(info_communication)			0.061	
				(0.020)
log(finance_and_insurance)				
log(prof_scientifie_teeh_activities)		0.151**		
				(0.027)
log(education)				
log(human_health_social_work)		0.323***		
				(0.034)
log(proportion_students)	0.295***	0.126***		
		(0.049)	(0.043)	
Constant	9.665***	9.994***	9.676***	7.557***
	(0.027)	(0.034)	(0.033)	(0.099)
Observations	753	712	618	519
R2	0.329	0.053	0.315	0.925
Adjusted R2	0.329	0.051	0.313	0.924
F Statistic	368.910***	36.506***	282.320***	763.738***

Significant codes: $p < 0.1$* , $p < 0.05$**, $p < 0.01$***
Source: Data was sourced from Eurostat (2022). Own calculations in R-studio

In Model RE (students), the focus shifts to the human capital dimension of the knowledge economy, specifically the proportion of students within the population. The model reveals a robust positive correlation between student proportions and GDP per capita (0.295, $p<0.01$), highlighting the essential role of education in economic development.

This finding is particularly significant in the context of a knowledge-based economy, where the ability to generate, absorb, and apply knowledge is paramount. A higher proportion of students suggests a region's strong commitment to education, which in turn translates into a more skilled and adaptable workforce. This workforce is better equipped to meet the demands of a rapidly changing economic landscape, driving innovation, productivity, and ultimately, economic growth.

The positive relationship observed here underscores the importance of investment in education—not just at the primary and secondary levels, but also in higher education and vocational training. Regions that prioritize educational attainment are likely to see long-term benefits in the form of sustained economic resilience and growth, as a well-educated populace is better positioned to engage in and contribute to knowledge-intensive industries.

Model RE (patents, students) offers a compelling synthesis of the interplay between innovation, represented by patent activity, and human capital, indicated by the proportion of students. The model provides a nuanced understanding of how these two critical elements interact to shape regional economic outcomes. The coefficient for patent activity (0.203, $p<0.01$) is not only statistically significant but also indicative of the powerful role that innovation plays in driving economic growth. This finding underscores the idea that regions with a strong capacity for generating patents—reflective of their innovation ecosystem—are better positioned to achieve robust economic performance. The significance of this coefficient highlights that innovation is not merely an isolated driver, but a critical component of a broader economic strategy that integrates human capital development.

Furthermore, the inclusion of the student proportion variable in the model reinforces the importance of an educated workforce in sustaining innovation-led growth. The collective potency of patents and human capital might suggest that regions excelling in both areas are likely to experience synergistic benefits, where the educated workforce enhances the innovation capacity, and vice versa. This interplay between human capital and innovation is central to the success of a knowledge-based economy, where the continuous development of skills and the generation of new ideas fuel sustained economic progress.

However, the model also reveals a complex dynamic when it comes to high-technology manufacturing. The statistically significant yet negative coefficient for employment in high-technology manufacturing suggests that, in the short term, increased employment in this sector may not immediately translate into positive economic outcomes. This finding could be interpreted in several ways. High-technology manufacturing often involves substantial initial investments, which might not yield immediate returns. Additionally, the transition to a high-tech economy may involve structural adjustments, where certain regions might initially experience disruptions before realizing the long-term benefits of such investments.

In the long run, however, it is reasonable to anticipate that sustained government investment in the high-technology manufacturing sector will eventually lead to economic growth. As noted by Naudé and Szirmai (2012) and Behun et al. (2018), the development of the manufacturing sector, particularly in high-tech industries, is crucial for long-term economic success. These sectors are often the engines of innovation, driving advancements in technology and productivity that are essential for sustaining economic competitiveness. Therefore, while the immediate impact of high-tech manufacturing employment might appear negative, this is likely a reflection of the initial costs and transitional challenges rather than a long-term trend.

The Model RE (reduced) provides a broader perspective by incorporating additional variables related to high-tech manufacturing, information and communication technology (ICT), and professional and scientific activities. Notably, the coefficient for Gross Domestic Expenditure on Research and Development (GERD) is positive and significant (0.235, $p<0.01$), reaffirming the critical role of R&D investment in economic growth. This finding is consistent with the view that R&D activities are a key driver of innovation, which in turn enhances productivity and economic output (Griliches, 1992).

The findings from these models collectively reinforce the hypothesis that the development of a knowledge-based economy is intricately linked to regional GDP per capita. The significance of patents, student proportions, GERD, and knowledge-intensive services highlights the multifaceted nature of economic growth in a knowledge-based economy.

After conducting a comprehensive analysis of various models and variable selection procedures, it became evident that the Random Effects (RE) models, particularly the RE model incorporating GERD (gross domestic expenditure on research and development) alongside other variables and the RE model focusing on significant variables, provided the most accurate representations of our data. Simultaneously, the results of the Fixed Effects (FE) model estimation were also considered. Although the Hausman test indicated a preference for the fixed effects model, the random effects model was reported due to its higher fit to the dataset. Notably, there was no significant difference in the magnitude and direction of effects reported by either model; both models included the same set of independent variables, and their coefficients did not differ considerably. This suggests that the choice of the model may not substantially impact the results; however, it remains crucial to consider both models to ensure the robustness of the analysis.

Table 14 illustrates that GERD, consistent with findings from other models, significantly influences economic growth. Within the manufacturing sector, employment in high-technology manufacturing and medium-high-technology manufacturing exhibits a negative and statistically significant relationship with economic growth. This result aligns with the complex and often delayed nature of returns on investment in high-technology sectors, where initial costs and the time required for R&D to translate into commercial products can temporarily dampen immediate economic gains.

Table 14. Random effects models

	Model RE (GERD and others)	Model RE (GERD and significant)	Model FE (GERD and others)	Model FE (GERD and significant)
log(patents)				
log (GERD)	0.243***	0.191***	0.267***	0.182***
	(0.014)	(0.015)	(0.02)	(0.02)
log(rd_personnel)		0.058***		0.032
		(0.022)		(0.02)
log(high_tech_sectors)	0.082***		0.081***	
	(0.027)		(0.027)	
log(high_tech_man)	-0.051***		-0.045***	
	(0.015)		(0.015)	
log(med_tech_man)	-0.040**		-0.035	
	(0.020)		(0.024)	
log(wholesale_retail_trade)	-0.160***		-0.221***	
	(0.057)		(0.058)	
log(knowledge_intense_services)		0.415***		0.187*
		(0.101)		(0.104)
log (knowledge_intense_ high_tech_services)				
log(knowledge_intense_market_services)	0.147**		0.093***	
	(0.030)		(0.03)	
log(knowledge_intense_other_serviees)				
log(info_communication)				
log(finance_and_insurance)				
log (prof_scientifie_ teeh_activities)		0.183***		0.066**
		(0.032)		(0.029)
log(education)				
log (human_health_ social_work)	0.270**	0.158**	0.132***	-0.012
	(0.034)	(0.049)	(0.04)	(0.049)
log(proportion_students)		-0.102***		-0.033
		(0.033)		(0.038)
Constant	8.089***	6.721***		
	(0.217)	(0.293)		
Observations	528	524	528	524
R2	0.923	0.930	0.464	0.262
Adjusted R2	0.922	0.929	0.222	-0.071
F Statistic	784.931 ***	713.383**	44.905***	21.358***

Significant codes: $p < 0.001$***, $p < 0.01$**, $p < 0.05$*, $p < 0.1$.
Source: Data was sourced from Eurostat (2022). Own calculations in R-studio

In the context of a KBE, the role of services cannot be overstated. The RE model underscores the critical importance of employment in knowledge-intensive sectors. The statistically significant coefficients in these sectors highlight a strong correlation between such employment and GDP per capita. This finding is consistent with previous research that emphasizes the pivotal role of services in a KBE (Boden & Miles, 2000; Miles, 2003). Knowledge-intensive services, which include sectors such as professional, scientific, and technical activities, as well as human health and social work, are essential engines of economic growth. They contribute directly to GDP and enhance other sectors' productivity by providing critical support and expertise.

According to the RE model, there is a correlation between R&D personnel and economic development; however, this correlation is not as strong as those between other variables. This suggests that while R&D personnel are crucial for fostering innovation, their impact on GDP per capita might be more indirect or long-term. The potential for a greater influence exists if regions were to invest more heavily in this area, particularly by enhancing the skills and capabilities of the R&D workforce. This would align with the human capital theory, which posits that investment in human capital is essential for sustaining long-term economic growth.

The main conclusion from this model is that employment in the knowledge-intensive services sector is highly associated with GDP per capita for European regions at the NUTS 2 level, where an increase of 1% in such employment is associated with a 0.4% increase in GDP per capita. Conversely, the proportion of students shows a negative association, suggesting that regions with a high concentration of students may not see immediate economic benefits from innovation. Instead, regions with higher employment in knowledge-intensive services are more likely to reap the economic rewards of innovation. These findings resonate with other scholarly investigations, such as those by Schwartz (2006) and Bak et al. (2022), which emphasise the significance of knowledge-intensive industries in driving economic growth.

It is important to highlight that while much of the existing research focusses on the significance of knowledge-intensive industries at the country level, this study provides a more granular analysis at the EU NUTS 2 regional level. Despite this focus, it is reasonable to infer that the importance of knowledge-intensive service sectors in various country regions could significantly impact overall national economic growth, as demonstrated in other studies. The apparent discrepancies in knowledge economy performance-related indicators across the selected country's regions suggest that regional knowledge spillover effects may be insufficient. This observation underscores the need for targeted regional policies that foster knowledge spillovers to enhance economic growth uniformly across regions.

After testing several different models and variable selection procedures, it was determined that the RE model (GERD and others) and the RE (GERD and significant) model provide the most accurate representations of the data (Table 14). Simultaneously, the estimation results of the fixed effects (FE) model are also reported. The results of the Hausman test showed that the fixed effects model should be preferable; however, the random effects model was also reported, as this model demonstrates a higher fit to the dataset. It should be noted that there is no significant difference in the magnitude and direction of effects reported by either model; both models contain the same set of independent variables, and their coefficients do not differ considerably. The results suggest that the choice of a model may not substantially impact the results, but it is important to consider both models to ensure the robustness of the analysis. Table 4 demonstrates that GERD, like other models, significantly affects economic growth. Within the manufacturing category, employment in high-technology manufacturing and employment in medium-high technology manufacturing have a negative and statistically significant relationship with economic growth.

Furthermore, our analysis indicates that despite efforts by national and regional governments to allocate resources proportionately, some regions' economies are more likely than others to become knowledge based. To bolster regional economic growth, regional governments should prioritise strengthening their scientific institutions, increasing investments in the R&D sector, and developing knowledge-intensive sectors. This strategy not only supports the direct growth of these regions but also facilitates the diffusion of knowledge and innovation across broader geographical areas, thereby contributing to the country's overall competitiveness and economic resilience.

5.3. Overview of Key Findings: R&D Investments and Real GDP per capita

Building on our previous findings, the next stage of our study delves into testing the third hypothesis (H4).

To lay the groundwork for this analysis, the correlations between real GDP per capita and various R&D-related factors across the EU-27 countries were thoroughly examined. The results of the correlation matrix, presented in the table, provide valuable insights into the relationships between key variables and their potential impact on economic performance (Table 15).

The correlation matrix revealed several important relationships that help us understand the dynamics between R&D investment and real GDP per capita. The strong positive correlation (0.752**) with real GDP per capita underscores the importance of GERD as a significant contributor to economic growth. This finding aligns with the broader literature, which emphasises that sustained investment in R&D is essential for fostering innovation and long-term economic development.

The correlation between national public funding to transnationally coordinated R&D and real GDP per capita indicates the importance of coordinated R&D efforts across national boundaries. This finding suggests that collaborative R&D initiatives, supported by national governments, can contribute to economic growth, especially in the context of the EU's integrated market.

Additionally, the positive correlation of Research and Innovation (R&I) Projects Total Cost Per Head with real GDP per capita further reinforces the importance of well-funded R&I projects. This finding suggests that the financial resources allocated to these projects are critical for driving economic growth, likely through the development of new technologies, processes, and products that enhance productivity.

Table 15. Correlation Matrix

	Real GDP per capita	GERD by sector of performance and fields of R&D	Number of Doctorate graduates	Researchers by sector of performance, age class and sex	R&D personnel by sector of performance, professional position and sex	Percentage of Population by educational attainment level	National public funding to transnationally coordinated R&D	Business enterprise expenditure on R&D	Government budget allocations for R&D (GBARD)	Patent applications to the EPO by priority year	Research and Innovation (R&I) projects Total cost per head
Real GDP per capita	1	0.752**	0.105**	0.163**	0.165**	0.555**	0.483**	0.698**	0.839**	0.535**	0.682**
GERD by sector of performance and fields of R&D	0.752**	1	0.290**	0.308**	0.289**	0.441**	0.760**	0.991**	0.911**	0.775**	0.672**
Number of Doctorate graduates	0.105**	0.290**	1	0.686**	0.683**	-0.088	0.330**	0.292**	0.297**	0.229**	-0.021
Researchers by sector of performance, age class and sex	0.163**	0.308**	0.686**	1	0.983**	-0.005	0.364**	0.304**	0.312**	0.293**	0.052**
R&D personnel by sector of performance, professional position and sex	0.165**	0.289**	0.683**	0.983**	1	-0.054	0.385**	0.284**	0.304**	0.281**	0.049**
Percentage of Population by educational attainment level	0.555**	0.441**	-0.088	-0.005	-0.054	1	0.297**	0.413**	0.435**	0.301**	0.632**
National public funding to transnationally coordinated R&D	0.483**	0.760**	0.330**	0.364**	0.385**	0.297**	1	0.766**	0.677**	0.592**	0.579**
Business enterprise expenditure on R&D	0.698**	0.991**	0.292**	0.304**	0.284**	0.413**	0.766**	1	0.860**	0.769**	0.648**
Government budget allocations for R&D (GBARD)	0.839**	0.911**	0.297**	0.312**	0.304**	0.435**	0.677**	0.860**	1	0.719**	0.672**
Patent applications to the EPO by priority year	0.535**	0.775**	0.229**	0.293**	0.281**	0.301**	0.592**	0.769**	0.719**	1	0.514**
Research and Innovation (R&I) projects Total cost per head	0.682**	0.672**	-0.021	0.052**	0.049**	0.632**	0.579**	0.648**	0.672**	0.514**	1

Significant codes: p < 0.001***, p < 0.01**, p < 0.05*, p < 0.1 .
Source: Own calculations in R-studio

The correlations observed provide a strong foundation for the next phase of our analysis, where we will rigorously test Hypothesis 3. The positive correlations between GDP per capita and various R&D-related variables suggest that there is indeed a significant relationship between R&D spending and economic performance. However, to establish a more robust understanding of this relationship, it is necessary to move beyond correlation and conduct more sophisticated statistical analyses.

In the following study, regression models will be employed to quantify the impact of R&D spending on real GDP per capita, controlling for other relevant factors. This will allow for testing whether the positive associations observed in the correlation matrix hold when accounting for potential confounding variables. By doing so, a comprehensive analysis of the extent to which R&D investments drive economic growth in the EU-27 countries is aimed for.

As part of the methodology, the Variance Inflation Factor (VIF) was utilized to evaluate multicollinearity in the model (Table 16).

Table 16. Multicollinearity statistics

	GERD by sector of performance and fields of R&D	Number of Doctorate graduates	Researchers by sector of performance, age class and sex	R&D personnel by sector of performance, professional position and sex	Percentage of Population by educational attainment level, sex, age, and citizenship	National public funding to transnationally coordinated R&D	Business enterprise expenditure on R&D	Government budget allocations for R&D (GBARD)	Patent applications to the EPO by priority year	Research and Innovation (R&I) projects Total cost per head
Tolerance	0.004	0.475	0.026	0.026	0.511	0.333	0.007	0.062	0.389	0.339
VIF	227.512	2.107	37.932	38.557	1.955	3.006	149.636	16.213	2.571	2.953

Source: Own calculations in R-studio

In our analysis, several variables displayed notably high VIF values. For instance, the GERD by sector of performance and fields of R&D exhibited a VIF of 227.512, while Business enterprise expenditure on R&D had a VIF of 149.636. These values significantly exceed the commonly accepted threshold of 10, suggesting substantial multicollinearity issues. High multicollinearity can obscure the individual effects of these variables on the dependent variable, in this case, real GDP per capita, making it difficult to draw precise conclusions from the regression analysis.

Given these findings, it is clear that certain variables are highly interrelated, which could potentially distort the regression results. Therefore, to improve the accuracy and comprehensibility of the regression analysis, a meticulous examination was conducted to identify and eliminate highly correlated variables. Only variables with low VIF were incorporated in the multiple linear regression analysis, as showcased in Table 17.

Table 17. Multiple linear regression results for the period 2011–2020. Dependent variable Real GDP per capita

	Coefficients	Std. Error	t value	Pr(>|t|)
(Intercept)	7.45277	0.47441	15.710	< 2e-16***
log (GERD)	0.40413	0.07483	5.401	3.37e-07***
log (Number of Doctorate graduates)	-0.08380	0.02328	-3.600	0.000463***
log (Percentage of population by education level)	0.03179	0.10894	0.292	0.770890
log (National public funding to transnationally coordinated R&D)	0.07875	0.04062	1.939	0.054873.
log (Patent applications to the European patent office (EPO) by priority year)	0.03105	0.05102	0.609	0.543843
log (R&I projects total cost per head)	0.18290	0.03889	4.703	6.87e-06***
Multiple R-squared	0.8443			
Adjusted R-squared	0.8366			
F-statistic	109.3 on 6 and 121 DF			
P-value	< 2.2e-16			

Significant codes: p < 0.001***, p < 0.01**, p < 0.05*, p < 0.1 .
Source: Own calculations in R-studio

Each coefficient in the model corresponds to the log-transformed independent variables, allowing us to interpret the results in terms of elasticities essentially, the percentage change in GDP per capita associated with a 1% change in the predictor variable.

The intercept coefficient of 7.45277, which is highly statistically significant ($p < 2e-16$), indicates the expected log of real GDP per capita when all independent variables are held at their reference values. This robust intercept underscores the strong baseline level of economic development within the EU-27 region over the observed period.

The log of GERD has a positive coefficient of 0.40413, with a very high level of significance ($p < 0.0001$). This suggests that a 1% increase in GERD is associated with approximately a 0.40% increase in real GDP per capita, holding other factors constant. This result strongly supports the hypothesis that higher R&D expenditure drives economic growth, reinforcing the critical role of innovation and research investments in fostering economic development within the EU-27.

Surprisingly, the number of doctorate graduates is associated with a negative coefficient (-0.08380), which is statistically significant. This inverse relationship suggests that an increase in the number of doctorate holders is correlated with a decrease in real GDP per capita. This counterintuitive result may indicate that an oversupply of highly educated individuals does not directly translate into economic growth, possibly due to mismatches between their skills and the needs of the labour market, or underutilization of advanced skills within the economy.

The percentage of the population with a certain education level shows a positive but statistically insignificant coefficient. This suggests that variations in educational attainment, within the scope of this study, do not have a significant direct impact on real GDP per capita. This finding could imply that while education is important, its effect on economic output may be mediated by other factors, such as the quality of education or the alignment of educational outcomes with labour market demands.

National Public Funding to Transnationally Coordinated R&D has a positive coefficient (0.07875), with a marginal level of significance ($p = 0.054873$). This suggests that increased national public funding for transnational R&D initiatives might contribute to economic growth, but the effect is not strongly significant. This may point to the complexities involved in transnational R&D coordination, where benefits are diffused and take longer to materialize.

The coefficient for patent applications is positive but not statistically significant. This indicates that, within the context of this model, the number of patent applications does not have a direct, significant impact on real GDP per capita. This could reflect the long lag between patent filings and the realization of their economic benefits, or it might suggest that the mere number of patents is less critical than their quality or commercial success.

Overall, this regression analysis highlighted the critical role of R&D expenditure, particularly GERD and R&I project funding, in driving economic growth within the EU-27 countries. The negative coefficient for the number of doctorate graduates, however, warrants further investigation to understand the underlying dynamics. As always, the implications of these results should be considered within the broader context of economic, social, and policy factors that may also influence real GDP per capita.

Building upon our previous analysis, the next phase of our study involved the application of the Fixed Effects (FE) model to further scrutinize the relationship between the selected independent variables and real GDP per capita. The FE model was particularly useful in controlling unobserved heterogeneity by allowing us to account for each country's unique characteristics that do not change over time. This method helped in isolating the effects of our variables of interest, thereby providing a clearer picture of the dynamic between R&D expenditure and economic performance.

The results from the FE model, as detailed in Table 18, present several noteworthy insights. The Gross Domestic Expenditure on Research and Development (GERD) once again emerges as a critical driver of economic growth, with its coefficient being both positive and statistically significant. This finding reinforces the central role of sustained R&D investment in fostering economic development. The significance of GERD in our model underscores the importance of long-term governmental commitment to R&D funding as a cornerstone of a robust knowledge-based economy.

Interestingly, the analysis also reveals a statistically significant yet negative relationship between the number of patent applications and real GDP per capita. This inverse correlation suggests that while patent activity is typically viewed as a proxy for innovation, the mere quantity of patents does not necessarily translate into immediate economic gains. The negative coefficient may reflect the complexity and time lag involved in transforming patents into commercially viable products or processes that contribute to GDP growth. It also raises questions about the efficiency and effectiveness of the innovation ecosystem in the countries studied particularly whether the patents being generated are sufficiently impactful or whether there might be an overemphasis on patent quantity over quality.

Notably, the other variables included in the model did not show a statistically significant correlation with real GDP per capita. This lack of significance could indicate that these factors, while important, may not have a direct or immediate impact on economic performance within the timeframe analysed. Alternatively, it could suggest that their influence is more nuanced, possibly interacting with other unmeasured variables or manifesting over a longer period than our study covers.

Table 18. Fixed effects model. Dependent variable Real GDP per capita

	Coefficients	Std. Error	t value	Pr(>|t|)
(Intercept)	-6837.35106	9418.83249	-0.7259	0.476733
log (GERD)	79.22718	21.39185	3.7036	0.001507**
log (Number of Doctorate graduates)	0.16296	0.41065	0.3968	0.695914
log (Percentage of population by education level)	353.94310	401.77916	0.8809	0.389359
log (National public funding to transnationally coordinated R&D)	-926.21789	795.38199	-1.1645	0.258638
log (Patent applications to the European patent office (EPO) by priority year)	-147.00522	63.34478	-2.3207	0.031581*
log (R&I projects total cost per head)	331.48448	277.53088	1.1944	0.247018
Multiple R-squared	0.74284			
Adjusted R-squared	0.66163			
F-statistic	9.14709 on 6 and 19 DF			
P-value	8.8755e-05			

Significant codes: $p < 0.001$***, $p < 0.01$**, $p < 0.05$*, $p < 0.1$.
Source: Own calculations in R-studio

These findings lead us to emphasise the critical nature of long-term strategies for government R&D expenditure. The positive impact of GERD on real GDP per capita highlights the need for consistent and targeted investment in R&D activities. Moreover, the negative relationship between patent applications and economic growth suggests that policymakers should not only focus on increasing patent counts but also on enhancing the quality and market applicability of innovations. By fostering an environment where high-quality, impactful innovations can thrive, governments can better leverage R&D activities to drive sustainable economic growth.

In conclusion, the FE model results add a nuanced layer to our understanding of the complex interplay between R&D investment, innovation, and economic performance. While GERD remains a vital component of economic development, the role of patents and other factors requires careful consideration and strategic alignment with broader economic goals. These insights are crucial for informing future policy directions, particularly in how R&D activities are prioritized and supported within the context of fostering long-term economic growth.

Following the exploration of the Fixed Effects (FE) model, which allowed for control of unobserved heterogeneity by focusing on within-group variations, the Random Effects (RE) model was subsequently employed. This model offers greater flexibility by accommodating both within-group and between-group variations, making it particularly advantageous when dealing with panel data that includes individual or group-specific effects.

The results from the RE model, as illustrated in Table 19, present a compelling analysis of the determinants of real GDP per capita across the sample.

Notably, the Gross Domestic Expenditure on Research and Development (GERD) continues to show a statistically significant and positive relationship with GDP per capita. This reinforces our earlier findings from the FE model, further solidifying the crucial role of R&D expenditure as a driver of economic growth in the EU-27 countries.

Table 19. Random effects model. Dependent variable Real GDP per capita

	Coefficients	Std. Error	t value	Pr(>|t|)
(Intercept)	4092.148630	3495.345504	1.1707	0.24170
log (GERD)	20.094690	4.999998	4.0189	5.846e-05***
log (Number of Doctorate graduates)	0.072443	0.151613	0.4778	0.63278
log (Percentage of population by education level)	420.714419	96.958502	4.3391	1.431e-05***
log (National public funding to transnationally coordinated R&D)	-5.771105	219.658975	-0.0263	0.97904
log (Patent applications to the European patent office (EPO) by priority year)	3.418447	11.550037	0.2960	0.76725
log (R&I projects total cost per head)	43.319005	20.991988	2.0636	0.03906*
Multiple R-squared	0.34094			
Adjusted R-squared	0.30826			
F-statistic	62.3688 on 6 DF			
P-value	1.4841e-11			

Significant codes: $p < 0.001$***, $p < 0.01$**, $p < 0.05$*, $p < 0.1$.
Source: Own calculations in R-studio

Moreover, the percentage of the population by education level also emerged as a significant predictor, suggesting that a well-educated workforce is essential for fostering economic development. This result aligns with the broader literature emphasising the importance of human capital in knowledge-based economies. The statistically significant coefficient for this variable highlights the need for continuous investment in education to sustain economic growth and competitiveness.

Interestingly, the total cost per head of Research and Innovation (R&I) projects was also found to have a significant positive impact on GDP per capita. This finding underscores the importance of not just the quantity but also the quality of R&I investments. It suggests that higher per capita spending on R&I projects is associated with greater economic returns, likely due to the enhanced capacity for innovation and technological advancement that such investments support.

In contrast, other variables, such as the number of doctorate graduates and patent applications to the European Patent Office (EPO), did not demonstrate a statistically significant relationship with GDP per capita in the RE model. This lack of significance could indicate that while these factors are important, their effects might be more indirect or take longer to manifest in measurable economic outcomes. For instance, the process of translating academic research into commercial products can be protracted, and the mere accumulation of patents may not immediately correlate with economic growth if those patents are not effectively utilised.

The RE model as a whole is statistically significant, with a p-value of 1.4841e-11, indicating that the combination of predictors used in this model provides a robust explanation for the variations in real GDP per capita. The adjusted R-squared value of 0.30826, while moderate, reflects the model's ability to capture the influence of key variables on economic performance across different regions.

These findings reinforce the importance of sustained and strategic investments in R&D and education. However, the results also point to the need for a more nuanced understanding of how different factors contribute to economic development, as some variables may require more time or more favourable conditions to exert their full impact.

In conclusion, the RE model offered valuable insights into the determinants of real GDP per capita, confirming the critical roles of GERD, education, and R&I project investments. While some variables did not show immediate significance, their potential long-term effects should not be overlooked, particularly in the context of building a resilient and knowledge-driven economy. These results provide a strong foundation for future research and policy initiatives aimed at fostering sustainable economic growth in the EU-27 and beyond.

Building upon the results from the Fixed Effects (FE) and Random Effects (RE) models, an effort was made to address potential endogeneity issues that could undermine the robustness of the findings. The presence of endogeneity can lead to biased estimates, particularly when independent variables are correlated with the error term in a regression model. This potential concern was initially suggested by the correlation studies, which indicated possible multicollinearity and endogeneity among the variables under consideration.

To mitigate these issues, the Instrumental Variable Two-Stage Least Squares (IV 2SLS) method was employed. Table 20 presents the results of the IV 2SLS model.

The 2SLS model identified several variables with a statistically significant positive impact on real GDP per capita. Notably, GERD and national public funding to transnationally coordinated R&D demonstrate a robust and positive relationship with GDP per capita. Specifically, a 1% increase in GERD is associated with a 0.36% increase in GDP per capita, highlighting the pivotal role of R&D investment in driving economic development. This finding confirms that economies with higher R&D spending tend to experience more robust knowledge-based economic growth.

Interestingly, the coefficient for the number of doctorate graduates is negative and statistically significant. This unexpected result may suggest potential issues such as underutilization of highly skilled labor or a mismatch between the skills of doctorate holders and the needs of the economy. Additionally, the coefficient for educational attainment is negative but statistically insignificant ($p = 0.309$), reflecting the complexity of how educational attainment translates into economic growth. While higher education levels are typically associated with improved human capital, the immediate impact on economic performance may not always be straightforward. This result may indicate a lag effect, where the returns on educational investment take time to manifest, or it may highlight inefficiencies in aligning the education system with labor market demands.

Table 20.IV 2SLS Model. Dependent variable Real GDP per capita

	Coefficients	Std. Error	t value	Pr(>|t|)
(Intercept)	10.89568	1.35716	8.028	1.19e-12 ***
log (GERD)	0.35785	0.08718	4.105	7.80e-05 ***
log (Number of Doctorate graduates)	-0.30997	0.05912	-5.243	7.72e-07 ***
log (Percentage of population by education level)	-0.47389	0.34811	-1.361	0.176
log (National public funding to transnationally coordinated R&D)	0.62175	0.11966	5.196	9.45e-07 ***
	df1	df2	statistic	p-value
Weak instruments (GERD)	6	108	902.560	< 2e-16 ***
Weak instruments (Number of Doctorate graduates)	6	108	193.870	< 2e-16 ***
Weak instruments (Percentage of population by education level)	6	108	19.712	1.96e-15 ***
Weak instruments (National public funding to transnationally coordinated R&D)	6	108	47.958	< 2e-16 ***
Wu-Hausman	4	106	17.469	4.88e-11 ***
Sargan	2	NA	1.008	0.604
Instruments	Researchers by sector of performance, Percentage of Population by educational attainment level, Business enterprise expenditure on R&D, Government budget allocations for R&D (GBARD), Patent applications to the EPO by priority year, Research and Innovation (R&I)			
Residual standard error	0.4001 on 110 degrees of freedom			
Multiple R-Squared	0.6116			
Adjusted R-squared Multiple R-squared	0.5975			
Wald test Adjusted R-squared	61.93 on 4 and 110 DF			
p-value	< 2.2e-16			

Significant codes: p < 0.001***, p < 0.01**, p < 0.05*, p < 0.1 .
Source: Own calculations in R-studio

On the other hand, national public funding to transnationally coordinated R&D emerges as a highly significant positive predictor of GDP per capita. A 1% increase in such funding leads to a 0.62% increase in GDP per capita. This underscores the importance of public sector support for R&D, particularly in fostering international collaboration. Coordinated R&D efforts across borders not only enhance the scope and impact of innovation but also drive long-term economic performance through collective advancements in technology and knowledge.

The diagnostic tests confirm the robustness and validity of the model. The weak instruments test indicating that the instruments used in the model are sufficiently strong and relevant. The Wu-Hausman test strongly rejects the null hypothesis of exogeneity ($p < 0.001$), confirming the presence of endogeneity in the model. This justifies the use of instrumental variables, as it shows that ordinary least squares (OLS) would produce biased estimates due to the correlation between the endogenous regressors and the error term. Finally, the Sargan test for over-identifying restrictions validates the instruments with a p-value of 0.81, confirming that they are uncorrelated with the error term, thus strengthening confidence in the IV approach.

The findings of our study are consistent with those of previous research, which have also established a noteworthy positive correlation between public expenditure on R&D and economic development. For instance, Szarowská (2017), Pegkas et al. (2019), and İpek and Çağaçan (2023) all found a positive relationship between public R&D expenditure and economic growth. This consensus among researchers underscores the importance of R&D investments in fostering economic growth.

Additionally, our study findings highlight the significant contribution of strategic investments in R&D activities to economic development, as measured by real GDP per capita within the EU-27. However, the findings also reveal the complexity of the factors influencing economic performance, as certain variables exhibited negative relationships with real GDP per capita.

In addition to our finding, Czarnitzki and Hussinger (2004) found that public funding can stimulate private R&D efforts and contribute to patent applications, thereby enhancing economic development. Furthermore, Leogrande, Costantiello, and Laureti (2022) found a positive correlation between the value of patent applications and public and private expenditure in R&D. The convergence of these findings suggests that a robust innovation ecosystem, characterized by increased R&D investments and a high number of patent applications, is crucial for fostering economic development.

Our study provides evidence that R&D expenditure, measured by the variable GERD, plays a key role in fostering real GDP per capita within the EU-27. Furthermore, several limitations warrant consideration when interpreting the findings. First, the study's exclusive focus on the EU-27 limits its generalizability. Second, potential measurement errors and reporting biases associated with self-reported data from official sources could exist. Finally, the available data's limitations restrict our understanding of the intricate dynamics between R&D expenditure and economic development. Future research employing more comprehensive datasets and alternative methodologies could offer a more nuanced perspective.

While rigorous methods were used, the analysis relies on readily available data, which might not capture the full complexity of the R&D-GDP relationship. Additionally, contextual factors like regional variations and industry nuances may influence these correlations. Future research could delve deeper into the causal mechanisms and specific government policies fostering innovation and long-term knowledge-based economic development.

Furthermore, several limitations warrant consideration when interpreting the findings. First, the research focusses exclusively on the EU-27 member states, limiting its generalisability to other countries with potentially different economic structures and institutional frameworks. Second, the data employed originates from official sources, which may contain measurement errors and reporting biases inherent in self-reported data. Third, the study is constrained by the limitations of the available data, which may not capture the full complexity of the relationship between R&D expenditure and economic development. Further research using more comprehensive datasets and employing alternative methodologies could provide a more nuanced understanding of these intricate dynamics.

5.4. Overview of Key Findings: Government Budget Allocations for R&D and BERD

Our next study stage begins with a correlation matrix (Table 21) analysis to explore the relationships between the key variables employed and test our H5. Specifically, this initial step aimed to identify potential dependencies among the independent variables that could influence the regression model.

The correlation matrix revealed a positive correlation (0.519) between government budget allocations for R&D (per capita) and R&D personnel (per capita), suggesting a potential link between government funding and the size of the national R&D workforce. This indicates that countries with higher government investment in R&D may also have a larger pool of researchers.

The weak negative correlation (-0.030) between government budget allocations and indirect government support through R&D tax incentives suggests that these policies might not always be implemented in tandem. Countries with high budgetary allocations might not necessarily have robust tax incentive programs, and vice versa.

The positive correlation (0.078) between FDI (per capita) and government budget allocations for R&D suggests a potential association between foreign investment and national R&D prioritization. Countries with higher levels of foreign direct investment might also have governments that place greater emphasis on R&D spending. However, the relatively low coefficient indicates a weak association.

The weak correlations between government R&D expenditures (both budgetary allocations and tax incentives) and business enterprise and private non-profit sector R&D expenditure suggest a limited interplay between public and private R&D funding. This might indicate that government R&D policies have a less pronounced effect on private sector R&D investment decisions in these countries.

Table 21. Correlation matrix

	Government budget allocations for R&D (per capita)	Indirect government support through R&D tax incentives (per capita)	FDI (per capita)	R&D personnel (per capita)	Business enterprise and private non - profit sector R&D expenditure (per capita)
Government budget allocations for R&D (per capita)	1	-0.030	0.078	0.519***	0.101
Indirect government support through R&D tax incentives (per capita)	-0.030	1	0.067	0.030	0.070
FDI (per capita)	0.078	0.067	1	0.161*	-0.037
R&D personnel (per capita)	0.519***	0.030	0.161*	1	0.044
Business enterprise and private non - profit sector R&D expenditure (per capita)	0.101	0.070	-0.037	0.044	1

Significant codes: p < 0.001***, p < 0.01**, p < 0.05*, p < 0.1 .
Source: Own calculations in R-studio

Following the correlation matrix analysis, we conducted a multicollinearity analysis to assess the potential for linear dependencies among the given variables (Table 22).

Table 22. Multicollinearity statistics

	Government budget allocations for R&D (per capita)	Indirect government support through R&D tax incentives (per capita)	FDI (per capita)	R&D personnel (per capita)
Tolerance	0.728	0.992	0.970	0.714
VIF	1.373	1.008	1.031	1.400

Source: Own calculations in R-studio

In this table, all tolerance values are above 0.7, suggesting a moderate to weak presence of multicollinearity. The lowest tolerance (0.714) is observed for government budget allocations for R&D (per capita) and R&D personnel (per capita), which aligns with the high positive correlation (0.519) identified earlier. Additionally, all VIF values fall below 1.4, suggesting a relatively weak to moderate concern with multicollinearity. The highest VIF (1.400) is again associated with government budget allocations for R&D (per capita) and R&D personnel (per capita), corroborating the potential collinearity between these variables.

The results from the random effects (Table 23) and fixed effects (Table 24) models provide valuable insights into the determinants of BERD expenditure across different country groups.

The RE model presented offered valuable insights into the relationship between key variables and the outcome variable across different groups of OECD countries. This model assumes that country-specific effects are randomly distributed and uncorrelated with the explanatory variables, allowing us to observe variations across groups of countries.

The intercept estimates for each group were found to be statistically insignificant, suggesting no significant differences in the baseline levels of the dependent variable prior to accounting for additional factors. This indicates that the intrinsic characteristics of the countries involved, which are not captured by the selected variables, may have minimal independent effects across these groups.

Government budget allocations for R&D show a highly significant and positive impact on the dependent variable for nearly all groups, particularly for all OECD countries, EU-15, and non-European OECD countries. The positive and statistically significant coefficients indicate that government R&D spending per capita is a crucial driver, with the highest impact observed outside the EU. This finding underscores the importance of public R&D funding in fostering economic outcomes, particularly in regions that invest heavily in R&D.

Indirect government support through R&D tax incentives is significant at the level of all OECD countries and non-European OECD countries, suggesting that tax incentives for R&D have a measurable impact in these groups. However, the lack of significance for EU-15 and newly joined EU countries may reflect different R&D incentive structures or policy effectiveness within the EU. It implies that direct budget allocations might be more influential than tax-based support in these regions.

FDI shows a negative and significant coefficient only for the EU-15 countries, indicating that, in this group, increased FDI per capita may have a counterintuitive, potentially competitive effect on domestic R&D outputs. This could reflect substitution effects where FDI crowds out local R&D efforts. In other country groups, FDI shows no significant effect, implying that its role varies widely across different economic contexts.

R&D personnel does not show statistical significance in any group, suggesting that, across these OECD countries, R&D personnel does not independently drive the BERD. This result could indicate that it's not just the quantity of R&D personnel but other factors like funding or infrastructure that amplify R&D productivity (Khan et al., 2010).

Table 23. Random Effects Model. Dependent variable BERD

		All OECD countries in the sample	**EU-15**	**Newly joined EU countries**	**Other European countries not in the EU, and non-European OECD countries**
(Intercept)	Estimate	2.7553e-05	-1.9107e-05	-3.9885e-05	4.2631e-06
	Pr(>|t|)	0.6967	0.7260	0.8069	0.9569
log (Government budget allocations for R&D (per capita)	Estimate	9.5141e-01	7.7885e-01	6.4827e-01	1.1375e+00
	Pr(>|t|)	<2e-16***	<2e-16***	0.1361	< 2.2e-16***
log (Indirect government support through R&D tax incentives (per capita))	Estimate	2.0184e-04	8.9146e-02	4.3031e-01	2.0882e-04
	Pr(>|t|)	<2e-16***	0.3056	0.1912	4.758e-05***
log (FDI (per capita))	Estimate	-7.2185e-03	-2.2542e-02	2.0961e-02	-4.0394e-03
	Pr(>|t|)	0.4720	3.422e-05***	0.3251	0.8597
log (R&D personnel (per capita))	Estimate	-1.0285e-02	8.4089e-03	1.8941e-02	-2.2938e-02
	Pr(>|t|)	0.5929	0.5674	0.7117	0.2418
R-Squared		0.81222	0.9475	0.26447	0.91445
Adj. R-Squared		0.80812	0.94417	0.20789	0.90855
Chisq		767.831 on 4 DF	1136.99 on 4 DF	18.6971 on 4 DF	619.97 on 4 DF
p-value		< 2.22e-16	< 2.22e-16	0.00090127	< 2.22e-16

Significant codes: p < 0.001***, p < 0.01**, p < 0.05*, p < 0.1 .
Source: Own calculations in R-studio

Following the RE model, a fixed effects model was tested to ensure robustness and to account for any unobserved heterogeneity that might affect the results (Table 24). Similar to the RE model, the FE model identified government budget allocations for R&D (per capita) as a significant determinant of R&D expenditure (all p-values < 0.001),technological development. This finding aligns with existing literature (Becker, 2015; Celli & Pellegrini, 2021).

In the FE model, the impact of indirect government support through R&D tax incentives per capita is significant for the entire OECD sample, indicating a positive contribution. However, this effect does not reach statistical significance for the EU-15, newly joined EU, or other European and non-EU countries. This suggests that while R&D tax incentives are impactful on a broad OECD level, their influence varies across specific regional groups.

FDI per capita does not have a statistically significant effect on the overall OECD sample. However, it shows a negative and significant impact within the EU-15 group, a positive and significant effect in newly joined EU countries, and a non-significant effect in other European and non-European OECD countries. That strengthens the previous assumption that FDI's role in influencing the dependent variable is context-specific and varies widely between these countries.

R&D personnel per capita does not have a statistically significant impact across any of the groups, indicating that R&D personnel density alone might not directly influence the dependent variable in a measurable way within this dataset.

The comparison of RE and FE models, alongside the confirmation of structural differences among country groups, highlights the intricate influence of particular R&D investment channels, including direct government funding, tax incentives, and FDI, across various regional contexts. This indicates that policy measures should be tailored to the individual structural conditions of each group to optimise the efficacy of R&D spending. Findings that are similar across RE and FE models support their validity.

Table 24. Fixed Effects Model. Dependent Variable BERD

		All OECD countries in the sample	EU-15	Newly joined EU countries	Other European countries not in the EU, and non-European OECD countries
(Intercept)	Estimate	3.0467e-05	9.5591e-05	-2.2014e-04	-9.9423e-06
	Pr(>|t|)	0.695370	0.398441	0.05544	0.889077
log (Government budget allocations for R&D (per capita)	Estimate	9.1599e-01	9.2772e-01	4.1596e-01	1.0243e+00
	Pr(>|t|)	1.846e-07***	0.003495**	0.13454	0.001735**
log (Indirect government support through R&D tax incentives (per capita))	Estimate	1.5270e-04	5.9845e-02	4.9152e-02	6.9560e-05
	Pr(>|t|)	0.001748**	0.377497	0.74488	0.556813
log (FDI (per capita))	Estimate	-2.9800e-02	-3.0247e-02	2.5118e-01	-6.7381e-02
	Pr(>|t|)	0.130354	0.009361**	0.01136*	0.257284
log (R&D personnel (per capita))	Estimate	-5.6486e-03	-2.2904e-02	4.8007e-02	-2.9564e-03
	Pr(>|t|)	0.789150	0.441627	0.12470	0.880457
R-Squared		0.99371	0.99839	0.99014	0.9996
Adj. R-Squared		0.99231	0.99624	0.97043	0.99908
F-statistic		465.288 on 4 and 3 DF	465.288 on 4 and 3 DF	50.2188 on 4 and 2 DF	1893.12 on 4 and 3 DF
p-value		< 2.22e-16	0.00016124	0.019619	1.9697e-05

Significant codes: $p < 0.001$***, $p < 0.01$**, $p < 0.05$*, $p < 0.1$.
Source: Own calculations in R-studio

Endogeneity, potentially arising from omitted variable bias or reverse causality, can threaten the validity of regression results. A two-stage least squares (2SLS) model was employed to address this concern (Table 25). The 2SLS model allows us to mitigate the effects of potential correlations between the independent variables and the error term. The results from the 2SLS model show similar findings to the other models. Government budget allocations for R&D (per capita) remain a significant and positive determinant of R&D expenditure across all country groups, except for newly joined EU countries, where significance is observed at $p < 0.15$. This underscores the critical role of government funding.

The 2SLS model shows a stronger and more consistent positive effect of indirect government support through R&D tax incentives (per capita) compared to the random effects model. This suggests that addressing potential endogeneity issues through 2SLS might reveal a clearer picture of tax incentives' impact, particularly for groups like all OECD countries and other European countries (significant at p<0.001).

The findings for FDI and R&D personnel are similar to the fixed and random effects models. FDI has a significant negative effect in the EU-15 group (p-value < 0.001) but no significant impact in other country groups. R&D personnel show no statistically significant relationship with R&D expenditure in any group.

Table 25.Two Stage Least Square (2SLS) Model

		All OECD countries in the sample	**EU-15**	**Newly joined EU countries**	**Other European countries not in the EU, and non-European OECD countries**
(Intercept)	Estimate	4.647e-05	-1.911e-05	-3.988e-05	4.263e-06
	Pr(> |t|)	0.387	0.727167	0.808	0.957038
log (Government budget allocations for R&D (per capita))	Estimate	9.673e-01	7.788e-01	6.483e-01	1.137e+00
	Pr(> |t|)	<2e-16***	<2e-16***	0.142	3.36e-13***
log (Indirect government support through R&D tax incentives (per capita))	Estimate	1.892e-04	8.915e-02	4.303e-01	2.088e-04
	Pr(> |t|)	3.92e-14***	0.309557	0.197	0.000145***
log (FDI (per capita))	Estimate	-1.306e-02	-2.254e-02	2.096e-02	-4.039e-03
	Pr(> |t|)	0.167	0.000104***	0.330	0.860361
log (R&D personnel (per capita))	Estimate	-1.327e-02	8.409e-03	1.894e-02	-2.294e-02
	Pr(>|t|)	0.356	0.569415	0.713	0.246578
Residual standard error:		0.0002039 on 183 degrees of freedom	6.314e-05 on 63 degrees of freedom	0.0002712 on 52 degrees of freedom	0.0002177 on 58 degrees of freedom
Multiple R-squared		0.844	0.9475	0.2645	0.9145
Adjusted R-squared		0.8406	0.9442	0.2079	0.9086
F-statistic		247.6 on 4 and 183 DF	284.2 on 4 and 63 DF	4.674 on 4 and 52 DF	155 on 4 and 58 DF
p-value		<2.2e-16	<2.2e-16	0.002679	<2.2e-16

Significant codes: p < 0.001***, p < 0.01**, p < 0.05*, p < 0.1 .
Source: Own calculations in R-studio

Despite our analysis revealed mild to moderate correlations between the independent variables, as evidenced by the tolerance values ranging from 0.714 to 0.992 and VIFs between 1.008 and 1.400. While 2SLS addresses endogeneity concerns, it can be less efficient and reliable than multiple linear regression, especially when multicollinearity is substantial. According to Greene (2003), VIF values above 10 indicate severe multicollinearity, which can significantly impact the reliability of 2SLS estimates (Wooldridge, 2010). In such cases, multiple linear regression offers a more robust approach, even if there is a potential for some bias due to endogeneity. Based on these moderate VIF values, the benefits of a simpler model and potentially more reliable estimates outweigh the potential for a slight bias in this instance.

To further substantiate the suitability of the multiple linear regression model in this context, diagnostic tests were conducted to assess endogeneity concerns. The Wu-Hausman test yielded a non-significant p-value ($p > 0.05$), indicating that endogeneity might not be a major concern in the model.

Given the non-significant result of the Wu-Hausman test, the multiple linear regression model appears to be a more suitable choice in this study. It avoids the complexities and potential biases inherent in the 2SLS approach. Future research encountering stronger evidence of endogeneity or substantially higher levels of multicollinearity might benefit from employing a more robust technique like 2SLS. However, in comparison to the 2SLS model, multiple linear regression offers a more straightforward estimation procedure and can often yield more reliable results.

Table 26 shows the results of a multiple linear regression analysis examining the relationship between business enterprise R&D expenditure (per capita) and several independent variables across different country groups.

The coefficient for government budget allocations for R&D (per capita) has a statistically significant positive relationship with business R&D expenditure (p-value < 0.001) in all given groups of countries. This indicates that higher government budgetary allocations for R&D are generally associated with increased BERD.

The coefficient values for government budget allocations range from 0.04 to 0.11. It is much stronger in the economically integrated regions (EU-15) with a solid economic history compared to the newly accepted EU countries or OECD. It suggests that the EU-15 might effectively leverage private R&D. One of the aspects can be that in the case of multinational corporations (MNC), it is primarily the parent company operating in the old member countries that focusses on R&D, not the subsidiaries in the new member countries (Uzunidis & Boutillier, 2012; Hamida & Piscitello, 2013). For this reason, public R&D expenditure cannot play a more significant role in the complementary effect of supporting private R&D.

Table 26. Multiple linear regression model

		All OECD countries in the sample	**EU-15**	**Newly joined EU countries**	**Other European countries not in the EU, and non-European OECD countries**
(Intercept)	Estimate	-0.03448	0.18212	3.86150	-0.721174
	Pr(>|t|)	0.936	0.866	0.017264*	0.1866
log (Government budget allocations for R&D (per capita)	Estimate	0.58401	0.83584	0.34853	0.924579
	Pr(>|t|)	< 2e-16***	1.09e-06***	0.001787**	5.98e-06***
log (Indirect government support through R&D tax incentives (per capita))	Estimate	0.08306	0.04143	0.11159	0.060548
	Pr(>|t|)	4.89e-06***	0.339	0.005416**	0.0469*
log (FDI (per capita))	Estimate	-0.01670	-0.04919	0.10694	-0.053608
	Pr(>|t|)	0.570	0.234	0.172448	0.2137
log (R&D personnel (per capita))	Estimate	0.52421	0.31285	1.38420	-0.008967
	Pr(>|t|)	3.53e-05***	0.506	0.000207***	0.9712
Residual standard error		0.4458 on 162 degrees of freedom	2903 on 60 degrees of freedom	0.577 on 46 degrees of freedom	0.3382 on 46 degrees of freedom
		(328 observations deleted due to missingness)	(160 observations deleted due to missingness)	(69 observations deleted due to missingness)	(99 observations deleted due to missingness)
Multiple R-squared		0.8082	0.8331	0.7158	0.8946
Adjusted R-squared		0.8034	0.8219	0.6911	0.8855
F-statistic		170.6 on 4 and 162 DF	74.86 on 4 and 60 DF	28.97 on 4 and 46 DF	97.63 on 4 and 46 DF
p-value		< 2.2e-16	< 2.2e-16	4.73e-12	< 2.2e-16

Significant codes: p < 0.001***, p < 0.01**, p < 0.05*, p < 0.1 .
Source: Own calculations in R-studio

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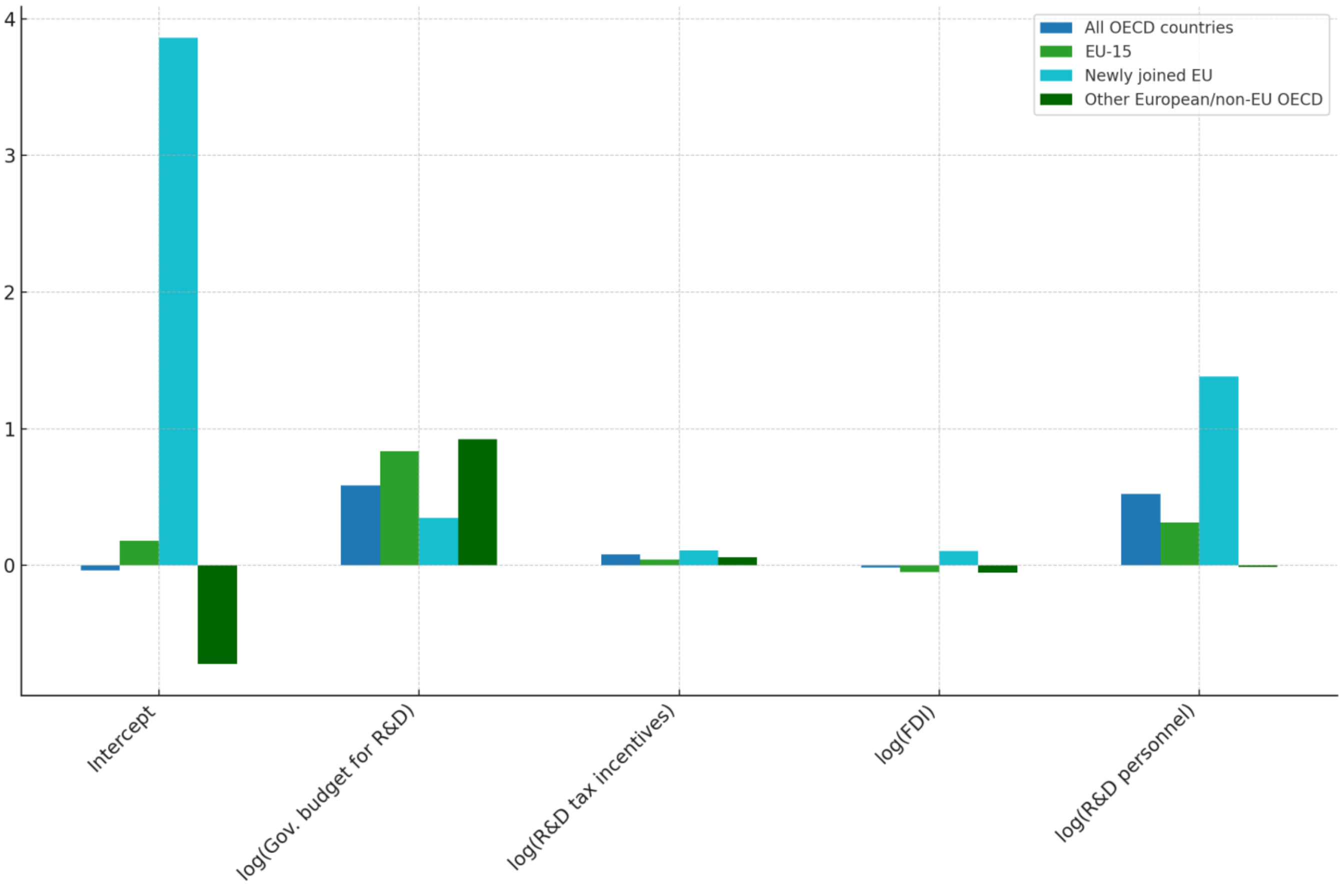
To better illustrate the results of the multiple linear regression model, Figure 3 presents the coefficient estimates for each variable across different country groups. This visualization highlights the varying impacts of selected variables.

Figure 3. Multiple linear regression model coefficients by country groups



Source: Own calculations

Another factor to consider is the current structure of EU R&D funding. While national governments contribute the majority of funds, the EU's Horizon Europe program offers limited support for breakthrough innovation. Additionally, the recently established European Innovation Council (EIC) faces criticism for its bureaucratic processes and limited focus on high-risk, high-reward research (European Commission, 2024). These limitations may hinder the effectiveness of public funding in driving private R&D.

This report highlighted the importance of private sector involvement in driving innovation. While government funding plays a role, a strong ecosystem with high levels of private R&D spending is crucial for technological advancement. The report offers a compelling critique of the current EU approach, particularly the focus on mid-tech industries and the limitations of the EIC.

This finding is consistent with previous studies that have found a positive relationship between government R&D funding and private-sector R&D investment (Levy & Terleckyj, 1983). The positive and statistically significant relationship between government R&D funding and BERD might be explained by the following factor: government funding acts as a catalyst, reducing the financial risks associated with R&D for businesses. This can be achieved through direct grants, research project co-funding, or shared research infrastructure funding. By lowering the upfront costs, government investment "crowds-in" private sector resources, encouraging businesses to invest in their R&D activities.

Indirect government support through R&D tax incentives (per capita) demonstrated mixed results. While statistically significant in the all-OECD countries in the sample, newly joined EU countries, and other European countries not in the EU, and non-European OECD countries categories, it does not reach significance in the EU-15 category. This suggests that the effectiveness of R&D tax incentives in stimulating business R&D expenditure may vary across different economic contexts, possibly due to tax policies and business environments. One possible explanation for this result could be differences in the design and implementation of R&D tax incentive schemes across countries. The generosity of tax credits may influence the effectiveness of such incentives, the ease of access to incentives, and the overall business climate.

The coefficient for FDI (per capita) is negative and statistically insignificant (p-value > 0.05) for most groups. This suggests no clear relationship between FDI and BERD in these countries.

The negative and statistically insignificant coefficient for FDI in most country groups challenges the assumption of a straightforward positive relationship between FDI and BERD. Therefore, we might assume that foreign firms might not always prioritise R&D activities in host countries, particularly if their focus is on market access or resource extraction (Sultana & Turkina, 2020).

Furthermore, the impact of FDI on BERD might be stronger in countries with weaker domestic technological capabilities, where foreign firms can play a crucial role in knowledge transfer and R&D stimulation (Erdal, 2015).

Interestingly, the coefficient for R&D personnel (per capita) presents mixed results across country groups. While it is statistically significant for all OECD countries in the sample, it fails to reach significance for other groups. This suggests that the availability of R&D personnel might not be a significant determinant of R&D expenditure in specific country contexts, possibly due to other factors such as institutional frameworks or technological capabilities (Griliches, 1980; Aghion & Howitt, 1992).

The possibility that industry composition influences the R&D personnel effect aligns with the concept of sectoral systems of innovation (SSI) (Malerba, 2003). Countries with a higher concentration of R&D-intensive industries, might exhibit a stronger association between R&D personnel and BERD. This suggests that the mere presence of researchers is not as impactful as having researchers with the specific skillsets aligned with the dominant industries in a particular country group.

Furthermore, the model's inability to differentiate between skill levels is a limitation. Countries with a significant effect on R&D personnel might have a higher engagement of highly skilled researchers. This builds on human capital theory, which emphasises the importance of skilled labour for innovation and economic development (Fresé & Rauch, 2001). Further research employing data that distinguishes skill levels within the R&D workforce can provide more nuanced insights.

In conclusion, this analysis highlights the crucial role of government R&D funding in stimulating private sector R&D investment across different country contexts. While the effectiveness of R&D tax incentives appears to vary, a focus on strengthening institutional frameworks and technological capabilities alongside human capital development could further enhance the impact of government policies. Future research employing more sophisticated techniques and potentially incorporating qualitative data can provide even deeper insights into the complex interplay between these factors. This knowledge can inform the design of effective policy measures that foster innovation and drive economic growth.

5.5. Overview of Key Findings: Innovation in Agriculture

The next part of the study begins by performing a multiple linear regression analysis presented in log-log form, as shown in Table 27, where the dependent variable is the total crops output (€/ha). The log-log transformation enabled us to understand the coefficients as elasticities, indicating the percentage change in the dependent variable resulting from a 1 % change in the independent variable.

However, it is important to note that after performing the multicollinearity analysis (Table 27), significant multicollinearity was observed between R&D spending in agriculture and population density, with VIF values above 30 and low tolerance values. The trade balance displayed moderate to high multicollinearity, indicated by a VIF of around 19.65 and a tolerance at 0.05, suggesting potential complications within the model. The intention was to exclude the trade balance from the models, as removing it reduced overall multicollinearity without impacting the core relationships under examination, resulting in a more robust and accurate model while preserving the key variables of interest (R&D expenditure and population density).

Table 27. Multicollinearity statistics in log-log form

	R&D expenditure in agriculture (per ha)	Population density (inhab/km2)	Trade Balance (per ha)	Co2 Emissions (per ha)	Real factor income in agriculture per annual work (chain linked volumes)	Subsidies (per ha)
Tolerance	0.03013273	0.02557199	0.05089327	0.23870413	0.28468222	0.50399519
VIF	33.186507	39.105289	19.648962	4.189287	3.512689	1.984146

Source: Own calculations in R-studio

From Table 28, we see that the R&D spending in agriculture showed a positive and statistically significant impact on total crops output. A 1 % increase in agricultural R&D spending is associated with a 0.20% increase in total crop output per hectare. This positive relationship emphasises the importance of investing in R&D to enhance agricultural output. R&D in agriculture contributes to technological advancements, improved agricultural practices, and increased crop output, directly benefiting overall output.

This model showed that population density had a highly substantial association with crop output, with a coefficient of 0.60153 ($p < 2e-16$), indicating that a 1 % increase in population density corresponds with a 0.60 % increase in total crop output. This outcome indicates that increased population density may stimulate demand for agricultural production or enable more effective use of land resources, maybe owing to improved infrastructure or market accessibility. The substantial volume and importance of this coefficient underscore the vital role of population-driven agricultural practices and market access in affecting productivity.

Table 28. Multiple linear regression (OLS) model in log-log form

Dependent variable: Total crops output (per/ha)				
	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	3.21141	0.74909	4.287	3.05e-05***
log (R&D expenditure in agriculture (per ha))	0.20083	0.05606	3.582	0.000447***
log (Population density (inhab/km2))	0.60153	0.05460	11.016	<2e-16***
log (Co2 Emissions (per ha))	0.03499	0.08211	0.426	0.670615
log (Real factor income in agriculture per annual work (chain linked volumes))	0.15437	0.05863	2.633	0.009255**
log (Subsidies (per ha))	-0.04523	0.01316	-3.437	0.000742***
Residual standard error	0.3715 on 167 degrees of freedom			
	(367 observations deleted due to missingness)			
Multiple R-squared	0.7688			
Adjusted R-squared	0.7619			
F-statistic	111.1 on 5 and 167 DF			
p-value	<2.2e-16			

Significant codes: p < 0.001***, p < 0.01**, p < 0.05*, p < 0.1 .
Source: Own calculations in R-studio

The coefficient for CO2 emissions per hectare is 0.03499; however, it is not statistically significant (p = 0.6706). This suggests that variations in CO2 emissions do not significantly influence total crop output in this model. While CO2 emissions may contribute to broader environmental and sustainability challenges, they seem to have no direct impact on productivity within the scope of this dataset (Ali et al., 2022). The absence of importance may indicate that other variables, such as agricultural methods or technology, ease the impact of emissions on production.

The coefficient for real factor income is statistically significant (p = 0.009255). An elevated factor income signifies enhanced productivity and profitability within the agricultural sector, which may result in more effective resource utilisation, investments in production, and augmented output. This finding highlights the necessity of maintaining strong agricultural income to improve productivity development.

The coefficient for subsidies per hectare is negative and statistically significant ($p = 0.000742$). This result, however odd, may suggest that ineffectively targeted subsidies might lead to inefficiencies or misallocation of resources. Subsidies may promote excessive utilisation of inputs that do not directly improve productivity or may discourage farmers from innovating or optimising output. This outcome necessitates a thorough analysis of subsidy programs and their efficacy in enhancing production rather than just providing financial assistance (Kumbhakar et al., 2023). The findings by Rizov et al. (2013) highlight the importance of subsidy design. When subsidies were tied directly to production, they had negative effects on productivity, primarily because they encouraged inefficient and unsustainable farming practices. However, once subsidies were decoupled from production, farmers became more efficient and responsive to market signals, resulting in increased productivity in many countries.

As a next step, both the RE (Table 29) and FE models ("within") (Table 30) were employed to account for the unobserved heterogeneity across selected countries and to test the robustness of the relationships between the variables.

The RE model (Table 29) offered important insights into how the selected variables are related. Significant positive effects were noted for population density ($p<0.001$) and real factor income in agriculture, indicating that these elements contribute significantly to increases in total crop output.CO_2 emissions per hectare demonstrate a notable negative correlation ($p<0.01$), underscoring the possible negative effects of emissions on agricultural results. Other scholars have reported similar findings, observing the negative effect of CO_2 on productivity (Afjal, 2023; Otim et al., 2023). Nevertheless, R&D spending in agriculture and subsidies per hectare show no statistically significant effects, indicating a limited direct impact on the outcome variable given the current model specifications.

Table 29. Random Effects Model

	Estimate	Std.Error	z-value	Pr(> |z|)
(Intercept)	-0.2740252	0.9303198	-0.2945	0.768338
log (R&D expenditure in agriculture (per ha))	0.0870106	0.0614271	827277,00	0.156634
log (Population density (inhab/km2))	0.6984273	0.1301219	648428,00	7.984e-08***
log (Co2 Emissions (per ha))	-0.4712783	0.1635570	-2.8814	0.003959**
log (Real factor income in agriculture per annual work (chain linked volumes))	0.5081643	0.0656272	2020705,00	9.695e-15***
log (Subsidies (per ha))	-0.0057691	0.0151033	-0.3820	0.702478
Total Sum of Squares	49.47			
Residual Sum of Squares	8.5266			
R-Squared	0.82796			
Adj. R-Squared	0.82281			
Chisq	118.603 on 5 DF			
p-value	<2.22e-16			

Significant codes: p < 0.001***, p < 0.01**, p < 0.05*, p < 0.1 .
Source: Own calculations in R-studio

Before examining the results of the fixed effects "within" model, it is crucial to emphasise that by focusing on the variation within each entity over time, this model accounts for unobserved, time-invariant characteristics specific to each entity, thereby strengthening the reliability of the findings. Most importantly, the "within" transformation eliminates the constant term since each variable is centred around its specific average, which helps to highlight the effect of time-varying predictors on the dependent variable. Further, similar to the RE effects model, the FE model (Table 30) showed that CO2 emissions have a negative impact. This negative relationship could indicate that increased CO2 emissions per hectare are associated with detrimental effects in the agricultural sector, highlighting the possible environmental costs tied to intensive farming methods (Zafeiriou and Azam, 2017).

On the other hand, the real factor income in agriculture per annual work unit revealed a highly significant positive effect ($p < 0.001$), highlighting the strong relationship with the dependent variable. This finding underscored the important impact of income produced for each unit of agricultural labour on agricultural performance, possibly indicating advancements in productivity or efficiency.

Table 30. Fixed Effects Model "within"

	Estimate	Std. Error	t-value	Pr(> |t|)
log (R&D expenditure in agriculture (per ha))	0.029200	0.061272	0.4766	0.6344
log (Population density (inhab/km2))	0.463549	0.505541	0.9169	0.3606
log (Co2 Emissions (per ha))	-1.649152	0.304397	-5.4178	2.352e-07 ***
log (Real factor income in agriculture (per annual work))	0.650856	0.069295	740226,00	<2.2e-16***
log (Subsidies (per ha))	0.010184	0.015273	0.6668	0.5059
Total Sum of Squares	10.664			
Residual Sum of Squares	187158,00			
R-Squared	0.41472			
Adj. R-Squared	0.32887			
F-statistic	21.2571 on 5 and 150 DF			
p-value	4.9083e-16			

Significant codes: $p < 0.001$***, $p < 0.01$**, $p < 0.05$*, $p < 0.1$.
Source: Own calculations in R-studio

Based on the results of both RE and FE models, it is reasonable to presume that increased CO2 emissions could lead to a decline in agricultural productivity. This outcome indicates that rising environmental damage, especially due to CO2 emissions, might negatively impact crop yields, potentially by worsening climate change, causing unfavourable weather patterns, or diminishing soil fertility.

It is reasonable to think that increased CO2 emissions could lead to a decline in agricultural productivity. This outcome indicates that rising damage to the environment, especially due to CO2 emissions, might negatively impact crop yields, potentially by worsening climate change, causing unfavourable weather patterns, or diminishing soil fertility. The finding corresponds with wider concerns regarding the harmful impacts of environmental stressors on sustainable farming practices (Ali et al., 2022; Otim et al., 2023). Nonetheless, the positive connection between real factor income in agriculture and total crop output underscores the significance of economic incentives and income growth in enhancing productivity in the agricultural sector. Furthermore, it highlights how financial backing and profitability are crucial for advancing agriculture, as improved income enables farmers to embrace innovative methods and invest in modern tools, resulting in increased productivity.

The findings additionally indicate that areas with higher population density could benefit from improved access to infrastructure, markets, and labour, potentially resulting in enhanced agricultural efficiency. High-density areas often exhibit more efficient transportation systems, improved access to farming resources, and greater opportunities for knowledge exchange and innovation, leading to better agricultural outcomes. This body of literature highlights the complex relationship between population density and agricultural productivity, emphasizing that under the right conditions, higher population density can positively impact total crop output (Ricker-Gilbert et al., 2014; Komarek & Msangi, 2019).

In order to determine whether the model with RE or FE was more appropriate for analysing the relationship between selected variables, the Hausman test was employed. The Hausman test assessed the null hypothesis that the RE model yields consistent and efficient estimates, in contrast to the FE model, which addresses unobserved heterogeneity by emphasising within-group variance. The test revealed a chi-squared statistic of 17,903 with 5 degrees of freedom and a p-value of less than 2.2e-16. Due to the very low p-value, we reject the null hypothesis, asserting the consistency of the random effects model.

The null hypothesis rejection in the Hausman test strongly suggests that the random effects model is inconsistent and possibly biased due to the probable correlation between individual effects and explanatory factors. Consequently, the fixed effects model is the more suitable option for this study.

In the next step of the analysis, an IV 2SLS model (Table 31) was applied to address potential endogeneity issues in the regression analysis. In the first stage of the IV 2SLS model, specified instruments (population density, trade balance, CO2 emissions, real factor income in agriculture per annual work, and subsidies) were used to explain the dependent variable, R&D expenditure in agriculture. Each instrumental variable, except CO2 emissions, demonstrated significant coefficients. Furthermore, the F-statistic result (105.5) and a significant p-value <2.2e16 indicate that these variables play a crucial role in predicting R&D expenditure in agriculture. This strengthened the 2SLS approach, as robust instruments are essential for addressing the endogeneity in the second stage.

Table 31. IV 2 Stage Least Square Model in log-log form

	Estimate	Std. Error	t-value	Pr(> |t|)
(Intercept)	5.60396	1.12245	4.993	1.89e-05***
log (R&D expenditure in agriculture (per ha))	0.32738	0.07341	4.460	8.98e-05***
log (Real factor income in agriculture (per annual work))	0.27185	0.09918	2.741	0.00981**
Diagnostic tests				
	df1	df2	statistic	p-value
Weak instruments	2,00	32,00	282.987	<2e-16***
Wu-Hausman	1,00	32,00	6.704	0.0144*
Sargan	1,00	NA	0.004	0.9504
Instruments	Population density, real factor income in agriculture and subsidies.			
Residual standard error	0.3303 on 33 degrees of freedom			
Multiple R-Squared	0.682			
Adjusted R-squared	0.6628			
Wald test 37.43 on 2 and 33 DF	p-value = 3.309e-06			
chisq = 28.192, df = 3, p-value = 3.309e-06				
alternative hypothesis: one model is inconsistent				

Significant codes: $p < 0.001$***, $p < 0.01$**, $p < 0.05$*, $p < 0.1$.
Source: Own calculations in R-studio

In the second stage, R&D expenditure in agriculture was incorporated, acknowledging the complexity of the agricultural system and economic development, as well as real factor income in agriculture as a control variable due to its direct relevance to agricultural productivity (Grigg, 1974). Various alternative model specifications were explored by including additional control variables. However, examinations revealed that the model featuring R&D expenditure in agriculture and real factor income in agriculture as primary variables provided the most robust results.

Specifically, results demonstrated that R&D expenditure in agriculture is positive and statistically significant. A 1 % rise in R&D spending in agriculture correlates with an approximate 0.33% increase in total crops outputs. The residuals indicated a satisfactory fit of the model. Our finding eligns with the result of other scholars (Heisey & Fuglie, 2018; Guesmi & Gil, 2022). This highlights the essential role of R&D expenditure in enhancing agricultural productivity, supporting the broad consensus in the existing literature that innovation is a key factor in agricultural productivity development.

Real factor income in agriculture, on the other hand, has demonstrated a positive and statistically significant coefficient of 0.27185 (p-value 0.00981), confirming its influence on agricultural productivity. This is in line with studies such as those highlighting that higher income levels enable farmers to adopt innovations and increase efficiency, ultimately resulting in greater productivity ("Productivity Growth in Global Agriculture," 2013). Additionally, OECD reports have shown that as incomes in agriculture improve, farmers have more financial flexibility to implement advanced practices, purchase higher-quality inputs, and adopt precision farming techniques, all of which contribute to higher yields.

Furthermore, the Wald test and Weak instruments test reinforced the strength and reliability of the instruments, while the Sargan test validated our instrument selection with a p-value of 0.9504, suggesting no overidentification problem. The Wu-Hausman test revealed a p-value of 0.0144, which confirms the presence of endogeneity. Therefore, we rejected the null hypothesis. Hence, the OLS model lacks consistency, causing the implementation of IV an appropriate replacement to OLS.

The decision to exclude other variables stemmed from their statistical insignificance and the potential risk of overfitting. Thus, the final model in our study offers robust empirical evidence and serves as the most accurate representation of whether or not R&D expenditure in agriculture affects agricultural productivity. This relationship remains valid even when considering the impact of other significant factors such as real factor income. The model validated its strength and reliability, indicating that R&D expenditure in agriculture ought to be a key focus for policymakers looking to boost agricultural productivity.

6. Conclusion

6.1. Summary of Findings

In an era where knowledge and innovation are the primary drivers of economic development, this study provides critical insights into how entrepreneurship, R&D investments, government funding, and agricultural productivity collectively influence economic prosperity. By analysing data from diverse countries and regions, our findings shed light on the key factors driving growth, offering a nuanced understanding of how these elements interact to shape national and regional economic outcomes.

The first part of our study focused on the relationship between entrepreneurship, measured by the Global Entrepreneurship Index (GEI), and GDP per capita across 98 countries from 2015 to 2019. The aim was to assess whether entrepreneurship significantly impacts economic development in both developed and developing economies. The analysis corroborated hypothesis (H1), revealing a significant positive relationship: a 1% increase in GEI is associated with a 3.04% rise in GDP per capita. This finding suggests that countries with higher entrepreneurial activity experience greater economic growth.

Furthermore, our study highlights the importance of key variables such as health and primary education, higher education and training, business sophistication, and market size supporting entrepreneurial activities and fostering long-term economic development. Importantly, our analysis also suggests that while some variables may negatively impact entrepreneurship and GDP per capita in the short term, they contribute positively to long-term economic development. Policymakers can leverage these findings to design policies that strike a balance between immediate economic needs and long-term development goals.

In addition to entrepreneurship, this study investigated the knowledge-based economy (KBE) in the EU-28 NUTS 2 regions. Empirical findings revealed that GERD significantly enhances growth performance, and the percentage of employment in knowledge-intensive services positively affects regional economic outcomes, which confirmed our hypothesis (H2). The KBE manufacturing sector had less impact on GDP per capita compared to the service sectors, reflecting varying priorities across countries.

Furthermore, our analysis supports the hypothesis (H4) that a positive and significant relationship exists between R&D spending (GERD) and real GDP per capita in the EU-27 countries. The estimated models provided robust evidence of a statistically significant positive effect of GERD on real GDP per capita, underscoring the crucial role of R&D expenditure in fostering economic development across EU member states.

It is important to recognize, however, that potential variations in the GERD-real GDP per capita relationship may exist across different countries and contexts. Factors such as the effectiveness of R&D investments, public-private sector collaboration, and the alignment of research goals with economic needs can all influence this relationship (OECD, 2011). Given the importance of R&D for economic development, governments should prioritize effective and targeted increases in R&D expenditure, along with policy initiatives aimed at maximizing the impact of these investments.

Lastly, the study examined the relationship between government R&D funding and private-sector R&D expenditure across 33 OECD countries between 2005 and 2019. Our results confirmed that increased government funding positively influences private R&D investments, with a 1% increase in government funding translating into a rise in Business Enterprise R&D (BERD) (H5). This complementary relationship between public funding and private investment suggests that government support can stimulate innovation and drive economic growth.

Agricultural productivity in the EU-27 was also analyzed from 2000 to 2019, finding that R&D expenditure in agriculture positively influences crop output. A 1% increase in R&D spending is associated with a 0.33% rise in crop productivity, emphasizing the importance of research and technological advancements in agricultural performance (H6).

6.2. Study Limitations

While this study provides insights into the relationship between entrepreneurship, R&D investments, and economic development, several limitations must be acknowledged. First, the sample size was 98 countries, and the study duration from 2015 to 2019 was relatively small and short. This limited timeframe may restrict the generalizability of the results, particularly regarding long-term economic trends. A longer observation period would offer a more comprehensive understanding of the dynamics at play.

Additionally, while significant associations were observed between variables such as the GEI and GDP per capita, the study did not establish causality. Further research using more advanced econometric techniques, such as instrumental variable approaches or dynamic panel models, is needed to determine causal relationships between the variables under investigation. Moreover, the analysis did not explicitly account for external factors such as political stability, trade policies, or environmental conditions that could have influenced economic outcomes.

The study's focus on the EU-28 NUTS2 regions also presents certain limitations. While the research offers robust insights into the relationship between the KBE and GDP growth in these regions, it may not be directly applicable to non-EU countries. The regional context of the EU introduces unique factors such as regulatory frameworks, regional development policies, and funding mechanisms that may not be present in other parts of the world. Furthermore, the data used in this study were drawn from official sources, which, while reliable, may contain measurement errors or reporting biases that were not independently verified.

In addition, this study's cross-sectional structure limits the capacity to draw strong conclusions about causality. Although the analysis is rigorous and grounded in comprehensive data, the cross-sectional nature restricts our ability to capture the temporal dimension of R&D policy, productivity, and economic development interactions over time. Future research could employ longitudinal data or time-series models to examine these relationships more dynamically and in-depth.

Moreover, the complexity of the factors influencing R&D investment—particularly economic and institutional variables—necessitates further investigation. Potential data gaps and variations in data quality across countries may have affected the reliability of some of our findings. Future studies could incorporate qualitative data to enrich the understanding of how different countries or regions implement and benefit from R&D policies. Additionally, exploring sector-specific dynamics could offer more nuanced insights into the factors driving economic growth in particular industries.

Regarding the study's analysis of agricultural innovation, there are additional limitations to consider. The study focuses solely on internal factors, such as R&D spending and real factor income in agriculture, without addressing external factors such as global market conditions, climate change, or policy shifts—which could significantly impact agricultural productivity. The cross-sectional nature of the data also restricts our capacity to assess the causal relationships between innovation and economic development in agriculture. Moreover, the availability and quality of agricultural data vary significantly across different countries, which may influence the robustness of the results.

Nevertheless, the study contributes valuable empirical evidence to the growing body of literature on agricultural innovation and its role in the knowledge-based economy. The findings emphasise the importance of R&D investment in enhancing agricultural productivity and economic performance. However, there is ample room for future research to explore additional factors, such as technological adoption rates, farmer education, and the use of digital tools in precision agriculture. Investigating how these factors interact with innovation could deepen the understanding of the pathways through which external factors and technological advancements shape agricultural outcomes.

In conclusion, while this study offers meaningful insights into the interplay between entrepreneurship, R&D, and economic development, the limitations highlighted suggest avenues for further research. By extending the scope of the analysis to incorporate longer timeframes, broader geographical contexts, and a more detailed exploration of external factors, future studies can provide a more holistic view of the complex relationships at the heart of knowledge-based economic growth.

6.3. Policy Implications

In light of the findings of this study, several policy implications emerge that are crucial for fostering a knowledge-based economy and driving sustainable economic growth. To maximise the impact of innovation, entrepreneurship, and sectoral development, governments play a pivotal role in creating the right conditions.

To begin with, enhanced support for entrepreneurship is essential. Governments should create an enabling environment for startups by offering targeted financial incentives such as tax breaks, seed funding, and loan guarantees. These measures reduce barriers to entry and provide the financial backing needed for innovative startups to thrive. However, financial support alone is not enough. Simplifying bureaucratic procedures and easing regulatory burdens would enable businesses to scale more efficiently. Government-sponsored mentorship programs and business incubators could further foster a culture of innovation, providing entrepreneurs with access to networks and resources that are critical for long-term success.

Additionally, targeted regional development initiatives should focus on the unique strengths of different areas to address regional disparities. Governments can do this by investing in knowledge infrastructure, such as research centres and technology parks, particularly in underserved regions. Enhancing digital connectivity is also crucial in rural areas, where improved access to technology can drive local innovation. By identifying competitive regional advantages, whether in agriculture, technology, or manufacturing governments can tailor development strategies to foster specialized industries that contribute to national growth.

Equally important is increased R&D investment with clearly defined objectives. Policymakers should prioritize long-term investments in sectors with high potential for innovation, such as technology, healthcare, and clean energy. Competitive grants and tax incentives that foster collaboration between academia and industry can achieve this. To ensure these investments translate into real economic growth, governments should set clear, measurable objectives and continuously monitor progress to avoid inefficiencies and misallocation of resources.

One cannot overstate the importance of strategic education and workforce development. Investment in education, particularly in STEM (science, technology, engineering, and mathematics), is essential to building a workforce capable of thriving in a knowledge-based economy. Governments should update curricula to meet the demands of modern industries and foster lifelong learning opportunities that allow workers to adapt to evolving technological landscapes. Reskilling and upskilling programs should be central to government policy, ensuring the workforce remains competitive and adaptable.

Moreover, a balanced approach to public and private R&D funding is necessary to avoid crowding out private investment. Public funds should complement private sector initiatives, particularly in early-stage, high-risk research where private entities may be unwilling to invest. Public-private partnerships (PPPs) are an effective mechanism to encourage collaboration between government, academia, and industry, foster synergy, and ensure that innovations have a pathway to commercialization.

Institutional reforms are equally critical for ensuring the effective deployment of R&D investments. Governments must facilitate decision-making processes and improve resource allocation by decentralizing innovation councils and forming specialized task forces with industry experts. Attracting top scientific talent to leadership positions in national and regional innovation bodies will enhance decision-making and enable governments to address challenges such as the "middle technology trap", where economies struggle to move beyond middle-income status due to a lack of high-tech innovation.

Strategic investment in agricultural innovation is also essential, particularly in countries where agriculture plays a key role in the economy. Governments should invest in agricultural R&D, focusing on precision farming, digital tools, and sustainable practices. By doing so, they can drive productivity gains while addressing critical challenges such as climate change and food security. Restructuring subsidies to incentivize innovation rather than keeping traditional, often inefficient mechanisms will align agricultural policies with sustainability goals and increase productivity in the sector.

In conclusion, these policy recommendations offer a roadmap for fostering an innovation-driven, knowledge-based economy. By strategically supporting entrepreneurship, enhancing regional development, increasing R&D investments, and reforming educational and institutional frameworks, governments can promote sustainable economic growth, resilience, and societal well-being. The insights provided by this study illustrate the critical role of strategic investment in driving long-term growth and competitiveness in the global economy.

6.4. Final Remarks

As we enter a new era, it is evident that knowledge has become the most valuable asset. The shift to a knowledge-based economy encompasses more than just economic changes; it signifies a significant transformation in society, where innovation, creativity, and knowledge take center stage. This study has underscored the pivotal role of entrepreneurship, R&D investment, government funding, and agricultural innovation in driving economic development within this framework.

A comprehensive strategy is essential to effectively harnessing the opportunities of a knowledge-driven future. Prioritising the development of human capital is critical, as a skilled, knowledgeable, and adaptable workforce is necessary for innovation and economic advancement. Governments, enterprises, and educational institutions must invest in lifelong learning, upskilling, and reskilling initiatives to ensure individuals acquire the competencies needed to thrive in the 21st century.

R&D serves as the foundation for technological progress and innovation. By investing in R&D, governments can catalyse the creation of new technologies and products that have the potential to transform industries and enhance quality of life. Collaboration among governments, businesses, and educational institutions is essential to foster an innovative culture that encourages creativity, experimentation, and risk-taking.

Government policy plays a crucial role in shaping the parameters of a knowledge-based economy. By implementing effective economic policies, investing in infrastructure, and establishing a supportive regulatory framework, governments can promote innovation, attract investment, and stimulate economic growth. Additionally, government funding can facilitate research, education, and technological development, accelerating the transition to a knowledge-driven future.

The agriculture sector, often overlooked, is undergoing a substantial transformation. By adopting technological innovations, such as precision agriculture, biotechnology, and artificial intelligence, farmers can enhance productivity, minimize environmental impacts, and secure food supplies for a growing global population. Governments can support this transformation through subsidies, research grants, and extension services.

Regional development is another critical aspect of the transition to a knowledge-based economy. By investing in infrastructure, education, and innovation in underdeveloped regions, governments can reduce imbalances and promote inclusive growth. Establishing technology clusters, promoting entrepreneurship, and attracting talent to regional locations are effective strategies for achieving this.

As this study demonstrates, the findings provide valuable insights for policymakers seeking to foster innovation-driven growth and address sustainable development challenges.

Addressing the challenges of the 21st century requires leveraging knowledge to tackle global issues. Investment in education, innovation, and technology is essential for creating a more profitable, fair, and sustainable future. By leveraging insights from this research, governments and institutions can design policies that address short-term economic challenges while laying the foundation for sustainable, knowledge-driven growth that promotes innovation, job creation, and enhanced quality of life for future generations.

Furthermore, additional research is essential to explore sector-specific dynamics for a broader group of countries and longer-term trends in developing knowledge-based economies. This investigation would enable a deeper understanding of how such economies evolve, particularly in industries or regions that were not fully examined in this study. Additionally, cross-border collaboration in R&D can amplify the benefits of knowledge-driven growth by fostering the exchange of best practices and technological advancements.

In summary, this study’s findings offer a roadmap for policymakers and entrepreneurs aiming to promote a sustainable and resilient economy, anchored in knowledge, innovation, and long-term strategic investments.

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Appendix

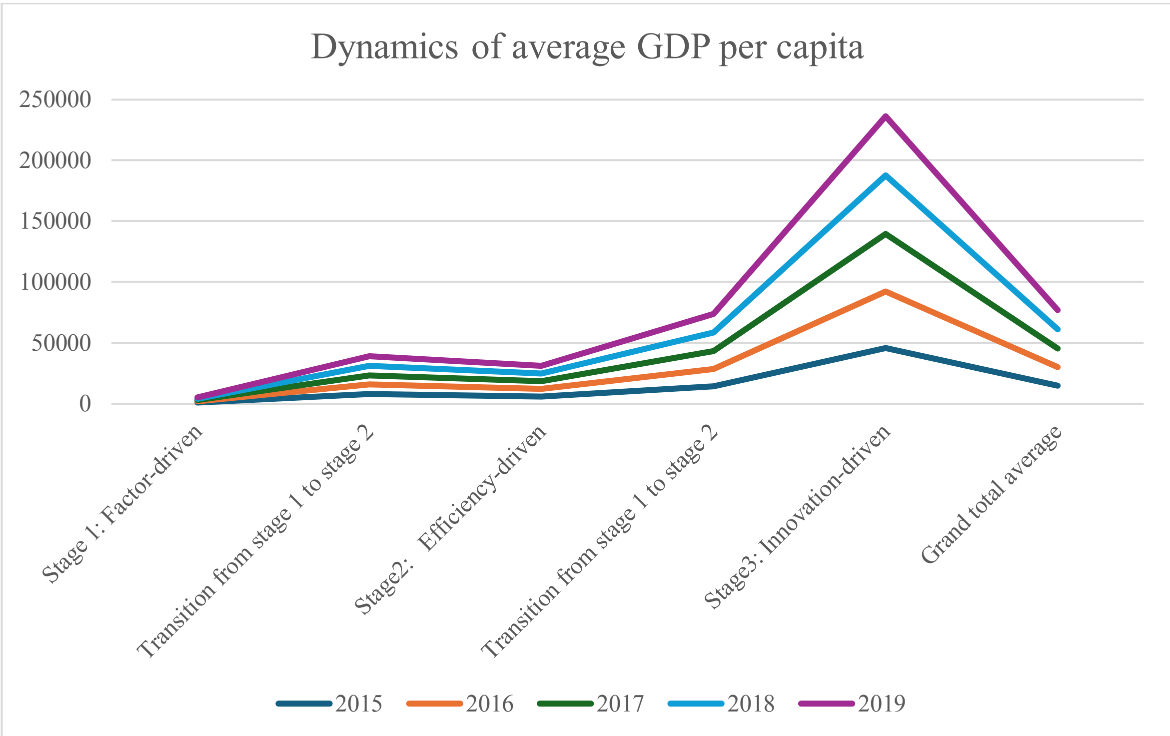
Appendix 1

Table 32. Dynamics of average GDP per capita (constant 2010 USD $) for the countries, according to by each stage of development considered in the analysis

	2015	2016	2017	2018	2019
Stage 1: Factor-driven	994	1011	1036	1065	1091
Transition from stage 1 to stage 2	7,870	7,911	7,705	7,770	7,809
Stage2: Efficiency-driven	6,024	6,107	6,229	6,384	6,496
Transition from stage 1 to stage 2	14,189	14,387	14,728	15,084	15,304
Stage3: Innovation-driven	45,791	46,472	47,332	48,139	48,581
Grand total average	14,973	15,178	15,406	15,689	15,856

Source: World Bank 2015–-2019. Note: Authors' own calculation

Figure 4. Dynamics of average GDP per capita (constant 2010 USD $) for the countries, according to by each stage of development considered in the analysis



Source: Own calculations

Appendix 2

Table 33. Multiple regression results for the period 2015–-2019

	Regression Statistics; Using 98 observations				
	2015	**2016**	**2017**	**2018**	**2019**
Multiple R	0.88	0.89	0.87	0.88	0.85
R- sSquared	0.78	0.79	0.75	0.78	0.72
Adjusted R- sSquared	0.76	0.78	0.73	0.76	0.70
Standard eError	11,092.18	10,809.23	11,958.37	11,490.72	12,942.77
	Model Pproperties				
	Intercept				
Coefficient	-54,076.58	-52,778.65	-62,226.36	-55,126.80	1,644.72
p-value	0.000	0.000	0.000	0.000	0.887
	GEI				
Coefficient	646.36	691.01	266.46	631.03	988.64
p-value	0.000	0.000	0.012	0.000	0.000
	Infrastructure				
Coefficient	2,097.10	365.75	3,210.21	-1,915.86	-822.51
p-value	0.437	0.106	0.256	0.348	0.683
	Health and pPrimary eEducation				
Coefficient	2,925.28	3,419.98	2,567.38	4,010.70	1,292.91
p-value	0.306	0.187	0.416	0.204	0.522
	Higher education and trainingsHigher education and training				
Coefficient	-6,837.04	-7,392.73	-2,369.15	-3,601.74	2,070.72
p-value	0.035	0.021	0.484	0.302	0.546
	Market Size				
Coefficient	-3,420.25	-3,839.70	-4,715.69	-3,273.97	-904.82
p-value	0.005	0.001	0.000	0.012	0.555
	Business sSophistication				
Coefficient	9,524.80	9,648.24	10,434.47	9,990.03	-7,805.61
p-value	0.096	0.059	0.088	0.077	0.072
	Innovation				
Coefficient	6,993.85	8,679.18	8,360.96	6,563.66	2,228.71
p-value	0.091	0.030	0.059	0.122	0.360

Significant codes: $p < 0.001$***, $p < 0.01$**, $p < 0.05$*, $p < 0.1$.
Source: GEI Report 2015-–2019; GCI Report 2015–2019; World Bank 2015-2019. Own Calculations in R studio

Appendix 3.

Table 34. Multicollinearity analysis

	Patent applications to EPO	R&D personnel	Gross Domestic Expenditure on Research & Development (GERD) by sector	Employment in high-technology sectors (high-technology manufacturing and knowledge-intensive high-technology services), in % of total.	Employment in the high-technology manufacturing sector, in % of total	Employment in medium high-technology manufacturing sector, in % of total	Employment in wholesale and retail trade; accommodation and food services activities; activities of households as employers, in % of total	Employment in total knowledge-intensive services sector, in % of total	Employment in knowledge-intensive high-technology services sector, in % of total
Tolerance	0.5	0.2	0.2	0.1	0.1	0.4.	0.4	0.004	0.02
VIF	1.9	4.6	4.2	18.1	7.0	2.5	2.8	265.7	40.8
	Employment in knowledge-intensive market services (expect financial intermediation and high-technology services) sector, in % of total	Employment in other knowledge-intensive sectors, in % of total	Employment in information and communication sector, in % of total	Employment in financial and insurance activities sector, in % of total	Employment in professional, scientific and technical activities sector, in % of total	Employment in education sector, in % of total	Employment in human health and social work activities sector, in % of total	Ratio of the proportion of students (ISCED 5-6) over the proportion of the population by NUTS 2 regions	
Tolerance	0.04	0.006	0.03	0.15	0.05	0.3	0.09	0.6	
VIF	24.3	172.8	38.6	6.9	19.3	3.2	10.7	1.8	

Source: Own calculations in R-studio

Appendix 4.

Table 35. 2SLS Model

	Estimate	**Std. Error**	**t -value**	**Pr(>|t|)**
(Intercept)	9.79226	0.47250	20.724	< 2e-16***
log (Patent applications to EPO)	0.06046	0.01331	4.543	7.81e-06***
log (R&D personnel)	0.25510	0.05328	4.787	2.57e-06***
log (Gross Domestic Expenditure on Research & Development (GERD) by sector)	0.19410	0.02258	8.597	3.52e-16***
log (Employment in the high-technology manufacturing sector, in % of total)	-0.10827	0.03127	-3.463	0.000606***
log (Employment in medium high-technology manufacturing sector, in % of total)	-0.04113	0.03393	-1.212	0.226291
log (Employment in wholesale and retail trade; accommodation and food services activities; activities of households as employers, in % of total)	-0.36270	0.11801	-3.073	0.002295**
log (Employment in financial and insurance activities sector, in % of total)	0.33462	0.05714	5.856	1.16e-08***
log (Employment in education sector, in % of total)	-0.21471	0.09680	-2.218	0.027239*
log (Ratio of the proportion of students (ISCED 5-6) over the proportion of the population by NUTS 2 regions)	-0.14965	0.04570	-3.275	0.001171**
Residual standard error	0.3084 on 325 degrees of freedom			
Multiple R-Squared	0.7276			
Adjusted R-squared	0.7201			
Wald test	96.48 on 9 and 325 DF, p-value: < 2.2e-16			

Significant codes: p < 0.001***, p < 0.01**, p < 0.05*, p < 0.1 .
Source: Data was sourced from Eurostat (2022). Own calculations in R-studio