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**STRATEGIC ECONOMICS**

**Emilija Navickaitė**  
**MASTER'S THESIS**

<p><b>MOKSLINIŲ TYRIMŲ IR EKSPERIMENTINĖS PLĖTROS INTENSYVUMO VAIDMUO EKONOMIKOS KOMPLEKSIŠKUME: EUROPOS SĄJUNGOS ŠALIŲ PAVYZDYS</b></p>	<p><b>THE ROLE OF RESEARCH AND DEVELOPMENT INTENSITY IN ECONOMIC COMPLEXITY: EVIDENCE FROM THE EUROPEAN UNION</b></p>
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**Supervisor Assoc. Prof. Dr. Giedrė Dzemydaitė**

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## INTRODUCTION

**Relevance of the topic.** In recent years, concerns regarding the resilience of Europe's industrial base have become increasingly prominent in policy discussions. According to simulations by the European Central Bank, if the Chinese electric vehicle industry were to follow a subsidy trajectory similar to that observed in the solar photovoltaic sector (where state-backed Chinese manufacturers captured over 80% of the European market within six years, driving dozens of EU firms into insolvency), domestic EU production of electric vehicles could decline by up to 70%. To put this potential impact into perspective, the automotive industry alone employs, directly and indirectly, almost 14 million people across the European Union (European Commission, 2025). Although such statements may appear strong, the reality of Europe's industrial challenges has been persistent over time. As early as 2014, the European Commission launched the European Industrial Renaissance initiative to strengthen the competitiveness of EU industry (European Commission, 2014a). Alarmed by the declining share of manufacturing in EU gross domestic product, a growing trade deficit with China and the rapid catch-up of Chinese firms in high value-added production, the Commission introduced a series of initiatives aimed at bringing manufacturing capacity in strategic sectors back to Europe. Yet, a decade later, Mario Draghi, in an EU Commission report, declares: "Europe is stuck in a static industrial structure," with limited emergence of dynamic new industries (European Commission, 2025). This persistence highlights an important policy reality: manufacturing structures remain foundational to the European economy and any erosion of their role would entail substantial economic and social adjustment costs. As a result, European competitiveness strategies have increasingly relied on research and development as a central instrument for sustaining and upgrading the manufacturing base. Based on Eurostat data, gross domestic expenditure on Research and Development in the EU reached €381 billion in 2023, reflecting substantial public and private efforts to support technological upgrading. Nevertheless, in the context of highly competitive and open markets, questions remain regarding the effectiveness of these investments and their ability to translate into sustained industrial transformation.

Much of the policy debate regarding the role of innovation in shaping industrial performance relies on aggregated indicators of innovation output and economic growth. While useful, such measures often provide limited insight into the underlying structures of production and the distribution of capabilities across industries. The Economic Complexity Index and its network-based approach focus on the embedded knowledge within an economy and its potential for diversification based on global trade data. Exploring this framework is particularly relevant at a time when both national and

EU-level policies place increasing emphasis on smart specialization, innovation ecosystems and evidence-based growth strategies, yet the link between policy effort and structural industrial outcomes remains insufficiently understood.

**The level of exploration of the topic.** Economic complexity, operationalized through the Economic Complexity Index (ECI), measures the amount of productive knowledge embedded in an economy. This index reflects both what an economy produces and how sophisticated and knowledge-intensive its production structure is. Scholars have increasingly linked economic complexity to long-term development outcomes, productivity growth and competitiveness. However, while the explanatory power of the ECI has gained broad recognition, the underlying structural mechanisms that drive changes in economic complexity remain less thoroughly examined. Given the relatively recent emergence of this framework, the majority of existing studies focus on legitimizing the index as a meaningful indicator for analyzing economic development challenges and potential growth pathways. In addition, empirical applications of the ECI present a number of econometric challenges, including issues related to endogeneity, path dependence and data limitations. When scholars have attempted to examine the relationship between economic complexity and research and development (R&D), analyses have often relied on global datasets, with results largely driven by lower-income and emerging economies. In the context of the heterogeneous European Union, R&D has more frequently been included as a control variable rather than examined as a key explanatory factor in shaping economic complexity. It is also worth noting that disaggregated data on R&D efforts by sector has received limited attention in the economic complexity literature. By contrast, R&D investment has been extensively studied within the broader innovation literature as a core component of national innovation systems, especially in relation to productivity growth, patenting activity and technological advancement. Yet, the extent to which R&D investment contributes to structural transformation of production systems, as captured by economic complexity measures, remains insufficiently explored.

**The novelty of the thesis.** The thesis relies on a panel analysis covering 25 EU countries over a 23-year period to examine the relationship between national R&D investment and economic complexity. Beyond estimating the relationship between the key variables, the analysis is used to identify broad and persistent trends in productive structure and R&D effort across European economies. Standard data testing and robustness checks are applied to ensure the consistency of the empirical results, while the extended time horizon allows the study to focus on structural developments rather than short-term fluctuations. This thesis is novel in its use of economic

complexity to evaluate R&D outcomes and in its focus on long-run cross-country patterns, offering policy-relevant insights into the structural role of public R&D investment.

**The problem of the thesis.** The central research question of this thesis is: To what extent does the national R&D investment contribute to economic complexity in the European Union, and how is this relationship reflected across disaggregated categories of R&D expenditure?

**The aim of the thesis.** The aim of this thesis is to analyze long-run patterns in the relationship between national R&D investment and economic complexity across European Union countries.

**The objectives of the thesis.**

1. To review the concept of economic complexity and its theoretical foundations.
2. To review and compare the main approaches used to measure economic complexity, distinguishing between aggregated indices (such as ECI and related measures) and network-based representations.
3. To identify and systematize the key determinants of economic complexity, with particular emphasis on the role of national R&D investment within innovation systems.
4. To analyze long-run patterns and trends in economic complexity and R&D intensity across European Union countries over the period 2000-2023
5. To empirically assess the relationship between national R&D intensity and economic complexity in the EU using panel regression analysis.
6. To empirically assess whether disaggregated components of national R&D expenditure (business, government and higher education) are associated differently with economic complexity.

**The methods deployed by the Masters thesis.** The thesis applies logical analysis methods, including induction and deduction, as well as scientific literature analysis, systematization, synthesis and comparison of theoretical insights. Descriptive statistical methods are used for data systematization and graphical presentation of trends in economic complexity and R&D investment. The empirical analysis is based on quantitative methods. Panel data are processed and analyzed using RStudio statistical software. Econometric analysis is conducted using fixed-effects panel regression models with lagged explanatory variables. Diagnostic tests and robustness checks are applied to ensure the reliability of the empirical results. Additional calculations, result systematization, and the presentation of tables and figures are supported using Microsoft Excel.

**Use of artificial intelligence (hereinafter - AI).** During the preparation of this thesis, artificial intelligence (AI) tools were used as supportive instruments at different stages of the research process. ChatGPT (OpenAI) was employed for linguistic editing, clarification of academic formulations and improvement of stylistic coherence in selected sections of the manuscript. Claude (Anthropic) was used to assist with troubleshooting and resolving unexpected errors in RStudio code written by the author, particularly in relation to logical consistency and formatting procedures applied in the construction of empirical tables. Data visualization, specifically the preparation of graphs with country flags, was conducted using Visual Studio Code with the Python programming language, with the assistance of GitHub Copilot. All empirical analyses, data transformations, and results reported in the thesis were designed, implemented, and interpreted by the author.

**Structure of the thesis.** This thesis is structured as follows. Chapter 1 provides the theoretical framework for the analysis by introducing the concept of economic complexity, discussing its main measurement approaches, and reviewing the key determinants of economic complexity with particular emphasis on research and development and innovation systems. The chapter also situates economic complexity within the context of European Union innovation policy. Chapter 2 outlines the research design, presenting the research aim, objectives, and hypotheses, describing the data and variables used, and explaining the empirical approach and diagnostic procedures applied in the analysis. Chapter 3 presents empirical results, beginning with a descriptive overview of economic complexity and R&D patterns across EU countries, followed by the main estimation results and robustness checks. The final section summarizes the main findings and discusses their implications.

# **1. THEORETICAL ANALYSIS OF THE RELATIONSHIP BETWEEN R&D INVESTMENT AND ECONOMIC COMPLEXITY**

This chapter analyzes the scientific literature on economic complexity and its relationship with national research and development (R&D) investment. It reviews the emergence of the economic complexity concept and its theoretical foundations, as well as the key mechanisms linking productive capabilities, structural change, and long-run development. The chapter systematizes the main determinants of economic complexity, with particular emphasis on the role of R&D. Subsequently, the literature examining economic complexity in the context of the European Union is reviewed, highlighting both knowledge diffusion mechanisms and persistent heterogeneity across member states. Finally, the chapter reviews the main approaches used to measure economic complexity.

## **1.1. Conceptual Foundations of Economic Complexity**

The roots of understanding economic complexity lie in the name itself. It reflects the idea that the Economy is built not just from labor, machines, and materials, but from something more complex: know-how. In their introduction to economic complexity theory, Ricardo Hausmann and Cesar A. Hidalgo illustrate this with a simple example. The significance of producing toothpaste lies not in the final product itself, but in the capabilities behind it (Hausmann & Hidalgo, 2011). Toothpaste is the result of understanding chemistry, of combining tools, substances and processes to create something that protects and cleans our teeth. What matters most is not just having expertise, but how different pieces of expertise connect and interact. A country may have access to all the necessary raw materials, but without this interconnected knowledge infrastructure, production can be more than challenging. This reflects a broader economic principle first introduced by Adam Smith in his theory of the division of labor (Smith, 1776). While Smith focused on how efficiency grows through the separation of tasks among individuals, economic complexity extends this insight to the distribution of specialized knowledge across entire societies. It asks how capabilities in science, engineering, design, logistics and more accumulate and interact at scale. From this perspective, production is not just the result of labor inputs, but a reflection of how deeply know-how is embedded, shared and recombined.

The economic complexity literature does not present itself as a radical break from existing theories of economic development. Economists have for decades questioned the predictability of specialization patterns and recognized that not all goods carry the same growth potential (Hausmann et al., 2007). Similarly, endogenous growth models emphasize that learning-by-doing, increasing

returns, and knowledge spillovers make long-run growth dependent on economic structure and the pace of structural transformation (Grossman & Helpman, 1991; Aghion & Howitt, 1998; Barro & Sala-i-Martin, 2003). In this sense, economic complexity can be viewed as a natural extension of endogenous growth theory. While endogenous growth models conceptually identify knowledge as the fundamental driver of growth, their empirical implementation relies on indirect proxies that capture only limited, codified dimensions of knowledge (Hidalgo, 2021). The economic complexity framework builds on this insight by proposing a method to infer tacit, distributed, and capability-embedded knowledge from observable economic outputs. By linking production structures to underlying capabilities, economic complexity operationalizes empirically what endogenous growth models describe primarily at a theoretical level (Hidalgo & Hausmann, 2009; Hausmann et al., 2011).

Earlier research made clear that specialization matters, but much of the empirical literature has relied on highly aggregated representations of the economy. Differences across countries have typically been summarized through measures of physical and human capital accumulation, broad institutional indicators or aggregate productivity residuals, with limited attention paid to their specificity or complementarity. As a result, detailed information on firms, products, and production technologies is often collapsed into macroeconomic indicators such as GDP, investment or total factor productivity, obscuring what countries actually produce and the capabilities required to do so (Balland et al., 2022). Economic complexity shifts the focus back to production itself. Rather than treating countries as variations of the same economy operating at different efficiency levels, it starts from the observation that rich and poor countries tend to produce very different sets of goods, using distinct combinations of capabilities. By exploiting disaggregated production and trade data, complexity-based measures such as the Economic Complexity Index capture information about the diversity and interaction of capabilities embedded in an economy: information that standard income-based indicators leave aside. Empirically, these measures have been shown to be closely associated with income levels, future growth, and patterns of structural change (Mealy & Teytelboym, 2022).

It is important to note, that economic complexity theory is cautious about explaining how capabilities are built in the first place (Hidalgo & Hausmann, 2009). Its main contribution lies in measurement and in showing clear patterns between productive structure and development outcomes. Important questions about how countries expand their capabilities, what constraints they face and how demand, institutions, and policy influence these processes remain open. Therefore, economic

complexity does not replace existing theories of development but complements them by making the structure of production and its limits visible in the data.

It is of course not without its limitations. Economic complexity, as originally introduced, focuses on goods exports as the main signal of competitiveness and growth, which means that services, for example, are largely left out of the picture. That bias partly comes from an older view that services are low-productivity activities and mainly serve as inputs into manufacturing (Loungani et al., 2020). But this assumption is increasingly outdated. With the rise of ICT, cheaper transport and globalization, many services have become tradable final exports in their own right, not just support for goods production. In fact, as countries develop and income levels rise, services tend to account for an increasing share of overall economic activity (Stojkoski et al., 2016). This matters because many modern services like ICT, business services, finance, are complex and deeply embedded in global value chains, yet they are not captured by goods-based trade statistics (Loungani et al., 2020). As a result, economies with advanced service sectors can look less complex than their real capabilities suggest. This is especially relevant for European economies such as Ireland, the Netherlands and the Nordic countries, where sophisticated services strongly shape competitiveness. It is also relevant for Lithuania, where fintech and ICT services have been actively growing and supported by policymakers, yet remain largely invisible in goods-based ECI measures. A similar issue arises in logistics. Within the economic complexity framework, logistics is treated mainly as a supporting service to manufacturing. Income generated from activities such as transport services, vehicle leasing, or foreign operations related to goods produced elsewhere does not enter the country-product export matrix used to compute the ECI. As a result, these activities do not contribute to measured economic complexity, even though they may represent significant sources of value added.

To summarize, economic complexity looks at development through what countries are able to produce and the knowledge needed to produce it, rather than through income or growth alone. By relying on detailed trade data, it reveals differences in productive structure that aggregate indicators tend to hide. At the same time, because these measures are built on goods trade, they mainly reflect manufacturing. This means that countries where knowledge-intensive services play a growing role, including several European economies, may appear less complex than their actual productive capabilities would suggest.

## **1.2. Determinants of Economic Complexity**

This section reviews the literature on capability formation relevant to economic complexity growth, with particular emphasis on the role of R&D investment. It begins with a concise overview of structural, institutional and human capital factors that condition capability accumulation across countries. It then examines in more detail how R&D investment contributes to capability building, drawing on insights from growth theory, innovation systems research and the literature on learning and knowledge diffusion. Finally, the section reviews empirical studies that explicitly link R&D activity to changes in economic complexity.

### **1.2.1. Structural and Institutional Drivers of Economic Complexity**

Since the introduction of the economic complexity framework, researchers and policymakers have extensively used the Economic Complexity Index (ECI) to explain cross-country differences in diversification patterns, long-run economic growth, income inequality and sustainability outcomes (Hidalgo, 2023). Alongside descriptive and predictive applications, the literature has increasingly addressed causal relationships involving economic complexity. Broadly, existing studies can be grouped into two strands: those examining the effects of economic complexity on economic outcomes (ECI → economic performance) and those analyzing the determinants of economic complexity itself (economic factors → ECI). While the former strand is now well established, the latter remains comparatively underexplored. This reflects both the initial focus on validating ECI as a meaningful development indicator and the methodological challenges associated with identifying the drivers of complexity, including path dependence and bidirectional causality (Nguyen et al., 2020). Understanding which factors causally drive complexity accumulation, and through what mechanisms, remains an active area of empirical investigation.

Among the most robust findings in this literature is the central role of institutional quality in shaping countries' productive structures. Early economic complexity studies highlighted that weak institutional frameworks can fundamentally constrain structural transformation by distorting incentives for capability accumulation (Hausmann et al., 2007). Hartmann et al. (2017) show that economic complexity is strongly correlated with institutional quality and they argue conceptually and empirically that productive structures, institutions and human capital co-evolve. These effects operate through multiple channels: by securing property rights and reducing uncertainty, strong institutions provide incentives for innovation, facilitate patent development and protection, and accelerate

knowledge accumulation (Lapatinas & Litina, 2019). More fundamentally, Vu (2022) highlights that institutional quality alters the relative returns to different economic activities, raising returns to sophisticated, knowledge-intensive production relative to extractive or rent-seeking activities. This mechanism provides a compelling explanation for why countries with similar resource endowments but different governance structures exhibit dramatically different complexity trajectories.

The accumulation of productive capabilities, however, depends not only on favorable institutional environments but on the availability of skilled labor to implement and develop complex production processes. Economic complexity fundamentally reflects embodied knowledge, skills, and know-how that enable countries to produce increasingly sophisticated goods (Hausmann & Hidalgo, 2011), making human capital essential for developing complex productive structures (Vu, 2022). Countries with higher levels of education and training capacity are better able to absorb foreign technologies and diversify into more sophisticated production activities, thereby achieving higher levels of export sophistication (Zhu & Li, 2017). The relationship between education and complexity appears to operate through both direct and indirect mechanisms. Kamguia et al. (2024) show, using mediation analysis, that R&D affects economic complexity both directly and indirectly, with human capital and innovation acting as significant transmission channels accounting for roughly one-fifth of the total effect each. Beyond its role in innovation, human capital also shapes the distributional consequences of productive sophistication. Lee and Vu (2020) show that the relationship between economic complexity and income inequality is strongly conditional on human capital endowments. Their results indicate that higher levels of education amplify the inequality-reducing association between economic complexity and income inequality in cross-sectional analyses, suggesting that human capital enhances the capacity of societies to more broadly distribute the gains from complex productive structures. There are however some contradictory opinions in the economic complexity literature (Veselinović et al., 2025). A recent study based on a sample of Central and Eastern European countries finds a negative relationship between tertiary education enrolment and the Economic Complexity Index. The authors caution against interpreting enrolment as a straightforward proxy for the role of education in structural transformation, noting that this result may reflect brain drain, skill mismatches, or saturation effects in systems where educational expansion has outpaced modernization. Overall, the literature suggests that while human capital is a key enabler of economic complexity its contribution depends on education quality, labor market alignment, and complementary domestic capabilities, as expansion in tertiary enrolment alone may fail to translate into higher complexity.

Beyond institutional conditions, the structural characteristics of economies play a central role in shaping both the feasibility of developing complex production capabilities and the returns to specialization in sophisticated activities. Larger populations provide greater market scale and a higher likelihood of diverse productive capabilities, enabling more specialized labor markets and supporting niche production (Lee & Vu, 2020; Kamguia et al., 2024). Empirically, countries with populations above 20 million tend to exhibit higher levels of economic complexity at comparable income levels, suggesting the presence of scale economies in capability accumulation. However, population size alone is insufficient in the absence of integration into international markets. Trade openness can facilitate learning-by-exporting, provide access to knowledge-embedded imported inputs, and expose domestic firms to international best practices, thereby supporting diversification into more complex product spaces, particularly when absorptive capacity is sufficiently developed (Fatima et al., 2020; Lapatinas, 2019).

The effects of trade openness and population, however, are far from uniform across countries. In economies with weak institutions or low human capital, trade integration may simply reinforce comparative advantage in low-complexity primary commodities or resource extraction, potentially even reducing productive sophistication through Dutch Disease mechanisms as resources flow toward traditional sectors. Conversely, in economies with strong absorptive capacity, characterized by sound institutions and adequate education levels, openness exhibits positive effects on complexity accumulation by enabling technology transfer and learning. This heterogeneity in openness effects helps explain why most empirical studies treat trade integration as a conditional factor whose benefits depend critically on complementary domestic capabilities, rather than as a primary driver of complexity in its own right.

Beyond structural determinants, macroeconomic outcomes also interact closely with economic complexity, though the direction of causality differs from conventional accounts. Using panel data for 94 countries over the period 1970-2014, Al-Marhubi (2021) shows that economic complexity has a negative and causal effect on inflation, estimated using dynamic panel GMM techniques. The results indicate that economies with more diversified and sophisticated productive structures experience lower inflation, as complexity dampens macroeconomic shocks and reduces inflationary biases associated with discretionary policymaking. From a policy perspective, this evidence suggests that development strategies centered on export diversification and capability accumulation, core elements of economic complexity, are more conducive to macroeconomic stability

than reliance on narrow export specialization. Foreign direct investment presents a more complex dynamics. Another tested determinant of economic complexity is foreign direct investment. Research shows that it can facilitate the transfer of embodied technology, managerial know-how and access to global value chains. It is also systematically attracted to countries with pre-existing productive sophistication, giving rise to simultaneity and selection biases in conventional estimates (Antonietti & Franco, 2021; Apostol & Musyoka, 2024). When endogeneity is explicitly addressed using dynamic or instrumental-variable approaches, the empirical evidence suggests that FDI exerts at most a modest and short-lived positive effect on economic complexity, concentrated primarily in economies with sufficiently high levels of human capital, financial development and absorptive capacity.

Cutting across all these specific determinants is the pervasive role of income level in empirical studies of economic complexity. GDP per capita correlates strongly with more sophisticated productive structures (Hausmann et al., 2011; Hartmann et al., 2017; Lapatinas, 2019), making income the single strongest bivariate predictor of complexity. This strong association reflects the long-run co-evolution of income, capabilities and diversification: wealthier countries can afford greater investment in R&D, education and infrastructure that build complexity, while higher complexity generates productivity gains that raise income. Yet this creates both an empirical and conceptual challenge. The literature demonstrates convincingly that income alone does not determine complexity outcomes, as countries with similar income levels often display markedly different ECI values depending on their institutional quality, innovation systems, and structural characteristics. Resource-rich economies such as Saudi Arabia or Russia tend to exhibit substantially lower levels of economic complexity than manufacturing-oriented economies with comparable GDP per capita, underscoring that the structure of production matters as much as income levels themselves. This pattern highlights a central tension in the empirical literature: while income is one of the strongest correlates of economic complexity, it is insufficient to explain cross-country differences in productive sophistication. This insight has important methodological implications for the inclusion of income controls in empirical models of economic complexity. GDP per capita is almost universally included as a control variable in complexity regressions, serving as a benchmark against which the effects of R&D, institutions, human capital or other determinants can be isolated. The research question then becomes: conditional on income level, which factors explain remaining cross-country variation in productive sophistication? This specification allows researchers to identify which policies and structural factors enable countries to "punch above their weight" in complexity terms, achieving greater productive sophistication than their income level alone would predict. Other determinants also appear in the

literature but remain relatively underexplored. Studies have also examined the role of Internet use, green trade openness and related structural characteristics in shaping economic complexity, with evidence suggesting that these factors can influence productive sophistication in specific cultural contexts (Lapatinas, 2018; Neagu et al., 2022; Kamguia et al., 2024). However, the empirical findings are not uniform, and the strength and direction of these relationships often vary across country groups and institutional settings, indicating that their effects are highly context dependent.

In sum, the literature suggests that economic complexity emerges from the interaction of innovation inputs, institutional quality, human capital, structural scale, openness and macroeconomic conditions. These determinants exhibit strong complementarities, path dependence, and bidirectional causality, which complicate empirical identification. This helps explain why, despite growing academic and policy interest in economic complexity, the mechanisms underlying its formation remain insufficiently explored and continue to motivate empirical research focused on innovation-driven capability accumulation.

### **1.2.2. R&D and Knowledge Diffusion**

R&D and innovation research has long been a cornerstone of academic research. Early growth models acknowledged the central role of technological progress but treated it as exogenous. In the Solow - Swan framework, sustained growth in output per capita depends on technological change that occurs outside the economic system rather than as a result of purposeful economic activity (Solow, 1956; Swan, 1956). While this approach clarified the limits of capital accumulation and convergence dynamics, it offered little insight into why innovation capacity differs persistently across countries or how economies move into increasingly sophisticated activities. Endogenous growth theory addressed this limitation by internalizing technological change as the outcome of intentional investment. Romer (1990) formalized growth as driven by R&D that expands the stock of ideas, emphasizing the non-rival nature of knowledge and the presence of spillovers that prevent diminishing returns in the same way as physical capital. Schumpeterian models further conceptualized innovation as a process of creative destruction, in which firms invest in R&D to obtain temporary monopoly rents, linking long-run growth to innovation incentives, market structure, and institutional conditions (Aghion & Howitt, 1992, 1998). Subsequent theoretical refinements moderated the strong scale effects predicted by early endogenous growth models. Empirical evidence showed that increases in R&D employment and expenditure did not lead to proportionally higher growth rates in advanced economies. In response, semi-endogenous and non-scale growth models emphasized the role of research productivity,

absorptive capacity, and distance from the technological frontier rather than R&D levels alone. These insights imply that R&D is more likely to generate level effects, raising the sophistication and quality of an economy's productive structure, than immediate acceleration of growth, particularly in countries close to the frontier.

Innovation systems theory complements endogenous growth models by shifting attention from aggregate R&D investment to the institutional and organizational context in which innovation occurs. From this perspective, innovation is cumulative, path dependent and shaped by interactions among firms, universities, public research organizations and government agencies. R&D effectiveness therefore depends not only on expenditure levels but on coordination mechanisms, knowledge diffusion channels, and the alignment between research activities as well. This system-level view is consistent with the capability-based understanding of development, where complex production requires the coordinated interaction of multiple complementary forms of knowledge.

Empirical research highlights important differences across R&D-performing sectors. Business-sector R&D is most directly linked to applied research, process upgrading and commercialization, while government and higher-education R&D contribute primarily through basic research, human capital formation and long-term knowledge accumulation (Guellec & Van Pottelsberghe de la Potterie, 2004). Public R&D can crowd in private investment and strengthen innovation capacity, but its effectiveness depends critically on institutional quality and the ability of firms to absorb and exploit publicly generated knowledge. Evidence from firm- and regional-level studies shows that public R&D spending enhances innovation efficiency (Bronzini & Piselli, 2016), stimulates exploratory research activities (Criscuolo, Haskel & Slaughter, 2019), and strengthens regional innovation capacity when embedded in coherent innovation systems. A central mechanism linking R&D to capability accumulation is absorptive capacity, the ability to recognize, assimilate, and apply external knowledge. R&D investment can generate new knowledge, but it also enhances learning from external sources, including foreign technologies, multinational firms, and global value chains. This mechanism is particularly important for small and open economies, where upgrading often relies on adapting and recombining existing knowledge rather than frontier innovation.

To summarize, these patterns help explain why capability accumulation follows path-dependent trajectories, with diversification occurring more readily into activities that are technologically and cognitively related rather than into distant sectors (Boschma et al., 2015). Taken together, the innovation and growth literature suggests that R&D contributes to development by

expanding the stock of productive knowledge, deepening capabilities within existing activities, and enhancing the capacity to recombine knowledge across domains. However, these effects are conditional rather than automatic. Institutional quality, coordination among innovation actors, and the existing structure of production shape whether R&D investment translates into meaningful capability accumulation or remains disconnected from productive transformation. This conditionality provides a conceptual foundation for examining how R&D relates to broader structural outcomes, such as economic complexity, which is addressed explicitly in the following section.

### **1.2.3. Evidence on R&D-Complexity Linkages**

Empirical research directly examining the relationship between R&D investment and economic complexity remains relatively limited compared to the extensive literature linking R&D to innovation, productivity or economic growth. This gap reflects both the novelty of economic complexity metrics and their demanding informational requirements: economic complexity captures only those productive capabilities that are successfully embodied in exportable goods, rather than broader knowledge creation or innovation potential. As a result, the empirical relationship between R&D and complexity is more conditional and heterogeneous than standard R&D, growth relationships.

Early contributions to economic complexity literature established strong correlations between complexity levels and income, growth, and structural transformation, but largely abstracted from the role of direct innovation inputs such as R&D (Hidalgo & Hausmann, 2009; Hausmann et al., 2014). Subsequent work began to explore the determinants of complexity dynamics, showing that countries' movements in the product space depend on their existing capability base, institutional quality, and access to knowledge spillovers (Felipe et al., 2012; Hartmann et al., 2017). Within this framework, R&D is conceptualized not as an automatic driver of complexity, but as a mechanism that can expand and deepen productive capabilities when it is effectively integrated into the production system. One of the most systematic cross-country analyses linking R&D expenditure to economic complexity directly is provided by Kamguia et al. (2023). Using a dynamic panel of 67 countries over the period 1998-2017 and employing a system GMM estimator to address endogeneity, the authors find that increases in public R&D expenditure lead to statistically significant improvements in economic complexity. However, the effect is highly heterogeneous. R&D-driven complexity gains are substantial in resource-poor countries but weaker in resource-rich economies, indicating that existing specialization patterns constrain the translation of research investment into diversified production.

The results further show that R&D can promote economic complexity indirectly through improvements in innovation, highlighting the central role of absorptive capacity in mediating complexity outcomes. Related evidence emerges from studies focusing on innovation systems and structural change rather than complexity indices per se. Sweet and Eterovic (2019), while primarily analyzing patent rights and innovation systems, provide indirect evidence that innovation embedded in firms' production and commercialization activities is more closely associated with structural upgrading than innovation generated through public or academic channels.

Several studies examining economic complexity in Central and Eastern European (CEE) countries reinforce this conditional view. Research on ECI dynamics in the region shows that despite increasing R&D expenditures and participation in EU innovation programs, many CEE economies experience slow or uneven improvements in economic complexity (Lapatinas, 2019). Recent evidence from Central and Eastern European (CEE) countries further refines the understanding of how R&D relates to economic complexity. Veselinović et al. (2025) examine the joint effects of foreign direct investment, R&D expenditure and tertiary education enrolment on the Economic Complexity Index. Authors find that R&D expenditure exerts a positive and statistically significant effect on economic complexity, indicating that research investment contributes to industrial sophistication in transition economies when it is embedded in productive and investment-driven processes. These findings help explain why empirical studies, particularly those focusing on smaller or middle-income economies, often find weak or statistically insignificant effects of public and academic R&D on economic complexity, alongside strong and robust effects of business-sector R&D.

### **1.3. Measuring Economic Complexity**

This section reviews the main approaches used to measure economic complexity. It distinguishes between aggregate indices that summarize productive structure in a single metric and network-based representations that emphasize the relational structure of economic development.

#### **1.3.1. Aggregated metrics (ECI, Fitness, GENEPI)**

Since Hidalgo and Hausmann (2009) introduced the Economic Complexity Index, a growing body of literature has sought to refine, reinterpret and critique the way productive capabilities are measured using trade data. The original ECI framework combines two core dimensions: the diversity of products a country exports and the ubiquity of those products across the global economy. Countries

that are able to export a wide range of goods that few other countries produce, are assumed to possess a rich and sophisticated set of productive capabilities. In practice, advanced economies such as Germany, Italy, and Switzerland display both high economic complexity and high GDP per capita (Loungani et al., 2020).

Despite this widespread adoption in empirical research and policy analysis, the index has attracted significant methodological criticism. A key concern relates to how product complexity is inferred. In the original formulation, the complexity of a product is proxied by the average complexity of the countries that export it. Tacchella et al. (2012) and Cristelli et al. (2013) argue this approach is fundamentally misleading: highly complex countries tend to export almost all products, including simple ones, whereas low-complexity countries export only a narrow subset of basic goods. Averaging across exporters therefore blurs meaningful distinctions in product sophistication. Tacchella et al. (2012) proposed an alternative. Their nonlinear approach introduces the concepts of country "Fitness" and product "Quality," with the contribution of each exporting country to a product's estimated quality weighted asymmetrically. Their logic is straightforward: if a low-Fitness country can export a product competitively, that product is unlikely to require highly complex capabilities. This iterative scheme produces rankings that differ markedly from the ECI, particularly for countries with diversified but predominantly low-technology export baskets.

The Fitness algorithm itself, however, has come under scrutiny. Morrison et al. (2017) identify potential issues related to convergence and stability, showing that the iterative process can be sensitive to initial conditions and data noise. Servedio et al. (2018) address some of these concerns through refinements that improve numerical stability while preserving the core intuition. These contributions underscore an important point: complexity metrics are not purely empirical constructs but depend critically on underlying mathematical assumptions. More recently, researchers have attempted to reconcile competing measures within a unified framework. Sciarra et al. (2020) demonstrate that ECI and Fitness can be understood as specific cases within a broader class of spectral methods applied to bipartite country-product networks. Building on this insight, they introduce the GENEPEY index, which combines information from both measures into a single metric derived from an entropy-based formulation. One advantage is its interpretation as a standard network centrality measure defined on a product similarity network, facilitating comparison across datasets and time periods. Related work has clarified the statistical foundations of these measures. Mealy et al. (2019) show that the ECI can be interpreted through the lens of spectral clustering, explaining why the index successfully groups

countries with similar export structures and development trajectories. From this perspective, ECI captures dominant patterns in the global organization of production rather than directly measuring export sophistication.

But can any single index adequately summarize economic complexity? Some authors remain skeptical. Brummitt et al. (2020) tried to adopt a data-driven approach, applying machine learning techniques to identify dominant patterns in the evolution of export baskets over several decades. Their analysis reveals a latent variable that explains a substantial share of variance in global trade patterns and can be interpreted as a complexity-weighted measure of diversification. The finding supports the general intuition behind economic complexity, suggesting that different methodological approaches may capture complementary aspects of productive structure. A growing strand of literature now emphasizes the need for greater conceptual clarity. Valverde-Carbonell (2025) argues that many debates on different complexity measures stem from the absence of a formal definition of economic complexity. Specifically, from implicit assumptions about what trade-based data can actually reveal. Complexity indices, according to the author, should be understood as measures of countries structural positioning and export competitiveness rather than direct proxies for technological sophistication or capability accumulation. This interpretation helps reconcile differences across metrics and aligns with earlier work showing that these indices capture patterns in the global organization of production rather than underlying mechanisms of innovation or learning (Mealy et al., 2019).

To summarize, ECI, Fitness and GENEPY should be viewed as members of a broader family of complexity measures. Each embodies different assumptions and methodological choices, implying trade-offs between interpretability, robustness and sensitivity to data structure. The continued use of ECI reflects not the absence of alternatives, but its relative transparency, empirical robustness and well-established association with income levels, innovation outcomes and long-run development patterns, provided that its interpretation remains consistent with the limits of trade-based data.

### **1.3.2. Network based representations of economic complexity**

While aggregate complexity indices summarize countries' productive structures in a single metric, a substantial part of the economic complexity literature argues that such measures alone are insufficient to understand how structural transformation unfolds (Hidalgo et al., 2007; Hausmann & Hidalgo, 2009; Hausmann et al., 2011). When presenting their framework, the authors frequently rely on a metaphor to illustrate this point. They describe the set of all products as a forest that is highly

heterogeneous, with some areas dense and rich in opportunities and others sparse and isolated (Hidalgo et al., 2007). In this metaphor, countries are likened to monkeys that move from one tree to another as they develop new activities. The authors contrast this view with standard growth models, which implicitly assume that there is always another tree within easy reach. In reality, they argue, monkeys can jump only limited distances and because the forest is unevenly structured, it is not guaranteed that a suitable next tree lies nearby. As a result, the structure of the forest itself becomes crucial. Understanding where trees are located and how closely they are connected allows one to identify the paths that are realistically available. Translated into economic complexity terms, the forest corresponds to the product space and the monkey represents a country. Development is therefore shaped by a heterogeneous space of activities, where some upgrading paths are close and feasible while others remain distant. This intuition is formalized in the product space introduced by Hidalgo et al. (2007).

The product space maps goods according to the probability that they are co-exported by the same countries, with high co-export probabilities interpreted as evidence that products rely on overlapping sets of capabilities. Its construction reveals that more sophisticated products tend to cluster in a densely connected core, offering many potential diversification pathways, whereas less sophisticated products occupy a sparsely connected periphery with fewer opportunities for upgrading (Hidalgo et al., 2007). This structure has important implications for development trajectories: products located in the core are typically capital-intensive, technologically advanced and associated with higher income elasticity of demand, while peripheral products are often resource-based or simple manufactures with limited links to other activities (Felipe et al., 2012). Felipe et al. (2012) further document that countries specializing in more complex products tend to follow more favorable development trajectories, reinforcing the idea that structural transformation depends on the types of activities an economy is able to enter.

Subsequent research has extended this network logic beyond goods trade to innovation and knowledge creation. Technology spaces, constructed using patent data, map technological fields as nodes and define proximity through patterns of co-patenting or technological co-classification (Kogler et al., 2013; Balland et al., 2019). These studies demonstrate that technological diversification follows similar patterns of relatedness as product diversification, with new technologies emerging more easily when they build on existing knowledge bases. Kogler et al. (2013) analyzed the knowledge space of U.S. cities and found that metropolitan areas are more likely to develop new technological capabilities

in fields that are technologically related to their existing patent portfolios. Boschma et al. (2015) extended this analysis to examine how cities experience both rises and falls in their technological knowledge base over time, showing that both entry into and exit from technological fields follow relatedness patterns. Cities are more likely to develop new technologies in related domains and to abandon technological fields that are peripheral to their core competencies.

What is particularly interesting is more recent work by Balland and Boschma (2022), who examined European regions and found a substantial heterogeneity across Europe. Although they found that EU does consist of a certain technological capability, Northern and Western European regions are more likely to translate scientific excellence into technological leadership, while Southern and Eastern European regions, although possessing certain capabilities, often struggle to convert them into patenting activity. This leaves us not with a unified picture of Europe, but rather with a clear distinction between technological leaders and followers. These findings reinforce what is established in the literature: both technological and product spaces provide a way to identify which areas countries are already active in and where future development is most likely to occur. In this sense, network-based approaches help link existing capabilities with plausible future pathways of technological and productive upgrading.

Research in economic geography also extends the network perspective to industries, showing that industrial diversification is similarly shaped by patterns of relatedness. Scientific literature demonstrates that regions tend to develop new industries that are technologically and cognitively proximate to their existing industrial base, rather than shifting arbitrarily across sectors (Neffke et al., 2011; Boschma, 2017). Using plant-level data for Swedish regions, Neffke et al. (2011) show that industries related to pre-existing regional industries are significantly more likely to enter, while unrelated industries are more likely to exit, highlighting a strong path dependence in industrial evolution. The implications of this scientific literature for development policy are significant. Countries and regions located in well-connected parts of the product, technology or industry space can leverage their existing capabilities to move into increasingly sophisticated activities through sequences of related diversification. However, these network-based representations inherit the same challenges as discussed in the previous chapter. Like aggregated complexity indices, economic spaces rely on export data and revealed comparative advantage, meaning they capture only activities that are successfully exported rather than the full set of productive capabilities present in an economy. In the context of global value chains (GVCs), gross export data cannot distinguish between countries that

contribute high domestic value added and those that primarily perform assembly tasks using imported inputs (Koch, 2021). Moreover, production oriented towards non-tradable sectors does not enter these networks at all.

Altogether, network-based representations add an important layer to aggregate complexity measures by shifting attention away from how complex an economy is, toward how its productive activities are structured and connected. While indices such as the Economic Complexity Index provide a concise summary of a country's position in the global production system, economic spaces highlight the constraints and opportunities that condition future diversification (Hausmann & Hidalgo, 2010; Balland et al., 2022). These approaches have been particularly useful in showing that industrial upgrading is not simply a matter of ambition or policy intent, but depends on whether new activities are sufficiently related to existing capabilities. The relatedness perspective is especially relevant in the context of the European Union, where geographic proximity and institutional integration facilitate knowledge spillovers across regions, yet persistent differences in local capabilities continue to shape which development paths are realistically open to lagging regions.

## 2. RESEARCH METHODOLOGY FOR EVALUATING THE IMPACT OF NATIONAL R&D EFFORT ON ECONOMIC COMPLEXITY

Building on the insights provided in the literature review and the theoretical section, this chapter presents the empirical methodology applied in the study. It first outlines the analytical approach used to examine the link between national R&D effort and economic complexity, including the formulation of the empirical focus and underlying hypothesis. The chapter then introduces the variables employed in the analysis, discusses the rationale for selecting them and identifies data sources used. This is followed by a description of the empirical model and the estimation methods, together with an explanation of why the chosen econometric strategy is appropriate for the research question and how diagnostic tests are used to evaluate the reliability of the results. The chapter concludes by setting out the principles that guide the interpretation of empirical findings.

### 2.1. Research Aim, Objectives and Hypothesis

The aim of this research is to evaluate whether national R&D intensity influences economic complexity in European Union countries. To achieve this aim, the study sets the following objectives:

1. Examine the levels and trends of economic complexity and R&D intensity across EU countries during 2000-2023.
2. Estimate the relationship between R&D intensity and economic complexity using panel regression techniques.
3. Estimate the relationship between disaggregated R&D components (business, government and higher education) to determine which segments of the R&D effort are most strongly associated with economic complexity.

Prior studies argue that sustained investment in research and development helps generate codified and tacit knowledge, support technology adoption and expand the range of sophisticated products an economy can produce and export. R&D activity strengthens firm-level capabilities, enables entry into technologically demanding industries, and facilitates the accumulation of productive know-how that underpins economic diversification and upgrading (Kamguia et al., 2024; Veselinović et al., 2025). Guided by this reasoning, the primary hypothesis is formulated as follows:

*H1: Higher R&D intensity is positively associated with higher levels of economic complexity among EU countries.*

The innovation systems literature further suggests that different R&D-performing sectors contribute unequally to productive upgrading (Moutinho, 2017; Pop Silaghi et al., 2014). Business-sector R&D usually targets applied research, new products and improvements in production processes. These activities generate practical innovations and at the same time strengthen a firm's absorptive capacity, the ability to recognize, interpret and use external knowledge. A stronger absorptive capacity allows firms to innovate more effectively, adopt more advanced technologies and improve their competitive performance (Cohen & Levinthal, 1990). In contrast, government and higher-education R&D often focus on more general research, public goods provision or long-term knowledge generation. Based on these insights, the second hypothesis is proposed:

*H2: Business-sector R&D exhibits a stronger positive relationship with economic complexity than government or higher-education R&D, as measured by relative effect sizes in panel regressions.*

The next section introduces the variables selected to test these hypotheses, describes the data sources and transformations applied in preparing the empirical dataset.

## **2.2. Description of Variables and Data**

This study uses an annual panel covering 25 EU member states from 2000 to 2023. Luxembourg and Malta are excluded because ECI values are not reported for these countries under the HS92 classification. The year 2000 is selected as the starting point because it is the first in which all core variables, economic complexity, R&D expenditure, GDP per capita, population, trade openness and institutional quality, are jointly available for the full sample. Economic complexity is measured using the ECI based on the HS92 (Harmonized System 1992). HS92 is chosen because it provides consistent annual coverage across the entire study period, whereas newer systems such as HS12 are only available from 2012 onward and would substantially reduce the number of usable observations. HS92 is also widely used in applied economic complexity research, ensuring comparability with existing studies.

Overall data availability is strong. R&D expenditure (% of GDP) is missing in only six observations (approximately 1.0% of the sample), all occurring in the early 2000s for Greece, Croatia, and Sweden. Institutional quality indicators are missing for one year per country, reflecting the reporting structure of the Worldwide Governance Indicators and resulting in 25 missing observations (4.2%). All remaining variables are fully observed. Importantly, each country is present in every year of the sample, so the panel is structurally balanced. Missingness is confined to specific variables rather

than entire country-year observations. When lagged variables are introduced in the econometric specifications, the effective sample size is mechanically reduced due to the loss of the initial period, but this affects all countries symmetrically and does not alter the balanced structure of the panel.

With the dataset defined, the next step is the selection of control variables that meaningfully isolate the effect of R&D. Research on economic complexity employs a wide range of controls, largely because existing studies rely on heterogeneous country samples and institutional environments. However, variables that are informative in global datasets often contribute little explanatory power in an EU-only sample. For instance, Kamguia et al. (2024) include indicators such as mobile phone subscriptions, which are appropriate for their broad sample of countries. In the EU context, however, mobile penetration is already high across all member states and exhibits almost no cross-country variation, rendering the variable largely uninformative.

Accordingly, the choice of control variables in this study follows three complementary principles. First, controls are selected based on broad consensus in the literature regarding the key determinants of economic complexity, namely income level, institutional quality, population size, and trade openness. These variables appear consistently across empirical studies and are supported by strong theoretical foundations (Hausmann et al., 2014; Hartmann et al., 2017; Lapatinas, 2019; Lee & Vu, 2020). Second, the selection is adapted to the EU analytical context. Variables commonly used in global samples, such as primary education enrolment, electricity access, or mobile subscriptions, display limited or no variation within the EU and therefore offer little explanatory value. Third, the inclusion of country fixed effects absorbs time-invariant national characteristics, reducing the need for additional structural controls that would be redundant or could introduce multicollinearity.

Table 1 provides an overview of all variables used in the empirical analysis, including data sources, abbreviations, and applied transformations. Detailed theoretical justifications for each variable are presented in Annex 1. Although several control variables frequently used in economic complexity research, most notably GDP per capita and institutional quality, are theoretically endogenous, they are retained in the baseline specification because omitting them would risk omitted variable bias (Kamguia et al., 2023; Lapatinas, 2019; Hartmann et al., 2017). Both variables are widely regarded as necessary conditioning factors when estimating the relationship between R&D and economic complexity.

**Table 1***Summary of variables and their data sources*

<b>Variable (in)dependent / control)</b>	<b>Abbrev</b>	<b>Indicators</b>	<b>Data source</b>
Economic Complexity (dependent)	eci	Economic Complexity Index (ECI), calculated using the HS92 export classification system	Atlas of Economic Complexity
Total R&D Expenditure (independent)	rd_total	Gross domestic expenditure on R&D (% of GDP)	Eurostat
Business R&D Expenditure (independent)	rd_priv	Business enterprise R&D expenditure (% of GDP)	Eurostat
Government R&D Expenditure (independent)	rd_gov	Government R&D expenditure (% of GDP)	Eurostat
Higher Education R&D Expenditure (independent)	rd_higher	Higher education R&D expenditure (% of GDP)	Eurostat
Income Level (control)	ln_gdppc	Log GDP per capita (PPP, constant 2021 USD)	World Bank (WDI)
Institutional Quality (control)	instqual	WGI institutional quality index (CC, RL, GE, RQ, VA, PS)	World Bank (WGI)
Population (control)	ln_pop	Log population (total residents)	World Bank (WDI)
Trade Openness (control)	ln_open	Log trade openness (exports + imports, % of GDP)	World Bank (WDI)

Source: Author's calculations

By contrast, foreign direct investment (FDI) is excluded from the empirical specification not only due to endogeneity concerns, but also because its relationship with economic complexity is highly context-dependent and likely operates as a transmission mechanism rather than as a structural determinant. Treating FDI as an exogenous control would therefore risk simultaneity bias and could obscure the causal pathways through which R&D affects economic complexity. Given this conceptual ambiguity and the absence of a clear theoretical role as a conditioning variable in the EU context, FDI is not included in the analysis. Human capital is likewise excluded from the model. Although it plays a central role in long-run capability accumulation, existing evidence suggests that human capital often functions as an intermediate channel linking R&D investment to economic complexity rather than as an independent driver (Kamguia et al., 2023). Controlling for human capital would therefore risk “over-conditioning” the model by absorbing part of the effect through which R&D operates. For this reason, human capital is omitted to preserve the interpretation of the estimated R&D coefficient.

Additionally, sectorial R&D components (business, government, higher education) are examined in alternative specifications because they test a different hypothesis from total R&D intensity. Including sectorial and total R&D simultaneously would create mechanical collinearity, as the components sum to the aggregate by construction.

Finally, continuous variables such as GDP per capita, population, openness enter the model in logarithmic form, consistent with empirical practice in the economic complexity literature, reducing skewness and improving coefficient interpretability (Hartmann et al., 2017; Lee & Vu 2020).

**Table 2**

*Descriptive Statistics of the baseline model*

Variable	N	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis
ECI	600	1.14	0.519	1.17	0.006	2.36	2.35	0.0187	-0.837
RD_TOTAL	594	1.55	0.907	1.32	0.23	3.87	3.64	0.649	-0.703
LN_GDPC	600	10.6	0.369	10.6	9.44	11.7	2.29	-0.431	0.0717
INSTQUAL	575	0.97	0.507	0.934	-0.173	1.98	2.15	0.036	-0.882
LN_POP	600	16	1.16	16.1	13.8	18.2	4.48	0.204	-0.635
LN_OPEN	600	4.61	0.383	4.62	3.81	5.52	1.71	-0.0449	-0.947

Source: Author's calculations

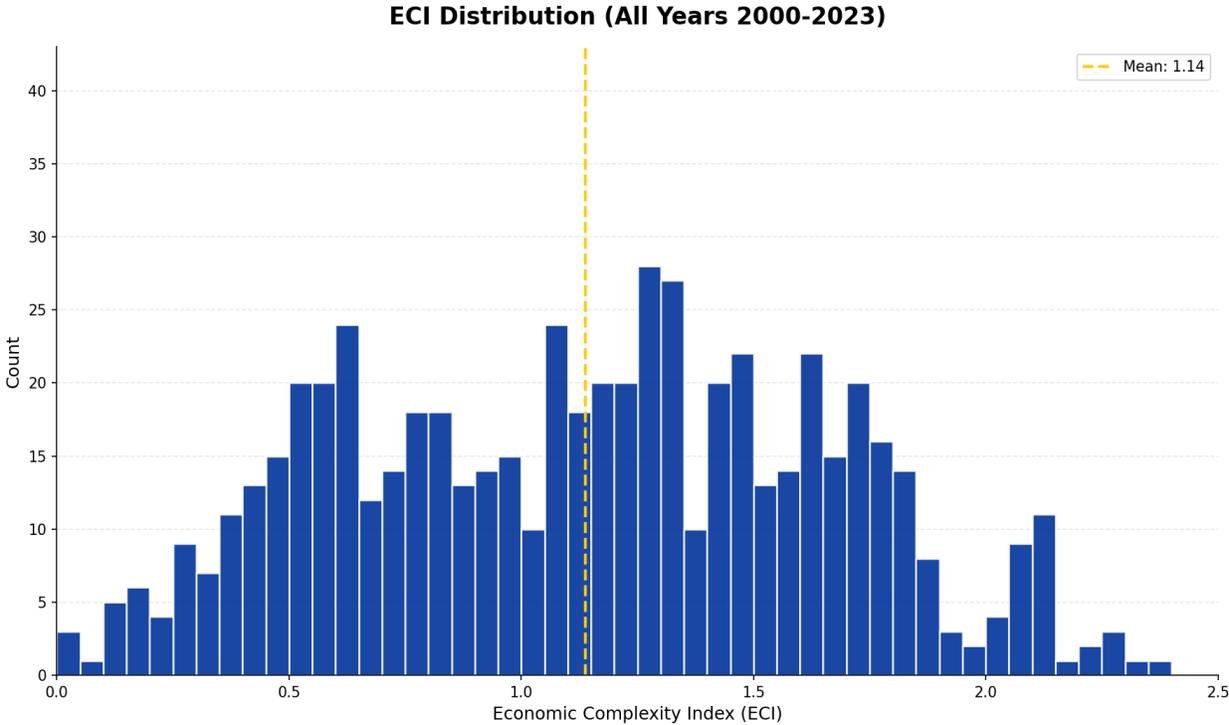
Table 2 summarizes the main features of the dataset. The Economic Complexity Index shows considerable variation across EU member states (mean 1.14, SD 0.52), ranging from 0.006 to 2.36. The lowest observation (ECI = 0.006) corresponds to Greece in 2018, occurring during the country's prolonged economic crisis. Although such values may influence the estimations, they are retained because they provide meaningful information about how economic complexity behaves under conditions of economic stress. The distribution of ECI across the sample period is shown in Figure 1. R&D intensity also varies widely across the sample (mean 1.55%, SD 0.91; range 0.23 - 3.87% of GDP), reflecting the well-known gap between Europe's high and low innovation countries. Institutional quality shows a similarly broad range (mean 0.97, SD 0.51; -0.173 to 1.98), indicating persistent governance differences within the EU. The log-transformed controls for GDP per capita, population, and openness display moderate dispersion and mild skewness, all within acceptable limits for fixed-effects regression.

Table 3 reports on the pairwise correlations. ECI is strongly related to R&D intensity (0.695), institutional quality (0.612), and GDP per capita (0.584), in line with expectations that innovation, institutions, and development are linked to productive sophistication. Institutional quality correlates

highly with both R&D intensity (0.783) and GDP per capita (0.763), while GDP and R&D intensity are also strongly related (0.698). Population shows only a modest correlation with ECI (0.284) but a strong negative correlation with openness (-0.593), which is consistent with the idea that larger countries tend to be less trade-intensive.

**Figure 1**

*Distribution of Economic Complexity Index among EU member states*



Source: Author’s calculations

Even though some correlations are high, multicollinearity does not seem to be present. VIF scores range from 1.76 (openness) to 3.88 (institutional quality), all well below the commonly used threshold of 5. This indicates that the explanatory variables still contribute independent information to the model. Overall, the descriptive statistics show meaningful variation across countries without structural problems in the data. The few extreme values are economically interpretable and justify further robustness checks.

It is worth noting that these correlation patterns change when using a disaggregated dataset in which R&D intensity is separated into business, higher-education and government components. In this specification, the correlation matrix reveals a relatively strong association between private-sector and higher-education R&D expenditures, suggesting a potential risk of multicollinearity. However,

subsequent variance inflation factor (VIF) diagnostics indicate that this correlation does not translate into problematic multicollinearity. The correlation matrix for the disaggregated specification is reported in Annex 2.

**Table 3**

*Correlation Analysis of the baseline model*

	ECI	RD_TOTAL	LN_GDPC	INSTQUAL	LN_POP	LN_OPEN
ECI	1.000					
RD_TOTAL	0.695	1.000				
LN_GDPC	0.584	0.698	1.000			
INSTQUAL	0.612	0.783	0.763	1.000		
LN_POP	0.284	0.198	0.195	-0.001	1.000	
LN_OPEN	0.086	-0.039	0.121	0.092	-0.593	1.000

Source: Author's calculations

In summary, the dataset provides substantial cross-country and over-time variation, with no evidence of structural anomalies, excessive missingness or problematic multicollinearity. The variables exhibit patterns consistent with expectations for the EU context, and the few extreme observations are economically interpretable and therefore retained for analytical completeness. Overall, these characteristics indicate that the data are well suited for panel regression techniques exploiting within-country variation over time. With the data environment and key variables defined, the next section outlines the empirical strategy used to identify the effect of national R&D intensity on economic complexity.

### **2.3. Model specification, Research methods and Tests**

Building on the dataset described in Section 2.2, the empirical analysis examines the relationship between national R&D effort and economic complexity across EU member states using a lagged fixed-effects panel framework with country effects only. Given the panel structure (N = 25 countries, T = 23 years), country fixed effects ( $\alpha_i$ ) are included to control for time-invariant national characteristics such as geography, historical development paths and persistent institutional differences. This specification isolates within-country variation over time, which is central to identifying the role of R&D intensity economic complexity. Year fixed effects were formally tested but found to be statistically insignificant and are therefore not included in the baseline specification.

Excluding year fixed effects also preserves identifying variation in slowly evolving variables such as economic complexity and R&D intensity, which may otherwise be overly absorbed by time dummies.

Accordingly, the baseline model is specified as a one-year lagged country fixed-effects regression:

$$ECI_{it} = \alpha_i + \beta_1 rd\_total_{i,t-1} + \beta_2 \ln\_gdppci_{i,t-1} + \beta_3 instqual_{i,t-1} + \beta_4 \ln\_popi_{i,t-1} + \beta_5 \ln\_openi_{i,t-1} + \varepsilon_{it} \quad (1)$$

where  $ECI_{it}$  denotes the Economic Complexity Index for country  $i$  in year  $t$ ,  $\alpha_i$  represents country fixed effects,  $rd\_total_{it}$  is total R&D expenditure expressed as a percentage of GDP,  $\ln(gdppc_{it})$  denotes the logarithm of GDP per capita in purchasing power parity terms (constant 2021 USD),  $instqual_{it}$  is an index of institutional quality,  $\ln(pop_{it})$  denotes the logarithm of population,  $\ln(open_{it})$  denotes the logarithm of trade openness measured as a percentage of GDP, and  $\varepsilon_{it}$  is the idiosyncratic error term.

The use of lagged regressors is motivated by both theoretical considerations and identification concerns. From a theoretical standpoint, R&D investments are not expected to translate immediately into changes in productive capabilities or export structures. From an econometric standpoint, lagging the explanatory variables helps reduce concerns about contemporaneous reverse causality, whereby more complex economies may be better positioned to invest in R&D due to higher income levels, stronger institutions, and greater absorptive capacity (Kamguia et al., 2024). At the same time, it is important to acknowledge that fixed-effects models, even when combined with lagged regressors, cannot fully eliminate endogeneity. Feedback effects and omitted time-varying country-specific factors may still bias the estimated relationship between R&D and economic complexity. Some studies have attempted to address these concerns by applying instrumental variable approaches, such as IV-2SLS with external instruments. However, as emphasized by Kamguia (2024), identifying valid instruments in the context of the R&D - economic complexity nexus is particularly challenging. Common candidates, including R&D tax incentives or trade-related policy variables (Naveed & Wang, 2023), are likely to affect export structures and innovation capacity simultaneously through multiple channels, thereby violating the exclusion restriction.

In response to these limitations, much of the recent literature has adopted dynamic panel estimators such as system Generalized Method of Moments (system GMM), which rely on internal

instruments constructed from lagged levels and differences (Blundell & Bond, 1998). Nevertheless, the applicability of system GMM is constrained in panels with a relatively small cross-sectional dimension and long time series, as is the case in this study ( $N = 25$ ,  $T = 23$ ). In such settings, instrument proliferation and weak identification can undermine estimator reliability (Roodman, 2009). Following standard practice in innovation and economic complexity studies with comparable data structures (Pessoa, 2010), this analysis therefore relies on a lagged country fixed-effects framework supplemented by robust inference procedures. Dumitrescu-Hurlin test, although frequently employed in related empirical work, are not used as an identification tool in this study. In the EU context, economic complexity and R&D intensity evolve slowly, particularly among advanced economies such as Germany or Switzerland, limiting the ability of time-series causality tests to detect meaningful variation. While Granger causality may provide insights for faster-growing or catching-up economies, its explanatory power is limited for the predominantly gradual structural dynamics observed in this sample (Neagu et al., 2022). To ensure the validity of the empirical results, a comprehensive set of diagnostic tests is conducted prior to estimation, following approaches commonly used in studies of economic complexity and innovation in European and transition economies (Neagu et al., 2022; Veselinović et al., 2025; Kamguia et al., 2024). Cross-sectional dependence is first examined using Pesaran's CD test, reflecting the high degree of economic integration among EU member states. The Modified Wald test is applied to assess groupwise heteroskedasticity, while the Wooldridge test is used to detect first-order serial correlation within panels. In addition, the joint significance of country and year fixed effects is evaluated using standard F-tests. The results confirm the relevance of country fixed effects in capturing time-invariant structural heterogeneity, while year fixed effects are found to be statistically insignificant and are therefore excluded from the baseline specification.

Given the presence of cross-sectional dependence, heteroskedasticity and serial correlation, the baseline lagged fixed-effects model is estimated using Panel-Corrected Standard Errors (PCSE) following Beck and Katz (1995). This estimator is well suited to panels where the time dimension exceeds the cross-sectional dimension and is widely applied in recent empirical studies on economic complexity. As an additional robustness-oriented inference method, the model is also estimated using Driscoll-Kraay standard errors, which are robust to general forms of cross-sectional dependence and serial correlation. The use of both covariance estimators ensures that the reported statistical significance of the estimated coefficients is not driven by a particular treatment of the error structure. To assess the stability of the estimated R&D effect, additional sensitivity analyses are conducted in

line with the literature. The model is augmented with alternative control variables, such as human capital and foreign direct investment, that are frequently associated with productive upgrading but may operate as intermediate channels rather than independent determinants (Lectard & Rougier, 2018; Apostol & Musyoka, 2024). In addition, total R&D expenditure is decomposed into business, government, and higher education components in separate specifications. This decomposition is not treated as a robustness check in the strict sense, but rather as an extension of the baseline analysis, allowing for a more nuanced interpretation of the aggregate R&D effect.

Overall, this methodological framework prioritizes transparency and interpretability while acknowledging the inherent identification challenges of observational macro-panel data. Although the modest cross-sectional dimension precludes the use of more complex dynamic estimators, the lagged country fixed-effects design: combined with extensive diagnostic testing and robust inference, provides a credible empirical basis for analyzing the relationship between R&D and economic complexity in the EU context.

### **3. RESULTS OF RESEARCH AND DEVELOPMENT INTENSITY IN THE ECONOMIC COMPLEXITY**

After establishing the research methodology and constructing the empirical dataset, this chapter presents the results of the empirical analysis examining the relationship between research and development activity and economic complexity in European Union member states. The chapter begins with a descriptive overview of the main variables in order to identify general trends and cross-country differences. It then proceeds to the econometric analysis, where alternative model specifications and variable constructions are applied, and the resulting estimates are analyzed, tested and compared, highlighting their key similarities and differences. Finally, the findings are related to existing empirical evidence in the literature, and implications for future research are discussed.

#### **3.1. Patterns of Economic Complexity and R&D Intensity in the EU**

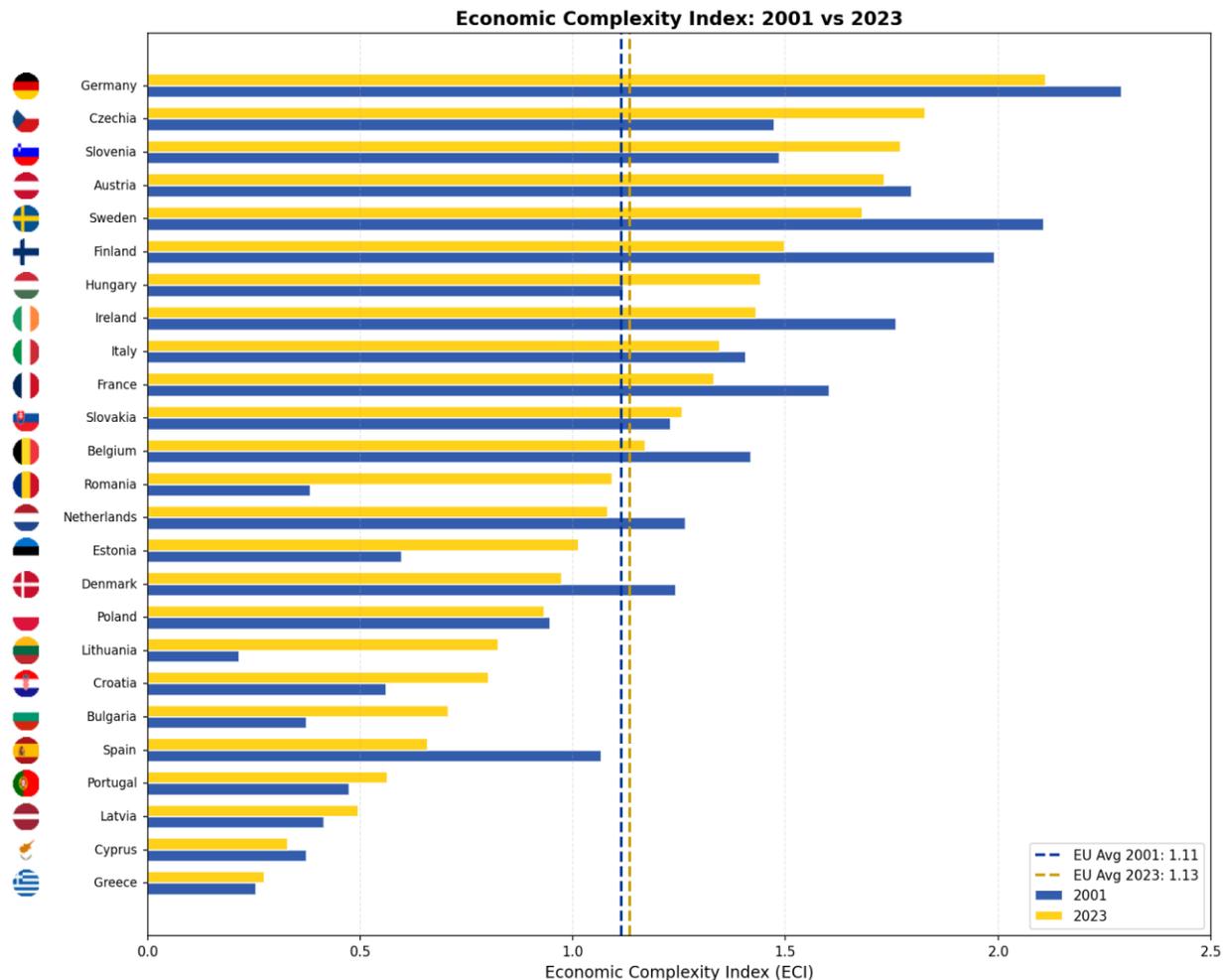
Although econometric analysis of panel data allows for structured inference regarding the relationship between R&D efforts and economic complexity, a comprehensive interpretation of the results requires careful consideration of the broader structural context. The Economic Complexity Index was originally developed as a trade-based measure of export sophistication, grounded in countries' revealed comparative advantage across products of varying complexity. Subsequent

research has demonstrated that the index captures deeper aspects of productive capabilities, making it informative about both current export structures and potential development trajectories (Hidalgo, C. A. 2023). However, movements in economic complexity over time can also provide a retrospective account of structural change, reflecting shifts in specialization, integration into global value chains and the reallocation of production across regions. In this sense, the evolution of economic complexity can be interpreted as a condensed representation of economic history, linking past industrial transformations to observed patterns of development.

Figure 2 compares Economic Complexity Index (ECI) values across EU member states in 2001 and 2023 and highlights the persistence of substantial structural heterogeneity within the Union. The distribution of economic complexity remains highly uneven, with a relatively stable group of high-complexity economies coexisting alongside countries with markedly lower ECI levels. The EU average ECI changes only marginally over the period, indicating that aggregate stability conceals considerable cross-country reallocation beneath the surface. Beneath this stability, the figure reveals asymmetric dynamics between the “leaders” and “latecomers”. Several traditionally high-complexity economies display limited gains or mild declines in ECI over time, whereas a number of initially lower-complexity countries, particularly in Central and Eastern Europe, experience pronounced upward movements.

**Figure 2**

*Economic Complexity Index among current European Union member states in 2001 and 2023*



Source: Author's calculations

Overall, the evidence points to differentiated development trajectories rather than a uniform process of convergence within the EU. It is important to note that the long-run comparison incorporates the early 2000s, when several Central and Eastern European countries were not yet members of the European Union. Their subsequent accession, deeper integration into European production networks and technology transfer may have contributed to improvements in their economic complexity over time. To fully understand the role of economic complexity and to meaningfully interpret the empirical results, it is essential to clarify how economic complexity index operates in practice. Within this framework, the Economic Complexity Index implicitly “rewards” products that are rare and exported by only a limited number of countries. Consequently, economies that specialize in widely produced or highly standardized goods may exhibit lower levels of measured

economic complexity, even when these goods are in strong global demand. Economic complexity therefore does not capture export success per se but rather reflects the uniqueness and knowledge intensity embedded in a country’s productive structure.

**Table 4**

*Products with the highest Product Complexity Index (PCI) in EU exports, by period*

Period	Product description	HS code	Avg. PCI	Main EU exporters
2000-2008	Nucleic acids and heterocyclic compounds	2934	2.250	Ireland, Germany, Belgium
	Cermets	8209	2.117	Germany, Sweden, Belgium
	Photographic plates and film (developed)	3705	2.095	Germany, France, Italy
	Advanced machine tools (laser, plasma, etc.)	8456	2.024	Germany, Italy, France
	Silicones in primary forms	3910	2.000	Germany, Belgium, France
2008-2016	Machining centers and transfer machines	8457	2.385	Germany, Italy, Czechia
	Photographic plates and film (developed)	3705	2.273	Germany, Italy, France
	Cermets	8209	2.271	Germany, Netherlands, Sweden
	Advanced machine tools (laser, plasma, etc.)	8456	2.146	Germany, Italy, France
	Nickel tubes and fittings	7507	1.951	France, Germany, Sweden
2016-2023	Photographic plates and film (developed)	3705	2.655	Germany, Ireland
	Cermets	8209	2.284	Germany, Sweden, Belgium
	Photographic laboratory equipment	9010	2.244	Netherlands, Germany
	Doped wafers for electronics	3818	2.218	Germany, France, Finland
	Machining centers and transfer machines	8457	2.217	Germany, Italy

Source: Author’s calculations based on data from the Atlas of Economic Complexity.

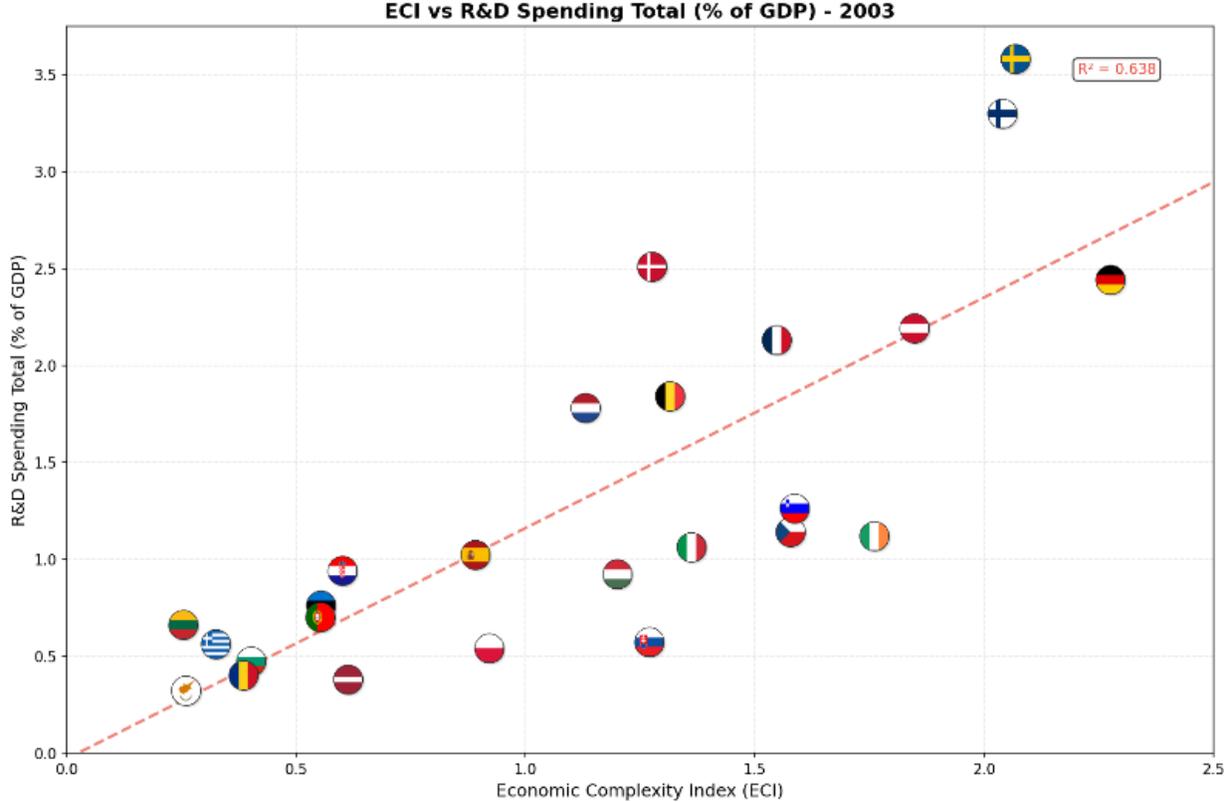
Table 4 reports the products with the highest Product Complexity Index in EU exports across periods of 2000-2023. The table highlights that the most complex products are concentrated in advanced manufacturing, chemical and high-technology sectors and that their production is typically dominated by a small group of EU economies. Together, country-level dynamics in Figure 2 and the product-level patterns in Table 4 indicate that improvements in economic complexity can be driven less by export scale and more by sustained specialization in a small set of highly complex products. The patterns observed are also consistent with the possibility that, for smaller economies,

specialization in a narrow set of highly complex niche products may translate into relatively large gains when it comes to measured economic complexity.

However, economic complexity cannot be fostered in a vacuum. The accumulation of productive capabilities captured by the Economic Complexity Index is closely linked to investments in knowledge creation and innovation. A first indication of this relationship can be obtained by examining the cross-sectional association between economic complexity and research and development (R&D) intensity. Figure 3 and 4 plots the Economic Complexity Index against total R&D expenditure as a share of GDP for EU member states in 2003 and 2023, with 2003 selected as the earliest year with full data coverage.

**Figure 3**

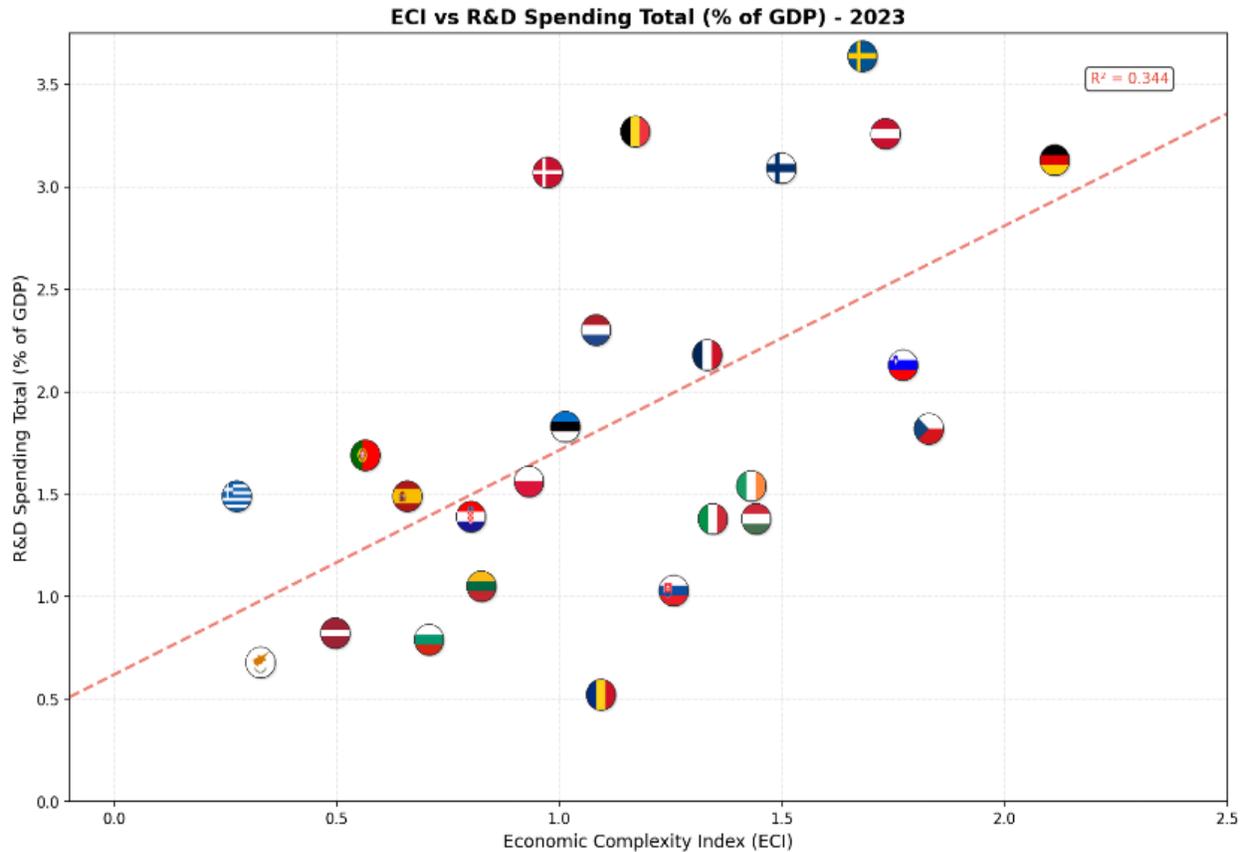
*Cross-sectional Relationship between Economic Complexity and R&D Intensity in the EU 2003*



Source: Author's calculations

**Figure 4**

*Cross-sectional Relationship between Economic Complexity and R&D Intensity in the EU 2023*



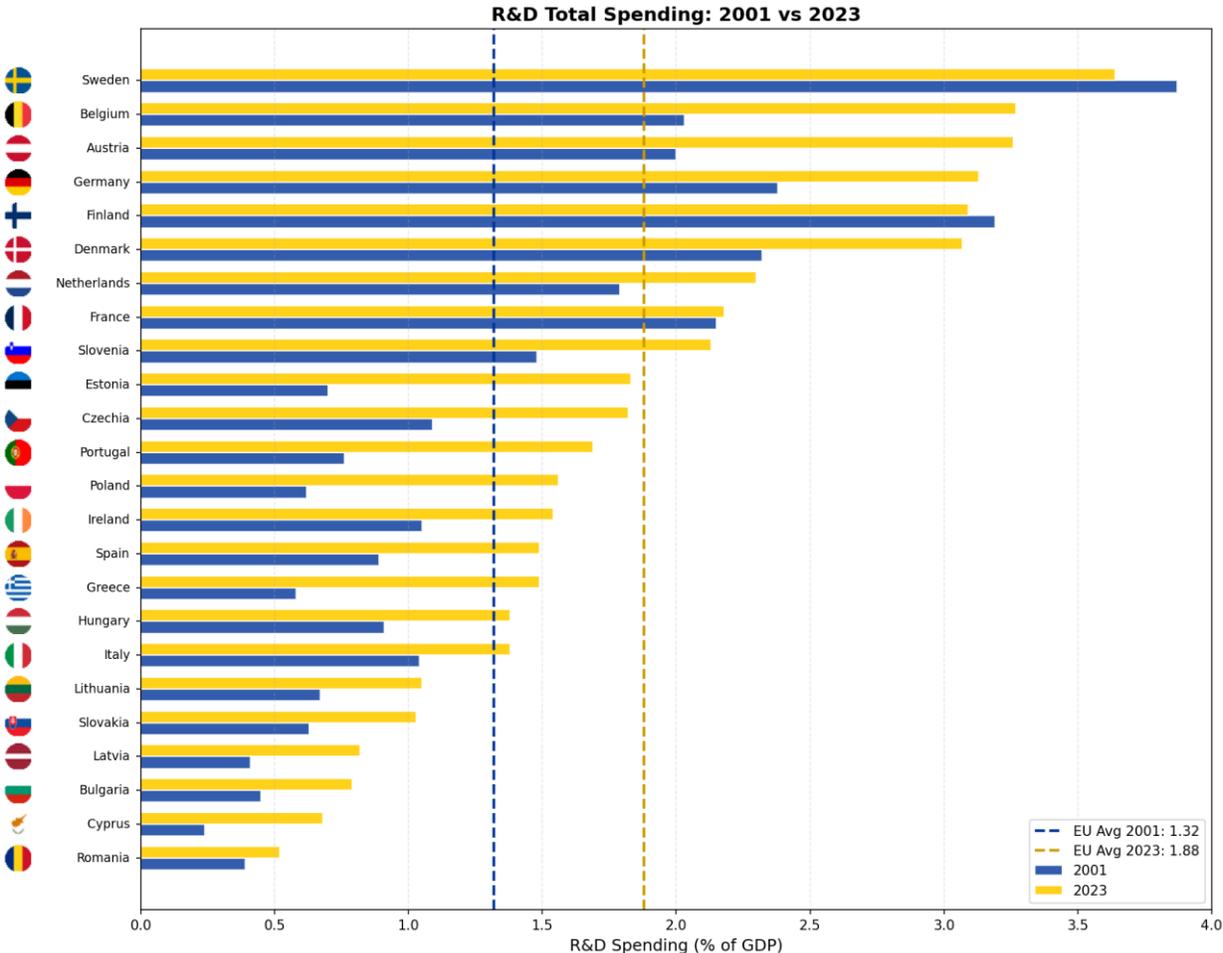
Source: Author's calculations

In both periods, a positive association is evident, suggesting that countries with higher R&D intensity tend, on average, to exhibit more complex export structures. While this relationship appears less tightly aligned in 2023 than in the early 2000s, as reflected in the greater dispersion of observations, the overall pattern remains consistent with a positive role of R&D in shaping economic complexity. The observed variation indicates that the impact of R&D on economic complexity is not uniform across countries, with some economies translating R&D investment into higher complexity more effectively than others. Several countries combine relatively high R&D intensity with only moderate levels of complexity, while others achieve comparatively high complexity outcomes with more modest R&D spending. Overall, the figures point to a nuanced relationship in which R&D investment contributes positively to economic complexity, while its effectiveness varies depending on broader structural conditions.

Figure 5 complements the analysis of economic complexity by documenting the evolution of total R&D expenditure across EU member states between 2001 and 2023. The figure shows a substantial increase in R&D intensity at the EU level, with the average rising from approximately 1.3% of GDP in 2001 to nearly 1.9% in 2023. This broad-based strengthening of research and innovation effort reflects a sustained emphasis on R&D investment within the EU over the past two decades. However, the expansion has been particularly pronounced among countries already positioned close to the technological frontier, reinforcing their role as key contributors to knowledge creation within the Union..

**Figure 5**

*R&D Total Spending among the current EU member states in 2001 and 2023*



Source: Author’s calculations

To summarize, across the period 2000–2023, economic complexity and R&D intensity in the EU display both continuity and change. Economic complexity remains unevenly distributed across

member states, with a stable group of highly complex economies, largely located in Northern and Western Europe, alongside countries with significantly lower complexity levels. At the same time, this aggregate stability conceals meaningful reordering beneath the surface. Several traditionally advanced economies show limited progress or mild declines in complexity, while many Central and Eastern European countries record substantial gains, consistent with gradual upgrading following EU accession and deeper integration into European value chains. Product-level evidence reinforces this picture, indicating that higher economic complexity is associated with sustained specialization in technologically demanding, low-ubiquity goods rather than export scale alone. Over the same period, R&D intensity increased markedly at the EU level, rising from around 1.3% of GDP in 2001 to nearly 1.9% in 2023. Despite this overall expansion, the relationship between R&D spending and economic complexity has become more heterogeneous over time. Countries with comparable levels of R&D investment increasingly display different complexity outcomes, suggesting that innovation inputs are translated into productive capabilities in uneven ways across the EU. These descriptive patterns provide empirical background for the analysis that follows, which examines the extent to which R&D investment affects economic complexity within a panel data framework.

### **3.2. Diagnostic Assessments of the Econometric Panel structure**

Before estimating the relationship between national R&D intensity and economic complexity, a series of diagnostic tests were conducted to assess the suitability of the fixed-effects framework and to identify potential violations of classical assumptions. This approach is consistent with recent macro-panel studies on economic complexity, which emphasize the importance of accounting for cross-country interdependence and complex error structures in integrated economic areas such as the European Union (Neagu et al., 2022, Veselinović et al., 2025).

The first diagnostic concerns cross-sectional dependence. Given the high degree of trade integration, shared policy frameworks, and dense production linkages among EU member states, shocks affecting one economy are likely to spill over to others. The Pesaran CD test strongly rejects the null hypothesis of cross-sectional independence ( $z = -2.625$ ,  $p = 0.009$ ), indicating the presence of contemporaneous correlation across countries. The presence of such dependence implies that conventional fixed-effects standard errors would be inconsistent, motivating the use of robust covariance estimators. Second, serial correlation within countries is examined using the Breusch-

Godfrey/Wooldridge test. The null hypothesis of no first-order serial correlation is decisively rejected ( $\chi^2 = 232.06$ ,  $p < 0.001$ ), indicating persistent error dynamics over time.

**Table 5**

*Diagnostic Results of the baseline model*

Test / Interpretation	Statistic	df	p-value
Cross-sectional dependence (Pesaran CD)	$z = -2.625$	-	0.009
<b>Dependence Detected</b>			
Serial correlation (Breusch-Godfrey/Wooldridge)	$\chi^2 = 232.06$	20	< 0.001
<b>Serial correlation present</b>			
Heteroskedasticity (Breusch-Pagan)	BP = 22.3	5	< 0.001
<b>Heteroskedasticity present</b>			
Country FE vs Pooled OLS	F = 146.34	45, 494	< 0.001
<b>Country FE justified</b>			
Time FE (Two-way vs Individual FE)	F = 1.378	21, 494	0.122
<b>FE not significant</b>			
Note: All tests conducted on the fixed-effects specification with ECI as dependent variable. Year fixed effects were subsequently dropped in the baseline model based on joint insignificance ( $p = 0.122$ )			

Source: Author's calculations

Third, heteroskedasticity across countries is assessed using the Breusch-Pagan test, which also rejects the null of homoskedasticity ( $BP = 22.30$ ,  $p < 0.001$ ). This reflects substantial heterogeneity in country size, institutional structures, and productive specialization across EU economies. Finally, model selection tests strongly favor the inclusion of country fixed effects over pooled OLS ( $F = 146.34$ ,  $p < 0.001$ ), confirming the importance of time-invariant national characteristics in shaping economic complexity. By contrast, the joint significance test for year fixed effects fails to reject the null ( $F = 1.378$ ,  $p = 0.122$ ), indicating that once country heterogeneity is controlled for, common EU wide time effects do not significantly improve explanatory power.

Taken together, these diagnostics imply that a standard two-way fixed-effects estimator with conventional standard errors would be inappropriate. The presence of cross-sectional dependence, serial correlation, and heteroskedasticity motivates the use of panel-corrected standard errors (PCSE) as the primary inference method, with Driscoll-Kraay standard errors employed as a robustness check given their explicit correction for cross-sectional dependence. In addition, formal tests indicate that

year fixed effects do not provide statistically significant explanatory power once country-specific heterogeneity is controlled for. Accordingly, the baseline results are estimated using country fixed effects and PCSE.

### 3.3. Main Estimation and Robustness Check Results

This section presents the main fixed-effects estimates examining the relationship between national R&D intensity and economic complexity. Consistent with the identification strategy outlined in the methodology section, the baseline specification employs one-year lagged explanatory variables. The model is estimated with country fixed effects, while statistical inference is conducted using panel-corrected standard errors (PCSE) to account for cross-sectional dependence, serial correlation, and heteroskedasticity identified in Section 3.1.

Table 6 reports the baseline results from the lagged country fixed-effects model estimated with panel-corrected standard errors. The coefficient on lagged R&D intensity is positive and statistically significant at the 10% level ( $\beta = 0.066$ ,  $p = 0.080$ ), indicating that higher R&D expenditure is associated with higher subsequent levels of economic complexity. While the magnitude of the effect is modest on an annual basis, it is economically meaningful given the slow-moving nature of the Economic Complexity Index. In other words, one-percentage-point increase in R&D expenditure as a share of GDP is associated with an increase of approximately 0.066 points in the Economic Complexity Index in the following year. The control variables behave consistently with theoretical expectations and prior empirical evidence. GDP per capita and institutional quality display strong positive associations with economic complexity, underscoring the role of economic development and governance quality in supporting sophisticated production structures. Population enters with a negative and statistically significant coefficient ( $\beta = -0.773$ ,  $p = 0.003$ ). This indicates that, conditional on lagged income, institutional quality, R&D expenditure and trade openness, larger EU member states tend to exhibit lower measured economic complexity in the subsequent period. This pattern largely reflects the construction of the Economic Complexity Index, which is based on HS92 merchandise export data and rewards specialization in low-ubiquity products. Larger economies typically export a broader range of standardized and widely traded goods and have a greater share of economic activity in services, which are not captured by goods-based complexity measures. By contrast, trade openness is not statistically significant, suggesting that once country fixed effects and other structural determinants are controlled for, the volume of trade does not independently explain

variation in economic complexity, which depends primarily on export composition rather than trade intensity.

**Table 6**

*Results of lagged country fixed-effects model with PCSE*

Variable	Coefficient	PCSE Std. Error	t-value	p-value
rd total (t-1)	0.0657	0.0375	1.75	0.080*
ln_gdppc (t-1)	0.2461	0.0800	3.08	0.002***
Instqual (t-1)	0.3400	0.0869	3.91	<0.001***
ln_pop (t-1)	-0.7728	0.2627	-2.94	0.003***
ln_open (t-1)	-0.1243	0.0796	-1.56	0.119
Observations	545			
Countries	25			
R-squared	0.424			
Country FE	Yes			
Year FE	No			
Notes: *** denote significance at the 0.1% level, ** at the 1% level, * at the 5% level, and at the 10% level Dependent variable: eci.				

Source: Author's calculation

Overall, the model explains approximately 42% of the within-country variation in economic complexity, a substantial proportion given that country fixed effects absorb all time-invariant heterogeneity across EU member states. To further assess the robustness of the baseline results, statistical inference is also conducted using Driscoll-Kraay standard errors, which are robust to general forms of cross-sectional and temporal dependence. The Driscoll-Kraay estimates, reported in Table 8, confirm the main findings: the coefficient on lagged R&D intensity remains positive and statistically significant at conventional levels, while the signs and relative magnitudes of all control variables remain unchanged. Although trade openness becomes statistically significant under Driscoll-Kraay standard errors, this effect is not robust across covariance estimators and is therefore interpreted with caution. Overall, the convergence of results across alternative robust inference methods indicates that the estimated relationship between R&D intensity and economic complexity is not driven by a particular treatment of the error structure, thereby reinforcing confidence in the baseline findings. These findings provide robust empirical support for Hypothesis H1: national R&D intensity positively and significantly affects economic complexity in EU member states, with effects materializing after a one-year lag.

**Table 7***Robustness check - lagged country fixed-effects model (Driscoll-Kraay SE)*

Variable	Coefficient	DK Std. Error	t-value	p-value
rd_total (t-1)	0.0657	0.0190	3.47	< 0.001***
ln_gdppc (t-1)	0.2461	0.0354	6.96	< 0.001***
Instqual (t-1)	0.3400	0.0300	11.32	< 0.001***
ln_pop (t-1)	-0.7728	0.0553	-13.97	< 0.001***
ln_open (t-1)	-0.1243	0.0485	-2.56	0.011 *
Observations	545			
Countries	25			
R-squared	0.424			
Country FE	Yes			
Year FE	No			
Notes: Notes: *** denote significance at the 0.1% level, ** at the 1% level, * at the 5% level, and at the 10% level				
Dependent variable: eci.				

Source: Author's calculation

While the baseline results establish a positive relationship between overall R&D intensity and economic complexity, R&D expenditure is not a homogeneous input. Innovation systems theory suggests that R&D performed by different institutional sectors may contribute to productive upgrading through distinct channels. To explore this heterogeneity, the next analysis decomposes total R&D expenditure into business-sector, government and higher-education components.

Tables 8 and 9 report the results from a decomposition of total R&D expenditure into business-sector, government and higher-education components, estimated within a lagged country fixed-effects framework. All R&D variables enter with a one-year lag to reflect the delayed nature of innovation-driven structural change and to mitigate contemporaneous endogeneity concerns. Table 8 presents estimates with panel-corrected standard errors (PCSE), while Table 9 reports Driscoll-Kraay standard errors, which are robust to heteroskedasticity, cross-sectional dependence, and serial correlation. Diagnostic tests provided in the annex 3 conducted on the decomposition model confirm the presence of cross-sectional dependence (Pesaran CD:  $z = 2.61$ ,  $p = 0.009$ ), serial correlation (Breusch-Godfrey:  $\chi^2 = 212.4$ ,  $p < 0.001$ ), and heteroskedasticity (Breusch-Pagan:  $BP = 58.9$ ,  $p < 0.001$ ), justifying the use of robust covariance estimators. Year fixed effects were tested but found to be only marginally insignificant and are therefore not included in the preferred specification.

**Table 8***Decomposition of R&D effects on Economic Complexity (Country FE, PCSE)*

Variable	Coefficient	PCSE Std. Error	t-value	p-value
rd_priv (t-1)	0.1286	0.0440	2.9224	0.0036**
rd_gov (t-1)	0.1481	0.1997	0.7417	0.4586
rd_higher (t-1)	-0.1506	0.1170	-1.2864	0.1989
ln_gdppc (t-1)	0.2299	0.0783	2.9365	0.0035**
Instqual (t-1)	0.3623	0.0820	4.4198	<0.001 ***
ln_pop (t-1)	-0.7607	0.2411	-3.1552	0.0017**
ln_open (t-1)	-0.1112	0.0767	-1.450	0.11477
Observations	547			
Countries	25			
R-squared	0.449			
Country FE	Yes			
Year FE	No			
Notes: Notes: *** denote significance at the 0.1% level, ** at the 1% level, * at the 5% level, and at the 10% level Dependent variable: eci.				

Source: Author's calculation

**Table 9***Decomposition of R&D effects on Economic Complexity (Driscoll-Kraay SE)*

Variable	Coefficient	DK Std. Error	t-value	p-value
rd_priv (t-1)	0.1286	0.0284	4.5323	<0.001***
rd_gov (t-1)	0.1481	0.0813	1.8230	0.06889
rd_higher (t-1)	-0.1506	0.0655	-2.2978	0.0220*
ln_gdppc (t-1)	0.2299	0.0363	6.3324	<0.001 ***
Instqual (t-1)	0.3623	0.0364	9.9664	<0.001 ***
ln_pop (t-1)	-0.7607	0.0604	-12.5932	<0.001 ***
ln_open (t-1)	-0.1112	0.0521	-2.1326	0.0334*
Observations	547			
Countries	25			
R-squared	0.449			
Country FE	Yes			
Year FE	No			
Notes: Notes: *** denote significance at the 0.1% level, ** at the 1% level, * at the 5% level, and at the 10% level Dependent variable: eci.				

Source: Author's calculations

Across both inference methods, business-sector R&D exhibits a positive, stable, and statistically significant association with subsequent economic complexity. The estimated coefficient is identical across PCSE and Driscoll-Kraay specifications ( $\beta \approx 0.129$ ) and remains statistically significant at conventional levels under both approaches. This robustness indicates that the positive relationship between aggregate R&D intensity and economic complexity documented in the baseline results is primarily driven by private-sector R&D activity. Given the slow-moving nature of the Economic Complexity Index, the magnitude of the coefficient is economically meaningful and suggests that firm-level R&D plays a central role in enabling product upgrading, capability accumulation, and entry into more complex export niches (Sweet & Eterovic, 2019; Zhu & Li, 2017). This finding is consistent with theoretical accounts emphasizing absorptive capacity, learning-by-doing, and commercialization-oriented innovation as key mechanisms linking R&D investment to export sophistication.

Government R&D enters with a positive coefficient in both tables but does not exhibit a statistically significant independent effect on economic complexity in the joint decomposition. Under PCSE, the coefficient is clearly insignificant, and although it approaches marginal significance under Driscoll-Kraay inference, it does not meet conventional confidence thresholds consistently across estimators. This pattern suggests that, once business-sector and higher-education R&D are simultaneously controlled for, government R&D does not directly translate into short-run changes in export complexity. A plausible interpretation is that public R&D contributes primarily through indirect or complementary channels, such as infrastructure provision, regulatory capacity, mission-oriented research, or support for private innovation, rather than through immediate effects on the composition of goods exports captured by the Economic Complexity Index.

Higher-education R&D enters with a consistently negative coefficient across all specifications, although its statistical significance depends on the choice of inference method. Under PCSE, the estimate is statistically insignificant, while under Driscoll-Kraay standard errors it becomes significant at the five percent level. Importantly, the point estimate is identical across estimators, indicating that differences in statistical significance reflect alternative assumptions about the error structure rather than coefficient instability or model misspecification. While the negative sign may appear counterintuitive relative to parts of the innovation literature, it is important to emphasize that the coefficient captures the partial, short- to medium-run association between higher-education R&D and trade-based economic complexity, conditional on private-sector R&D. University-based research

is typically oriented toward basic science and long-term knowledge creation, with commercialization occurring through indirect and delayed pathways that may not be captured by goods-based export measures within a one-year horizon. Moreover, the strong correlation between business-sector and higher-education R&D suggests that the negative coefficient in the joint specification is consistent with a suppression-type mechanism rather than a genuine negative causal relationship.

When higher-education R&D was entered alone, without controlling for business-sector R&D, the estimated coefficient becomes substantially smaller in magnitude and statistically insignificant across inference methods. This pattern supports the interpretation that higher-education R&D contributes to economic complexity primarily through complementarities with private-sector innovation, rather than through an independent short-run effect detectable in export-based complexity measures. The control variables behave consistently with theoretical expectations and the baseline results. GDP per capita and institutional quality enter positively and are highly statistically significant across both specifications, underscoring the importance of development level and governance quality in supporting complex production structures. Population size exhibits a negative and statistically significant association with economic complexity, reflecting scale and composition effects inherent in the construction of the Economic Complexity Index. Trade openness is weakly negative and statistically significant only under Driscoll–Kraay inference, suggesting that trade intensity per se plays a limited role once export composition and structural characteristics are controlled for.

Taken together, the empirical findings provide clear support for both hypotheses advanced in this study. The baseline and robustness results confirm Hypothesis H1, showing that higher national R&D intensity is positively associated with subsequent levels of economic complexity in EU member states. The decomposition analysis further verifies Hypothesis H2 by demonstrating that this relationship is primarily driven by business-sector R&D, which exhibits a stronger and more robust effect than government or higher-education R&D. These results are consistent with innovation systems theory and underscore the central role of firm-level R&D in driving short-run structural upgrading and export sophistication.

## CONCLUSIONS AND RECOMMENDATIONS

1. Economic complexity theory provides a capability-based lens for understanding development that complements traditional growth frameworks. However, the reliance on goods-based trade data means that economies with sophisticated service sectors, including several EU member states specializing in finance, ICT, or logistics, may appear less complex than their actual productive capabilities suggest. Consequently, economic complexity measures should be interpreted primarily as indicators of countries' structural positioning within global goods markets and their export competitiveness, rather than as direct proxies for overall technological sophistication or capability accumulation. The review of complexity measurement methods shows that aggregated indices such as the Economic Complexity Index are well suited for comparative panel analysis, while network-based approaches provide complementary structural insights but are less applicable in long-run cross-country regressions.
2. The scientific literature establishes that economic complexity emerges from the interaction of multiple determinants, with institutional quality, human capital, and R&D investment consistently identified as central factors. Among these, R&D plays a distinctive role by expanding the stock of productive knowledge, deepening capabilities within existing activities, and enhancing absorptive capacity for external technology. However, the literature emphasizes that R&D effects are conditional rather than automatic, their translation into complexity gains depends critically on innovation system coherence, commercialization channels and alignment with existing productive structures.
3. Descriptive analysis of EU member states between 2001 and 2023 reveals persistent structural heterogeneity in both economic complexity and R&D intensity. Germany maintains its position at the complexity frontier ( $ECI > 2.0$ ), while Central European economies, particularly Czechia, Slovenia, and Hungary, achieved substantial upgrading through integration into European value chains. Conversely, several historically complex Nordic economies experienced declining goods-based complexity despite high R&D investment.
4. The econometric analysis provides robust empirical support for Hypothesis H1: national R&D intensity positively and significantly affects economic complexity in EU member states, with effects materializing after a one-year lag. The baseline fixed-effects estimate ( $\beta = 0.066$ ) indicates that a one-percentage-point increase in R&D expenditure as a share of GDP is associated with approximately 0.066-point increase in the Economic Complexity Index in the following year. While modest on an annual basis, this effect is economically meaningful given the slow-moving nature of economic

complexity. The model explains approximately 42% of within-country variation, and results remain stable across alternative robust inference methods (PCSE and Driscoll-Kraay standard errors).

5. Decomposition analysis strongly supports Hypothesis H2: business-sector R&D exhibits a substantially stronger and more robust positive association with economic complexity ( $\beta = 0.129$ ) than government or higher-education R&D. This coefficient is statistically significant at conventional levels across all inference methods and approximately twice the magnitude of the aggregate R&D effect. Government R&D shows a positive but statistically insignificant coefficient, while higher-education R&D enters with a negative coefficient that reflects suppression dynamics in the joint specification rather than a genuine adverse causal relationship. These findings indicate that the aggregate R&D-complexity relationship is primarily driven by firm-level innovation activity oriented toward commercialization and product upgrading.

### **Recommendations**

1. Given the robust evidence that business-sector R&D drives complexity gains more effectively than public or academic R&D, EU innovation policy should prioritize instruments that stimulate private-sector research activity. This includes maintaining and expanding R&D tax incentives, strengthening co-funding mechanisms that leverage public investment to crowd in private R&D, and reducing administrative barriers that discourage firm-level innovation. Member states with R&D intensity below the EU average should focus particularly on creating favorable conditions for business R&D rather than expanding public research expenditure in isolation.

2. The weak direct effect of higher-education R&D on economic complexity does not imply that university research is unimportant, but rather that its benefits materialize through complementary channels with business-sector innovation. Policymakers should therefore strengthen university-industry linkages, support technology transfer offices, and incentivize collaborative research programs that connect academic knowledge creation with commercial application. Smart Specialization Strategies should explicitly identify mechanisms through which publicly funded research can be translated into products within the country's feasible diversification space.

3. The significant positive coefficients on institutional quality across all specifications underscore that R&D investment operates most effectively within strong governance frameworks. EU cohesion and structural funds should therefore maintain conditionality linking innovation support to governance reforms, transparency in public procurement, and protection of intellectual property rights. For

countries in Central and Eastern Europe seeking to escape 'dependent development' within German-led value chains, institutional upgrading is a necessary complement to increased R&D expenditure.

### **Limitations and Directions for Future Research**

While this study provides robust evidence on the R&D-complexity nexus in the EU context, several considerations point toward promising avenues for future research. The lagged fixed-effects framework employed here represents a methodologically sound approach that successfully mitigates contemporaneous endogeneity concerns while maintaining interpretability—an advantage over more complex dynamic estimators that can be sensitive to instrument proliferation in panels with modest cross-sectional dimensions. Nevertheless, continued development of credible instrumental variable strategies remains a valuable direction for strengthening causal identification in this literature. In particular the use of System of Generalized Methods Of Moments would highly beneficial for this thesis. The treatment of EU member states as analytically distinct units, while standard in the economic complexity literature, opens opportunities for future research to incorporate spatial econometric methods that explicitly model the rich cross-border interdependencies characterizing European economic integration. Such extensions could further illuminate how innovation spillovers propagate across the Union and whether R&D investments in one member state generate complexity gains in neighboring economies. Finally, while the one-year lag specification effectively captures the short-run dynamics most relevant for policy evaluation, the cumulative and path-dependent nature of capability formation suggests that extended lag structures and distributed lag models could reveal additional long-horizon effects, particularly for government and higher-education R&D whose benefits may materialize over longer time frames than business-sector investments.

## REFERENCES

- Aghion, P., & Howitt, P. (1998). *Endogenous growth theory*. MIT Press.
- Al-Marhubi, F. (2021). Economic complexity and inflation. *Economic Change and Restructuring*, 54(3), 755–781 <https://doi.org/10.1007/s11293-021-09727-0>
- Apostol, S., & Musyoka, M. W. (2024). Complexity and FDI in market-dependent economies: The hidden effect of industrial offshoring. *Acta Oeconomica*, 74(2), 187–212. <https://doi.org/10.1556/032.2024.00009>
- Antonietti, R., & Franco, C. (2021). From FDI to economic complexity: A panel Granger causality analysis. *Structural Change and Economic Dynamics*, 56, 225–239. <https://doi.org/10.1016/j.strueco.2020.11.001>
- Balland, P.-A., & Boschma, R. (2022). Do scientific capabilities in specific domains matter for technological diversification in European regions? *Research Policy*, 51(8), 104594. <https://doi.org/10.1016/j.respol.2022.104594>
- Balland, P.-A., Broekel, T., Diodato, D., Giuliani, E., Hausmann, R., O'Clery, N., & Rigby, D. (2022). The new paradigm of economic complexity. *Research Policy*, 51(3), 104450. <https://doi.org/10.1016/j.respol.2021.104450>
- Barro, R. J., & Sala-i-Martin, X. (2003). *Economic growth* (2nd ed.). MIT Press.
- Boschma, R. (2017). *Relatedness as driver behind regional diversification: A research agenda* (Papers in Evolutionary Economic Geography No. 17.02). Utrecht University. <https://ideas.repec.org/p/egu/wpaper/1702.html>
- Boschma, R., Balland, P.-A., & Kogler, D. F. (2015). Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, 24(1), 223–250. <https://doi.org/10.1093/icc/dtu012>
- Bronzini, R., & Piselli, P. (2016). The impact of R&D subsidies on firm innovation. *Research Policy*, 45(2), 442–457. <https://doi.org/10.1016/j.respol.2015.10.008>
- Brummitt, C. D., Pomeroy, J., & Valverde, S. (2020). Machine learning reveals complexity in the evolution of global trade. *Nature Human Behaviour*, 4(7), 682–691. <https://doi.org/10.1038/s41562-020-0846-5>
- Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128–152. <https://doi.org/10.2307/2393553>
- Cristelli, M., Tacchella, A., & Pietronero, L. (2013). The heterogeneous dynamics of economic complexity. *PLoS ONE*, 10(2), e0117174. <https://doi.org/10.1371/journal.pone.0117174>
- European Commission. (2014). *For a European Industrial Renaissance* (COM(2014) 014 final). <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52014DC0014>

European Commission. (2024). *The Draghi report on EU competitiveness*. [https://commission.europa.eu/topics/competitiveness/draghi-report\\_en](https://commission.europa.eu/topics/competitiveness/draghi-report_en)

Felipe, J., Kumar, U., Abdon, A., & Bacate, M. (2012). Product complexity and economic development. *Structural Change and Economic Dynamics*, 23(1), 36–68. <https://doi.org/10.1016/j.strueco.2011.08.003>

Grossman, G. M., & Helpman, E. (1991). *Innovation and growth in the global economy*. MIT Press.

Guellec, D., & Van Pottelsberghe de la Potterie, B. (2004). From R&D to productivity growth: Do the institutional settings and the source of funds matter? *Oxford Bulletin of Economics and Statistics*, 66(3), 353–378. <https://doi.org/10.1111/j.1468-0084.2004.00083.x>

Hartmann, D., Guevara, M. R., Jara-Figueroa, C., Aristarán, M., & Hidalgo, C. A. (2017). Linking economic complexity, institutions, and income inequality. *World Development*, 93, 75–93. <https://doi.org/10.1016/j.worlddev.2016.12.020>

Hausmann, R., & Hidalgo, C. A. (2011). *The atlas of economic complexity: Mapping paths to prosperity*. MIT Press.

Hausmann, R., Hwang, J., & Rodrik, D. (2007). What you export matters. *Journal of Economic Growth*, 12(1), 1–25. <https://doi.org/10.1007/s10887-006-9009-4>

Hidalgo, C. A. (2023). The policy implications of economic complexity. *Research Policy*, 52, 104863. <https://doi.org/10.1016/j.respol.2023.104863>

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, 106(26), 10570–10575. <https://doi.org/10.1073/pnas.0900943106>

Hidalgo, C. A., Klinger, B., Barabási, A.-L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, 317(5837), 482–487. <https://doi.org/10.1126/science.1144581>

Kamguia, B., Keneck-Massil, J., Njangang, H., & Tadadjeu, S. (2024). Sophistication gap between countries: The effect of research and development expenditure. *Economics of Transition and Institutional Change*, 32(3), 739–778. <https://doi.org/10.1111/ecot.12400>

Koch, P. (2021). Economic complexity and growth: Can value-added exports better explain the link? *Economics Letters*, 198, 109682. <https://doi.org/10.1016/j.econlet.2020.109682>

Kogler, D. F., Rigby, D. L., & Tucker, I. (2013). Mapping knowledge space and technological relatedness in US cities. *Regional Studies*, 47(9), 1374–1391. <https://doi.org/10.1080/09654313.2012.755832>

Lapatinas, A. (2018). The effect of the Internet on economic sophistication: An empirical analysis. *Economics Letters*, 174, 35–38. <https://doi.org/10.1016/j.econlet.2018.10.013>

Lapatinas, A., & Litina, A. (2019). Intelligence and economic sophistication. *Empirical Economics*, 57(5), 1731–1750. <https://doi.org/10.1007/s00181-018-1511-y>

Lee, K., & Vu, T. V. (2020). Economic complexity, human capital and income inequality. *Review of Evolutionary Political Economy*, 1(1–2), 75–100. <https://doi.org/10.1007/s42973-019-00026-7>

Loungani, P., Mishra, S., Papageorgiou, C., & Wang, K. (2020). World trade in services: Evidence from a new dataset. *Journal of Economic Dynamics and Control*, 113, 103880. <https://doi.org/10.1016/j.strueco.2020.03.002>

Matsuyama, K. (1992). Agricultural productivity, comparative advantage, and economic growth. *Journal of Economic Theory*, 58(2), 317–334. [https://doi.org/10.1016/0022-0531\(92\)90057-O](https://doi.org/10.1016/0022-0531(92)90057-O)

Mealy, P., & Teytelboym, A. (2022). Economic complexity and the green economy. *Research Policy*, 51(8), 103948. <https://doi.org/10.1016/j.respol.2020.103948>

Mealy, P., Farmer, J. D., & Teytelboym, A. (2019). Interpreting economic complexity. *Science Advances*, 5(1), eaau1705. <https://doi.org/10.1126/sciadv.aau1705>

Morrison, G., Buldyrev, S. V., Imbruno, M., Arrieta, O. A., & Pammolli, F. (2017). On economic complexity and the fitness of nations. *Scientific Reports*, 7, 15332. <https://doi.org/10.1038/s41598-017-14603-6>

Moutinho, R. (2017). Inside the 'black-box of innovation': Translating R&D outlays into economic and employment growth. *Journal of Engineering and Technology Management*, 45, 37–53. <https://doi.org/10.1016/j.jengtecman.2017.06.002>

Naveed, A., & Wang, C. (2023). Innovation and labour productivity growth moderated by structural change: Analysis in a global perspective. *Technovation*, 119, 102554. <https://doi.org/10.1016/j.technovation.2022.102554>

Neagu, O., Neagu, M.-I., & Gavurova, B. (2022). How green is the economic complexity in the Central and Eastern European Union countries? *Frontiers in Environmental Science*, 10, 910454. <https://doi.org/10.3389/fenvs.2022.910454>

Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography*, 87(3), 237–265. <https://doi.org/10.1111/j.1944-8287.2011.01121.x>

Nguyen, C. P., Schinckus, C., & Su, T. D. (2020). The drivers of economic complexity: International evidence from financial development and patents. *International Economics*, 164, 140–150. <https://doi.org/10.1016/j.inteco.2020.09.004>

Pop Silaghi, M. I., Alexa, D., Jude, C., & Litan, C. (2014). Do business and public sector research and development expenditures contribute to economic growth in Central and Eastern

European countries? *Economic Modelling*, 36, 108–119.  
<https://doi.org/10.1016/j.econmod.2013.08.035>

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5, Part 2), S71–S102. <https://doi.org/10.1086/261725>

Sciarra, C., Chiarotti, G. L., Ridolfi, L., Laio, F., & Pietronero, L. (2020). Reconciling contrasting views on economic complexity. *Nature Communications*, 11, 3354. <https://doi.org/10.1038/s41467-020-16992-1>

Servedio, V. D. P., Tacchella, A., Zaccaria, A., & Cristelli, M. (2018). A new and stable numerical algorithm for the fitness–complexity model. *Entropy*, 20(10), 783. <https://doi.org/10.3390/e20100783>

Simoes, A. J. G., & Hidalgo, C. A. (2011). The Economic Complexity Observatory: An analytical tool for understanding the dynamics of economic development. In *Workshops at the Twenty-Fifth AAAI Conference on Artificial Intelligence*. <https://aaai.org/papers/aaaiw-ws0763-11-3948/>

Smith, A. (1776). *An inquiry into the nature and causes of the wealth of nations*. W. Strahan and T. Cadell.

Sweet, C., & Eterovic, D. (2019). Do patent rights matter? 40 years of innovation, complexity and productivity. *World Development*, 115, 78–93. <https://doi.org/10.1016/j.worlddev.2018.10.009>

Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70(1), 65–94. <https://doi.org/10.2307/1884513>

Stojkoski, V., Utkovski, Z., & Kocarev, L. (2016). The impact of services on economic complexity: Service sophistication as route for economic growth. *PLoS ONE*, 11(8), e0161633. <https://doi.org/10.1371/journal.pone.0161633>

Stokey, N. L. (1988). Learning by doing and the introduction of new goods. *Journal of Political Economy*, 96(4), 701–717. <https://doi.org/10.1086/261570>

Swan, T. W. (1956). Economic growth and capital accumulation. *Economic Record*, 32(2), 334–361. <https://doi.org/10.1111/j.1475-4932.1956.tb00434.x>

Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A., & Pietronero, L. (2012). A new metrics for countries' fitness and products' complexity. *Scientific Reports*, 2, 723. <https://doi.org/10.1038/srep00723>

Veselinović, N., Ćuzović, Đ., & Bugarčić, F. Ž. (2025). Economic complexity in CEE countries: The role of innovations, investments and education. *Management: Journal of Sustainable Business and Management Solutions in Emerging Economies*, 30(2). <https://doi.org/10.7595/management.fon.2025.0009>

Vu, T. V. (2022). Does institutional quality foster economic complexity? The fundamental drivers of productive capabilities. *Empirical Economics*, 63(3), 1–34. <https://doi.org/10.1007/s00181-021-02175-4>

Young, A. (1991). Learning by doing and the dynamic effects of international trade. *Quarterly Journal of Economics*, 106(2), 369–405. <https://doi.org/10.2307/2937942>

Zhu, S., & Li, R. (2017). Economic complexity, human capital and economic growth: Empirical research based on cross-country panel data. *Applied Economics*, 49(38), 3815–3828. <https://doi.org/10.1080/00036846.2016.1270413>

**THE ROLE OF RESEARCH AND DEVELOPMENT INTENSITY IN ECONOMIC  
COMPLEXITY:  
EVIDENCE FROM EUROPEAN UNION COUNTRIES**

**Emilija Navickaitė**

**Master's Thesis**

**Economics of Strategy**

Faculty of Economics and Business Administration, Vilnius University

Supervisor – Assoc. Prof. Dr. Giedrė Dzemydaitė

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**ABSTRACT**

**61 pages, 5 figures, 9 tables, 55 references.**

The aim of this thesis is to examine the long-term relationship between national research and development (R&D) investment and economic complexity in European Union countries. The main research question addresses the extent to which national R&D investment contributes to economic complexity and how this relationship differs across disaggregated categories of R&D expenditure.

The thesis consists of three main parts. The first part reviews the theory of economic complexity, its measurement methods, and key determinants, with particular emphasis on the role of R&D within innovation systems. The second part presents the research methodology, hypotheses, and diagnostic procedures. The third part provides a descriptive analysis of EU trends and reports the results of the econometric estimations.

The empirical analysis employs a lagged fixed-effects panel regression for 25 EU countries over the period 2000–2023, using panel-corrected standard errors to account for cross-sectional dependence and heteroskedasticity. The results indicate that R&D intensity has a positive effect on economic complexity ( $\beta = 0.066$ ). The decomposition analysis reveals that business-sector R&D has the strongest impact ( $\beta = 0.129$ ), while government and higher-education R&D exhibit weaker and more indirect relationships. The novelty of the study lies in the application of economic complexity as an outcome measure of R&D performance and in the analysis of long-term cross-country dynamics within the EU context.

The findings provide policy-relevant insights into the structural role of R&D investment, suggesting that innovation policy should prioritize business-sector R&D instruments and strengthen linkages between universities and industry.

# MOKSLINIŲ TYRIMŲ IR EKSPERIMENTINĖS PLĖTROS INTENSYVUMO VAIDMUO EKONOMIKOS KOMPLEKSIŠKUME: EUROPOS SĄJUNGOS ŠALIŲ PAVYZDYS

Emilija Navickaitė

Magistro baigiamasis darbas

Strategijos ekonomika

Vilniaus universiteto Ekonomikos ir verslo administravimo fakultetas

Darbo vadovas(ė) – doc. dr. Giedrė Dzemydaitė

Vilnius, 2026

## SANTRAUKA

61 puslapiai, 5 paveikslėliai, 9 lentelės, 55 literatūros šaltiniai.

Šio darbo tikslas - išanalizuoti ilgalaikius nacionalinių MTEP investicijų ir ekonomikos kompleksškumo ryšius Europos Sąjungos šalyse. Pagrindinis tyrimo klausimas – koku mastu nacionalinės MTEP investicijos prisideda prie ekonomikos kompleksškumo ir kaip šis ryšys skiriasi tarp disagreguotų MTEP kategorijų.

Darbą sudaro 3 pagrindinės dalys. Pirmoje dalyje apžvelgiama ekonomikos kompleksškumo teorija, matavimo metodai ir pagrindiniai veiksniai, ypatingą dėmesį skiriant MTEP vaidmeniui inovacijų sistemose. Antroje dalyje pristatoma tyrimo metodologija, hipotezės ir diagnostinės procedūros. Trečioje dalyje pateikiama ES tendencijų aprašomoji analizė ir ekonometriniai vertinimo rezultatai.

Empirinė analizė atlikta taikant fiksuotųjų efektų panelinę regresiją su vėluojančiais kintamaisiais 25 ES šalims 2000-2023 m. laikotarpiu, naudojant paneliais koreguotas standartinės paklaidas, siekiant įvertinti tarpvalstybinę priklausomybę ir heteroskedastiškumą. Rezultatai rodo, kad MTEP intensyvumas teigiamai veikia ekonomikos kompleksškumą ( $\beta = 0,066$ ). Dekompozicijos analizė atskleidė, kad verslo sektoriaus MTEP turi stipriausią poveikį ( $\beta = 0,129$ ), o valdžios ir aukštojo mokslo MTEP rodo silpnesnius netiesioginius ryšius. Darbo naujumas pasireiškia ekonomikos kompleksškumo naudojimu MTEP rezultatams vertinti ir ilgalaikių tarpvalstybinių tendencijų analize ES kontekste.

Tyrimo rezultatai teikia politikai aktualių įžvalgų apie struktūrinį MTEP investicijų vaidmenį, siūlant inovacijų politikoje prioritetą teikti privataus sektoriaus MTEP priemonėms ir stiprinti universitetų bei pramonės ryšius.

## ANNEXES

### Annex 1. Variables Used in the Panel Regression and Their Theoretical Rationale

Variable Name	Scientific Sources	Theoretical Rationale
Economic Complexity Index (ECI)(Abbreviation: eci)	Hausmann et al. (2007); Mealy & Teytelboym (2019); Kamguia et al. (2024); Neagu et al. (2022); Veselinović et al. (2025); Apostol & Musyoka (2024); Sweet & Eterovic (2019)	The ECI captures the amount of productive knowledge embedded in an economy by combining export diversity with product ubiquity. Higher values reflect more complex capability structures enabling sophisticated production. Because the index is already normalized, it is used in levels without transformation.
Total R&D Expenditure (% of GDP)(Abbreviation: rd_total)	Kamguia et al. (2024); Neagu et al. (2022); Veselinović et al. (2025);	Total R&D intensity (GERD) captures national investment in knowledge creation and innovation. It is the central explanatory variable reflecting the premise that R&D stimulates capability accumulation, technological upgrading, and diversification into more complex products. Sectoral R&D components are excluded from the baseline due to mechanical collinearity.
Business R&D Expenditure (%)(Abbreviation: rd_priv)	Moutinho et al. (2016); Kamguia et al. (2024); Veselinović et al. (2025)	Business-sector R&D (BERD) reflects firm-level innovation, which is directly tied to product development, applied research, and production upgrades. Empirical studies find BERD is often the strongest driver of export sophistication.
Government R&D Expenditure (%)(Abbreviation: rd_gov)	Kamguia et al. (2024)	Government R&D finances basic research, research infrastructure, and long-term scientific capabilities. Its effect may differ from private R&D due to public-good characteristics.
Higher Education R&D Expenditure (Abbreviation: rd_higher) (%)	Kamguia et al. (2024)	Higher-education R&D (HERD) contributes to scientific output, fundamental research and advanced human capital formation. Its inclusion tests whether academic research intensity modifies the R&D complexity relationship.

Table continued.

Variable Name	Scientific Sources	Theoretical Rationale
Income Level: Log GDP per capita (PPP)(Abbreviation: ln_gdppc)	Hartmann et al. (2017); Lapatinas (2019)	GDP per capita (PPP) captures the structural development level that co-evolves with capability accumulation. Higher incomes correlate with more sophisticated production. Using log form reduces skewness and allows elasticity interpretation. Serves as a baseline control to isolate R&D-specific effects.
Institutional Quality (WGI Index)(Abbreviation: instqual)	Hartmann et al. (2017); Mealy & Teytelboym (2019)	Institutional quality supports capability upgrading by reducing coordination failures, enhancing contract enforcement, and improving the efficiency of innovation systems. Strong institutions are consistently associated with higher complexity even after controlling for income.
Population (log)(Abbreviation: ln_pop)	Hartmann et al. (2017); Lee & Vu (2020);	Population size proxies market scale and availability of diverse skills. Larger countries can support deeper specialization and more varied capability combinations. Logarithmic form accounts for diminishing returns and reduces skewness.
Trade Openness (log)(Abbreviation: ln_open)	Fatima et al. (2020); Lapatinas (2019)	Trade openness facilitates technology diffusion, learning-by-exporting and access to knowledge-embedded imports. Openness can accelerate entry into complex product spaces. Logged to correct skewness and interpret coefficients as semi-elasticities.

**Annex 2. Correlation matrix for the disaggregated specification**

	<b>eci</b>	<b>rd_priv</b>	<b>rd_gov</b>	<b>rd_higher</b>	<b>ln_gdppc</b>	<b>instqual</b>	<b>ln_pop</b>	<b>ln_open</b>
<b>eci</b>	1.000	0.730	0.388	0.378	0.584	0.612	0.284	0.086
<b>rd_priv</b>	0.730	1.000	0.259	0.755	0.700	0.759	0.196	0.000
<b>rd_gov</b>	0.388	0.259	1.000	-0.036	-0.041	0.010	0.333	-0.222
<b>rd_higher</b>	0.378	0.755	-0.036	1.000	0.637	0.776	0.056	-0.038
<b>ln_gdppc</b>	0.584	0.700	-0.041	0.637	1.000	0.763	0.195	0.121
<b>instqual</b>	0.612	0.759	0.010	0.776	0.763	1.000	-0.001	0.092
<b>ln_pop</b>	0.284	0.196	0.333	0.056	0.195	-0.001	1.000	-0.593
<b>ln_open</b>	0.086	0.000	-0.222	-0.038	0.121	0.092	-0.593	1.000