

FROM R&D INVESTMENT TO INNOVATION OUTPUT: EVIDENCE FROM TRANSFORMATION GAPS IN EU COUNTRIES

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ABSTRACT

This paper examines the relationship between research and development (R&D) expenditure and innovation outputs across European Union (EU) member states, with particular emphasis on identifying differences between observed and expected innovation performance after controlling for the structural characteristics of national economies. Special attention is given to the cross-country heterogeneity and temporal evolution of these deviations. The empirical analysis is based on panel data for 27 EU countries covering the period 2011-2024. The relationship between R&D investment and innovation outcomes is estimated using a Correlated Random Effects panel model. Innovation performance is assessed through two complementary indicators: patent activity and high-tech exports. Using the residual component of the model, the paper develops a transformation gap indicator, which measures the extent to which actual innovation output deviates from its expected level, given R&D investment and relevant structural conditions. The findings reveal substantial heterogeneity among EU countries, as well as distinct dynamic patterns in the evolution of the transformation gap. While some countries demonstrate signs of convergence toward expected innovation performance, others experience widening deviations. The paper contributes to the literature by combining static and dynamic perspectives and by providing new empirical evidence on the performance of national innovation systems within the EU.

Keywords: *research and development, transformation gap, patents, high-tech exports, European Union*

1. INTRODUCTION

Innovation is widely recognized as a key driver of economic growth, productivity improvement, and international competitiveness. R&D investment plays a central role in this process by generating new knowledge, technological solutions, and innovations that may later be commercialized through new products, services, or advanced production processes. In the European Union, support for research, technological development, and innovation represents one of the main pillars of economic policy, particularly in the context of strengthening a knowledge-based economy and improving the technological competitiveness of member states.

The empirical literature generally confirms a positive association between R&D intensity and

innovation outputs. Patent activity and high-tech exports are among the most frequently used indicators of innovation performance, as they capture different stages of the innovation process. Patents reflect the creation of new technological knowledge, whereas high-tech exports indicate the capacity of an economy to commercialize such knowledge and compete successfully in international markets. Previous studies suggest that R&D investment can stimulate both patenting activity and the export performance of technology-intensive sectors (Sözen & Tufaner, 2020; Khan et al., 2016; Kiseľáková et al., 2020; Kozuň-Ciešlak, 2024).

However, the relationship between R&D expenditure and innovation output is neither automatic nor strictly proportional. Countries with comparable levels of R&D investment may achieve markedly different innovation outcomes. This suggests that national economies differ in their ability to convert research inputs into technological and commercial outputs. Comparative analyses of EU member states confirm considerable variation in innovation performance relative to R&D investment, with more technologically advanced economies generally producing stronger innovation results at similar levels of input (Gavurová et al., 2019). Such differences are closely related to the broader characteristics of national innovation systems. Innovation performance depends not only on the number of financial resources allocated to research but also on the quality of institutions, the availability of human capital, cooperation between research organizations and firms, and the capacity of the economy to absorb and apply new knowledge. Accordingly, empirical studies emphasize the importance of absorptive capacity, governance quality, and the structure of innovation financing in explaining cross-country differences in innovation outcomes (Karahan, 2017; InSoo & Kim, 2019; Medase & Barasa, 2019; Abdikadirova et al., 2024). Despite the growing body of research on R&D and innovation, relatively limited attention has been paid to the extent to which R&D investment produces expected innovation outcomes once the structural characteristics of economies are considered. Most existing studies focus either on the direct relationship between R&D inputs and innovation outputs or on static comparisons across countries. Less emphasis has been placed on analysing the deviation between actual and model-expected innovation performance and on examining how these deviations evolve over time. The aim of this paper is therefore to analyse the relationship between R&D expenditure and innovation outputs in EU countries and to assess differences in their relative ability to generate measurable innovation outcomes. The empirical analysis uses panel data for 27 EU member states over the period 2011-2024. It examines the effect of R&D expenditure on two key dimensions of innovation performance: patent activity and high-tech exports, while controlling for the structural features of national economies. The paper contributes to the literature in two main ways. First, it analyses innovation performance through two complementary dimensions: the creation of technological knowledge, measured by patents, and its commercialization, measured by high-tech exports. Second, it introduces a transformation gap indicator based on the residual component of the econometric model. This indicator enables the identification of deviations between actual and expected innovation outcomes and allows their dynamics to be examined over time.

2. LITERATURE REVIEW

The transformation of R&D investment into innovation outputs is a central issue in innovation economics. Patent activity, technological innovation, and high-tech exports are commonly used to assess this process. In the EU context, this issue is particularly important because of the Union's strategic orientation toward knowledge-based growth, technological modernization, and global competitiveness. Previous research generally confirms a positive relationship between R&D intensity and innovation outcomes, while also identifying substantial differences in the effectiveness with which countries convert research inputs into measurable outputs

(Gavurová et al., 2019; Grafström & Alm, 2024).

Several studies emphasize the close link between R&D expenditure and technological outputs. Evidence from OECD countries indicates bidirectional causality between R&D expenditure, patents, and high-tech exports. This suggests that R&D investment stimulates innovation outputs, while stronger export performance may, in turn, encourage further research activity (Sözen & Tufaner, 2020). Similar findings for European economies indicate that higher R&D intensity is generally associated with greater patenting activity and a larger share of high-tech exports (Aumeboonsuke & Caplanova, 2026; Alsharaideh et al., 2026).

The macroeconomic relevance of R&D is also confirmed in studies of EU member states. Panel regression evidence for EU-28 countries shows that R&D intensity, commonly measured by gross domestic expenditure on R&D as a share of GDP, is an important determinant of economic growth and innovation performance. High-tech exports represent one of the channels through which research investment contributes to broader economic outcomes (Khan et al., 2016; Kiseľáková et al., 2020; Kozuń-Cieślak, 2024; Hunady et al., 2025).

Studies on competitiveness in EU member states further reveal strong associations between R&D expenditure, patent activity, and exports of technologically advanced products. Teclean (2022) identifies particularly strong links between competitiveness and indicators such as R&D expenditure and high-tech exports. At the same time, the study suggests that institutional changes, including Brexit, may influence the relationship between innovation inputs and outputs, underlining the need for continuous assessment of innovation policy effectiveness within the EU. Although most empirical studies confirm a positive relationship between R&D investment and technological output, higher expenditure does not necessarily result in a proportional increase in innovation performance. For this reason, efficiency-oriented methods such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are frequently used to evaluate the capacity of economies to transform inputs into outputs. Using a super-efficiency DEA model, Gavurová et al. (2019) demonstrate significant differences among countries in their ability to convert inputs such as R&D expenditure, researchers, and human resources in science and technology into outputs such as scientific publications and high-tech exports. Their findings point to persistent regional disparities in the efficiency of innovation systems across the EU.

Other model-based studies stress the importance of the composition of R&D investment. Research on low-carbon technologies shows that private R&D expenditure often has a stronger effect on export competitiveness and GDP growth than public expenditure, particularly in economies with a well-developed technological base (Kheyfets & Chernova, 2021). This indicates that the structure and allocation of research investment are as important as its overall volume in generating technological outputs (Spišáková, 2010). Cross-country differences in innovation outcomes can also be interpreted through the concept of national innovation systems. This approach views innovation as the result of interaction among firms, universities, research institutions, public policies, and other actors that collectively shape a country's innovation ecosystem (Karahan, 2017; InSoo & Kim, 2019; Dobrzański et al., 2021). From this perspective, the link between R&D inputs and innovation outputs is not linear. Rather, innovation performance depends on institutional quality, collaboration intensity, and the capacity of the economy to absorb, adapt, and apply new knowledge (Abdikadirova et al., 2024).

A particularly important concept in this regard is absorptive capacity, which refers to the ability of economic actors to identify, assimilate, and exploit external knowledge. Empirical evidence indicates that stronger absorptive capacity improves the efficiency of innovation processes and enhances the effect of external knowledge and cooperation on patenting performance (Azizi et al., 2025; Wang et al., 2024; Rosli, 2020). In the EU context, investments in human capital, research infrastructure, and international research networks can therefore improve the conver-

sion of R&D expenditure into technological outputs (Medase & Barasa, 2019).

The effectiveness of this conversion process is also influenced by the availability and structure of financial resources. Venture capital, liquidity, and specialized financing for high-tech sectors play an important role in supporting innovation. Margaryan and Terzyan (2023) show that greater access to venture capital is associated with a higher share of high-tech exports, indicating a possible transmission channel from financing to export performance through patent activity. Gatari et al. (2024) similarly emphasize the positive role of liquidity inflows and credit financing in sustaining patent generation. However, the role of debt financing appears more complex. Shahzad et al. (2021) identifies an inverted U-shaped relationship, suggesting that debt may support R&D intensity up to an optimal level, after which excessive indebtedness can weaken innovation performance. In this context, private R&D investment appears to be a particularly important driver of export competitiveness, especially in economies with an already substantial stock of knowledge. At the firm level, empirical evidence also confirms that R&D investment, technological innovation, and patents can positively affect export intensity. Research on Spanish manufacturing firms shows that technological resources and innovation activities increase both the probability of firms entering export markets and their competitiveness abroad (Rodríguez & López-Rodríguez, 2011).

Another important strand of the literature examines convergence in technological capabilities among EU member states. Analyses based on indicators such as R&D expenditure, high-tech exports, and human capital suggest the existence of a moderate process of technological catch-up. However, this process remains slow, and significant differences in innovation performance persist across countries (Grafström & Alm, 2024). This implies that convergence in R&D inputs does not automatically translate into convergence in innovation outputs, highlighting the need for policy measures aimed at strengthening technological capacities in less developed regions. In the empirical literature, differences in countries' ability to convert R&D inputs into innovation outputs are often analysed through DEA and SFA approaches. These methods identify best-practice frontiers and measure technical efficiency relative to an estimated production possibility set. The transformation gap proposed in this paper differs from these approaches. It does not seek to estimate technical efficiency or benchmark countries against an efficiency frontier. Instead, it captures the residual deviation between actual and model-expected innovation performance, conditional on observed inputs and structural characteristics. The transformation gap therefore reflects relative overperformance or underperformance compared with statistically expected outcomes, rather than efficiency in the strict production sense.

From a theoretical standpoint, the transformation gap can be interpreted within the framework of national innovation system theory. Innovation output is understood as the result of complex interactions among actors, institutions, and structural conditions, rather than as a mechanical outcome of R&D expenditure alone. The residual component captured by the transformation gap may therefore reflect the combined influence of unobserved systemic factors, including institutional quality, absorptive capacity, coordination among innovation actors, and integration into global value chains. In this sense, the transformation gap complements innovation system approaches by offering an empirically grounded indicator of relative system performance, while remaining neutral regarding the precise causal mechanisms behind these deviations.

Overall, regression-based models estimate average relationships between innovation inputs and outputs, while efficiency methods focus on benchmarking economies against best-practice frontiers. The transformation gap introduced in this study complements both approaches by identifying systematic deviations from model-expected innovation outcomes. It therefore provides a comparative and dynamic measure of relative innovation system performance without relying on frontier-based assumptions.

3. METHODOLOGY

3.1. MAIN AIM, HYPOTHESES AND DATA SOURCES

The aim of this paper is to examine the relationship between research and development (R&D) expenditure and innovation outputs in EU countries, as well as to assess cross-country differences in the relative capacity to convert R&D inputs into measurable innovation outcomes.

The following hypotheses are tested:

H₁: R&D expenditure is positively associated with innovation outputs, although the strength of this relationship may differ depending on the type of innovation output considered.

H₂: EU countries differ significantly in their ability to convert R&D expenditure into innovation outputs.

H₃: The transformation gap evolves over time and follows heterogeneous development patterns across EU countries.

The empirical analysis is grounded in the concept of the innovation production function, which explains innovation outputs as a function of R&D inputs and other relevant economic characteristics. This framework is commonly used to examine how research investment contributes to measurable innovation outcomes, such as patents or technologically advanced production (Griliches, 1990; Hall et al., 2010). Similar approaches have also been applied in international studies assessing the performance of national innovation systems (Fagerberg & Srholec, 2008; Castellacci & Natera, 2013; Tebaldi & Elmslie, 2013). Within this analytical framework, innovation performance is interpreted as the outcome of both direct research inputs and broader structural features of the economy.

The empirical investigation is based on panel data for 27 EU member states over the period 2011–2024. The econometric analysis focuses on the relationship between R&D expenditure and innovation outputs at the country level. The first dependent variable is patent applications submitted to the European Patent Office (EPO) by country of inventors, expressed per million inhabitants (Patents). This indicator captures the geographical origin of innovation activity and is therefore appropriate for analysing the relationship between domestic R&D investment and innovation output. Since R&D activities are undertaken within a specific national context and are closely linked to domestic research capacity, assigning patent activity to the country of the inventor provides a more accurate measure of national innovation performance. By contrast, patents classified by country of applicants may introduce bias, as the applicant may be a foreign company or institution, even when the underlying research was conducted elsewhere. For this reason, patent applications by country of inventors are widely used in empirical research on R&D and innovation outcomes.

The second dependent variable is high-tech exports as a share of manufactured exports (Htech). This indicator measures the export share of technologically advanced products whose production typically requires substantial R&D activity and a high level of technological knowledge. High-tech products generally include goods from sectors such as aerospace, pharmaceuticals, computers and electronics, telecommunications equipment, and scientific instruments. In empirical innovation studies, high-tech exports are frequently used as a proxy for the commercialization of innovation, as they reflect the ability of an economy to transform technological knowledge into internationally competitive products. While patents capture the creation of new knowledge, high-tech exports indicate its economic application and market-oriented utilization. The use of these two dependent variables enables innovation performance to be analysed from two complementary perspectives: the generation of new technological knowledge, measured

by patent activity, and the commercialization of that knowledge through technologically advanced exports. This dual approach also provides the basis for identifying deviations between actual and expected innovation performance, which are later expressed through the transformation gap indicator.

The main explanatory variable is Gross Domestic Expenditure on Research and Development (GERD), expressed as a percentage of GDP. GERD measures the overall intensity of R&D investment in an economy and represents the principal input in the innovation production process. The model also includes several control variables that account for the structural characteristics of national economies. The share of the population aged 25-34 with tertiary education (Tertiary education) is used as an indicator of human capital quality and the availability of a skilled labour force. A higher level of tertiary education strengthens the absorptive capacity of the economy and supports the development and application of new technologies.

The share of industry value added in GDP (Industry Value Added - IVA) is included to capture the productive structure of the economy. Economies with a stronger industrial base are generally expected to have greater potential for technological innovation and the production of high-tech goods.

GDP per capita is also included as a proxy for the level of economic development. More developed economies usually possess stronger research infrastructure, more advanced institutions, and more favourable conditions for both the creation and commercialization of innovation.

Data for Patents, GERD, Tertiary education, and GDP per capita were obtained from the Eurostat database, while data for Htech and IVA were collected from the World Bank database.

3. 2. ECONOMETRIC MODEL SPECIFICATION

To empirically assess the relationship between R&D expenditure and innovation outputs, this study applies an econometric framework that enables the estimation of the effects of R&D investment and selected control variables on patent activity and high-tech exports. Given the cross-country and time-series structure of the data, a panel regression approach is employed.

In line with the nature of the variables and the objective of deriving an interpretable transformation gap indicator, the variables Patents, Htech, and GERD are transformed into logarithmic form. The use of logarithmic transformation is common in empirical innovation studies, as it reduces the influence of extreme observations, improves the distributional properties of the variables, and allows the estimated coefficients to be interpreted as elasticities (Griliches, 1990; Hall et al., 2010).

The GERD variable is included in the model with a time lag, since the effects of R&D investment are not expected to materialize immediately. A natural delay exists between the allocation of resources to research and development and the emergence of measurable innovation outcomes, such as patent applications or high-tech exports. This delay reflects the stages of the innovation process, including research, technological development, testing, implementation, and eventual commercialization.

The relationship between R&D inputs and innovation outputs is specified using the following baseline panel regression model:

$$\ln(Y_{it}) = \alpha + \beta_1 \ln(GERD_{i,t-k}) + \beta_2 X_{it} + u_i + \varepsilon_{it} \quad (1)$$

Where:

- Y_{it} represents patents or high-tech exports,
- X_{it} is a vector of control variables,
- u_i captures unobserved country heterogeneity,
- ε_{it} is the idiosyncratic error.

Given the log-log specification of the model, the coefficient β_1 can be interpreted as the elasticity of innovation output with respect to R&D expenditure. In other words, it measures the percentage change in innovation output associated with a one-percent change in R&D expenditure, holding other factors constant.

The choice of the appropriate panel data specification was guided by a sequence of standard diagnostic tests. First, the Breusch-Pagan Lagrange Multiplier test was applied to assess whether a pooled OLS model or a panel-effects specification was more appropriate (Breusch & Pagan, 1980). The results obtained for both model specifications indicated the presence of significant panel effects, suggesting that unobserved country-specific heterogeneity should be considered:

- Model 1 (patents): LM $\chi^2 = 93.54$, $p < 0.001$
- Model 2 (high-tech): LM $\chi^2 = 168.97$, $p < 0.001$

This implies that pooled OLS is not an appropriate specification.

The consistency of the random effects (RE) model was verified using the Hausman test (Hausman, 1978):

- Model 1: $\chi^2 = 1.107$, $df = 4$, $p = 0.893$
- Model 2: $\chi^2 = 0.114$, $df = 4$, $p = 0.998$

In both cases, the null hypothesis was not rejected, indicating that the random effects (RE) estimator is consistent relative to the fixed effects (FE) estimator.

Accordingly, the Correlated Random Effects (CRE) model, based on the Mundlak approach, was selected as the preferred specification (Mundlak, 1978). This specification extends the standard RE model by incorporating the country-specific means of time-varying regressors. By doing so, the CRE model allows potential correlation between unobserved country-specific effects and the explanatory variables to be explicitly modelled, while retaining the advantages of random effects estimation (Mundlak, 1978; Wooldridge, 2010).

Although Wooldridge (2019) focuses primarily on unbalanced panel data, his formalization of the CRE approach provides a broader methodological framework and highlights its practical relevance and efficiency in applied panel data analysis.

The CRE specification is expressed as follows:

$$\ln(Y_{it}) = \alpha + \beta_1 \ln(GERD_{i,t-k}) + \beta_2 X_{it} + \gamma \bar{X}_i + u_i + \varepsilon_{it} \quad (2)$$

Where $\bar{X}_i$ represents the country-specific means of the time-varying regressors. This specific approach is suitable for the subsequent measurement of the efficiency of transforming R&D expenditure into patents and high-tech exports in each country.

To support the CRE specification, a Wald test for the joint significance of the Mundlak means was performed:

- Model 1 (patents): $\chi^2 = 125.77$, $df = 4$, $p < 0.001$
- Model 2 (high-tech): $\chi^2 = 4.73$, $df = 4$, $p = 0.316$

In the high-tech export model, the Mundlak means are not statistically significant ($p = 0.316$), indicating that the correlation between unobserved country-specific effects and the explanatory variables is not pronounced. This suggests that, for this dimension of innovation output, the CRE specification performs empirically very similarly to a standard random effects model. The absence of significant Mundlak terms implies that time-invariant unobserved heterogeneity is not systematically associated with the included regressors in the high-tech export equation. Nevertheless, the CRE specification is retained for the high-tech export model to ensure

methodological consistency across both innovation dimensions and to enable a harmonised calculation of the transformation gap. Applying the same modelling framework facilitates a coherent interpretation of residual-based deviations and prevents specification-driven differences between the patent and export models. Robustness checks further confirm that the estimated transformation gaps and country rankings are not sensitive to the choice between the CRE and standard random effects specifications in this model.

Diagnostic tests were conducted to assess the validity of the model assumptions and ensure reliable statistical inference. The Breusch-Pagan test for heteroscedasticity (Breusch & Pagan, 1979) indicates a violation of the homoscedasticity assumption in both models ($p < 0.01$). Accordingly, robust standard errors clustered at the country level are used in all estimations.

Autocorrelation was tested using the Wooldridge test for panel data (Wooldridge, 2010):

- Model 1 (patents): $p = 0.967$ (no evidence of autocorrelation)
- Model 2 (high-tech): $p \ll 0.001$ (strong evidence of autocorrelation)

For this reason, inference for Model 2 is based on a cluster-robust variance-covariance matrix at the country level, which is the standard solution for panel data exhibiting both heteroscedasticity and serial correlation.

Table 1. Summary statistics of variables

Variable	N	Mean	Std.Dev	Min	P25	Median	P75	Max
lnPatents	378	3.917	1.420	0.900	2.753	3.704	5.318	6.153
lnHighTech	378	2.595	0.480	1.416	2.250	2.563	2.896	3.980
lnGERD_lag1	378	0.331	0.581	-0.967	-0.127	0.322	0.797	1.311
lnGERD_lag2	378	0.331	0.581	-0.967	-0.127	0.322	0.797	1.311
lnGDP	378	10.269	0.386	9.370	9.989	10.264	10.481	11.489
Tertiary	378	41.080	9.573	20.9	33.4	41.1	47.25	65.2
IVA	378	22.248	6.09	9.113	19.112	22.211	25.955	40.756

Source: Author's calculation

Tables A and B in the Appendix provide the results of all diagnostic tests, as well as the correlation matrix results. Table 1 presents basic descriptive statistics for the analysed variables, including the number of observations, mean, standard deviation, and percentiles.

3. 3. CALCULATION OF THE TRANSFORMATION GAP AND DYNAMIC ANALYSIS OF THE TRANSFORMATION GAP

The primary objective of this paper is to calculate the transformation gap, which is defined as the residual component of the CRE model:

$$Gap_{it} = \ln(Y_{it}) - \ln(\hat{Y}_{it}) \quad (3)$$

The value Gap_{it} measures the relative deviation of actual innovation performance from its model-expected level. A positive value indicates that a country achieves a higher innovation output than predicted by the model, implying above-expected performance. Conversely, a negative value indicates that actual innovation output falls below the expected level, suggesting relative underperformance. These deviations should therefore be interpreted as performance relative to statistically expected outcomes, rather than as a direct measure of transformational capability or technical efficiency.

It is important to note that the transformation gap does not represent technical efficiency in the strict production-function sense, as is the case in DEA or SFA models. Instead, it serves

as a proxy for relative innovation performance by capturing the unexplained component of cross-country heterogeneity. This residual component may reflect the influence of factors not explicitly included in the model, such as institutional quality, absorptive capacity, the effectiveness of innovation governance, or the degree of integration into global value chains.

The robustness of Gap_{it} was assessed by comparing residuals obtained from the FE and CRE specifications. The correlations between the two sets of residuals were almost perfect:

- Model 1 - patents: $\text{Corr}(\text{Gap_FE}, \text{Gap_CRE}) = 0.9986$
- Model 2 - high-tech exports: $\text{Corr}(\text{Gap_FE}, \text{Gap_CRE}) = 0.9997$

These results indicate that the estimated transformation gap, as well as the subsequent classification of countries, is not sensitive to the choice between the FE and CRE specifications.

To examine the temporal stability and evolution of the transformation gap, a country-specific linear trend was estimated:

$$Gap_{it} = \alpha_i + \delta_i t + \varepsilon_{it} \quad (4)$$

The coefficient δ_i represents the average annual change in the transformation gap for each country, while its statistical significance is assessed using a t -test. A positive value of δ_i indicates an improvement in a country's relative innovation performance over time, suggesting that actual innovation outcomes are moving closer to, or above, their model-expected level. By contrast, a negative value points to a deterioration in relative performance, indicating a widening negative deviation from expected innovation outcomes. The use of panel data enables the analysis to account for unobserved time-invariant country-specific characteristics and reduces the risk of omitted variable bias, thereby improving the reliability of the empirical estimates (Baltagi, 2021).

4. RESULTS

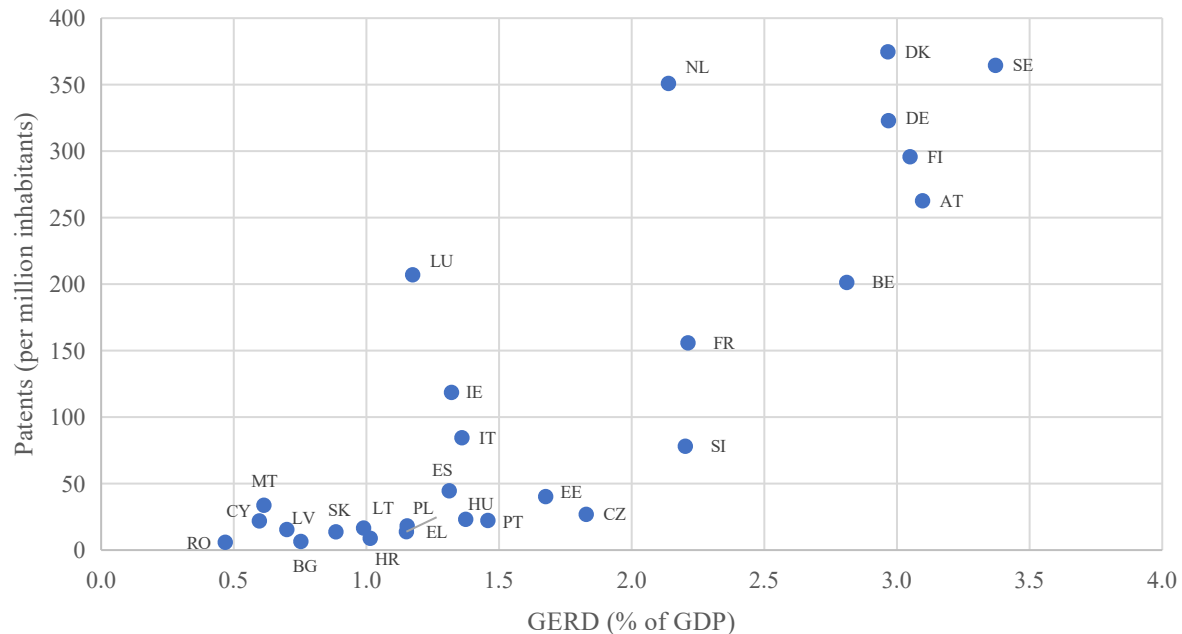
This section presents the empirical results on the relationship between R&D expenditure and innovation outputs in EU countries. The estimates are obtained using panel regression based on the Correlated Random Effects specification, following the Mundlak approach. This specification enables the analysis to account for unobserved country-specific heterogeneity while also allowing for potential correlation between individual effects and the explanatory variables. The section first reports the baseline model estimates for two dimensions of innovation output: patent activity and high-tech exports (Table 2). The residual component of the estimated model is then used to construct the transformation gap indicator, which captures the deviation of actual innovation output from its model-expected level, conditional on R&D inputs and the structural characteristics of the economy. This indicator allows countries to be classified according to whether they achieve above- or below-expected innovation performance relative to their observed input conditions. Finally, the dynamic analysis of the transformation gap examines its evolution over time and identifies different trajectories of relative innovation performance across EU countries.

4.1. ANALYSIS OF THE RELATIONSHIP BETWEEN R&D EXPENDITURES AND INNOVATION OUTPUTS

The analysis of average values for the period 2011–2024 indicates a strong positive association between R&D expenditure, measured by GERD as a percentage of GDP, and patent activity (Figure 1). Countries with higher R&D intensity generally record a larger number of patent applications. This pattern is further supported by the correlation analysis, which reveals a strong positive correlation between the two variables ($r \approx 0.85$). Sweden, Denmark, Germany,

Finland and Austria stand out as some of the most technologically advanced EU economies, combining above-average R&D investment with high levels of patent activity. These countries form the core of Europe's knowledge-based economies, where research investment is comparatively more successful in generating new technological solutions.

Figure 1. Relationship between GERD and patent activity (mean for the period 2011-2024)

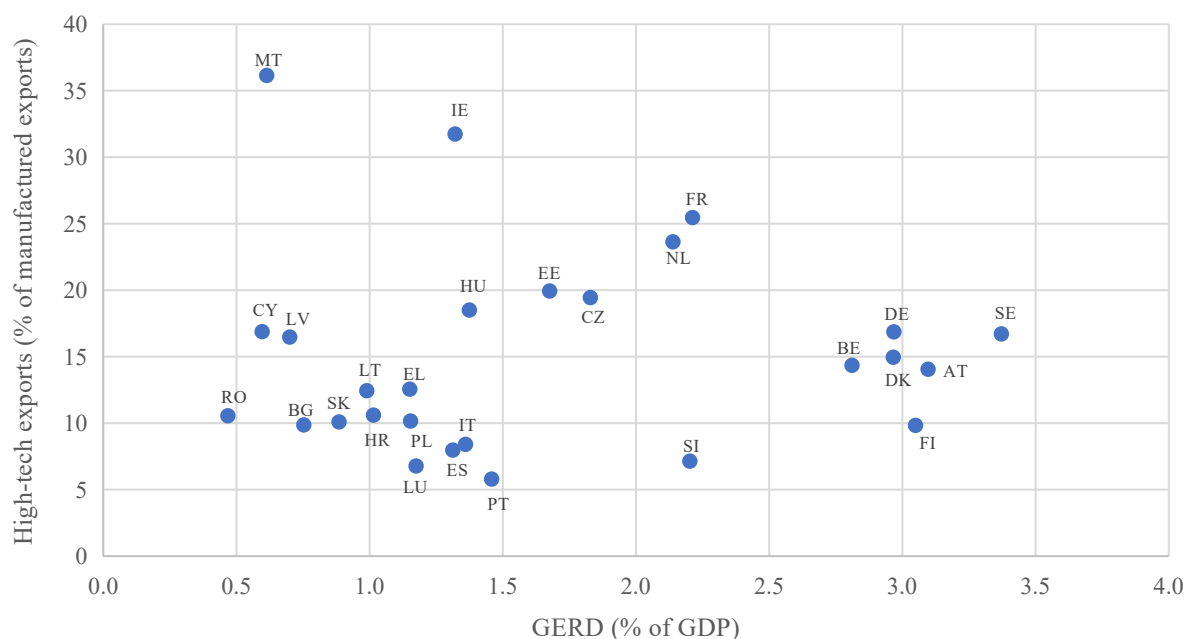


* BE (Belgium), BG (Bulgaria), CZ (Czechia), DK (Denmark), DE (Germany), EE (Estonia), IE (Ireland), EL (Greece), ES (Spain), FR (France), HR (Croatia), IT (Italy), CY (Cyprus), LV (Latvia), LT (Lithuania), LU (Luxembourg), HU (Hungary), MT (Malta), NL (Netherlands), AT (Austria), PL (Poland), PT (Portugal), RO (Romania), SI (Slovenia), SK (Slovakia), FI (Finland), SE (Sweden)

Source: Own processing

By contrast, Romania, Bulgaria, and Croatia are positioned at the lower end of the distribution, combining low levels of R&D expenditure with very limited patent activity. This pattern points to persistent disparities in innovation capacity among EU member states. The analysis also identifies several country-specific deviations from the general trend. Luxembourg and Ireland, for instance, record relatively high patent activity despite only moderate levels of R&D intensity. This may reflect the role of multinational technology companies, specific features of their innovation ecosystems, and the international organization of research and patenting activities. Conversely, Austria and Slovenia, despite relatively high R&D investment, show more moderate patent intensity, suggesting that higher research expenditure does not automatically translate into proportional patent output. A similar analytical approach is applied to the relationship between R&D expenditure and high-tech export performance in EU countries. The results suggest a positive but less clearly defined association between research intensity and technologically advanced exports. Although countries with higher GERD shares often tend to record higher proportions of high-tech products in manufactured exports, cross-country dispersion is substantially greater than in the case of patent activity.

Figure 2. Relationship between GERD and high-tech exports (mean for the period 2011-2024)



Source: Own processing

Countries that combine relatively high R&D intensity with a substantial share of high-tech exports include Germany, the Netherlands, and France. These economies are characterized by a strong industrial base, advanced technological capabilities, and well-developed innovation systems, which support the commercialization of research outcomes through internationally competitive products. At the same time, some countries, such as Ireland and Luxembourg, record high shares of high-tech exports despite comparatively lower levels of domestic R&D expenditure. In these cases, export performance is likely influenced by the presence of multinational technology companies, foreign direct investment, and the specific structure of internationally integrated production and innovation networks. By contrast, several Central and Eastern European countries, including Romania, Bulgaria, and Croatia, combine low R&D intensity with a limited share of high-tech products in manufactured exports. This pattern points to persistent differences in the technological composition of exports across EU member states and suggests that weaker domestic research capacity is often accompanied by lower participation in technology-intensive export segments.

4. 2. ECONOMETRIC ANALYSIS RESULTS

Table 2 reports the estimates of the Correlated Random Effects models based on the Mundlak specification, examining the relationship between R&D expenditure and innovation outputs in EU countries. Model (1) focuses on patent activity, while Model (2) analyses high-tech export performance. Both models include control variables that capture the level of economic development and key structural characteristics of national economies. The results indicate important differences between the two dimensions of innovation output. Patent activity appears to be more directly related to R&D investment, as it represents a relatively immediate outcome of research and technological development. This is reflected in the higher explanatory power of the patent model, which is consistent with the stronger conceptual and empirical link between R&D expenditure and the generation of new technological knowledge. By contrast, high-tech exports represent a broader and more complex dimension of innovation performance. Their development depends not only on domestic R&D capacity but also on industrial specialization,

participation in global value chains, the presence of foreign direct investment, export-oriented production structures, and external market demand. Accordingly, the lower explanatory power of the high-tech export model should not be interpreted as a weakness of the empirical specification, but rather as evidence of the more multifaceted nature of this indicator. As a robustness check, the high-tech export model was re-estimated using an alternative time lag (lag 1 instead of lag 2). The elasticity estimate for $\ln(\text{GERD})$ remained numerically identical, and the values of the control variables did not change. The components of determination were the same in both specifications (R^2 overall = 0.572). The correlation between the average transformation gap values calculated based on both models reaches 1.00 (both Pearson and Spearman), with the country ranking remaining unchanged. The results therefore indicate full robustness of the empirical conclusions to the choice of time lag length. The inclusion of both patent activity and high-tech exports therefore provides a more comprehensive assessment of innovation performance. While patents capture the creation of technological knowledge, high-tech exports reflect the ability of an economy to commercialize and apply this knowledge in international markets. This distinction is particularly important for the construction and interpretation of the transformation gap, as it enables the analysis to capture both knowledge generation and its economic utilization.

Table 2. Correlated Random Effects (Mundlak) estimates of innovation output models

Variable	(1) $\ln(\text{Patents})$	SE	(2) $\ln(\text{High-tech})$	SE.2
$\ln(\text{GERD})$ (lag 1)	0.252*	(0.138)		
$\ln(\text{GERD})$ (lag 2)			0.223**	(0.108)
$\ln(\text{GDP per capita})$	0.699***	(0.175)	0.404***	(0.085)
Tertiary education	0.019*	(0.010)	-0.005	(0.005)
Industry value added	-0.025*	(0.013)	0.010**	(0.004)
Mean $\ln(\text{GERD})$	1.287***	(0.260)	-0.252	(0.223)
Mean $\ln(\text{GDP})$	1.251***	(0.380)	-0.223	(0.548)
Mean tertiary education	-0.021	(0.015)	0.014	(0.013)
Mean industry value added	0.001	(0.016)	-0.004	(0.021)
Constant	-15.976***	(3.482)	0.291	(5.117)
Observations	378		378	
Countries	27		27	
R-squared (overall)	0.908		0.572	

Notes: Models are estimated using correlated random effects (Mundlak) specification. Robust standard errors are given in parentheses. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. For clarity, Mundlak country means are omitted from the table, but are included in the estimation and used in the calculation of transformation gaps.

Source: Author's calculation

Results confirm a positive elasticity of innovation outputs with respect to GERD in both models. Structural characteristics of the economy (such as tertiary education levels and the share of industry value added) also influence the patent and export dimensions differently. Since significant unexplained heterogeneity between countries remains even after accounting for these factors, the next step involves constructing transformation gaps based on the residuals from the estimated models, summarized through a matrix.

4. 3. TRANSFORMATION GAP AND MATRIX CLASSIFICATION OF COUNTRIES

To account for unexplained cross-country heterogeneity, the transformation gap indicator is derived from the residuals of the Correlated Random Effects models. This indicator measures the extent to which a country's actual innovation performance deviates from its model-expected level, after controlling for R&D expenditure and the structural characteristics of the economy.

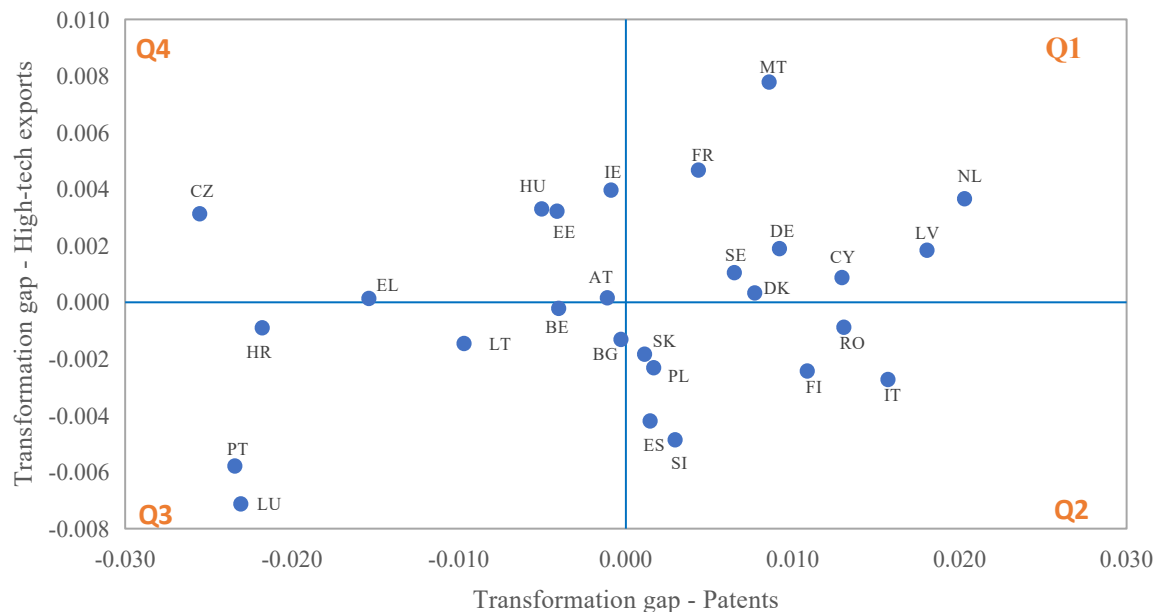
A positive transformation gap indicates that a country achieves a higher level of innovation output than predicted by the model, given its observed input and structural conditions. Such a result points to above-expected relative innovation performance. Conversely, a negative transformation gap suggests that actual innovation output falls below the expected level. The estimated transformation gap values are reported in Table C in the Appendix.

Based on the average transformation gap values for patent activity and high-tech exports, a classification matrix is constructed, as presented in Figures 3 and 4. This matrix divides EU countries into four groups according to their relative performance in the two dimensions of innovation output:

- **Q1- High relative performance systems:** Countries in this group record above-expected innovation performance in both dimensions. They consistently outperform model expectations in terms of both knowledge creation and the commercialization of technological outputs.
- **Q2 - Patent-oriented systems:** This group includes countries with above-expected patent activity but below-expected high-tech export performance. These economies appear relatively successful in generating technological knowledge, but less effective in translating it into technologically advanced exports.
- **Q3 - Low relative performance systems:** Countries in this quadrant underperform in both dimensions, recording below-expected levels of patent activity and high-tech exports relative to their R&D inputs and structural characteristics.
- **Q4 - Export-oriented systems:** This group consists of countries with above-expected high-tech export performance but below-expected patent activity. Such economies may be more strongly oriented toward production, export specialization, and integration into global value chains than toward the domestic creation of intellectual property.

The results reveal substantial structural diversity among EU member states. Some economies achieve above-expected innovation performance in both dimensions, whereas others display a more one-sided specialization or consistently fall below model expectations. It is important to emphasize that this classification is based on relative rather than absolute innovation performance. Therefore, countries with high levels of R&D investment are not necessarily classified as leading performers if their innovation outputs correspond only to the levels predicted by the model. Conversely, countries with lower levels of R&D expenditure may record above-expected performance if their innovation outcomes exceed what would be expected given their input conditions and structural characteristics.

Figure 3. Transformation gap matrix: patents vs. high-tech exports in EU countries (mean for the period 2011-2024)



Source: Own processing

The robustness of the classification was assessed by constructing an alternative matrix based on median values of the transformation gap instead of mean values (Figure 4). The comparison between the mean-based and median-based classifications indicates that the overall structure of country distribution remains relatively stable, although some shifts between quadrants are observed. These changes suggest that the results are partly sensitive to outliers, since mean values are more strongly influenced by extreme observations than median values.

Several country-specific changes are evident. Belgium and Croatia move from the below-average performance quadrant to the group of countries with above-expected patent performance when the median-based classification is applied, while Cyprus shifts in the opposite direction. Changes are also observed for Denmark, Finland, and the Netherlands, whose positions vary across the patent and high-tech export dimensions. In addition, Poland, Portugal, and Slovakia move closer to the group of countries with above-expected performance in both dimensions when median values are used, whereas Slovenia shifts toward the below-expected performance group.

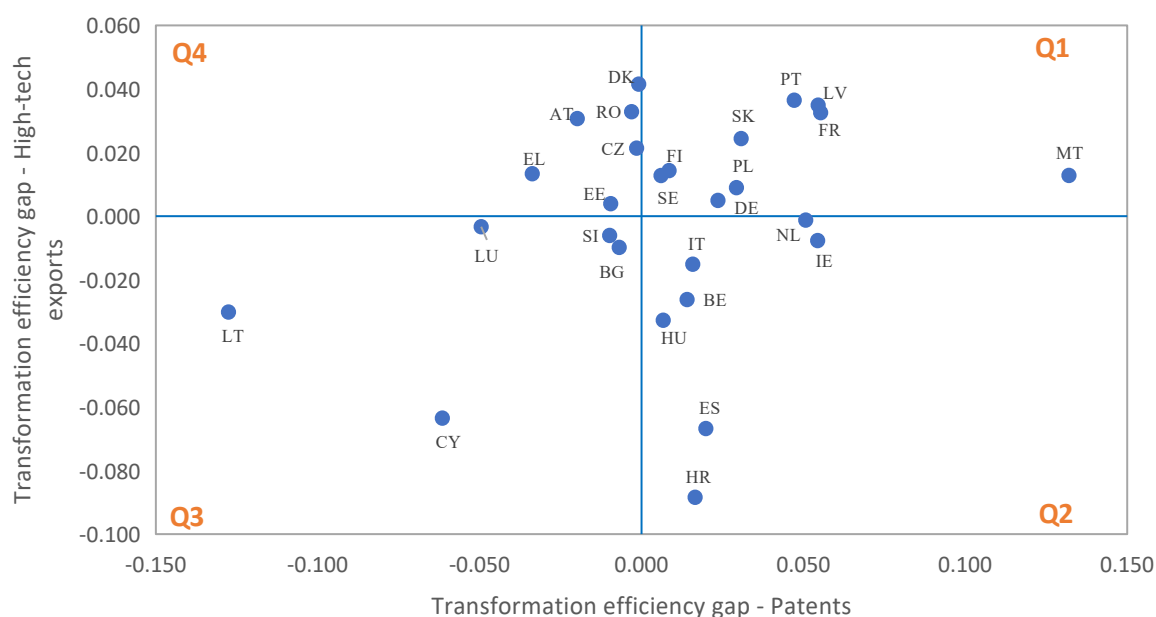
Overall, the comparison confirms that the main classification pattern is robust, while also indicating that some countries occupy borderline positions and are therefore more sensitive to the choice of averaging method.

The analysis also indicates the existence of geographical and historical patterns in relative innovation performance. Western and Northern European economies are more frequently positioned in quadrants associated with above-expected performance in both patent activity and high-tech exports. By contrast, several Central and Eastern European countries display less balanced innovation profiles, often characterized by a divergence between the generation of technological knowledge and its commercialization.

These patterns may reflect long-standing differences in the development of national innovation systems, institutional quality, industrial specialization, and the extent to which countries are integrated into global value chains. They also suggest that innovation performance is shaped not only by the volume of R&D investment, but also by broader systemic conditions that in-

fluence the capacity to transform research inputs into economically relevant outputs.

Figure 4. Transformation gap matrix: patents vs. high-tech exports in EU countries (median for the period 2011-2024)

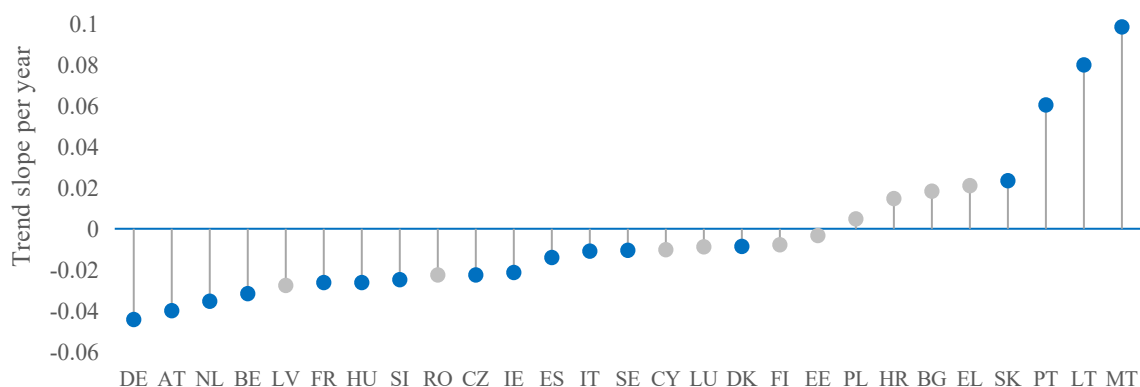


Source: Own processing

4. 4. DYNAMIC DEVELOPMENT OF THE TRANSFORMATION GAP

The dynamic dimension of the transformation gap is examined by estimating a separate linear time trend for each country. The slope coefficient of the trend line represents the average annual change in the deviation between actual and model-expected innovation performance. The statistical significance of this coefficient is assessed using a t-test. The graphical presentation of the results is provided in Figure 5 for the patent dimension and Figure 6 for the high-tech export dimension, while detailed estimates, including p-values, are reported in Table D in the Appendix.

Figure 5. Patent transformation gap trends



Note: Countries where the estimated trend is statistically significant at least one of the significance levels (10%, 5% or 1%) are marked in blue. Statistically insignificant estimates are shown in grey.

Source: Own processing

The trend analysis for the patent dimension, presented in Figure 5, reveals substantial het-

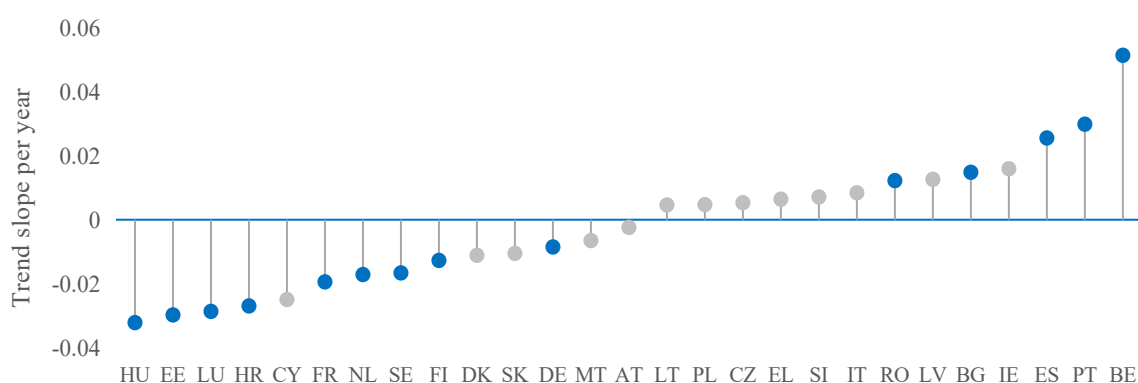
erogeneity in the evolution of the transformation gap across EU member states. In several technologically advanced economies, the estimated trend is negative, indicating that actual patent output is increasing more slowly than the level predicted by the model. This pattern is observed, for example, in Germany, Austria, the Netherlands, and Belgium.

Conversely, several countries exhibit a positive transformation gap trend, suggesting an improvement in relative innovation performance. The most notable cases include Malta, Lithuania, and Portugal. A positive and statistically significant trend also appears in the Slovak Republic, pointing to a gradual improvement in its relative performance in the field of patent activity.

The results for the high-tech export dimension, presented in Figure 6, also indicate heterogeneous developments across EU countries. In some economies, the transformation gap follows a negative trend, suggesting that growth in high-tech export performance lags the level expected based on R&D investment and structural characteristics. This pattern is observed, for example, in Hungary, Estonia, and Luxembourg.

By contrast, another group of countries shows an improvement in relative performance in this dimension. The most pronounced positive trends are identified in Belgium, Portugal, and Spain, while favourable developments are also observed in Bulgaria, Romania, Latvia, and Greece.

Figure 6. High-tech transformation gap trends



Note: Countries where the estimated trend is statistically significant at least one of the significance levels (10%, 5% or 1%) are marked in blue. Statistically insignificant estimates are shown in grey.

Source: Own processing

A comparison of the patent and high-tech export dimensions reveals several broader patterns. In some technologically advanced economies, including Germany, the Netherlands, and France, negative trends are evident in both dimensions, indicating a gradual decline in actual innovation performance relative to model expectations. Conversely, countries such as Portugal, Bulgaria, and Greece display positive trends in both areas, suggesting an improvement in their relative capacity to generate and commercialize innovation outputs.

Overall, the findings confirm that the evolution of the transformation gap within the EU is far from uniform. The dynamic analysis reveals processes of convergence, stagnation, and relative performance erosion that cannot be fully captured through a static classification of countries.

4. 5. INTEGRATED STATIC-DYNAMIC TYPOLOGY OF INNOVATION SYSTEMS

An integrated assessment of the transformation gap, combining countries' static positions based on average gap values with their dynamic trajectories derived from trend analysis, enables a more nuanced identification of structural differences among national innovation sys-

tems in the EU. The resulting classification, presented in Table 3, shows that countries differ not only in their current level of relative innovation performance but also in the direction and intensity of its evolution over time.

The group of catch-up economies includes Bulgaria, Lithuania, and Portugal. Although these countries are positioned in the negative deviation quadrant (Q3), indicating that their innovation performance remains below the model-expected level, they show signs of gradual improvement in the transformation gap. In the patent dimension, the positive trend is statistically significant for Lithuania and Portugal, while in the high-tech export dimension it is significant for Portugal and Bulgaria. These results suggest that these economies are progressively reducing their negative deviations from expected performance, although the improvement is uneven across the two innovation dimensions.

At the opposite end of the spectrum are the eroding leaders, comprising Denmark, France, Germany, the Netherlands, and Sweden. These countries are in the positive deviation quadrant (Q1), which means that they continue to achieve innovation performance above the level predicted by the model. However, their negative trend dynamics, particularly in the high-tech export dimension, indicate a gradual narrowing of this positive deviation. This suggests a process of convergence toward model-expected performance levels rather than continued expansion of their relative advantage.

A more stable pattern is observed among the stable high performers, represented by Cyprus and Latvia. These countries record positive deviations from expected innovation performance without statistically significant changes over time, indicating that their above-expected position has remained relatively stable during the observed period. Malta represents a distinct case of a strengthening leader, as its positive deviation continues to increase, particularly in the patent dimension.

The classification also identifies countries with persistent asymmetries between the two dimensions of innovation performance. Ireland and Greece are classified as cases of persistent export patent mismatch (Q4), as they show relatively stronger performance in high-tech exports than in patent activity. By contrast, Poland, Romania, and Slovakia represent cases of persistent patent export mismatch (Q2), where relative patent performance exceeds high-tech export performance. In both groups, the dynamics of the transformation gap are not statistically significant, suggesting that these structural imbalances remain relatively persistent over time.

Spain represents a specific case of reallocation in progress. In this case, a decline in the positive deviation, or a deepening of the negative deviation, in the patent dimension occurs simultaneously with an improvement in the high-tech export dimension. This pattern may indicate a gradual shift from knowledge generation toward the economic utilization and commercialization of innovation outputs.

Table 3. Static-dynamic typology of innovation systems

Country	Quadrant (means)	Gap patents (mean)	Gap high-tech (mean)	Trend patents (sig)	Trend high-tech (sig)	Dynamic typology (means)
BG	Q3	0	-0.001	~	↑	Catch-up economies
LT	Q3	-0.01	-0.001	↑	~	Catch-up economies
PT	Q3	-0.023	-0.006	↑	↑	Catch-up economies
DK	Q1	0.008	0	↓	~	Eroding leaders
FR	Q1	0.004	0.005	↓	↓	Eroding leaders
DE	Q1	0.009	0.002	↓	↓	Eroding leaders
NL	Q1	0.02	0.004	↓	↓	Eroding leaders
SE	Q1	0.006	0.001	~	↓	Eroding leaders

Country	Quadrant (means)	Gap patents (mean)	Gap high-tech (mean)	Trend patents (sig)	Trend high-tech (sig)	Dynamic typology (means)
HR	Q3	-0.022	-0.001	~	↓	Falling behind economies
LU	Q3	-0.023	-0.007	~	↓	Falling behind economies
EL	Q4	-0.015	0	~	~	Persistent export–patent mismatch
IE	Q4	-0.001	0.004	~	~	Persistent export–patent mismatch
PL	Q2	0.002	-0.002	~	~	Persistent patent–export mismatch
RO	Q2	0.013	-0.001	~	~	Persistent patent–export mismatch
SK	Q2	0.001	-0.002	~	~	Persistent patent–export mismatch
ES	Q2	0.001	-0.004	↓	↑	Reallocation in progress (mixed preformance)
CY	Q1	0.013	0.001	~	~	Stable high performers
LV	Q1	0.018	0.002	~	~	Stable high performers
MT	Q1	0.009	0.008	↑	~	Strengthening leaders
BE	Q3	-0.004	0	↓	↑	Unstable underperformers
FI	Q2	0.011	-0.002	~	↓	Widening commercialisation gap (relative)
IT	Q2	0.016	-0.003	↓	~	Widening commercialisation gap (relative)
SI	Q2	0.003	-0.005	↓	~	Widening commercialisation gap (relative)
AT	Q4	-0.001	0	↓	~	Widening knowledge-creation gap (relative)
CZ	Q4	-0.026	0.003	↓	~	Widening knowledge-creation gap (relative)
EE	Q4	-0.004	0.003	~	↓	Widening knowledge-creation gap (relative)

Notes: Q1 (High relative performance), Q2 (Patent-oriented), Q3 (Low relative performance), Q4 (Export-oriented)

Source: Author's calculation

A deepening commercialization gap is observed in Finland, Italy, and Slovenia, where the negative deviation in high-tech export performance increases over time. This suggests a growing difficulty in translating innovation inputs and structural capacities into technologically advanced export outcomes. By contrast, Austria, the Czech Republic, Estonia, and Hungary face deterioration primarily in knowledge creation, as reflected in a widening negative deviation in the patent dimension. These cases indicate a weakening of patent performance relative to the level expected based on R&D expenditure and structural characteristics. Croatia and Luxembourg, classified as falling-behind economies, experience a deepening of negative deviations, particularly in the high-tech export dimension. This points to a deterioration in relative innovation performance and suggests that actual outcomes are increasingly lagging model-expected levels. Belgium represents a case of an unstable underperformer. Its development is characterized by a decline in the patent dimension, reflected in an increasing negative deviation, combined with an improvement in high-tech exports, reflected in a decreasing negative deviation. This pattern indicates volatility and an uneven adjustment process between knowledge generation and com-

mercialization. Overall, the findings point to simultaneous processes of convergence, stability, and divergence among EU countries. The evolution of the transformation gap indicates that differences between actual and expected innovation performance are shaped not only by the volume of R&D expenditure, but also by the structural characteristics of national innovation systems and their capacity to connect knowledge creation with economic application.

5. DISCUSSION

The empirical findings provide a new perspective on the relationship between R&D expenditure and innovation outputs in EU countries by introducing the concept of the transformation gap. Consistent with the innovation production function framework, the results confirm that R&D investment represents an important input into the innovation process. However, the volume of R&D expenditure alone does not fully explain cross-country differences in innovation performance. The transformation gap captures this unexplained component by measuring the deviation of actual innovation output from its model-expected level, conditional on R&D investment and the structural characteristics of the economy. In this respect, the proposed approach is consistent with the literature emphasizing the role of broader national innovation system conditions in shaping innovation outcomes.

The first hypothesis assumed a positive relationship between R&D expenditure and innovation outputs. The econometric results support this hypothesis, as the estimated elasticity of innovation output with respect to R&D expenditure is positive in both models. This confirms that higher R&D intensity is generally associated with stronger innovation performance, both in terms of patent activity and high-tech exports. The finding is in line with previous empirical studies that identify a significant link between R&D investment, patenting, and technology-intensive exports (Sözen & Tufaner, 2020). At the same time, the results indicate that the strength and nature of this relationship differ depending on the type of innovation output. Patent activity represents a more direct and immediate outcome of R&D investment, as it is closely linked to the generation of new technological knowledge. By contrast, high-tech exports reflect a broader process of commercialization and are influenced by additional factors, including industrial structure, participation in global value chains, the presence of multinational companies, and external market demand. The lower explanatory power of the high-tech export model therefore does not indicate a weakness of the specification, but rather reflects the more complex and multi-dimensional nature of knowledge commercialization. The second hypothesis referred to the existence of cross-country differences in relative transformation performance. The results obtained from the transformation matrix and the transformation gap analysis clearly support this hypothesis. Even after controlling for R&D expenditure and selected structural variables, substantial heterogeneity remains across EU member states. These differences indicate that countries vary significantly in their ability to achieve innovation outputs that exceed, correspond to, or fall below model expectations. This finding is consistent with previous research documenting persistent differences in innovation performance across EU countries and regions (Gavurová et al., 2019). In the context of this study, such differences are interpreted as systematic deviations from expected innovation performance. They may reflect unobserved factors such as institutional quality, absorptive capacity, innovation governance, the effectiveness of research-industry linkages, and the degree of integration into global value chains. The third hypothesis assumed that the transformation gap evolves heterogeneously over time. The trend analysis confirms that EU countries follow different development trajectories. In some cases, negative deviations are gradually reduced, or positive deviations increase, indicating an improvement in relative innovation performance. In other cases, the gap between actual and expected performance widens, suggesting deterioration or erosion of rela-

tive performance. One particularly relevant finding is that some technologically advanced economies display a negative trend in the transformation gap. This means that their innovation outputs are growing more slowly than would be expected given their R&D investment and structural characteristics. Such a pattern may be associated with decreasing marginal returns to additional R&D expenditure, increasing complexity of innovation processes, or difficulties in sustaining high levels of technological performance over time. Conversely, some less advanced economies show an improvement in the transformation gap, indicating gradual convergence toward model-expected performance. Similar conclusions are reported in studies examining technological capability development in the EU, which point to slow convergence processes alongside persistent cross-country disparities (Grafström & Alm, 2024). Overall, the results suggest that the transformation gap reflects a complex interaction between R&D expenditure, economic structure, institutional conditions, and the functioning of national innovation systems. Increasing R&D expenditure does not automatically lead to stronger innovation performance unless it is accompanied by mechanisms that support the effective connection between knowledge creation and its economic application. This conclusion is also consistent with studies emphasizing the importance of financial, institutional, and systemic factors in shaping the export performance of technology-intensive sectors (Margaryan & Terzyan, 2023; Gatari et al., 2024). The empirical results should be interpreted as evidence of statistically robust associations rather than strict causal relationships. Although the use of lagged R&D expenditure partly reduces the risk of simultaneity, potential endogeneity cannot be fully excluded. Reverse causality may exist, since countries with stronger innovation performance may subsequently increase their R&D investments, thereby reinforcing the observed relationship. The modelling strategy applied in this paper is consistent with the innovation production function approach, which is widely used to examine the relationship between R&D inputs and innovation outputs at the macroeconomic level. The aim of the analysis is not to estimate the causal effect of R&D expenditure, but to determine expected innovation outcomes conditional on observable inputs and structural characteristics. Within this framework, the transformation gap is derived from the residual component of the model and should be interpreted as a relative indicator of overperformance or underperformance, rather than as a direct measure of causal inefficiency. Importantly, potential endogeneity does not undermine the main contribution of the paper, which lies in the comparative and dynamic assessment of transformation gaps across EU countries. Since the transformation gap is interpreted as a relative performance indicator rather than a causal parameter, its analytical value does not depend on strong causal assumptions. Nevertheless, future research could extend the analysis by applying dynamic panel models or instrumental variable approaches to address endogeneity more explicitly and examine the direction of causality between R&D investment and innovation outputs. The proposed transformation gap typology also offers useful implications for innovation policy. For high relative performance systems (Q1), the main policy challenge is to prevent performance erosion and sustain innovation dynamics. In these countries, policy measures should focus on improving knowledge diffusion, supporting breakthrough and mission-oriented innovation, and strengthening the commercialization of advanced research outputs, particularly in contexts where marginal returns to additional R&D investment may be declining. For patent-oriented systems (Q2), which show relatively strong knowledge creation but weaker high-tech export performance, policy should prioritize the commercialization of domestic knowledge. This includes strengthening links between research institutions and industry, improving technology transfer mechanisms, expanding scale-up financing, and supporting deeper integration into global value chains. The key policy objective for this group is to reduce the persistent asymmetry between invention and market utilization. Low relative performance systems (Q3) face broader structural challenges, as they underperform relative to model expectations in both

innovation dimensions. For these economies, increasing R&D expenditure alone is unlikely to be sufficient. Policy efforts should therefore focus on strengthening absorptive capacity, improving institutional quality, investing in human capital, developing basic innovation infrastructure, and enhancing coordination among actors within national innovation systems. Finally, export-oriented systems (Q4), which achieve relatively strong high-tech export performance despite weaker patent activity, often rely on foreign technologies, multinational firms, or externally embedded production networks. While integration into global value chains represents an important source of competitiveness, long-term innovation sustainability requires stronger domestic knowledge creation. Policy in these countries should therefore support indigenous R&D capabilities, encourage learning and spillovers from foreign firms, and promote the development of domestic intellectual property.

6. CONCLUSION

The aim of this paper was to analyse the relationship between R&D expenditure and innovation outputs in EU countries and to identify deviations between actual and model-expected innovation performance through the concept of the transformation gap. The analysis was based on panel data for 27 EU member states over the period 2011–2024. Methodologically, the study combined a panel econometric approach based on the Correlated Random Effects model with the construction of a residual-based transformation gap indicator and an analysis of its dynamic development over time. The results confirm that R&D expenditure is positively associated with innovation outputs, although the strength of this relationship differs between the patent and high-tech export dimensions. Patent activity primarily captures the creation of new technological knowledge and is more directly related to R&D investment. High-tech exports, by contrast, reflect the economic utilization and commercialization of knowledge, which depends on a broader set of structural and market-related factors. This distinction is also reflected in the higher variability of the transformation gap in the export dimension. The empirical findings also reveal substantial heterogeneity across EU countries in deviations from expected innovation performance. The transformation matrix identifies different types of national innovation systems, ranging from countries that outperform model expectations in both dimensions to economies characterized by persistent asymmetry between knowledge creation and commercialization. The dynamic analysis further shows that the transformation gap is not a fixed characteristic, but changes over time and follows heterogeneous trajectories across countries. From a policy perspective, the results indicate that increasing R&D expenditure alone is not sufficient to improve relative innovation performance. The effectiveness of R&D investment depends on the broader capacity of national innovation systems to absorb, generate, diffuse, and commercialize knowledge. Innovation policy should therefore focus not only on the volume of resources allocated to research, but also on institutional quality, absorptive capacity, industrial linkages, technology transfer mechanisms, and the integration of research activities with economic practice. The results also point to different development paths among EU countries. Converging economies such as Bulgaria, Lithuania, and Portugal show a gradual reduction in negative deviations in selected dimensions, suggesting movement toward model-expected performance. In contrast, some technologically advanced countries experience deterioration in the transformation gap, indicating that their innovation outputs are no longer increasing in line with model expectations. This may reflect the limits of further performance gains at high levels of technological development or the increasing complexity of innovation processes. Countries with persistent asymmetry between patent activity and high-tech exports require policy attention, as they reveal a mismatch between knowledge creation and its economic application. Despite its analytical contribution, the study has several limitations. First,

the linear specification of the models may not fully capture potential nonlinear relationships between R&D expenditure and innovation outputs. Second, the time lag between R&D investment and innovation outcomes may differ across countries and sectors and may extend beyond the lag structure applied in this study. Third, since the transformation gap is derived from the residual component of the model, it captures unexplained variation but does not directly identify the specific causal factors underlying these deviations. Fourth, the results may be affected by unobserved institutional, structural, and global value chain-related factors that are not explicitly included in the model. Future research could extend the analysis by incorporating nonlinear and dynamic modelling approaches, including dynamic panel models that better capture the temporal structure of innovation processes and the potential endogeneity between R&D expenditure and innovation outputs. Further studies could also include additional institutional and structural variables to explain more precisely the sources of cross-country heterogeneity identified through the transformation gap. Finally, extending the analysis beyond the EU context would allow for a broader comparative assessment of how national innovation systems differ in their ability to transform R&D inputs into technological and economic outcomes.

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Appendix

Table A Diagnostic tests and model specification for panel regression models

Model	Test	Statistics	df	p-value	Implication for specification
Model 1 (Patents)	Breusch–Pagan LM (RE vs pooled)	93.537	1	<0.001	Panel effect present → do not use pooled; RE/FE appropriate.
Model 1 (Patents)	Hausman (FE vs RE)	1.107	4	0.893	RE consistent → RE (and possibly CRE) appropriate.
Model 1 (Patents)	Mundlak (joint means = 0)	125.769	4	<0.001	Correlation of regressors with effect → prefer CRE (Mundlak).
Model 1 (Patents)	Wooldridge AR(1)			0.967	No autocorrelation → standard SE less problematic (still robust).
Model 1 (Patents)	Breusch–Pagan heteroskedasticity	21.429		<0.001	Heteroskedasticity → robust/cluster SE required.
Model 2 (High-tech export)	Breusch–Pagan LM (RE vs pooled)	168.968	1	<0.001	Panel effect present → do not use pooled; RE/FE appropriate.
Model 2 (High-tech export)	Hausman (FE vs RE)	0.114	4	0.998	RE consistent → RE (and possibly CRE) appropriate.
Model 2 (High-tech export)	Mundlak (joint means = 0)	4.727	4	0.316	No evidence of correlation → RE sufficient (CRE possible for consistency).
Model 2 (High-tech export)	Wooldridge AR(1)			<0.001	Autocorrelation present → robust/cluster SE required.
Model 2 (High-tech export)	Breusch–Pagan heteroskedasticity	98.523		<0.001	Heteroskedasticity → robust/cluster SE required.

Source: Author's calculation

Table B Correlation matrix of model variables

	lnGERD_lag1	lnGDP	Tertiary	IVA
lnGERD_lag1	1	0.475	0.155	0.117
lnGDP	0.475	1	0.567	-0.178
Tertiary	0.155	0.567	1	-0.286
IVA	0.117	-0.178	-0.286	1

Note: The table presents Pearson correlation coefficients between the time-varying explanatory variables used in the model. The values do not indicate the presence of significant multicollinearity (no coefficient exceeds the threshold of 0.7). For Model 2, in which the ln(GERD) variable is used lagged by two periods (lnGERD_lag2), the correlation relationships are practically identical, reflecting the high persistence of R&D spending over time.

Source: Author's calculation

Table C Mean and median values of patent and high-tech transformation gaps by country

Country	Gap_Patents_Mean	Gap_HighTech_Mean	Gap_Patents_Median	Gap_HighTech_Median
AT	-0.0011	0.0002	-0.0198	0.0307
BE	-0.0040	-0.0002	0.0141	-0.0262
BG	-0.0003	-0.0013	-0.0069	-0.0098
HR	-0.0218	-0.0009	0.0165	-0.0884
CY	0.0129	0.0009	-0.0615	-0.0635
CZ	-0.0255	0.0031	-0.0015	0.0214
DK	0.0077	0.0003	-0.0009	0.0415
EE	-0.0041	0.0032	-0.0095	0.0039
FI	0.0109	-0.0024	0.0085	0.0143
FR	0.0043	0.0047	0.0553	0.0326
DE	0.0092	0.0019	0.0236	0.0050
EL	-0.0154	0.0001	-0.0338	0.0134
HU	-0.0050	0.0033	0.0067	-0.0327
IE	-0.0009	0.0040	0.0544	-0.0077
IT	0.0157	-0.0027	0.0158	-0.0151
LV	0.0180	0.0018	0.0545	0.0349
LT	-0.0097	-0.0015	-0.1276	-0.0302
LU	-0.0231	-0.0071	-0.0495	-0.0033
MT	0.0086	0.0078	0.1320	0.0128
NL	0.0203	0.0037	0.0507	-0.0012
PL	0.0017	-0.0023	0.0293	0.0090
PT	-0.0234	-0.0058	0.0472	0.0365
RO	0.0131	-0.0009	-0.0031	0.0329
SK	0.0011	-0.0018	0.0308	0.0244
SI	0.0029	-0.0049	-0.0099	-0.0061
ES	0.0015	-0.0042	0.0199	-0.0668
SE	0.0065	0.0010	0.0060	0.0128

Source: Author's calculation

Table D Trends in patent and high-tech transformation gaps across EU countries

Country	n_years_pat- ents/hightech	slope_per_ year_patents	se_slope_pat- ents	p_value_pat- ents	t_stat_patents	r2_patents	sig_patents	slope_per_ year_hightech	se_slope_ hightech	p_value_ hightech	t_stat_hightech	r2_hightech	sig_hightech
AT	14	-0.040	0.005	0.000	-7.422	0.821	***	-0.002	0.009	0.803	-0.255	0.005	
BE	14	-0.032	0.003	0.000	-11.635	0.919	***	0.051	0.008	0.000	6.360	0.771	***
BG	14	0.018	0.012	0.152	1.528	0.163		0.015	0.005	0.011	3.024	0.433	**
HR	14	0.015	0.016	0.385	0.901	0.063		-0.027	0.011	0.032	-2.427	0.329	**
CY	14	-0.010	0.020	0.612	-0.520	0.022		-0.025	0.015	0.119	-1.677	0.190	
CZ	14	-0.023	0.009	0.025	-2.553	0.352	**	0.005	0.005	0.322	1.033	0.082	
DK	14	-0.009	0.003	0.020	-2.668	0.372	**	-0.011	0.008	0.189	-1.394	0.139	
EE	14	-0.003	0.008	0.700	-0.395	0.013		-0.030	0.006	0.000	-4.721	0.650	***
FI	14	-0.008	0.005	0.169	-1.464	0.151		-0.013	0.004	0.004	-3.510	0.507	***
FR	14	-0.026	0.003	0.000	-8.272	0.851	***	-0.019	0.004	0.000	-4.996	0.675	***
DE	14	-0.044	0.002	0.000	-21.470	0.975	***	-0.008	0.004	0.040	-2.298	0.306	**
EL	14	0.021	0.012	0.118	1.686	0.191		0.006	0.007	0.376	0.919	0.066	
HU	14	-0.026	0.007	0.002	-3.808	0.547	***	-0.032	0.007	0.001	-4.429	0.620	***
IE	14	-0.021	0.011	0.078	-1.924	0.236	*	0.016	0.012	0.226	1.276	0.119	
IT	14	-0.011	0.003	0.003	-3.737	0.538	***	0.008	0.006	0.162	1.490	0.156	
LV	14	-0.028	0.038	0.480	-0.729	0.042		0.013	0.012	0.306	1.070	0.087	
LT	14	0.080	0.015	0.000	5.155	0.689	***	0.005	0.006	0.452	0.777	0.048	
LU	14	-0.009	0.016	0.599	-0.540	0.024		-0.029	0.006	0.000	-4.735	0.651	***
MT	14	0.098	0.028	0.005	3.464	0.500	***	-0.006	0.015	0.669	-0.438	0.016	
NL	14	-0.035	0.006	0.000	-5.653	0.727	***	-0.017	0.002	0.000	-9.503	0.883	***
PL	14	0.005	0.010	0.638	0.483	0.019		0.005	0.008	0.582	0.565	0.026	
PT	14	0.060	0.010	0.000	6.227	0.764	***	0.030	0.007	0.002	4.074	0.580	***
RO	14	-0.022	0.028	0.436	-0.806	0.051		0.012	0.006	0.085	1.881	0.228	*
SK	14	0.023	0.013	0.100	1.783	0.210	*	-0.011	0.008	0.230	-1.264	0.117	
SI	14	-0.025	0.010	0.034	-2.400	0.324	**	0.007	0.005	0.167	1.470	0.153	
ES	14	-0.014	0.005	0.016	-2.790	0.393	**	0.025	0.008	0.008	3.157	0.454	***
SE	14	-0.010	0.005	0.061	-2.066	0.262	*	-0.017	0.006	0.024	-2.572	0.355	**

Note: Estimates of trend directions, standard errors, t-statistics, p-values, and coefficient of determination (R2) are reported. Statistical significance is indicated as follows: *** p < 0.01, ** p < 0.05, * p < 0.10.

Source: Author's calculation

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