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Economic Complexity in CEE Countries: The Role of Innovations, Investments and Education

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Abstract:

Research Question: How do foreign direct investment (FDI), research and development (R&D) expenditure, and tertiary education enrolment influence economic complexity in Central and Eastern European (CEE) countries? **Motivation:** Economic complexity is a key driver of industrial sophistication and long-term competitiveness. While prior research (Hidalgo & Hausmann, 2009; Liu & Gao, 2020; Neagu, Neagu, & Gavurova, 2022) links complexity to growth, limited studies focus on its determinants in transition economies. CEE countries provide an ideal case to examine how FDI, R&D, and tertiary education affect economic sophistication. This study fills a gap by assessing whether these factors enhance complexity or introduce inefficiencies. A key novelty is the negative relationship between tertiary education and economic complexity, suggesting labour market misalignment, brain drain, and educational inefficiencies. **Idea:** This research examines the relationship between FDI, R&D, and tertiary education enrolment as key determinants of the Economic Complexity Index (ECI). It explores whether FDI facilitates technology transfer, R&D enhances industrial sophistication, and education strengthens human capital, or whether inefficiencies hinder transformation. **Data:** A balanced panel dataset (1998–2021) covering 11 CEE countries, sourced from the Atlas of Economic Complexity, UNCTAD, and the World Bank. **Tools:** Applied methodology includes Pesaran's CD test, CIPS unit root test, Westerlund cointegration, PCSE regressions, and robustness checks via FGLS. Nonlinear effects are examined through quadratic and categorical models. **Findings:** FDI and R&D positively influence complexity. Tertiary enrolment negatively correlates with complexity. **Contribution:** The study offers policy insights for aligning investment, innovation, and education systems in CEE countries.

Keywords: economic complexity, foreign direct investment, research and development, tertiary education, panel analysis

JEL classification: F14, F21, O32, I25, C23

1. Introduction

Economic complexity, an advanced measure of a country's productive capabilities and knowledge accumulation, has emerged as a critical determinant of long-term economic development. Countries with higher economic complexity tend to have more diversified and sophisticated production structures, which in turn facilitate innovation, technological advancement, and sustained economic growth (Hausmann, Hidalgo, Bustos, Coscia, & Simoes, 2014). The ECI captures the degree of embedded knowledge in an economy's export basket, making it a valuable tool for assessing a nation's ability to compete in global markets. As countries climb the complexity ladder, they enhance their capacity to produce and export high-value-added goods and services, reducing dependency on primary commodities and low-tech industries (Hidalgo & Hausmann, 2009).

CEE countries represent an intriguing case for studying the determinants of economic complexity. These economies underwent profound transformations following the collapse of centrally planned systems in the early 1990s, transitioning toward market-oriented policies and European integration.The transition period was marked by structural adjustments, privatization, and substantial inflows of FDI, which played a crucial role in restructuring industrial bases and integrating these economies into global value chains (Radosevic &

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Yoruk, 2016). Concurrently, many CEE nations have prioritized investment in R&D to drive innovation and enhance their competitiveness. However, despite significant progress, disparities remain in economic complexity across the region, raising important questions about the relative importance of FDI, R&D, and human capital formation in fostering economic sophistication.

FDI drives technological diffusion and productivity growth, particularly in emerging economies (Dimelis & Papaioannou, 2010). Multinational enterprises (MNEs) enhance knowledge spillovers and technological capabilities (Xu, 2000), yet FDI's impact on economic complexity remains debated. Some studies confirm its role in industrial upgrading (Fu, Pietrobelli, & Soete, 2011), while others argue that FDI in CEE is concentrated in low- to medium-tech sectors, limiting its transformative potential (Ban & Adascalitei, 2022; Hlavacek & Bal-Domanska, 2016).

R&D investment is another key driver of economic complexity, fostering innovation, competitiveness, and knowledge-intensive industries (Radosevic, 2017). The role of R&D in fostering innovation and industrial upgrading in CEE countries varies significantly, with nations like the Czech Republic and Estonia benefiting from stronger research and development ecosystems, while others face challenges due to weaker industry-research collaboration and reliance on foreign technologies (Prokop, Stejskal, Klimova, & Zitek, 2021).

Human capital, often measured through tertiary education enrolment, is widely seen as essential for technological advancement and complexity (Barro, 2013). However, recent studies suggest that higher enrolment does not guarantee economic complexity, as brain drain, skills mismatches, and misaligned education systems hinder its effectiveness in CEE (Ienciu & Ienciu, 2015). Aligning education with labour market demands is crucial for maximising its impact.

Given these considerations, this study aims to empirically assess the relationship between FDI inflows, R&D expenditure, tertiary enrollment, and economic complexity in eleven selected CEE economies. While the primary focus is on these three structural drivers, the empirical model also includes broader developmental indicators to control for the baseline level of economic and investment capacity across countries. Using a balanced panel dataset covering the period 1998–2021, the analysis applies panel econometric techniques, including tests for cross-sectional dependence, unit root tests, and cointegration analysis. To ensure the robustness of the findings, the study employs Prais-Winsten regression with PCSE and FGLS estimations.

The remainder of this paper is organized as follows: Section 2 provides a comprehensive review of the existing literature, identifying key theoretical frameworks and empirical findings relevant to the study. Section 3 outlines the research methodology, including data sources, variable selection, and econometric techniques employed in the analysis. Section 4 presents the empirical results. Section 5 presents the discussion, offering a detailed analysis of the implications of the findings in the context of prior research. Finally, Section 6 concludes the study by summarizing the key findings, acknowledging limitations, and suggesting avenues for future research.

2. Literature Review

According to Web of Science (2025), there is a growing trend of publications on the term „Economic complexity" in the fields of Economics, Management, and Business. Most of the findings come from the USA and Western European economies, leaving very rare evidence in this area at the level of CEE countries. In general, the complexity of an economy is connected with growth, development, and the inclusivity of its institutions. Related literature admits that economic complexity mirrors the countries' economic strength and future growth prospects (Schetter, 2019). Using the ECI, Hartmann, Guevara, Jara-Figueroa, Aristaran, and Hidalgo (2017) provide evidence that countries that export complex products have lower levels of income inequality than countries exporting simpler products. At the same time, it follows the main sustainability goal and provides the reason for gaining economic complexity.

Also, there is a strong link between economic complexity and economic development where certain authors (Bishop & Mateos-Garcia, 2019) stated the gap regarding mechanisms that explain these links. Mao and An (2021) tried to empirically test ECI and the level of economic development. They found that if the ECI increases by 1%, it leads to an increase by about 30% in the level of development in middle- and high-income economies. Also, Human capital, FDI outflow, and participation in the global value chains (GVC) are important in stimulating countries' economic complexity.

Breitenbach, Chisadza, and Clance (2021) find differences in the effects of ECI in high and low-income countries. Low-income countries have less diversified and less complex exports. It raises the risk of external shocks and reduces their ability to adjust quickly. In addition, the authors found that economic complexity is more effective in Asia than in Africa. Rising economic complexity together with trade openness could also stimulate environmental quality (Caglar, Zafar, Bekun, & Mert, 2022). This evidence comes from BRICS countries and could be important for policymakers in developing regions. Policies aimed at improving economic complexity could develop the environmental quality in countries that mainly rely on natural resources and primary products.

On the other side, economic complexity increases the pressure on the ecological footprint in OCED countries. Using Cross-Sectional Augmented Autoregressive Distributed Lag with additional methods, Hassan, Batool, Wang, Zhu, and Sadiq (2023), found that high scores of ECI increase the pressure on the ecological footprints and demonstrate the importance of nuclear energy production in OECD. Le, Niem, & Kim (2022) used ECI for 197 countries over the period from 2000-2017. The results explain the reason for the development of ASEAN countries in observed years due to shifting from low to medium and high-complexity products. The export quality of ASEAN countries has improved based on economic complexity which can be the pattern for economic development in other countries and regions. ECI also impacts economic growth while the infrastructure, education level, trade and financial openness contribute to countries' development.

Moreno-Casas and Bagus (2022) tried to explain the development process through economic complexity and dynamic efficiency. The assumption is that high complexity implies more domestic value-added products which means that one economy can produce and export more sophisticated products in the same period. The reason behind this is higher efficiency and indirectly higher level of economic development. Malicka (2024) observed the economic convergence in EU countries through economic complexity and found that they converge economically but also in terms of economic complexity. This approach presents a shift from quantitative to qualitative measures of economic performance. In line with this, several studies also incorporate GDP per capita and capital formation as control variables (Gala, Rocha, & Magacho, 2018; Sadeghi, Shahrestani, Kiani, & Torabi, 2020), acknowledging their relevance in capturing baseline economic conditions that may influence the relationship between structural factors and economic complexity.

Since previous evidence mainly focuses on the explanation and contribution of economic complexity, we try to supplement the existing theory by finding its antecedents. Our research is based on the latest recommendations for future research (Malicka, 2024) that might focus on the potential for increasing the economic complexity considering countries with specific limitations in the context of various expressions of economic complexity. In this regard, the evidence from CEE countries could close this gap.

Grounded in theoretical insights, the following hypotheses will be examined empirically:

H1: FDI positively influences economic complexity in CEE countries.
H2: R&D expenditures enhance economic complexity in CEE countries.
H3: Tertiary education enrolment has a positive effect on economic complexity in CEE countries.

3. Methodology

The study leverages a balanced annual panel dataset spanning from 1998 to 2021, encompassing eleven selected Central and Eastern European countries: Bulgaria, Croatia, the Czech Republic, Latvia, Lithuania, Hungary, Poland, Romania, Slovenia, Slovakia, and Estonia. The primary focus is on the ECI as the dependent variable, which measures the diversity and sophistication of a country's productive capabilities. ECI is a comprehensive metric designed to capture the extent of knowledge accumulation and the level of sophistication within an economy (Sadeghi et al., 2020). The index assigns higher values to economies that demonstrate higher complexity and sophistication in their productive capabilities and export structures. As such, a higher ECI score indicates an economy's advanced capacity to produce and export a diverse range of specialized products, reflecting a more intricate and developed economic structure.

To explore the determinants of economic complexity, the analysis includes three key independent variables: inward FDI stocks, which capture the impact of foreign direct investment inflows; R&D expenditure, reflecting the investment in research and development as a percentage of GDP; and the tertiary enrollment ratio, indicating the gross enrollment rate in higher education. These variables are critical in understanding the channels through which economic complexity can be enhanced. In addition to these core variables, two control variables are included to capture baseline economic conditions across countries: GDP per capita (constant 2015 USD) and gross capital formation (as a percentage of GDP). These indicators are widely used in the literature to reflect levels of development and investment capacity, helping isolate the net effects of the main structural drivers of complexity. To normalize the data and reduce skewness, FDI, tertiary enrollment, GDP per capita, and gross capital formation were log-transformed.

Table 1 provides a detailed overview of the variable names, their descriptions, and the data sources used in this study, ensuring clarity and transparency in the research methodology.

Table 1: Variables

Variable	Description	Sources
ECI	Economic Complexity Index	The atlas of economic complexity
FDI	Yearly inward FDI stocks (in Millions of US dollars)	UNCTAD World Investment Report Database
R&D	Research and development expenditure (% of GDP)	World development indicators
Enrol	School enrollment, tertiary (% gross)	World development indicators
GDP_PC	GDP per capita (constant 2015 USD)	World Development Indicators
Cap_Form	Gross capital formation (% of GDP)	World Development Indicators

Source: Authors' compilations

The descriptive statistics and correlation analysis for the panel data presented in Table 2, reveal several key insights into the determinants of economic complexity. ECI, with a mean of approximately 1.017 and a standard deviation of 0.45, indicates moderate variability in economic sophistication across these nations. Inward FDI (log-transformed) shows a mean of 10.13 and a relatively large standard deviation, suggesting notable differences in foreign capital inflows across countries. R&D expenditure, averaging 0.96% of GDP, and tertiary enrollment ratios, with a mean of 4.07%, suggest moderate but varied investment in innovation and education. Among the control variables, GDP per capita (log-transformed) averages 9.35, and gross capital formation (log-transformed) shows a mean of 3.20. These values indicate relatively stable but varying levels of development and investment capacity in the region. The correlation analysis highlights a moderate positive relationship between ECI and FDI inflows (0.5248), and a strong positive correlation between ECI and R&D expenditure (0.6219), underscoring the critical roles these factors play in enhancing economic complexity. Conversely, the very weak correlation between ECI and tertiary enrollment (0.0393) suggests that higher education levels alone do not directly translate into increased economic complexity. The gross capital formation variable shows minimal correlation with the dependent variable (0.1177), reflecting its weaker direct association with complexity. By contrast, GDP per capita shows the strongest positive correlation with ECI (0.6557), indicating that more developed countries tend to have more sophisticated and diversified production structures. All pairwise correlations fall below the conventional multicollinearity threshold of 0.80. To assess potential multicollinearity among independent variables, a Variance Inflation Factor (VIF) test was conducted. The mean VIF is 1.83, with all individual values well below the threshold of 5, confirming that multicollinearity is not a concern in this model. This further strengthens the robustness of the regression estimates.

Table 2: Descriptive statistics and correlation analysis

Variables	ECI	FDI	R&D	Enrol	GDP_PC	Cap_Form
Mean	1.01655	10.12773	0.956348	4.067348	9.353268	3.200011
Std. Dev.	0.44955	1.257802	0.487513	0.302252	0.407318	0.185403
Minimum	0.16	7.350592	0.35183	2.953916	8.171132	2.563398
Maximum	1.85	12.50883	2.56487	4.55245	10.11291	3.776567
Obs.	264	264	264	264	264	264
Correlation						
Variables	**ECI**	**FDI**	**R&D**	**Enrol**	**GDP_PC**	**Cap_Form**
ECI	1					
FDI	0.5248	1				
R&D	0.6219	0.1819	1			
Enrol	0.0393	0.2425	0.3660	1		
GDP_PC	0.6557	0.3067	0.7453	0.5007	1	
Cap_Form	0.1177	-0.0958	-0.0346	-0.1095	0.1319	1

Source: Authors' calculations

The empirical analysis begins with the implementation of cross-sectional dependence test to determine the appropriate econometric techniques to apply. Given the geographical proximity and potential shared characteristics of these nations, the risk of cross-sectional dependence is notably high. This high likelihood is compounded by the significant level of economic interactivity among the analyzed countries, which heightens the probability of spatial spillover effects. These spillover effects are a core foundation of cross-sectional dependence, making it essential to account for such dependencies to ensure the robustness and accuracy of the empirical findings. The study employs the Pesaran test for cross-sectional dependency, suitable for both small and large panel datasets. The null hypothesis stating the absence of cross-sectional dependence can be rejected at the 1%, 5%, and 10% significance levels, and formulated as:

$$\mathrm{CD} = \sqrt{2\mathrm{T}/\mathrm{N}(\mathrm{N}-\mathrm{N})}\ \left(\sum_{i=1}^{N-1} * \sum_{k=i+1}^{N} \widehat{\mathrm{P}}_{i,k}\right) \tag{1}$$

If cross-sectional dependence is detected, the data are subjected to second-generation unit root tests to prevent spurious results. Specifically, the cross-sectional augmented Im, Pesaran, and Shin (CIPS) test developed by Pesaran (2007) is used.

$$\mathrm{CIPS}(\mathrm{N},\mathrm{T}) = \mathrm{N}^{-1} \sum_{i=1}^{N} t_i(\mathrm{N},\mathrm{T}) \tag{2}$$

After verifying the stationarity of the data, it is crucial to determine the existence of a long-run relationship among the variables. This is achieved by employing the second-generation panel cointegration tests developed by Westerlund (2007), which is robust to cross-sectional dependence and particularly suitable for macroeconomic panel data The Westerlund test allows for the rejection of the null hypothesis of no cointegration, thereby confirming the presence of a statistically significant long-run association between economic complexity and its explanatory variables. Given evidence of cointegration, the model is estimated in levels, as the long-run equilibrium relationship between the variables justifies this specification. Moreover, in order to reinforce the validity of this choice, panel unit root tests (Levin–Lin–Chu and Im–Pesaran–Shin) are applied to the model residuals, both of which confirm their stationarity. This supports the statistical adequacy of the level specification, ensuring that coefficient estimates are not spurious despite the potential non-stationarity of the individual variables.

The empirical model is specified as follows:

$$\mathrm{ECI}_{it} = \alpha + \beta_1 \ln(\mathrm{FDI})_{it} + \beta_2 \mathrm{R\&D}_{it} + \beta_3 \ln(\mathrm{Enrol})_{it} + \beta_4 (\ln \mathrm{GDP\_PC})_{it} + \beta_5 (\ln \mathrm{Cap\_Form})_{it} + \gamma_t + \varepsilon_{it} \tag{3}$$

Where i denotes countries, t denotes years, γ_t captures time-fixed effects, and ε_{it} is the idiosyncratic error term.

The empirical strategy further incorporates diagnostic testing to address key econometric concerns. The Modified Wald test reveals the presence of groupwise heteroskedasticity, while the Wooldridge test confirms first-order autocorrelation in the residuals. Testing for fixed effects supports the inclusion of time-fixed effects, which are used to control global or regional shocks that affect all countries simultaneously, in line with standard practice. Country-specific fixed effects are not included. Given a relatively short time dimension (T = 24) and modest number of cross-sectional units (N = 11), their inclusion could introduce efficiency losses and multicollinearity without providing substantial gains in explanatory power. Furthermore, since the aim is to explain structural cross-country differences in economic complexity, including individual effects would absorb much of the variation of interest.

Given these diagnostic outcomes, estimation was conducted using two complementary techniques: Panel-Corrected Standard Errors (PCSE) and Feasible Generalized Least Squares (FGLS). The PCSE estimator corrects contemporaneous correlation and panel-level heteroskedasticity, making it suitable for macro-panel data with moderate time dimensions. As a robustness check, the FGLS method is employed to further account for heteroskedasticity, serial correlation, and cross-sectional dependence. The consistency of results across both estimation strategies enhances the credibility and robustness of the findings.

Recognizing the possibility that the impact of tertiary enrolment on economic complexity may not follow a strictly linear pattern, we extend the baseline model by estimating two alternative specifications aimed at capturing potential nonlinearities. First, a quadratic specification is estimated by including both the natural logarithm of tertiary enrolment and its squared term. To reduce potential multicollinearity between the linear and quadratic terms, the log-enrolment variable was mean-centered prior to squaring. This allows us to assess whether the marginal effect of enrolment changes across different levels of attainment. Second, a categorical specification is introduced by dividing the enrolment data into tertiles, generating a three-level ordinal variable (edcat). Two dummy variables represent the middle and upper tertiles, while the lowest tertile serves as the reference group. This setup enables the identification of possible threshold effects, whereby the impact of education on economic complexity differs across the enrolment distribution. Both strategies offer complementary insights into the nature of the relationship between education and economic sophistication and allow for a more flexible functional form.

4. Results

The findings from Table 3 point to a notable degree of interdependence among the CEE countries, as evidenced by the strong rejection of the assumption of cross-sectional independence at the strict 1% significance level. This suggests that economic disturbances originating in one of the CEE countries are likely to have ripple effects on others in the region. Furthermore, the panel unit root tests suggest that the variables exhibit different orders of integration. While most become stationary after first differencing, indicating integration of order one, some variables (such as ECI, GDP per capita, and capital formation) are found to be stationary already in levels. Therefore, this heterogeneity in integration order underscores the importance of applying cointegration techniques and supports the estimation of the model in levels.

Table 3: Cross-Sectional Dependence and Unit Root Tests Results

Variables	CSD statistics	CIPS	
		level	first difference
ECI	24.567***	-2.476***	-5.096***
FDI	35.622***	-2.154*	-4.241***
R&D	21.102***	-1.973	-4.075***
Enrol	29.567***	-1.934	-2.905***
GDP_PC	35.28***	-2.571***	-3.888***
Cap_Form	15.082***	-2.470***	-4.326***
Notes: *, **, and ***denote significance at 10%, 5%, and 1%, respectively.			

Source: Authors' calculations

The Westerlund error-correction-based panel cointegration tests detailed in Table 4, which incorporate robust p-values, provide valuable insights. This study employs a limited number of lags and leads, as well as a narrower kernel width, as the test results can be sensitive to these parameters when analyzing a small dataset. Specifically, a Bartlett kernel window width of 1, a maximum lag length of 1, and a lead length of 1 were selected based on the Akaike Information Criterion. The null hypothesis of no cointegration is rejected at the 1% level for three out of four test statistics (Gt, Pt, and Pa) based on their robust p-values (0.010, 0.010, and 0.000, respectively). These statistics are particularly relevant as they allow for heterogeneity across cross-sectional units and are suitable in small samples. The Ga statistic, on the other hand, does not provide evidence against the null. Overall, the results strongly suggest the existence of a long-run equilibrium relationship between economic complexity and its explanatory variables across the panel of countries.

To further validate the adequacy of estimating the model in levels, panel unit root tests on the residuals from the cointegration regression were conducted. Both the Levin–Lin–Chu (LLC) and Im–Pesaran–Shin (IPS) tests confirm that the residuals are stationary at conventional significance levels. This supports the conclusion that the variables are cointegrated and justifies the estimation of the long-run relationship in levels, mitigating concerns about potential spurious regression results due to non-stationarity.

Table 4: Westerlund Panel Cointegration and Residual Stationarity Tests

Test	H_0	Statistics	Robust P-value
Westerlund Gt	No cointegration	-3.568	0.010
Westerlund Ga	No cointegration	-4.839	0.300
Westerlund Pt	No cointegration	-10.038	0.010
Westerlund Pa	No cointegration	-11.078	0.000
LLC (Levin–Lin–Chu)	Panels contain unit roots	-2.4200	0.007
IPS (Im–Pesaran–Shin)	Panels contain unit roots	-1.9943	0.002

Source: Authors' calculations

Table 5 presents key diagnostic tests. Results indicate heteroskedasticity, serial correlation, and the need for time-fixed effects, while individual effects are excluded due to efficiency concerns.

Table 5: Diagnostic tests

Test	Statistics	P-value
Modified Wald test	$\chi^2(11)=500.56$	0.000
Wooldridge test	F(1,10)=14.43	0.003
F-test (Time FE)	F(23,235)=2.33	0.000
F-test (Individual FE)	F(10,248)=91.13	0.000

Source: Authors' calculations

Given the confirmation of cross-sectional dependence and cointegration among the variables, we employed the PCSE to estimate the model. To further validate the robustness and consistency of our findings, we applied FGLS techniques. Composite results are shown in Table 6. Our analysis yielded intriguing results regarding the drivers of economic complexity, measured by ECI. The positive and statistically significant coefficients for inward FDI stocks in both the PCSE and FGLS models underscore the crucial role FDI plays in driving structural transformation towards more sophisticated and knowledge-intensive economic activities, thereby confirming H1.

Our results also highlight the enduring importance of R&D expenditure in propelling economic complexity. The positive and significant coefficients for R&D expenditure in both the PCSE and FGLS models reinforce the well-established link between innovation and economic sophistication, confirming H2.

Interestingly, our analysis revealed a counterintuitive negative relationship between tertiary education enrolment and economic complexity. The tertiary enrolment ratio exhibits a negative and statistically significant relationship with ECI in both models, with coefficients of -0.2178 (p = 0.025)and -0.1845 (p = 0.006) in the PCSE and FGLS models, respectively. This finding challenges the conventional belief that higher education levels automatically translate into higher economic sophistication, leading to the rejection of H3.

Among the control variables, GDP per capita is positively and significantly associated with economic complexity across both models, while gross capital formation shows limited or model-sensitive significance.

Table 6: PCSE and FGLS results

Variables	**PCSE**		**FGLS**	
dependent variable: ECI	coef.	P-value	coef.	P-value
FDI	0.1380	0.000	0.2161	0.000
R&D	0.1068	0.026	0.1670	0.000
Enrol	-0.2178	0.025	-0.1845	0.006
GDP_PC	0.6625	0.000	0.6523	0.000
Cap_Form	-0.0329	0.573	-0.0967	0.023
Obs.	264		264	
R-squared	0.5158			
Wald statistics	6646	0.000	9921.82	0.000

Source: Authors' calculations

To further investigate the nature of the negative relationship between tertiary enrolment and economic complexity, we estimated two additional specifications focusing on potential nonlinear effects. The results, presented in Table 7, indicate that the magnitude of the negative association intensifies at higher levels of enrolment. Specifically, both the quadratic and categorical specifications confirm that the strongest negative effects are concentrated in the upper end of the enrolment distribution. Other covariates remain stable and are not discussed here for brevity.

Table 7: Quadratic and Threshold Effects of Tertiary Enrolment on ECI

Variable	Model 1 (Quadratic)	Model 2 (Categorical: edcat)
ln_enrol_c	-2.1887***	
ln_enrol_c2	-3.3453**	
edcat2 (middle tertile)		-0.18834***
edcat3 (highest tertile)		-0.43676***
Fixed effects	Year	Year
Observations	264	264
R-squared	0.7885	0.7352

Notes: Dependent variable is ECI. Both models include time-fixed effects and standard controls. Model 1 uses a quadratic term for mean-centered log enrolment; Model 2 uses enrolment tertiles (lowest as reference). P-values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' calculations

These empirical results provide strong evidence on the distinct roles of foreign direct investment, research and development, and education in shaping economic complexity, highlighting both expected and counterintuitive relationships that warrant further policy consideration and academic exploration.

5. Discussion

These findings align with broader discussions in the literature regarding the role of FDI, R&D, and education in economic transformation. The positive impact of FDI is consistent with prior research on FDI spillovers, where access to advanced technologies, managerial expertise, and global market linkages are seen as catalysts for enhancing economic complexity (Liu & Gao, 2020). While Liu & Gao (2020) primarily examined outward FDI, the underlying mechanisms of technology transfer and diffusion are equally relevant to the role of inward FDI in fostering economic sophistication. However, our findings contrast with those of Neagu et al. (2022), who identified a negative association between FDI and economic complexity for the period 2003–2016 in CEE countries. This divergence in results may stem from differences in the time periods analyzed, prevailing economic conditions, and econometric methodologies used. Our study, covering a longer timeframe from 1998 to 2021, suggests that the positive effects of FDI become more pronounced over extended periods, allowing for deeper structural transformations and the maturation of FDI's impact. The methodological approach in this study, incorporating PCSE and FGLS estimations, also ensures that results are not confounded by heteroskedasticity or serial correlation, further explaining why our findings offer a more optimistic perspective on FDI's role in enhancing economic complexity.

The strong positive impact of R&D on economic complexity further supports existing literature emphasizing the role of innovation in technological progress, productivity growth, and the development of high-value industries (Bayarcelik & Tasel, 2012). The results reinforce the importance of fostering a conducive environment for R&D investment, as research activities contribute to technological breakthroughs, process improvements, and the diversification of economic output. Similar conclusions were drawn by Neagu et al. (2022), who found a positive elasticity of R&D with economic complexity using FMOLS and DOLS models, indicating that economic complexity is an expression of a country's innovative capacity and R&D intensity.

A more complex and unexpected result is the negative relationship between tertiary education enrolment and economic complexity, which contradicts conventional expectations. One possible explanation lies in the brain drain phenomenon, where highly educated individuals migrate to more developed economies, reducing the availability of domestic talent essential for industrial upgrading (Ienciu & Ienciu, 2015). Even as enrolment rates rise, the outflow of skilled labour limits the potential for increased economic complexity, exacerbating domestic skills shortages and impeding the growth of high-tech industries. Additionally, mismatches between education systems and labour market needs could explain this outcome. As Chen and Dahlman (2004) argue, expanding tertiary education without ensuring its alignment with industrial demands may not yield the desired economic outcomes. If educational institutions emphasize theoretical knowledge over practical, industry-relevant skills, this could lead to underemployment of graduates or a misallocation of resources within the labour market.

To explore this further, we estimated nonlinear models that indicate the adverse effects of enrolment are more pronounced at higher levels. This pattern may reflect a saturation effect, where additional expansion does not translate into complexity gains. One possible interpretation is that of "massification without modernization", in which access to higher education increases, but without equivalent improvements in quality or relevance for technologically intensive sectors. This could lead to educational inflation, limited practical applicability of skills, and weak integration with productive sectors.

This interpretation is consistent with evidence pointing to broader systemic limitations in the educational landscape of CEE countries. For instance, Kwiek (2013) argues that tertiary education in the region can act as a barrier to industrial transformation when educational structures are not aligned with industrial needs. An oversupply of graduates in non-technical or low-demand sectors, combined with a shortage of professionals in science, technology, and engineering fields, weakens the capacity for complexity-enhancing structural shifts. Mukhtarova et al. (2024) similarly highlight that expanding tertiary education does not automatically contribute to technological advancement. Skill mismatches and migration trends may dilute the potential impact of rising enrolment on domestic industrial capacities.

Simionescu, Pelinescu, Khouri, and Bilan (2021) emphasize structural inefficiencies within educational systems, particularly the lack of integration between universities and the private sector. This gap reduces the ability of graduates to enter knowledge-intensive fields, further weakening the link between tertiary education and economic complexity growth. Additionally, public investment in education in CEE countries often lacks strategic focus, with insufficient funding directed toward programmes that directly enhance economic complexity. Simionescu et al. (2021) also highlight rigid academic structures and outdated curricula, which fail to adapt to the rapidly evolving skill demands of high-value industries.

Finally, our control variables also merit reflection. The consistent positive association between GDP per capita and economic complexity reflects the strong link between overall development levels and structural sophistication. On the other hand, the mixed results for capital formation suggest that the quality and direction of investment may matter more than its volume alone, particularly in the context of complexity-building strategies.

In summary, these findings emphasize the importance of targeted policies that not only promote FDI and R&D, but also focus on better integrating education systems with the needs of modern, knowledge-intensive sectors. While increased access to higher education remains valuable, its contribution to structural upgrading will depend on its capacity to generate relevant skills, retain talent, and support innovation.

Conclusion

Economic complexity has become a key indicator of a country's ability to compete in a knowledge-driven global economy. As nations seek to enhance their industrial structures and transition towards high-value-added production, understanding the factors that drive economic complexity is crucial. This study provides empirical insights into the determinants of economic complexity in eleven Central and Eastern European countries over the period 1998–2021, focusing on the roles of FDI, R&D expenditure, and tertiary education enrollment. Utilizing panel-corrected standard errors and feasible generalized least squares estimations, the analysis addresses key econometric challenges, ensuring robust and reliable findings.

The results reveal several important conclusions. First, FDI inflows significantly contribute to economic complexity, reinforcing the argument that foreign investment facilitates technological upgrading, knowledge spillovers, and integration into global value chains. This finding aligns with previous studies emphasizing the positive role of multinational enterprises in driving structural transformation. However, it also highlights the need for policies that channel FDI into high-tech and knowledge-intensive sectors, ensuring that its long-term benefits translate into industrial sophistication rather than mere capital accumulation.

Second, R&D expenditure emerges as a critical determinant of economic complexity, underscoring the importance of innovation-driven growth strategies. Countries that allocate greater resources to R&D are better positioned to develop new technologies, enhance productivity, and diversify their production structures. This finding reinforces the view that sustained investment in research and innovation is a prerequisite for achieving economic complexity and long-term competitiveness. For CEE economies, strengthening the linkages between academia, research institutions, and the private sector could further amplify the positive effects of R&D on industrial sophistication.

Third, and perhaps most surprisingly, tertiary education enrollment exhibits a negative relationship with economic complexity. Contrary to standard assumptions, enrolment in tertiary education is negatively associated with economic complexity. This result invites caution in interpreting enrolment as a straightforward proxy for the role of education in structural transformation. It may reflect brain drain, educational mismatches, or saturation effects in systems where expansion has outpaced modernization. Additional estimations suggest that these negative effects become more pronounced at higher enrolment levels, possibly indicating diminishing returns or misalignment with the needs of high-complexity sectors.

Although these results may appear counterintuitive, they align with growing concerns about the massification of higher education without corresponding improvements in quality or labour market alignment. This may lead to underemployment, educational inflation, or skill mismatches. Importantly, the use of tertiary enrolment as a proxy reflects data availability rather than conceptual preference. Alternative indicators, such as those from the Barro-Lee database or labour force surveys, may better capture dimensions such as educational quality, attainment, or field-specific alignment. Unfortunately, such data were not consistently available for the full time span and country sample analyzed, due to temporal discontinuities. This limitation may partly explain the observed effects and suggests directions for future research.

These findings carry significant policy implications for countries aiming to strengthen their economic complexity. First, foreign direct investment strategies should prioritize sectors that can contribute to structural upgrading and increased product sophistication. This means targeting FDI into industries with high technological intensity, strong learning effects, and integration into complex global value chains. Policymakers should also establish institutional frameworks that promote technology transfer, domestic supplier upgrading, and knowledge spillovers from foreign firms to local enterprises, directly contributing to more complex and diversified export baskets. Second, research and development policies must move beyond basic funding commitments and aim to embed innovation within the industrial base. Supporting R&D-intensive sectors through collaborative programmes between universities, public labs, and private firms is essential. Incentives should be structured to encourage the commercialization of research and development of exportable high-tech products, thereby expanding the range and sophistication of domestically produced goods, which are key components of higher ECI scores. Third, education policies should aim to ensure that the expansion of tertiary enrolment translates into sector-relevant capabilities. A reorientation toward STEM disciplines, stronger linkages between academic institutions and knowledge-intensive industries, and curricula aligned with the demands of globally competitive sectors are crucial. In addition, retention strategies, such as career pipelines in high-tech industries or incentives for return migration, are necessary to prevent the erosion of domestic skills through brain drain. Only through such targeted reforms can tertiary education meaningfully contribute to upgrading the productive structure and, ultimately, to enhancing a country's position on the economic complexity ladder.

This study is not without limitations. The use of aggregate national data may obscure within-country heterogeneity and structural nuances that vary at the regional or sectoral level. Future research could benefit from employing regional or firm-level analyses to better capture micro-level dynamics of economic complexity. Additionally, while the methodology rigorously addresses cross-sectional dependence, heteroskedasticity, and serial correlation, it does not explicitly account for potential endogeneity. Although PCSE and FGLS provide robust estimates under certain assumptions, omitted variable bias or reverse causality such as more complex economies attracting greater FDI or R&D may still influence the results. Acknowledging this limitation, future studies may consider using instrumental variable techniques or dynamic panel estimators such as system GMM to strengthen causal inference. In conclusion, economic complexity is shaped by a dynamic interplay between investment, innovation, and the evolving role of education. As CEE countries continue to integrate into global markets, targeted interventions in these domains are essential to foster structural transformation and long-term competitiveness. The findings offer a foundation for rethinking policy strategies aimed at upgrading industrial capabilities and aligning institutional frameworks with the demands of an increasingly knowledge-based global economy.

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