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How Does Export Concentration Affect Economic Complexity? Applying the Seemingly Unrelated Regression Approach for Selected Central and Eastern European Countries

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Abstract

Countries' export concentration can reduce foreign trade competitiveness because product and geographical concentration indicate that a country is dependent on other countries. Such circumstances can undermine countries' competitiveness and prevent them from having a significant global influence. Countries' economic complexity is determined using many macroeconomic indicators. If a country's complexity is higher, its competitiveness is higher. In particular, exporting products with high added value and innovative technologies is a significant approach for competing in the world market. Therefore, this study examines how the concentration of high-tech product exports affects the complexity of Central and Eastern European (CEE) countries with high export competitiveness potential. This study contributes to the literature in two ways. First, we calculate the concentration of high-tech product exports in CEE countries using the Herfindahl–Hirschman Index (HHI) to determine the degree of export concentration, revealing that Slovakia and Slovenia have the highest concentrations. Second, we use the HHI value as an independent variable in our econometric model to examine its effect on economic complexity using the seemingly unrelated regression estimator. The findings reveal that HHI affects economic complexity in the majority of CEE countries. A one-unit increase in concentration decreases economic complexity in other countries, with the exception of Slovakia and Slovenia. Increased export concentration will also negatively affect countries' global competitiveness as it decreases economic complexity.

Keywords: Export Concentration, Economic Complexity, Seemingly Unrelated Regression Estimator, Central and Eastern European Countries

JEL Codes: F10, F14, C51, C52

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1. INTRODUCTION

This study investigates the impact of the concentration of high-tech product exports on economic complexity in eight Central and Eastern European countries (CEE) countries (Bulgaria, Czechia, Hungary, North Macedonia, Poland, Romania, Slovakia and Slovenia) because producing and exporting high value-added products directly affects countries' complexity and competitiveness. Many factors influence global competitiveness, but innovation and technological development are at the top of them. A country that produces and exports more innovative products will increase its global competitiveness (Çetin & Erkişi, 2023) as increased complexity is positively affects competitiveness. However, a rise in export concentration can negatively affect countries' complexity and competitiveness.

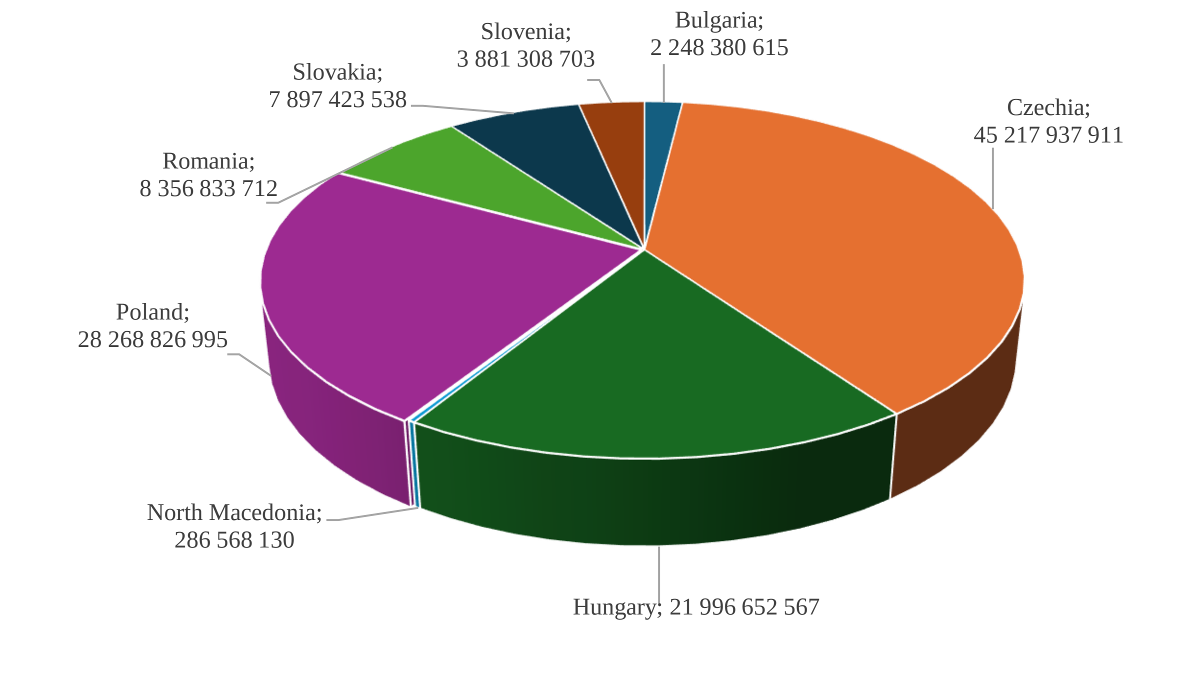

Figure 1: High-tech exports of selected CEE countries (2022; current $)
Source: World Bank Open Data (2024)

As shown in Figure 1, Czechia, Poland, and Hungary export the highest technology among these countries, with exports of that are worth approximately $100 billion. The countries that export the highest technology also have the highest complexity. Likewise, according to the Observatory of Economic Complexity country rankings, Czechia ranks 6th, Slovenia 9th, Hungary 13th, Slovakia 15th, Romania 22nd, Poland 25th, Bulgaria 38th, and North Macedonia 52nd (OEC, Complexity Rankings, 2024).

When considering countries' geographical locations and potential export levels, it is vital to examine the relationship between product concentration and complexity to understand subsequent competitiveness. Because countries' aim is to not only decrease the concentration of innovative products through export diversification but also to enhance export competitiveness and increase economic complexity. In this context, this study analyzes selected CEE countries' competitiveness using export concentration and economic complexity.

Therefore, after conceptualizing complexity, we conduct a concentration analysis of the selected CEE countries' high-tech products. Finally, we examine the relationship between export concentration and economic complexity employing the seemingly unrelated regression (SUR) approach.

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

2.1 Literature Review

A large body of literature has analyzed the relationships between economic complexity and income inequality, globalization, urbanization, human capital, and related concerns (Lee & Vu, 2020; Kazemzadeh et al., 2022; Lee & Wang, 2021), and studies examining the relationship between environment and complexity have also been frequently conducted (Aluko et al., 2022; Doğan et al., 2019; Ntang et al., 2024; Chu, 2021; Romero & Gramkow, 2021). Erkan and Yıldırım (2015) analyzed complexity and competitiveness and their influencing factors in Türkiye, determining that the nation is below the required level of competitiveness and complexity. Ivanova et al. (2017) examined the relationship between economic complexity (ECI), patent complexity, and the triple helix complexity indices, introducing triple interaction terms between information, wealth, and national control for 34 member countries of the Organisation for Economic Co-operation and Development; Brazil, Russia, India, China and South Africa; and some developing countries. According to the results, Japan scores highest across all three indicators, while China is more successful in combining technological and economic complexity.

Şeker (2019) analyzed the relationship of Türkiye's ECI with technological development, exports of high-tech products, and capital investments. Results reveal a long-term relationship between the ECI and high-tech product exports, domestic patent applications, and fixed capital investments, and revealed a two-way causal relationship between ECI, high-tech product exports, and domestic patent applications. Doyar and Yaman (2020) analyzed the relationship between complexity, income, and high-tech exports using a vector autoregression approach for Türkiye, determining income to be the variable that most affects ECI and high-tech exports, and ECI to be the variable that most affects income. Erkan and Ceylan (2021) analyzed the relationship between economic growth, foreign direct investment (FDI), the Human Development Index (HDI), Economic Freedom Index (EFI), and ECI for 22 transitioning economies employing the causality method with the Granger causality test. Results demonstrate a one-way Granger causality relationship between economic growth, FDI, HDI, and EFI and ECI in some countries and a two-way relationship in others.

Handoyo et al. (2021) empirically examined the relationship between export diversification, per capita income, human capital, and research and development (R&D) expenditure for 62 developing countries. The authors found that gross domestic product (GDP) promoted export diversification in low- and medium-income samples and for all countries and reduced it in high-income countries, Furthermore, human capital and R&D expenditure were found to increase diversification. Canh and Thanh (2022) analyzed the relationship between economic complexity, export diversification, and economic growth for 70 countries (32 high-income countries, 38 low- and middle-income countries). The results revealed a positive effect between economic complexity and export diversification and a negative effect between economic growth.

Gnangnon (2022) analyzed the impact of complexity on service export diversification and FDI, demonstrating that complexity positively affects service export diversification and the magnitude of this effect is higher in developed countries. In particular, as complexity and the share of net FDI inflow in GDP rise, service export diversification also increases. Can et al. (2023) examined the relationship between trade openness, export concentration, and complexity in G7 countries using three empirical models. Results revealed a positive long-term relationship between per capita income, urbanization, trade openness, export concentration, complexity, and energy use across all three models.

Saad et al. (2023) analyzed the relationship between economic complexity, economic diversification, and economic development in 133 countries, revealing that per capita GDP strongly affects economic complexity, while human capital and economic policy affect it less. Sultanova and Naser (2024) examined the export concentration of information and communication technologies (ICT) in 110 developing countries, while also investigating the effect of ICT and human capital on export concentration using the generalized method of moments. The findings demonstrated that ICT development has significantly accelerated developing countries' export diversification and aligned export structures with global standards.

The interaction between ICT and human capital positively affects export concentration. Altıner et al. (2024) examined the relationship between export product diversification and growth, FDI, capital, labor, inflation, and public expenditure in 85 developing countries in Africa, America, Asia, and Oceania regions within a framework employing three different models. The results of the analysis demonstrated that increased capital, labor, public expenditure, and productive capacity has a positive effect on export product diversification, whereas economic growth and trade openness adversely affect diversification.

In summary, many studies have examined export concentration, economic complexity, and high-tech product exports. However, no research has examined the export concentration of high-tech products and its relationship with economic complexity. Therefore, the study contributes by filling this gap in the literature.

2.1 Theoretical Background

We use ECI to estimate and explain countries' complexity values and the dynamics of associated economic magnitudes. ECI is a measurement method that connects countries' capacity to economic activities, which can be deduced from the data obtained. The ECI predicts a country's income level, economic growth, income inequality, and macroeconomic data such as greenhouse gas (GHG) emissions (Hidalgo, 2023). The index is divided into ECI, which concerns geographical complexity and a product complexity index (PCI), which examines product complexity. The PCI is a measure of the complexity required to produce a product or engage in an economic activity. In contrast, ECI measurement uses data that connect macroeconomic positions based on countries' geographical location to quantify economic capacity. The ECI estimates macroeconomic outcomes such as a country's income level, economic growth, income inequality, and GHG emissions. In addition, trade, employment, stock market, and patent data are used to predict the ECI (OEC, 2024). The ECI is based on the following revealed comparative advantage (RCA) coefficient described by Balassa (1965):

$$RCA_{cp} = \frac{X_{cp}}{\sum_p X_{cp}} \Bigg/ \frac{\sum_c X_{cp}}{\sum_c \sum_p X_{cp}} \tag{1}$$

The RCA index compares a country's sectoral export share with the global sectoral export share to quantify countries' export competitiveness. An RCA of 1 indicates a comparative export competitiveness advantage. In contrast, ECI measurement constructs a matrix using the RCA coefficient to calculate the complexity index based on this matrix, where the complexity of location *c* (e.g., country or city) is defined as K_c, and the complexity of activity *p* (e.g., product or industry) is defined as K_p. In addition, M_{cp} is a matrix that summarizes the activities (*p*) in location (*c*). (Generally, M_{cp} is defined as equal to 1). This matrix is defined as location c's output for activity p being greater than expected for a location of the same size and an activity with the same total output (Hidalgo & Hausmann, 2009).

$$M_{cp} = 1 \text{ ise RCA} > 1$$

$$X_c = \sum_p X_{cp}, X_p = \sum_c X_{cp} \text{ and } X = \sum_{cp} X_{cp} \tag{2}$$

$$K_c = f\,(M_{cp}\ K_p) \text{ and } K_c = f\,(M_{cp}\ g\,(M_{cp}\ K_c) \tag{3}$$

$$K_c = \frac{1}{M_c} \sum_p M_{cp}, K_p \tag{4}$$

$M_c = \sum_p M_{cp}$ indicates a country's diversity, $M_p = \sum_c M_{cp}$ indicates the number of locations where a country's activities take place. After normalizing these results by performing a Z transformation, the ECI is formulated as follows:

$$\text{ECI} = \frac{Kc - \widehat{Kc}}{\sigma(Kp)} \tag{5}$$

where $\widehat{Kc}$ is the average of Kc, and $\sigma(Kp)$ denotes the standard-grade deviation of Kc (Hidalgo, 2021).

3. RESEARCH OBJECTIVE, METHODOLOGY AND DATA

The primary objective of this study is to investigate the effect of export concentration on economic complexity in selected CEE countries. Our main hypotheses are as follows:

- H1: Increased export concentration will adversely affect export competitiveness and decrease economic complexity.
- H2: Increased R&D expenditure will increase economic complexity; therefore, R&D expenditure is included as an independent variable in our model (Equation (14)), along with export concentration.

This study investigates the accuracy of the above hypotheses by conducting export concentration analysis for selected CEE countries and investigating whether export concentration affects economic complexity.

While other indices have been used to measure concentration than the Herfindahl–Hirschman index (HHI) such as the Theil index, the Concentration Ratio index, the Gini–Hirschman index, and the Entropy index, we select the HHI to produce concentration results that are more suitable for empirical analysis.

3.1 Herfindahl–Hirschman Index

The HHI is one of the few most used indices in product and geographic concentration analysis (Kozáková & Barteková, 2020). The index is calculated by squaring the export shares of a particular sector in all countries and is formulated as follows (Meilak, 2008):

$$\text{HHI} = (Si)^2 \tag{6}$$

where *Si* represents the total export share of each of the groups of selected size (geography or product), and the square values of each *Si* are summed to obtain concentration rate, with index values ranging from 0 to 1. As HHI approaches 1, the concentration increases and vice versa (Vaid, 2018).

3.2 Breusch–Pagan Lagrange Multiplier Test

We employ Breusch–Pagan LM and Pesaran CD tests to quantify the correlations between units. If the time dimension is greater than the unit size (N < T), the LM test produces more accurate results and vice versa (Tatoğlu, 2018). The Breusch–Pagan LM test is constructed as follows (Breusch & Pagan, 1980):

$$\text{LM} = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{P}_{ij}^{2} \tag{7}$$

where $\hat{P}_{ij}^{2}$ denotes the correlation coefficient between units i and j residuals. It is expressed as Ho: There is no cross-sectional dependence and H1: there is a cross-sectional dependence.

3.3 Unit Root Test

We use the multivariate extended Dickey–Fuller (MADF) test, which considers cross-sectional dependence to test the stationarity of the series, which was proposed by Abuaf and Jorion (1990) and developed by Taylor and Sarno (1998) and is formulated as follows (Tatoğlu, 2018):

$$\text{MADF}=\frac{(\iota-\Psi\hat{\beta})\{\Psi\,[Z'(\hat{\Lambda}^{-1}\otimes I_T)Z]^{-1}\Psi'\}\,(\iota-\Psi\hat{\beta})N\,(T-k-1)}{(Y-Z\hat{\beta})'(\hat{\Lambda}^{-1}\otimes I_T)(Y-Z\hat{\beta})} \tag{8}$$

H0: All series contain unit roots, and H1: All series are stationary. If the MADF value is greater than the critical value, the series is stationary, and if it is smaller, the series is nonstationary, indicating that the unit contains roots.

3.4 Homogeneity Test

The most commonly used tests for measuring the homogeneity of parameters in an economic model are the delta test proposed by Pesaran and Yamagata (2008) and the S test constructed by Swamy (1970). If the time dimension is higher than the unit dimension (N < T), the S test will be more consistent, and if the unit dimension is higher than the time dimension (N > T), the delta test will be more consistent. The S test is formulated as follows (Swamy, 1970):

$$\hat{S} = X_{k(N-1)}^{2} = \sum_{i=1}^{N}(\hat{\beta}\iota - \bar{\beta})'\,\hat{V}_i^{-1}(\hat{\beta}\iota - \bar{\beta}) \tag{9}$$

H0: $\beta_i = \beta$ indicates that the series is expressed as homogeneous. Therefore, the results of Swamy's S test can determine whether the variables are heterogeneous to select tests accordingly.

3.5 Seemingly Unrelated Regression

The SUR method was first proposed by Zellner (1962), representing a procedure that is more efficient than ordinary least squares (OLS) with a single equation for estimating parameters associated with sets of SUR equations (Zellner & Huang, 1962). Generally, the slope coefficients in empirical panel data models are assumed to be homogeneous between units; however, the SUR equation is particularly attractive when the cross-sectional dimension (N) is smaller and the time dimension (T) is larger (N < T) because it automatically addresses the error correlations of cross sections. In contrast, the estimator will be inconsistent in a situation with many N > Ts (Pesaran & Yamagata, 2008).

If correlation is evident between the units and the variables are heterogeneous, the SUR estimator will be more consistent. This estimator method is appropriate if the heterogeneous parameters in the panel are assumed to be constant (Tatoğlu, 2018). It can also produce predictions that are resistant to simultaneous correlations in variance and errors between equations (Inuwa et al., 2022).

SUR includes two main stages. The first is to construct different equations for each variable, combine the information about these equations, and ensure that the predictions are consistent. The second is to apply and/or test constraints involving parameters in different equations (Moon & Perron, 2006). A classic linear SUR model includes linear regression equations in the following linear panel data model:

$$Y = X\beta + u \tag{10}$$

When this model is constructed using the SUR estimator, new equations are created for each parameter as follows.

$$Y_i = X_i \beta_i + u_{i.} \tag{11}$$

The SUR approach includes classical linear regression models in which no variable in the equation is taken; that is, the system of equations is not a simultaneous system (İsmiç, 2015). Therefore, the SUR method estimates a system's parameters considering variance and simultaneous correlation in errors between equations. The SUR model can be considered a simplification of linear models in which the coefficients in the matrices created are equally limited to zero (Khan et al., 2014).

We then construct a general variance–covariance matrix (Ω) to be used in the estimation. The diagonal elements in this matrix can reveal the residual variances of the regression models established separately for each unit, and the nondiagonal elements reveal the covariance between the residuals (Tatoğlu, 2018). Therefore, the SUR model's prediction is obtained as follows:

$$\hat{\beta} = \left(X'^{\Omega^{-1}} X\right)^{-1} (X'\Omega^{-1} Y), \tag{12}$$

using the generalized least squares (GLS) method. The correlation matrix is created as follows:

$$\begin{bmatrix} y1 \\ y2 \\ . \\ . \\ ym \end{bmatrix} = \begin{bmatrix} x1 & 0 & . & . & . & 0 \\ 0 & x2 & . & . & . & 0 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0 & 0 & . & . & . & Xm \end{bmatrix} \begin{bmatrix} \beta1 \\ \beta2 \\ . \\ . \\ \beta m \end{bmatrix} + \begin{bmatrix} u1 \\ u2 \\ . \\ . \\ um \end{bmatrix} \tag{13}$$

where X is the diagonal matrices, and $m\,T \times 1$ is the vector of error terms. In cross-sectional regressions, t represents time, implying constant variance and covariance across time and the absence of autocorrelation or correlation in error terms. Therefore, Equations (10) or (12) in the model are considered to be regression models with one equation for which we apply Aitken's GLS method (Zellner, 1962).

Since the diagonality of Σ is central to using SUR estimation methods, it is essential to employ tests for H0: Σ is diagonal. Breusch and Pagan (1980) derived a simple and easy-to-use LM statistic to test H0 that can also be used for cross-sectional dependence testing, which is based on the sample correlation coefficients of OLS residuals. In the case of cross-sectional dependence, the SUR approach is popular because it can capture the efficiency resulting from the correlation of error terms between equations (Baltagi, 2008 and Baltagi, 2005).

4. RESULTS AND DISCUSSION

This study's analysis consists of two parts. In the first part, we calculate the high-tech product concentration data according to the International Standard Industrial Classification (ISIC) Revision 3, technology classification of selected CEE countries. In the second part, we conduct an empirical study using the data calculated employing the econometric model. For both analyses, the base year was the period from 2000 to 2021. The ECI data are obtained from the OEC, and R&D data are sourced from the World Bank HDI database. We calculate HHI using data from the COMTRADE database. The econometric model is as follows:

$$\mathrm{ECI} = \alpha + \beta_1\,\mathrm{RD} + \beta_2\,\mathrm{HHI} + \mu_1 \tag{14}$$

where ECI denotes the economic complexity index, α is constant coefficient, RD represents the proportion of R&D expenditure in % GDP, HHI refers to the concentration index calculated by the author. β_1 coefficient of R&D expenditures, β_2 The coefficient of the HHI value, μ refers to the term error.

Table 1: ISIC Revision 3 High Technology Products

353	Aircraft and spacecraft manufacturing
2423	Pharmaceuticals, medicinal chemicals, and botanical products manufacturing
30	Office, accounting, and computing machinery manufacturing
32	Radio, television and communication equipment, and apparatus manufacturing
33	Medical, precision and optical instruments, watches, and clocks manufacturing

Source: World Integrated Trade Solution, COMTRADE Database (2024)

Table 1 presents the chosen ISIC Rev. 3 high-tech products. We obtain the data for the product groups referencing the COMTRADE database. Table 2 presents the concentration analysis of CEE countries. The HHI results reveal that the countries with the highest concentration are Slovakia, Slovenia, and North Macedonia. Over the years, the product concentration of Slovakia and Slovenia has followed rising trajectories, while other countries exhibit decreasing trends.

Table 2: HHI Analysis of CEE Countries (ISIC Rev. 3 High Tech.)

	Bulgaria	Czechia	Hungary	North Macedonia	Poland	Romania	Slovakia	Slovenia
2000	0.37031602	0.35577722	0.41625562	0.665931193	0.43822441	0.43585332	0.30464636	0.33418401
2001	0.33806634	0.33868505	0.42675731	0.694070993	0.47781304	0.44947467	0.36146179	0.34871561
2002	0.28272348	0.37742966	0.46433656	0.645790194	0.51194301	0.62801314	0.34454495	0.37446142
2003	0.27682587	0.34216966	0.46656179	0.629254572	0.49353435	0.48511241	0.31233235	0.41041454
2004	0.24177346	0.34673288	0.49135638	0.654995710	0.41184851	0.45431484	0.34296596	0.40551068
2005	0.25801676	0.33874232	0.46209245	0.692666598	0.41536737	0.32730852	0.41126645	0.43568442
2006	0.22610917	0.3579062	0.44235755	0.663148184	0.47541269	0.26344431	0.56897870	0.43624976
2007	0.28077935	0.34162245	0.42891888	0.638212159	0.48538166	0.26602946	0.70411982	0.45323464
2008	0.27657921	0.34443674	0.45189135	0.539335493	0.39345766	0.30903751	0.73829168	0.43298137
2009	0.28346008	0.32058093	0.48428952	0.574882547	0.37144096	0.44953254	0.78515084	0.46080666
2010	0.31306405	0.34171728	0.49784749	0.609217396	0.35556112	0.47334061	0.76619734	0.48318655
2011	0.3042632	0.34968485	0.44098242	0.563416294	0.31931346	0.47615682	0.70776048	0.51306209
2012	0.30705056	0.34315304	0.35910661	0.588971791	0.3041622	0.34039866	0.70028636	0.52722219

2013	0.32394319	0.32493836	0.32368751	0.514471895	0.29036684	0.31353183	0.66746308	0.54188908
2014	0.33629797	0.32303071	0.2813559	0.454027693	0.30164521	0.30997614	0.66158184	0.53474756
2015	0.32298847	0.31729987	0.2826250	0.402180238	0.28461553	0.29917935	0.65704954	0.50292523
2016	0.31213363	0.30684482	0.27229449	0.414453864	0.25207623	0.29236686	0.66507302	0.51166522
2017	0.29820179	0.30827297	0.26416357	0.401347618	0.22566326	0.30873023	0.67152514	0.48871662
2018	0.29592497	0.32257614	0.2675244	0.437845154	0.22531222	0.31258246	0.63794301	0.50157390
2019	0.28387657	0.32441992	0.29245557	0.410770383	0.21708531	0.30264859	0.61442559	0.59102726
2020	0.28587353	0.33634595	0.29023655	0.433134338	0.23217397	0.29713632	0.58815153	0.67903015
2021	0.26930127	0.32377336	0.29637602	0.423424497	0.23866804	0.29242219	0.58277947	0.64204322

Source: Author' calculation

In the empirical model, it is essential first to test the parameters' stationarity for appropriate analyses. We use the Breusch–Pagan LM test to determine whether correlation is evident between the parameters. Table 3 reveals a correlation between the cross-sectional units according to the LM test results. Therefore, we apply the MADF test, which is one of the unit root tests that considers correlation, to test the stationarity.

Table 3: Breusch–Pagan LM Test

Test	Statistic	p-value
LM	95.3	0.0000*
LM adj*	21.13	0.0000*
LM CD*	3.903	0.0001*

Note: * denotes a 1% significance level.

The MADF test results in Table 4 indicate that the dependent variable (ECI) and the independent variables (RD and HHI) are greater than the critical value in the test. This demonstrates that they are stationary at level values. Therefore, the variables' difference values are not examined and we continue the analysis using a homogeneity test.

Table 4: MADF Unit Root Test

ECI			
Obs	Lags	MADF	Approx 5% CV
21	1	57.924	36.616
RD			
Obs	Lags	MADF	Approx 5% CV
21	1	40.482	36.616
HHI			
Obs	Lags	MADF	Approx 5% CV
21	1	40.571	36.616

Homogeneity analysis of constant and slope parameters according to units enables consistent selection of analytical approaches. As some estimates are inconsistent because some tests are performed under the homogeneity assumption, a homogeneity test must be applied. The results of the homogeneity test in Table 5 reject H0 and confirm that the parameters are heterogeneous.

Table 5: Swamy (1970) S Test (heterogeneity test)

ECI	Coef.	Std. Err.	z	p > |z|	[95% Conf. Interval]	
RD	.5267103	.3625591	1.45	0.146	−.1838925	1.237
HHI	−.3523631	.4299307	−0.82	0.412	−1.195.012	.4902
_cons	.5631103	.2874488	1.96	0.050	−.0002791	1.265
Test of parameter constancy: chi2(21) = 1,713.73; Prob > chi2 = 0.0000*						

Note: * denotes a 1% significance level.

For heterogeneous panel data models with correlation between parameters, SUR analysis is a consistent estimator. The SUR analysis (Table 6) created a separate equation for each country in the empirical model and made estimations accordingly. According to the results obtained for the overall panel, equation estimates are significant in all CEE countries (P value). The model's R2 results are over 50% in all countries except North Macedonia and Romania. Accordingly, it is possible to say that the unit-based estimates outside of North Macedonia and Romania are consistent and explain the model.

Table 6: SUR Analysis Results (overall panel)

Equation	RMSE	R^2	chi2	p-value
Bulgaria	.1034288	0.5544	21.04	0.0000
Czechia	.1003126	0.5944	28.98	0.0000
North Macedonia	.1372214	0.0393	13.73	0.0010
Hungary	.1467022	0.5787	42.90	0.0000
Poland	.0888831	0.6656	42.06	0.0000
Romania	.2568495	0.4640	20.73	0.0000
Slovakia	.0772183	0.8332	110.25	0.0000
Slovenia	.0704172	0.6692	44.26	0.0000

According to the SUR analysis results in Table 7, the RD variable is significant in explaining the ECI for Bulgaria, Czechia, Hungary, Romania, Slovakia, and Slovenia. The RD variable is insignificant in explaining ECI only for North Macedonia and Poland. On a per unit basis, a one-unit RD increase, raises the ECI by 0.50 units in Bulgaria, 0.20 units in Czechia, 0.49 units in Hungary, 2.69 units in Romania, 0.36 units in Slovakia, and 0.05 units in Slovenia.

Table 7: SUR Analysis Results (by country)

Bulgaria						
Dependent variable: ECI	Coef.	Std. Err.	z	p > |z|	[95% Conf. Interval]	
RD	.5082142	.1137384	4.47	0.000*	.285291	.7311375
HHI	−.0987343	.4906485	−0.20	0.841	−1.060.388	.8629192
cons	.0553008	.1441026	0.38	0.701	−.227135	.3377367
Czechia						
Dependent variable: ECI	Coef.	Std. Err.	z	p > |z|	[95% Conf. Interval]	
RD	.2054125	.0472827	4.34	0.000*	.1127401	.2980849
HHI	−.5859291	.7693228	−0.76	0.446	−2.093.774	.9219158
cons	1.361.609	.2994063	4.55	0.000	.7747832	1.948.434

North Macedonia						
Dependent variable: ECI	Coef.	Std. Err.	z	p > |z|	[95% Conf. Interval]	
RD	−.1166752	.2156079	−0.54	0.588	−.539259	.3059085
HHI	−.8096241	.229713	−3.52	0.000*	−1.259.853	−.359395
cons	.337995	.169187	2.00	0.046	.0063945	.6695954
Hungary						
Dependent variable: ECI	Coef.	Std. Err.	z	p > |z|	[95% Conf. Interval]	
RD	.4937749	.0828887	5.96	0.000*	.3313161	.6562338
HHI	−.0002202	.2254204	−0.00	0.999	−.4420361	.4415957
cons	.644221	.156825	4.11	0.000	.3368497	.9515924
Poland						
Dependent variable: ECI	Coef.	Std. Err.	z	p > |z|	[95% Conf. Interval]	
RD	−.0862746	.0946415	−0.91	0.362	−.2717685	.0992194
HHI	−1.183.488	.271854	−4.35	0.000*	−1.716.312	−.6506637
cons	1.401.708	.1679039	8.35	0.000	1.072.623	1.730.794
Romania						
Dependent variable: ECI	Coef.	Std. Err.	z	p > |z|	[95% Conf. Interval]	
RD	2.698.778	1.130.632	2.39	0.017 **	.4827806	4.914.775
HHI	−1.189.695	.6066258	−1.96	0.050**	−237.866	−.0007304
cons	−.1988609	.6568385	−0.30	0.762	−1.486.241	1.088.519
Slovakia						
Dependent variable: ECI	Coef.	Std. Err.	z	p > |z|	[95% Conf. Interval]	
RD	.3660826	.0747877	4.89	0.000*	.2195014	.5126638
HHI	.7406111	.0878406	8.43	0.000*	.5684466	.9127756
cons	.4474517	.0688146	6.50	0.000	.3125774	.5823259
Slovenia						
Dependent variable: ECI	Coef.	Std. Err.	z	p > |z|	[95% Conf. Interval]	
RD	.0577789	.0336002	1.72	0.086***	−.0080762	.1236341
HHI	.6825258	.1754018	3.89	0.000*	.3387447	1.026.307
cons	.9062789	.0675906	13.41	0.000	.7738037	1.038.754

Note: *, **, and *** denote the significance levels of 1%, 5%, and 10%, respectively.

According to Table 7, the HHI variable is significant in explaining the ECI variable in North Macedonia, Poland, Romania, Slovakia, and Slovenia; however, it is insignificant in explaining ECI in Bulgaria, Czechia, and Hungary. On a unit basis, a one-unit HHI increase decreases the ECI by 0.80 units in North Macedonia, 1.18 units in Poland, and 1.18 units in Romania, while it increases ECI by 0.74 units in Slovakia and 0.68 units in Slovenia.

In Table 8, the Breusch–Pagan test at the bottom of the matrix refers to the correlation between error terms. For the SUR estimator to be effective, the Breush–Pagan LM test results must reject the null hypothesis (chi2(28) = 95.298 and p-value = 0.0000).

Table 8: Correlation Matrix of Error Terms

	Bulgaria	Czechia	North Macedonia	Hungary	Poland	Romania	Slovakia	Slovenia
Bulgaria	1.0000							
Czechia	0.4000	1.0000						
North Macedonia	−0.0171	−0.5029	1.0000					
Hungary	0.3750	0.7583	−0.7861	1.0000				
Poland	0.5078	0.5982	−0.1880	0.5357	1.0000			
Romania	0.3452	0.0987	0.1977	−0.0404	−0.0317	1.0000		
Slovakia	0.1592	0.3024	0.1095	−0.0067	0.0448	0.3490	1.0000	
Slovenia	0.1329	0.5243	−0.5260	0.7141	0.3492	−0.1065	0.1062	1.0000
Breusch–Pagan test of independence: chi2(28) = 95.298; p = 0.0000*								

Note: * denotes a 1% significance level.

Examining the correlation matrix between the units of the residuals reveals a 75% correlation between Hungary and Czechia, over 50% between Poland and Bulgaria and Czechia and Hungary, 52% between Slovenia and Czechia, and 71% between Slovenia and Hungary. Therefore, the correlation between units can also be tested using this estimator to produce separate estimates for each unit and consider the correlations between units. To predict the SUR models, the Breush–Pagan LM test results must reject the null hypothesis.

The results of the concentration analysis in Table 2 demonstrates that export concentration of high-tech products in the selected CEE countries is minimal as the results are generally closer to 0. The results indicate that increased R&D expenditure expands economic complexity, and increased export concentration decreases economic complexity (except in Slovakia and Slovenia). Therefore, the results confirm our proposed hypotheses in section 3.

Developing countries generally concentrate exports in labor- and raw material-intensive sectors, resulting in a lower level of economic complexity wherein fluctuations in global commodity prices can directly affect these economies. Therefore, these countries are more vulnerable to external economic shocks. Such circumstances negatively affect countries' global competitiveness. In contrast, economies with high economic complexity (i.e., Germany, Japan, and South Korea) export a variety of products by diversifying different sectors and can be more resilient to economic shocks. This diversification also increases global competitiveness by enabling countries to increase participation in global trade and supply chains. While increased economic complexity enables the production of more advanced technology and high value-added products, export concentration limits countries to producing low technology or basic products.

5. CONCLUSION

To achieve sustainable economic growth, countries must produce high-tech and innovative products and be able to market them to the outside world successfully. When a country is dependent only on specific countries when exporting technological products can cause major economic problems. Likewise, high export intensity is not desirable for countries' foreign trade. Macroeconomic instability in countries' trading partners will adversely affect trade volume and national income. Therefore, the concentration in the countries' foreign trade should be low, meaning that export diversification is high.

From this perspective, this study analyzes the concentration of technological product exports of selected CEE countries and its effect on economic complexity. The fact that CEE countries are geographically advantageous and members of the European Union (EU) (except for North Macedonia) demonstrates that high-tech product export diversification can be improved. Furthermore, our concentration analysis indicates that concentration is high in three of the eight CEE countries and low in five.

Our empirical analysis tests two main hypotheses. The first hypothesis posits that increased R&D expenditure has a positive effect on the ECI, and the second is that export concentration negatively affects the ECI, and the results support our hypotheses. Considering the overall results of our analysis, while high-tech export concentration and R&D expenditure affect ECI in five countries (North Macedonia, Poland, Romania, Slovakia, and Slovenia), the low R^2 values of North Macedonia and Romania cast doubt on the reliability of these countries' analyses.

The unit-based findings reveal a significant and positive relationship between R&D expenditures and ECI in six countries, excluding North Macedonia and Poland. As R&D expenditure increases in these countries, ECI also increases. Other countries also exhibit a significant relationship between HHI and ECI, with the exception of Bulgaria and Hungary. In Slovakia and Slovenia, increased export concentration raises the ECI, while the opposite holds in other countries, which is consistent with our hypothesis.

The selected CEE countries have achieved a higher level of economic complexity and relatively low export concentration compared with other developing nations due to integration with the EU, which has allowed them to engage in more high-tech production processes and diversify exports. In addition, our empirical analysis demonstrated that HHI affects ECI. Therefore, these countries should actively increase their competitiveness by emphasizing product and geographic export diversification.

Therefore, CEE countries and other developing countries must diversify internal industrial structures and foreign trade relations to adapt to the dynamics of global trade. The key to achieving this is to diversify foreign trade strategies with a focus on opening new markets and supply chains. In addition, logistics infrastructure must be improved to decrease concentration and increase competitiveness. Furthermore, export of services and high-tech products such as software, artificial intelligence, engineering services, and financial technology must increase. These measures will raise economic competitiveness, reduce vulnerability in foreign trade, and make economies less dependent on specific sectors, enabling countries to have a more flexible foreign trade structure that can withstand exchange rate fluctuations and other disruptions. These countries should benefit from economies of scale, particularly in the production of high-tech products, and governments should offer incentives to increase exports, also raising global competitiveness by entering into foreign free trade agreements when necessary. It is vital to promote trade deals and investments, particularly in growing markets such as China, India, the Middle East, and Africa.

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