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PAPER

Determinants of Economic Complexity in Transitional Economies

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Abstract Which country is more developed? Which country's foreign trade policies are more rational? In a globalized world, which country has higher added value and competitiveness in its exports? Questions like this are not easy to answer. Because there are many criteria for measuring the development of the economy and foreign trade of countries. In this context, an important index called The Economic Complexity Index (ECI) was created by Hidalgo and Hausmann to measure and compare the development of the country's economies and foreign trade. For this purpose, we test whether economic growth, foreign direct investment, Human Development Index, Economic Freedom Index cause economic complexity, vice versa in this study.

We analyze annual data for 1996-2017 for 22 countries called Transitional Economies using the panel causality method. Considering all of Transitional Economies, according to the Bootstrap Granger causality test results, we were not able to determine a Granger causality relationship between economic growth, foreign direct investment, Human Development Index, Economic Freedom Index, and Economic Complexity Index. However, when we consider country-specific variables defined as Transitional Economies, we identify both one-way and two-way Granger causal relationships in some countries between economic growth, foreign direct investment, Human Development Index and Economic Freedom Index, and Economic Complexity Index. Therefore, some Transitional Economies need to increase their level of economic complexity to get a larger share from global added value and increase their competitiveness. In this context, economic complexity needs to be taken more seriously by scientists, policymakers, and decision-makers.

Keywords: Economic Complexity, Human Development Index, Economic Freedom Index, Bootsrapt Panel Granger Causality, Transitional Economies.

JEL Classification: O10, O150, O43, C58, P20.

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1. Introduction

The economic complex is an area of research involving export competitiveness, intensification, and diversification. The ECI has filled a significant gap both in terms of a more precise understanding of the economic development levels of countries and in terms of a more obvious definition of foreign trade structures. Also, the legs of the concepts of foreign trade competitiveness and foreign trade concentration have stepped more firmly on the ground thanks to the ECI. However, human development and economic growth of per-capita income countries and macro socio-economic variable started to be more clearly and accurately estimated using this index.

Countries' income level is significantly connected to the mix of products that they export, as measured by their ECI. Countries with an income that is lower than what would be expected from their ECI tend to grow faster than those with an income that exceeds what would be expected from their current level of economic complexity. So, what countries export, as proxied by the ECI, is a solid leading indicator of economic growth (Bustos et al., 2012).

Hidalgo and Hausmann investigated the relationship between diversity and ubiquity in exports (Hidalgo and Hausmann, 2009). Studies show that if countries increase product sophistication, product diversity also increases. In other words, the simultaneous availability of manufacturing products, especially high added value, is becoming easier in many parts of the world. However, the production of these sophisticated products by limited countries around the world will also increase the country's competitiveness.

The competitiveness, development, and sustainability of countries' economies cannot be explained only by GDP, GDP per capita, total export amount, natural resources, and mineral wealth such as oil, natural gas, and gold. However, this index shows the level of specialization in technological products, whether the country is one of the few countries that export high-value-added products. In this context, it is clear to what extent the country diversifies its exports by looking at the ECI.

In this study, we aim to investigate the effects of the Human Development and Economic Freedom Index, economic growth, and foreign direct investment levels in determining the levels of economic complexity of Transitional Economies. In the first part of the study, we give information about the formation and structure of the ECI. In the second part, we present examples of literature on Economic Complexity. In the third part, we test whether economic growth, foreign direct investment, Human Development, and Economic Freedom Index cause economic complexity, vice versa with the panel causality analysis.

1.1 Economic Complexity Index

The main production and export source of most underdeveloped countries in the world is mining industries. As a result, the country's source of income and economic growth is also limited by the amount of reserves of the mentioned mines. Therefore, in order for these countries to increase their economic growth and development levels, they need to increase the productivity of the factors of production and make them sustainable. In addition, these countries need to diversify the products they produce and export. These countries will only be able to increase their level of development if they diversify in production and produce more innovative (high value added) products. The basic condition for producing more innovative products is the productive knowledge and skill level of the society. For example, products such as medical imaging devices, space shuttles are more innovative and require a higher level of knowledge. However, the production of products such as wheat, sesame requires much less knowledge. In this context, countries need to raise the level of productive knowledge in order to produce and export more innovative and sophisticated products (Yildirim, 2014).

The ECI shows the characteristics of production through exports. Higher index value means a more diversified export agenda and complex economy (Ferraz et al., 2017). The complexity of an economy is related to the multiplicity of useful knowledge embedded in it. Economic complexity is expressed in the composition of a country's productive output and reflects the structures that emerge to hold and combine the knowledge. Complex economies can weave vast quantities of relevant knowledge and increased economic complexity is necessary for a society to be able to hold and use a larger amount of productive knowledge. On the contrary, simpler economies have a narrow base of productive knowledge and produce fewer and simpler products (Hausmann et al., 2011). The more productive knowledge countries have, the more opportunities they have to recombine that knowledge in new ways to develop new products and products that are more complex (Yildirim, 2014).

Governance is important to allow individuals and organizations to cooperate, share knowledge and make more complex products, it should be reflected in the kind of industries that a country can support. Therefore, the ECI indirectly captures information about the quality of governance in the country (Hausmann et al., 2011). The economic complexity and its index (ECI) are important. Because, they don't only carry information about the productive structure of countries but also income, income distribution, human development, and future economic growth rate (Yildirim, 2014). At the same time, the economic complexity has been used successfully and extensively both for academic purposes and for policy and strategic management by policymakers and firms (Pietronero, Gabrielli, Kupers, & Tachella, 2017). For an economy to remain complex, individuals from diverse areas such as finance, marketing, technology, human resources, operations, law, etc. must interact and combine their knowledge (Ferraz et al., 2017).

Understanding economic complexity and creating quantitative measures that capture it can help to illuminate the path of economic development. Measurement of economic complexity and product sophistication provide us with objective metrics for country's level of industrial development, economic growth, income and can inform strategic decision making, as the sophistication of the products that a country currently exports, together with their location in the product space, are relevant for the future development of that country's economy (Hidalgo, 2009).

The positive effect of the level of economic complexity on economic growth in a country depends on the level of education and knowledge, institutional structure, know-how and technology level in the country. The level of economic complexity can be measured in different ways. These measurements can give results in different ways according to the information density in the economies. These metrics help to define the information density of economic activities internally from the data, and these internal definitions are simply linear techniques. For example, the original version of the ECI expresses economic complexity as the average complexity of countries exporting a particular product. This circular argument can be traced mathematically through linear algebra. It also has a solution as the eigenvector, which constitutes an intrinsic definition of economic complexity and information density (Albeaik, 2017).

According to Albeaik et al., this technical innovation helped separate these measures of economic complexity from other measures relying on exogenous definitions of knowledge intense activities. This innovation also helped these measures become adopted in other domains; for instance, they have been used to estimate the innovative capacity of cities using patent data (Albeaik, 2017).

Measurement of the ECI has some limitations. The most important point is that the index requires defining which countries export which products. However, it is not easy to do in a world where the markets for products and the size of economies vary by multiple orders of magnitude. The convention has been to consider as exports only the products that a country has a revealed comparative advantage in. Yet, this definition introduces a hard threshold that introduces noise around the boundary. The metric of the new economic complexity called ECI+ presented by Albeaik et al. avoids this limitation by using a continuous definition. ECI+ defines the complexity of an economy as the total exports of a country corrected by how difficult it is to export each product and by the size of that country's export economy. In addition, ECI+ provides consistent estimators for a wide variety of econometric specifications (OLS, Random Effects and Fixed Effects models).

Economic complexity is a measure of the knowledge in a society that gets translated into the products it makes. The most complex products are sophisticated chemicals and machinery. However, the least complex products are raw materials and unprocessed agricultural products. The economic complexity of a country depends on the complexity of the products it exports. A country is considered complex if it exports not only highly complex products but also a large number of different products. To measure the economic complexity of a country, it is calculated the average ubiquity of the exported products. Then, the average diversity of the products exported by a country is calculated (Hidalgo and Hartmann, 2016).

Diversification is related to the number of capabilities available in a country, albeit imperfectly. This is because countries producing the same number of products could be making goods that require different numbers of capabilities. In such cases, the diversification of countries would not be the most accurate estimator of the number of capabilities available in those countries, and it will be needed a measure of the number of capabilities required by a product to correct for this (Hartmann et al., 2016). Ubiquity is related to the number of countries that a product is connected to. This is equal to the number of links that this product has in the network (Hausmann et al., 2011).

According to Hidalgo (2009) and Hausmann et al. (2011) the ECI is calculated as follows:

$M_{cp} = 1 \ if \ RCA_{cp} \geq 1$

$M_{cp} = 0 \ if \ RCA_{cp} < 1$

The RCA (Balassa Index) is used to define a discrete matrix M_{cp} which is equal to 1 if country c has the RCA in product p and 0 otherwise. The matrix M_{cp} allows to define the diversity of a country and the ubiquity of a product, respectively, as the number of products that are exported by a country with revealed comparative advantage, and the number of countries that export a product with revealed comparative advantage.

$$Diversity = k_{c,0} = \sum_{p} M_{cp}$$

$$Ubiquity = k_{p,0} = \sum_{p} M_{cp}$$

Diversity and ubiquity are inversely related. A conspicuous fact of the structure of the network connecting countries to the products that they make or export is that poorly diversified countries export products that are, on average, exported by many other countries, whereas highly diversified countries make products which are made, on average, by fewer other countries (Hausmann and Hidalgo, 2011). Higher diversity means that a country has an export basket with many different products. In this condition, the country has a high amount of know-how. On the other hand, higher ubiquity means that a product is included in many countries' export baskets, and thus it needs fewer capabilities to be produced. However, both diversity and ubiquity are simple graph characteristics of the bipartite network represented by the adjacency matrix M which carry limited information about the productive structure of a country or complexity of a product as they do not take into account who else export the same products. As a result, a careful assessment is required if any of these simple measures are to be used for the explanation of economic phenomena (Stojkoski et al., 2016)

To generate a more accurate measure of the number of capabilities available in a country, or required by a product, it is needed to correct the information that diversity and ubiquity carry by using each one to correct the other. For countries, this requires us to calculate the average ubiquity of the products that it exports, the average diversity of the countries that make those products and so forth. For products, this requires us to calculate the average diversity of the countries that make them and the average ubiquity of the other products that these countries make. This can be expressed by the recursion (Hausmann et al., 2011):

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} k_{p,N-1} \tag{1}$$

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} k_{p,N-1} \tag{2}$$

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} \cdot \frac{1}{k_{p,0}} \sum_{c'} M_{c'p} \cdot k_{c',N-2} \tag{3}$$

$$k_{c,N} = \sum_{c} k_{c',N-2} \sum_{c'} \frac{M_{cp} M_{c'p}}{k_{c,0} k_{p,0}} \tag{4}$$

$$k_{c,N} = \sum_{c'} \tilde{M}_{cc'} k_{c',N-2} \tag{5}$$

Next, a matrix can be defined that connects countries exporting similar products, weighted by the inverse of the ubiquity of a product (to discount common products), and normalized by the diversity of a country:

$$\tilde{M}_{cc'} = \frac{1}{k_{c,0}} \sum_{p} \frac{M_{cp} M_{c'p}}{k_{p,0}} \tag{6}$$

Finally, the ECI is defined as:

$$ECI_c = \frac{\vec{K} - \langle \vec{K} \rangle}{stdev(\vec{K})} \tag{7}$$

where $\vec{K}_c$ is the eigenvector $\tilde{M}_{cc'}$ associated with the second argest eigenvalue (the vector associated with the largest eigenvalue is a vector of ones).

2. Literature Review

When the literature is examined, it is seen that scientific studies analyze the relationship between the ECI and the economic growth rates of countries and their national incomes per capita (Hausmann et al., 2011; Ferrarini and Scaramozzino, 2013; Albeaik et al., 2017; Mkrtchyan, 2016; Çeştepe and Çağlar, 2017).

Hausmann et al. analyze the economies of Ghana and Thailand between 1970 and 2010. They conclude that both competitiveness and economic complexity are important determinants of GDP and economic growth per capita in these countries (Hausmann et al., 2011). In addition, Ferrarini and Scaramozzino study 89 countries with different levels of development from different continents. Their study, which covers the period 1990-2009, examines the link between economic complexity and per capita income and economic growth (Ferrarini and Scaramozzino, 2013). Albeaik et al. analyze the period 1962-2014 in their studies on 250 countries (Albeaik et al., 2017). In the studies mentioned above, the authors reveal that economic complexity positively affects the variables of economic growth and GDP per capita. In addition, Gnutzmann-Mkrtchyan also conducts a similar study on Transitional Economies. They emphasize that the per capita income of countries that diversify their products in their exports also increases and that politicians should take economic complexity more seriously (Mkrtchyan, 2016). Çeştepe and Çağlar also analyze the relationship between the ECI values of 86 countries between 1982 and 2012 and the growth of per capita income using panel data method. The results show that there is a positive relationship between the two variables. However, rises in the ECI value increased the growth rate to a greater extent, especially in countries with a per capita income of less than \$ 20,395 (Çeştepe and Çağlar, 2017).

Herrera et al. (2020) compare the economic complexity index in the states of Brazil. Their studies for the period 1997-2017 emphasize that the index decreases or is stable in the south and southeastern states (Herrera et al., 2020). Sahdev (2016) determines a positive correlation between economic complexity and the increase in technology and productivity level in the economy. From the literature, we know that knowledge grows through re-combinatory processes where new knowledge builds on previous knowledge. Therefore, if economic complexity or the total amount of productive knowledge in the economy grows over time, there has to be a mechanism to foster complexity growth (Sahdev, 2016).

When we examine the literature, we see that there are studies that measure the relationship between the economic complexity index and the human development and income inequality of countries (Savenkov, 2015; Hartman et al., 2016; Çoban, 2020; Morais et al., 2021). For example, Hartmann et al. compare the income inequality and productivity structure of Latin American and Caribbean countries (LAC) with China and High-Performing Asian economies (HPAE) using the ECI in their study for 1962-2012. The results show that HPAE countries can increase the level of Economic Complexity and reduce income inequality through product diversification. Despite their recent successful policies, the LAC countries have not been able to increase their level of Economic Complexity, have not been successful in preventing income inequality, and have not created an efficient production structure and social structure (Hartmann et al., 2016). In addition, Savenkov analyzes the relationship between the ECI and government data openness of 94 countries by correlation analysis. The results show a moderate to strong correlation between the economic complexity index and government data openness (Savenkov, 2015). Çoban (2020) examines the relationship between economic complexity and human development. He examines the period 1993-2017 in his study on E7 countries. He does not find a cointegration relationship between the two variables in his study, in which he examines the long-term relationship between two variables using the Westerlund Panel Cointegration test. Dumitrescu-Hurlin panel causality analysis results show a one-way causality relationship between human development and economic complexity (Çoban, 2020). Morais et al. (2021) examine the relationship between economic complexity and income inequality in the states of Brazil. In their study, where they analyze the period of 2002-2014 with the panel regression method, they conclude that the mentioned relationship is at different levels in different states and that economic complexity is affected by regional development levels.

3. Empirical Analysis

3.1 Data

In this study, we analyze the causality relationship between ECI and Economic Growth Rate (GR), Economic Freedom Index (EFI), Human Development Index (HDI), and Foreign Direct Investment (FDI) for 22 countries[1] called Transitional Economies. We analyze annual data for the 1996-2017 period using the panel causality method. We obtained the ECI data we used in the study from the Atlas Media database (https://atlas.cid.harvard.edu/rankings, 2021) and the other variables from the World Bank database (https://data.worldbank.org/, 2021). We consider the net inflows of foreign direct investment as the share of GDP.

The model we use in the analysis is as follows:

$$ECI = f(GR, EFI, HDI, FDI)$$

Table 1 contains descriptive statistics for the variables we use in the model. We analyzed the 22 Transitional Economies discussed in the study over 21 years, and 462 observations are revealed. The average ECI for these economies is about 0.5. In the whole sample, the lowest ECI score is in Azerbaijan in 2012, while the highest score is in the Czech Republic's economy in the same year. During this period, the average economic growth rate of Transitional Economies is 4%. Bosnia and Herzegovina reached the highest economic growth rate after the civil war in 1996. The Transitional Economy most affected by the 2009 global crisis was Lithuania. Azerbaijan's economic freedom index doubled in 2017 from its lowest level in 1996. It is seen that the economic freedom index increased in 21 years in all Transitional Economies and reached the highest value in Estonia in 2017.

Similarly, the human development index shows an upward trend in all countries. However, the lowest level was calculated in Moldava in 1996 and the highest in Slovenia in 2017. The share of foreign direct investments in GDP is 5.5% on average for Transitional Economies.

[1] Albania, Azerbijan, Bosnia, Belarus, Bulgaria, Crotia, Czech Republic, Estonia, Georgia, Hungary, Kazakhstan, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russia, Slovakia, Slovenia, Ukraine

Table 1. Descriptive Statistics

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
ECI	462	0.479	0.606	-1.51	1.69
GR	462	4.106	6.382	-14.8	88.96
EFI	462	59.34	9.148	30	79.1
HDI	462	0.761	0.065	0.602	0.899
FDI	462	5.532	6.825	-15.7	55.08

We calculate the correlation matrix to evaluate a priori whether there are multiple linear regression problems among the variables used in this study. Table 2 contains the correlation matrix of the variables. According to the correlation matrix, it is seen that there is no multiple linear regression problem between variables. Accordingly, the highest correlation between the variables emerged between the economic freedom index and the human development index variables. The variable with the highest correlation with ECI is the human development index.

Table 2. Correlation Matrix of Variables

Variables	ECI	GR	EFI	HDI	FDI
ECI	1				
GR	-0.15	1			
EFI	0.148	-0.12	1		
HDI	0.562	-0.19	0.65	1	
FDI	-0.19	0.169	0.05	-0.13	1

3.2 Methodology

3.2.1 Testing for Cross-Sectional Dependence

Cross-section dependency has an important role in determining the causality relationship between economic variables in panel data models. Especially in Transitional Economies, a high degree of economic integration can increase the probability of spreading shocks occurring in a country. If the spillover effects of shocks between countries are not considered, the estimation results can be misleading. In a panel data study, Pesaran (2006) emphasizes that when an inter-country dependency is ignored, estimation results may be biased and thus the importance of testing inter-country dependency (Pesaran, 2006).

Cross-section dependency is necessary in determining the unit root test in panel data models and selecting the appropriate test model for panel causality analysis. For this reason, we first test whether there is cross-section dependency between countries. For cross-section dependency, we first apply the Lagrange Multiplier (LM) test developed by Breusch and Pagan (1980), which is frequently used in empirical studies.

The LM test primarily requires estimation of the panel data model:

$$y_{it} = \alpha_i + \beta_i x_{it} + \varepsilon_{it} \quad i = 1,2,\ldots N; t = 1,2,\ldots T \tag{8}$$

In this Equation (8), 'i' represents the cross-sectional size, 't' represents the time dimension, '' represents the vector of explanatory variables.

- H_0= There is no cross-sectional dependency
- H_a = There is a cross-sectional dependency

To test the null hypothesis from the LM test;

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} \acute{p}_{ij}^2 \tag{9}$$

$\acute{p}_{ij}^2$ is the sample estimate of binary correlations of error terms obtained from the least-squares estimator for each country. The LM test is valid in samples for relatively small N and sufficiently large T. When time (T) and country (N) dimensions are both large, it is possible to investigate whether there is a cross-sectional dependency with the CD_{LM} test developed by Pesaran (2004). CD_{LM} is as follows:

$$CD_{LM} = \left(\frac{N}{N-1}\right)^{1/2} \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} (Tp'^2_{ij} - 1) \sim N(0,1) \tag{10}$$

In cases where N large T is small, the CD_{LM} test may be subject to size distortions. Pesaran (2004) developed more general CD test statistics. The CD test is as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} p'^2_{ij} \backsim N(0,1) \tag{11}$$

Pesaran (2004) states that the mean of the CD test for fixed T and N is zero. At the same time, this test is resistant to heterogeneous dynamic models with multiple breaks in slope coefficients and/or error variances. However, the CD test may be weak in some cases where the binary correlations of the sample mean are zero.

In large panels *($T \to \infty$ ve $N \to \infty$)*, Pesaran et al. (2008) converted the LM test using the mean and variance of the LM statistics *(LM_{adj})*. In Equation (12), Pesaran et al. (2008) obtain the mean μ'^2_{Tij} and variance v'^2_{Tij} with respect to $(T-k)p'^2_{ij}$.

$$LM_{adj} = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} p'^2_{ij} \frac{(T-k)p'^2_{ij} - \mu'^2_{Tij}}{\sqrt{v^2_{Tij}}} \sim N(0,1) \tag{12}$$

3.2.2 Testing for Slope Homogeneity

Another important issue in panel data analysis is to decide whether the slope coefficients are homogeneous. In other words, it is necessary to take into account country-specific heterogeneity before making panel data estimates (Pesaran and Yamagata, 2008). In addition, the assumption of homogeneity for parameters cannot capture heterogeneity due to country-specific characteristics (Breitung, 2005).

It is possible to test the slope uniformity with the standard F test. Accordingly, the null hypothesis is tested as $H_0=\beta_i=\beta$ and the alternative hypothesis is tested as $H_a=\beta_i\neq\beta_j$ for all countries. However, the F test is valid for $T>N$ panel data, and the exogenous and error terms of the explanatory variables have fixed variances. Swamy (1970) developed a new slope homogeneity test by stretching the condition of constant variance of error terms. However, both the F test and Swamy's test require panel data models where N is smaller than T. Pesaran and Yamagata (2008) developed the delta test $(\tilde{\Delta})$ as a standardized version of the Swamy (1970) test for large panels.

The delta test is valid without any restrictions in cases of relative expansion of country (*N*) and time (*T*) dimension. In the delta test approach, the following modified version of the Swamy test is first calculated:

$$\tilde{S}=\sum_{i=1}^{N}(\hat{\beta}_i-\hat{\beta}_{WFE})'\frac{x_{i'}M_\tau x_i}{\tilde{\sigma}^2}(\hat{\beta}_i-\hat{\beta}_{WFE}) \tag{13}$$

The standardized version of the Swamy (1970) test (Equation (13)) by Pesaran and Yamagata (2008) is as follows:

$$\tilde{\Delta}=\sqrt{N}\frac{N^{-1}\tilde{S}-k}{\sqrt{2k}} \tag{14}$$

Errors are asymptotically distributed normally due to the large sample characteristics of the delta test . However, an adapted Delta test version of the statistic can be used under the normal assumption of errors in small samples. The adapted Delta test version accordingly is calculated as follows:

$$\tilde{\Delta}_{adj}=\sqrt{N}\left(\frac{N^{-1}\tilde{S}-E(\tilde{z}_{it})}{\sqrt{Var(\tilde{z}_{it})}}\right) \tag{15}$$

Hypotheses of the delta test:

- $H_0=\beta_i=\beta$ (Slope coefficients are homogeneous.)
- $H_a=\beta_i\neq\beta_j$ (Slope coefficients are heterogeneous.)

3.2.3. Unit Root Tests

We applied two different unit root tests to variables to investigate the integrated degrees of all countries in this study. Im et al. (2003) developed a unit root test based on the mean of independent unit root statistics for dynamic heterogeneous panels. Specifically, they propose a standardized t-bar test statistic based on Dickey-Fuller statistics augmented across countries.

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \sum_{j=1}^{p_i} \Delta y_{i,t-j} + \varepsilon_{it,} \quad i = 1,\ldots,N, t = 1,\ldots,T \tag{16}$$

In the unit root test, the null hypothesis is for all countries, and the alternative hypothesis is for all countries.

There are two steps to creating the T-bar test statistic. First, the average of the ADF t statistics for each country in the sample; secondly, the standardized t-bar[2] statistics are calculated. However, a potential problem with t-bar testing is that the test is no longer applicable when there is cross-section dependence. For this reason, the CIPS (Cross-sectionally augmented IPS) test, which was developed by Pesaran (2007) and took into account the cross-sectional dependency, was applied as the second unit root test to determine the degree of integration for variables with cross-section dependence.

In the test developed by Pesaran (2007), CADF test statistics values are calculated for all units that make up the panel. Then, the statistical values of the CIPS (Cross Sectionally Augmented IPS) test for the panel are calculated by taking the arithmetic mean of these tests. In addition, the CADF test results make the stationarity analysis for each country that makes up the panel, while the CIPS test results make the stationary analysis for the panel in general. It has also shown that it gives good results in small samples and in data sets where T and N are close to each other. Moreover, it is a powerful test in the presence of low cross-sectional dependency and even in small samples (Pesaran, 2007). The CIPS statistic can be derived as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + y_i \bar{y}_{t-1} + \sum_{j=0}^{\phi_i} \delta_{ij} \Delta \bar{y}_{i,t-j} + \sum_{j=1}^{\phi_i} \theta_{ij} \Delta y_{i,t-j} + \varepsilon_{it,} \tag{17}$$

$$CIPS = \left(\frac{1}{N}\right) \sum_{i=1}^{N} CADF_i \tag{18}$$

The CIPS test takes into account both cross-sectional dependency and residual series correlation. Pesaran (2007) reports critical values based on N, T using Equation (18) for various deterministic terms used in the equation.

3.2.4. Causali*ty* Analysis

The analysis suggested by Emirmahmutoglu and Kose (2011) was used in determining the causality test due to cross-sectional dependence and country-specific heterogeneity in the a priori tests. In this context, bootstrap panel causality analysis is used, which considers both cross-sectional dependency and slope heterogeneity. Here, it does not require a preliminary test for cointegration, except for determining the delayed structure. Variables can be used with level states.

Emirmahmutoglu and Kose (2011) causality test includes a Granger causality test procedure combined with Toda and Yamamoto's (1995) LA-VAR approach for

[2] For detailed information: "Im, K. S., Pesaran, M. H., and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of econometrics, 115(1), 53-74.

heterogeneous panels. Fisher test statistics were used to test the Granger causality hypothesis in heterogeneous panels. The Fisher test statistic (λ) is defined as follows:

$$\lambda = -2\sum_{i=1}^{N} \ln(\rho_i) \quad i = 1,\dots,N \tag{19}$$

According to Equation (19), ρ_i gives the probability values (p-value) of the Wald statistics values of each country.

This test statistic has a chi-square distribution with 2 N degrees of freedom. However, the limit distribution of Fisher's test statistic is no longer valid in the presence of cross-sectional dependency between countries. For this reason, Bootstrap Granger causality methodology is proposed for panel data models with cross-section dependency. In heterogeneous and variable panel data models with different degrees of integration, the delay level VAR model is as follows:

$$x_{i,t} = \mu_x^i + \sum_{j=1}^{k_i + d\max_i} A_{11,ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} A_{12,ij} y_{i,t-j} + u_{i,t}^x \tag{20}$$

$$y_{i,t} = \mu_y^i + \sum_{j=1}^{k_i + d\max_i} A_{21,ij} x_{i,t-j} + \sum_{j=1}^{k_i + d\max_i} A_{22,ij} y_{i,t-j} + u_{i,t}^y \tag{21}$$

$dmax_i$ is the maximum degree of integration suspected in the system for each i (country). Equations (20) and (21) are estimated without applying any parameter constraints, and then the null hypothesis in the causality relationship for each country is calculated by the Wald statistics for each country separately. The Fisher test statistic is then calculated by Equation (19). In Equation (20), causality from x to y is tested, whereas, in Equation (21), causality from y to x is tested. Equations (20) and (21) are tested with bootstrap methodology in case of cross-sectional dependency.

4. Empirical Results

We make preliminary tests to choose the appropriate estimation method in the study. First of all, we test the slope homogeneity specific to the variables used in the study. Accordingly, the null hypothesis that "slope coefficients are homogeneous" in both and slope homogeneity tests are rejected in all variables for both tests. Thus, there is country-specific heterogeneity in all variables used in the study.

Another important issue in panel data is the cross-section dependency test for variables. In the LM (Breusch-Pagan 1980) and CD_{LM} (Pesaran 2004) cross-sectional dependency tests, the null hypothesis that "there is no cross-sectional dependency" is rejected for all variables. According to the test results of CD (Pesaran 2004), the null hypothesis of "no cross-sectional dependency" for Gr, RFI, and HDI variables is rejected. According to the LMadj (PUY, 2008) test results, only the GR variable is rejected at the 10% significance level. When the test results are evaluated, the null hypothesis that "there is no cross-sectional dependency in all variables except the GR variable" cannot be strongly rejected. Test results are shown in Table 3.

Table 3. Cross-section dependence and homogeneity tests.

CD/Delta Tests	ECI	GR	EFI	HDI	FDI
LM (Breusch, Pagan 1980)	472.363*** (0.000)	354.175*** (0.000)	351.962*** (0.000)	296.605*** (0.000)	280.611*** (0.001)
CD_{LM} (Pesaran 2004)	12.802*** (0.000)	7.035*** (0.000)	6.927*** (0.000)	4.226*** (0.000)	3.445*** (0.000)
CD (Pesaran 2004)	0.271 (0.393)	-1.888** (0.030)	-2.590*** (0.005)	-2.341*** (0.010)	0.336 (0.368)
LM_{adj} (PUY, 2008)	-0.239 (0.594)	1.395* (0.081)	-1.517 (0.935)	-2.194 (0.986)	-0.193 (0.577)
$\tilde{\Delta}$	3.727*** (0.000)	1.350* (0.094)	1.865** (0.030)	1.827** (0.033)	3.695*** (0.000)
$\tilde{\Delta}_{adj}$	4.011*** (0.000)	1.437* (0.081)	2.007** (0.021)	1.966** (0.025)	3.976*** (0.000)

Notes: The numbers in parentheses are p-values. * Indicate significance at the 10% level., ** Indicate significance at the 5% level., *** Indicate at the 10% level.

Panel unit root tests can be differentiated according to the characteristics of the cross-section units that make up the panel. If there is no dependency between the horizontal sections that make up the panel, first-generation unit root tests are preferred. If there is dependence between horizontal sections, second-generation unit root tests are preferred. We do not prefer homogeneous panel unit root tests due to the detection of country-specific heterogeneity in all variables used in the study. Accordingly, we conduct two different panel unit root tests because the time dimension is short, and the cross-sectional dependency specific to the variables cannot be strongly rejected. We try to determine both panel data and country-specific integrated levels using IPS (Im et al., 2003) for traditional unit root tests and CIPS (Pesaran, 2007) for second-generation panel unit root tests. We show the panel unit root test results in Table 4:

Table 4. Panel unit root tests

Variables	IPS		CIPS	
	Constant	Constant and Trend	Constant	Constant and Trend
ECI	-1.281* (0.09)	-0.942 (0.17)	-2.001	-1.787
GR	-6.52***(0.00)	-5.08***(0.00)	-2.905***	-3.387***
EFI	-1.81***(0.03)	-2.06***(0.01)	-2.557***	-2.364
HDI	-0.42 (0.33)	-0.35 (0.36)	-2.098	-2.758*
FDI	-6.61***(0.00)	-5.48***(0.00)	-2.587***	-2.971***

Notes: CIPS test statistics crticial values are -2.40, -2.21 ve -2.10, respectively, at the significance level of %1, %5 and %10 for constant. For constant and trend , the critical values are -2.92, -2.73 ve -2.60, respectively at 1, 5 and 10 percent significance levels. The maximum lag lengths are selected using Schwarz information criterion.

The panel unit root test results show that the null hypothesis that “the series contains unit root” for both tests is not rejected for ECI and HDI variables. When the first difference is taken, the null hypothesis that “the series contains unit root” is rejected. Accordingly, the integrated level of ECI and HDI variables in the panel data was determined as I (1). The integrated level of GR, EFI, FDI variables was determined as I (0). In addition, since it occurs in a country-specific process, the highest level of suspected integration was determined by IPS (Im et al., 2003) and CADF (Pesaran, 2007) unit root tests. The highest level of integration (*dmax*) results of the countries in the VAR system is shown in appendix 1.

Slope homogeneity and cross-section dependency should be considered in determining the appropriate causality test method in panel causality analyses. For this reason, in the study, to analyze the causality relationship, we first analyze whether there is cross-sectional dependency and heterogeneity among Transitional Economies in models.

Table 5. Results of Granger causality test.

	GR→ECI			ECI→GR			EFI→ECI			ECI→EFI		
Country	**Lag (ki)**	**Wald**	**p-val**	**Lag (ki)**	**Wald**	**p-val**	**Lag (ki)**	**Wald**	**p-val**	**Lag (ki)**	**Wald**	**p-val**
Albania	3	4.946	0.176	3	7.196	0.066*	1	0.937	0.333	1	1.145	0.285
Azerbaijan	1	0.232	0.63	1	0.099	0.753	1	1.159	0.282	1	0.758	0.384
Bosnia	1	1.423	0.233	1	1.602	0.206	1	1.69	0.194	1	0.779	0.378
Belarus	2	7.795	0.02**	2	1.077	0.584	2	27.67	0.00***	2	2.031	0.362
Bulgaria	1	0.842	0.359	1	7.702	0.00***	1	2.805	0.094*	1	1.966	0.161
Croatia	1	2.87	0.09*	1	5.003	0.025**	3	0.998	0.802	3	12.995	0.00***
Czech Republic	1	0.6	0.438	1	5.221	0.022**	1	1.114	0.291	1	3.568	0.059*
Estonia	3	10.311	0.016**	3	7.172	0.067*	1	1.439	0.23	1	0.616	0.432
Georgia	1	9.162	0.00***	1	1.363	0.243	1	1.018	0.313	1	2.186	0.139
Hungary	1	0.1	0.751	1	1.057	0.304	2	1.604	0.448	2	18.737	0.00***
Kazakhstan	1	1.971	0.16	1	1.639	0.2	1	0.987	0.32	1	3.321	0.068*
Latvia	1	0.859	0.354	1	0.144	0.704	1	12.92	0.00***	1	2.014	0.156
Lithuania	1	0.977	0.323	1	0.402	0.526	2	1.159	0.56	2	5.09	0.078*
Macedonia	1	2.908	0.088*	1	0.052	0.819	1	0.638	0.424	1	0.515	0.473
Moldova	1	5.575	0.018**	1	0.575	0.448	2	2.42	0.298	2	0.636	0.727
Poland	1	1.622	0.203	1	1.586	0.208	1	0.172	0.678	1	0.334	0.563
Romania	1	0.321	0.571	1	3.811	0.051*	3	8.676	0.034**	3	11.903	0.00***
Russia	1	0.136	0.712	1	1.161	0.281	4	1.202	0.878	4	9.296	0.054*
Slovakia	1	1.333	0.248	1	5.129	0.024**	4	5.701	0.223	4	6.57	0.16
Slovenia	1	1.519	0.218	1	1.169	0.28	1	2.692	0.101	1	0.184	0.668
Ukraine	1	0.037	0.848	1	2.235	0.135	1	1.838	0.175	1	1.572	0.21

Panel Fisher	76.447	67.939	68.315	67.14
Asymptotic p-value	0.005***	0.007***	0.006***	0.007***
Bootstrap p-value	0.939	0.771	0.895	0.549
LM (Breusch and Pagan 1980)	558.22***	639.27***	558.22***	389.57***
	0.00	0.00	0.00	0.00
CDlm (Pesaran 2004)	16.992***	20.946***	16.992***	8.762***
	0.00	0.00	0.00	0.00
CD (Pesaran 2004)	2.056***	17.741***	2.056***	3.044***
	0.00	0.00	0.00	0.00
LMadj	16.125***	21.255***	16.125***	10.837***
	0.00	0.00	0.00	0.00
Delta_tilde	9.483***	3.664***	9.483***	9.580***
	0.00	0.00	0.00	0.00
Delta_tilde_adj	10.787***	4.169***	10.787***	10.898***
	0.00	0.00	0.00	0.00

Notes: The numbers in parentheses are p-values. * Indicate significance at the 10% level., ** Indicate significance at the 5% level., *** Indicate at the 10% level. Lag orders k_i are selected by minimizing the Schwarz Bayesian criteria. Critical values are based on 2000 bootstrap replications.

The slope homogeneity and cross-section dependency test results of the models are included in Table 3. Accordingly, the null hypothesis that “there is no cross-sectional dependency” is rejected in all models established. This shows that a shock that occurs in one of the Transitional Economies can spread to all Transitional Economies. According to the test results for the determination of slope homogeneity, the empty hypothesis that “slope coefficients are homogeneous in all models” is rejected. Thus, country-specific heterogeneity has been identified.

Table 6. Results of Granger causality test.

	HDI→ECI			ECI→HDI			FDI→ECI			ECI→FDI		
Country	**Lag (ki)**	**Wald**	**p-val**	**Lag (ki)**	**Wald**	**p-val**	**Lag (ki)**	**Wald**	**p-val**	**Lag (ki)**	**Wald**	**p-val**
Albania	2	1.667	0.434	2	17.103	0.00***	2	12.372	0.00***	2	0.522	0.77
Azerbaijan	1	0.094	0.76	1	1.936	0.164	2	0.306	0.858	2	0.483	0.785
Bosnia	1	0.326	0.568	1	0.522	0.47	1	0.212	0.645	1	0.147	0.701
Belarus	2	3.14	0.208	2	8.343	0.015**	1	0.929	0.335	1	0.355	0.551
Bulgaria	1	1.488	0.223	1	8.566	0.00***	1	0.67	0.413	1	1.373	0.241
Crotia	4	12.20	0.016**	4	4.012	0.404	1	0.599	0.439	1	2.544	0.111
Czech Re-public	4	1.806	0.771	4	52.131	0.00***	1	4.707	0.03**	1	0.944	0.331
Estonia	1	1.228	0.268	1	0.206	0.65	1	0.283	0.595	1	0.749	0.387
Georgia	2	22.02	0.00***	2	0.972	0.615	1	1.199	0.273	1	2.842	0.092*
Hungary	1	1.725	0.189	1	1.449	0.229	1	2.967	0.085*	1	5.507	0.02**
Kazakhstan	4	1.163	0.884	4	18.806	0.00***	1	0.688	0.407	1	6.56	0.01**
Latvia	1	1.373	0.241	1	5.782	0.016**	1	0.012	0.911	1	1.434	0.231
Lithuania	1	3.253	0.071*	1	1.436	0.231	1	6.278	0.012**	1	1.106	0.293
Macedonia	1	1.553	0.213	1	2.064	0.151	1	3.38	0.066*	1	0.001	0.978
Moldova	1	3.145	0.076*	1	0.26	0.61	1	0.716	0.397	1	0.119	0.73
Poland	1	3.035	0.081*	1	2.285	0.131	1	5.611	0.018**	1	1.234	0.267
Romania	2	8.134	0.017**	2	12.975	0.00***	1	4.688	0.03**	1	1.271	0.26
Russia	1	0.357	0.55	1	0.288	0.591	1	5.965	0.015**	1	9.286	0.00***
Slovakia	2	1.713	0.425	2	2.852	0.24	4	6.436	0.169	4	9.515	0.04**
Slovenia	1	0.182	0.67	1	2.694	0.101	1	5.2	0.023**	1	1.359	0.244
Ukraine	1	0.099	0.753	1	0.336	0.562	1	0.161	0.688	1	7.521	0.00***

Panel Fisher	44.74	114.93	58.812	68.319
Asymptotic p-value	0.358	0.000***	0.044**	0.006***
Bootstrap p-value	0.815	0.152	0.882	0.749
LM (Breusch and Pagan 1980)	558.22*** (0.00)	467.75*** (0.00)	558.22*** (0.00)	408.71*** (0.00)
CDlm (Pesaran 2004)	16.992*** (0.00)	12..577*** (0.00)	16.992*** (0.00)	9.670*** (0.00)
CD (Pesaran 2004)	2.056*** (0.00)	12.268*** (0.00)	2.056*** (0.00)	10.696*** (0.00)
LMadj	16.125*** (0.00)	9.252*** (0.00)	16.125*** (0.00)	9.001*** (0.00)
Delta_tilde	9.483*** (0.00)	3.779*** (0.00)	9.483*** (0.00)	4.574*** (0.00)
Delta_tilde_adj	10.787*** (0.00)	4.299*** (0.00)	10.787*** (0.00)	5.204*** (0.00)

Notes: The numbers in parentheses are p-values. * Indicate significance at the 10% level., ** Indicate significance at the 5% level., *** Indicate at the 10% level. Lag orders k_i is selected by minimizing the Schwarz Bayesian criteria. Critical values are based on 2000 bootstrap replications

Considering the preliminary test results and sampling structure, we use Toda-Yomamato's (1995) LA-VAR approach and Granger causality test in heterogeneous panels using the meta-analysis developed by Emirmahmuoğlu and Köse (2011) in this study. This test does not require a pre-test for cointegration, except for determining the delayed structure. Variables can be used with their level states without being noticed. Also, according to Monte Carlo simulation results, it shows that the LA-VAR approach is strong even if *N* and *T* are small, both under cross-sectional dependency and under cross-sectional independence. (Emirmahmuoğlu and Köse, 2011:875). In the panel data, when there is no cross-country dependency, the Asymptotic p-value is taken into consideration for Panel Fisher test statistics, and the Bootstrap p-value is taken into consideration in cases where there is inter-country dependency. The bootstrap p-value is used in panel data due to cross-country dependency. Accordingly, the causality analysis test results between ECI and the variables of GR, EFI, HDI, FDI are shown in Table 5 and Table 6.

According to the Granger causality analysis test results applied using the LA-VAR approach; both the null hypothesis "GR is not the Granger cause of ECI" and the null hypothesis "ECI is not the Granger cause of GR" cannot be rejected according to Bootstrap probability values between ECI and GR variables in Transitional Economies. Therefore, we cannot identify a causality relationship between ECI and GR between

1995 and 2017 when we take into account all Transitional Economies. When country-specific causality relationships are analyzed, the null hypothesis that "GR is not the cause of ECI" is rejected for Georgia at the 1% significance level, for Moldova, Estonia, and Belarus at the 5% significance level, and Croatia and Macedonia countries at the 10% significance level. On the other hand, the null hypothesis that "ECI is not the Granger cause of GR" is rejected at a 1% significance level in Bulgaria, at 5% significance level in Croatia, Czech Republic, and Slovakia, at 10% significance level in Romania, Estonia and Albania countries.

Considering all Transitional Economies between ECI and EFI variables, both the null hypothesis that "EFI is not the Granger cause of ECI" and the null hypothesis that "ECI is not the Granger cause of EFI" cannot be rejected according to Bootstrap probability values. When country-specific causality relationships are analyzed, the null hypothesis that "EFI is not the cause of ECI" is rejected for Latvia and Belarus at 1% significance level, Romania at 5% significance level, and Bulgaria at 10% significance level. The null hypothesis that "ECI is not the Granger cause of EFI" is rejected for Croatia, Hungary, and Romania at the 1% significance level and the Czech Republic, Kazakhstan, Lithuania, and Russia at the 10% significance level. We detect a bidirectional causality relationship between ECI and EFI variables in Romania according to the test results.

Considering all Transitional Economies; between ECI and HDI variables, both the null hypothesis that "HDI is not the Granger cause of ECI" and the null hypothesis that "ECI is not the Granger cause of HDI" cannot be rejected according to Bootstrap probability values. Therefore, we cannot identify a causality relationship between ECI and HDI between 1995 and 2017 when considering all Transitional Economies. When country-specific causality relationships are analyzed, the null hypothesis that "HDI is not the cause of ECI" is rejected for Georgia at 1% significance level, Romania at 5% significance level, Lithuania, Moldova, and Poland at 10% significance level. On the other hand, the null hypothesis that "ECI is not the Granger cause of HDI" is rejected at the 1% significance level in Albania, Bulgaria, Czech Republic, Kazakhstan and Romania, at the 5% significance level in Belarus and Latvia. Accordingly, we cannot detect a bidirectional causality relationship between ECI and HDI variables in Romania.

Finally, we examine the causality relationship between ECI and FDI variables in Transitional Economies, including all panel data. Both the null hypothesis that "FDI is not the Granger cause of ECI" and the null hypothesis that "ECI is not the Granger cause of FDI" between ECI and FDI variables cannot be rejected according to Bootstrap probability values. When considering all Transitional Economies, we cannot identify a causality relationship between ECI and HDI variables. When country-specific causality relationships are analyzed; the null hypothesis that "FDI is not the cause of ECI" is rejected for Albania at the 1% significance level, Czech Republic, Lithuania, Poland, Romania, Russia, and Slovenia at the 5% significance level, and

Hungary and Macedonia countries at the 10% significance level. On the other hand, the null hypothesis that "ECI is not the Granger cause of FDI" is rejected in Russia and Ukraine at the 1% significance level, Hungary, Kazakhstan, and Slovakia at the 5% significance level, and Georgia at the 10% significance level. In this case, we cannot detect a bidirectional causality relationship between ECI and FDI variables in Russia and Hungary.

5. Discussion and Results

In today's world, where global competition is increasing, developed countries constantly impose sanctions on other countries, and trade wars are raging, foreign trade competitiveness is perhaps the most important concept. The increase in the exports of the countries does not indicate that their competitiveness has increased. Because the content of the exported products in terms of added value, the diversity on the product and market basis is also important. In this context, the concepts of "economic complexity" and "economic complexity index", which encompass both product and global market diversity, and the rankings of countries are critical.

For this purpose, we analyze the determinants of the economic complexity levels of countries within the scope of Transitional Economies in this study. In this context, we investigate the causality relationship between the economic complexity index and economic growth, foreign direct investments, human development index, and economic freedom index of these countries. According to Bootstrap Granger causality test results, we cannot identify a Granger causality relationship between the variables in question and economic complexity when considering all Transitional Economies. However, we identify both one-way and two-way Granger causality relationships between economic growth, foreign direct investment, human development, and economic freedom index and economic complexity in some countries when we consider the variables specific to these countries.

Countries' global competitiveness, export diversification, in short, economic complexity index scores are determined not only by product type but by human capital. There is a need for a more educated workforce stock with a higher level of competence to produce more complex products. In this context, countries should build their economic policies, development, and foreign trade strategies based on qualified labor and products to improve their economic complexity and development levels.

The per capita income and economic growth rates of countries that succeed in product and market diversification in their exports are increasing. In other words, countries need to increase their level of economic complexity to get a larger share from global added value and increase their competitiveness. In this context, economic complexity needs to be taken more seriously by scientists, policymakers, and decision-makers.

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APPENDIX 1.

Table 1. Maximal Order of Integration

	ECI	GR	EFI	HDI	FDI
	dmax	**dmax**	**dmax**	**dmax**	**dmax**
Albania	1	1	1	2	1
Azerbaijan	1	1	0	1	1
Bosnia	1	0	1	1	1
Belarus	0	0	1	2	0
Bulgaria	0	0	1	1	0
Crotia	1	1	1	2	1
Czech Repub-lic	0	1	1	1	0
Estonia	1	0	0	1	1
Georgia	1	0	1	1	1
Hungary	0	1	1	1	0
Kazakhstan	2	1	1	1	1
Latvia	1	0	1	2	1
Lithuania	2	0	0	1	1
Macedonia	1	0	1	1	1
Moldova	2	0	1	1	1
Poland	1	0	1	1	1
Romania	1	0	1	1	1
Russia	1	0	1	1	1
Slovakia	0	0	1	1	0
Slovenia	1	0	0	1	1
Ukraine	1	0	1	1	1