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THE PARTICIPATION OF G20 COUNTRIES IN GLOBAL VALUE CHAINS AND THEIR EFFECTS ON ECONOMIC COMPLEXITY

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Abstract:

Today, it is almost impossible for countries to reach a higher level of growth and development just by maintaining their existing production and export structures. Therefore, there has been an increased interest recently in examining the concept of economic complexity in the literature. The foundational premise of these studies is that countries can achieve higher levels of development by producing and exporting more complex products. In this study examines how the integration of various G20 countries into the global value chain affects the economic complexity of these countries. Integration in the global value chain occurs in the form of backward and forward participation. In this context, the study establishes two separate models and explores how these connections affect economic complexity. According to the analysis, GVC participation has a positive effect on the level of economic complexity in China, Korea, Mexico and Türkiye. No significant effect was found in India, Indonesia and Saudi Arabia. In developed countries such as Germany, the US, Australia, France, the United Kingdom, Italy, Japan and Canada the effects of GVC participation were negative. A statistically significant negative effect was also found in developed countries such as Argentina, Brazil, South Africa and Russia.

Key words: *Economic Complexity Index, Global Value Chains, G20*

1. Introduction

Empirical studies on economic complexity have gained momentum as new data and methods have emerged in recent years. Similar to traditional approaches, an economic complexity approach focuses on the duality between economic inputs and outputs. However, unlike traditional approaches that treat total output as GDP or evaluate input types with factors such as capital, labor and information, economic complexity methods cover detailed data on thousands of economic activities by examining intangible factors of production and how they relate to thousands of outputs (Hidalgo, 2021).

Economic complexity measurements try to measure the amount of productive knowledge that countries have. The goal of these measurements is to create a map that captures how similar the products are in terms of their technical expertise and the information required to produce the product. This map, which is also referred to as the product space, depicts a product web and shows ways in which technical product knowledge can be developed. Accordingly, it defines the current production capacity of a country and its area of production by using data related to a country's exports of goods and services. Undoubtedly, increasing complexity increases the capacity to develop a variety of products with high added value, which in turn increases specialized product knowledge (Hausmann *et al*., 2013)

Specialized productive knowledge is the basis of the increase in the standard of living. An important reason for the enormous income gaps between countries is the large differences in specialized product knowledge that countries have accumulated. Not only is there a difference in the amount of product knowledge that countries have acquired, but the products produced are also different. The amount of knowledge required to produce a certain product may be significantly more than for other products. Therefore, the amount of knowledge required for production may vary from product to product. To take advantage of the benefits of technical product knowledge, this knowledge needs to be obtained through organizations and markets. More developed regions can obtain this within their market structures and use their diverse knowledge and specialization to produce a wider variety of better products (Hausmann *et al*., 2013).

Many countries from both the developed and developing world are striving to increase their share of the world economic market by increasing their competitiveness in global trade. One of the ways to achieve this is to increase the production and export of value-added goods. Countries with highly competitive markets are also observed to be the main exporters of the most complex and technical products. In general, there is a high level of economic complexity in developed countries, and these countries lead the world rankings in GDP and export revenues per capita. Thus, countries that are at the top of the economic complexity index such as Japan, Germany and the US are also leaders in world trade and in producing the most complex products for the global market. Today, economic complexity has become extremely important for national economies. The most obvious indicator of its growing priority in the global markets is the increasing investment in research and development and the constant efforts to make products more complex (Erkan and Yildirimci, 2015). Economic complexity reflects the amount of information embedded in an economy's production structure and helps explain differences in national income levels. However, more importantly, economic complexity drives future economic growth. Therefore, countries which have a high level of economic complexity have obtained significant economic gains (Hausmann *et al*., 2013).More specifically, complex products provide countries with a global competitive advantage and significantly raise the level of their overall earnings (Erkan and Yildirimci, 2015).

The increasing importance of the concept of economic complexity has created a need for more refined research in this area. This study examines the level of economic complexity by using an important tool called the economic complexity index (ECI). The study also explores the variables which affect ECI. The reason for this focus is that ECI is an important measure of the level of development of a country's economic production structure and it is also considered a predictive component of future competitive advantage

(Ivanova *et al., 2017*). In this context, this study examines how foreign direct investment (FDI), indirect value added (FVA), gross capital formation (GFC), foreign value added (DVX) and GDP per capita affect ECI. Therefore, two models are used in the study and the effect of participating in the global value chains on the product knowledge and know-how of the G20 countries is examined. The structure of the study is as follows: First, the conceptual framework of ECI and the structure of global value chains (GVCs) are outlined, and then the literature summary is presented. Afterwards, the methodology this study uses is explained and the findings are presented.

2. Economic Complexity Index

The quantity of specialized knowledge available in an economy can be measured by data that gauge the complexity of the products that are exported by that economy. This approach, which is expressed as a measurement of economic complexity, is also highly successful in predicting the future growth of economies (Albeaik *et al.*, 2017). Increasing economic complexity is required to retain and use larger amounts of specialized product knowledge. In this sense, economic complexity is a measure of how much product knowledge a society mobilizes and it expresses the composition of a country's production output. In other words, economic complexity reflects the emerging structures of an economy in the ways it maintains and brings together its knowledge (Hausmann *et al.*, 2013). As a measure of economic complexity, the economic complexity index indicates the complexity of an economy as the average complexity of its products. The complexity of its products is expressed in terms of the average diversity of a country's exports (Albeaik *et al.*, 2017).

ECI links the production structure of a country to the amount of knowledge and know-how contained in the goods it produces. It can be expressed as follows: M_{cp}, is a matrix where rows represent different countries and columns represent different products; If country c produces product p, the corresponding element of the matrix is equal to 1, if not, it is equal to 0. Diversity and ubiquity can be measured by addition over the rows or columns of the matrix. Accordingly (Hausmann *et al.*, 2013);

$$Diversity = k_{c,0} = \sum_{p} M_{cp} \qquad (1)$$

$$Ubiquity = k_{p,0} = \sum_{c} M_{cp} \qquad (2)$$

However, to more accurately measure the amount of production capabilities available in a country or that are required for a product, it is necessary to calculate the average ubiquity of exported products and the average diversity of countries which produce these products. Starting from Equations (1) and (2);

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{c,p} . k_{p,N-1} \qquad (3)$$

$$k_{p,N} = \frac{1}{k_{p,0}} \sum_{c} M_{c,p} . k_{c,N-1} \qquad (4)$$

By placing equation (4) in equation (3);

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{c,p} \cdot \frac{1}{k_{p,0}} \sum_{c'} M_{c',p} \cdot k_{c',N-2} \qquad (5)$$

$$k_{c,N} = \sum_{c'} k_{c',N-2} \sum \frac{M_{c,p} M_{c',p}}{k_{c,0} k_{p,0}} \qquad (6)$$

The equation can be rewritten as:

$$k_{c,N} = \sum \widetilde{M}_{cc'} k_{c',N-2} \qquad (7)$$

The expression $\widetilde{M}_{cc'}$ in equation (7) is

$$\widetilde{M}_{cc'} = \sum \frac{M_{cp} M_{c'p}}{k_{c,0} k_{p,0}} \qquad (8)$$

Equation (7) is valid in case: $k_{c,N} = k_{c,N-2} = 1$. This corresponds to the eigenvector of $\widetilde{M}_{cc'}$ which is associated with the largest eigenvalue. However, this eigenvector is not helpful as it is a vector of '1s'. Therefore, by creating an eigenvector associated with the second largest eigenvalue, the eigenvector that captures the largest variance in the system is obtained and thus the value of economic complexity is reached. Accordingly, *ECI* in equation (9) below (Hausmann *et al.*, 2013);

$$ECI = \frac{\vec{K} - < \vec{K} >}{stdev(\vec{K})} \qquad (9)$$

$\vec{K}$ is the eigenvector of $\widetilde{M}_{cc'}$ which is associated with the second largest eigenvalue, “< >” indicates the mean and “stdev” expresses standard deviation.

ECI combines the number of products a country exports (diversity) and the number of countries exporting that product (the ubiquity of its products) and thus measures the complexity of that country's production structure. The logic behind ECI is that sophisticated economies are diverse and, on average, they export products which have low ubiquity because only a few different countries can produce these sophisticated products. In that case, less developed economies are expected to produce and export more ubiquitous products. ECI highlights this variation in the product diversity of countries and the ubiquity of its products (Hartman, 2017).

The ubiquity and diversity of a country’s exports are two basic concepts used to measure whether a country is economically complex. In ECI, export-related data is gathered and a country's economic system is analyzed on two dimensions: (i) the 'diversity' (i.e. the number of types) of products that are exported and (ii) the 'ubiquity' of the products that are exported (i.e. the number of countries exporting similar products). The least complex countries at the bottom of the ECI ranking are those that export a minimal variety of products (that is, their exports are not highly diversified), and the products they export are also exported by many other countries (Breitenbac *et al.*, 2021). On the other hand, economies can also produce rare and complex goods that are not ubiquitous. These are cases where there exists an advanced production structure. Rare and complex goods are products that have high technological content and are therefore difficult to produce (such as airplanes) or are very scarce in nature (such as diamonds). At this stage, Hidalgo et al. use an ingenious technique that compares the ubiquity of a product produced in a particular country with the diversity of the exports in the countries that produce and export this product. Thus, economic complexity means an economy whose products are not ubiquitous and that maintain high levels of product diversity. Therefore, countries that export a diverse set of ubiquitous goods (e.g. fish, meat, fruit) do not show high economic complexity since they export what many other countries already produce (Gala *et al.*, 2018)

3. Global Value Chain

In the last 30 years, the increasing importance of GVCs has fragmented the production process. This has caused trade in intermediate goods to grow faster than trade in final goods. A GVC can be defined as a network of interconnected production stages for the production of goods and services across international borders. A GVC generally involves combining imported intermediate goods and domestic goods and services into exported products for use as intermediate goods in the next stage of production. Participating in GVCs and developing more concentrated and specialized production creates comparative advantages and subtle niches and it offers the ability to obtain greater benefits from economies of scale and scope. Considering the positive relationship between productivity and growth in per capita income, making use of GVCs is seen as a way for emerging economies to get out of the middle-income trap and for low-income economies to achieve sustainable strong growth in the medium term (IMF Paper, 2015).

GVCs effectively increase productivity and long-term growth and the research on GVCs shows that they offer significant opportunities for technology transfer and knowledge diffusion. It also shows that these opportunities are particularly advantageous for domestic companies. GVCs bring together the knowledge of local companies with foreign suppliers, they encourage greater diversity in industry and provide higher quality products and services in international commerce. By making use of existing foreign knowledge and technology, domestic firms will also increase their capabilities for innovation and thus their productivity. However, the existence of policies that encourage productivity is of course very important to increase competitiveness in the long run. Therefore, understanding how participation in GVCs affect productivity can help shape and guide these policies (IMF Paper, 2020).

Participation in GVCs increase efficiency and the companies that benefit the most are typically firms that export their products or large companies. The impact of participating in a GVC is understood in two ways, upstream and downstream activities. A standard GVC covers a number of production stages, from the concept of upstream products and mid-assembly production to sub-branding and marketing. To understand where an economy is along a GVC, the concepts of upstream and downstream are used. According to the scale developed by Fally (2012), the farther a country is along the production chain from final demand indicates that a country is upstream (e.g. producer of raw materials). The shorter a country is from final demand indicates that a country is downstream (e.g. customer service). While large firms and highly productive firms benefit more from upstream-type industries within a GVC, they tend to benefit less from participating in downstream industries in a GVC (IMF Paper, 2015; 2020).

GVCs include those involved in the production of a good or service which covers the purchasing, distribution and after-sales activities in the production process. To determine an economy's participation and position in GVCs the concepts of Foreign Value Added in Exports (FVA) and Indirect Domestic Value Added in Exports (DVX) are used. FVA is the added value in exports, the outputs of which are produced by foreign industries, and it specifically refers to backward participation. The added value in exports whose outputs are produced by domestic industries is called domestic value added in exports (DVA). DVX is the portion of domestic added value which becomes an export for other countries and is considered forward participation. The GVC Participation Index is obtained by dividing the total value of FVA and DVX by gross exports. The index is an important indicator that reflects how various sectors are connected through forward and backward participation (UNCTAD, 2019).

4. Literature Review

Due to its increasing importance in recent years, many studies that examine the relationship between ECI and various economic indicators have appeared in the literature. For this study, the research that analyzes the relationship between ECI and foreign trade indicators is significant and it is summarized in the literature review section.

A study by Akın and Güneş (2018) investigated the relationship between the economic complexity index and the foreign trade index for Türkiye between 1982 and 2016. The authors conducted their analysis by including a variable they established for the real effective exchange rate index within their model. According to the results of the analysis, the authors found a positive and significant relationship between all three variables. Furthermore, they found a unidirectional causal relationship from both the economic complexity index and the real effective exchange rate to the terms of trade.

Sepehrdoust, Davarikish, and Setarehie's (2019) study analyzed the effects of trade liberalization on economic complexity. The authors decided to analyze the developing countries of the Middle East and used the data between 2002 and 2017 for their study. According to their findings, a positive shock in trade liberalization, FDI and gross fixed capital formation causes an increase in economic complexity. In addition, a positive shock in imports of intermediate and capital goods initially increases economic complexity, but these effects are not permanent. After about three years, the effects were found to gradually decrease.

Şeker (2019), in his study, examined the effects of exports of high-tech products, technological development and capital investments on the economic complexity index between 1989 and 2017 in Türkiye. The author's analysis found a long-term relationship between all three variables. Accordingly, while there is a bidirectional causal relationship between economic complexity and high-tech exports and technological development, there is a one-way causal relationship between economic complexity and capital investments.

A study by Şeker and Şimdi (2019) examined the interaction of exports and the range of exported products between Türkiye and Central Asia and the Turkic Republics. The authors, using the economic complexity index for this purpose, investigated how the export levels of these countries and the economic complexity index scores interacted with each other. In other words, they tried to show how exports affect economic complexity. More specifically, they analyzed the possible relationships between the mutual trade volume of these countries and their scores on the economic complexity index. Accordingly, they found a long-term relationship between Türkiye's exports to these countries and their economic complexity index scores. The study found that an increase in the trade volume between Türkiye and these countries mutually increases the export of complex products.

Recently, Canh and Thanh (2022) investigated the dynamics of export diversification, economic complexity and economic growth cycles. The study, which analyzed the economies of 70 countries between 1996 and 2014, obtained the following findings: There is bidirectional Granger causality between economic complexity and export diversification, and both variables significantly affect each other. Moreover, the study determined a one-way Granger causality from economic complexity to cycles of economic growth and observed a negative effect of economic complexity on the cycles of economic growth.

Gnangnon (2022,a) discussed in his study the effect of economic complexity on the diversity of exports in the service sector. The author analyzed 109 countries between 1985 and 2014 and found that the level of economic complexity and the diversity of exports in the service sector are related. The study observed that the degree of positive effects between the two variables is higher in high-income countries than in developing countries. Another important finding of the study is related to the inflow of foreign direct investment (FDI). Accordingly, as the share of net FDI inflows in GDP increases, the economic complexity variable has a higher positive effect on the diversity of service-related exports.

In another recent study, Gnangnon (2022,b) investigated the effect of non-reciprocal trade preferences on economic complexity for the beneficiary country. The study analyzed 110 countries during the period between 2002 and 2018. According to the findings, non-reciprocal trade preferences positively affect the economic complexity of the beneficiary country. This result arises when the beneficiary country's share of exports within the scope of non-reciprocal trade preferences is very high in terms of total goods exported.

5. Research Design and Methodology

5.1. Empiricial Model

In addition to the initial explanations of Hausmann et al. (2011) above, it is important to clarify the relationship between specialization, diversification and economic complexity. Balland et al. (2022) outline the types of product knowledge underlying economic complexity under three headings: embodied knowledge in tools, codified knowledge in texts, and tacit knowledge or general know-how. Balland et al. (2022) draw attention to the limitations in the levels of know-how knowledge in certain societies and they state that these levels are constrained by the division of tacit knowledge among the individuals within that society. In other words, an increase in know-how depends on the level of specialization in the society. If individuals obtain more specialization, then firms and countries become more diversified. Ultimately, as a result, societies have more diversified knowledge (Balland *et al*., 2022).

Based on this understanding of ECI, the empirical model used in this study examines how participating in global value chains affects this type of know-how knowledge for the G20 countries. Hence, the following models are used to examine the effect of some variables on the economic complexity level.

$$ECI_{it} = \beta_0 + \beta_{1i} FVA_{it} + \beta_{2i} FDI_{it} + \beta_{3i} GCF_{it} + \beta_{4i} PCGDP_{it} + \varepsilon_{it} \qquad (\boldsymbol{Model\ 1})$$

$$ECI_{it} = \beta_0 + \beta_{1i} DVX_{it} + \beta_{2i} FDI_{it} + \beta_{3i} GCF_{it} + \beta_{4i} PCGDP_{it} + \varepsilon_{it} \qquad (\boldsymbol{Model\ 2})$$

The main explanatory variables which affect ECI are FVA and DVX in these models. Since the flow of goods and services within global value chains cannot be reflected in conventional measures of international trade, some measurements have been developed to solve this issue. Hence, gross export has been broken down into domestic value-added (DVA) and foreign value-added (FVA) for exports. Afterwards, DVX is obtained by breaking down DVA further into domestic value-added for exports to a third country which, in turn, also export the product. DVX refers to the intermediate goods which are sent to another country that also reexports the product themselves. These measurements enable us to examine global value chains in terms of the related links between buyers and sellers. Accordingly, DVX (domestic value-added inputs sent to third countries for further processing and export) represents what is called forward GVC participation. FVA represents backward GVC participation and applies to the buyer perspective in the global value chains. In other words, it refers to situations where an economy imports intermediate inputs to produce its own exports (Riera, n.d.). The symbols on these variables may differ depending on the effect of their participation in global value chains.

Apart from these, some control variables have been added to our models. Foreign direct investment is known to provide technology transfer to the host country through productivity spillovers (Rahman and Inaba, 2021). Therefore, we include an FDI variable in order to test the presence of the spillover effect. Gross capital formation is the other control variable and it is measured by adding up the expenditures related to the fixed assets (factory, machinery and equipment purchases, construction of roads, railways, schools, industrial buildings, offices, etc.) and the net changes in the inventories (World Bank, 2022). The short-term effects of these investments on the economy may be positive, neutral or negative depending on which industry is invested. However, gross capital formation is expected to enhance technology (Stojkoski and Kocarev, 2017). Finally, we added GDP per capita as a control variable. An increase in GDP per capita refers to an increase in wealth. However, the effect of GDP per capita on the economic complexity level depends on how this wealth is distributed throughout the society. If it is distributed equally in the society and used to enhance human capital (via increasing expenditures on education, health, etc.), then the effect of GDP per capita is expected to be positive. Otherwise, this effect may be negative.

Table 1. Variables, definitions, data sources and a statistical summary

Variable	Explanation	Data Source	No. of Obs.	Mean	Std. Dev.
ECI	Economic complexity index	Harvard - Atlas of Economic Complexity	418	0.8869	0.8505
DVX	Logarithm of foreign value added	The UNCTAD-Eora Global Value Chain (GVC) database	418	13.8452	0.5309
FVA	Logarithm of indirect value added	The UNCTAD-Eora Global Value Chain (GVC) database	418	13.6919	0.6085
FDI	Foreign direct investment, net inflows (% of GDP)	World Bank	418	2.1817	1.8772
GCF	Gross capital formation (% of GDP)	World Bank	418	24.2528	6.6146
PCGDP	Logarithm of GDP per capita (constant 2015 US$)	World Bank	418	4.1556	0.4766

In Table 1, the set of variables for Model 1 and Model 2 is shown. The analysis covers the period from 1997 to 2018. Each variable contains 418 observations, meaning the data have no loss of any observations and a balanced panel data exists. Moreover, the value of the standard deviation remains low, which indicates a modest level of instability in the variables.

5.2. Econometric Methodology

In econometric analysis, testing the stationarity of the series is important in order to avoid the issue of spurious regression. In a panel data analysis, testing the presence of cross-section dependence in a series is required in order to decide which unit root test to apply. First-generation unit root tests are utilized when there is a lack of cross-section dependence while second-generation unit root tests are utilized in the case of cross-section dependence (Brooks, 2014). After detecting whether there is cross-section dependence (see Appendix A), the Pesaran (2007) CADF test was applied as a second-generation test, to determine the stationarity of the series. Afterwards, Swamy's random coefficient panel regression methodology was applied to the stationary series. In this section of the study, the methodologies that are followed are introduced in order to examine the models.

5.3. Panel Unit Root Tests

The Pesaran (2007) CADF test can be used in the case of both T>N and N>T. The Monte-Carlo simulation results also revealed that the CADF test provides satisfactory results even for small N and T values. Based on the assumption that y_{it} is generated according to the simple dynamic linear heterogeneous panel data model, Pesaran used the following model (Pesaran, 2007):

$$y_{it} = (1-\phi_i)\mu_i + \phi_i y_{i,t-1} + u_{it}, \quad i = 1, \ldots, N; \quad t = 1, \ldots, T \qquad (10)$$

error term u_{it} has the single factor structure as follows (Pesaran, 2007):

$$u_{it} = \gamma_i f_t + \varepsilon_{it} \qquad (11)$$

In Eq. (11), f_t represents the unobserved common effect, and e_{it} is the individual-specific error. By rewriting the Eq. (10) and Eq. (11), we obtain the following equation (Pesaran, 2007):

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i f_t + \varepsilon_{it} \qquad (12)$$

Where $\alpha_i = (1-\phi_i)\mu_i,\ \beta_i = -(1-\phi_i)\ and\ \Delta y_{it} = y_{it} - y_{i,t-1}$.

Now, the unit-root hypothesis, $\phi_i = 1$, can be expressed as $H_0: \beta_i = 0$ for each i, meaning there is a unit-root for all cross-section units. The heterogeneous alternative hypothesis is (Pesaran, 2007):

$$H_1: \beta_1 < 0, \quad i = 1, 2, \ldots, N_1, \ \beta_i = 0, \quad i = N_1 + 1, N_1 + 2, \ldots, N$$

As a result of the CADF test, test statistics are obtained for both overall panel and cross-section units. The test statistics for the overall panel (CIPS) are obtained by taking the average of the test statistics for each cross-section unit (Pesaran, 2007):

$$CIPS = N^{-1} \sum_{i=1}^{N} t_i^*(N,T) \qquad (13)$$

5.4. Swamy's Random Coefficient Panel Regression Estimator

When variations exist in population depending on time or unit, then it does not make sense to examine this structure with fixed coefficient models. As an alternative to this fixed coefficient model, the random coefficient model has been developed by Swamy (1970). The random coefficient model allows coefficients to differ from cross-section unit to cross-section unit or from time to time. Hence, the number of parameters to be estimated increases with this approach (Hsiao and Pesaran, 2004). Swamy (1970) described random coefficient models with the following matrix notation (Poi, 2003):

$$y_i = X_i \beta_i + \epsilon_i \qquad (14)$$

In Eq. (14), $i = 1,2,\dots,N$ refers to cross-section units, y_i refers to the observation vector with the $T_i x 1$ dimension, X_i refers to the non-stochastic variable vector with the $T_i x k$ dimension, β_i refers to the parameter vector with the $kx1$ dimension, and ϵ_i is the error term with a zero average and $\sigma_{ii} I$ variance. β_i, which is specific to each cross-section unit, is related to β, which is a joint parameter vector. This relation is represented with the following formula (Poi, 2003):

$$\beta_i = \beta + v_i \qquad (15)$$

Swamy (1970) stated that β_i parameter vectors must be tested before estimates of the model are calculated to ensure the heterogeneity of the cross-sections. The null hypothesis of this parameter constancy test refers to homogeneity and is written as follows in Eq. (16):

$$H_0' : \beta_1 = \beta_2 = \cdots = \beta_N = \beta \qquad (16)$$

If the null hypothesis cannot be rejected, then the relationships between the variables are represented with a single coefficient vector. However, if the null hypothesis is rejected, then it is not possible to pool the data and estimate a unique coefficient vector that represents the relationships between the variables. The statistics used to test parameter constancy are represented with the formula in Eq. (17) (Swamy, 1970):

$$H_\beta = \sum_{i=1}^{N} \frac{(b_i - \hat{\beta})' X_i' X_i (b_i - \hat{\beta})}{s_{ii}} \qquad (17)$$

where $b_i = (X_i' X_i)^{-1} X_i' y_i$ and $\hat{\beta} = \left[\sum_{i=1}^{N} \frac{x_i' x_i}{s_{ii}}\right]^{-1} \sum_{i=1}^{N} \frac{x_i' x_i}{s_{ii}} b_i$.

5.5. Empirical Results

First, the cross-section dependence test was used to select the unit-root test. Based on the cross-section dependence tests (see Appendix A), the null hypothesis of no cross-section dependence for all variables was rejected. Therefore, the second-generation unit-root test for all variables was required. The results of the Pesaran (2007) CADF unit root test are summarized in Table 2.

Table 2. Pesaran (2007) CADF unit-root test

Variables	CIPS statistics
ECI	-3.29***
DVX	-3.674***
FVA	-4.571***
FDI	-3.349***
GCF	-2.819*

PCGDP	-2.626
Δ PCGDP	-3.647***

*** and * refer to 1% and 10% levels of significance, respectively.

Accordingly, all variables, except PCGDP, are stationary at level. The PCGDP variable becomes stationary when the first difference is taken. As mentioned in the methodological summary, stationarity is important in order to avoid issues of spurious regression. For this reason, the difference of the PCGDP variable was taken before estimating the regression coefficient. However, it is also required to test the homogeneity of the coefficient vectors before the Swamy estimation. The parameter constancy test results for both models are given in Table 3.

Table 3. Parameter constancy test

Test statistics	Model 1	Model 2
χ^2	21731.65***	21606.06***
p-value	(0.000)	(0.000)

*** refers to a 1% significance level.

Based on the p-values in Table 3, the null hypothesis of homogeneity is rejected. Therefore, since the coefficient vectors are heterogeneous, we estimated the coefficient vectors separately for each of the cross-section units. The estimated results for Model 1 are summarized in Table 4.

Table 4. Random coefficient panel regression estimation for model 1

Dependent variable: ECI				
Countries	FVA	FDI	GCF	PCGDP
Germany	-0.567*** (0.000)	0.001 (0.883)	-0.029*** (0.000)	2.887** (0.036)
United States	-0.673*** (0.000)	0.039* (0.053)	-0.006 (0.443)	5.544*** (0.000)
Argentina	-0.223** (0.018)	0.003 (0.884)	0.003 (0.702)	0.707 (0.494)
Australia	-0.790*** (0.000)	-0.009 (0.450)	0.018* (0.060)	2.573** (0.023)
Brazil	-0.686*** (0.000)	0.000 (0.983)	0.010 (0.147)	3.017** (0.015)
China	0.842*** (0.000)	-0.078*** (0.000)	0.000 (0.997)	-2.495* (0.055)
Indonesia	0.133 (0.451)	-0.013 (0.277)	-0.006 (0.323)	2.928*** (0.000)
France	-0.347***	-0.006	-0.023***	0.391

	(0.000)	(0.580)	(0.003)	(0.749)
South Africa	-0.533*** (0.000)	-0.010 (0.388)	0.017** (0.040)	1.800 (0.160)
South Korea	0.819*** (0.000)	-0.047** (0.041)	-0.028*** (0.003)	0.235 (0.858)
India	0.032 (0.598)	0.002 (0.931)	-0.008* (0.093)	-1.746 (0.208)
United Kingdom	-1.013*** (0.000)	0.004 (0.366)	-0.029*** (0.000)	3.223** (0.014)
Italy	-0.132*** (0.000)	0.000 (0.980)	-0.015*** (0.000)	2.297*** (0.000)
Japan	-0.682*** (0.000)	0.092*** (0.000)	-0.007 (0.426)	6.420*** (0.000)
Canada	-0.768*** (0.000)	0.008 (0.245)	-0.016** (0.053)	2.778** (0.023)
Mexico	0.687*** (0.000)	0.023 (0.390)	-0.024*** (0.005)	-1.592 (0.279)
Russia	-0.878*** (0.000)	-0.008 (0.698)	0.000 (0.971)	1.494 (0.166)
Saudi Arabia	-0.048 (0.867)	-0.068*** (0.003)	-0.006 (0.547)	-0.880 (0.527)
Türkiye	0.711*** (0.000)	0.003 (0.830)	-0.001 (0.820)	-0.362 (0.568)

***, ** and * refer to 1%, 5% and 10% levels of significance, respectively.

As mentioned above, Model 1 is built to examine how backward participation in global value chains affects the economic complexity level of an economy. Accordingly, FVA has a negative effect in Germany, the US, Argentina, Australia, Brazil, France, South Africa, the United Kingdom, Italy, Japan, Canada and Russia. However, FVA has a statistically significant positive effect on the economic complexity level of China, South Korea, Mexico and Türkiye. There was no significant effect found for India, Indonesia and Saudi Arabia.

When it comes to control variables, FDI has a statistically significant positive effect on ECI in the US and Japan while it has a negative effect in China, South Korea and Saudi Arabia. GCF has a positive effect in Australia and South Africa while it has a negative effect on ECI in Germany, France, South Korea, India, the United Kingdom, Italy, Canada and Mexico. PCGDP has a positive effect in Germany, the US, Australia, Brazil, Indonesia, the United Kingdom, Italy, Japan, Canada while it has a negative effect in China.

Table 5. Random coefficient panel regression estimates for model 2

Dependent variable: ECI				
Countries	DVX	FDI	GCF	PCGDP
Germany	-0.651***	-0.005	-0.022**	2.517*

	(0.000)	(0.554)	(0.015)	(0.077)
United States	-0.977*** (0.000)	0.008 (0.618)	-0.004 (0.630)	5.315*** (0.000)
Argentina	-0.246** (0.048)	0.006 (0.718)	0.005 (0.617)	0.452 (0.685)
Australia	-0.792*** (0.000)	-0.002 (0.840)	0.026** (0.012)	1.169 (0.305)
Brazil	-0.644*** (0.000)	-0.012 (0.465)	0.017** (0.037)	2.379* (0.081)
China	0.721*** (0.000)	-0.029** (0.039)	0.008 (0.153)	-2.555** (0.042)
Indonesia	0.103 (0.443)	-0.013 (0.293)	-0.007 (0.296)	2.756*** (0.003)
France	-0.401*** (0.000)	-0.008 (0.451)	-0.016 (0.106)	-0.820 (0.506)
South Africa	-0.515*** (0.000)	-0.003 (0.789)	0.014 (0.156)	1.890 (0.175)
South Korea	1.004*** (0.000)	-0.017 (0.154)	-0.038*** (0.000)	1.319 (0.351)
India	0.042 (0.519)	0.002 (0.919)	-0.007* (0.089)	-1.854 (0.188)
United Kingdom	-0.979*** (0.000)	0.003 (0.467)	0.007 (0.408)	2.753** (0.044)
Italy	-0.131*** (0.000)	0.001 (0.933)	-0.014*** (0.000)	2.157*** (0.002)
Japan	-1.081*** (0.000)	0.006 (0.604)	-0.003 (0.747)	5.655*** (0.000)
Canada	-0.539*** (0.000)	0.007 (0.301)	-0.009 (0.413)	3.144** (0.017)
Mexico	0.523*** (0.000)	0.021 (0.194)	-0.031*** (0.001)	-0.670 (0.644)
Russia	-0.691*** (0.000)	-0.015 (0.349)	0.001 (0.895)	1.521 (0.200)
Saudi Arabia	-0.127 (0.684)	-0.047*** (0.005)	-0.003 (0.832)	-0.253 (0.851)
Türkiye	0.865*** (0.000)	0.012 (0.425)	-0.005 (0.608)	0.174 (0.854)

In Model 2, DVX was examined and its effects on ECI. According to the results, DVX has a negative effect on ECI in Germany, the US, Argentina, Australia, Brazil, France, South Africa, the United Kingdom, Italy, Japan, Canada, Russia and Saudi Arabia. However, DVX has a positive effect on ECI in China, South Korea, Mexico and Türkiye. FDI has a negative effect on ECI in China and Saudi Arabia. GCF has a positive effect in

Australia and Brazil while it has a negative effect in Germany, South Korea, India, Italy and Mexico. Finally, PCGDP has a positive effect on ECI in Germany, the US, Brazil, Indonesia, the United Kingdom, Italy, Japan and Canada while it has a negative effect in China.

6. Conclusion

Today, the efforts of many countries around the world to increase their share of global trade have made it necessary for them to turn to products with high technology and high added value in the world markets. Of course one of the goals is to increase foreign trade which has a significant share in national income and to sustain the economic growth that foreign trade provides. However, it is the question of 'what' is exported rather than 'how much' is exported that is most important. Alongside indicators such as GDP, exports and employment a significant indicator of structural transformation for economies in the development process is a transition from primary goods with low added value to secondary goods with high added value. Therefore, it is essential for economies to cultivate this type of development over time, especially developing countries. The priority for developing countries must be development more than growth and development is one of the important outcomes that come with this type of structural transformation.

GVCs have gained greater importance since the 2000s. This study explores the participation of the G20 countries in the global value chain (See Appendix B and Appendix C) and its impact on the level of economic complexity. It is economic complexity that has become an important tool to measure the structural transformation in these countries. It is common to understand the role countries play in GVCs in terms of backward and forward participation. Therefore, these two dynamics were examined using two separate models in this study. The analysis of the effects of a country's GVC participation found that they have a positive effect statistically on the level of economic complexity for countries such as China, Korea, Mexico and Türkiye. In other words, while integration into the global value chain has increased in these countries, this integration has also positively affected the level of economic complexity. While the levels of economic complexity increased between 1997 and 2018 within the G20 countries, no significant effect was found in India, Indonesia and Saudi Arabia. In developed countries such as Germany, the US, Australia, France, the United Kingdom, Italy, Japan and Canada, the level of economic complexity was trending downward in the same period. In these countries, the effect is negative. In addition to these developed countries, a statistically significant negative relationship was found in Argentina, Brazil, South Africa and Russia. The results of the study is in line with the literature considered that in terms of the effect of foreign direct investment (FDI), gross capital formation (GFC) and GDP per capita variables on ECI. In this sense, it can be said that it is especially compatible with the studies of Sepehr Dust, Dwarakish and Setarehaye (2019) and Gnangnon (2022,a). On the other hand, indirect value added (FVA) and foreign value added (DVX) variables were also used in the analysis of the study, unlike the literature reviewed. In this sense, it is thought that it is important to carry out analyzes dealing with these variables in future studies, both to contribute to this study and to carry the literature in question further.

Historically, developed countries have tended to shift their production structures to developing countries where they can produce products at lower costs through multinational companies. The negative effect observed in developed countries can be explained by this trend. Moreover, there is also a decreasing trend in the economic complexity levels of Argentina, Brazil, South Africa and Russia in that period (see Appendix A). It can be stated that these countries are only quantitatively integrated into the global value chain and the quality of their productivity is quite limited.

Especially with the COVID-19 pandemic, being connected to global value chains had caused problems in the transfer of goods between countries. As a result, many experts have drawn attention to some of the negative aspects of being connected to global value chains. While the debates continue about whether globalization will produce new economic dimensions, it is quite clear that a rapid backward transformation cannot be sustained within the current global economic system. Therefore, it is important for countries to take steps to position themselves well within the global economy. In particular, developing countries will find many opportunities for growth and development by actively integrating into GVCs.

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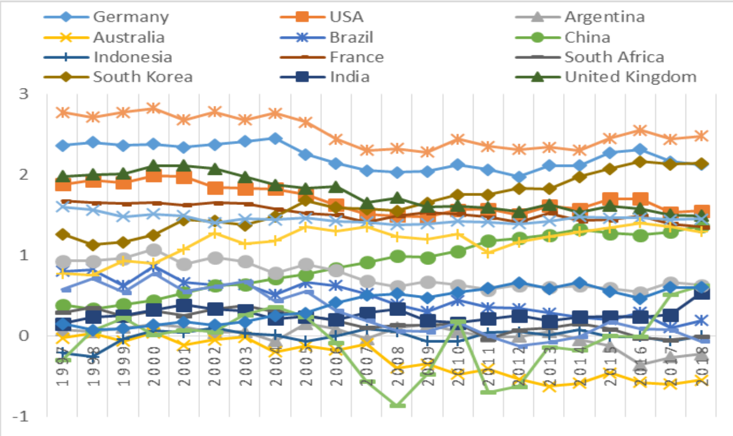
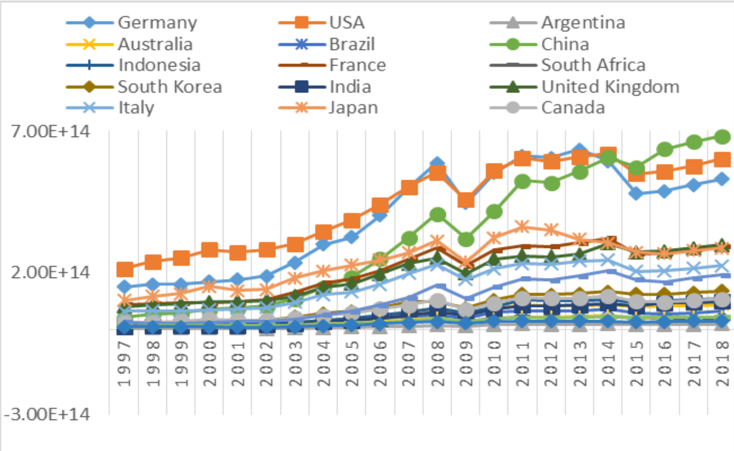
Appendix A. Cross-section dependence test

Variables	CDLM1	CDLM2	Lmadj
ECI	1609.259 (0.000)	76.745 (0.000)	76.292 (0.000)
DVX	3614.908 (0.000)	185.198 (0.000)	184.746 (0.000)
FVA	3522.523 (0.000)	180.202 (0.000)	179.750 (0.000)
FDI	337.749 (0.000)	7.989 (0.000)	7.537 (0.000)
GCF	822.196 (0.000)	34.185 (0.000)	33.733 (0.000)
PCGDP	2747.140 (0.000)	138.274 (0.000)	137.822 (0.000)

Appendix B. Economic complexity index (1997-2018)



Appendix C. Forward linkages (DVX, 1997-2018)



Appendix D. Backward linkages (FVA, 1997-2018)