

Economic complexity and income inequality in EU countries

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Abstract. The article studies the relationship between economic complexity and income inequality across EU countries from 1995 to 2020. The analysed period characterises high globalisation in which "new" EU countries experienced a high transformation of their productive structure. Production structure largely determines income distribution and, thus, income inequality. We employed panel data methodology to assess the relationship between economic complexity and income inequality. To control for economic activity and education, GDP per capita and average years of secondary schooling are also included in the analysis. Expectedly, our findings point to the correlation between economic complexity and income inequality in EU countries. However, the results also indicate an opposite effect between the "old" EU member states and a group of "new" EU member states. This finding suggests that "new" EU members needed more economic complexity in the observed period to reduce income inequality.

Keywords: income inequality, economic complexity, panel model

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1. Introduction

Economic growth and development are connected with the transformation of productive structure in which the economy moves from simple-low-teach activities to more technologically advanced production processes. In that manner, the economy creates more complex products. Such sophisticated economies, as Hartmann and Pinheiro ([16], pp.1) state: "…tend to outsource products that are less desirable (e.g., in terms of wage and inequality effects), and instead focus on complex products requiring networks of skilled labour and more inclusive institutions".

Although economic complexity and growth preoccupy economists the most, economic complexity and income inequality nexus have been increasingly examined in the last ten years.

Countries with an increase in economic complexity have also experienced declining income inequality, even when controlling for income and human capital measures. There are several reasons why a country's production structure can be associated with its income inequality [13]:

1. The country's product variety limits workers' and unions' occupational choices, learning opportunities, and bargaining power. Countries with more complex products have lower income inequality levels than those with simpler products.

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2. The complexity and diversity of the products the country exports are a good proxy for the knowledge and know-how available in the economy, which are not covered by aggregate measures of human capital (like, for example, years of education).

3. Non-diverse economies, like high-income countries mainly based on natural resources, are more vulnerable to suffering from economic and political capture.

Since the beginning of the 21st century, academics and international financial institutions have raised public awareness of inequality and its threats to social and economic development. Indisputably, exacerbating inequality has devastating effects on well-being.

The literature states a plethora of factors contributing to aggravating/mitigating inequality. One essential issue is the existence of a clear-cut positive or negative relationship. The relationship's sign and its existence are not the only things disputed in the empirical literature. There are doubts regarding the appropriateness of aggregate measures like GDP as a proxy for economic development for explaining variations in income inequality. For that reason, Hidalgo and Hausmann [18] defined the economic complexity index which captures the notion that an economy that can produce more diverse products is more complex. While Hidalgo and Hausmann [18] found that the indicator is strongly correlated with economic performance, its relationship with income inequality is yet to be systematically investigated. Even though recent studies show a negative relationship between economic complexity and inequality, generally, that link is not unique.

This paper aims at analysing the correlation between income inequality and economic complexity in EU member states. We are interested if there exists a significant difference in the effect of economic complexity on income inequality between "old" and "new" EU member states that joined the EU in three enlargement waves in the 21st century. Upon accession, trade of "new" EU member countries with "old" EU member states has increased. Previous research [11] found that trade with economically complex countries (like "old" EU member states) is negatively correlated with income inequality.

The European Commission aims at boosting Europe's competitiveness through innovation, which implies the need for structural transformation accompanied by cross-sectoral policy support. In this way, the toolbox of economic complexity becomes more significant in the European Commission's programs. Pugliese and Tachella [29] show that the concept of economic complexity enables bringing new insight for shaping the EU industrial policy.

Considering that income inequality has risen substantially in the EU [2], the issue of inequality is of great importance in EU countries as it challenges their economic outlook. Therefore, the aim of this research is to assess the connection between economic complexity and income inequality in EU countries from 1995 to 2020. The empirical analysis uses panel data methodology with income inequality as a dependent variable and economic complexity as a regressor, using income and schooling as control variables.

The contribution of our paper to the existing literature is twofold. First, the results of the analysis point to the correlation between economic complexity and income inequality in EU countries during high globalisation. Second, we show that there is an opposite effect of economic complexity on income inequality between "old" and "new" EU member states in the period in which the "new" EU countries experienced a high transformation of their production structure. Although there are papers that included EU countries [24], this is (to our knowledge) the first paper that explicitly models the potential differences in the inequality-complexity relationship between "old" and "new" EU member states.

The paper is structured as follows. After the introductory remarks, the second section presents the related literature. Data and adopted methodology are described in the third section, while section 4 discusses the obtained results. Finally, section 5 concludes, providing policy recommendations, limitations of our research, and prospects for future research in this field.

2. Related literature

The link between productive structure, economic growth, and income inequality has long been a topic in the economic literature. It is well known that the productive structure is the main factor influencing income distribution.

Economic development is an essential factor in changing production structure. Kuznets [22] finds no clear-cut positive or negative relationship between economic development and income inequality. Instead, the inverted U-shaped "Kuznets curve" highlights that economic development initially increases inequality. Later, the relationship turns positive to negative, contributing to mitigating inequality. Nevertheless, the claim is not without disputes as Perotti [28], Galbraith [12], and Palma [27] obtained evidence only of the negative relationship, while Deininger and Squire [8] claim that the two are not related at all.

Kuznets and Murphy [23], and Chenery and Taylor [6] emphasized the role of economic transformation as a process leading to change from low to higher productivity. That is why countries whose economic structure has changed in favour of sophisticated products are developing at a greater pace in comparison with countries that specialize in simple products [10].

The problem of measuring the production structure existed until Hidalgo and Hausmann [18] created the Economic complexity index (ECI), which gave economists the opportunity to investigate empirically the relationship between economic complexity and income inequality. A more detailed overview of the theory behind economic complexity and its empirical applications can be found in [17] and [4].

Hartmann et al. [15] used OLS and fixed effects panel regression to show that increasing economic complexity leads to lowering income inequality.

Based on cross-country OLS regression, [24] show that an increase in complexity is connected with lower inequality. However, the authors obtain the opposite result when employing a dynamic panel model. The explanation is that the degree of income inequality increases when the economy experiences structural changes toward more sophisticated products. However, the long-term effects of increasing complexity are positively correlated with the level of inequality, so increasing economic complexity increases income inequality.

[15] showed that from 1962-2000, income inequality was lower in countries that exported more complex products. Moreover, they state (pp. 85): "...production structures are a high-resolution expression of a range of factors, from institutions to education, that co-evolve with a country's export mix and the inclusiveness of its economy". They also show that the ECI can predict and provide information on the income gap. Their findings are similar to [24].

Although most research assumes a linear relationship between economic complexity and income inequality, specific studies are based on a non-linear relationship, e.g., [3]. The authors find a non-linear relationship between economic complexity and the income gap. They show that countries with low and high levels of ECI have low-income inequality in contrast to countries with medium levels of ECI that experience higher income inequality. Nevertheless, all the previously mentioned studies point out that ECI is a significant factor influencing income inequality.

ECI growth can reduce income inequality by affecting employment and learning opportunities [1], [15]. In this way, a higher ECI also means a sophisticated production structure and offers a greater selection of occupations and study opportunities for workers. That process leads to more equality in society. Hartmann et al. [14] find that occupational structure is an essential mechanism through which ECI affects income inequality. Thus, for example, a production structure whose basic output is the primary good usually refers to a vertical occupational structure instead of a production structure that mainly produces sophisticated products. A complex production structure in which more workers participate in activities with higher productivity and increasing returns to scale reduces inequality [24].

Fawaz and Rahnama-Moghadamm [11], using data from 1964-2013, show that trade with economically complex countries is negatively correlated with income inequality.

While growing economic complexity is associated with strong economic growth and cross-country convergence, its impact on across- and within-country inequality is less clear. Additional research is needed, especially to establish the causal mechanism. [26] show that less income inequality comes with greater complexity of green technologies. They emphasise the role of the middle class, which creates demand for green innovations and enables economies of scale in production.

Although some papers [24] include EU countries, there are no papers that explicitly model the potential differences in the inequality-complexity relationship between "old" and "new" EU member states. Consequently, this is the literature gap that this paper covers. Splitting down the sample based on when the countries joined the EU ("new" and "old"), we analysed the differences between the groups and examined whether the level of economic complexity is a good determinant of inequality in each group.

3. Data and methodology

Our sample includes data for EU countries from 1995 to 2020 ($T = 26$), the period of high globalisation (until the COVID economic crisis) in which "new" EU countries passed through a high transformation of their production structure.

To analyse the connection between economic complexity and income inequality, we estimated a panel model with income inequality as a dependent variable and economic complexity as a regressor, using income and schooling as control variables.

The model specification is

$$y_{it} = X_{it}' \ \beta + \alpha_i + \varepsilon_{it}, i = 1, \ldots N, t = 1, \ldots T. \tag{1}$$

where y_{it} is a dependent variable, X_{it} is the matrix of regressors, α_i is the (unobserved) country effect, and ε_{it} is the error (idiosyncratic) term with $E(\varepsilon_{it}) = 0$, and $E(\varepsilon_{it}\varepsilon_{js}) = \sigma_\varepsilon^2$ if $j = i$ and $t = s$ and $E(\varepsilon_{it}\varepsilon_{js}) = 0$ otherwise.

The dependent variable in the paper is the Gini coefficient, which measures income inequality. As regressors, the model includes a measure of the set of productive capabilities available in a country given by the Economic complexity index (ECI), ln- transformed GDP per capita (lnGDPPC) and average years of secondary schooling (Secondary), which act primarily as control variables for economic activity and human capital.

Since we are also interested in whether there is a substantial difference in the effect of economic complexity on income between the group of "old" and "new" EU members, the model includes an interaction term ($ECI \cdot \text{new}$), where new is a dummy variable representing the group countries ("new" or "old").

Barro and Lee [5] provide the source for data on secondary years of schooling. As data on schooling are available only at 5-year intervals, we assigned the data at the beginning year of every period, i.e., data on years of secondary schooling in 1995 were used for the first period (1995–1999), data in 2000 were used for the period (2000–2004) etc.

Table 1 describes the variables and data sources.

Descriptive statistics for our panel data for all countries and two sub-samples "old" and "new" are presented in Table 2. The sub-sample "new" (the countries that joined the EU in three enlargement waves in the 21st century) includes nine countries for which data on ECI are available, namely: Bulgaria, Croatia, Czech Republic, Hungary, Lithuania, Romania, Poland, Slovenia and the Slovak Republic since ECI data are not available for Cyprus, Estonia, Latvia and Malta. The "old" EU member states, for which ECI data are available, include thirteen countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain and Sweden, as data on ECI are not available for Luxembourg.

Variables	Description	Data source	Period
GINI	GINI index estimation based on household disposable income	Standardized World Income Inequality Solt, F. (2019). The standardized world income inequality database, versions 8-9. Harvard Dataverse, 5. https://doi.org/10.7910/DVN/LM4OWF	1995-2019
ECI	Economic complexity index	https://oec.world/en/rankings/eci/hs6/hs96	1995-2020
GDPPC	GDP per capita (constant 2015 US$)	World Bank's World Development Indicators	1995-2020
Secondary	Average years of secondary schooling, representing the stock of human capital, accumulated over every 5 years.	Barro and Lee (2013)	1995-2020
new	Binary variable (equals 1 for "new" EU member states and zero otherwise)		

Table 1: List of variables and data sources

Label	Variable	Mean	Standard deviation (overall)	Standard deviation (between)	Standard deviation (within)	Number of observations
all EU countries						
GINI	GINI index	28.77251	3.559317	3.442205	1.162728	553
ECI	Economic complexity index	1.056334	0.5179469	0.4985967	0.1714989	568
lnGDPPC	GDP per capita (constant 2015 US$)	9.968888	0.7024247	0.691883	0.1888315	572
Secondary	Average years of secondary schooling	4.256945	1.023536	0.9081517	0.5088625	550
"OLD"						
GINI	GINI index	28.79235	3.375549	3.363272	0.9536336	327
ECI	Economic complexity index	1.221021	0.4945712	0.5039341	0.0825431	334
lnGDPPC	GDP per capita (constant 2015 US$)	10.46034	0.3326305	0.3244025	0.1149476	338
Secondary	Average years of secondary schooling	4.599631	1.021902	0.9336517	0.4869792	325
"NEW"						
GINI	GINI index	28.74381	3.81.082	3.759402	1.413897	226
ECI	Economic complexity index	0.821268	0.4570284	0.4058478	0.2486674	234
lnGDPPC	GDP per capita (constant 2015 US$)	9.259019	0.4389552	0.373312	0.2612907	234
Secondary	Average years of secondary schooling	3.761956	0.8004042	0.6252298	0.5400167	225

Table 2: *Panel data descriptive statistics*

The results from Table 2 show variation in the time series. However, variation within countries is generally lower than across countries for all variables and all groups of countries (all EU, "old" and "new"). The average value of the GINI index is almost the same in both groups (around the EU average). In contrast, the value of the ECI is, on average higher in the group of "old" EU countries with higher GDP per capita and more years of secondary schooling. As the analysed period is relatively long and covers 26 years, the stationarity of the variables was also assessed. We employed a battery of unit root tests, Table 3.

Variable	CIPS test	IPS test		Fisher test		LLC test	
Levels		W-t-bar	p-value	Inverse chi-squared	p-value	Adjusted p-value	t-value
GINI	-2.301***	-2.1507	0.0157	111.5586	0.0000	-2.9598	0.0015
ECI	-2.011**	-1.6819	0.0463	71.9211	0.0050	-2.5575	0.0053
lnGDPPC	-1.993	-2.8351	0.0023	20.7610	0.9989	0.0553	0.5220
Secondary	-1.555	0.9084	0.8182	34.3903	0.8503	-2.0822	0.0187
First differences							
ΔSecondary	-4.404***	-17.8750	0.0000	294.3647	0.0000	-22.3597	0.0000
ΔlnGDPPC	-3.000***	-8.2597	0.0000	160.0945	0.0000	-9.0333	0.0000

Notes: TCIPS- Pesaran panel unit root test for unit roots in heterogeneous panels (in the presence of cross-section dependence). Im-Pesaran-Shin test (IPS), Fisher unit root test, Levin–Lin–Chu unit root test (LLC). For IPS and LLC tests, the lag length is chosen using the Akaike information criterion (AIC). Fisher-type tests are based on augmented Dickey-Fuller tests.

Table 3: *Panel Unit Root Test*

The null hypothesis of non-stationarity was rejected for GINI and ECI variables (Table 3) but not for lnGDPPC and Secondary. Therefore, we conclude that GINI and ECI are $I(0)$ processes. On the other hand, lnGPDPC and Secondary are $I(1)$ and were hence transformed using the first differences.

4. Empirical results

For all EU countries for which data on ECI is available (22 countries as data for ECI for Malta, Republic of Cyprus, Luxembourg, Estonia and Latvia are not available), we estimated the model (1) with the interaction term:

$$GINI_{it} = \beta_1 \cdot ECI_{it} + \beta_2 \cdot \Delta\text{Secondary}_{it} + \beta_3 \cdot \Delta lnGDPPC_{it} + \beta_4 \cdot new \cdot \text{ECI}_{it} + \alpha_i + \varepsilon_{it},$$
$$i = 1, \dots N, t = 1, \dots T. \tag{2}$$

Before estimating the model (2), we tested for the existence of individual effects, cross-sectional independence, groupwise heteroscedasticity and autocorrelation to determine whether panel models are superior to the ordinary OLS regression. The rejection of the null hypothesis ($p - value = 0.000$) in all tests for fixed and random effects confirms the appropriateness of the panel model. The results of the Pesaran cross-section dependence (CD) test ($CD = 5.708$, $p - value = 0.000$), the Wald test for groupwise heteroscedasticity ($chi2(22) = 166.22$, $p-value = 0.000$), and the Wooldridge test for autocorrelation ($F = 711.253$, $p-value = 0.000$) confirm the problem of heteroscedasticity and autocorrelation in our data.

As the number of countries in each group was a significant factor in choosing the methodology (small values of N compared to T) we opted to estimate static models with corrected standard errors which give the estimators with adequate statistical properties [30].

Accordingly, FE and RE models employ robust standard errors that are robust to heteroscedasticity and autocorrelation. Additionally, $FE_{driscoll}$ models were estimated using Driscoll and Kraay standard errors (Driscoll and Kraay, 1998) [9]. Driscoll and Kraay used a nonparametric technique for estimating standard errors. They applied a Newey-West type correction to the series of cross-sectional averages of the moment conditions. Adjusting the standard error estimates ensures consistency of the covariance matrix estimator which is independent of the cross-sectional dimension N. In addition to $AR(1)$ autocorrelation, this approach accounts for the error structure that is assumed to be heteroscedastic, autocorrelated up to some lag, and possibly correlated between the groups. Driscoll and Kraay's standard

Variable	FE	RE	$FE_{driscoll}$
ECI	-4.8413813*	-2.2957403	-4.8413813***
ΔSecondary	-0.21202686	-0.28832779*	-0.21202686
ΔlnGDPPC	0.70507172	0.33063114	0.70507172
$new \cdot$ ECI	8.1509441**	5.0526901**	8.1509441***
constant	31.192598***	29.555909***	31.192598***
Hausman (p-value)	5.68 (0.2243)		
F-statistic/ Wald	$F-statistic = 46.42$	Wald chi2(4) = 121.36	$F-statistic = 68,01$
(p-value)	0.0000	0.0000	0.0000
No. of observations	525	525	525

Note: $*p < 0.10$; $**p < 0.05$; $***p < 0.01$

Table 4: *Estimation results for all EU countries (dependent variable GINI)*

errors are robust to general forms of cross-sectional ("spatial") as well as temporal dependence when the time dimension becomes large. Monte Carlo study showed that Driscoll and Kraay standard errors have significantly better small sample properties over alternative covariance estimators when cross-sectional dependence is present [19]. Using Driscoll and Kraay standard errors, and thus eliminating the negative effects of cross-sectional dependence, autocorrelation and heteroscedasticity, ensured obtaining more accurate estimator values in our models.

To differentiate between the models, we used the robust Hausman specification test, which performs a (cluster-) robust version of Hausman's specification test [20]. The obtained results are in Table 4.

The results from Table 4 point to the significant correlation between economic complexity and inequality in EU countries. The estimated coefficient of the interaction term between complexity and dummy variable representing a group is positive and statistically significant, suggesting a significant difference in sign and size of the effect between groups. For "old" EU countries, economic complexity has a strong negative effect on income inequality, implying that an increase in economic complexity in "old" countries is connected with lower income inequality.

On the other hand, for "new" EU countries, the estimated coefficient of ECI is significant and positive, suggesting that greater economic complexity is connected with an increase in income inequality. One simple and reasonable explanation for such a relationship is that in these countries, despite the change in the production structure, a sufficient degree of economic complexity has yet to be reached to decrease income inequality.

The coefficient for secondary education is negative and statistically significant in the RE model, showing that schooling reduces income inequality.

Splitting the sample and estimating the model (2) for two sub-samples of "old" and "new" countries gives the results presented in Table 5 and Table 6.

The results confirm the negative correlation between economic complexity and inequality for a group of "old" countries and the positive for "new" countries. However, secondary education is significant only in the "old" group with an expected negative sign, suggesting that the negative effect of secondary education (Table 5) is mainly driven by "old" EU countries.

As a robustness check, instead of GINI, as a measure of income inequality, we used the income share held by the highest 10% income distribution, a variable TOP10 (data were obtained from World Development Indicators). The results are almost the same (Table 7). ECI remains a positive and significant predictor of income inequality. In this way, we confirmed the previous result, according to which the achieved degree of economic complexity in "new" EU countries still needs to be improved to reduce income inequality.

Variable	FE	RE	$FE_{driscoll}$
ECI	-4.8544593*	-4.7494173**	-4.8544593***
ΔSecondary	-0.3047553*	-0.30291126*	-0.30475529
ΔlnGDPPC	-4.223583	-4.2031272	-4.223583
constant	34.869546***	34.723074***	34.869546***
Hausman (p-value)	0.30 (0.9602)		
F-statistic/ Wald	$F = 3.67$	Wald chi2(3) =11.75	$F = 18.40$
(p-value)	0.0439	0.0083	0.0001
No. of observations	309	309	309

Note: $*p < 0.10$; $**p < 0.05$; $***p < 0.01$

Table 5: *Estimation results for "old" EU member countries (dependent variable GINI)*

Variable	FE	RE	$FE_{driscoll}$
ECI	3.4146407*	2.1519195*	3.4146407***
ΔSecondary	0.02987212	-0.07567353	0.02987213
ΔlnGDPPC	4.7375564	4.0841008	4.7375564
constant	25.830229***	26.900003***	25.830229***
Hausman (p-value)	0.35 (0.9502)		
F-statistic/ Wald	$F = 3.92$	Wald chi2(3) =7.88	$F = 97.02$
(p-value)	0.0544	0.0486	0.0000
No. of observations	216	216	216

Note: $*p < 0.10$; $**p < 0.05$; $***p < 0.01$

Table 6: *Estimation results for "new" EU member countries (dependent variable GINI)*

Variable	FE	RE	$FE_{driscoll}$
ECI	5.4231542***	4.7068314***	5.4231542***
ΔSecondary	0.23295986	0.19267828	0.23295985
ΔlnGDPPC	4.1658264	3.7239252	4.1658264
constant	28.94355***	29.5517***	28.94355***
Hausman (p-value)	0.53 (0.9131)		
F-statistic/ Wald	$F = 16.27$	Wald chi2(3) = 28.89	$F = 28.55$
(p-value)	0.0009	0.0000	0.0001
No. of observations	216	216	216

Note: $*p < 0.10$; $**p < 0.05$; $***p < 0.01$

Table 7: *Estimation results for TOP10 as a measure of income inequality for 'new' EU member countries*

5. Conclusion

Based on the panel data methodology, we find a correlation between economic complexity and income inequality in EU countries from 1995-2020. The classification of EU countries into "old" and "new" shows that the two groups have different signs of the link between economic complexity and income inequality. While the economic complexity works to reduce income inequality in the "old" EU member states, we find the opposite in the "new" member states. One possible explanation could be that the "new" members, in the empirical period, did not have a sufficient degree of economic complexity that led to the reduction of inequality. However, additional research is needed to be able to confirm it unequivocally. In our panel model, we use GDP per capita and the average years of secondary education as control variables for economic activity and education. While education is statistically significant in the group of "old" members and affects the reduction of inequality, it is not statistically significant in the case of "new" members. More research is required to study the moderating impact of countries' educational levels on the relationship between ECI and economic inequality. Furthermore, regarding the positive relationship between economic complexity and economic inequality in post-transition countries, future research efforts should investigate whether there are differences among the post-transition countries themselves.

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