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The effect of economic complexity on income levels across countries: A dynamic panel quantile approach

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Abstract

Purpose — This study investigates the impact of economic complexity on income levels across countries at different stages of economic development, with particular emphasis on how these effects vary across the income distribution.

Method — A dynamic panel quantile regression approach is employed to analyse panel data from 115 countries over the period 1995–2020. GDP per capita is used as a proxy for income, allowing the analysis to capture heterogeneous effects across different quantiles of income distribution. The key control variables include human capital, population, trade openness, institutional quality, and inflation.

Findings — The results reveal significant heterogeneity in the effects of economic complexity across income levels. Economic complexity has a positive and significant impact on income at higher quantiles, indicating that more advanced economies benefit from increased productive capabilities. Conversely, at lower quantiles, the effect is negative, suggesting that less-developed countries are unable to fully capitalise on rising complexity.

Implications — The findings suggest that policy strategies should be tailored to different stages of development. Low-income countries need to enhance skill formation and structural transformation to benefit from complexity, while high-income countries should focus on innovation and diversification. Strengthening human capital and institutional quality is essential to mitigating the effects of inequality.

Originality — This study contributes to the literature by highlighting the heterogeneous effects of economic complexity using a dynamic panel quantile framework, offering new insights into income differences across development levels, an aspect largely overlooked in previous research.

Keywords: Economic Complexity, Income Disparity, Panel Quantile Regression, Within-Group Disparity.

Introduction

Decades of research have focused on differences and disparities in income distribution across countries. In this study, income disparity refers to the differences in income levels across countries, capturing variations between lower- and higher-income economies rather than within-country inequality. In 2024, the World Bank estimated that approximately 692 million people lived below the international poverty line of $2.15 per day (in 2017 purchasing power parity terms). The largest percentage of these individuals lived in the least developed regions, such as Sub-Saharan Africa (67%) and South Asia (21%), while high-income countries accounted for only 1%.

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These disparities are unsurprising, as previous studies have shown that developed countries, which produce a diverse and complex range of products, generally exhibit low or modest income disparities (Amarante, Lanzilotta, & Torres-Pérez, 2024; Hartmann, Guevara, Jara-Figueroa, Aristarán, & Hidalgo, 2017; Lee & Vu, 2020). In contrast, least-developed countries tend to produce less complex products and rely heavily on natural resource exports, often exhibiting high levels of disparity (Hartmann, Jara-Figueroa, Guevara, Simoes, & Hidalgo, 2017; Pham, Truong, & Hoang, 2024). Together, these studies provide important evidence that the diversity and sophistication of a country's productive capabilities influence its income distribution.

Studies on income disparity and economic complexity have proposed a measure of the diversity of knowledge that can be translated into products or services (Hausmann, Hidalgo, Bustos, Coscia, & Simoes, 2014; Hidalgo, 2021). Unlike previous approaches that focused on aggregate output and input factors, economic complexity emphasises the productive capabilities embedded in goods and services through the use of machine learning and network techniques (Hidalgo, 2021).

A country with diverse productive capabilities can develop highly sophisticated industries and manufacture complex products, thereby offering a wide range of job opportunities. These countries also have a greater proportion of skilled workers than unskilled workers (Chu & Hoang, 2020). Countries with a higher complexity index can create more complex products and distribute income more fairly (Hartmann, Guevara, et al., 2017). They are highly diversified and export a large number of complex products. In contrast, widening disparities translate to the quality of human capital available in the country. Disparities persist where productive capabilities depend on unskilled workers and primary sector economies. This also implies limited occupational choices in countries with low complexity (Hartmann, Guevara, et al., 2017). Consequently, this constrains their ability to generate and distribute income fairly (Hartmann, Jara-Figueroa, et al., 2017), leading to high-income disparities and low wages for the majority of the population (Chu & Hoang, 2020).

In addition, changes in productive capabilities create more employment opportunities, thereby increasing demand for skilled workers (Hartmann, Guevara, et al., 2017; Lee & Vu, 2020). This enables workers to bargain for wage increases, resulting in lower income disparities. However, the effect of economic complexity on income across countries remains poorly understood. Several studies have found both negative (Hartmann, Guevara, et al., 2017; Lee & Vu, 2020) and positive (Chu & Hoang, 2020) impacts of economic complexity on income disparities.

Existing research often fails to consider whether economic complexity and disparity vary across different income levels. For example, Hartmann, Guevara, et al. (2017) assume that the inequality-reducing effects of complexity are homogeneous across countries. In contrast, Chu and Hoang (2020) find that disparities tend to increase as economies become more complex. However, as Buchinsky (1994) and Martins and Pereira (2004) argue, these studies largely overlook within-group disparities that can be mitigated using quantile regression. Moreover, for cross-country studies, there is a need for a more refined approach that accounts for income distribution at varying levels of complexity. There is a significant income disparity between developed and least developed countries.

This study investigates the impact of economic complexity on income across countries with different development levels. A panel dataset of 115 countries from 1995 to 2020, consisting of developed, developing, and least developed countries, was used. In contrast to past studies (Amarante et al., 2024; Chu & Hoang, 2020; Hartmann, Guevara, et al., 2017; Hartmann, Jara-Figueroa, et al., 2017; Lee & Wang, 2021; Lee & Vu, 2020; Pham et al., 2024; Sepehrdoust, Tartar, & Gholizadeh, 2022), this study utilizes dynamic panel quantiles to estimate the relationship between economic complexity and income disparity. Panel quantiles were selected because economic complexity may also affect the distribution of income across levels of GDP per capita, and the conventional conditional mean regression approach (e.g., GMM, OLS) may obscure substantial parameter heterogeneity in the association between income and economic complexity. Furthermore, this study uses GDP per capita as a proxy for income disparity between countries, unlike many studies that mainly use the Gini index. We take a different approach, objectively, because studies involving the Gini index in cross-country comparisons require careful consideration. Specifically, the Gini coefficient primarily captures within-country income disparities and may not adequately reflect differences across countries.

Measurement of income disparity using GDP per capita

The Gini index is commonly used as a proxy for studies of income disparity. The use of quantiles to examine the entire within-group income distribution (Buchinsky, 1994) has been rendered moot by the Gini index in methods such as quantile regression that rely on the concept of estimating conditional distributions. For this reason, the Gini index does not have a quantile structure (because it is a relative measure rather than an absolute value) suitable for use as the dependent variable. Hence, quantile regression is typically used to estimate the effect of independent variables at different quantiles of the dependent variable's distribution.

Therefore, in this study, GDP per capita is preferred as a proxy for cross-country income gaps rather than for within-country income inequality, for data and methodological reasons. In this study, GDP per capita is also viewed as an approximation of a country's average income (Nolan, Roser, & Thewissen, 2019). For instance, if the impact is positive for the upper quantiles and negative for the lower quantiles, this is taken as evidence of widening income disparity. This approach, also known as within-group income disparity, can be used to measure differences across relevant quantiles (Buchinsky, 1994; Martins & Pereira, 2004). The application of this method highlights the results of the estimation from the longer tails at the end of the income distribution, especially towards less (or more) complex countries.

Furthermore, this technique shows that the impacts of economic complexity differ across income distributions, or, in this case, between low-, medium-, and high-income countries. Finally, by using quantiles, the magnitude of the increase in complexity of GDP per capita can be observed at different points along the income distribution. This provides a clearer and more meaningful basis for comparisons of various income quantiles. Figure 1 shows a positive relationship between economic complexity and GDP per capita, suggesting that greater complexity is associated with higher income levels.

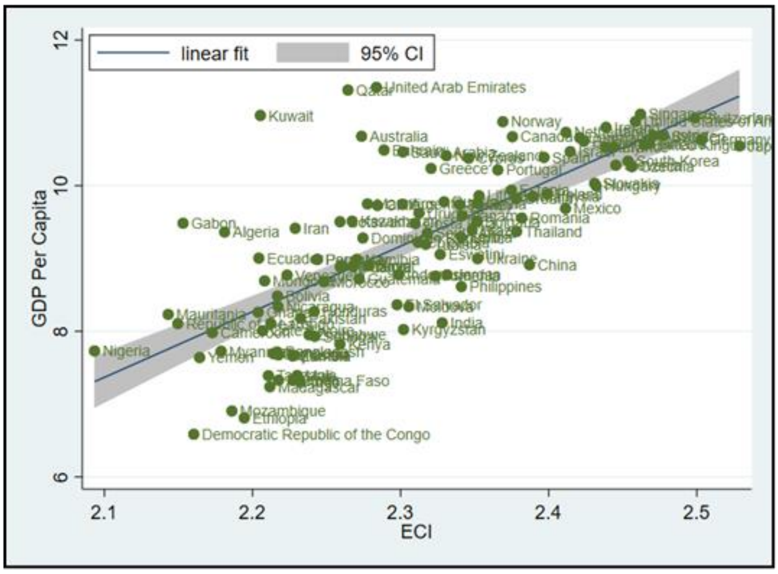


Figure 1. Scatter Plot of Economic Complexity and GDP Per Capita

Methods

This study follows a model proposed by Hartmann, Guevara, et al. (2017), Chu and Hoang, (2020) and Lee and Vu (2020), which stems from the theoretical model of the Kuznets (1955). The effects of economic complexity on income can be expressed in a dynamic form as follows:

$$\mathrm{GDPPC}_{i,t} = \beta_0 + \beta_1 \mathrm{GDPPC}_{i,t-1} + \beta_2 \mathrm{ECI}_{i,t} + \beta_3 \mathrm{HC}_{i,t} + \beta_4 \mathrm{POP}_{i,t} + \beta_5 TO_{i,t} + \beta_6 \mathrm{INS}_{i,t} + \beta_7 \mathrm{INF}_{i,t} + \mu_{i,t} \quad (1)$$

where *i* represents the country, *t* represents time, and μ_t is an error term. *GDPPC*, GDP per capita; ECI, economic complexity index; HC, human capital; POP, total population; TO, trade openness; INS, institutions; and INF, inflation.

Economic complexity, pioneered by Hausmann et al. (2014), refers to the productive capabilities embedded in a country. These capabilities represent the outcome of combining production factors with knowledge, enabling the creation of products or services (Hidalgo & Stojkoski, 2025). In this sense, economic complexity studies the interaction and exchange of knowledge embedded in the economy, weighing and assigning complexity in producing products, thereby contributing to explaining the rate of development, economic growth, and income disparity between countries (Hausmann et al., 2014; Hidalgo, 2021; Hidalgo & Stojkoski, 2025).

By utilizing a method of reflection, the range of products a country can export (diversity) and the number of countries that can make a given product (ubiquity) are iteratively computed. In the concept of economic complexity, a product that can be produced by many is seen as abundant (in terms of productive capabilities). In contrast, products manufactured by a single or a few countries are seen as scarce.

The formulae for deriving the ECI (Hausmann et al., 2014):

$$\text{Diversity} = k_{c,0} = \sum_p M_{cp} \quad (2)$$

$$\text{Ubiquity} = k_{p,0} = \sum_c M_{cp} \quad (3)$$

where M_{cp} is a matrix in which the rows represent different countries and columns represent different products; *c* denotes country, and *p* denotes product. They then jointly and iteratively compute the mean value of diversity and ubiquity to generate a more accurate measure of the number of capabilities available in a country, as follows:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_p M_{cp} \,.\, k_{p,N-1} \quad (4)$$

$$k_{p,N} = \frac{1}{k_{c,0}} \sum_p M_{cp} \,.\, k_{c,N-1} \quad (5)$$

where *N* denotes the number of iterations. By inserting Equation (5) into Equation (4), we obtain the following equation:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_p M_{cp} \frac{1}{k_{p,0}} \sum_{c\prime} M_{c\prime p} \,.\, k_{c\prime,N-2} = \sum_{c\prime} k_{c',N-2} \sum \frac{M_{cp} M_{c\prime p}}{k_{c,0} k_{p,0}} \quad (6)$$

This can be rewritten as:

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

In which,

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

where $\widetilde{M}_{cc'}$ is a matrix connecting countries exporting similar products. Finally, the ECI is computed as follows:

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

where $\vec{K}$ is the eigenvector of $\widetilde{M}_{cc'}$ associated with the second largest eigenvalue, < > represents an average, and stdev denotes the standard deviation.

Data

This study employs an unbalanced panel dataset of 115 countries covering the period 1995–2020, with year selection determined by the availability of economic complexity data. The dependent variable is income, proxied by GDP per capita (constant 2015 US$) from the World Development Indicators (WDI). The independent variable, economic complexity, is represented by the ECI as the primary indicator of productive capabilities. Any changes in productive capabilities are hypothesized to affect income generation, increase complexity, and reduce income disparity in the economy (Hartmann, Guevara, et al., 2017). The data for the control variables are as follows: human capital (HC), population (POP), trade openness (TO), institutions (INS), and inflation (INF). Table 1 summarizes the data used in this study.

Table 1. Data summary

Variable Notation	Variable Name	Variable Description	Measurement Unit	Reference
GDPPC	GDP Per Capita	A proxy to measure income disparity	US$ in 2015	(Buchinsky, 1994; Martins & Pereira, 2004; Nolan et al., 2019)
ECI	Economic Complexity	Economic Complexity Index	Index between -3 and 3.	(Chu & Hoang, 2020; Hartmann, Guevara, et al., 2017; Lee & Vu, 2020)
HC	Human Capital	Human Capital Index	Index between 0 and 5	(Chu & Hoang, 2020; Lee & Vu, 2020)
POP	Population	Population in a country	Sum of the total population	(Lee & Wang, 2021; Lee & Vu, 2020; Morais, Swart, & Jordaan, 2021)
TO	Trade Openness	The sum of exports and imports of goods and services over GDP	Percentage (%) of GDP	(Lee & Wang, 2021; Lee & Vu, 2020; Morais et al., 2021)
INS	Institutions	Institutional Quality	Percentile 0-100	(Chu & Hoang, 2020; Hartmann, Guevara, et al., 2017; Law & Azman-Saini, 2012; Lee & Vu, 2020)
INF	Inflation	Annual percentage change of the consumer price index	Annual percentage (%)	(Glawe & Wagner, 2024; Kamguia, Tadadjeu, Miamo, & Njangang, 2022)

Estimation Techniques

To analyse the effect of economic complexity on income, we utilised quantile regression (Buchinsky, 1994; Koenker & Bassett, 1978; Koenker & Hallock, 2001; Lin, Lee, & Law, 2021; Martins & Pereira, 2004). This technique allows estimation of the conditional quantile function and analysis of the effect of economic complexity on income at different points in the conditional distribution of GDP per capita. It has been chosen because economic complexity may also affect the distribution of income across levels of GDP per capita. Specifically, we are interested in studying the different effects of low- and high-complexity countries at the various quantiles of income distribution.

Furthermore, the dynamic quantile regression approach has been increasingly adopted in empirical growth and inequality studies for its ability to capture heterogeneous effects across the income distribution (Galvao, 2011; Machado & Santos Silva, 2019). It extends the standard quantile framework by incorporating lagged dependent variables, thereby accounting for persistence and dynamic adjustment. Compared to static estimates, our approach provides a more nuanced picture of how economic complexity influences income-disparity segments over time. The advantages of quantile regression include the following: (i) flexibility for modeling data with heterogeneous conditional distributions (Chernozhukov & Hansen, 2008), (ii) median regression is more robust to outliers than ordinary least-squares (OLS) regression (Coad & Rao, 2008), and (iii) it allows for accurate fitting of data with skewed distributions (Kottas & Krnjajić, 2009), which are commonly observed in income datasets.

Additionally, the traditional conditional mean regression approach (such as GMM or OLS) may conceal substantial parameter heterogeneity in the relationship between income and the ECI.

In this case, this technique minimizes $\Sigma_i q|e_i| + \Sigma_i(1-q)|e_i|$, a sum that provides asymmetric penalties $q|e_i|$ for under-prediction and $(1\text{-}q)|e_i|$ for over-prediction. If ε_i is the model prediction error, OLS minimizes $\Sigma_i e^2{}_i$. In the case of median regression, this technique minimizes $\Sigma_i|e_i|$, which is also known as the least absolute deviations (LAD).

To test the effect of economic complexity on income, the proposed dynamic quantile regression model is as follows:

$$Q_\tau \tau \mid GDPPC_{i,t-1}, X'_{it} = \alpha(\tau)GDPPC_{i,t-1} + X'_{i,t}\beta(\tau) + \mu \quad (10)$$

where X'_{it} is a vector of independent variables; βτ is a k × 1 vector of regression parameters associated with the τ-th percentile. Thus, this study limits the estimations of country-specific effects to be independent of τ across the quantiles. Here, $Q_\tau(GDPPC_{it}|X_{it})$ is τth quantile regression function of $GDPPC$. This estimation recounts projections of quantile functions at the median of the size distribution (50th percentile) and interquartile regressions (0th and 90th percentile) by projecting nine quantile regression functions: Q (0.10), Q (0.20), Q (0.30), Q (0.40), Q (0.50), Q (0.60), Q (0.70), Q (0.80) and Q(0.90). In this framework, the impact of economic complexity on income disparity is assessed by examining the differential effects of economic complexity on GDP per capita across high- and low-income groups.

Results and Discussions

Table 2 provides the summary statistics for the variables used, based on annual data from 115 countries over the 1995–2020 period. The GDPPC ranges from 5.53 (Venezuela in 2019) to 12.02 (Qatar in 2011), with a mean of 9.24. The economic complexity mean is 2.31, ranging between 1.99 (Kyrgyzstan in 1997) and 2.55 (Japan in 2011). The standard deviation of 2.31 (ECI) implies that the ECI scores of the data are clustered around the mean. In contrast, the GDPPC standard deviation of 1.19 indicates a greater spread from the mean. A considerable range is evident across institutions, with a minimum of 0.17 (the Democratic Republic of the Congo in 1998) and a maximum of 4.60 (Finland in 2005).

Table 3 presents the results of the correlation coefficients for all variables used in this analysis. The table shows that two variables (i.e., population and inflation) are negatively correlated with the dependent variable GDPPC, whereas all other variables are positively correlated. It also shows that our main independent variable (i.e., economic complexity) is positively associated with GDP per capita (0.32), which is consistent with the theoretical perspective. In general, all correlation coefficients are below 0.8, indicating no possible problem of collinearity among the variables.

Table 2. Descriptive statistics

Variables	Mean	Std. Dev.	Min.	Max.
GDPPC	9.24	1.19	5.53	12.02
Economic Complexity (ECI)	2.31	0.1	1.99	2.55
Human Capital (HCI)	0.90	0.6	0.05	1.47
Population (POP)	16.50	1.47	13.15	21.07
Trade Openness (TO)	4.27	0.49	2.47	6.08
Institutions (INS)	3.78	0.66	0.17	4.60
Inflation (INF)	4.68	0.15	4.29	7.91

Table 3. Correlation matrix

	GDPPC	ECI	HC	POP	TO	INS	INF
GDPPC	1						
ECI	0.32	1					
HCI	0.76	0.34	1				
POP	-0.16	-0.002	-0.12	1			
TO	0.28	0.13	0.28	-0.61	1		
INS	0.74	0.33	0.58	-0.21	0.25	1	
INF	-0.24	-0.01	-0.13	0.07	-0.11	-0.34	1

To investigate the impact of economic complexity on income, Table 4 presents the results of our main estimates using quantile regression. The table reports the dynamic panel quantile regression results for τ = 0.1,…,0.9. Overall, the effects of economic complexity on income are heterogeneous across quantiles. Quantiles with significant economic complexity coefficients are the 10th, 20th, 40th, 50th, 60th, 70th, 80th, and 90th percentiles. This empirical result demonstrates that the effect is more pronounced at high quantiles, indicating significant positive effects from the 60th to the 90th percentile. At high quantiles, the impact of economic complexity on income is notable at the 90th percentile. This finding seems consistent with the view that more sophisticated capabilities are associated with high-income and developed countries. Thus, improving the productive capabilities of the economy is necessary.

In contrast, the effects of economic complexity on income are negative and significant at lower quantiles, with more substantial effects at the 10th, 20th, and 40th percentiles. Therefore, the positive impact at higher quantiles and the negative impact at the lower quantiles support the idea that economic complexity has widening effects on income disparity. This result aligns with Chu and Hoang (2020) and Hartmann, Guevara, et al. (2017), who found that an increase in economic complexity leads to higher income disparity. The main reason for this widening effect is that much of the workforce in the least-developed countries primarily consists of unskilled workers (Chu & Hoang, 2020; Hartmann, Guevara, et al., 2017; Hartmann, Jara-Figueroa, et al., 2017). However, unlike Amarante et al. (2024), who reported a mitigating effect of complexity on inequality in high-income economies, our results suggest that complexity reinforces disparities when low-income countries lack the absorptive capacity to utilize new capabilities effectively. Thus, improving productive capabilities in lower-quantile countries did not directly increase their incomes or narrow the disparity. It is also possible that low-income countries could only partially absorb this impact. Unequal opportunity distribution benefited only skilled workers and upper-ladder income in the economy. Consequently, this exacerbates disparities in the country.

Interestingly, at several mid-quantiles (30th–50th), the coefficients for ECI appear weak or statistically insignificant, indicating a period of transition among middle-income countries. This pattern suggests that economies in this range are in a structural adjustment phase, benefiting partially from growing productive capabilities but still constrained by limited technological absorption, uneven skill distribution, and institutional inefficiencies. These transitional economies may be developing new industries and capabilities but have not yet achieved the level of diversification and knowledge intensity seen in higher-quantile countries. Consequently, while economic complexity begins to stimulate income growth, its full potential to reduce disparities remains unrealised due to persistent structural constraints.

Across the quantiles, Table 4 shows that trade openness and inflation were positively and significantly associated with GDP per capita in all quantiles. This suggests that, as trade openness and inflation improve, they do not directly influence income disparity, as income tends to increase across all countries regardless of development level. In other words, the effects of trade and inflation on income appear uniform across low- and high-income economies. At the same time, human capital, population, and institutional quality exhibit varying effects across income distribution. This finding is consistent with Chu (2023), which finds that these variables generally have a reducing effect on income disparity, as indicated by their positive impact at lower quantiles and negative impact at higher quantiles. Institutional quality positively affects income per capita across the 10th to 70th percentiles, suggesting that institutional improvements enhance income generation in developing and emerging economies. However, in the 80th and 90th percentiles, the coefficient turns negative, suggesting that further institutional improvements in already high-income countries may yield diminishing returns on income growth.

We then estimate the quantile results simultaneously by testing the equality of the coefficients across quantiles. In doing so, we intend to determine whether the coefficients at lower quantiles differ statistically from those at higher quantiles. Table 5 presents the results for four estimated quantiles: $10^{th} = 90^{th}$, $20^{th} = 80^{th}$, $30^{th} = 70^{th}$, and $40^{th} = 60^{th}$. At the 10^{th} and 90^{th} percentiles, and at the 20^{th} and 80^{th} percentiles, the joint F-statistics results indicate that all coefficients are statistically significant. Thus, the result confirms that the coefficients at lower quantiles are statistically different from those at higher quantiles. However, as we approach the middle quantiles, we see that the F-statistic for the population is not significant at the 30th -70th and 40th - 60th percentiles.

Table 4. Dynamic panel quantile regression

Regressor	Dependent variable: GDPPC								
	Quantile								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
$\ln GDPPC_{t-1}$	0.968*	0.976*	0.978*	0.974*	0.982*	0.987*	0.990*	0.994*	0.995*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnECI	-0.001*	-0.004*	0.000	0.003*	0.000*	0.003*	-0.000*	0.001*	0.002*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnHCI	0.014*	0.016*	0.008*	0.020*	0.012*	0.007*	0.009*	0.003*	-0.005*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnPOP	0.007*	0.003*	0.003*	0.003*	0.003*	0.002*	0.002*	-0.002*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnTO	0.013*	0.009*	0.008*	0.0167*	0.024*	0.017*	0.0186*	0.011*	0.0127*
	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
lnINS	0.072*	0.038*	0.036*	0.025*	0.014*	0.005*	0.005*	-0.003*	-0.002***
	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
lnINF	0.015*	0.000	0.017*	0.098*	0.143*	0.216*	0.385*	0.449*	0.534*
	(0.001)	(0.004)	(0.005)	(0.003)	(0.003)	(0.000)	(0.001)	(0.003)	(0.002)
Observations	2,357	2,357	2,357	2,357	2,357	2,357	2,357	2,357	2,357
Number of countries	115	115	115	115	115	115	115	115	115

Note: Standard errors in parentheses. *, **, and *** refer to statistical significance at the 1, 5, and 10% levels, respectively

Table 5. Coefficient differences between lower and upper quantiles

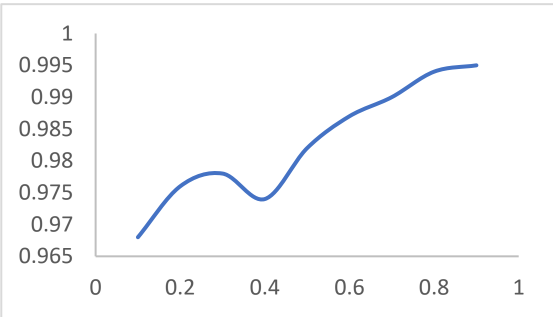
Variables	0.1 = 0.9	0.2 = 0.8	0.3 = 0.7	0.4 = 0.6
	F-stat	*F*-stat	*F*-stat	*F*-stat
ECI	13.03*	15.91*	3.59***	4.93**
HC	8.14*	10.25*	3.23***	2.09**
lnPOP	7.75*	3.50**	0.03	0.01
lnTO	9.35*	2.51**	6.60**	2.73***
lnINS	27.75*	27.83*	17.11*	7.15*
lnINF	74.70*	56.23*	81.22*	25.56*

Note: *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

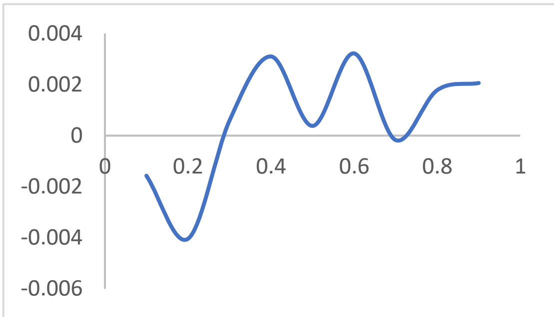
Figure 2 graphically illustrates the impact of economic complexity and other control variables on GDP per capita. The horizontal *x*-axis in the figures shows the quantile scale, and the vertical *y*-axis shows the estimated coefficients for each variable. As shown in Figure 2(a), past income significantly affects current income, with the effect increasing toward higher quantiles. Figure 2(b) suggests that ECI is significantly negative in low quantiles and positive in medium and high quantiles. This growing effect of economic complexity, which intensifies at higher quantiles, is consistent with Chu and Hoang (2020), who found that disparity increases as countries develop more complex economies. Figure 2(g) shows that lagged GDPPC and inflation have an increasing trend, in contrast to Figures 2(c), (d), and (f), which indicate a decreasing trend for human capital, population, and institutions. Here, we infer that the impact of these variables decreases marginally as quantiles increase. Finally, Figure 2(e) shows sustained fluctuations in the coefficient across quantiles for trade openness.

Robustness Checks

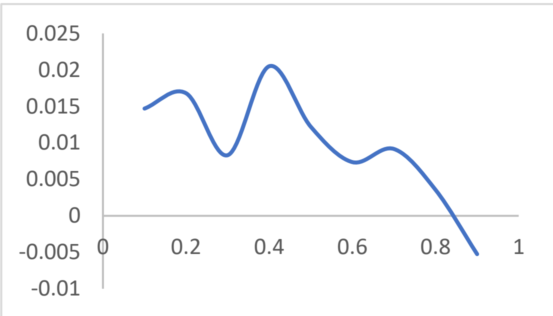
To further validate the dynamic panel quantile results, this study employed a two-step system GMM estimation using a different proxy for income disparity: the Gini index. The Gini index was obtained from the Standardized World Income Inequality Database (SWIID, version 9.5) (Solt, 2020). We utilised the data for the period of 1996 to 2020, and the data were also averaged for 5-year periods in this section. To ensure comparability, the same control variables were retained in both the quantile and GMM estimations. The difference lies only in the dependent variable, GDP per capita (main model) and Gini index (robustness test), which capture different aspects of income disparity. Data for the independent and control variables – ECI, human capital, population, institutions, and inflation – were obtained from previous estimations. However, to successfully investigate the sensitivity of the last result, we selected countries with lower-than-average World GDP per capita in 2020, which was $10,499.6 (constant 2015 US dollars).



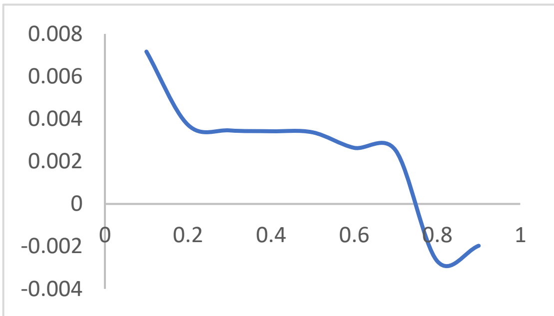
(a) Coefficient for lag GDPPC



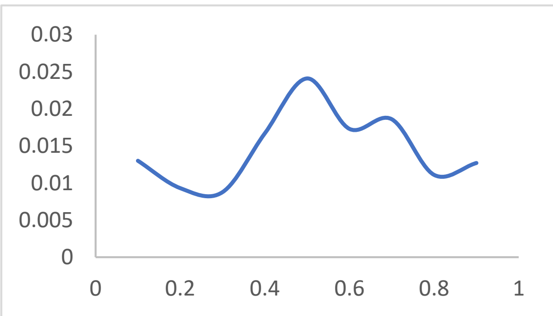
(b) Coefficient for ECI



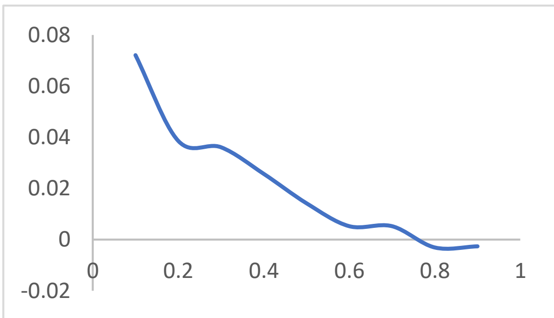
(c) Coefficient for human capital



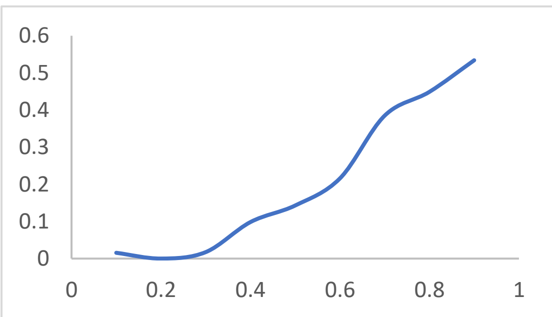
(d) Coefficient for population



(e) Coefficient for trade openness



(f) Coefficient for institution



(g) Coefficient for inflation

Figure 2. Changes in panel quantiles regression as quantiles vary from 0 to 1

Thus, this sample amounts to 69 countries, representing some middle- and all low-income countries from the quantile estimation. This reduction in sample size may affect the external validity of the robustness check and, if the countries with available Gini data differ systematically from the full panel, introduce sample selection bias. Nevertheless, the direction and significance of the relationship between economic complexity and disparity remain consistent in this subset, offering partial validation of the main findings.

Table 6 shows the robustness test for our estimation, indicating that economic complexity has a statistically significant positive effect on income disparity at the 1% level. The GMM estimates confirm the positive relationship between ECI and Gini, consistent with the upper-quantile results of the dynamic quantile regression, in which economic complexity is associated with higher income disparities. Thus, this result supports previous estimates and shows that increasing productive capabilities in middle- and low-income countries leads to widening disparities in these regions. Furthermore, the persistence of ECI's positive effect across both models suggests that the widening influence of economic complexity on income disparity is not model-specific. However, the stronger effects observed in higher quantiles suggest that the dynamic quantile regression model captures heterogeneity in the income distribution that the GMM approach cannot fully account for.

Additionally, the lagged Gini also affects the current Gini, indicating that this dynamic model is appropriate. Trade openness and inflation appear to positively influence income disparity, whereas human capital and institutions negatively influence the Gini. In addition, the population was found to be insignificant in this estimation. Overall, we can conclude that increasing economic complexity in middle- and low-income countries increases income disparity.

Table 6. System GMM using Gini as a proxy for income disparity without outliers

Regressor	Coefficient	Robust Standard Error
Constant	-0.471*	0.081
Gini $_{t-1}$	0.945*	0.006
ECI	0.084*	0.014
HC	-0.099*	0.035
lnPOP	-0.009	0.049
lnTO	0.089*	0.044
lnINS	-0.008**	0.012
lnINF	0.019**	0.021
Observations	232	
Number of countries	66	
No. of instruments	14	
AR1 (*p*-value)	0.00	
AR2 (*p*-value)	0.413	
Hansen (*p*-value)	0.592	

Note: *, **, and *** refer to statistical significance at the 1, 5, and 10% levels, respectively

Conclusion

This study analyses the effect of economic complexity on income in 115 countries over the 1995–2020 period. The study found significant cross-country impacts using dynamic panel quantile regression. At a high quantile, economic complexity is associated with higher income per capita. Thus, an increase in a country's productive capabilities is linked to higher workers' incomes in developed countries. This study also found that economic complexity negatively impacts income per capita at a low quantile. This implies that an increase in productive capabilities in these countries did not benefit the incomes of low-skilled workers. Thus, the positive impact at higher quantiles and the negative impact at lower quantiles support the idea that economic complexity had a widening effect on income disparity. Meanwhile, increasing human capital, population, and institutional quality reduces income disparity between low- and high-income countries. Finally, increases in trade openness and inflation do not affect income disparity, as income tends to increase across all quantiles.

Based on our findings that economic complexity has a widening effect on income disparity, policy formulation should be strategized to effectively narrow the disparity between high- and low-income countries. The governments of low-income countries should aim to venture into new industries that add value by introducing new productive capabilities in the economy. New productive capabilities not only increase a country's complexity but also contribute to a chain effect in the economy. In high-income countries, policy formation should be structured to foster more complex and diversified activities, especially those that build existing productive capabilities.

Although this study offers useful insights into the relationship between economic complexity and income, several limitations should be noted. First, using GDP per capita as a proxy for income disparity captures differences between countries but not within-country inequality. Second, despite accounting for heterogeneity across income levels, the dynamic panel quantile approach may be subject to endogeneity due to omitted variables, such as labour market structure or capital formation. Lastly, the dataset is unbalanced because not all 115 countries have continuous observations from 1995 to 2020, which may affect the precision of estimates at the lower and upper quantiles. Future research could extend this analysis by incorporating within-country income data to better capture inequality at the individual level. Further studies may also expand the scope to include regional or sectoral data, which could provide a more detailed view of how productive capabilities shape income outcomes across different economic contexts.

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Author contribution
All authors contributed to the conception and design of the study, data collection, analysis and interpretation of the results, and the writing of the manuscript. All authors read and approved the final version of the manuscript.

Use of AI tools declaration
Artificial intelligence tools were used to assist with language editing and to enhance the clarity and readability of the manuscript. The authors remain fully responsible for the content and conclusions of this study.

Conflict of interest
The authors declare that there are no competing interests related to this manuscript.

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