İSTANBUL UNIVERSITY PRESS

Sosyal Siyaset Konferansları Dergisi
Journal of Social Policy Conferences

Sosyal Siyaset Konferansları Dergisi
Journal of Social Policy Conferences
JSPC 2026, (90): 32–58

https://doi.org/10.26650/jspc.2026.90.1913275
Submitted 20.03.2026
Revision Requested 04.06.2026
Last Revision Received 10.06.2026
Accepted 11.06.2026

Research Article

Open Access

The Impact of Export Complexity on Income Inequality: A Dynamic Panel Data Analysis for Developing Countries

Aytuğ Zekeriya Bolcan [1]

[1] Istanbul University, Faculty of Economics, Department of Economic Theory, İstanbul, Türkiye

Abstract

This study empirically investigates the effect of export complexity on income inequality across a panel of 96 developing countries over the 1990-2023 period. Employing the Economic Complexity Index (ECI) developed by the Harvard Growth Lab alongside the disposable income Gini coefficient from the Standardized World Income Inequality Database (SWIID v9.9), we apply dynamic panel data methods to address endogeneity, persistence, and unobserved heterogeneity. The two-step Arellano-Bover/Blundell-Bond System GMM estimator reveals no statistically significant relationship between economic complexity and disposable-income inequality in the full sample: neither the linear ECI term (β = 0.692, p = 0.127) nor the quadratic term (β = 0.278, p = 0.127) achieves conventional significance levels. Dumitrescu–Hurlin panel Granger causality tests reject the null hypothesis of non-causality in both directions between ECI and the Gini coefficient (p < 0.001 in each direction), providing strong evidence of bidirectional predictive causality. Subgroup analyses by World Bank income classification reveal no statistically significant ECI effect in either the lower-middle-income or upper-middle-income groups; the low-income group (17 countries) cannot be validly estimated by System GMM because its time dimension exceeds its cross-sectional dimension (T ≥ N). A Türkiye-specific case study examines how the structural transformation of Türkiye's export basket has coevolved with income distribution across three subperiods. However, robustness checks show that this null result is specific to the disposable-income measure: when inequality is measured by the market (pre-redistribution) Gini, and in a trimmed sample, both the linear and quadratic ECI terms become positive and statistically significant (market-income Gini: $\beta_{ECI} = 1.246$, $\beta_{ECI^2} = 0.425$, both p < 0.05), indicating that export complexity is associated with higher pre-redistribution inequality (a within-country pattern consistent with Lee and Vu (2020) and Chu and Hoang (2020)). The results suggest that the relationship between export complexity and inequality is context-dependent (conditional on the inequality concept employed and the extent of fiscal redistribution) and that export upgrading alone is insufficient for reducing inequality without targeted education investments, institutional quality improvements, and labour market policies.

Keywords

Economic complexity · income inequality · dynamic panel data · System GMM · developing countries

Citation: Bolcan, A. (2026). The impact of export complexity on income inequality: A dynamic panel data analysis for developing countries. *Sosyal Siyaset Konferansları Dergisi–Journal of Social Policy Conferences*, (90), 32-58. https://doi.org/10.26650/jspc.2026.90.1913275

This work is licensed under Creative Commons Attribution-NonCommercial 4.0 International License.

© 2026. Bolcan, A.

Corresponding author: Aytuğ Zekeriya Bolcan abolcan@istanbul.edu.tr

The Impact of Export Complexity on Income Inequality: A Dynamic Panel Data Analysis for Developing Countries

The relationship between what countries produce and export, on the one hand, and how income is distributed within those countries, on the other, lies at the intersection of trade theory, development economics, and social policy. While classical trade models following Stolper and Samuelson (1941) predict that trade liberalisation should benefit the abundant factor (unskilled labour in developing countries) and thereby reduce inequality, the empirical record has been far more ambiguous. Decades of trade integration have coincided with rising within-country inequality across much of the developing world (Goldberg & Pavcnik, 2007; Milanovic, 2005), challenging the theoretical consensus and demanding new analytical frameworks.

The economic complexity paradigm, pioneered by Hidalgo and Hausmann (2009) and elaborated in the *Atlas of Economic Complexity* (Hausmann et al., 2014), offers a promising lens through which to examine this puzzle. The Economic Complexity Index (ECI) measures the diversity and sophistication of a country's export basket, capturing the accumulated productive knowledge embedded in a nation's economy. Countries with higher ECI produce a wider range of technologically sophisticated goods, reflecting deeper human capital, institutional capacity, and interfirm coordination. The question of whether this structural sophistication translates into approximately equitable income distribution is not merely academic (it carries direct implications for industrial policy design and social protection systems).

The seminal contribution linking economic complexity to inequality is Hartmann et al. (2017), who demonstrated a robust negative cross-sectional association between ECI and the Gini coefficient across more than 150 countries. Their analysis introduced the Product Gini Index, showing that commodity-dependent economies exhibit systematically higher inequality than those producing complex manufactures. However, subsequent studies employing more rigorous endogeneity controls have yielded conflicting results. Lee and Vu (2020), using System GMM estimation across 96 countries, found that the relationship reverses to positive when accounting for the persistence of inequality and reverse causality (suggesting that within-country increases in complexity may initially exacerbate inequality). Chu and Hoang (2020) corroborated this finding, while Nguyen et al. (2023) and Amarante et al. (2024) identified a nonlinear, inverted-U pattern wherein complexity increases inequality up to a threshold before reducing it.

Despite this growing literature, several gaps remain. First, there is limited dynamic panel evidence focusing on developing countries, where the structural transformation channel is most policy-relevant. Second, the heterogeneity of the ECI–inequality relationship across income groups has received insufficient attention, even though the mechanisms linking complexity to distribution likely differ between low-income agricultural economies and upper-middle-income industrialising nations. Third, country-specific case studies that trace the co-evolution of export basket upgrading, labour market change, and income distribution are scarce, particularly for countries like Türkiye that have undergone substantial structural transformation since the mid-1990s.

This work addresses these gaps by conducting a comprehensive empirical analysis of the ECI – inequality nexus across a panel of developing countries over the 1990-2023 period. Our methodological approach employs the Arellano-Bover/Blundell-Bond System GMM estimator (Arellano & Bover, 1995; Blundell & Bond, 1998) with Windmeijer (2005) corrected standard errors, explicitly addressing the Nickell (1981) bias inherent in dynamic panel models with country fixed effects. We test for nonlinear effects through a quadratic specification, conduct Dumitrescu-Hurlin panel Granger causality tests, and perform subgroup analyses by

World Bank income classification. A dedicated Türkiye case study descriptively examines the co-evolution of Türkiye's export transformation (from textiles and basic manufactures towards automotive components, machinery, and electronics) and disposable-income inequality across three analytically meaningful sub-periods.

Our contribution to this journal's scope is direct: the structure of a country's export basket shapes employment quality, wage differentials, skill premiums, and labour market formalisation—all channels through which trade policy intersects with social policy. Understanding whether and how export complexity affects inequality informs industrial strategy and the design of education systems, social safety nets, and labour market institutions. By connecting the economic complexity literature to distributional outcomes, this study bridges the gap between trade analysis and social policy evaluation.

The remainder of this study is organised as follows. Section 2 reviews the theoretical and empirical literature on economic complexity, trade structure, and income inequality. Section 3 describes the data sources, variable definitions, and econometric methodology. Section 4 presents the empirical results, including the full-sample System GMM estimates, Granger causality tests, subgroup analyses, and the Türkiye case study. Section 5 discusses the findings considering theoretical predictions and existing evidence. Section 6 concludes with policy implications and directions for future research.

Literature Review

Economic Complexity and Growth

The economic complexity framework emerged from network science applied to international trade data. Hidalgo et al. (2007) introduced the product space (a network representation of international trade where the proximity between products reflects the likelihood of co-exportation) and demonstrated that countries develop new comparative advantages by moving into "nearby" products in this network. The product space exhibits a core-periphery structure, with sophisticated manufactures clustered in a densely connected core and primary commodities occupying the sparse periphery. This topological feature helps explain persistent development traps: countries specialising in peripheral products face structural barriers to diversification.

Hidalgo and Hausmann (2009) formalized the Economic Complexity Index using the Method of Reflections, an iterative algorithm applied to the bipartite country-product network. They showed that ECI correlates strongly with income levels, but crucially, *deviations* from this correlation predict future growth —countries with higher complexity than expected for their income level grow faster in subsequent decades. Hausmann et al. (2014) expanded this framework in the *Atlas of Economic Complexity*, demonstrating that ECI outperforms governance indicators, the World Economic Forum's competitiveness index, and human capital measures in growth prediction. An alternative nonlinear approach, the Fitness-Complexity method by Tacchella et al. (2012), generates similar country rankings but captures different dynamics for low-income economies.

The related finding of Hausmann et al. (2007) (that "what you export matters" for growth) established that export composition, not merely volume, drives development trajectories. More recently, Hidalgo (2021) provided a comprehensive synthesis in *Nature Reviews Physics*, reviewing how complexity methods predict not only growth but also inequality, emissions, and labour market outcomes across countries and regions. Balland et al. (2022) argued that economic complexity constitutes a new paradigm for understanding regional diversification and structural change.

Recent panel studies continue to investigate the complexity – growth nexus. Orsolin-Teixeira, Missio, and Dathein (2022) used system-GMM estimators to study the effect of economic complexity on growth and structural transformation across Brazilian regions, and Molele and Ncanywa (2022) reported a positive

long-run relationship between economic complexity and GDP per capita for Sub-Saharan African and BRICS economies.

Trade structure and income inequality

The theoretical relationship between trade and income distribution has been debated since Stolper and Samuelson (1941) demonstrated that in a Heckscher-Ohlin framework, trade liberalisation raises the real return to the abundant factor. For developing countries, this implied that openness should benefit unskilled labour and reduce inequality. However, the comprehensive survey by Goldberg and Pavcnik (2007) found overwhelming evidence contradicting this prediction: trade liberalisation across Latin America, India, and other developing regions coincided with rising wage inequality. Davis and Mishra (2007) argued that Stolper-Samuelson predictions fail because labour-abundant countries globally may be capital-abundant relative to their immediate trading partners.

The dominant explanation for rising inequality alongside trade integration invokes skill-biased technological change (SBTC). Acemoglu (2002, 2003) showed that trade induces technological adoption that disproportionately increases demand for skilled labour, even in developing countries. Feenstra and Hanson (1996, 1997) demonstrated that outsourcing from developed to developing countries shifts the least skill-intensive activities from the North to the South, but these activities are the most skill-intensive from the South's perspective—thereby raising the skill premium in both regions simultaneously. Meschi and Vivarelli (2009), using dynamic panel estimation across 65 developing countries, found that trade with high-income countries worsens distribution through technology transfer channels.

The structural change dimension was articulated by McMillan and Rodrik (2011), who showed that in Africa and Latin America, structural change was growth-reducing as labour moved from high- to low-productivity sectors. The question of whether trade-induced structural change improves or worsens inequality depends critically on whether workers displaced from contracting sectors can access employment in expanding, higher-productivity activities. Spilimbergo et al. (1999) demonstrated that the distributional effects of trade openness depend on factor endowments, whereas Milanovic (2005) found a nonlinear relationship contingent on initial income levels. More recently, Dorn et al. (2022), using instrumental variable methods across 139 countries, showed that trade openness benefits the poorest in developing countries while enriching the top deciles in advanced economies.

Recent studies confirm that productive structure shapes income distribution, although the estimated direction is sensitive to context and method. Sepehrdoust, Tartar, and Gholizadeh (2022) examine the link between economic complexity and income inequality across developing economies, and Basile and Cicerone (2022) document the link between complexity and productivity polarisation across Italian provinces.

Economic Complexity and Income Distribution

The direct link between economic complexity and inequality was established by Hartmann et al. (2017), whose cross-sectional analysis of over 150 countries using the Estimated Household Income Inequality dataset found a significant negative association between ECI and the Gini coefficient. They showed that this relationship is robust to controlling for GDP per capita, institutional quality, export concentration, and education, and that ECI explains more cross-country inequality variation than income alone. Their Product Gini Index revealed that commodity-based products are systematically associated with higher inequality, while complex manufactures correlate with equal distribution.

However, studies employing endogeneity-robust estimators challenged this cross-sectional finding. Lee and Vu (2020) replicated the negative OLS result across 113 countries but found that two-step System GMM estimation with five-year averages produced a positive coefficient—indicating that within-country increases

in complexity are associated with rising inequality. They argued that the OLS estimate is biased by endogeneity from reverse causality and the persistence of Gini coefficients. Chu and Hoang (2020) confirmed this reversal using FE-2SLS and System GMM across 88-99 countries, while emphasising that human capital and efficient public spending moderate the complexity – inequality relationship.

The resolution to this apparent contradiction may lie in nonlinearity. Nguyen et al. (2023) found an inverted U-shaped relationship between ECI and inequality across low-, lower-middle-, and upper-middle-income countries, with the effect reversing at high complexity levels. Amarante et al. (2024) confirmed this pattern using System GMM across 88 countries, demonstrating that the positive impact on inequality diminishes and eventually turns negative at very high complexity levels. Sbardella et al. (2017) documented a Kuznets-type inverted-U using the Fitness-Complexity framework, whereas Bandeira Morais et al. (2021) found similar nonlinearity at the subnational level in Brazilian states.

Additional nuance comes from studies examining moderating factors. Lee and Wang (2021) showed that country risk moderates the nexus, with ECI reducing inequality only in low-risk environments. Ghosh et al. (2023) found heterogeneous effects across income groups using System GMM. Bedemo Beyene (2024) demonstrated that governance quality moderates the complexity – inequality relationship in Africa. The spatial dimension is highlighted by Hartmann and Pinheiro (2024), who documented Simpson's paradox: while ECI and inequality are negatively correlated at the national level, complex activities concentrate spatially, creating regional winner-take-most effects. Pinheiro et al. (2025) confirmed this for European NUTS2 regions.

Key gaps in this literature include: (i) limited dynamic panel evidence focused specifically on developing countries with heterogeneous effects by income group; (ii) sparse country-level case studies tracing the inequality consequences of export basket upgrading; and (iii) insufficient connection between complexity findings and social policy design. This work addresses all three gaps.

Türkiye's export transformation and distributional outcomes

Türkiye's post 1980 structural adjustment under the Özal reforms constitutes a canonical case of trade-driven structural change in the developing world. Atiyas and Bakış (2015) demonstrated that approximately two-thirds of Türkiye's aggregate labour productivity increase arose from employment reallocation across sectors, with one-third from within-sector improvements. Türkiye's export basket shifted dramatically from textiles and agricultural products towards automotive components, machinery, and electronics, significantly increasing its world export share (Yükseler & Türkan, 2006; Kaya & Çiçekçi, 2023). However, Erkan and Yıldırımcı (2015) noted that Türkiye remains labour-intensive, with an ECI ranking around 41st globally, suggesting incomplete transformation.

Javorcik et al. (2018) provided firm-level evidence that foreign direct investment boosts production complexity in Turkish manufacturing, with a 10-percentage-point increase in foreign presence translating into measurably higher complexity of newly introduced products. On the inequality side, Tekgüç and Eryar (2025) documented that Türkiye's market income Gini was approximately 0.51 in 2003, with substantial redistribution through fiscal policy. Meschi et al. (2011, 2016) used firm-level data to demonstrate imported SBTC in Turkish manufacturing, finding that firms importing inputs from industrialised countries experienced higher increases in skilled workers' labour cost share. Örnek and Elveren (2010), using Engle–Granger cointegration and Granger causality tests, reported a long-run and Granger-type relationship between rising trade openness and worsening income inequality in Türkiye during 1980–2001. Elveren and Galbraith (2009), by contrast, documented the evolution of manufacturing pay inequality over the same neoliberal period

using Theil-index decomposition rather than a causal design, whereas Topuz and Dağdemir (2020) identified a nonlinear U-shaped relationship.

Despite this rich literature on Türkiye's trade and inequality, no study directly situates Türkiye's ECI trajectory within a broader cross-country dynamic panel framework while also describing its domestic inequality path through the product-space perspective. This work addresses this gap by embedding a descriptive Türkiye case study within the broader developing-country analysis.

Data and Methodology

Data sources and variable definitions

This study draws on four primary data sources. The dependent variable, income inequality, is measured by the Gini coefficient for disposable (post-tax, post-transfer) income (*gini_disp*) from the Standardised World Income Inequality Database (SWIID) version 9.9 (Solt, 2020). The SWIID provides comparable Gini estimates across countries and time by using the Luxembourg Income Study as a benchmark and applying a custom missing-data algorithm. We also use the market income Gini (*gini_mkt*) for robustness checks.

The key independent variable, the Economic Complexity Index (ECI), is sourced from the Harvard Growth Lab's Atlas of Economic Complexity data set. ECI measures the diversity and sophistication of a country's export basket using the Method of Reflections applied to international trade data. Higher ECI values indicate more complex, knowledge-intensive export structures.

Control variables are drawn from the World Bank's World Development Indicators (WDI): log GDP per capita (constant 2015 USD), trade openness (trade as a percentage of GDP), secondary school enrolment (gross), government final consumption expenditure (percentage of GDP), domestic credit to the private sector (percentage of GDP), foreign direct investment net inflows (percentage of GDP), consumer price inflation, and log population. The Rule of Law estimate from the Worldwide Governance Indicators (WGI) serves as a proxy for institutional quality. Table 1 provides variable definitions and sources.

Table 1

Variable Definitions and Sources

Variable	Notation	Definition	Source
Panel A: Dependent variables			
Gini (disposable)	*gini_disp*	Gini coefficient for disposable (post-tax, post-transfer) household income, 0-100 scale	SWIID v9.9 (Solt, 2020)
Gini (market)	*gini_mkt*	Gini coefficient for market (pre-tax, pre-transfer) household income, 0-100 scale	SWIID v9.9 (Solt, 2020)
Panel B: Key Independent Variable			
Economic Complexity Index	*ECI*	Measures the diversity and sophistication of a country's export basket using the Method of Reflections on product-level trade data.	Harvard Growth Lab, Atlas of Economic Complexity
ECI squared	ECI^2	Squared term of ECI to capture potential nonlinear (inverted-U) relationship with inequality	Computed
Panel C: Control variables			
GDP per capita (log)	*ln_gdp_pc*	Natural logarithm of GDP per capita in constant 2015 U.S. dollars	WDI (NY.GDP.PCAP.KD)
Trade openness	*trade_open*	Sum of exports and imports of goods and services as a percentage of GDP	WDI (NE.TRD.GNFS.ZS)

Variable	Notation	Definition	Source
Human capital	*school_enrl*	School enrolment, secondary (gross percentage); ratio of total enrolment to the population of the age group	WDI (SE.SEC.ENRR)
Government expenditure	*govt_exp*	General government final consumption expenditure as a percentage of GDP	WDI (NE.CON.GOVT.ZS)
Financial development	*dom_credit*	Domestic credit to the private sector by banks as a percentage of GDP	WDI (FS.AST.PRVT.GD.ZS)
FDI inflows	*fdi*	Foreign direct investment, net inflows as a percentage of GDP	WDI (BX.KLT.DINV.WD.GD.ZS)
Inflation	*inflation*	Annual percentage change in the consumer price index (CPI)	WDI (FP.CPI.TOTL.ZG)
Population (log)	*ln_pop*	Natural logarithm of the total population	WDI (SP.POP.TOTL)
Institutional quality	*rule_of_law*	Rule of Law estimate: perceptions of confidence in and adherence to the rules of society; ranges approximately −2.5 to +2.5	WGI (RL.EST)

Note : SWIID = Standardized World Income Inequality Database; WDI = World Development Indicators (World Bank); WGI = Worldwide Governance Indicators (World Bank). WDI indicator codes are shown in parentheses. The sample covers developing countries classified as low-income, lower-middle-income, or upper-middle-income by the World Bank over the 1990-2023 period.

Sample

The sample comprises developing countries classified as low-income, lower-middle-income, or upper-middle-income by the World Bank's income group classification. After merging all datasets and applying data availability filters, the final unbalanced panel includes 96 countries (17 low-income, 37 lower-middle-income, and 42 upper-middle-income) over the 1990–2023 period. The exact country composition and data coverage are detailed in the appendix. Türkiye is included in the upper-middle-income subgroup and is additionally analysed as a standalone case study.

Descriptive Statistics

Table 2

Summary statistics

Variable	N	Mean	Std. Dev.	Min	P25	Median	P75	Max
gini_disp	2286	41.241	6.957	23.900	36.600	41.000	45.500	65.200
eci	2286	−0.364	0.878	−4.539	−0.938	−0.310	0.334	1.488
eci_sq	2286	0.902	1.516	0.000	0.101	0.384	1.020	20.603
gini_mkt	2286	45.270	6.655	32.200	40.525	45.000	49.200	72.500
ln_gdp_pc	2286	7.767	0.942	5.426	7.057	7.836	8.522	9.621
trade_openness	2139	70.262	31.820	14.772	46.364	63.731	88.024	220.407
school_enrollment	1553	67.240	27.850	5.044	42.986	74.650	88.957	138.903
govt_expenditure	2092	13.790	4.422	2.048	10.858	13.569	16.619	35.938
domestic_credit	1867	34.023	30.266	1.095	12.320	25.786	46.957	189.607
fdi_inflows	2280	3.580	5.543	−37.173	1.121	2.486	4.463	103.337
inflation	2149	11.194	35.822	−10.067	2.822	5.707	9.996	1058.374
ln_population	2286	16.722	1.417	13.806	15.702	16.639	17.564	21.078
rule_of_law	1973	−0.606	0.540	−2.352	−0.959	−0.601	−0.268	1.029

Notes: Unbalanced panel of 96 developing countries over the 1990-2023 period (17 low-income, 37 lower-middle-income, 42 upper-middle-income). gini_disp = Gini coefficient for disposable income (0–100 scale); eci = Economic Complexity Index; gini_mkt = Gini coefficient for market income.
Source: Author's calculations using SWIID v9.9, Harvard Growth Lab, and World Bank WDI.

Table 2 presents the summary statistics for the variables used in the analysis. The panel comprises 2286 country-year observations drawn from 96 developing countries over the 1990-2023 period, including 17 low-income, 37 lower-middle-income, and 42 upper-middle-income economies. The disposable income Gini coefficient (*gini_disp*) has a mean of 41.241 with a standard deviation of 6.957, ranging from 23.9 to 65.2 on the 0-100 scale. The ECI averages −0.364 with considerable cross-country variation (SD = 0.878), ranging from −4.539 to 1.488. This wide distribution reflects the substantial heterogeneity in productive sophistication across developing countries, from commodity-dependent low-income economies to industrialising upper-middle-income nations. The squared ECI term has a mean of 0.902 (SD = 1.516). The market income Gini (*gini_mkt*) averages 45.270, approximately four points higher than the disposable income measure, reflecting the redistributive impact of fiscal policy.

Figure 1 depicts the temporal evolution of mean ECI and Gini values for the developing-country sample over the 1990–2023 period, revealing a broad divergence between increasing productive sophistication (rising ECI) and gradually declining average inequality (falling Gini).

Figure 1
Average ECI and Gini Index for Developing Countries, 1990-2023.

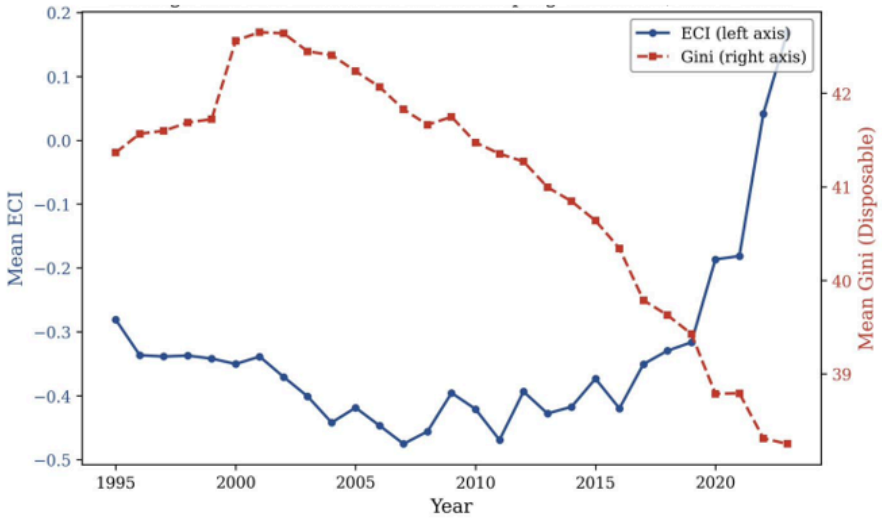


Figure 2 disaggregates the inequality trend by World Bank income classification, revealing that the decline in average Gini has been most pronounced among upper-middle-income countries, whereas low-income economies have experienced a more volatile trajectory with convergence across groups in recent years.

Figure 2

Income Inequality Trends by Income Group, 1990-2023.

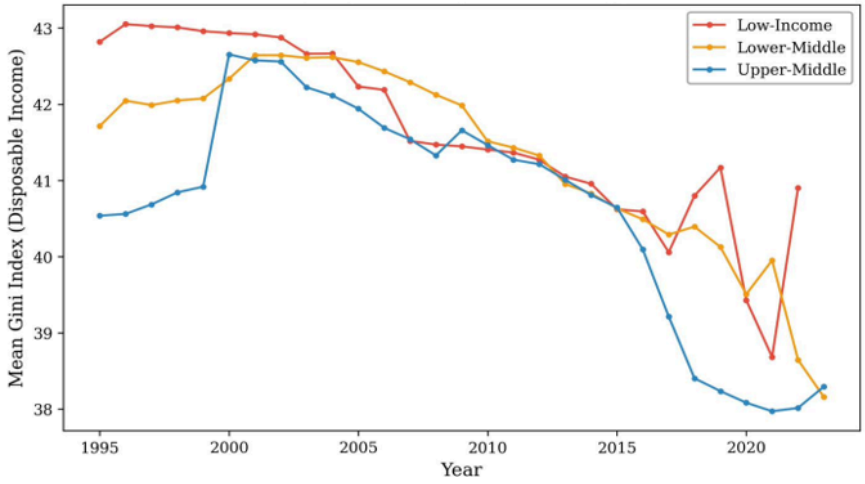
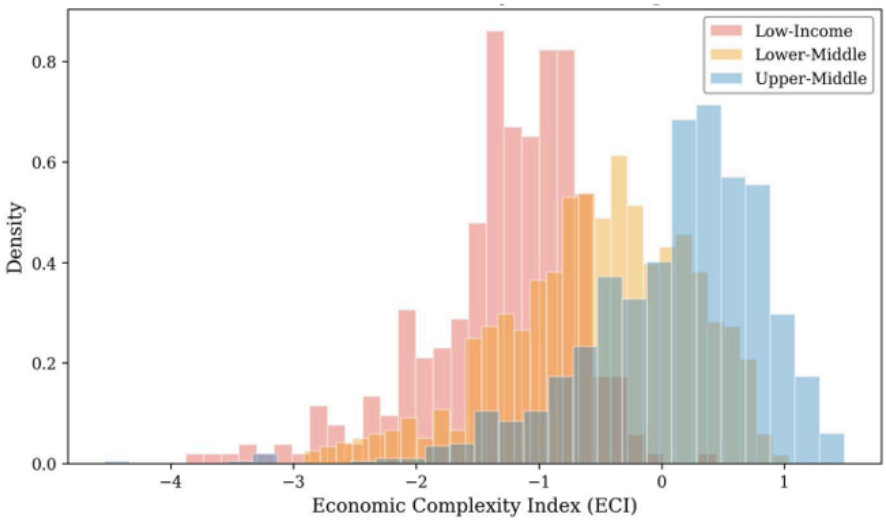


Figure 3 presents the distribution of ECI values across income groups, confirming the expected gradient: low-income countries cluster at negative ECI values reflecting commodity-dependent export baskets, whereas upper-middle-income economies exhibit higher and more dispersed complexity scores.

Figure 3

Distribution of ECI by Income Group.



Log GDP per capita averages 7.767 (SD = 0.942), trade openness averages 70.26% of GDP (SD = 31.82), and secondary school enrolment averages 67.24% (SD = 27.85). Government expenditure averages 13.79% of GDP, domestic credit to the private sector averages 34.02% of GDP, and FDI inflows average 3.58% of GDP. Inflation exhibits considerable right-skewness with a mean of 11.19% but a maximum exceeding 1,058%. The Rule of Law indicator averages −0.606 (SD = 0.540), reflecting the generally weaker institutional environments in the sample.

Table 3 presents the pairwise correlation matrix. The ECI – Gini correlation is negative (r = −0.165), consistent with the cross-sectional pattern documented by Hartmann et al. (2017), but modest in magnitude. ECI is positively correlated with log GDP per capita (r = 0.519), school enrolment (r = 0.632), domestic credit (r = 0.588), and rule of law (r = 0.491), confirming that more complex economies tend to be wealthier, better educated, and more institutionally developed. Trade openness is negatively correlated with inequality (r =

−0.240). Notably, the positive correlation between ECI and the Rule of Law (r = 0.491) highlights the potential role of institutional quality in the complexity–inequality nexus.

Table 3

Correlation matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) gini_disp	1.000	—	—	—	—	—	—	—	—	—
(2) eci	−0.165	1.000	—	—	—	—	—	—	—	—
(3) ln_gdp_pc	−0.026	**0.519**	1.000	—	—	—	—	—	—	—
(4) trade_openness	−0.240	0.191	0.239	1.000	—	—	—	—	—	—
(5) school_enroll.	−0.176	**0.632**	**0.782**	0.267	1.000	—	—	—	—	—
(6) govt_expend.	0.009	0.167	0.205	0.224	0.239	1.000	—	—	—	—
(7) domestic_credit	−0.018	**0.588**	**0.475**	0.369	**0.464**	0.202	1.000	—	—	—
(8) fdi_inflows	−0.090	−0.017	0.000	0.301	0.060	0.097	0.025	1.000	—	—
(9) inflation	−0.087	0.018	0.000	0.017	−0.007	−0.008	−0.096	−0.003	1.000	—
(10) rule_of_law	0.118	**0.491**	0.339	0.225	0.348	0.217	**0.420**	0.073	−0.153	1.000

Notes;: Pairwise Pearson correlation coefficients. Bold entries indicate |r| ≥ 0.40. Upper triangle suppressed for readability. The sample comprises 2286 country-year observations from 96 developing countries over the 1990-2023 period.
Source: Author's calculations using SWIID v9.9, Harvard Growth Lab, and World Bank WDI.

Econometric Methodology

The persistence of income inequality, combined with the potential endogeneity of ECI and several control variables, necessitates a dynamic panel framework. The baseline model is specified as

$$\mathrm{Gini}_{i,t} = \alpha + \rho \cdot \mathrm{Gini}_{i,t-1} + \beta 1 \cdot \mathrm{ECI}_{i,t} + \beta 2 \cdot \mathrm{ECI2}_{i,t} + \gamma' \mathrm{X}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

where *Gini* is the disposable income Gini coefficient for country *i* at time *t*; *ECI* is the Economic Complexity Index; *ECI²* captures potential nonlinear (inverted-U) effects; *X* is a vector of control variables; μ_i denotes country fixed effects; λ_t denotes time fixed effects; and $\varepsilon_{i,t}$ is the idiosyncratic error term.

The inclusion of the lagged-dependent variable $Gini_{i,t-1}$ captures the well-documented persistence of income inequality. However, this creates a mechanical correlation between the lagged dependent variable and the country fixed effects, producing the Nickell (1981) bias that renders standard fixed-effects estimation inconsistent for panels with short time dimensions. The System GMM estimator, developed by Arellano and Bover (1995) and Blundell and Bond (1998), addresses this by combining first-differenced equations (instrumented with lagged levels) and level equations (instrumented with lagged first-differences), generating additional moment conditions that improve efficiency relative to the difference GMM estimator of Arellano and Bond (1991).

We employ two-step estimation with the Windmeijer (2005) finite-sample correction for standard errors, which addresses the well-known downward bias in two-step GMM standard errors. Following Roodman (2009), we collapse instruments to mitigate the instrument proliferation problem and report the Sargan–Hansen J-test for overidentifying restrictions (Sargan, 1958; Hansen, 1982) alongside the Arellano-Bond AR(1) and AR(2) tests for serial correlation. The validity of the System GMM requires that AR(2) is insignificant (no second-order serial correlation in the first-differenced residuals) and that the Hansen test does not reject the null of instrument validity (Hansen, 1982).

The lagged-dependent variable and potentially endogenous regressors (ECI, GDP per capita, and trade openness) are instrumented using their second through fourth lags. Strictly exogenous regressors (insti-

tutional quality, population) enter as standard instruments. We assess sensitivity to these choices in the robustness section.

Panel Granger causality is tested using the Dumitrescu and Hurlin (2012) approach, which accommodates heterogeneous coefficients across cross-sectional units. The test statistic is the standardised average of individual Wald statistics from country-level Granger regressions, with the Z-bar statistic following a standard normal distribution under the null hypothesis of noncausality. We tested both directions: ECI → Gini and Gini → ECI.

For the Türkiye case study, given the single-country limitation, we employ a combination of descriptive trend analysis across three sub-periods (1990–2001, 2002–2012, 2013–2023) and a vector autoregression (VAR) framework to assess the dynamic interrelationship between Türkiye's ECI and Gini trajectories.

Empirical Results

Panel Unit Root Tests

Before estimating the dynamic panel model, we assess the stationarity properties of the key variables using Im-Pesaran-Shin (IPS) panel unit root tests (Im et al., 2003). The IPS test aggregates individual augmented Dickey-Fuller statistics across countries, allowing heterogeneous autoregressive coefficients. Results are presented in Table 4.

Table 4

Panel Unit Root Tests (Im-Pesaran-Shin)

Variable	Number of Countries	t-bar (IPS)	Z-t bar	p-value	Reject at 5%
gini_disp	94	−1.705	−1.893	0.029	Yes
eci	94	−2.217	−7.126	0.000	Yes
ln_gdp_pc	94	−0.933	5.996	1.000	No
trade_openness	87	−1.721	−1.974	0.024	Yes
school_enrollment	75	−1.860	−3.105	0.001	Yes
govt_expenditure	86	−1.945	−4.154	0.000	Yes
domestic_credit	87	−1.203	3.114	0.999	No
fdi_inflows	94	−2.876	−13.855	0.000	Yes
inflation	91	−5.541	−40.430	0.000	Yes
rule_of_law	92	−2.197	−6.848	0.000	Yes

Notes: Im-Pesaran-Shin (2003) panel unit root test. H_0: All panels contain unit roots. Lag length selected by AIC. Individual reject rate indicates the proportion of country-level ADF tests rejecting at 5%.
Source: Author's calculations.

The unit root tests yield a mixed stationarity pattern across the variables. The Gini coefficient rejects the unit root null at the 5% level (Z-tbar = −1.893, p = 0.029), though the modest test statistic indicates high persistence. ECI rejects more strongly (Z-tbar = −7.126, p < 0.001), reflecting greater variability in export structures over time. Among the control variables, log GDP per capita (Z-tbar = 5.996, p = 1.000) and domestic credit (Z-tbar = 3.114, p = 0.999) fail to reject the unit root null, suggesting non-stationarity in levels. Trade openness (p = 0.024), school enrolment (p = 0.001), government expenditure (p < 0.001), FDI inflows (p < 0.001), inflation (p < 0.001), and rule of law (p < 0.001) all reject the unit root null at conventional significance levels. This mixed stationarity pattern further justifies the System GMM approach, which is robust to persistent processes and does not require all variables to be stationary.

System GMM Results—Full Sample

Table 5 reports the System GMM estimates for the full sample of developing countries. We present three specifications: Model 1 includes only the ECI and the lagged dependent variable; Model 2 adds the full set of control variables; and Model 3 incorporates the quadratic ECI term to test for nonlinearity.

Figure 4 provides a visual overview of the ECI – Gini relationship. Panel (a) displays the pooled scatter plot with a quadratic fit, suggesting a mild inverted-U pattern in the raw data. Panel (b) disaggregates the observations by income group, revealing substantial overlap and heterogeneity across development levels.

Figure 4

Scatter Plot of ECI and Gini Index: (a) pooled sample with quadratic fit; (b) income group.

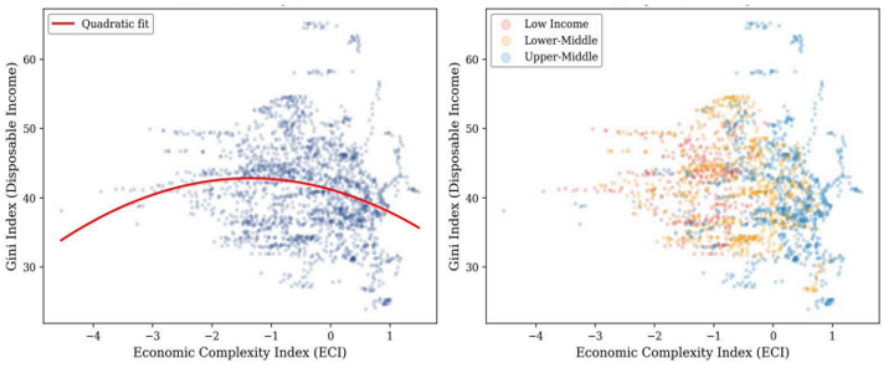


Table 5

System GMM Estimation Results: Full sample and robustness checks

Variable	model 1	model 2	model 3	R1: Market Gini	R4: Trimmed
L. Gini (lagged dep.)	1.0469***	0.8575***	0.8999***	0.9882***	0.9096***
	(0.0493)	(0.0647)	(0.0473)	(0.0707)	(0.0553)
ECI	−0.2634	0.2681	0.6923	1.2458**	1.4126**
	(0.3316)	(0.3714)	(0.4534)	(0.5629)	(0.6480)
ECI²	—	—	0.2778	0.4246**	1.0128***
			(0.1822)	(0.1949)	(0.3788)
ln GDP (per capita)	—	−0.2077	−0.3164	−0.4807	−0.4914
		(0.7243)	(0.6256)	(0.8322)	(0.7585)
Trade openness	—	−0.0041	−0.0060	−0.0144**	−0.0115*
		(0.0077)	(0.0063)	(0.0066)	(0.0062)
School enrolment	—	−0.0096	−0.0048	−0.0004	0.0041
		(0.0166)	(0.0160)	(0.0169)	(0.0164)
Govt. expenditure	—	−0.0241	−0.0251	0.0024	−0.0238
		(0.0512)	(0.0390)	(0.0322)	(0.0333)
Domestic credit	—	−0.0030	−0.0036	0.0020	−0.0068
		(0.0092)	(0.0077)	(0.0096)	(0.0070)
FDI inflows	—	0.0056	0.0121	0.0381**	0.0133
		(0.0219)	(0.0200)	(0.0180)	(0.0163)
Inflation	—	−0.0015	0.0008	0.0065	−0.0009
		(0.0057)	(0.0047)	(0.0054)	(0.0069)
Rule of law	—	0.4271	0.3589	0.0563	0.5189
		(0.2791)	(0.2592)	(0.4221)	(0.3685)

Variable	model 1	model 2	model 3	R1: Market Gini	R4: Trimmed
Constant	−2.1129 (2.0390)	8.9882 (5.9091)	7.8593* (4.3392)	5.0714 (8.0800)	8.5550 (5.7425)
AR(1) p value	0.032	0.028	0.013	0.023	0.003
AR(2) p value	0.376	0.183	0.113	0.075	0.188
Hansen J p value	0.073	0.394	0.258	0.071	0.454
No. of instruments	9	23	27	27	27
Observations	2094	893	893	893	840
No. of groups	96	96	96	96	95

Notes: Two-step system GMM (Arellano–Bover/Blundell–Bond). Windmeijer-corrected standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Instruments are collapsed (Roodman, 2009). Models 1-3 use disposable-income Gini; R1 uses market-income Gini as the dependent variable; and R4 trims ECI/Gini outliers (1st–99th percentiles). The lower panel reports the Arellano – Bond AR(1)/AR(2) tests, the Hansen J-test of overidentifying restrictions, and the instrument count.

Source: Author's calculations using SWIID v9.9, Harvard Growth Lab, and World Bank WDI.

Across all specifications, the lagged dependent variable is highly significant ($p < 0.001$), confirming the strong persistence of income inequality and validating the dynamic panel approach. In the fully specified models (Models 2 and 3) the autoregressive coefficient is 0.857 and 0.900, respectively, implying that roughly 86–90% of the current Gini is explained by its one-period lag—consistent with the well-documented inertia of income distribution in developing countries. In the bivariate Model 1, the coefficient is 1.047, marginally above unity, signalling near-unit-root behaviour in the absence of controls; therefore, we treat Model 1 as a reference specification and base inference on Models 2 and 3.

In Model 1, which includes only the lagged Gini and ECI, the ECI coefficient is negative and statistically insignificant ($\beta = -0.263$, $p = 0.427$). Once the strong persistence of inequality is accounted for, the within-country variation in export complexity does not contribute meaningfully to changes in disposable-income Gini across the full developing-country sample. This differs from the positive and significant bivariate coefficient reported by Lee and Vu (2020)—a divergence we revisit below, since the positive association does reemerge in the market-income and trimmed specifications.

In Model 2, with the full set of controls, the ECI coefficient is positive but statistically insignificant ($\beta = 0.268$, $p = 0.470$). None of the control variables is statistically significant: log GDP per capita ($\beta = -0.208$, $p = 0.774$), trade openness ($\beta = -0.004$, $p = 0.594$), school enrolment ($\beta = -0.010$, $p = 0.563$), government expenditure ($\beta = -0.024$, $p = 0.638$), domestic credit ($\beta = -0.003$, $p = 0.744$), FDI inflows ($\beta = 0.006$, $p = 0.797$), inflation ($\beta = -0.001$, $p = 0.794$), and rule of law ($\beta = 0.427$, $p = 0.126$). The pervasive insignificance of the control variables likely reflects the dominance of the lagged-dependent variable in absorbing cross-country variation in inequality.

In Model 3, the introduction of the quadratic ECI term does not change the qualitative conclusion. Both the linear term ($\beta 1 = 0.692$, $p = 0.127$) and quadratic term ($\beta 2 = 0.278$, $p = 0.127$) are positive but fall short of conventional significance. Consequently, in the full developing-country sample, the data do not support a statistically significant nonlinear (inverted-U) relationship between economic complexity and disposable-income inequality, and a turning point calculation is not warranted. The control-variable coefficients remain insignificant, as in model 2.

The constant term is statistically insignificant in Models 1, 2, and 3.

Across all three specifications, the diagnostic tests support the validity of the estimator. The Arellano-Bond AR(2) tests fail to reject the null of no second-order serial correlation ($p = 0.376$, 0.183, and 0.113 for

Models 1–3), and the Hansen J-tests do not reject the validity of the instruments (p = 0.073, 0.394, and 0.258). The number of instruments (9, 23, and 27) is well below the number of country groups (96) in every case, mitigating the instrument-proliferation concern (Roodman, 2009). These diagnostics, reported in the lower panel of Table 5, confirm that the System GMM specifications are well-behaved.

Granger Causality Results

Table 6 presents the Dumitrescu-Hurlin (2012) panel Granger causality test results for the ECI – Gini relationship, covering 95 countries.

Table 6

Dumitrescu-Hurlin Panel Granger Causality Tests

Direction	N countries	W-bar	Z-bar	p value	Result
ECI → Gini	95	5.566	12.290	0.000	Yes***
Gini → ECI	95	6.806	16.561	0.000	Yes***

Notes: Dumitrescu – Hurlin [2012] heterogeneous panel Granger non-causality test. H_0: no Granger-type predictive content. *** denotes rejection at the 1% level. Results indicate bidirectional predictive feedback between ECI and disposable-income Gini; they should not be interpreted as structural causal effects.

Source: Author's calculations.

The results reveal **bidirectional** Granger causality between the ECI and the Gini coefficient. In the direction from ECI to Gini, the test strongly rejects the null of noncausality (W-bar = 5.566, Z-bar = 12.290, p < 0.001). In the reverse direction from Gini to ECI, the rejection is even stronger (W-bar = 6.806, Z-bar = 16.561, p < 0.001). This bidirectional pattern indicates a mutual feedback relationship: changes in export complexity Granger-cause subsequent changes in inequality, but changes in inequality also Granger-cause subsequent changes in export complexity.

The presence of bidirectional causality has important methodological and substantive implications. Methodologically, this finding reinforces the need for endogeneity-robust estimators, such as system GMM, because reverse causality can bias OLS and fixed-effects estimates. Substantively, it suggests that income distribution may affect a country's capacity to upgrade its export basket—for instance, through the human capital accumulation channel (more equal societies may invest more broadly in education) or the political economy channel (inequality may shape trade and industrial policies). This finding is inconsistent with the assumption of unidirectional causation from complexity to inequality and suggests a more complex, reciprocal dynamic.

Sub-Group Analysis

Table 7 reports the System GMM estimates for the lower-middle-income (37 countries) and upper-middle-income (42 countries) subgroups. The low-income subgroup (17 countries) could not be validly estimated: because its time dimension exceeds its cross-sectional dimension (T ≥ N), the System GMM estimator (designed for panels with many cross-sectional units relative to time periods) is inappropriate, and the estimation failed the Arellano-Bond serial-correlation diagnostics. We therefore report results only for the two groups in which the estimator is valid; the low-income limitation is discussed below.

Table 7

System GMM Estimation Results by Income Group

Variable	Low-Income	Lower-Middle-Income	Upper-Middle-Income
L. Gini (lagged dep.)	n / a (T ≥ N)	0.9199*** (0.0514)	0.9555*** (0.1401)
ECI	—	1.4134 (1.1647)	0.1990 (0.8334)
ECI²	—	0.7897 (0.8604)	0.3500 (0.6706)
ln GDP (per capita)	—	−1.3633 (1.5171)	−0.4917 (2.6819)
Trade openness	—	−0.0074 (0.0075)	−0.0228 (0.0167)
School enrolment	—	0.0071 (0.0244)	−0.0089 (0.0190)
Govt. expenditure	—	0.0460 (0.0828)	−0.0522 (0.0693)
Domestic credit	—	−0.0048 (0.0067)	0.0085 (0.0214)
FDI inflows	—	0.0609 (0.0471)	0.0345 (0.0647)
Inflation	—	0.0035 (0.0154)	0.0003 (0.0301)
Rule of law	—	−0.1823 (0.5954)	1.0732 (0.7524)
Constant	—	12.5951 (8.7155)	8.9128 (27.4906)
AR(1) p value	—	0.225	0.081
AR(2) p value	—	0.114	0.318
Hansen J p value	—	0.623	0.249
No. of instruments	—	27	27
Observations	—	340	433
No. of groups	—	37	42

Notes: Two-step system GMM by World Bank income group; Windmeijer-corrected standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. The low-income group (17 countries) could not be validly estimated because its time dimension exceeds its cross-sectional dimension (T ≥ N), which violates the large-N assumption of the System GMM estimator. The estimation produced a large-T warning and failed the Arellano–Bond serial-correlation test and is therefore not reported.
Source: Author's calculations.

Low-income countries. The limited number of observations prevented us from estimating the model for the low-income subgroup using system GMM. With only 17 cross-sectional units observed over more than two decades, the panel violates the large-N assumption underlying the Arellano-Bover/Blundell-Bond estimator (T ≥ N); the estimation produced an explicit large-T warning and failed the Arellano-Bond test, rendering its coefficients uninterpretable. Therefore, we do not report estimates for this group. This is informative: the distributional consequences of export upgrading in the poorest economies cannot be reliably identified with dynamic panel GMM on so few countries and would require either a longer cross-section or an estimator suited to small-N panels (e.g., a bias-corrected least-squares dummy-variable model). We flag this as a priority for future research.

Lower-middle-income countries. For the lower-middle-income subgroup, the linear ECI coefficient is positive but statistically insignificant (β = 1.413, p = 0.225), and the quadratic term is similarly insignificant (β = 0.790, p = 0.359). None of the control variables achieved statistical significance, and the lagged Gini was 0.920*** (p < 0.001). The insignificance of the ECI terms in this group (which contains the most actively industrialising economies) indicates that the within-country variation in complexity does not translate into detectable inequality effects once persistence and other controls are accounted for. The specification passed the standard diagnostics (AR(2) p = 0.114; Hansen p = 0.623; 27 instruments for 37 groups).

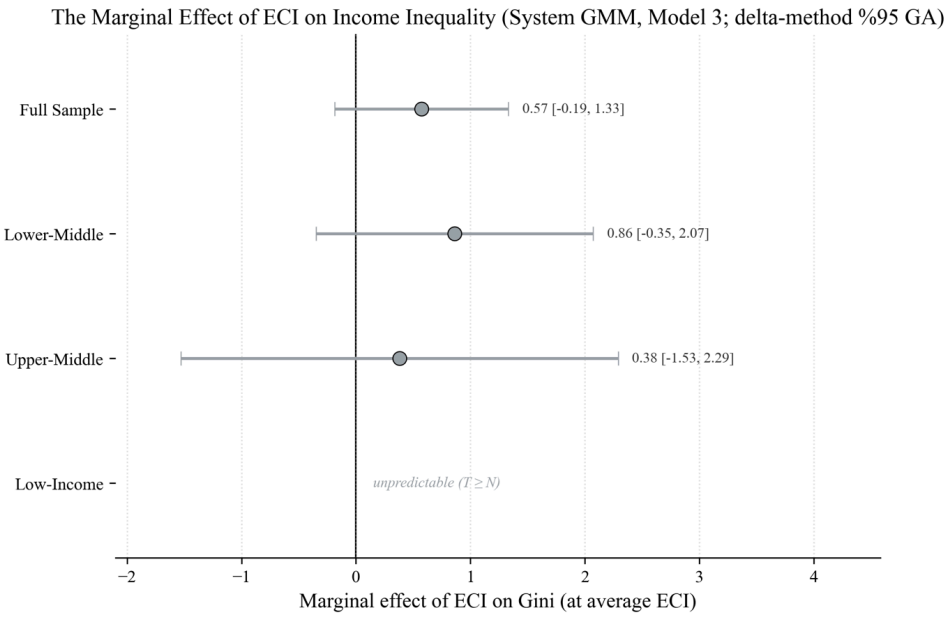
Upper-middle-income countries. In the upper-middle-income subgroup, both the linear ECI term (β = 0.199, p = 0.811) and quadratic term (β = 0.350, p = 0.602) are positive but statistically insignificant. None of the control variables was significant, and the lagged Gini was 0.956*** (p < 0.001), confirming very high persistence. The specification passed the diagnostics (AR(2) p = 0.318; Hansen p = 0.249; 27 instruments for 42 groups). The absence of a significant ECI effect implies that, at intermediate-to-higher development levels, year-to-year variation in export complexity does not measurably shift the disposable-income distribution.

In summary, among the subgroups that can be validly estimated, neither the lower-middle-income nor the upper-middle-income group exhibits a statistically significant ECI–inequality relationship in levels or in the quadratic specification. This absence of a robust inverted-U pattern is inconsistent with the hypothesis of Nguyen et al. (2023). The low-income group—where the distributional effects of early-stage upgrading might be most pronounced—cannot be identified with the present data and estimator, which we treat as a limitation rather than a substantive result.

Figure 5 visualises the estimated ECI coefficients only for the samples that can be validly interpreted: the full sample, the lower-middle-income group, and the upper-middle-income group. The low-income group is excluded from the figure because System GMM does not yield a valid estimate for that subgroup. The confidence intervals for the full sample and both middle-income groups include zero, reinforcing the absence of a statistically detectable ECI effect on disposable-income inequality in the estimable specifications.

Figure 5

The Marginal Effect of ECI on Income Inequality



Note: Points show ECI coefficients, and bars show 95% confidence intervals. The low-income subgroup is excluded because the System GMM cannot be validly estimated for that group.

Türkiye Case Study

Türkiye provides an instructive case study for examining the distributional consequences of export structural transformation. Figure 6 presents Türkiye's ECI and Gini trajectories over the 1990-2023 period, divided into three analytically meaningful subperiods. Table 8 presents the descriptive statistics for each subperiod.

Figure 6

Türkiye ECI and Gini Trends, 1990-2023

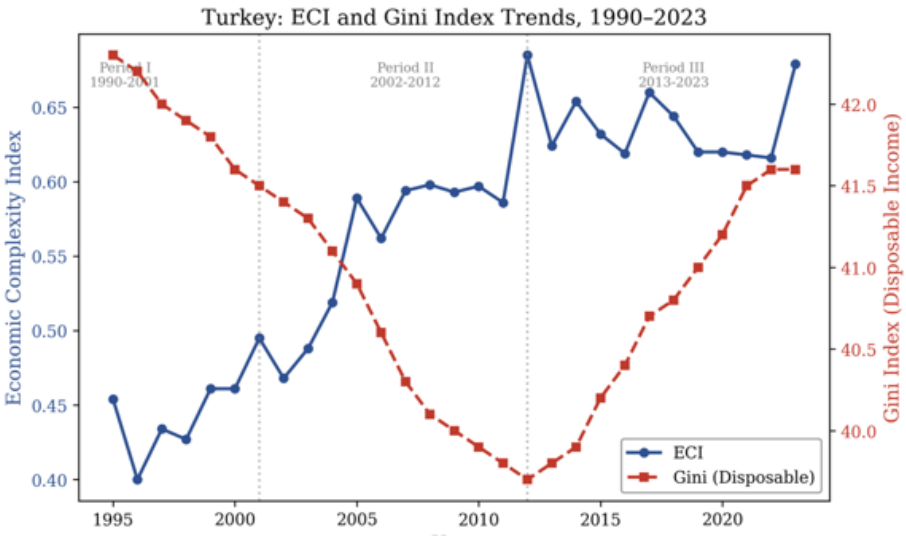


Table 8

Türkiye Sub-Period Descriptive Statistics

	Period I (1990–2001)	Period II (2002–2012)	Period III (2013–2023)
Number of Years	11	10	10
Gini (disp.) mean:	41.900	40.464	40.791
Gini (disp.) s.d.	0.294	0.625	0.656
ECI mean	0.447	0.571	0.635
ECI s.d.	0.030	0.060	0.021
ln(GDP p.c.) mean	8.703	8.975	9.408
ln(GDP p.c.) s.d.	0.045	0.137	0.120
Trade open. mean	41.252	48.952	60.476
Trade open. s.d.	4.527	2.597	9.045

Notes: Descriptive statistics for Türkiye by subperiod. Gini refers to disposable income Gini from SWIID v9.9. ECI from Harvard Growth Lab. GDP per capita in constant 2015 USD (log). Trade openness percentage of GDP.
Source: Author's calculations.

Period I (1990–2001) featured incomplete trade liberalisation, macroeconomic instability, and recurrent financial crises. Türkiye's average ECI during this period was 0.447 (SD = 0.030), reflecting a unsophisticated export basket dominated by textiles and low-technology manufactures. The disposable income Gini averaged 41.900 (SD = 0.294), the highest among the three sub-periods, reflecting the structural duality between the modern industrial sector and the large informal agricultural sector. Trade openness averaged 41.25% of GDP (SD = 4.527), and log GDP per capita was 8.703 (SD = 0.045).

Period II (2002–2012) witnessed rapid economic growth, significant structural change, and a notable shift in export composition towards medium-technology products, particularly in automotive components and machinery. Türkiye's average ECI increased to 0.571 (SD = 0.060), a significant improvement. Simultaneously, the average Gini coefficient declined to 40.464 (SD = 0.625), representing a reduction of approximately 1.4 Gini points relative to Period I. Trade openness increased to 48.95% (SD = 2.597), and log GDP per capita rose to 8.975 (SD = 0.137). The co-movement of rising complexity and declining inequality during this period is consistent with the hypothesis that export upgrading, when accompanied by formalisation of employment and expansion of social transfers, can contribute to more equitable distribution.

Period III (2013–2023) has been ambiguous. Türkiye's average ECI continued to increase modestly to 0.635 (SD = 0.021), but the pace of structural upgrading slowed. The Gini coefficient averaged 40.791 (SD = 0.656), slightly above the Period II average. Descriptively, this pattern is consistent with a plateau or modest reversal in inequality reduction. Trade openness expanded substantially to 60.48% (SD = 9.045), while log GDP per capita reached 9.408 (SD = 0.120). The divergence between continued complexity gains and stalling inequality improvement suggests that the distributional benefits of export upgrading may require sustained structural transformation and active social policies—mere incremental gains in complexity at already moderate levels may be insufficient.

As illustrated in Figure 6, Türkiye's ECI trajectory shows a clear upward trend across the entire 1990-2023 period, rising from approximately 0.40 in the mid-1990s to above 0.60 by the 2010s. The Gini trajectory is approximately mirror-imaged: declining from around 42.5 in the mid-1990s to approximately 39.5 around 2012, before reversing modestly in the post 2013 period. This visual co-movement suggests a negative long-run relationship between complexity and inequality for Türkiye, though the reversal in Period III indicates that the relationship is not monotonic and is conditioned by macroeconomic and policy environments.

The subperiod comparison in Table 8 is descriptive. To assess whether the observed co-movement reflects a causal relationship, we estimated a bivariate vector autoregression (VAR) on Türkiye's annual series of ECI and the disposable-income Gini (29 observations, 1995–2023); the lag order of three was selected by the Akaike Information Criterion. Granger causality tests provide no evidence of a causal link in either direction: ECI does not Granger-cause Gini (F = 0.683, p = 0.568), and Gini does not Granger-cause ECI (F = 1.376, p = 0.265). We therefore interpret the parallel movement of rising complexity and modestly declining inequality during 2002-2012 as a correlation rather than evidence of a causal effect. This null result is consistent with the limited statistical power of time-series causality tests applied to a short series of roughly 29 annual observations and reinforces the central message of the paper: the distributional consequences of export upgrading are neither automatic nor, in Türkiye's case, statistically detectable at the aggregate time-series level.

Table 9

Türkiye VAR Granger Causality Test Results

Direction	**F-statistic**	**p value**
ECI → Gini	0.683	0.568
Gini → ECI	1.376	0.265

Note: Bivariate VAR on Türkiye, 1995-2023 (29 annual observations); lag order 3 (AIC). Neither direction is statistically significant at conventional levels.

5. Discussion

The findings of this analysis contribute to the evolving and contested understanding of how productive structures shape income distribution. The core result (the absence of a statistically significant relationship between economic complexity and disposable-income inequality in the full developing-country sample) merits careful interpretation. It does not imply that export structure is irrelevant for distribution, but rather that the within-country, year-to-year variation in ECI does not generate detectable effects on disposable-income Gini once the strong persistence of inequality and other macroeconomic conditions are controlled for through dynamic panel methods. As we discuss below, this null is specific to the disposable income measure and does not survive when inequality is measured before redistribution.

These full-sample disposable income results contribute to the ongoing debate in the literature. The null finding in the baseline specification is inconsistent with the negative cross-sectional association reported by Hartmann et al. (2017) and with the inverted-U pattern identified by Nguyen et al. (2023) and Amarante et al. (2024). Importantly, however, our robustness analysis qualifies this null: when inequality is measured by the market (pre-redistribution) Gini, and in a trimmed sample, the ECI and ECI^2 terms are positive and significant, reproducing the within-country positive effect that Lee and Vu (2020) and Chu and Hoang (2020) obtained with System GMM. The divergence between our baseline disposable income result and these studies appears to stem from the inequality concept (disposable vs. market income) and sample composition and estimation choices, rather than from a fundamental absence of any complexity–inequality link.

The contrast between disposable-income and market-income results is substantively important. Export complexity is positively and significantly associated with the market-income Gini coefficient but not with the disposable-income Gini coefficient. This pattern is consistent with the interpretation that fiscal redistribution through taxes and transfers absorbs part of the distributional pressure associated with structural transformation. The complexity-driven widening of pre-redistribution inequality (through skill premia and the sectoral concentration of sophisticated activities) appears, on average, to be offset by the tax-and-transfer systems of the developing countries in our sample, leaving post-redistribution inequality broadly unchanged. This reading is consistent with the redistribution evidence for Türkiye in Tekgüç and Eryar (2025) and reinforces the conclusion that the equity consequences of export upgrading depend heavily on the strength of redistributive institutions.

The overwhelming dominance of the lagged dependent variable—with autoregressive coefficients of 0.857 and 0.900 in the fully specified models 2 and 3 (and 1.047 in the bivariate Model 1)—is itself an important finding. It indicates that income inequality in majority world is overwhelmingly determined by its history, leaving limited room for contemporaneous policy levers—including export structure—to generate rapid changes. This persistence is consistent with the theoretical models of institutional hysteresis (Acemoglu, 2002) and the empirical observation that inequality is deeply embedded in labour market structures, asset distributions, and fiscal systems that change slowly.

The bidirectional Granger causality between ECI and Gini represents an important finding that complicates the standard narrative of complexity driving inequality. The feedback from inequality to complexity may operate through several channels: highly unequal societies may underinvest in broad-based education, limiting the human capital base necessary for export diversification (Lee & Vu, 2020); inequality may concentrate political power among elites who favour extractive rather than productive economic structures (Acemoglu, 2002); and unequal access to finance may constrain the entrepreneurial activity that drives product innovation. This bidirectionality also has implications for identification: even System GMM, which instruments with lagged levels and differences, may not fully resolve the simultaneity bias when the feedback loop is tightly coupled. It is worth clarifying why no significant bidirectional Granger relationship is

contradicted by the insignificant contemporaneous ECI coefficient in the System GMM models. The two tests answer different questions: the Dumitrescu-Hurlin test asks whether past values of one variable improve the prediction of the other's future values (temporal precedence in a heterogeneous panel), whereas the System GMM coefficient measures the contemporaneous structural effect of ECI on the Gini, which is conditional on the lagged Gini and the controls. A variable can carry predictive content for another's future path while exerting no measurable same-period effect once persistence and covariates are netted out; therefore, the joint pattern—predictive feedback alongside a small, imprecisely estimated contemporaneous coefficient—is internally consistent rather than contradictory.

The subgroup analysis is constrained by the small size of the low-income group. With only 17 countries, the low-income panel cannot be validly estimated by System GMM (its time dimension exceeds its cross-section), so we cannot test the early-stage structural transformation hypothesis—namely, that in economies with very low baseline complexity, initial export upgrading is concentrated in a narrow set of firms or enclaves, thereby widening the distribution. This is a genuine limitation rather than a null result, and it confirms a concern raised in the review process: dynamic panel GMM is ill-suited to such a small cross-section. For the two groups that can be estimated—lower-middle and upper-middle income—the ECI coefficients are statistically indistinguishable from zero, suggesting that at intermediate-to-higher development levels, the distributional consequences of year-to-year complexity changes are muted or that other factors (institutional quality, labour -market policies, and fiscal redistribution) dominate.

The Türkiye case study illustrates these ambiguities concretely. During 2002–2012, average ECI rose from 0.447 to 0.571, whereas the average Gini coefficient declined from 41.9 to 40.5, documenting an inverse comovement between economic complexity and income inequality. However, as an upper-middle-income country with insignificant ECI effects in the panel analysis, Türkiye's experience may reflect the combined impact of complexity gains and concurrent social policy innovations—particularly the formalisation of employment, expansion of social transfers, and rising real wages (Tekgüç and Eryar, 2025)—rather than a direct causal channel from complexity to equality. The modest reversal in Period III (2013–2023), with complexity gains slowing and inequality plateauing, reinforces the interpretation that sustained distributional improvement requires structural upgrading and supportive policy environments.

Several limitations merit acknowledgments. First, SWIID, while providing the best available cross-country Gini comparisons, relies on imputation for many developing country observations, introducing measurement uncertainty. Second, the ECI measures export complexity, which may not fully capture the complexity of domestic production. Third, while System GMM addresses several endogeneity concerns, the causal identification ultimately depends on the validity of the moment conditions—an assumption that, while supported by diagnostic tests, cannot be definitively verified. Fourth, the Türkiye case study, based on descriptive trend analysis for a single country, cannot establish causality. Fifth, the pervasive insignificance of the ECI terms may reflect insufficient within-country variation in annual ECI changes to detect distributional effects, suggesting that longer-horizon analyses (e.g., five- or 10-year panels) may be better suited to capturing the structural channels through which complexity affects inequality. Sixth, the small number of low-income countries (17) prevents valid System GMM estimation for that group, leaving the distributional effects of export upgrading in the poorest economies unresolved by this study and motivating the use of small-N estimators in future work.

6. Conclusion

This study investigated the relationship between export complexity and income inequality across a panel of 96 developing countries over the 1990-2023 period using Arellano-Bover/Blundell-Bond System GMM estimation. The key finding is that there is no statistically significant relationship between economic

complexity and disposable-income inequality in the full sample of developing countries, in either the linear or quadratic specification. This null result, however, is specific to the disposable-income measure: when inequality is measured before redistribution (the market-income Gini) and in a trimmed sample, both the linear and quadratic ECI terms are positive and statistically significant, indicating that export complexity is associated with higher pre-redistribution inequality. The lagged-dependent variable overwhelmingly dominates the model, with coefficients of 0.86–0.90 in the fully specified full-sample models, confirming the strong persistence of income inequality.

Dumitrescu-Hurlin panel Granger causality tests reveal bidirectional causality between ECI and the Gini coefficient (both $p < 0.001$), indicating mutual feedback between productive structure and income distribution. Subgroup analyses found no statistically significant ECI effect in either the lower-middle-income or upper-middle-income group; the low-income group (17 countries) could not be validly estimated by System GMM because its time dimension exceeded its cross-sectional dimension. The Türkiye case study illustrates the coevolution of rising export complexity and declining inequality during the 2002-2012 structural transformation period, though the subsequent plateau underscores the limits of complexity gains without sustained social policy support.

These findings carry several important policy implications. First, for industrial policy, the results caution against expecting automatic distributional benefits from export upgrading. Indeed, the market-income results suggest that complexity gains may widen pre-redistribution inequality; the fact that disposable-income inequality is unaffected indicates that this pressure is, on average, neutralised by tax-and-transfer systems rather than absent. While upgrading complexity remains a worthy objective for growth and structural development, policymakers should not assume that rising ECI will mechanically lower inequality and should anticipate the redistributive demands that accompany structural transformation. Other factors (labour-market institutions, fiscal redistribution, and education access) remain more proximate determinants of inequality in developing countries.

Second, although the low-income group could not be estimated directly, the positive complexity–inequality association found in the market-income and trimmed specifications points to a real risk that structural transformation may exacerbate pre-redistribution inequality where upgrading is concentrated in narrow sectors or benefits only skilled workers. This underscores the importance of proactive distributional safeguards during the early phases of export upgrading (investments in vocational education, support for small and medium enterprises participating in new value chains, and social protection for workers displaced from traditional sectors) so that the gains from sophistication are broadly shared.

Third, the bidirectional causality between complexity and inequality implies that high inequality may constrain a country's capacity to upgrade its export structure. Policies addressing inequality (broad-based education investments, progressive taxation, and inclusive financial systems) may therefore serve a dual purpose: improving distributional outcomes directly while also facilitating human capital accumulation and institutional development necessary for export sophistication.

Fourth, the Türkiye case study highlights the role of complementary social policies in translating structural transformation into distributional benefits. Türkiye's experience during 2002-2012 demonstrates that export upgrading, when accompanied by employment formalisation, social transfer expansion, and real wage growth, can reduce inequality. The stalling of these gains in Period III (2013–2023) highlights the risk that distributional improvements may plateau when structural transformation slows or when supportive policy conditions erode.

For future research, three directions are promising. First, the mechanisms linking complexity to inequality could be explored using firm-level data to trace how upgrading in specific industries affects wage structures

and employment composition. Second, the temporal dimension warrants further investigation: 5- or 10-year panel models may better capture the structural channels through which complexity affects distribution, given the slow-moving nature of both ECI and inequality. Third, the integration of green complexity metrics, following Mealy and Teytelboym (2022) and Stojkoski et al. (2023), could illuminate whether the transition to sustainable export structures carries distributional consequences. These extensions would deepen our understanding of the conditions under which structural transformation can become a tool for inclusive development. Fourth, the distributional effects of export upgrading in low-income economies—unidentifiable here owing to the small number of such countries—warrant a dedicated study using estimators suited to small-N panels (e.g., bias-corrected LSDV) or longer cross-sections.

Peer Review Externally peer reviewed.
Conflict of Interest The author has no conflict of interest to declare.
Grant Support The author declared that this study has received no financial support.

Author Details Aytuğ Zekeriya Bolcan (Dr.)
[1] Istanbul University, Faculty of Economics, Department of Economic Theory, İstanbul, Türkiye
0000-0002-5162-4337 abolcan@istanbul.edu.tr

References

Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature*, *40*(1), 7–72. https://doi.org/10.1257/jel.40.1.7

Acemoglu, D. (2003). Patterns of skill premia. *The Review of Economic Studies*, *70*(2), 199–230. https://doi.org/10.1111/1467-937X.00242

Amarante, V., Lanzilotta, B., & Torres-Pérez, J. (2024). Income inequality and complexity of the productive structure: New evidence at the world level. *Economic Analysis and Policy*, *84*, 628–645. https://doi.org/10.1016/j.eap.2024.09.029

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277. https://doi.org/10.2307/2297968

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal Of Econometrics*, *68*(1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-D

Atiyas, İ., & Bakiş, O. (2015). Structural change and industrial policy in Turkey. *Emerging Markets Finance and Trade*, *51*(6), 1209–1229. https://doi.org/10.1080/1540496X.2015.1080523

Balland, P.-A., Broekel, T., Diodato, D., Giuliani, E., Hausmann, R., O'Clery, N., & Rigby, D. (2022). The new paradigm of economic complexity. *Research Policy*, *51*(3), 104450. https://doi.org/10.1016/j.respol.2021.104450

Bandeira Morais, M., Swart, J., & Jordaan, J. A. (2021). Economic complexity and inequality: Does regional productive structure affect income inequality in Brazilian states? *Sustainability*, *13*(2), 1006. https://doi.org/10.3390/su13021006

Basile, R., & Cicerone, G. (2022). Economic complexity and productivity polarization: Evidence from Italian provinces. German Economic Review, 23(4), 567–594. https://doi.org/10.1515/ger-2021-0070

Bedemo Beyene, A. (2024). Income inequality and economic complexity in Africa: The moderating role of governance quality. *Cogent Social Sciences*, *10*(1), 1–14. https://doi.org/10.1080/23311886.2024.2338024

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Chu, L. K., & Hoang, D. P. (2020). How does economic complexity influence income inequality? New evidence from international data. *Economic Analysis and Policy*, *68*, 44–57. https://doi.org/10.1016/j.eap.2020.08.004

Davis, D. R., & Mishra, P. (2007). Stolper-Samuelson is dead: And other crimes of both theory and data. In A. Harrison (Ed.), *Globalization and Poverty* (pp. 87–108). University of Chicago Press. https://doi.org/10.7208/chicago/9780226318004.003.0004

Dorn, F., Fuest, C., & Potrafke, N. (2022). Trade openness and income inequality: New empirical evidence. *Economic Inquiry*, *60*(1), 202–223. https://doi.org/10.1111/ecin.13029

Dumitrescu, E.-I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling*, *29*(4), 1450–1460. https://doi.org/10.1016/j.econmod.2012.02.014

Elveren, A. Y., & Galbraith, J. K. (2009). Pay inequality in Turkey in the neo-liberal era, 1980-2001. *The European Journal of Comparative Economics*, *6*(2), 177–206.

Erkan, B., & Yıldırımcı, E. (2015). Economic complexity and export competitiveness: The case of Turkey. *Procedia, Social and Behavioral Sciences*, *195*, 524–533. https://doi.org/10.1016/j.sbspro.2015.06.262

Feenstra, R. C., & Hanson, G. H. (1996). Globalization, outsourcing, and wage inequality. *American Economic Review*, *86*(2), 240–245. https://doi.org/10.1257/aer.86.2.240

Feenstra, R. C., & Hanson, G. H. (1997). Foreign direct investment and relative wages: Evidence from Mexico's Maquiladoras. *Journal Of International Economics*, *42*(3–4), 371–393. https://doi.org/10.1016/S0022-1996(96)01475-4

Ghosh, S., Doğan, B., Can, M., Shah, M. I., & Apergis, N. (2023). Does economic structure matter for income inequality? *Quality & Quantity*, *57*(3), 2507–2527. https://doi.org/10.1007/s11135-022-01465-0

Goldberg, P. K., & Pavcnik, N. (2007). Distributional effects of globalization in developing countries. *Journal of Economic Literature*, *45*(1), 39–82. https://doi.org/10.1257/jel.45.1.39

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*, *50*(4), 1029–1054. https://doi.org/10.2307/1912775

Hartmann, D., Guevara, M. R., Jara-Figueroa, C., Aristarán, M., & Hidalgo, C. A. (2017). Linking economic complexity, institutions, and income inequality. *World Development*, *93*, 75–93. https://doi.org/10.1016/j.worlddev.2016.12.020

Hartmann, D., & Pinheiro, F. L. (2024). Economic complexity and inequality at the national and regional levels. In P. Chen, W. Elsner, & A. Pyka (Eds.), *Routledge International Handbook of Complexity Economics* (pp. 551–566). Routledge. https://doi.org/10.4324/9781003290506-40

Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M., Simoes, A., & Yildirim, M. A. (2014). *The Atlas of Economic Complexity: Mapping Paths to Prosperity*. MIT Press.

Hausmann, R., Hwang, J., & Rodrik, D. (2007). What you export matters. *Journal of Economic Growth*, *12*(1), 1–25. https://doi.org/10.1007/s10887-006-9009-4

Hidalgo, C. A., Klinger, B., Barabási, A.-L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, *317*(5837), 482–487. https://doi.org/10.1126/science.1144581

Hidalgo, C. A. (2021). Economic complexity theory and applications. *Nature Reviews. Physics*, *3*(2), 92–113. https://doi.org/10.1038/s42254-020-00275-1

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(26), 10570–10575. https://doi.org/10.1073/pnas.0900943106

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal Of Econometrics*, *115*(1), 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7

Javorcik, B. S., Lo Turco, A., & Maggioni, D. (2018). New and improved: Does FDI boost production complexity in host countries? *Economic Journal*, *128*(614), 2507–2537. https://doi.org/10.1111/ecoj.12530

Kaya, A. I., & Çiçekçi, C. (2023). Structural transformation and sources of growth in Turkey. In *UNU-WIDER Working Papers* (No. 2023/71; Issue 2023/71). https://doi.org/10.35188/UNU-WIDER/2023/371-2

Lee, C.-C., & Wang, E.-Z. (2021). Economic complexity and income inequality: Does country risk matter? *Social Indicators Research*, *154*(1), 35–60. https://doi.org/10.1007/s11205-020-02567-w

Lee, K.-K., & Vu, T. V. (2020). Economic complexity, human capital and income inequality: A cross-country analysis. *Japanese Economic Review*, *71*(4), 695–718. https://doi.org/10.1007/s42973-019-00026-7

McMillan, M., & Rodrik, D. (2011). Globalization, structural change and productivity growth. In M. Bacchetta & M. Jansen (Eds.), *Making Globalization Socially Sustainable* (pp. 49–84). World Trade Organization - International Labour Office.

Mealy, P., & Teytelboym, A. (2022). Economic complexity and the green economy. *Research Policy*, *51*(8), 103948. https://doi.org/10.1016/j.respol.2020.103948

Meschi, E., Taymaz, E., & Vivarelli, M. (2011). Trade, technology and skills: Evidence from Turkish microdata. *Labour Economics*, *18*, S60–S70. https://doi.org/10.1016/j.labeco.2011.07.001

Meschi, E., Taymaz, E., & Vivarelli, M. (2016). Globalization, technological change and labor demand: A firm-level analysis for Turkey. *Review of World Economics*, *152*(4), 655–680. https://doi.org/10.1007/s10290-016-0257-z

Meschi, E., & Vivarelli, M. (2009). Trade and income inequality in developing countries. *World Development*, *37*(2), 287–302. https://doi.org/10.1016/j.worlddev.2008.02.003

Milanovic, B. (2005). Can we discern the effect of globalization on income distribution? Evidence from household surveys. *The World Bank Economic Review*, *19*(1), 21–44. https://doi.org/10.1093/wber/lhi004

Molele, S. B., & Ncanywa, T. (2022). Effects of economic complexity as a development index on economic performance: A Sub-Saharan Africa and BRICS comparative analysis. Journal of Studies in Social Sciences and Humanities, 8(3), 332–347.

Nguyen, C. P., Nguyen, B. Q., & Tran, D. T. L. (2023). Economic complexity and income inequality: New evidence of a nonlinear effect. *Social Science Quarterly*, *104*(4), 829–868. https://doi.org/10.1111/ssqu.13270

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society*, *49*(6), 1417–1426. https://doi.org/10.2307/1911408

Orsolin-Teixeira, F., José Missio, F., & Dathein, R. (2022). Economic complexity, structural transformation and economic growth in a regional context: Evidence for Brazil. PSL Quarterly Review, 75(300), 63–79. https://doi.org/10.13133/2037-3643/17505

Örnek, İ., & Elveren, A. Y. (2010). Trade liberalization and income inequality in Turkey: An empirical analysis. *Çukurova Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, *19*(2), 62–70.

Pinheiro, F. L., Balland, P.-A., Boschma, R., & Hartmann, D. (2025). The dark side of the geography of innovation: Relatedness, complexity and regional inequality in Europe. *Regional Studies*, *59*(1), 1–16. https://doi.org/10.1080/00343404.2023.2187729

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, *71*(1), 135–158. https://doi.org/10.1111/j.1468-0084.2008.00542.x

Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica: Journal of the Econometric Society*, *26*(3), 393–415. https://doi.org/10.2307/1907619

Sbardella, A., Pugliese, E., & Pietronero, L. (2017). Economic development and wage inequality: A complex system analysis. *PloS One*, *12*(9), 1–26. https://doi.org/10.1371/journal.pone.0182774

Sepehrdoust, H., Tartar, M., & Gholizadeh, A. (2022). Economic complexity, scientific productivity and income inequality in developing economies. Economics of Transition and Institutional Change, 30(4), 737–752. https://doi.org/10.1111/ecot.12309

Solt, F. (2020). Measuring income inequality across countries and over time: The Standardized World Income Inequality Database. *Social Science Quarterly*, 101(3), 1183–1199. https://doi.org/10.1111/ssqu.12795

Spilimbergo, A., Londoño, J. L., & Székely, M. (1999). Income distribution, factor endowments, and trade openness. *Journal Of Development Economics*, *59*(1), 77–101. https://doi.org/10.1016/S0304-3878(99)00010-X

Stojkoski, V., Koch, P., & Hidalgo, C. A. (2023). Multidimensional economic complexity and inclusive green growth. *Communications Earth & Environment*, *4*(130), 1–12. https://doi.org/10.1038/s43247-023-00764-y

Stolper, W. F., & Samuelson, P. A. (1941). Protection and Real Wages. *The Review of Economic Studies*, *9*(1), 58–73. https://doi.org/10.2307/2967638

Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A., & Pietronero, L. (2012). A new metrics for countries' Fitness and Products' Complexity. *Scientific Reports*, *2*(723), 1–7. https://doi.org/10.1038/srep00723

Tekgüç, H., & Eryar, D. (2025). Redistribution trends in Turkey: Unintended consequences vs. deliberate policies. *Review of Development Economics*, *29*(4), 2196–2210. https://doi.org/10.1111/rode.13150

Topuz, S. G., & Dağdemir, Ö. (2020). Analysis of the relationship between trade openness, structural change, and income inequality under Kuznets curve hypothesis: The case of Turkey. *The Journal of International Trade & Economic Development*, *29*(6), 647–664. https://doi.org/10.1080/09638199.2019.1699964

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal Of Econometrics*, *126*(1), 25–51. https://doi.org/10.1016/j.jeconom.2004.02.005

Yükseler, Z., & Türkan, E. (2006). Türkiye'nin Üretim ve Dış Ticaret Yapısında Dönüşüm: Küresel Yönelimler Ve Yansımalar. In TÜSİAD-Koç University Economic Research Form. https://research.ku.edu.tr/wp-content/uploads/2026/01/Uretim_ve_DisTicaret_Yapisindaki_Donusum.pdf

Appendix

Sample countries by income group (as added to the revised manuscript)

The estimation sample comprises 96 developing countries classified by the World Bank income groups: 17 low-income, 37 lower-middle-income, and 42 upper-middle-income economies, for a total of 2,286 country-year observations. The panel is unbalanced; each country's coverage period reflects the joint availability of the Economic Complexity Index and SWIID Gini data. "Obs." denotes the number of annual observations for the country.

A.1 Low-income economies (17)

Country	Coverage	Obs.
Afghanistan	2007-2017	11
Burkina Faso	1995-2021	27
Chad	2003-2022	20
Congo, Dem. Rep.	2004-2020	17
Ethiopia	1995–2021	27
Guinea	1995-2018	24
Liberia	2005-2016	12
Madagascar	1995-2012	18
Malawi	1995-2019	25
Mali	1995–2021	27
Mozambique	1996-2019	24
Niger	1995–2021	27
Rwanda	1995-2016	22
Sudan	1995-2014	20
Togo	2005-2021	17
Uganda	1995-2019	25
Yemen	1995-2014	20

A.2 Lower-middle-income economies (37)

Country	Coverage	Obs.
Angola	2000-2018	19
Bangladesh	1995-2022	28
Benin	2002-2021	20
Bolivia	1995-2023	29
Cambodia	1997-2012	16
Cameroon	1996-2021	26
Côte d'Ivoire	1995–2021	27
Egypt	1995-2023	29
El Salvador	1995-2023	29
Ghana	1995-2016	22
Haiti	2001-2012	12
Honduras	1995-2023	29

Country	Coverage	Obs.
India	1995-2022	28
Indonesia	1995-2023	29
Iran	1995-2023	29
Kenya	1995–2021	27
Kyrgyz Republic	1995-2023	29
Lao PDR	1995-2018	24
Mauritania	1995-2019	25
Mongolia	1995-2022	28
Morocco	1995-2020	26
Myanmar	2010-2017	8
Nepal	1995-2022	28
Nicaragua	1995-2014	20
Nigeria	1995-2018	24
Pakistan	1995-2018	24
Papua New Guinea	1996-2009	14
Philippines	1995-2023	29
Senegal	1995–2021	27
Sri Lanka	1995-2019	25
Tanzania	1995-2018	24
Tunisia	1995–2021	27
Ukraine	1995-2020	26
Uzbekistan	1995-2023	29
Vietnam	1995-2023	29
Zambia	1995-2022	28
Zimbabwe	1995-2019	25

A.3 Upper-middle-income economies (42)

Country	Coverage	Obs.
Albania	1996-2020	25
Algeria	1995-2011	17
Argentina	1995-2023	29
Armenia	1995-2023	29
Azerbaijan	1995-2008	14
Belarus	1995-2023	29
Bosnia and Herzegovina	2001-2015	15
Botswana	2000-2015	16
Brazil	1995-2023	29
Bulgaria	1995-2023	29
China	1995-2023	29
Colombia	1995-2023	29
Costa Rica	1995-2023	29

Country	Coverage	Obs.
Dominican Republic	1995-2023	29
Ecuador	1995-2023	29
Equatorial Guinea	2006-2022	17
Gabon	2005-2017	13
Georgia	1995-2023	29
Guatemala	1995-2023	29
Iraq	2006-2023	18
Jamaica	1995–2021	27
Jordan	1995-2017	23
Kazakhstan	1995-2023	29
Lebanon	1995-2022	28
Libya	2003-2008	6
Malaysia	1995-2022	28
Mauritius	1995-2017	23
Mexico	1995-2022	28
Moldova	1995-2023	29
Namibia	2000-2016	17
North Macedonia	1995–2021	27
Paraguay	1995-2023	29
Peru	1995-2023	29
Romania	1995-2023	29
Russian Federation	1995-2022	28
Serbia	2006-2022	17
South Africa	2000-2017	18
Thailand	1995-2023	29
Trinidad and Tobago	1995-2005	11
Turkey	1995-2023	29
Turkmenistan	1995-2005	11
Venezuela	1995–2021	27

Note: Income classification follows the World Bank (2024 fiscal year). Country names follow common usage.
Source: SWIID v9.9; Harvard Growth Lab (Atlas of Economic Complexity); World Bank World Development Indicators.