Multidimensional Economic Complexity: How the Geography of Trade, Technology, and Research Explain Inclusive Green Growth

Viktor Stojkoski, Philipp Koch & César A. Hidalgo

Papers in Evolutionary Economic Geography

22.28

Utrecht University Human Geography and Planning

Multidimensional Economic Complexity: How the Geography of Trade, Technology, and Research Explain Inclusive Green Growth

Viktor Stojkoski[a], Philipp Koch[a,b], César A. Hidalgo[a,c,d,*]

[a] Center for Collective Learning, ANITI, TSE-R, IAST, IRIT, Université de Toulouse, 31000 Toulouse, France
[b] EcoAustria – Institute for Economic Research, 1030 Vienna, Austria
[c] Alliance Manchester Business School, University of Manchester, United Kingdom
[d] School of Engineering and Applied Sciences, Harvard University, United States

Abstract

To achieve inclusive green growth, countries need to consider a multiplicity of economic, social, and environmental factors. These are often captured by metrics of economic complexity derived from the geography of trade, thus missing key information on innovative activities. To bridge this gap, we combine trade data with data on patent applications and research publications to build models that significantly and robustly improve the ability of economic complexity metrics to explain international variations in inclusive green growth. We show that measures of complexity built on trade and patent data combine to explain future economic growth and income inequality and that countries that score high in all three metrics tend to exhibit lower emission intensities. These findings illustrate how the geography of trade, technology, and research combine to explain inclusive green growth.

Keywords: economic complexity, inclusive green growth, complex systems
JEL: F14, F43, O12, O15, O47, Q56

[*] Corresponding author, e-mail: cesifoti@gmail.com

Introduction

Sustainable development is often defined as the process of meeting human development goals while simultaneously sustaining the natural environment[1–4]. This approach implies that development and environment are interdependent, and that economic growth can be sustained only if it is inclusive and green[5,6].

To achieve sustainable development, countries need to consider the interconnections between economic, social, and environmental factors[7–12] . This multiplicity of factors, however, can be hard to quantify and compare. Economic complexity methods provide a solution to this problem[13,14]. By leveraging data on the geographic distribution of economic activities, these methods can be used to estimate the implicit presence of multiple economic factors, and consequently, to explain international variations in economic growth[15–24], income inequality[25–27], and emissions[28–31].

Today, the most commonly used metrics of complexity are based on trade data[23,30,32]. Trade data, however, can miss key information about innovative activities, such as patent applications and research publications that could be relevant for the geography of inclusive green growth. For example, research and technology can shape production processes, affecting the skills and compensation of workers and the emission intensity of industrial activities. Moreover, trade-based metrics of complexity can systematically underestimate the complexity of economies that are distant from global markets, which in turn might distort predictions about their inclusive green growth[33,34]. That is, the complexity of some economies that are rich in natural resource exports, but distant to markets, such as Australia, Chile, and New Zealand, might be better reflected in their ability to produce outputs such as scientific research and patentable innovations than sophisticated exports. The same may be true, but in reverse, for manufacturing heavy economies that are deeply integrated into their neighbors' value chains, such as Mexico or Czechia. These are countries with a complex tradeable product sector, but as we will show, with comparatively less sophisticated research and innovation sectors.

That is why the recent literature in economic complexity has begun using data on patents[35], employment[36,37], and research papers[38], to estimate the complexity of countries, cities, and regions. But these metrics are rarely combined in work using complexity methods to explain the geography of inclusive green growth[39,40].

To bridge this gap, we introduce a multidimensional approach to economic complexity that combines data on the geography of exports by product, patents by technology, and scientific publications by field of research. We use this approach to explain variations in economic growth, income inequality, and greenhouse emissions.

But why would the complexity of economies explain the geographic variation of inclusive green growth? Economic complexity metrics capture information about productive structures that escapes simple aggregate, such as GDP. Unlike GDP, which sums value added regardless of the activities involved, economic complexity metrics capture information about the sophistication of these activities. Consider the exports of X-rays and iron ore. The contribution of these exports to GDP is equal to their export value, but their contribution to economic complexity is quite different, since X-rays are a high complexity product (pushing the complexity of an economy up) while iron ore is not. In fact, according to data on the Observatory of Economic Complexity[41], X-rays have a product complexity of 1.46 whereas iron ore has a product complexity of -1.84. Since complexity metrics are related to the knowledge intensity of economic activities, a unit of GDP generated through the production of X-rays should be cleaner and more inclusive than a unit of GDP generated through iron ore mining.

This is an opportunity cost argument. Consider the economies of Switzerland, Singapore, or Sweden. These economies engage an important part of their population in relatively sophisticated activities (they are high complexity economies). While these activities have an associated level of emissions, an ability to contribute to economic growth, and affect the way in which income is distributed, complexity metrics do not capture their contribution to these outcomes in absolute terms. Instead, they capture their contribution relative to other activities. In simple terms, they capture the idea that, in the absence of X-ray equipment production, some of these engineers would be involved in mining.

Thus, we expect measures of economic complexity to help us explain variations in macroeconomic outcomes if they are effective at capturing information about economic structures. Also, we expect these methods to benefit from data about multiple activities (e.g. trade, patents, and research).

In fact, we find that the combination of trade, patent, and research publication data significantly and robustly improves the ability of economic complexity methods to explain inclusive green growth. In particular, metrics of trade and technology complexity—but not of research complexity—combine to explain international differences in economic growth and income inequality. In addition, countries that score high in all three metrics tend to have lower emission intensities. We also find that there is a negative interaction between trade and technology complexity when explaining growth, indicating that some of the information captured by these two metrics is redundant (and hence the metrics are partly substitutes). However, we find no negative interaction when explaining income inequality. Finally, when it comes to emissions, we find that interaction terms dominate the models, meaning that countries with lower emissions tend to score high in all complexity metrics. These results are robust to a variety of controls (total exports, number of patents, number of publications, GDP per capita, etc.) and are confirmed by an instrumental variable robustness check where the complexity of each country is replaced by the average of its most structurally similar neighbors.

These findings expand the knowledge about the role of economic complexity in inclusive green growth and help open a new avenue of research that explores the combination of multiple sources of data to create improved policies for achieving sustainable development.

Methods

Economic complexity metrics are derived from specialization matrices, summarizing the geography of multiple economic activities (using dimensionality reduction techniques akin to Singular Value Decomposition or Principal Component Analysis)[28,42]. In particular, given an output matrix X_{cp}, summarizing the exports, patents, or publications of an economy *c* in an activity *p*, we can estimate the economic complexity index ECI_c of an economy and the product complexity index PCI_p of an activity, by first normalizing and binarizing this matrix:

$$R_{cp} = {X_{cp}X}\Big/{X_pX_c},$$
$$M_{cp} = \begin{cases} 1 & if\ R_{cp} \geq 1 \\ 0 & otherwise \end{cases}, \qquad (1)$$

where muted indexes have been added over (e.g., $X_p = \sum_c X_{cp}$) and R_{cp} stands for the revealed comparative advantage of economy *c* in activity *p*. And then defining the iterative mapping:

$$ECI_c = \frac{1}{M_c} \sum_p M_{cp} PCI_p,$$
$$PCI_p = \frac{1}{M_p} \sum_c M_{cp} ECI_c \ . \qquad (2)$$

That is, according to (2), the complexity of an economy *c* is defined as the average complexity of the activities *p* present in it (and vice-versa). The normalization steps in (1) and (2) are required to make the units of observation comparable (e.g. China and Uruguay are very different in terms of size). The solution of (2) can be obtained by calculating the eigenvector corresponding to the second largest eigenvalue of the matrix:

$$M_{cc'} = \sum_{pc'} \frac{M_{cp} M_{c'p}}{M_c M_p} \qquad (3)$$

Which is a matrix of similarity between economic *c* and *c'* normalized by the sum of the rows and columns of the binary specialization matrix M_{cp} (it considers similarity among economies counting more strongly rare coincidences).

To obtain ECI_c, the values of the eigenvector are normalized using a z-score transformation (meaning that the average complexity is 0). In regression analyzes we further normalize the values of ECI_c to be non-negative using a max-min technique (i.e., they are between 0 and 1).

We use this method to estimate three separate metrics of economic complexity: 1) trade complexity (*ECI (trade)*), using export data from the Observatory of Economic Complexity[41], 2) technology complexity (*ECI (technology)*), using patent applications data from World Intellectual Property Organization's International Patent System; and 3) research complexity (*ECI (research)*), using published documents data from SCImago Journal & Country Rank portal[42]. We investigate their individual and combined contribution to explaining international variations in economic growth, income inequality, and emissions intensity. The economic growth and emissions intensity of a country are estimated using GDP and emissions data from the World Development Indicators[43], whereas the income inequality data are taken from the Estimated Household Income Inequality[44,45]. See Supplementary Information (SI) for a detailed description of the data.

Results

International differences in Multidimensional Economic Complexity

Figure 1a presents three binary specialization matrices (M_{cp}) for countries' exports by product, patents by technology, and publications by research area for the year 2014. Colored dots indicate that a country is specialized in an activity, i.e., that its exports, patent applications, or number of papers are larger than what is expected from that country's or that activity's output ($M_{cp} = 1$).

Figs. 1b and c compare the three ECI rankings and Fig. 2 compares the ECI values. These show that, while these metrics are correlated, they recover the qualitative behavior motivating this research: that trade-based measures of complexity tend to underestimate the complexity of some countries that are far from global markets (e.g., Australia and New Zealand) and overestimate the complexity of some manufacturing economies (e.g., Mexico and Czechia).

For example, consider Mexico (MEX), Czechia (CZE), Australia (AUS), and New Zealand (NZL). Mexico and Czechia rank high in trade complexity (MEX is #24 and CZE is #6) but lower in technology and research complexity. Mexico drops to #26 in the technology rankings and to #44 in the research rankings, whereas Czechia ranks #22 in technology and #34 in research. This could be explained in part by the fact that Mexico's and Czechia's exports do not serve global markets, but the value chains of their neighbors. In fact, over the last decade, 76% of Mexico's exports went to the United States (ranked #12 in trade complexity) and 31% of Czechia's exports went to Germany (ranked #3 in trade complexity)[41]. For comparison, the number one export destination of the median country represents 21% of its total exports, meaning that the United States and Germany are, respectively, heavily overrepresented in Mexico and Czechia's exports.

Australia and New Zealand show the opposite pattern. Both countries rank relatively low in trade complexity (AUS is #76 and NZL is #47) but are global leaders in technology and research rankings. Australia ranks #8 in technology complexity and #3 in research complexity, while New Zealand ranks respectively #12 and #10. This is explained in part by the fact that Australia and New Zealand are far from global markets and export commodities to China, a country that is over 7,000 kilometers away from their capitals. Thus, trade data misses key aspects of the complexity of these economies that is recovered using data on patents and research.

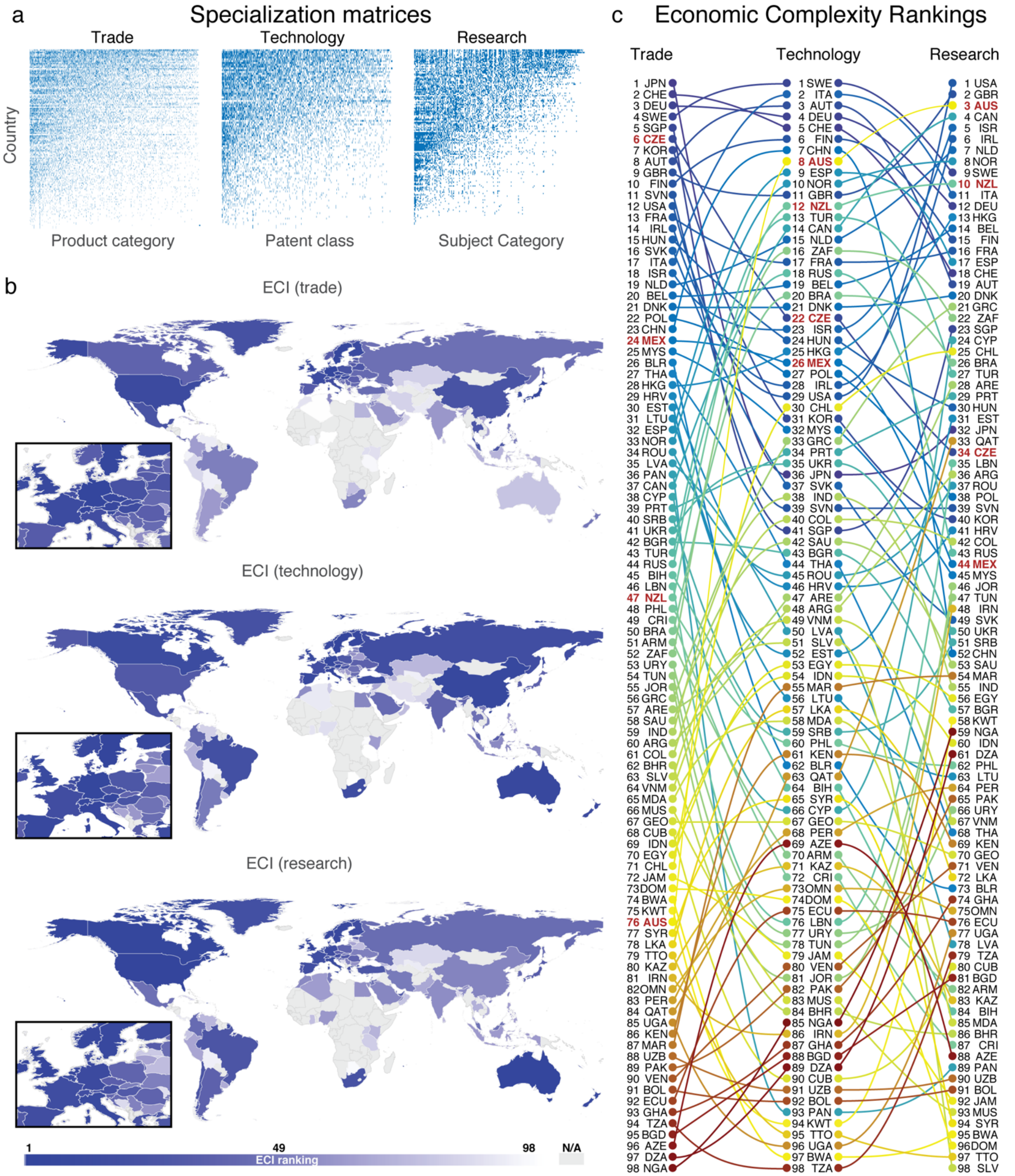

Fig. 1. Multidimensional Economic Complexity. a Specialization matrices of countries considering exports by product, patents by technology, and publications by subject category. **b** Maps showing the rankings of ECI (trade), ECI (technology), and ECI (research). **c** Comparison between the ECI rankings of countries based on ECI (trade), ECI (technology), and ECI (research). **a-c** All data is from the year 2014.

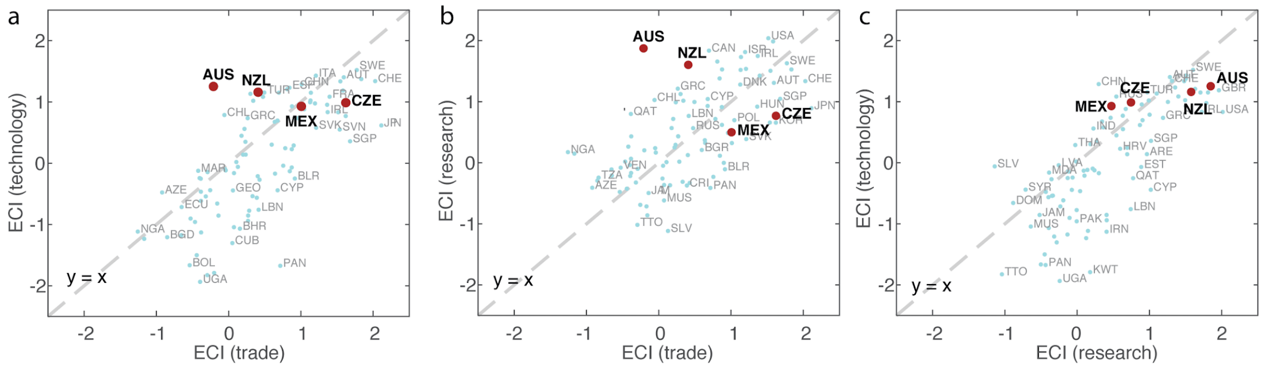

Fig. 2. Comparison between trade, technology, and complexity ECI using 2014 data. a Scatterplot for the relationships between ECI (trade) and ECI (technology) (R^2= 0.51, p-value<10^{-12}), **b** ECI (trade) and ECI (research) (R^2= 0.44, p-value<10^{-12}), and **c** ECI (research) and ECI (technology) (R^2= 0.54, p-value < 10^{-12}).

Multidimensional Economic Complexity and Inclusive Green Growth

Next, we explore how the information provided by technology and research complexity combines with trade complexity to explain international variations in future economic growth, income inequality, and greenhouse gas emissions. We investigate this question piecemeal, first by employing models that include each variable separately, then, by including variables together, and finally, by using interaction terms. In addition, we test for robustness by using an instrumental variable approach and several controls.

We follow the literature[15,30,32] and set up panel regressions of the form

$$y_{ct} = f\left(ECI_{ct}^{d}\right) + a^T X_{ct} + \mu_t + b_0 + e_{ct},$$

where y_{ct} is the dependent variable for country c in year t (economic growth, income inequality, emission intensity), $f\left(ECI_{ct}^{d}\right)$ is a function of the three complexity indices (d = trade, technology, or research), X_{ct} is a vector of control variables that account for other key factors (e.g. population, GDP per capita, etc.), μ_t describes time-fixed effects to account for any unobserved period-specific factors, b_0 is the intercept, and e_{ct} is the error term, (see Supplementary Information (SI) Section 1 for more information about the data and SI Section 2 about the regression specification).

We then validate and select a separate "multidimensional model" for growth, inequality, and emission intensity using the following criteria. First, the multidimensional model must lead to the largest significant increase in explanatory power over the baseline model (given by the coefficient of determination R^2 and validated by a Wald F-test). The baseline model includes GDP per capita (and its square in the case of inequality) and time-fixed effects. Second, in the multidimensional model all included complexity coefficients (individual and interaction terms) must be statistically significant. Finally, we require the model to pass two types of robustness checks. First, we check for robustness by exploring whether the effects hold after including additional explanatory variables. These are measures of size (population), human capital (years of education), dependence on natural resources (natural resource exports per capita), and metrics of the intensity of each respective output (exports per capita, patent applications per capita, and number of research documents per capita). We also try alternative definitions of complexity[46,47] and check whether the results hold for non-complexity metrics, such as measures of market concentration (Shannon information entropy and the Herfindahl–Hirschman index (HHI)) (see SI Sections 3.1 and 3.2). We call the model with all significant and robust explanatory variables the "final model." This is the best model at explaining variations in economic growth, income inequality, and emission intensity.

Second, we also use an instrumental variable approach, where complexity values are replaced by the average complexities of three similarly specialized countries. This is designed to address the possibility that the relationship inferred in the multidimensional and final models between economic complexity and the studied macroeconomic outcomes may be endogenous when local conditions lead to both higher complexity and better outcomes. By replacing complexity estimates with the average of countries with similar specialization patterns, we decouple complexity estimates from other local conditions.

Economic growth: Economies with high levels of complexity relative to their GDP per capita are known to experience faster long-term economic growth[15–18,21,24,48–51]. The idea is that higher complexity economies can participate in sophisticated sectors that support higher wages. But while this relationship has been repeatedly validated using trade[15–17,51] and employment data[21,37], there is a lack of research exploring whether technology and research complexity play a similar role.

Here we test the effect of trade, technology, and research complexity on economic growth by looking at the 10-year annualized GDP per capita growth (in constant PPP dollars) using two periods 1999-2009 and 2009-2019. The baseline model includes the log of the initial GDP per capita (in constant

PPP dollars) and time fixed-effects (see SI Section 4.1). This captures Solow's idea of economic convergence[52] (baseline model is presented in column 1 of table 1, $R^2 = 0.26$).

Table 1 shows the effect of the three complexity metrics and their interactions. We find that trade complexity is a significant and positive predictor of economic growth (column 2, $R^2 = 0.36$) and that technological complexity has a similar explanatory power (column 3, $R^2 = 0.34$). Research complexity, however, is not significantly related to future economic growth (column 4, $R^2 = 0.26$) (see SI Section 4.2). We also find that technological complexity significantly enhances the ability of trade complexity to explain future economic growth (columns 5-7 of table 1). This effect increases when we interact them (columns 8-11 of table 1), leading to our multidimensional model (column 9). The multidimensional model leads to an improvement in explanatory power over the trade complexity regression of 7 percentage points ($R^2 = 0.43$). In this regression, both trade and technology complexities have a positive impact on growth, but their interaction term is negative and significant, suggesting a strong substitute relationship. In general, countries with larger trade ECI than technology ECI experience higher growth, but countries that score poorly in both dimensions experience lower growth. Also, the F-statistics imply that the coefficients of the trade and technology ECI remain significant even when including the log of population and the log of human capital. In addition, the multidimensional model clearly outperforms similar models based on production intensity, measures of diversification, and other measures of complexity. Trade and technology ECIs also outperform measures of concentration (entropy and Herfindahl-Hirschman). The final model includes the multidimensional ECI (trade, technology, and their interaction), the Solow term (GDP per capita), the log of the human capital, and the log of natural resource exports per capita (see SI Section 4.3).

Table 1. Multidimensional Complexity and Economic Growth

	Dependent variable: Annualized GDP pc growth (1999-09, 2009-19)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ECI (trade)		5.658***			4.006***	5.981***		4.022***	12.255***	12.134***		17.331*
		(1.163)			(1.459)	(1.246)		(1.446)	(2.627)	(3.339)		(9.283)
ECI (technology)			2.577***		1.351*		3.323***	2.098**	9.099***		5.483***	12.756
			(0.590)		(0.730)		(0.715)	(0.826)	(2.203)		(2.063)	(7.921)
ECI (research)				1.184		-0.890	-2.541*	-2.563*		6.318	0.380	-5.469
				(1.221)		(1.219)	(1.397)	(1.366)		(3.829)	(2.966)	(10.205)
ECI (trade) x ECI (technology)									-12.260***			-22.692*
									(3.305)			(12.817)
ECI (trade) x ECI (research)										-10.111**		-3.392
										(5.098)		(17.385)
ECI (research) x ECI (technology)											-3.856	0.435
											(3.455)	(13.627)
ECI (trade) x ECI (research) x ECI (technology)												9.443
												(21.513)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Log of population F-Statistic		26.673***	27.730***	1.509					20.719***			
Log of human capital F-Statistic		9.371***	10.163***	0.936					11.371***			
Log of natural resource exports per capita F-Statistic		39.471***	25.484***	2.695					19.988***			
Log of production intensity F-Statistic		21.359***	6.964***	0.569					18.803***			
HHI F-Statistic		8.494***	5.679**	0.437					11.479***			
Entropy F-Statistic		8.164***	5.349**	0.480					11.595***			
Log of Fitness F-Statistic		7.673***	5.406**	2.562					17.645***			
Instrumental variables model F-Statistic		22.630***	13.044***	0.195					21.300***			
Observations	152	152	152	152	152	152	152	152	152	152	152	152
R^2	0.256	0.358	0.341	0.260	0.373	0.361	0.355	0.388	0.427	0.377	0.361	0.452
Adjusted R^2	0.246	0.345	0.327	0.245	0.356	0.343	0.338	0.367	0.407	0.356	0.339	0.417

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01. The F-statistics for the models in columns 1-3 were estimated using models given in tables S2-S4. The F-statistics for the model in column 9 were estimated using models estimated in tables S4-S8.

Income inequality: Economies with less complex trade structures are also known to exhibit higher levels of income inequality[25–27]. The idea is that firms operating in knowledge intense activities promote inclusive institutions because of their need to attract and retain talent. Firms in less complex activities, do not face this constraint, and benefit from a more extractive institutional environment. Thus, we should expect higher levels of economic complexity to be associated with lower levels of inequality.

To explore the ability of multidimensional complexity to explain variations in income inequality we model an economy's Gini coefficient, a standard measure of inequality. Larger values for the Gini coefficient indicate larger income inequality. We divide the data into four four-year panels: 1996-1999, 2000-2003, 2004-2007, 2008-2011, and 2012-2015 and set up a baseline model given by the Kuznets curve: the idea that as an economy develops market forces first increase and then decrease income inequality[53] (Gini ~ GDP per capita, its square, and time fixed-effects, see SI Section 5.1).

We find that trade and technology ECIs are significant and negative predictors of income inequality with, respectively, $R^2 = 0.55$ (column 2 of table 2) and $R^2 = 0.50$ (column 3 of table 2). Trade and technology ECIs also outperform measures of concentration (entropy and Herfindahl-Hirschman, see SI Section 5.2). Moreover, they provide an important improvement over the baseline model, which has an $R^2 = 0.35$ (column 1 of table 2). Research ECI, however, is only a minor predictor of income inequality providing little improvement to the explanatory power ($R^2 = 0.37$, column 4 of table 2).

Again, the model combining trade and technology provides the best explanatory power (columns 5-11 of table 2). However, the interaction term between trade and technology is not significant, meaning that the two complexities do not behave as substitutes or complements. The multidimensional model is given by column 5 of table 2 ($R^2 = 0.57$). This model is also robust when including the log of population and log of human capital and outperforms similar models based on production intensity, measures of diversification, and other measures of complexity. The final model—the one that best explains international variations in income inequality—includes the log of population and human capital in addition to the multidimensional ECI and the Kuznets term, (see SI Section 5.3).

Table 2. Multidimensional Complexity and Income Inequality

	Dependent variable: Gini coefficient (1996-99, 2000-03, 2004-07, 2008-11, 2012-15)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ECI (trade)		-23.543***			-17.902***	-23.116***		-17.778***	-9.279	-21.289***		-18.449
		(1.933)			(2.353)	(2.025)		(2.352)	(5.930)	(5.467)		(19.023)
ECI (technology)			-11.211***		-5.269***		-12.317***	-6.216***	1.208		-3.964	11.923
			(1.141)		(1.310)		(1.353)	(1.487)	(4.294)		(3.831)	(14.230)
ECI (research)				-7.654***		-1.336	3.400	2.783		0.649	16.132***	21.084
				(2.117)		(1.873)	(2.248)	(2.076)		(5.825)	(5.906)	(19.516)
ECI (trade) x ECI (technology)									-11.449			-8.570
									(7.230)			(24.817)
ECI (trade) x ECI (research)										-2.990		-0.339
										(8.307)		(33.956)
ECI (research) x ECI (technology)											-16.026**	-31.788
											(6.883)	(25.028)
ECI (trade) x ECI (research) x ECI (technology)												12.933
												(41.573)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Log of population F-Statistic		202.34***	188.310***	23.556***	68.373***							
Log of human capital F-Statistic		99.848***	79.305***	10.291***	18.220***							
Log of natural resource exports per capita F-Statistic		180.630***	101.550***	13.828***	16.661***							
Log of production intensity F-Statistic		146.900***	7.150***	1.714	32.781***							
HHI F-Statistic		57.804***	42.456***	8.666***	23.111***							
Entropy F-Statistic		53.369***	41.057***	8.075***	21.213***							
Log of Fitness F-Statistic		69.147***	20.938***	2.690	6.679***							
Instrumental variables model F-Statistic		162.400***	79.958***	13.208***	49.536***							
Observations	332	332	332	332	332	332	332	332	332	332	332	332
R^2	0.346	0.551	0.496	0.371	0.573	0.552	0.500	0.575	0.576	0.552	0.508	0.590
Adjusted R^2	0.334	0.542	0.485	0.358	0.562	0.541	0.487	0.563	0.564	0.540	0.494	0.573

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01. The F-statistics for the models in columns 1-3 were estimated using models given in tables S9-S11. The F-statistics for the model in column 9 were estimated using models estimated in tables S12-S16.

Emission intensity: Trade complexity is known to be associated with lower greenhouse gas emissions per unit of output[30] and better environmental performance[54,55]. The idea is that the emissions required to, for instance, produce a unit of GDP by extracting tin ore are larger than the emissions required to produce a unit of GDP by manufacturing metal cutting machines. Here, we explore whether the technology and research dimensions add to the ability of trade complexity to explain emission intensity by modelling the logarithm of a country's yearly greenhouse gas emissions per unit of GDP (in kilotons of CO_2 equivalent per dollar of GDP). Larger values represent larger emission intensity. We divide our analysis into five panels: 1996-1999, 2000-2003, 2004-2007, 2008-2011, 2012-2015, and 2016-2018 (the last panel is three years due to limited emissions data). The baseline model includes the log of the GDP per capita (constant PPP dollars), capturing the idea that more developed economies should have lower emission intensities[30], and time fixed-effects (see SI Section 6.1).

Unlike in the previous two cases, here we find that individual ECI measures do not perform better than metrics of concentration (Entropy, Herfindahl-Hirschman index) and other complexity measures (Fitness) (see SI Section 6.2). Nevertheless, the best multidimensional complexity model is robust and includes the three-way interaction between trade, technology, and research complexity ($R^2 = 0.30$, column 11 of table 3, Fig. 3 c). This implies that countries that score high in all dimensions (e.g., Sweden, France, Austria) have the lowest emission intensities (see SI Section 6.3). The final model includes also measures of population size, human capital, natural resource exports per capita and production intensity: the logarithms of exports per capita, patents per capita, and publications per capita ($R^2 = 0.45$, column (14) of Table S21 in SI Section 6.3). This means that the measures of complexity explain variation in emission intensities that go beyond the variation accounted for by the natural resource export intensity of an economy.

Table 3. Multidimensional Complexity and Emission Intensity

	Dependent variable: Log of GHG emissions per GDP (1996-99, 2000-03, 2004-07, 2008-11, 2012-15, 2016-18)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ECI (trade)		-0.802***			-0.927***	-0.769***		-0.917***	0.193	0.376		-3.499***
		(0.165)			(0.206)	(0.177)		(0.206)	(0.419)	(0.401)		(1.246)
ECI (technology)			-0.200**		0.123		-0.116	0.190	1.008***		0.368	-2.767***
			(0.098)		(0.120)		(0.118)	(0.134)	(0.313)		(0.285)	(1.032)
ECI (research)				-0.324**		-0.083	-0.228	-0.193		1.185***	0.457	-3.723***
				(0.148)		(0.156)	(0.177)	(0.174)		(0.429)	(0.407)	(1.323)
ECI (trade) x ECI (technology)									-1.571***			5.104***
									(0.513)			(1.786)
ECI (trade) x ECI (research)										-1.948***		6.820***
										(0.614)		(2.413)
ECI (research) x ECI (technology)											-0.935*	6.477***
											(0.501)	(1.854)
ECI (trade) x ECI (research) x ECI (technology)												-11.270***
												(3.084)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Log of population F-Statistic		23.020***	3.333**	4.005***								26.645***
Log of human capital F-Statistic		52.675***	11.187***	7.707***								28.221***
Log of natural resource exports per capita F-Statistic		6.832***	0.507	0.708								34.048***
Log of production intensity F-Statistic		24.345***	0.236	3.771*								19.235***
HHI F-Statistic		1.203	0.134	2.476								50.436***
Entropy F-Statistic		0.654	0.101	2.089								51.000***
Log of Fitness F-Statistic		0.256	0.470	0.37s								58.842***
Instrumental variables model F-Statistic		17.386***	3.119*	3.225*								18.239***
Observations	529	529	529	529	529	529	529	529	529	529	529	529
R^2	0.240	0.272	0.246	0.247	0.274	0.273	0.248	0.276	0.287	0.287	0.253	0.308
Adjusted R^2	0.231	0.263	0.235	0.236	0.263	0.262	0.236	0.263	0.274	0.274	0.240	0.291

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01. The F-statistics for the models in columns 1-3 were estimated using models given in tables S17-S19. The F-statistics for the model in column 9 were estimated using models estimated in tables S20-S24.

In Fig. 3 we summarize our empirical findings. Adding complexity metrics for technology and research can improve the ability of the regression models to explain variations in economic growth, income inequality, and emission intensity. In fact, our final models explain more than 50% of cross-country variation in economic growth, income inequality, and emission intensity (Figs. 3a-c), a drastic increase compared to including only trade metrics. Technology complexity adds to the ability of trade complexity to explain economic growth and income inequality, and trade, technology, and research complexity complement each other in their ability to explain greenhouse gas emissions (Figs. 3d-f). We also calculate the overall marginal effect of the different ECI coefficients by creating a multidimensional ECI by weighting each ECI coefficient according to the size of the regression coefficient in the final model, and re-estimating the final model of economic growth, income inequality and emissions intensity. The multidimensional ECI is correlated with increases in economic growth and decreases in income inequality and emissions intensity (Figs. 3g-i).

Nevertheless, we find that the individual effect of different dimensions of complexity is not always linear since complexity estimates interact. In the case of economic growth, the negative interaction suggests a mild substitution between these two variables (high complexity in exports and technology help explain growth, but there is no additional effect of scoring high on both). In the case of inequality, the effects seem to be linear and additive since the interaction term here is not significant. Finally, for emission intensities, we find significance across all interaction terms, meaning that we expect to observe lower emissions in economies that score high in the three complexity metrics. This validates the idea that complexities in different forms of activities combine to explain inclusive green growth. But are these results robust to possible omitted variables?

To further validate these results, we pursue an instrumental variable approach where we replace a country's complexity values with those of its three most similar neighbors. The idea is that there might be factors that are either local (e.g., culture, geography) or relevant only to certain dependent variables (e.g., country-specific environmental policies for GHG emission intensity) that could drive both complexity and macroeconomic outcomes. To decouple local factors and conditions from our complexity estimates, we replace the complexity values of each country with the average of the three countries with the most similar specialization pattern (based on the conditional probability that two countries are specialized in the same vector of activities[56] (exports, technologies, research areas), see SI Section 7.1). For example, in 2014 Japan's export structure was similar to that of Germany, South Korea, and Great Britain whereas Australia's technological structure was similar to Great Britain, Spain, and Canada. In SI Section 7.1 we provide a full list of the three most similar economies in 2014 for every country and dimension used in our analysis. We find the results remain virtually unchanged, reducing the risk that the explanatory value of these complexity metrics comes from an omitted local factor (F-statistics for the Wald restriction tests are given in Tables 1-3, see also SI Section 7.2, 7.3, and 7.4).

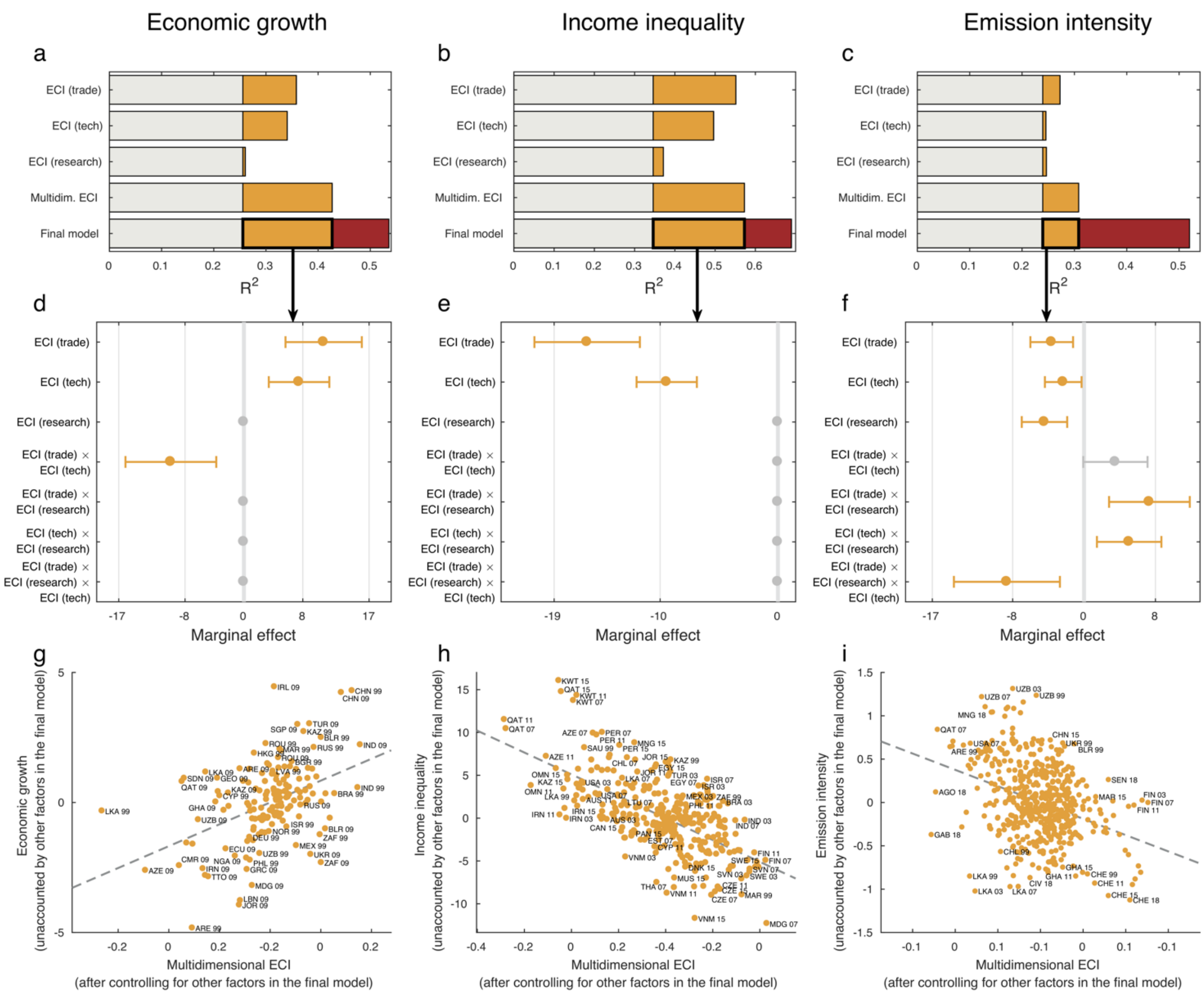

Fig. 3. Explaining international variations in economic growth, income inequality, and emission intensity with multidimensional economic complexity. a-c Contribution of the baseline, ECIs, and other covariates to the variance explained by various models (R^2) for **a** economic growth, **b** income inequality, and **c** emission intensity. The baseline R^2s are presented in grey, the contributions of the three individual ECIs and of the multidimensional ECI in orange, and the variance explained by additional factors in the final model is shown in in red. **d-f** Error bars for the marginal effects (with 95% confidence intervals) for the ECI coefficients in the final models for **d**, economic growth (Table S4, column 17), **e** income inequality (Table S12, column 17) and, **f** emission intensity (Table S21, column 14). **g-i** The conditional correlation between the multidimensional ECI (created by weighting each ECI coefficient according to the size of the regression coefficient in the final model) and **g** economic growth, **h** income inequality, and **i** emission intensity. Conditional correlations are obtained by controlling for all other factors included in the final models.

Discussion

Economic complexity methods have become important tools to explain regional and international variations in inclusive green growth[57–64]. Yet, most applied work on economic complexity relies on metrics derived from trade data that are limited in their ability to capture information from non-trade activities. This can lead to distorted estimates for the complexity of certain countries and limited information about how different types of activities combine to explain variations in inclusive green growth.

Here, we combined trade, technology, and research data, to explore the role of complexity metrics in inclusive green growth. We found that technology complexity adds to the ability of trade complexity to explain economic growth and income inequality, and that trade, technology, and research complexity complement each other in their ability to explain greenhouse gas emissions. We also found that complexities expressed in different forms of activities sometimes interact. Trade and technology complexities are partly substitutes in the growth regression, but not in the inequality model. Moreover, in the emission intensities model the highest predictive power was obtained by the model with the triple interaction, meaning that lower emission intensities correlate with countries that score high in all three metrics of complexity.

But what do these results mean?

On the one hand, product exports and patent applications can be easily tied to monetary outcomes such as economic growth or income inequality (e.g., product exports generate revenues, whereas patents generate royalties). Thus, the structure of these activities should contribute directly to monetary outcomes, unlike the geography of research papers which may have a more indirect effect. Emission intensities, on the other hand, seem to correlate negatively with the presence of complexity in trade, technology, and research, suggesting that countries with lower emissions are sophisticated across these three dimensions. For instance, Australia's high emission intensity can be explained by its lack of sophistication in exports[65]. Yet, we should also expect Australia's emission intensity to be relatively low compared to countries with a similar export structure, because of Australia's high complexity in technology and research.

These results are relevant for identifying strategic areas for economic diversification and development, as they provide a more holistic target than the one provided by metrics of trade complexity alone[30,32]. This should be of interest to policy makers using complexity metrics for inclusive green development and reinforce the idea that metrics of economic complexity go beyond measures of trade sophistication[33,34,62,66,67]. In fact, our results show that the combination of multiple metrics of complexity is key to extract information about the role of economic structures in inclusive green growth.

Yet, this approach is not without limitations.

First, patent application and research publication data also have limitations. For instance, since patent applications and research documents are usually written in English, these datasets can favor both, English speaking countries (e.g., USA, Australia) and countries with high proficiency in English (e.g., Netherlands, Sweden).

Second, there are plenty of activities that are not captured in either trade, patent, or research publication data—such as services, digital products, and cultural activities. These may capture additional aspects of the complexity of economies that would need to be included in a more comprehensive multidimensional framework[16,68,69]. Unfortunately, the current state of the art does not include internationally comparable fine-grained datasets for these additional activities (e.g. service trade data is too aggregate to approximate the productive structure of an economy, see Ref.[70] and SI Section 8).

Third, our research is also limited by differences in the granularity of the three datasets: trade data is the most granular, with about 1,200 unique products, while research publication data involves only about 300 subject categories. This may be one of the reasons why we do not see strong effects from research complexity in economic growth and income inequality, and one of the reasons why combining these datasets into a unified matrix (e.g., by concatenating or multiplying these matrices) is non-trivial.

Fourth, these results cannot be readily generalized to other geographic scales, such as states and provinces. For instance, while future economic growth has been shown to correlate with the complexity of countries[15,17,20,51,64] and regions[70], the relationship between complexity and inequality is known to reverse at the regional scale[21,71–74]. Thus, this approach cannot tell us much about regional effects, which could be different from those observed at the international scale[21,72–75].

Yet, despite these limitations, multidimensional complexity improves upon the state-of-the-art when explaining international differences in economic growth, income inequality, and greenhouse gas emissions. These findings advance our understanding of the role of economic complexity in inclusive green growth and should motivate new research on comprehensive metrics of complexity and sustainable development.

Acknowledgements:

We thank Eva Coll, Ron Boschma, Koen Frenken, Eduardo Hernández, the attendees of the 2022 Economic Geography and Networks PhD school in Utrecht, and the members of the Center for Collective Learning for valuable feedback. We thank Pierre-Alexandre Balland for facilitating patent data. This project was supported by: ANR-19-PI3A-0004

References:

1. SDG, U. Sustainable development goals. *The energy progress report. Tracking SDG* **7**, (2019).
2. Sachs, J. D. *et al.* Six transformations to achieve the sustainable development goals. *Nature sustainability* **2**, 805–814 (2019).
3. Hák, T., Janoušková, S. & Moldan, B. Sustainable Development Goals: A need for relevant indicators. *Ecological indicators* **60**, 565–573 (2016).
4. Sachs, J. D. From millennium development goals to sustainable development goals. *The lancet* **379**, 2206–2211 (2012).
5. Bank, W. *Inclusive green growth: The pathway to sustainable development*. (The World Bank, 2012).
6. Barbier, E. B. The green economy post Rio+ 20. *Science* **338**, 887–888 (2012).
7. Bryan, B. A., Hadjikakou, M. & Moallemi, E. A. Rapid SDG progress possible. *Nature Sustainability* **2**, 999–1000 (2019).
8. Agarwala, M., Atkinson, G., Baldock, C. & Gardiner, B. Natural capital accounting and climate change. *Nature Climate Change* **4**, 520–522 (2014).
9. Soergel, B. *et al.* A sustainable development pathway for climate action within the UN 2030 Agenda. *Nature Climate Change* **11**, 656–664 (2021).

10. Biermann, F. *et al.* Scientific evidence on the political impact of the Sustainable Development Goals. *Nature Sustainability* 1–6 (2022).
11. Murakami, K., Itsubo, N. & Kuriyama, K. Explaining the diverse values assigned to environmental benefits across countries. *Nature Sustainability* 1–9 (2022).
12. Basheer, M. *et al.* Balancing national economic policy outcomes for sustainable development. *Nature Communications* **13**, 1–13 (2022).
13. Hidalgo, C. A. Economic complexity theory and applications. *Nature Reviews Physics* **3**, 92–113 (2021).
14. Balland, P.-A. *et al.* The new paradigm of economic complexity. *Research Policy* **51**, 104450 (2022).
15. Hidalgo, C. A. & Hausmann, R. The building blocks of economic complexity. *Proceedings of the national academy of sciences* **106**, 10570–10575 (2009).
16. Stojkoski, V., Utkovski, Z. & Kocarev, L. The impact of services on economic complexity: Service sophistication as route for economic growth. *PloS one* **11**, e0161633 (2016).
17. Stojkoski, V. & Kocarev, L. The relationship between growth and economic complexity: evidence from Southeastern and Central Europe. (2017).
18. Koch, P. Economic Complexity and Growth: Can value-added exports better explain the link? *Economics Letters* **198**, 109682 (2021).
19. Poncet, S. & de Waldemar, F. S. Economic complexity and growth. *Revue economique* **64**, 495–503 (2013).
20. Domini, G. Patterns of specialization and economic complexity through the lens of universal exhibitions, 1855-1900. *Explorations in Economic History* **83**, 101421 (2022).

21. Chávez, J. C., Mosqueda, M. T. & Gómez-Zaldívar, M. Economic complexity and regional growth performance: Evidence from the Mexican Economy. *Review of Regional Studies* **47**, 201–219 (2017).

22. Ourens, G. Can the Method of Reflections help predict future growth? *Documento de Trabajo/FCS-DE; 17/12* (2012).

23. Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M. & Simoes, A. *The atlas of economic complexity: Mapping paths to prosperity*. (Mit Press, 2014).

24. Li, Y. & Rigby, D. Relatedness, Complexity, and Economic Growth in Chinese Cities. *International Regional Science Review* 01600176221082308 (2022).

25. Hartmann, D. The economic diversification and innovation system of Turkey from a global comparative perspective. in *International Innovation Networks and Knowledge Migration* 53–71 (Routledge, 2016).

26. Sbardella, A., Pugliese, E. & Pietronero, L. Economic development and wage inequality: A complex system analysis. *PloS one* **12**, (2017).

27. Bandeira Morais, M., Swart, J. & Jordaan, J. A. Economic Complexity and Inequality: Does Productive Structure Affect Regional Wage Differentials in Brazil? *USE Working Paper series* **18**, (2018).

28. Neagu, O. The Link between Economic Complexity and Carbon Emissions in the European Union Countries: A Model Based on the Environmental Kuznets Curve (EKC) Approach. *Sustainability* **11**, 4753 (2019).

29. Lapatinas, A. The effect of the Internet on economic sophistication: An empirical analysis. *Economics Letters* **174**, 35–38 (2019).

30. Romero, J. P. & Gramkow, C. Economic complexity and greenhouse gas emissions. *World Development* **139**, 105317 (2021).

31. Can, M. & Gozgor, G. The impact of economic complexity on carbon emissions: evidence from France. *Environmental Science and Pollution Research* **24**, 16364–16370 (2017).

32. Hartmann, D., Guevara, M. R., Jara-Figueroa, C., Aristarán, M. & Hidalgo, C. A. Linking economic complexity, institutions, and income inequality. *World development* **93**, 75–93 (2017).

33. Ding, X. & Hadzi-Vaskov, M. *Composition of Trade in Latin America and the Caribbean*. (International Monetary Fund, 2017).

34. Salinas, G. & Muñoz, S. Proximity and Horizontal Policies: The Backbone of Export Diversification and Complexity. *IMF Working Papers* **2021**, (2021).

35. Balland, P.-A. & Rigby, D. The geography of complex knowledge. *Economic Geography* **93**, 1–23 (2017).

36. Fritz, B. S. & Manduca, R. A. The economic complexity of US metropolitan areas. *Regional Studies* 1–12 (2021).

37. Hane-Weijman, E., Eriksson, R. H. & Rigby, D. How do occupational relatedness and complexity condition employment dynamics in periods of growth and recession? *Regional Studies* **56**, 1176–1189 (2022).

38. Balland, P.-A. & Boschma, R. *Do scientific capabilities in specific domains matter for technological diversification in European regions?* (2021).

39. Ivanova, I., Strand, Ø., Kushnir, D. & Leydesdorff, L. Economic and technological complexity: A model study of indicators of knowledge-based innovation systems. *Technological forecasting and social change* **120**, 77–89 (2017).

40. Lybbert, T. J. & Xu, M. Innovation-adjusted economic complexity and growth: Do patent flows reveal enhanced economic capabilities? *Review of Development Economics* **26**, 442–483 (2022).

41. Simoes, A. J. G. & Hidalgo, C. A. The economic complexity observatory: An analytical tool for understanding the dynamics of economic development. in *Workshops at the twenty-fifth AAAI conference on artificial intelligence* (2011).

42. SJR - About Us. https://www.scimagojr.com/aboutus.php.

43. Bank, W. *World development indicators 2007*. (The World Bank, 2007).

44. Galbraith, J. K., Halbach, B., Malinowska, A., Shams, A. & Zhang, W. UTIP global inequality data sets 1963-2008: Updates, revisions and quality checks. (2014).

45. Galbraith, J. K., Halbach, B., Malinowska, A., Shams, A. & Zhang, W. *The UTIP global inequality datasets: 1963-2008*. (2015).

46. Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A. & Pietronero, L. A new metrics for countries' fitness and products' complexity. *Scientific reports* **2**, 1–7 (2012).

47. Cristelli, M., Gabrielli, A., Tacchella, A., Caldarelli, G. & Pietronero, L. Measuring the intangibles: A metrics for the economic complexity of countries and products. *PloS one* **8**, e70726 (2013).

48. Poncet, S. & de Waldemar, F. S. Economic Complexity and Growth. *Revue économique* **64**, 495–503 (2013).

49. Domini, G. Patterns of specialization and economic complexity through the lens of universal exhibitions, 1855-1900. *Explorations in Economic History* **83**, 101421 (2022).

50. Ourens, G. Can the Method of Reflections help predict future growth? *Documento de Trabajo/FCS-DE; 17/12* (2012).

51. Hausmann, R. *et al. The atlas of economic complexity: Mapping paths to prosperity*. (MIT Press, 2014).

52. Solow, R. M. A contribution to the theory of economic growth. *The quarterly journal of economics* **70**, 65–94 (1956).

53. Kuznets, S. *Economic growth and income inequality*. (Routledge, 2019).

54. Boleti, E., Garas, A., Kyriakou, A. & Lapatinas, A. Economic complexity and environmental performance: evidence from a world sample. *Environmental Modeling & Assessment* **26**, 251–270 (2021).

55. Mealy, P. & Teytelboym, A. Economic complexity and the green economy. *Research Policy* 103948 (2020).

56. Hidalgo, C. A., Klinger, B., Barabási, A.-L. & Hausmann, R. The product space conditions the development of nations. *Science* **317**, 482–487 (2007).

57. Economía, S. de. Diversificación inteligente. *gob.mx* http://www.gob.mx/se/acciones-y-programas/diversificacion-inteligente.

58. Economic Complexity | IRI. https://iri.jrc.ec.europa.eu/areas-of-work/complexity.

59. IMFBlog. How Countries Can Diversify Their Exports. *IMF Blog* https://blogs.imf.org/2021/09/22/how-countries-can-diversify-their-exports/.

60. How and why should we study 'economic complexity'? *Our World in Data* https://ourworldindata.org/how-and-why-econ-complexity.

61. Montresor, S. & Quatraro, F. Green technologies and Smart Specialisation Strategies: a European patent-based analysis of the intertwining of technological relatedness and key enabling technologies. *Regional Studies* **54**, 1354–1365 (2020).

62. Mealy, P. & Coyle, D. To them that hath: economic complexity and local industrial strategy in the UK. *International Tax and Public Finance* **29**, 358–377 (2022).

63. Hausmann, R. *et al.* Construyendo un mejor futuro para la República Dominicana: herramientas para el desarrollo. *Informe técnico. Cambridge, MA: Center for International Development, Universidad de Harvard* (2011).

64. Hidalgo, C. A. Economic complexity theory and applications. *Nature Reviews Physics* 1–22 (2021).

65. Allen, C., Metternicht, G., Wiedmann, T. & Pedercini, M. Greater gains for Australia by tackling all SDGs but the last steps will be the most challenging. *Nature Sustainability* **2**, 1041–1050 (2019).

66. Balland, P. A., Boschma, R., Crespo, J. & Rigby, D. L. Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Regional Studies* 1–17 (2018) doi:10.1080/00343404.2018.1437900.

67. Hidalgo, C. A. The Policy Implications of Economic Complexity. *arXiv preprint arXiv:2205.02164* (2022).

68. Mishra, S., Tewari, I. & Toosi, S. Economic complexity and the globalization of services. *Structural Change and Economic Dynamics* **53**, 267–280 (2020).

69. Brynjolfsson, E., Collis, A. & Eggers, F. Using massive online choice experiments to measure changes in well-being. *Proceedings of the National Academy of Sciences* **116**, 7250–7255 (2019).

70. Saltarelli, F., Cimini, V., Tacchella, A., Zaccaria, A. & Cristelli, M. Is Export a Probe for Domestic Production? *Frontiers in Physics* **8**, 180 (2020).

71. Hartmann, D. & Pinheiro, F. L. *Economic complexity and inequality at the national and regional level*. http://arxiv.org/abs/2206.00818 (2022) doi:10.48550/arXiv.2206.00818.

72. Gao, J. & Zhou, T. Quantifying China's regional economic complexity. *Physica A: Statistical Mechanics and its Applications* **492**, 1591–1603 (2018).

73. Zhu, S., Yu, C. & He, C. Export structures, income inequality and urban-rural divide in China. *Applied Geography* **115**, 102150 (2020).

74. Wang, Y. & Turkina, E. Economic complexity, product space network and Quebec's global competitiveness. *Canadian Journal of Administrative Sciences/Revue Canadienne des Sciences de l'Administration* **37**, 334–349 (2020).

75. Reynolds, C. *et al.* A sub-national economic complexity analysis of Australia's states and territories. *Regional Studies* **52**, 715–726 (2018).

Supplementary Information for:

Multidimensional Economic Complexity: How the Geography of Trade, Technology, and Research Explain Inclusive Green Growth

Viktor Stojkoski[a], Philipp Koch[a,b], César A. Hidalgo[a,c,d,*]

[a] Center for Collective Learning, ANITI, TSE-R, IAST, IRIT, Université de Toulouse, 31000 Toulouse, France
[b] EcoAustria – Institute for Economic Research, 1030 Vienna, Austria
[c] Alliance Manchester Business School, University of Manchester, United Kingdom
[d] School of Engineering and Applied Sciences, Harvard University, United States

Table of Contents

[*] Corresponding author, e-mail: cesifoti@gmail.com

1. Data

We analyze the spatial distribution of trade of goods, scientific knowledge, and new technologies, across 150 countries and 24 years (spanning from 1996 up to 2019). For each country and a given year, we approximate the magnitude of trade in a particular product category through the export value, the level of activity in a research area through the number of published articles in that field, and the number of innovations in a technological class via the number of patent applications in the class.

In each year, we restrict our analysis to countries which:

- had population above 1 million;
- had a total product export value of more than 1 billion USD;
- had more than 4 patent applications;
- had more than 30 scientific publications.

Adding a threshold for the minimum intensity in trade, patent applications or scientific publications is a standard in the economic complexity literature. It helps reduce the noise in the data arising from small economies whose specialization structure greatly varies over the years[1–3].

1.1. Product exports data

We look at country-goods associations by using international trade data with goods disaggregated into categories according to the HS4 classification. With this classification we end up with 1241 product categories. More detailed classifications which disaggregate the goods into more categories, such as the HS6, can also be used. However, then the number of categories is not comparable to the number of scientific fields and patent classes, thus making distortions in the level of the disaggregation of the different dimensions. For each year, we remove from the analysis the products whose total world exports were less than 500 000 USD.

The data are taken from the Observatory of Economic Complexity [4].

Figure S1 gives the histogram for the distribution of the share of exports to the main export partner for each country (for the period 2010-2019), which was used to argue that Mexico and Czechia are integrated into their neighbors' value chains.

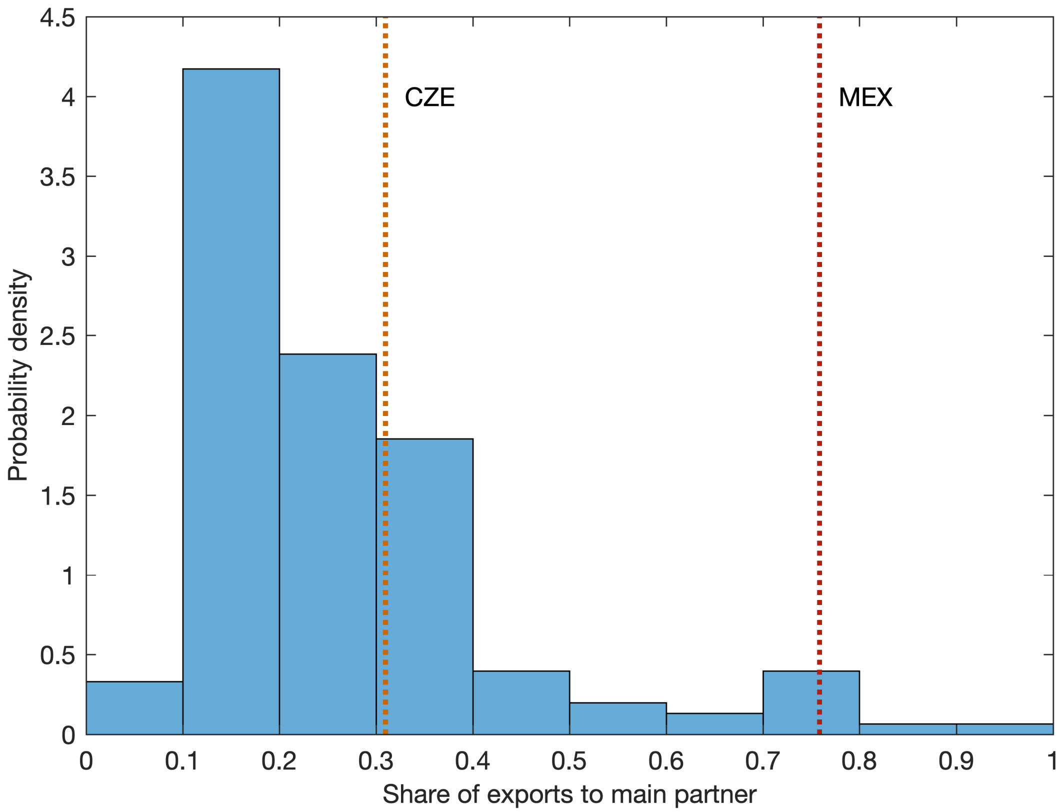

Figure S1. Histogram for the Distribution of the Share of Exports to the Main Export Partner (2010-2019)

1.2.Patent applications data

The patent data are gathered from the World Intellectual Property Organization's International Patent System. The patent data in this system are based on the Patent Cooperation Treaty (PCT). Each patent application under the PCT simultaneously seeks protection for an invention in many countries. This reduces the potential home bias which may arise when using patent data that come from a single Patent Office. We classify the patents by residence of inventors according to the Cooperative Patent Classification, disaggregated to a 4-digit level, and in each year include only patent classes for which there were more than 5 applications. After clearing the data, we end up with 668 distinct technological classes.

1.3.Research publications data

The research article data come from the SCImago Journal & Country Rank portal[5]. The portal contains information on data available in the Scopus database and disaggregates the scientific fields into 313 specific categories according to Scopus Classification. For a given year, we set each country-research category pair to be equal to 0 if there were less than 3 documents, or if the number of citations of the documents published in the past four years was less than 400 (average of 100 citations per year). Also, each year we remove from the analysis each research category which had less than 30 publications.

2. Regression analysis setup

2.1. Individual regressions setup

In order to assess the ability of each dimension to explain variations in economic growth, income inequality and greenhouse gas emissions, we estimate period fixed effects panel regression models of the form

$$y_{ct} = b_0 + \boldsymbol{a}^{\boldsymbol{T}} X_{ct} + bECI_{ct}^{d} + \mu_t + e_{ct},$$

where y_{ct} is the dependent variable (economic growth, income inequality or extent of greenhouse gas emissions) for country c in year t, b_0 is the intercept term, X_{ct} is a vector of control independent variables that account for observed factors that are not related with the economic complexity. The coefficient b is of particular interest to us as it is an estimate of the marginal effect of the economic complexity of the country in dimension d. The μ_t coefficient are period fixed effects that help to control for any unobserved factors that are period-specific and apply to all countries, and e_{ct} is the error term.

2.2.Interactions regressions setup

To infer how different forms of output (trade, technology, and research) combine to help explain geographic variations in economic growth, income inequality, and greenhouse gas emissions, we resort to three different specifications of interaction regression analyses. In the first specification, we assume that there is no interaction between the dimensions and that they share an additive relationship in explaining the economic outcome. The regression form of this specification is

$$y_{ct} = b_0 + \boldsymbol{a}^{\boldsymbol{T}} X_{ct} + \sum_{d} b_d ECI_{ct}^{d} + \mu_t + e_{ct},$$

Where d is a superscript used to differentiate between trade ECI, technology ECI, and research ECI. We conduct four different no-interaction regressions, depending on which dimensions are included in the analysis. They are 1) trade and technology, 2) trade and research, 3) technology and research, and 4) trade, technology, and research.

In the second setup, we study the pairwise relationship between two dimensions $d_1$and d_2. This specification includes the interaction term between the two dimensions and is formally written as

$$y_{ct} = b_0 + \boldsymbol{a}^{\boldsymbol{T}} X_{ct} + b_1 ECI_{ct}^{d_1} + \ b_2 ECI_{ct}^{d_2} + \ b_{12} ECI_{ct}^{d_1} \times ECI_{ct}^{d_2} + \mu_t + e_{ct}.$$

The interaction coefficient b_{12} allows us to infer how the two dimensions combine in explaining the variations of growth, inequality, or emission intensity. Specifically, if b_{12} is significant and has the same sign as b_1 and b_2, then it is said that the two dimensions are complements in explaining the economic outcome (economic growth, income inequality, or greenhouse gas emissions). If b_{12} is significant and negative then the dimensions are substitutes, and if it is insignificant then there is no relationship between the dimensions. Given that we investigate the performance of three dimensions of economic complexity, we end up doing three pairwise regressions: 1) trade and technology, 2) trade and research, and 3) technology and research interactions.

In the third specification, we study the three-way interaction between every dimension. In this case, the regression is specified as

$$\begin{aligned} y_{ct} = b_0 + \boldsymbol{a}^{\boldsymbol{T}} X_{ct} + b_1 ECI_{ct}^{d_1} + \ b_2 ECI_{ct}^{d_2} + \ b_3 ECI_{ct}^{d_1} \\ + \ b_{12} ECI_{ct}^{d_1} \times ECI_{ct}^{d_2} \ + \ b_{13} ECI_{ct}^{d_1} \times ECI_{ct}^{d_3} \ + \ b_{23} ECI_{ct}^{d_2} \times ECI_{ct}^{d_3} \\ + \ b_{123} ECI_{ct}^{d_1} \times ECI_{ct}^{d_2} \times ECI_{ct}^{d_3} + \mu_t + e_{ct}. \end{aligned}$$

In this specification if b_{kl} and b_{klm} are significant and have the same sign as b_k and b_l, then it is said that dimensions k and l are complements in explaining the economic outcome (economic growth, income inequality, or greenhouse gas emissions). Otherwise, their relationship is dependent on the third dimension m and may range from complementary to substitute or no relationship.

To compare the performances of different models, we use the coefficient of determination R^2, a standard measure for the explanatory power of a model. It's magnitude ranges between 0 and 1, with higher values implying that one can predict a higher amount of the variation in the dependent variable from the independent variables. We select the model that has the highest R^2 and in which every included complexity metric is significant as the *multidimensional ECI* model.

3. Robustness check setup

We check the robustness of the multidimensional economic complexity regression model in explaining variations in two different ways.

First, we add 1) the log of the population and 2) the log of the initial human capital to the regressions. These variables may affect the dependent variable but are not related with the complexity of the economy. Second, we compare the multidimensional economic complexity regression model to alternate models that account for the intensity and concentration of production, and to alternate models for economic complexity.

3.1. Additional explanatory variables robustness check setup

We add three possible additional explanatory variables to the regression specification (separately and together): 1) the log of the population, 2) the log of the initial human capital, and 3) the log of natural resource exports per capita to the regressions.

The first variable, the log of the initial population is our measure for the "size" of the economy. The data for this variable are taken from the World Bank's World Development Indicators database and are available at

https://data.worldbank.org/indicator/SP.POP.TOTL .

The second variable, the log of the initial human capital, is an aggregate measure for the "formal knowledge" in the country. We quantify the human capital using the human capital index provided by the Penn World Tables. The index is based on data for the average years of schooling of the population[6], and is available at

https://www.rug.nl/ggdc/productivity/pwt/?lang=en .

The last variable, the log of natural resource exports per capita, is a measure for the extent to which a country's economy depends on natural resources. Countries that are endowed with more natural resources usually grow faster, but also have larger emissions. This variable is estimated using data from the Observatory of economic complexity and using the methodology given in Ref.[7].

3.2. Comparison with alternate models' setup

We compare the multidimensional ECI model to four alternate regression models based on: 1) the intensity of a country in exports, patent applications and published documents (Intensity), 2) the diversification of the exports, patent applications and published documents based on the Herfindahl-Hirschman index (HHI), 3) the concentration of the exports, patent applications and published documents based on Shannon's Information entropy (Entropy), and 4) the complexity of a country in terms of exports, patent applications and published documents based on the Fitness indicator (Fitness).

Each of these models has indicators that are defined on a dimension level. Therefore, we use the same procedure as ECI and estimate a multidimensional Intensity, HHI, Entropy, and Fitness models (the model which has the highest R^2 and all included coefficients are significant) in which the variables are normalized to be between 0 and 1 and compare them with the multidimensional ECI model. The Intensity, HHI, Entropy, and Fitness indicators for each dimension are estimated using the data described in Section 1.

In what follows, we describe in short how we define the indicators of the four alternate models for each dimension.

Production intensity: The production intensity describes the "aggregate" output of each dimension. By comparing the multidimensional ECI model to the production intensity allows us to investigate whether the structure of the dimension is more related and/or offers different information than the aggregate output in explaining economic growth, income inequality, and emission intensity.

Formally, we define the production intensity as the log of exports per capita, log of patent applications per capita, and the log of the number of published scientific documents per capita.

Herfindahl-Hirschman index: The Herfindahl-Hirschman index HHI_c of country c is defined as

$$HHI_c = \sum_p (S_{cp})^2,$$

where $S_{cp} = X_{cp} / \sum_p X_{cp}$ is the share of output belonging to activity p. The index ranges between 0 and 1, with lower HHI values suggesting higher diversification.

Shannon's Information entropy: The Entropy E_c of country c is defined as

$$E_c = -\sum_p S_{cp} \log S_{cp}.$$

High entropy values are characteristic of diversified economies, whereas low entropy values are associated with economies whose production is concentrated in a small number of activities.

Fitness: The Fitness F_c of a country is an alternate measure for the complexity of an economy and it is estimated as the limiting value of the following coupled equations

$$\widetilde{F_c}^{(n)} = \sum_p M_{cp} Q_p^{(n-1)}\ ; \quad F_c^n = \frac{\widetilde{F_c}^{(n)}}{\mathrm{mean}(\widetilde{F_c}^{(n)})},$$

$$\widetilde{Q_p}^{(n)} = \frac{1}{\sum_p M_{cp} \frac{1}{F_c^{(n-1)}}}; \quad Q_p^n = \frac{\widetilde{Q_p}^{(n)}}{\mathrm{mean}(\widetilde{Q_p}^{(n)})},$$

where F_c^n is the fitness of country c in step n and Q_p^n is the complexity of activity p in step n. Because the distribution of Fitness is right-skewed, in regression analysis we use its logarithmic value.

4. Economic growth regression analysis setup and robustness checks

4.1.Economic growth regression setup

In the economic growth regression analysis, the dependent variable is defined as the 10-year annualized growth rate of the GDP per capita in constant 2017 dollars adjusted for power purchasing parity (PPP), i.e.,

$$y_{ct} = 100 \times \frac{1}{\Delta} \log\left(\frac{GDP_{ct+\Delta}}{GDP_{ct}}\right),$$

where $\Delta = 10$. In the regressions, as a control variable we include only the log of the initial GDP per capita in constant 2017 dollars (PPP), GDP_{ct}. In the economic development literature, this variable is known as the Solow term[8]. It is used to account for the "convergence" phenomenon which suggests that, on average, poorer countries should grow faster than rich countries and thus catch up. The data for the GDP per capita were taken from the World Bank's World Development Indicators database and are available at

https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD .

The regression analysis is focused on two time periods 1999-2009 and 2009-2019. We focus on these years as they are they encompass the longest periods for which all the data are available. Moreover, this way we are the closest to constructing regressions that are consistent with the "original" growth regression analysis performed in [2] with trade data (there the periods were 1978-1988,1988-1998,1998-2008).

4.2. Economic growth individual regressions

In Tables S1-S3, we present the results for the individual economic growth regressions for ECI (trade), ECI (technology), and ECI (research), respectively. These results were used to estimate the F-statistics for testing the robustness of the individual regressions discussed in the main text.

Table S1. ECI (trade) Economic Growth Regressions

	Dependent variable:									
	Annualized GDP pc growth (1999-09, 2009-19)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ECI (trade)	5.658***	6.218***	3.569***	7.323***	4.865***	5.352***	4.365***	4.339***	4.843***	
	(1.163)	(1.204)	(1.166)	(1.166)	(1.265)	(1.158)	(1.498)	(1.519)	(1.748)	
ECI (trade), instrumented										5.606***
										(1.179)
Log of initial population		-0.158*			0.096					
		(0.095)			(0.096)					
Log of initial human capital			3.300***		3.001***					
			(0.679)		(0.702)					
Log of natural resource exports per capita				0.882***	0.767***					
				(0.205)	(0.208)					
Intensity (trade)						3.701**				
						(1.722)				
HHI (trade)							-1.532			
							(1.122)			
Entropy (trade)								1.411		
								(1.049)		
Fitness (trade)									0.962	
									(1.537)	
Log of initial GDP per capita	-1.825***	-2.000***	-2.201***	-3.262***	-3.311***	-2.574***	-1.700***	-1.697***	-1.764***	-1.725***
	(0.204)	(0.228)	(0.205)	(0.385)	(0.366)	(0.403)	(0.224)	(0.225)	(0.227)	(0.193)
Observations	152	152	152	152	152	152	152	152	152	152
R^2	0.358	0.370	0.447	0.430	0.494	0.378	0.366	0.366	0.360	0.354
Adjusted R^2	0.345	0.353	0.432	0.415	0.473	0.361	0.349	0.349	0.343	0.341

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S2. ECI (technology) Economic Growth Regressions

	Dependent variable:									
	Annualized GDP pc growth (1999-09, 2009-19)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ECI (technology)	2.577***	3.487***	1.786***	2.945***	2.113***	2.043***	1.888**	1.863**	3.358**	
	(0.590)	(0.662)	(0.560)	(0.583)	(0.673)	(0.774)	(0.792)	(0.806)	(1.444)	
ECI (technology), instrumented										2.269***
										(0.628)
Log of initial population		-0.292***			0.007					
		(0.104)			(0.112)					
Log of initial human capital			3.523***		3.316***					
			(0.652)		(0.698)					
Log of natural resource exports per capita				0.659***	0.543***					
				(0.205)	(0.204)					
Intensity (technology)						1.231				
						(1.156)				
HHI (technology)							-1.291			
							(0.994)			
Entropy (technology)								1.292		
								(0.995)		
Fitness (technology)									-0.822	
									(1.386)	
Log of initial GDP per capita	-1.568***	-1.914***	-2.108***	-2.553***	-2.878***	-1.785***	-1.612***	-1.612***	-1.536***	-1.485***
	(0.179)	(0.215)	(0.192)	(0.352)	(0.332)	(0.271)	(0.182)	(0.182)	(0.188)	(0.180)
Observations	152	152	152	152	152	152	152	152	152	152
R^2	0.341	0.374	0.450	0.384	0.478	0.346	0.348	0.348	0.342	0.316
Adjusted R^2	0.327	0.357	0.435	0.367	0.457	0.328	0.330	0.330	0.324	0.302

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S3. ECI (research) Economic Growth Regressions

	Dependent variable:									
	Annualized GDP pc growth (1999-09, 2009-19)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ECI (research)	1.184	1.715	1.054	2.052	0.960	-1.133	0.873	0.930	3.726	
	(1.221)	(1.396)	(1.090)	(1.250)	(1.238)	(1.502)	(1.320)	(1.342)	(2.328)	
ECI (research), instrumented										0.529
										(1.200)
Log of initial population		-0.089			0.163					
		(0.112)			(0.107)					
Log of initial human capital			4.055***		4.182***					
			(0.649)		(0.657)					
Log of natural resource exports per capita				0.559**	0.569***					
				(0.224)	(0.211)					
Intensity (research)						4.231**				
						(1.651)				
HHI (research)							-1.437			
							(2.286)			
Entropy (research)								0.997		
								(2.152)		
Fitness (research)									-3.398	
									(2.651)	
Log of initial GDP per capita	-1.311***	-1.445***	-2.063***	-2.216***	-2.762***	-1.705***	-1.294***	-1.298***	-1.379***	-1.213***
	(0.233)	(0.289)	(0.240)	(0.429)	(0.394)	(0.276)	(0.235)	(0.236)	(0.239)	(0.220)
Observations	152	152	152	152	152	152	152	152	152	152
R^2	0.260	0.264	0.416	0.290	0.445	0.292	0.262	0.262	0.269	0.257
Adjusted R^2	0.245	0.243	0.400	0.271	0.422	0.273	0.242	0.241	0.249	0.242

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

4.3. Economic growth multidimensional regression model robustness checks

Additional explanatory variables robustness check: In Table S4 we reproduce the main results for the economic growth regression analysis (Columns (1-12)) and test the robustness of the multidimensional economic growth regression by adding the log of the population, the log of the initial human capital, and the log of natural resource exports per capita as additional explanatory variables, separately (Columns (13-15)) and together (Column (16)). In each case the product ECI, technology ECI, and their interaction term remain significant predictors of economic growth, thus confirming the robustness of the regression results. More importantly, the human capital and natural resources appear also significant. Therefore, in column (17) we re-estimate the economic growth model by including only these two as additional explanatory variables. This is our final economic growth model, i.e., the model that has the best explanatory power out of all economic growth regression analyses ($R^2 = 0.536$). Figure S2 gives the correlation between the variables used in these regressions.

Production intensity robustness check: In Table S5, Columns (2-12), we estimate the production intensity economic growth models. We find that the multidimensional model includes only the technological intensity ($R^2 = 0.315$). By comparing this model directly to the multidimensional ECI model (Column (13)), in a regression specification which also all of the potential explanatory variables (Column (14)), and in the final model regression specification (Column (15)), we find that the multidimensional ECI model clearly outperforms the multidimensional production intensity model as the coefficients of the former remain highly significant, whereas the coefficients of the later lose significance. Figure S3 gives the correlations between the variables used in these regressions.

HHI robustness check: In Table S6, Columns (2-12), we estimate the HHI economic growth models. We find that the multidimensional model includes the trade and technological HHI, but not their interaction term ($R^2 = 0.362$). By comparing this model directly to the multidimensional ECI model (Column (13)), in a regression specification which also all of the potential explanatory variables (Column (14)), and in the final model regression specification (Column (15)), we find that the multidimensional ECI model clearly outperforms the multidimensional HHI model as the coefficients of the former remain highly significant, whereas the coefficients of the later lose significance. Figure S4 gives the correlations between the variables used in these regressions.

Entropy robustness check: In Table S7, Columns (2-12), we estimate the Entropy economic growth models. Identically to the HHI case, we find that the multidimensional model includes the trade and technological Entropy, but not their interaction term ($R^2 = 0.362$). By comparing this model directly to the multidimensional ECI model (Column (13)), in a regression specification which also all of the potential explanatory variables (Column (14)), and in the final model regression specification (Column (15)), we find that the multidimensional ECI model clearly outperforms the multidimensional Entropy model as the coefficients of the former remain highly significant, whereas the coefficients of the later lose significance. Figure S5 gives the correlations between the variables used in these regressions.

Fitness robustness check: In Table S8, Columns (2-12), we estimate the Fitness economic growth models. We find that the multidimensional Fitness model includes the trade, and technological Fitness, and their interaction term ($R^2 = 0.375$). By comparing this model directly to the multidimensional ECI model (Column (13)), in a regression specification which also all of the potential explanatory variables (Column (14)), and in the final model regression specification (Column (15)), we find that the multidimensional ECI model outperforms the multidimensional Fitness model as the coefficients of the former remain highly significant, whereas the coefficients of the later lose significance. Only in the case when we add all additional explanatory variables (Column (14)), the ECI interaction term loses significance, but regains significance in the final model comparison (Column (15)). Figure S6 gives the correlations between the variables used in these regressions.

Table S4. Economic Growth Regressions: Additional Explanatory Variables Robustness Check

	Dependent variable:																
	Annualized GDP pc growth (1999-09, 2009-19)																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
ECI (trade)		5.658***			4.006***	5.981***		4.022***	12.255***	12.134***		17.331*	11.471***	8.597***	14.030***	10.891***	10.832***
		(1.163)			(1.459)	(1.246)		(1.446)	(2.627)	(3.339)		(9.283)	(2.605)	(2.646)	(2.494)	(2.606)	(2.592)
ECI (technology)			2.577***		1.351*		3.323***	2.098**	9.099***		5.483***	12.756	9.243***	7.033***	9.141***	7.409***	7.490***
			(0.590)		(0.730)		(0.715)	(0.826)	(2.203)		(2.063)	(7.921)	(2.169)	(2.150)	(2.066)	(2.076)	(2.056)
ECI (research)				1.184		-0.890	-2.541*	-2.563*		6.318	0.380	-5.469					
				(1.221)		(1.219)	(1.397)	(1.366)		(3.829)	(2.966)	(10.205)					
ECI (trade) x ECI (technology)									-12.260***			-22.692*	-11.254***	-9.208***	-12.368***	-9.987***	-9.922***
									(3.305)			(12.817)	(3.279)	(3.223)	(3.100)	(3.099)	(3.083)
ECI (trade) x ECI (research)										-10.111**		-3.392					
										(5.098)		(17.385)					
ECI (research) x ECI (technology)											-3.856	0.435					
											(3.455)	(13.627)					
ECI (trade) x ECI (research) x ECI (technology)												9.443					
												(21.513)					
Log of initial population													-0.239**			0.036	
													(0.099)			(0.106)	
Log of initial human capital														2.799***		2.309***	2.227***
														(0.677)		(0.708)	(0.664)
Log of natural resource exports per capita															0.885***	0.766***	0.742***
															(0.193)	(0.204)	(0.191)
Log of initial GDP per capita	-1.147***	-1.825***	-1.568***	-1.311***	-1.848***	-1.740***	-1.337***	-1.616***	-1.877***	-1.809***	-1.376***	-1.612***	-2.151***	-2.186***	-3.317***	-3.337***	-3.331***
	(0.160)	(0.204)	(0.179)	(0.233)	(0.203)	(0.235)	(0.219)	(0.236)	(0.195)	(0.236)	(0.221)	(0.231)	(0.223)	(0.200)	(0.364)	(0.353)	(0.352)
Observations	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152
R^2	0.256	0.358	0.341	0.260	0.373	0.361	0.355	0.388	0.427	0.377	0.361	0.452	0.449	0.487	0.499	0.536	0.536
Adjusted R^2	0.246	0.345	0.327	0.245	0.356	0.343	0.338	0.367	0.407	0.356	0.339	0.417	0.426	0.466	0.479	0.510	0.513

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S5. Economic Growth Regressions: Production Intensity Robustness Check

	Dependent variable:														
	Annualized GDP pc growth (1999-09, 2009-19)														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ECI (trade)	12.255***												12.372***	10.646***	10.611***
	(2.627)												(2.624)	(2.668)	(2.627)
ECI (patents)	9.099***												9.750***	7.105***	7.096***
	(2.203)												(2.260)	(2.187)	(2.177)
ECI (trade) x ECI (patents)	-12.260***												-13.934***	-9.112**	-9.021**
	(3.305)												(3.563)	(3.657)	(3.479)
Intensity (trade)		4.678**			2.939	3.955**		2.983	4.821*	4.863		-3.041			
		(1.823)			(1.877)	(1.826)		(1.891)	(2.448)	(4.017)		(8.736)			
Intensity (technology)			3.207***		2.735***		3.089**	2.474*	5.131**		10.236***	22.587**	1.652	-0.678	-0.737
			(0.898)		(0.943)		(1.320)	(1.370)	(2.214)		(3.481)	(10.537)	(1.329)	(1.493)	(1.308)
Intensity (research)				3.480***		2.979**	0.232	0.500		3.660	2.692	2.684			
				(1.316)		(1.321)	(1.899)	(1.897)		(2.993)	(2.179)	(6.995)			
Intensity (trade) x Intensity (technology)									-3.368			-10.103			
									(2.817)			(18.373)			
Intensity (trade) x Intensity (research)										-1.096		7.600			
										(4.319)		(13.276)			
Intensity (research) x Intensity (technology)											-7.731**	-25.996*			
											(3.493)	(13.254)			
Intensity trade x Intensity (research) x Intensity (technology)												14.050			
												(20.434)			
Log of initial population														0.010	
														(0.121)	
Log of initial human capital														2.380***	2.369***
														(0.727)	(0.711)
Log of natural resource exports per capita														0.756***	0.750***
														(0.206)	(0.192)
Log of initial GDP per capita	-1.877***	-2.139***	-1.940***	-1.736***	-2.447***	-2.490***	-1.950***	-2.476***	-2.574***	-2.522***	-2.059***	-2.421***	-2.101***	-3.267***	-3.260***
	(0.195)	(0.417)	(0.270)	(0.273)	(0.421)	(0.440)	(0.284)	(0.437)	(0.434)	(0.460)	(0.284)	(0.456)	(0.266)	(0.386)	(0.374)
Observations	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152
R^2	0.427	0.287	0.315	0.289	0.326	0.311	0.315	0.326	0.333	0.312	0.337	0.369	0.433	0.537	0.537
Adjusted R^2	0.407	0.273	0.301	0.275	0.308	0.293	0.296	0.303	0.310	0.288	0.314	0.329	0.409	0.507	0.511

Notes: Each regression includes period fixed effects. Standard errors in brackets. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table S6. Economic Growth Regressions: Herfindahl-Hirschman Index Robustness Check

	Dependent variable:														
	Annualized GDP pc growth (1999-09, 2009-19)														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ECI (trade)	12.255***												11.777***	8.612***	8.690***
	(2.627)												(3.233)	(3.140)	(3.131)
ECI (patents)	9.099***												8.765***	6.026**	6.199**
	(2.203)												(2.591)	(2.453)	(2.433)
ECI (trade) x ECI (patents)	-12.260***												-11.869***	-8.304**	-8.262**
	(3.305)												(3.645)	(3.420)	(3.413)
HHI (trade)		-3.601***			-2.776***	-3.558***		-2.819***	-3.513*	-3.113***		-4.077	-0.241	-1.424	-1.218
		(0.891)			(0.922)	(0.909)		(0.928)	(1.801)	(1.162)		(2.519)	(1.137)	(1.092)	(1.041)
HHI (technology)			-2.877***		-2.119***		-2.940***	-2.237***	-2.343**		-2.403***	-1.853	-0.163	-0.315	-0.418
			(0.750)		(0.773)		(0.794)	(0.807)	(0.906)		(0.914)	(1.347)	(0.983)	(0.915)	(0.898)
HHI (research)				-2.004		-0.530	0.536	1.096		0.686	4.361	5.955			
				(2.115)		(2.055)	(2.143)	(2.093)		(2.854)	(3.873)	(4.827)			
HHI (trade) x HHI (technology)									2.545			4.003			
									(5.340)			(8.657)			
HHI (trade) x HHI (research)										-8.796		-1.308			
										(14.279)		(33.874)			
HHI (research) x HHI (technology)											-11.363	-15.844			
											(9.591)	(21.120)			
HHI trade x HHI (research) x HHI (technology)												7.854			
												(110.778)			
Log of initial population														0.073	
														(0.113)	
Log of initial human capital														2.456***	2.299***
														(0.717)	(0.673)
Log of natural resource exports per capita														0.826***	0.770***
														(0.214)	(0.195)
Log of initial GDP per capita	-1.877***	-1.216***	-1.496***	-1.183***	-1.457***	-1.225***	-1.494***	-1.452***	-1.456***	-1.219***	-1.458***	-1.404***	-1.860***	-3.297***	-3.292***
	(0.195)	(0.154)	(0.178)	(0.165)	(0.174)	(0.158)	(0.179)	(0.175)	(0.175)	(0.158)	(0.181)	(0.180)	(0.219)	(0.355)	(0.354)
Observations	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152
R^2	0.427	0.330	0.323	0.260	0.362	0.330	0.323	0.364	0.363	0.332	0.330	0.374	0.427	0.542	0.541
Adjusted R^2	0.407	0.316	0.309	0.245	0.345	0.312	0.305	0.342	0.342	0.309	0.307	0.334	0.399	0.510	0.512

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S7. Economic Growth Regressions: Entropy Robustness Check

	Dependent variable:														
	Annualized GDP pc growth (1999-09, 2009-19)														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ECI (trade)	12.255***												11.897***	8.564***	8.649***
	(2.627)												(3.233)	(3.138)	(3.130)
ECI (patents)	9.099***												8.838***	6.012**	6.187**
	(2.203)												(2.602)	(2.462)	(2.443)
ECI (trade) x ECI (patents)	-12.260***												-11.964***	-8.304**	-8.256**
	(3.305)												(3.643)	(3.418)	(3.410)
Entropy (trade)		3.346***			2.527***	3.350***		2.606***	1.604	12.105		-1.660	0.163	1.390	1.181
		(0.821)			(0.860)	(0.843)		(0.866)	(3.420)	(10.978)		(55.948)	(1.063)	(1.026)	(0.976)
Entropy (technology)			2.863***		2.058***		3.021***	2.277***	0.878		12.665	5.275	0.130	0.265	0.381
			(0.738)		(0.770)		(0.791)	(0.809)	(4.302)		(8.259)	(62.076)	(0.985)	(0.918)	(0.900)
Entropy (research)				1.607		-0.044	-1.122	-1.734		7.716	5.553	4.392			
				(1.961)		(1.915)	(2.008)	(1.966)		(9.888)	(6.033)	(47.276)			
Entropy (trade) x Entropy (technology)									1.322			9.596			
									(4.739)			(75.773)			
Entropy (trade) x Entropy (research)										-9.302		2.264			
										(11.629)		(60.359)			
Entropy (research) x Entropy (technology)											-10.231	-6.167			
											(8.721)	(66.854)			
Entropy trade x Entropy (research) x Entropy (technology)												-6.860			
												(81.287)			
Log of initial population														0.076	
														(0.113)	
Log of initial human capital														2.464***	2.300***
														(0.717)	(0.673)
Log of natural resource exports per capita														0.836***	0.776***
														(0.215)	(0.195)
Log of initial GDP per capita	-1.877***	-1.218***	-1.503***	-1.182***	-1.457***	-1.217***	-1.498***	-1.447***	-1.457***	-1.208***	-1.460***	-1.400***	-1.865***	-3.299***	-3.294***
	(0.195)	(0.153)	(0.179)	(0.166)	(0.175)	(0.159)	(0.179)	(0.175)	(0.175)	(0.159)	(0.182)	(0.181)	(0.221)	(0.354)	(0.354)
Observations	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152
R^2	0.427	0.331	0.324	0.259	0.362	0.331	0.326	0.365	0.362	0.334	0.332	0.375	0.427	0.542	0.541
Adjusted R^2	0.407	0.317	0.311	0.244	0.345	0.313	0.308	0.344	0.340	0.311	0.309	0.335	0.399	0.510	0.512

Notes: Each regression includes period fixed effects. Standard errors in brackets. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table S8. Economic Growth Regressions: Fitness Robustness Check

	Dependent variable:														
	Annualized GDP pc growth (1999-09, 2009-19)														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ECI (trade)	12.255***												11.111***	7.816**	7.861**
	(2.627)												(3.525)	(3.410)	(3.404)
ECI (patents)	9.099***												8.469***	5.460*	5.571**
	(2.203)												(2.941)	(2.792)	(2.783)
ECI (trade) x ECI (patents)	-12.260***												-8.747**	-6.459	-6.829*
	(3.305)												(4.275)	(4.005)	(3.965)
Log of fitness (trade)		4.136***			2.786*	5.575***		3.413**	7.773***	16.705***		19.540	2.240	3.888	3.434
		(1.048)			(1.419)	(1.213)		(1.377)	(2.140)	(5.515)		(12.142)	(2.733)	(2.592)	(2.509)
Log of fitness (technology)			2.119***		1.090		3.734***	2.632***	11.099***		8.787***	31.173	3.925	3.149	2.904
			(0.576)		(0.775)		(0.753)	(0.864)	(3.368)		(2.975)	(21.343)	(4.040)	(3.728)	(3.706)
Log of fitness (research)				0.218		-3.481**	-5.587***	-6.138***		8.843	-1.942	7.172			
				(1.395)		(1.537)	(1.746)	(1.731)		(6.151)	(2.706)	(13.225)			
Log of fitness (trade) x Log of fitness (technology)									-12.147***			-34.186	-6.995	-4.944	-4.015
									(3.983)			(26.181)	(4.752)	(4.574)	(4.379)
Log of fitness (trade) x Log of fitness (research)										-16.073**		-17.172			
										(7.773)		(18.430)			
Log of fitness (research) x Log of fitness (technology)											-7.133*	-26.734			
											(4.066)	(27.937)			
Log of fitness trade x Log of fitness (research) x Log of fitness (technology)												32.016			
												(34.332)			
Log of initial population														0.089	
														(0.124)	
Log of initial human capital														2.398***	2.260***
														(0.715)	(0.687)
Log of natural resource export per capita														0.828***	0.780***
														(0.213)	(0.202)
Log of initial GDP per capita	-1.877***	-1.302***	-1.560***	-1.165***	-1.464***	-1.063***	-1.405***	-1.272***	-1.413***	-0.996***	-1.344***	-1.220***	-1.863***	-3.228***	-3.254***
	(0.195)	(0.158)	(0.191)	(0.199)	(0.195)	(0.188)	(0.191)	(0.195)	(0.190)	(0.189)	(0.193)	(0.194)	(0.230)	(0.369)	(0.367)
Observations	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152
R^2	0.427	0.327	0.318	0.256	0.336	0.349	0.362	0.388	0.375	0.368	0.376	0.433	0.444	0.544	0.542
Adjusted R^2	0.407	0.313	0.304	0.241	0.317	0.332	0.345	0.367	0.354	0.346	0.354	0.397	0.413	0.508	0.509

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

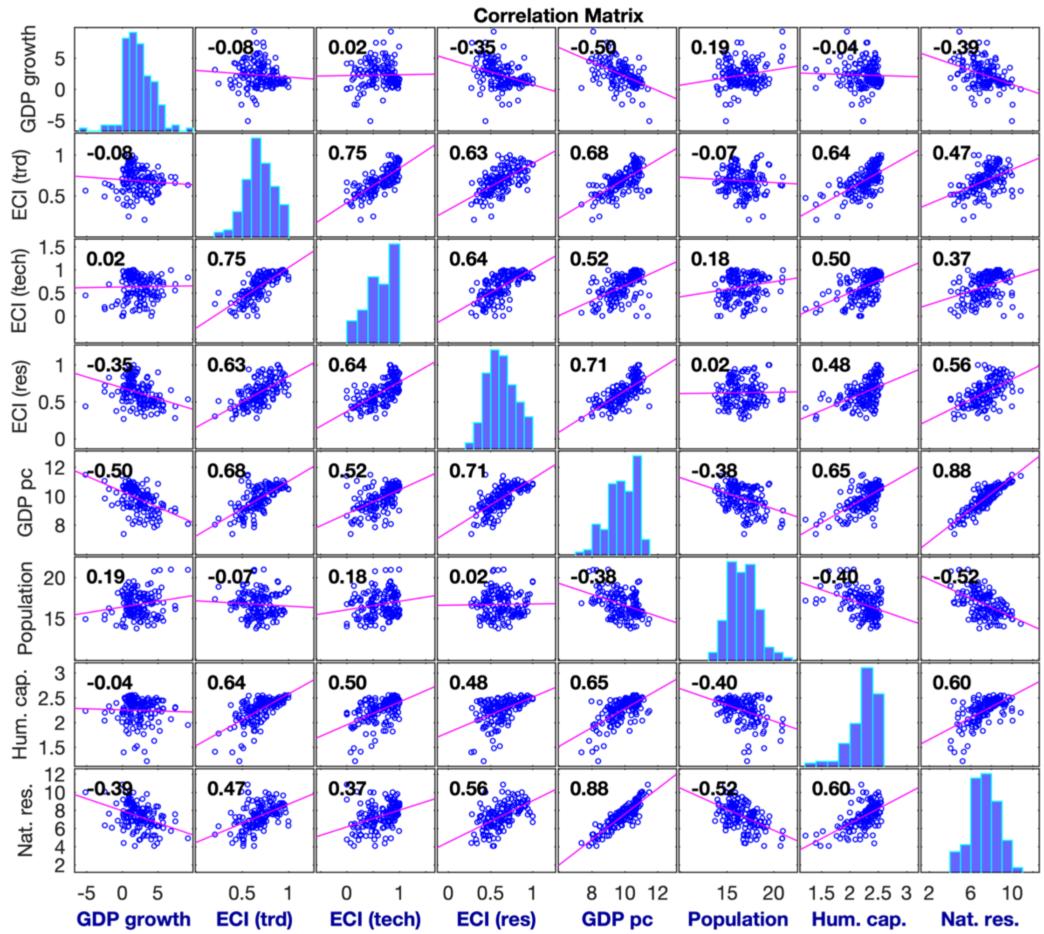

Figure S2. Correlations Between the Variables used in the Additional Explanatory Variables Robustness Check Regression Analysis

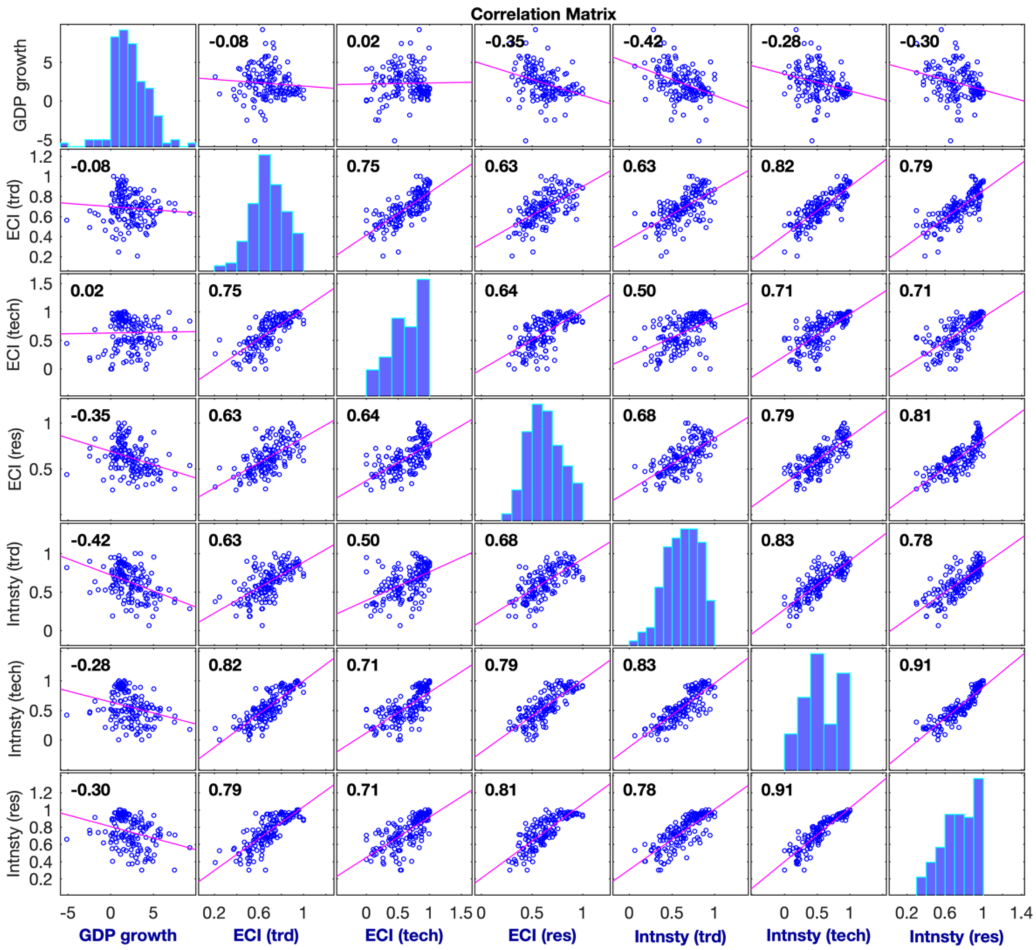

Figure S3. Correlations Between the Variables used in the Production Intensity Economic Growth Robustness Check Regression Analysis

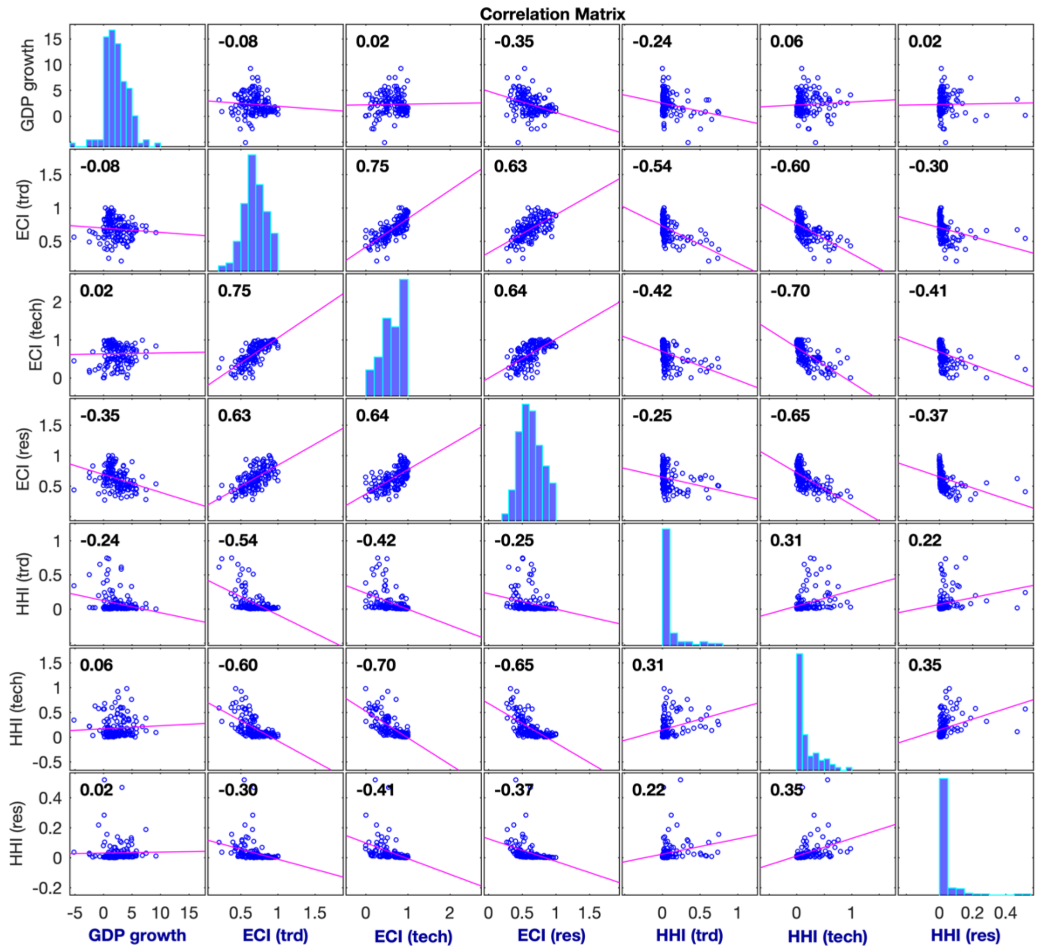

Figure S4. Correlations Between the Variables used in the HHI Economic Growth Robustness Check Regression Analysis

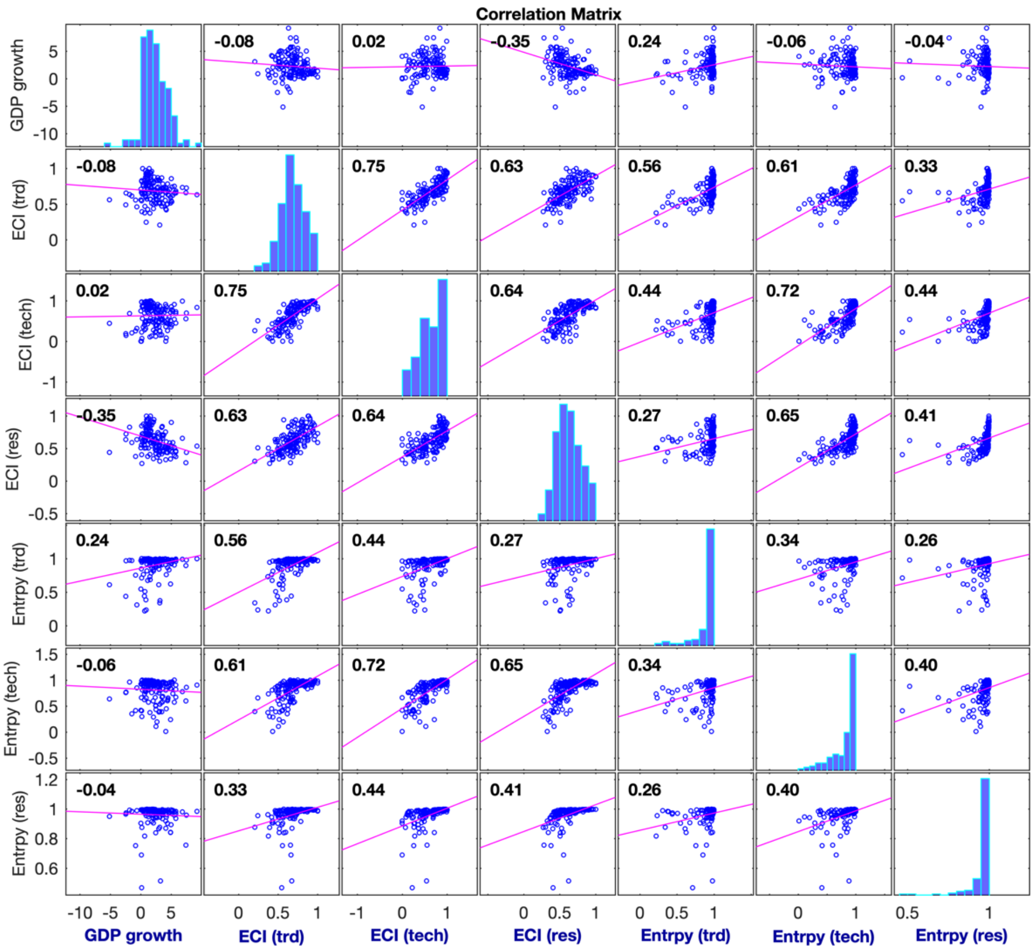

Figure S5. Correlations Between the Variables used in the Entropy Economic Growth Robustness Check Regression Analysis

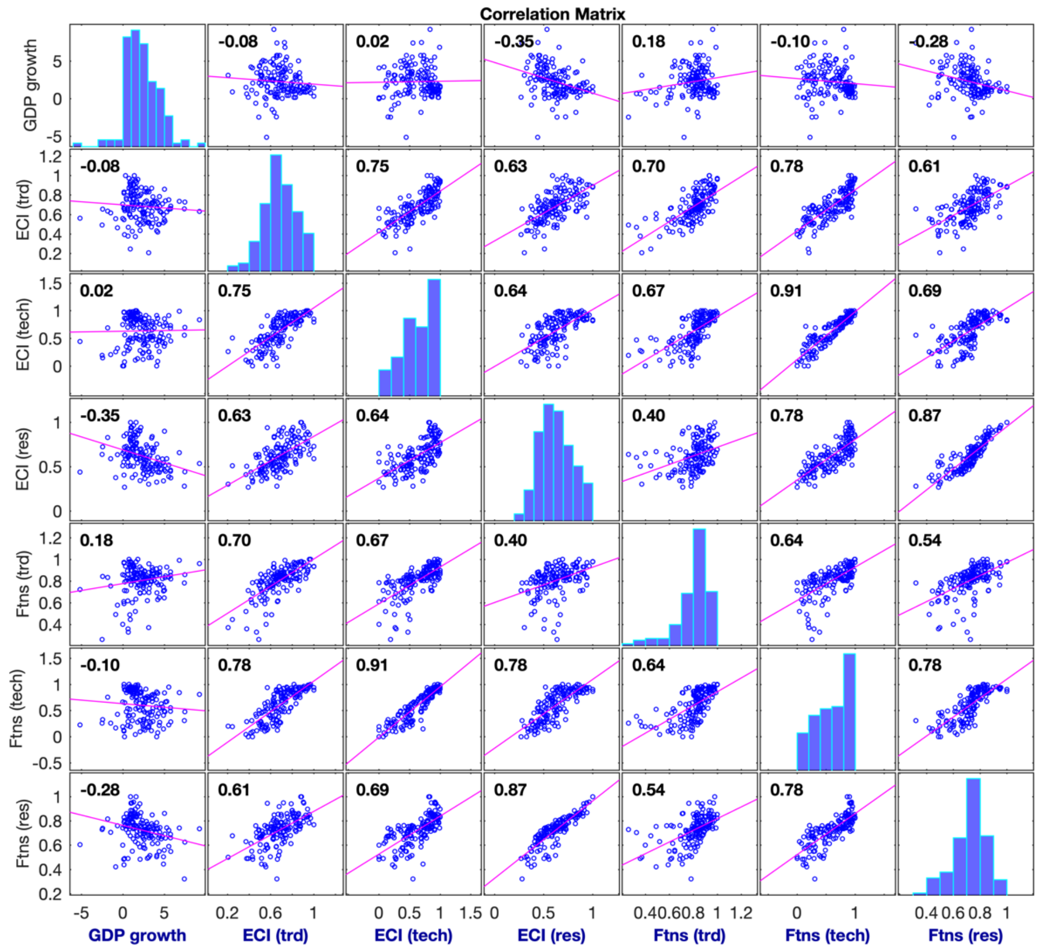

Figure S6. Correlations Between the Variables used in the Fitness Economic Growth Robustness Check Regression Analysis

5. Income inequality regression analysis

5.1. Income inequality regression setup

In the income inequality regression analysis, the dependent variable is quantified through the Gini coefficient $GINI_{ct}$, i.e.,

$$y_{ct} = GINI_{ct}.$$

The Gini coefficient quantifies the extent to which the observed income distribution differs from the line of perfect equality, i.e., the income distribution in a hypothetical society where every individual has the same income[9]. The coefficient is a normalized quantity whose values are between 0 and 1, with larger values indicating higher income inequality. The data for the Gini coefficient were taken from the Estimated Household Income Inequality dataset and are available at

https://utip.gov.utexas.edu/datasets.html .

In the regressions, as control variables we include the log of the initial GDP per capita in constant 2017 dollars (PPP) and its squared value. In the income inequality literature, these two terms are known as the Kuznets hypothesis[10]. According to this hypothesis, as an economy develops, market forces first increase and then decrease economic inequality.

The regression analysis is focused on the periods 1996-1999, 2000-2003, 2004-2007, 2008-2011 and 2012-2015. Because of the sparseness of the Gini dataset and slow temporal changes in the coefficients within a country, we follow[11] and use average values for each panel.

5.2. Income inequality individual regressions

In Tables S9-S11, we present the results for the individual income inequality regressions for ECI (trade), ECI (technology), and ECI (research), respectively. These results were used to estimate the F-statistics for testing the robustness of the individual regressions discussed in the main text.

Table S9. ECI (trade) Income Inequality regressions

	Dependent variable:									
	Gini coefficient (1996-99, 2000-03, 2004-07, 2008-11, 2012-15)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ECI (trade)	-23.543***	-27.481***	-19.151***	-26.876***	-24.144***	-22.173***	-17.531***	-17.015***	-21.007***	
	(1.933)	(1.932)	(1.917)	(2.000)	(2.119)	(1.829)	(2.306)	(2.329)	(2.526)	
ECI (trade), instrumented										-24.685***
										(1.937)
Log of population		0.973***			0.600***					
		(0.155)			(0.165)					
Log of human capital			-9.073***		-6.730***					
			(1.316)		(1.357)					
Log of natural resource exports per capita				-1.742***	-0.748**					
				(0.367)	(0.376)					
Intensity (trade)						-17.753***				
						(2.691)				
HHI (trade)							8.897***			
							(1.979)			
Entropy (trade)								-8.636***		
								(1.832)		
Fitness (trade)									-0.637	
									(0.410)	
Log of GDP per capita	-8.070	-2.789	4.605	-6.778	5.142	-7.788	-7.267	-6.841	-9.258*	-10.812**
	(5.357)	(5.133)	(5.336)	(5.195)	(5.173)	(5.037)	(5.208)	(5.196)	(5.400)	(5.277)
Log of GDP per capita, squared	0.361	0.152	-0.235	0.452*	-0.171	0.547**	0.278	0.253	0.414	0.490*
	(0.276)	(0.263)	(0.272)	(0.268)	(0.267)	(0.261)	(0.269)	(0.268)	(0.277)	(0.272)
Observations	332	332	332	332	332	332	332	332	332	332
R^2	0.551	0.600	0.609	0.581	0.637	0.605	0.578	0.580	0.555	0.564
Adjusted R^2	0.542	0.590	0.599	0.570	0.626	0.595	0.567	0.570	0.544	0.555

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S10. ECI (technology) Income Inequality regressions

	Dependent variable:									
	Gini coefficient (1996-99, 2000-03, 2004-07, 2008-11, 2012-15)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ECI (technology)	-11.211***	-16.507***	-9.385***	-11.673***	-13.896***	-3.673***	-11.284***	-11.341***	-13.502***	
	(1.141)	(1.203)	(1.054)	(1.158)	(1.208)	(1.374)	(1.732)	(1.770)	(2.951)	
ECI (technology), instrumented										-10.955***
										(1.225)
Log of population		1.482***			1.239***					
		(0.173)			(0.188)					
Log of human capital			-11.094***		-8.344***					
			(1.299)		(1.296)					
Log of natural resources per capita				-0.769**	0.615*					
				(0.382)	(0.360)					
Intensity (technology)						-16.469***				
						(1.970)				
HHI (technology)							-0.120			
							(2.158)			
Entropy (technology)								0.208		
								(2.163)		
Fitness (technology)									2.301	
									(2.734)	
Log of GDP per capita	-3.795	6.686	11.132**	-3.091	15.631***	-11.642**	-3.863	-3.921	-3.439	-5.439
	(5.709)	(5.306)	(5.453)	(5.693)	(5.172)	(5.269)	(5.847)	(5.866)	(5.728)	(5.812)
Log of GDP per capita, squared	0.071	-0.372	-0.606**	0.098	-0.830***	0.638**	0.074	0.077	0.048	0.153
	(0.293)	(0.270)	(0.277)	(0.292)	(0.264)	(0.275)	(0.300)	(0.301)	(0.295)	(0.299)
Observations	332	332	332	332	332	332	332	332	332	332
R^2	0.496	0.589	0.589	0.503	0.639	0.586	0.496	0.496	0.497	0.476
Adjusted R^2	0.485	0.579	0.579	0.490	0.628	0.576	0.484	0.484	0.485	0.464

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S11. ECI (research) Income Inequality regressions

	Dependent variable:									
	Gini coefficient (1996-99, 2000-03, 2004-07, 2008-11, 2012-15)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ECI (research)	-7.654***	-11.330***	-6.067***	-8.095***	-7.660***	2.943	-6.997***	-6.898***	-6.715	
	(2.117)	(2.334)	(1.891)	(2.177)	(2.150)	(2.248)	(2.377)	(2.428)	(4.093)	
ECI (research), instrumented										-6.851***
										(1.885)
Log of population		0.704***			0.381*					
		(0.202)			(0.204)					
Log of human capital			-13.035***		-12.512***					
			(1.403)		(1.445)					
Log of natural resources per capita				-0.379	0.397					
				(0.432)	(0.419)					
Intensity (research)						-24.325***				
						(2.750)				
HHI (research)							5.666			
							(9.294)			
Entropy (research)								-5.002		
								(7.847)		
Fitness (research)									-1.484	
									(5.533)	
Log of GDP per capita	-14.997**	-13.806**	4.766	-15.063**	4.689	-5.600	-14.633**	-14.576**	-14.909**	-15.432**
	(6.486)	(6.387)	(6.151)	(6.489)	(6.147)	(5.924)	(6.520)	(6.525)	(6.504)	(6.510)
Log of GDP per capita, squared	0.616*	0.609*	-0.289	0.652*	-0.295	0.293	0.596*	0.592*	0.610*	0.633*
	(0.338)	(0.332)	(0.316)	(0.341)	(0.319)	(0.306)	(0.340)	(0.340)	(0.339)	(0.339)
Observations	332	332	332	332	332	332	332	332	332	332
R^2	0.371	0.394	0.504	0.373	0.509	0.494	0.372	0.372	0.372	0.372
Adjusted R^2	0.358	0.379	0.492	0.357	0.494	0.482	0.357	0.357	0.356	0.358

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

5.3. Income inequality multidimensional regression model robustness checks

Additional explanatory variables robustness check: In Table S12 we reproduce the main results for the income inequality regression analysis (Columns (1-12)) and test the robustness of the multidimensional income inequality regression by adding the log of the population, the log of the initial human capital, and the log of natural resource exports as additional explanatory variables, separately (Columns (13-15)) and together (Column (16)). In each case the product ECI and the technology ECI remain significant predictors of income inequality, thus confirming the robustness of the regression results. More importantly, the human capital and populations appear also significant. Therefore, in column (17) we re-estimate the income inequality model by including only these two as additional explanatory variables. This is our final model, i.e., the model that has the best explanatory power out of all income inequality regression analyses ($R^2 = 0.689$). Figure S7 gives the correlations between the variables used in these regressions.

Production intensity robustness check: In Table S13, Columns (2-12), we estimate the production intensity income inequality models. We find that the multidimensional model includes the trade, technological, and research intensities but not their interaction terms ($R^2 = 0.619$). By comparing this model directly to the multidimensional ECI model (Column (13)), in a regression specification which also all of the potential explanatory variables (Column (14)), and in the final model regression specification (Column (15)), we find that the multidimensional ECI model coefficients remain significant. Hence the multidimensional ECI income inequality model is robust against the model of production intensity. Figure S8 gives the correlations between the variables used in these regressions.

HHI robustness check: In Table S14, Columns (2-12), we estimate the HHI income inequality models. We find that the multidimensional model includes the trade and technological HHI, but not their interaction term ($R^2 = 0.362$). By comparing this model directly to the multidimensional

ECI model (Column (13)), in a regression specification which also all of the potential explanatory variables (Column (14)), and in the final model regression specification (Column (15)), we find that the multidimensional ECI model clearly outperforms the multidimensional HHI model as the coefficients of the former remain highly significant, whereas the coefficients of the later lose significance. Figure S9 gives the correlations between the variables used in these regressions.

Entropy robustness check: In Table S15, Columns (2-12), we estimate the Entropy income inequality models. Identically to the HHI case, we find that the multidimensional model includes the trade and technological Entropy, but not their interaction term ($R^2 = 0.362$). By comparing this model directly to the multidimensional ECI model (Column (13)), in a regression specification which also all of the potential explanatory variables (Column (14)), and in the final model regression specification (Column (15)), we find that the multidimensional ECI model clearly outperforms the production intensity model as the coefficients of the former remain highly significant, whereas the coefficients of the later lose significance. Figure S10 gives the correlations between the variables used in these regressions.

Fitness robustness check: In Table S16, Columns (2-12), we estimate the Fitness economic growth models. We find that the multidimensional Fitness model includes the trade, and technological Fitness, and their interaction term ($R^2 = 0.375$). By comparing this model directly to the multidimensional ECI model (Column (13)), in a regression specification which also all of the potential explanatory variables (Column (14)), and in the final model regression specification (Column (15)), we find that the multidimensional ECI model coefficients remain significant. Hence the multidimensional ECI income inequality model is robust against the multidimensional Fitness income inequality. Figure S11 gives the correlations between the variables used in these regressions.

Table S12. Income Inequality Regressions: Additional Explanatory Variables Robustness Check

	Dependent variable:																
	Gini coefficient (1996-99, 2000-03, 2004-07, 2008-11, 2012-15)																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
ECI (trade)		-23.543***			-17.902***	-23.116***		-17.778***	-9.279	-21.289***		-18.449	-18.418***	-13.587***	-21.293***	-16.195***	-15.680***
		(1.933)			(2.353)	(2.025)		(2.352)	(5.930)	(5.467)		(19.023)	(2.071)	(2.277)	(2.384)	(2.238)	(2.107)
ECI (technology)			-11.211***		-5.269***		-12.317***	-6.216***	1.208		-3.964	11.923	-10.520***	-5.214***	-5.176***	-9.442***	-9.611***
			(1.141)		(1.310)		(1.353)	(1.487)	(4.294)		(3.831)	(14.230)	(1.272)	(1.221)	(1.268)	(1.279)	(1.254)
ECI (research)				-7.654***		-1.336	3.400	2.783		0.649	16.132***	21.084					
				(2.117)		(1.873)	(2.248)	(2.076)		(5.825)	(5.906)	(19.516)					
ECI (trade) x ECI (technology)									-11.449			-8.570					
									(7.230)			(24.817)					
ECI (trade) x ECI (research)										-2.990		-0.339					
										(8.307)		(33.956)					
ECI (research) x ECI (technology)											-16.026**	-31.788					
											(6.883)	(25.028)					
ECI (trade) x ECI (research) x ECI (technology)												12.933					
												(41.573)					
Log of population													1.517***			1.219***	1.264***
													(0.155)			(0.175)	(0.162)
Log of human capital														-9.038***		-5.449***	-5.554***
														(1.282)		(1.268)	(1.258)
Log of natural resource exports per capita															-1.720***	-0.244	
															(0.359)	(0.355)	
Log of GDP per capita	-10.019	-8.070	-3.795	-14.997**	-5.612	-8.974	-0.970	-3.287	-9.554	-9.697*	-3.620	-6.090	5.067	6.988	-4.380	10.741**	11.031**
	(6.455)	(5.357)	(5.709)	(6.486)	(5.271)	(5.509)	(5.996)	(5.543)	(5.818)	(5.870)	(6.063)	(6.089)	(4.765)	(5.229)	(5.107)	(4.849)	(4.827)
Log of GDP per capita, squared	0.300	0.361	0.071	0.616*	0.239	0.415	-0.092	0.104	0.442	0.452	0.042	0.252	-0.210	-0.353	0.331	-0.466*	-0.499**
	(0.333)	(0.276)	(0.293)	(0.338)	(0.271)	(0.286)	(0.312)	(0.289)	(0.300)	(0.304)	(0.315)	(0.317)	(0.243)	(0.267)	(0.263)	(0.250)	(0.245)
Observations	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332
R^2	0.346	0.551	0.496	0.371	0.573	0.552	0.500	0.575	0.576	0.552	0.508	0.590	0.670	0.630	0.601	0.690	0.689
Adjusted R^2	0.334	0.542	0.485	0.358	0.562	0.541	0.487	0.563	0.564	0.540	0.494	0.573	0.661	0.620	0.590	0.679	0.680

Notes: Each regression includes period fixed effects. Standard errors in brackets. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table S13. Income Inequality Regressions: Production Intensity Robustness Check

	Dependent variable:														
	Gini coefficient (1996-99, 2000-03, 2004-07, 2008-11, 2012-15)														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ECI (trade)	-17.902***												-10.748***	-11.182***	-13.670***
	(2.353)												(2.424)	(2.587)	(2.362)
ECI (technology)	-5.269***												-3.017**	-9.119***	-8.575***
	(1.310)												(1.326)	(1.507)	(1.498)
Log of intensity (trade)		-21.455***			-14.519***	-19.247***		-15.104***	-4.776	22.323***		25.613*	-16.230***	-15.248***	-10.307***
		(3.220)			(2.710)	(2.848)		(2.699)	(4.063)	(7.944)		(14.616)	(2.604)	(3.338)	(2.559)
Log of intensity (technology)			-19.928***		-18.307***		-17.212***	-14.854***	-6.191		1.830	16.722	-7.109***	1.998	1.837
			(1.500)		(1.471)		(2.065)	(2.019)	(4.073)		(6.162)	(13.805)	(2.390)	(2.494)	(2.509)
Log of intensity (research)				-22.407***		-21.222***	-5.574*	-6.950**		10.873*	1.578	23.169**	-4.873*	-5.277**	-5.506**
				(2.329)		(2.191)	(2.925)	(2.808)		(6.131)	(3.617)	(11.209)	(2.709)	(2.549)	(2.564)
Log of intensity (trade) x Log of intensity (technology)									-17.888***			-49.815*			
									(5.619)			(26.134)			
Log of intensity (trade) x Log of intensity (research)										-52.374***		-52.405**			
										(9.402)		(21.310)			
Log of intensity (research) x Log of intensity (technology)											-21.497***	-36.498**			
											(6.567)	(16.947)			
Log of intensity (trade) x Log of intensity (research) x Log of intensity (technology)												58.659**			
												(27.985)			
Log of population														1.055***	0.968***
														(0.185)	(0.182)
Log of human capital														-5.988***	-5.693***
														(1.310)	(1.312)
Log of natural resource exports per capita														1.034**	
														(0.453)	
Log of GDP per capita	-5.612	-9.542	-14.450***	-7.712	-13.766***	-7.405	-13.272**	-12.270**	-28.783***	-39.790***	-25.113***	-35.952***	-8.172*	10.671**	10.188**
	(5.271)	(6.063)	(5.212)	(5.707)	(5.004)	(5.350)	(5.228)	(5.002)	(6.827)	(7.745)	(6.294)	(7.772)	(4.877)	(5.122)	(5.151)
Log of GDP per capita, squared	0.239	0.529*	0.800***	0.405	0.915***	0.605**	0.758***	0.867***	1.666***	2.210***	1.367***	2.055***	0.641**	-0.393	-0.335
	(0.271)	(0.314)	(0.271)	(0.294)	(0.261)	(0.277)	(0.270)	(0.259)	(0.349)	(0.392)	(0.325)	(0.393)	(0.253)	(0.268)	(0.268)
Observations	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332
R^2	0.573	0.425	0.577	0.491	0.611	0.554	0.581	0.619	0.623	0.594	0.595	0.639	0.654	0.712	0.707
Adjusted R^2	0.562	0.412	0.568	0.480	0.602	0.543	0.571	0.608	0.613	0.582	0.584	0.624	0.642	0.699	0.695

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S14. Income Inequality Regressions: Herfindahl-Hirschman Index Robustness Check

	Dependent variable:														
	Gini coefficient (1996-99, 2000-03, 2004-07, 2008-11, 2012-15)														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ECI (trade)	-17.902***												-14.351***	-14.745***	-14.117***
	(2.353)												(2.518)	(2.340)	(2.308)
ECI (patents)	-5.269***												-3.594**	-7.256***	-8.035***
	(1.310)												(1.809)	(1.745)	(1.671)
HHI (trade)		17.627***			14.905***	17.744***		15.320***	13.758***	17.575***		18.041***	7.315***	4.365**	3.190*
		(1.748)			(1.829)	(1.816)		(1.855)	(2.582)	(2.308)		(3.500)	(2.033)	(1.988)	(1.835)
HHI (technology)			10.444***		6.103***		10.386***	6.586***	5.292***		10.765***	8.966***	0.646	1.397	1.281
			(1.512)		(1.478)		(1.596)	(1.523)	(1.961)		(2.079)	(2.678)	(1.957)	(1.706)	(1.708)
HHI (research)				18.060**		-1.858	0.961	-9.979		-2.425	3.529	3.464			
				(8.383)		(7.653)	(8.320)	(7.685)		(9.021)	(12.279)	(12.965)			
HHI (trade) x HHI (technology)									5.187			-13.822			
									(8.235)			(11.391)			
HHI (trade) x HHI (research)										4.656		-116.491*			
										(39.045)		(67.945)			
HHI (research) x HHI (technology)											-11.774	-98.861*			
											(41.349)	(58.421)			
HHI (trade) x HHI (research) x HHI (technology)												524.349**			
												(221.620)			
Log of population														1.061***	1.198***
														(0.191)	(0.168)
Log of human capital														-5.402***	-5.610***
														(1.266)	(1.261)
Log of natural resource exports per capita														-0.581	
														(0.383)	
Log of GDP per capita	-5.612	-7.442	-0.620	-10.222	-2.348	-7.404	-0.684	-1.741	-2.621	-7.398	-1.007	-1.635	-5.185	10.630**	11.387**
	(5.271)	(5.646)	(6.187)	(6.420)	(5.648)	(5.656)	(6.220)	(5.661)	(5.670)	(5.665)	(6.332)	(5.780)	(5.299)	(4.927)	(4.911)
Log of GDP per capita, squared	0.239	0.166	-0.135	0.321	-0.067	0.163	-0.131	-0.102	-0.057	0.162	-0.113	-0.111	0.181	-0.462*	-0.537**
	(0.271)	(0.291)	(0.317)	(0.331)	(0.290)	(0.292)	(0.319)	(0.290)	(0.290)	(0.292)	(0.326)	(0.297)	(0.273)	(0.254)	(0.250)
Observations	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332
R^2	0.573	0.502	0.430	0.355	0.527	0.502	0.430	0.530	0.528	0.502	0.430	0.538	0.589	0.695	0.693
Adjusted R^2	0.562	0.492	0.418	0.341	0.516	0.490	0.416	0.517	0.515	0.489	0.414	0.520	0.577	0.682	0.681

Notes: Each regression includes period fixed effects. Standard errors in brackets. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table S15. Income Inequality Regressions: Entropy Robustness Check

	Dependent variable:														
	Gini coefficient (1996-99, 2000-03, 2004-07, 2008-11, 2012-15)														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ECI (trade)	-17.902***												-13.992***	-14.387***	-13.738***
	(2.353)												(2.530)	(2.346)	(2.321)
ECI (patents)	-5.269***												-3.556*	-6.891***	-7.768***
	(1.310)												(1.836)	(1.760)	(1.687)
Entropy (trade)		-16.592***			-14.066***	-16.815***		-14.572***	-18.637***	-25.472		-277.069**	-7.159***	-4.760**	-3.502**
		(1.588)			(1.678)	(1.663)		(1.704)	(5.891)	(28.301)		(112.759)	(1.887)	(1.852)	(1.701)
Entropy (technology)			-10.379***		-5.759***		-10.389***	-6.411***	-10.662*		7.725	-266.731**	-0.515	-1.524	-1.413
			(1.480)		(1.452)		(1.583)	(1.505)	(6.229)		(31.994)	(122.434)	(1.957)	(1.707)	(1.711)
Entropy (research)				-15.885**		2.887	0.122	10.262		-4.804	14.320	-192.646**			
				(6.924)		(6.322)	(6.955)	(6.399)		(25.884)	(25.996)	(92.048)			
Entropy (trade) x Entropy (technology)									5.966			338.822**			
									(7.370)			(149.506)			
Entropy (trade) x Entropy (research)										9.062		271.120**			
										(29.573)		(118.218)			
Entropy (research) x Entropy (technology)											-18.871	268.347**			
											(33.291)	(128.325)			
Entropy (trade) x Entropy (research) x Entropy (technology)												-349.203**			
												(156.287)			
Log of population														1.034***	1.187***
														(0.191)	(0.168)
Log of human capital														-5.421***	-5.644***
														(1.262)	(1.259)
Log of natural resource exports per capita														-0.650*	
														(0.384)	
Log of GDP per capita	-5.612	-6.619	-0.143	-10.244	-1.657	-6.533	-0.132	-0.788	-1.976	-6.514	-0.836	-0.970	-4.929	10.857**	11.648**
	(5.271)	(5.600)	(6.186)	(6.414)	(5.618)	(5.610)	(6.227)	(5.631)	(5.635)	(5.618)	(6.356)	(5.768)	(5.307)	(4.924)	(4.916)
Log of GDP per capita, squared	0.239	0.124	-0.157	0.324	-0.102	0.117	-0.158	-0.152	-0.090	0.116	-0.119	-0.146	0.165	-0.473*	-0.554**
	(0.271)	(0.289)	(0.317)	(0.331)	(0.288)	(0.289)	(0.320)	(0.289)	(0.288)	(0.290)	(0.327)	(0.296)	(0.274)	(0.254)	(0.250)
Observations	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332
R^2	0.573	0.511	0.432	0.357	0.534	0.511	0.432	0.537	0.535	0.511	0.433	0.546	0.591	0.697	0.694
Adjusted R^2	0.562	0.500	0.420	0.343	0.522	0.499	0.418	0.524	0.522	0.498	0.417	0.527	0.578	0.684	0.682

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S16. Income Inequality Regressions: Fitness Robustness Check

	Dependent variable:														
	Gini coefficient (1996-99, 2000-03, 2004-07, 2008-11, 2012-15)														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ECI (trade)	-17.902***												-17.071***	-10.191***	-8.937***
	(2.353)												(2.581)	(2.415)	(2.373)
ECI (patents)	-5.269***												-12.658***	-5.845**	-5.992**
	(1.310)												(2.576)	(2.303)	(2.319)
Log of fitness (trade)		-2.837***			-1.659***	-3.006***		-1.889***	-10.123***	-15.735***		-33.908***	-7.299***	-5.626***	-4.891***
		(0.344)			(0.436)	(0.400)		(0.433)	(1.443)	(2.381)		(8.377)	(1.370)	(1.238)	(1.207)
Log of fitness (technology)			-9.234***		-5.862***		-11.962***	-8.733***	-13.243***		0.530	6.653	2.589	-5.529**	-5.811**
			(1.089)		(1.387)		(1.439)	(1.584)	(1.784)		(6.522)	(12.284)	(2.877)	(2.645)	(2.662)
Log of fitness (research)				-9.247***		2.559	9.975***	12.208***		-11.197***	19.025***	15.360			
				(2.873)		(3.085)	(3.488)	(3.434)		(3.898)	(5.772)	(10.048)			
Log of fitness (trade) x Log of fitness (technology)									10.319***			28.018***	8.183***	4.321***	3.679**
									(1.686)			(10.790)	(1.560)	(1.436)	(1.421)
Log of fitness (trade) x Log of fitness (research)										15.642***		31.076***			
										(2.887)		(11.923)			
Log of fitness (research) x Log of fitness (technology)											-17.109*	-31.438*			
											(8.715)	(16.081)			
Log of fitness (trade) x Log of fitness (research) x Log of fitness (technology)												-23.753			
												(14.704)			
Log of population														1.403***	1.571***
														(0.210)	(0.199)
Log of human capital														-5.051***	-5.410***
														(1.203)	(1.202)
Log of natural resource exports per capita														-0.834**	
														(0.353)	
Log of GDP per capita	-5.612	-14.374**	-6.347	-13.276**	-10.236*	-13.732**	-1.750	-5.147	-5.985	-8.631	-5.152	-6.110	-2.467	8.511*	9.724**
	(5.271)	(5.902)	(5.865)	(6.444)	(5.837)	(5.955)	(6.020)	(5.910)	(5.576)	(5.787)	(6.239)	(5.565)	(5.106)	(4.633)	(4.638)
Log of GDP per capita, squared	0.239	0.565*	0.202	0.508	0.393	0.524*	-0.052	0.109	0.128	0.237	0.133	0.113	0.021	-0.338	-0.455*
	(0.271)	(0.305)	(0.302)	(0.334)	(0.300)	(0.309)	(0.311)	(0.305)	(0.287)	(0.301)	(0.324)	(0.289)	(0.263)	(0.240)	(0.236)
Observations	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332
R^2	0.573	0.459	0.465	0.366	0.488	0.461	0.478	0.507	0.541	0.506	0.484	0.610	0.622	0.725	0.720
Adjusted R^2	0.562	0.448	0.453	0.353	0.475	0.447	0.465	0.493	0.528	0.492	0.470	0.594	0.609	0.712	0.708

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

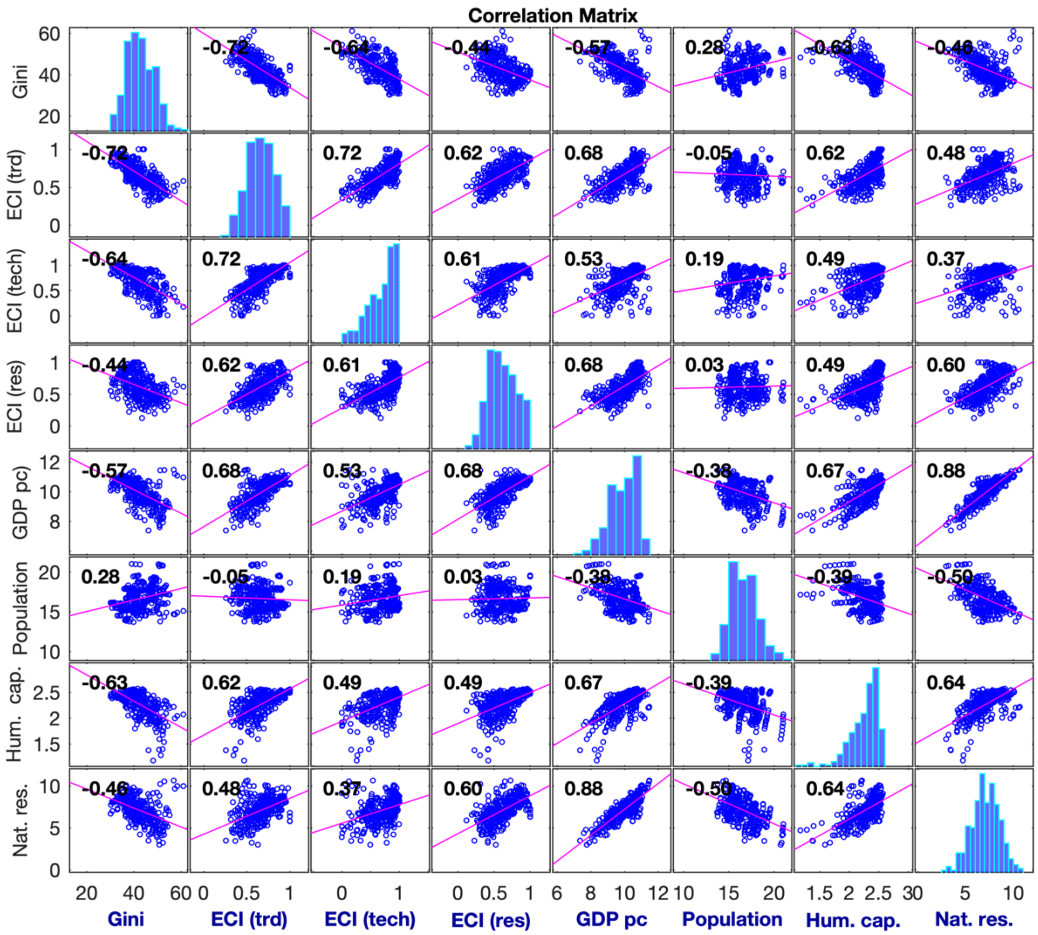

Figure S7. Correlations Between the Variables used in the Additional Explanatory Variables Robustness Check Regression Analysis

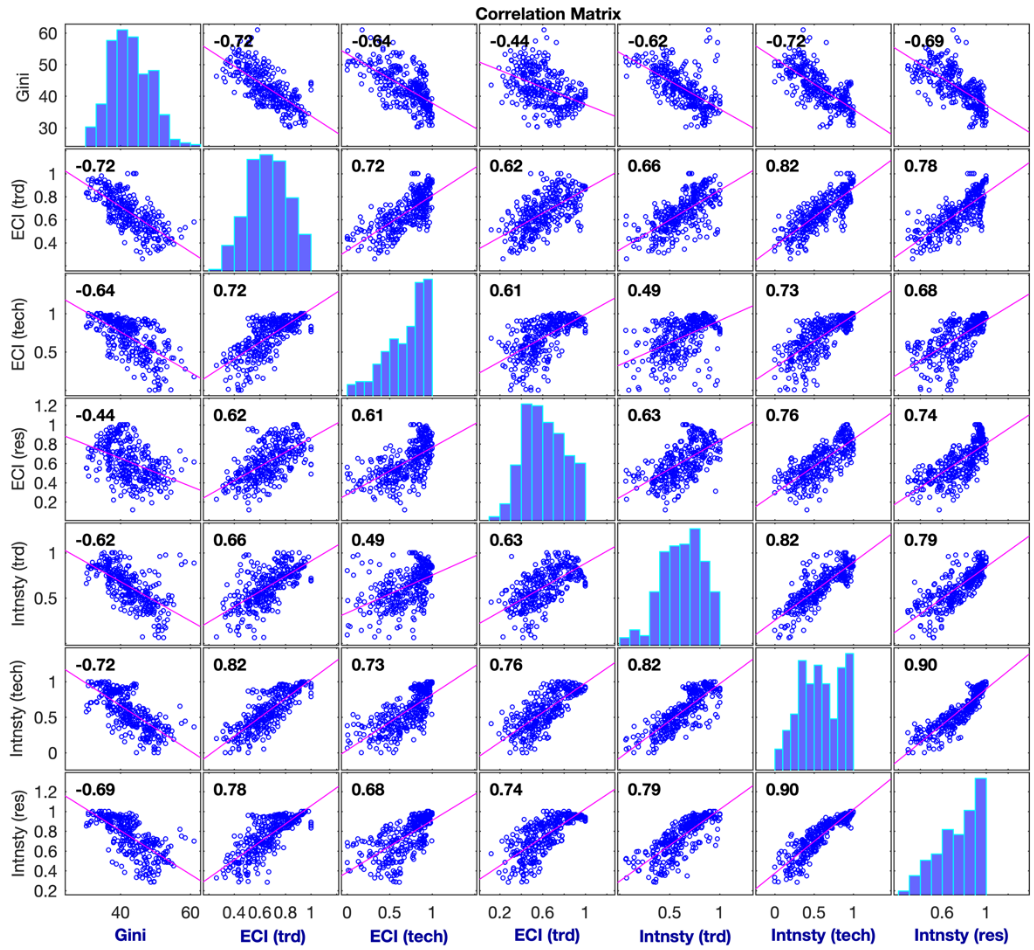

Figure S8. Correlations Between the Variables used in the Production Intensity Income Inequality Robustness Check Regression Analysis

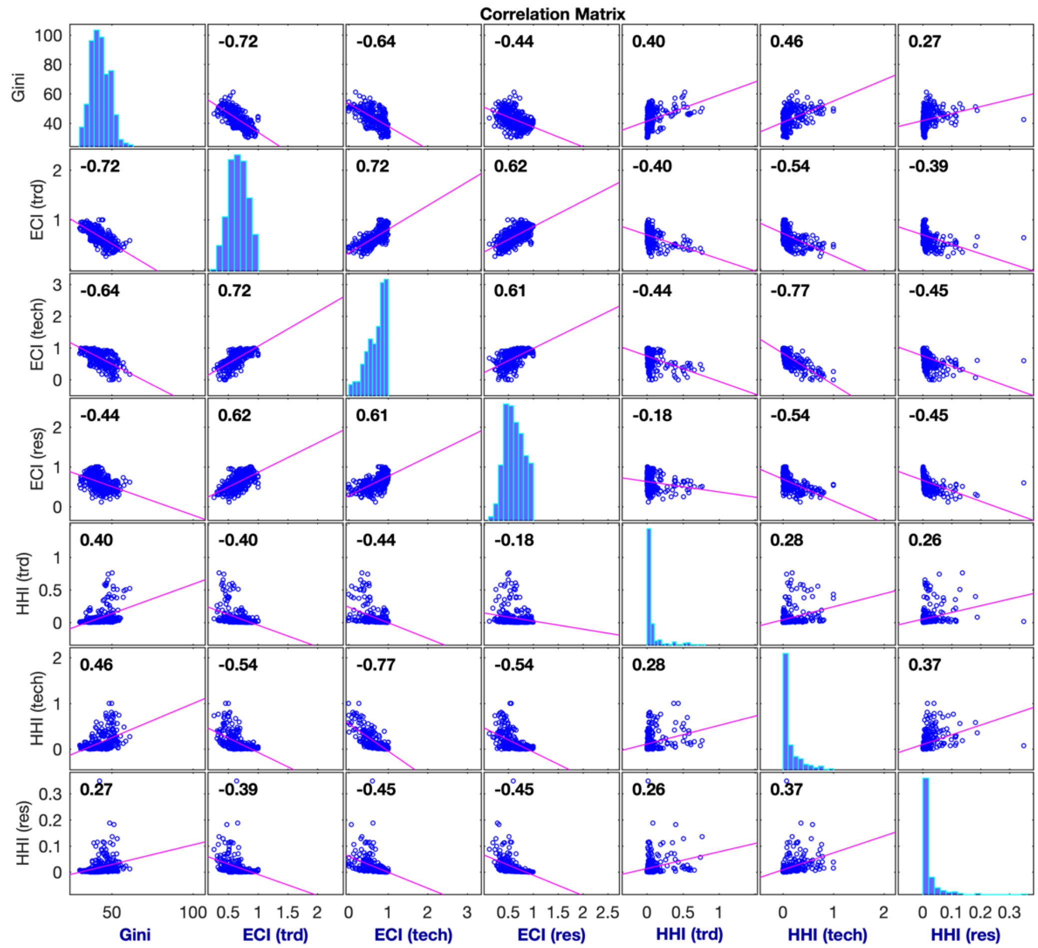

Figure S9. Correlations Between the Variables used in the HHI Income Inequality Robustness Check Regression Analysis

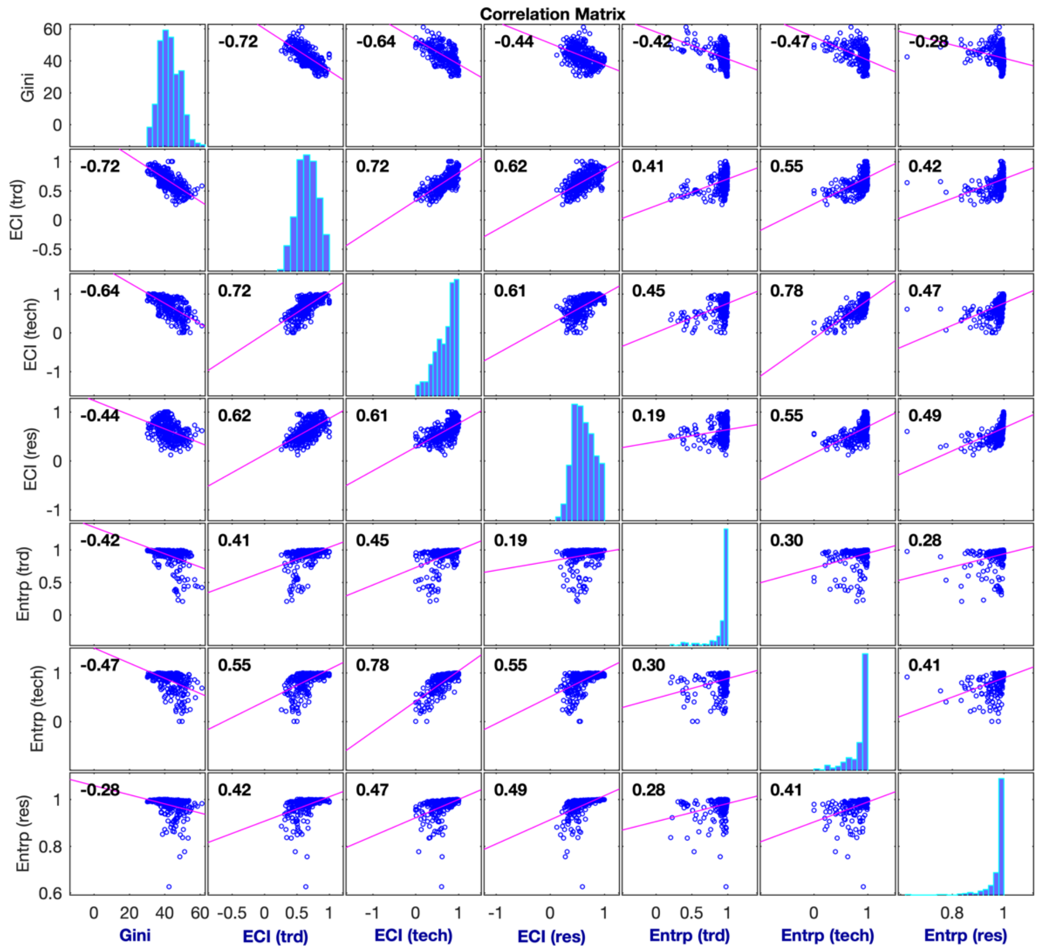

Figure S10. Correlations Between the Variables used in the Entropy Income Inequality Robustness Check Regression Analysis

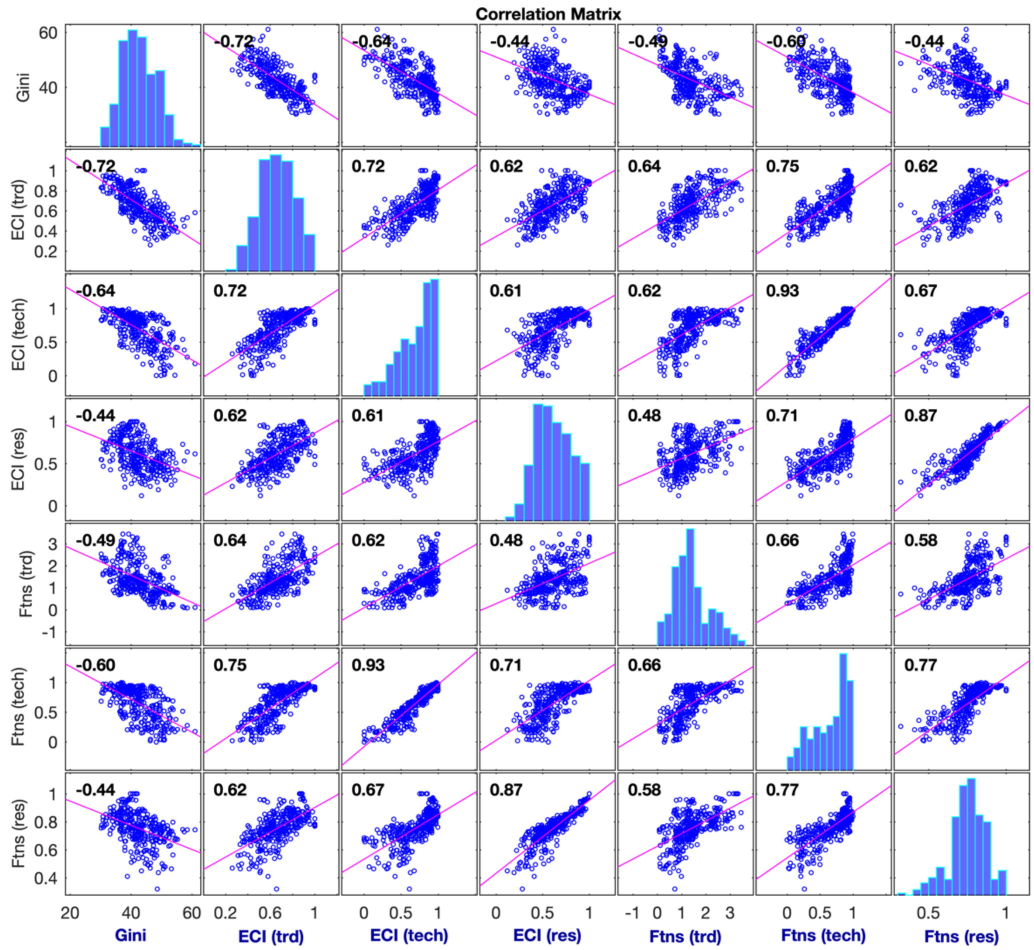

Figure S11. Correlations Between the Variables used in the Fitness Income Inequality Robustness Check Regression Analysis

6. Emission intensity regression analysis

6.1. Emission intensity regression setup

In the emission intensity regression analysis, the dependent variable is defined as the log of the amount of greenhouse gas emissions (in kilotons of CO2 equivalent, CO2e), GHG_{ct}, as a share of GDP, GDP_{ct}, i.e.,

$$y_{ct} = \log\left(\frac{GHG_{ct}}{GDP_{ct}^{per\ captia} \times POP_{ct}}\right),$$

where POP_{ct} is the population of country c in year t. A larger value implies higher emission intensity. The data for greenhouse gas emissions were taken from the World Bank's World Development Indicators, and are available at

https://data.worldbank.org/indicator/EN.ATM.GHGT.KT.CE .

In the regressions, as control variables we only include the log of the GDP per capita. Countries with larger GDP per capita should have lower emission intensity.

The regression analysis is focused on the periods 1996-1999, 2000-2003, 2004-2007, 2008-2011, 2012-2015 and 2016-18. Because of the sparseness of the greenhouse gas emissions dataset and slow temporal changes in the coefficients within a country, we follow [12] and use average values for each panel.

6.2. Emission intensity individual regressions

In Tables S17-S19, we present the results for the individual emission intensity regressions for ECI (trade), ECI (technology), and ECI (research), respectively. These results were used to estimate the F-statistics for testing the robustness of the individual regressions discussed in the main text.

Table S17. ECI (trade) Emission Intensity Regressions

	Dependent variable:									
	GHG emissions per GDP (1996-99, 2000-03, 2004-07, 2008-11, 2012-15, 2016-18)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ECI (trade)	-0.802***	-0.833***	-1.221***	-0.455***	-1.118***	-0.821***	-0.229	-0.172	0.131	
	(0.165)	(0.174)	(0.168)	(0.174)	(0.184)	(0.166)	(0.209)	(0.213)	(0.258)	
ECI (trade), instrumented										-0.698***
										(0.167)
Log of population		0.009			0.066***					
		(0.015)			(0.015)					
Log of human capital			0.764***		0.819***					
			(0.106)		(0.107)					
Log of natural resource exports per capita				0.168***	0.181***					
				(0.032)	(0.032)					
Intensity (trade)						0.260				
						(0.267)				
HHI (trade)							0.768***			
							(0.176)			
Entropy (trade)								-0.751***		
								(0.164)		
Fitness (trade)									-1.067***	
									(0.229)	
Log of GDP per capita	-0.178***	-0.169***	-0.276***	-0.472***	-0.530***	-0.231***	-0.249***	-0.256***	-0.259***	-0.204***
	(0.031)	(0.035)	(0.033)	(0.064)	(0.060)	(0.063)	(0.035)	(0.035)	(0.035)	(0.030)
Observations	529	529	529	529	529	529	529	529	529	529
R^2	0.272	0.273	0.338	0.309	0.387	0.274	0.298	0.301	0.302	0.264
Adjusted R^2	0.263	0.262	0.328	0.299	0.375	0.263	0.287	0.290	0.291	0.254

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S18. ECI (technology) Emission Intensity Regressions

	Dependent variable:									
	GHG emissions per GDP (1996-99, 2000-03, 2004-07, 2008-11, 2012-15, 2016-18)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ECI (technology)	-0.200**	-0.215*	-0.330***	-0.069	-0.554***	-0.061	-0.050	-0.044	0.164	
	(0.098)	(0.118)	(0.099)	(0.097)	(0.118)	(0.126)	(0.136)	(0.139)	(0.239)	
ECI (technology), instrumented										-0.184*
										(0.104)
Log of population		0.004			0.092***					
		(0.017)			(0.018)					
Log of human capital			0.584***		0.749***					
			(0.107)		(0.108)					
Log of natural resource exports per capita				0.194***	0.244***					
				(0.030)	(0.031)					
Intensity (technology)						-0.316*				
						(0.179)				
HHI (technology)							0.260			
							(0.165)			
Entropy (technology)								-0.259		
								(0.165)		
Fitness (technology)									-0.363*	
									(0.217)	
Log of GDP per capita	-0.255***	-0.250***	-0.352***	-0.562***	-0.657***	-0.200***	-0.253***	-0.253***	-0.241***	-0.258***
	(0.028)	(0.034)	(0.032)	(0.055)	(0.054)	(0.042)	(0.028)	(0.028)	(0.029)	(0.028)
Observations	529	529	529	529	529	529	529	529	529	529
R^2	0.246	0.246	0.287	0.301	0.370	0.250	0.249	0.249	0.250	0.244
Adjusted R^2	0.235	0.234	0.276	0.290	0.358	0.238	0.238	0.238	0.238	0.234

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S19. ECI (research) Emission Intensity Regressions

	Dependent variable:									
	GHG emissions per GDP (1996-99, 2000-03, 2004-07, 2008-11, 2012-15, 2016-18)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ECI (research)	-0.324**	-0.342**	-0.404***	-0.123	-0.536***	-0.385*	-0.267	-0.252	-0.181	
	(0.148)	(0.171)	(0.145)	(0.146)	(0.162)	(0.198)	(0.170)	(0.174)	(0.295)	
ECI (research), instrumented										-0.261*
										(0.145)
Log of population		0.003			0.070***					
		(0.016)			(0.017)					
Log of human capital			0.529***		0.620***					
			(0.105)		(0.102)					
Log of natural resource exports per capita				0.193***	0.237***					
				(0.030)	(0.031)					
Intensity (research)						0.109				
						(0.235)				
HHI (research)							0.220			
							(0.317)			
Entropy (research)								-0.228		
								(0.290)		
Fitness (research)									-0.190	
									(0.339)	
Log of GDP per capita	-0.242***	-0.237***	-0.338***	-0.555***	-0.648***	-0.253***	-0.246***	-0.246***	-0.245***	-0.254***
	(0.031)	(0.037)	(0.035)	(0.057)	(0.057)	(0.039)	(0.031)	(0.031)	(0.031)	(0.029)
Observations	529	529	529	529	529	529	529	529	529	529
R^2	0.247	0.247	0.282	0.301	0.356	0.247	0.247	0.247	0.247	0.244
Adjusted R^2	0.236	0.235	0.271	0.291	0.344	0.235	0.236	0.236	0.235	0.234

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

6.3. Emission intensity multidimensional regression model robustness checks

Additional explanatory variables robustness check: In Table S20 we reproduce the main results for the emission intensity regression analysis (Columns (1-12)) and test the robustness of the multidimensional emission intensity regression by adding the log of the population, the log of the human capital, and the log of natural resource exports as additional explanatory variables, separately (Columns (13-15)) and together (Column (16)). In each case the ECI (trade), ECI (technology), ECI (research), their interactions terms, and the three-way term remain significant predictors of emission intensity, thus confirming the robustness of the multidimensional regression model. Figure S12 gives the correlations between the variables used in these regressions.

Production intensity robustness check: In Table S21, Columns (2-12), we estimate the production intensity emission intensity models. We find that the best model includes all the intensities (trade, technology, and research), their pairwise interaction terms, and the three-way interaction term ($R^2 = 0.343$). By comparing this model directly to the multidimensional ECI model (Column (13)) we find that the multidimensional intensity model outperforms the ECI model. However, in a regression specification which also all of the additional explanatory variables (Column (14)), the multidimensional ECI variables regain significance. This suggests that the multidimensional ECI variables and the multidimensional production intensity variables complement each other and offer different, but significant, information for the international variations in emission intensity. This model is also the final emission intensity regression model, i.e., the model that has the best explanatory power out of all emission intensity regression analyses ($R^2 = 0.520$). Figure S13 gives the correlation between the variables used in these regressions.

HHI robustness check: In Table S22, Columns (2-12), we estimate the HHI emission intensity models. We find that the multidimensional model includes only the trade HHI ($R^2 = 0.297$). By comparing this model directly to the multidimensional ECI model (Column (13)) and in a regression specification which also includes all of the additional explanatory variables (Column (14)), we find that the multidimensional ECI model coefficients remain significant. Hence the multidimensional ECI emission intensity model is robust against the multidimensional HHI model. Figure S14 gives the correlation between the variables used in these regressions.

Entropy robustness check: In Table S23, Columns (2-12), we estimate the Entropy emission intensity models. Identically to the HHI case, we find that the multidimensional model includes only the trade ($R^2 = 0.278$). By comparing this model directly to the multidimensional ECI model (Column (13)) and in a regression specification which also includes all of the additional explanatory variables (Column (14)), we find that the multidimensional ECI model coefficients remain significant. Hence the multidimensional ECI emission intensity model is robust against the multidimensional Entropy model. Figure S15 gives the correlation between the variables used in these regressions.

Fitness robustness check: In Table S24, Columns (2-12), we estimate the Fitness emission intensity models. We find that the multidimensional Fitness model includes the trade, and technological Fitness, but not their interaction term ($R^2 = 0.312$). By comparing this model directly to the multidimensional ECI model (Column (13)) and in a regression specification which also all of the additional explanatory variables (Column (14)), we find that the multidimensional ECI model coefficients remain significant. Hence the multidimensional ECI emission intensity model is robust against the multidimensional Fitness model. Figure S16 gives the correlation between the variables used in these regressions.

Table S20. Emission Intensity Regressions: Additional Explanatory Variables Robustness Check

	Dependent variable:															
	GHG emissions per GDP (1996-99, 2000-03, 2004-07, 2008-11, 2012-15, 2016-18)															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
ECI (trade)		-0.802***			-0.927***	-0.769***		-0.917***	0.193	0.376		-3.499***	-3.430***	-5.576***	-3.157***	-4.849***
		(0.165)			(0.206)	(0.177)		(0.206)	(0.419)	(0.401)		(1.246)	(1.251)	(1.221)	(1.208)	(1.163)
ECI (technology)			-0.200**		0.123		-0.116	0.190	1.008***		0.368	-2.767***	-2.798***	-3.930***	-2.416**	-3.949***
			(0.098)		(0.120)		(0.118)	(0.134)	(0.313)		(0.285)	(1.032)	(1.034)	(0.997)	(1.002)	(0.952)
ECI (research)				-0.324**		-0.083	-0.228	-0.193		1.185***	0.457	-3.723***	-3.788***	-4.881***	-3.751***	-5.641***
				(0.148)		(0.156)	(0.177)	(0.174)		(0.429)	(0.407)	(1.323)	(1.327)	(1.271)	(1.282)	(1.214)
ECI (trade) x ECI (technology)									-1.571***			5.104***	5.031***	7.291***	4.767***	6.554***
									(0.513)			(1.786)	(1.790)	(1.729)	(1.731)	(1.642)
ECI (trade) x ECI (research)										-1.948***		6.820***	6.794***	9.174***	7.590***	10.167***
										(0.614)		(2.413)	(2.414)	(2.323)	(2.340)	(2.205)
ECI (research) x ECI (technology)											-0.935*	6.477***	6.538***	7.885***	6.284***	8.384***
											(0.501)	(1.854)	(1.857)	(1.778)	(1.796)	(1.692)
ECI (trade) x ECI (research) x ECI (technology)												-11.270***	-11.259***	-14.096***	-11.656***	-14.825***
												(3.084)	(3.086)	(2.965)	(2.988)	(2.814)
Log of population													0.012			0.105***
													(0.017)			(0.018)
Log of human capital														0.783***		0.888***
														(0.108)		(0.109)
Log of natural resource exports per capita															0.188***	0.220***
															(0.032)	(0.032)
Log of GDP per capita	-0.287***	-0.178***	-0.255***	-0.242***	-0.181***	-0.171***	-0.236***	-0.166***	-0.190***	-0.181***	-0.237***	-0.183***	-0.167***	-0.277***	-0.524***	-0.551***
	(0.022)	(0.031)	(0.028)	(0.031)	(0.032)	(0.034)	(0.031)	(0.034)	(0.031)	(0.034)	(0.031)	(0.034)	(0.041)	(0.035)	(0.067)	(0.062)
Observations	529	529	529	529	529	529	529	529	529	529	529	529	529	529	529	529
R^2	0.240	0.272	0.246	0.247	0.274	0.273	0.248	0.276	0.287	0.287	0.253	0.308	0.309	0.373	0.352	0.439
Adjusted R^2	0.231	0.263	0.235	0.236	0.263	0.262	0.236	0.263	0.274	0.274	0.240	0.291	0.290	0.356	0.335	0.421

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S21. Emission Intensity Regressions: Production Intensity Robustness Check

	Dependent variable:													
	GHG emissions per GDP (1996-99, 2000-03, 2004-07, 2008-11, 2012-15, 2016-18)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ECI (trade)	-3.499***												-2.361*	-3.621***
	(1.246)												(1.282)	(1.195)
ECI (technology)	-2.767***												-0.909	-2.331**
	(1.032)												(1.102)	(1.027)
ECI (research)	-3.723***												-2.078	-4.435***
	(1.323)												(1.401)	(1.273)
ECI (trade) x ECI (technology)	5.104***												1.707	3.512*
	(1.786)												(1.900)	(1.801)
ECI (trade) x ECI (research)	6.820***												3.705	7.327***
	(2.413)												(2.477)	(2.261)
ECI (research) x ECI (technology)	6.477***												2.957	5.054***
	(1.854)												(1.964)	(1.807)
ECI (trade) x ECI (research) x ECI (technology)	-11.270***												-4.901	-8.645***
	(3.084)												(3.236)	(2.969)
Intensity (trade)		0.108			0.290	0.145		0.304	1.619***	2.739***		-3.125***	-2.863***	-6.293***
		(0.271)			(0.277)	(0.273)		(0.277)	(0.362)	(0.537)		(1.049)	(1.071)	(1.007)
Intensity (technology)			-0.370***		-0.406***		-0.478**	-0.522***	1.201***		1.728***	-4.601***	-4.350***	-4.634***
			(0.140)		(0.144)		(0.187)	(0.192)	(0.324)		(0.477)	(1.274)	(1.348)	(1.225)
Intensity (research)				-0.195		-0.206	0.202	0.216		1.693***	0.976***	-2.612***	-1.776**	-2.385***
				(0.176)		(0.177)	(0.234)	(0.235)		(0.383)	(0.276)	(0.855)	(0.903)	(0.804)
Intensity (trade) x Intensity (technology)									-2.254***			10.977***	12.174***	13.694***
									(0.409)			(2.339)	(2.373)	(2.120)
Intensity (trade) x Intensity (research)										-3.162***		6.079***	4.832***	7.067***
										(0.569)		(1.662)	(1.741)	(1.572)
Intensity (research) x Intensity (technology)											-2.406***	7.160***	6.498***	6.579***
											(0.480)	(1.640)	(1.750)	(1.559)
Intensity (trade) x Intensity (research) x Intensity (technology)												-15.507***	-15.295***	-16.989***
												(2.559)	(2.625)	(2.342)
Log of GDP per population														0.113***
														(0.021)
Log of human capital														0.787***
														(0.106)
Log of natural resource exports per capita														0.353***
														(0.041)
Log of GDP per capita	-0.183***	-0.311***	-0.197***	-0.253***	-0.250***	-0.282***	-0.206***	-0.263***	-0.368***	-0.391***	-0.253***	-0.415***	-0.426***	-0.623***
	(0.034)	(0.062)	(0.041)	(0.039)	(0.066)	(0.067)	(0.042)	(0.067)	(0.067)	(0.068)	(0.043)	(0.068)	(0.071)	(0.066)
Observations	529	529	529	529	529	529	529	529	529	529	529	529	529	529
R^2	0.308	0.240	0.250	0.241	0.251	0.242	0.251	0.252	0.293	0.284	0.285	0.343	0.379	0.520
Adjusted R^2	0.291	0.230	0.240	0.231	0.240	0.230	0.239	0.239	0.280	0.272	0.273	0.327	0.355	0.498

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S22. Emission Intensity Regressions: Hirschman-Herfindahl Index Robustness Check

	Dependent variable:													
	GHG emissions per GDP (1996-99, 2000-03, 2004-07, 2008-11, 2012-15, 2016-18)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ECI (trade)	-3.499***												-1.804	-4.002***
	(1.246)												(1.235)	(1.178)
ECI (technology)	-2.767***												-3.107***	-4.101***
	(1.032)												(0.999)	(0.943)
ECI (research)	-3.723***												-4.303***	-5.774***
	(1.323)												(1.282)	(1.203)
ECI (trade) x ECI (technology)	5.104***												4.583***	6.375***
	(1.786)												(1.727)	(1.627)
ECI (trade) x ECI (research)	6.820***												6.783***	9.905***
	(2.413)												(2.331)	(2.184)
ECI (research) x ECI (technology)	6.477***												8.338***	9.291***
	(1.854)												(1.816)	(1.696)
ECI (trade) x ECI (research) x ECI (technology)	-11.270***												-12.411***	-15.269***
	(3.084)												(2.985)	(2.788)
HHI (trade)		0.889***			0.875***	0.873***		0.869***	0.725***	0.926***		0.454*	1.146***	0.651***
		(0.137)			(0.147)	(0.138)		(0.148)	(0.219)	(0.158)		(0.268)	(0.186)	(0.192)
HHI (technology)			0.302**		0.032		0.270**	0.011	-0.060		0.277*	-0.247		
			(0.118)		(0.123)		(0.122)	(0.126)	(0.158)		(0.143)	(0.208)		
HHI (research)				0.463*		0.225	0.312	0.219		0.337	0.348	-0.161		
				(0.277)		(0.270)	(0.285)	(0.276)		(0.315)	(0.462)	(0.605)		
HHI (trade) x HHI (technology)									0.596			1.706**		
									(0.642)			(0.824)		
HHI (trade) x HHI (research)										-0.925		4.823		
										(1.340)		(4.410)		
HHI (research) x HHI (technology)											-0.144	1.773		
											(1.462)	(2.606)		
HHI (trade) x HHI (research) x HHI (technology)												-11.669*		
												(6.364)		
Log of population														0.081***
														(0.019)
Log of human capital														0.850***
														(0.109)
Log of natural resource exports per capita														0.177***
														(0.034)
Log of GDP per capita	-0.183***	-0.280***	-0.257***	-0.278***	-0.277***	-0.275***	-0.254***	-0.274***	-0.282***	-0.275***	-0.254***	-0.287***	-0.317***	-0.577***
	(0.034)	(0.022)	(0.025)	(0.023)	(0.025)	(0.022)	(0.025)	(0.025)	(0.025)	(0.022)	(0.026)	(0.026)	(0.040)	(0.062)
Observations	529	529	529	529	529	529	529	529	529	529	529	529	529	529
R^2	0.308	0.297	0.249	0.244	0.297	0.297	0.251	0.297	0.298	0.298	0.251	0.306	0.356	0.451
Adjusted R^2	0.291	0.287	0.239	0.233	0.286	0.287	0.239	0.285	0.286	0.286	0.238	0.288	0.338	0.433

Notes: Each regression includes period fixed effects. Standard errors in brackets. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table S23. Emission Intensity Regressions: Entropy Robustness Check

	Dependent variable:													
	GHG emissions per GDP (1996-99, 2000-03, 2004-07, 2008-11, 2012-15, 2016-18)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ECI (trade)	-3.499***												-1.702	-3.937***
	(1.246)												(1.230)	(1.178)
ECI (technology)	-2.767***												-3.134***	-4.109***
	(1.032)												(0.995)	(0.942)
ECI (research)	-3.723***												-4.395***	-5.805***
	(1.323)												(1.278)	(1.202)
ECI (trade) x ECI (technology)	5.104***												4.581***	6.368***
	(1.786)												(1.720)	(1.625)
ECI (trade) x ECI (research)	6.820***												6.881***	9.923***
	(2.413)												(2.322)	(2.182)
ECI (research) x ECI (technology)	6.477***												8.513***	9.375***
	(1.854)												(1.811)	(1.696)
ECI (trade) x ECI (research) x ECI (technology)	-11.270***												-12.590***	-15.336***
	(3.084)												(2.975)	(2.786)
Entropy (trade)		-0.836***			-0.835***	-0.819***		-0.828***	-1.362***	-0.511		2.783	-1.128***	-0.643***
		(0.125)			(0.136)	(0.127)		(0.136)	(0.452)	(1.035)		(2.571)	(0.174)	(0.181)
Entropy (technology)			-0.296**		-0.004		-0.257**	0.021	-0.591		-0.019	7.503*		
			(0.116)		(0.122)		(0.121)	(0.125)	(0.495)		(1.172)	(4.200)		
Entropy (research)				-0.449*		-0.200	-0.297	-0.210		0.081	-0.113	3.914**		
				(0.247)		(0.240)	(0.256)	(0.248)		(0.968)	(0.936)	(1.848)		
Entropy (trade) x Entropy (technology)									0.714			-8.218*		
									(0.583)			(4.764)		
Entropy (trade) x Entropy (research)										-0.330		-4.772*		
										(1.100)		(2.846)		
Entropy (research) x Entropy (technology)											-0.253	-8.867**		
											(1.243)	(4.415)		
Entropy (trade) x Entropy (research) x Entropy (technology)												9.854*		
												(5.018)		
Log of GDP per population														0.079***
														(0.019)
Log of human capital														0.841***
														(0.109)
Log of natural resource exports per capita														0.173***
														(0.035)
Log of GDP per capita	-0.183***	-0.278***	-0.256***	-0.277***	-0.278***	-0.273***	-0.253***	-0.275***	-0.285***	-0.273***	-0.252***	-0.287***	-0.329***	-0.578***
	(0.034)	(0.022)	(0.025)	(0.023)	(0.025)	(0.022)	(0.026)	(0.025)	(0.026)	(0.022)	(0.026)	(0.026)	(0.040)	(0.062)
Observations	529	529	529	529	529	529	529	529	529	529	529	529	529	529
R^2	0.308	0.300	0.249	0.244	0.300	0.301	0.251	0.301	0.302	0.301	0.251	0.310	0.361	0.452
Adjusted R^2	0.291	0.290	0.239	0.234	0.289	0.290	0.239	0.289	0.290	0.289	0.238	0.292	0.343	0.434

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S23. Emission Intensity Regressions: Fitness Robustness Check

	Dependent variable:													
	GHG emissions per GDP (1996-99, 2000-03, 2004-07, 2008-11, 2012-15, 2016-18)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ECI (trade)	-3.499***												-1.460	-3.502***
	(1.246)												(1.249)	(1.179)
ECI (technology)	-2.767***												-2.736***	-4.293***
	(1.032)												(1.000)	(0.939)
ECI (research)	-3.723***												-3.987***	-5.999***
	(1.323)												(1.272)	(1.185)
ECI (trade) x ECI (technology)	5.104***												4.617**	7.207***
	(1.786)												(1.815)	(1.694)
ECI (trade) x ECI (research)	6.820***												6.847***	10.390***
	(2.413)												(2.332)	(2.162)
ECI (research) x ECI (technology)	6.477***												8.054***	10.571***
	(1.854)												(1.844)	(1.734)
ECI (trade) x ECI (research) x ECI (technology)	-11.270***												-12.345***	-16.964***
	(3.084)												(3.062)	(2.854)
Log of fitness (trade)		-0.977***			-1.363***	-1.064***		-1.360***	-1.596***	-1.845***		-1.709*	-1.689***	-1.235***
		(0.144)			(0.198)	(0.164)		(0.198)	(0.312)	(0.632)		(0.940)	(0.257)	(0.248)
Log of fitness (technology)			-0.227**		0.335***		-0.174	0.361***	-0.058		-0.172	0.408	-0.129	-0.604**
			(0.089)		(0.118)		(0.118)	(0.137)	(0.425)		(0.453)	(2.279)	(0.257)	(0.264)
Log of fitness (research)				-0.370**		0.208	-0.154	-0.080		-0.580	-0.153	-0.272		
				(0.170)		(0.186)	(0.224)	(0.215)		(0.643)	(0.324)	(1.022)		
Log of fitness (trade) x Log of fitness (technology)									0.507			-0.055		
									(0.526)			(2.798)		
Log of fitness (trade) x Log of fitness (research)										1.108		0.296		
										(0.867)		(1.535)		
Log of fitness (research) x Log of fitness (technology)											-0.003	-0.400		
											(0.589)	(2.769)		
Log of fitness (trade) x Log of fitness (research) x Log of fitness (technology)												0.492		
												(3.360)		
Log of population														0.127***
														(0.019)
Log of human capital														0.865***
														(0.107)
Log of natural resource exports per capita														0.173***
														(0.033)
Log of GDP per capita	-0.183***	-0.245***	-0.242***	-0.255***	-0.296***	-0.259***	-0.239***	-0.294***	-0.298***	-0.266***	-0.239***	-0.298***	-0.355***	-0.565***
	(0.034)	(0.022)	(0.029)	(0.027)	(0.029)	(0.026)	(0.029)	(0.029)	(0.029)	(0.026)	(0.030)	(0.030)	(0.042)	(0.061)
Observations	529	529	529	529	529	529	529	529	529	529	529	529	529	529
R^2	0.308	0.301	0.249	0.246	0.312	0.303	0.250	0.312	0.313	0.305	0.250	0.313	0.364	0.471
Adjusted R^2	0.291	0.292	0.239	0.236	0.301	0.292	0.238	0.300	0.301	0.293	0.237	0.296	0.346	0.453

Notes: Each regression includes period fixed effects. Standard errors in brackets. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

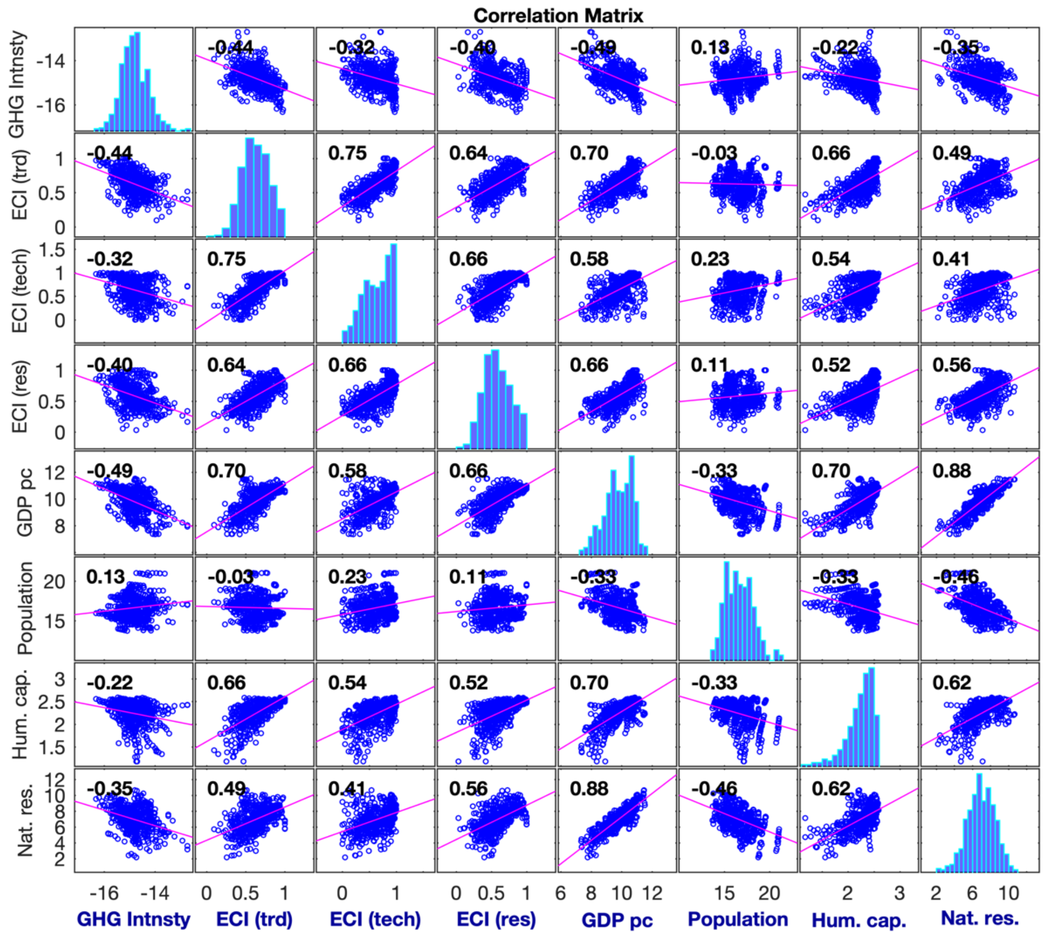

Figure S12. Correlations Between the Variables used in the Additional Explanatory Variables Emission Intensity Robustness Check Regression Analysis

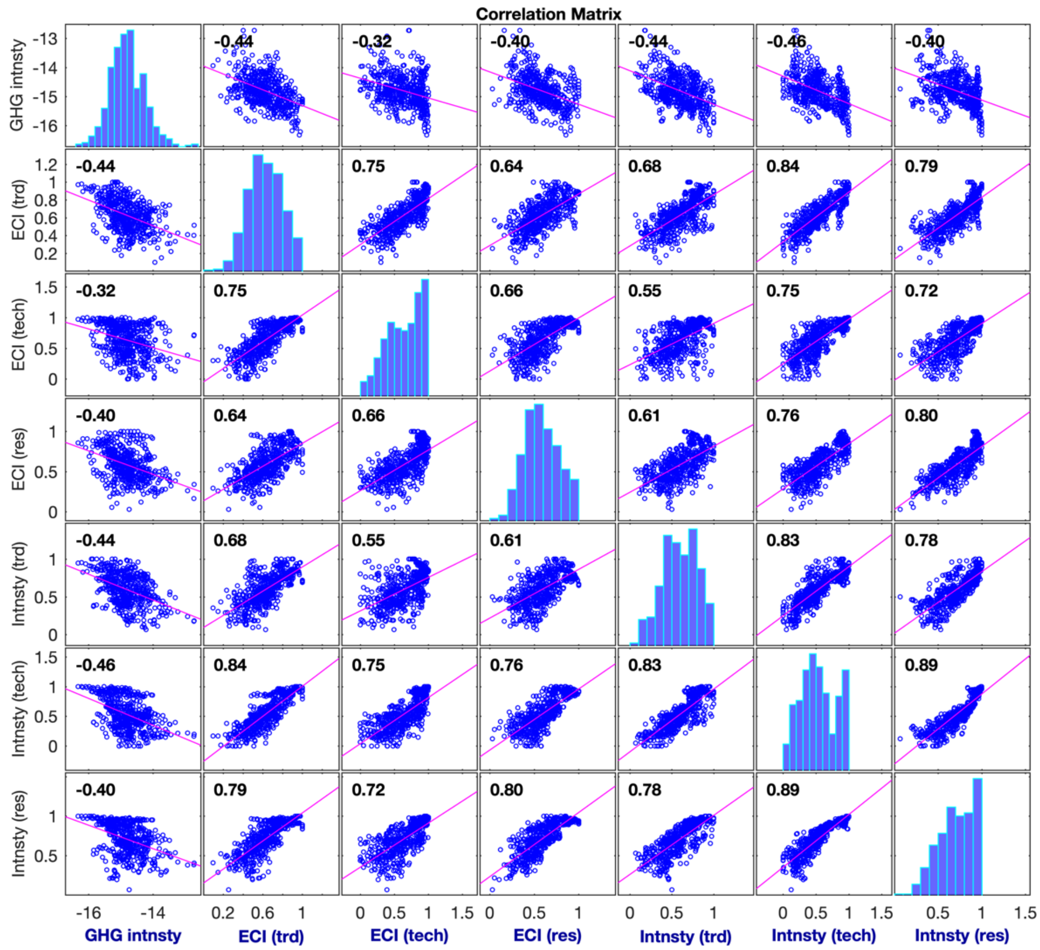

Figure S13. Correlations Between the Variables used in the Production Intensity Emission Intensity Robustness Check Regression Analysis

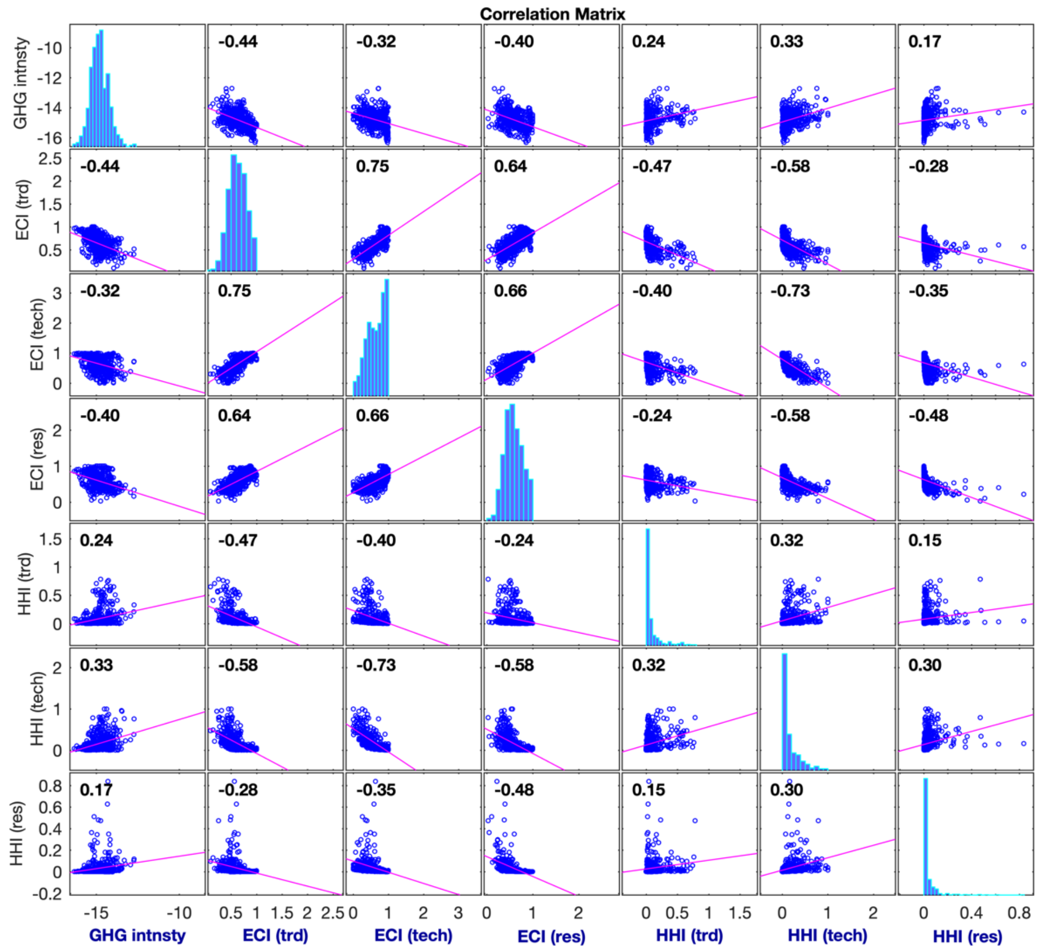

Figure S14. Correlations Between the Variables used in the HHI Emission Intensity Robustness Check Regression Analysis

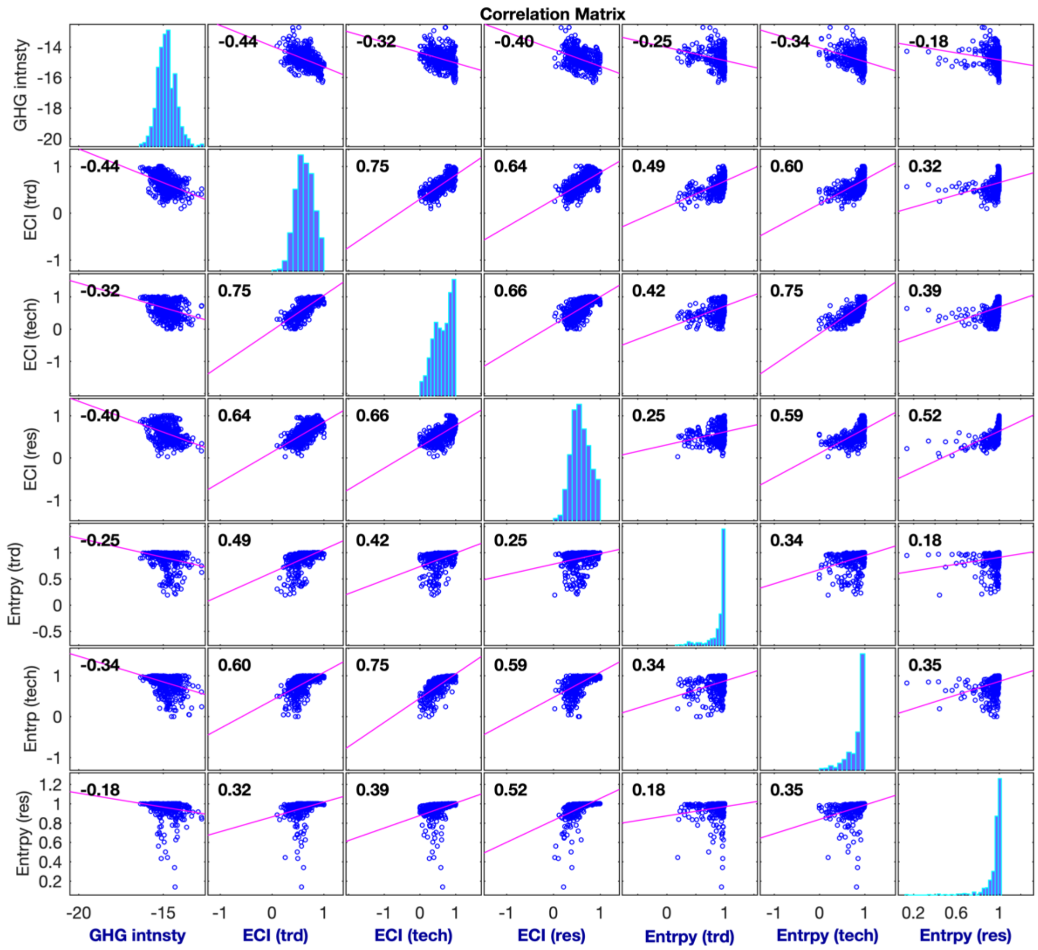

Figure S14. Correlations Between the Variables used in the Entropy Emission Intensity Robustness Check Regression Analysis

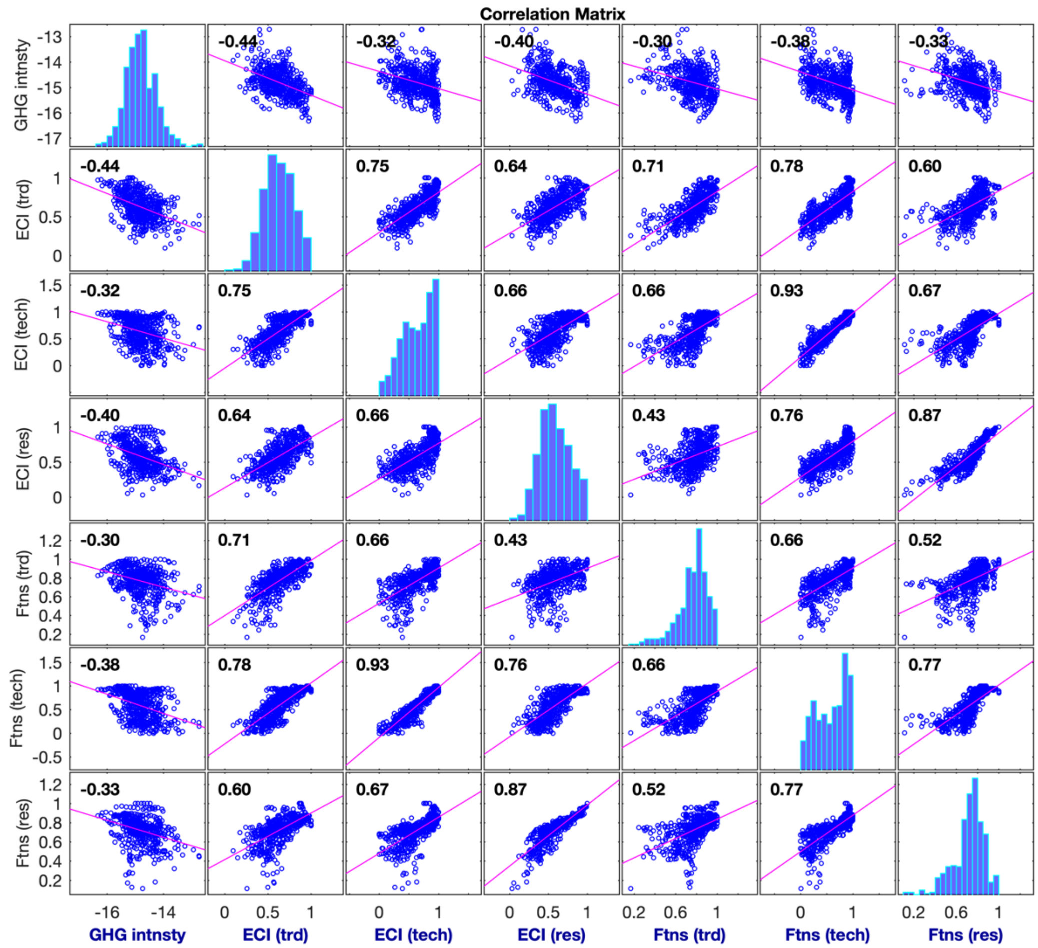

Figure S16. Correlations Between the Variables used in the Fitness Emission Intensity Robustness Check Regression Analysis

7. Instrumental variables robustness check

To account for the possible endogeneity between the various dimensions of ECI and economic growth, income inequality or emission intensity of a country, we re-estimate our results by using an instrumental variables (IV) approach. Endogeneity may arise because there might be omitted variables which affect both ECI and the macroeconomic outcome. The IV estimation approach corrects for possible endogeneity by using instruments: variables that do not belong in the explanatory equation but are correlated with ECI.

7.1. Defining the instrumental variable

For each country c, we use the average complexity of the three economies that have the most similar specialization pattern as instrument. The rationale behind using this variable as an instrument is that countries with similar specialization patterns should also have similar complexity as the target country, but the complexity of the similar economies should not affect the macroeconomic outcome of the target country and it should not be related to other country specific features.

We quantify the similarity of the specialization patterns between the target country c and a paired country c' by using the minimum conditional probability,

$$\phi_{cc'}^{d} = \frac{\sum_p M_{cp}^{d} M_{c'p}^{d}}{\max(M_c^d, M_{c'}^d)},$$

for the countries to be specialized in the same activity.

Tables S25, S26, and S27 list, respectively, the countries and their 3 most similar economies in terms of trade, technology, and research specialization patterns in 2014. Even though, in some cases there is a geographical and/or cultural overlap between the target country and some of the most similar countries, there is no general pattern. For example, in 2014 Japan was similar in terms of exports to Germany, South Korea, and Great Britain and Australia was closest in terms of technology to Great Britain, Spain, and Canada. This suggests that the similarity-based metrics are not determined by the similarity in local conditions.

Figure S17 gives the correlation between the instrument and the real ECI values for the data used in the regression analysis. We can easily observe that the metrics are highly correlated, hence implying that the similarity based ECI metrics can serve as strong instruments. Therefore, we use them to re-estimate the multidimensional ECI economic growth, income inequality, and emission intensity models, and compare the resulting instrumented models to the same specifications that were described in Sections 4-7.

Table S25. List of Countries and their 3 Most Similar Economies in Terms of Trade Specialization Patterns in 2014

Country	Similar country 1	Similar Country 2	Similar Country 3	Country	Similar country 1	Similar Country 2	Similar Country 3	Country	Similar country 1	Similar Country 2	Similar Country 3
AGO	GNQ	GAB	DZA	**GNQ**	AGO	GAB	LBY	**NLD**	BEL	FRA	DEU
ALB	MAR	MKD	BIH	**GRC**	LBN	EGY	SRB	**NOR**	NAM	RUS	PRK
ARE	TGO	IRN	GEO	**GTM**	SLV	DOM	HND	**NZL**	URY	ARG	CAN
ARG	URY	NZL	BRA	**HKG**	CHN	THA	PAN	**OMN**	SAU	IRN	TTO
ARM	JAM	GEO	KGZ	**HND**	SLV	GTM	DOM	**PAK**	SYR	LKA	EGY
AUS	URY	NZL	IRL	**HRV**	SRB	LVA	SVN	**PAN**	HKG	CHN	LKA
AUT	DEU	CZE	FRA	**HUN**	POL	ROU	HRV	**PER**	MAR	KEN	CHL
AZE	YEM	TKM	SDN	**IDN**	VNM	LKA	PHL	**PHL**	IDN	LKA	MYS
BEL	NLD	FRA	POL	**IND**	CHN	PAK	TUR	**PNG**	GIN	CMR	YEM
BEN	TGO	CIV	PRY	**IRL**	URY	AUS	NZL	**POL**	CZE	PRT	LTU
BFA	MLI	SDN	NER	**IRN**	UZB	SYR	KGZ	**PRK**	ALB	MMR	MAR
BGD	KHM	LSO	LKA	**IRQ**	SSD	DZA	LBY	**PRT**	TUR	ESP	POL
BGR	ROU	SRB	HRV	**ISR**	CYP	CHE	JOR	**PRY**	BEN	BOL	NIC
BHR	TTO	OMN	IRN	**ITA**	ESP	DEU	CHN	**QAT**	KWT	VEN	LBY
BIH	HRV	SRB	MKD	**JAM**	ARM	CRI	UGA	**ROU**	BGR	HUN	SRB
BLR	LTU	HRV	LVA	**JOR**	GTM	SYR	DOM	**RUS**	UKR	AUS	KAZ
BOL	PER	PRY	BEN	**JPN**	DEU	KOR	GBR	**SAU**	QAT	OMN	YEM
BRA	ARG	URY	NZL	**KAZ**	RUS	OMN	ZMB	**SDN**	BFA	MLI	NER
BWA	NAM	MNG	COD	**KEN**	GTM	UGA	JOR	**SEN**	UGA	TZA	KEN
CAN	FIN	SWE	NZL	**KGZ**	SYR	MKD	PAK	**SGP**	MYS	CHE	JPN
CHE	JPN	DEU	ISR	**KHM**	BGD	LSO	LAO	**SLE**	GIN	LBR	COD
CHL	PER	ARG	MMR	**KOR**	JPN	THA	HKG	**SLV**	HND	GTM	DOM
CHN	ITA	PRT	ESP	**KWT**	QAT	VEN	LBY	**SRB**	HRV	LVA	BGR
CIV	GHA	CMR	TGO	**LAO**	MMR	KHM	NIC	**SSD**	IRQ	AGO	DZA
CMR	CIV	GHA	BEN	**LBN**	EGY	GRC	SYR	**SVK**	HUN	HRV	CZE
COD	COG	GIN	SLE	**LBR**	GIN	SLE	COG	**SVN**	AUT	CZE	HRV
COG	COD	GAB	LBR	**LBY**	DZA	VEN	QAT	**SWE**	FIN	AUT	CZE
COL	CRI	CIV	KEN	**LKA**	PAK	VNM	IDN	**SWZ**	SLV	MDG	MUS
CRI	HND	GTM	SLV	**LSO**	BGD	KHM	ETH	**SYR**	EGY	JOR	PAK
CUB	YEM	MOZ	ZMB	**LTU**	LVA	DNK	POL	**TCD**	SDN	MLI	COD
CYP	ISR	LVA	GRC	**LVA**	LTU	EST	HRV	**TGO**	BEN	SEN	CIV
CZE	AUT	POL	DEU	**MAR**	TUN	ALB	SYR	**THA**	IDN	PRT	VNM
DEU	USA	FRA	ITA	**MDA**	GTM	MKD	SYR	**TKM**	BFA	MLI	SDN
DNK	LTU	POL	AUT	**MDG**	LKA	MMR	KEN	**TTO**	BHR	OMN	QAT
DOM	GTM	SLV	JOR	**MEX**	TUN	HUN	DOM	**TUN**	MAR	DOM	PAK
DZA	LBY	QAT	IRQ	**MKD**	ALB	BIH	MDA	**TUR**	PRT	ITA	ESP
ECU	GHA	CIV	CRI	**MLI**	BFA	SDN	NER	**TZA**	UGA	SEN	KEN
EGY	SYR	TUR	LBN	**MMR**	LAO	MDG	NIC	**UGA**	TZA	SEN	KEN
ESP	ITA	DEU	FRA	**MNG**	SDN	NGA	BOL	**UKR**	SRB	HRV	LVA
EST	LVA	LTU	DNK	**MOZ**	ZWE	MWI	TZA	**URY**	ARG	NZL	SEN
ETH	TZA	NIC	PAK	**MRT**	YEM	LBR	GIN	**USA**	DEU	FRA	GBR
FIN	SWE	AUT	EST	**MUS**	SLV	HND	GTM	**UZB**	IRN	ETH	KGZ
FRA	DEU	USA	ITA	**MWI**	TZA	UGA	ZWE	**VEN**	QAT	LBY	KWT
GAB	COG	AGO	GNQ	**MYS**	IDN	SGP	THA	**VNM**	IDN	LKA	TUN
GBR	USA	FRA	DEU	**NAM**	NOR	AUS	NZL	**YEM**	SDN	NER	PNG
GEO	ALB	ARM	CHL	**NER**	BFA	SDN	MLI	**ZAF**	EGY	BGR	GRC
GHA	CIV	CMR	LAO	**NGA**	COD	GIN	SLE	**ZMB**	ZWE	MWI	TZA
GIN	LBR	SLE	COD	**NIC**	HND	ETH	LAO	**ZWE**	MOZ	MWI	ZMB

Table S26. List of Countries and their 3 Most Similar Economies in Terms of Technology Specialization Patterns in 2014

Country	Similar country 1	Similar country 2	Similar country 3	Country	Similar country 1	Similar country 2	Similar country 3
ARE	ROU	BGR	MAR	**KAZ**	QAT	BLR	MAR
ARG	EGY	COL	MAR	**KEN**	MDA	SYR	CYP
ARM	CYP	GEO	TUN	**KOR**	HKG	TUR	UKR
AUS	GBR	ESP	CAN	**KWT**	PAN	MUS	BOL
AUT	DEU	ITA	ESP	**LBN**	IRN	URY	BGD
AZE	QAT	VEN	KAZ	**LKA**	LVA	IDN	SRB
BEL	PRT	NLD	CHE	**LTU**	EST	MAR	PHL
BGD	CUB	CRI	BHR	**LVA**	LKA	VNM	SRB
BGR	EGY	MAR	ROU	**MAR**	LTU	BGR	HRV
BHR	BGD	JOR	UZB	**MDA**	KEN	JOR	BLR
BIH	DZA	AZE	ECU	**MEX**	ZAF	ESP	POL
BLR	KAZ	IDN	LVA	**MUS**	KWT	OMN	TTO
BOL	GHA	TTO	UZB	**MYS**	IRL	FIN	NOR
BRA	AUS	GBR	ESP	**NGA**	JAM	UZB	ECU
BWA	CUB	GHA	JAM	**NLD**	NZL	DNK	BEL
CAN	AUS	ESP	RUS	**NOR**	DNK	AUS	FIN
CHE	FRA	ITA	DEU	**NZL**	AUS	ZAF	ESP
CHL	COL	PRT	THA	**OMN**	MUS	DZA	BHR
CHN	KOR	HKG	IND	**PAK**	KAZ	QAT	PER
COL	SVN	CHL	THA	**PAN**	KWT	JOR	NGA
CRI	CUB	BGD	ECU	**PER**	PHL	KAZ	PAK
CUB	BGD	CRI	BWA	**PHL**	LTU	EST	HRV
CYP	ARM	TUN	VEN	**POL**	MEX	ZAF	ESP
CZE	RUS	ZAF	POL	**PRK**	ARM	DZA	CRI
DEU	AUT	ITA	FRA	**PRT**	GRC	SVN	MEX
DNK	NOR	NZL	MEX	**QAT**	KAZ	PAK	MAR
DOM	DZA	PER	AZE	**ROU**	ARE	HRV	SVK
DZA	TUN	ECU	BIH	**RUS**	AUS	GBR	CAN
ECU	CUB	DZA	UZB	**SAU**	IND	MAR	LTU
EGY	BGR	ARG	MAR	**SGP**	PRT	IRL	MYS
ESP	AUS	ITA	ZAF	**SLV**	BWA	UGA	BGD
EST	LTU	PHL	EGY	**SRB**	LTU	LVA	EGY
FIN	NOR	SWE	CAN	**SVK**	SVN	GRC	UKR
FRA	GBR	ESP	DEU	**SVN**	GRC	COL	PRT
GBR	AUS	BRA	RUS	**SWE**	NZL	AUS	DEU
GEO	ARM	VEN	QAT	**SYR**	URY	AZE	BIH
GHA	BOL	BWA	CUB	**THA**	SVN	COL	CHL
GRC	PRT	SVN	MEX	**TTO**	BOL	UGA	GHA
HKG	KOR	MEX	GRC	**TUN**	DZA	IRN	ARM
HRV	ROU	SVN	MAR	**TUR**	ESP	MEX	ITA
HUN	CZE	PRT	MEX	**TZA**	UGA	KWT	MUS
IDN	MAR	LTU	PHL	**UGA**	TTO	BOL	PRK
IND	SGP	SAU	CAN	**UKR**	RUS	ZAF	GRC
IRL	DNK	NZL	MYS	**URY**	LBN	KAZ	CUB
IRN	VEN	TUN	KAZ	**USA**	ISR	GBR	CAN
ISR	USA	IRL	HKG	**UZB**	NGA	BGD	ECU
ITA	DEU	ESP	AUS	**VEN**	IRN	PER	KAZ
JAM	NGA	BWA	CUB	**VNM**	THA	LTU	LVA
JOR	BGD	BHR	CRI	**ZAF**	AUS	ESP	NZL
JPN	DEU	UKR	SVK				

Table S27. List of Countries and their 3 Most Similar Economies in Terms of Research Specialization Patterns in 2014

Country	Similar country 1	Similar country 2	Similar country 3	Country	Similar country 1	Similar country 2	Similar country 3	Country	Similar country 1	Similar country 2	Similar country 3
AFG	COD	TGO	AGO	**GNQ**	AGO	GIN	LBR	**NOR**	FIN	NZL	NLD
AGO	GIN	LBR	COD	**GRC**	ITA	PRT	ESP	**NPL**	ETH	UGA	TZA
ALB	PNG	MUS	RWA	**GTM**	JAM	LAO	COG	**NZL**	AUS	CAN	NLD
ARE	MYS	CYP	QAT	**HKG**	SGP	PRT	FIN	**OMN**	IRQ	KWT	DZA
ARG	HUN	MEX	CHL	**HND**	SLV	DOM	COD	**PAK**	THA	SAU	SRB
ARM	MDA	BLR	GEO	**HRV**	NGA	JOR	SRB	**PAN**	BFA	CRI	ETH
AUS	GBR	CAN	NZL	**HTI**	SLV	COD	TGO	**PER**	TZA	KEN	GHA
AUT	DEU	DNK	ESP	**HUN**	ARG	CZE	CHL	**PHL**	KEN	GHA	TZA
AZE	MDA	BHR	UZB	**IDN**	MYS	NGA	COL	**PNG**	RWA	NIC	GAB
BEL	NLD	SWE	DNK	**IND**	SAU	KOR	EGY	**POL**	CZE	SVN	SVK
BEN	MDG	MLI	CIV	**IRL**	NZL	NLD	DNK	**PRT**	SVN	GRC	TUN
BFA	SDN	MLI	PAN	**IRN**	SAU	EGY	IND	**PRY**	DOM	NIC	PNG
BGD	ETH	KEN	GHA	**IRQ**	OMN	DZA	LTU	**PSE**	IRQ	YEM	SDN
BGR	SRB	SVK	VNM	**ISR**	NLD	IRL	ITA	**QAT**	ARE	KWT	DZA
BHR	AZE	MDA	YEM	**ITA**	DEU	AUT	FRA	**ROU**	CHN	SRB	DZA
BIH	MKD	YEM	KAZ	**JAM**	GTM	NER	TTO	**RUS**	UKR	BGR	DZA
BLR	MDA	UKR	ARM	**JOR**	MYS	TUN	CYP	**RWA**	MDG	PNG	MOZ
BOL	PAN	BFA	CRI	**JPN**	KOR	IND	EGY	**SAU**	IND	IRN	EGY
BRA	ARG	TUR	MEX	**KAZ**	BLR	YEM	MNG	**SDN**	BFA	PAN	SEN
BWA	ZWE	MLI	COG	**KEN**	ETH	GHA	PHL	**SEN**	BFA	ZMB	MWI
CAN	AUS	GBR	USA	**KGZ**	ALB	MNG	NAM	**SGP**	HKG	ARE	CHN
CHE	DEU	AUT	NLD	**KHM**	MLI	CIV	MOZ	**SLE**	SWZ	MMR	AGO
CHL	MEX	ZAF	ARG	**KOR**	JPN	IND	CHN	**SLV**	HND	HTI	COD
CHN	DZA	KOR	SAU	**KWT**	OMN	QAT	JOR	**SRB**	SVN	SVK	SAU
CIV	KHM	MOZ	MLI	**LAO**	MDG	GAB	KHM	**SVK**	CZE	SRB	BGR
CMR	ETH	TZA	NPL	**LBN**	GRC	TUN	CYP	**SVN**	SRB	PRT	POL
COD	TGO	AFG	AGO	**LBR**	AGO	GIN	COD	**SWE**	NLD	DNK	GBR
COG	MLI	ZWE	GAB	**LBY**	YEM	TTO	MDA	**SWZ**	SLE	MMR	AGO
COL	IDN	NGA	CHL	**LKA**	TZA	ETH	GHA	**SYR**	BFA	SDN	ZWE
CRI	TZA	ETH	ECU	**LTU**	DZA	IRQ	OMN	**TGO**	COD	AFG	AGO
CUB	BFA	CMR	UGA	**LVA**	IRQ	DZA	PSE	**THA**	NGA	PAK	IND
CYP	ARE	JOR	HKG	**MAR**	DZA	PAK	BGR	**TJK**	NAM	UZB	ARM
CZE	POL	SVK	HUN	**MDA**	BLR	ARM	AZE	**TTO**	NER	RWA	JAM
DEU	CHE	FRA	AUT	**MDG**	GAB	BEN	MLI	**TUN**	PRT	VNM	IRN
DNK	NLD	SWE	BEL	**MEX**	CHL	ARG	SVN	**TUR**	EGY	IRN	GRC
DOM	HND	PRY	COD	**MKD**	BIH	PSE	CUB	**TZA**	UGA	ETH	GHA
DZA	CHN	IRQ	MYS	**MLI**	KHM	BFA	CIV	**UGA**	TZA	ETH	KEN
ECU	TZA	ETH	CRI	**MMR**	SLE	SWZ	AGO	**UKR**	RUS	DZA	BLR
EGY	SAU	IND	IRN	**MNG**	BWA	BOL	KAZ	**URY**	ETH	CMR	KEN
ESP	BEL	AUT	NZL	**MOZ**	KHM	CIV	GAB	**USA**	GBR	CAN	AUS
EST	ARG	FIN	CHL	**MRT**	AGO	GIN	GNQ	**UZB**	MNG	AZE	ARM
ETH	KEN	TZA	GHA	**MUS**	JAM	NAM	LAO	**VEN**	PER	URY	TZA
FIN	SWE	NOR	NZL	**MWI**	ZMB	ZWE	UGA	**VNM**	TUN	DZA	IDN
FRA	DEU	ITA	CHE	**MYS**	IDN	JOR	ARE	**YEM**	PSE	LBY	SDN
GAB	MDG	MOZ	CIV	**NAM**	PNG	LAO	NIC	**ZAF**	NZL	CHL	NOR
GBR	AUS	USA	CAN	**NER**	BEN	TTO	CIV	**ZMB**	ZWE	MWI	SEN
GEO	ARM	PSE	ZMB	**NGA**	GHA	IDN	BGD	**ZWE**	ZMB	MWI	COG
GHA	KEN	ETH	TZA	**NIC**	PNG	LAO	PRY				
GIN	AGO	LBR	COD	**NLD**	GBR	BEL	SWE				

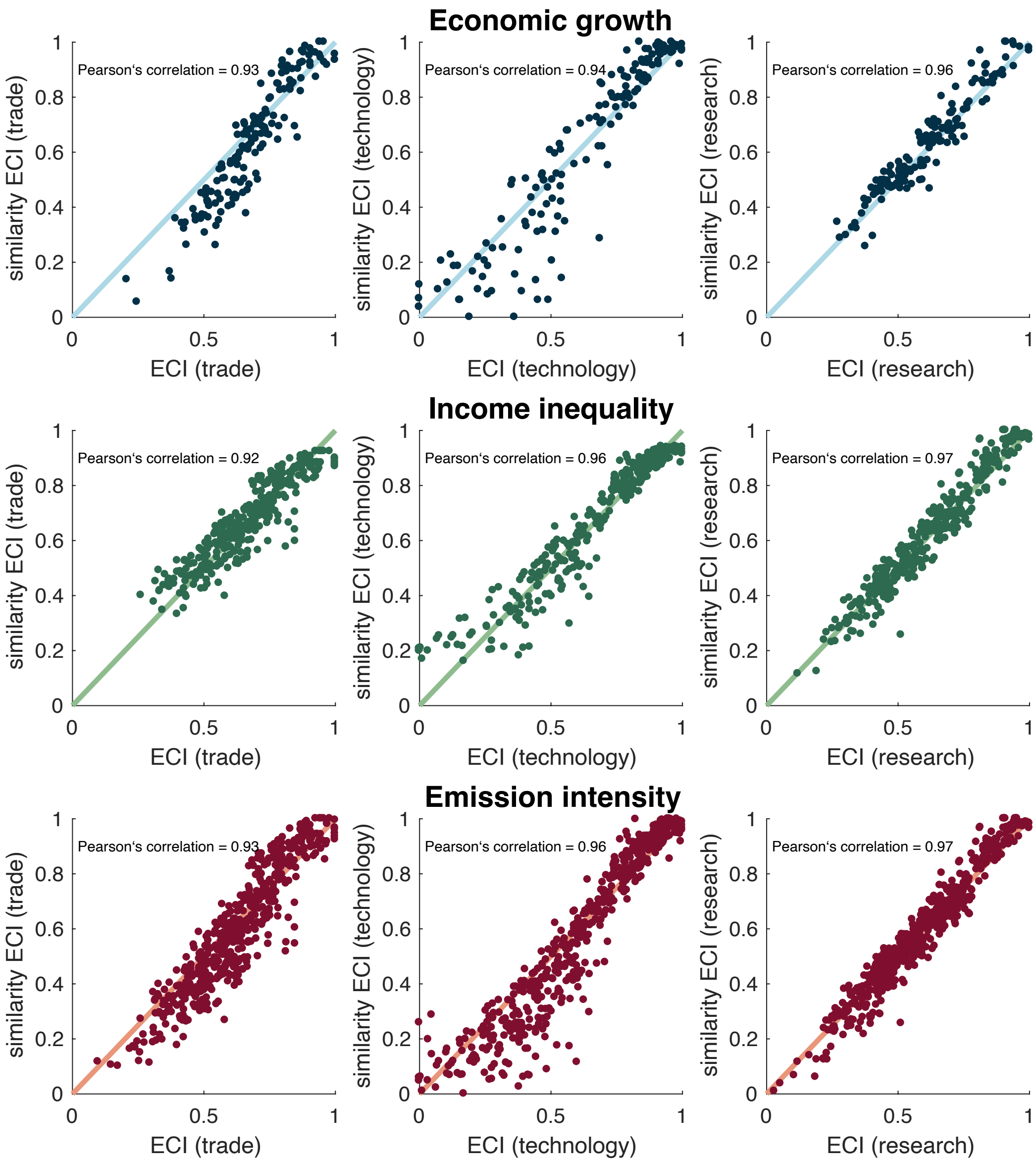

Figure S17. Correlations Between the Real ECI and the Similarity-based Metrics in the Economic Growth (top panel), Income Inequality (middle panel), and Emission intensity (bottom panel) Regression Analyses

7.2. Economic growth IV estimation results

The coefficients of the multidimensional ECI economic growth model remain significant, even when using the IV estimation approach (Table S28, column (2)). Moreover, they remain robust even after including the additional explanatory variables (Table S28, columns (3-7)), the multidimensional production intensity model (Table S28, columns (8-10)), the multidimensional HHI model (Table S19, columns (11-13)), the multidimensional Entropy model (Table S28, columns (14-16)), and the multidimensional Fitness model (Table S28, columns (17-19)).

Table S28. Economic Growth Regressions: Instrumental Variables Robustness Check

	Dependent variable:																		
	Annualized GDP pc growth (1999-09, 2009-19)																		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
ECI (trade), instrumented		16.709***	15.666***	12.544***	17.273***	13.688***	13.525***	16.767***	13.840***	13.455***	16.782***	11.429***	11.706***	16.934***	11.326***	11.633***	18.572***	12.033***	12.128***
		(3.007)	(3.023)	(2.983)	(2.869)	(2.909)	(2.888)	(2.983)	(3.011)	(2.932)	(3.794)	(3.606)	(3.583)	(3.810)	(3.629)	(3.604)	(4.717)	(4.482)	(4.462)
ECI (patents), instrumented		12.457***	12.267***	10.206***	12.448***	10.431***	10.471***	13.467***	10.620***	10.345***	11.926***	8.474***	8.788***	12.004***	8.418***	8.744***	12.688***	9.034**	9.109**
		(2.715)	(2.690)	(2.606)	(2.587)	(2.520)	(2.513)	(2.751)	(2.690)	(2.643)	(3.320)	(3.098)	(3.067)	(3.340)	(3.119)	(3.088)	(4.313)	(4.002)	(3.985)
ECI (trade), instrumented x ECI (patents), instrumented		-18.605***	-17.101***	-14.849***	-18.207***	-15.239***	-14.966***	-21.015***	-15.740***	-14.691***	-18.371***	-12.957***	-13.007***	-18.491***	-12.894***	-12.952***	-18.781***	-14.019**	-14.279**
		(4.096)	(4.126)	(3.949)	(3.905)	(3.844)	(3.805)	(4.275)	(4.565)	(4.192)	(4.706)	(4.382)	(4.376)	(4.711)	(4.392)	(4.385)	(6.362)	(5.919)	(5.861)
Log of initial population			-0.205**			0.062			0.077			0.090			0.094			0.046	
			(0.104)			(0.107)			(0.131)			(0.117)			(0.118)			(0.123)	
Log of initial human capital				2.885***		2.660***	2.536***		2.618***	2.582***		2.730***	2.555***		2.737***	2.554***		2.670***	2.585***
				(0.651)		(0.672)	(0.635)		(0.704)	(0.700)		(0.678)	(0.638)		(0.679)	(0.638)		(0.684)	(0.644)
Log of natural resource exports per capita					0.757***	0.678***	0.641***		0.684***	0.643***		0.730***	0.661***		0.739***	0.666***		0.721***	0.697***
					(0.191)	(0.195)	(0.184)		(0.198)	(0.185)		(0.211)	(0.191)		(0.213)	(0.192)		(0.213)	(0.203)
Intensity (technology)								2.292*	0.321	-0.204									
								(1.263)	(1.564)	(1.282)									
HHI (trade)											0.340	-1.055	-0.721						
											(1.169)	(1.176)	(1.092)						
HHI (technology)											-0.718	-0.625	-0.707						
											(1.003)	(0.919)	(0.911)						
Entropy (trade)														-0.396	1.046	0.711			
														(1.096)	(1.114)	(1.030)			
Entropy (technology)														0.703	0.586	0.680			
														(1.009)	(0.925)	(0.917)			
Fitness (trade)																	-1.290	1.150	0.881
																	(3.193)	(3.055)	(2.963)
Fitness (technology)																	2.075	0.898	0.756
																	(4.673)	(4.297)	(4.268)
Fitness (trade) x Fitness (technology)																	-2.344	-0.358	0.168
																	(5.599)	(5.327)	(5.126)
Log of initial GDP per capita	-1.147***	-1.643***	-1.895***	-2.048***	-2.827***	-3.001***	-3.002***	-1.967***	-3.031***	-2.983***	-1.691***	-3.017***	-3.019***	-1.697***	-3.020***	-3.021***	-1.774***	-3.050***	-3.067***
	(0.160)	(0.183)	(0.222)	(0.195)	(0.346)	(0.333)	(0.332)	(0.255)	(0.366)	(0.356)	(0.199)	(0.334)	(0.334)	(0.200)	(0.334)	(0.334)	(0.213)	(0.350)	(0.346)
Observations	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152	152
R^2	0.256	0.437	0.451	0.504	0.492	0.544	0.542	0.449	0.544	0.543	0.439	0.547	0.545	0.439	0.548	0.545	0.445	0.545	0.545
Adjusted R^2	0.246	0.417	0.429	0.483	0.471	0.518	0.520	0.426	0.515	0.517	0.412	0.515	0.517	0.412	0.515	0.517	0.414	0.509	0.512

Notes: Each regression includes period fixed effects. Standard errors in brackets. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

7.3. Income inequality IV estimation results

The coefficients of the multidimensional ECI income inequality model remain significant, even when using the IV estimation approach (Table S29, column (2)). Moreover, they remain robust even after including the additional explanatory variables (Table S29, columns (3-7)), and the multidimensional Fitness model (Table S29, columns (17-19)). Some of the coefficients of the multidimensional ECI model lose significance when we add solely the variables included in the multidimensional production intensity model (Table S29, column (8)), the multidimensional HHI model (Table S29, column (11)), and the multidimensional Entropy model (Table S29, column (14)), but regain significance when we also add the additional explanatory variables to the respective specifications (Table S29, columns (9-10) for production intensity, (12-13) for the HHI, and (15-16) for Entropy). This signifies the robustness of the multidimensional ECI income inequality model even when using the IV approach.

Table S29. Income Inequality Regressions: Instrumental Variables Robustness Check

	Dependent variable:																		
	Gini coefficient (1996-99, 2000-03, 2004-07, 2008-11, 2012-15)																		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
ECI (trade), instrumented		-21.316***	-21.230***	-15.948***	-23.207***	-18.150***	-18.111***	-14.915***	-16.518***	-17.899***	-17.470***	-17.507***	-17.496***	-17.060***	-17.153***	-17.173***	-22.550***	-10.981***	-11.008***
		(2.530)	(2.171)	(2.470)	(2.508)	(2.289)	(2.231)	(2.549)	(2.498)	(2.488)	(2.752)	(2.512)	(2.509)	(2.780)	(2.545)	(2.542)	(3.138)	(2.900)	(2.906)
ECI (technology), instrumented		-2.999**	-10.523***	-3.777***	-3.464**	-9.855***	-9.870***	-0.546	-9.460***	-8.947***	0.045	-8.148***	-8.383***	0.159	-7.816***	-8.125***	-9.738**	-6.569*	-6.571*
		(1.458)	(1.433)	(1.361)	(1.426)	(1.416)	(1.402)	(1.410)	(1.723)	(1.737)	(1.990)	(1.961)	(1.896)	(2.032)	(1.990)	(1.924)	(4.013)	(3.456)	(3.464)
Log of population			1.740***			1.479***	1.484***		1.357***	1.221***		1.393***	1.441***		1.365***	1.427***		1.525***	1.623***
			(0.161)			(0.180)	(0.168)		(0.203)	(0.200)		(0.205)	(0.179)		(0.206)	(0.178)		(0.206)	(0.196)
Log of human capital				-9.202***		-5.359***	-5.368***		-5.541***	-5.267***		-5.268***	-5.309***		-5.288***	-5.336***		-5.356***	-5.487***
				(1.286)		(1.241)	(1.234)		(1.288)	(1.301)		(1.251)	(1.246)		(1.250)	(1.247)		(1.220)	(1.220)
Log of natural resource exports					-1.495***	-0.026			1.233***			-0.177			-0.230			-0.531	
					(0.356)	(0.335)			(0.406)			(0.371)			(0.374)			(0.347)	
Intensity (trade)								-17.030***	-16.201***	-10.618***									
								(2.580)	(3.091)	(2.518)									
Intensity (technology)								-8.092***	2.271	1.568									
								(2.273)	(2.410)	(2.430)									
Intensity (research)								-3.272	-1.517	-1.987									
								(2.717)	(2.570)	(2.599)									
HHI (trade)											7.274***	1.852	1.429						
											(2.063)	(2.076)	(1.873)						
HHI (technology)											2.992	1.646	1.613						
											(1.985)	(1.706)	(1.703)						
Entropy (trade)														-7.063***	-2.300	-1.766			
														(1.926)	(1.954)	(1.749)			
Entropy (technology)														-2.952	-1.773	-1.738			
														(1.999)	(1.719)	(1.716)			
Fitness (trade)																	-6.338***	-4.902***	-4.347***
																	(1.423)	(1.281)	(1.231)
Fitness (technology)																	0.140	-5.382	-5.436
																	(3.968)	(3.496)	(3.503)
Fitness (trade) x Fitness (technology)																	8.171***	3.937***	3.494**
																	(1.584)	(1.450)	(1.423)
Log of GDP per capita	-10.019	-9.449*	2.559	4.271	-8.444	8.766*	8.796*	-11.352**	8.577*	7.722	-6.842	9.343*	9.548**	-6.377	9.537*	9.775**	-5.127	8.218*	8.856*
	(6.455)	(5.292)	(4.677)	(5.284)	(5.167)	(4.795)	(4.772)	(4.786)	(5.030)	(5.087)	(5.339)	(4.877)	(4.852)	(5.358)	(4.884)	(4.864)	(5.153)	(4.677)	(4.668)
Log of GDP per capita, squared	0.300	0.424	-0.071	-0.221	0.503*	-0.370	-0.374	0.808***	-0.298	-0.214	0.255	-0.403	-0.423*	0.229	-0.413	-0.438*	0.163	-0.339	-0.406*
	(0.333)	(0.273)	(0.239)	(0.269)	(0.267)	(0.247)	(0.242)	(0.248)	(0.263)	(0.265)	(0.276)	(0.251)	(0.247)	(0.277)	(0.251)	(0.248)	(0.266)	(0.241)	(0.238)
Observations	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332	332
R^2	0.346	0.570	0.684	0.629	0.592	0.702	0.702	0.662	0.726	0.718	0.589	0.703	0.703	0.590	0.704	0.704	0.611	0.720	0.718
Adjusted R^2	0.334	0.559	0.675	0.619	0.581	0.692	0.693	0.650	0.714	0.706	0.576	0.691	0.692	0.577	0.692	0.693	0.598	0.708	0.707

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

7.4. Emission intensity IV estimation results

The main variables of the multidimensional ECI emission intensity model remain significant (the three-way term), even when using the IV estimation approach (Table S30, column (2)). Moreover, the model is robust even after including the additional explanatory variables (Table S30, columns (3-6)), the multidimensional HHI model (Table S30, columns (9-10)), the multidimensional Entropy model (Table S30, columns (11-12)), and the multidimensional Fitness model (Table S30, columns (13-14)). The multidimensional ECI model loses significance when we add solely the variables included in the multidimensional production intensity model (Table S30, column (7)), but regain significance when we also add the log of population and the log of human capital to the respective specifications (Table S30, column (8)), as was the case with the original robustness check. This signifies the robustness of the multidimensional ECI emission intensity model even when using the IV approach.

Table S30. Emission Intensity Regressions: Instrumental Variables Robustness Check

	Dependent variable:													
	GHG emissions per GDP (1996-99, 2000-03, 2004-07, 2008-11, 2012-15, 2016-18)													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ECI (trade), instrumented		-2.031	-2.051	-4.329**	-1.169	-3.793**	-1.132	-2.836*	0.635	-2.300	0.817	-2.174	1.606	-1.313
		(1.773)	(1.773)	(1.745)	(1.717)	(1.656)	(1.784)	(1.616)	(1.736)	(1.679)	(1.730)	(1.682)	(1.728)	(1.639)
ECI (technology), instrumented		-2.316	-2.538*	-3.290**	-1.536	-4.027***	-1.070	-2.505*	-2.501*	-3.879***	-2.439*	-3.817***	-0.952	-3.166**
		(1.426)	(1.448)	(1.382)	(1.382)	(1.335)	(1.490)	(1.332)	(1.363)	(1.318)	(1.357)	(1.317)	(1.361)	(1.281)
ECI (research), instrumented		-2.511	-2.744	-3.820**	-1.871	-4.859***	-1.438	-3.878**	-2.913*	-4.753***	-2.936*	-4.730***	-2.155	-4.934***
		(1.812)	(1.831)	(1.757)	(1.752)	(1.686)	(1.808)	(1.632)	(1.733)	(1.664)	(1.725)	(1.663)	(1.709)	(1.611)
ECI (trade), instrumented x ECI (technology), instrumented		3.622	3.765	5.743**	2.702	5.958***	0.942	3.097	2.433	5.121**	2.306	5.016**	1.639	5.487**
		(2.411)	(2.417)	(2.346)	(2.332)	(2.228)	(2.515)	(2.265)	(2.310)	(2.209)	(2.301)	(2.209)	(2.297)	(2.162)
ECI (trade), instrumented x ECI (research), instrumented		4.154	4.388	6.904**	3.507	8.181**	1.773	5.549*	3.404	7.305**	3.408	7.248**	3.228	7.953***
		(3.445)	(3.456)	(3.346)	(3.328)	(3.177)	(3.433)	(3.070)	(3.294)	(3.144)	(3.280)	(3.141)	(3.245)	(3.038)
ECI (research), instrumented x ECI (technology), instrumented		5.564**	5.950**	6.805***	4.523*	8.399***	2.989	5.299**	7.572***	9.060***	7.607***	9.037***	6.176***	10.139***
		(2.496)	(2.534)	(2.412)	(2.415)	(2.323)	(2.536)	(2.266)	(2.402)	(2.299)	(2.391)	(2.296)	(2.352)	(2.239)
ECI (trade), instrumented x ECI (technology), instrumented x ECI (research), instrumented		-8.571**	-9.024**	-11.386***	-7.487*	-13.648***	-3.128	-7.685**	-9.381**	-13.392***	-9.380**	-13.313***	-8.245**	-15.024***
		(4.289)	(4.320)	(4.155)	(4.144)	(3.966)	(4.359)	(3.885)	(4.101)	(3.914)	(4.083)	(3.910)	(4.044)	(3.812)
Log of population			0.016			0.113***		0.119***		0.082***		0.080***		0.138***
			(0.018)			(0.019)		(0.023)		(0.020)		(0.021)		(0.019)
Log of human capital				0.698***		0.813***		0.736***		0.765***		0.754***		0.813***
				(0.109)		(0.109)		(0.106)		(0.108)		(0.109)		(0.105)
Log of natural resource exports per capital					0.193***	0.234***		0.363***		0.178***		0.173***		0.160***
					(0.031)	(0.032)		(0.038)		(0.034)		(0.035)		(0.033)
Intensity (trade)							-3.237***	-6.866***						
							(1.074)	(0.999)						
Intensity (technology)							-4.412***	-5.126***						
							(1.356)	(1.237)						
Intensity (research)							-2.388***	-3.014***						
							(0.884)	(0.781)						
Intensity (trade) x Intensity (technology)							6.025***	8.247***						
							(1.720)	(1.539)						
Intensity (trade) x Intensity (research)							11.598***	14.042***						
							(2.370)	(2.133)						
Intensity (research) x Intensity (technology)							6.863***	7.645***						
							(1.759)	(1.565)						
Intensity (trade) x Intensity (technology) x Intensity (research)							-15.817***	-18.262***						
							(2.619)	(2.337)						
HHI (trade)									1.352***	0.785***				
									(0.191)	(0.204)				
Entropy (trade)											-1.322***	-0.771***		
											(0.178)	(0.193)		
Fitness (trade)													-2.144***	-1.575***
													(0.278)	(0.281)
Fitness (technology)													-0.532*	-1.172***
													(0.312)	(0.306)
Log of initial GDP per capita	-0.287***	-0.213***	-0.192***	-0.308***	-0.539***	-0.574***	-0.434***	-0.637***	-0.344***	-0.588***	-0.355***	-0.588***	-0.388***	-0.540***
	(0.022)	(0.032)	(0.040)	(0.034)	(0.061)	(0.058)	(0.070)	(0.064)	(0.036)	(0.057)	(0.036)	(0.057)	(0.038)	(0.056)
Observations	529	529	529	529	529	529	529	529	529	529	529	529	529	529
R^2	0.240	0.289	0.290	0.342	0.339	0.418	0.367	0.512	0.352	0.435	0.358	0.436	0.373	0.471
Adjusted R^2	0.231	0.271	0.271	0.324	0.321	0.400	0.342	0.490	0.334	0.416	0.340	0.417	0.354	0.453

Notes: Each regression includes period fixed effects. Standard errors in brackets. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

8. What about services?

Services are an integral part of an economy, and the service sector is becoming a rising share of international trade and within-country employment. Due to this, there have been several studies which produced attempts to incorporate the service dimension into the economic complexity framework. Nevertheless, the studies have found that the service dimension only moderately improves the complexity rankings and does not lead to significant improvement in macroeconomic outcomes regressions[13].

To explore whether the service dimension is significant in explaining international variations in economic growth, income inequality and emission intensity, we collect service trade data from OECD's Input Output Database. This database distinguishes 20 service sectors across 61 countries. We use these data to estimate the service dimension ECI, and then use it as an independent variable in individual regression analyses which are defined in the same way as the ones described in Section 3.1.

The results are given in Table S31-S33, respectively for the economic growth, income inequality, and emission intensity regressions. In each case, the service ECI is not a significant or robust explanatory variable. Thus, we assert that services data still does not provide enough information to be included in the multidimensional economic complexity analysis.

Table S31. ECI (services) Economic Growth Regressions

	Dependent variable:										
	Annualized GDP pc growth (1999-09, 2009-19)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ECI (services)		0.486	0.994	0.320	0.531	0.400	0.726	0.426	0.430	2.956***	
		(0.593)	(0.620)	(0.526)	(0.569)	(0.565)	(0.634)	(0.600)	(0.601)	(0.866)	
ECI (services), instrumented											0.410
											(0.545)
Log of initial population			-0.234**			-0.016					
			(0.100)			(0.105)					
Log of natural resource exports per capita				3.990***		3.583***					
				(0.718)		(0.734)					
Log of initial human capital					0.673***	0.437*					
					(0.207)	(0.222)					
Intensity (services)							-2.649				
							(2.472)				
HHI (services)								-0.755			
								(1.015)			
Entropy (services)									0.665		
									(1.006)		
Fitness (services)										-3.134***	
										(0.837)	
Log of initial GDP per capita	-1.484***	-1.579***	-1.906***	-2.419***	-2.491***	-2.948***	-0.874	-1.641***	-1.634***	-1.693***	-1.565***
	(0.182)	(0.216)	(0.253)	(0.244)	(0.348)	(0.331)	(0.692)	(0.232)	(0.232)	(0.206)	(0.212)
Observations	113	113	113	113	113	113	113	113	113	113	113
R^2	0.378	0.382	0.412	0.519	0.437	0.543	0.388	0.385	0.384	0.453	0.381
Adjusted R^2	0.367	0.365	0.390	0.501	0.416	0.517	0.366	0.362	0.361	0.433	0.364

Notes: Each regression includes period fixed effects. Standard errors in brackets. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

Table S32. ECI (services) Income Inequality Regressions

	Dependent variable:										
	Gini coefficient (1996-99, 2000-03, 2004-07, 2008-11, 2012-15)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ECI (services)		-1.035	-2.583**	0.367	-1.062	-0.826	-0.233	-0.135	-0.164	-1.879	
		(1.284)	(1.267)	(1.191)	(1.258)	(1.223)	(1.162)	(1.225)	(1.223)	(1.880)	
ECI (services), instrumented											-1.337
											(1.175)
Log of population			0.907***			0.587***					
			(0.182)			(0.203)					
Log of human capital				-10.535***		-9.147***					
				(1.478)		(1.492)					
Log of natural resource exports					-1.362***	-0.252					
					(0.396)	(0.427)					
Intensity (services)							-21.851***				
							(2.816)				
HHI (services)								16.783***			
								(3.007)			
Entropy (services)									-15.011***		
									(2.666)		
Fitness (services)										1.029	
										(1.673)	
Log of GDP per capita	4.707	1.770	7.096	20.899***	3.184	22.091***	1.890	5.691	5.810	1.085	1.271
	(7.380)	(8.235)	(7.948)	(7.998)	(8.077)	(7.835)	(7.422)	(7.821)	(7.815)	(8.320)	(7.970)
Log of GDP per capita, squared	-0.494	-0.333	-0.544	-1.209***	-0.304	-1.225***	-0.102	-0.544	-0.549	-0.295	-0.304
	(0.378)	(0.428)	(0.411)	(0.410)	(0.419)	(0.403)	(0.387)	(0.406)	(0.406)	(0.433)	(0.413)
Observations	264	264	264	264	264	264	264	264	264	264	264
R^2	0.462	0.463	0.511	0.553	0.487	0.576	0.566	0.522	0.523	0.464	0.465
Adjusted R^2	0.450	0.449	0.496	0.539	0.471	0.559	0.552	0.507	0.508	0.447	0.450

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

Table S33. ECI (services) Emission intensity Regressions

	Dependent variable:										
	GHG emissions per GDP (1996-99, 2000-03, 2004-07, 2008-11, 2012-15, 2016-18)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ECI (services)		-0.080	-0.196*	-0.116	-0.066	-0.336***	0.070	-0.020	-0.023	-0.096	
		(0.102)	(0.106)	(0.097)	(0.102)	(0.097)	(0.111)	(0.102)	(0.102)	(0.141)	
ECI (services), instrumented											-0.105
											(0.095)
Log of initial population			0.053***			0.114***					
			(0.016)			(0.017)					
Log of initial human capital				0.832***		0.934***					
				(0.134)		(0.128)					
Log of natural resource exports per capita					0.075**	0.170***					
					(0.036)	(0.038)					
Intensity (services)							-1.239***				
							(0.395)				
HHI (services)								0.836***			
								(0.252)			
Entropy (services)									-0.724***		
									(0.225)		
Fitness (services)										0.022	
										(0.138)	
Log of initial GDP per capita	-0.328***	-0.312***	-0.239***	-0.498***	-0.423***	-0.617***	0.021	-0.328***	-0.326***	-0.311***	-0.305***
	(0.029)	(0.036)	(0.042)	(0.045)	(0.064)	(0.062)	(0.112)	(0.036)	(0.036)	(0.037)	(0.036)
Observations	342	342	342	342	342	342	342	342	342	342	342
R^2	0.273	0.275	0.299	0.350	0.284	0.432	0.296	0.298	0.297	0.275	0.276
Adjusted R^2	0.260	0.260	0.282	0.335	0.267	0.415	0.279	0.281	0.280	0.257	0.261

Notes: Each regression includes period fixed effects. Standard errors in brackets. *p<0.1, **p<0.05, ***p<0.01.

References

1. Albeaik, S., Kaltenberg, M., Alsaleh, M. & Hidalgo, C. A. Improving the economic complexity index. *arXiv preprint arXiv:1707.05826* (2017).
2. Hausmann, R., Hidalgo, C. A., Bustos, S., Coscia, M. & Simoes, A. *The atlas of economic complexity: Mapping paths to prosperity*. (Mit Press, 2014).
3. Morrison, G. *et al.* On economic complexity and the fitness of nations. *Scientific Reports* **7**, 1–11 (2017).
4. Simoes, A. J. G. & Hidalgo, C. A. The economic complexity observatory: An analytical tool for understanding the dynamics of economic development. in *Workshops at the twenty-fifth AAAI conference on artificial intelligence* (2011).
5. SJR - About Us. https://www.scimagojr.com/aboutus.php.
6. Barro, R. J. & Lee, J. W. A new data set of educational attainment in the world, 1950–2010. *Journal of development economics* **104**, 184–198 (2013).
7. Sachs, J. D. & Warner, A. Natural resource abundance and economic growth. (1995).
8. Solow, R. M. A contribution to the theory of economic growth. *The quarterly journal of economics* **70**, 65–94 (1956).
9. Stojkoski, V. *et al.* Income inequality and mobility in geometric Brownian motion with stochastic resetting: theoretical results and empirical evidence of non-ergodicity. *arXiv preprint arXiv:2109.01822* (2021).
10. Kuznets, S. *Economic growth and income inequality*. (Routledge, 2019).
11. Hartmann, D., Guevara, M. R., Jara-Figueroa, C., Aristarán, M. & Hidalgo, C. A. Linking economic complexity, institutions, and income inequality. *World development* **93**, 75–93 (2017).

12. Romero, J. P. & Gramkow, C. Economic complexity and greenhouse gas emissions. *World Development* **139**, 105317 (2021).

13. Stojkoski, V., Utkovski, Z. & Kocarev, L. The impact of services on economic complexity: Service sophistication as route for economic growth. *PloS one* **11**, e0161633 (2016).