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Multidimensional economic complexity and inclusive green growth

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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.

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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 the 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 multiple 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 to estimate the implicit presence of multiple factors. These estimates have been validated by their ability to explain international variations in economic growth[15–24], income inequality[25–27], and emissions[28–31]. The reason why complexity metrics work is that they capture information about productive structures that escapes simple aggregate metrics, such as GDP or market concentration indexes. Unlike these metrics, which aggregate values regardless of the activities involved, economic complexity metrics capture information about the sophistication of activities that is implicit in their geographic distribution. For instance, according to a market concentration index (such as the Herfindahl–Hirschman index or information entropy), a country that exports 80% bananas and 20% cars is the same as a country that exports 80% cars and 20% bananas. Economic complexity metrics break this symmetry by incorporating information about the sophistication of each activity that is implicit in spatial patterns of specialization.

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 to 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 on 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?

Consider the exports of X-rays and iron ore. The contribution of these exports to GDP is related 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 from 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 sophistication 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 non-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.

Results

We use the Economic Complexity Index (ECI) method (see the "Methods" section) 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

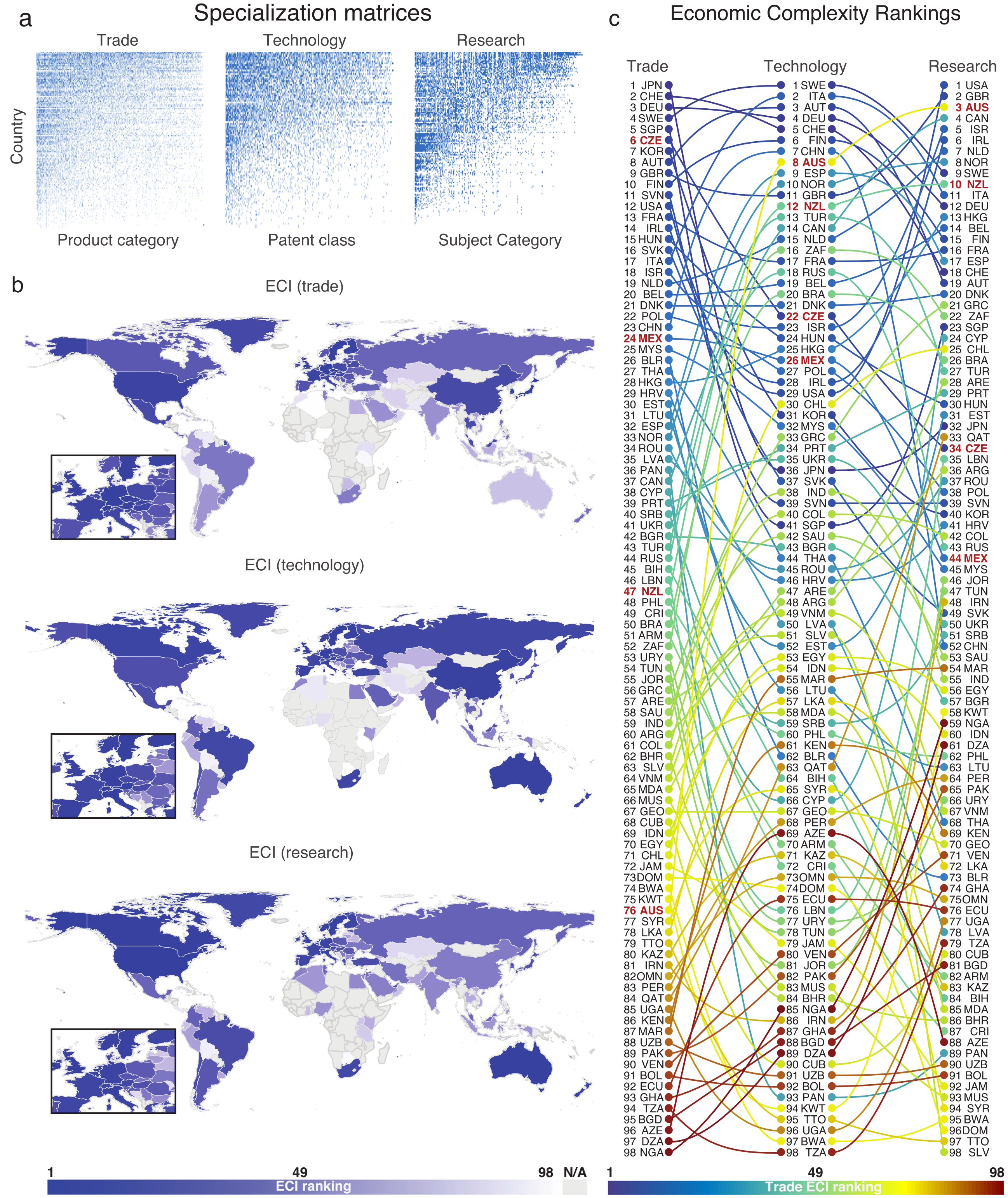

Fig. 1 Multidimensional economic complexity. a Specialization matrices of countries considering exports by product, patents by technology, and publications by subject category. **b** Maps showing the rankings of ECI (trade), ECI (technology), and ECI (research). **c** Comparison between the ECI rankings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

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 Note 1 for a detailed description of the data.

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 the

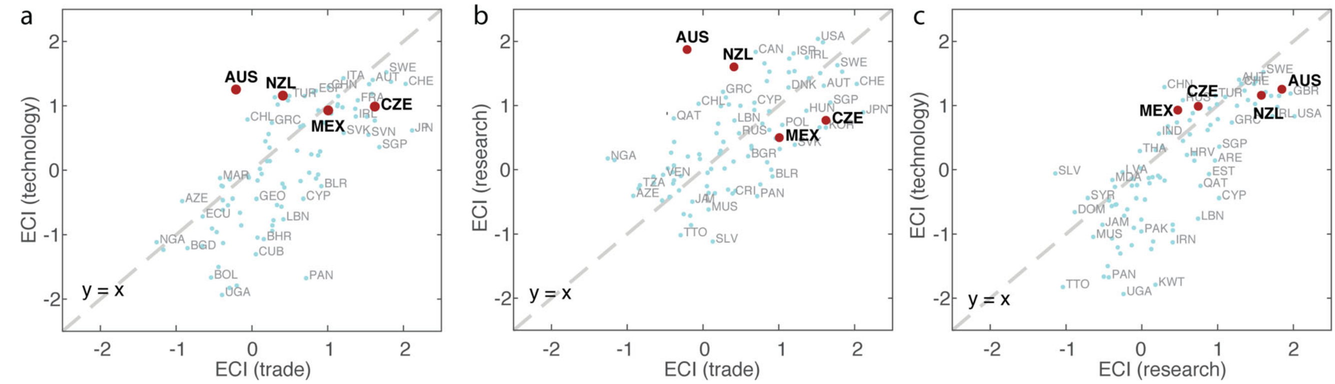

Fig. 2 Comparison between trade, technology, and complexity ECI using 2014 data. **a** Scatterplot for the relationships between ECI (trade) and ECI (technology) ($R^2 = 0.51$, p-value $< 10^{-12}$), **b** ECI (trade) and ECI (research) ($R^2 = 0.44$, p-value $< 10^{-12}$), and **c** ECI (research) and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

share of its exports, patent applications, or the number of papers are larger than the share of that activity in the world output ($M_{cp} = 1$).

Figure 1b, c compare the three ECI rankings, and Fig. 2 compares the ECI values. The figures show that, while the ECI 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 (see also Supplementary Note 1).

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 7000 km away from their capitals. Thus, trade data miss key aspects of the complexity of these economies that are recovered using data on patents and research.

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

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

where y_{ct} is the dependent variable for country c in year t (economic growth, income inequality, emission intensity), $f\left(ECI^d_{ct}\right)$ 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 Note 1 for more information about the data and Supplementary Note 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 adjusted-R^2 and validated by a Wald F-test). The baseline models are defined in each respective section. Second, in the multidimensional model, all included complexity coefficients (individual and interaction terms) must be statistically significant, considering clustered standard errors. 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 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 the number of research documents per capita). We also try alternative definitions of complexity[40,46,47] and check whether the results hold for noncomplexity metrics of economic structure, such as measures of market concentration (Shannon information entropy and the Herfindahl–Hirschman index (HHI)) (see Supplementary Note 3). Unfortunately, because of limited time series data, our panels do not allow us to control for country-fixed effects in the growth and inequality model (e.g., the growth model consists of only two time periods). We do add country-fixed effects as a robustness check to the emission intensity model. We call the model with all significant and robust explanatory variables the "final model." This is the best model for explaining variations in economic growth, income inequality, and emission intensity.

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
		(1.172)			(1.405)	(1.274)		(1.469)	(2.955)	(3.863)		(10.986)
ECI (technology)			2.577***		1.351		3.323***	2.098**	9.099***		5.483**	12.756
			(0.745)		(0.893)		(0.765)	(0.928)	(2.497)		(2.647)	(10.129)
ECI (research)				1.184		−0.890	−2.541	−2.563		6.318	0.380	−5.469
				(1.724)		(1.568)	(1.617)	(1.607)		(4.847)	(4.282)	(12.688)
ECI (trade) × ECI (technology)									−12.260***			−22.692
									(3.656)			(15.524)
ECI (trade) × ECI (research)										−10.111*		−3.392
										(5.831)		(20.029)
ECI (research) × ECI (technology)											−3.856	0.435
											(4.556)	(16.737)
ECI (trade) × ECI (research) × ECI (technology)												9.443
												(25.142)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Log of population F-statistic		34.15***	22.29***	0.88					14.87***			
Log of human capital F-statistic		7.81***	5.13**	0.50					5.06***			
Log of natural resource exports per capita F-statistic		32.51***	15.08***	1.46					12.52***			
Log of production intensity F-statistic		23.09***	3.49*	0.49					27.50***			
HHI F-statistic		8.96***	5.05**	0.15					13.70***			
Entropy F-statistic		8.61***	4.91**	0.48					13.60***			
Log of Fitness F-statistic		6.79**	0.34	2.31					9.10**			
i-ECI F-statistic		8.94***	4.26**	0.01					21.80***			
Instrumental variables model F-statistic		19.50***	8.2***	0.48					20.00***			
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

Each regression includes period-fixed effects. Clustered 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 Supplementary Tables 1–3. The F-statistics for the model in column 9 were estimated using models estimated in Supplementary Tables 4–9.

Second, we also use an instrumental variable approach where complexity values are replaced by the average complexities of three similarly specialized non-neighboring countries. This is designed to address the possibility that the relationship 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 non-neighboring 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[15–24]. 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[15–17,23] 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 Supplementary Note 4). This captures Solow's idea of economic convergence[48] (the baseline model is presented in column 1 of Table 1, adjusted $R^2 = 0.25$).

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, adjusted $R^2 = 0.34$) and that technological complexity has a similar explanatory power (column 3, adjusted $R^2 = 0.33$). Research complexity, however, is not significantly related to future economic growth (column 4, adjusted $R^2 = 0.24$). We also find that technological complexity significantly enhances the ability of trade complexity to explain future economic growth (columns 5–8 of Table 1). This effect increases when we interact trade and technology complexity (columns 9–12 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 (adjusted $R^2 = 0.41$). 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 Supplementary Note 4).

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 4-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[49] (Gini ~ GDP per capita, its square, and time-fixed effects, see Supplementary Note 5).

We find that trade and technology ECIs are significant and negative predictors of income inequality with, respectively, adjusted $R^2 = 0.54$ (column 2 of Table 2) and $R^2 = 0.48$ (column 3 of Table 2). Trade and technology ECIs also outperform measures of concentration (entropy and Herfindahl–Hirschman, see Supplementary Note 5). Moreover, they provide an important improvement over the baseline model, which has an adjusted $R^2 = 0.33$ (column 1 of Table 2). Research ECI, however, is only a minor predictor of income inequality, providing little improvement to the explanatory power (adjusted $R^2 = 0.36$, 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 in column 5 of Table 2 (adjusted $R^2 = 0.56$). 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 Supplementary Note 5).

Emission intensity. Trade complexity is known to be associated with lower greenhouse gas emissions per unit of output[30] and better environmental performance[50,51]. 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 modeling 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 2016–2019. The baseline model includes the logs of the GDP per capita (constant PPP dollars), population, human capital, and natural resource exports, as well as time-fixed effects (see Supplementary Note 6).

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 Supplementary Note 6). Nevertheless, the best multidimensional complexity model is robust and includes the three-way interaction between trade, technology, and research complexity (adjusted $R^2 = 0.40$, column 12 of Table 3, Fig. 3c). This implies that countries that score high in all dimensions (e.g., Sweden, France, Austria) have the lowest emission intensities. The final model also includes all of the variables from the baseline model: measures of population size, human capital, natural resource exports per capita, and production intensity (the model in column 11). This means that the measures of complexity explain variations in emission intensities that go beyond the variation accounted for by the natural resource export intensity of an economy.

Finally, we run an alternative model with embodied emission intensities as the dependent variable (see Supplementary Note 7). Embodied emissions add territorial and imported emissions and subtract exported emissions[52,53]. Thus, they are an indicator of the emissions related to local consumption. We expect embodied emissions to behave differently than emission intensities because they are a consumption indicator. Complexity metrics are estimators of productive capacities, and thus, we expect them to correlate with the characteristics of an economy's productive sectors. We should not expect, however, ECI to explain consumption patterns, especially those of imported products. As expected, we do not find a robust relationship between complexity and embodied emission intensity (the correlation is positive but not robust).

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 and income inequality and almost 40% of the variations in emission intensity (Fig. 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 (Fig. 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 (Fig. 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 helps

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
		(5.285)			(5.495)	(5.328)		(5.565)	(9.547)	(9.295)		(26.796)
ECI (technology)			−11.211***		−5.269**		−12.317***	−6.216**	1.208		−3.964	11.923
			(2.715)		(2.685)		(2.582)	(2.528)	(6.101)		(5.742)	(25.183)
ECI (research)				−7.654		−1.336	3.400	2.783		0.649	16.132	21.084
				(5.310)		(4.017)	(3.665)	(3.386)		(8.981)	(10.310)	(31.233)
ECI (trade) × ECI (technology)									−11.449			−8.570
									(10.851)			(41.156)
ECI (trade) × ECI (research)										−2.990		−0.339
										(13.710)		(54.046)
ECI (research) × ECI (technology)											−16.026	−31.788
											(12.629)	(42.894)
ECI (trade) × ECI (research) × ECI (technology)												12.933
												(69.991)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Log of population F-statistic		30.10***	38.50***	4.10**	59.00***							
Log of human capital F-statistic		16.50***	19.40***	1.90	27.10***							
Log of natural resource exports per capita F-statistic		31.30***	18.00***	2.50	37.10***							
Log of production intensity F-statistic		19.70***	2.10	0.33	6.40**							
HHI F-statistic		10.40***	8.90***	1.60	5.70*							
Entropy F-statistic		9.80***	8.90***	1.50	11.10**							
Log of Fitness F-statistic		5.50**	9.10***	0.75	10.90***							
i-ECI F-statistic		16.00***	7.20***	0.64	23.50***							
Instrumental variables model		18.90***	11.70***	2.50	44.10***							
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

Each regression includes period-fixed effects. Clustered 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 Supplementary Tables 10–12. The F-statistics for the model in column 9 were estimated using models estimated in Supplementary Tables 13–18.

Table 3 Multidimensional complexity and emission intensity.

	Dependent variable: **GHG emissions per GDP (1996–99, 2000–03, 2004–07, 2008–11, 2012–15, 2016–19)**											
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
ECI (trade)		−1.223***			−0.954**	−1.123**		−0.939*	0.495	−0.202		−5.007***
		(0.447)			(0.475)	(0.455)		(0.484)	(1.020)	(0.956)		(1.903)
ECI (technology)			−0.646***		−0.358*		−0.547**	−0.269	0.660		0.049	−4.059***
			(0.217)		(0.214)		(0.221)	(0.221)	(0.596)		(0.441)	(1.370)
ECI (research)				−0.647*		−0.478	−0.412	−0.390		0.530	0.440	−5.928***
				(0.340)		(0.311)	(0.339)	(0.317)		(0.859)	(0.611)	(1.987)
ECI (trade) × ECI (technology)									−1.878*			6.666***
									(1.097)			(2.419)
ECI (trade) × ECI (research)										−1.511		10.567***
										(1.258)		(3.564)
ECI (research) × ECI (technology)											−1.125	8.607***
											(0.799)	(2.662)
ECI (trade) × ECI (research) × ECI (technology)												−15.268***
												(4.293)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Log of population F-statistic		8.40	2.00	1.60								23.30***
Log of human capital F-statistic		11.20	2.90*	2.10								31.90***
Log of natural resource exports per capita F-statistic		2.80*	0.53	0.56								18.30**
Log of production intensity F-statistic		3.30*	2.50	2.60								15.10**
HHI F-statistic		2.90*	4.70**	2.60								24.50***
Entropy F-statistic		2.50	4.50**	2.50								24.10***
Log of Fitness F-statistic		0.50	10.90***	1.80								21.20***
i-ECI F-statistic		6.90***	6.20**	3.00*								33.80***
Country-fixed effects F-statistic		0.99	6.0**	2.20								19.10***
Instrumental variables model F-statistic		6.60**	6.20**	4.60**								24.40***
Observations	528	528	528	528	528	528	528	528	528	528	528	528
R^2	0.302	0.355	0.339	0.323	0.364	0.366	0.346	0.370	0.380	0.373	0.353	0.415
Adjusted R^2	0.290	0.342	0.326	0.309	0.350	0.352	0.332	0.356	0.366	0.359	0.338	0.397

Each regression includes period-fixed effects. Clustered 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 Supplementary Tables 19–21. The F-statistics for the model in column 9 were estimated using models estimated in Supplementary Tables 22–27.

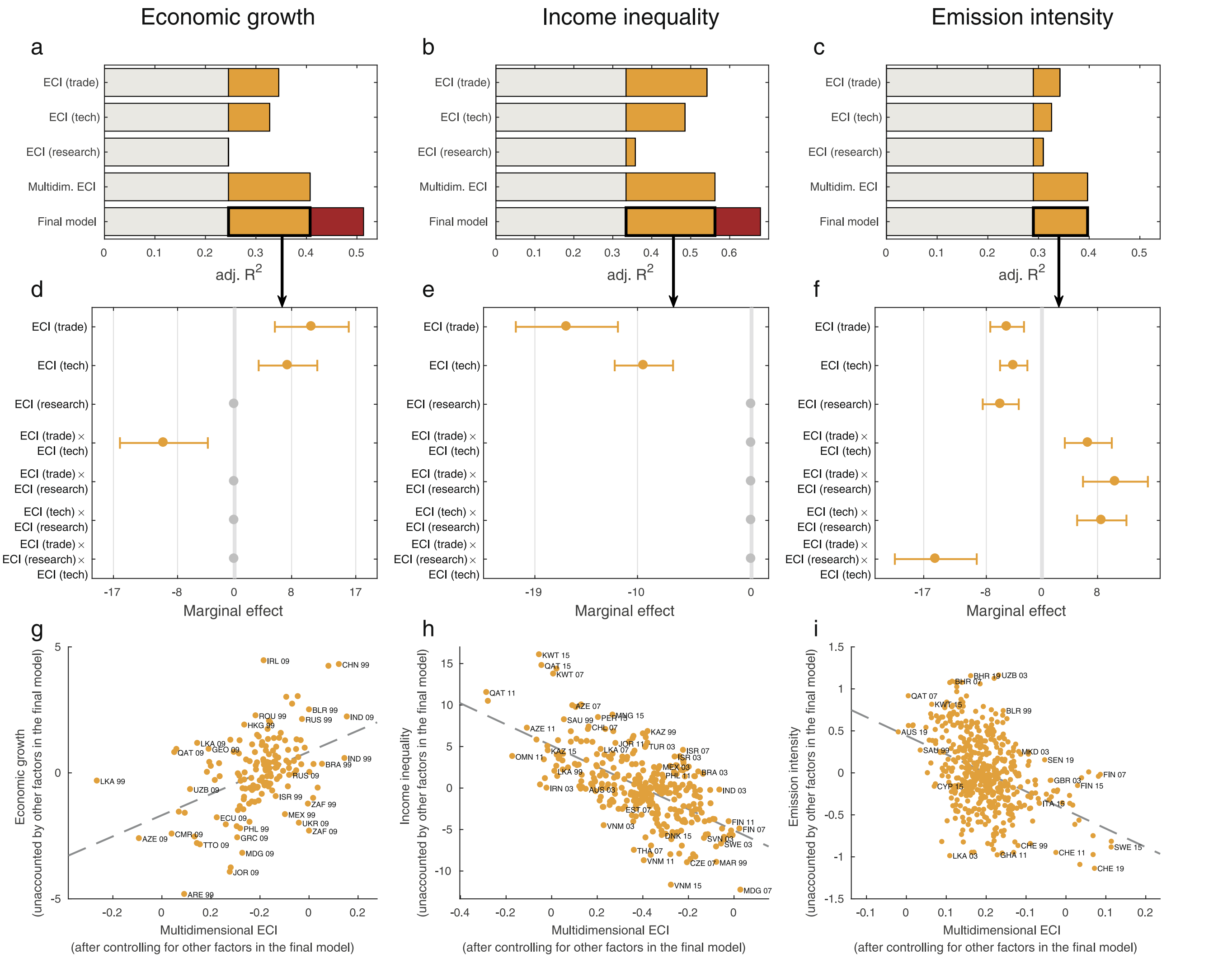

Fig. 3 Explaining international variations in economic growth, income inequality, and emission intensity with multidimensional economic complexity. **a**–**c** Contribution of the baseline, ECIs, and other covariates to the variance explained by various models (adjusted R^2) for **a** economic growth, **b** income inequality, and **c** emission intensity. The baseline adjusted R^2s are presented in gray, 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 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 (Supplementary Table 4, column 17), **e** income inequality (Supplementary Table 12, column 17), and **f** emission intensity (Supplementary Table 21, 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.

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?

Instrumental variable. 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 non-neighbors (countries with a similar specialization pattern but that do not share a land or maritime border). 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 non-neighboring countries with the most similar specialization pattern (based on the conditional probability that two countries are specialized in the same vector of activities[54] (exports, technologies, research areas), see Supplementary Note 8). For example, in 2014, Japan's export structure was similar to that of Germany, Great Britain, and Czechia, whereas Australia's technological structure was similar to Great Britain, Spain, and Canada. In Supplementary Note 8, 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 Supplementary Note 8 for first and second stage results).

Discussion

Economic complexity methods have become important tools to explain regional and international variations in inclusive green growth[13,55–61]. 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 of 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[53]. 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]. In fact, much of the recent work in smart specialization has focused on single relatedness-complexity diagrams in attempts to identify activities that are both accessible and attractive. Our approach can be used to expand this in two important ways, by evaluating multiple targets and considering multiple diversification options. For instance, beyond complexity, we can evaluate the inequality and emissions implications of a new activity (this was already anticipated in Hartmann et al.[25] for inequality and in Romero and Gramkow[30] for emissions, but it has not been put together). Similarly, we can look at relatedness across a series of activities (e.g., diversification not only in product exports but in patents and research areas). For instance, some countries may have an easier time climbing the technology ladder than the export ladder. Thus, putting these ideas together suggests a more comprehensive strategic landscape for strategic economic development, balancing multiple targets (growth, inequality, emissions) and opportunities (products, patents, and research). This should be of interest to policymakers using complexity metrics for inclusive green development and reinforce the idea that metrics of economic complexity go beyond measures of trade sophistication[33,34,60,62,63].

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). Moreover, patent applications may differ from granted patents and could potentially be used to game patent-based indicators by actors willing to submit spurious patents to increase their reported output in certain technologies. The use of patent applications, however, is common in the geography of innovation literature, and hence, our use of it makes our work comparable to previous research[40,62].

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[16,64,65]. Unfortunately, the current state of the art does not include internationally comparable fine-grained datasets for these additional activities (e.g., service trade data are too aggregate to approximate the productive structure of an economy, see ref. [66] and Supplementary Note 9).

Third, our research is also limited by differences in the granularity of the three datasets: trade data are the most granular, with about 1200 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 nontrivial.

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[13,15,17,20,23] and regions[64], the relationship between complexity and inequality is known to reverse at the regional scale[21,65–68]. Thus, this approach cannot tell us much about regional effects, which could be different from those observed on the international scale[21,68–71].

Fifth, our analysis is also limited by the potential multicollinearity of the variables (e.g., human capital is correlated with ECI). This multicollinearity, however, should lead to larger standard errors and would play against finding significance. Our results, however, are still robust despite this data limitation.

Finally, spelling out the implications of this multidimensional approach can be challenging. Not only because they lean on multiple targets but because not all countries may be simultaneously sophisticated. Indeed, the international (and even regional) division of labor pushes us to question the possibility that all countries and regions could become equally sophisticated. Still, there is the possibility for the world to make progress in that direction. For instance, extractive activities can vary from exploitative and labor-intensive manual operations to sophisticated and highly automated capital-intensive processes. The same applies to agriculture. Urban transportation systems can also be improved in ways that reduce emissions and travel times (e.g., electric bicycles, rail, etc.). So, while it may be hard for all economies to become sophisticated, there is plenty of room to sophisticate less advanced economies. While these increases in sophistication may not bring them to the top of the complexity ladder, they may still enable more sustainable, inclusive, and prosperous economies in the developing world.

Yet, 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.

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:

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

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. Then, we define the iterative mapping:

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

That is, according to Eq. (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 Eqs. (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 Eq. (2) can be obtained by calculating the eigenvector corresponding to the second largest eigenvalue of the matrix:

$$M_{cc'} = \sum_{pc'} \frac{M_{cp}M_{c'p}}{M_cM_p} \tag{3}$$

Which is a matrix of similarity between economies 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 analyses, we further normalize the values of ECI_c to be nonnegative using a max-min technique (i.e., they are between 0 and 1).

We build our results using the standard definition of ECI[13,15] because of multiple reasons. First, because this is a widely used definition, it makes our results more readily comparable with previous research. Second, because it is a definition designed for data on the geography of economic activities and focused on where activities come from instead of where they are consumed, we can apply it directly to our three datasets (without the need for special adaptations). Nevertheless, throughout the remainder of the paper, we also compare our results with two alternative definitions of economic complexity, the fitness index[46,47], and the innovation-adjusted ECI[40] (i-ECI). These controls and their definition are presented in the Supplementary Information. We find our results to be robust to controlling for these alternative definitions.

Data availability

The data that support the findings of this study are available at: https://doi.org/10.7910/DVN/K4MEFW.

Code availability

The code needed to reproduce the results is available from V.S. upon request.

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References

1. The World Bank. *Tracking SDG7: The Energy Progress Report* (The World Bank, 2019).
2. Sachs, J. D. et al. Six transformations to achieve the sustainable development goals. *Nat. Sustain.* **2**, 805–814 (2019).
3. Hák, T., Janoušková, S. & Moldan, B. Sustainable Development Goals: a need for relevant indicators. *Ecol. Indic.* **60**, 565–573 (2016).
4. Sachs, J. D. From millennium development goals to sustainable development goals. *Lancet* **379**, 2206–2211 (2012).
5. The World Bank. *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. *Nat. Sustain.* **2**, 999–1000 (2019).
8. Agarwala, M., Atkinson, G., Baldock, C. & Gardiner, B. Natural capital accounting and climate change. *Nat. Clim. Change* **4**, 520–522 (2014).
9. Soergel, B. et al. A sustainable development pathway for climate action within the UN 2030 Agenda. *Nat. Clim. Change* **11**, 656–664 (2021).
10. Biermann, F. et al. Scientific evidence on the political impact of the Sustainable Development Goals. *Nat. Sustain.* **5**, 795–800 (2022).
11. Murakami, K., Itsubo, N. & Kuriyama, K. Explaining the diverse values assigned to environmental benefits across countries. *Nat. Sustain.* **5**, 753–761 (2022).
12. Basheer, M. et al. Balancing national economic policy outcomes for sustainable development. *Nat. Commun.* **13**, 1–13 (2022).
13. Hidalgo, C. A. Economic complexity theory and applications. *Nat. Rev. Phys.* **3**, 92–113 (2021).
14. Balland, P. -A. et al. The new paradigm of economic complexity. *Res. Policy* **51**, 104450 (2022).
15. Hidalgo, C. A. & Hausmann, R. The building blocks of economic complexity. *Proc. Natl Acad. Sci. USA* **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*. MPRA Paper 77837 (University Library of Munich, 2017).
18. Koch, P. Economic complexity and growth: can value-added exports better explain the link? *Econ. Lett.* **198**, 109682 (2021).
19. Poncet, S. & de Waldemar, F. S. Economic complexity and growth. *Rev. Econ.* **64**, 495–503 (2013).
20. Domini, G. Patterns of specialization and economic complexity through the lens of universal exhibitions, 1855–1900. *Explor. Econ. Hist.* **83**, 101421 (2022).
21. Chávez, J. C., Mosqueda, M. T. & Gómez-Zaldívar, M. Economic complexity and regional growth performance: evidence from the Mexican economy. *Rev. Reg. Stud.* **47**, 201–219 (2017).
22. Ourens, G. *Can the Method of Reflections Help Predict Future Growth?* Discussion Paper 2013-8 (IRES, Université catholique de Louvain, 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. *Int. Reg. Sci. Rev.* **46**, 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**, e0182774 (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 18–11 (Utrecht School of Economics, 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. *Econ. Lett.* **174**, 35–38 (2019).
30. Romero, J. P. & Gramkow, C. Economic complexity and greenhouse gas emissions. *World Dev.* **139**, 105317 (2021).
31. Can, M. & Gozgor, G. The impact of economic complexity on carbon emissions: evidence from France. *Environ. Sci. Pollut. Res.* **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 Dev.* **93**, 75–93 (2017).
33. Ding, X. & Hadzi-Vaskov, M. *Composition of Trade in Latin America and the Caribbean*. Working Paper No. 2017/042 (International Monetary Fund, 2017).
34. Salinas, G. & Muñoz, S. *Proximity and Horizontal Policies: The Backbone of Export Diversification and Complexity*. Working Paper No. 2021/064 (International Monetary Fund, 2021).
35. Balland, P. -A. & Rigby, D. The geography of complex knowledge. *Econ. Geogr.* **93**, 1–23 (2017).
36. Fritz, B. S. & Manduca, R. A. The economic complexity of US metropolitan areas. *Reg. Stud.* **55**, 1299–1310 (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? *Reg. Stud.* **56**, 1176–1189 (2022).
38. Balland, P. -A. & Boschma, R. Do scientific capabilities in specific domains matter for technological diversification in European regions? *Res. Policy* **51**, 104594 (2021).

39. Ivanova, I., Strand, Ø., Kushnir, D. & Leydesdorff, L. Economic and technological complexity: a model study of indicators of knowledge-based innovation systems. *Technol. Forecast. Soc. Change* **120**, 77–89 (2017).
40. Lybbert, T. J. & Xu, M. Innovation-adjusted economic complexity and growth: do patent flows reveal enhanced economic capabilities? *Rev. Dev. Econ.* **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 *Proc. Twenty-Fifth AAAI Conference on Artificial Intelligence* (Association for the Advancement of Artificial Intelligence, 2011).
42. SCImago Journal & Country Rank (SJR). About Us. https://www.scimagojr.com/aboutus.php (2022).
43. The World Bank. *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*. UTIP Working Paper 68 (UTIP, 2014).
45. Galbraith, J. K., Halbach, B., Malinowska, A., Shams, A. & Zhang, W. *The UTIP Global Inequality Datasets: 1963–2008*. WIDER Working Paper No. 2015/019 (UNU-WIDER, 2015).
46. Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A. & Pietronero, L. A new metrics for countries' fitness and products' complexity. *Sci. Rep.* **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. Solow, R. M. A contribution to the theory of economic growth. *Q. J. Econ.* **70**, 65–94 (1956).
49. Kuznets, S. *Economic Growth and Income Inequality* (Routledge, 2019).
50. Boleti, E., Garas, A., Kyriakou, A. & Lapatinas, A. Economic complexity and environmental performance: evidence from a world sample. *Environ. Model. Assess.* **26**, 251–270 (2021).
51. Mealy, P. & Teytelboym, A. Economic complexity and the green economy. *Res. Policy* **51**, 103948 (2022).
52. Peters, G. P. & Hertwich, E. G. CO_2 embodied in international trade with implications for global climate policy. *Environ. Sci. Technol.* **42**, 1401–1407(2008).
53. 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. *Nat. Sustain.* **2**, 1041–1050 (2019).
54. Hidalgo, C. A., Klinger, B., Barabási, A. -L. & Hausmann, R. The product space conditions the development of nations. *Science* **317**, 482–487 (2007).
55. Secretaría de Economía, Gobierno de México. Diversificación inteligente. https://www.gob.mx/se/acciones-y-programas/diversificacion-inteligente (Gobierno de México, 2021).
56. European Commission, IRI. Economic Complexity and the race for industrial competitiveness. https://iri.jrc.ec.europa.eu/areas-of-work/complexity.
57. Salinas, G. How countries can diversify their exports. *IMF Blog* https://blogs.imf.org/2021/09/22/how-countries-can-diversify-their-exports/ (2021).
58. Ortiz-Ospina, E. & Beltekian, D. How and why should we study 'economic complexity'? *Our World in Data* https://ourworldindata.org/how-and-why-econ-complexity (2018).
59. 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. *Reg. Stud.* **54**, 1354–1365 (2020).
60. Mealy, P. & Coyle, D. To them that hath: economic complexity and local industrial strategy in the UK. *Int. Tax Public Finance* **29**, 358–377 (2022).
61. Hausmann, R. et al. *Construyendo un mejor futuro para la República Dominicana: herramientas para el desarrollo*. Informe técnico. (Center for International Development, Harvard University, 2011).
62. Balland, P. A., Boschma, R., Crespo, J. & Rigby, D. L. Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Reg. Stud.* **53**, 1252–1268 (2018).
63. Hidalgo, C. A. The policy implications of economic complexity. Preprint at https://arxiv.org/abs/2205.02164 (2022).
64. Mishra, S., Tewari, I. & Toosi, S. Economic complexity and the globalization of services. *Struct. Change Econ. Dyn.* **53**, 267–280 (2020).
65. Brynjolfsson, E., Collis, A. & Eggers, F. Using massive online choice experiments to measure changes in well-being. *Proc. Natl Acad. Sci. USA* **116**, 7250–7255 (2019).
66. Saltarelli, F., Cimini, V., Tacchella, A., Zaccaria, A. & Cristelli, M. Is export a probe for domestic production? *Front. Phys.* **8**, 180 (2020).
67. Hartmann, D. & Pinheiro, F. L. Economic complexity and inequality at the national and regional level. Preprint at https://arxiv.org/abs/2206.00818 (2022).
68. Gao, J. & Zhou, T. Quantifying China's regional economic complexity. *Phys. A Stat. Mech. Appl.* **492**, 1591–1603 (2018).
69. Zhu, S., Yu, C. & He, C. Export structures, income inequality and urban-rural divide in China. *Appl. Geogr.* **115**, 102150 (2020).
70. Wang, Y. & Turkina, E. Economic complexity, product space network and Quebec's global competitiveness. *Can. J. Adm. Sci.* **37**, 334–349 (2020).
71. Reynolds, C. et al. A sub-national economic complexity analysis of Australia's states and territories. *Reg. Stud.* **52**, 715–726 (2018).

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Author contributions

V.S.: conceptualization, methodology, software, data curation, validation, formal analysis, investigation, writing. P.K.: conceptualization, methodology, formal analysis, writing. C.A.H.: conceptualization, methodology, formal analysis, writing, supervision.

Competing interests

C.A.H. is a founder and creator of Datawheel and the OEC (oec.world). V.S. and P.K. declare no competing interests.

Additional information

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