

The Software Complexity of Nations

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Abstract

Despite the growing importance of the digital sector, research on economic complexity and its implications continues to rely mostly on administrative records—e.g. data on exports, patents, and employment—that fail to capture the nuances of the digital economy. In this paper we use data on the geography of programming languages used in open-source software projects to extend economic complexity ideas to the digital economy. We estimate a country’s software economic complexity and show that it complements the ability of measures of complexity based on trade, patents, and research papers to account for international differences in GDP per capita, income inequality, and emissions. We also show that open-source software follows the principle of relatedness, meaning that a country’s software entries and exits are explained by specialization in related programming languages. We conclude by exploring the diversification and development of countries in open-source software in the context of large language models (LLMs). Together, these findings help extend economic complexity methods and their policy considerations to the digital sector.

Introduction

The study of economic complexity has predominantly relied on administrative records, such as trade data (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009), patent filings (Balland and Rigby, 2017; Kogler et al., 2013), and employment statistics (Jara-Figueroa et al., 2018; Neffke and Henning, 2013), that while valuable, struggle to capture the importance of the digital economy. This “blind spot” is important because software capabilities—which are human capital intensive—represent a potentially more mobile and transmissible source of economic complexity that could be key for policy efforts focused on increasing the complexity of economies (Hidalgo, 2023). Yet, despite this evident need, we currently lack internationally comparable estimates of economic

complexity for the software sector that can help us understand the capabilities implicit in the production of software and its dynamics.

Here we use data on the geographic distribution of programming languages used in open-source software (OSS) projects hosted on GitHub to generate internationally comparable measures of economic complexity and to explore whether software follows the principle of relatedness (Hidalgo et al., 2018): the tendency of economies to enter economic activities that are related to their pattern of specialization.

But why software?

There are several factors that make the geography of software, and in particular of open-source software, a useful complement to our current understanding of economic complexity and development.

First, software development and the use of IT technology are key predictors of the productivity and innovation capacity of firms (Brynjolfsson and Hitt, 2003, 1998), and hence, of an economy's growth potential (Brynjolfsson and Saunders, 2010). In the case of OSS, firms creating and using OSS tend to be more productive (Nagle, 2019, 2018; Rock, 2019), while at the country-level, OSS participation predicts entrepreneurship (Wright et al., 2023). This is not constrained only to firms on the software sector, since software is a complementary input that has become increasingly prevalent across many industries (Rahmati et al., 2021). For instance, 40% of the cost of a new automobile is electronics—which rely on software for both their operation and production (Charette, 2021).

Second, OSS libraries are a key building block of most software projects (Eghbal, 2020), and thus, are supported by strategic investments. In the US alone, annual investment in OSS runs in the tens of billions of dollars (Korkmaz et al., 2024), indicating that OSS is not a fringe area of software development, but a fundamental building block of the global software ecosystem.

Third, the unique geographic aspects of OSS development indicate that the distribution of complex capabilities in software may deviate significantly from those in other industries. In particular, as it is known for complex and innovative activities (Audretsch and Feldman, 1996; Balland et al., 2020), OSS development is quite diffuse across countries but highly concentrated within sub-national regions (Wachs et al., 2022). Software is also amenable to international collaborations, which can occur quite fluidly across distances (Goldbeck, 2023). Together these aspects suggest that estimates of economic complexity based on (open-source) software can provide novel and complementary insights about the complexity and growth potential of economies.

We validate software complexity by comparing its ability to explain international variations in GDP per capita, income inequality, and emissions, with published measures of complexity, finding that software complexity robustly explains variance in these outcomes that is unaccounted for by these complexity measures (e.g. Hidalgo and Hausmann, 2009; Stojkoski et al., 2016; Stojkoski et al., 2023b). From a policy perspective, the accessibility and granularity of open-source software data offer a cost-effective means to track and potentially enhance economic complexity, allowing policymakers a new route to design interventions focused on fostering digital capabilities and drive sustainable economic growth (Stojkoski et al., 2023a).

Economic Complexity and the Digital Economy

Economic complexity involves the use of fine-grained sectoral data to generate indicators of economic structure that explain changes in specialization patterns (Guevara et al., 2016; Hausmann et al., 2014; Hidalgo, 2021; Hidalgo et al., 2007; Poncet and de Waldemar, 2015) and variation in macroeconomic outcomes, such as economic growth (Chávez et al., 2017; Domini, 2022; Hausmann et al., 2014; Hidalgo and Hausmann, 2009; Poncet and de Waldemar, 2013; Stojkoski et al., 2016; Vallim and Monasterio, 2023; Weber et al., 2021), income inequality (Bandeira Morais et al., 2018; Ben Saâd and Assoumou-Ella, 2019; Chu and Hoang, 2020; Hartmann et al., 2017; Le Caous and Huarng, 2020; Lee and Vu, 2019; Sbardella et al., 2017), and emissions (Can and Gozgor, 2017; Doğan et al., 2021; Lapatinas et al., 2019; Mealy and Teytelboym, 2020; Neagu, 2019; Romero and Gramkow, 2021). In the last fifteen years, these methods grew into popular indicators for international and regional development policy (Balland et al., 2022; Hidalgo, 2023,

2021). Yet, despite important efforts to expand these methods beyond the confines of trade data (Balland and Rigby, 2017; Chávez et al., 2017; Guevara et al., 2016; Stojkoski et al., 2023b), economic complexity research still suffers from a “digital blind-spot,” derived from the lack of work on datasets that could provide a fine-grained view of the software industry. This blind-spot blocks us from understanding how key insights from the economic complexity literature, like the principle of relatedness (Hidalgo et al., 2018) or the use of complexity metrics to explain macroeconomic outcomes, translate to the digital sector.

Two key ideas in economic complexity are the quantitative formalization of *relatedness* and *economic complexity*.

Relatedness is the idea that firms benefit from inter-industry spillovers when they are in close geographic proximity to firms in a related industry (e.g. industries sharing similar knowledge inputs) (Autant-Bernard, 2001; Jaffe, 1986). Recent formalization of relatedness involve the use of standard recommender system techniques, in particular collaborative filtering methods (Jannach et al., 2010), to estimate the potential of an economy in an activity starting from patterns of co-agglomeration (Ellison et al., 2010; Hidalgo et al., 2018, 2007; Neffke et al., 2011).

Economic complexity metrics involve the use of dimensionality reduction techniques (e.g. spectral methods such as eigendecomposition) on specialization matrices to produce estimates of the complexity of an economy. These estimates have been repeatedly shown to explain international variations in economic growth (Chávez et al., 2017; Domini, 2022; Hausmann et al., 2014; Hidalgo and Hausmann, 2009; Poncet and de Waldemar, 2013; Stojkoski et al., 2016; Vallim and Monasterio, 2023; Weber et al., 2021), income inequality (Bandeira Morais et al., 2018; Ben Saâd and Assoumou-Ella, 2019; Chu and Hoang, 2020; Hartmann et al., 2017; Le Caous and Huarng, 2020; Lee and Vu, 2019; Sbardella et al., 2017), and emissions (Can and Gozgor, 2017; Doğan et al., 2021; Lapatinas et al., 2019; Mealy and Teytelboym, 2020; Neagu, 2019; Romero and Gramkow, 2021), among other outcomes (Barza et al., 2024; Nguyen, 2022; Vu, 2020). This has motivated the use of the Economic Complexity Index (ECI) as an official policy target or instrument. For instance, Malaysia’s New Industrial Master Plan 2030 by the Ministry of Investment, Trade, and Industry, defines the advancement of economic complexity as its first

mission (Ministry of Investment Trade and Industry, 2023). Armenia’s 2021-2026 government plan includes a “*support toolkit for investment programmes involving economic complexity*” (Republic of Armenia, 2021), and Saudi Arabia’s vision 2030 declares a commitment to “*diversify the capabilities of our economy*” as a vital step towards their economic sustainability.

Yet, while economic complexity methods enjoy significant adoption in both academic and policy circles, their application is still limited by the availability of fine-grained data. The efforts have thus focused on international trade statistics (Hidalgo et al., 2007; Hidalgo and Hausmann, 2009), manufacturing, payroll, firm registry, and employment data for industries (Chávez et al., 2017; Fritz and Manduca, 2021; Hidalgo, 2021; Jara-Figueroa et al., 2018; Neffke et al., 2011; Neffke and Henning, 2013), as well as data on occupations (Alabdulkareem et al., 2018; Jara-Figueroa et al., 2018; Muneeppeerakul et al., 2013), patents (Balland and Rigby, 2017; Kogler et al., 2015, 2013), and research papers (Chinazzi et al., 2019; Guevara et al., 2016; Stojkoski et al., 2023b). This expansion recently led to the introduction of multidimensional economic complexity (Stojkoski et al., 2023b), the notion that metrics of complexity derived from multiple datasets complement each other to explain macroeconomic outcomes (e.g. trade and patent complexity estimates explain economic growth better together than alone). But with the exception of some recent work on digital trade (Stojkoski et al., 2023a) and digital infrastructure (Liang and Tan, 2024), the multidimensional expansion of economic complexity is yet to reach the digital sector, despite a growing number of works highlighting the importance of the software industry (Shapiro and Varian, 1999, Chattergoon and Kerr, 2022). For instance (Aum and Shin, 2024) emphasize the critical role of software in modern economies, highlighting that software and labor are substitutes with a high elasticity of substitution.

In this paper, we address economic complexity’s digital gap by using data on the geographic distribution of programming languages used in OSS projects to develop estimates of economic complexity for the software sector and to explore the principle of relatedness in the context of OSS. In the next section we present the data and methods used to calculate these indicators and then explore their ability to explain international variance in GDP per capita, income inequality, and emissions that is unaccounted for by measures of complexity based on trade, patents, and research papers. We then construct a network of related open-source languages to explore the

principle of relatedness in the context of software. The last section concludes and discusses open-source software in the context of large language models.

Data and methods

We use data on the geography of open-source software provided by the GitHub Innovation Graph (GHIG).¹ GitHub is the leading platform for OSS development, with over 100 million users worldwide. The dataset presents the number of GitHub users pushing code by country and programming language on a quarterly basis starting from Q1 2020 and continuing until Q4 2023. To estimate the location of developers, we leverage the fact that the GHIG data assigns software contributions to countries based on the IP address of the developer. This data provides a more accurate measure of a location’s software activity than sources relying on self-reported locations, which are known to suffer from bias (Hecht et al. 2011). After completing the basic data cleaning procedures explained in Section 1 of the Supplementary information, we are left with a sample of 163 countries and 150 programming languages for the period of 2020-2023.

We estimate the Economic Complexity Index (ECI) using the standard technique introduced by (Hidalgo and Hausmann, 2009).

Let X_{cl} be a matrix counting the number of developers with an IP in country c pushing code to GitHub in programming language l . We use X_{cl} to derive the matrix of specialization or revealed comparative advantage R_{cl} as:

$$R_{cl} = \frac{X_{cl}X}{X_cX_l},$$

where omitted indexes have been added over (e.g. $X_c = \sum_l X_{cl}$). We then binarize the matrix R_{cl} to generate the matrix $M_{cl} = 1$ if $R_{cl} \geq 1$ or 0 otherwise. Finally, we let the economic complexity index of a country c (ECI_c) and the language complexity index of an activity l (PCI_l) be defined as the stead state of the map:

¹GitHub Innovation Graph <https://github.com/github/innovationgraph>

$$ECI_c = \frac{1}{M_c} \sum_l M_{cl} PCI_l$$

$$PCI_l = \frac{1}{M_l} \sum_c M_{cl} ECI_c$$

As it is customary, we normalize ECI and PCI values by subtracting their respective mean and dividing them by their standard deviation.

Technically, ECI is a spectral-clustering method that assigns one number to each country, and one number to each product, that minimizes the distance between the number assigned to each country and the numbers assigned to its products (Bottai et al., 2024; Mealy et al., 2019; Servedio et al., 2024). That is, it provides an optimal one-factor split of the specialization matrix.

We compare ECI indicators derived from open-source software (ECI^{software}) with the multidimensional economic complexity data compiled by (Stojkoski et al., 2023b), which uses trade data from the Observatory of Economic Complexity (oec.world), patent data from the World Intellectual Property Organization’s International Patent System, and research publication data from SCImago Journal & Country Rank portal. These datasets are described in detail in Section 2 of the Supplementary information.

Software and economic complexity

We begin our analysis by comparing our estimate of economic complexity based on the geography of programming languages (ECI^{software}) with published estimates of economic complexity based on physical product exports (ECI^{trade}), patents (ECI^{tech}), and research publications (ECI^{research}) (Stojkoski et al., 2023b).

Figure 1A compares four specialization matrices (M) where countries are sorted by diversity (number of products, programming languages they specialize in, etc.) and columns are sorted by ubiquity (number of countries specialized in each language, product, etc.). Much like the specialization matrices for trade, patents, and research papers, the *country-programming language*

matrix exhibits a nested structure (Bustos et al., 2012; Mariani et al., 2019), meaning that low diversity economies tend to specialize in a subset of ubiquitous activities found in more diverse economies.

Figure 1B shows a map of $ECI^{software}$ based ranking of countries constructed from the country-programming language matrix and Figure 1C compares $ECI^{software}$ with the three other ECI measures, showing that the geography of software complexity is different from that expressed in data on products, patents, and research publications. For instance, Russia (RUS), a well-known natural resource exporters with a low ECI^{trade} score (0.119 on a normalized $[-1,1]$ scale), scores much higher in $ECI^{software}$ (0.884 on a normalized $[-1,1]$ scale). Similarly, India (IND) scores much higher in $ECI^{software}$ (0.585) than in $ECI^{research}$ (-0.257). Section 3 of the Supplementary information presents a table comparing the values of $ECI^{software}$, ECI^{trade} , ECI^{tech} , and $ECI^{research}$ for all countries in our sample.

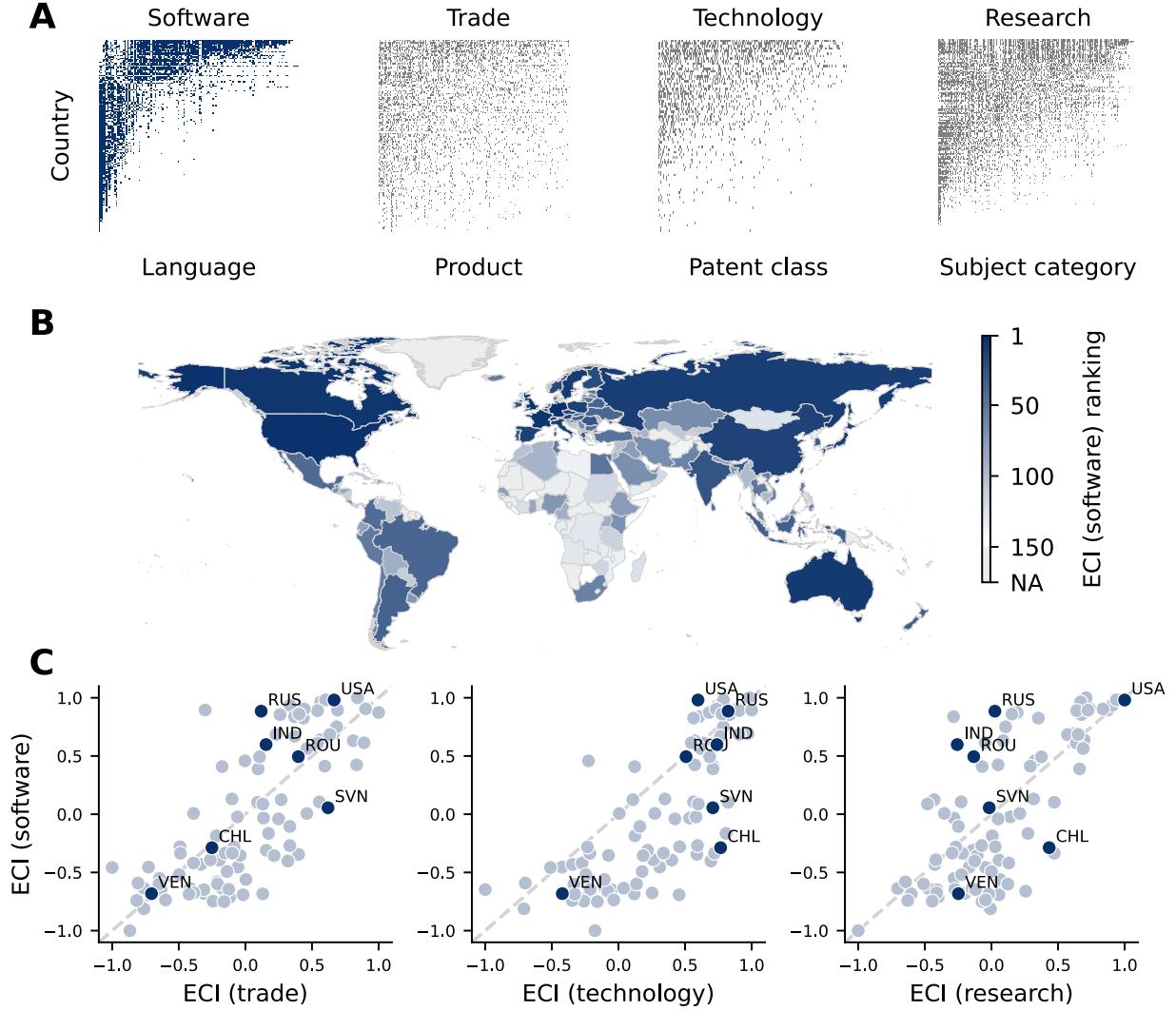


Figure 1 A Specialization matrices for countries and programming-languages, products, patents, and research papers. B Geographic distribution of software economic complexity. C Comparison between $ECI^{software}$ and ECI^{trade} , ECI^{tech} , and $ECI^{research}$ respectively ($R^2=0.597$, p-value <0.001 , $R^2=0.606$, p-value <0.001 and $R^2=0.523$, p-value <0.001). For visualization purposes, ECI values are normalized to a scale of $[-1, 1]$. All ECI measures presented above are calculated using 2020 data only.

Next, we explore the ability of $ECI^{software}$ to complement the ability of other measures of economic complexity to explain international variations in GDP per capita, income inequality, and emissions. We focus on GDP per capita instead of economic growth because the time series for $ECI^{software}$ is short (less than four years), limiting our model to a single panel cross-section with about 90 observations. Tables 2 to 4 explore how these measures of economic complexity explain cross-sectional differences in GDP per capita, income inequality, and emission intensities (emissions per unit of CO_2).

Table 1 ECI^{software} and GDP per capita (2020) in a multidimensional setting. Robust standard errors in parentheses. Significance codes: *p<0.1, **p<0.05, ***p<0.01

	GDP per capita (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECI ^{software}	0.299*** (0.042)				0.212*** (0.048)	0.261*** (0.041)	0.244*** (0.047)	0.138*** (0.048)
ECI ^{trade}		0.278*** (0.038)			0.129*** (0.032)			0.145*** (0.041)
ECI ^{technology}			0.228*** (0.042)			0.063 (0.038)		-0.003 (0.041)
ECI ^{research}				0.200*** (0.034)			0.075** (0.034)	0.089** (0.035)
Population (log)	-0.159*** (0.062)	-0.003 (0.052)	-0.068 (0.073)	-0.007 (0.065)	-0.135** (0.061)	-0.176*** (0.066)	-0.154** (0.059)	-0.125* (0.065)
Natural resources (log)	2.586*** (0.818)	2.876*** (0.871)	2.858*** (0.959)	3.397*** (0.841)	2.378*** (0.820)	2.363*** (0.869)	2.520*** (0.805)	2.286*** (0.863)
Observations	92	92	92	92	92	92	92	92
R ²	0.831	0.801	0.751	0.769	0.848	0.836	0.841	0.861
Adjusted R ²	0.825	0.794	0.742	0.761	0.841	0.828	0.834	0.852

Table 1 shows that the correlation between ECI^{software} and GDP per capita remains strong after controlling for other estimates of economic complexity. In fact, ECI^{software} works out to be as good as ECI^{trade} at explaining international variations in GDP per capita in the complete model (column 8). This validates ECI^{software} as a complementary indicator by showing that there is information about international variations in GDP per capita contained in ECI^{software} that is not redundant with the information captured by the other ECIs. Moreover, the robustness of results across different model specifications suggests ECI^{software} is a reliable and consistent predictor.

Next, we look at the ability of ECI^{software} to explain international variations in income inequality (Table 2). Here our data is even more limited, involving only 82 countries. Still, we find ECI^{software} is the only estimate of complexity that remains strong, negative, and significant across all specifications.

Table 2 ECI^{software} and income inequality in a multidimensional setting. ECI estimates are based on 2020 data, while the dependent variable is the average Gini coefficient between 2010 and 2020. Robust standard errors in parentheses. Significance codes: *p<0.1, **p<0.05, ***p<0.01

	Gini coefficient							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECI ^{software}	-0.729** (0.283)				-0.672** (0.269)	-0.767** (0.295)	-0.801*** (0.221)	-0.834*** (0.226)
ECI ^{trade}		-0.329* (0.196)			-0.129 (0.176)			0.017 (0.184)
ECI ^{technology}			-0.065 (0.225)			0.108 (0.222)		0.073 (0.201)
ECI ^{research}				0.591*** (0.196)			0.639*** (0.184)	0.639*** (0.197)
GPD per capita (log)	1.421* (0.831)	1.540 (0.959)	0.957 (0.831)	1.263 (0.787)	1.638* (0.933)	1.324 (0.846)	1.885** (0.839)	1.793* (0.907)
GPD per capita (log) ²	-0.507 (0.320)	-0.888** (0.352)	-0.806** (0.329)	-1.395*** (0.394)	-0.564** (0.331)	-0.484 (0.316)	-1.118*** (0.371)	-1.096*** (0.361)
Population (log)	0.924*** (0.274)	0.490** (0.190)	0.460** (0.207)	0.196 (0.167)	0.911*** (0.274)	0.885*** (0.271)	0.731*** (0.218)	0.706*** (0.220)
Natural resources (log)	1.634 (2.159)	1.169 (2.288)	1.530 (1.957)	0.775 (1.915)	1.548 (2.284)	1.314 (2.139)	1.065 (2.126)	0.862 (2.202)
Observations	82	82	82	82	82	82	82	82
R ²	0.288	0.224	0.198	0.312	0.292	0.291	0.421	0.423
Adjusted R ²	0.241	0.173	0.146	0.267	0.235	0.234	0.375	0.360

Finally, we look at the intensity of greenhouse gas emissions (emissions per unit of GDP per capita). This is a particularly interesting outcome for ECI^{software} because compared to the physical economy, software and information technologies are expected to be a less carbon-intensive way to generate GDP (Ciuriak and Ptashkina, 2020; Haberl et al., 2020; Hubacek et al., 2021; Romero and Gramkow, 2021; Stojkoski et al., 2023a; Wang and Zhang, 2021; Wiedenhofer et al., 2020).

Table 3 $ECI^{software}$ and greenhouse gas emission intensity (2020) in a multidimensional setting. Robust standard errors in parentheses. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Emissions per GDP							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ECI^{software}$	-0.487** (0.144)				-0.392** (0.168)	-0.393** (0.154)	-0.450*** (0.158)	-0.295 (0.185)
ECI^{trade}		-0.367** (0.162)			-0.214 (0.190)			-0.182 (0.203)
$ECI^{technology}$			-0.333** (0.158)			-0.203 (0.165)		-0.133 (0.178)
$ECI^{research}$				-0.188 (0.124)			-0.072 (0.129)	-0.098 (0.128)
GPD per capita (log)	-1.193*** (0.411)	-1.466*** (0.369)	-1.617*** (0.350)	-1.714*** (0.437)	-1.029** (0.393)	-1.105*** (0.388)	-1.137** (0.435)	-0.920** (0.416)
Population (log)	0.619*** (0.170)	0.360** (0.158)	0.490** (0.189)	0.347** (0.151)	0.605*** (0.173)	0.687*** (0.181)	0.623*** (0.168)	0.657*** (0.185)
Natural resources (log)	6.692*** (1.888)	6.948*** (1.846)	7.905*** (2.191)	6.952*** (2.237)	6.612*** (1.706)	7.184*** (1.999)	6.609*** (1.915)	6.835*** (1.929)
Observations	92	92	92	92	92	92	92	92
R^2	0.491	0.469	0.470	0.447	0.503	0.504	0.494	0.513
Adjusted R^2	0.468	0.445	0.445	0.422	0.474	0.475	0.464	0.472

Table 3 shows that software is the only complexity measure that remains significant across most specifications, supporting the notion that software complexity contributes to the creation of low carbon intensity forms of value added (GDP). To address potential endogeneity issues and illustrate the robustness of our results, we provide instrumental variable regressions for all three settings above, following the identification strategy of (Stojkoski et al., 2023b). Detailed explanation and all the related regression results can be found in Section 4 of the Supplementary information.

Related diversification in Open-Source Software

Having validated $ECI^{software}$ as a complementary measure of economic complexity, we now explore whether changes in the software specialization of countries is subject to the principle of relatedness: the notion that economies are more likely to enter—and less likely to exit—related activities (Autant-Bernard, 2001; Guevara et al., 2016; Hidalgo et al., 2018, 2007; Jaffe, 1986; Neffke et al., 2011; Neffke and Henning, 2013). We test the principle of relatedness following the

approach introduced in the product space (Hidalgo et al., 2007), which starts from the same specialization matrix (M) we used to derive measures of economic complexity. Formally, we define the proximity between two languages l and l' as the minimum of the conditional probability that two countries are specialized in the same programming languages:

$$\phi_{ll'} = \frac{\sum_c M_{cl} M_{cl'}}{\max(M_l, M_{l'})}$$

And define the relatedness between a county c and a programming language l as:

$$\omega_{cl} = \frac{\sum_{l'} M_{cl'} \phi_{ll'}}{\phi_l}$$

Where again, missing indices have been added over (e.g. $\phi_l = \sum_{l'} \phi_{ll'}$).

To test whether countries are more likely to enter programming languages that are related to their existing portfolio of open-source software specializations, we run linear probability models (Table 4) predicting entry events as a function of relatedness and the ubiquity of a language. We also include country and language fixed effects. We estimate relatedness using 2020 data and say that a country enters a language if they were not specialized in that language ($RCA < 1$) in 2020 and 2021 and then gained comparative advantage ($RCA \geq 1$) in 2022 and 2023 (e.g. $M_{cl} = \{0, 0, 1, 1\}$ for the years 2020 to 2023). We employ clustered standard errors by country to account for within-country correlations over time, ensuring robust and reliable standard errors in our regression models. Estimations based on logit models can be found in the Supplementary information.

Table 4 Entry models on countries gaining revealed comparative advantage ($RCA \geq 1$) in programming languages (2020-2023). Standard errors are clustered at the country level. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Entry						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Relatedness density	0.207*** (0.064)	0.262* (0.144)	0.384*** (0.081)	0.321** (0.136)		0.241*** (0.069)	0.218* (0.113)
Ubiquity					-0.026*** (0.009)	-0.034*** (0.009)	-0.049*** (0.008)
Country FE	No	Yes	No	Yes	No	No	Yes
Language FE	No	No	Yes	Yes	No	No	No
Observations	1584	1584	1584	1584	1584	1584	1584
R ²	0.021	0.095	0.188	0.277	0.011	0.038	0.121

Table 4 shows that open-source software specialization follows the principle of relatedness, with countries being more likely to specialize in programming languages that are related to those they are currently specialized in. The negative and significant effect of language ubiquity indicates that countries are less likely to enter common languages, which is reasonable since many countries already have comparative advantage in them. We note, however, that the explanatory power of the principle of relatedness in the case of OSS is rather mild, with a baseline R^2 of about 2%. Nevertheless, this effect is robust to country and programming language fixed effects.

Figure 2 shows the network of related programming languages following the visualization approach of (Hidalgo et al., 2007). Figure 2A highlights the position of specific languages and a fully labeled example is included in the Supplementary information. We then focus on the entrance and exit patterns of three countries on Figure 2B. In each case, most entries occur into languages adjacent to already existing specializations, while exits tend to occur out of more weakly connected languages. Canada, for instance, gained revealed comparative advantage in CUDA, a programming language created by Nvidia for parallel computing on graphics processors, a technique widely used in modern AI systems. This reflects a broader trend in the country's technological leadership in machine learning (Klinger et al., 2018). China gained comparative advantage in various programming languages, including for example Erlang. Erlang is a functional programming language designed by Ericsson and often used in the telecommunications sector. China exited PureBasic, a language related to BASIC which was otherwise disconnected from China's other previous specializations. Finally, Romania entered Perl, Rust, and SCSS, all well-

connected to previous specializations, and exited Objective-C, a disconnected previous specialization.

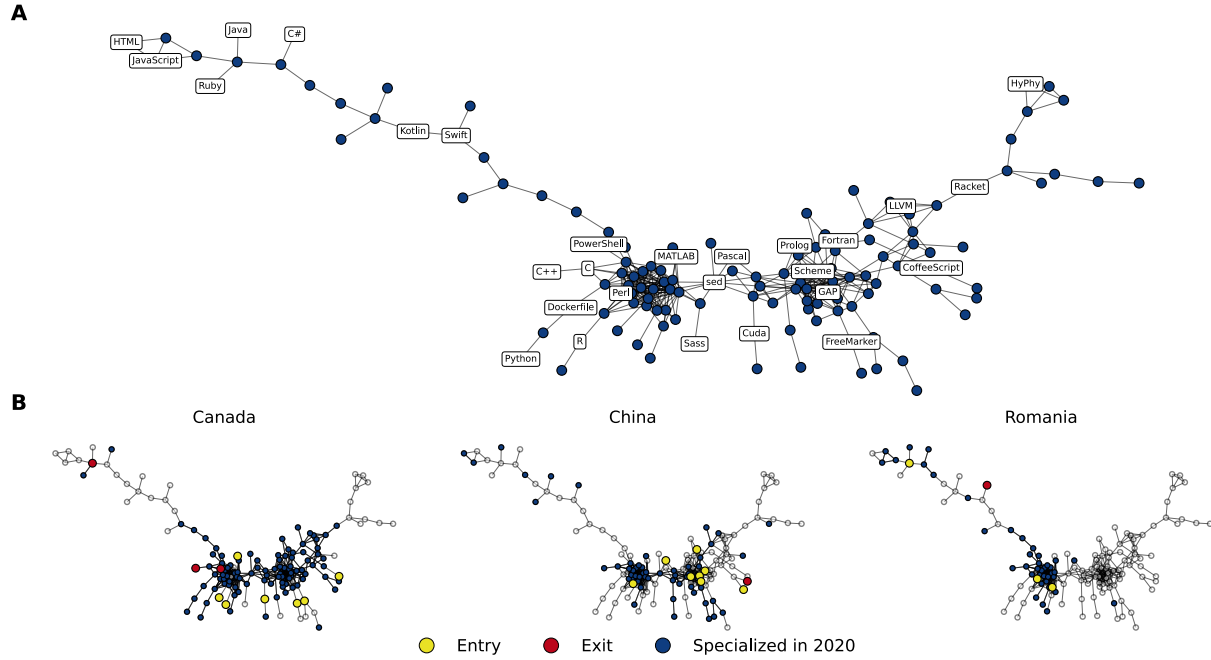


Figure 2 A Network representation of language relatedness. (B) Changes in revealed comparative advantage (RCA) in programming languages (2020-2023) in Canada, China, and Romania. Dark blue nodes indicate specialization in 2020-2021 ($RCA \geq 1$), while yellow nodes indicate subsequent (2022-2023) specialization in languages, and red nodes indicate exits. Countries are more likely to specialize in new languages adjacent to their previous specializations.

We then explore the principle of relatedness in the context of exits (Table 5). We consider as exits countries that were specialized in a programming language ($RCA \geq 1$) in 2020 and 2021 and later lost their comparative advantage ($RCA < 1$) in 2022 and 2023 (e.g. $M_{cF} = \{1, 1, 0, 0\}$ for the years going from 2020 to 2023). The negative and significant effect of relatedness indicates that countries are less likely to lose their advantage in programming languages that are related to those they currently specialize in. Again, the effects of relatedness are overall mild ($R^2 < 1\%$ on the baseline model) but are robust to the inclusion of country and language fixed-effects, showing that they go beyond what we can explained based on the statistic characteristics of a country or a language.

Table 5 Exit models on countries losing revealed comparative advantage ($RCA < 1$) in programming languages (2020-2023). Standard errors are clustered at the country level. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Exit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Relatedness density	-0.089*** (0.021)	-0.257*** (0.062)	-0.072*** (0.026)	-0.308*** (0.115)		-0.112*** (0.025)	-0.270*** (0.073)
Ubiquity					-0.002 (0.006)	-0.012** (0.006)	0.003 (0.010)
Country FE	No	Yes	No	Yes	No	No	Yes
Language FE	No	No	Yes	Yes	No	No	No
Observations	2978	2978	2978	2978	2978	2978	2978
R ²	0.009	0.101	0.097	0.181	0.000	0.011	0.101

Discussion

Here we expanded the study of economic complexity to include the software sector by leveraging recently published data on the geography of open-source software (OSS). By relying on the IP addresses of the developers contributing to OSS projects, instead of on self-reported locations (which can suffer from reporting bias (Hecht et al., 2011)), we were able to construct estimates of the geographic distribution of open-source software language knowledge for 100+ programming languages and use them to create internationally comparable economic complexity estimate for the software sector and study OSS in the context of the principle of relatedness.

When we explored the ability of ECI^{software} to explain variance in income, inequality, and emissions, we found that the correlation between ECI^{software} and each of these macroeconomic outcomes remain strong even after taking all three other measures of complexity into consideration. When we explored OSS entries and exits, we found that both behave as we would expect based on the principle of relatedness, albeit with a rather small size effect.

But what can we make of these findings?

The literature on economic development is rife with work advising economies to diversify towards more complex economic activities (Balland et al., 2018; Foray et al., 2009; Hausmann et al., 2014;

Hidalgo, 2023). High economic complexity activities are associated with better wages and may face less competition in international markets than the production of more ubiquitous commodities. But does this advice translate to software?

Unlike physical products, software relies less on immobile factors, such as large manufacturing or processing plants and natural resources. At the same time, software outputs are highly tradable (OECD, 2023; Stojkoski et al., 2024) and digital products are known to be—on average—of relatively high complexity compared to physical products (Stojkoski et al., 2024). This means that software provides new opportunities for structural upgrading that are less reliant on physical factors of production and more reliant on efforts to attract human capital.

Software-based economic complexity is also an interesting to track over time because it is uniquely exposed to a fast-changing and high growth sector. For instance, it is likely sensitive to recent changes in technology, such as the introduction of Large Language Models (LLMs). LLMs like ChatGPT, Mistral, or Perplexity, are reshaping the world of software development (Peng, Kalliamvakou, et al., 2023; Ozkaya 2023). Though it is unclear how AI will affect the software industry (Quispe and Grijalba, 2024), we can already observe that LLMs are better at providing programming advice in languages for which they have more training data (del Rio-Chanona et al. 2023), which are likely to be ubiquitous languages.

We can connect this idea with economic complexity by looking at the geographic distribution of the programming languages that are more likely to be impacted by LLMs. For this, we can use an estimate of the impact of ChatGPT on specific programming languages constructed by del Rio-Chanona et al. (2023) and compare that estimate with the ubiquity of each programming language (a measure of the number of countries specialized in a language (Figure 3)). This reveals a strong and significant correlation between the geographic ubiquity of a language and the expected impact of LLMs, meaning that LLMs are more likely to disrupt high ubiquity languages which are the ones used primarily by economies with low levels of software economic complexity.

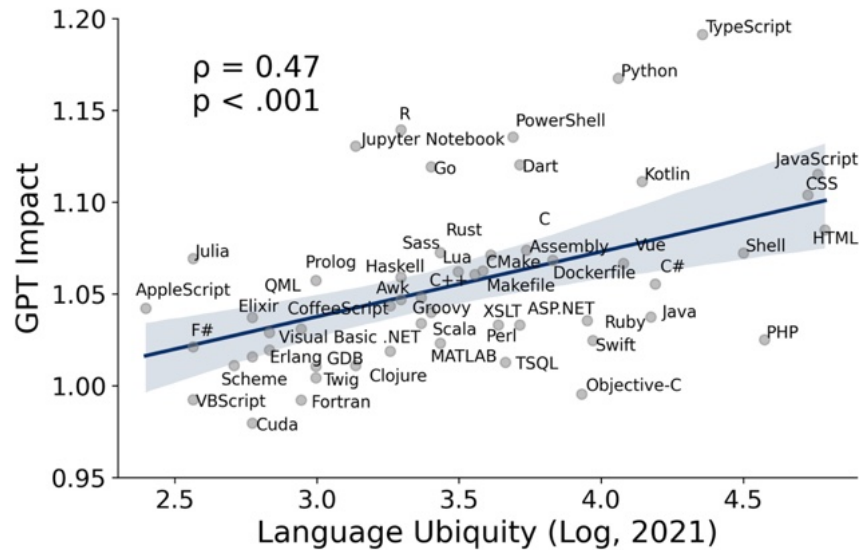


Figure 3 The relationship between software language ubiquity and the estimated impact of the release of ChatGPT on that language, taken from (del Rio-Chanona et al., 2023).

But while our study sheds light on how to estimate, validate, and use measures of economic complexity based on software, it is also subject to important limitations. Open-source software data does not capture information about all of the software capabilities of an economy. In fact, many important companies in the digital sector, such as Apple, have key closed source software solutions (e.g. iOS). Our analysis is blind to the geography of these capabilities. At the same time, since open-source software is a fundamental building block of the digital economy (Eghbal, 2020), its production and use should be correlated with digital innovation and productivity in firms and regions (Lerner and Tirole, 2005; Nagle, 2019, 2018; Wachs et al., 2022; Wright et al., 2023), including the development of proprietary software solutions. Another important limitation is that not all open-source software is on GitHub. While GitHub is the dominant host of OSS projects by volume, there are still other players in this space (e.g. SourceForge, GitLab) that are missing from our analysis. OSS projects hosted outside of GitHub are also different on average, for example they are more likely to be academic (Trujillo et al., 2022).

Also, our study has limitations that come from the combination of economic complexity methods with OSS data. For instance, the interpretation of a product complexity measure applied to programming languages is not straightforward, since programming languages are related by relationships of complementary (e.g. html and css) instead of shared common inputs (as in the case

of industries and products). This results in estimates of complexity that are more easily interpretable for the geographies (countries in our case) than the activities (programming languages). The use of programming languages is also not an ideal proxy for capturing software capabilities, or to study relatedness, since software capabilities could be better reflected in areas of application than the languages themselves. For instance, python is a programming language that can be used for tasks as simple as parsing a data file to the creation of advanced machine learning models. Going forward, well categorized data on software projects may provide an avenue towards better measures of software complexity and relatedness.

Nevertheless, despite these limitations, our work represents a valuable step towards extending economic complexity analysis to the digital realm, offering insights into the geographic distribution of software capabilities and their potential impact on macroeconomic outcomes. As the digital economy continues to evolve, further research integrating diverse data sources and accounting for emerging technologies like large language models will be crucial to refine our understanding of software economic complexity and its policy implications.

Acknowledgements

We acknowledge the support of the Agence Nationale de la Recherche grant number ANR-19-P3IA-0004, the 101086712-LearnData-HORIZON-WIDERA-2022-TALENTS-01 financed by European Research Executive Agency (REA) (<https://cordis.europa.eu/project/id/101086712>), IAST funding from the French National Research Agency (ANR) under grant ANR-17-EURE-0010 (Investissements d'Avenir program), the European Lighthouse of AI for Sustainability [grant number 101120237-HORIZON-CL4-2022-HUMAN-02], the Obs4SeaClim 101136548-HORIZON-CL6-2023-CLIMATE-01 and ANITI ANR-19-P3IA-0004. Sándor Juhász's work was supported by the European Union's Marie Skłodowska-Curie Postdoctoral Fellowship Program (SUPPED, grant number 101062606). Johannes Wachs acknowledges support from the Hungarian National Scientific Fund (OTKA FK 145960). The authors would like to thank Viktor Stojkoski for support in the multidimensional estimates of economic complexity and the econometric models. César A. Hidalgo is a founder of Datawheel LLC and a creator of the Observatory of Economic Complexity (oec.world).

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Supplementary Information

S1 GitHub data preparation

We leverage the open access datasets by GitHub’s Innovation Graph (GHIH). Software economic complexity is calculated from the *languages.csv* table that presents the number of GitHub users pushing code by country and programming language on a quarterly basis. The country of users is estimated using the IP address of each contributor. While not perfect, IP geolocation is a considerably more reliable indicator of the geography of software production than self-reported location, which can contain fictional information (e.g. Narnia, Hogwarts, etc.). The raw data captures the activity of tens of millions of developers from 164 countries in 379 languages between 2020 January and 2023 December on a quarterly basis (with regular updates). As an initial data cleaning, we excluded data formats and markup languages such as *yaml*, *json*, *text*, *svg*, *Markdown* and *xml* following (del Rio-Chanona et al., 2023). To focus on the most relevant language, we limit our exercise to the top 150 languages with the most contributors on average across the 2020-2023 period. We aggregate the quarterly data to yearly observations by considering the average number of developers in each country, language combination.

S2 Data preparation to compare economic complexity measures

We compare the economic complexity of open-source software production (ECI^{software}) with three other metrics of economic complexity constructed by (Stojkoski et al., 2023b): (1) trade complexity (ECI^{trade}) based on product export data from the Observatory of Economic Complexity², (2) technology complexity (ECI^{tech}) based on patent applications data from World Intellectual Property Organization’s International Patent System, and (3) research complexity (ECI^{research}) based on published research documents data from SCImago Journal & Country Tank portal³. The alternative ECI indicators are constructed in the similar fashion as ECI^{software} and are available for cross validation⁴.

² Observatory of Economic Complexity (OEC) <https://oec.world>

³ SCImago Journal & Country Rank (SJR) <https://www.scimagojr.com/aboutus.php>

⁴ <https://doi.org/10.7910/DVN/K4MEFW>

This means that, following Stojkoski et al. (2023b), we restrict the analysis to countries with a population of more than 1 million, total exports of more than 1 billion USD, and at least 4 patents. In order to refine the data on research publications, we focus on countries with at least 100 publications per year in research areas where at least 30 articles are published per year. Values for country, research area combinations where fewer than 3 articles were published per year were replaced by 0 to reduce noise. Where a country, research area combination did not receive 100 citations on average in the 2017-2020 period, the value was replaced with 0.

We connect the different versions of ECI to socio-economic indicators of countries. The economic performance of countries is measured through GDP per capita (2020) from the CEPII Gravity database (Conte et al., n.d.). The income inequality and emission indicators are taken from the online data repository of the World Bank⁵. Due to the uneven data coverage, we use the average Gini coefficient of countries for the period 2010-2023. The emission intensity indicators are from 2019.

⁵ World Bank <https://data.worldbank.org/indicator/>

S3 Comparison of different economic complexity values

Table S1A ECI values for all countries (2020) in our sample

Ranking	Country	ECI software	ECI trade	ECI technology	ECI research	Ranking	Country	ECI software	ECI trade	ECI technology	ECI research
1	DEU	2.059	1.885	1.514	1.848	51	PER	-0.011	-0.686	0.416	0.224
2	GBR	2.031	1.423	1.107	2.390	52	TUN	-0.015	0.098	-1.039	-0.479
3	USA	2.028	1.546	0.705	2.538	53	ISL	-0.015			
4	FRA	2.002	1.353	1.079	1.752	54	CHL	-0.024	-0.222	1.062	1.189
5	CAN	1.954	0.907	1.015	2.315	55	PHL	-0.061	0.565	-0.091	-0.174
6	CHE	1.905	2.003	1.336	1.913	56	VNM	-0.099	-0.031	0.161	-0.545
7	NLD	1.903	1.113	0.993	2.152	57	ZAF	-0.101	0.072	0.966	1.281
8	AUS	1.889	-0.320	1.146	2.241	58	PAK	-0.103	-0.678	-1.000	-0.360
9	SWE	1.887	1.597	1.551	1.882	59	LUX	-0.113			
10	ITA	1.881	1.307	1.354	1.680	60	CYP	-0.113			
11	RUS	1.873	0.491	1.180	0.220	61	MYS	-0.117	1.033	0.688	-0.287
12	JPN	1.854	2.191	0.883	0.618	62	CRI	-0.132	0.187	-0.706	-0.093
13	POL	1.833	1.041	1.084	0.524	63	SRB	-0.134	0.679	-0.160	-0.098
14	ESP	1.825	0.763	1.206	1.764	64	LVA	-0.145			
15	CHN	1.796	0.974	0.719	-0.519	65	KAZ	-0.193	-0.245	0.001	-0.834
16	HKG	1.776	1.103	0.634	0.995	66	IRN	-0.198	-0.114	0.292	0.295
17	CZE	1.656	1.583	1.105	0.411	67	SAU	-0.210	0.878	0.909	-0.142
18	AUT	1.560	1.540	1.494	1.608	68	KEN	-0.238	-0.489	-1.125	0.467
19	NOR	1.550	0.706	1.354	1.707	69	GTM	-0.257	-0.384	-1.276	-0.851
20	FIN	1.547	1.484	1.349	1.515	70	ARE	-0.294	0.153	0.101	0.087
21	DNK	1.524	0.976	1.058	1.697	71	BGD	-0.295	-1.140	-1.438	-0.238
22	BEL	1.475	1.342	1.023	1.815	72	NGA	-0.300	-1.667	-1.621	0.054
23	SGP	1.463	1.824	0.648	0.368	73	URY	-0.355	-0.004	-0.176	0.158
24	TWN	1.434	1.980	0.601	0.046	74	NPL	-0.358			
25	IRL	1.430	1.309	0.791	1.678	75	ETH	-0.373	-0.867		0.341
26	IND	1.409	0.561	1.004	-0.453	76	SEN	-0.399	-0.697	-1.063	-0.374
27	ISR	1.354	1.154	0.752	1.796	77	IRQ	-0.414	-0.671		-1.085
28	ROU	1.241	1.029	0.517	-0.157	78	MLT	-0.430			
29	PRT	1.239	0.467	0.890	1.051	79	ECU	-0.450	-0.982	-1.022	-0.51
30	GRC	1.183	0.256	-1.022	0.934	80	LBN	-0.467	0.270	-0.772	0.314
31	KOR	1.127	1.873	0.653	0.277	81	SLV	-0.474	-0.149		-1.377
32	HUN	1.109	1.413	0.946	0.852	82	DOM	-0.499	-0.146	-1.012	-1.377
33	IDN	1.103	-0.074	-0.293	-0.008	83	GHA	-0.516	-1.292	-2.019	0.313
34	NZL	1.071	0.446	0.941	1.731	84	HND	-0.517	-0.599		-0.851
35	ARG	0.653	0.068	0.183	0.912	85	MDA	-0.528	-0.142	-0.265	-1.054
36	BLR	0.642	0.780	-0.323	-0.866	86	PRI	-0.529			
37	SVK	0.612	1.332	0.635	-0.383	87	UGA	-0.530	-0.989	-1.251	0.451
38	BRA	0.606	0.439	1.181	1.281	88	BOL	-0.542	-0.981		-0.493
39	UKR	0.582	0.515	0.710	-0.985	89	CMR	-0.576	-1.234		-0.347
40	SVN	0.531	1.458	0.939	0.119	90	RWA	-0.578			
41	MEX	0.452	1.152	0.025	0.665	91	JOR	-0.586	-0.079	-0.976	-0.187
42	LKA	0.451	-0.488	-0.536	-0.684	92	DZA	-0.587	-1.206	-0.467	-0.976
43	COL	0.404	0.148	0.673	0.494	93	AZE	-0.590	-0.537	-0.760	-1.517
44	BGR	0.387	0.525	0.573	-0.509	94	MKD	-0.603	0.020	-0.995	-0.496
45	HRV	0.376	0.743	0.341	0.276	95	KHM	-0.606	-0.959	-2.651	-0.124
46	LTU	0.271	0.906	-0.212	-0.432	96	ARM	-0.608	-0.339	-0.657	-0.817
47	EST	0.245				97	MMR	-0.619	-1.140		-0.476
48	TUR	0.174	0.597	1.147	0.810	98	GEO	-0.629	-0.053	-0.716	0.769
49	EGY	0.140	-0.159	-0.291	0.172	99	PSE	-0.636			
50	THA	0.005	0.906	0.698	-0.017	100	SYR	-0.648			-2.007

Table S1B ECI values for all countries (2020) in our sample

Ranking	Country	ECI software	ECI trade	ECI technology	ECI research
101	MAR	-0.652	-0.486	-0.018	-0.821
102	ALB	-0.660	-0.337	-1.022	-0.315
103	VEN	-0.663	-1.097	-1.435	-0.432
104	BIH	-0.666	0.514	-0.301	-1.275
105	CUB	-0.667		-2.182	-1.030
106	UZB	-0.671	-0.553	-1.240	0.109
107	KGZ	-0.678	-0.212		-0.342
108	PAN	-0.679	0.229	0.407	0.291
109	PRY	-0.679	-0.422		-1.152
110	KWT	-0.712	0.037	-1.042	-0.795
111	NIC	-0.723	-1.072		-0.927
112	TZA	-0.744	-0.639		0.380
113	MUS	-0.748			
114	ZWE	-0.751	-0.894	-0.624	0.051
115	JAM	-0.751	-0.373		0.626
116	SDN	-0.758	-1.311	-1.279	-1.338
117	MAC	-0.768			
118	TTO	-0.768			
119	BHR	-0.768			
120	OMN	-0.768	-0.205	-1.095	-0.898
121	QAT	-0.774	-0.047	-0.883	-0.008
122	CIV	-0.825	-1.046		-0.616
123	MDG	-0.85	-1.222		-0.418
124	MNG	-0.873	-1.207	-2.040	0.140
125	REU	-0.900			
126	AGO	-0.900	-1.424		
127	BEN	-0.900			-0.397
128	COD	-0.900	-1.475		-0.975
129	MNE	-0.947			
130	ZMB	-0.947	-0.717		0.127
131	YEM	-0.947	-1.207		-1.455
132	MOZ	-1.053	-1.249		-0.330
133	LBY	-1.177	-1.41	-0.920	-2.221
134	HTI	-1.186			
135	TGO	-1.186	-0.882		-1.377
136	AFG	-1.186	-1.186		-1.152
137	LAO	-1.186	-0.973		-0.694
138	TJK	-1.186			
139	MWI	-1.245			0.515
140	SOM	-1.245			
141	BRB	-1.286			
142	BRN	-1.286			
143	MDV	-1.286			
144	BLZ	-1.286			
145	BFA	-1.286	-1.679		-0.517
146	BWA	-1.286	-0.574		-0.429
147	LBR	-1.286			

S4 Instrumental variables approach for assessing the impact of software on GDP, inequality and emissions

To address potential endogeneity issues and to further validate our results, we take an instrumental variables approach proposed by Stojkoski et al. (2023b) in which we instrument the $ECI^{software}$ values of a country with the average $ECI^{software}$ values of the three most similar non-neighboring countries (countries with similar specialization patterns but no common land or maritime borders). 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 social policies to mitigate inequalities) that could drive both complexity and other macroeconomic outcomes.

To decouple local factors and conditions from our complexity estimates, we identify the three non-neighboring countries with the most similar specialization pattern (using minimum conditional probability) and take the average of their $ECI^{software}$ values. Table S2, Table S3 and Table S4 present the same regression settings as in the main text, but using instrumental variable estimation in all possible cases. Our results remain unchanged.

Two diagnostic tests were performed to assess the strength of the instrumental variables. The Weak Instruments Test (Kleibergen and Paap, 2006) assesses whether the instruments are sufficiently correlated with the endogenous regressors to provide reliable estimates, and the Durbin-Wu-Hausman test (Hausman, 1978; Wu, 1974) examines whether the endogenous variables in the model are indeed exogenous or correlated with the error terms, suggesting potential endogeneity. Both tests confirmed the strength of our instrument and indicate no significant endogeneity problems for all models, with the Kleibergen-Paap rk Wald F statistics well above the critical value and Durbin-Wu-Hausman p-values consistently above 0.1.

Table S2 ECI^{software} and GPD per capita (2020) in a multidimensional setting using instrumental variables. Robust standard errors in parentheses. Significance codes: *p<0.1, **p<0.05, ***p<0.01

	GPD per capita (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECI ^{software}	0.308*** (0.043)				0.235*** (0.050)	0.278*** (0.044)	0.251*** (0.048)	0.157*** (0.050)
ECI ^{trade}		0.278*** (0.038)			0.114*** (0.033)			0.137*** (0.041)
ECI ^{technology}			0.228*** (0.042)			0.053 (0.040)		-0.006 (0.046)
ECI ^{research}				0.200*** (0.034)			0.071** (0.034)	0.082** (0.035)
Population (log)	-0.168*** (0.063)	-0.003 (0.052)	-0.068 (0.073)	-0.007 (0.065)	-0.149** (0.062)	-0.182*** (0.066)	-0.158*** (0.059)	-0.133*** (0.065)
Natural resources (log)	2.528*** (0.814)	2.876*** (0.871)	2.858*** (0.959)	3.397*** (0.841)	2.326*** (0.810)	2.334*** (0.864)	2.495*** (0.803)	2.271*** (0.859)
Instrument	Yes	No	No	No	Yes	Yes	Yes	Yes
Observations	92	92	92	92	92	92	92	92
R ²	0.830	0.801	0.751	0.769	0.847	0.835	0.841	0.861
Adjusted R ²	0.824	0.794	0.742	0.761	0.840	0.828	0.834	0.851

Table S3 ECI^{software} and income inequality in a multidimensional setting using instrumental variables. ECI estimates are based on 2020 data, while the dependent variable is the average Gini coefficient between 2010 and 2020. Robust standard errors in parentheses. Significance codes: *p<0.1, **p<0.05, ***p<0.01

	Gini coefficient							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECI ^{software}	-0.698** (0.286)				-0.646** (0.282)	-0.731** (0.298)	-0.850*** (0.232)	-0.889*** (0.244)
ECI ^{trade}		-0.329* (0.196)			-0.137 (0.1820)			0.031 (0.188)
ECI ^{technology}			-0.065 (0.225)			0.100 (0.223)		0.078 (0.201)
ECI ^{research}				0.591*** (0.196)			0.642*** (0.184)	0.644*** (0.198)
GPD per capita (log)	1.398* (0.839)	1.540 (0.959)	0.957 (0.831)	1.263 (0.787)	1.624* (0.935)	1.307 (0.852)	1.923** (0.846)	1.801* (0.906)
GPD per capita (log) ²	-0.520 (0.314)	-0.888** (0.352)	-0.806** (0.329)	-1.395*** (0.394)	-0.576* (0.326)	-0.500 (0.310)	-1.101*** (0.370)	-1.075*** (0.359)
Population (log)	0.902*** (0.281)	0.490** (0.190)	0.460** (0.207)	0.196 (0.167)	0.895*** (0.284)	0.865*** (0.275)	0.764*** (0.222)	0.736*** (0.223)
Natural resources (log)	1.621 (2.152)	1.169 (2.288)	1.530 (1.957)	0.775 (1.915)	1.533 (2.288)	1.324 (2.124)	1.083 (2.147)	0.870 (2.205)
Instrument	Yes	No	No	No	Yes	Yes	Yes	Yes
Observations	82	82	82	82	82	82	82	82
R ²	0.288	0.224	0.198	0.312	0.292	0.291	0.421	0.422
Adjusted R ²	0.241	0.173	0.146	0.267	0.235	0.234	0.374	0.359

Table S4 ECI^{software} and greenhouse gas emission intensity (2020) in a multidimensional setting using instrumental variables. Robust standard errors in parentheses. Significance codes: *p<0.1, **p<0.05, ***p<0.01

	Emissions per GPD							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECI ^{software}	-0.419*** (0.159)				-0.329* (0.177)	-0.324* (0.169)	-0.358** (0.172)	-0.202 (0.193)
ECI ^{trade}		-0.367** (0.162)			-0.238 (0.189)			-0.212 (0.198)
ECI ^{technology}			-0.333** (0.158)			-0.226 (0.166)		-0.145 (0.178)
ECI ^{research}				-0.188 (0.124)			-0.096 (0.130)	-0.121 (0.129)
GPD per capita (log)	-1.310*** (0.441)	-1.466*** (0.369)	-1.617*** (0.350)	-1.714*** (0.437)	-1.099*** (0.410)	-1.195*** (0.414)	-1.255*** (0.459)	-0.979** (0.429)
Population (log)	0.570*** (0.169)	0.360** (0.158)	0.490** (0.189)	0.347** (0.151)	0.566*** (0.171)	0.652*** (0.181)	0.567*** (0.165)	0.615*** (0.185)
Natural resources (log)	6.774*** (1.964)	6.948*** (1.846)	7.905*** (2.191)	6.952*** (2.237)	6.665*** (1.743)	7.310*** (2.073)	6.679*** (1.988)	6.903*** (1.962)
Instrument	Yes	No	No	No	Yes	Yes	Yes	Yes
Observations	92	92	92	92	92	92	92	92
R ²	0.490	0.469	0.470	0.447	0.502	0.503	0.492	0.511
Adjusted R ²	0.467	0.445	0.445	0.422	0.473	0.474	0.462	0.470

S5 Alternative entry and exit regression specifications

Table S5 Logit regressions on countries gaining revealed comparative advantage ($RCA \geq 1$) in programming languages (2020-2023). Standard errors are clustered at the country level. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Entry						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Relatedness density	2.891*** (0.778)	3.430** (1.612)	5.073*** (0.983)	1.333 (3.514)		2.826*** (0.699)	2.307* (1.373)
Ubiquity					-0.570*** (0.213)	-0.574*** (0.173)	-0.963*** (0.200)
Country FE	No	Yes	No	Yes	No	No	Yes
Language FE	No	No	Yes	Yes	No	No	No
Observations	1584	1043	982	612	1584	1584	1043
Pseudo R ²	0.038	0.083	0.203	0.362	0.026	0.068	0.144
BIC	778	1030	908	1050	788	762	994

Table S6 Logit regressions on countries losing revealed comparative advantage ($RCA < 1$) in programming languages (2020-2023). Standard errors are clustered at the country level. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Exit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Relatedness density	-2.165*** (0.675)	-4.493*** (1.089)	-1.911*** (0.658)	-6.921*** (2.149)		-2.546*** (0.632)	-4.862*** (1.305)
Ubiquity					-0.046 (0.132)	-0.260* (0.144)	0.093 (0.234)
Country FE	No	Yes	No	Yes	No	No	Yes
Language FE	No	No	Yes	Yes	No	No	No
Observations	2978	2160	1903	1281	2978	2978	2160
Pseudo R ²	0.024	0.153	0.112	0.258	0.000	0.030	0.154
BIC	1089	1385	1357	1584	1115	1090	1392

S6 Language space with all labels included

