Economic Complexity: How Machine Learning Helps us Understand Economic Growth and Development

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Thomas Thwaites

The world works not because a few people know a lot, but because many people know a little.

Economic complexity is about understanding how that knowledge comes together.

Economic complexity

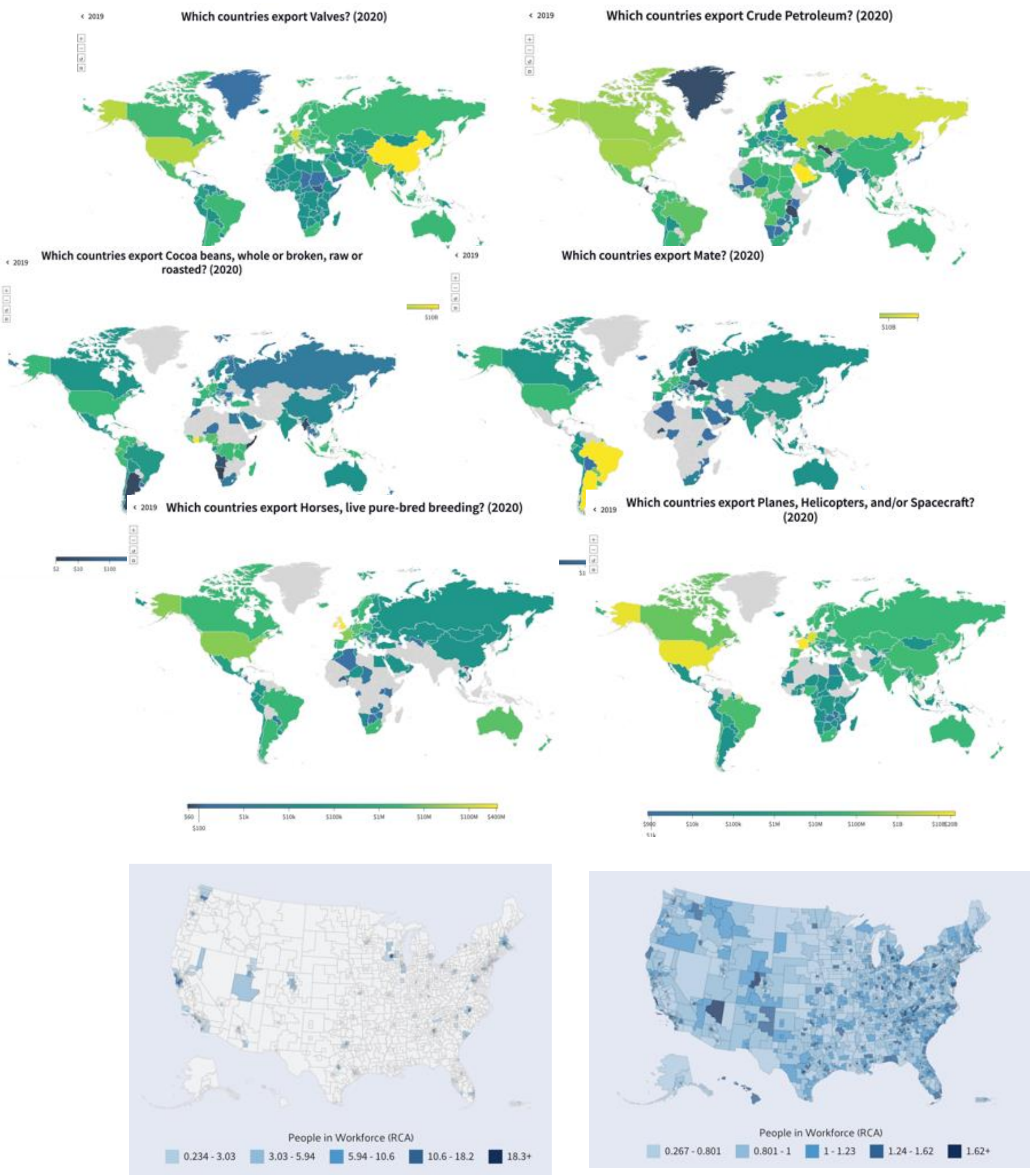
machine learning

+

economic data

=

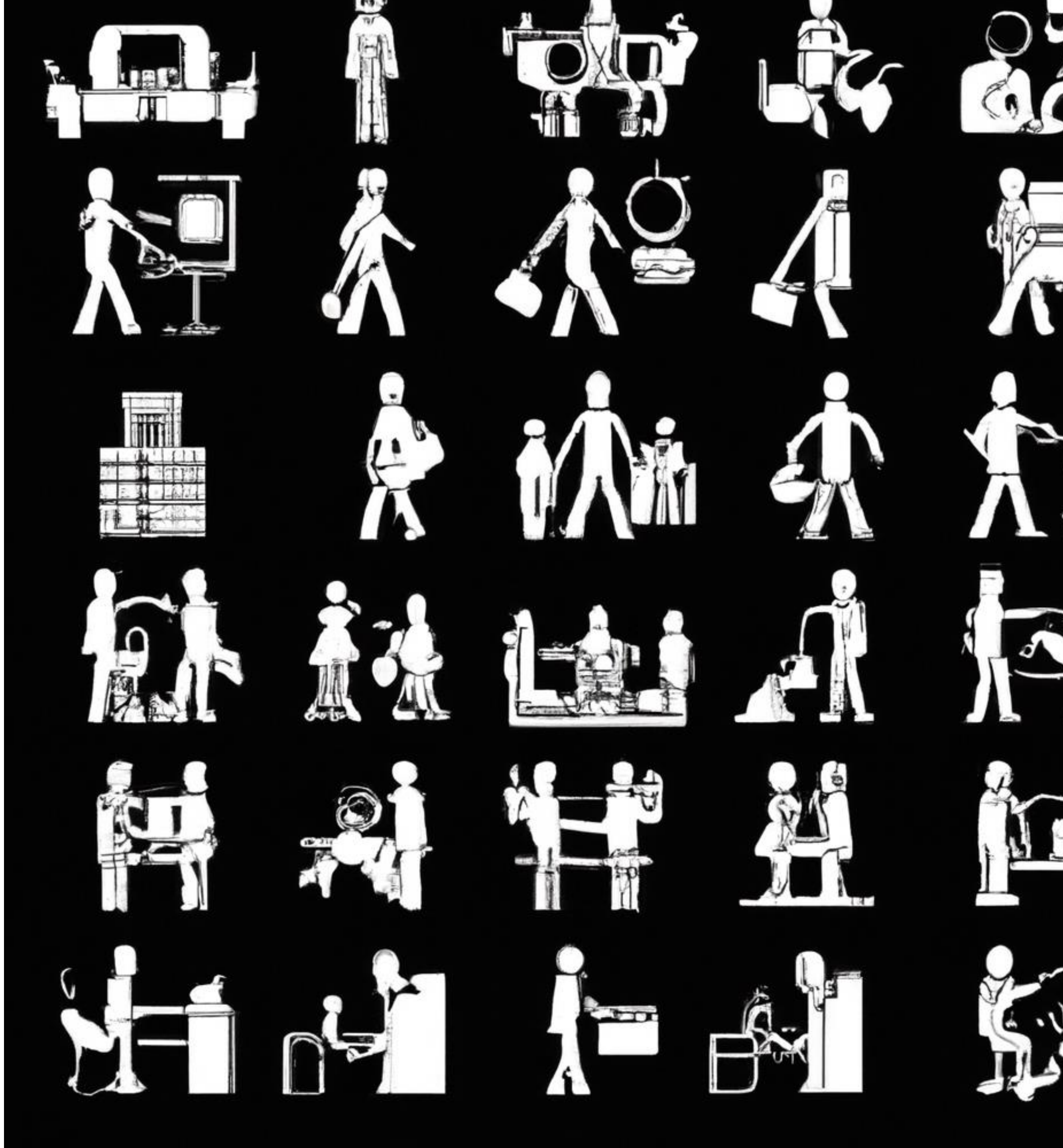
development outcomes



Starting in 2006-2007

Why Machine Learning?

Because factors of production, and in particular **knowledge**, are **non-interchangeable** or **non-fungible.**



chat.openai.com/chat

+ New chat

Phone models discussed.

AI Methods in Economics

Digital trade importance.

RQ: Papers, Ideas / T: Suggest

AI and Economics Revolution

Recommend TV Shows

New chat

New chat

Clear conversations

Upgrade to Plus NEW

Dark mode

Updates & FAQ

Log out

ChatGPT

Examples	Capabilities	Limitations
"Explain quantum computing in simple terms" →	Remembers what user said earlier in the conversation	May occasionally generate incorrect information
"Got any creative ideas for a 10 year old's birthday?" →	Allows user to provide follow-up corrections	May occasionally produce harmful instructions or biased content
"How do I make an HTTP request in Javascript?" →	Trained to decline inappropriate requests	Limited knowledge of world and events after 2021

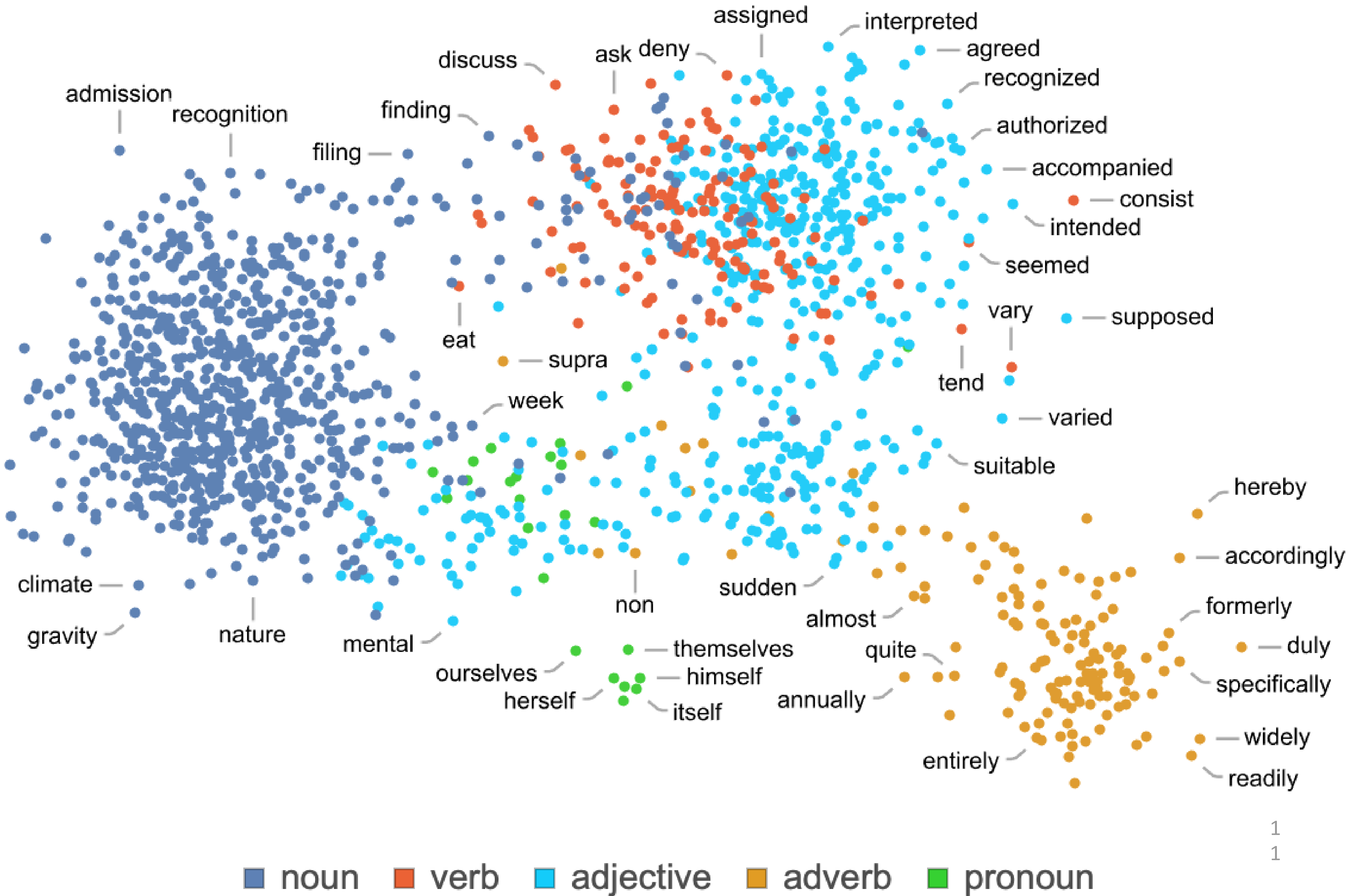
ChatGPT Feb 13 Version. Free Research Preview. Our goal is to make AI systems more natural and safe to interact with. Your feedback will help us improve.

Parts-of-speech representation of words do not honor their non-fungibility

Verb, Nouns, Adjectives, and Adverbs List

Verbs	Nouns	Adjectives	Adverbs
accuse	accusation	accusing	accusingly
argue	argument	arguable	arguably
characterize	character	characteristic	characteristically
condition	condition	conditional	conditionally
darken	dark, darkness	dark, darkened	darkly
destroy	destruction	destructive	destructively
drink	drink, drunkenness	drunk, drunken	drunkenly

Word Embeddings Provide Semantic Representations That Transcend Parts of Speech Limitations



“Parts of Speech” Representation of Products or Activities

Manufacture — Capital Intensive

Agriculture — Capital Intensive

Agriculture — Labor Intensive

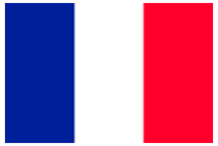
Manufacture — Labor Intensive

AI or LLMs

Just like we can count the number of words in each sentence or paragraph, and their co-occurrences, to create representations of their semantic meaning, we can count the number of economic activities that are present across cities, regions, and countries to create representations of the knowledge embedded in them.

Economic Complexity

Spark Ignition Engines, Tobacco, Engine Parts, Aircraft Parts, Vaccines, Plywood, Tractors, Coffee, Frozen Bovine Meat, etc…



Spark Ignition Engines, Engine Parts, Aircraft Parts, Aircraft, Wheat, Wine, Perfumes, Vaccines, etc…

Crude Petroleum, Refined Petroleum, Petroleum Gases, Wheat, Aircraft Parts, etc.

But...
Who cares about Economic Complexity?

Economic Complexity is the First Mission of Malaysia's New Industrial Master Plan

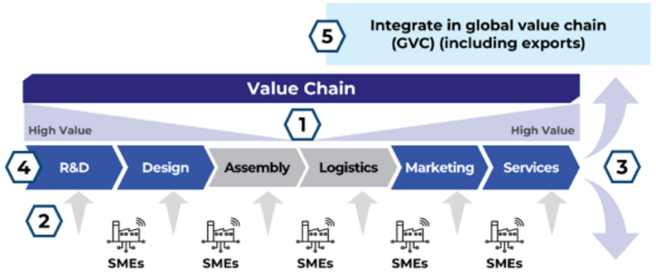
HOME NEW INDUSTRIAL MASTER PLAN MISSION ABOUT US EVENTS DOCUMENTS MEDIA FAQ

Home > Mission > Mission 1: Advance economic complexity

Mission 1: Advance economic complexity

Mission 1 focuses on encouraging the industry to innovate and produce more sophisticated products to increase economic complexity

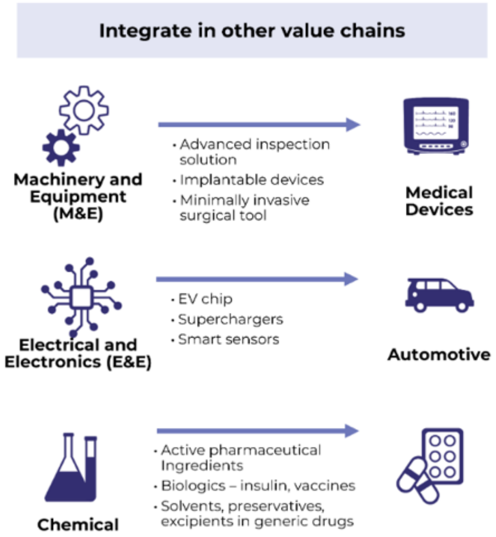
1. Expand to higher value-added activities
2. Develop ecosystem to support high value-added activities
3. Establish 'vertical integration' for GVC
4. Foster RDCI ecosystem
5. Increase manufacturing exports



Malaysia's strategic focus is on transitioning to higher value-added activities, moving beyond traditional manufacturing models towards an innovation-driven manufacturing hub.

This transformation involves fostering an ecosystem that encourages the growth of industries engaged in high-value economic activities, integrating value chains across sectors and promoting vertical integration among ASEAN countries.

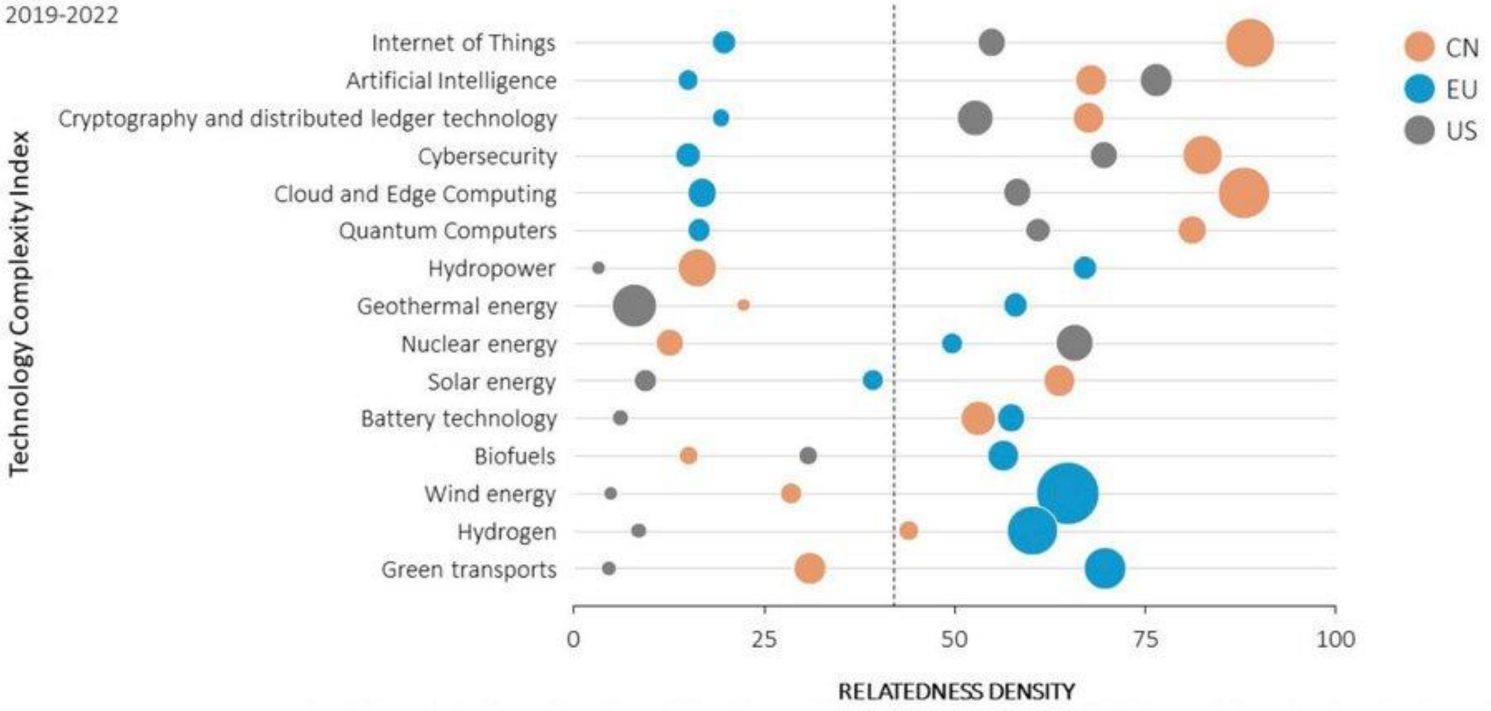
The Research, Development, Commercialisation, and Innovation (RDCI) cycle plays a pivotal role in enhancing economic complexity and cultivating high-skilled talent, facilitating the introduction of innovative products and services that drive job creation and economic expansion. Central to this approach is the goal of increasing manufacturing exports to bolster Malaysia's economic growth and global competitiveness



Economic Complexity was used in the recent Draghi Report to the EU

FIGURE 2

The EU's position in complex (digital and green) technologies



Notes: The results are based on an analysis of patent data to understand the complexity and potential for specialisation in different technology areas. On the y-axis, technologies are ranked according to how advanced or complex they are, with scores ranging between 0 (less complex) and 100 (more complex). The x-axis (showing the relatedness density) represents how easily a country can build comparative advantage in a particular technology, depending on how closely related it is to other technologies the country is already strong in. The size of the bubbles shows how much each country has already specialised in a technology, using a measure of "revealed comparative advantage"(RCA), which reflects their competitive strenght in that field.

Source: European Commission, DG RTD.

The future of European Competitiveness. "Draghi Report" 2024

COTEC LA COMPLEJIDAD ECONÓMICA EN ESPAÑA

INICIO FICHAS COMERCIO ¡NUEVO!

EXPLORA LOS ÚLTIMOS DATOS DE COMPLEJIDAD ECONÓMICA PARA ESPAÑA Y SUS PROVINCIAS

Descubrir datos de España

Comenzar a explorar

TOP PROVINCIAS — Ver fichas de España →

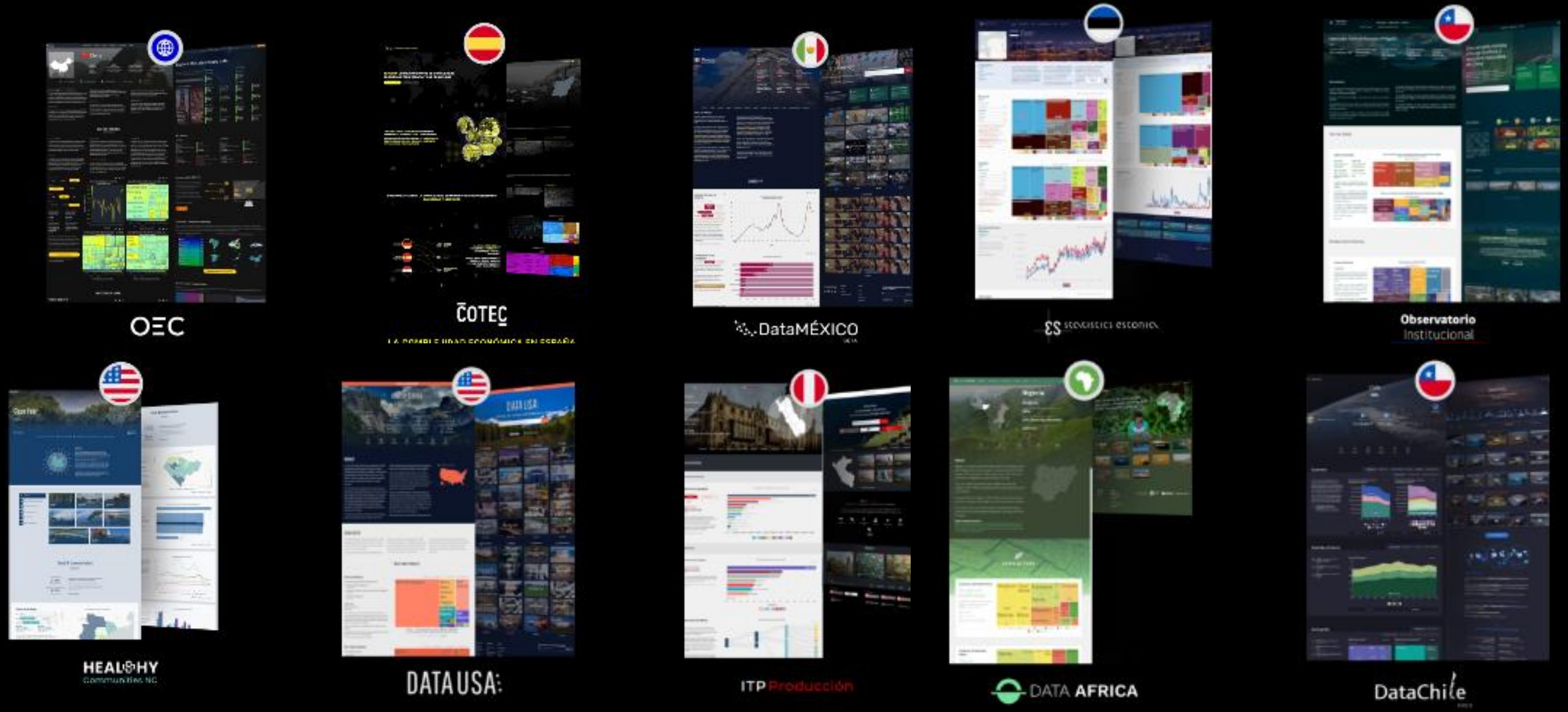
Barcelona	Madrid	Valencia
PROVINCIA	PROVINCIA	PROVINCIA

TOP PRODUCTOS ¡NUEVO! — Ver fichas de Productos →

Autos, tractores, camiones y piezas...	Combustibles minerales, aceites...	Maquinaria, electrodomésticos ...
HS2	HS2	HS2

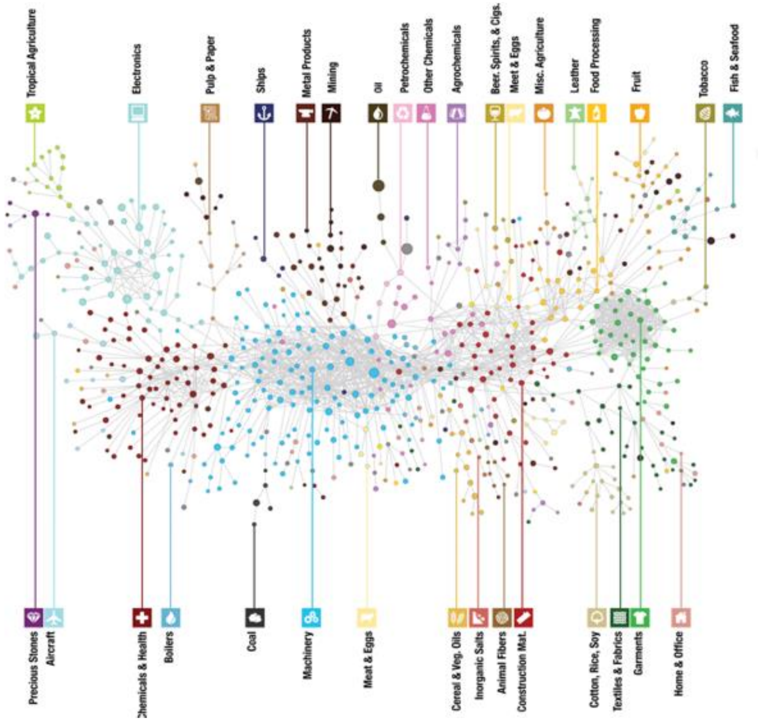
INDICADORES DE COMERCIO ¡NUEVO! — Ver herramienta de comercio →

Economic Complexity has motivated the creation of dozens of economic data observatories



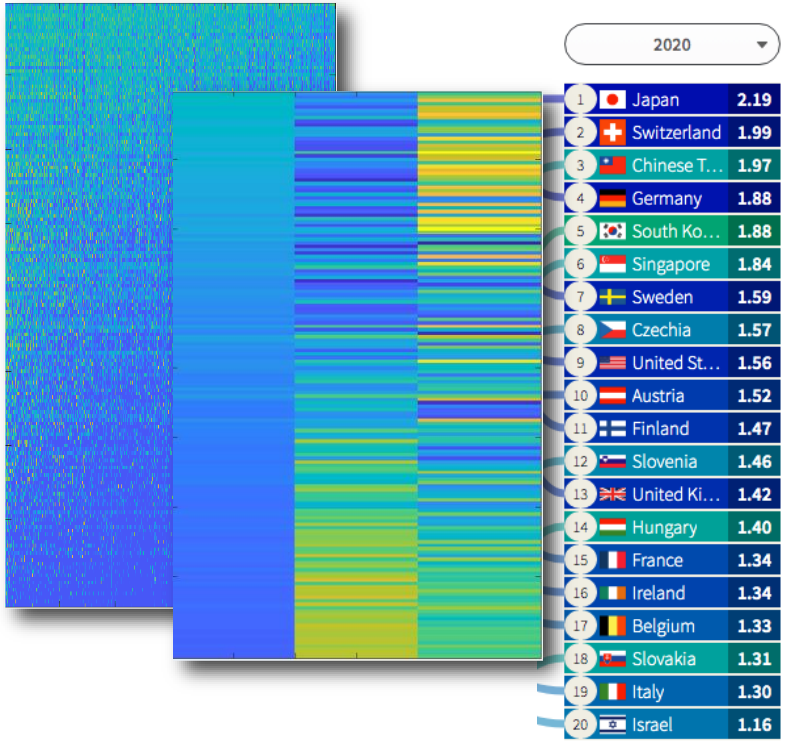
Two Key Concepts

Relatedness



Hidalgo et al. Science (2007)

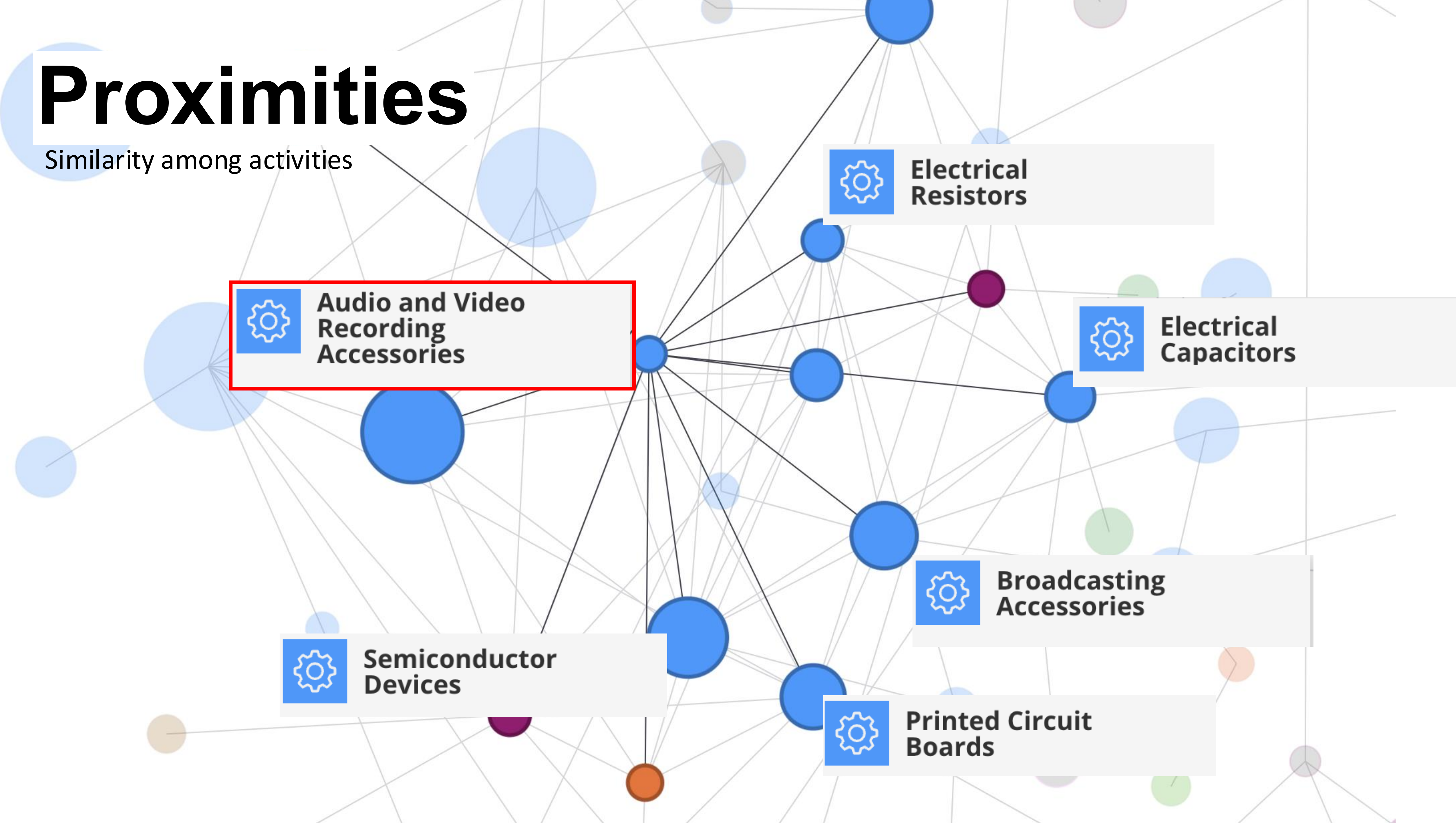
Complexity Indexes



Hidalgo & Hausmann. PNAS (2009)

Proximities

Similarity among activities

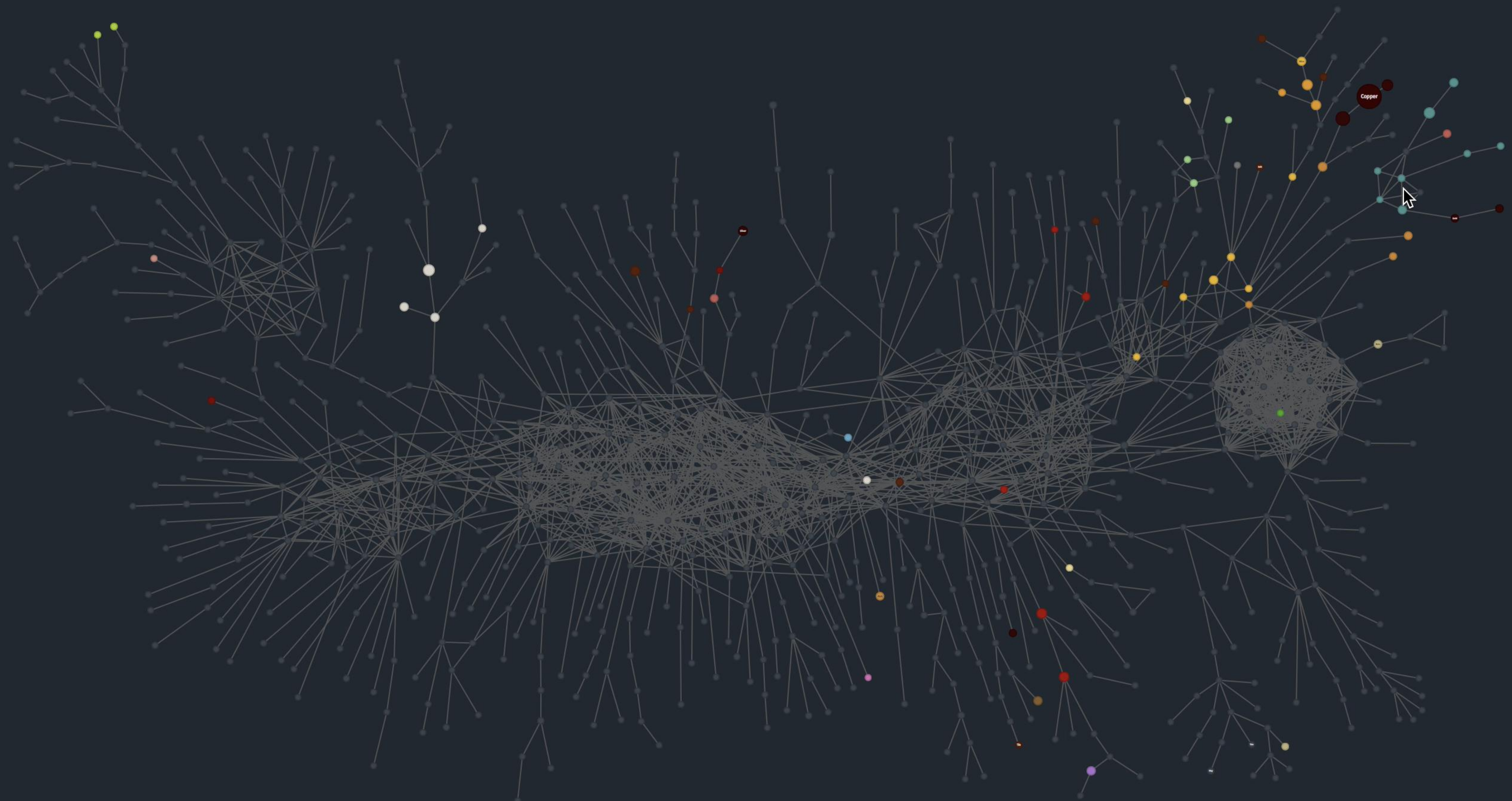


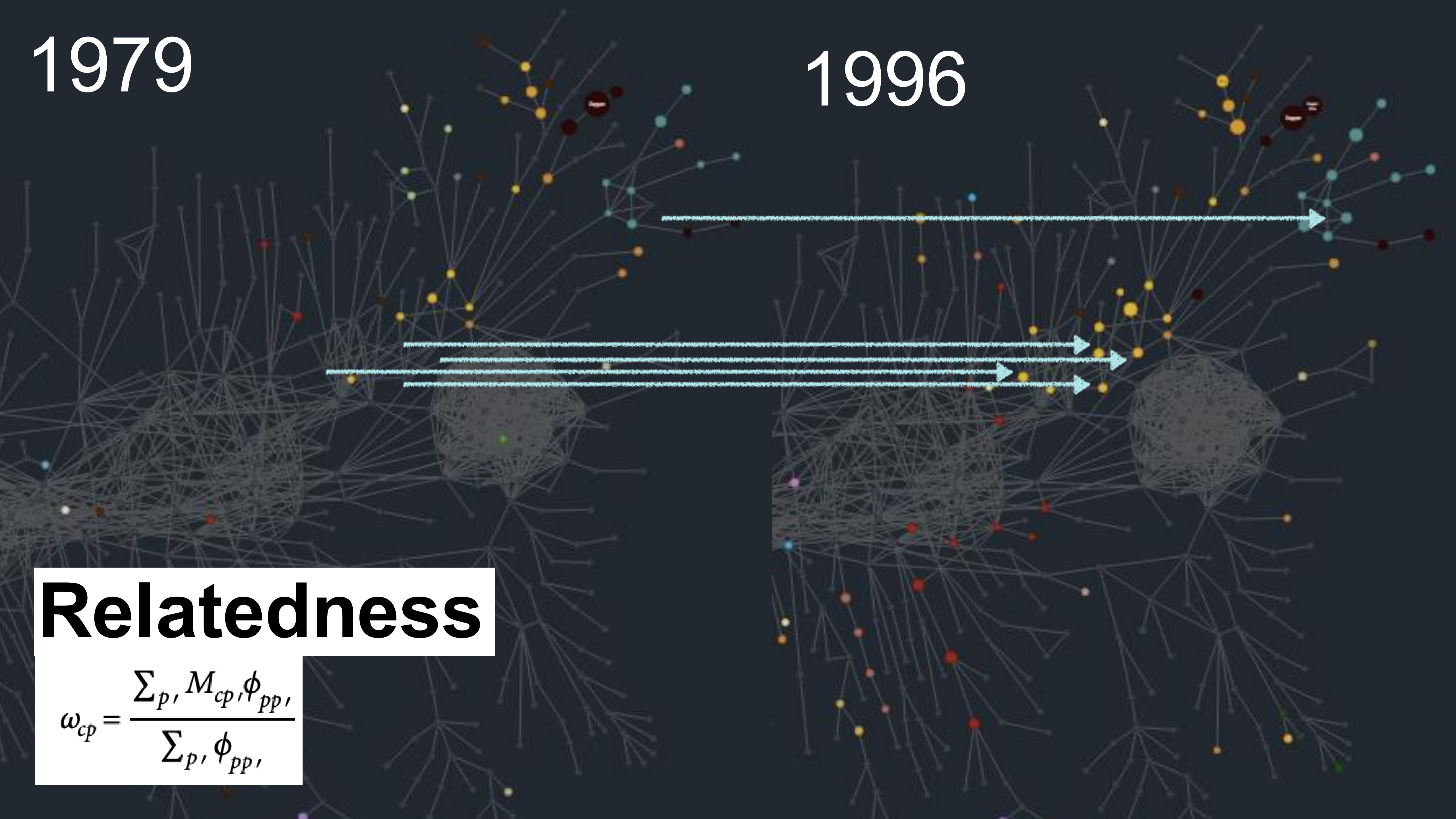
Knowledge flows are constrained by cognitive similarities among activities

Hidalgo et al. Science 2007

What are the export opportunities of Chile? (1979)

TOTAL: $3.67B





Relatedness

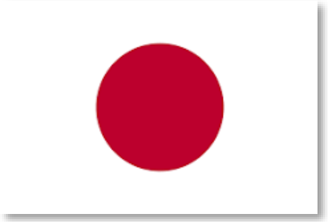
$$\omega_{cp} = \frac{\sum_{p'} M_{cp'} \phi_{pp'}}{\sum_{p'} \phi_{pp'}}$$


Vespa

Corradino D’Ascanio

Corradino D’Ascanio

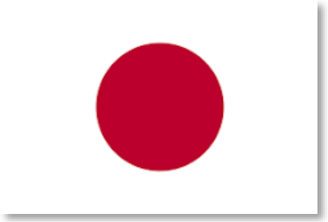
AICHI



Aichi E13A (Jake)

Heinkel He 111

AICHI

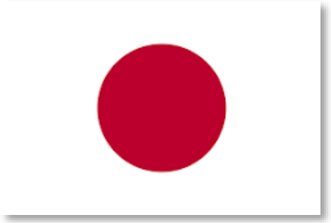


Giant AA1 minicar (1947)

Aichi Machine Industry

Brands

Giant
Cony



KAWANISHI

H8K, Flying boat (Emily)

Kawanishi N1K fighter (Rex)

KAWANISHI

Pointer/Super Lassie Motorcycle

HEINKEL

HE 178 (first to fly with a jet engine)

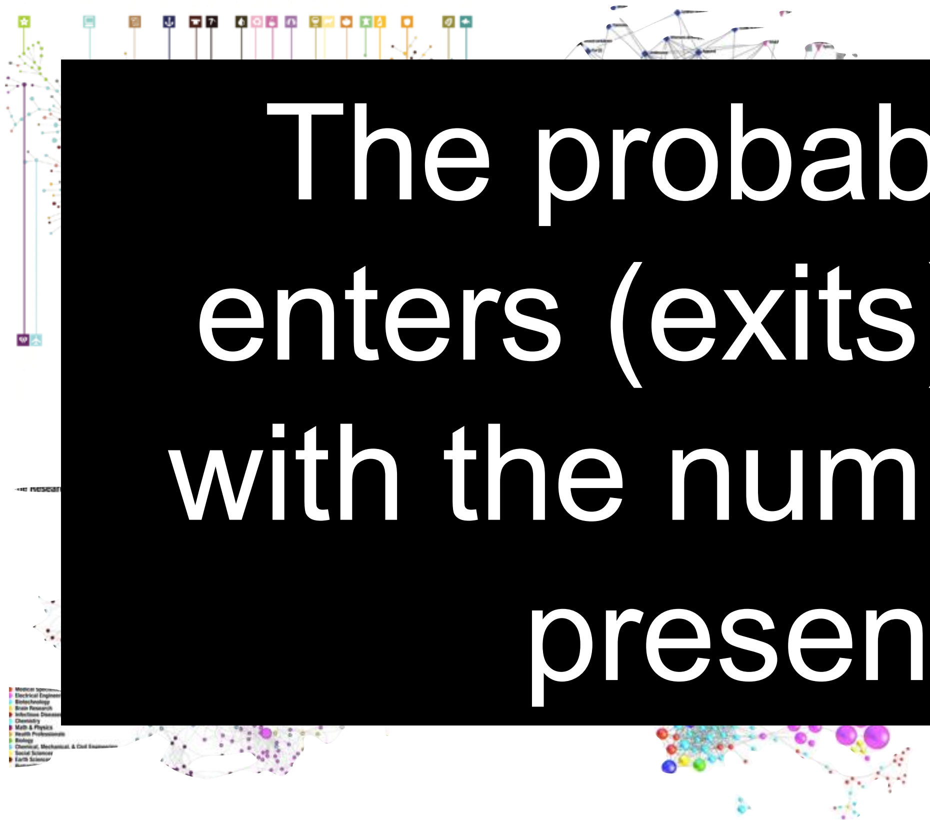
HEINKEL

Heinkel Tourist

THE PRINCIPLE OF RELATEDNESS

Products

Industries

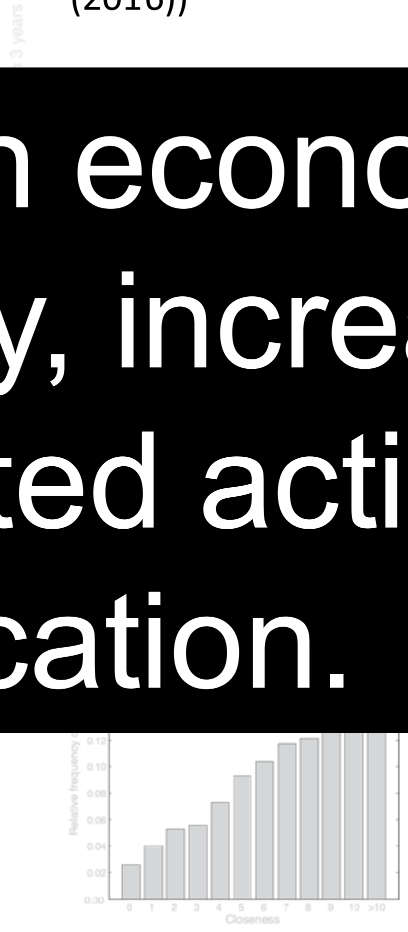


Products

(Hidalgo et al 2007)

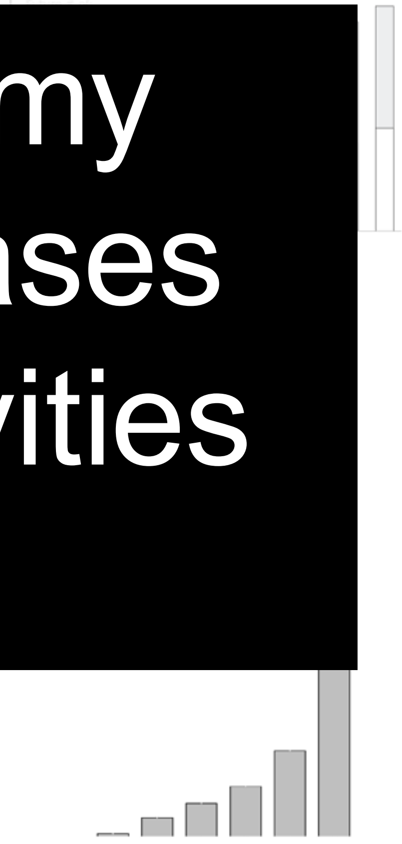
Research Areas

(Guevara et al. (2016))



Patents

(Kogler et al. (2013), Boschma et al. (2015), Alstott et al. (2016))



The probability that an economy enters (exits) an activity, increases with the number of related activities present in that location.

Research Areas

Patents

César A. Hidalgo, Pierre-Alexandre Balland, Ron Boschma, Mercedes Delgado, Maryann Feldman, Koen Frenken, Edward Glaeser, Dieter F. Kogler, Andrea Morrison, Frank Neffke, David Rigby, Scott Stern, Siqi Zheng, Canfei He, & Shengjun Zhu. "The Principle of Relatedness" CCS 2018. Springer Proceedings in Complexity. Springer (2018)

Let’s Look at Hungary

Yearly Trade

Exports | Imports

Trade Value | Growth

USD | %

HS2 | HS4 | HS6

2023

In 2023, Hungary exported a total of $150B, making it the number 35 exporter in the world.

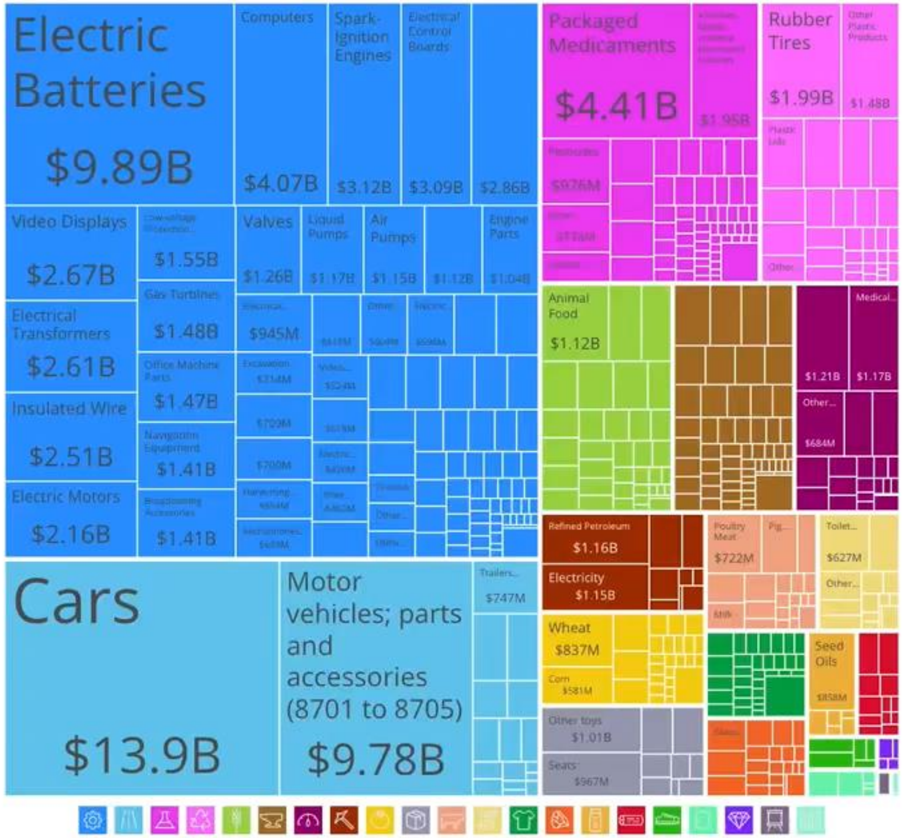
During the last five reported years, the exports of Hungary have increased by $31B from $119B in 2018 to $150B in 2023.

The most recent exports are led by **Cars** ($13.9B), **Electric Batteries** ($9.89B), **Motor vehicles; parts and accessories (8701 to 8705)** ($9.78B), **Packaged Medicaments** ($4.41B), and **Computers** ($4.07B).
The most common destination for the exports of Hungary are **Germany** ($37.4B), **Italy** ($9.08B), **Romania** ($8.43B), **United States** ($7.66B), and **Slovakia** ($6.54B).

Product Exports

[Click to select a Product]

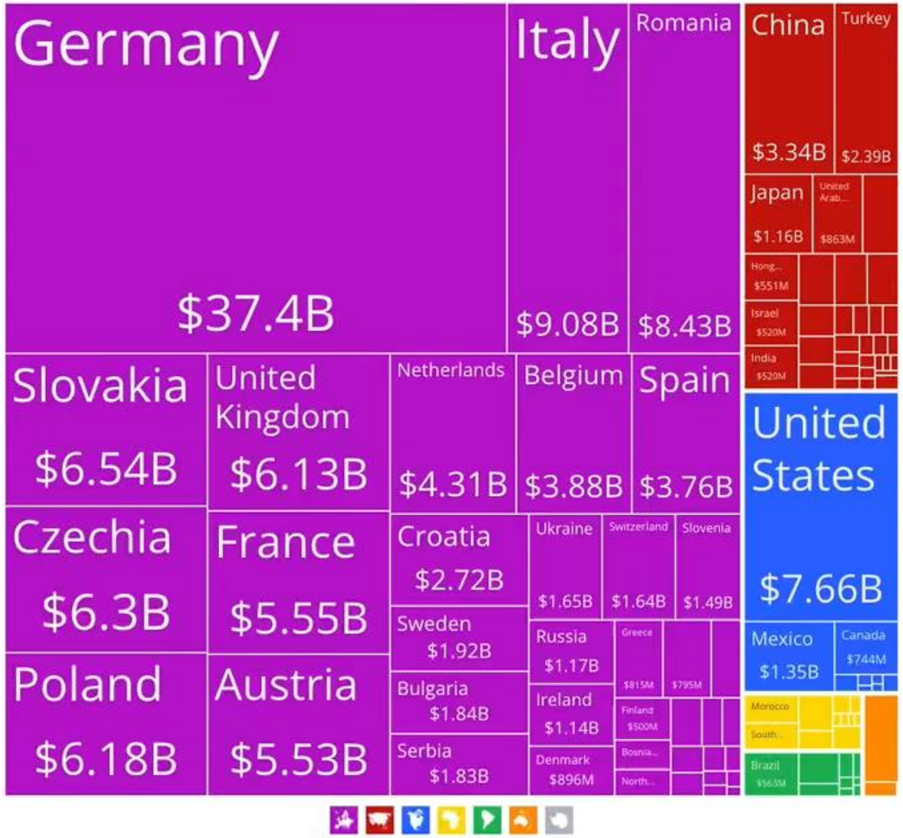
Total: $150B



Destinations

[Click to select a Country]

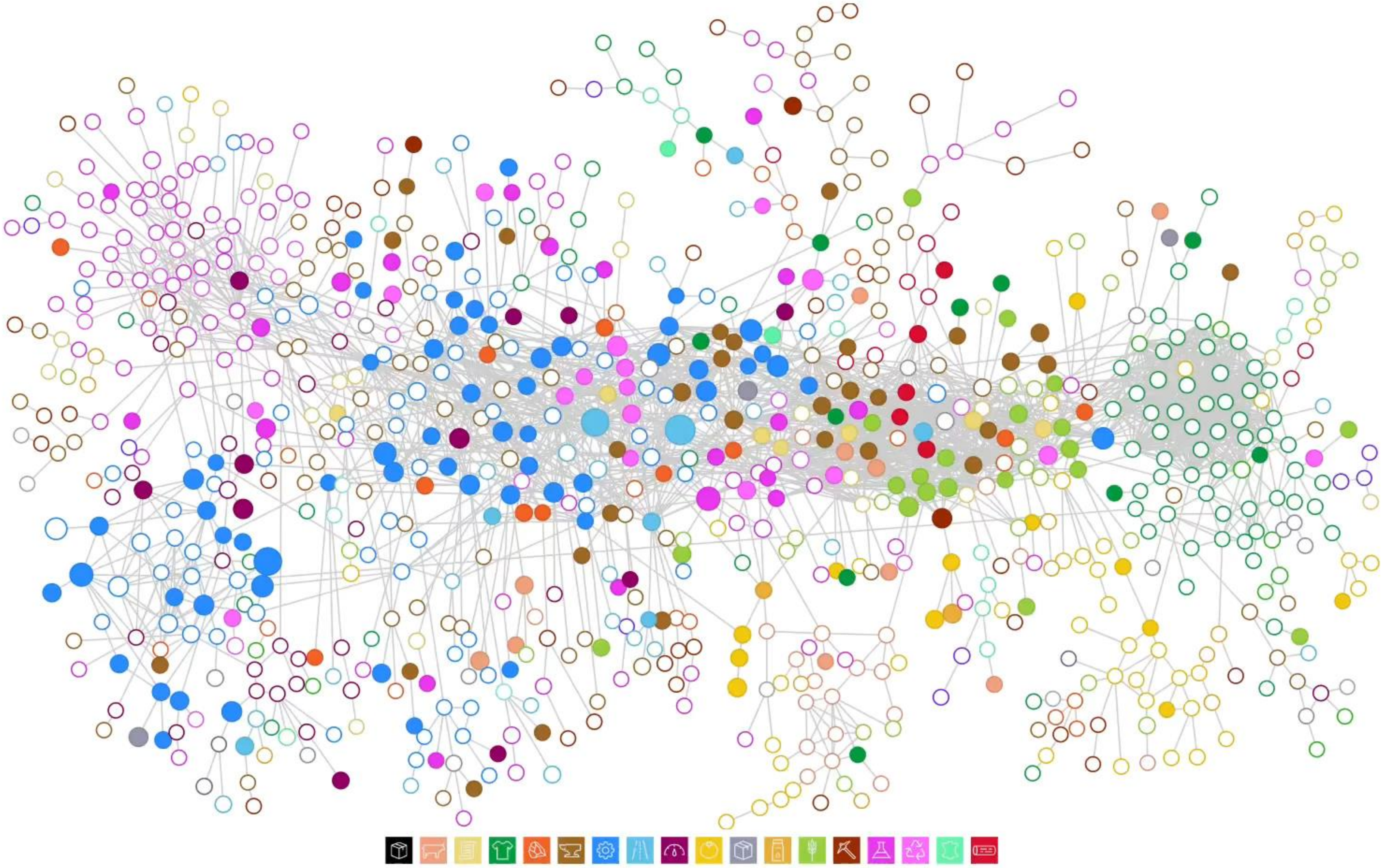
Total: $150B



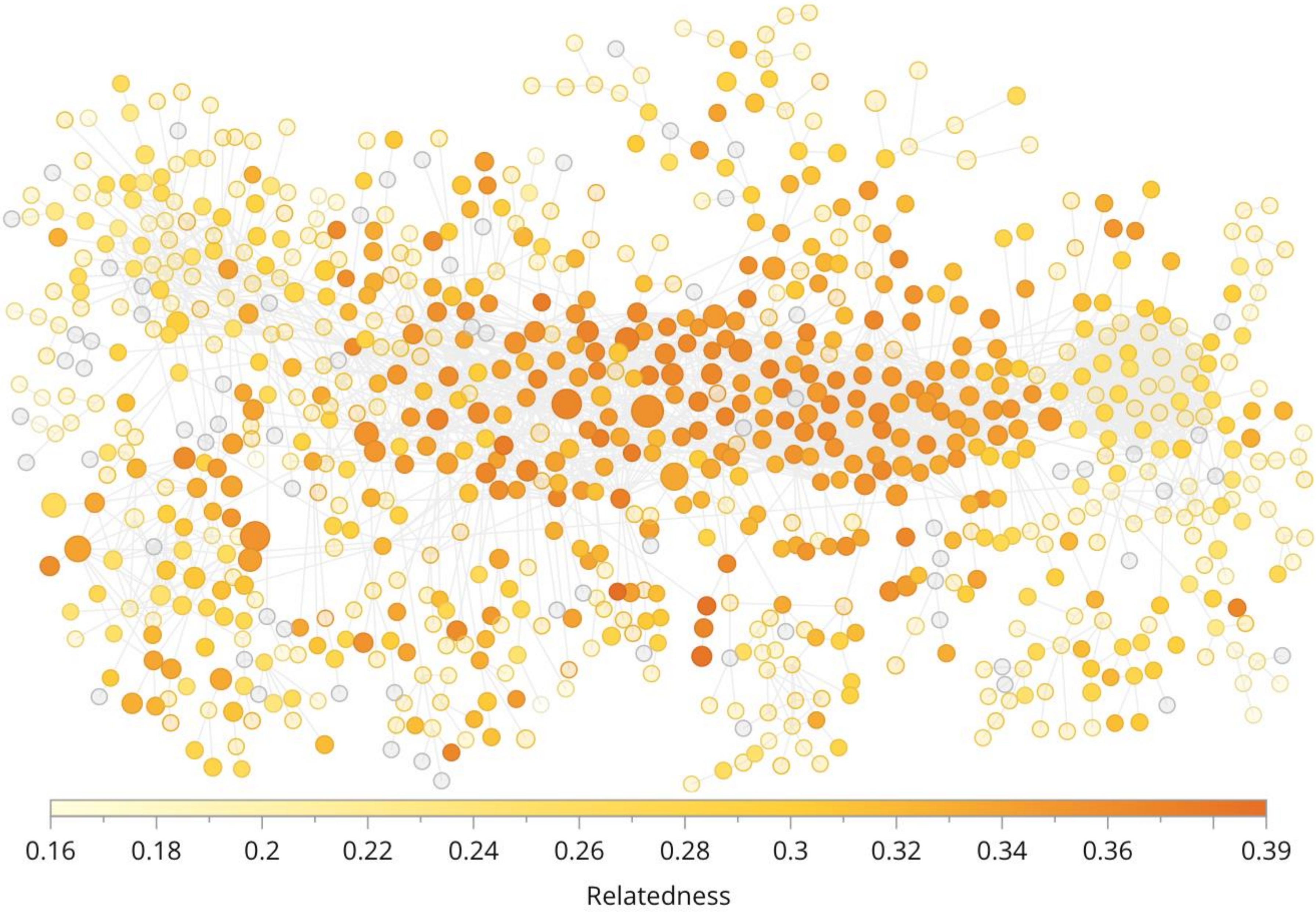
Market Growth

Market Growth between 2018 - 2023

Product Space of Hungary
(2023)



Relatedness Space for Hungary
(2023)

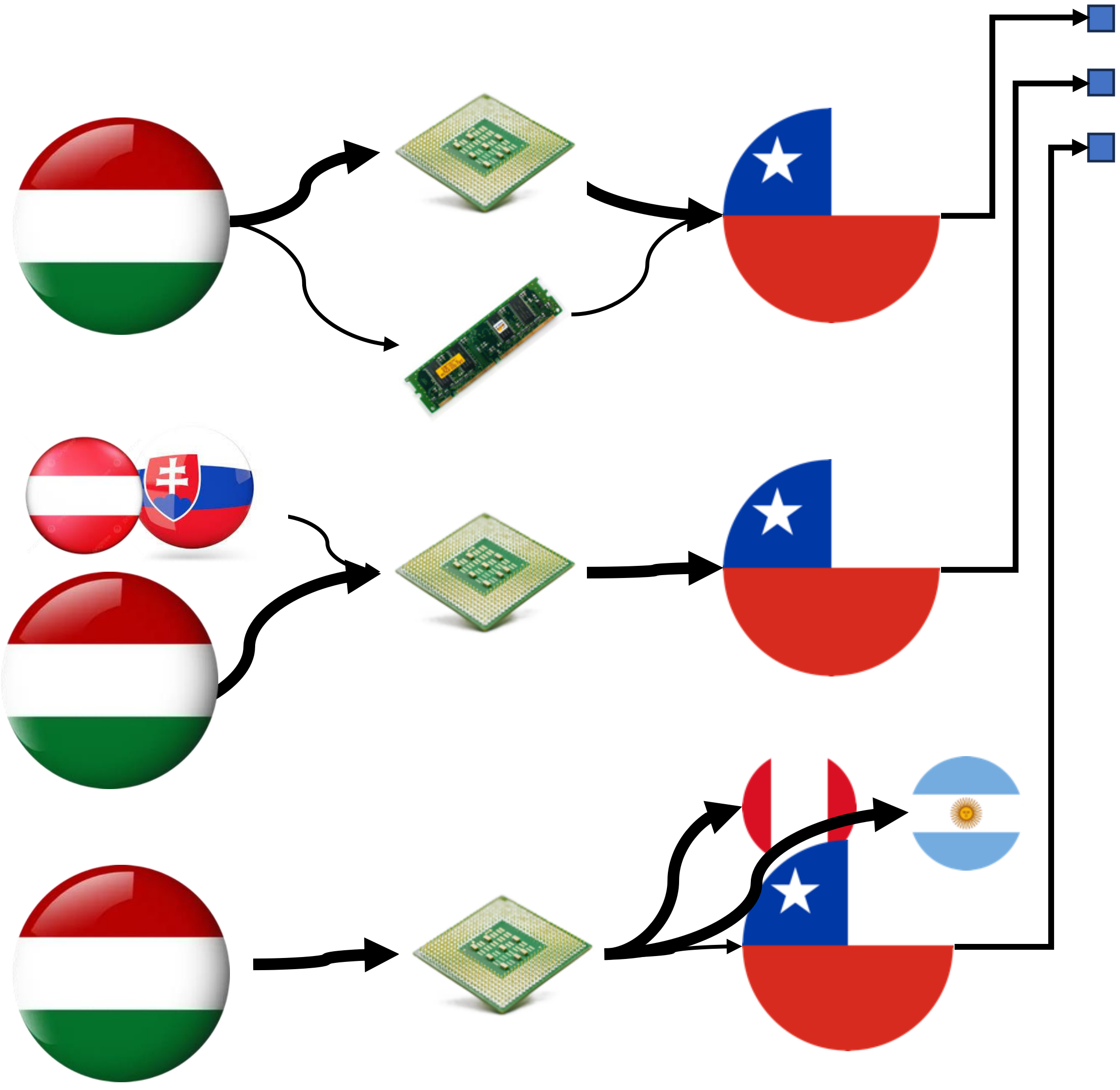


Bilateral Relatedness

Product Relatedness: Enter same market with similar product.

Exporter Relatedness: Enter same market as geographic neighbor.

Importer Relatedness: Enter the geographic neighbor of a current market



	Dependent variable: log x_{opd}^{t+2}		
	(1) 2000–2006	(2) 2007–2012	(3) 2012–2015
ω_{opd}^{t}	0.209***	0.180***	0.152***
	(0.017)	(0.017)	(0.015)
$\Omega_{opd}^{(d)}$	0.143***	0.143***	0.151***
	(0.025)	(0.047)	(0.036)
$\Omega_{opd}^{(o)}$	0.077***	0.105***	0.107***
	(0.020)	(0.023)	(0.020)
log x_{opd}^{t}	1.371***	1.600***	1.769***
	(0.055)	(0.057)	(0.057)
log x_{op}^{t}	0.961***	0.971***	0.915***
	(0.032)	(0.035)	(0.032)
log x_{pd}^{t}	0.529***	0.421***	0.406***
	(0.028)	(0.030)	(0.027)
log *Distance*	−0.485***	−0.423***	−0.432***
	(0.036)	(0.042)	(0.038)
log gdp_{o}^{t}	0.165***	0.200***	0.203***
	(0.035)	(0.042)	(0.042)
log gdp_{d}^{t}	0.226***	0.218***	0.281***
	(0.041)	(0.037)	(0.035)
log $Population_{o}$	0.472***	0.457***	0.455***
	(0.029)	(0.047)	(0.048)
log $Population_{d}$	0.344***	0.368***	0.338
	(0.029)	(0.030)	(0.028)
$Border_{od}$	0.712***	0.709***	0.611***
	(0.066)	(0.070)	(0.061)
$Colony_{od}$	0.052	0.135	0.193***
	(0.070)	(0.083)	(0.070)
$Language_{od}$	0.545***	0.436***	0.334***
	(0.061)	(0.070)	(0.071)
log$Lang.Proximity_{od}$	0.032*	0.000*	−0.001
	(0.000)	(0.000)	(0.019)
Constant	9.653***	9.828***	9.793***
	(0.045)	(0.047)	(0.045)
Observations	10,911,584	7,591,489	5,332,257
Adjusted R^2	0.495	0.516	0.558
Root MSE	2.5681	2.637	2.529

Three-way clustering robust standard errors are reported in parentheses and *p<0.1; **p<0.05; ***p<0.01

Jun et al. JEE 2020.

Growth Potential

Product | Country

Sector | Complexity

ALL PRODUCTS

Exports | Imports

Highest Potential | Most Saturated

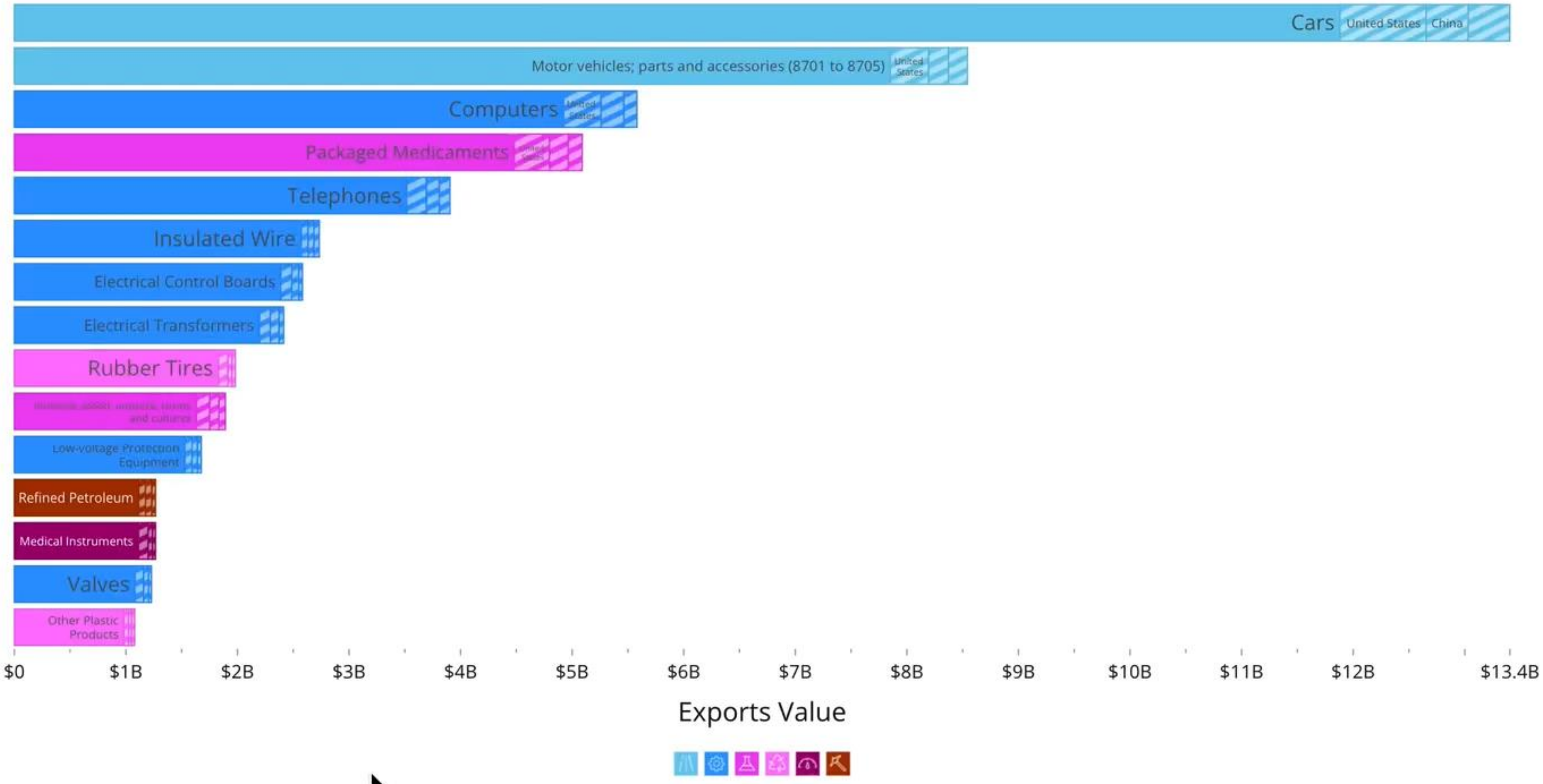
Bar Chart | Scatter

We estimate the export potential of an economy for each product and destination using an extension of the **bilateral relatedness model of Jun et al. (2019)**. This extended gravity model considers similarities among products and geographies and explains more than 50% of the variance in future trade flows.

The current trade value is a solid color and the our predicted value is on a lined box, showing by default the top 3 countries which has the most potential exports, and the key markets where Hungary can enter.

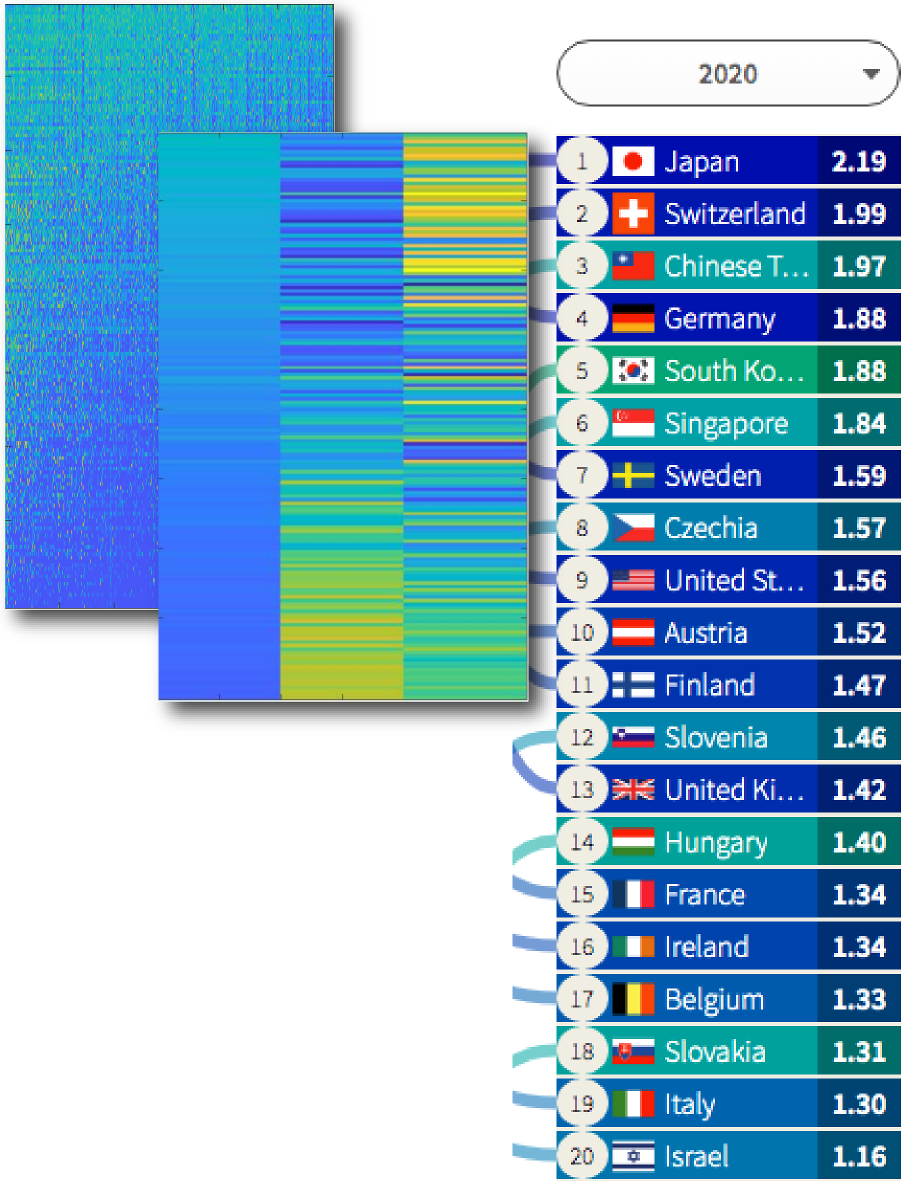
See methodology

Highest Potential Exports for Hungary



Economic Complexity

Measures of the value of an activity (e.g. a product, industry, etc.) and of the portfolio of activities present in an economy.



Hidalgo CA, Nature Review Physics (2021), PNAS (2009)

Economic Complexity

The complexity (*Kc*) of an economy is the complexity (*Kp*) of its activities.

The complexity (*Kp*) of an activity is the complexity (*Kc*) of the economies where that activity is produced.

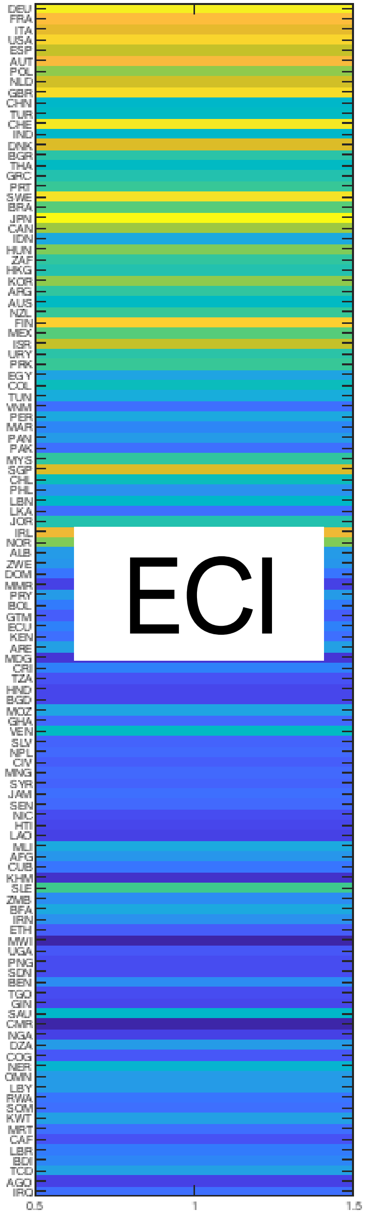
$$K_c = f(M_{cp}, K_p),$$

$$K_p = g(M_{cp}, K_c),$$

$$K_c = f\left(M_{cp}, g(M_{cp}, K_c)\right),$$

Complexity can be estimated as a solution to the following eigenproblem.

$$\tilde{M}_{cc'} K_{c'} = \lambda K_c$$



Hidalgo CA, Nature Review Physics (2021), PNAS (2009)

When f and g are defined as simple averages….

$$K_c = \frac{1}{M_c} \sum_p M_{cp} K_p$$

$$K_p = \frac{1}{M_p} \sum_c M_{cp} K_{c'}$$

$$\widetilde{M}_{cc'} = \frac{1}{M_c} \sum_p \frac{M_{cp} M_{c'p}}{M_p}$$

The "easy way" to estimate Kc and Kp is to simply iterate the mapping, starting with $Kp=Mp$ and $Kc=Mc$. The mapping converges after about 20 iterations.

Hidalgo CA, Nature Review Physics (2021), PNAS (2009)

The Economic Complexity Index as an optimization problem

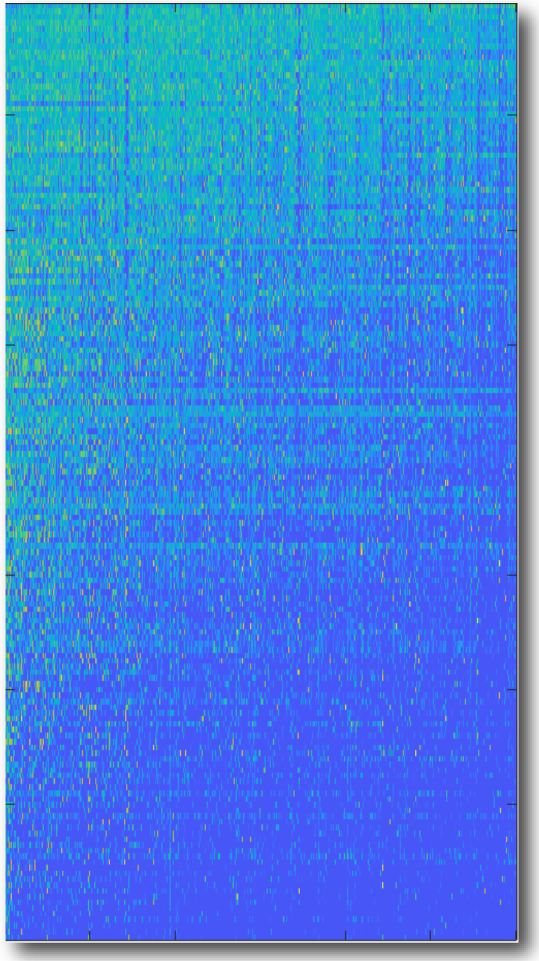
Let V_i be a vector whose entries describe a location (e.g. country) or an activity (e.g. product). Let A_{ij} be a matrix connecting locations and activities. Then ECI is a solution that minimizes the cost function U:

$$U(\vec{V}) = \frac{1}{4} \sum_{i,j} A_{ij} (V_i - V_j)^2$$

Servedio, Vito DP, Alessandro Bellina, Emanuele Calò, and Giordano De Marzo. "Economic Complexity in Mono-Partite Networks." *arXiv preprint arXiv:2405.04158* (2024).

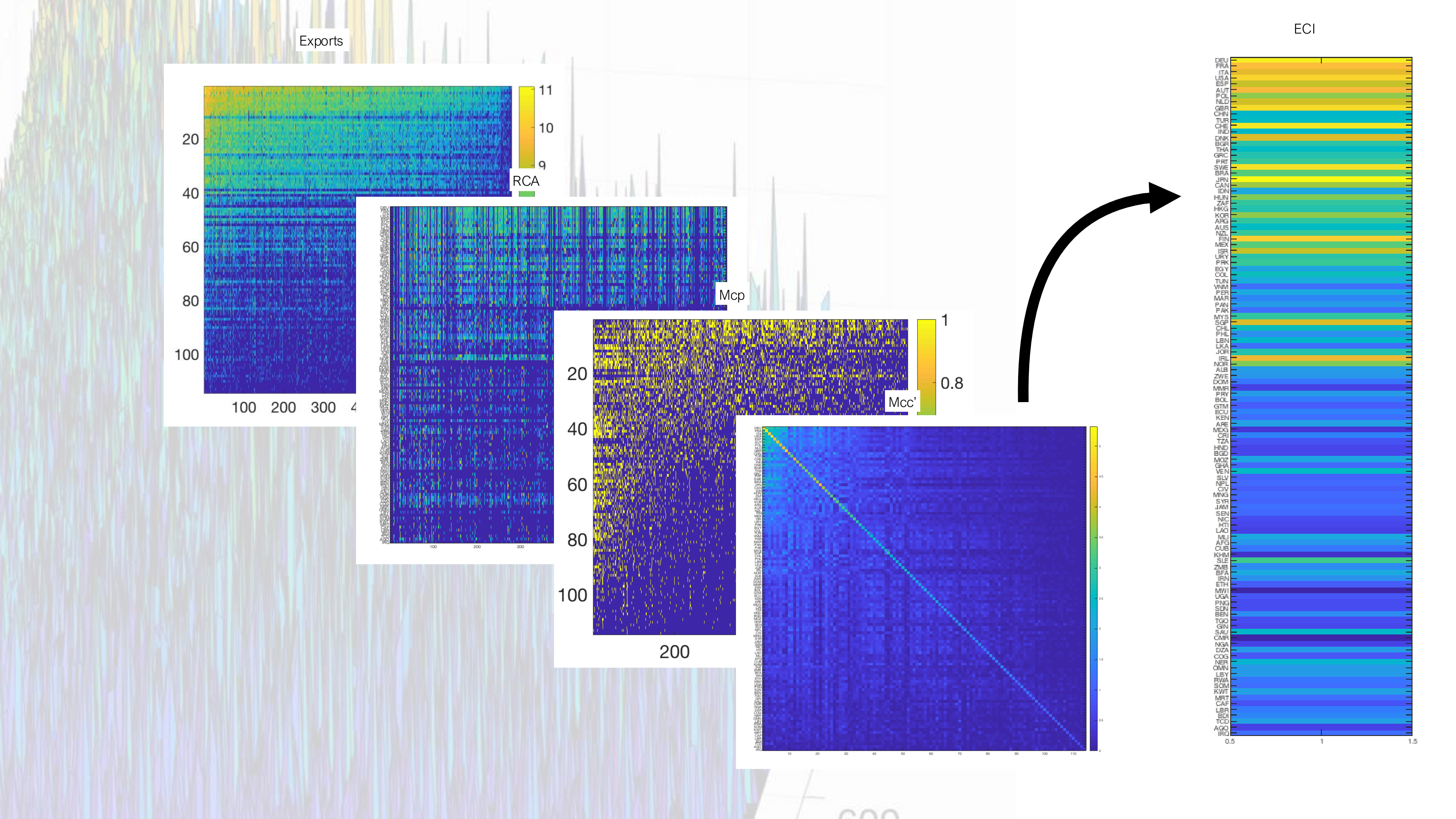
But is not that easy!

Units of observation are not comparable!

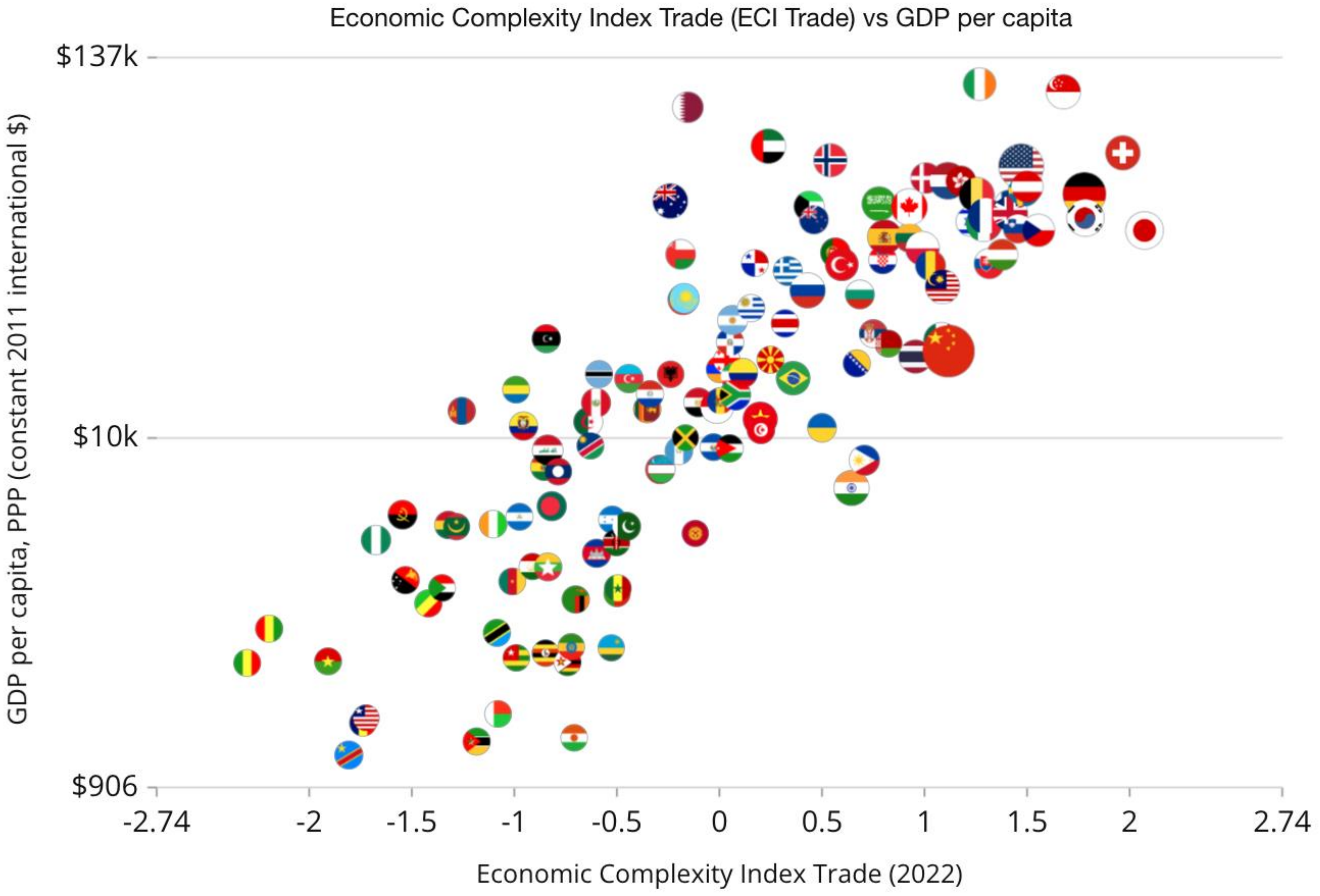


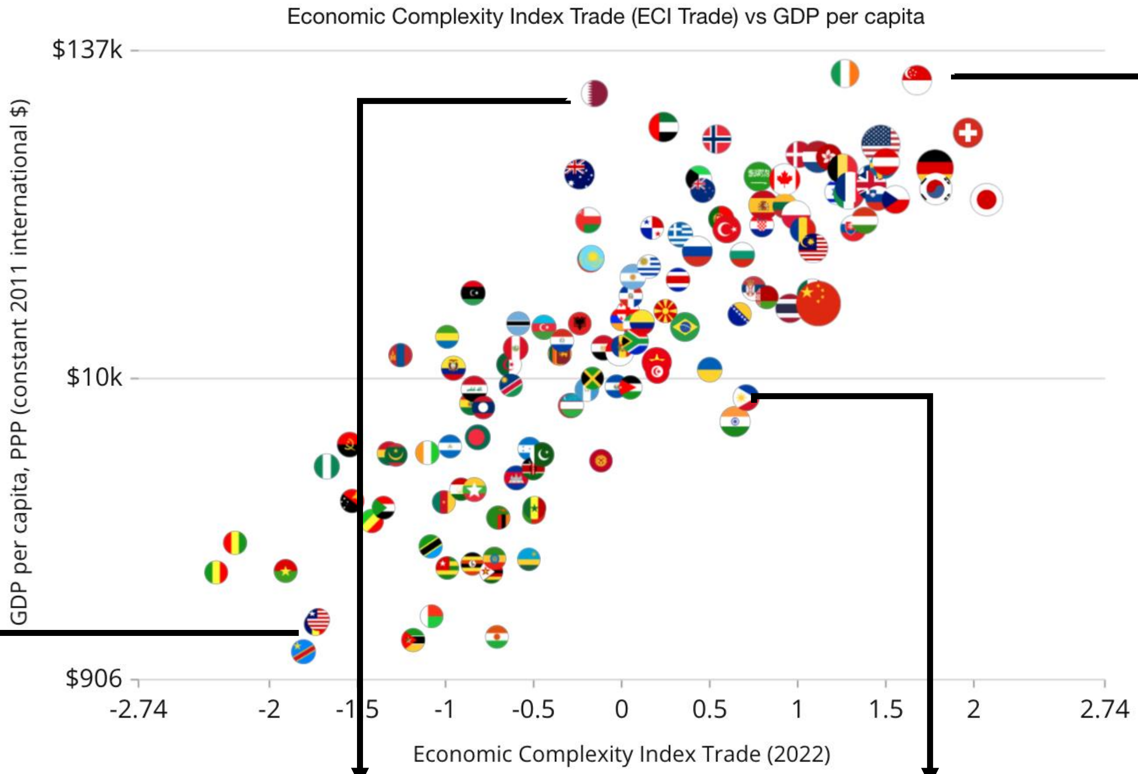
China & USA ~ 15 to 20 trillion GDP

Macedonia ~ 0.0012 trillion GDP

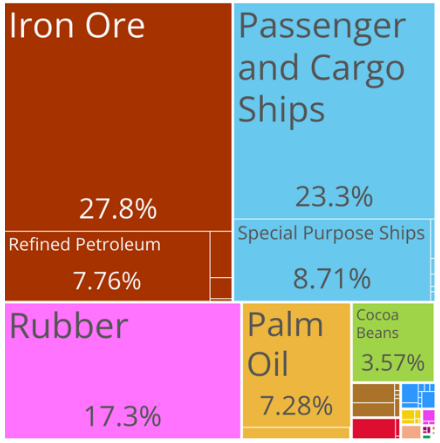


Exports
RCA
Mcp
Mcc'
ECI

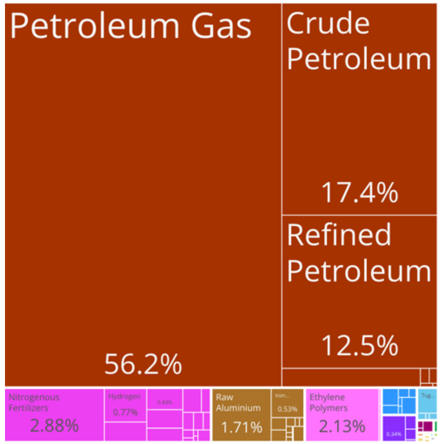

Economic Complexity Index Trade (ECI Trade) vs GDP per capita
$137k
$10k
$906
GDP per capita, PPP (constant 2011 international $)
-2.74
-2
-1.5
-1
-0.5
0
0.5
1
1.5
2
2.74
Economic Complexity Index Trade (2022)



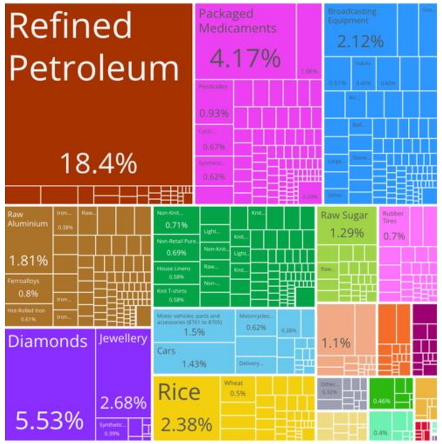
Liberia
(Poor & not complex)



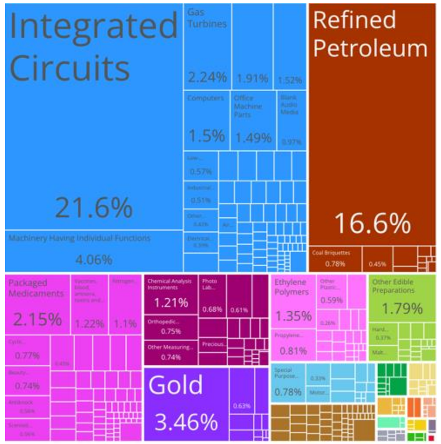
Qatar
(Rich & Not too Complex)



India
(Poor & quite complex)



Singapore
(Rich & Complex)



Economic Complexity Explains…

Economic Growth

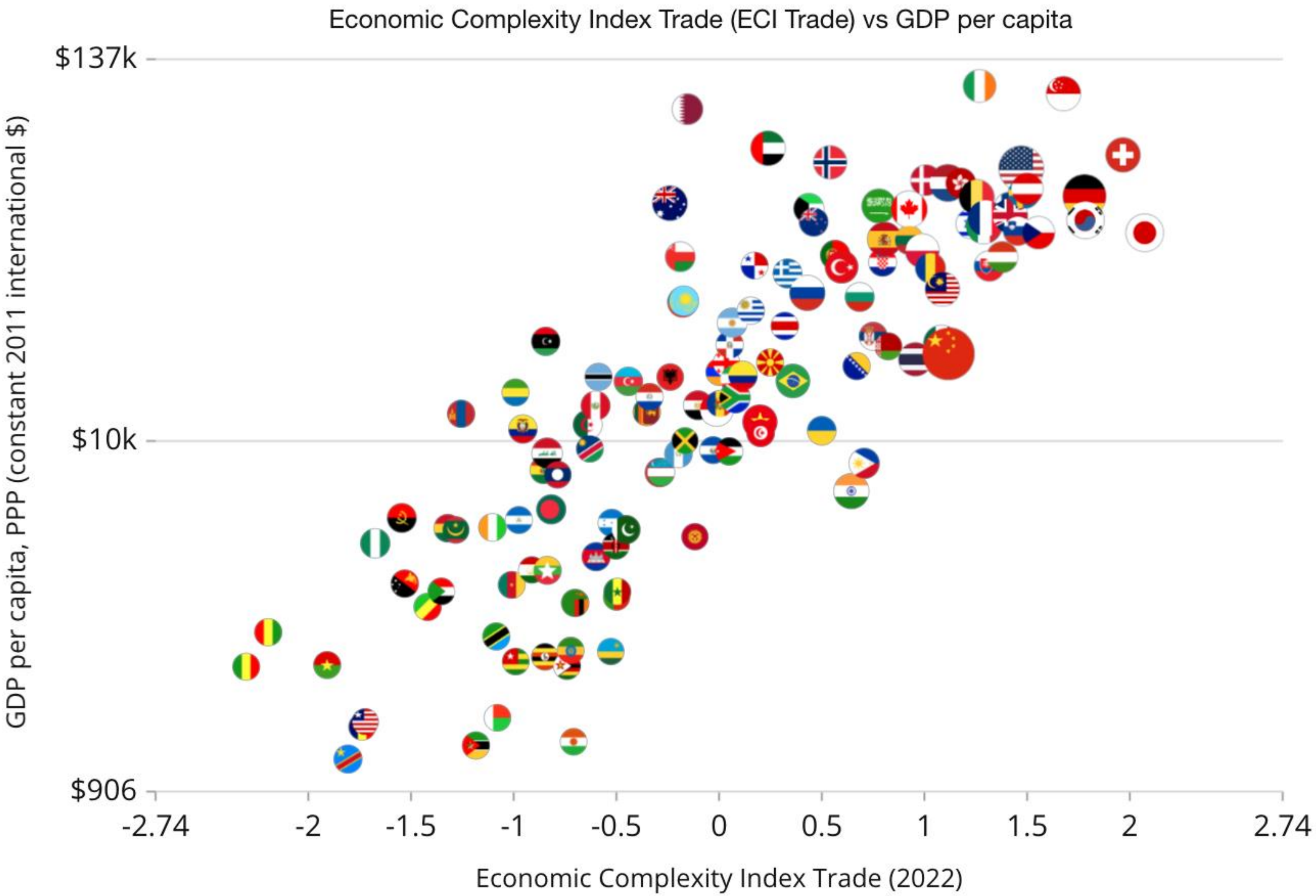
Hidalgo and Hausmann, 2009; Chávez et al., 2017; Domini, 2019; Hausmann et al., 2014; Koch, 2021; Lo Turco and Maggioni, 2020; Ourens, 2012; Stojkoski et al., 2016

Inequality

Hartmann et al., 2017,Barza et al., 2020; Ben Saâd and Assoumou-Ella, 2019; Chu and Hoang, 2020; Fawaz and Rahnama-Moghadamm, 2019

Emissions

Can and Gozgor, 2017; Dordmond et al., 2020; Fraccascia et al., 2018; Hamwey et al., 2013; Lapatinas et al., 2019; Mealy and Teytelboym, 2020; Neagu, 2019; Romero and Gramkow, 2021



Among other outcomes

Explorations in Economic History
Volume 83, January 2022, 101421

Patterns of specialization and economic complexity through the lens of universal exhibitions, 1855-1900

Giacomo Domini

	(3)	(4)
	Next-century growth	Next-century growth
ECI	0.509***	0.400***
	(0.154)	(0.128)
GDP per capita	-0.597***	-0.542**
	(0.161)	(0.219)
Constant	-0.128	-0.092**
	(0.121)	(0.043)
Country fixed effects	No	Yes
N of observations	96	96
N of countries	33	33
N of time periods	5	5
Adjusted R^2	0.221	0.770

Domini, Giacomo. *Explorations in Economic History* 83 (2022): 101421.

Economic Complexity Explains Variations in Income Inequality

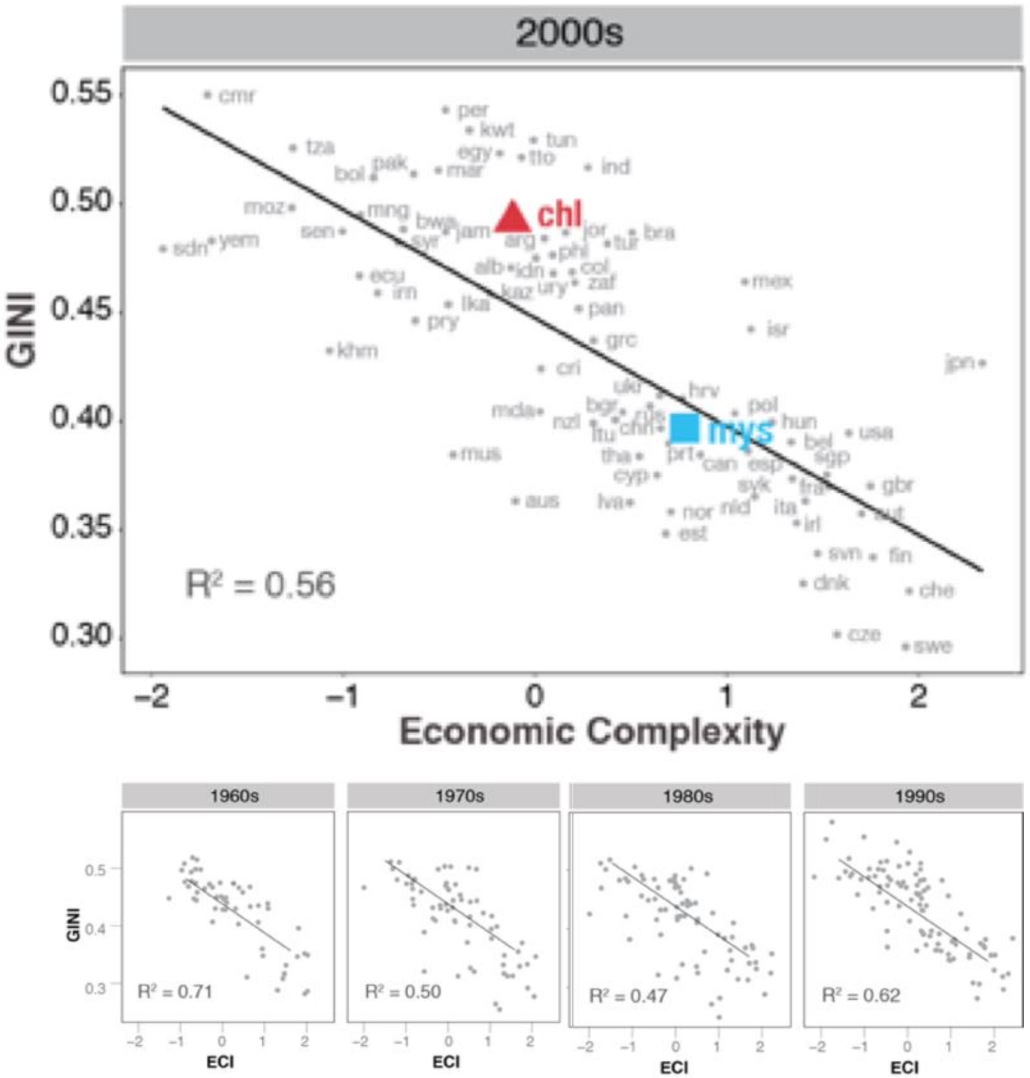


Table 10. *Cross-section regression results*

	Dependent variable: GINI EHII					
	(1)	(2)	(3)	(4)	(5)	(6)
ECI	-0.040^{***}					-0.036^{***}
	(0.007)					(0.007)
Fitness Index		-0.023^{***}				
		(0.005)				
Entropy			-0.025^{***}			
			(0.005)			
HHI				0.146^{***}		0.058
				(0.044)		(0.044)
ln(GDP PPP pc)	0.067^{**}	0.036	0.086^{***}	0.065^{**}	0.059^{*}	0.068^{**}
	(0.028)	(0.029)	(0.029)	(0.031)	(0.032)	(0.028)
ln(GDP PPPpc)^2	-0.004^{**}	-0.002	-0.005^{***}	-0.004^{**}	-0.004^{*}	-0.004^{**}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Schooling	-0.005^{***}	-0.008^{***}	-0.008^{***}	-0.008^{***}	-0.009^{***}	-0.005^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln population	0.007^{**}	0.010^{***}	0.008^{***}	0.004	0.0001	0.007^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Rule of law	-0.013	-0.008	-0.013	-0.017	-0.016	-0.014
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)
Corruption control	0.011	0.009	0.011	0.019	0.027^{*}	0.009
	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
Government effectiveness	0.002	-0.013	-0.007	-0.012	-0.022	0.003
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)
Political stability	-0.010	-0.011^{*}	-0.014^{**}	-0.017^{**}	-0.017^{**}	-0.011^{*}
	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)
Regulatory quality	-0.006	-0.006	0.001	-0.0002	-0.012	-0.002
	(0.012)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)
Voice and accountability	0.001	0.009	0.015^{*}	0.011	0.006	0.004
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
Constant	0.083	0.199	0.132	0.206	0.286^{**}	0.071
	(0.130)	(0.131)	(0.132)	(0.138)	(0.141)	(0.130)
Observations	142	142	142	142	142	142
R^2	0.717	0.698	0.703	0.667	0.639	0.721
Adjusted R^2	0.693	0.672	0.678	0.639	0.612	0.695
Residual std. error	0.035	0.036	0.035	0.037	0.039	0.034
	(df = 130)	(df = 130)	(df = 130)	(df = 130)	(df = 131)	(df = 129)

Hartmann, Guevara, Jara-Figueroa, Aristaran, & Hidalgo,. World Development (2017)

Economic Complexity Explains Greenhouse Emission Intensity

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Economic complexity and greenhouse gas emissions

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Table 2
Emission intensity fixed effects regressions.

Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
ECI	−0.0475	−0.0423	−0.0501	0.0676	−0.0709	−0.0840	0.0437	0.0912
	(0.119)	(0.136)	(0.125)	(0.0711)	(0.117)	(0.130)	(0.0879)	(0.0708)
Lagged ECI	−0.156**	−0.166*	−0.156**	−0.169**	−0.128*	−0.118	−0.166**	−0.137**
	(0.0763)	(0.0846)	(0.0777)	(0.0805)	(0.0749)	(0.0737)	(0.0721)	(0.0562)
Ln of GDP per capita	−0.470**	−0.450*	−0.472**	−0.628***	−0.438**	−0.491**	−0.382***	−0.408**
	(0.189)	(0.238)	(0.191)	(0.105)	(0.185)	(0.187)	(0.0956)	(0.172)
Ln of Agric. Share	0.172*	0.148	0.170*	0.138*	0.138	0.182*	0.143*	0.0678
	(0.0963)	(0.0994)	(0.0968)	(0.0792)	(0.0879)	(0.0931)	(0.0844)	(0.0778)
Ln of Openness	0.167**	0.171**	0.166**	0.151*	0.165**	0.174**	0.0594	0.0958
	(0.0768)	(0.0782)	(0.0736)	(0.0771)	(0.0742)	(0.0703)	(0.0626)	(0.0667)
Ln of Electricity Cons.		0.0112						0.158
		(0.125)						(0.110)
Ln of Urbanization			0.0280					−0.770***
			(0.247)					(0.232)
Ln of Sec. School Enrol.				0.0441				−0.00561
				(0.107)				(0.0922)
Ln of Population					0.253			0.419*
					(0.321)			(0.232)
Ln of Manuf. Share						0.114		−0.0526
						(0.0744)		(0.0660)
Ln of Patents							0.0000429	−0.00135
							(0.0217)	(0.0234)
Constant	9.977***	9.779***	9.900***	11.22***	5.635	9.774***	9.661***	4.991
	(1.589)	(1.690)	(1.769)	(0.847)	(5.466)	(1.725)	(0.836)	(3.752)
N. Obs.	485	469	485	439	485	469	383	344
Adj. R-sq.	0.358	0.359	0.357	0.515	0.361	0.406	0.636	0.728

Note: Dependent variable: Ln of GHG emissions (kilotons of CO2 equivalent) by units of output (billions of 2010 USD). Time dummies were included in all the regressions. Robust standard erros between brackets. Significance levels: *** = 1%; ** = 5%; * = 10%.
Source: Authors' elaboration.

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Economic Complexity and Environmental Performance: Evidence from a World Sample

Eirini Boleti, Antonios Garas, Alexandra Kyriakou & Athanasios Lapatinas

Table 2 The effect of economic complexity on environmental performance: pooled OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ECI	6.414***	4.869***	5.167***	3.904***	3.584***	3.459***	4.071***	3.220***
	(0.331)	(0.337)	(0.343)	(0.378)	(0.408)	(0.403)	(0.422)	(0.39)
GDP per capita	7.805***	7.770***	7.532***	7.704***	6.891***	7.158***	6.541***	5.760***
	(0.321)	(0.306)	(0.305)	(0.437)	(0.478)	(0.476)	(0.584)	(0.576)
GDP per capita^2	0.443***	0.639***	0.658***	0.883***	0.651***	0.591***	0.14	-0.262
	(0.136)	(0.149)	(0.149)	(0.157)	(0.169)	(0.165)	(0.182)	(0.179)
Population			-0.006***	-0.006***	-0.006***	-0.006***	-0.005***	-0.006***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Agriculture				-0.115***	-0.106***	-0.140***	-0.129***	-0.157***
				(0.038)	(0.038)	(0.039)	(0.046)	(0.044)
Industry				-0.057***	-0.028	-0.049**	0.005	0.012
				(0.022)	(0.022)	(0.023)	(0.027)	(0.026)
Corruption					1.248***	1.036***	2.144***	1.186***
					(0.377)	(0.371)	(0.383)	(0.354)
Trade						0.023***	0.006	0.015***
						(0.005)	(0.005)	(0.005)
Urban							0.028	0.026
							(0.02)	(0.02)
Education							-0.000***	-0.000***
							(0.000)	(0.000)
OECD								6.523***
								(0.774)
Observations	1283	1210	1210	1160	1160	1149	940	940
R-squared	0.814	0.855	0.857	0.865	0.866	0.87	0.89	0.9
F-statistic	555.8	525.3	521.8	479	466.7	460.2	483.9	526.2

Dependent variable: Environmental Performance Index (EPI). Main independent variable: Economic Complexity Index (ECI). Time fixed effects are included in all regressions. Regional dummies are also included: *europe*, *asia*, *oceania*, *north america*, *south america*. Robust standard errors in parentheses

Economic Complexity Index (ECI) vs CO2 emissions (kg per 2017 PPP $ of GDP)? (2016.2017.2018.2019.2020)

‹ 2015

2017 ›

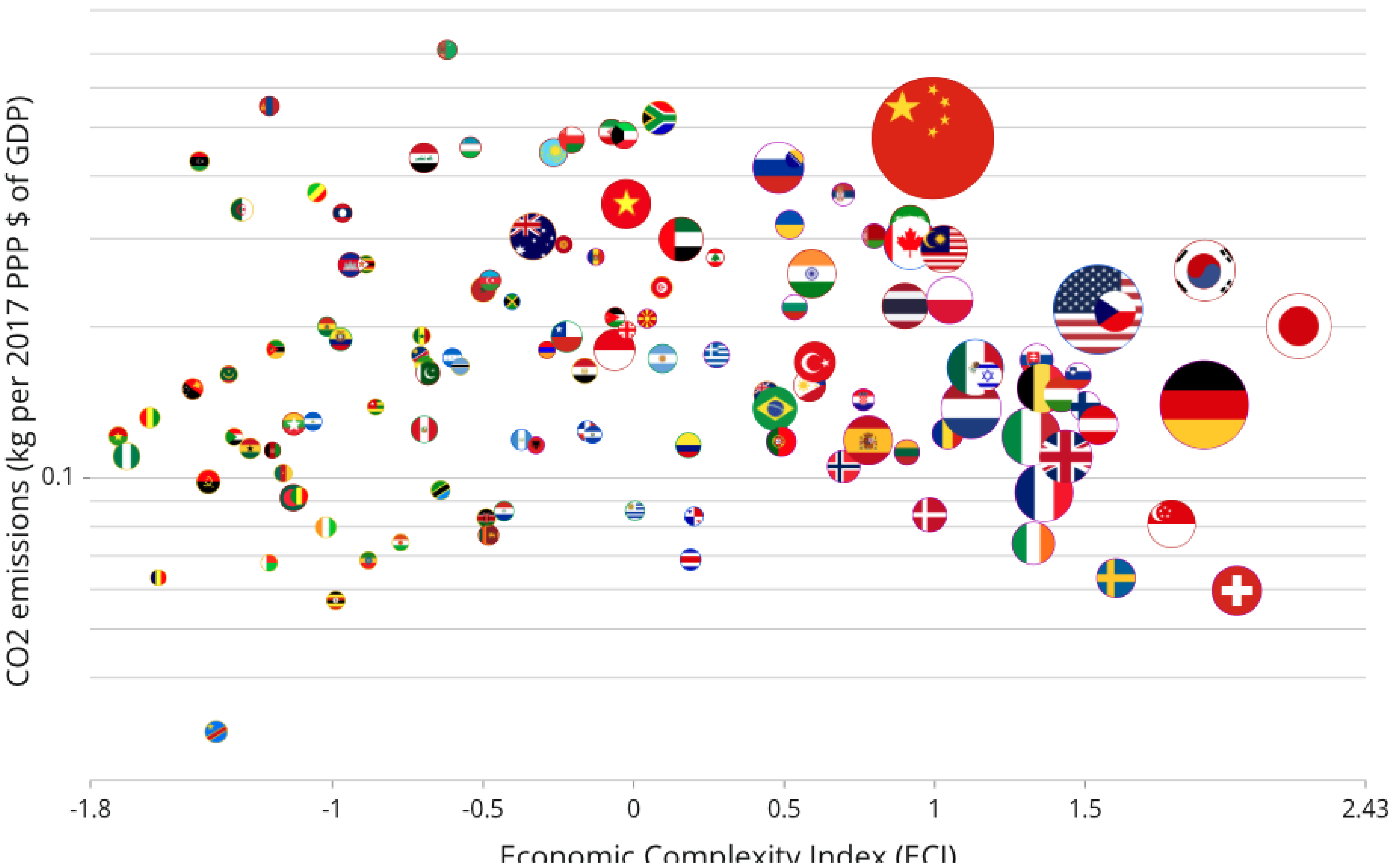


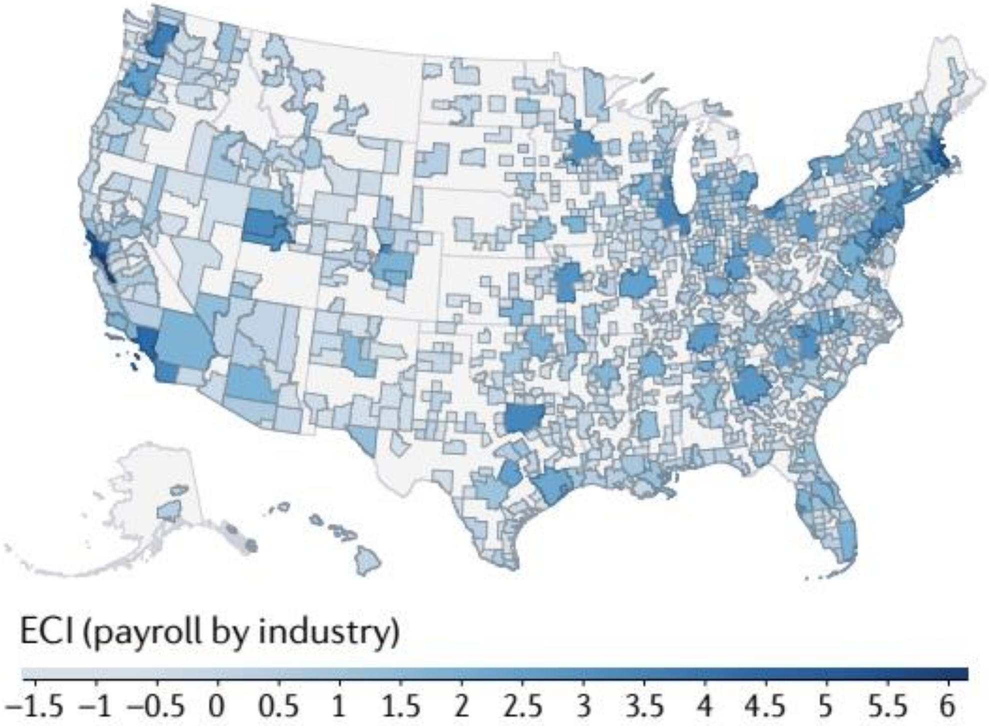
Table 9
The results of panel dynamic least squares (DOLS) technique.

Dependent Variable: $LnCO_2$				
Variables	Model 1	Model 2	Model 3	Model 4
LnECI	0.125886*	1.321669*	0.492520*	1.728731*
	[2.968107]	[6.018540]	[2.875593]	[6.125294]
	(0.0052)	(0.0000)	(0.0056)	(0.0000)
$LnECI^2$	−0.009419*	−0.009834**	−0.072346**	−0.090110**
	[-2.773225]	[-2.393340]	[-2.445368]	[-2.415379]
	(0.0086)	(0.0184)	(0.0174)	(0.0175)
$LnECI^3$	–	–	0.002709**	0.003779**
	–	–	[2.006267]	[2.127934]
	–	–	(0.0493)	(0.0358)
LnFDI	0.121000*	0.054114**	0.106670*	0.053204**
	[4.934391]	[2.478155]	[5.533860]	[2.269635]
	(0.0000)	(0.0148)	(0.0000)	(0.0254)
LnRNW	−0.324631*	−0.096508*	−0.253042*	−0.086649*
	[-5.966140]	[-5.632430]	[-6.700373]	[-4.604960]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LnURB	6.360863*	0.442070*	4.972434*	0.440405*
	[3.030411]	[25.25567]	[3.442980]	[34.46611]
	(0.0044)	(0.0000)	(0.0011)	(0.0000)
LnECI*LnURB	–	−0.282030*	–	−0.279430*
	–	[-5.602032]	–	[-5.374108]
	–	(0.0000)	–	(0.0000)
R-squared	0.990824	0.861855	0.978145	0.873724
Adjusted R-squared	0.966023	0.809411	0.947913	0.813712
S.E. of regression	0.042255	0.100436	0.052273	0.099296
S.D. dependent var	0.229238	0.230060	0.229039	0.230060
Long-run variance	0.000441	0.014559	0.001472	0.012780
Mean dependent var	1.932031	1.921959	1.930039	1.921959
Sum squared resid	0.066064	1.089440	0.163947	0.995833

Note: *, ** and *** significance at 1%, 5% and 10% respectively. t-statistics and probability values are reported in [ ], and ( ) respectively.

Balsalobre-Lorente, Daniel, Lucia Ibáñez-Luzón, Muhammad Usman, and Muhammad Shahbaz. "The environmental Kuznets curve, based on the economic complexity, and the pollution haven hypothesis in PIIGS countries." *Renewable Energy* 185 (2022): 1441-1455.

b Economic complexity of US MSAs
(industry payroll)



Economic complexity of US MSAs
(patents by technology class)

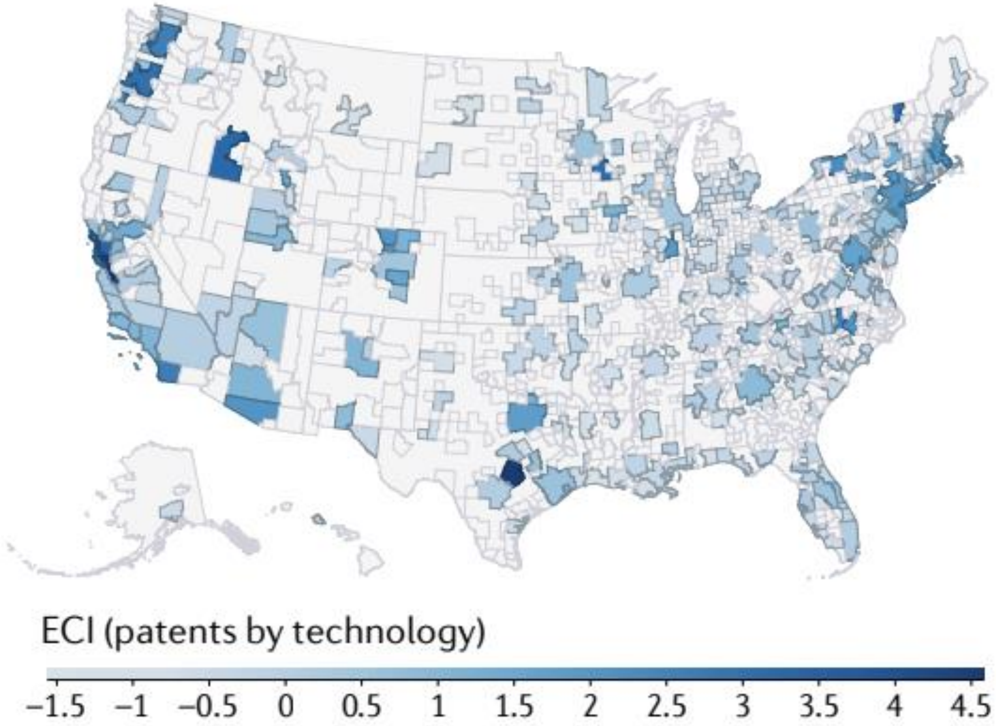
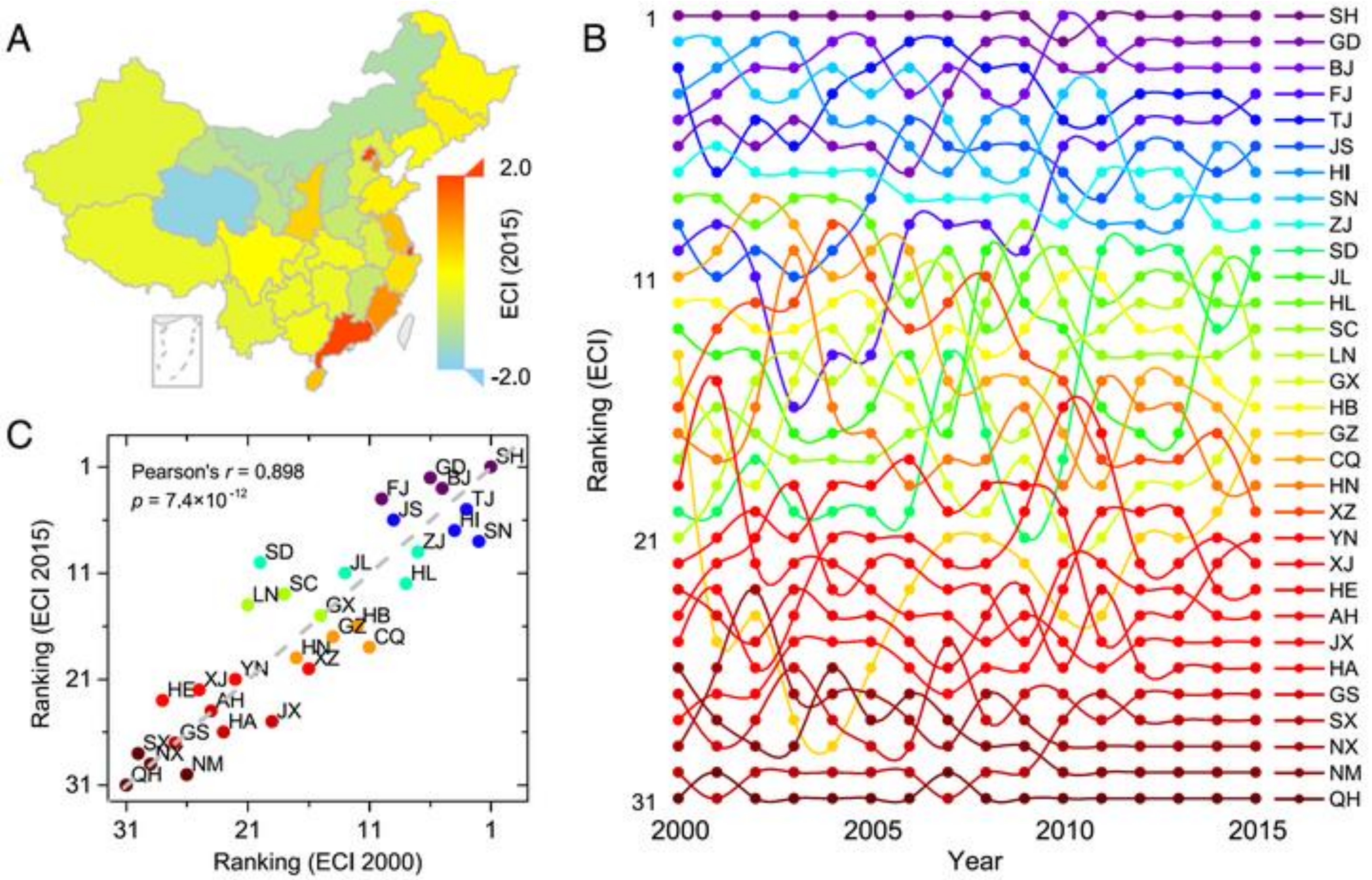


Table 1 | **Rankings of economic complexity**

Rank	Economic complexity rankings	
	US metro areas: payroll by industry (2018)	**US metro areas: patents by technology (2018)**
1	San Jose–Sunnyvale–Santa Clara, CA	San Jose–Sunnyvale–Santa Clara, CA
2	San Francisco–Oakland–Hayward, CA	Austin–Round Rock–San Marcos, TX
3	Boston–Cambridge–Newton, MA–NH	San Francisco–Oakland–Fremont, CA
4	Los Angeles–Long Beach–Anaheim, CA	Boise City–Nampa, ID
5	Seattle–Tacoma–Bellevue, WA	Rochester, MN

Hidalgo et al. Economic Complexity Theory and Applications. Nature Review Physics (2021)

Economic Complexity of Chinese Provinces Using Data on Publicly Listed Firms



Gao, Jian, and Tao Zhou. "Quantifying China's regional economic complexity." *Physica A: Statistical Mechanics and its Applications* 492 (2018): 1591-1603.

Economic Complexity of Mexican States Using Industry Data

Central Bank of Mexico

Map 1: States' Level of Economic Complexity, 2013

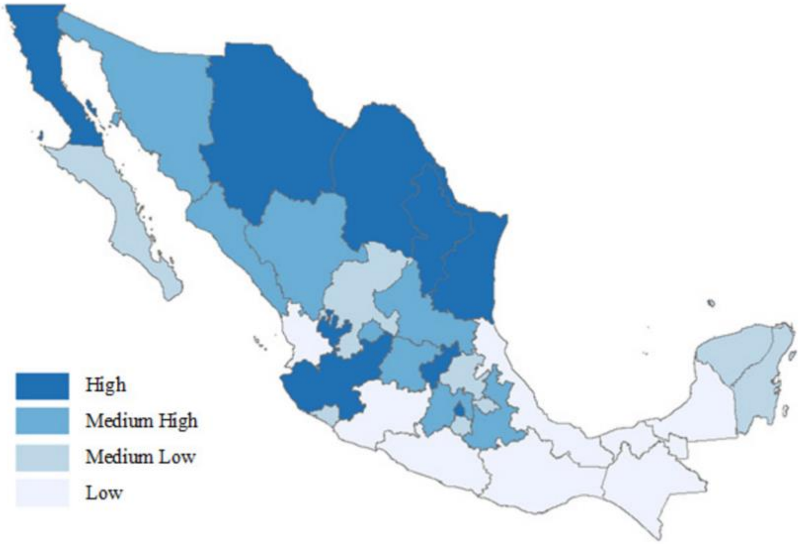
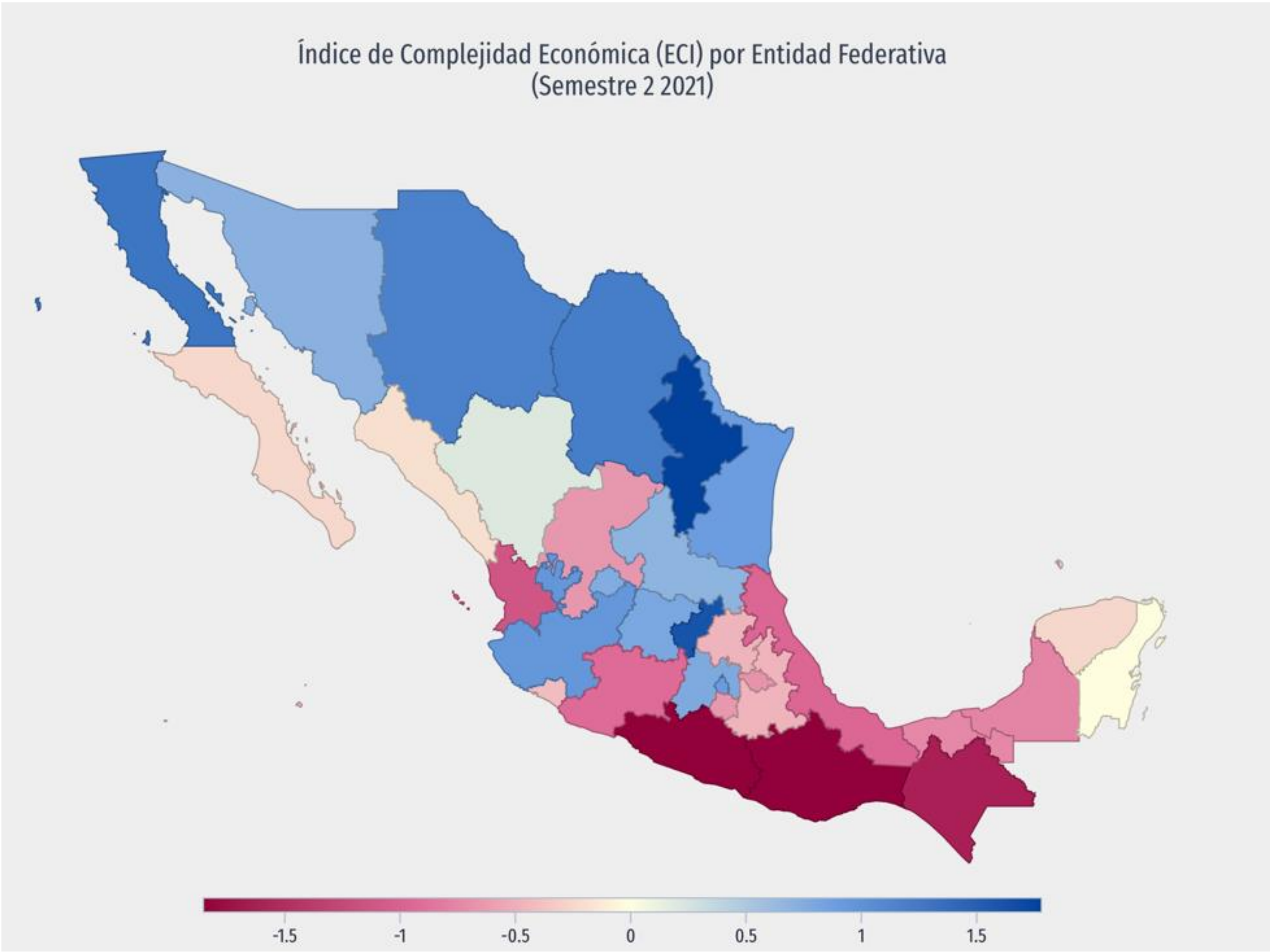


Table 3: Growth Rate of per capita GDP and Economic Complexity (1998–2003, 2003–2008, and 2008–2013)

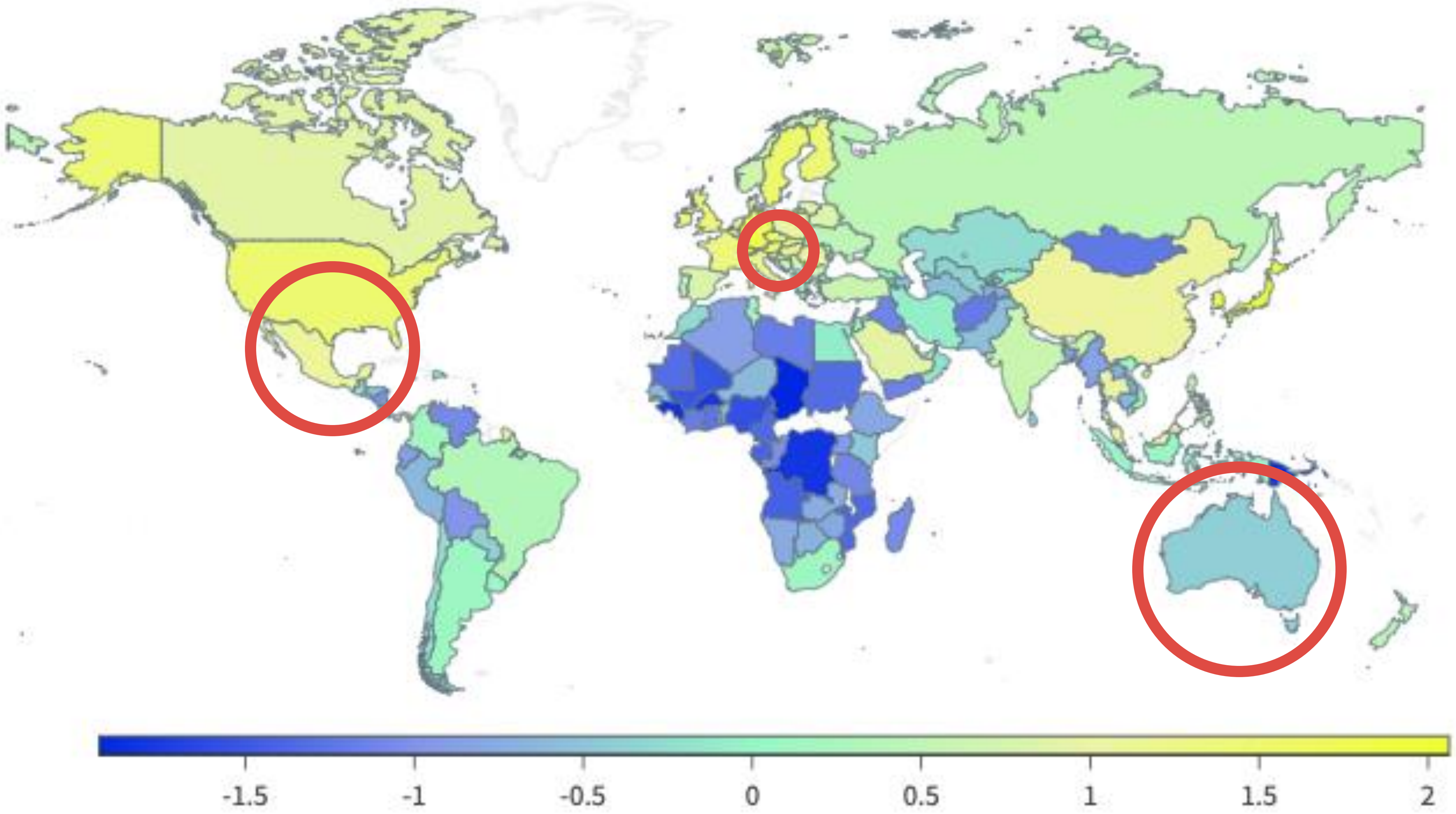
Variable	Estimated Parameters
Constant	5.500 ***
Log GDP per capita, (β_0)	-0.991 ***
Economic Complexity, (β_1)	0.407 ***
Dummy variable for oil-mining states (α_1)	-0.351
Dummy variable for the period 2003–2008 (α_2)	1.257****
Dummy variable for the period 2008–2013 (α_3)	-0.251
Observations	96
R^2	.35

The symbols *** denote statistical significance at 1 percent level.



DataMexico.org

Limitations of ECI trade



Stojkoski, Viktor, Philipp Koch, and César A. Hidalgo. "Multidimensional economic complexity and inclusive green growth." *Communications Earth & Environment* 4.1 (2023): 130.

Solution: Combine Different Data Sources

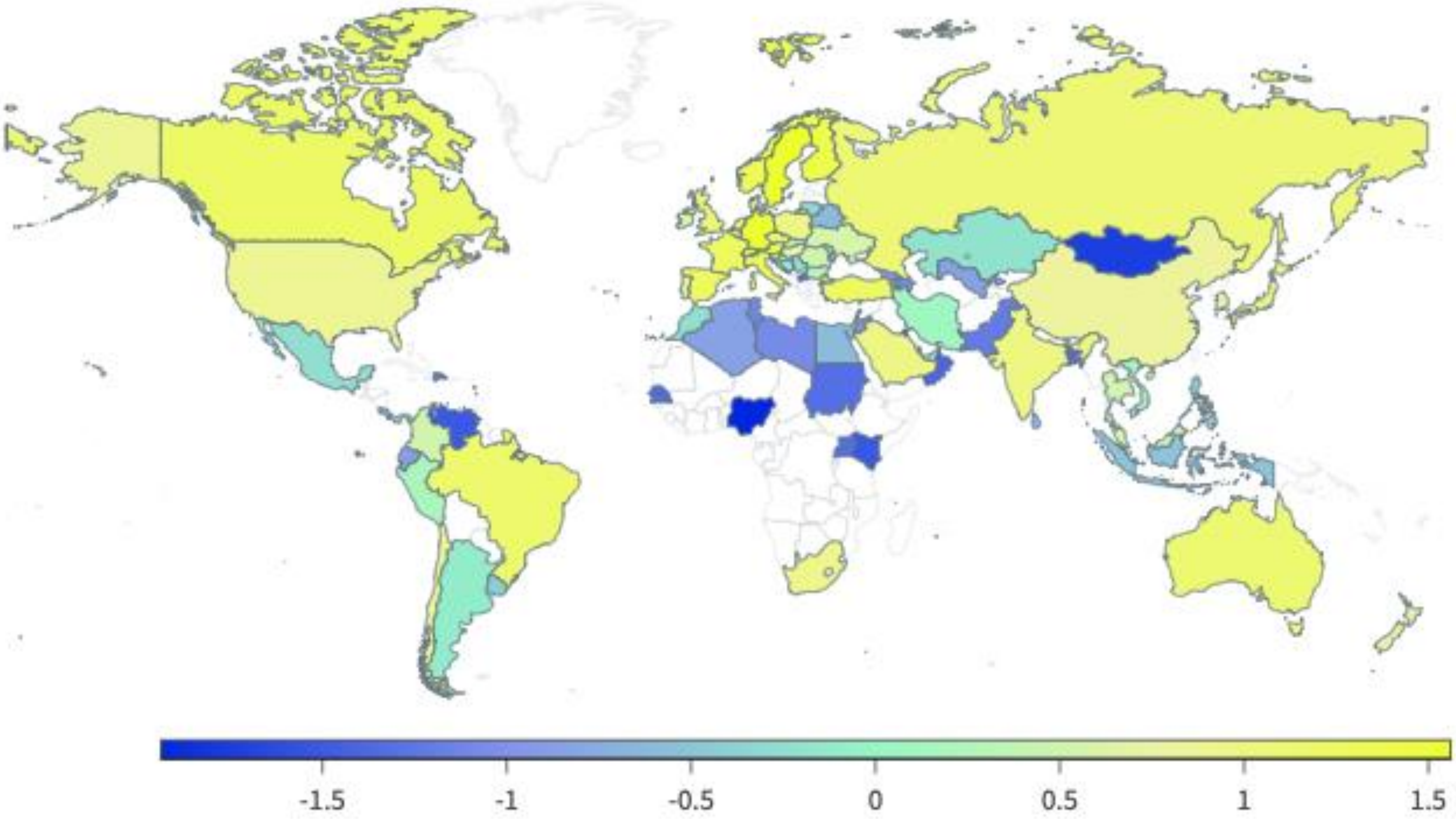
International Trade

Patents

Research Papers

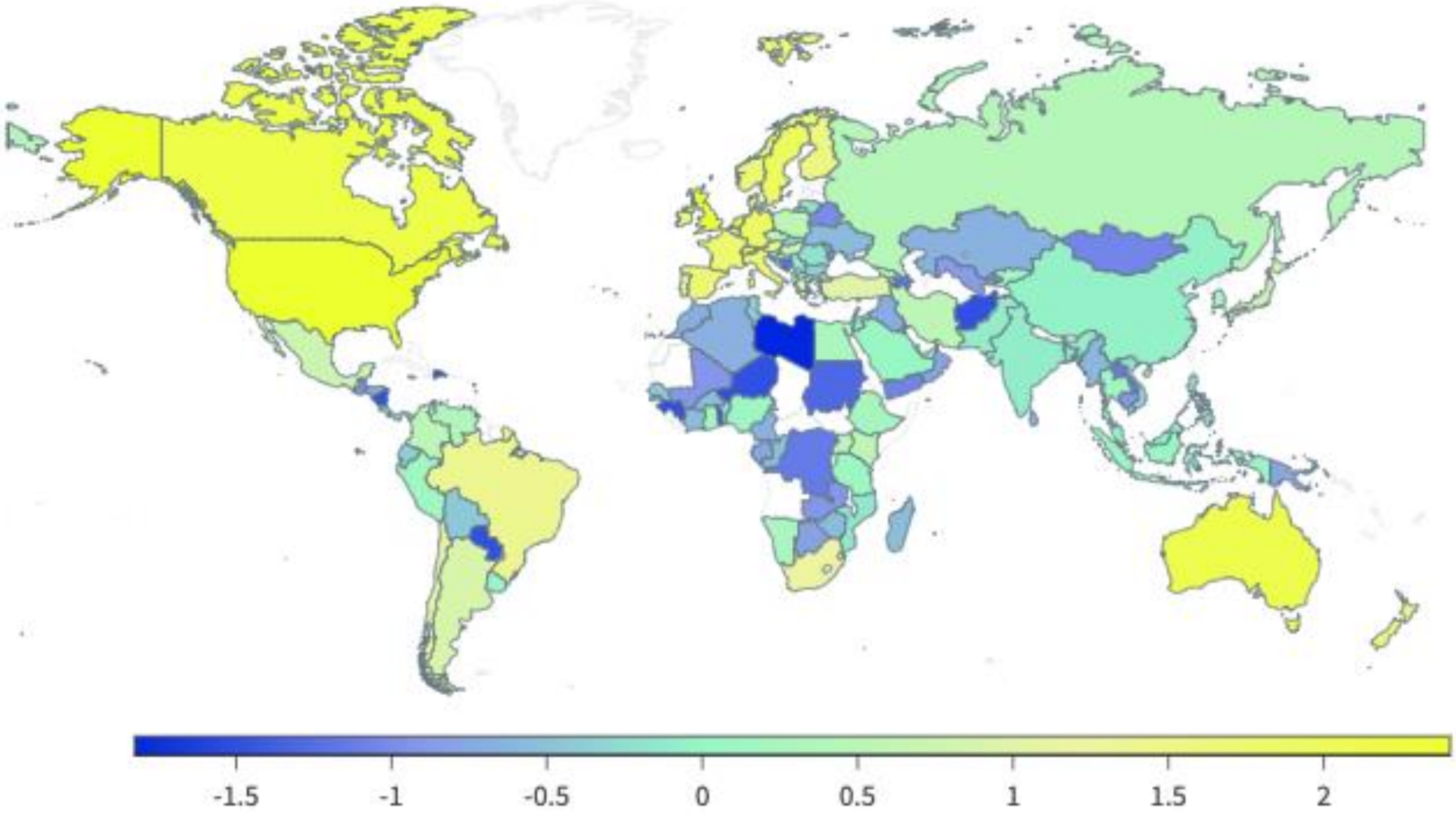
Stojkoski, Viktor, Philipp Koch, and César A. Hidalgo. "Multidimensional economic complexity and inclusive green growth." *Communications Earth & Environment* 4.1 (2023): 130.

ECI Tech



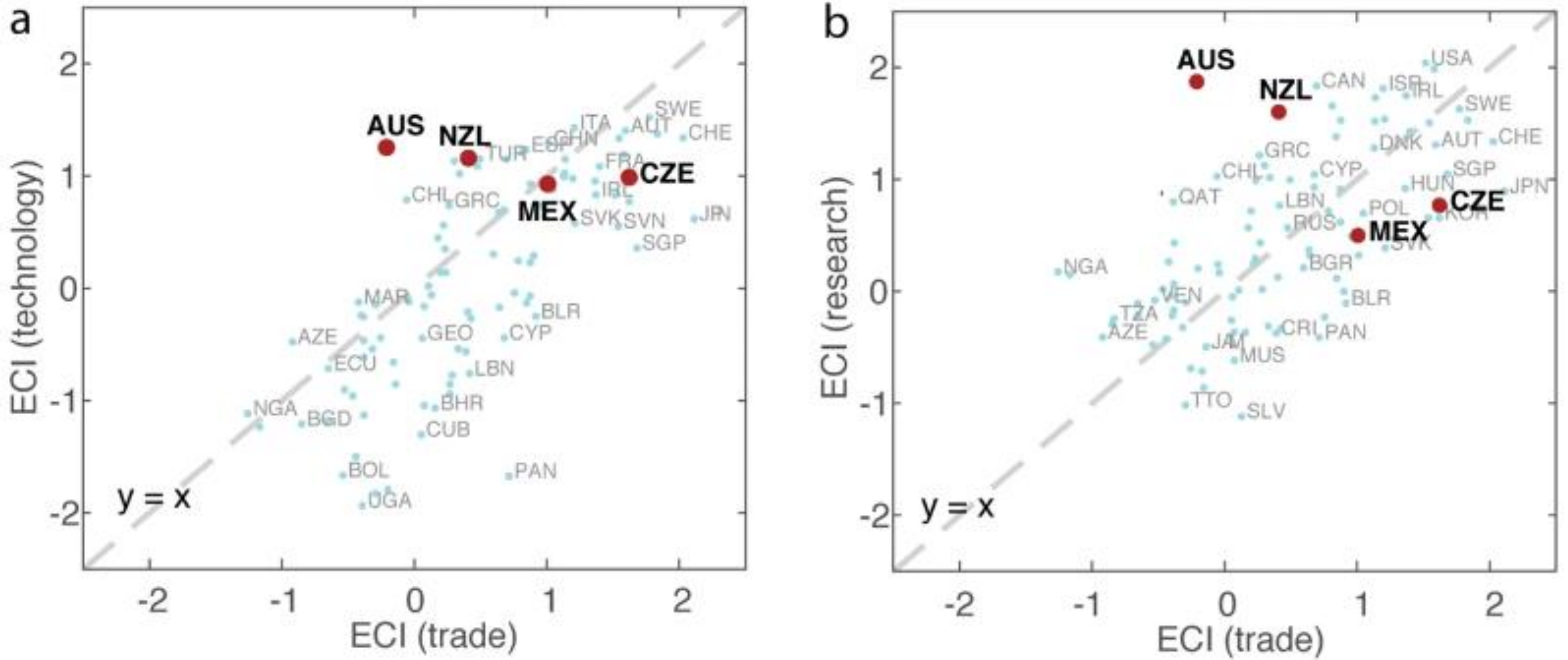
Stojkoski, Viktor, Philipp Koch, and César A. Hidalgo. "Multidimensional economic complexity and inclusive green growth." *Communications Earth & Environment* 4.1 (2023): 130.

ECI Research



Stojkoski, Viktor, Philipp Koch, and César A. Hidalgo. "Multidimensional economic complexity and inclusive green growth." *Communications Earth & Environment* 4.1 (2023): 130.

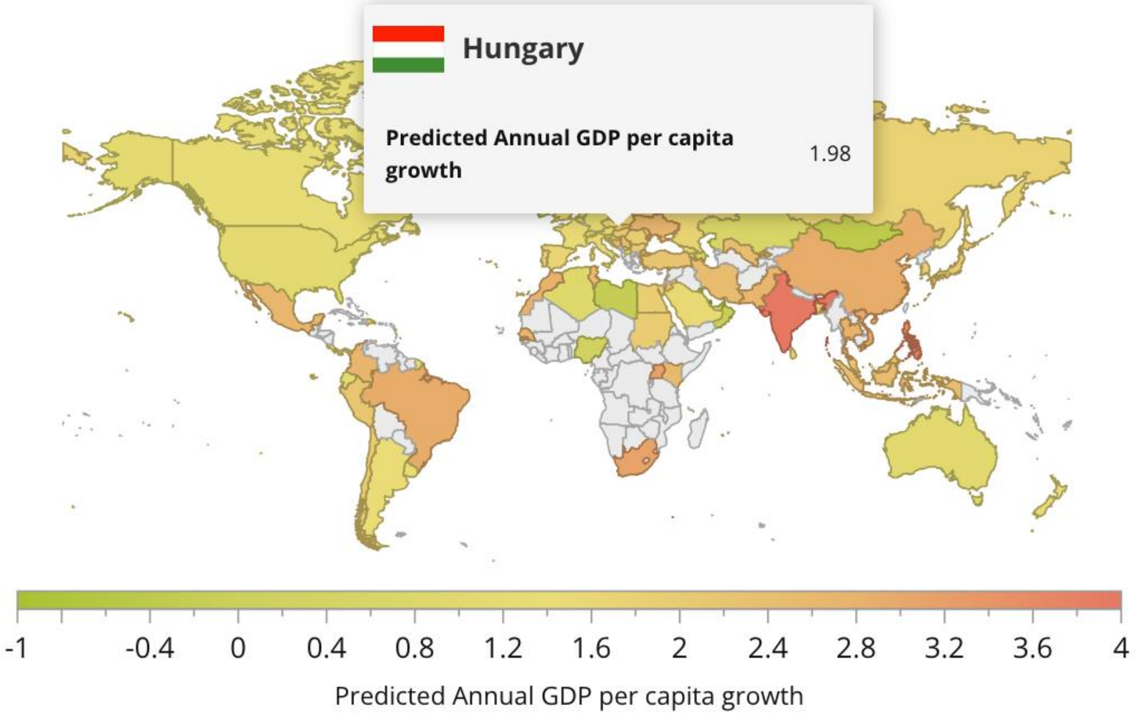
ECI Trade, Tech, & Research are complements

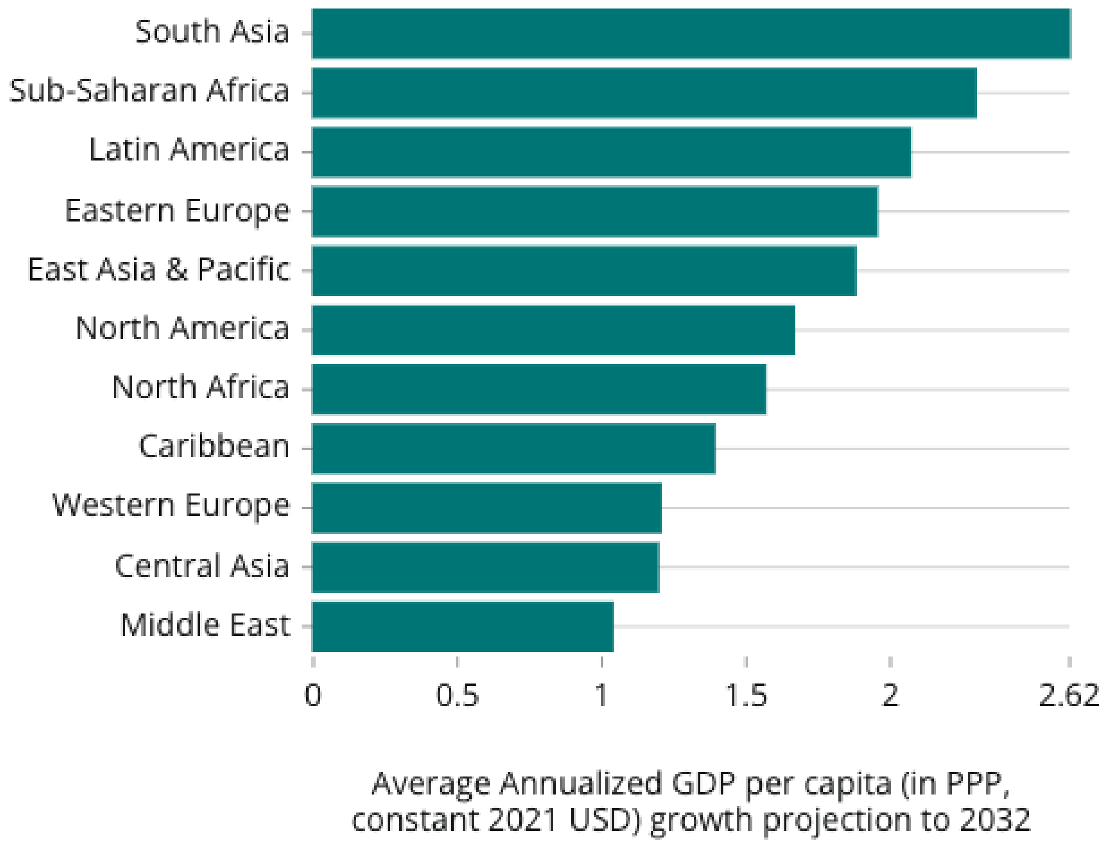


Stojkoski, Viktor, Philipp Koch, and César A. Hidalgo. "Multidimensional economic complexity and inclusive green growth." *Communications Earth & Environment* 4.1 (2023): 130.

Multidimensional ECI provides significantly better growth forecasts

Figure 1. Average Multidimensional ECI growth projections by region for 2032.





*Growth can be larger since these estimates suffer from regression to the mean.

http://oec.world

Moving into digital trade

International Trade

Patents

Research Papers

Digital Products

Stojkoski, Viktor, Philipp Koch, and César A. Hidalgo. "Multidimensional economic complexity and inclusive green growth." *Communications Earth & Environment* 4.1 (2023): 130.

Creating a dataset on digital products

2,502 Internet companies with revenues of USD 1B+

orbis

statista

Decompose revenue of each company into 29 sectors

13,013 firns and app developers

Google Play

App Store

Digital consumption Patterns for 2 sectors: mobile apps & games

Gradient-boosted regression tree.

(leave 20% out-of-sample cross-validation. MSE 0.048)

(Extends data to 129 additional countries and to 29 sectors)

Optimal Transport Reallocation

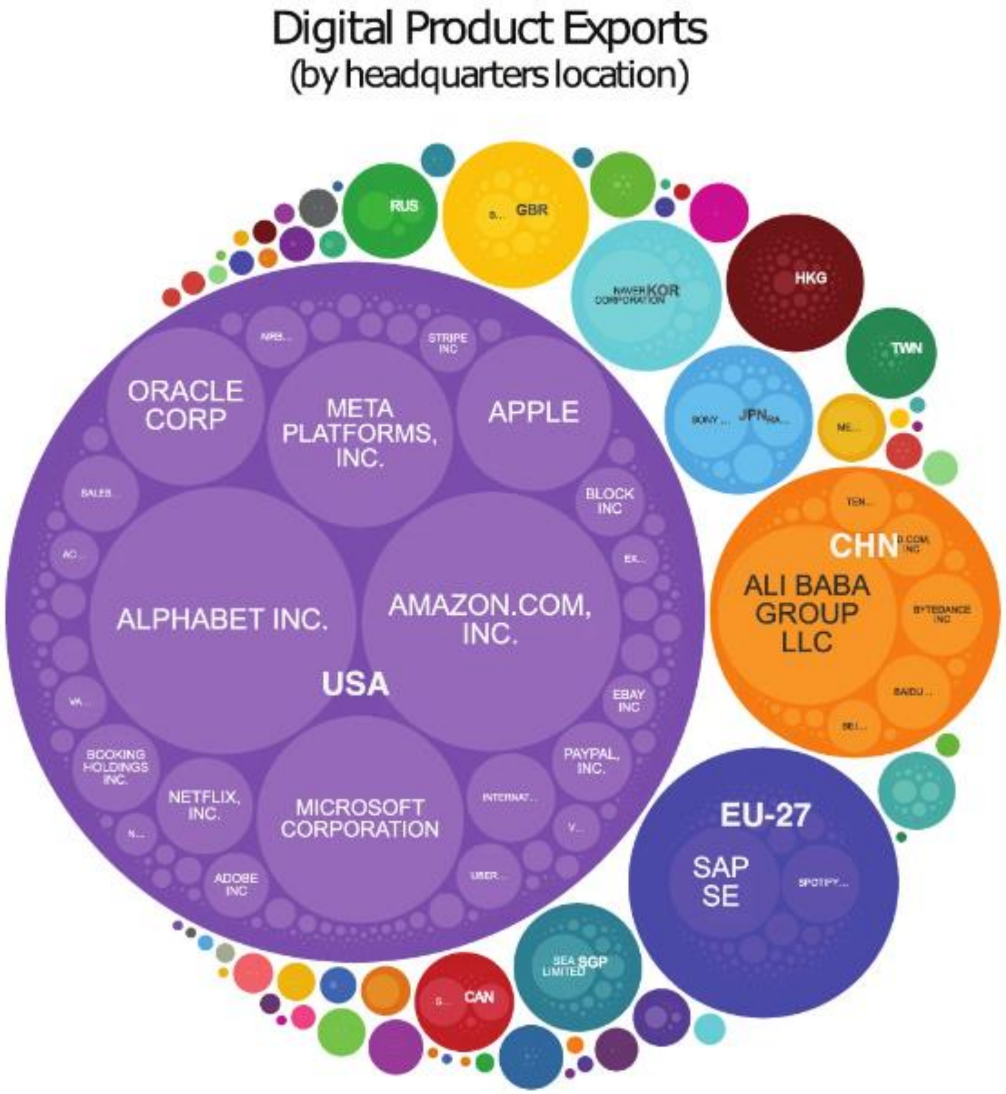
(Assigns trade to closest subsidiary constrained by total revenue amounts)

Resulting Dataset

Bilateral digital product trade estimates for 189 countries, 31 sectors, and 15,255 firms

Stojkoski et al. Nature Communications (2024)

Digital Product Trade Has Few Origins



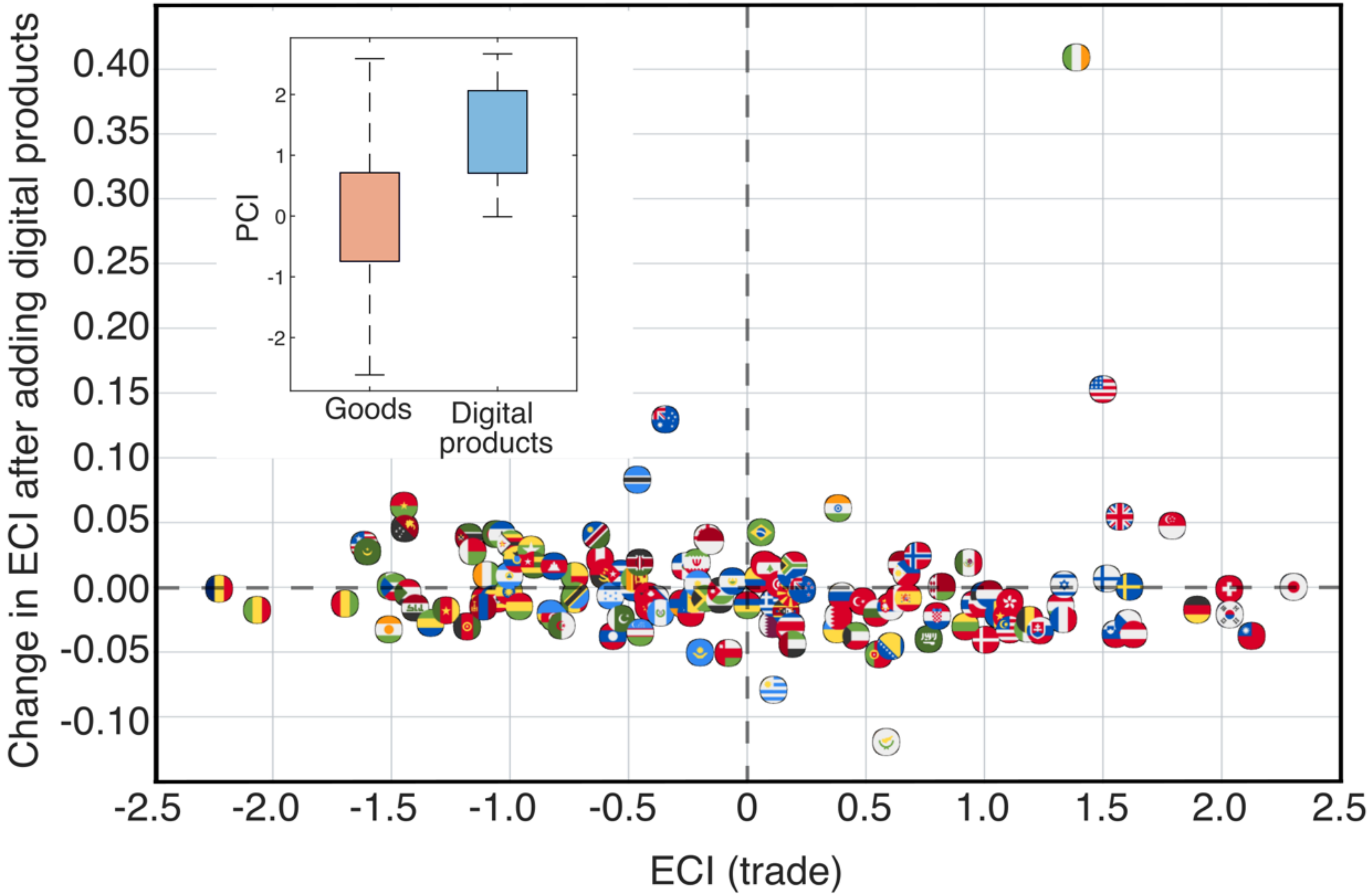
Stojkoski, Viktor, et al. "Estimating digital product trade through corporate revenue data." *Nature Communications* 15.1 (2024): 5262.

Digital Trade is Growing Fast

25% CAGR | 8% CAGR | 4% CAGR | 6% CAGR

Stojkoski, Viktor, et al. "Estimating digital product trade through corporate revenue data." *Nature Communications* 15.1 (2024): 5262.

Digital Trade is High Complexity



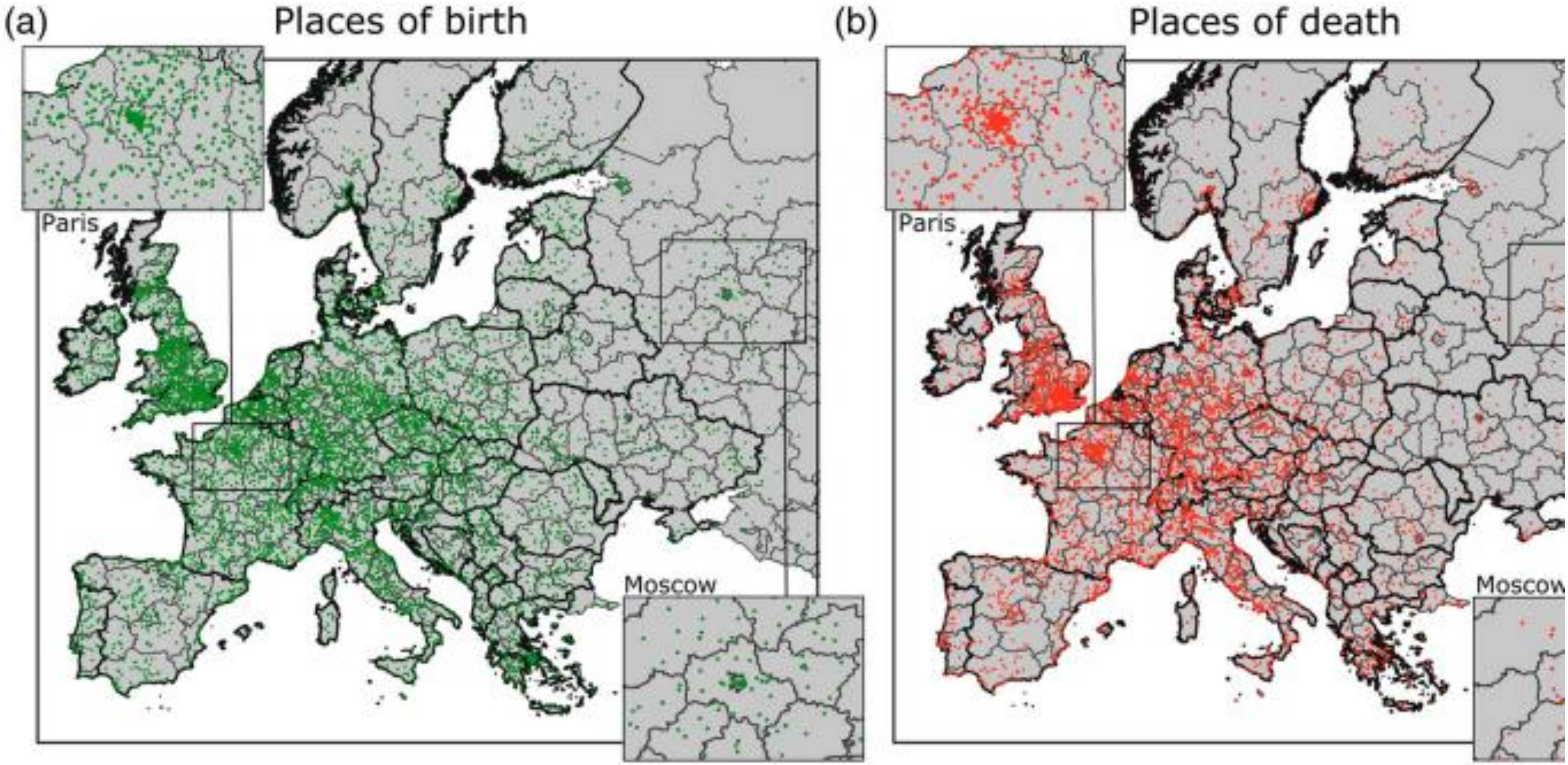
Stojkoski, Viktor, et al. "Estimating digital product trade through corporate revenue data." *Nature Communications* 15.1 (2024): 5262.


Economic complexity:
A telescope to understand the past & the future

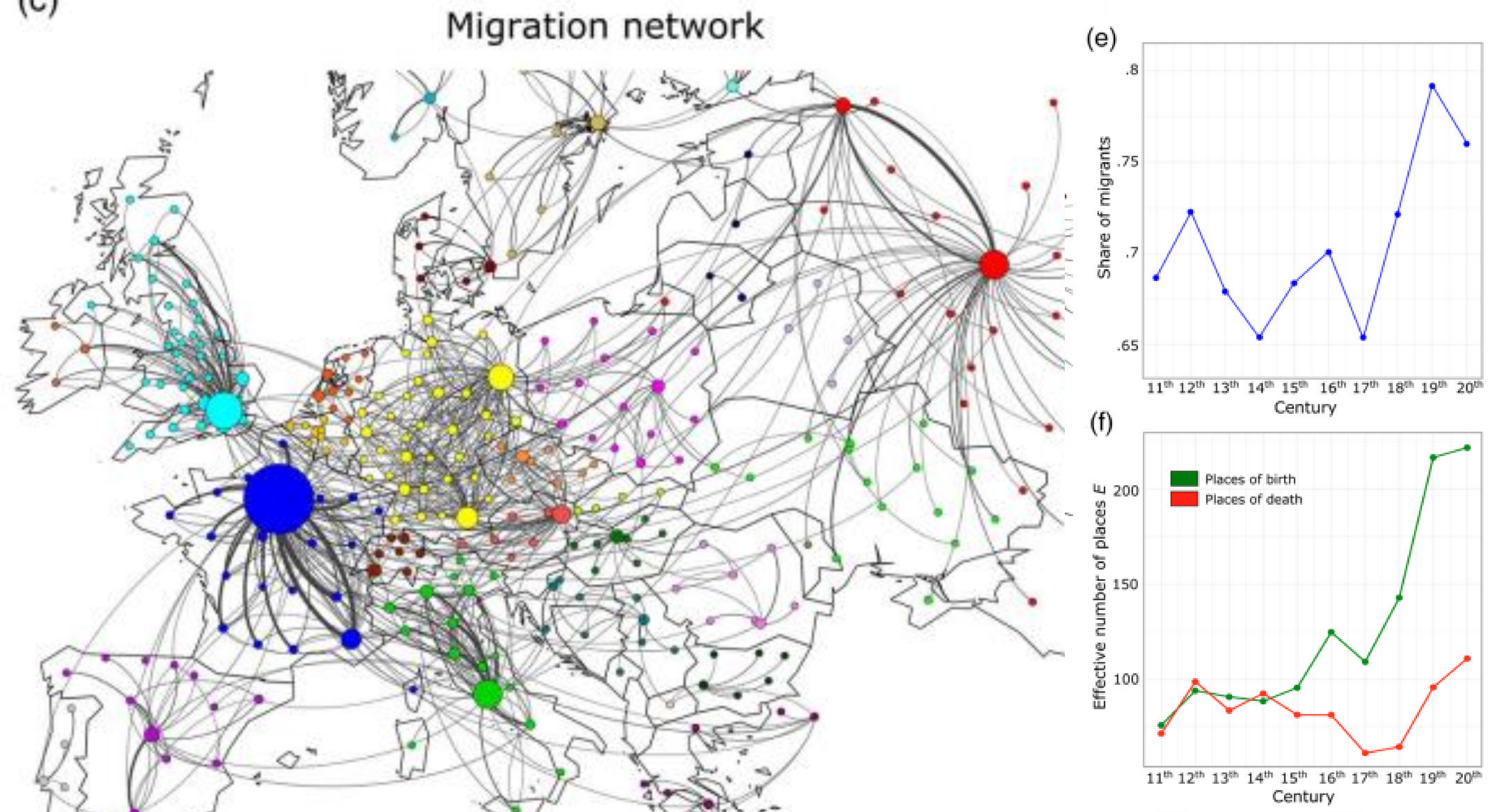
Migrants are well-known knowledge flow vectors

- Agrawal, A., Cockburn, I. & McHale, J. Gone but not forgotten knowledge flows, labor mobility, and enduring social relationships. *J Econ Geogr* **6**, 571–591 (2006).
- Balconi, M., Breschi, S. & Lissoni, F. Networks of inventors and the role of academia: an exploration of Italian patent data. *Research Policy* **33**, 127–145 (2004).
- Breschi, S. & Lissoni, F. Knowledge networks from patent data. in *Handbook of quantitative science and technology research* 613–643 (Springer, 2004).
- Singh, J. Collaborative Networks as Determinants of Knowledge Diffusion Patterns. *Management Science* **51**, 756–770 (2005).
- Moser, P., Voena, A. & Waldinger, F. German Jewish émigrés and US invention. *American Economic Review* **104**, 3222–3255 (2014).
- Waldinger, F. Peer Effects in Science: Evidence from the Dismissal of Scientists in Nazi Germany. *The Review of Economic Studies* **79**, 838–861 (2012).
- Waldinger, F. Quality matters: The expulsion of professors and the consequences for PhD student outcomes in Nazi Germany. *Journal of political economy* **118**, 787–831 (2010).
- Ganguli, I. Immigration and ideas: what did Russian scientists “bring” to the United States? *Journal of Labor Economics* **33**, S257–S288 (2015).
- Borjas, G. J. & Doran, K. B. Cognitive mobility: labor market responses to supply shocks in the space of ideas. *Journal of Labor Economics* **33**, S109–S145 (2015).
- Azoulay, P., Liu, C. C. & Stuart, T. E. Social influence given (partially) deliberate matching: Career imprints in the creation of academic entrepreneurs. *American Journal of Sociology* **122**, 1223–1271 (2017).
- Collins, H. M. The TEA Set: Tacit Knowledge and Scientific Networks. *Science Studies* **4**, 165–185 (1974).
- Parsons, C. & Vézina, P.-L. Migrant Networks and Trade: The Vietnamese Boat People as a Natural Experiment. *Economic Journal* (2017).
- Scoville, W. C. The Huguenots and the diffusion of technology. I. *Journal of Political Economy* **60**, 294–311 (1952).
- Scoville, W. C. The Huguenots and the diffusion of technology. II. *Journal of Political Economy* **60**, 392–411 (1952).
- Kerr, W. R. *The Gift of Global Talent: How Migration Shapes Business, Economy & Society.* (Stanford University Press, 2018).
- Lissoni, F. & Miguelez, E. Migration and Innovation: Learning from Patent and Inventor Data. *Journal of Economic Perspectives* **38**, 27–54 (2024).
- Autant-Bernard, C. Science and knowledge flows: evidence from the French case. *Research policy* **30**, 1069–1078 (2001).

Most research, however, focuses on a recent context and on knowledge flows within an activity (MAR spillovers)

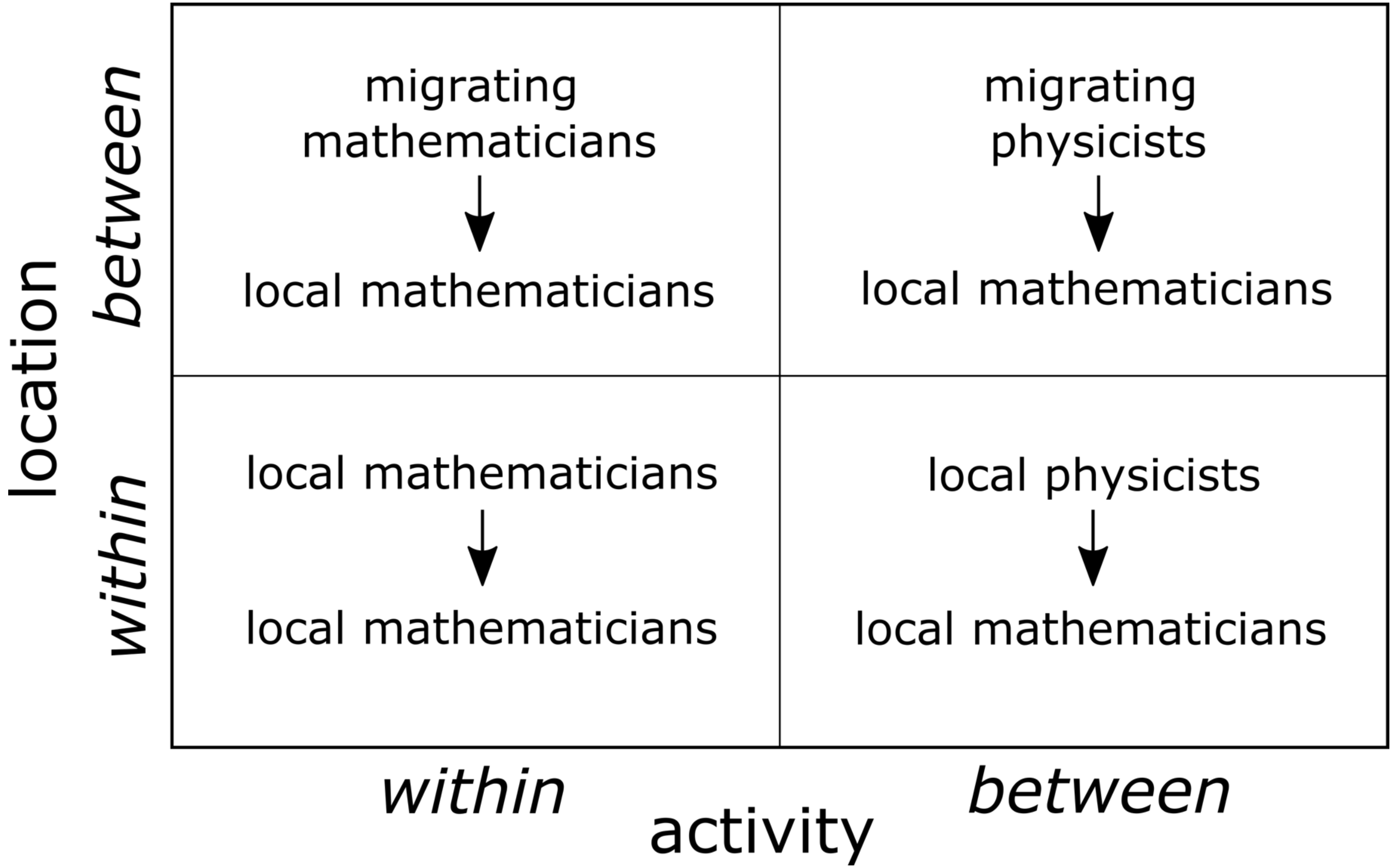


Koch et al. Regional Studies (2023)



Koch et al. Regional Studies (2023)

Knowledge spillovers can occur within and between both locations and activities:



Koch et al. Regional Studies (2023)

Methods

Spillovers between locations within the same activity

First, we estimate the ratio between the observed and expected number of famous immigrants or emigrants:

$$R_{ik,t}^{immi} = \frac{N_{ik,t}^{immi}}{\widehat{N}_{ik,t}^{immi}} \qquad R_{ik,t}^{emi} = \frac{N_{ik,t}^{emi}}{\widehat{N}_{ik,t}^{emi}}$$

- We use two models for the expected numbers:

(1) Revealed Comparative Advantage:

$$\widehat{N}_{ik,t} = \frac{\sum_k N_{ik,t} \sum_i N_{ik,t}}{\sum_{i,k} N_{ik,t}}$$

(2) Negative binomial model:

$$\widehat{N}_{ik,t} = f\left(\alpha_0 + \alpha_1 N_{ik,t-1} + \alpha_2 S_{ik,t-1}^{births} + \theta_{it} + \vartheta_{kt}\right)$$

- We create specialization matrices:

$$M_{ik,t}^{immi} = \begin{cases} 1 & if\ R_{ik,t}^{immi} \geq 1 \\ 0 & otherwise \end{cases} \qquad M_{ik,t}^{emi} = \begin{cases} 1 & if\ R_{ik,t}^{emi} \geq 1 \\ 0 & otherwise \end{cases}$$

Koch et al. Regional Studies (2023)

Estimate three relatedness effects

Immigrant Relatedness

$$R_{ik,t}^{immi} = \frac{N_{ik,t}^{immi}}{\widehat{N}_{ik,t}^{immi}}$$

$$M_{ik,t}^{immi} = \begin{cases} 1 & if\ R_{ik,t}^{immi} \geq 1 \\ 0 & otherwise \end{cases}$$

$$\varphi_{kk',t}^{immi} = \frac{\sum_i M_{ik,t}^{immi} M_{ik',t}^{immi}}{max\left(\sum_i M_{ik,t}^{immi}, \sum_i M_{ik',t}^{immi}\right)}$$

$$\omega_{ik,t}^{immi} = \frac{\sum_{k'} M_{ik',t}^{immi} \varphi_{kk',t}^{immi}}{\sum_{k'} \varphi_{kk',t}^{immi}}$$

Emigrant Relatedness

$$R_{ik,t}^{emi} = \frac{N_{ik,t}^{emi}}{\widehat{N}_{ik,t}^{emi}}$$

$$M_{ik,t}^{emi} = \begin{cases} 1 & if\ R_{ik,t}^{emi} \geq 1 \\ 0 & otherwise \end{cases}$$

$$\varphi_{kk',t}^{emi} = \frac{\sum_i M_{ik,t}^{emi} M_{ik',t}^{emi}}{max\left(\sum_i M_{ik,t}^{emi}, \sum_i M_{ik',t}^{emi}\right)}$$

$$\omega_{ik,t}^{emi} = \frac{\sum_{k'} M_{ik',t}^{emi} \varphi_{kk',t}^{emi}}{\sum_{k'} \varphi_{kk',t}^{emi}}$$

Local Relatedness

$$R_{ik,t}^{births} = \frac{N_{ik,t}^{births}}{\widehat{N}_{ik,t}^{births}}$$

$$M_{ik,t}^{births} = \begin{cases} 1 & if\ R_{ik,t}^{births} \geq 1 \\ 0 & otherwise \end{cases}$$

$$\varphi_{kk',t}^{births} = \frac{\sum_i M_{ik,t}^{births} M_{ik',t}^{births}}{max\left(\sum_i M_{ik,t}^{births}, \sum_i M_{ik',t}^{births}\right)}$$

$$\omega_{ik,t}^{births} = \frac{\sum_{k'} M_{ik',t}^{births} \varphi_{kk',t}^{births}}{\sum_{k'} \varphi_{kk',t}^{births}}$$

Koch et al. Regional Studies (2023)

Unpacking spillovers

location \ activity	*within*	*between*
between	$M_{ik,t}^{immi}$	$\omega_{ik,t}^{immi}$
within	$M_{ik,t}^{births}$	$\omega_{ik,t}^{births}$

+ emigrant terms

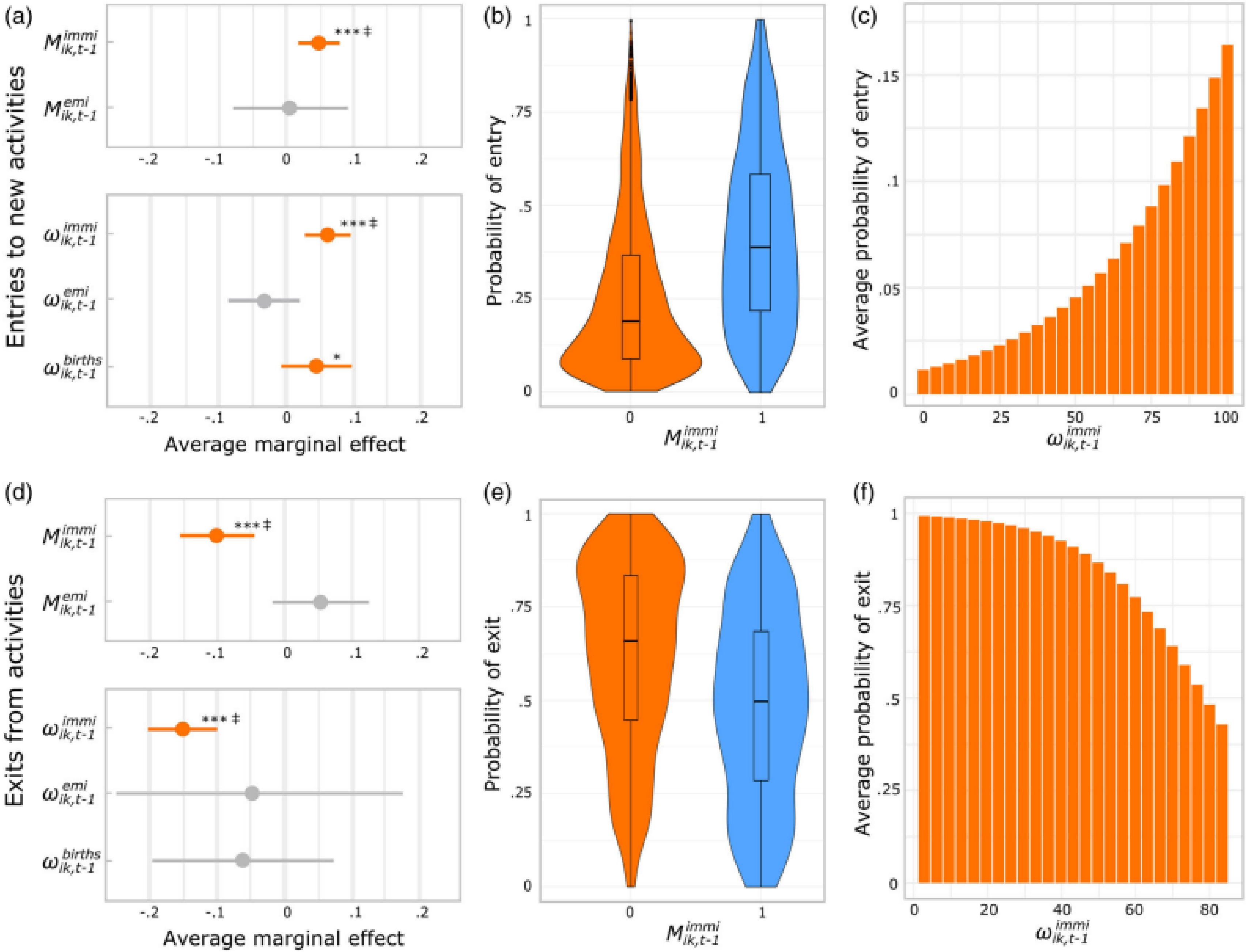
Koch et al. Regional Studies (2023)

Table 1. Main results of logistic regression models explaining entries and exits of activities.

	Dependent variable: $Entry_{ik,t}$					Dependent variable: $Exit_{ik,t}$				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$M^{immi}_{ik,t-1}$	0.334***	0.303***	0.336***	0.331***	0.300***	−0.603***	−0.584***	−0.591***	−0.587***	−0.571***
	(0.080)	(0.075)	(0.086)	(0.080)	(0.076)	(0.127)	(0.134)	(0.120)	(0.126)	(0.126)
$M^{emi}_{ik,t-1}$	0.115	0.045	0.106	0.121	0.018	0.310	0.330	0.233	0.306	0.291
	(0.261)	(0.278)	(0.261)	(0.255)	(0.270)	(0.240)	(0.232)	(0.216)	(0.222)	(0.203)
$\omega^{immi}_{ik,t-1}$		0.027***			0.028***		−0.067***			−0.064***
		(0.006)			(0.007)		(0.016)			(0.011)
$\omega^{emi}_{ik,t-1}$			−0.006		−0.024			−0.048		−0.025
			(0.012)		(0.019)			(0.038)		(0.063)
$\omega^{births}_{ik,t-1}$				0.011	0.027*				−0.059***	−0.034
				(0.008)	(0.015)				(0.018)	(0.041)
Further controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fixed effects										
Broad category–region–century	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Category–century	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3944	3944	3944	3944	3944	1051	1051	1051	1051	1051
Pseudo-R^2	0.213	0.214	0.213	0.213	0.215	0.224	0.230	0.226	0.226	0.232
BIC	9537.0	9539.4	9545.0	9544.5	9553.1	3619.6	3618.0	3623.4	3623.3	3628.8

Note: The fixed effects in these models are highly restrictive, amounting to more than 700 parameters in columns (1) to (5) and more than 350 parameters in columns (6) to (10). All regions included in the regression model exhibit a minimum number of births and migrants such that measures of specialisation and relatedness are defined (see Section 2.2 in the supplemental data online). Standard errors are clustered by region and period. For the full regression tables with all control variables, see Sections 3.2 and 3.3 online. BIC, Bayesian information criterion. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Koch et al. Regional Studies (2023)



Koch et al. Regional Studies (2023)

PNAS RESEARCH ARTICLE | ECONOMIC SCIENCES OPEN ACCESS

Augmenting the availability of historical GDP per capita estimates through machine learning

Philipp Koch[a,b,1], Viktor Stojkoski[a,c], and César A. Hidalgo[a,d,e,1]

Affiliations are included on p. 10.

Edited by Marshall Burke, Stanford University, Stanford, CA; received January 31, 2024; accepted August 9, 2024 by Editorial Board Member Ronald D. Lee

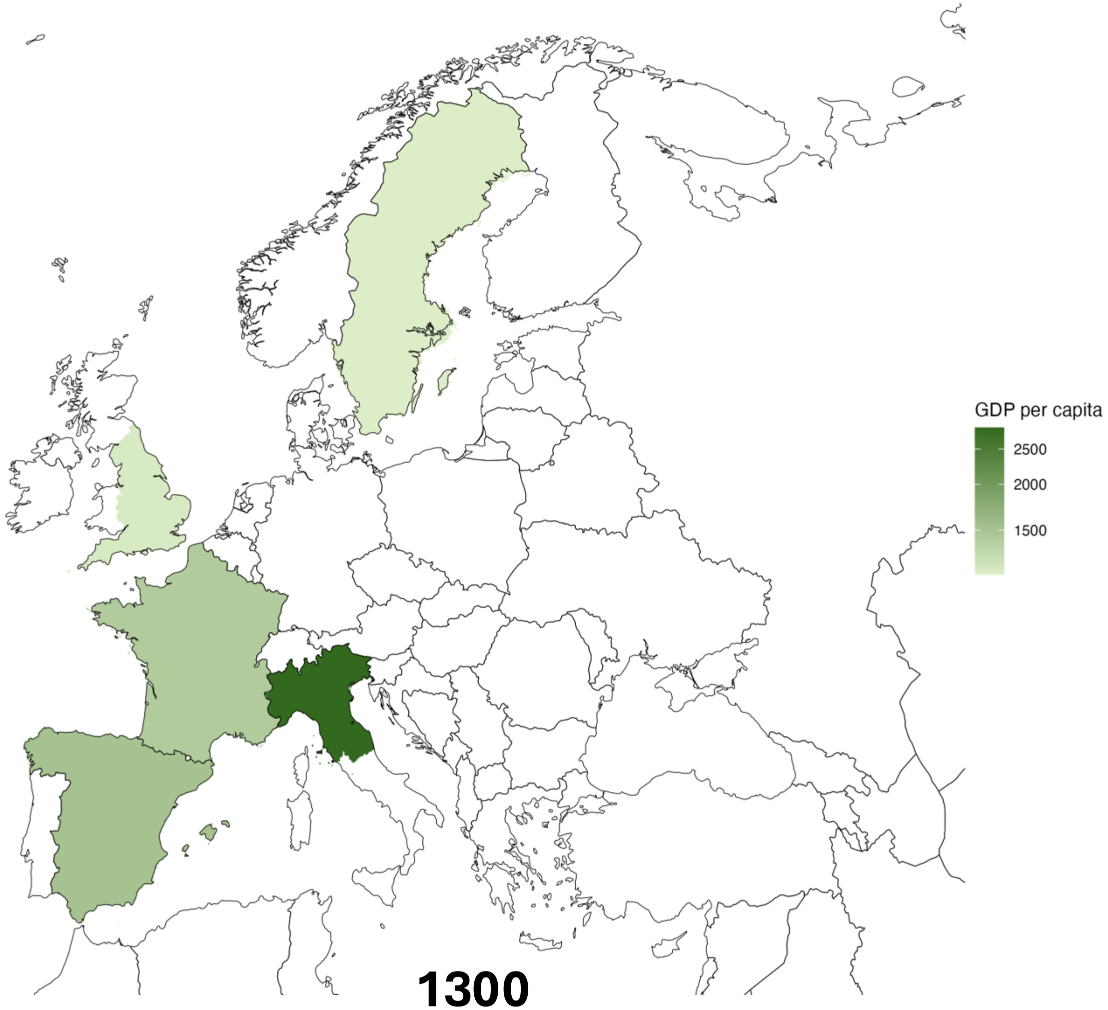
Can we use data on the biographies of historical figures to estimate the GDP per capita of countries and regions? Here, we introduce a machine learning method to estimate the GDP per capita of dozens of countries and hundreds of regions in Europe and North America for the past seven centuries starting from data on the places of birth, death, and occupations of hundreds of thousands of historical figures. We build an elastic net regression model to perform feature selection and generate out-of-sample estimates that explain 90% of the variance in known historical income levels. We use this model to generate GDP per capita estimates for countries, regions, and time periods for which these data are not available and externally validate our estimates by comparing them with four proxies of economic output: urbanization rates in the past 500 y, body height in the 18th century, well-being in 1850, and church building activity in the 14th and 15th century. Additionally, we show our estimates reproduce the well-known reversal of fortune between southwestern and northwestern Europe between 1300 and 1800 and find this is largely driven by countries and regions engaged in Atlantic trade. These findings validate the use of fine-grained biographical data as a method to augment historical GDP per capita estimates. We publish our estimates with CI together with all collected source data in a comprehensive dataset.

economic history | machine learning | economic development

Significance

The scarcity of historical GDP per capita data limits our ability to explore questions of long-term economic development. Here, we introduce a machine learning method using detailed data on famous biographies to estimate the historical GDP per capita of hundreds of regions in Europe and North America. Our model generates accurate out-of-sample estimates (R^2 = 90%) that quadruple the availability of historical GDP per capita data and correlate positively with

Estimating Historical GDPpc



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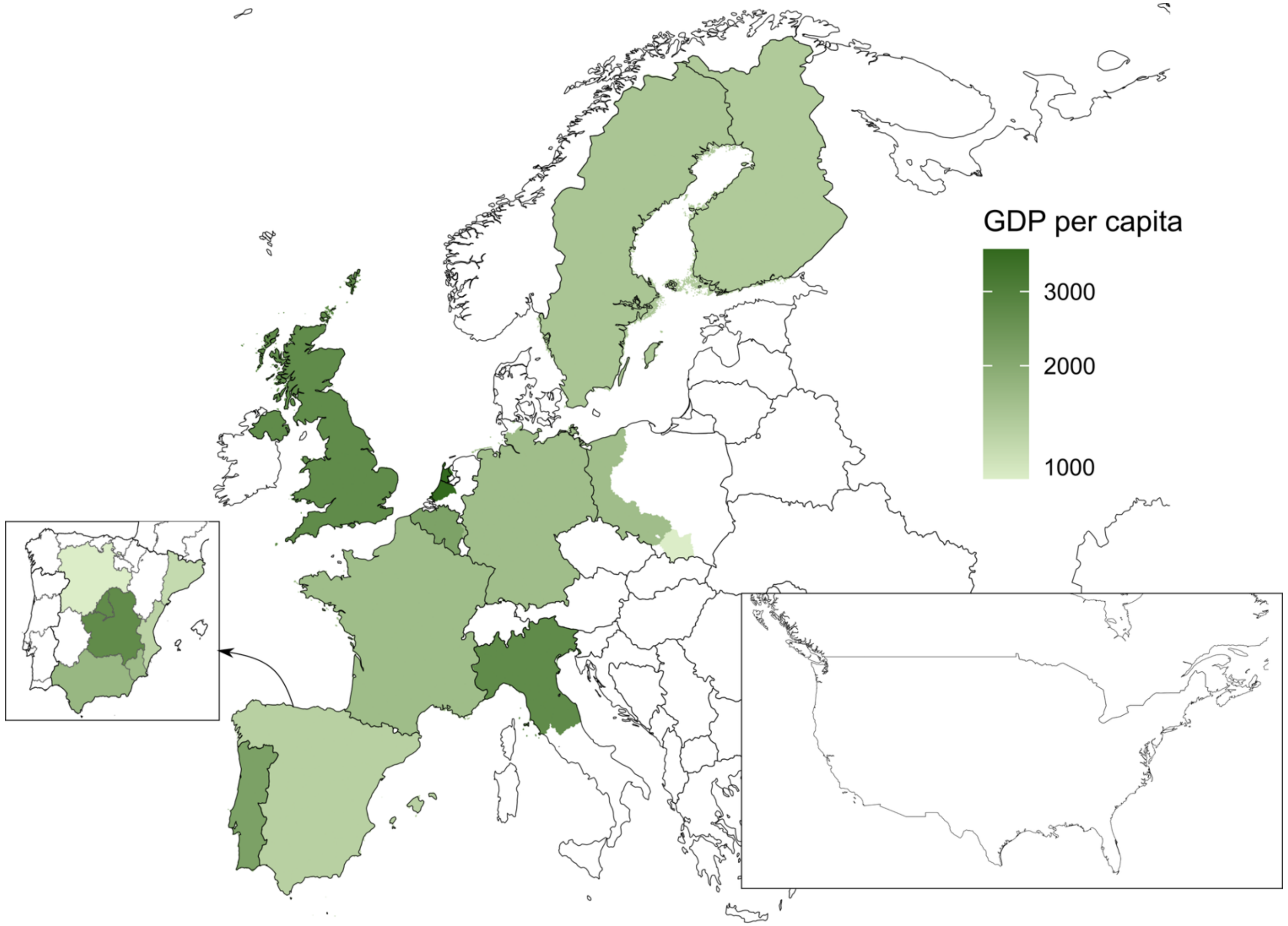
Maddison project



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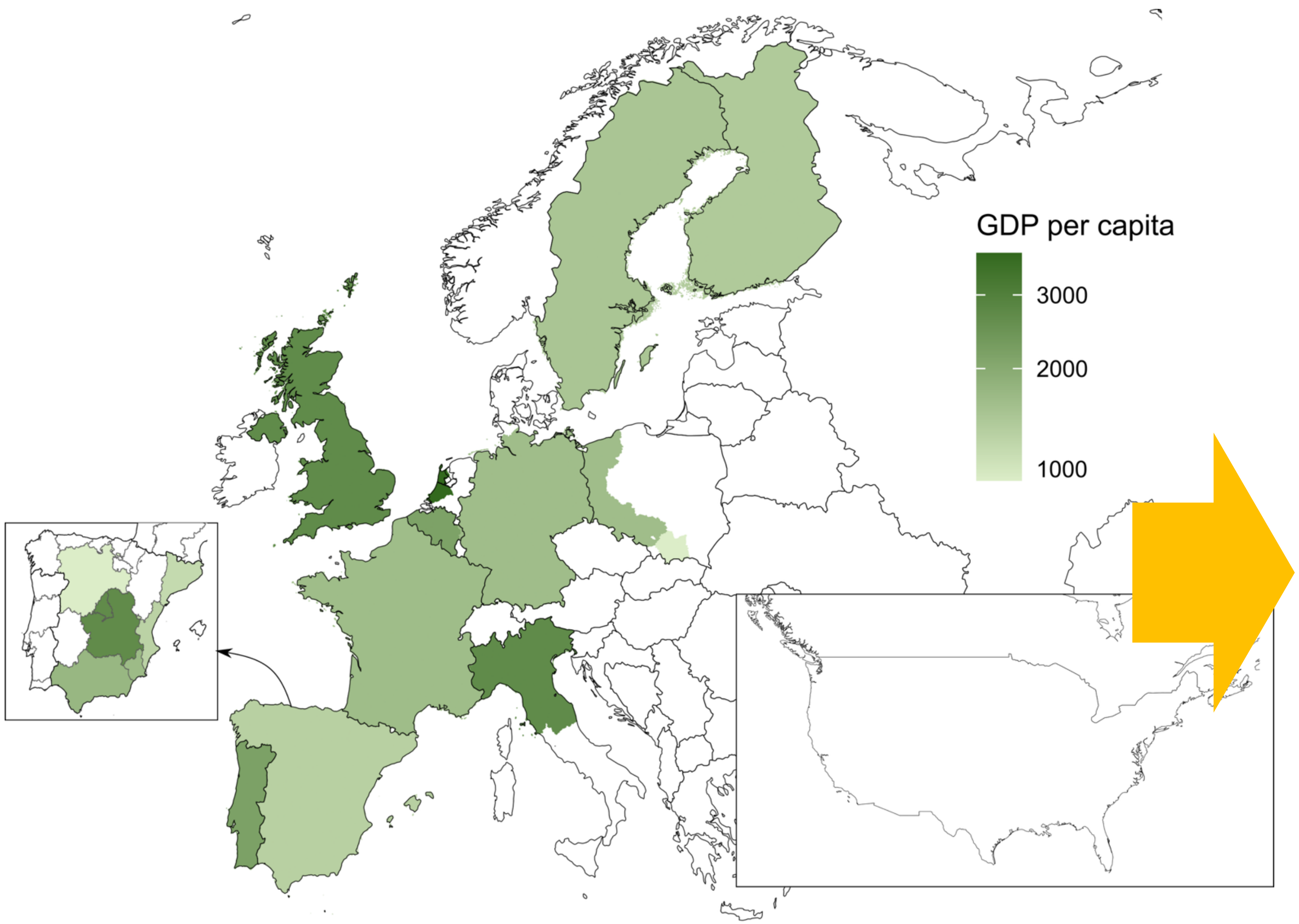
Maddison project

Getting from here…



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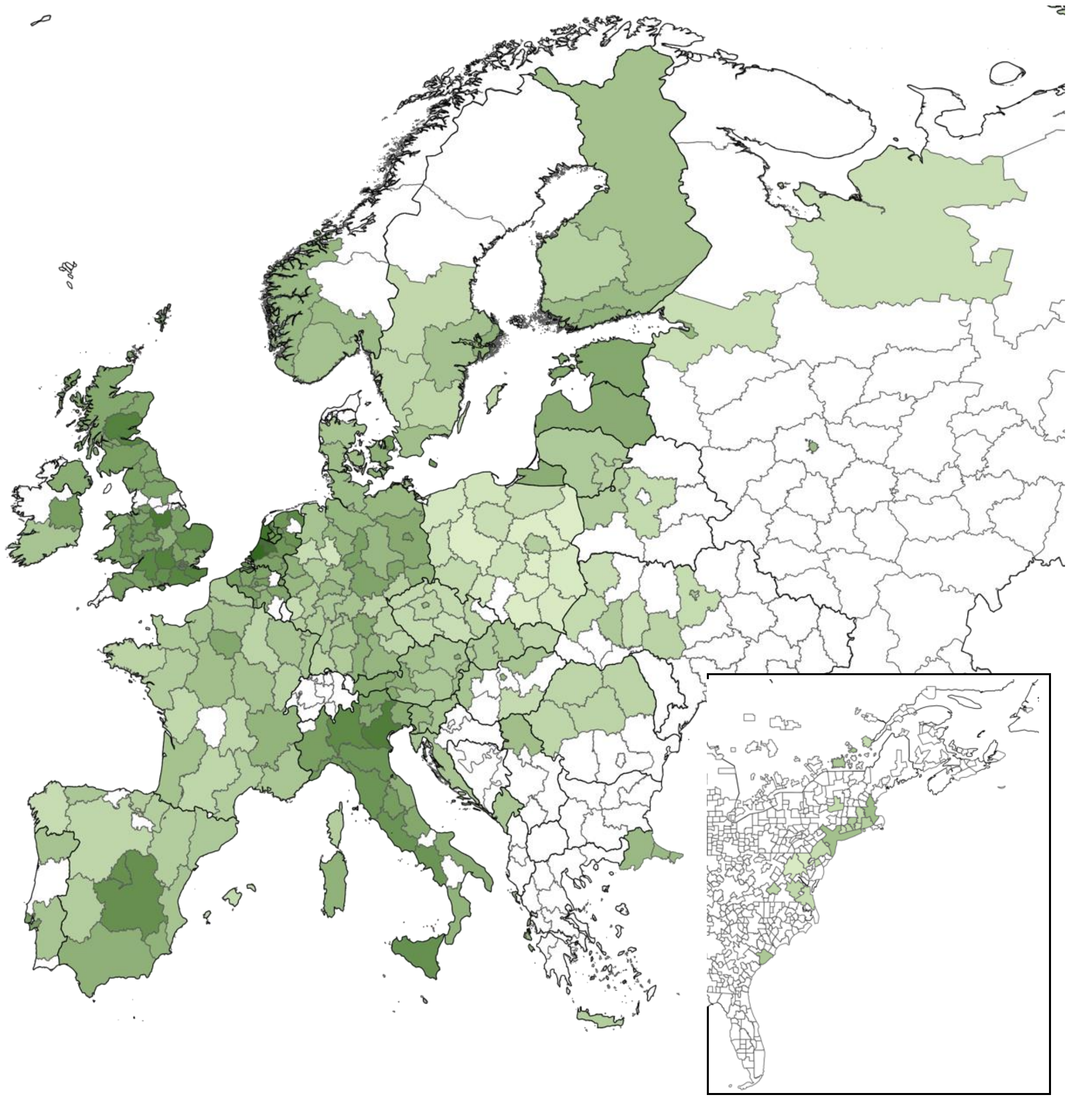
Maddison project

… to here



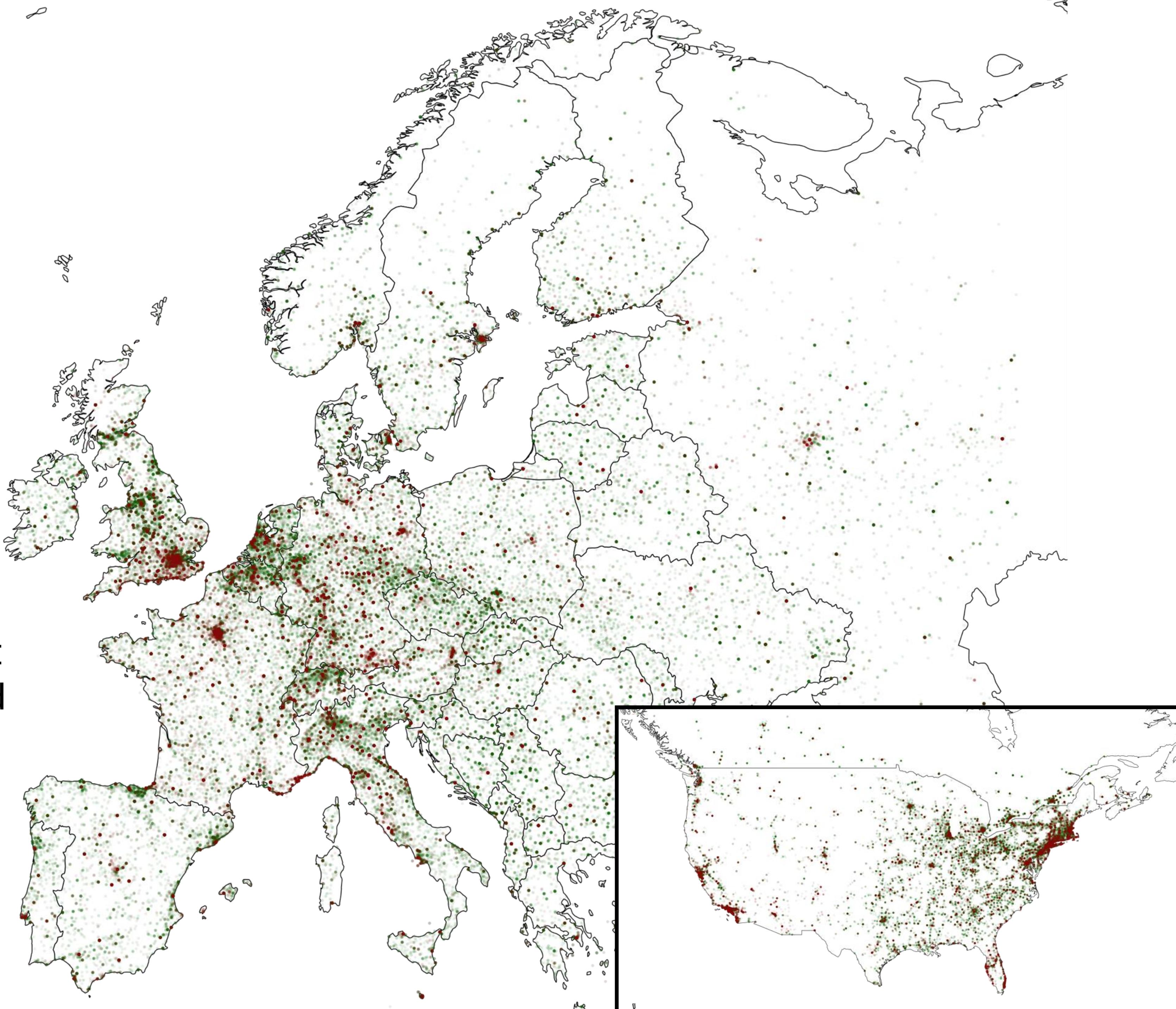
1750
Koch et al. PNAS 2024

Using This…

Place of birth, death, and occupation data of famous individuals from Wikipedia[9].

~561k famous individuals assigned to one of 49 occupations with a birth or death in Europe and North America between 1300 and 2000 (only individuals with at least 2 language editions and an identifiable occupation).

Koch, Stojkoski, Hidalgo, PNAS (2024)

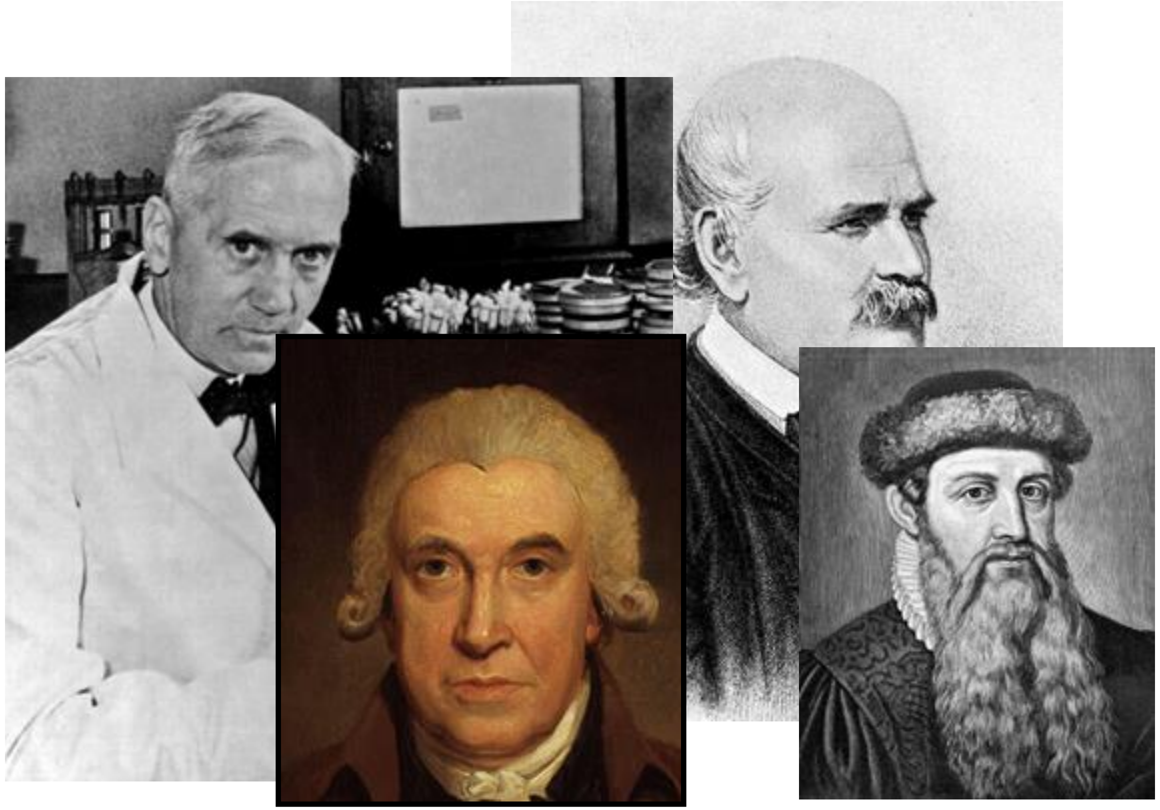


Why biographies?

Our collective memory on famous individuals is likely one of the most comprehensive representation of the historical geography of knowledge.

The famous individuals that were born at, have died at, immigrated to or emigrated from a specific place tell us something about the level of economic development.

Direct



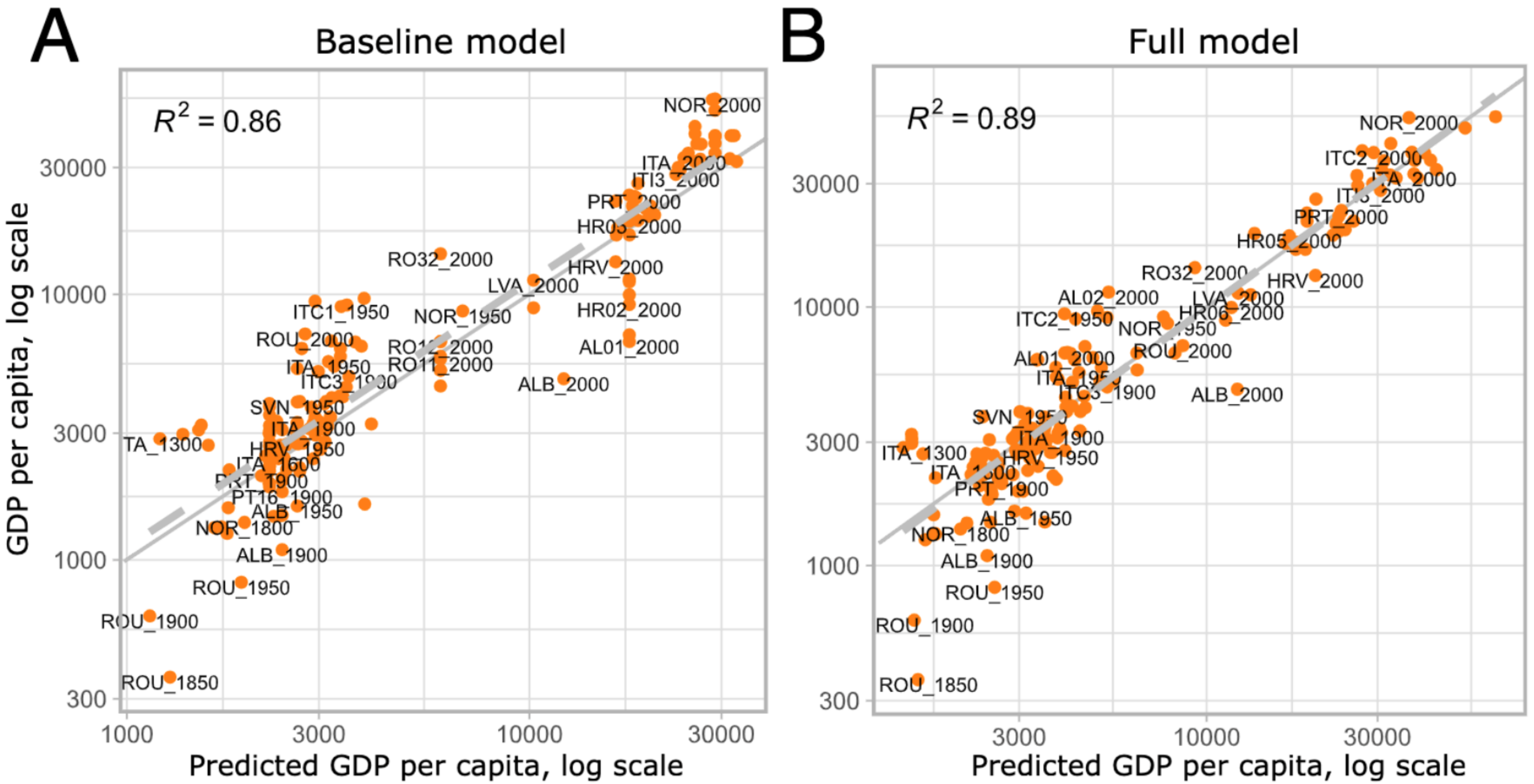
Indirect

Model

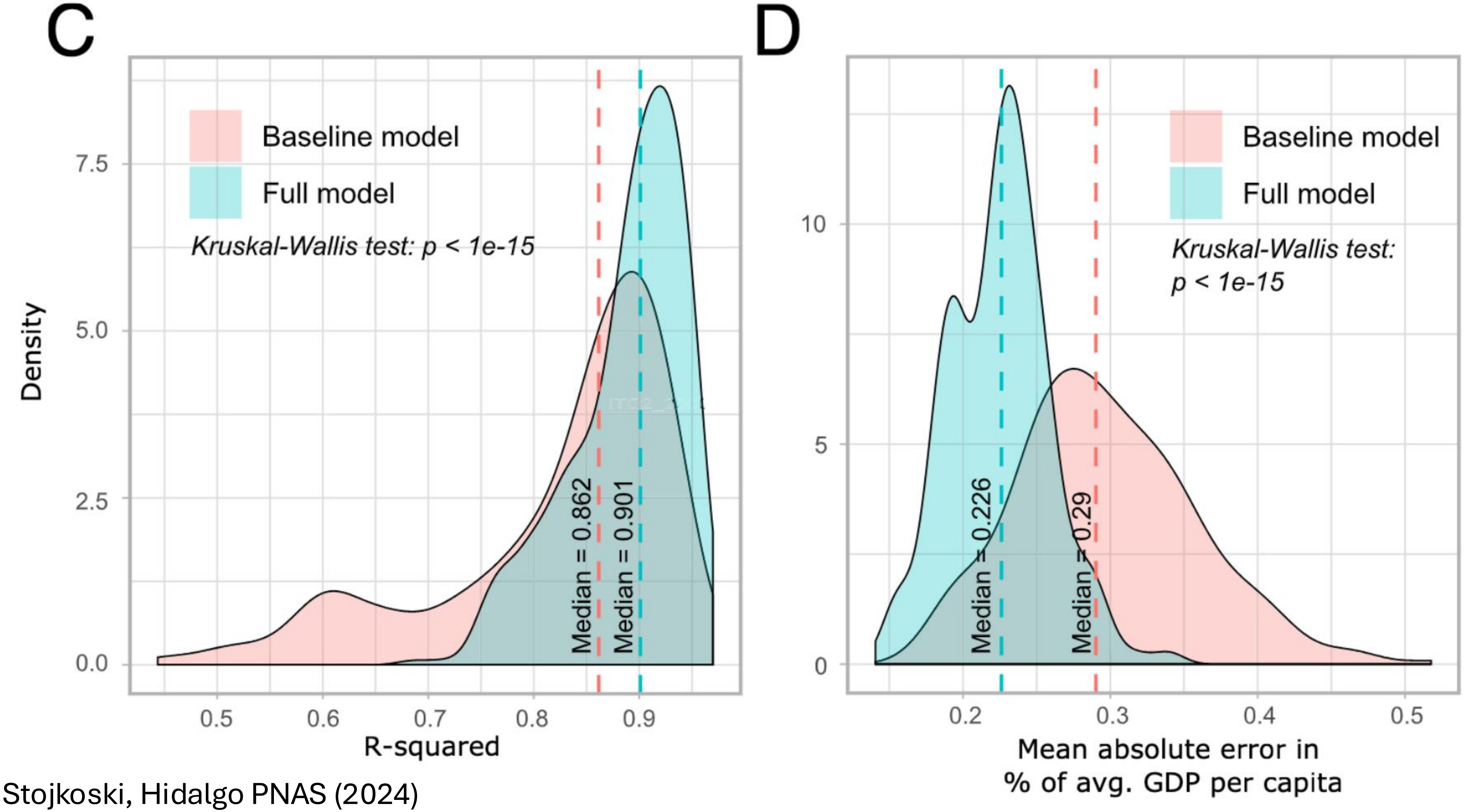
Regularized Elastic Net

Leave 20% out-of-sample cross validation

$$\widehat{\beta_{EN}} = min_{\beta}(\|y - X\beta\|^2 + \lambda[(1-\alpha)\|\beta\|_2^2 + \alpha\|\beta\|_1])$$



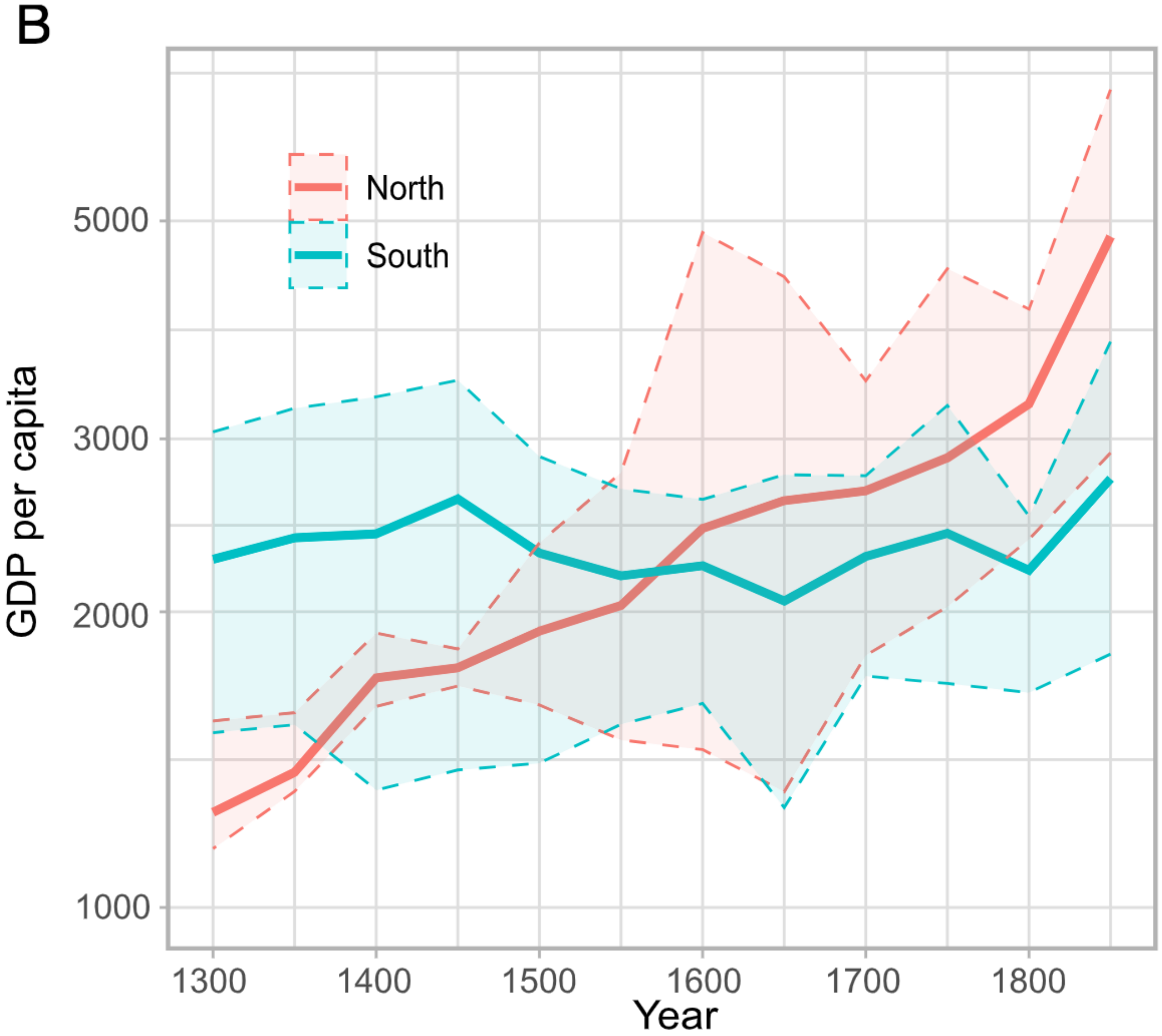
Model Performance



Koch, Stojkoski, Hidalgo PNAS (2024)

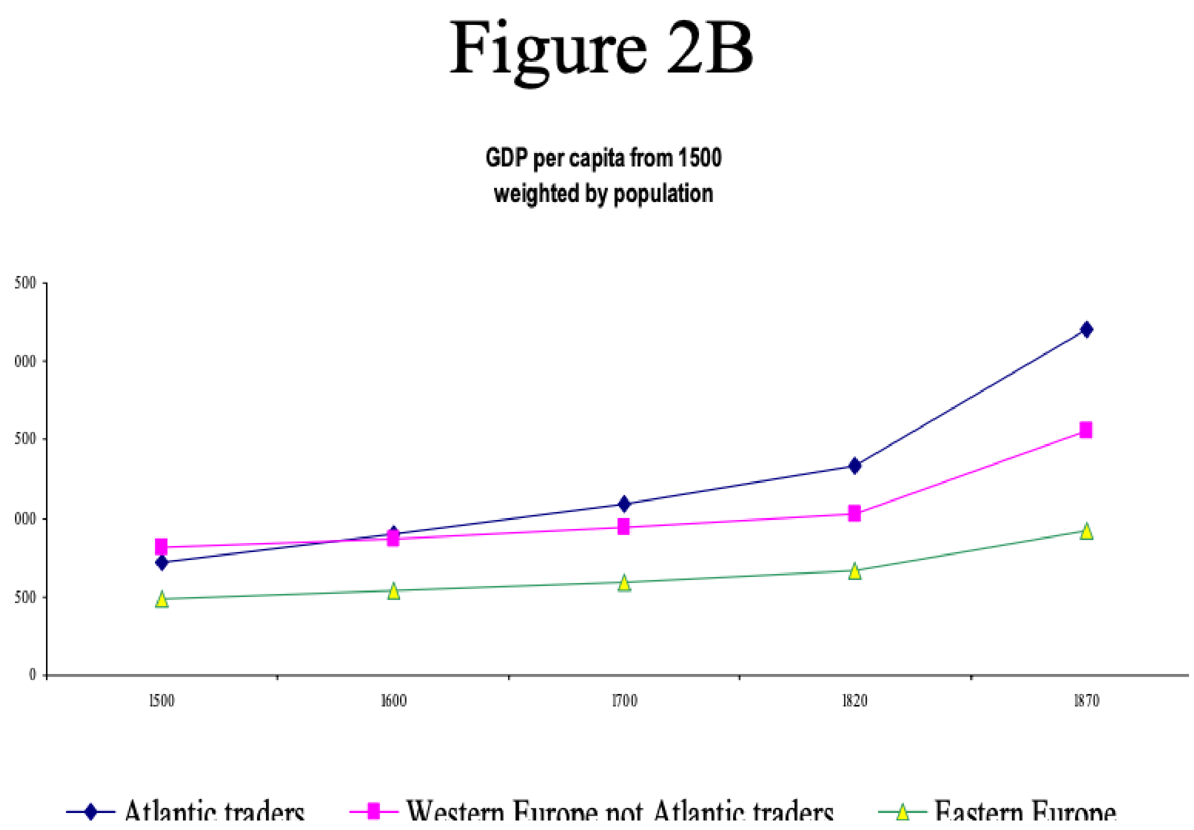
Validation - Little Divergence

In 1300, the bottom 10th percentile of the South has been as rich as the top 90th percentile of the North.
In 1800, the opposite holds: The bottom 10th percentile of the North exhibits a similar income level as the 90th percentile of the South.

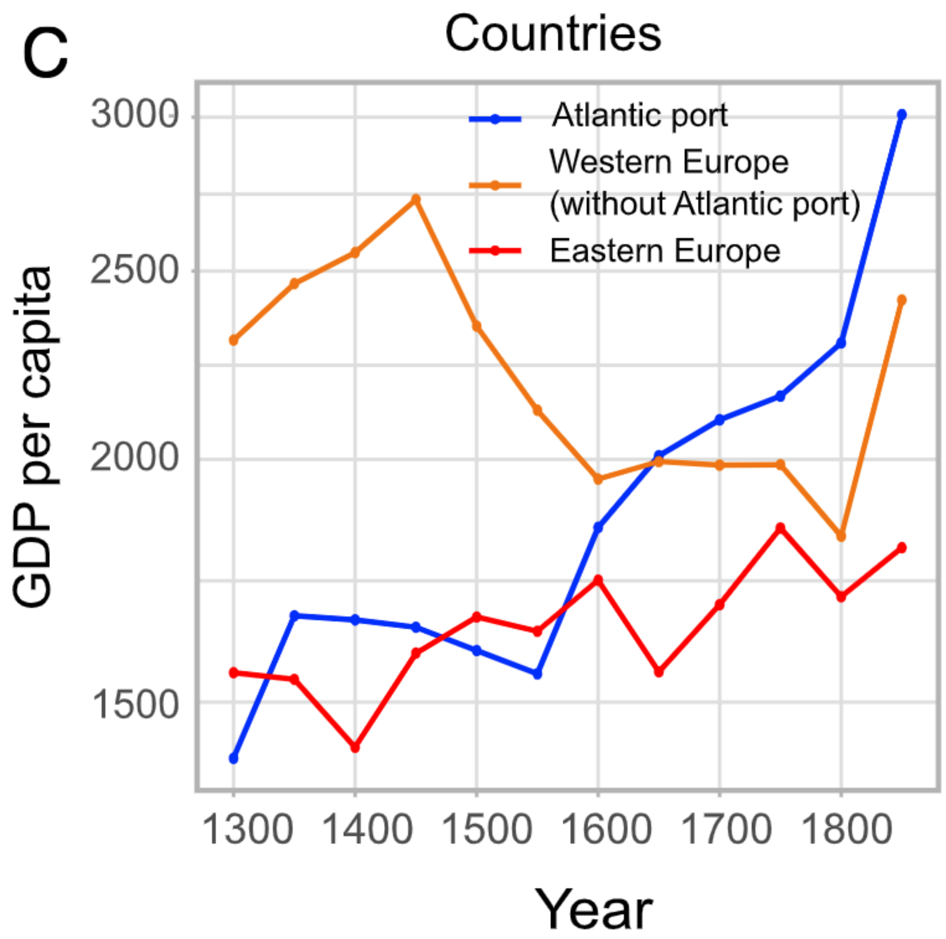


Koch, Stojkoski, Hidalgo PNAS (2024)

Validation – Acemoglu, Johnson, Robinson Atlantic Trade

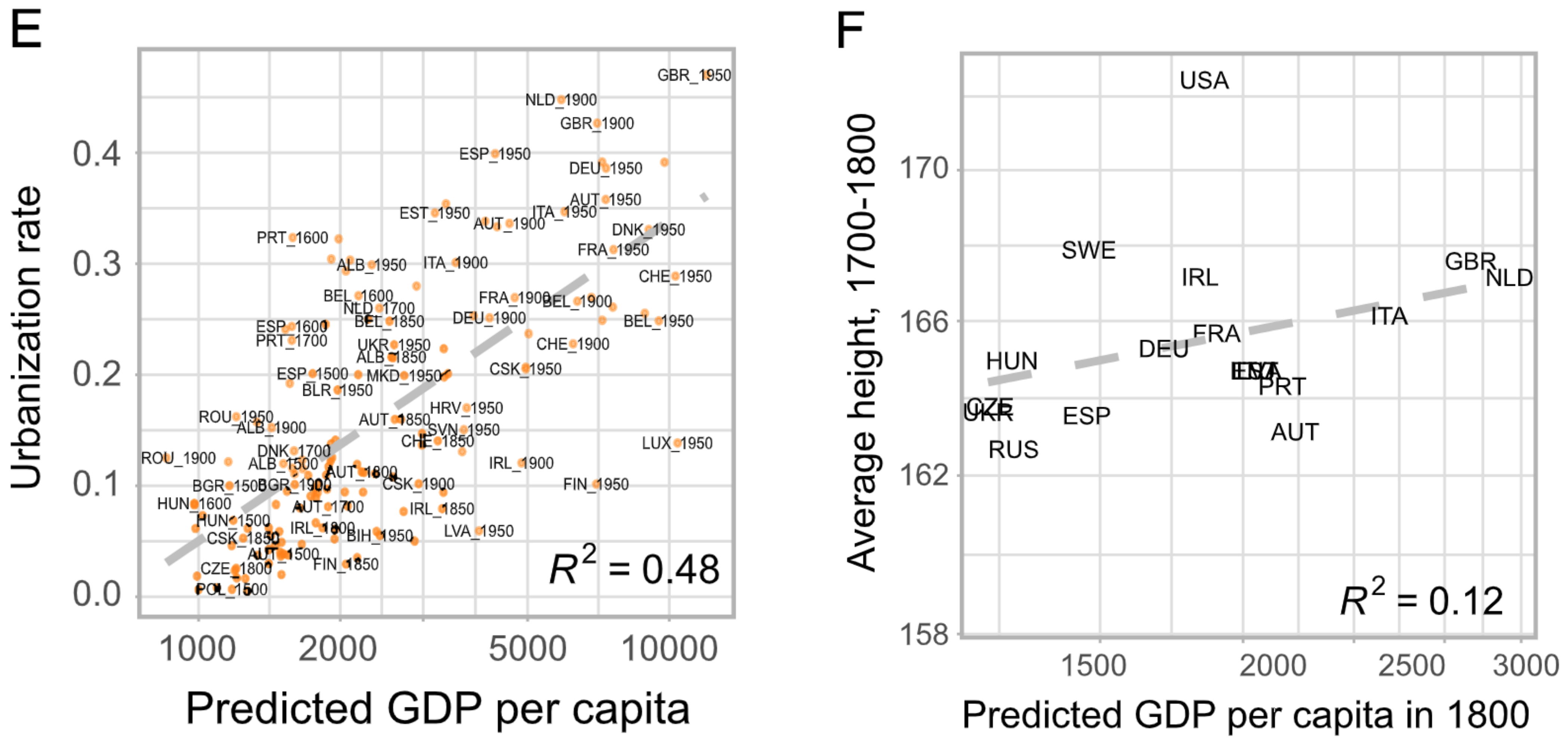


Acemoglu et al. 2005



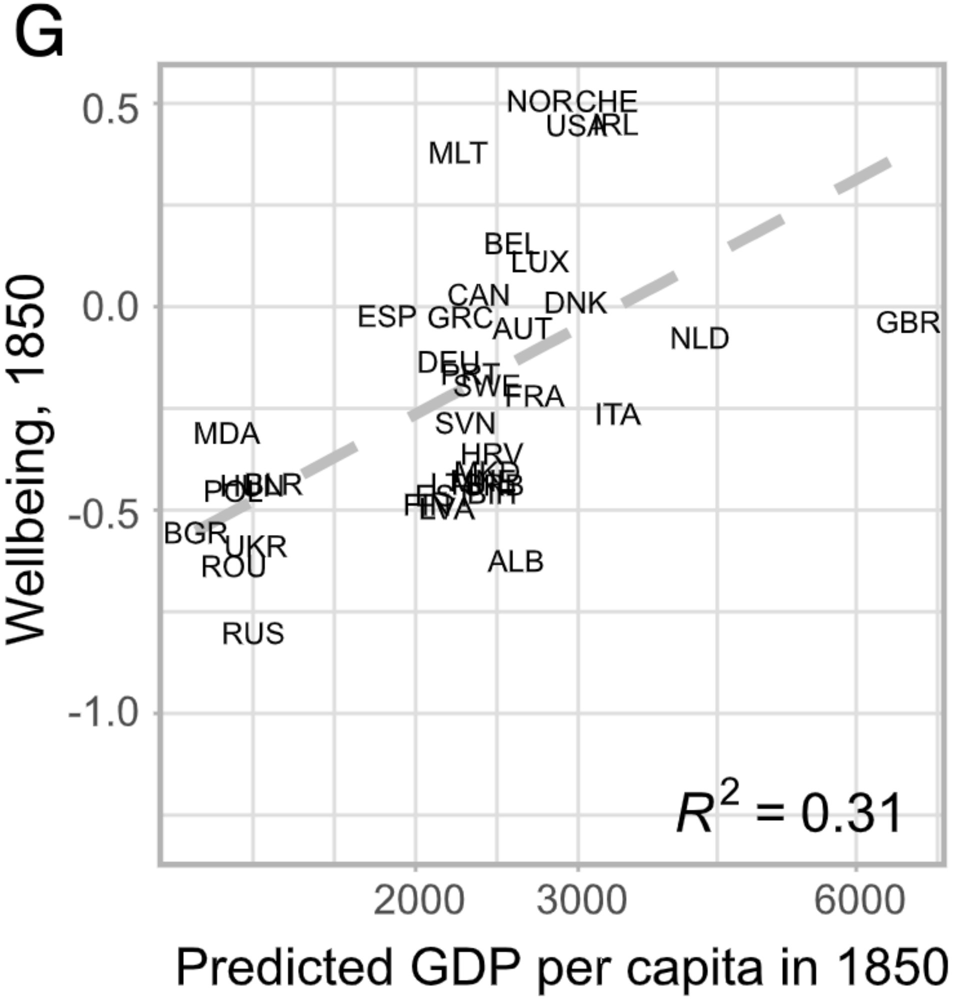
Koch et al. 2024

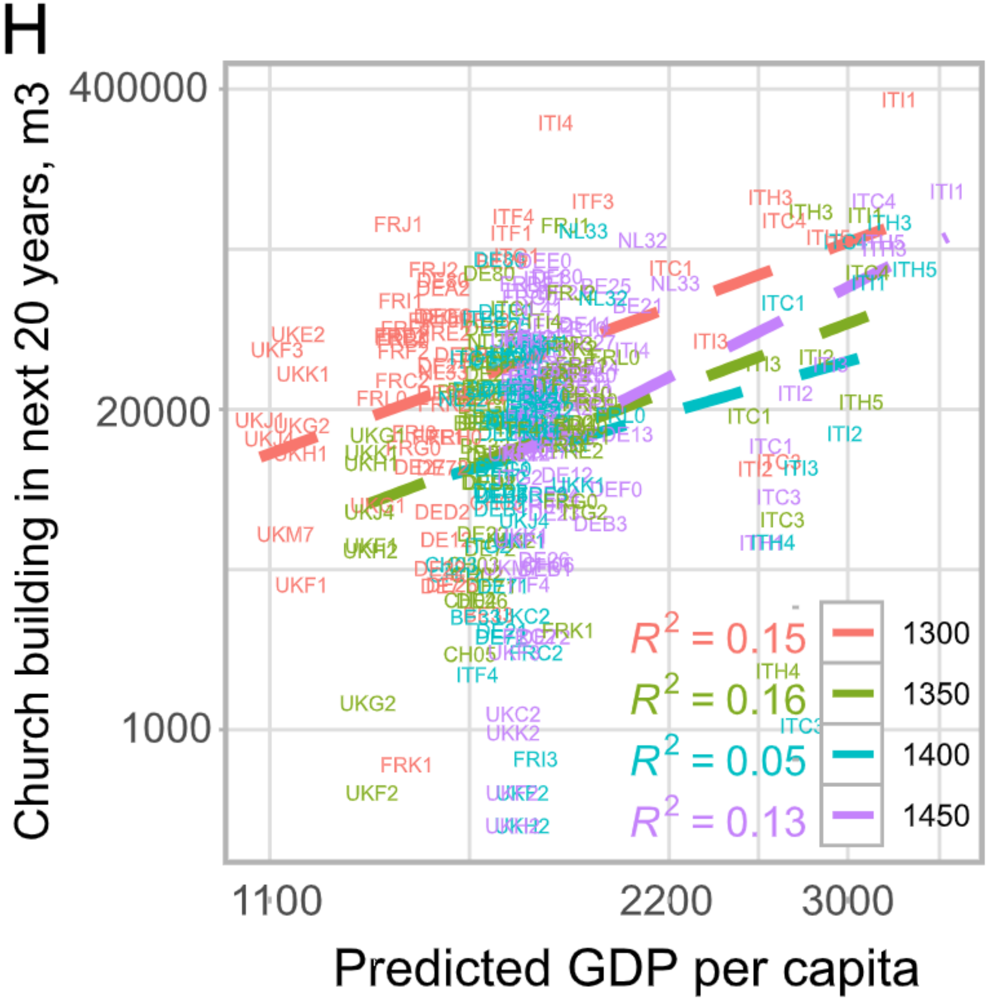
Validation - proxies of economic development



Koch, Stojkoski, Hidalgo PNAS (2024)

Validation - proxies of economic development





Koch, Stojkoski, Hidalgo PNAS (2024)

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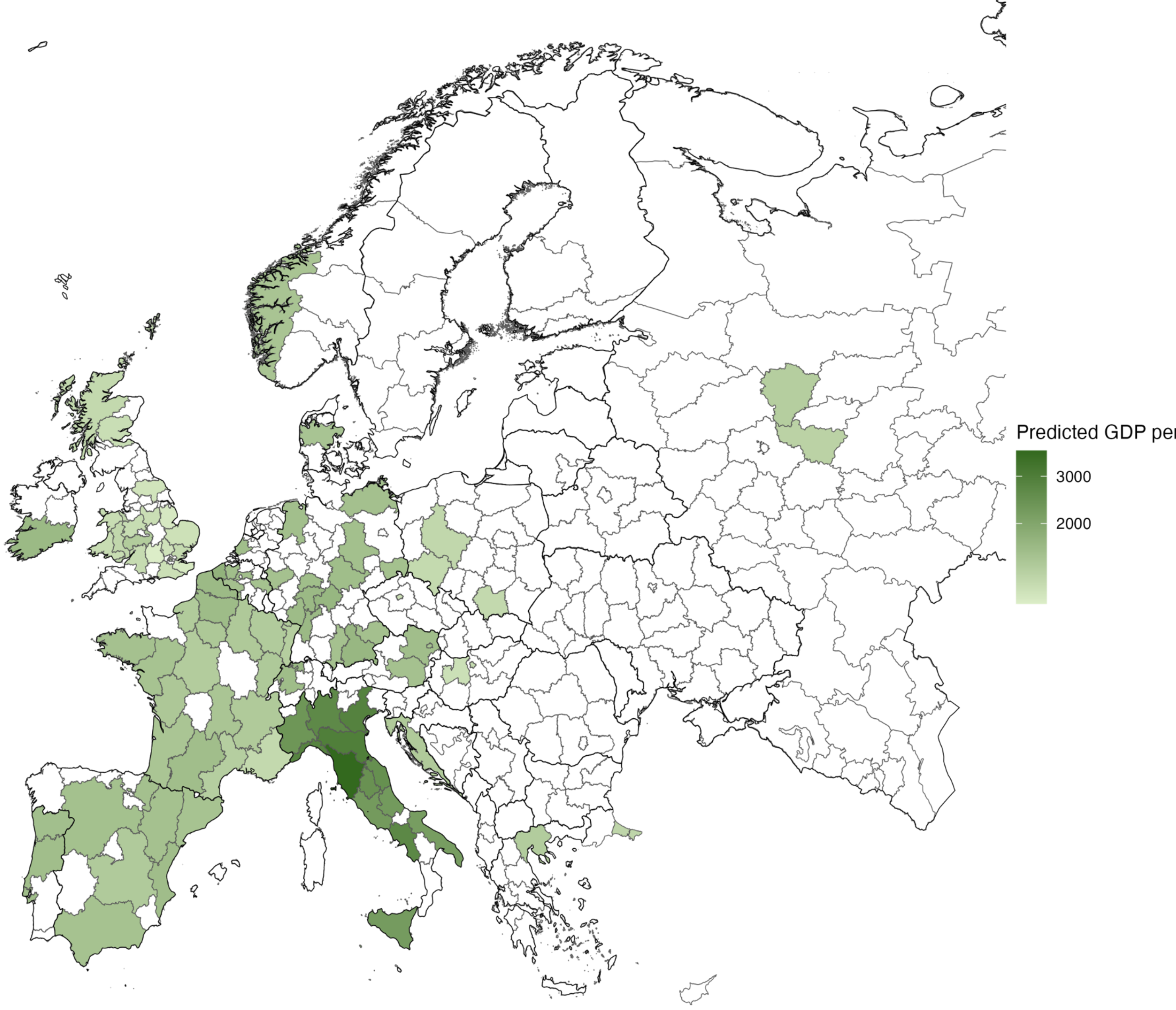

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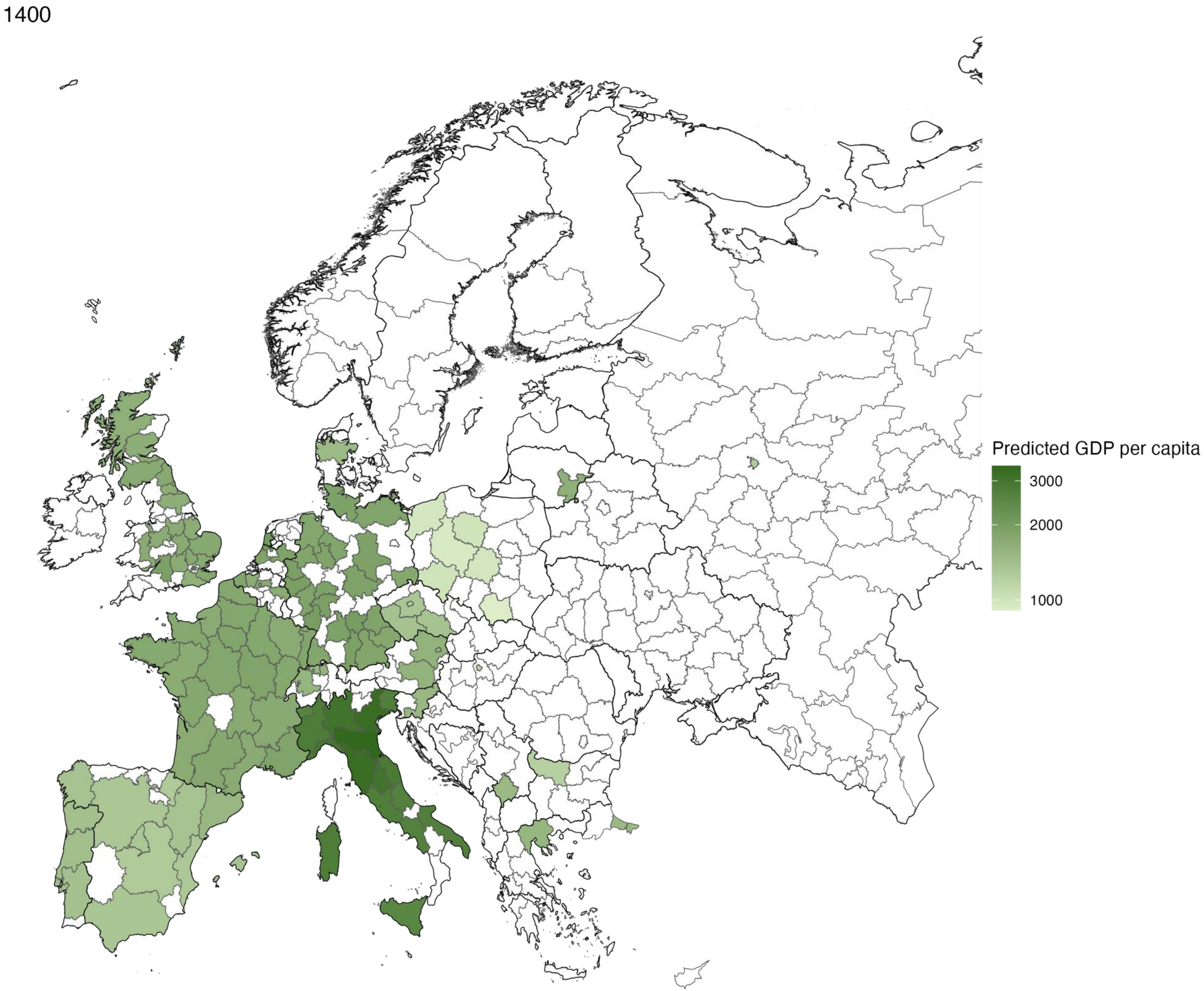
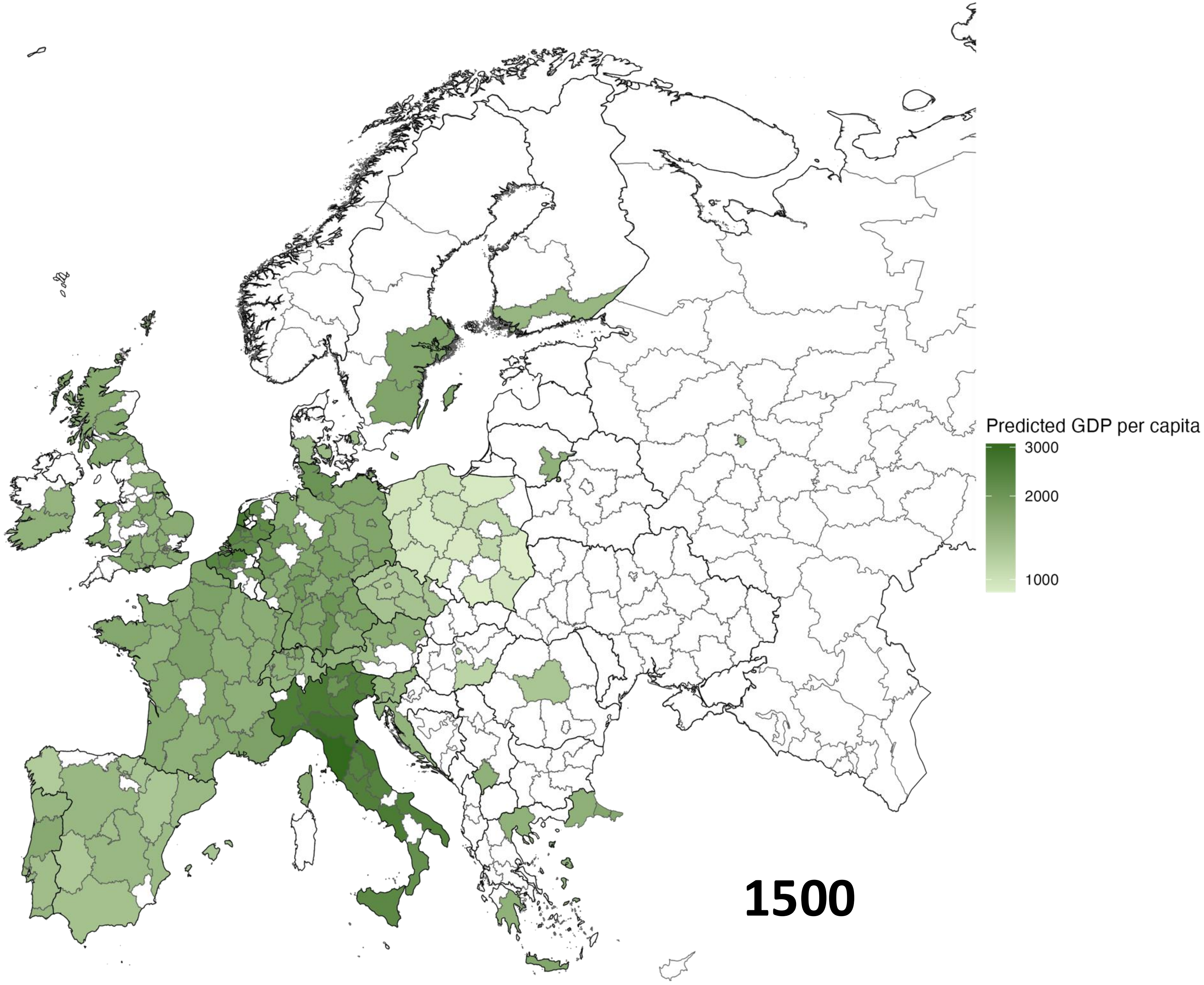


1500



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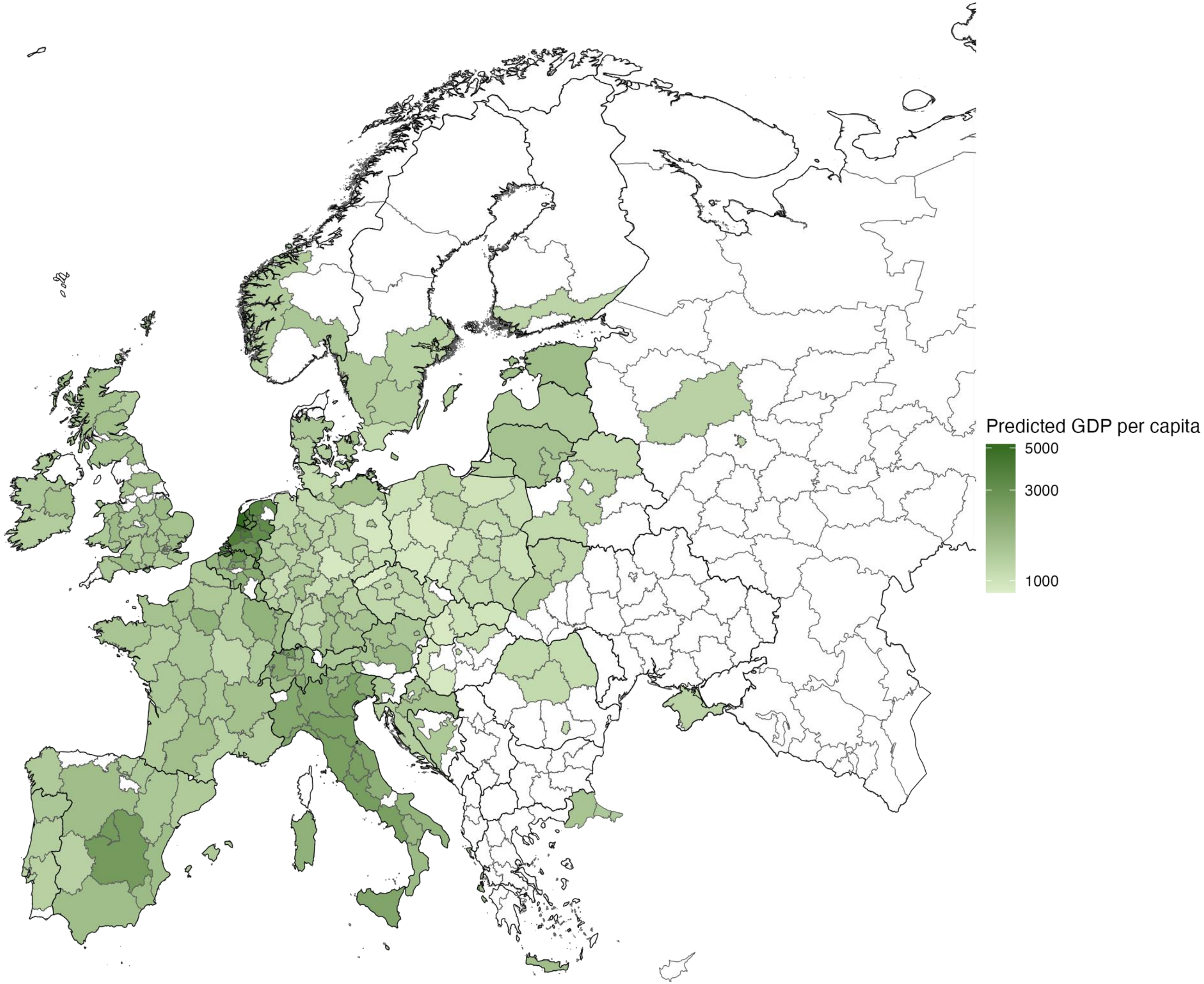

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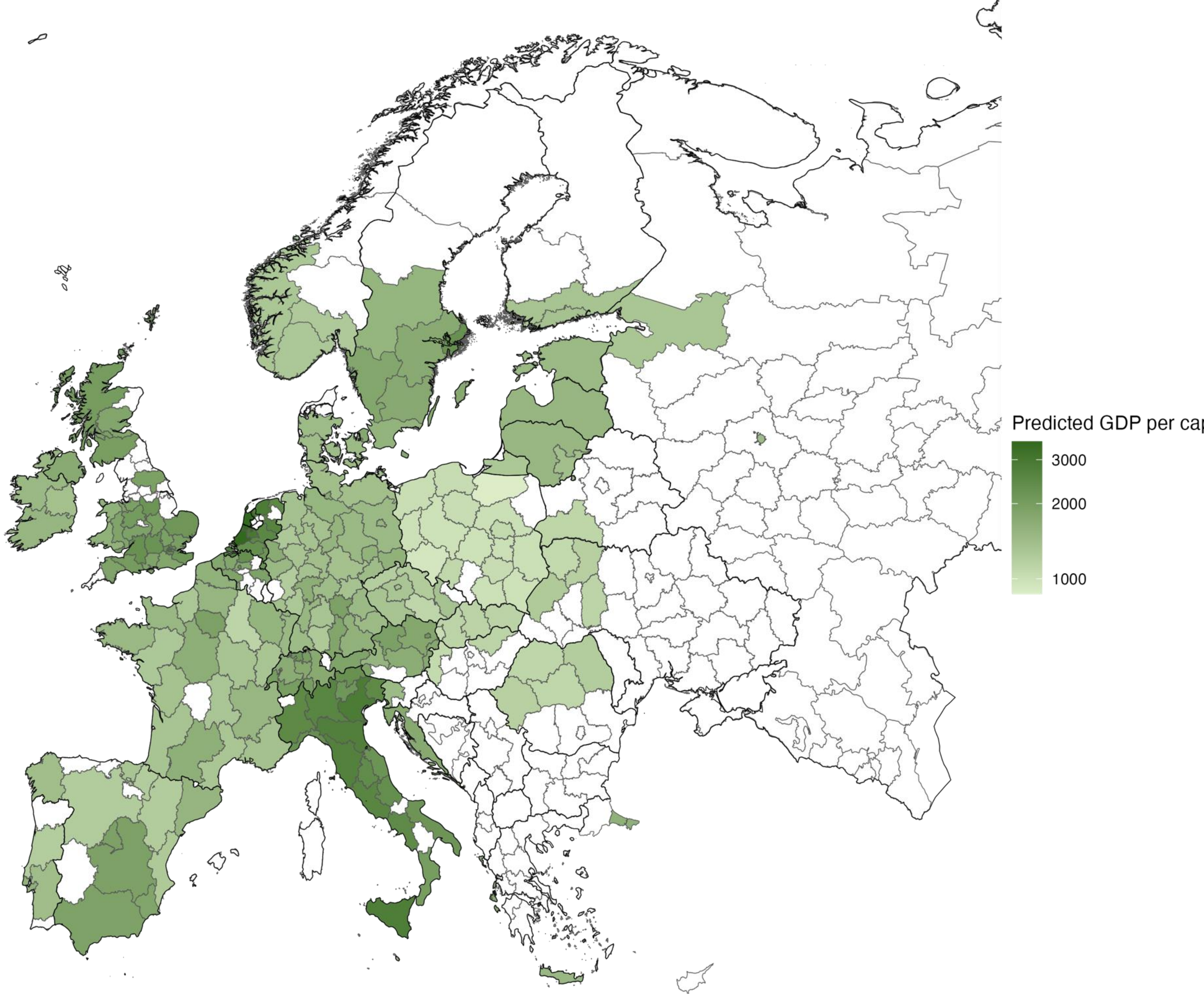

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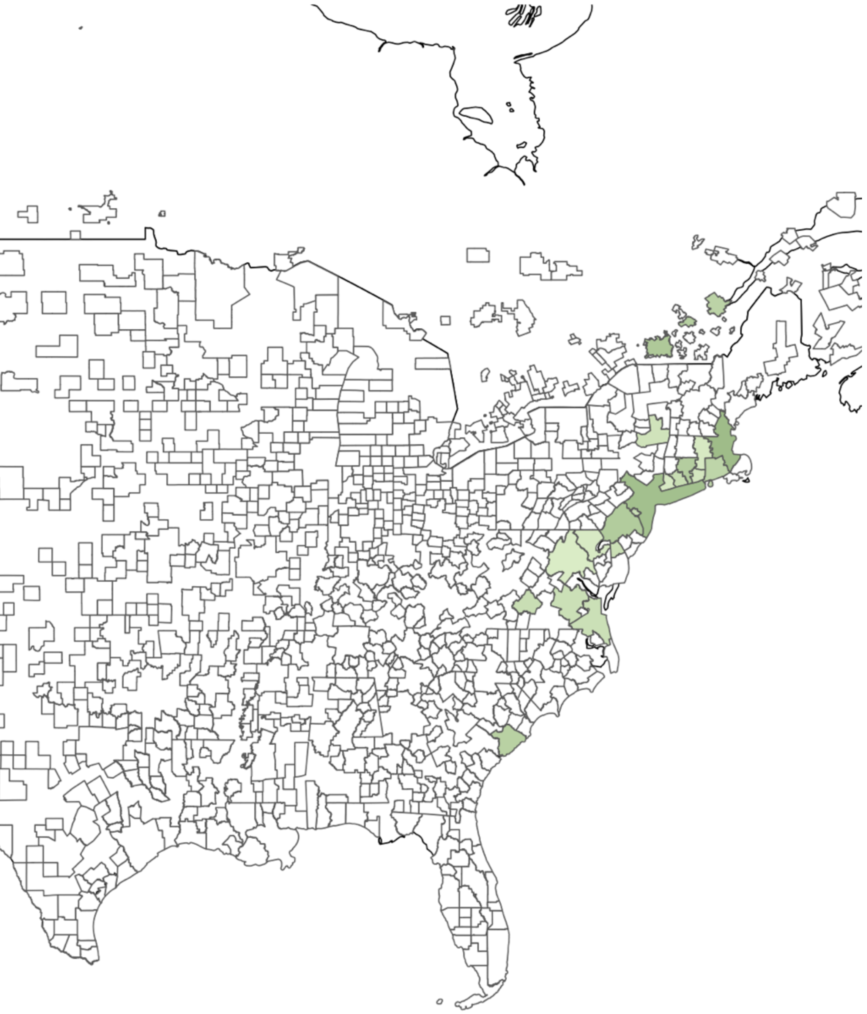
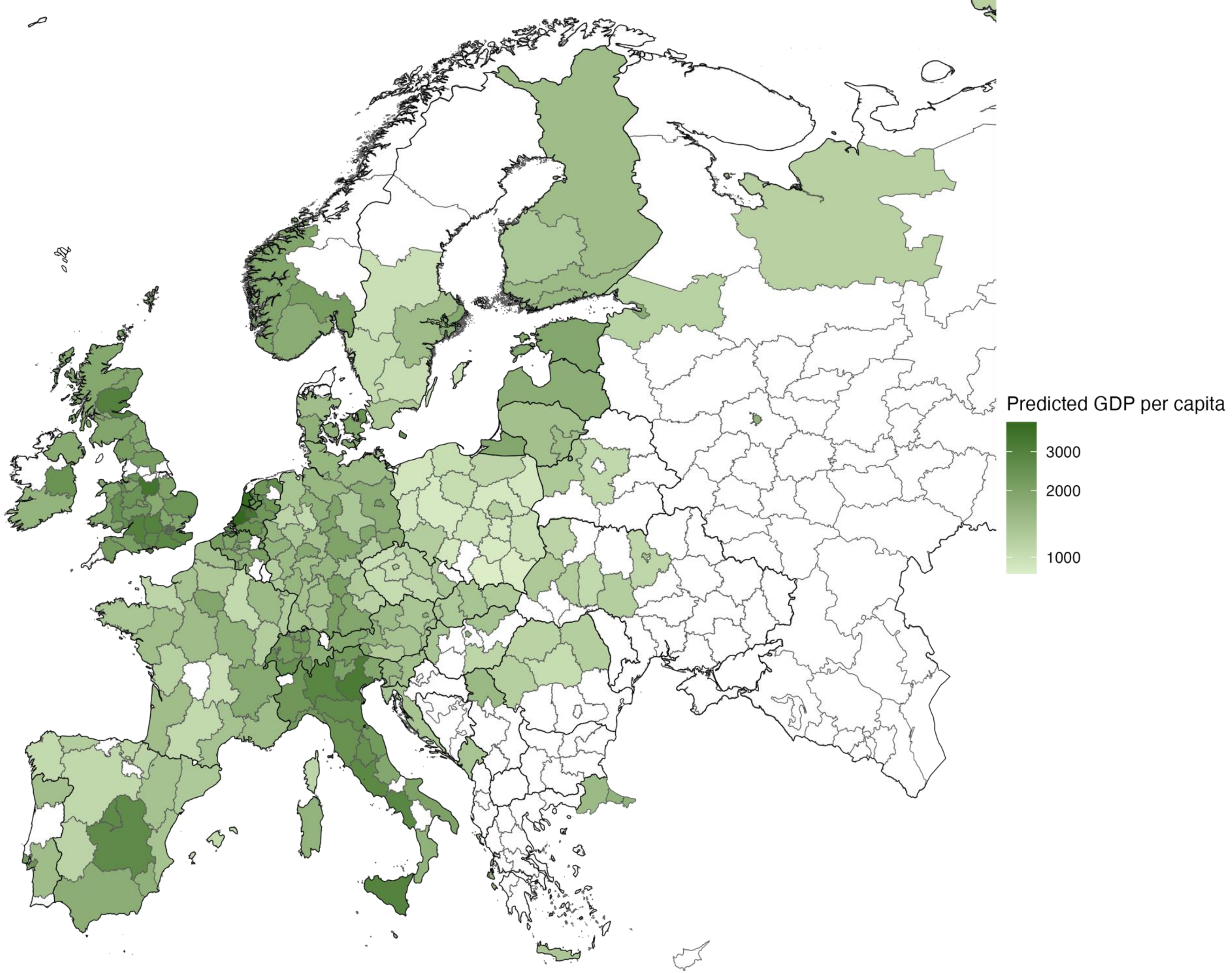
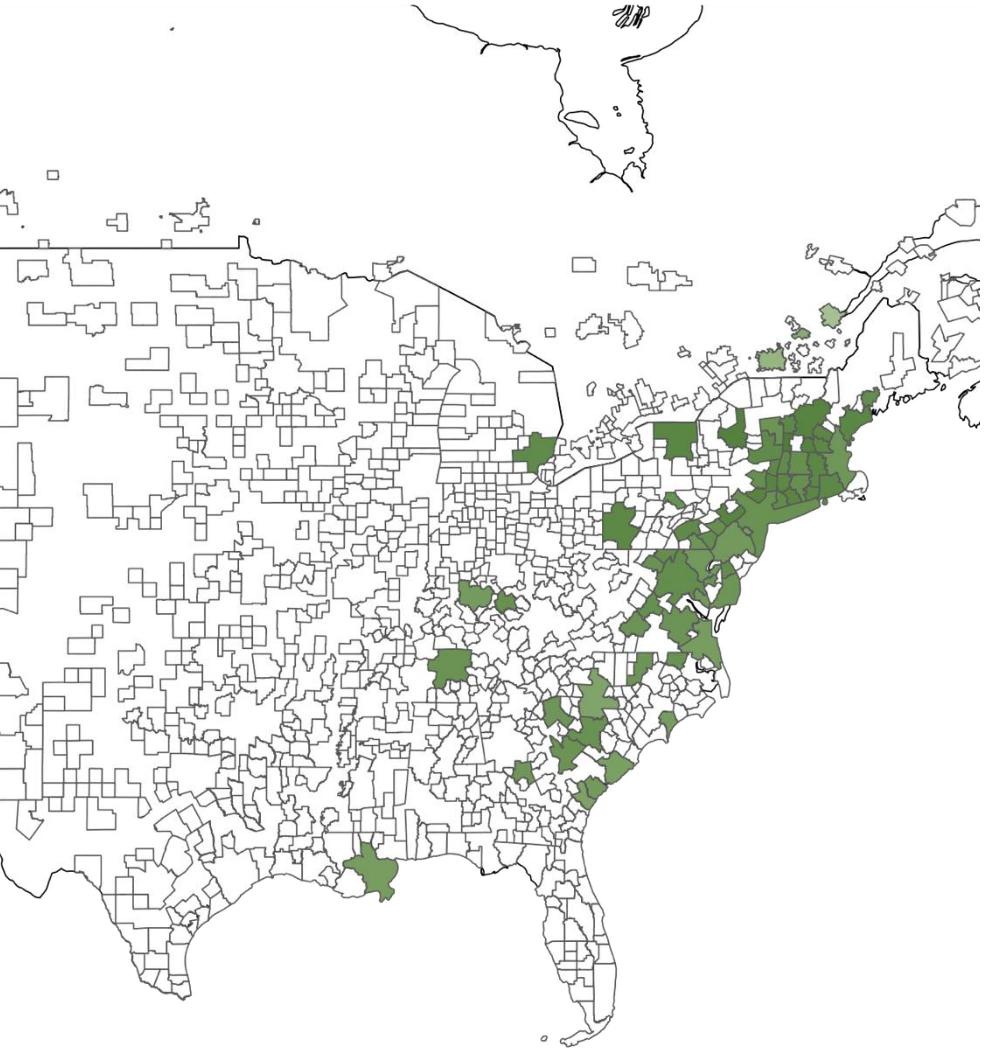
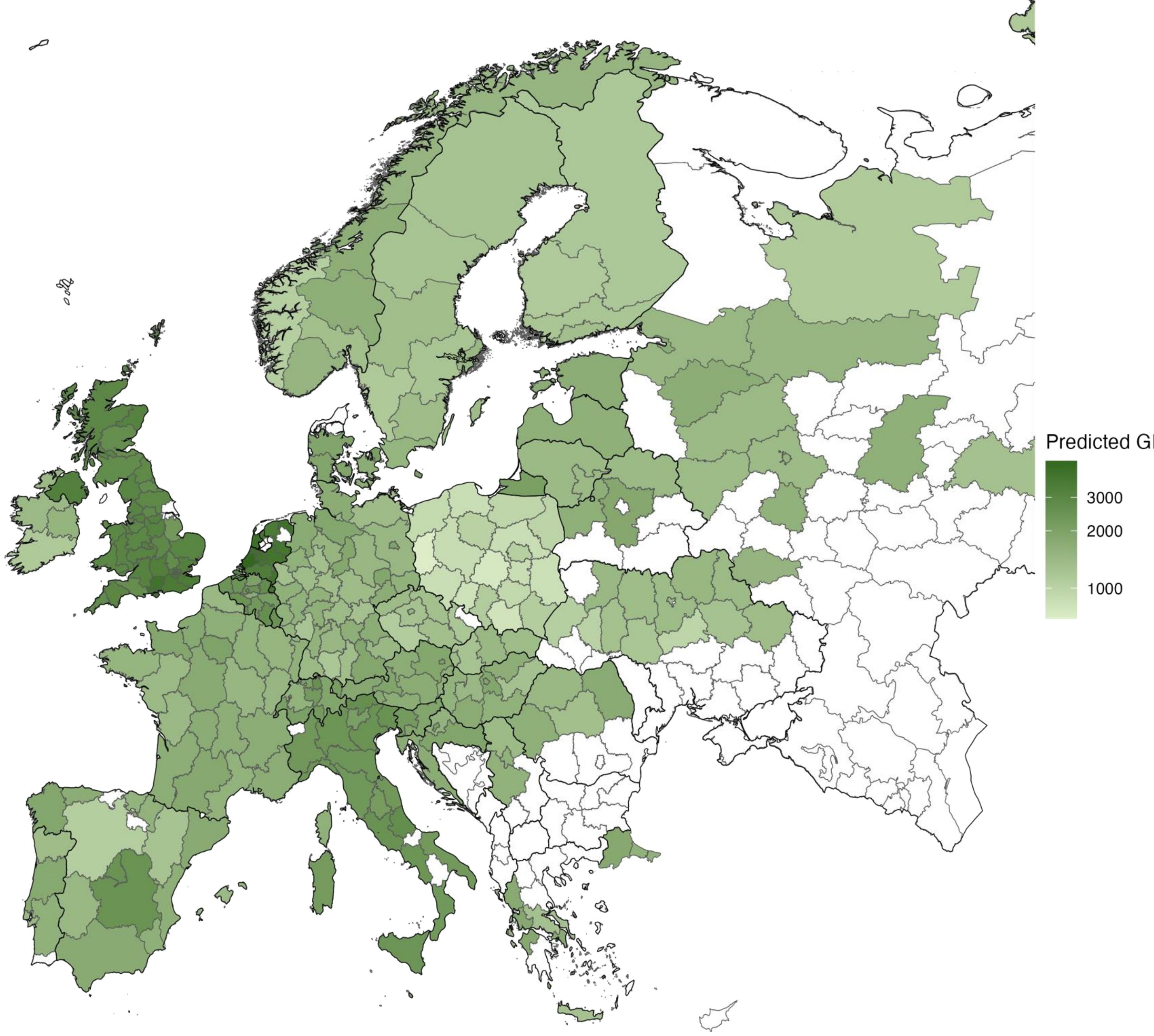




1800





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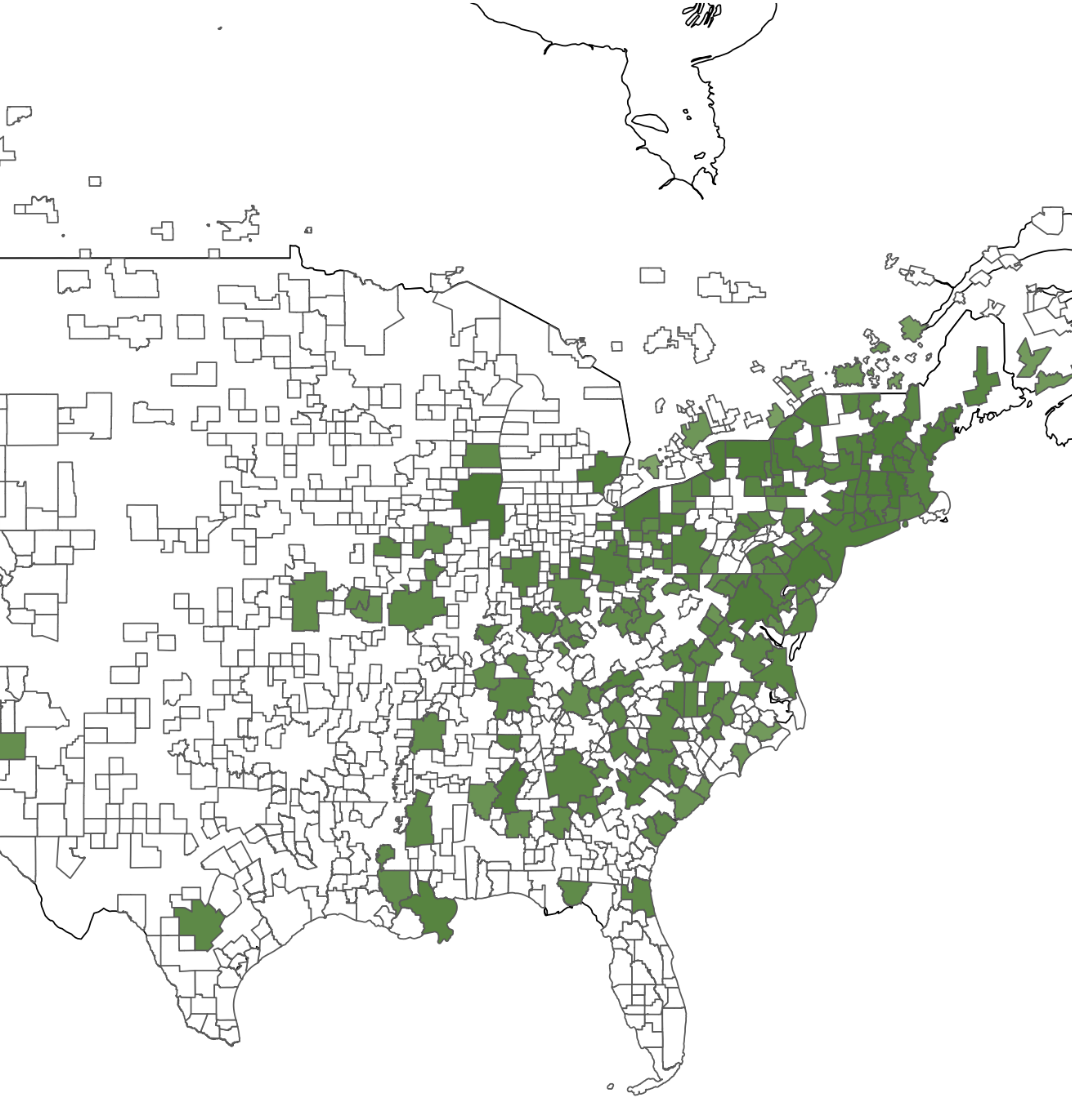
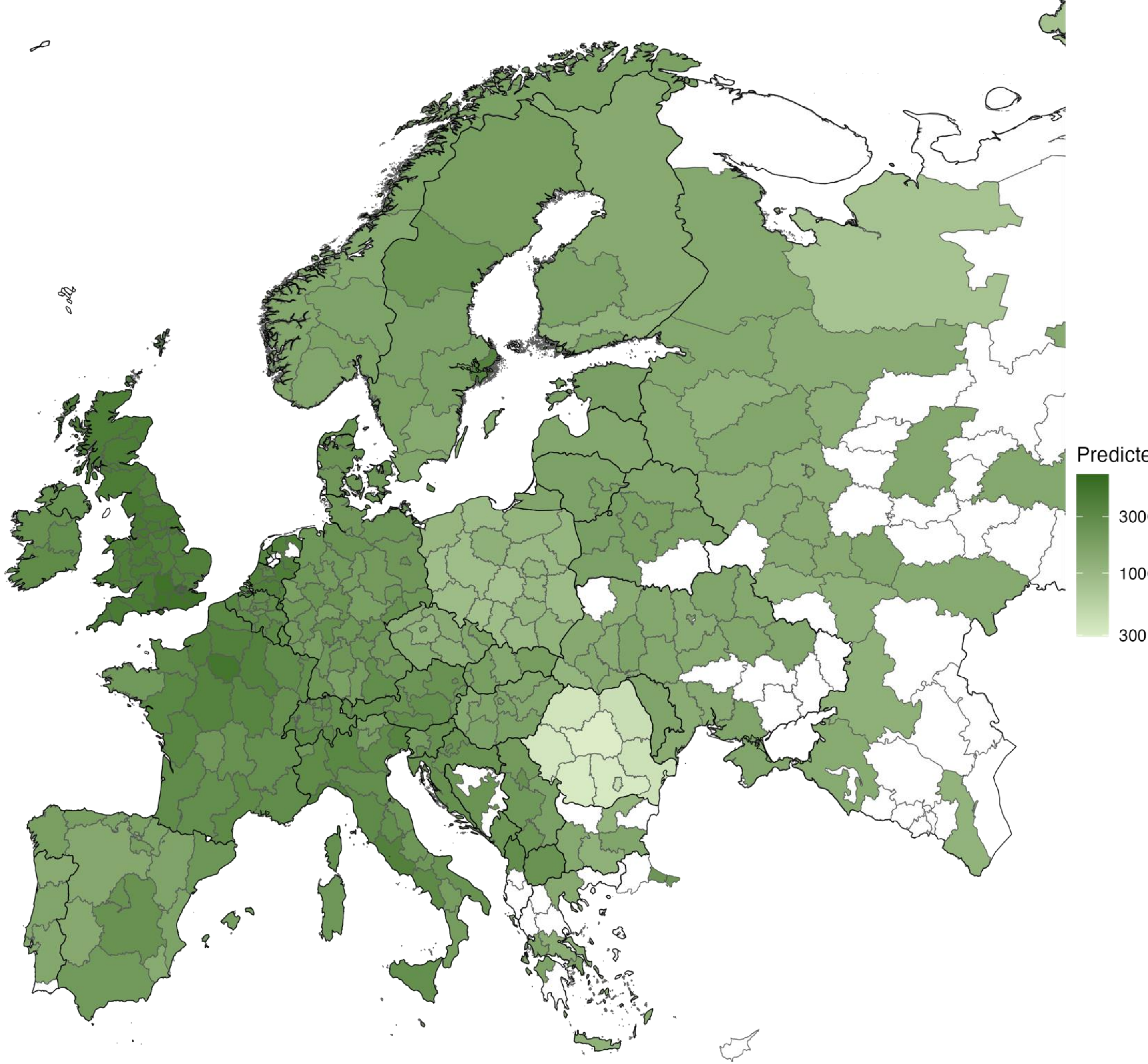
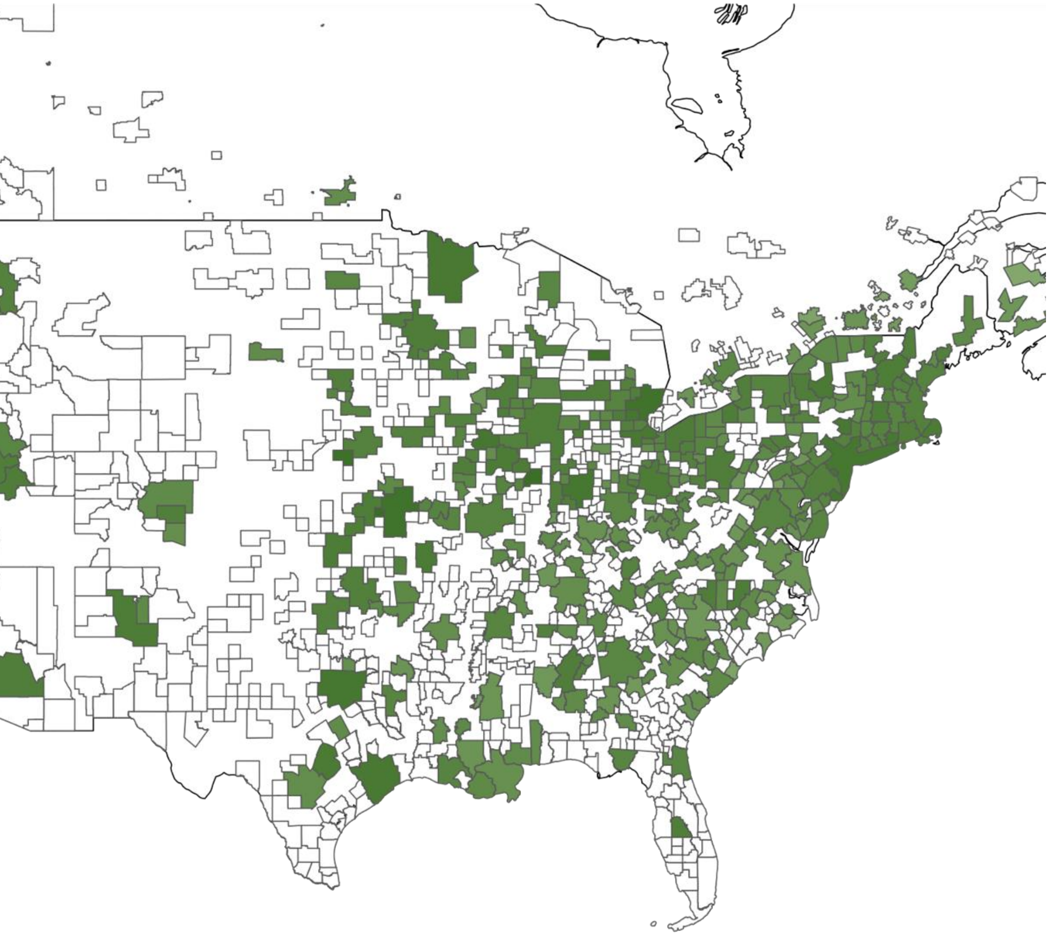
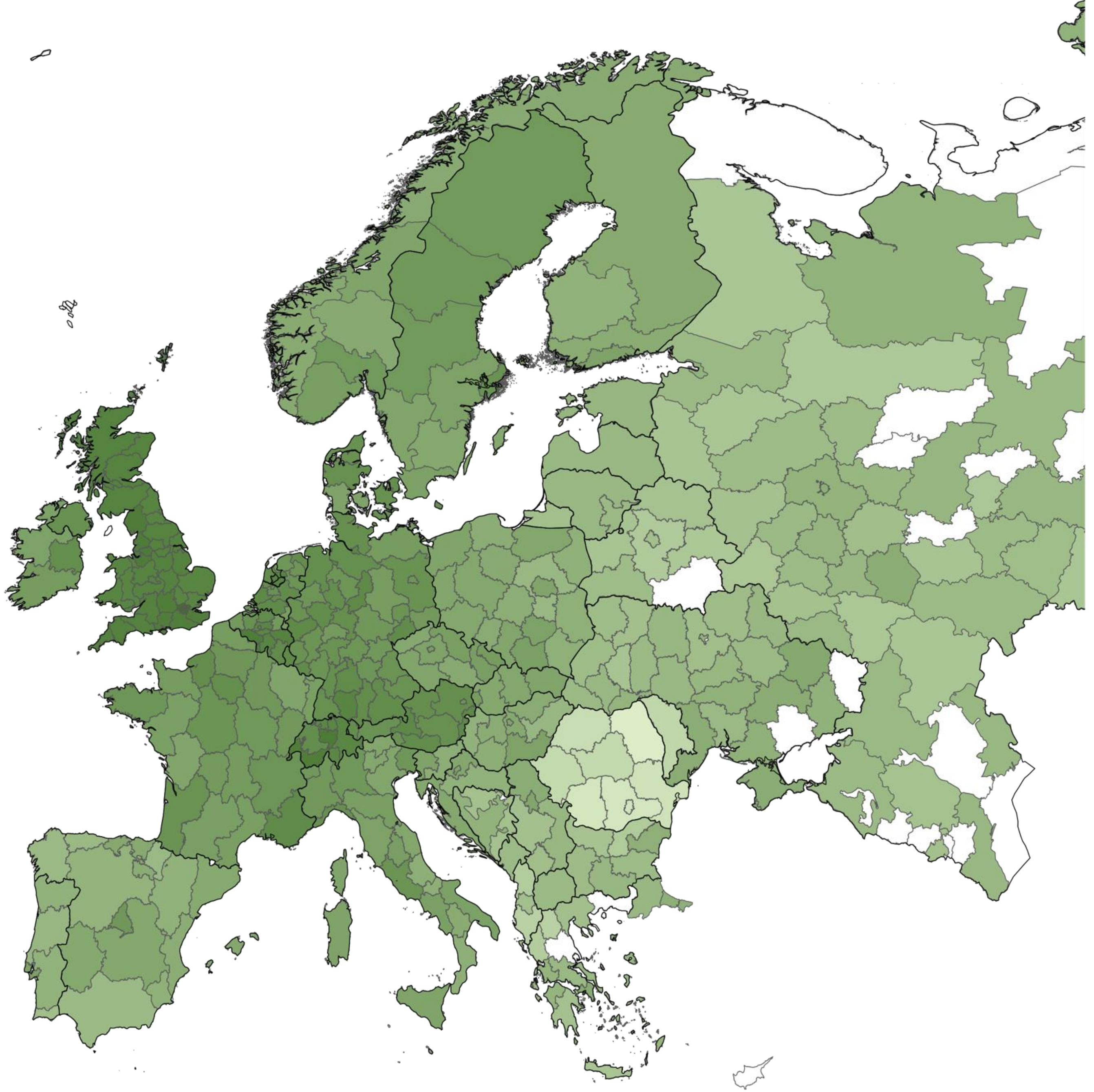




1900





Putting these ideas into practice

...to Conclude

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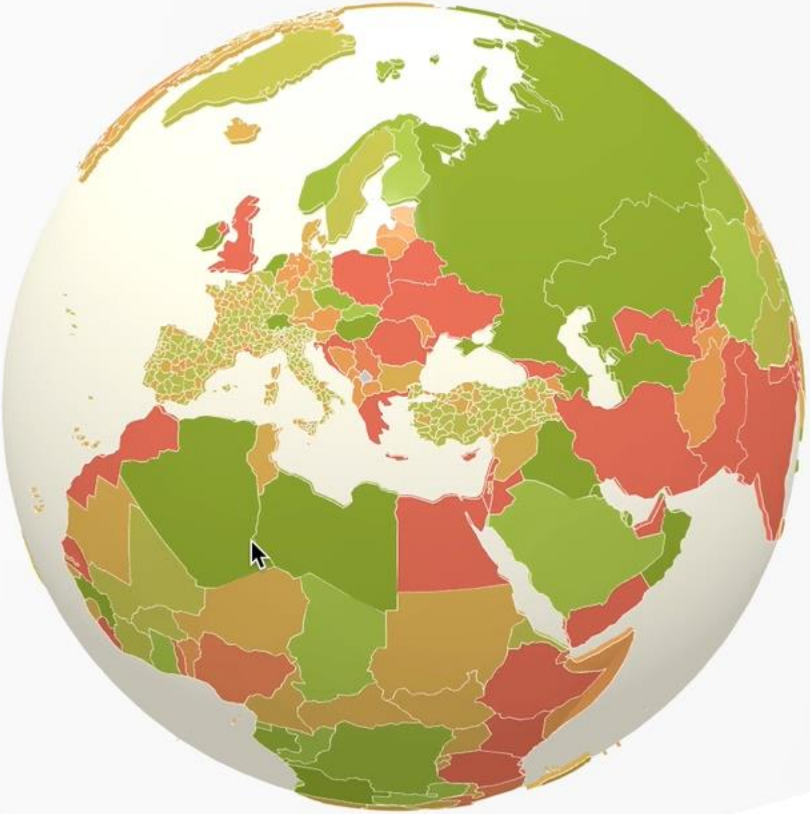

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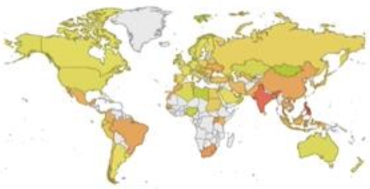
2032 Growth Predictions



NEW

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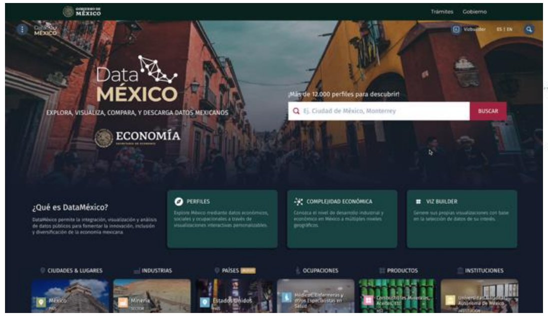
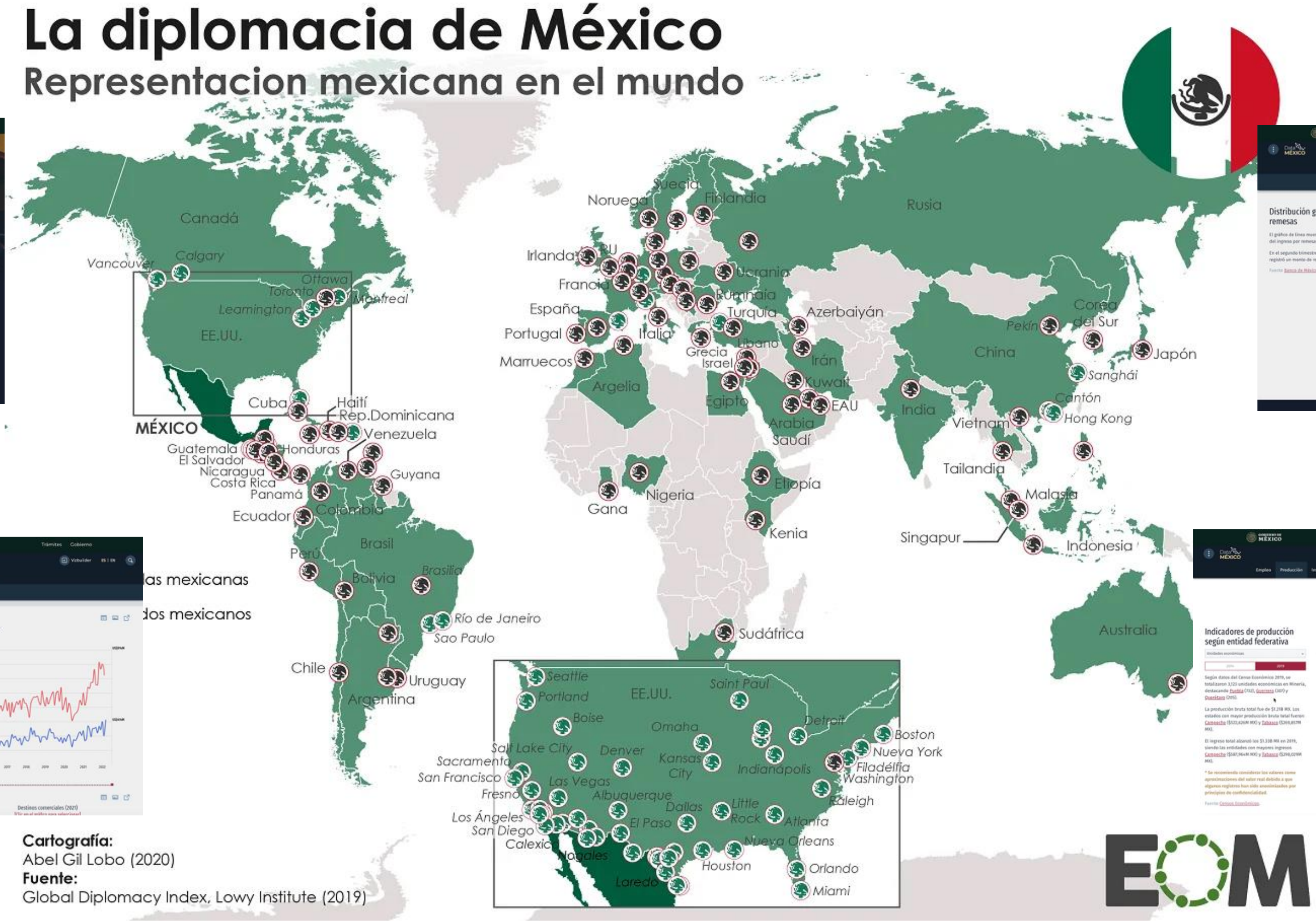
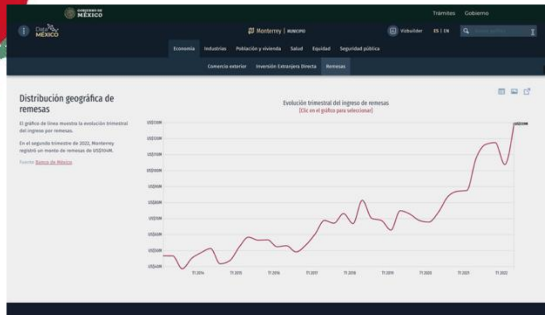
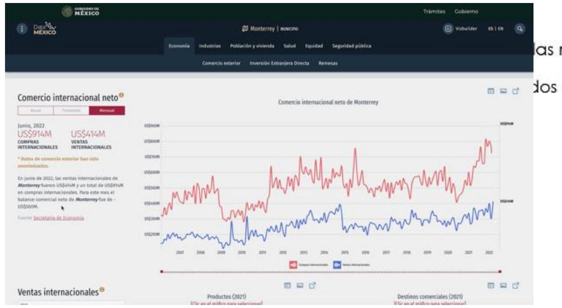
The best time to build a fire station is before the fire

Example 1: Mexico’s Foreign Direct Investment Efforts During Covid.

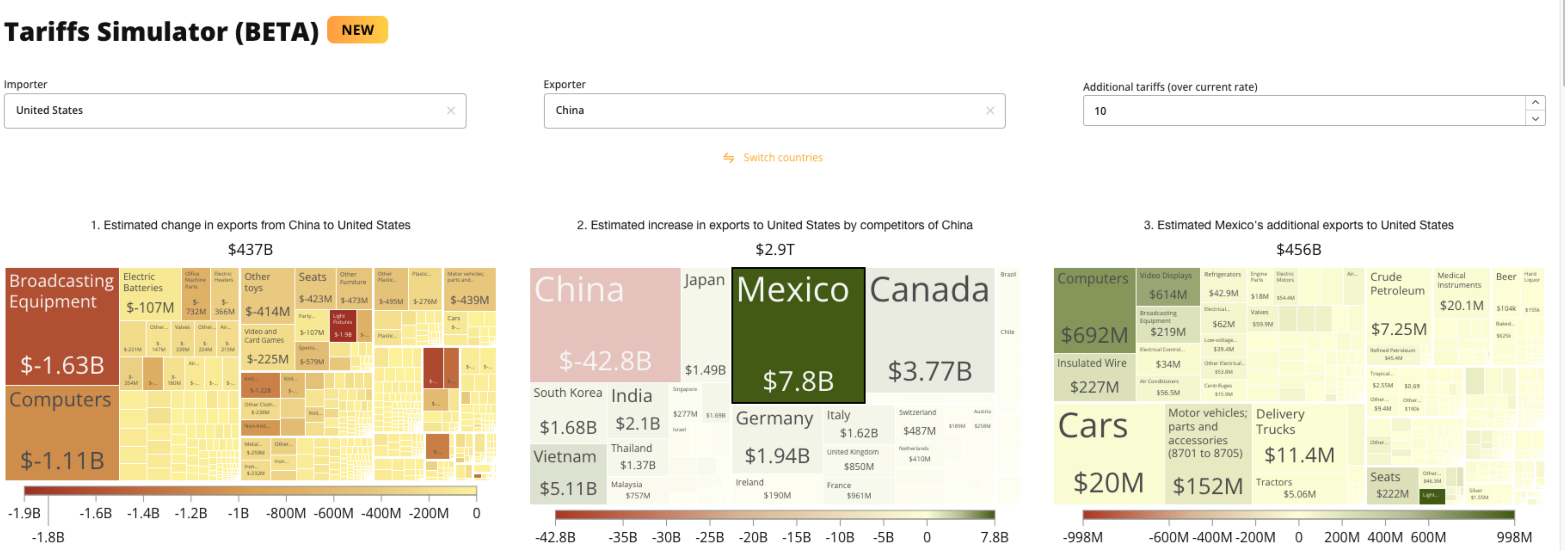








Example 2: Indonesia’s strategy during 2025 tariff uncertainty



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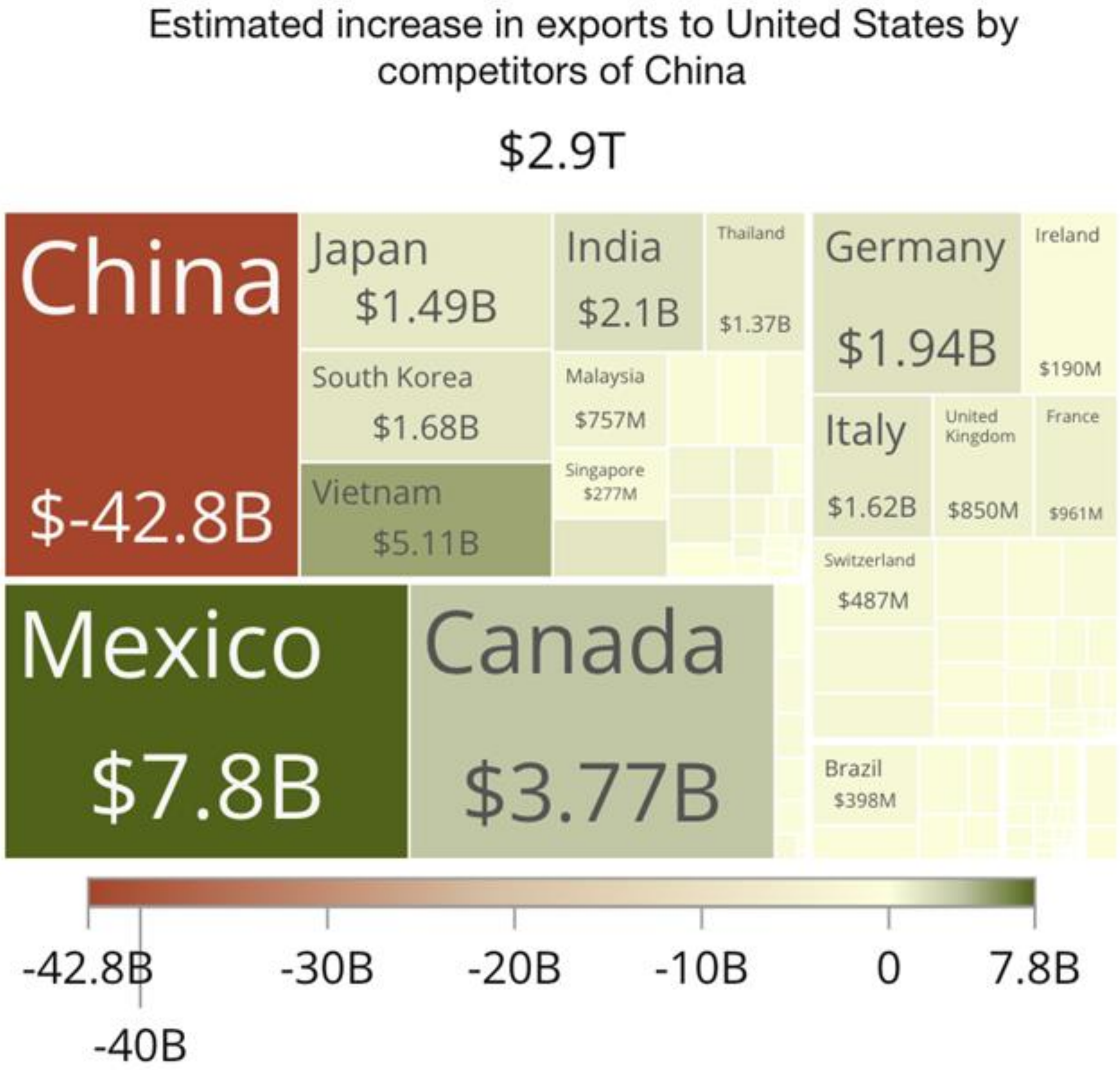
Impact on China and other Economies

We use the model to simulate a 10-p.p. increase in U.S. tariffs on Chinese goods.

We estimate that this will lead to a decrease in the predicted exports of China to the USA by **43B USD (average exports of China to the US between 2019-2022 of 487B USD)**

The countries that are expected to gain the most are:
1.Mexico $7.8B
2. Vietnam $5.11B
3. Canada $3.77B

Indonesia's expected increase in exports to the US in this scenario is:
6. Indonesia $1.69B

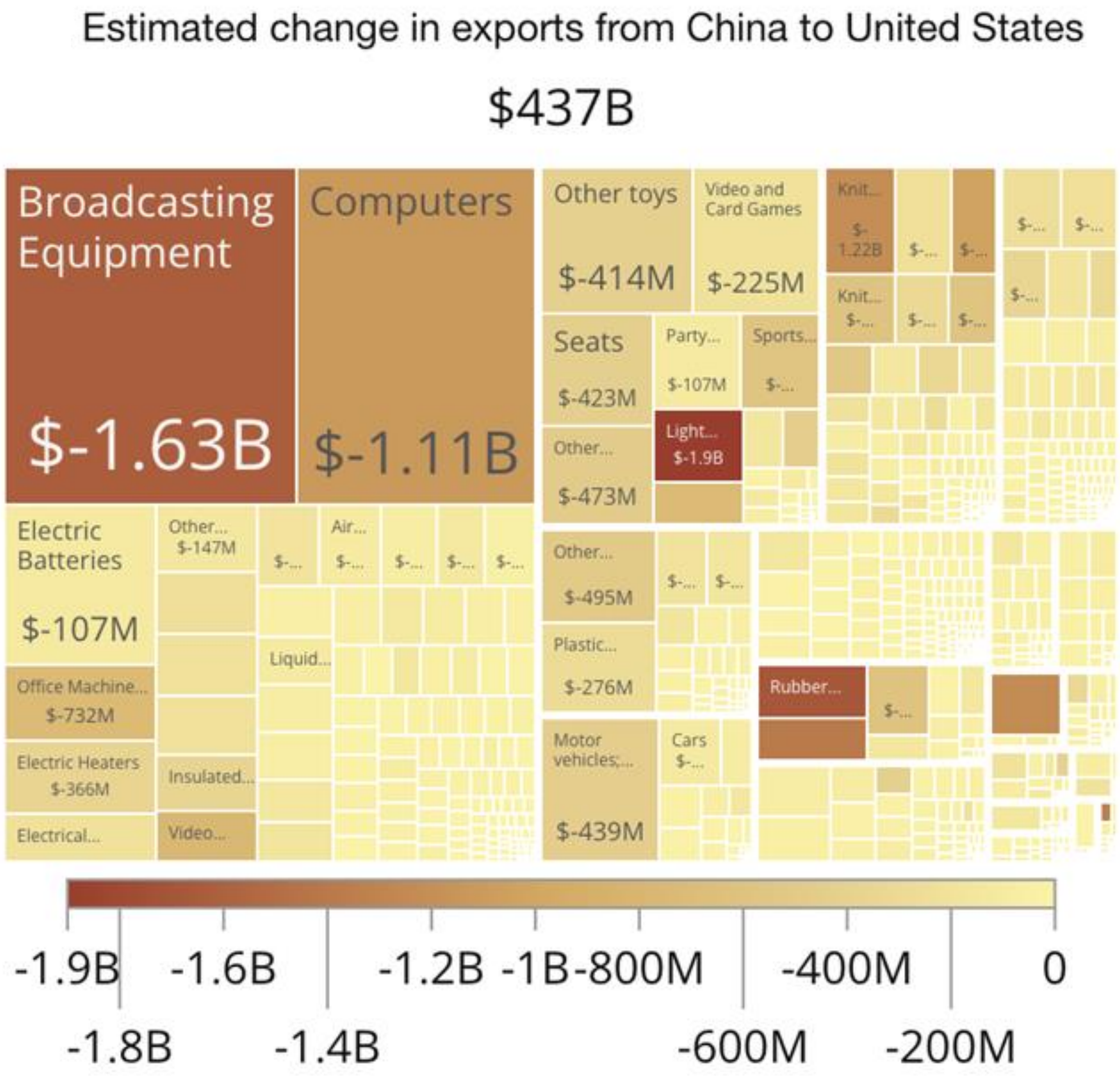


Impact on Chinese export sectors

We use the model to simulate a 10-p.p. increase in U.S. tariffs on Chinese goods and assess the impact of this change.

We estimate that this will lead to a decrease in the predicted exports of China to the USA by **43B USD (average exports between 2019-2022 of 487B USD)**

The products that China will lose the most are:
1. Light Fixtures $-1.9B
2. Rubber Footwear $-1.69B
3. Broadcasting Equipment $-1.63B

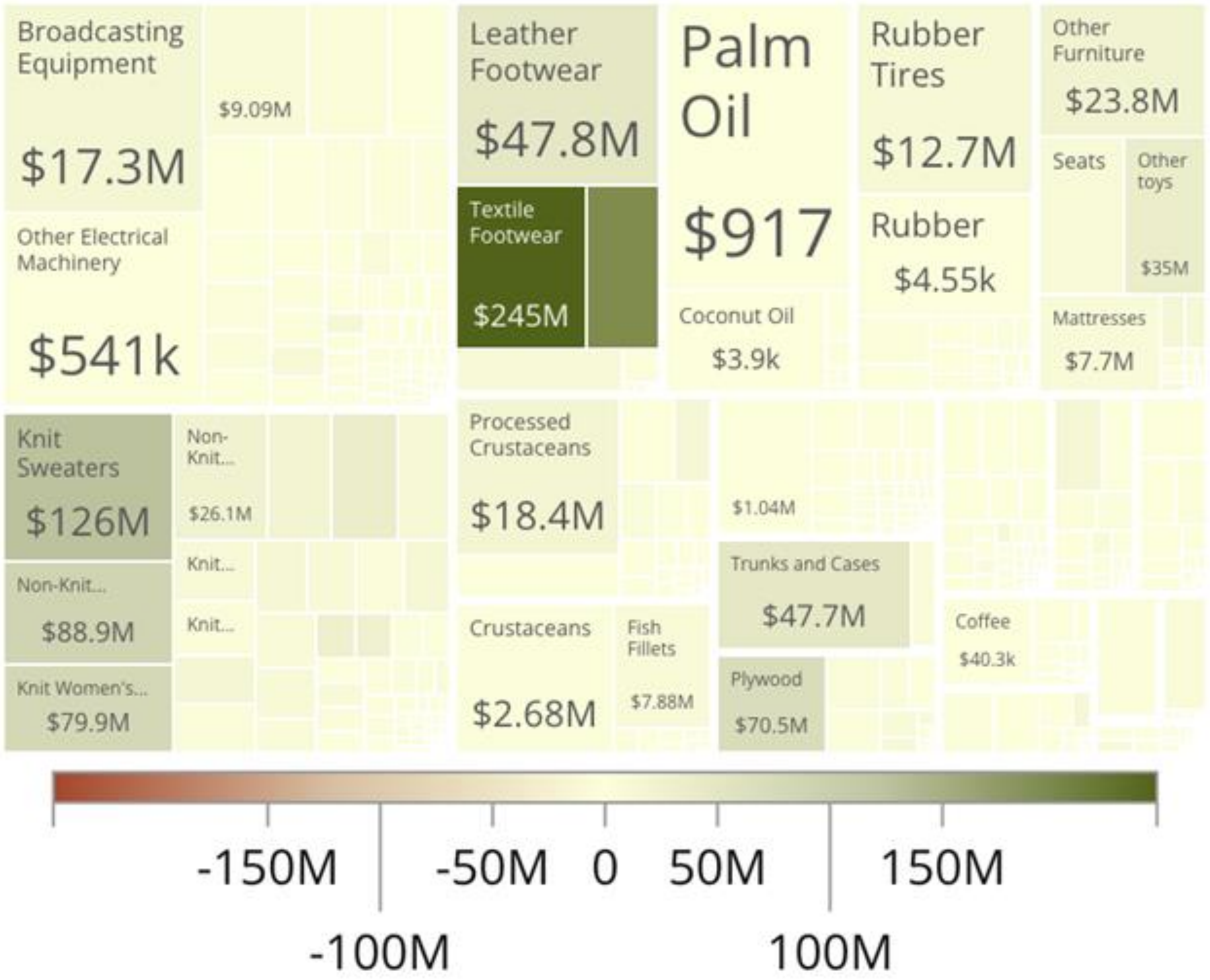


Impact on Indonesia's export potential

We estimate that a 10% increase in U.S. tariffs on China will lead to an increase in the predicted exports of Indonesia towards the U.S by **1.69B USD (average exports between 2019-2022 of 28B USD)**

The products that Indonesia can expect to grow the most in this scenario are:

1. Textile Footwear $245M
2. Rubber Footwear $193M
3. Knit Sweaters $126M



OEC PROFILES TOOLS DATA COMPLEXITY GAMES ABOUT ENGLISH CMS@OEC.WORLD

Tariffs Simulator (BETA) PRO | NEW MODEL

Estimate the direct and indirect impact of tariffs with a more comprehensive model. Check out the previous version for free here.
Project supported in part by: Open Society Foundation & Yayasan Berbakti Semangat Indonesia

SIMULATE SCENARIO

U.S. LIBERATION DAY

2026 trade predictions based US Liberation Day tariffs announcement. See Tariffs

IMPORTER

UNITED STATES

EXPORTER 1

CHINA

EXPORTER 2

MEXICO

Run Simulation

VISUALIZE DIFFERENCE

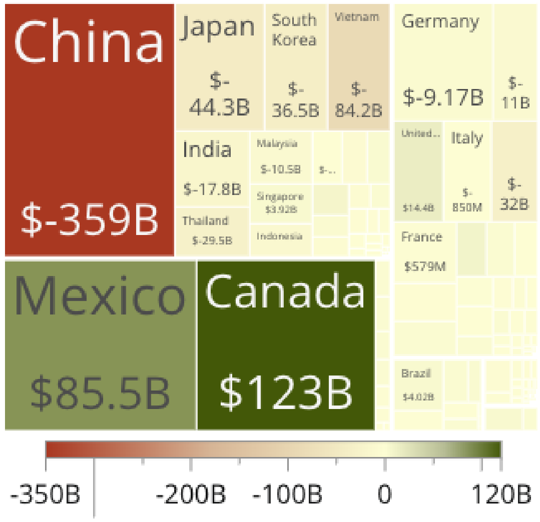
U.S. LIBERATION DAY - RECENT AVERAG

ORDER DIRECTION

ASCENDING

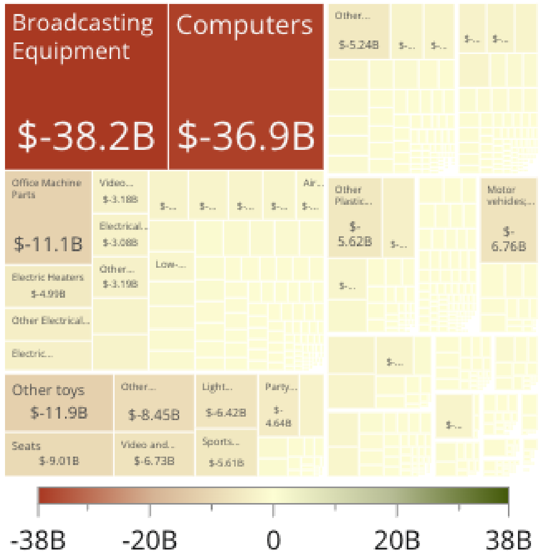
1. United States imports by country

(in USD)



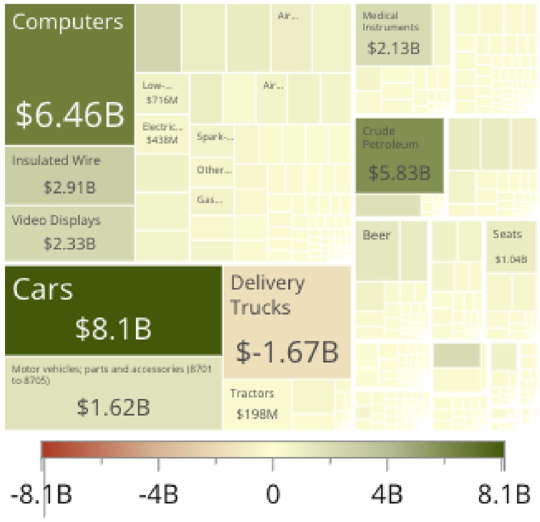
2. China exports to United States

$487B (in USD)

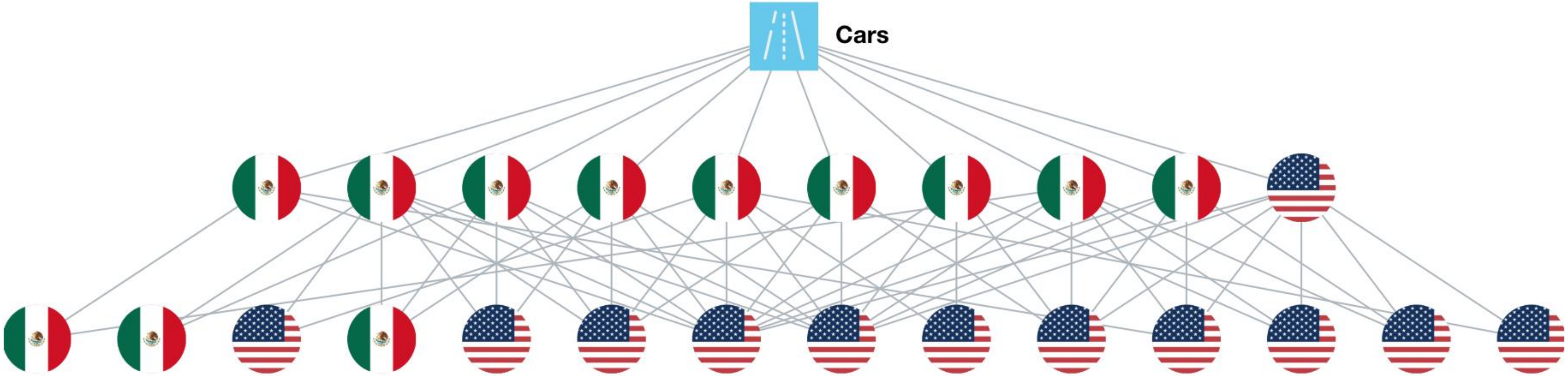


3. Mexico exports to United States

(in USD)

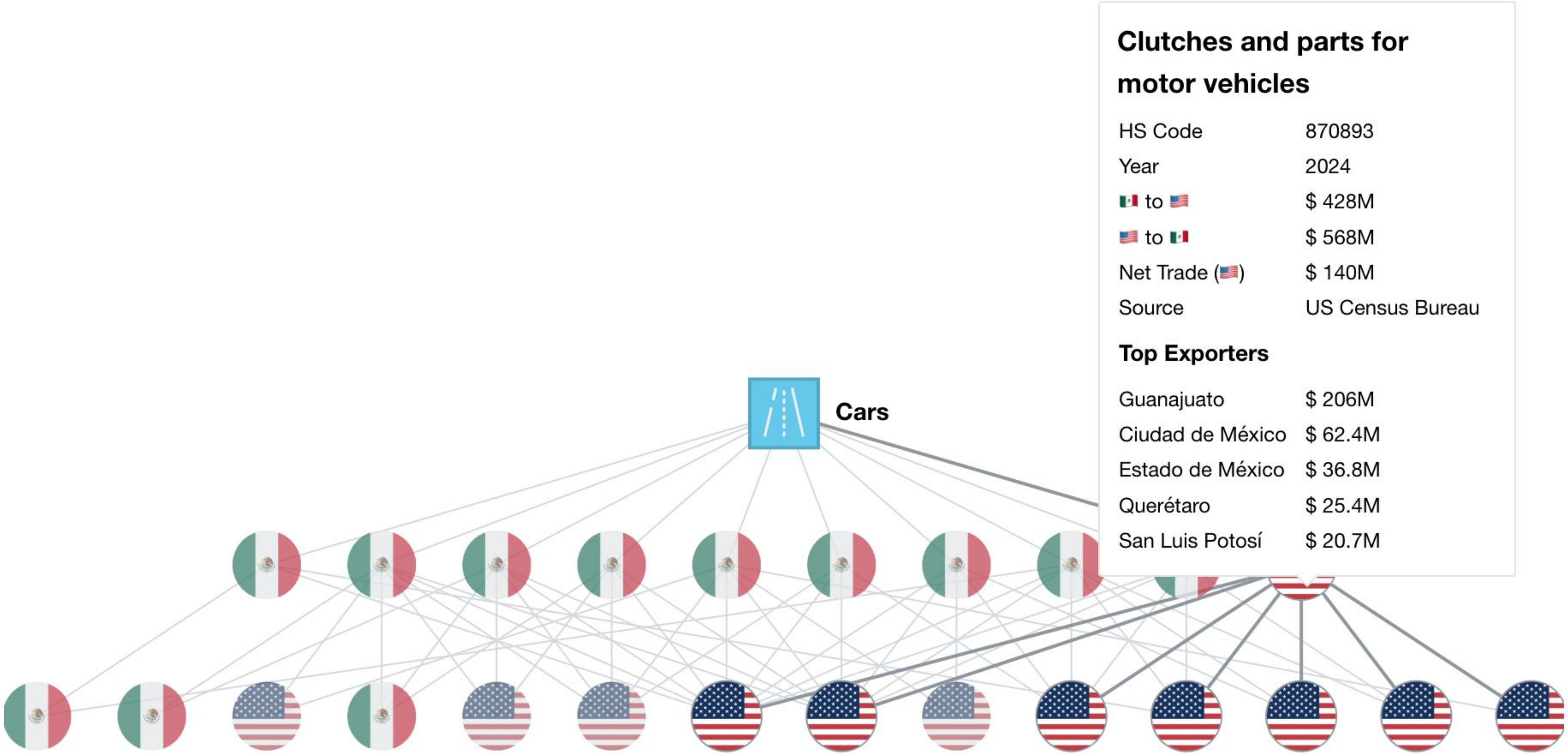


Example 3: Mexico-US Value Chain Relationship



In Collaboration with Mexico’s Secretary of the Economy

Example 3: Mexico-US Value Chain Relationship



In Collaboration with Mexico's Secretary of the Economy

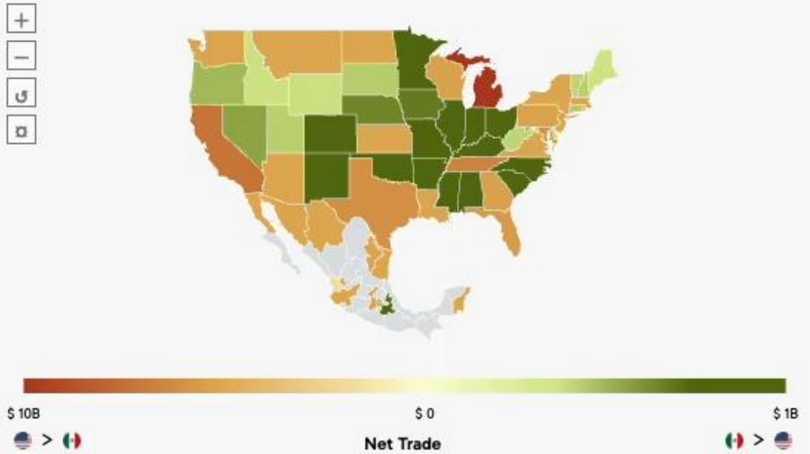
Cars

US - MX Trade | Global Trade

87.03 - Cars

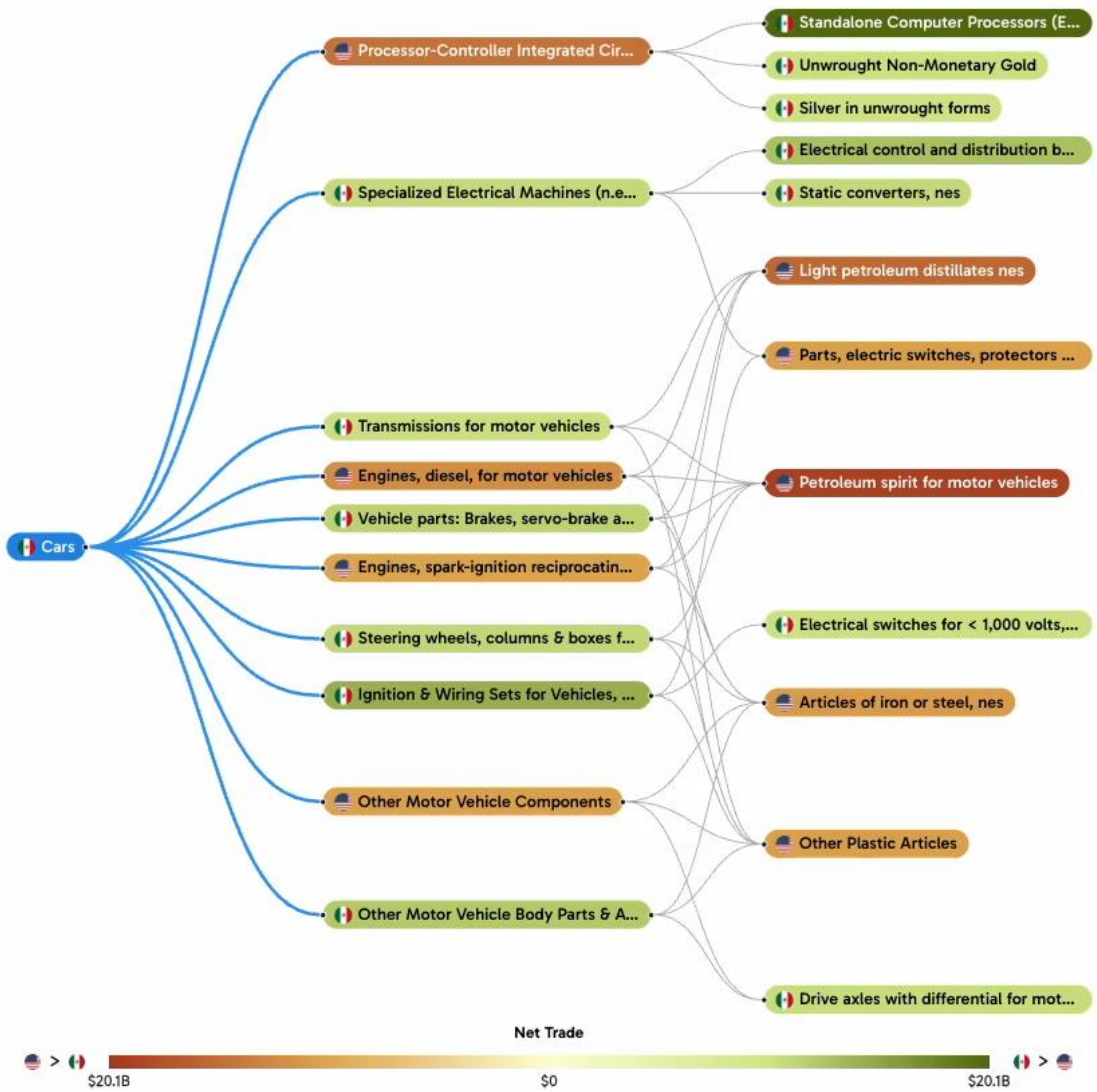
Year	2024
🇲🇽 to 🇺🇸	$ 11.4B
🇺🇸 to 🇲🇽	$ 4.6B
Net Trade 🇲🇽	$ 6.79B

Mexico - US Exports by State



Source: Secretaría de Economía and US Census Bureau

Copy link



Developed by Datawheel

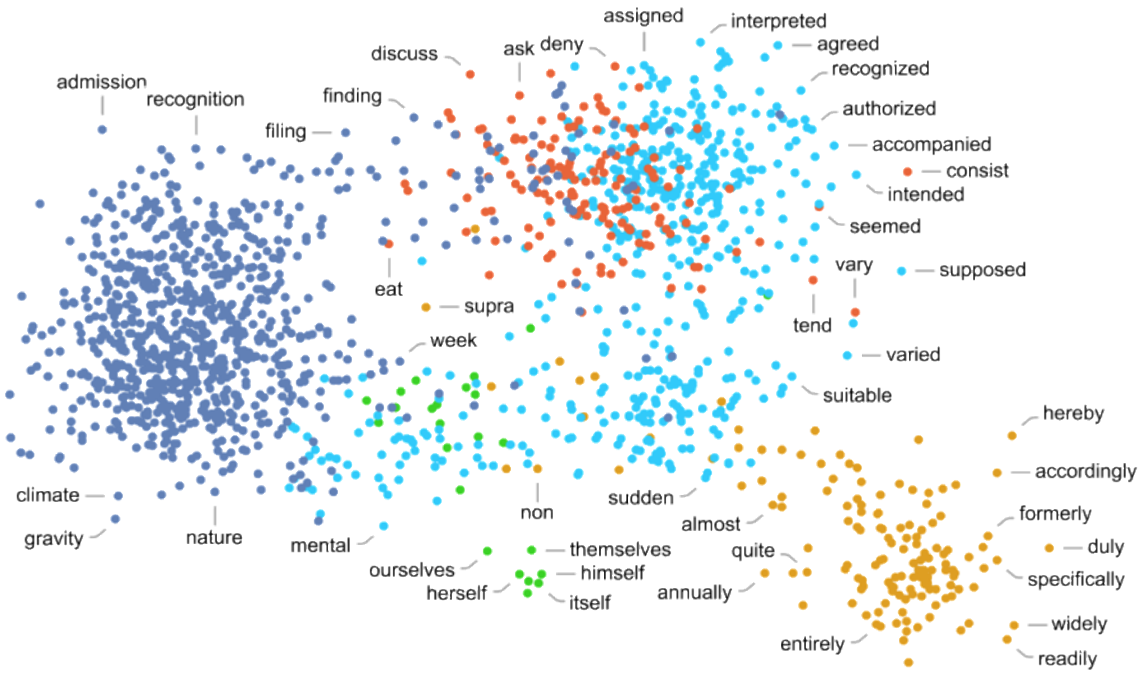
To Conclude

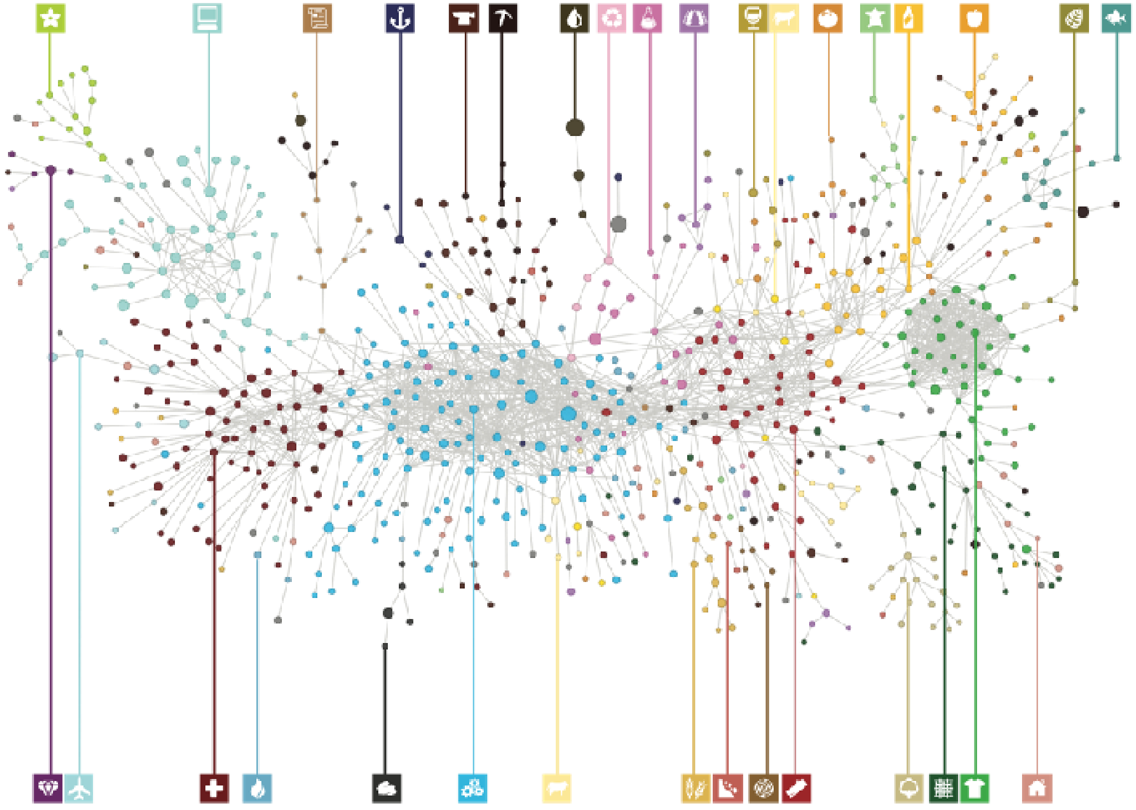
Economies are Complex

Because

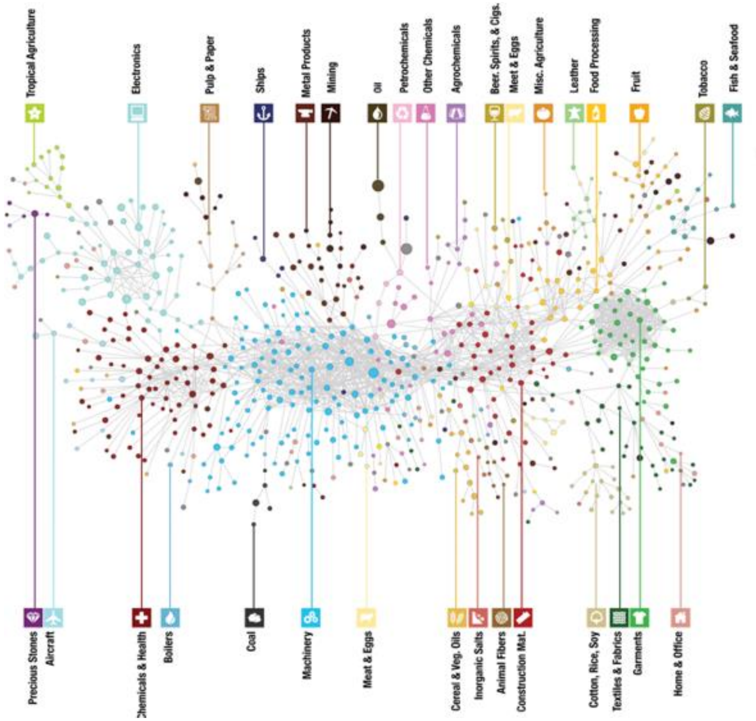
Knowledge is non-fungible !

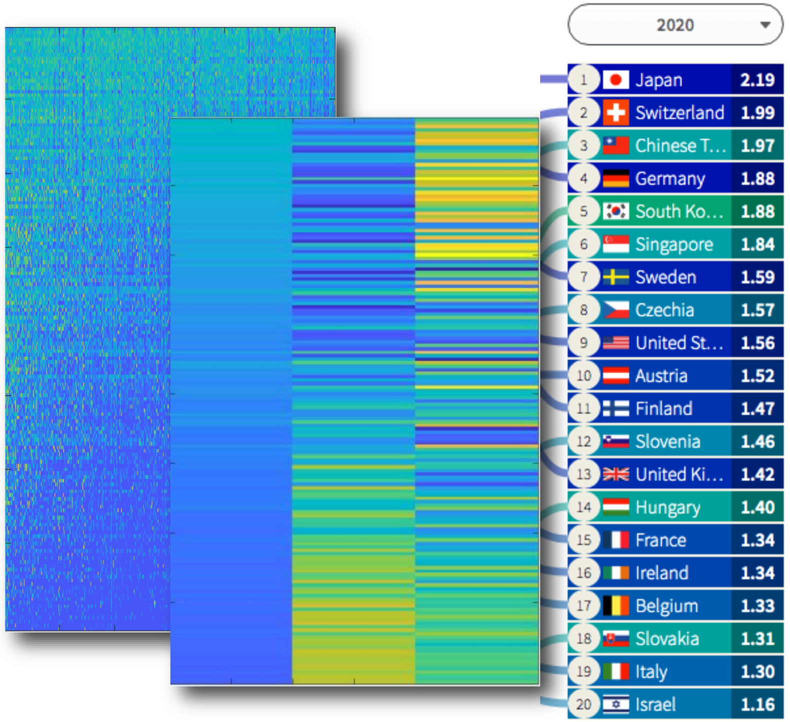
To understand the economy in detail we need granular representations





Economic complexity is that change!
It provides granular representations of economies that can help us understand where they stand and where they are going.





Research: centerforcollectivelearning.or
Tech: datawheel.us