Economic Complexity: How Machine Learning Is helping us Understand Sustainable Economic Development

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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

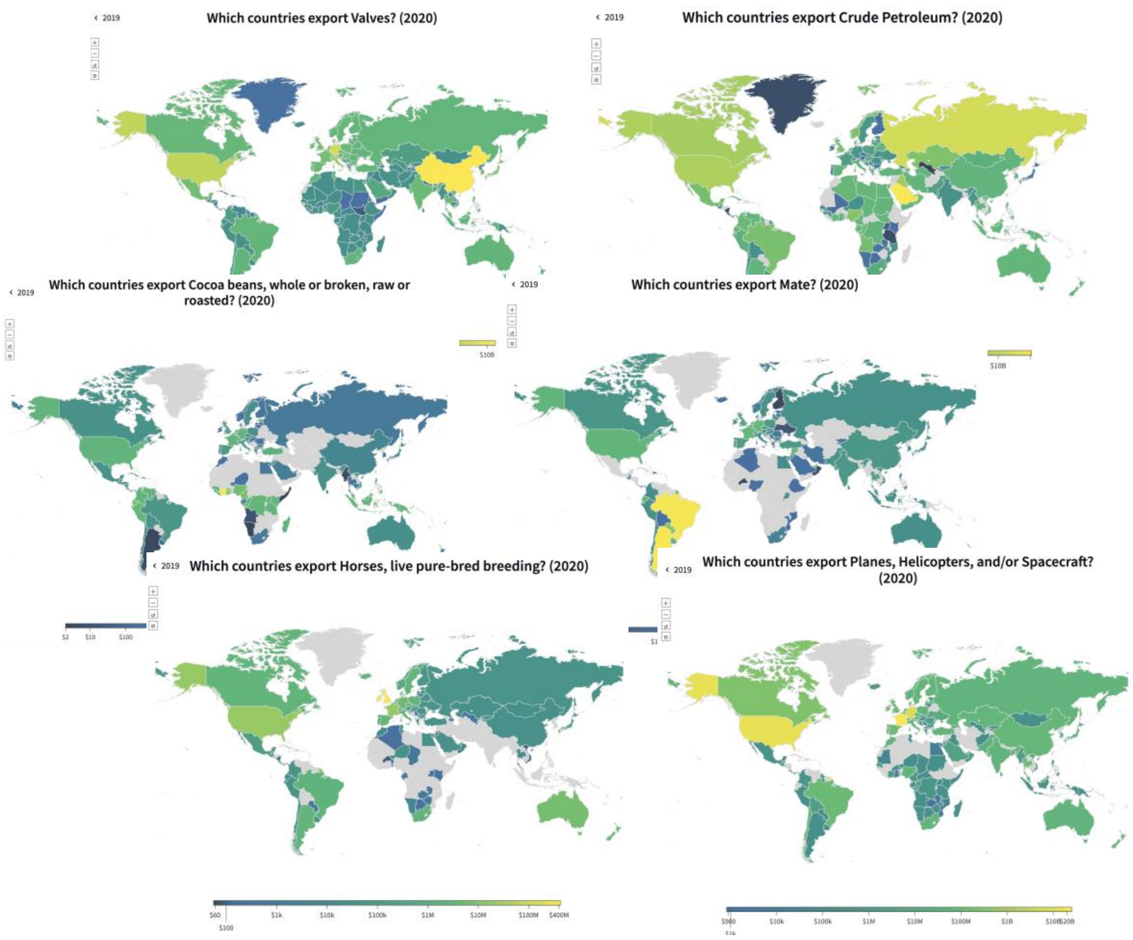
+

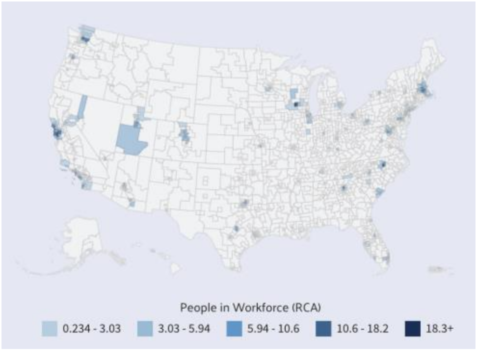
economic data

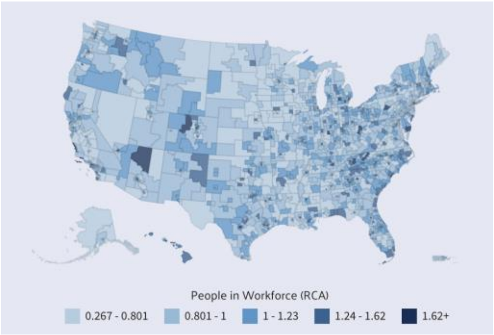
=

development outcomes

Starting from 2006-2007

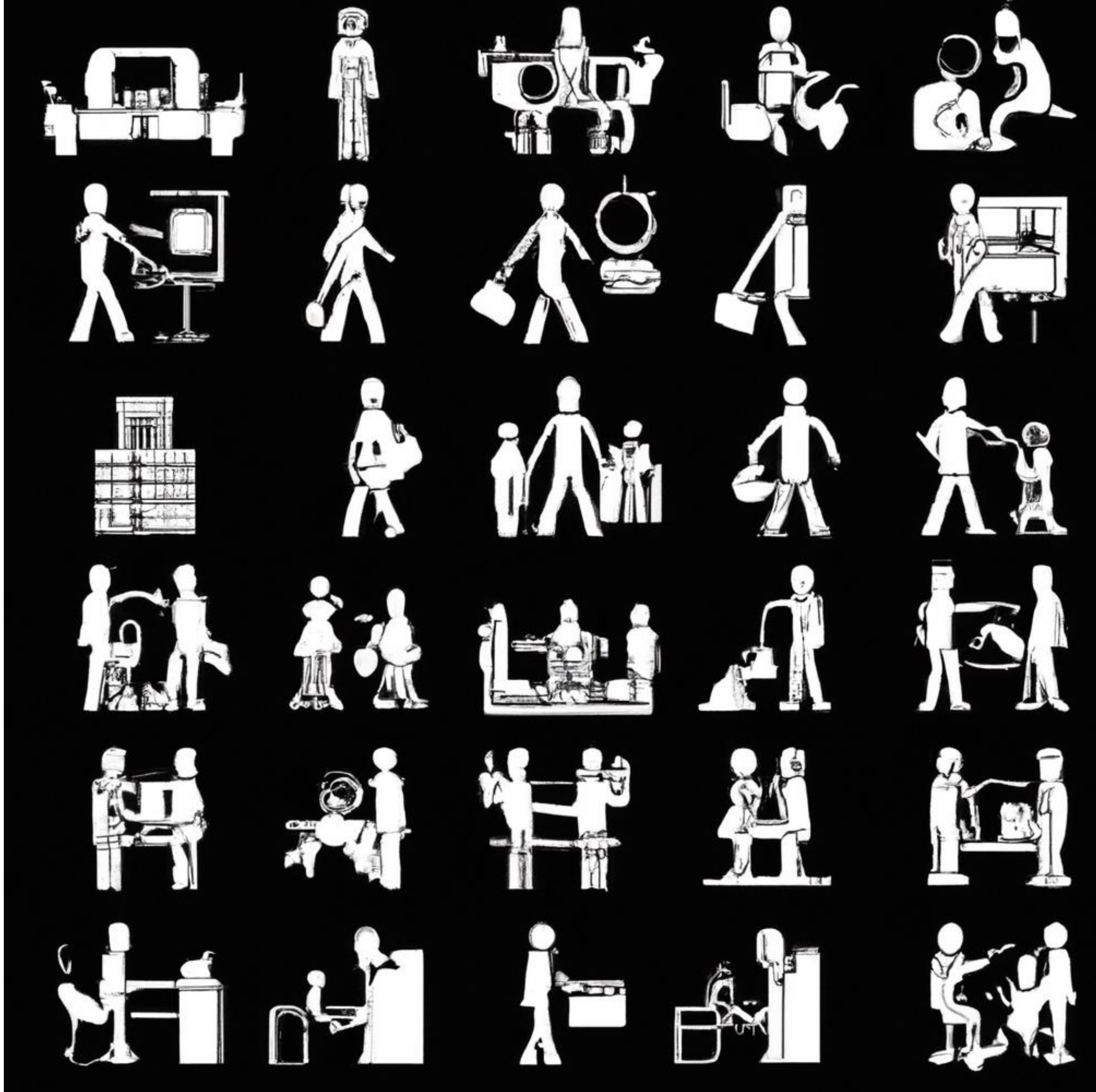


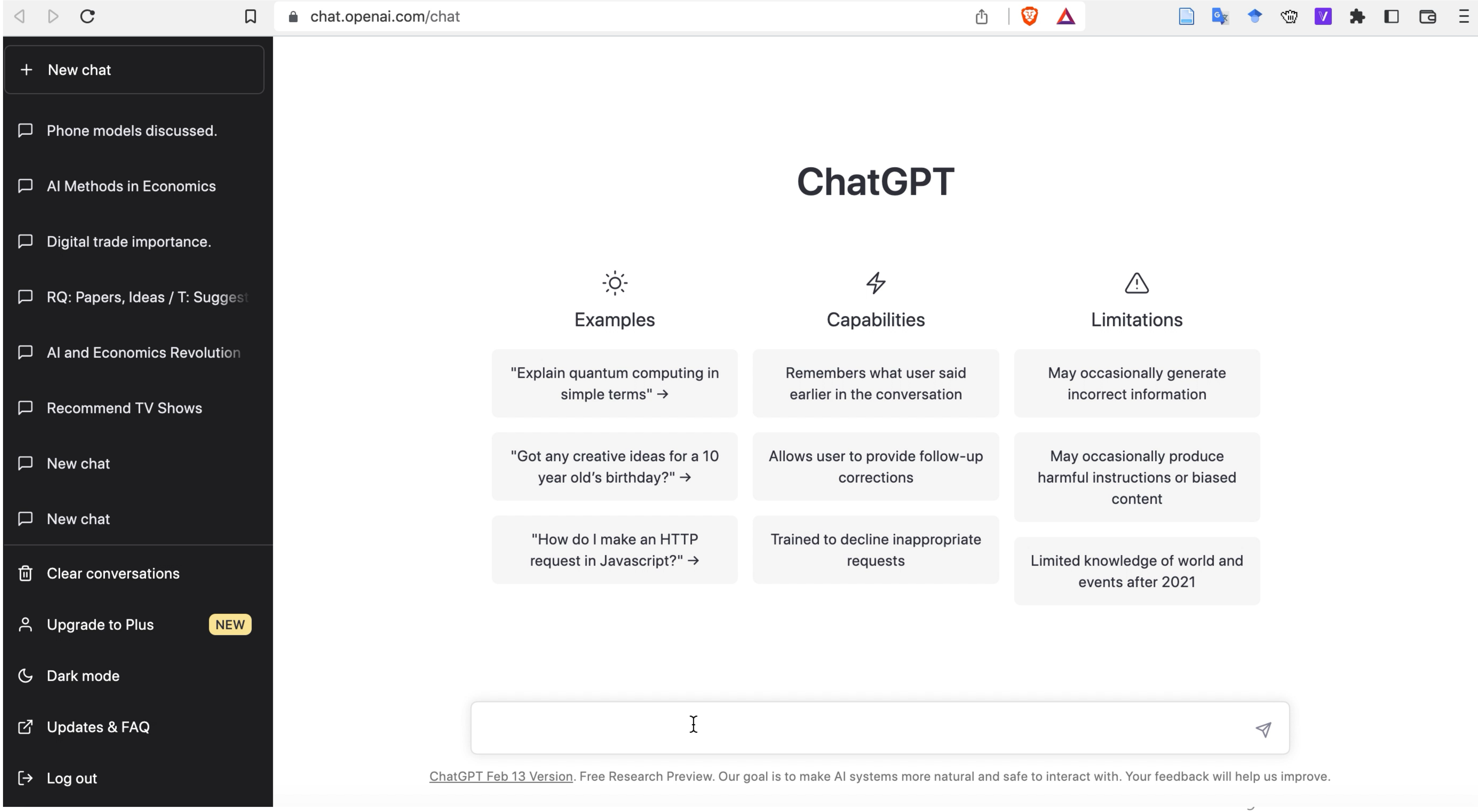




Why Machine Learning

Because factors of production, and in particular **knowledge**, are highly specific and **non-fungible** (not interchangeable).




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" →
"Got any creative ideas for a 10 year old's birthday?" →
"How do I make an HTTP request in Javascript?" →
Remembers what user said earlier in the conversation
Allows user to provide follow-up corrections
Trained to decline inappropriate requests
May occasionally generate incorrect information
May occasionally produce harmful instructions or biased content
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.

The best thing about AI is its ability to

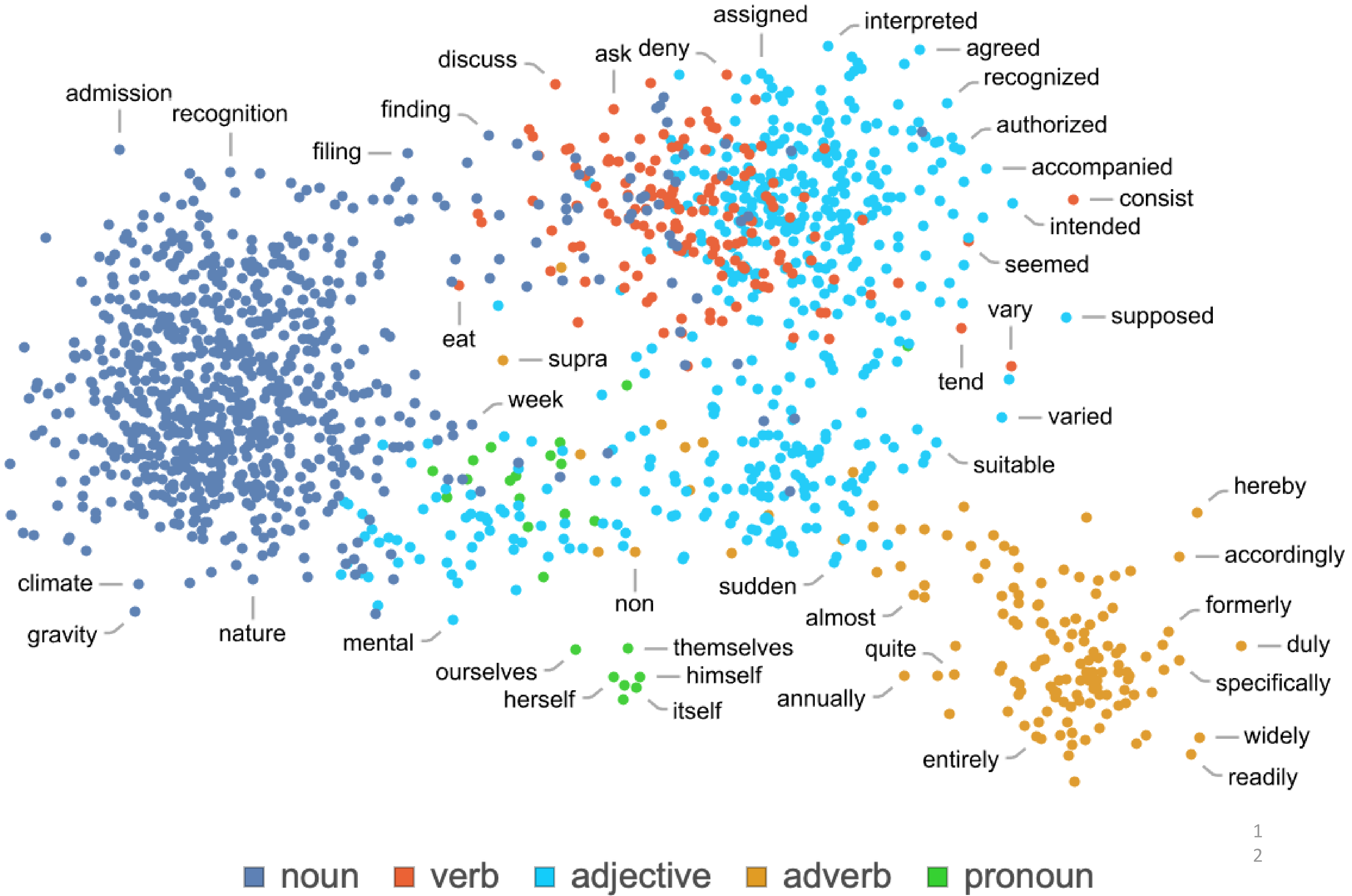
learn	4.5%
predict	3.5%
make	3.2%
understand	3.1%
do	2.9%

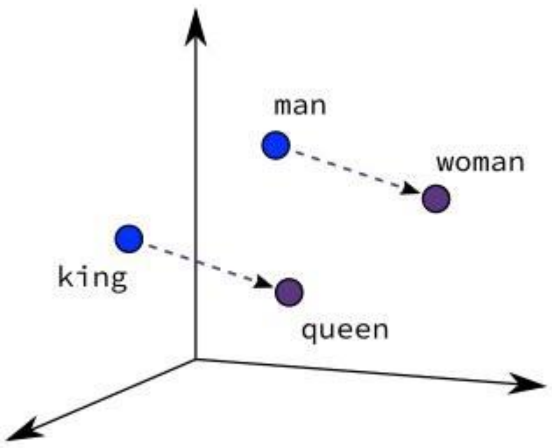
https://writings.stephenwolfram.com/2023/02/what-is-chatgpt-doing-and-why-does-it-work/

Verb, Nouns, Adjectives, and Adverbs List

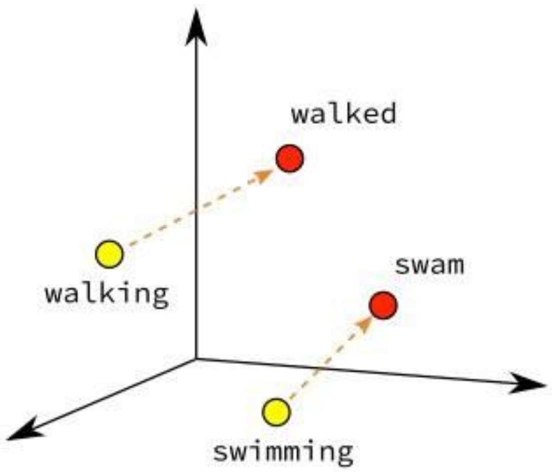
Verbs	Nouns	Adjectives	Adverbs
accuse	accusation	accusing	accusingly
argue	argument	arguable	arguably
characterize	character	characteristic	characteristically
condition	condition	conditional	conditionally
darken	dark, darkness	dark, darkened	darkly
destroy	destruction	destructive	destructively
drink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

Word Embeddings Provide Semantic Representations That Transcend Parts of Speech Grammar

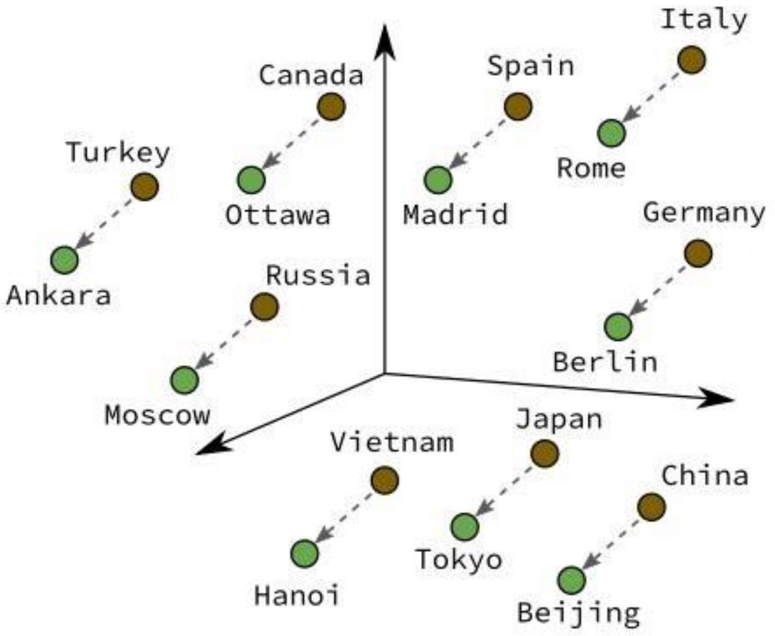




Male-Female



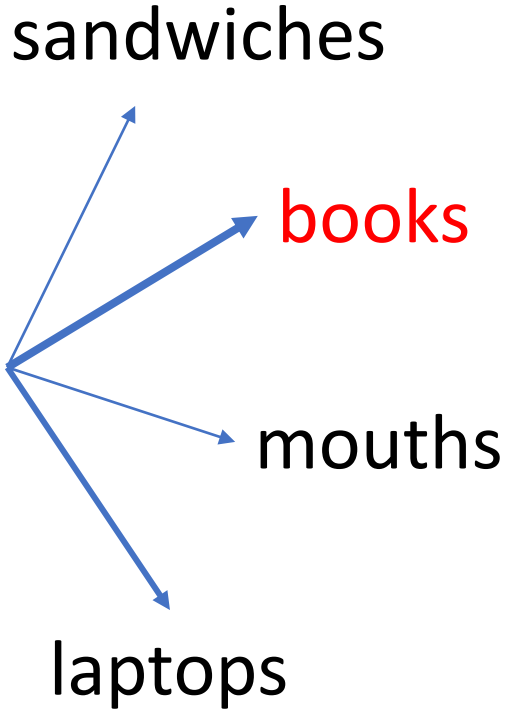
Verb Tense



Country-Capital

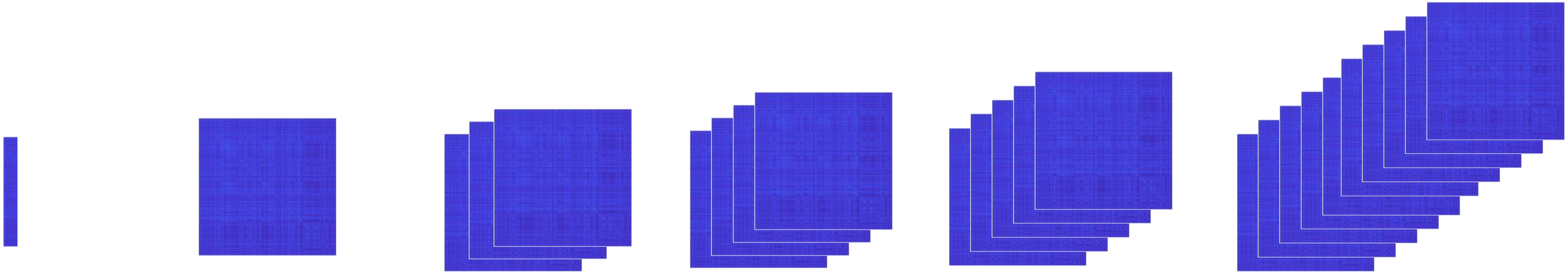
Attention!

At the **library**, the **students** opened their....



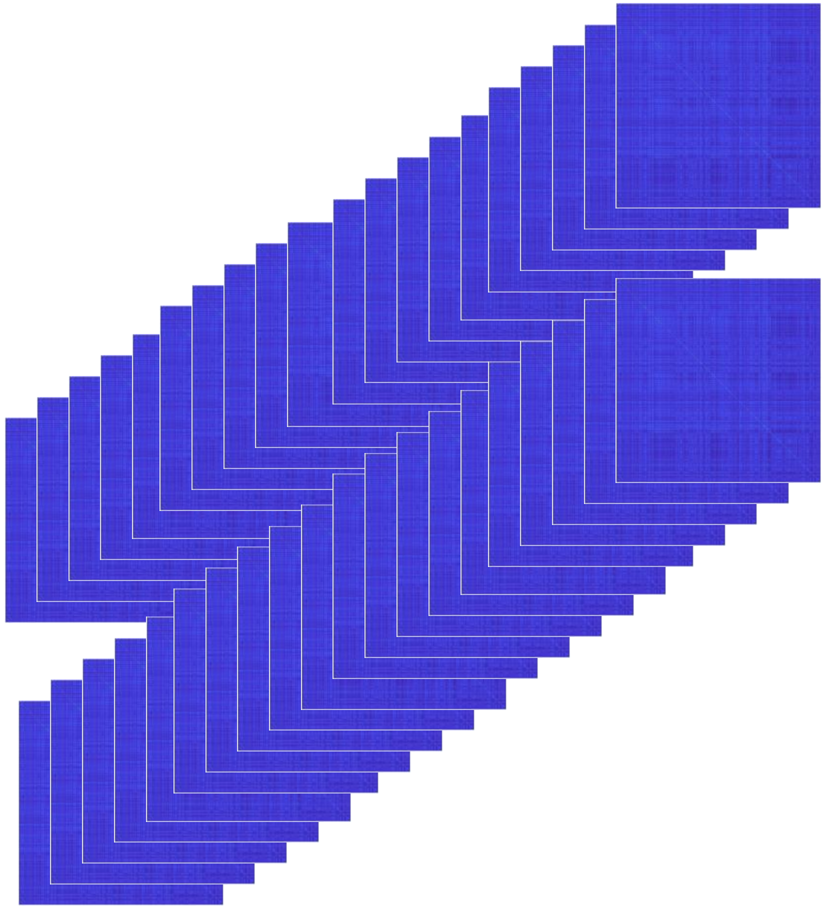
Vaswani, Ashish, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. **"Attention is all you need."** *Advances in neural information processing systems* 30 (2017).

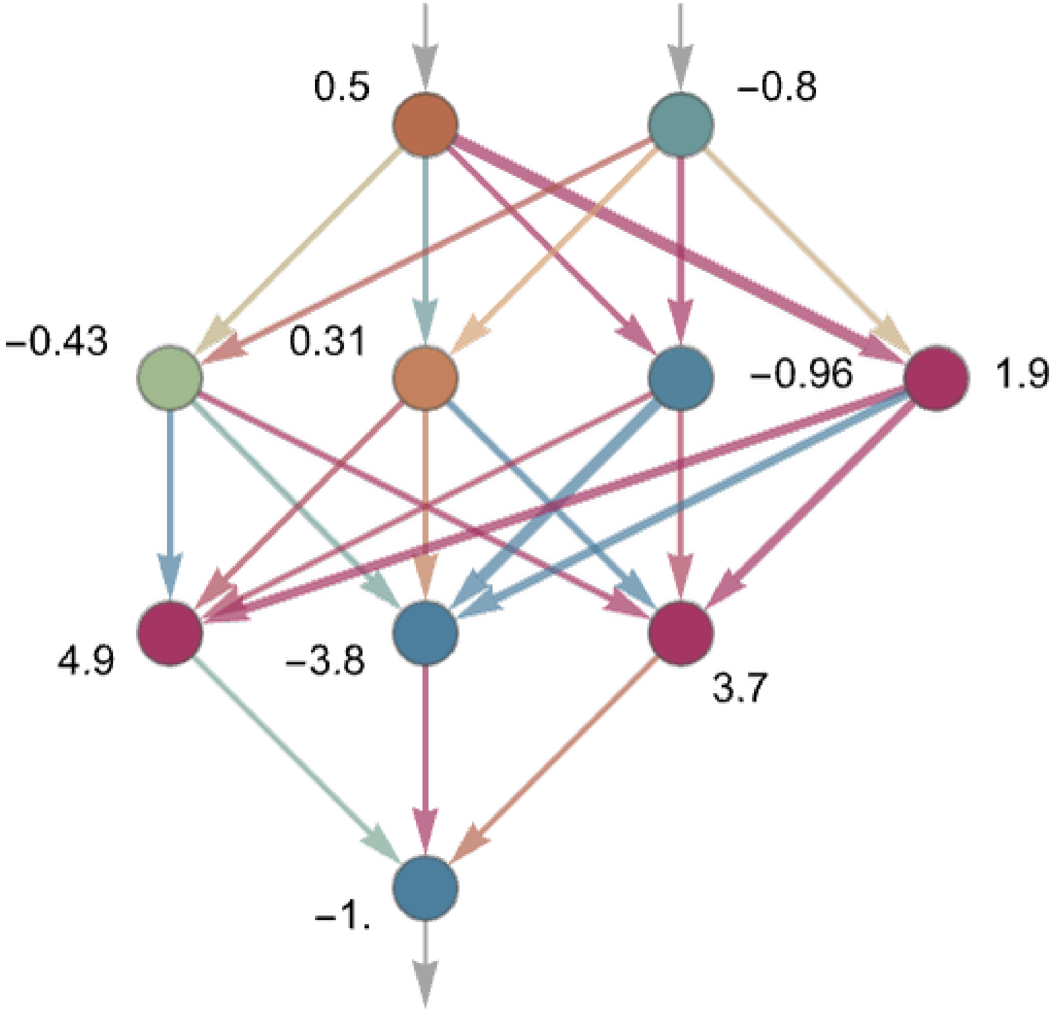
It is a BIG problem!



Words	Bigrams	Trigrams	4-grams	5-grams		20-grams
10,000 words	100 million pairs	1 trillion triplets	10,000 trillion 4-grams	100 million trillion 5-grams	…	20-grams
10^4	10^8	10^{12}	10^{16}	10^{20}		10^{80}

Use neural networks to approximate these functions





With only a “few“ billion parameters

“Parts of Speech” Economics

Manufacture — Capital Intensive

Agriculture — Capital Intensive

Agriculture — Labor Intensive

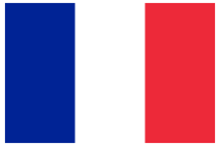
Manufacture — Labor Intensive

NLP, 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…

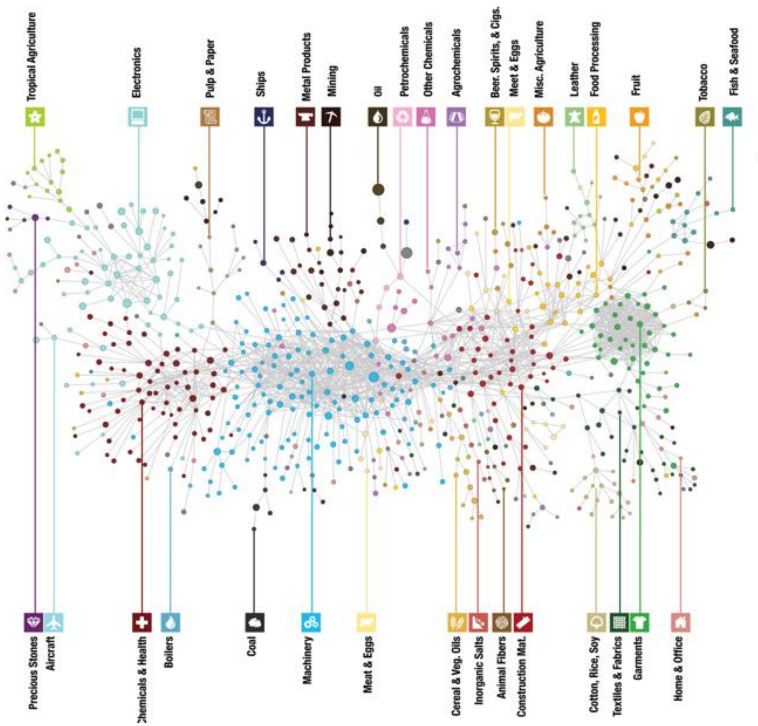


Spark Ignition Engines, Engine Parts, Aircraft Parts, Aircraft, Wheat, Wine, Perfumes, Vaccines, etc…

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

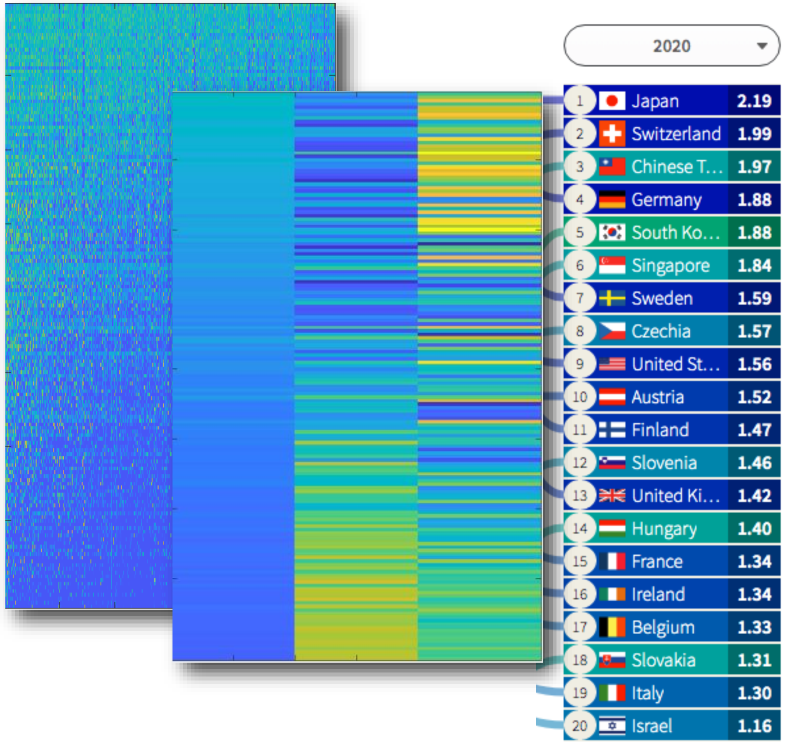
Two Main Methods in Economic Complexity

Relatedness



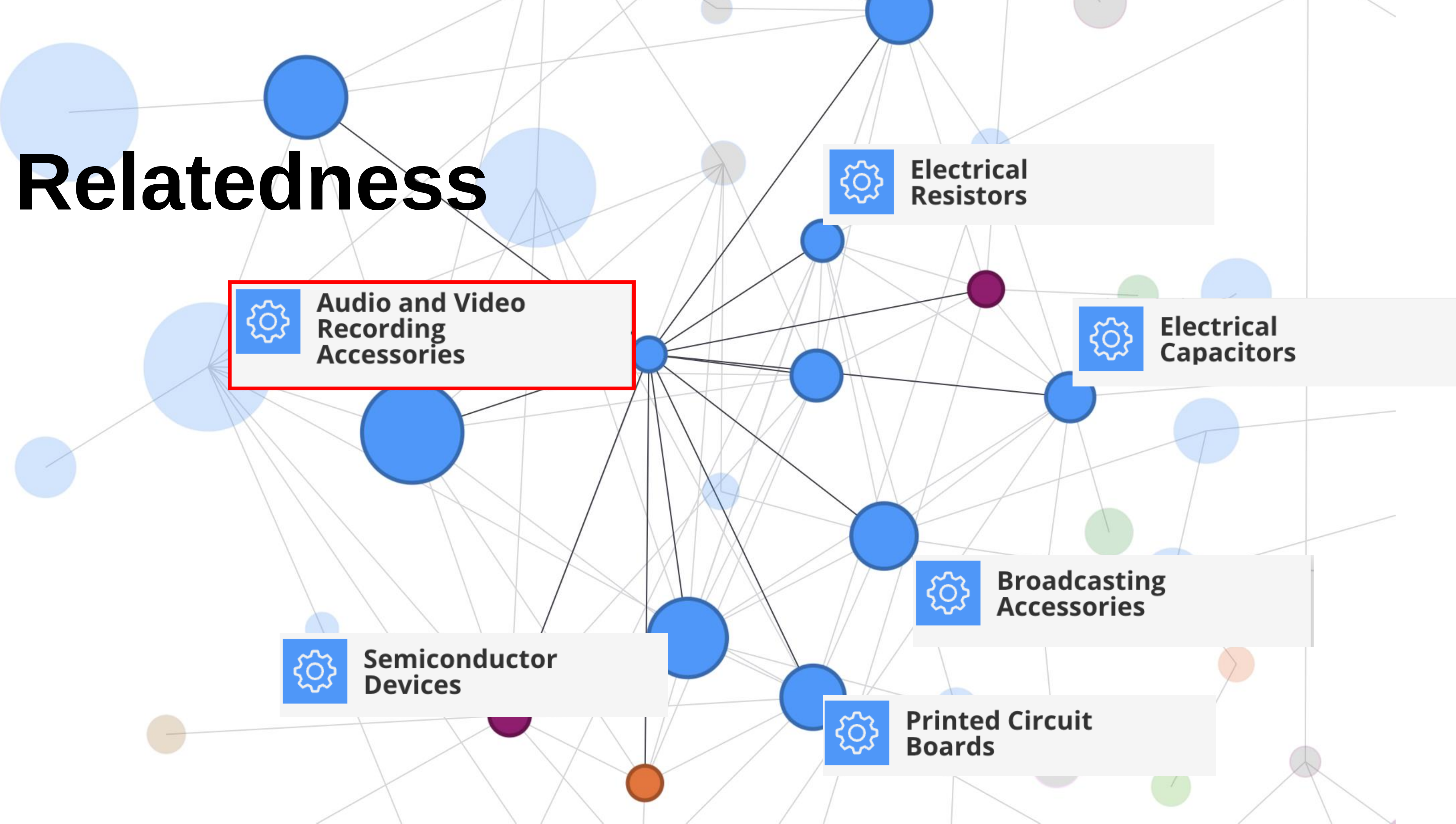
Hidalgo et al. Science (2007)

Complexity Indexes



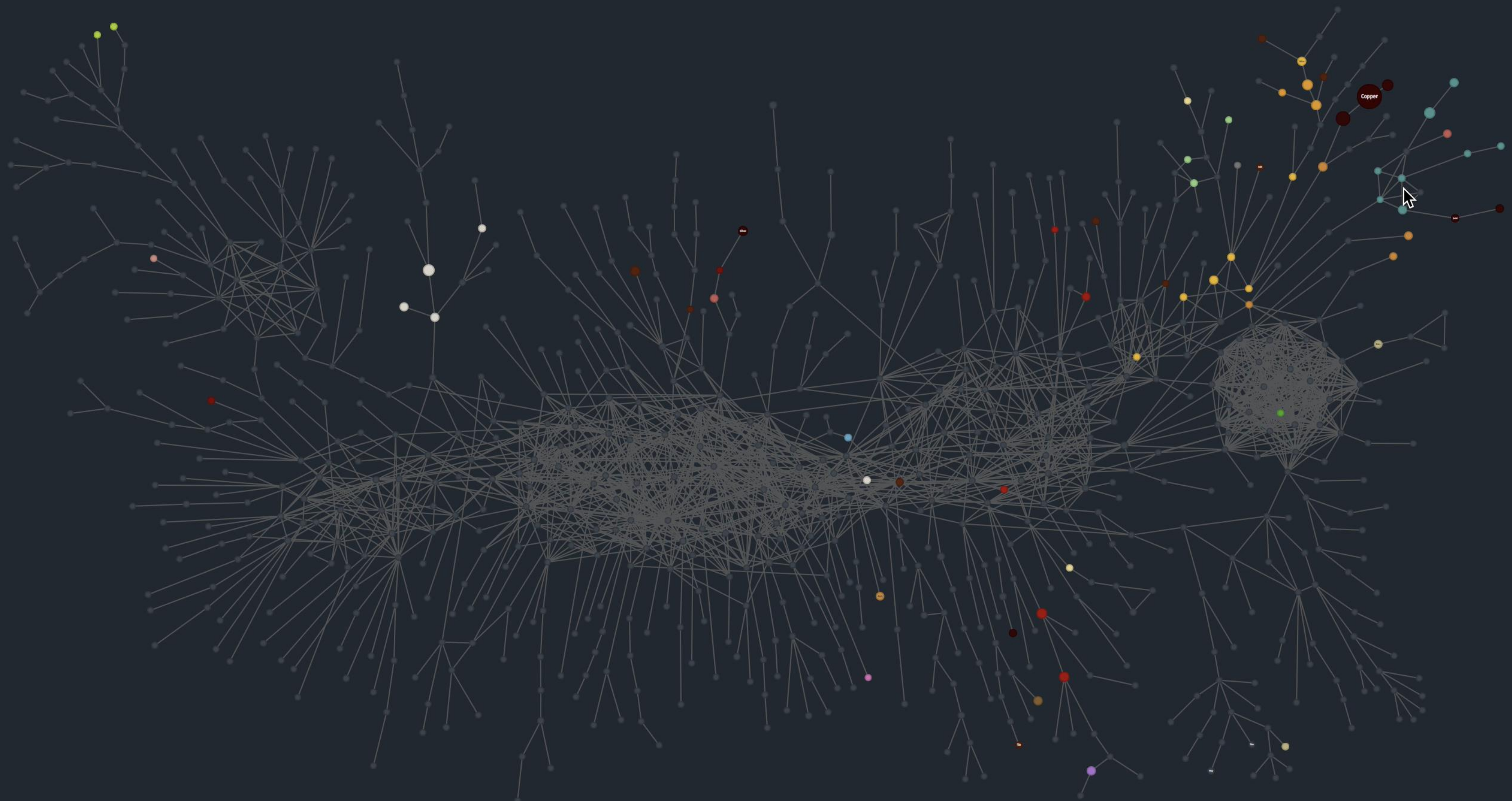
Hidalgo & Hausmann. PNAS (2009)

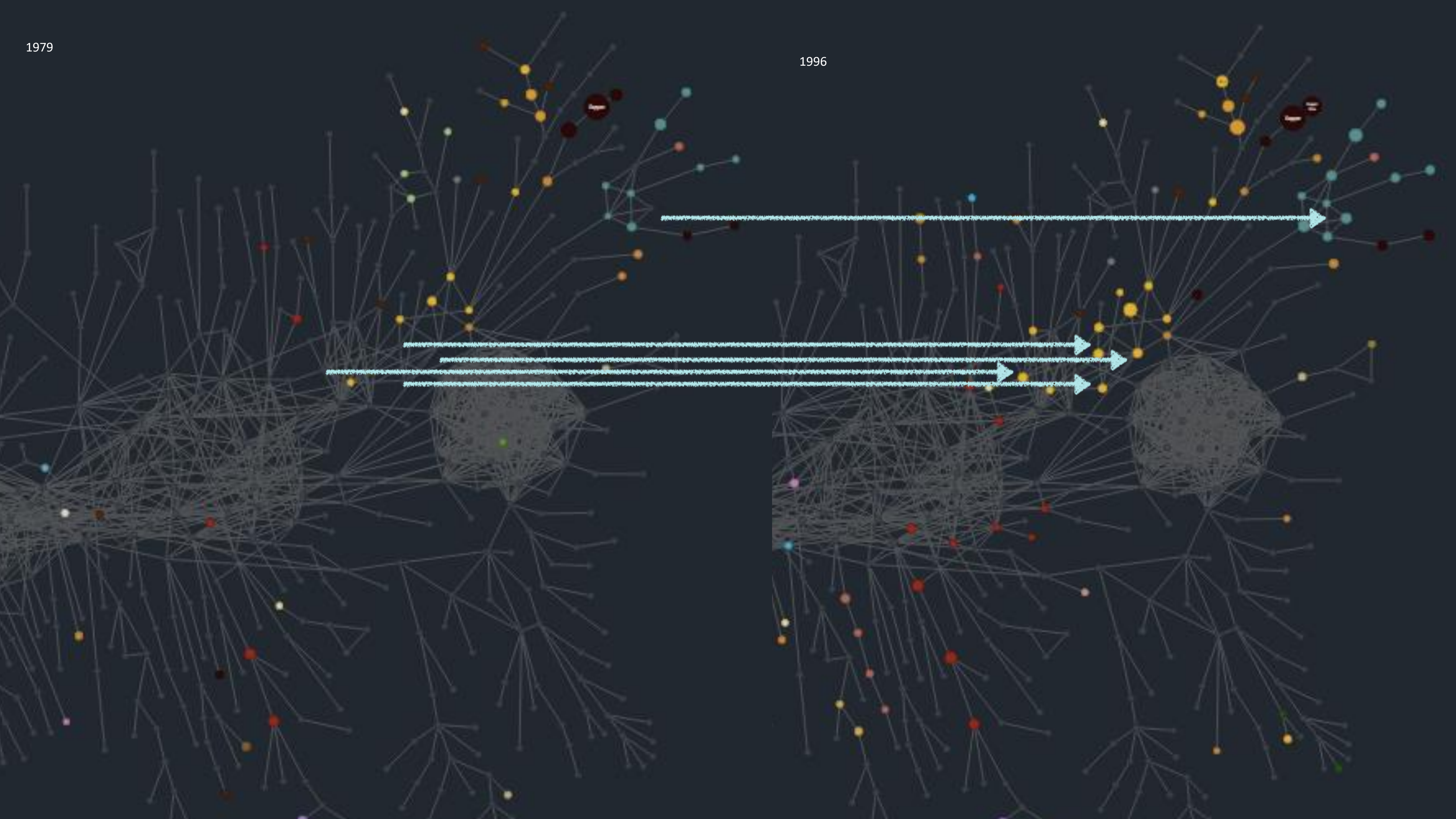
Relatedness



What are the export opportunities of Chile? (1979)

TOTAL: $3.67B

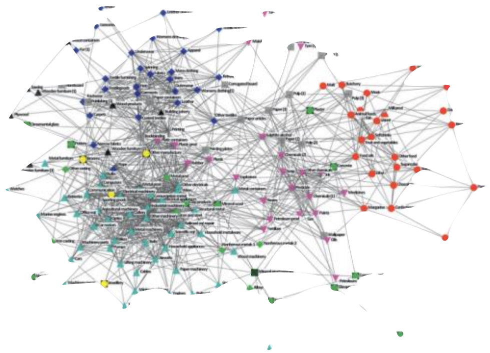


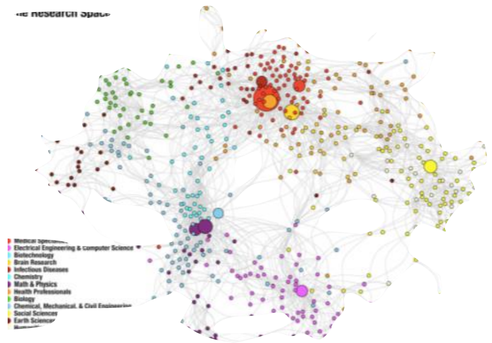

1979
1996

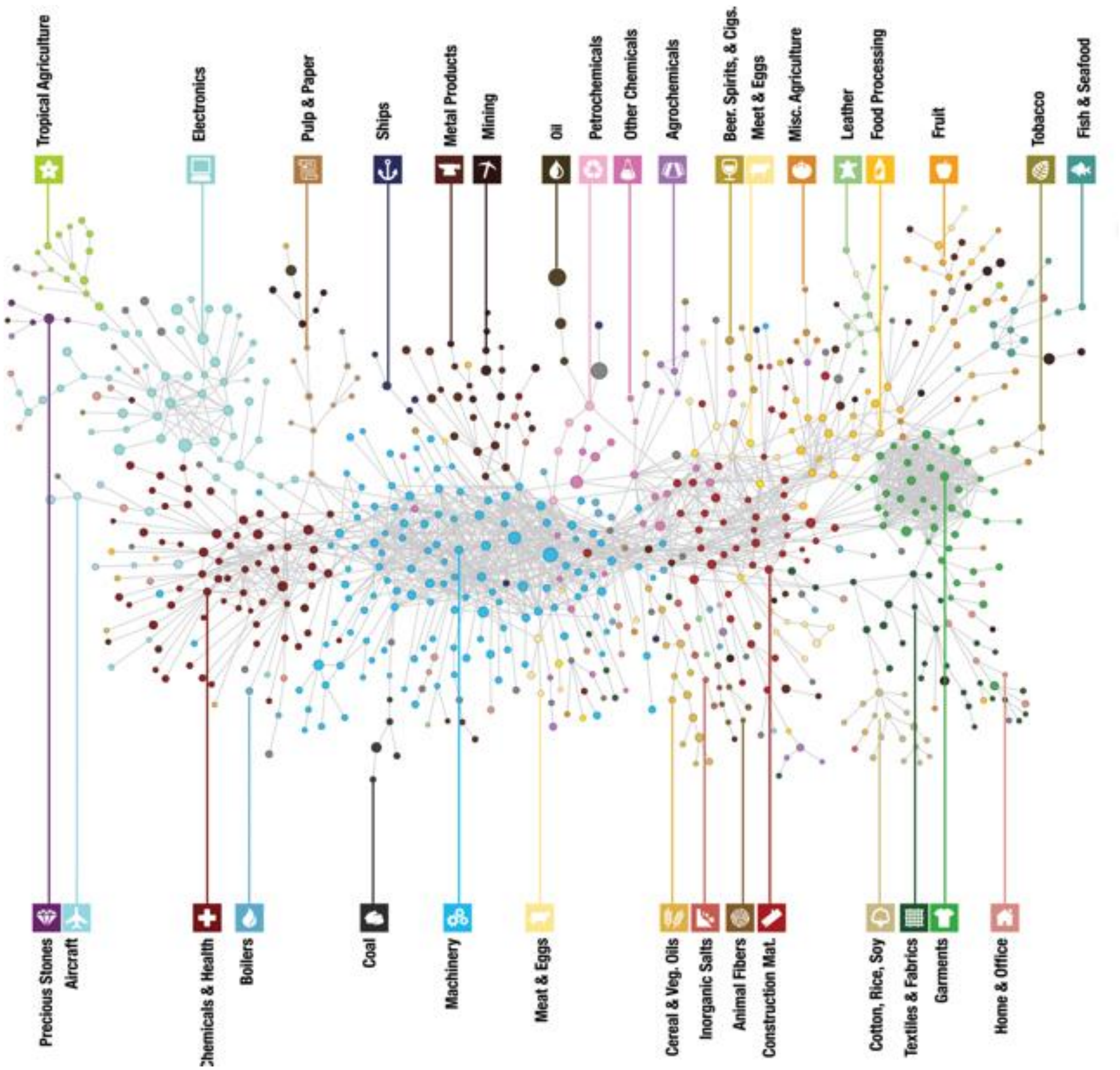
Relatedness

Measures affinity or distance between a location and an activity (e.g. how far is Yerevan from manufacturing Aircrafts).

It is the use of **recommender systems** to explain and predict changes in specialization patterns.

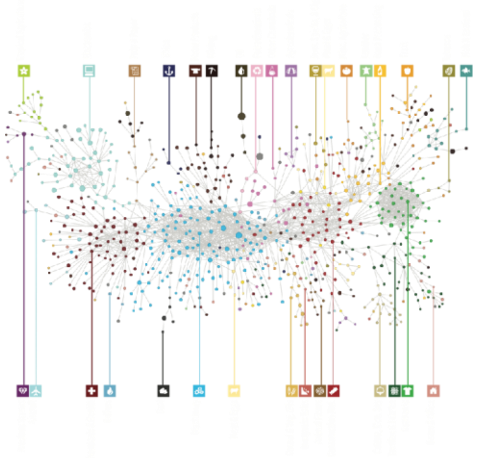




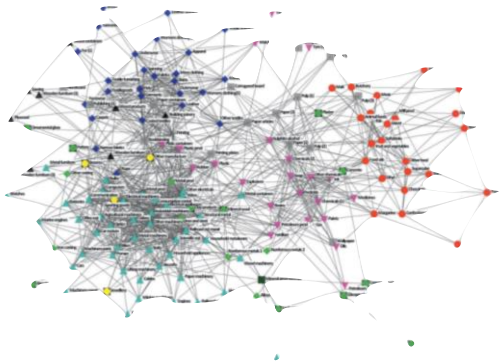


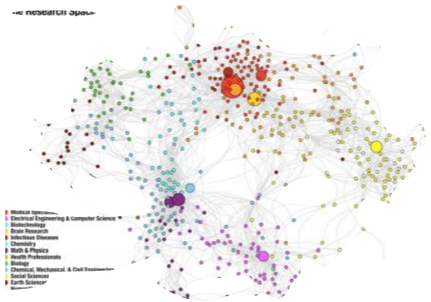
THE PRINCIPLE OF RELATEDNESS

Products

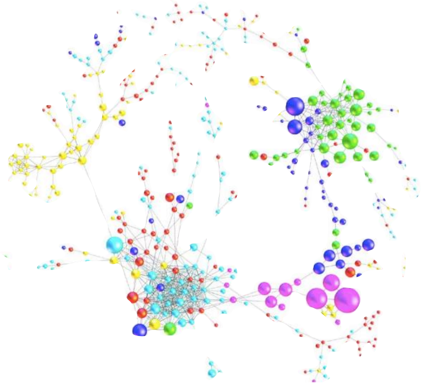


Industries





Research Areas



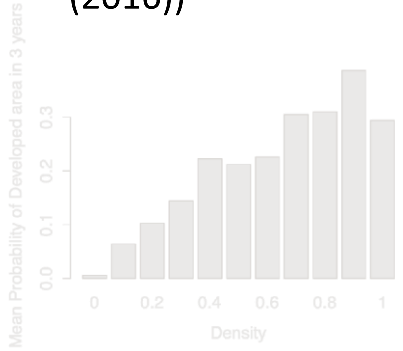
Patents

Products

(Hidalgo et al 2007)

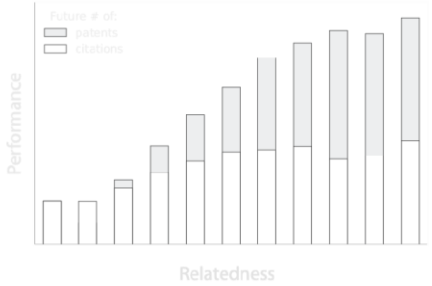
Research Areas

(Guevara et al. (2016))



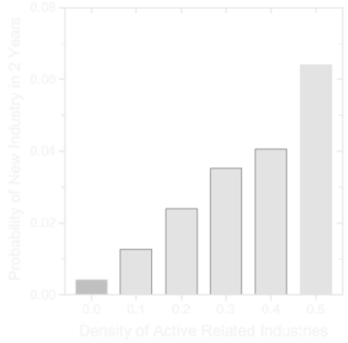
Patents

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

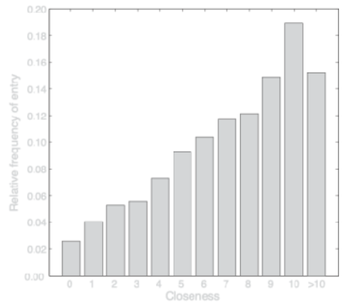


Industries

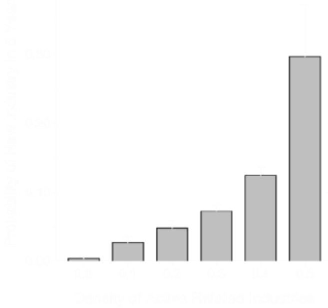
BRAZIL (Jara-Figueroa et al. 2018)



SWEDEN: (Neffke, Henning, Boschma 2011)



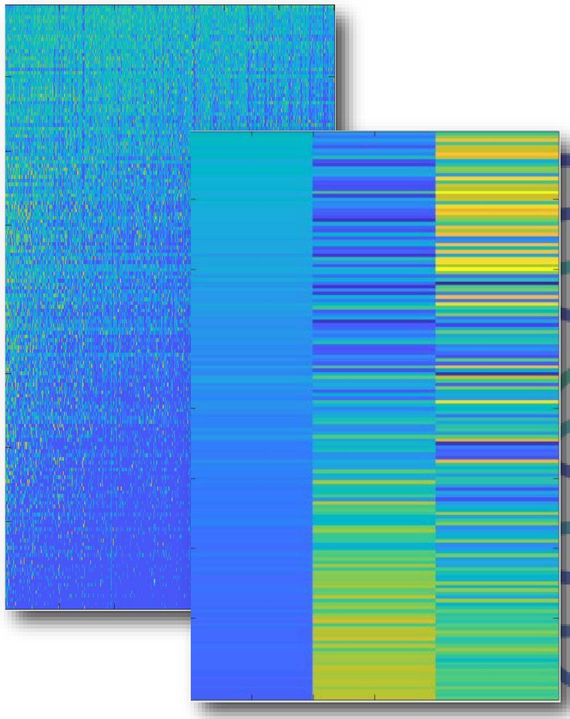
CHINA: (He et al. 2017 Gao et al. 2021)

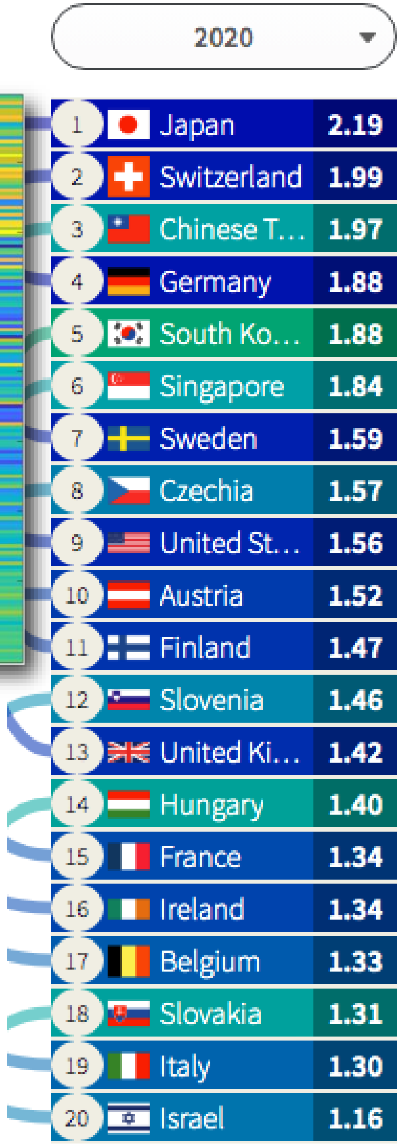


César A. Hidalgo, Pierre-Alexandre Balland, Ron Boschma, Mercedes Delgado, Maryann Feldman, Koen Frenken, Edward Glaeser, Dieter F. Kogler, Andrea Morrison, Frank Neffke, David Rigby, Scott Stern, Siqi Zheng, Canfei He, & Shengjun Zhu. “The Principle of Relatedness” CCS 2018. Springer Proceedings in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

Economic Complexity

The use of dimensionality reduction techniques (e.g. SVD) to summarize the sophistication of productive structures.





Economic Complexity Explains

Economic Growth

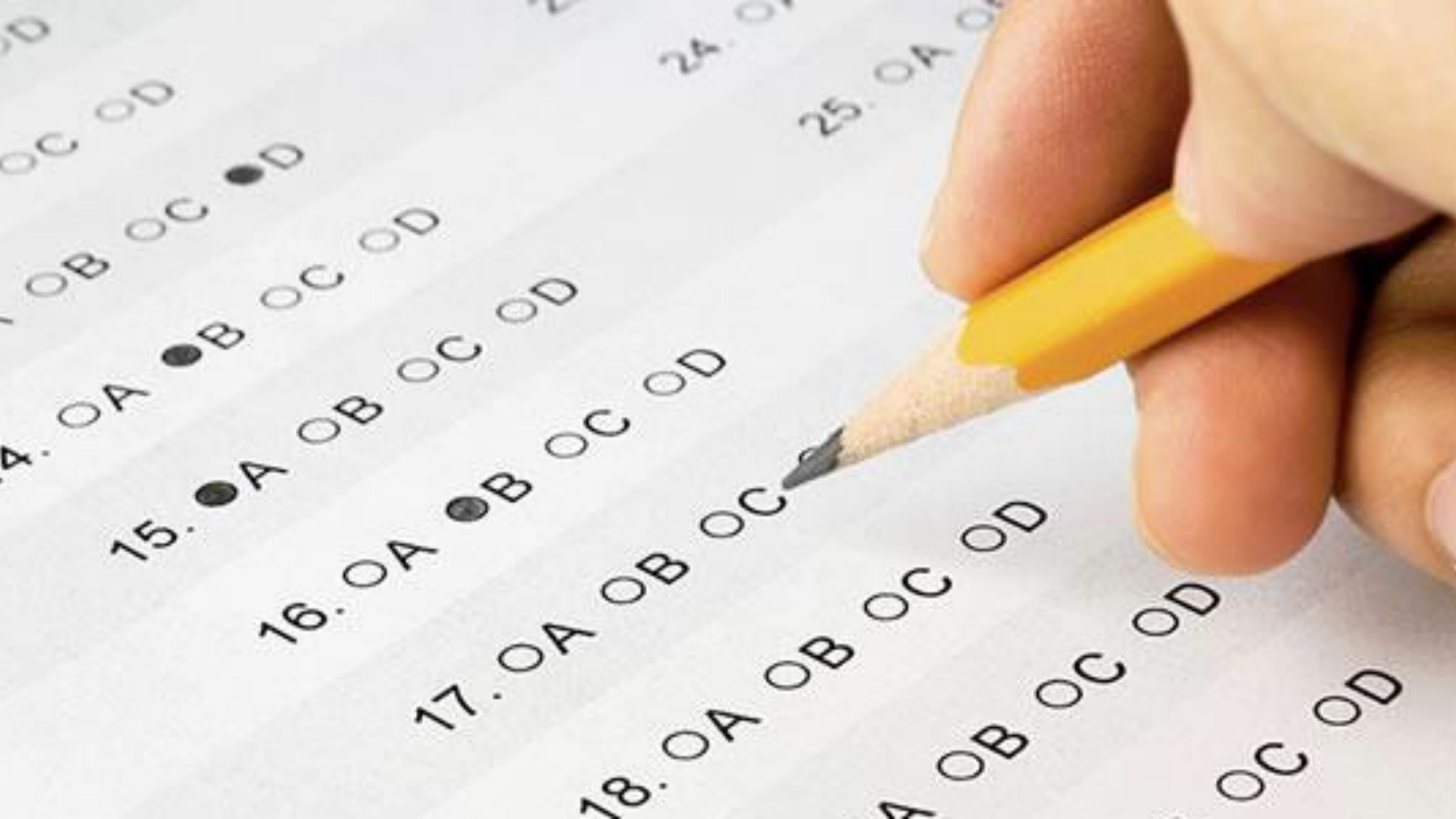
Hidalgo and Hausmann, 2009; Chávez et al., 2017; Domini, 2019; Hausmann et al., 2014; Koch, 2021; Lo Turco and Maggioni, 2020; Ourens, 2012; Stojkoski et al., 2016

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



24.
25. A
15. A B C D
16. A B C D
17. A B C D
18. A B C D

Economic Complexity

Knowledge of a place
is the knowledge of the activities
present in it

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

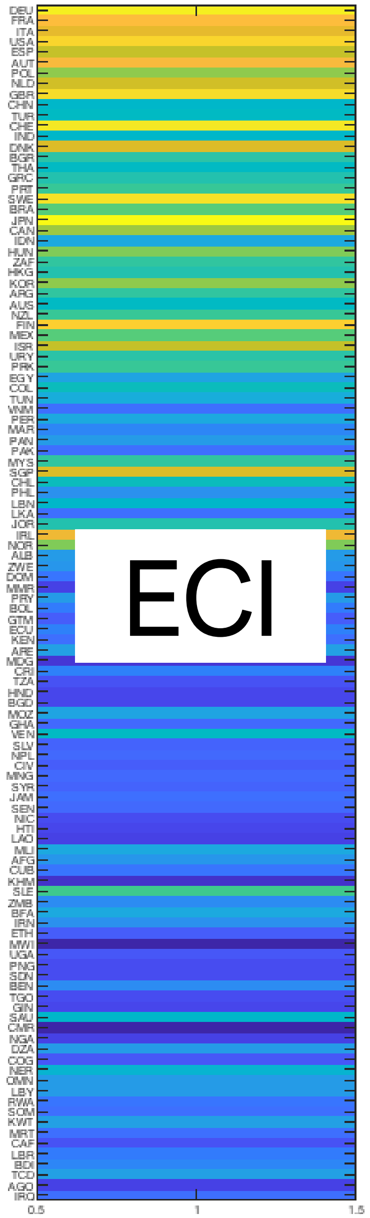
Knowledge of an activity
is the knowledge of the places
where it is present

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

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

Knowledge can be estimated
as the solution to a linear
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….

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

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

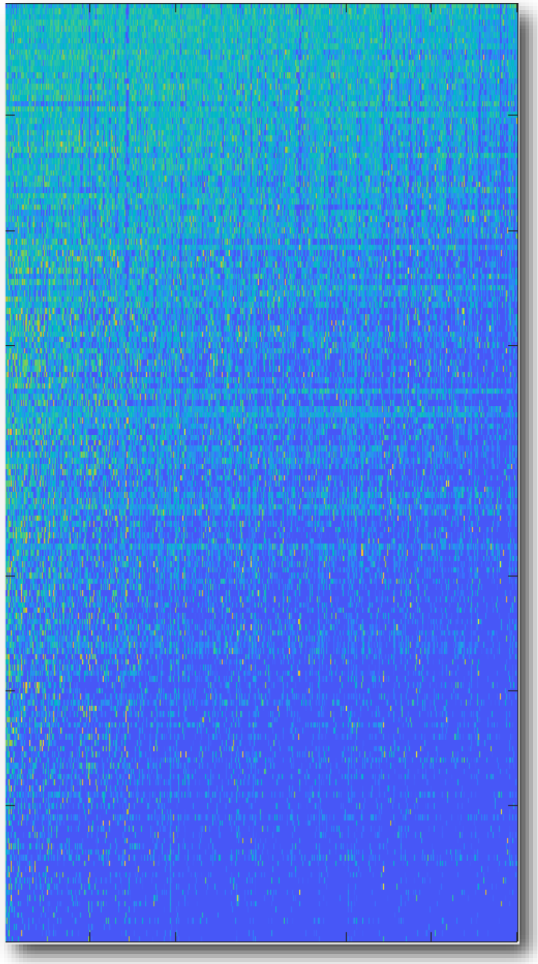
$$\widetilde{M}_{cc'} = \frac{1}{M_c} \sum_p \frac{M_{cp} M_{c'p}}{M_p}$$

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)

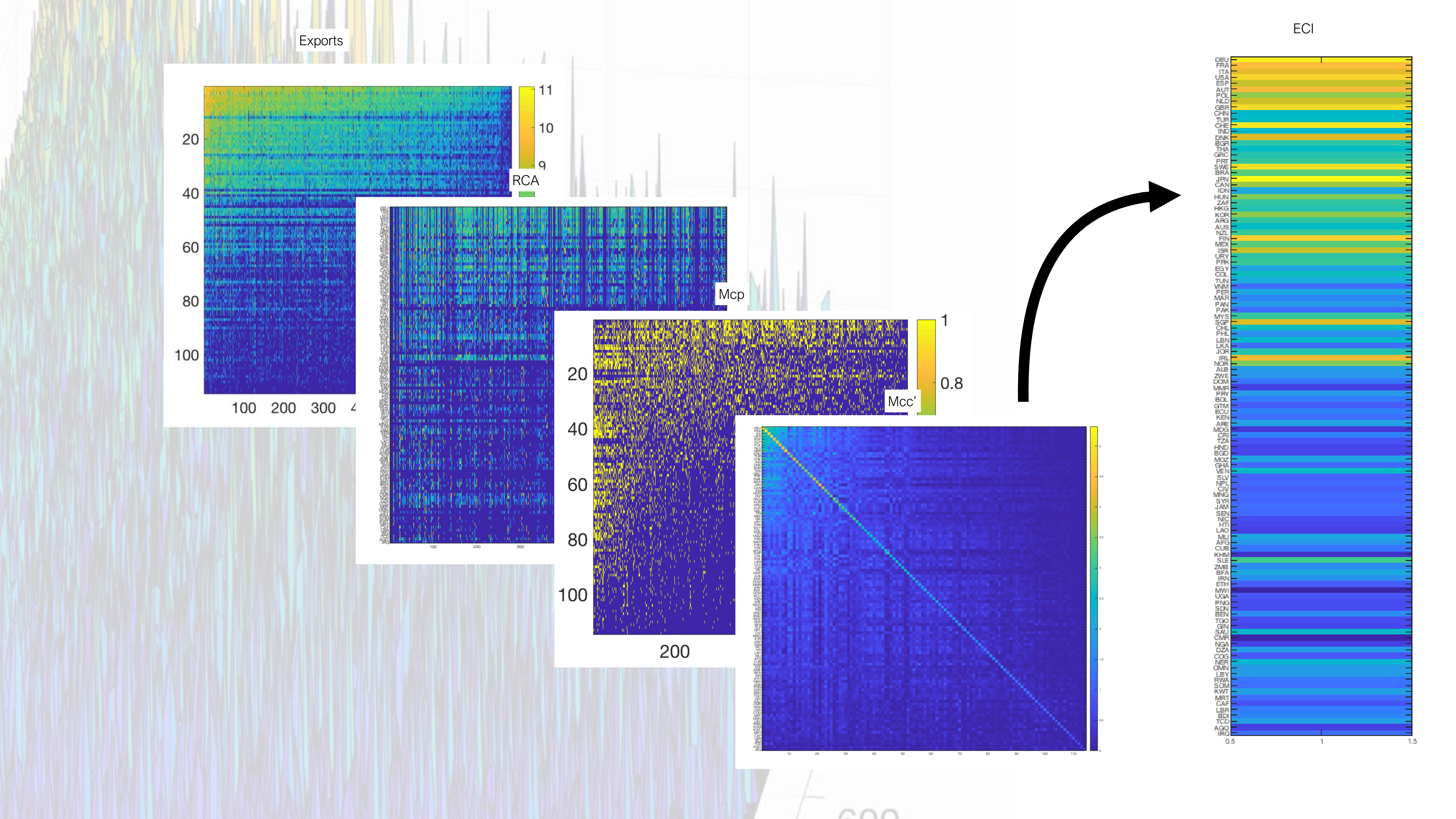
But is not that easy!

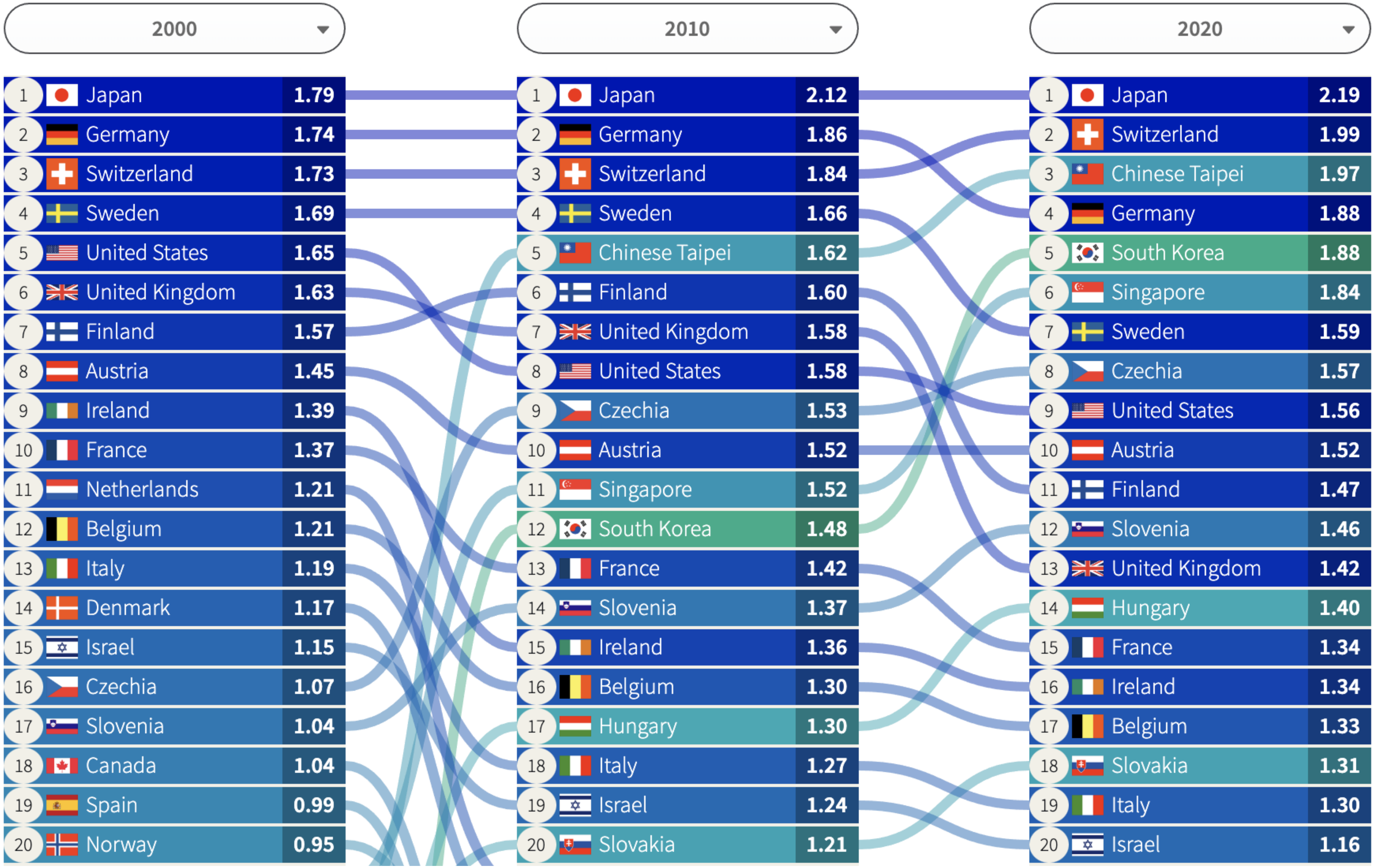
Units of observation are not comparable!



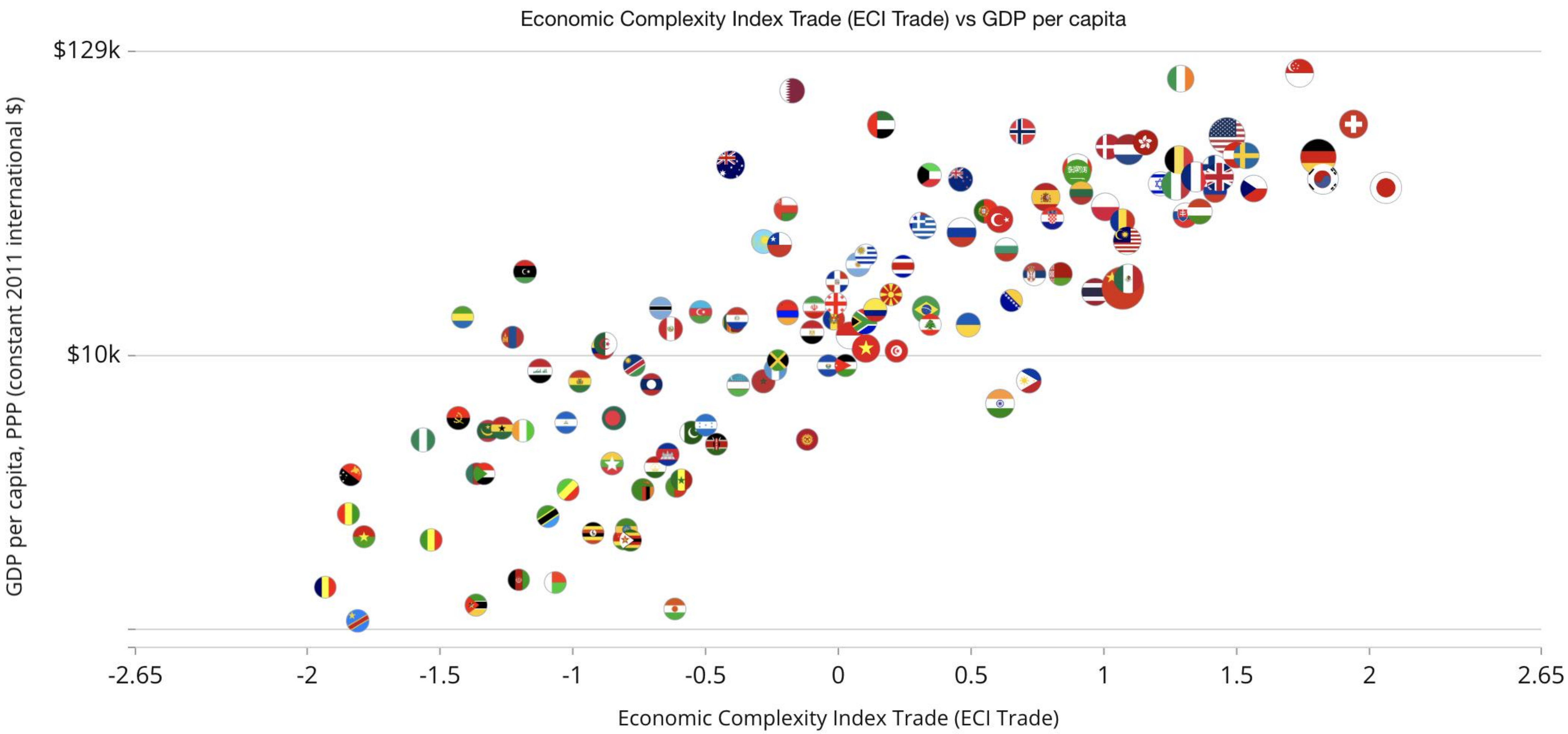
China & USA ~ 15 to 20 trillion GDP

Macedonia ~ 0.0012 trillion GDP


Exports
RCA
Mcp
Mcc'
ECI
20
40
60
80
100
100
200
300
11
10
9
1
0.8
200
0.5
1
1.5

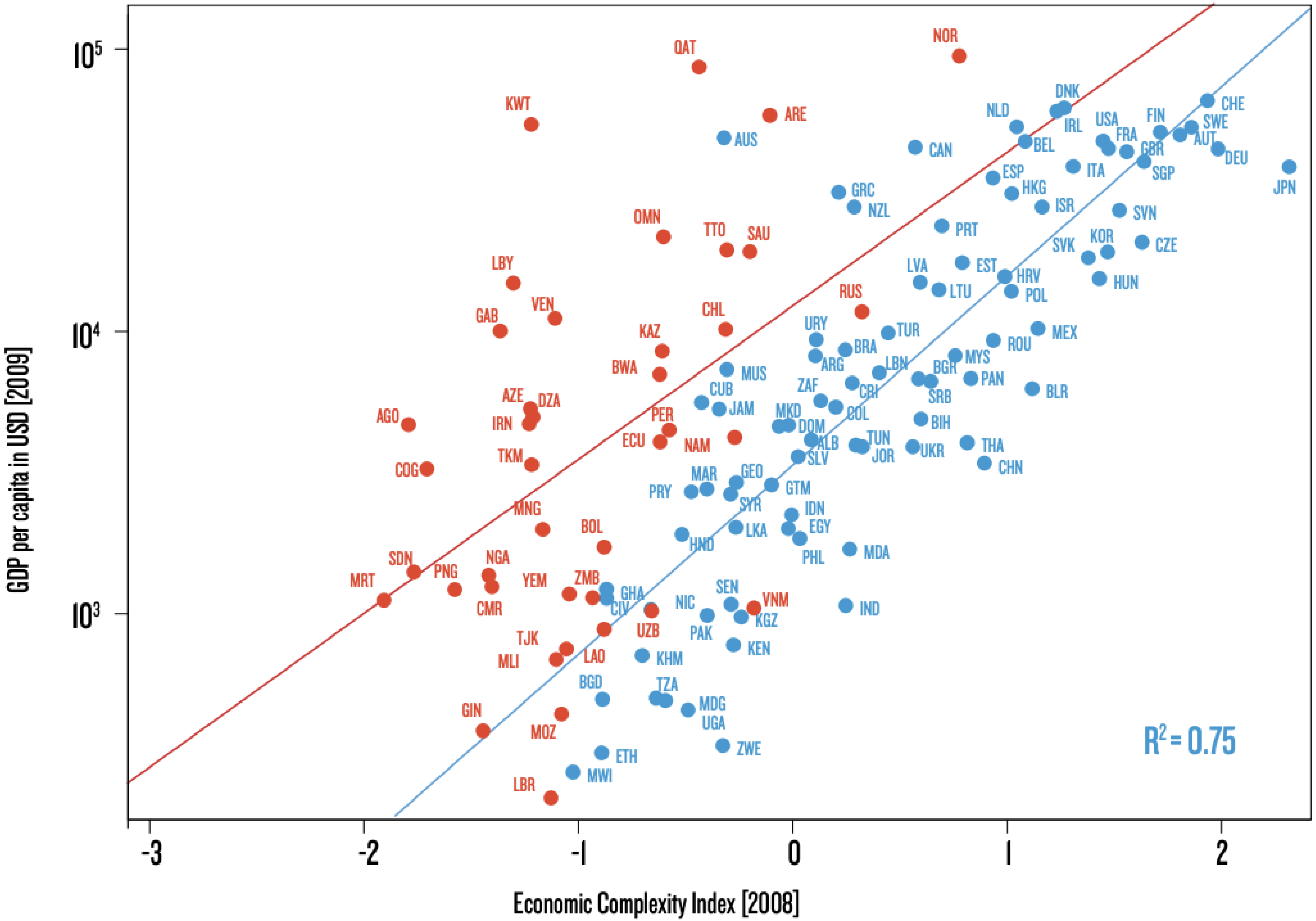


2000
2010
2020
1 Japan 1.79
2 Germany 1.74
3 Switzerland 1.73
4 Sweden 1.69
5 United States 1.65
6 United Kingdom 1.63
7 Finland 1.57
8 Austria 1.45
9 Ireland 1.39
10 France 1.37
11 Netherlands 1.21
12 Belgium 1.21
13 Italy 1.19
14 Denmark 1.17
15 Israel 1.15
16 Czechia 1.07
17 Slovenia 1.04
18 Canada 1.04
19 Spain 0.99
20 Norway 0.95
1 Japan 2.12
2 Germany 1.86
3 Switzerland 1.84
4 Sweden 1.66
5 Chinese Taipei 1.62
6 Finland 1.60
7 United Kingdom 1.58
8 United States 1.58
9 Czechia 1.53
10 Austria 1.52
11 Singapore 1.52
12 South Korea 1.48
13 France 1.42
14 Slovenia 1.37
15 Ireland 1.36
16 Belgium 1.30
17 Hungary 1.30
18 Italy 1.27
19 Israel 1.24
20 Slovakia 1.21
1 Japan 2.19
2 Switzerland 1.99
3 Chinese Taipei 1.97
4 Germany 1.88
5 South Korea 1.88
6 Singapore 1.84
7 Sweden 1.59
8 Czechia 1.57
9 United States 1.56
10 Austria 1.52
11 Finland 1.47
12 Slovenia 1.46
13 United Kingdom 1.42
14 Hungary 1.40
15 France 1.34
16 Ireland 1.34
17 Belgium 1.33
18 Slovakia 1.31
19 Italy 1.30
20 Israel 1.16

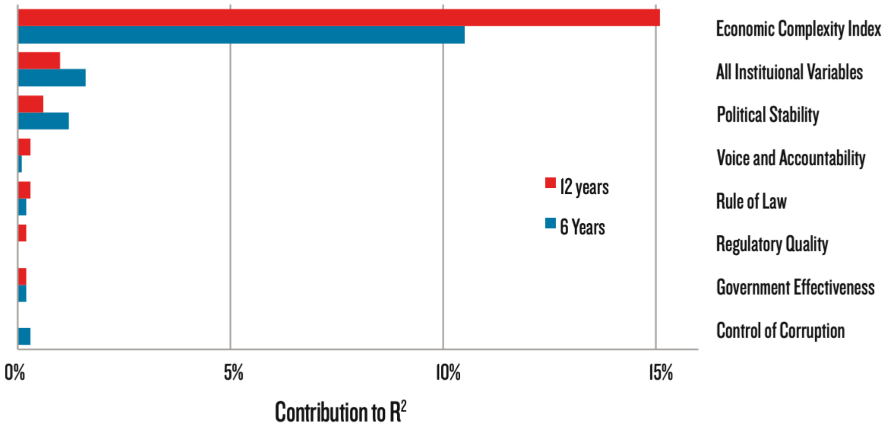


Economic Complexity Index Trade (ECI Trade) vs GDP per capita
$129k
$10k
GDP per capita, PPP (constant 2011 international $)
-2.65
-2
-1.5
-1
-0.5
0
0.5
1
1.5
2
2.65
Economic Complexity Index Trade (ECI Trade)

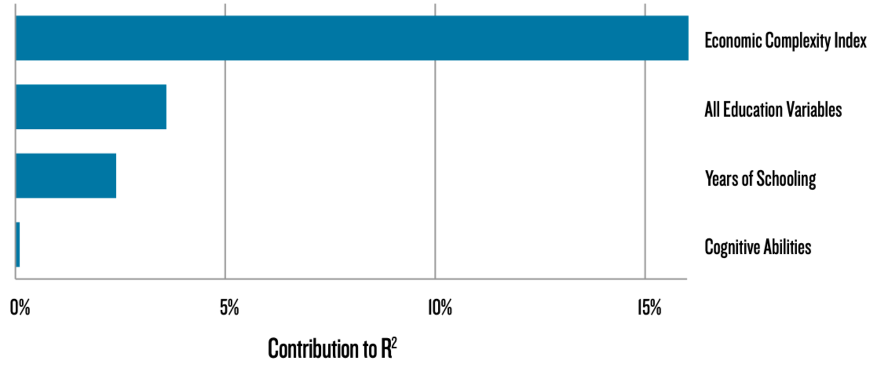
Economic Complexity and Economic Growth



Explains more growth than institutions



Explains more growth than education



Explorations in Economic History
Volume 83, January 2022, 101421

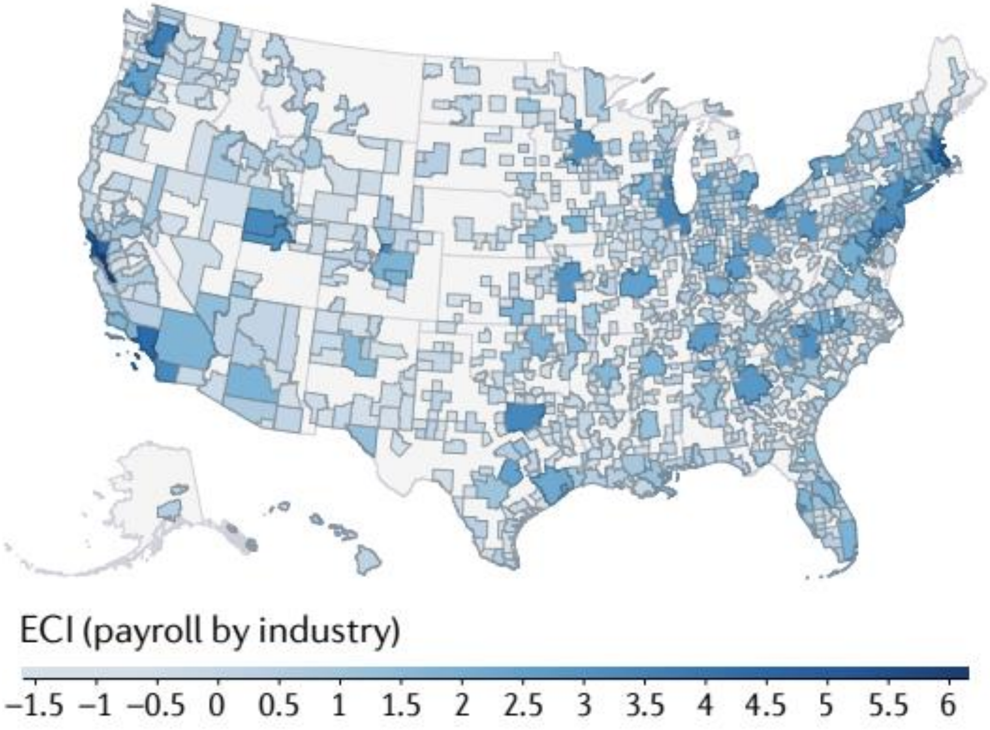
Patterns of specialization and economic complexity through the lens of universal exhibitions, 1855-1900

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.

b Economic complexity of US MSAs
(industry payroll)



Economic complexity of US MSAs
(patents by technology class)

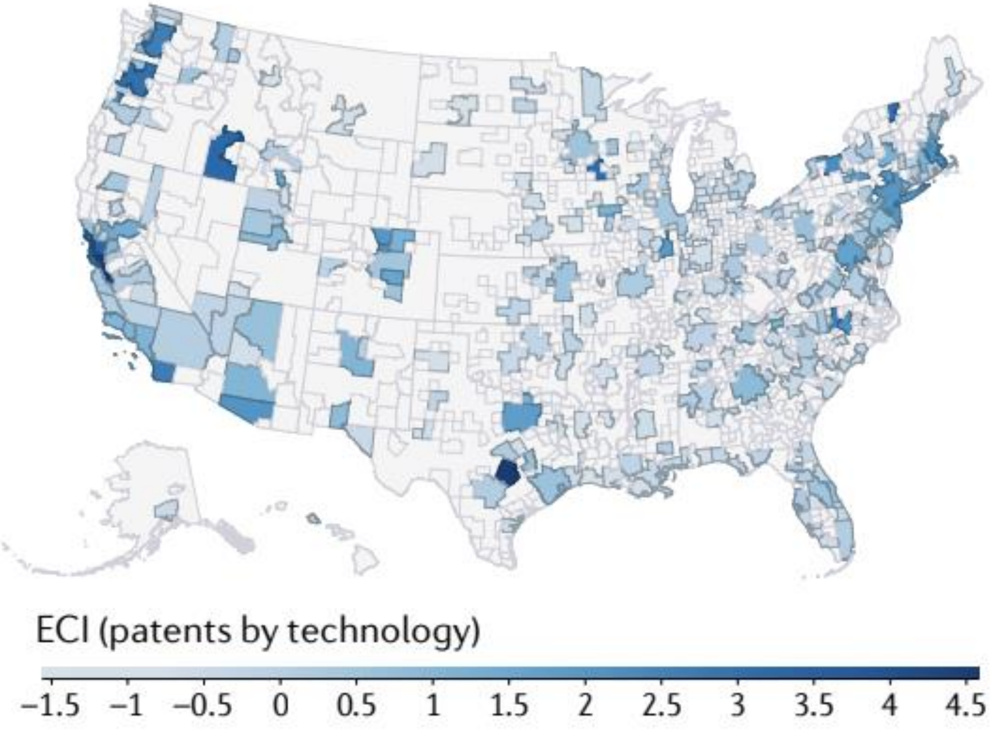
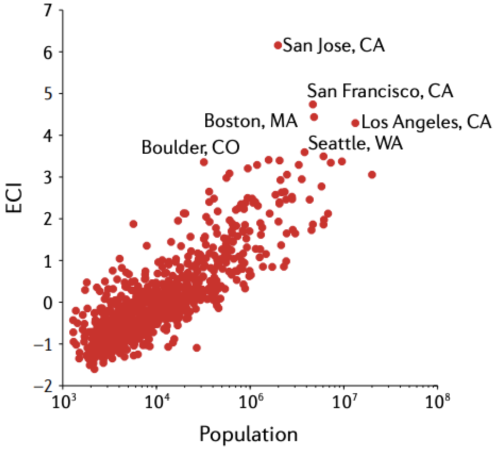


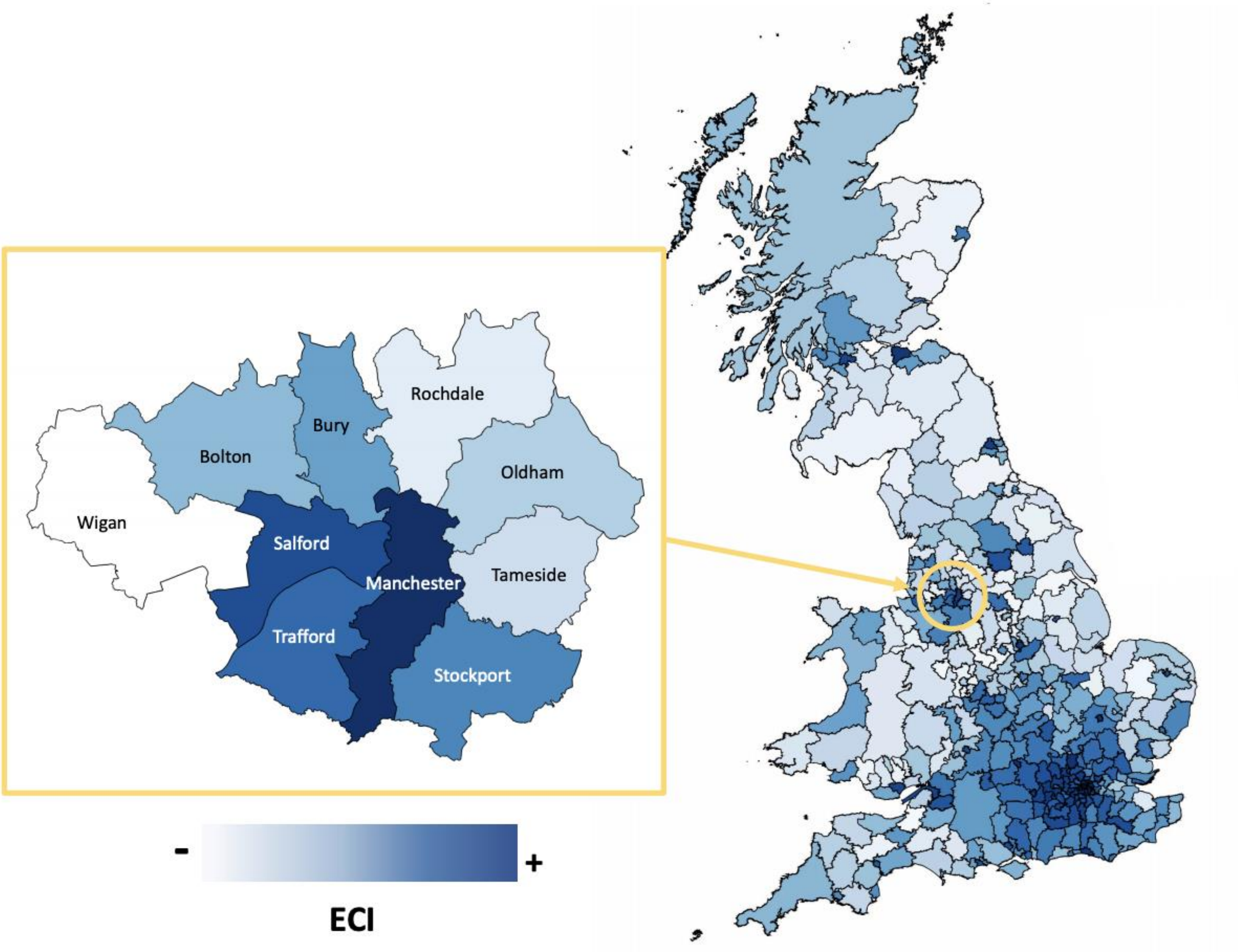
Table 1 | **Rankings of economic complexity**

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



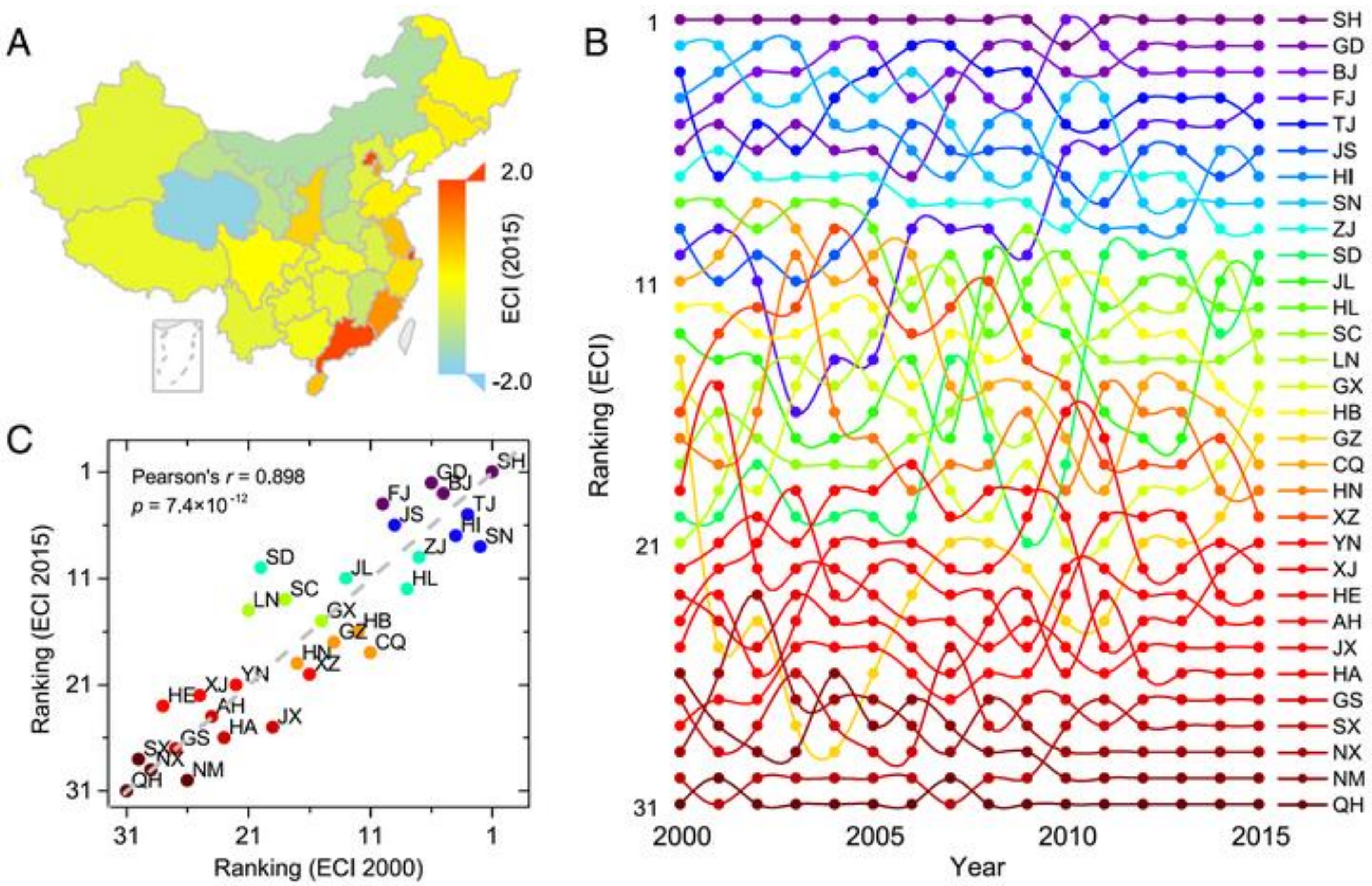
Hidalgo et al. Economic Complexity Theory and Applications. Nature Review Physics (2021)

Economic Complexity of UK Local Authorities by Industry



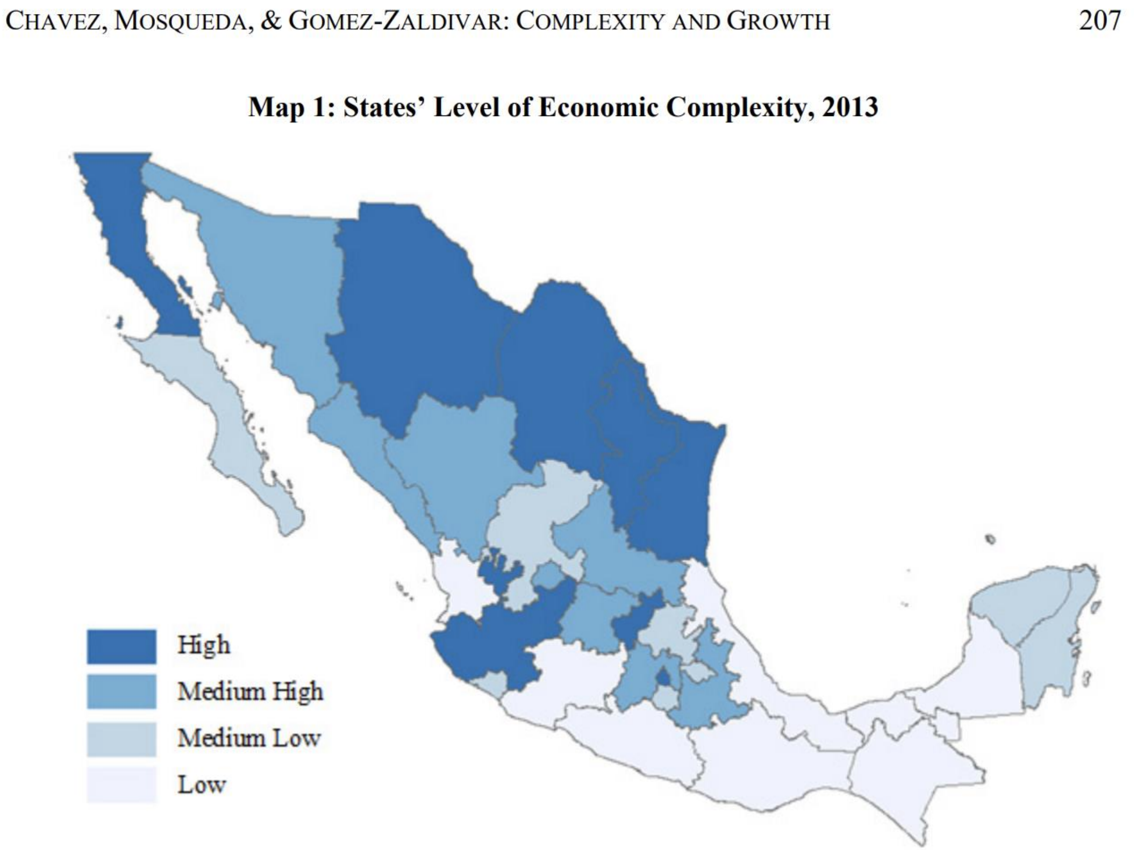
Mealy, Penny, and Diane Coyle. "To them that hath: economic complexity and local industrial strategy in the UK." *International Tax and Public Finance* (2021): 1-20.

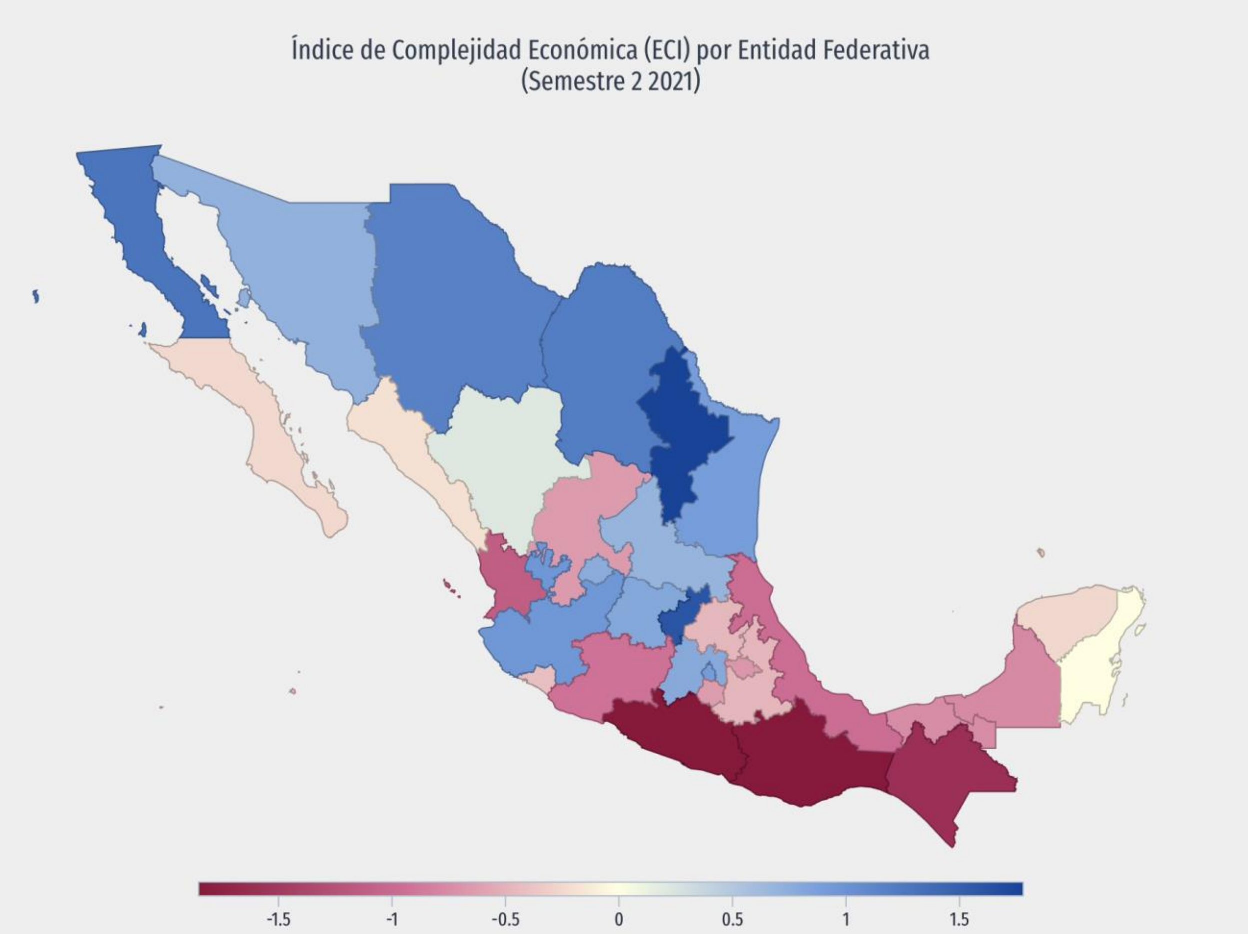
Economic Complexity of Chinese Provinces Using Data on Publicly Listed Firms



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

DataMexico.org

Economic Complexity Explains Variations in Income Inequality

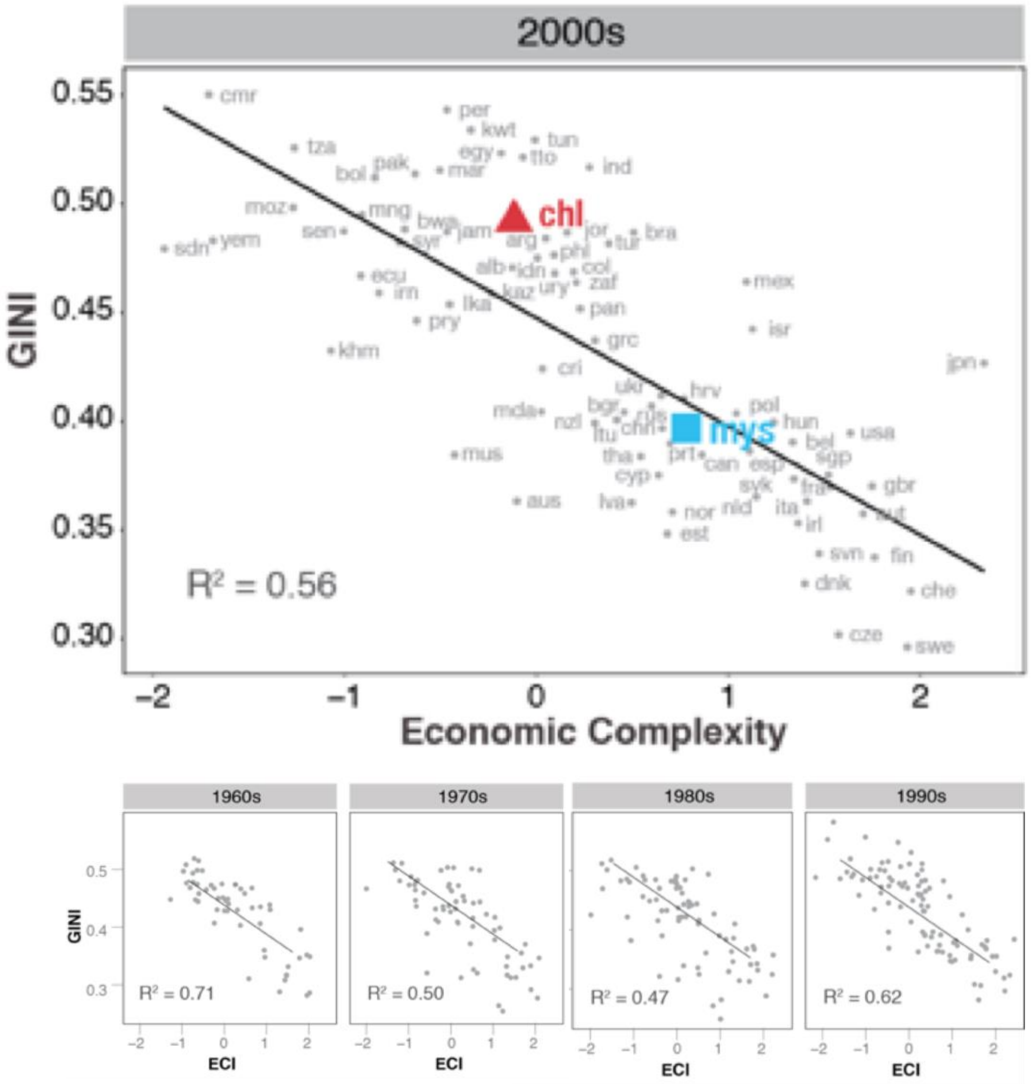


Table 10. *Cross-section regression results*

	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

João P. Romero [a,*], Camila Gramkow [b,1]

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[b] United Nations Economic Commission for Latin America and the Caribbean (ECLAC), Brazil and Chile

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 CO_2 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

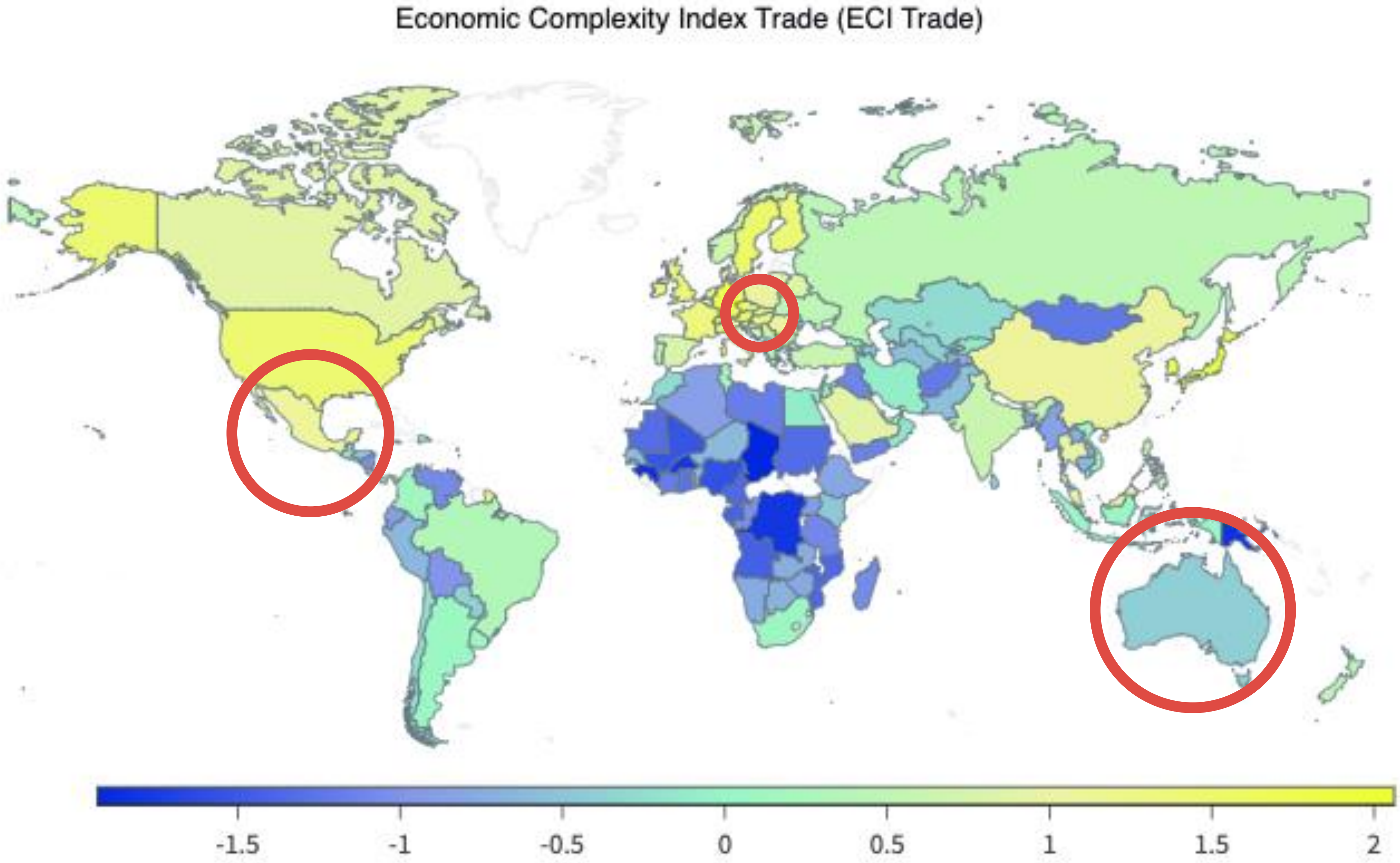
Eirini Boleti, Antonios Garas, Alexandra Kyriakou & Athanasios Lapatinas

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

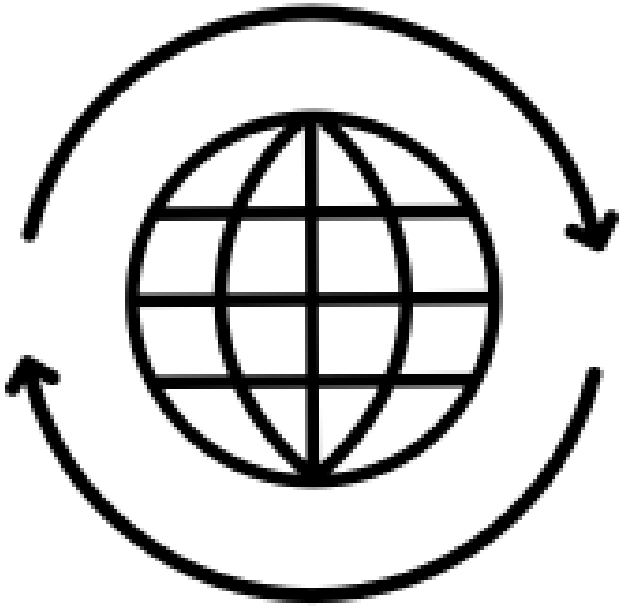
Dependent variable: Environmental Performance Index (EPI). Main independent variable: Economic Complexity Index (ECI). Time fixed effects are included in all regressions. Regional dummies are also included: *europe*, *asia*, *oceania*, *north america*, *south america*. Robust standard errors in parentheses

Limitations of trade ECI

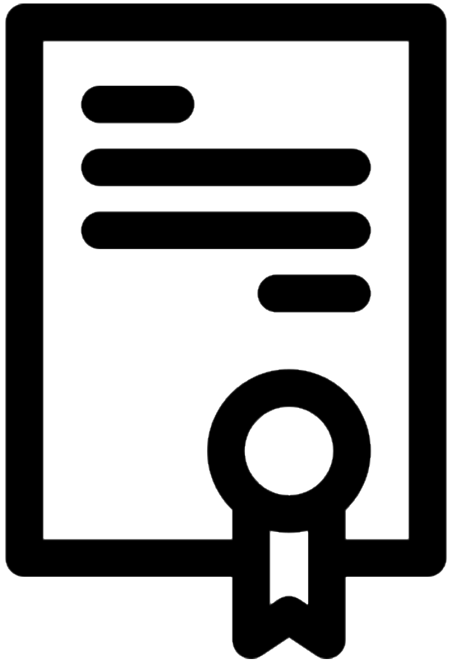


Stojkoski, Viktor, Philipp Koch, and César A. Hidalgo. "Multidimensional economic complexity and inclusive green growth." *Communications Earth & Environment* 4.1 (2023): 130.

Solution: Combine Data from Different Outputs



International Trade

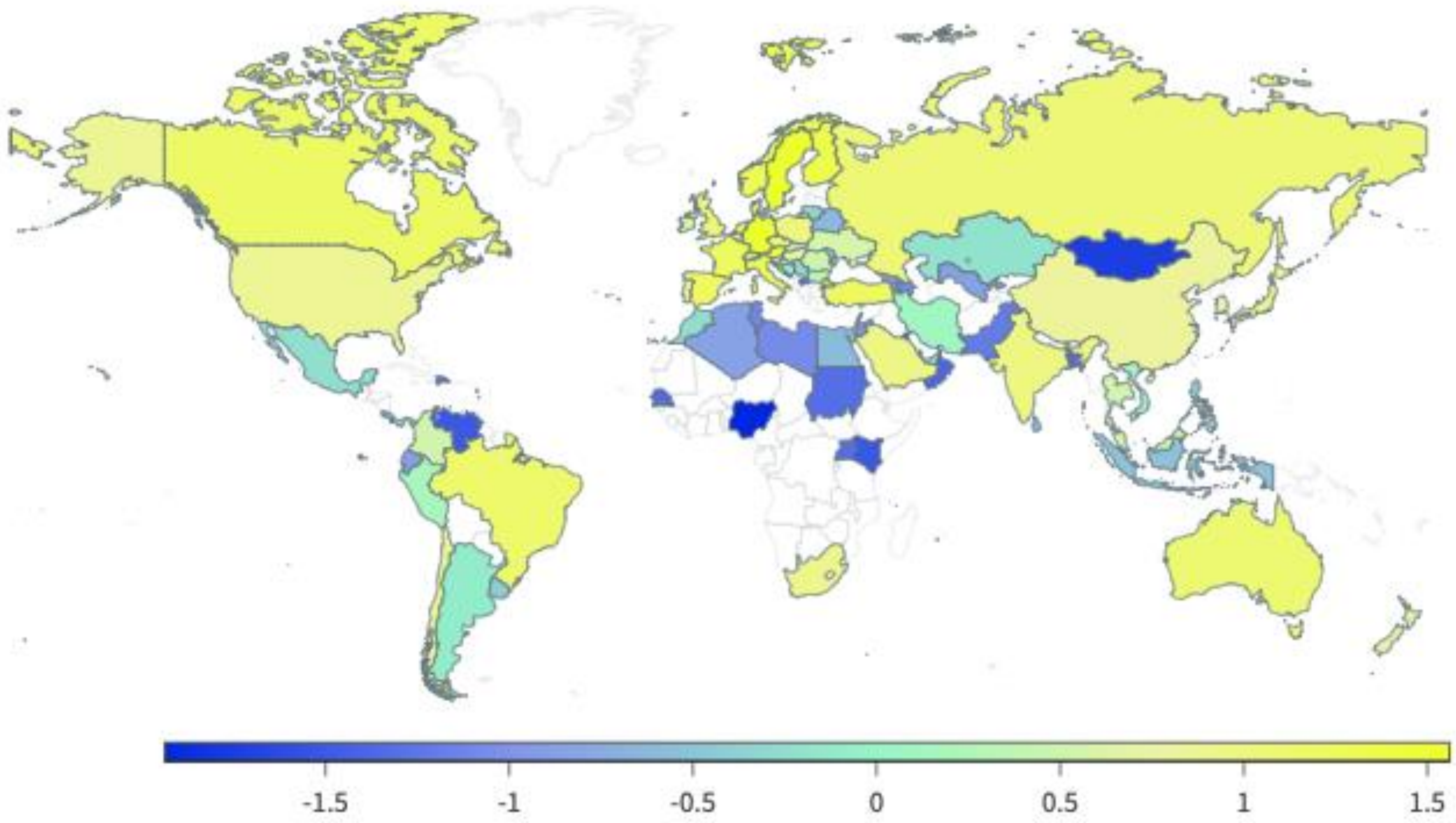


Patents

Research Papers

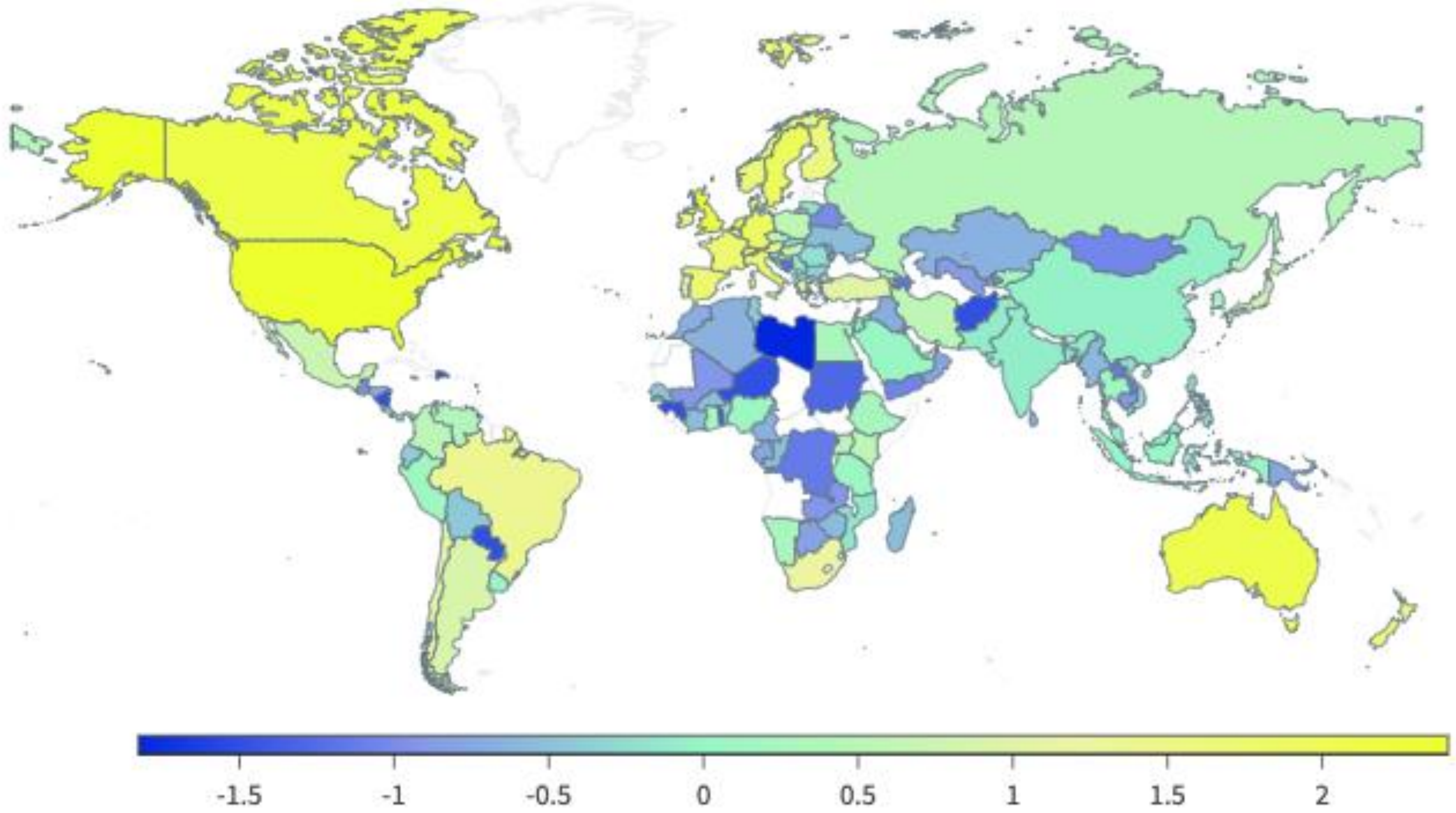
Stojkoski, Viktor, Philipp Koch, and César A. Hidalgo. "Multidimensional economic complexity and inclusive green growth." *Communications Earth & Environment* 4.1 (2023): 130.

Economic Complexity Index Technology (ECI Technology)

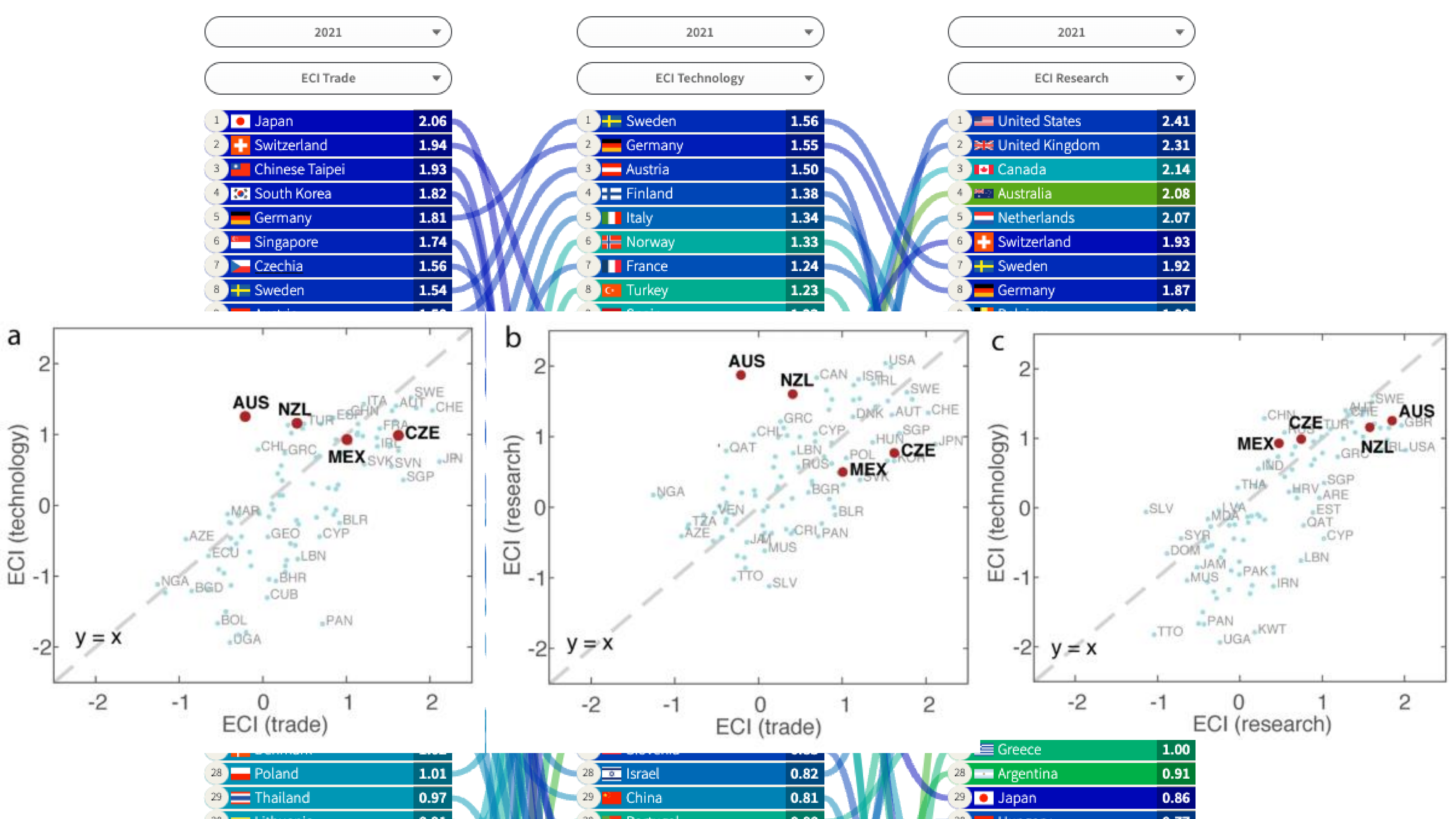


Stojkoski, Viktor, Philipp Koch, and César A. Hidalgo. "Multidimensional economic complexity and inclusive green growth." *Communications Earth & Environment* 4.1 (2023): 130.

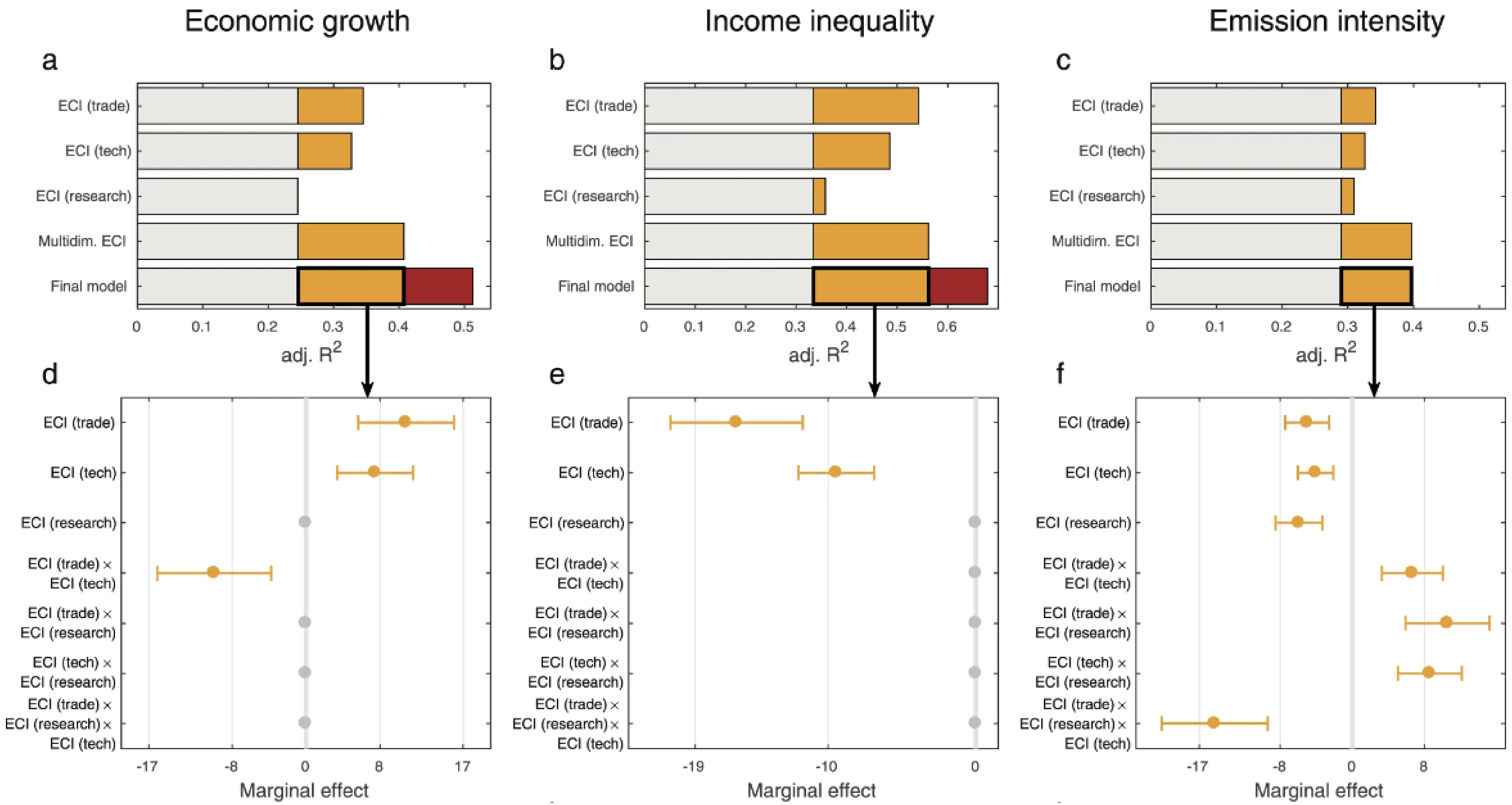
Economic Complexity Index Research (ECI Research)



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



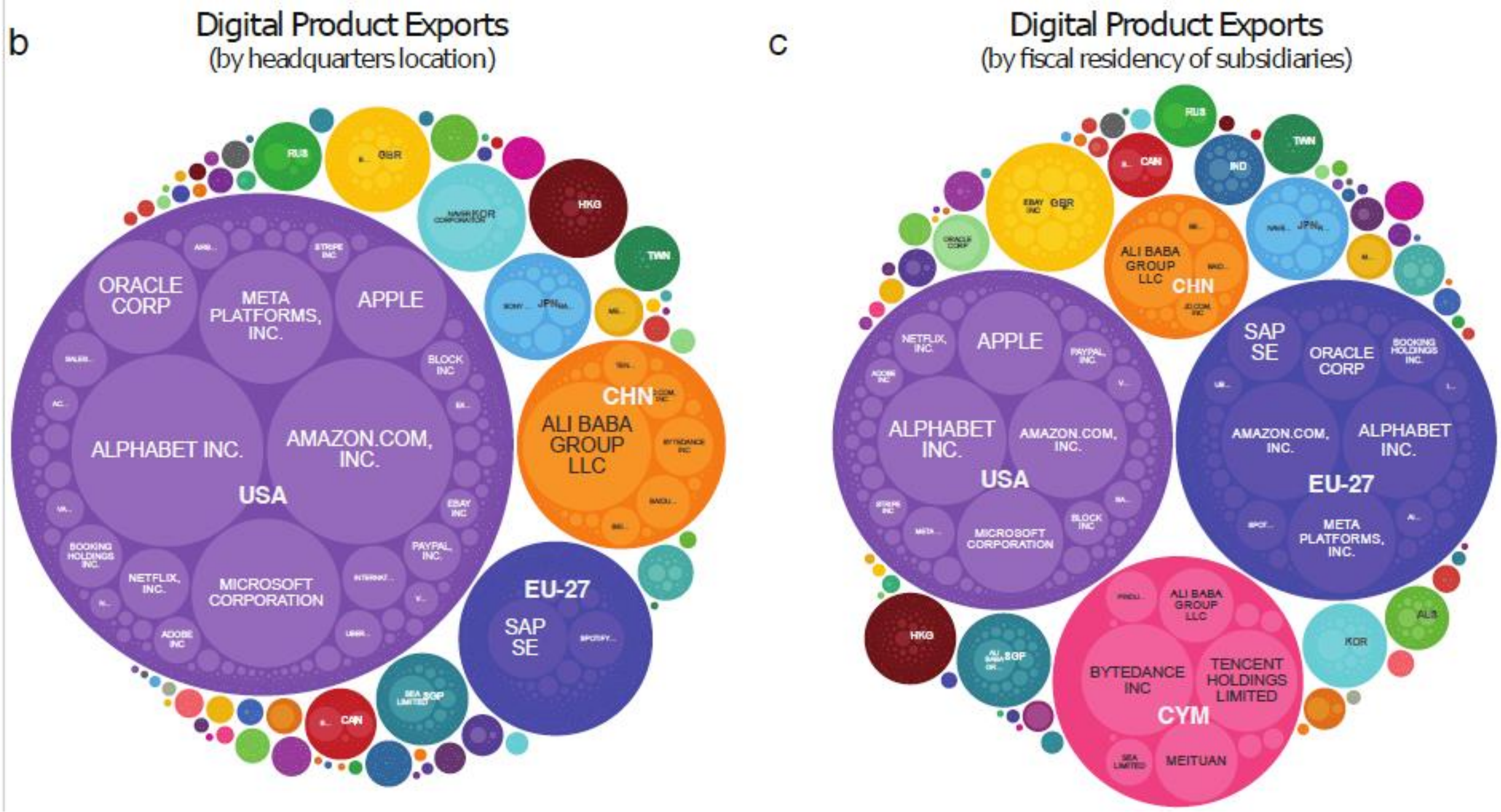
2021
ECI Trade
1 Japan 2.06
2 Switzerland 1.94
3 Chinese Taipei 1.93
4 South Korea 1.82
5 Germany 1.81
6 Singapore 1.74
7 Czechia 1.56
8 Sweden 1.54
28 Poland 1.01
29 Thailand 0.97
2021
ECI Technology
1 Sweden 1.56
2 Germany 1.55
3 Austria 1.50
4 Finland 1.38
5 Italy 1.34
6 Norway 1.33
7 France 1.24
8 Turkey 1.23
28 Israel 0.82
29 China 0.81
2021
ECI Research
1 United States 2.41
2 United Kingdom 2.31
3 Canada 2.14
4 Australia 2.08
5 Netherlands 2.07
6 Switzerland 1.93
7 Sweden 1.92
8 Germany 1.87
Greece 1.00
28 Argentina 0.91
29 Japan 0.86
a
ECI (technology)
ECI (trade)
AUS
NZL
MEX
CZE
y = x
b
ECI (research)
ECI (trade)
AUS
NZL
MEX
CZE
y = x
c
ECI (technology)
ECI (research)
AUS
NZL
MEX
CZE
y = x



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

Economic complexity:
A telescope for the past & the future

Digital Product Trade



Viktor Stojkoski, Koch, Philipp, Eva Coll and César A. Hidalgo. "The Geography of Digital Trade" Forthcoming Nature Communications (2024)

Digital Trade is Growing Fast

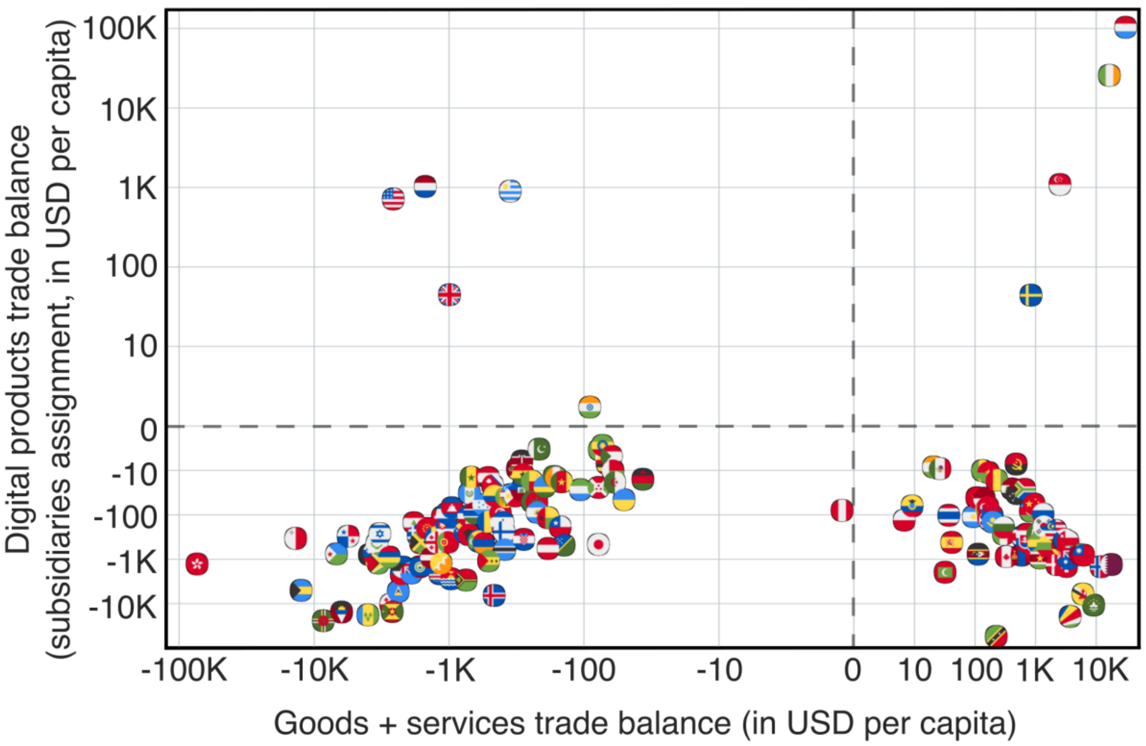
25% CAGR | 8% CAGR | 4% CAGR | 6% CAGR

Viktor Stojkoski, Koch, Philipp, Eva Coll and César A. Hidalgo. "The Geography of Digital Trade" Forthcoming Nature Communications (2024)

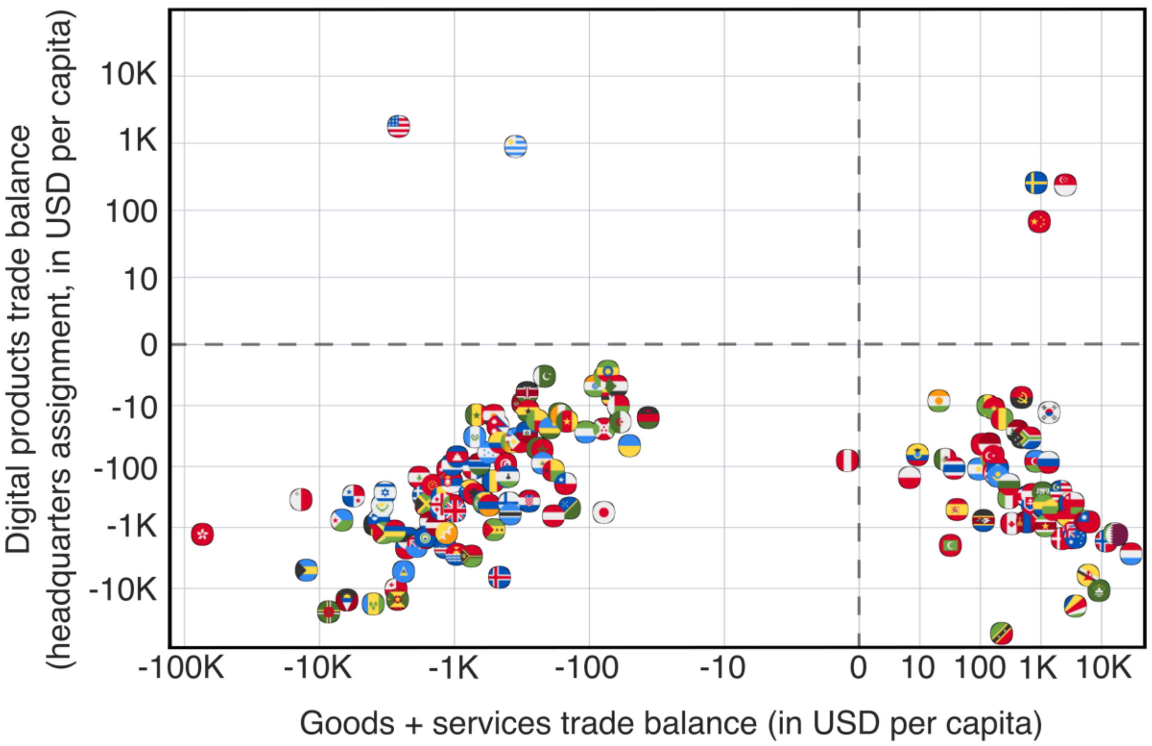
a
Digital products
b
DDS
c
Services
d
Goods
Eigenvector centrality
0
0.1
0.2
USA
IRL
CHN
JPN
GBR
DEU
LUX
NLD
SWE
KOR
CAN
SGP
MEX
AUS
FRA
IND
CHE
TWN
VNM
Digital products
DDS
Services
Goods
Asia
Oceania
Americas
Europe
Africa

It help us revisit trade balances

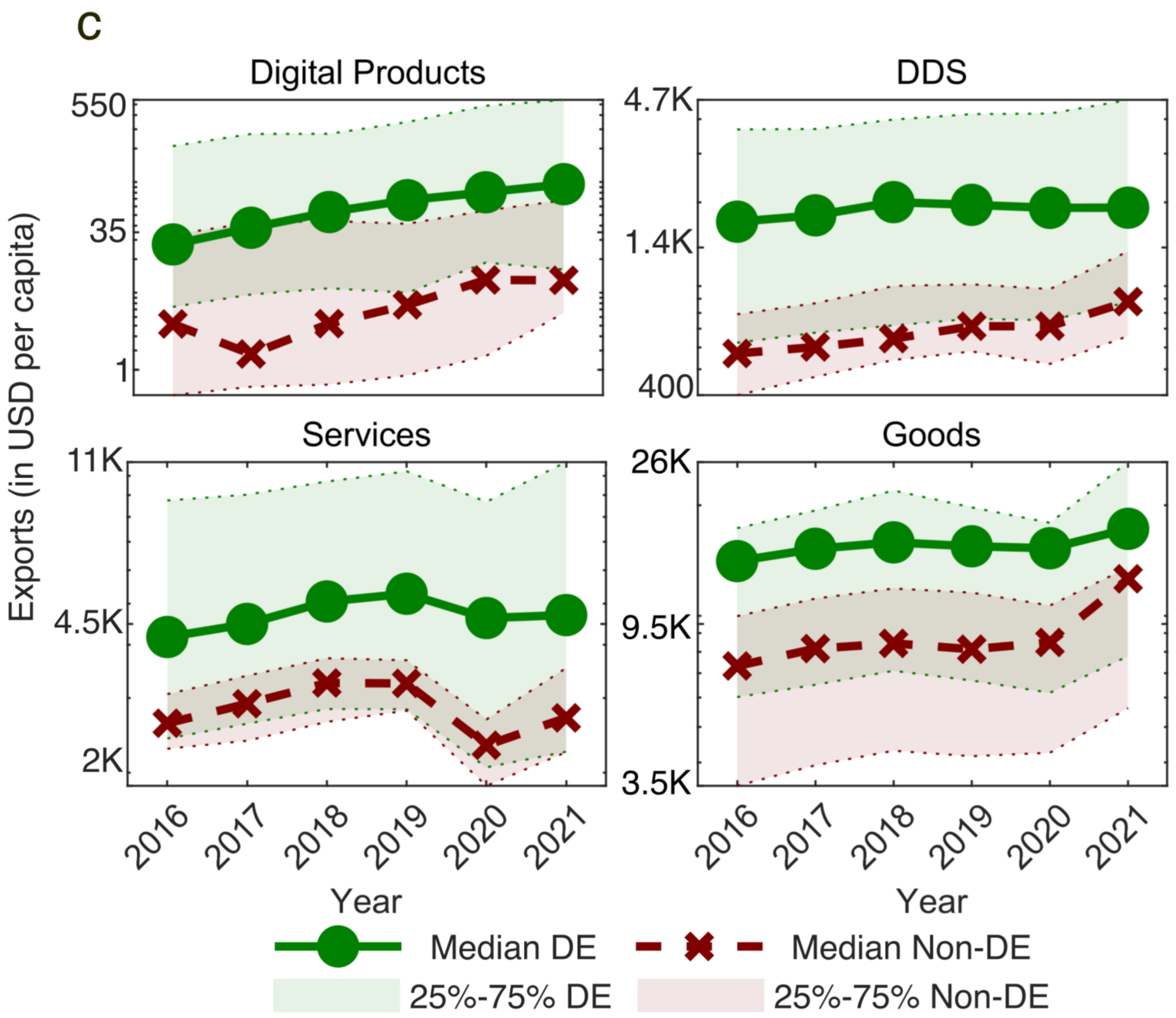
a



b

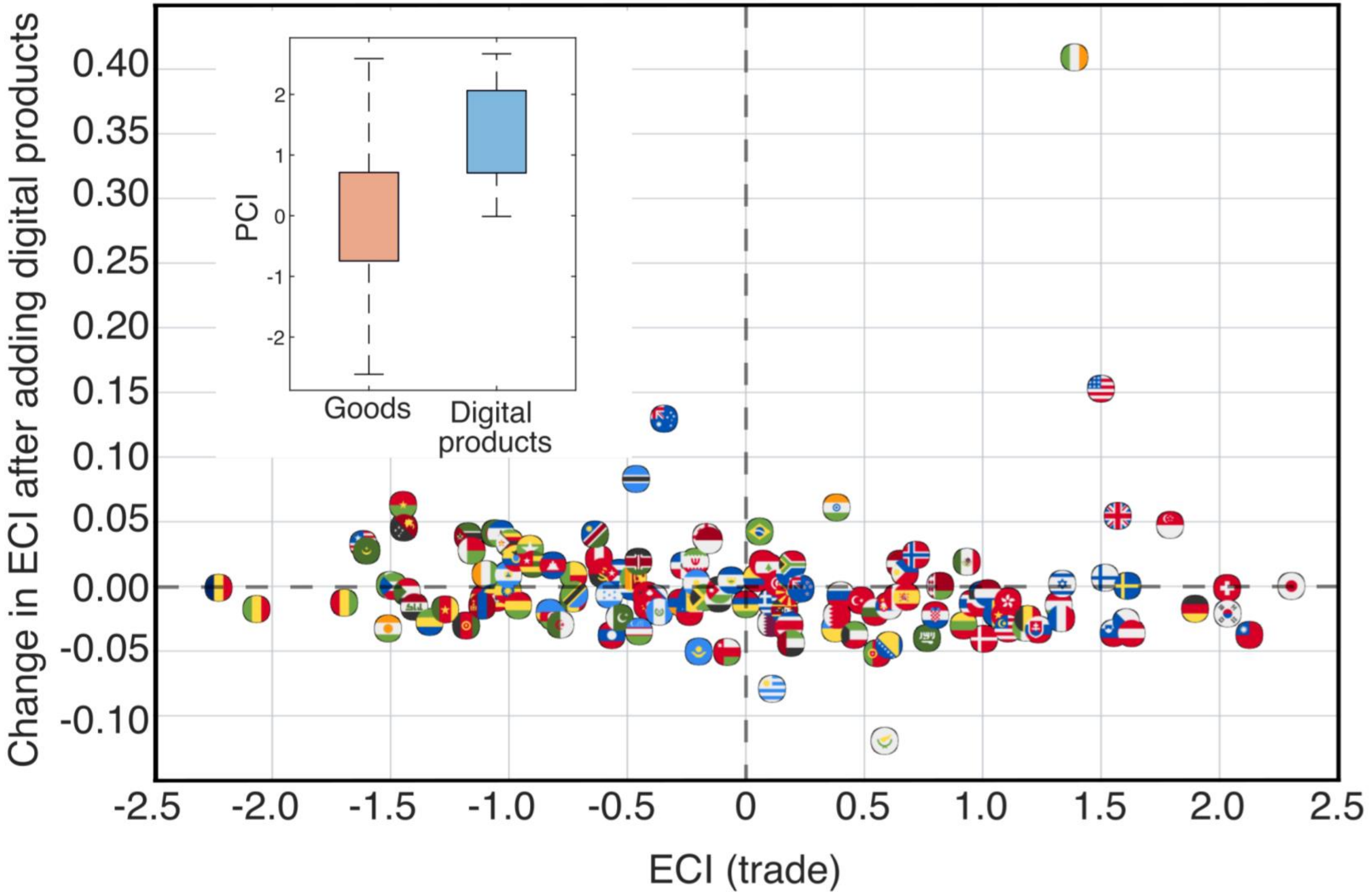


It is correlated with decoupling

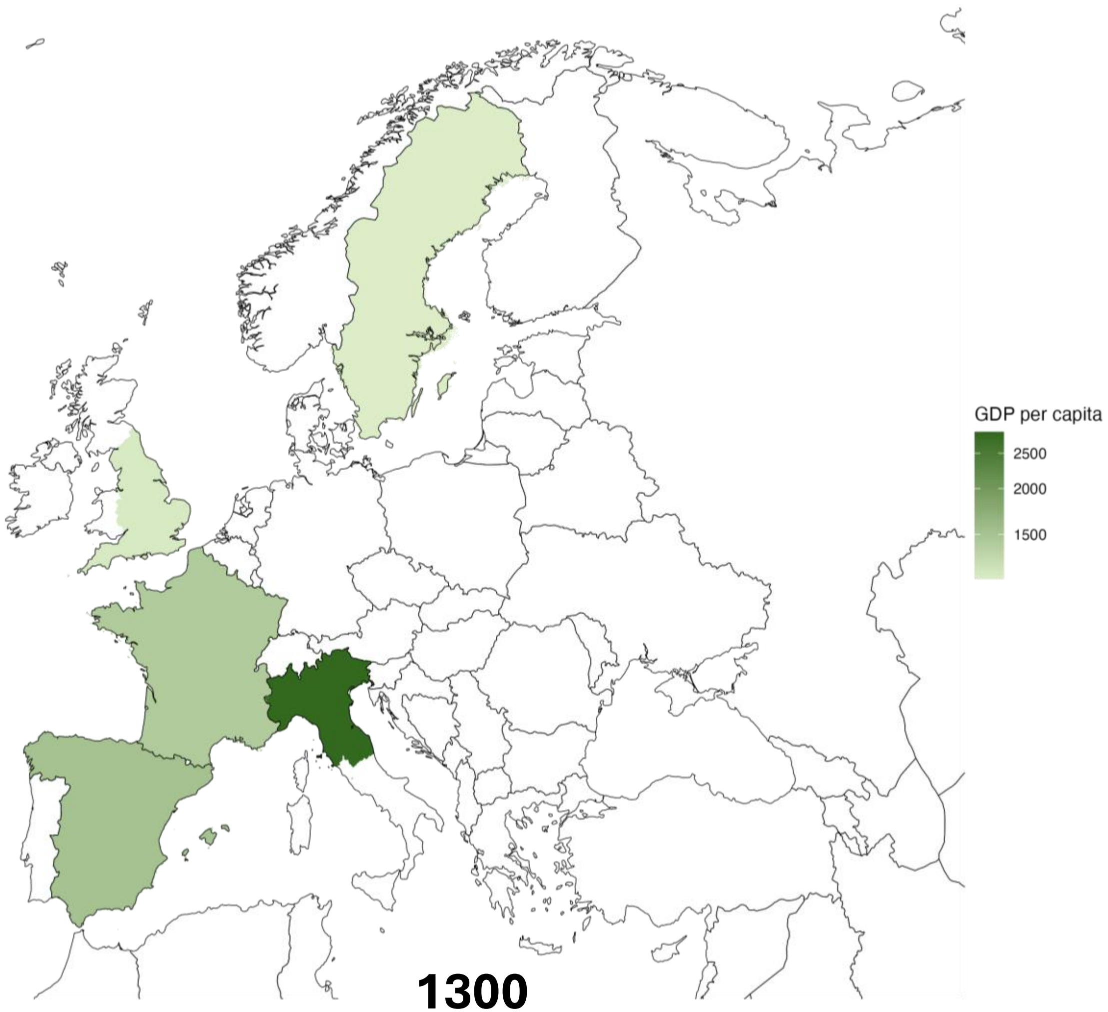


And it involves high complexity sectors

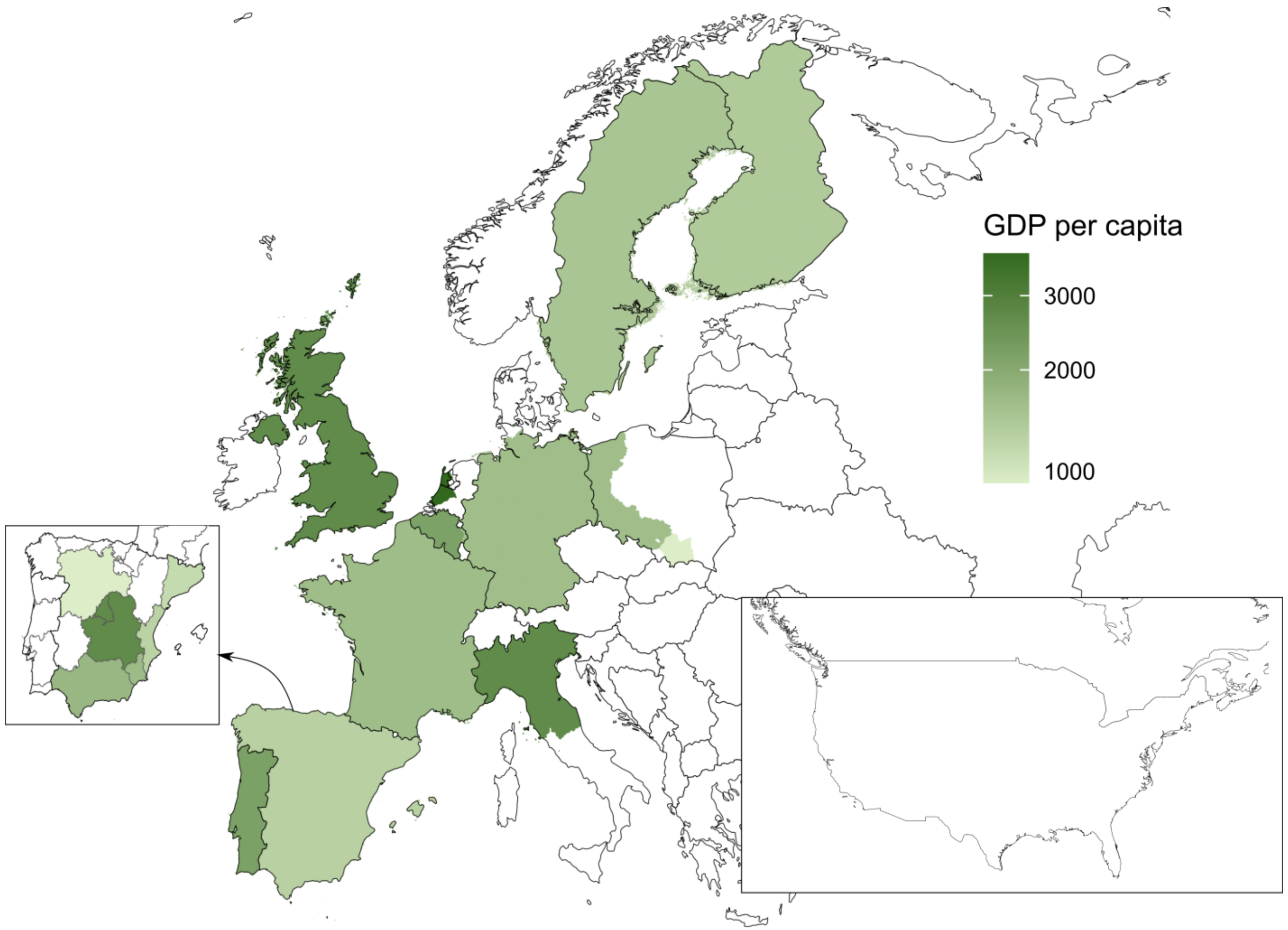
d



Estimating Historical GDPpc



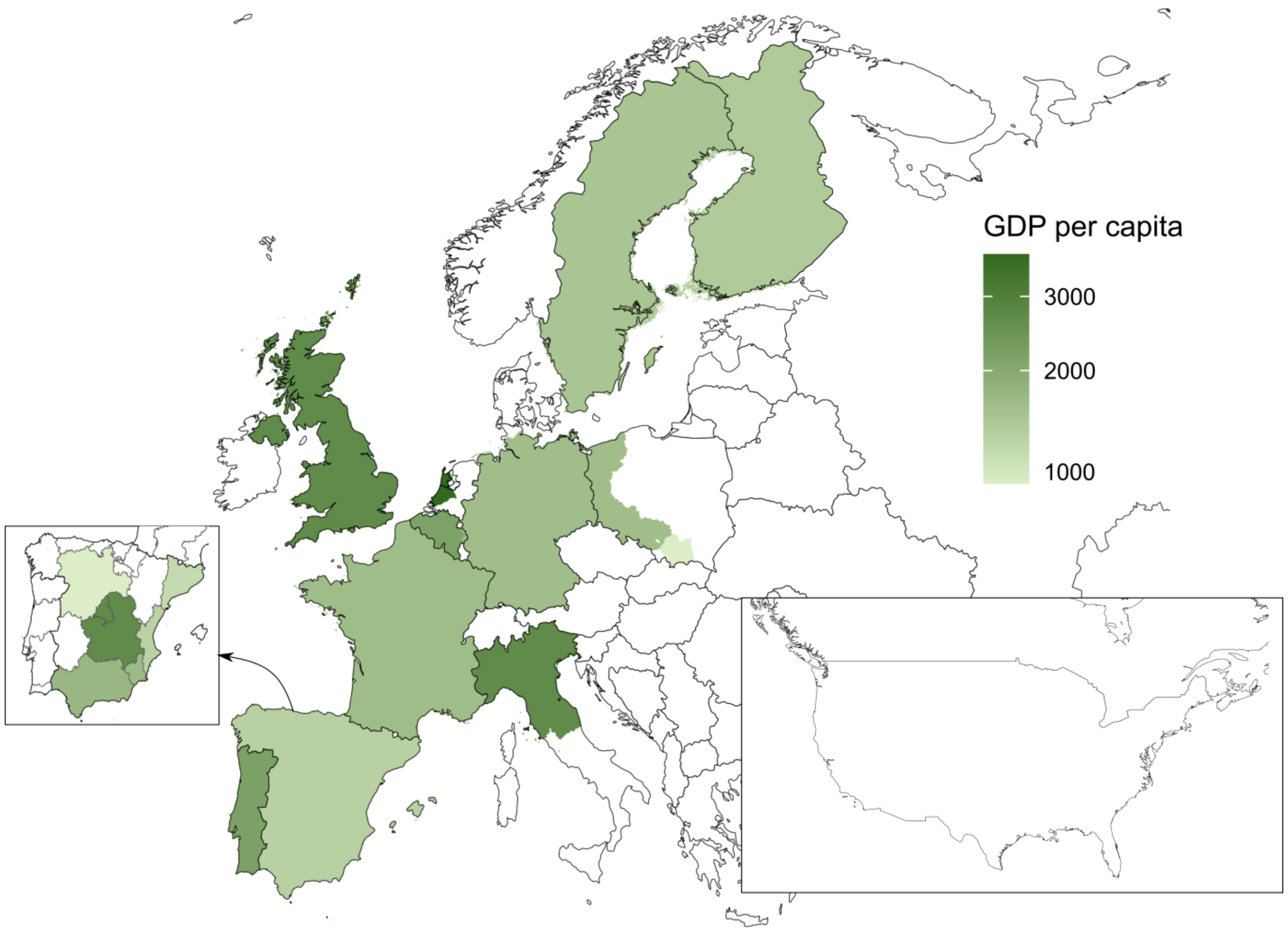
1300
Maddison project



1750
Maddison project

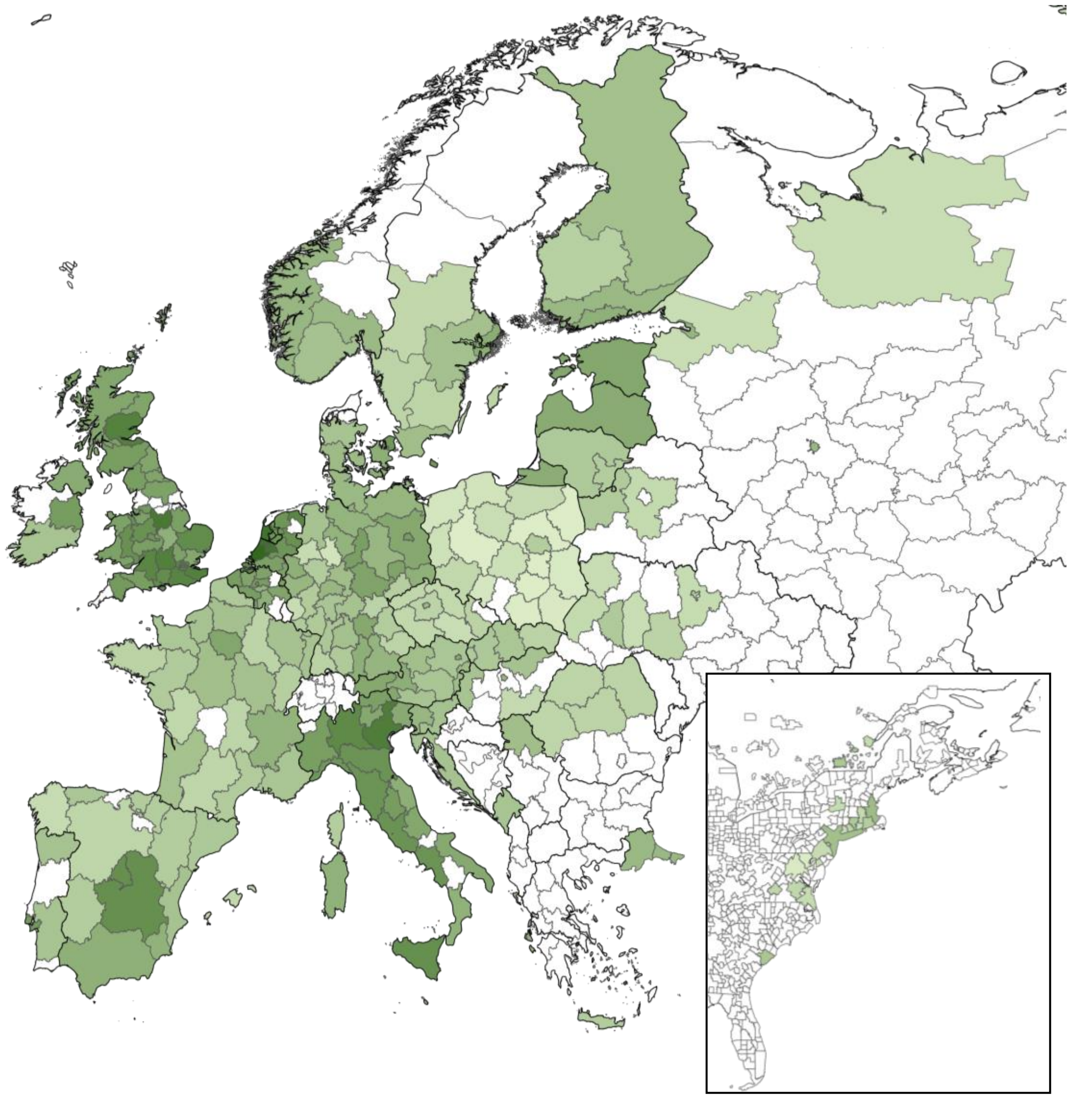
Koch, Stojkoski, Hidalgo (2024)

Getting from here…



1750
Maddison project

… to here



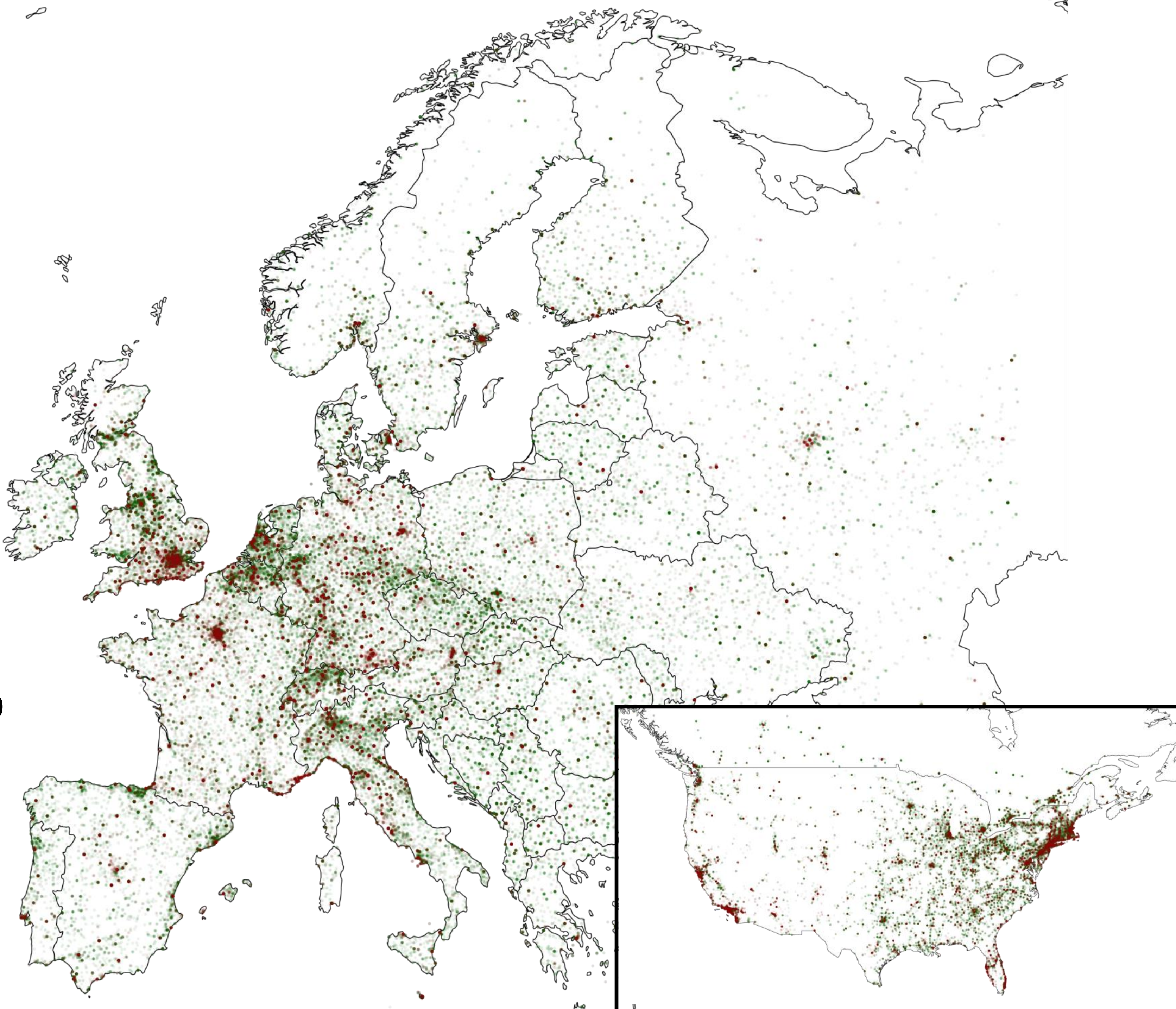
1750
Koch et al.

Data

Data on 2 million+ famous individuals from Wikipedia[9], including their geocoded places of birth and death as well as their occupation.

Looking at continental Europe and North America between 1300 and 2000 (and only using individuals with at least 2 language editions and an identifiable occupation), we end up using data on ~561k famous individuals assigned to one of 49 occupations.

Koch, Stojkoski, Hidalgo (2024)

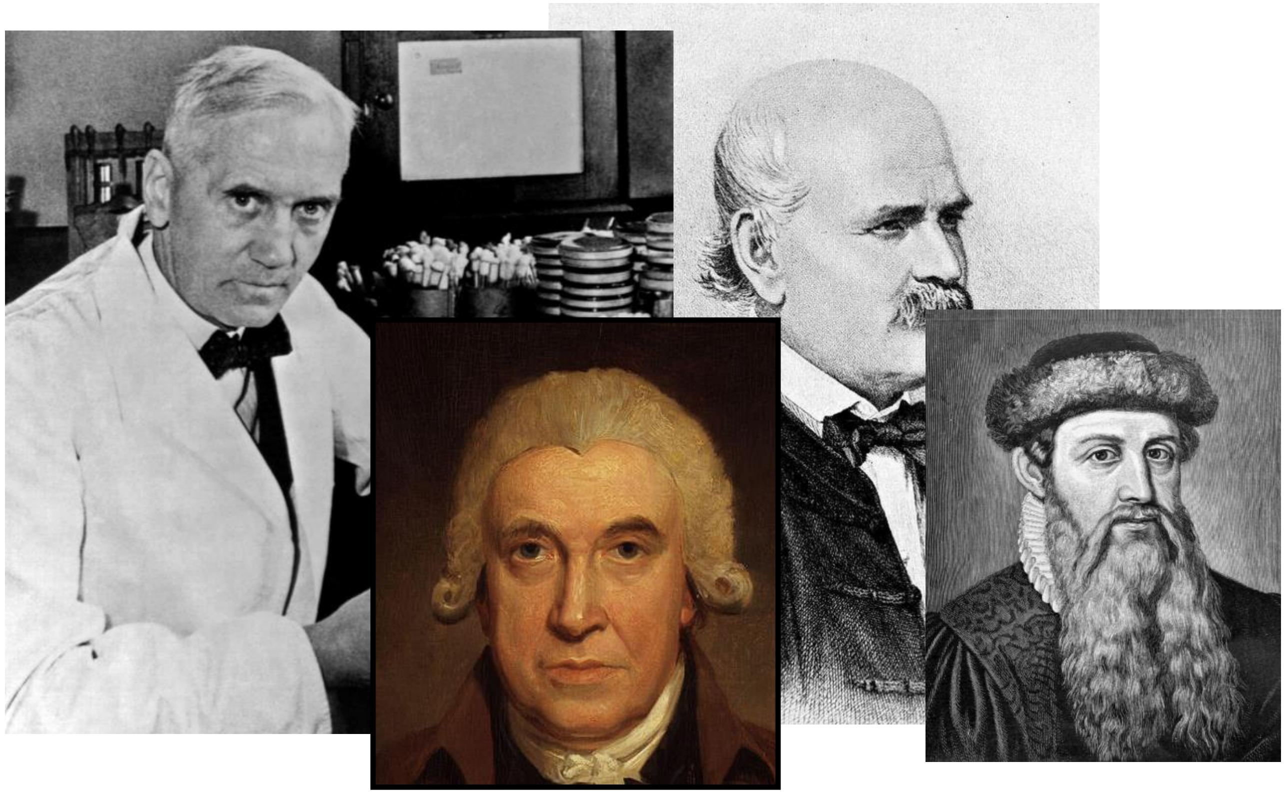


Why biographies?

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



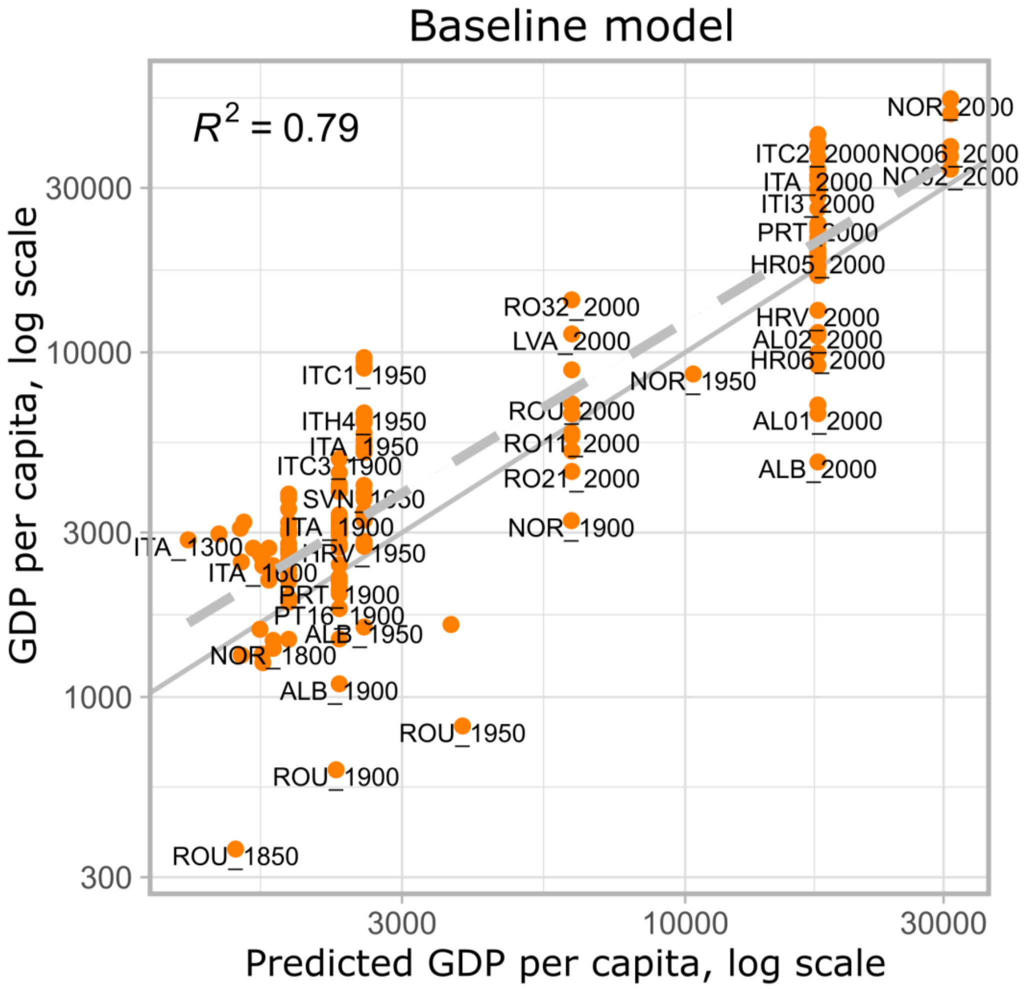
Indirect

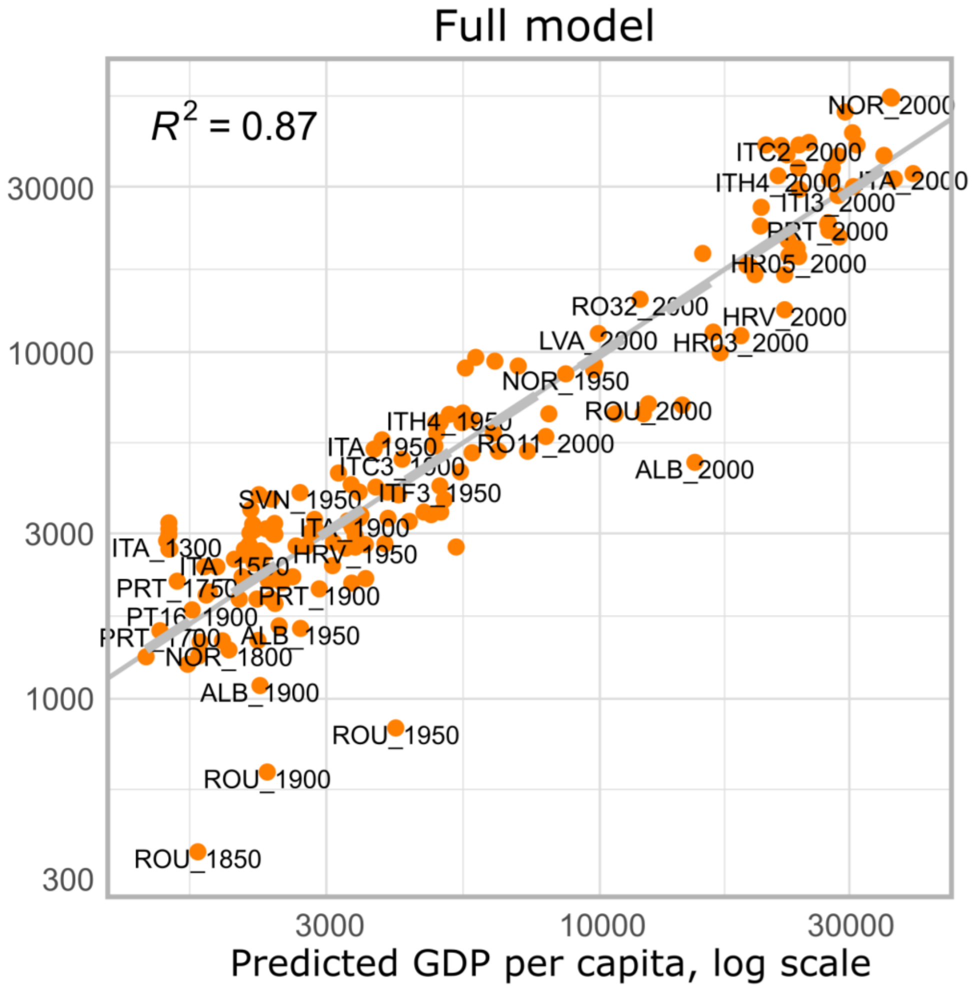
Model

Regularized Elastic Net

Leave 20% out-of-sample cross validation

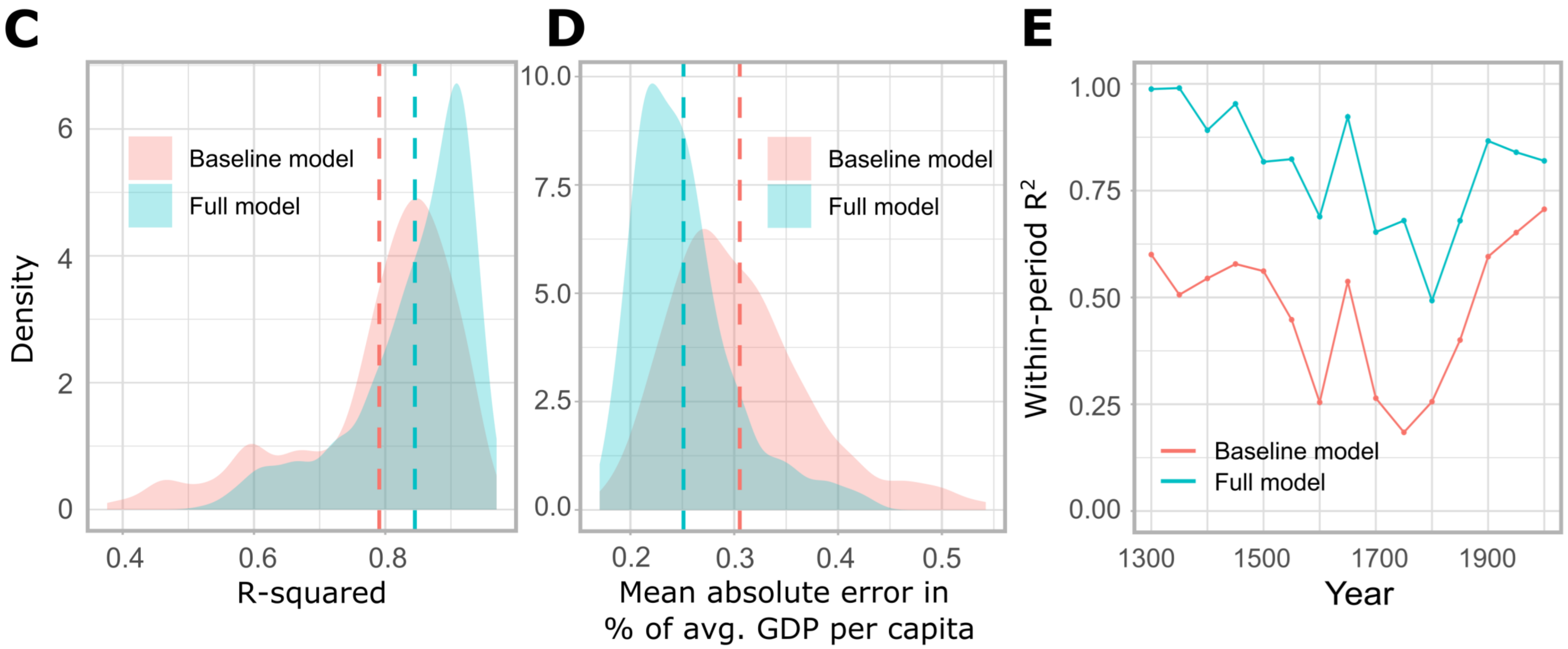
$$\widehat{\beta_{EN}} = min_{\beta}(\|y - X\beta\|^2 + \lambda[(1-\alpha)\|\beta\|_2^2 + \alpha\|\beta\|_1])$$





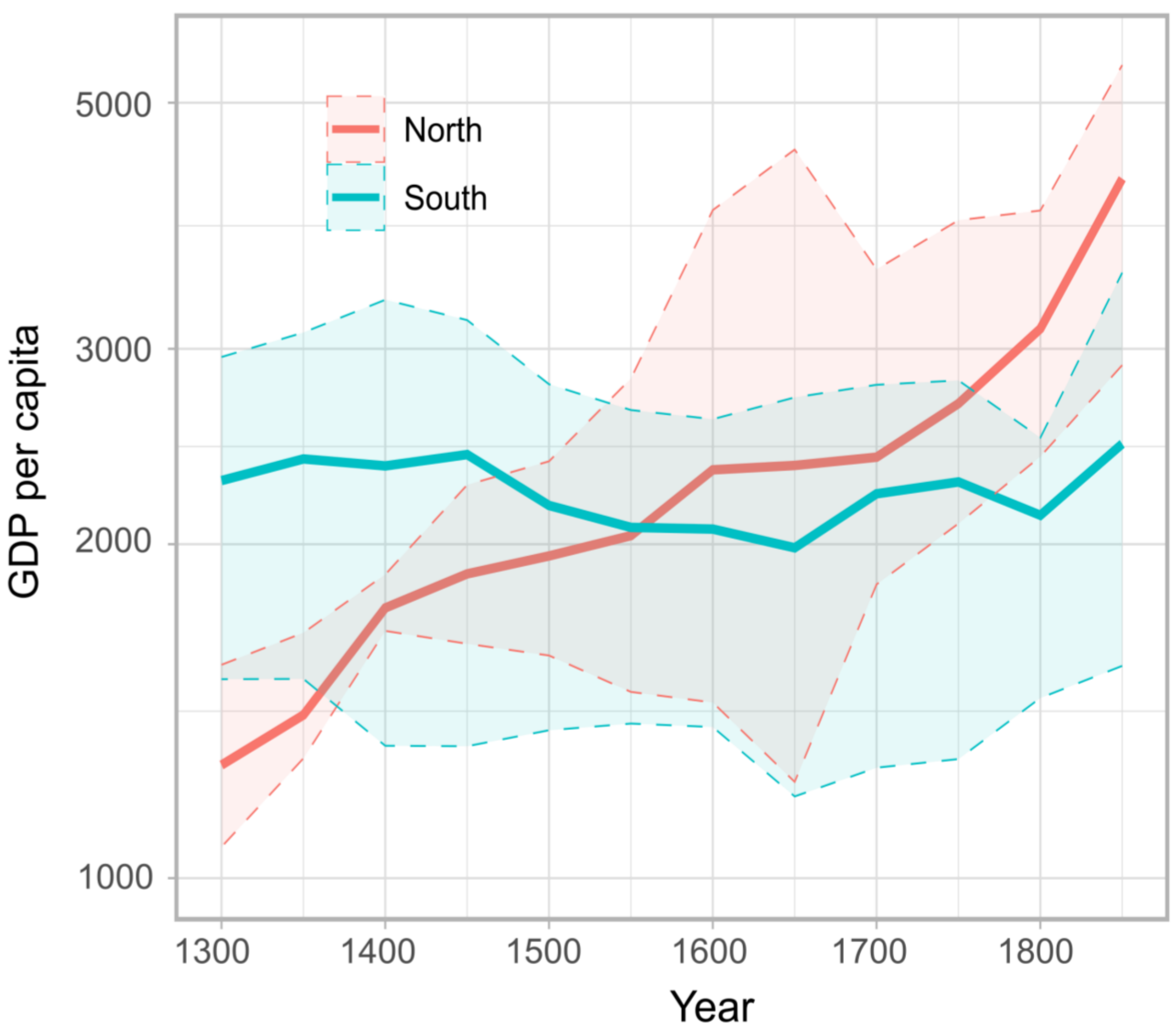
Model

Model performance



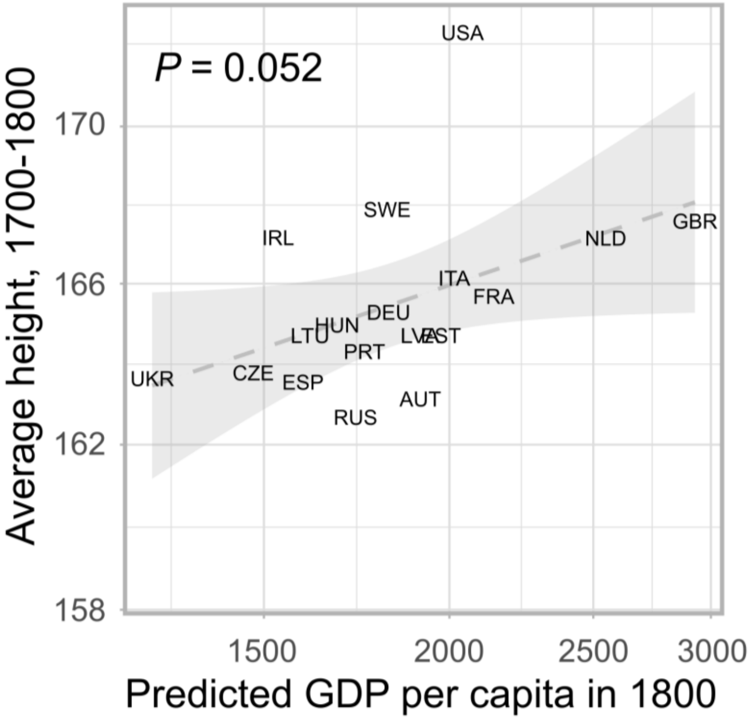
Validation - Little Divergence

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.

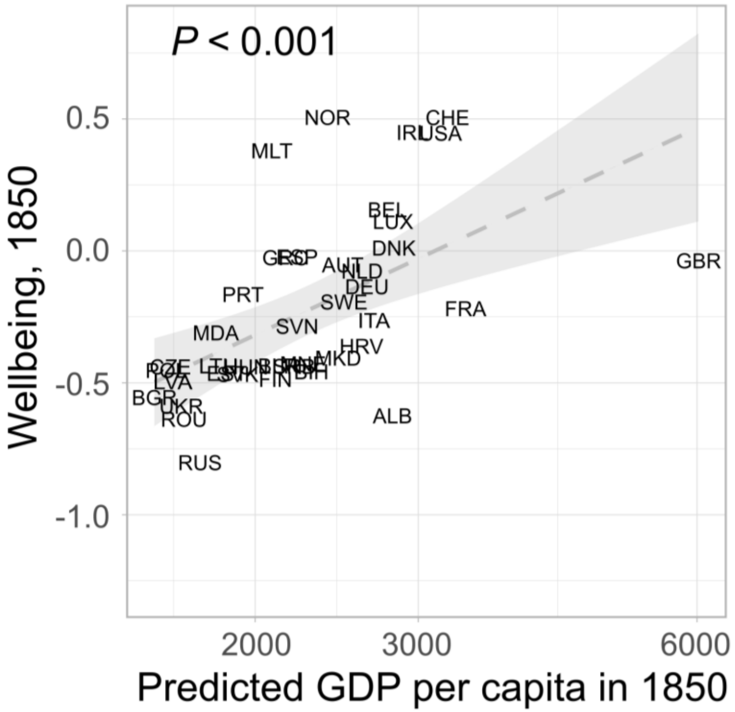


Validation - proxies of economic development

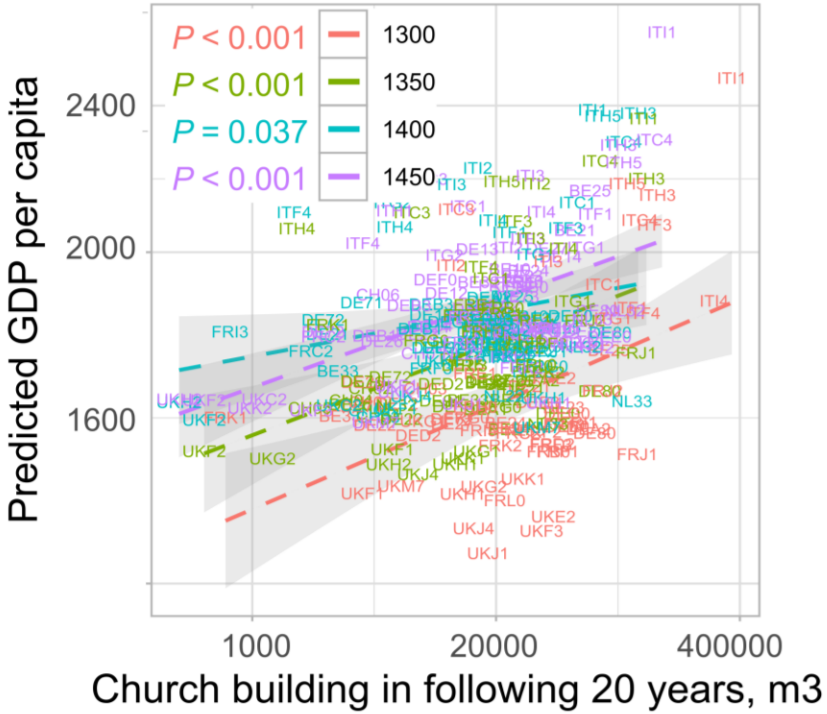
Body height in the 18th century



OECD Wellbeing indicator in 1850

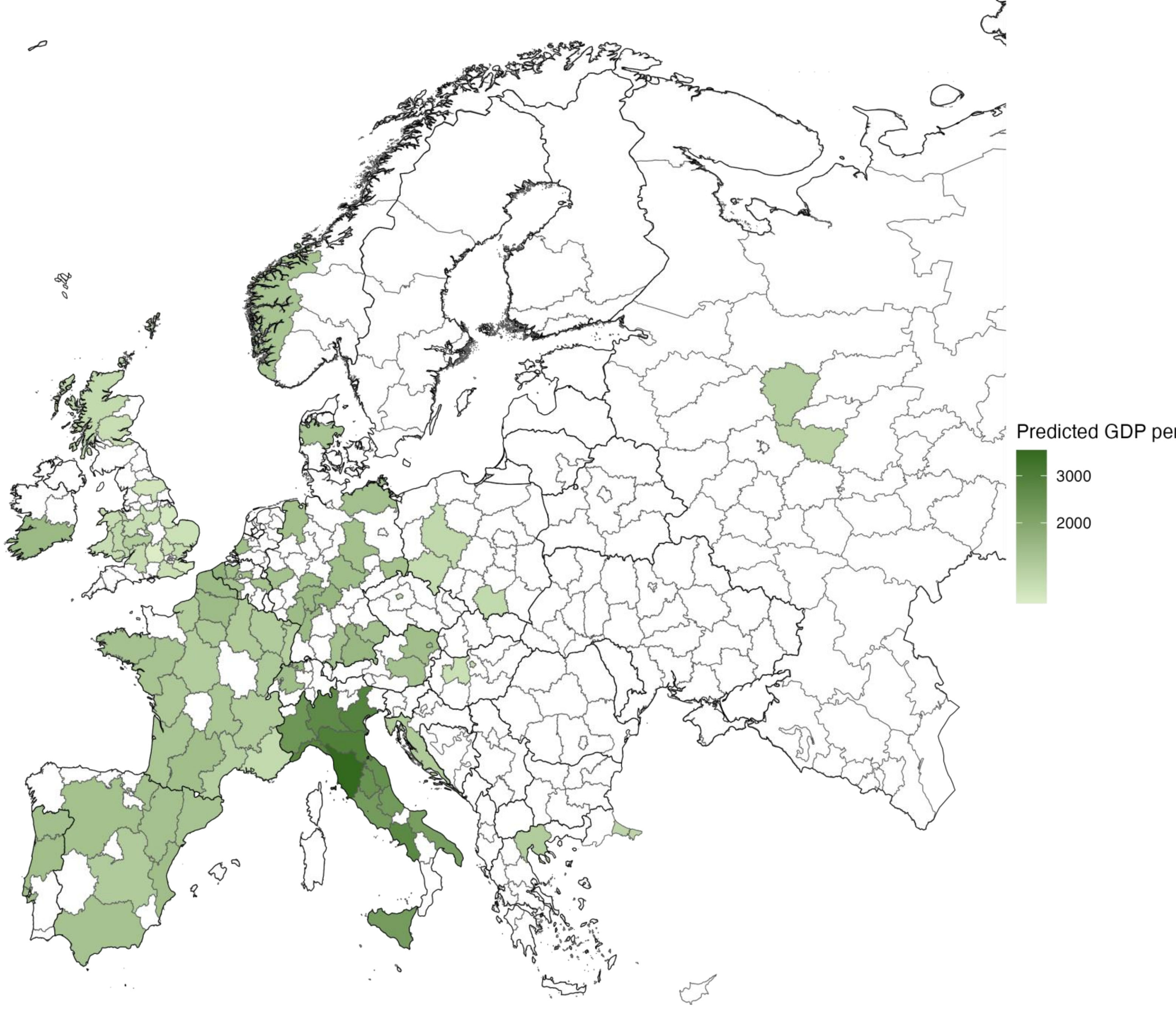


City-level church building activity

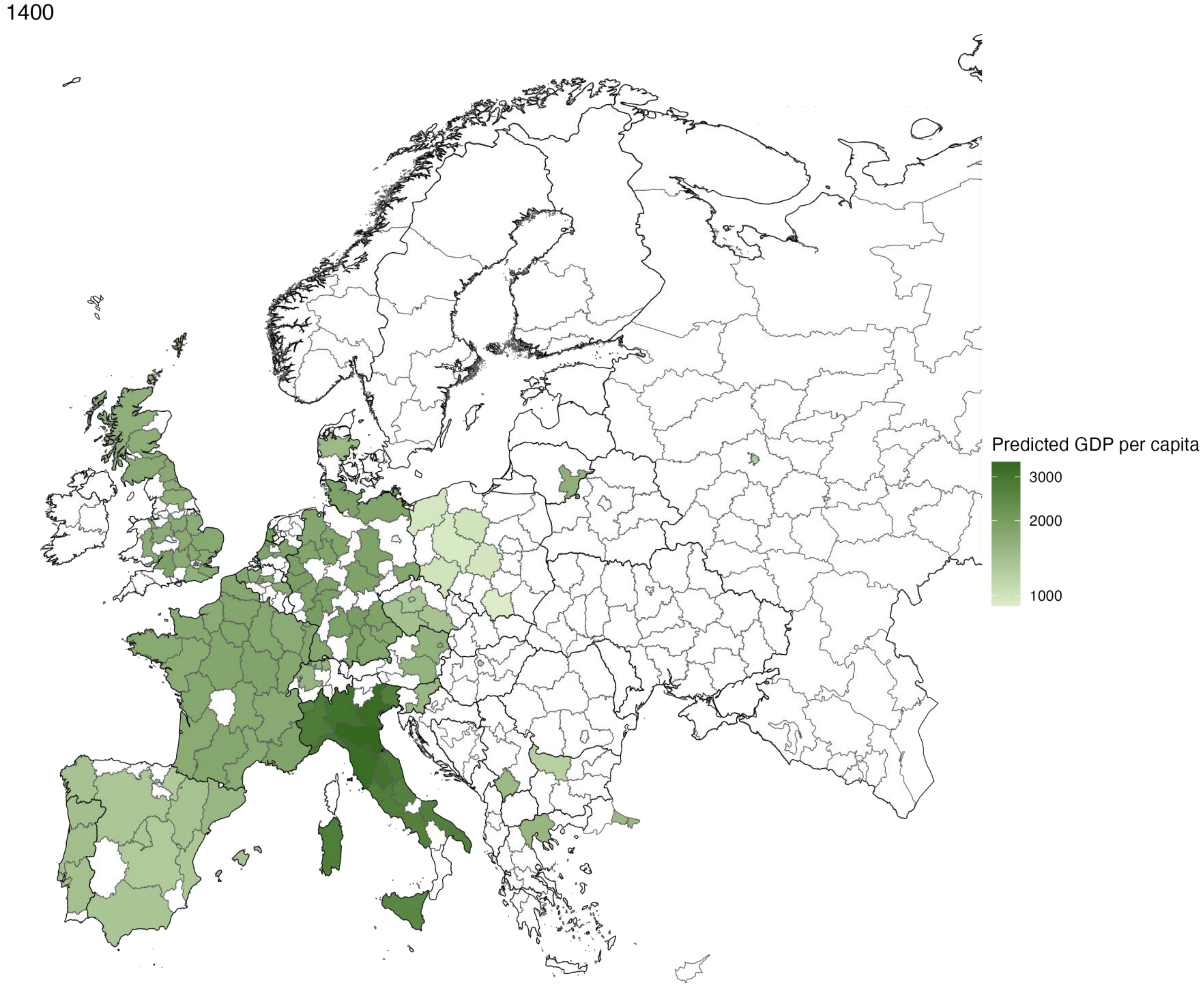


Results 1300

Our approach also allows for regional estimates of historical GDP per capita levels. Which regions in Europe had the highest per capita income levels in e.g. 1300?



1400



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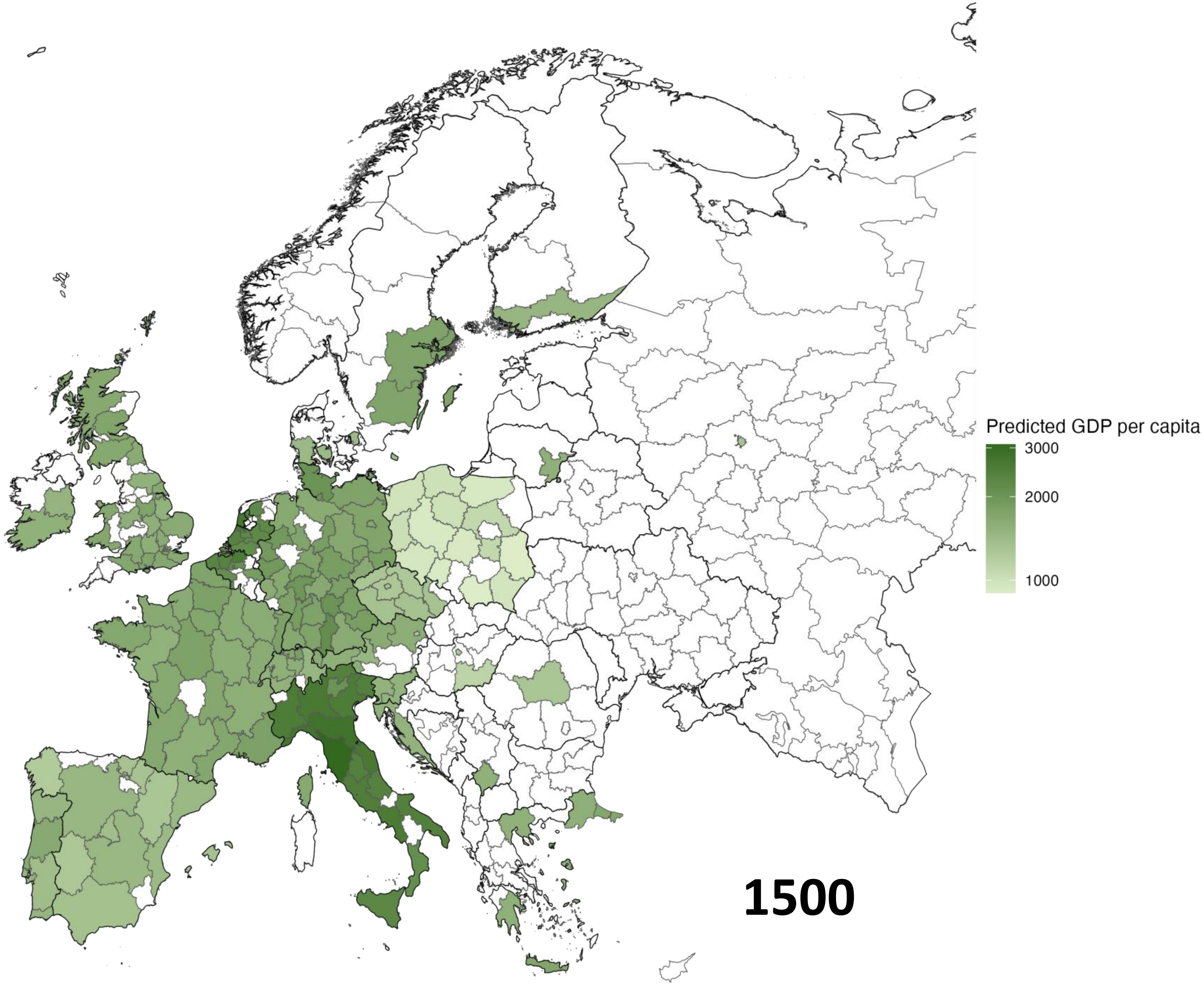

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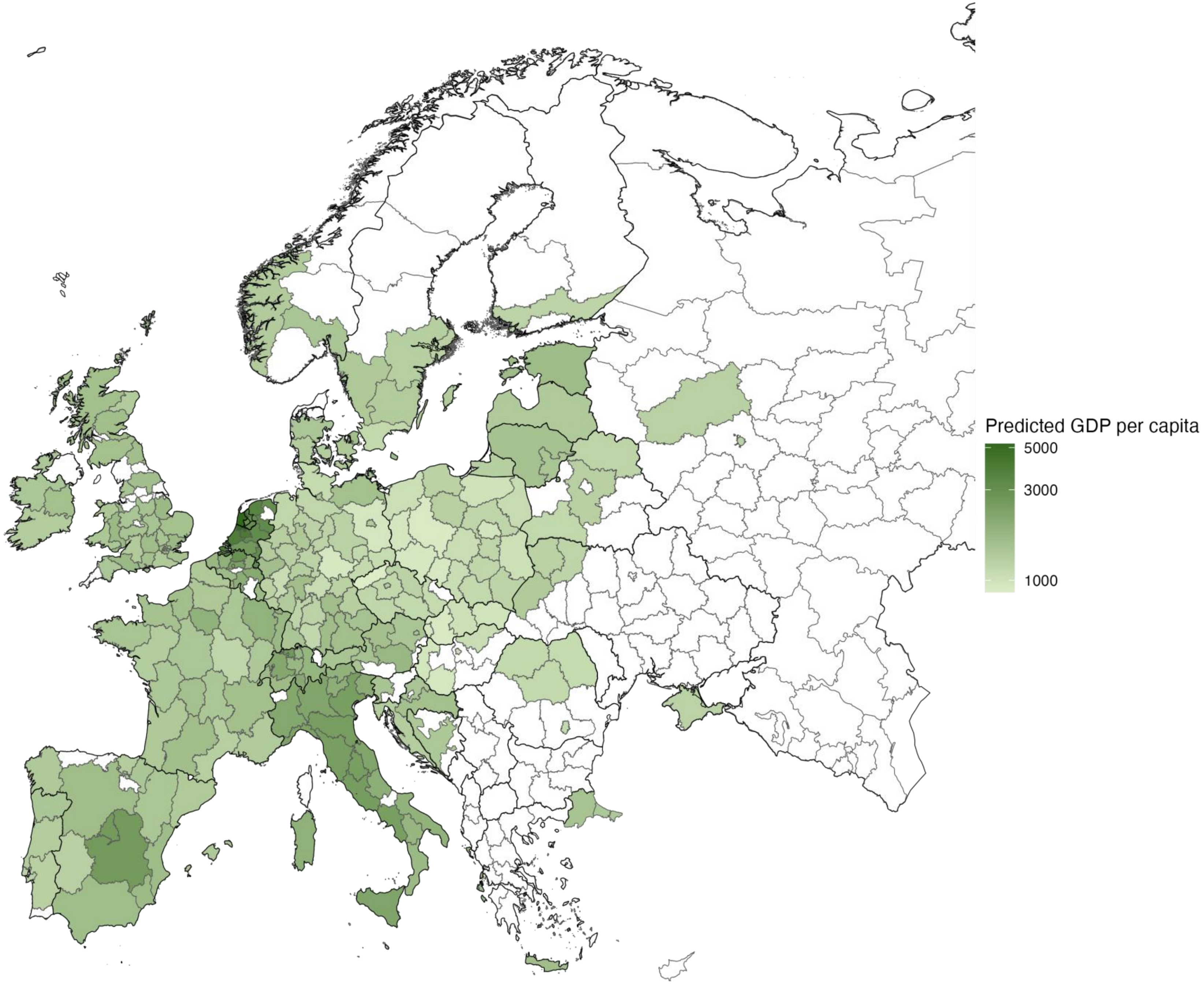

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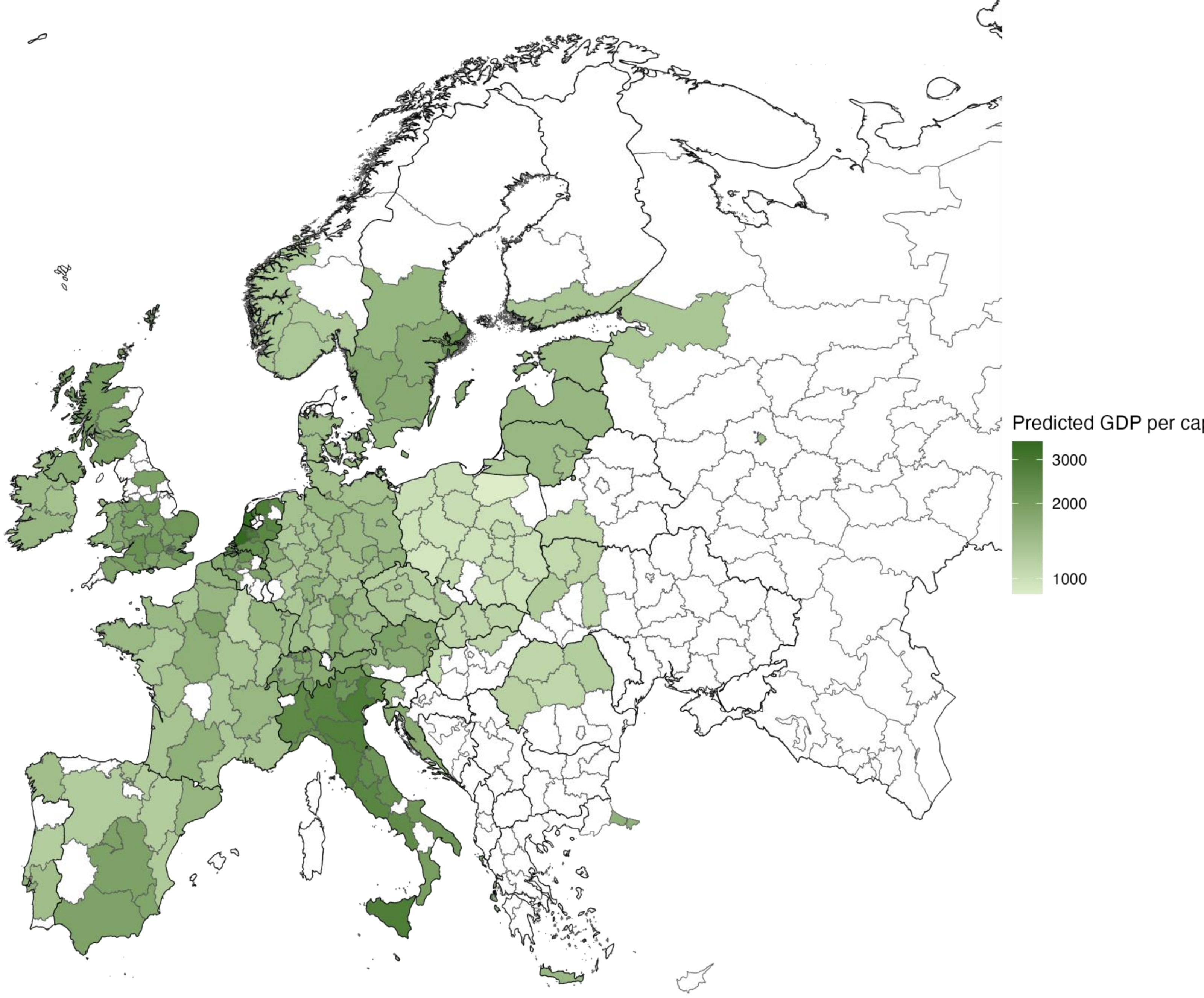

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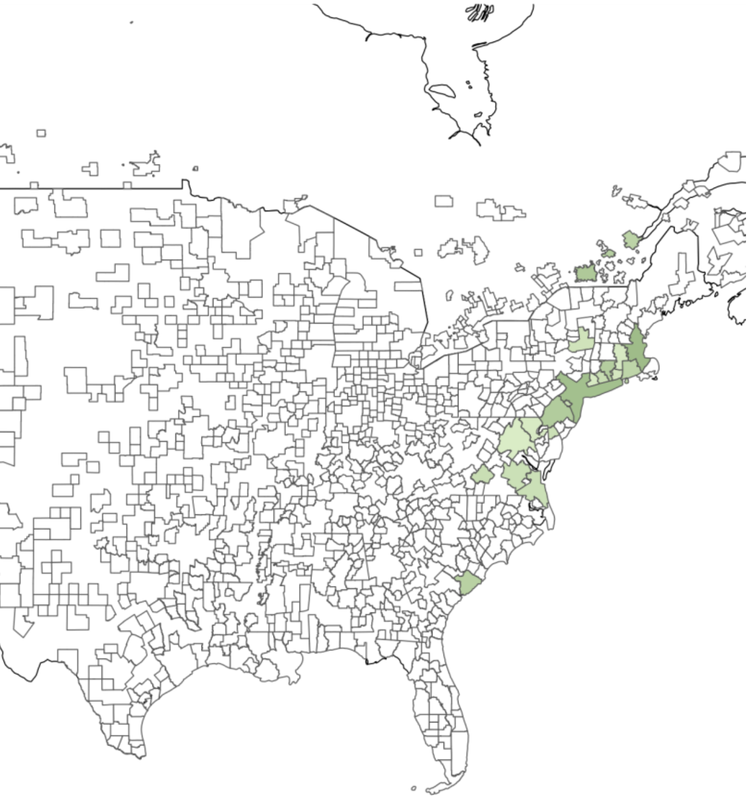

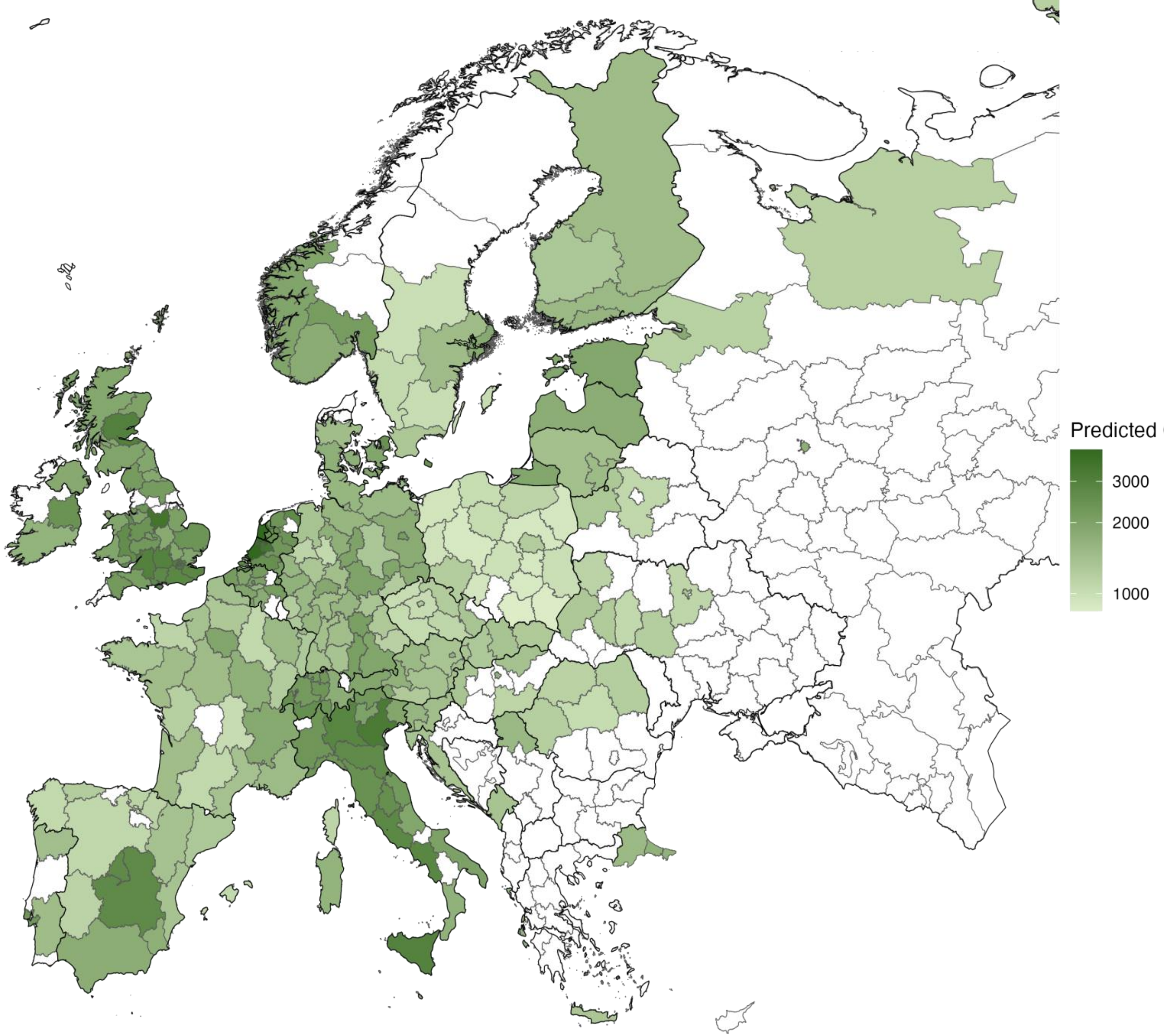

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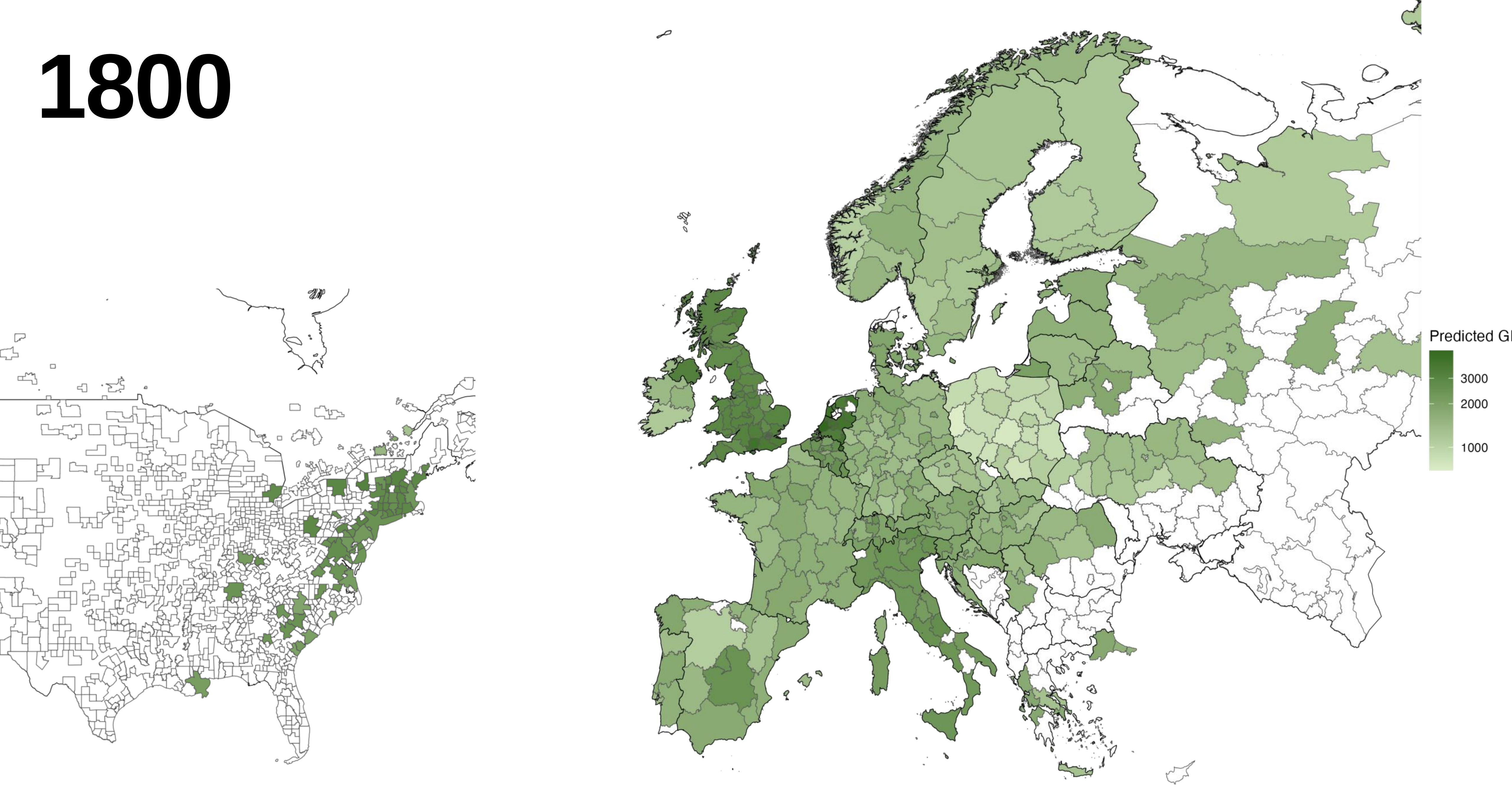

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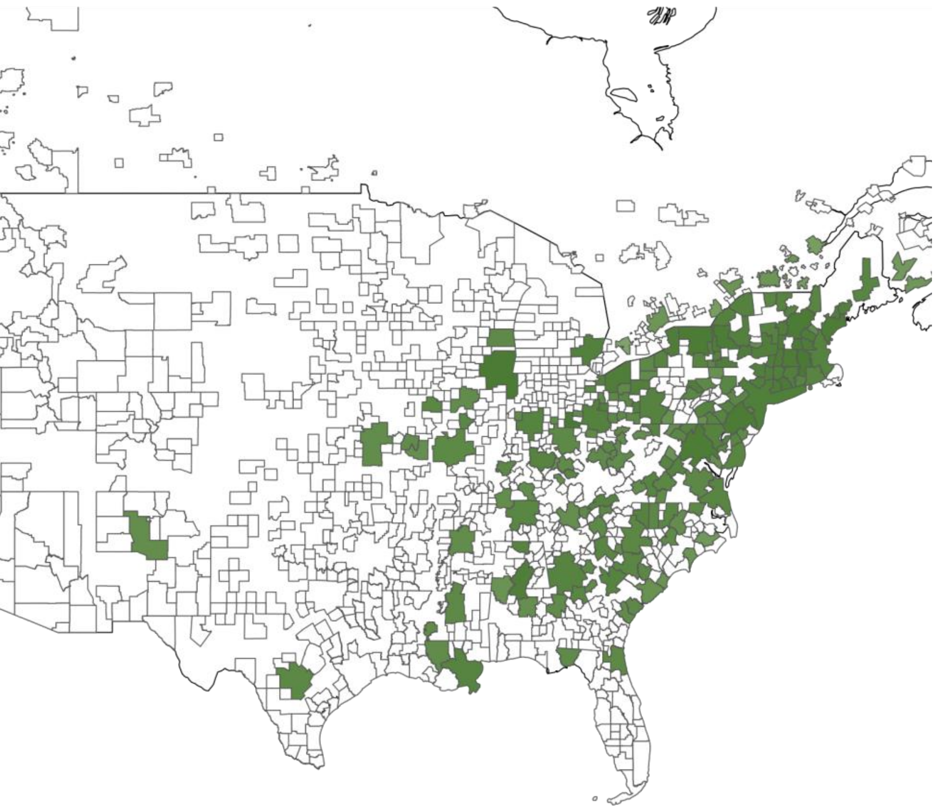

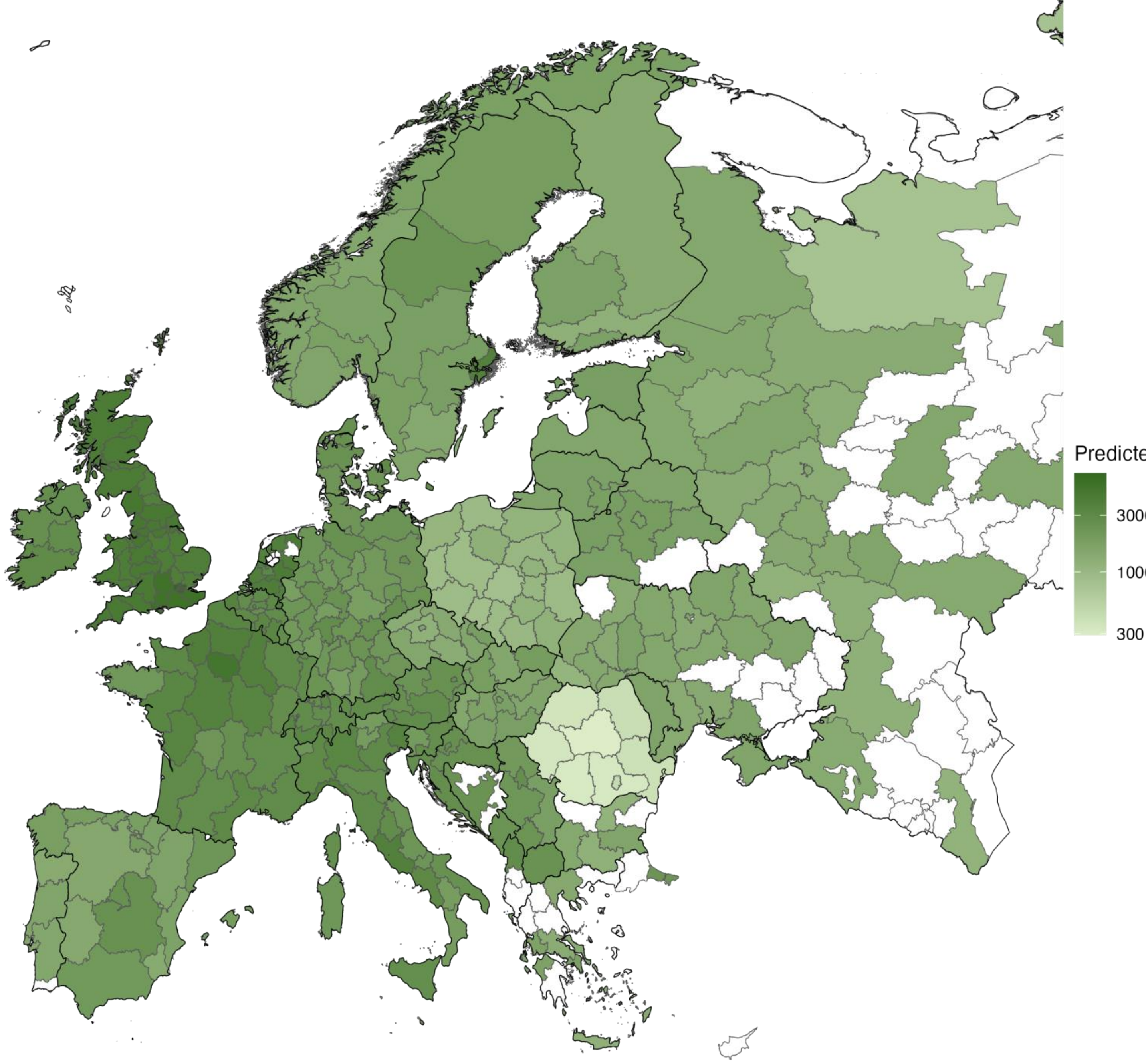

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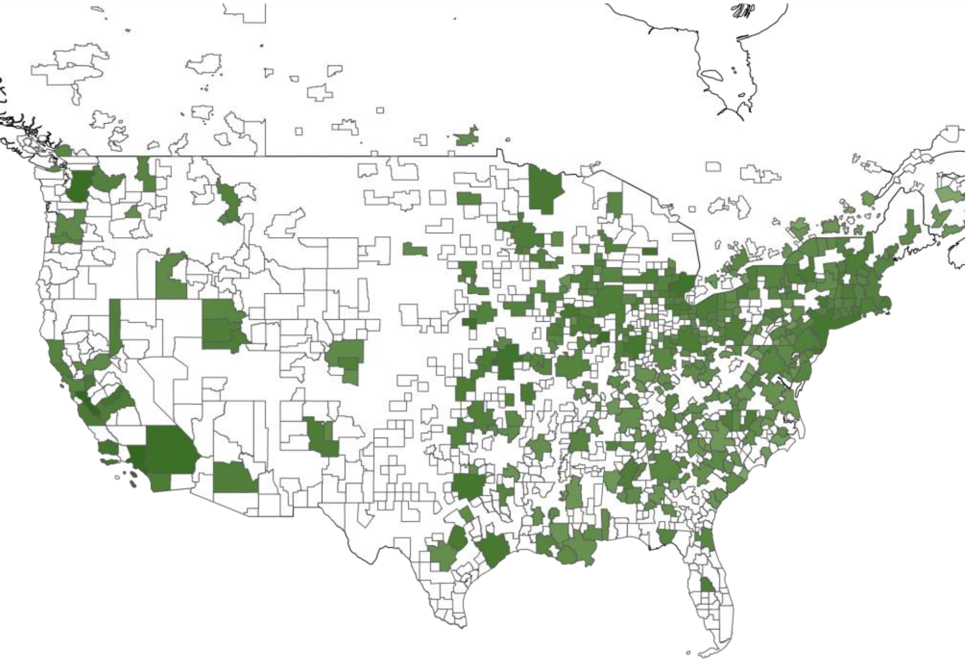

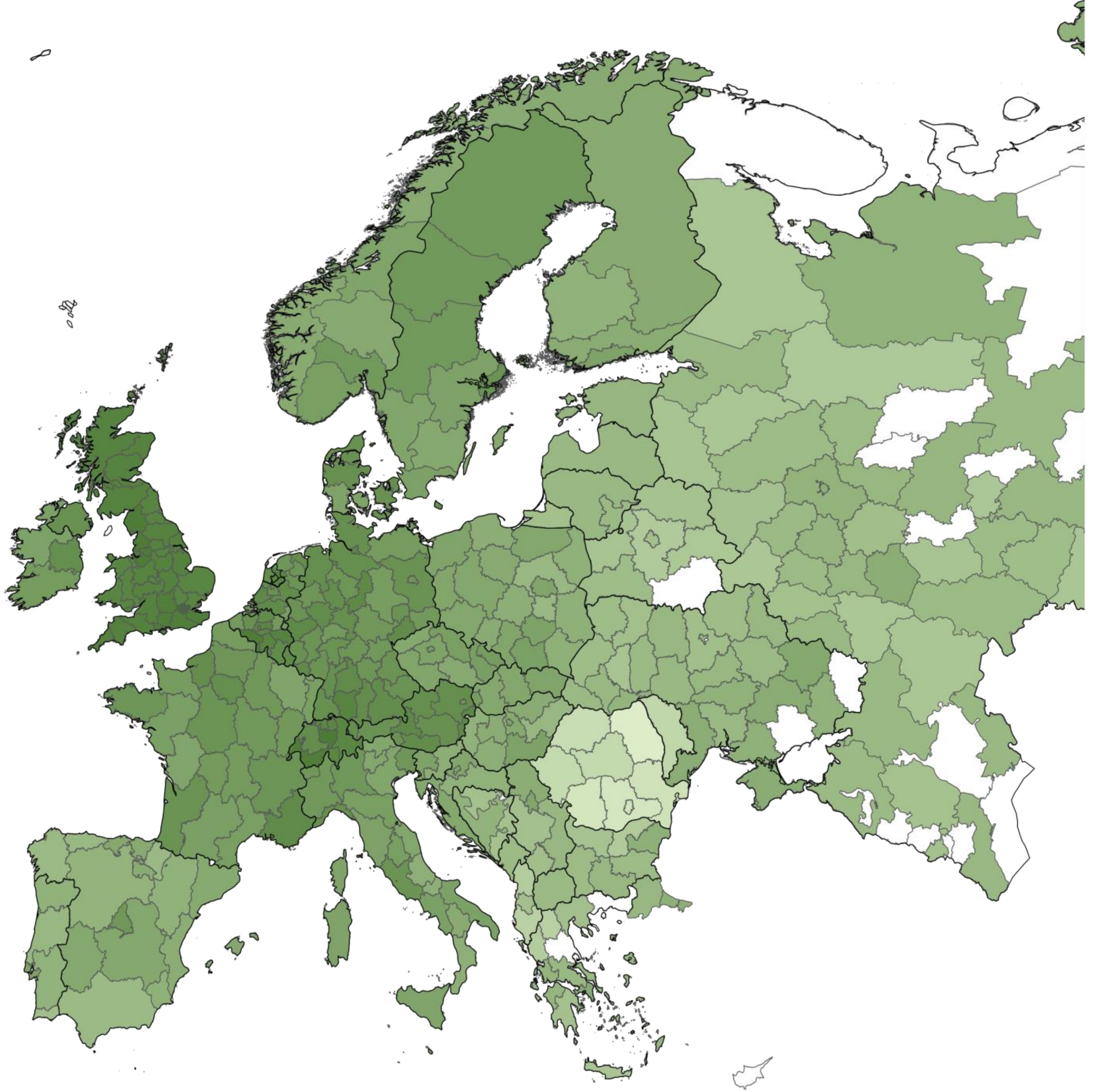

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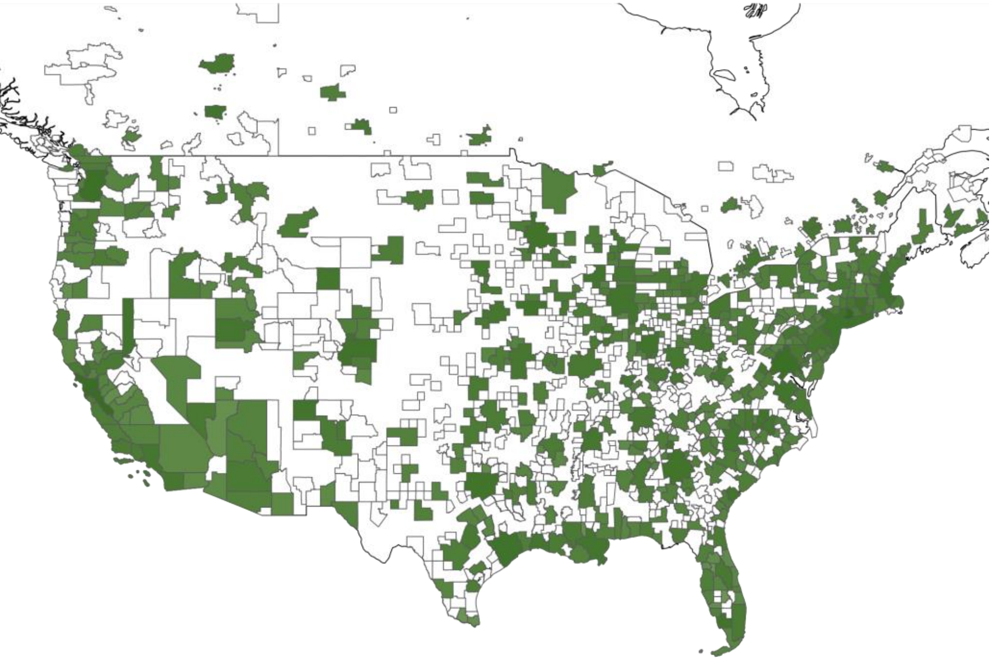
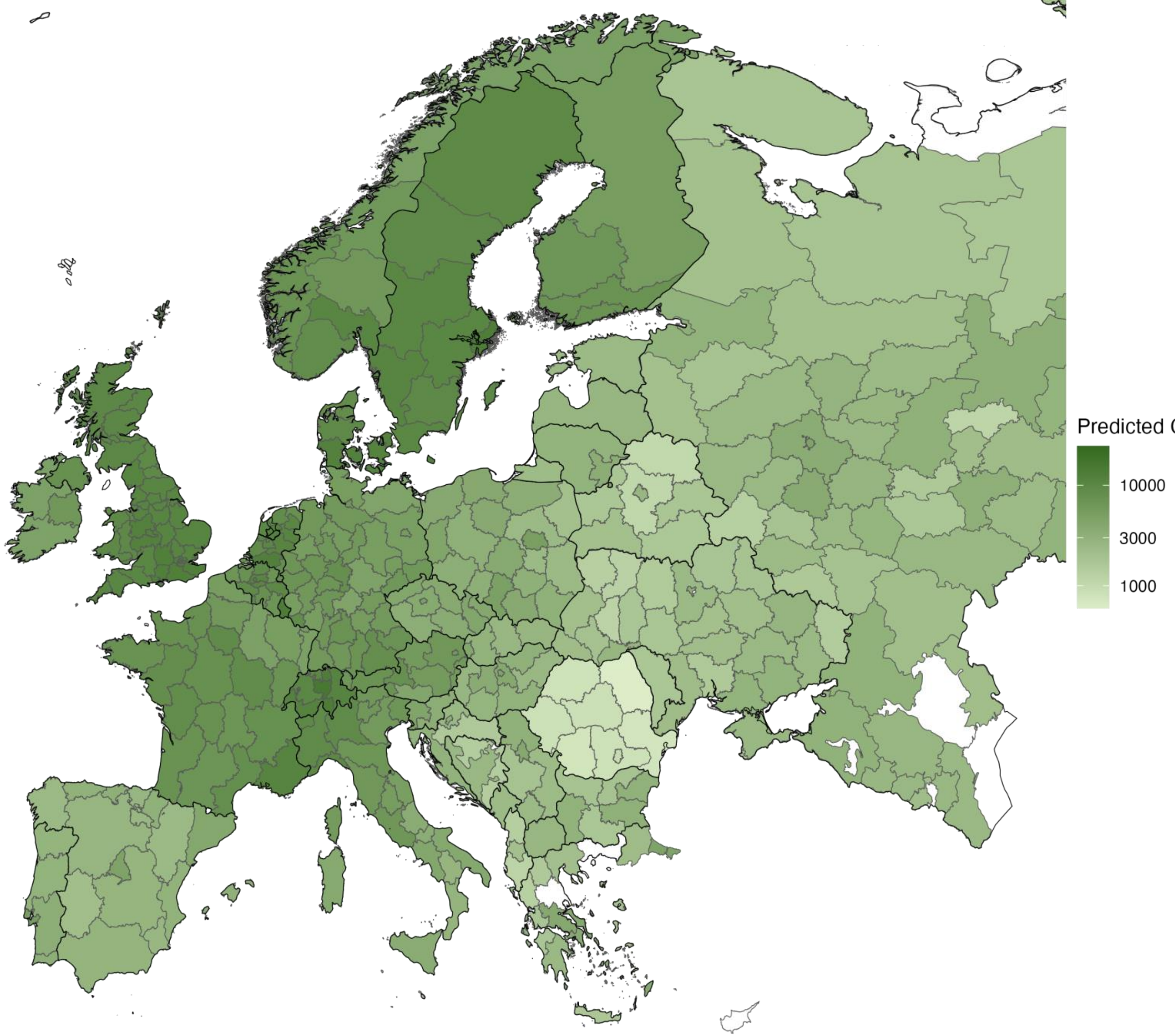
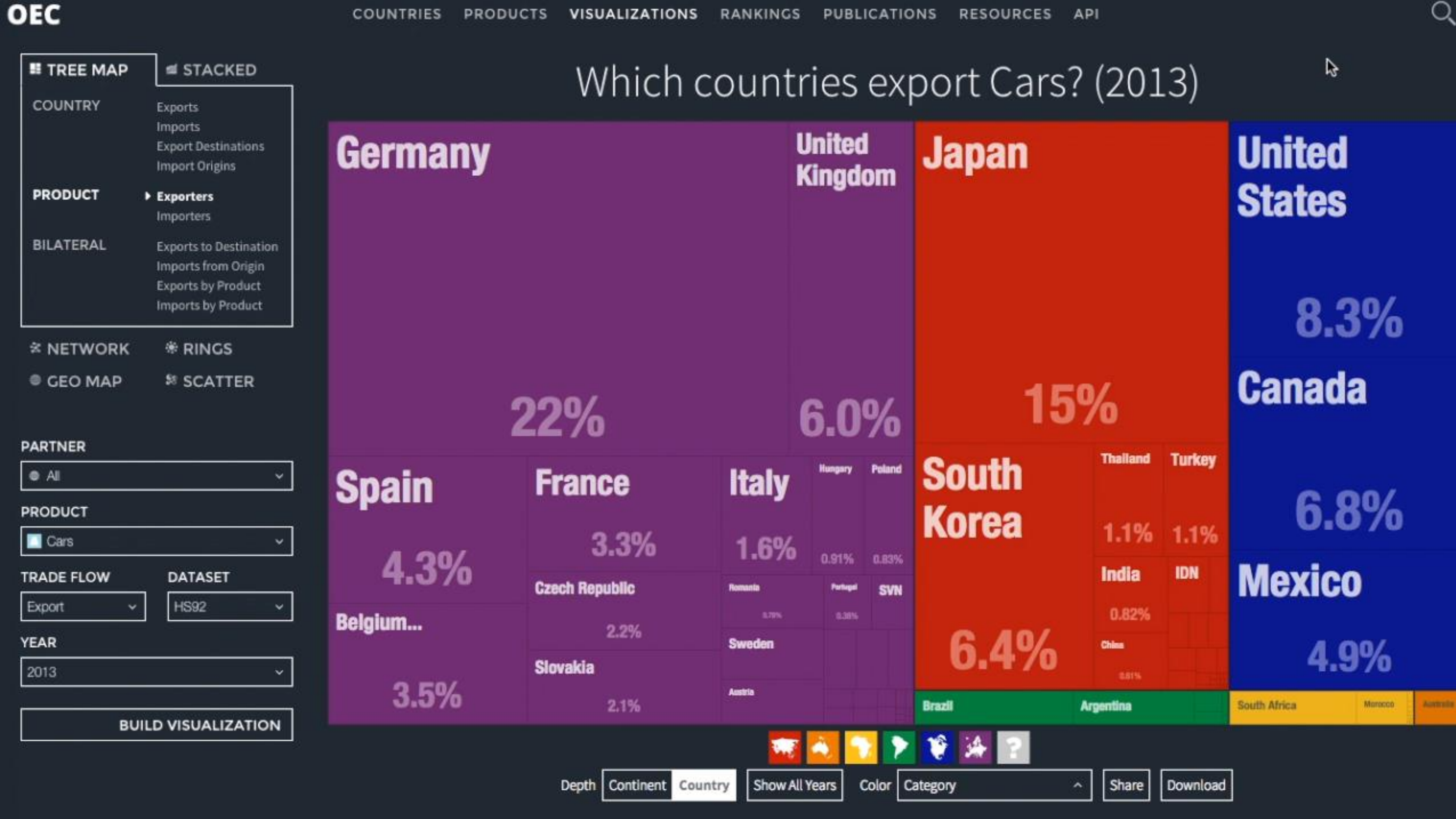




Putting these ideas in practice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6.0%
Japan
15%
United States
8.3%
Canada
6.8%
Mexico
4.9%
Spain
4.3%
France
3.3%
Italy
1.6%
Hungary
0.91%
Poland
0.83%
Belgium...
3.5%
Czech Republic
2.2%
Slovakia
2.1%
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SVN
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South Korea
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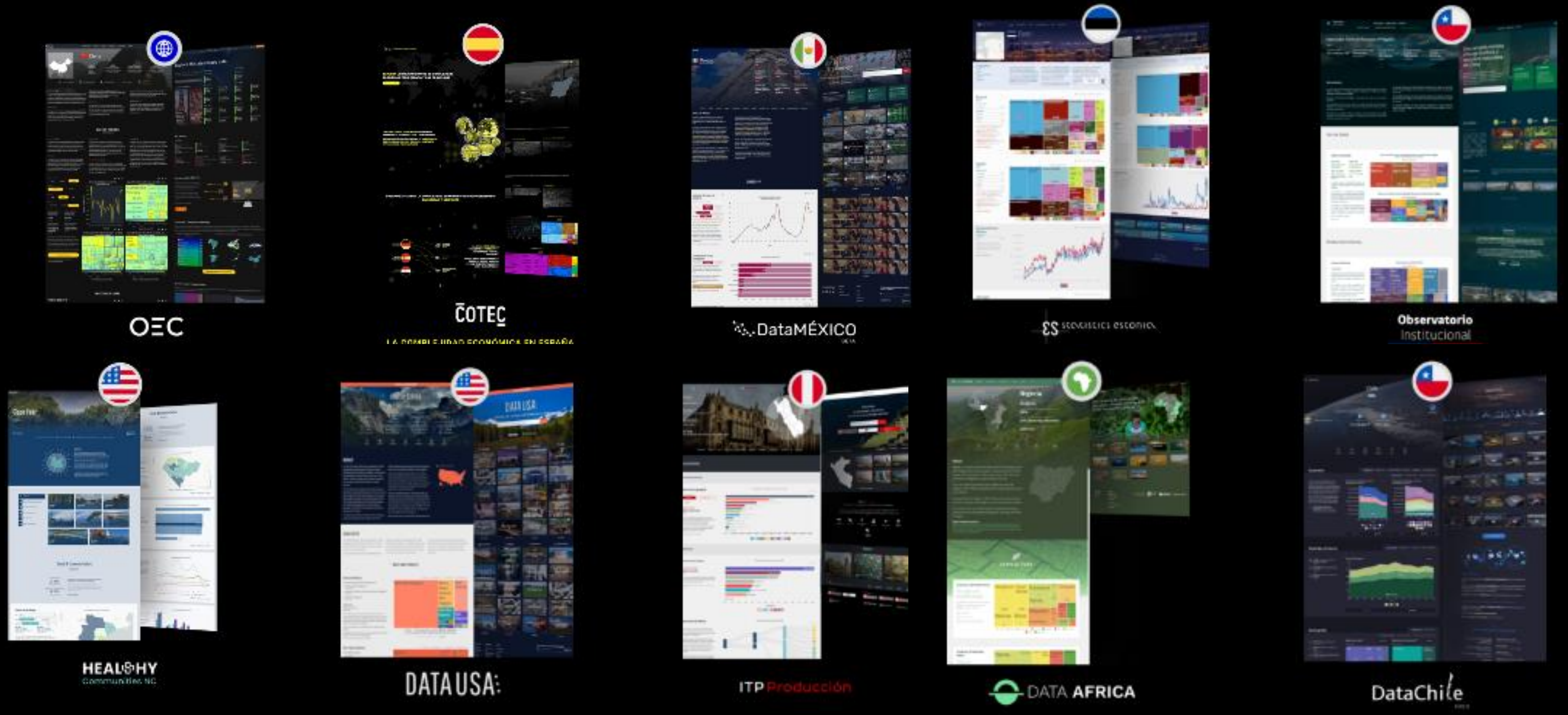

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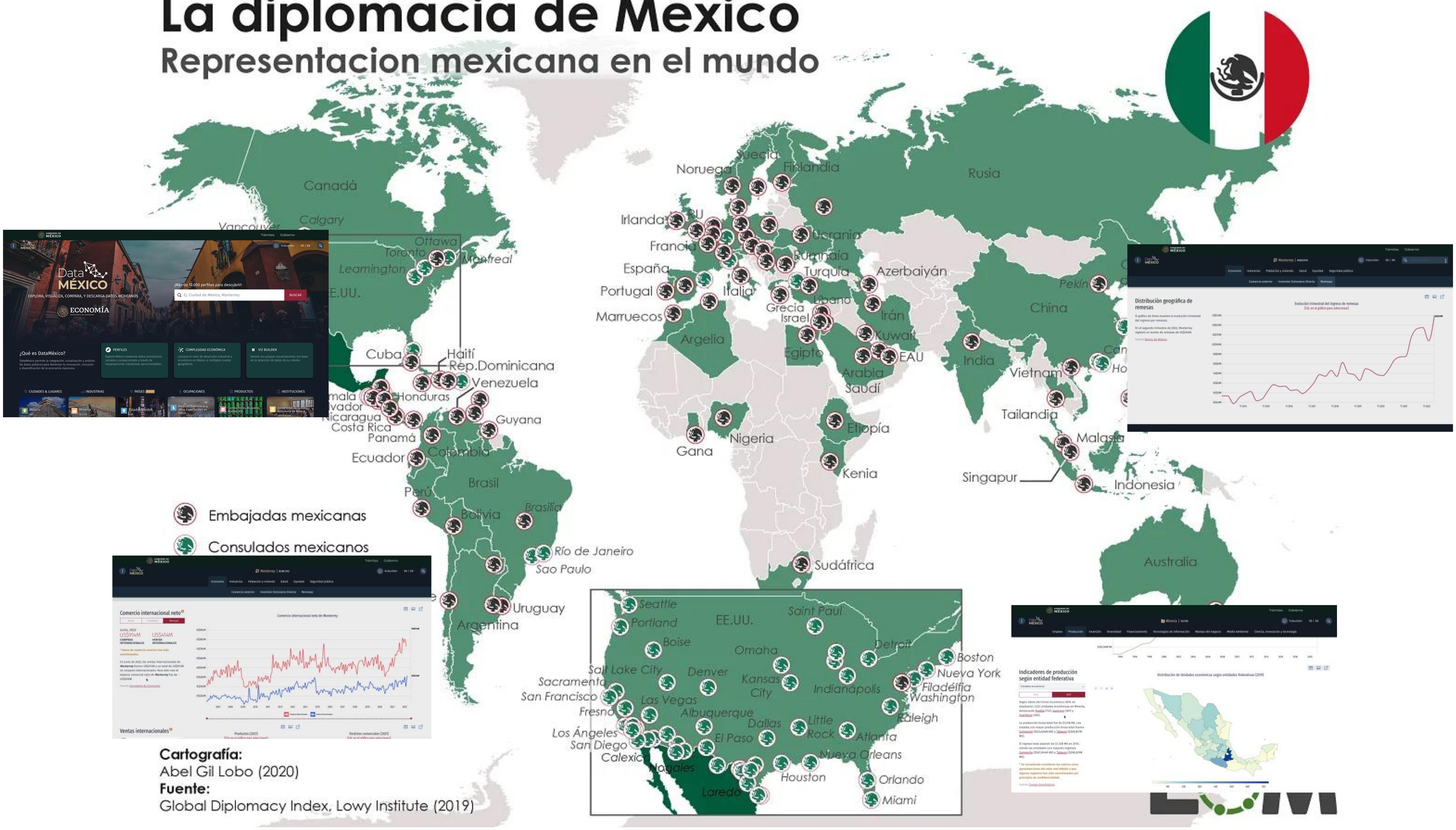

Cartografía:
Abel Gil Lobo (2020)
Fuente:
Global Diplomacy Index, Lowy Institute (2019)

The world is complex

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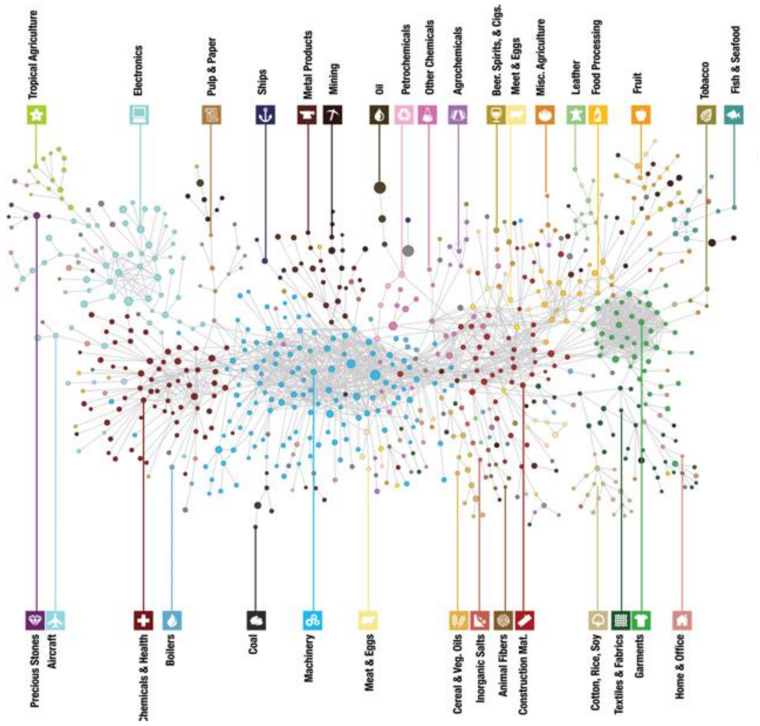
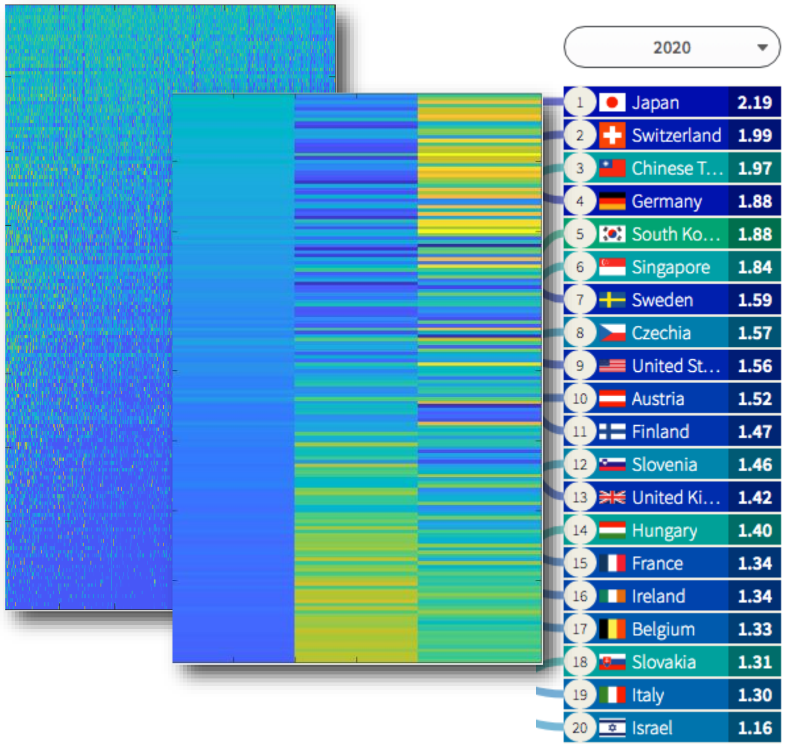
Economic complexity methods allow us to make high resolution representations of economies to understand where they stand and where they are going.



Hidalgo et al. Science (2007)



Hidalgo & Hausmann. PNAS (2009)