



R&I Policy Evaluation at the European Commission

Workshop “Economic Analyses of Science” - University of Oxford
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Why is R&I so important for the EU?



POPULATION AGING

Makes it crucial that labour productivity increases to support, with fewer workers, the social needs of an ageing society



MIGRATORY PRESSURES

Fostered by geopolitical events and natural disasters could put under stress the European social model and challenge the fiscal viability of its welfare states



GEOPOLITICAL DEVELOPMENTS

Economic security and trade dependencies may increase the short run the cost of the green transition, due to supply chain disruptions and reshoring



CLIMATE CHANGE

35% of cumulative CO₂ emissions reduction needed to meet our 2050 net zero goal depends on new technologies

The EU triangle of innovation



Underutilised ecosystem

Compared to its international competitors, the EU still underperforms in terms of R&D investments, R&I finance and excellence



Technology gap

EU publications tend to be of lower quality and EU patents on less sophisticated technologies, compared to international competitors such as the US and China



Innovation divide

The EU present relevant territorial disparities in term of R&I, and the national R&I ecosystem are not that interconnected

Evidence for EU policy making



The ***"Science, Research and Innovation Performance of the EU"*** report analyses Europe's performance in science, research and innovation and its drivers. It combines a thorough indicator-based analysis with deep dives into topical policy issues.

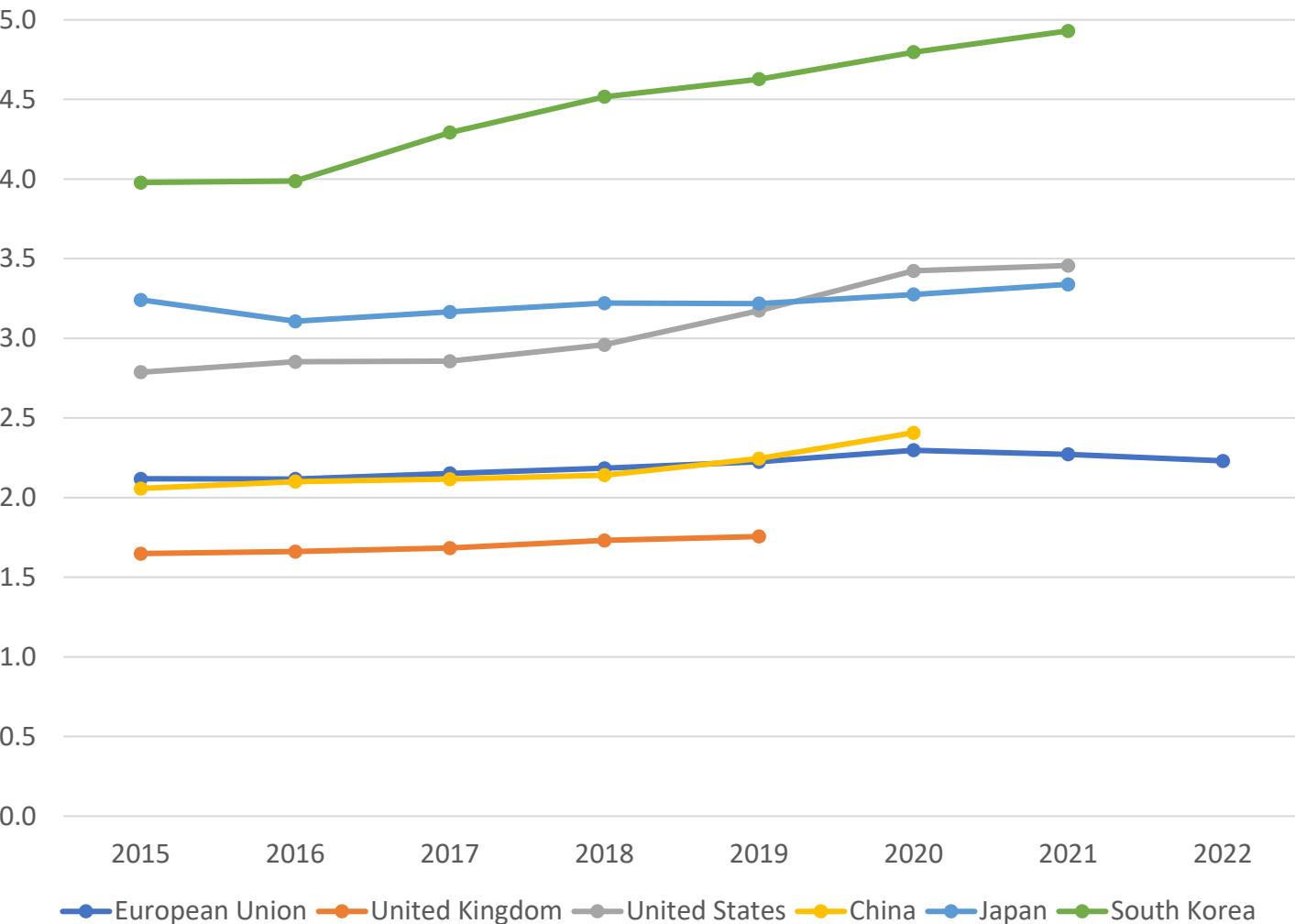
The triangle of innovation



Underutilised ecosystem

The EU thereby underperforms in comparison with the US (3.5%), Japan (3.3%), and China (2.4%).

GERD as percentage of GDP (R&D intensity)



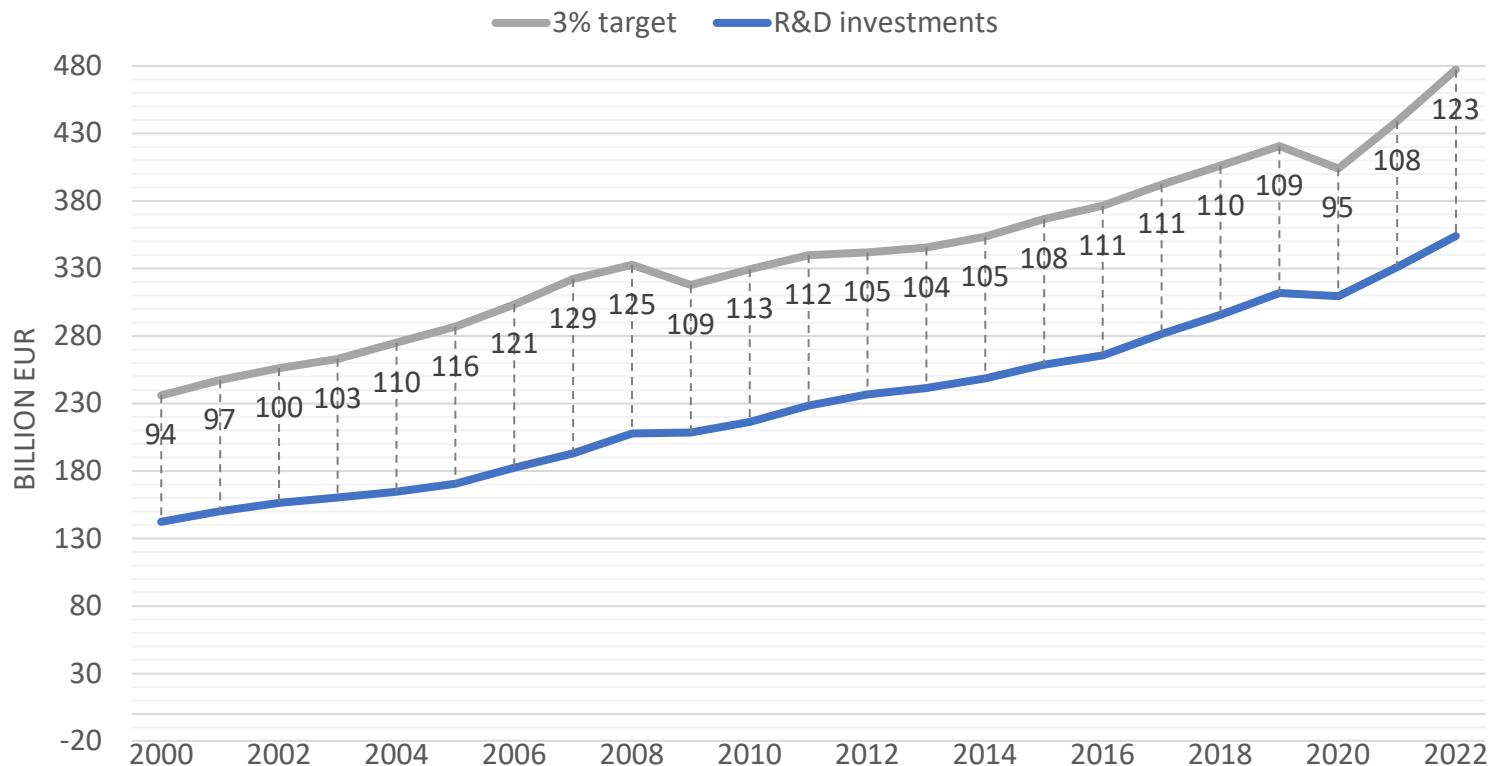
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Underutilised ecosystem

The EU still fall behind its own
3% R&D target

R&D investment gap in the EU in billion EUR, 2000-2022



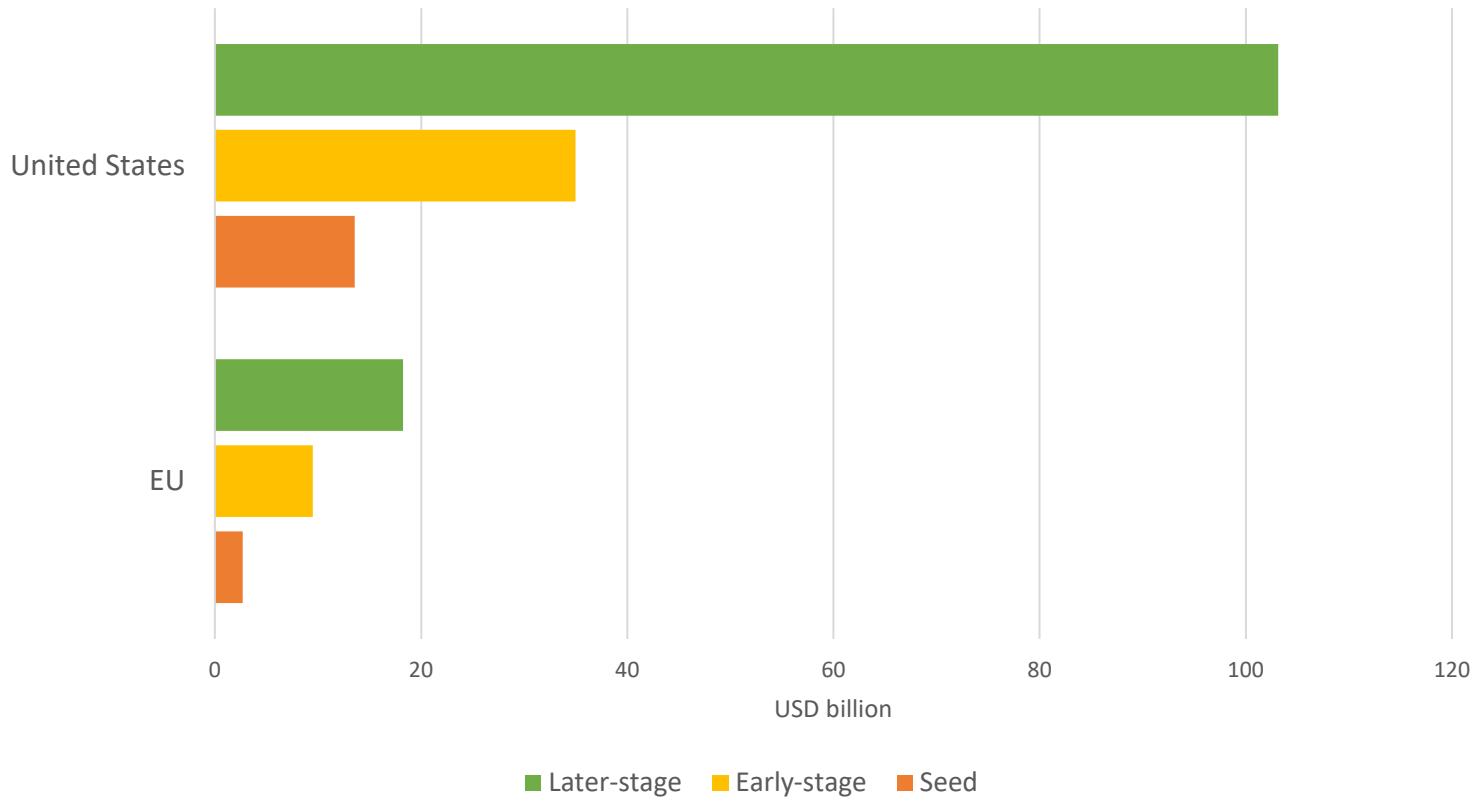
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Underutilised ecosystem

Furthermore, the EU still has 7 times less Venture Capital than the US

Venture Capital investments in the EU and the US, by development stage, 2023

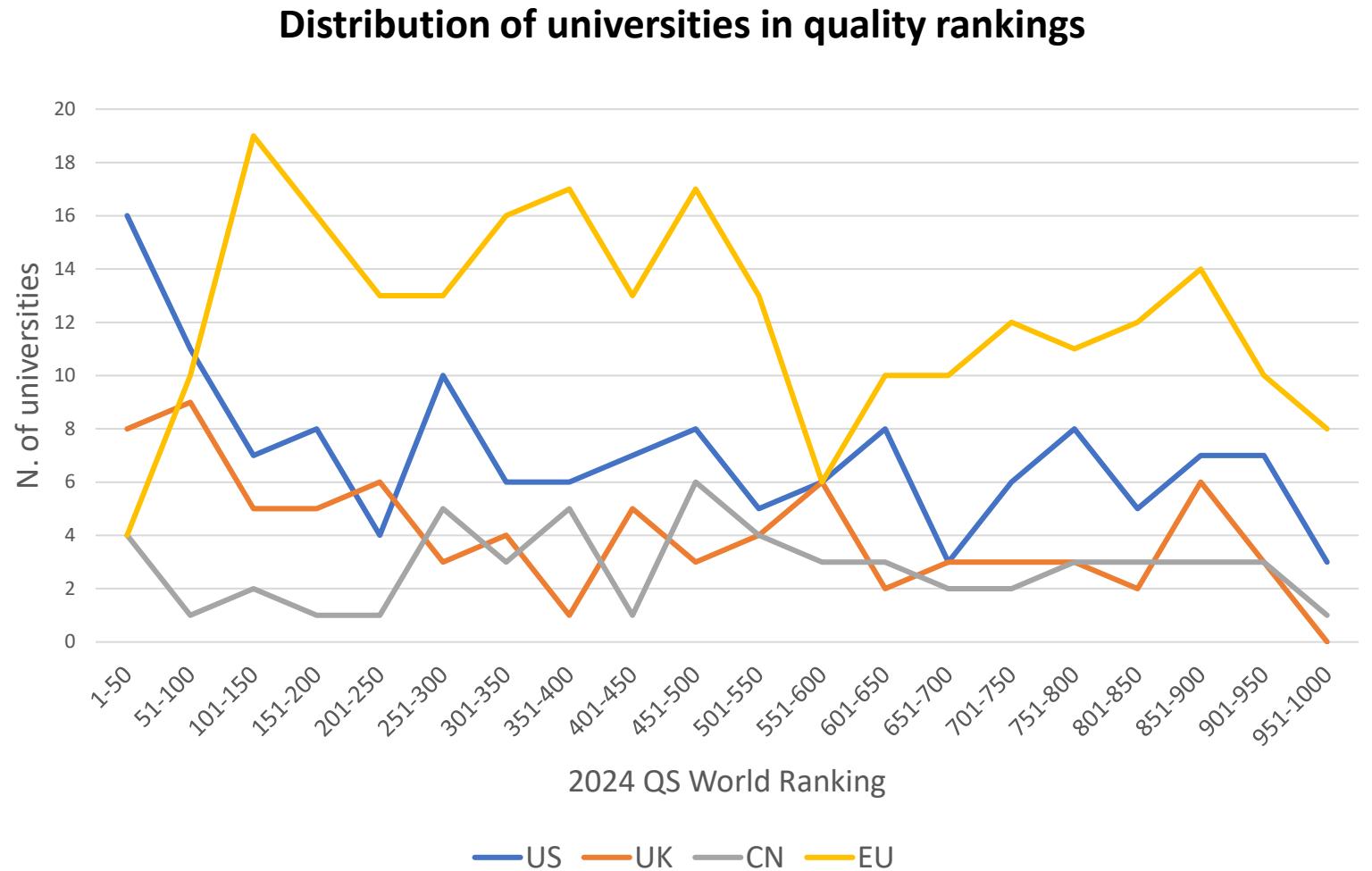


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Underutilised ecosystem

The Anglo-Saxon academic system features concentrated high-performing institutions, while the EU prioritises a broad moderate quality over exceptional peaks



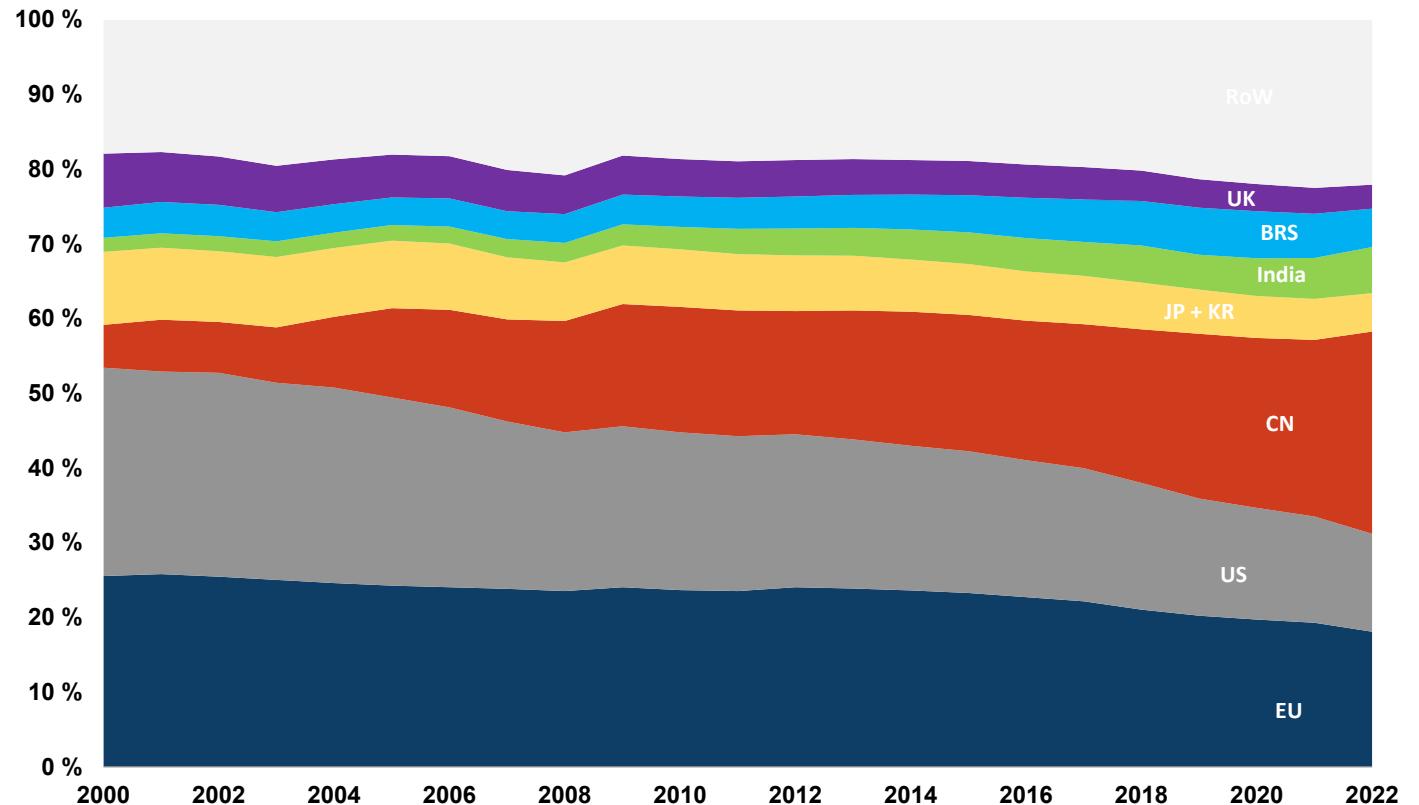
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Underutilised ecosystem

EU's share in world publication
has been declining.

World share (%) of scientific publications,
2000-2022



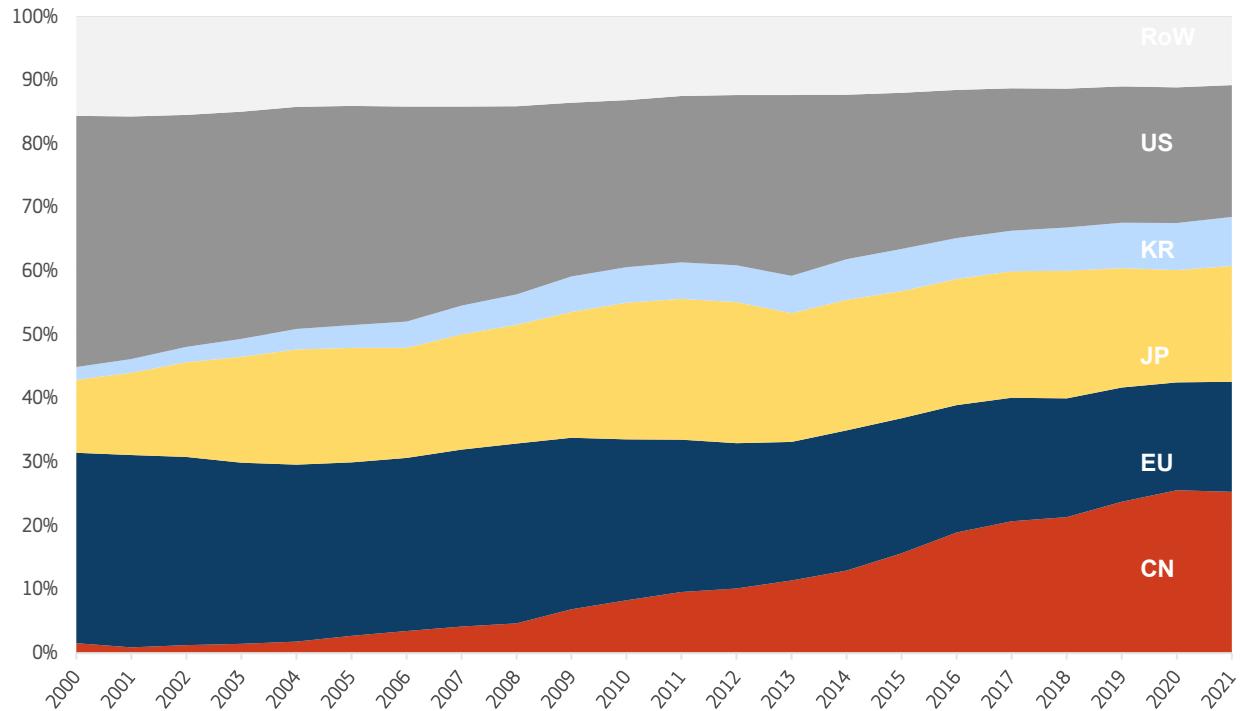
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Underutilised ecosystem

EU's share in world patents has been declining.

World share (%) of patent applications filed under PCT1, 2000-2021



Note: ⁽¹⁾ Patent Cooperation Treaty (PCT) patents. Fractional counting method, inventor's country of residence and priority date used.

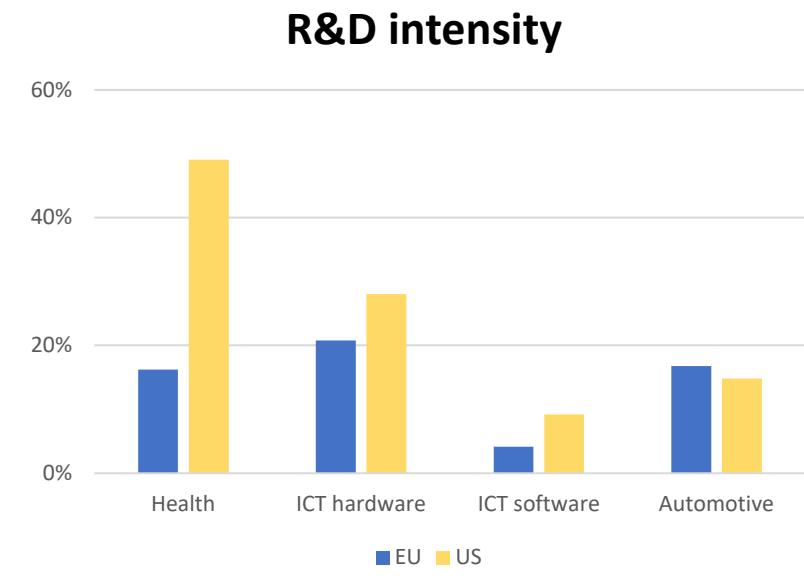
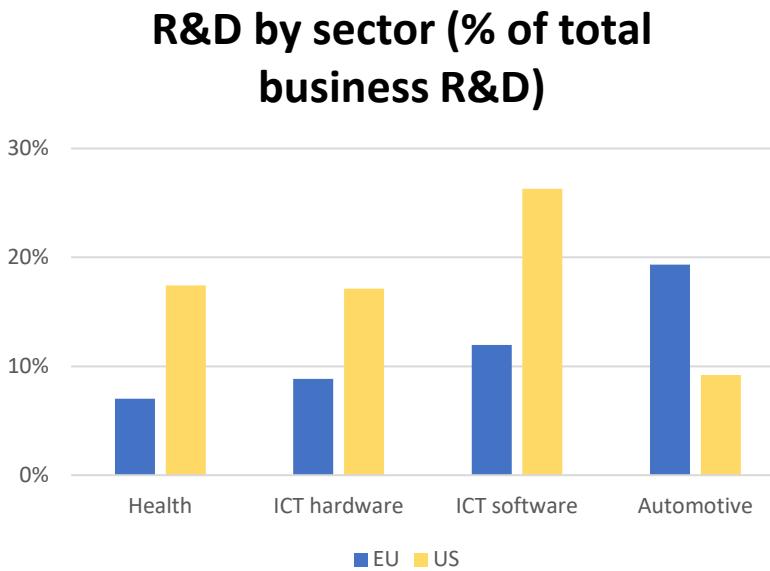
Source: European Commission, DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit based on Fraunhofer ISI, using PATSTAT.

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Technology gap

The EU R&D gap compared to the US is driven by both structural and intrinsic factors



The triangle of innovation



Technology gap

There is strong path-dependency in EU's structural composition

Top-3 R&D spenders and their industries compared over time

	2003	2012	2022
US	Ford (auto) Pfizer (pharma) GM (auto)	Microsoft (software) Intel (hardware) Merck (pharma)	Alphabet (software) Meta (software) Microsoft (software)
EU	Mercedes-Benz (auto) Siemens (electronics) VW (auto)	VW (auto) Mercedes-Benz (auto) Bosch (auto)	VW (auto) Mercedes-Benz (auto) Bosch (auto)
JPN	Toyota (auto) Panasonic (electronics) Sony (electronics)	Toyota (auto) Honda (auto) Panasonic (electronics)	Toyota (auto) Honda (auto) NTT (telecom)

Source: Industrial R&D Investment Scoreboard (2004, 2013 and 2023).

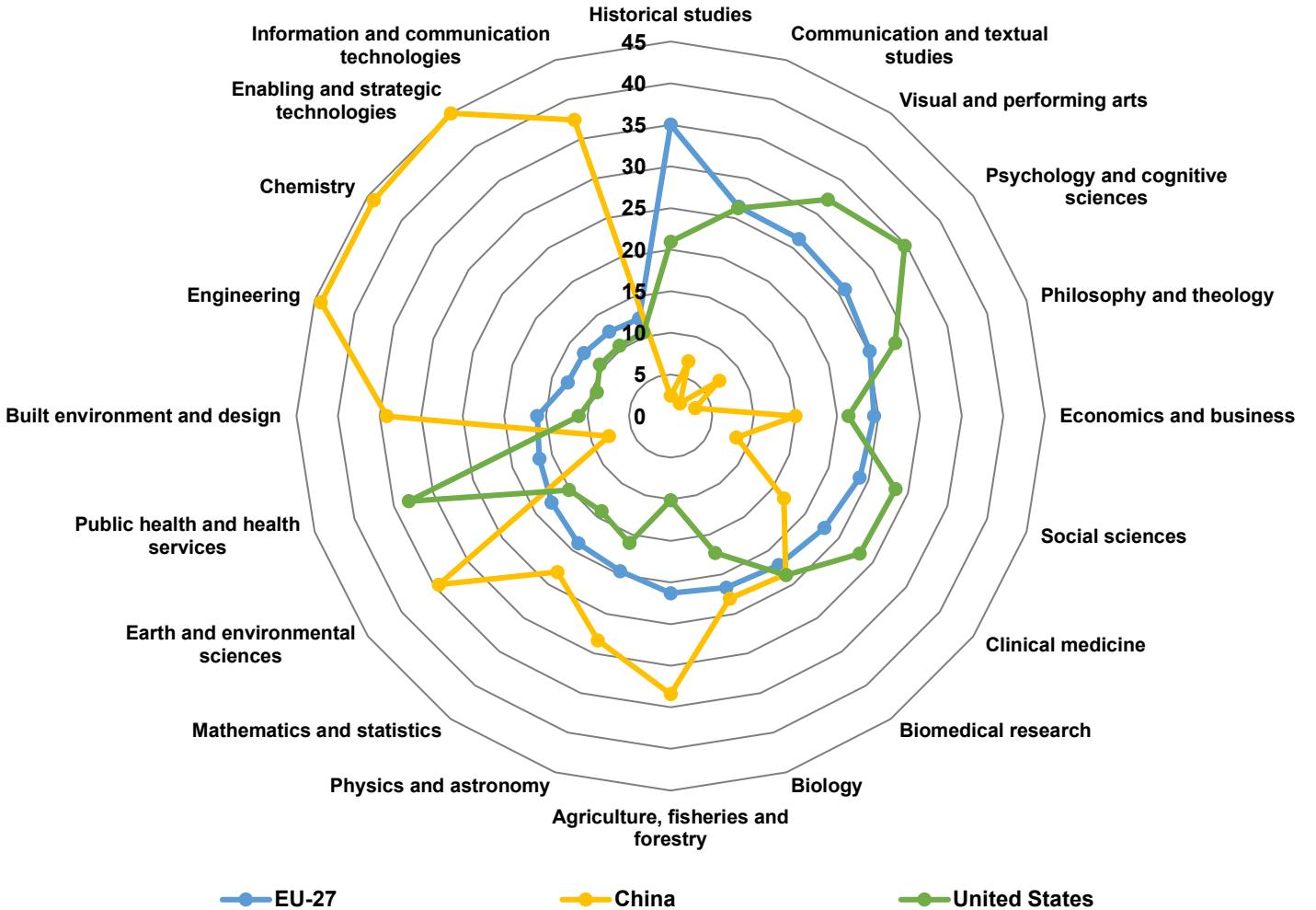
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Technology gap

The EU holds the highest shares in less technological fields such as “Historical studies”, “Economics and Business”, and “Communication and textual studies”

World shares of the top 10 % most-cited publications by country/region and scientific field (2020)



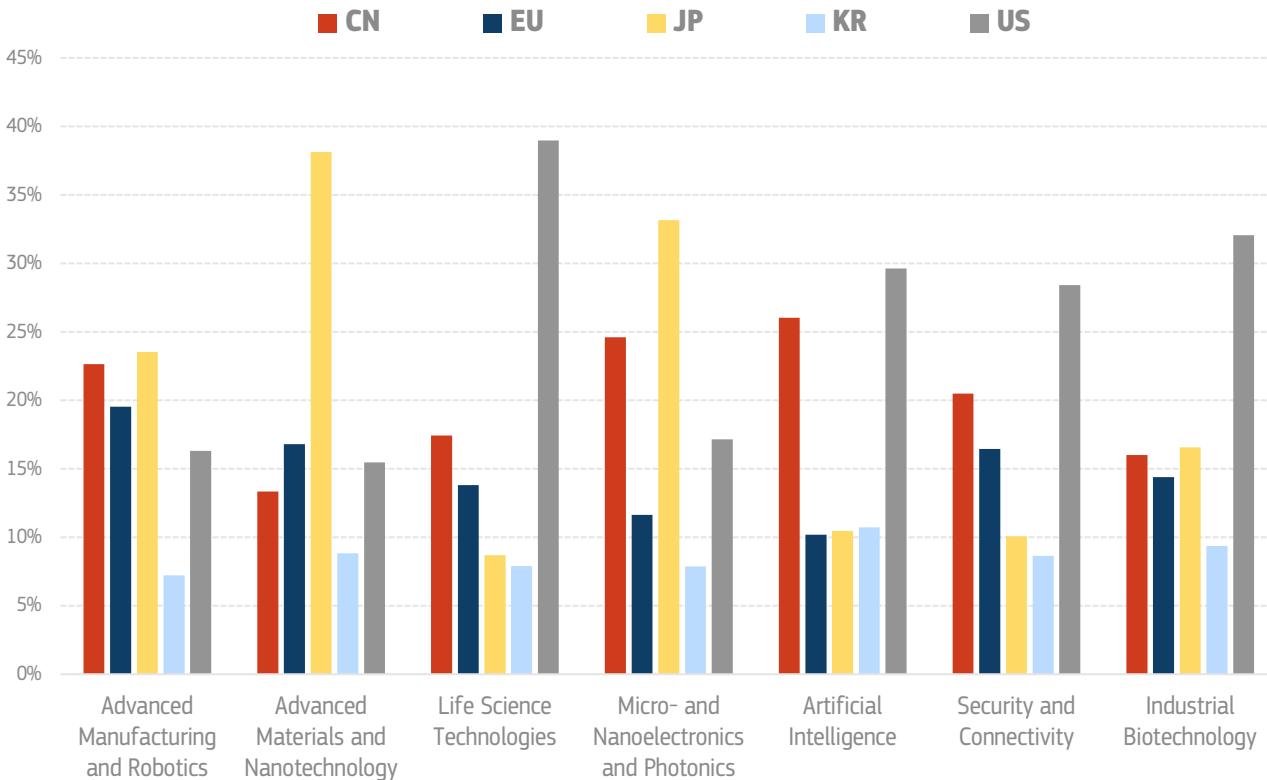
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Technology gap

The EU is not leading in patenting on any of the key enabling technologies

World share (%) of patent applications filed under PCT1, by key enabling technologies 2021



Note: ⁽¹⁾ Patent Cooperation Treaty (PCT) patents. Fractional counting method, inventor's country of residence and priority date used.

Source: European Commission, DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit based on Fraunhofer ISI, using PATSTAT.

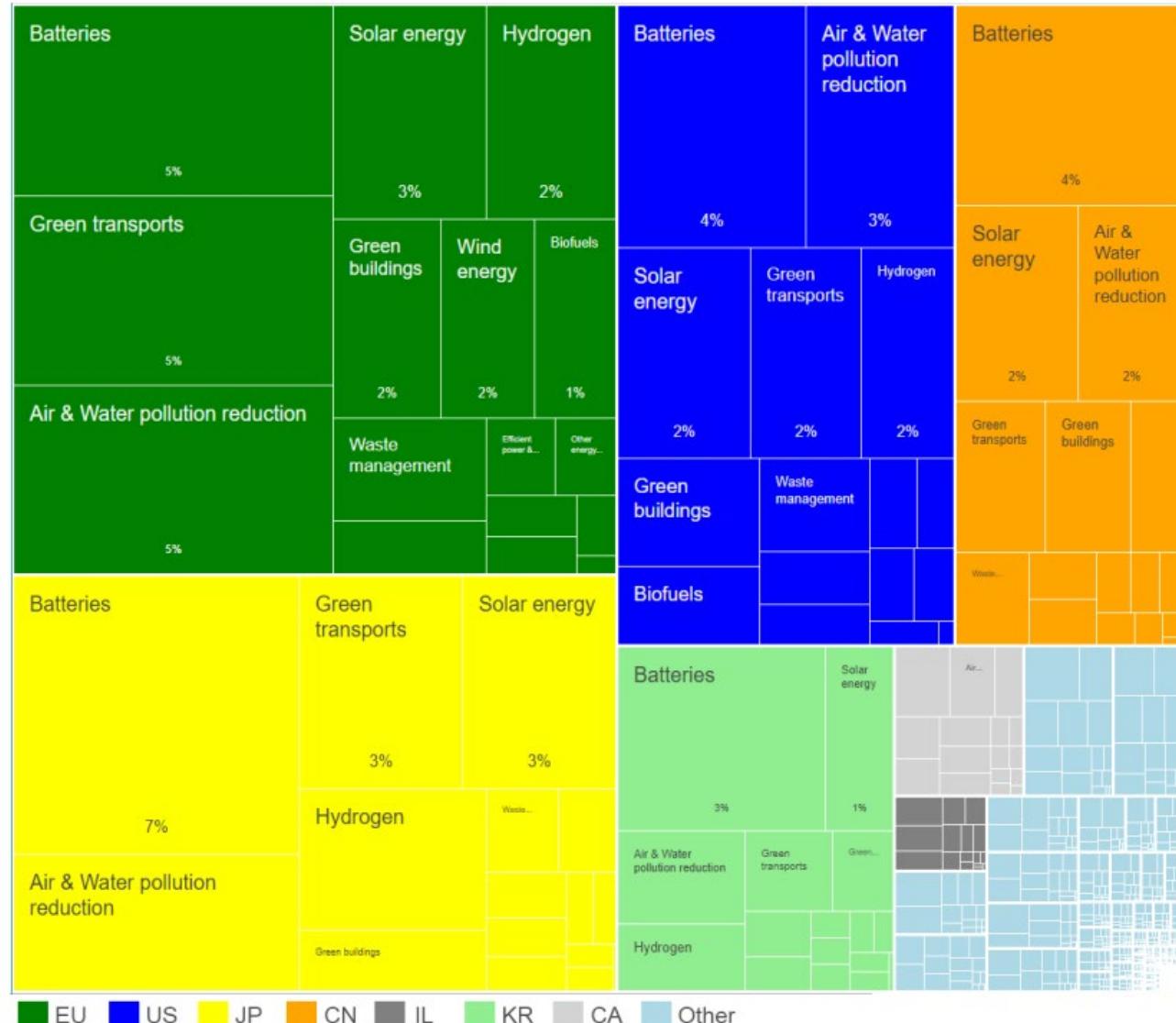
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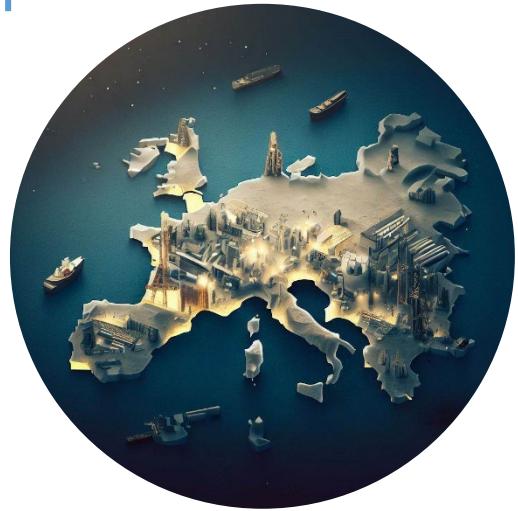
Technology gap

But has a strong position in green technologies.

World share (%) of green patent applications, 2016-2021



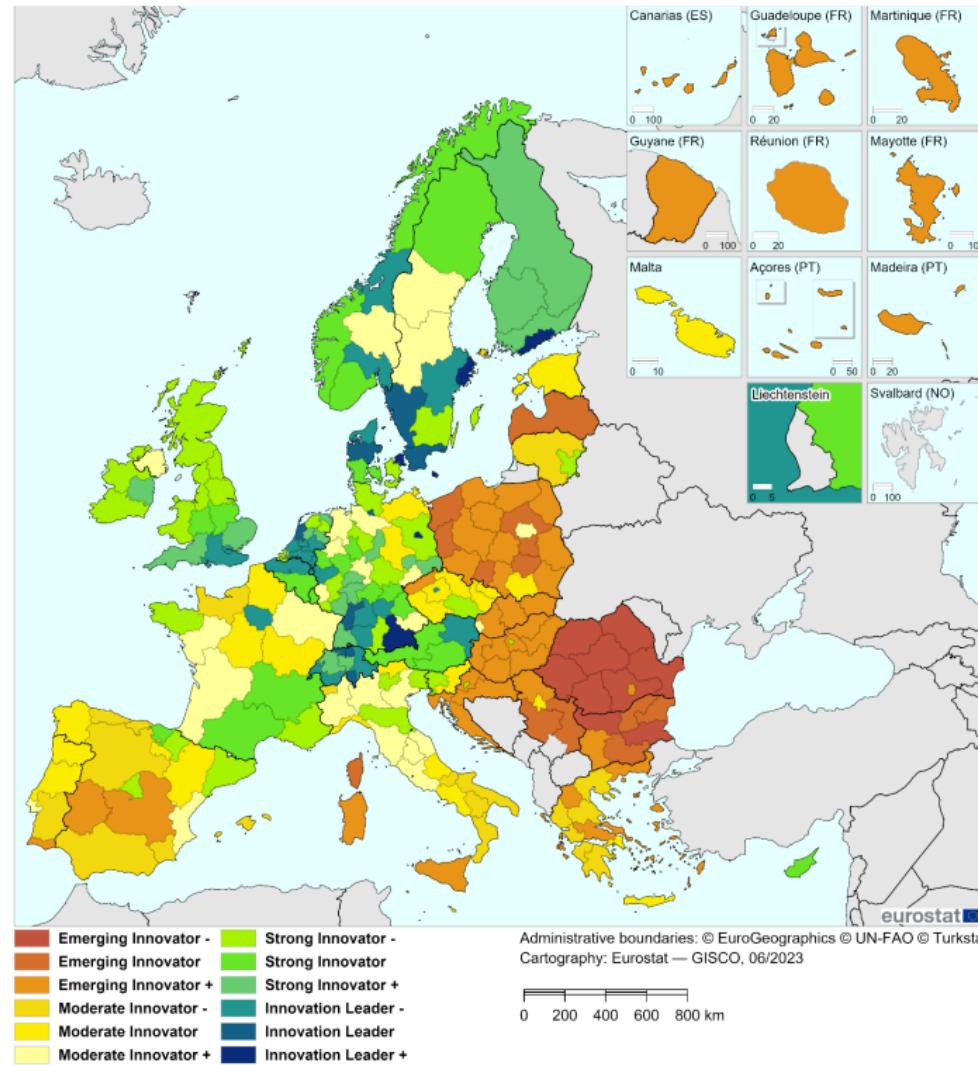
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Innovation divide

Innovation performance is
unequally distributed across and
within Member States.

Regional Innovation Scoreboard (RIS) 2024

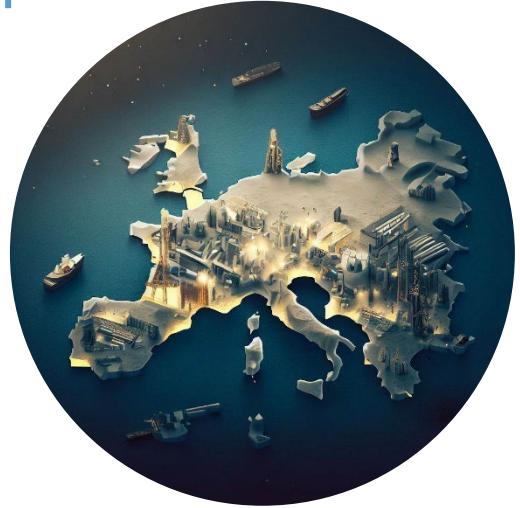


Emerging Innovator - Strong Innovator -
Emerging Innovator Strong Innovator
Emerging Innovator + Strong Innovator +
Moderate Innovator - Innovation Leader -
Moderate Innovator Innovation Leader
Moderate Innovator + Innovation Leader +

Administrative boundaries: © EuroGeographics © UN-FAO © Turkstat
Cartography: Eurostat — GISCO, 06/2023

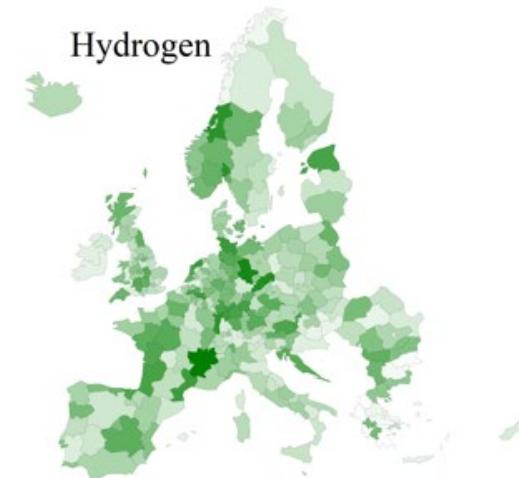
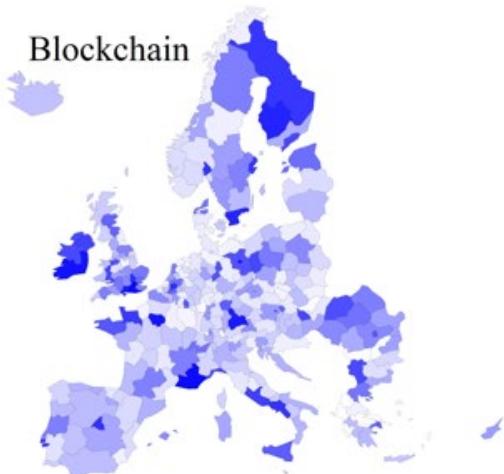
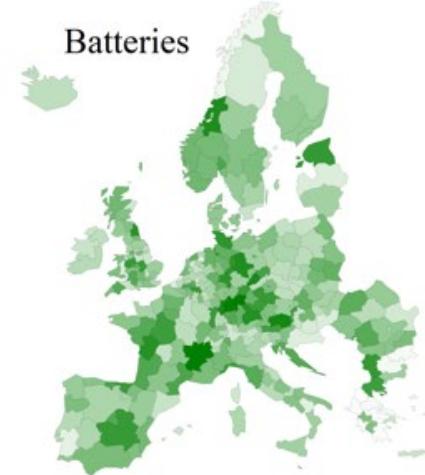
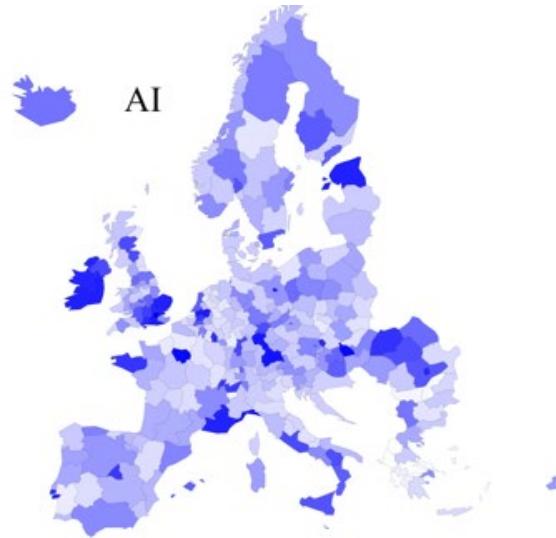
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The triangle of innovation



Innovation divide

Regions have different potential
to develop capacity in key
technologies

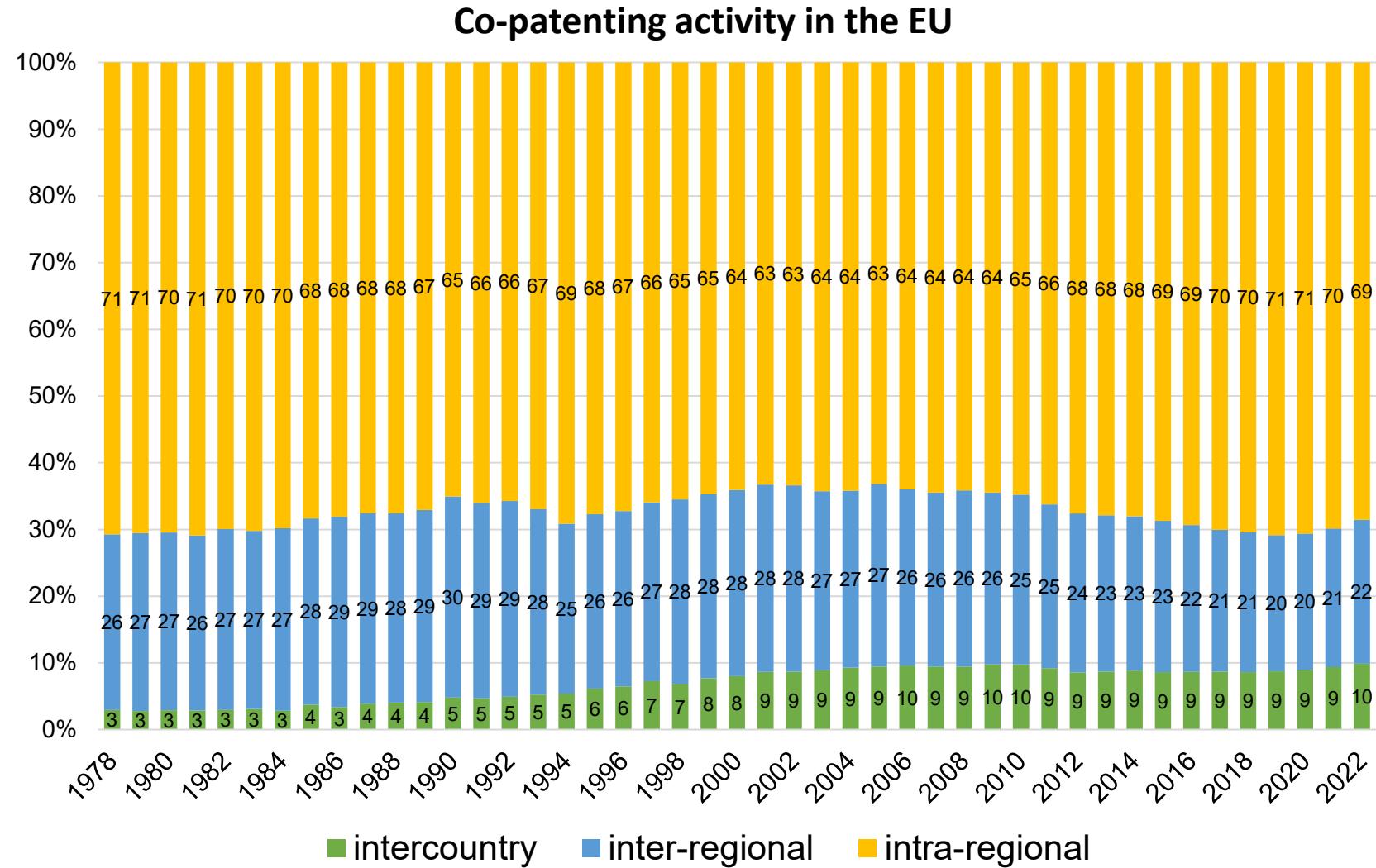


The triangle of innovation



Innovation divide

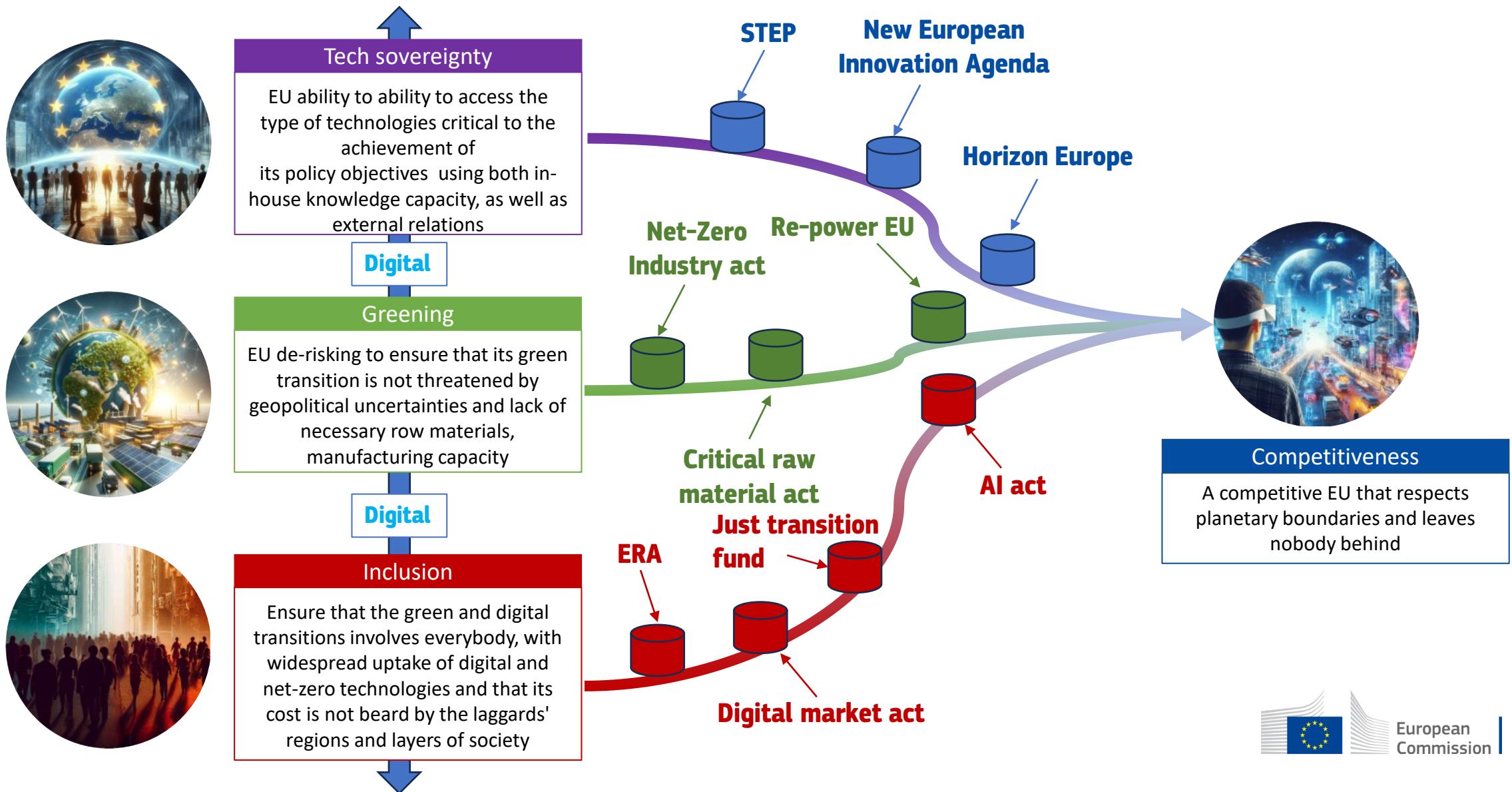
Most of EU co-patenting activity does not cross the Member States borders, losing on many technological complementarities



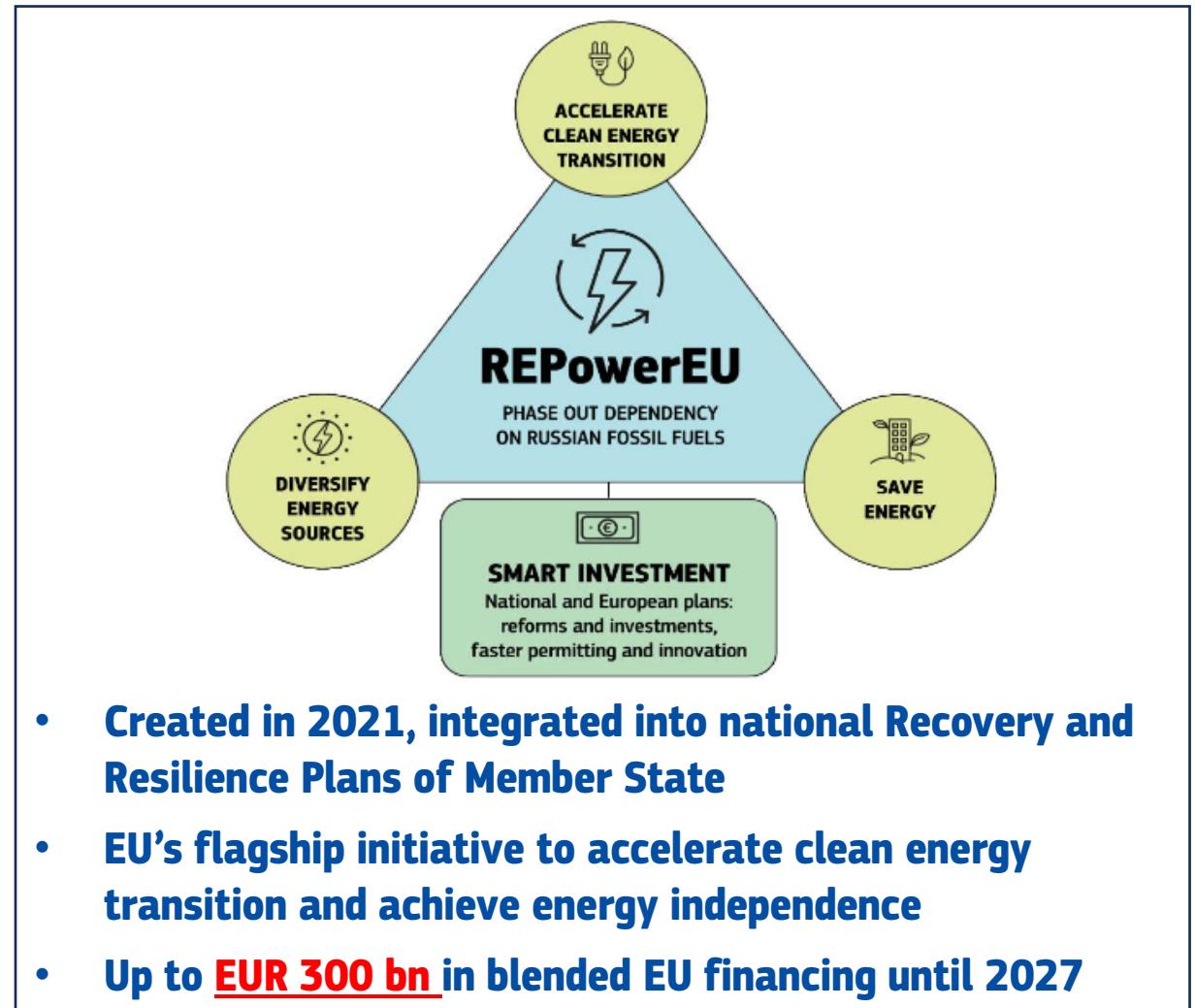
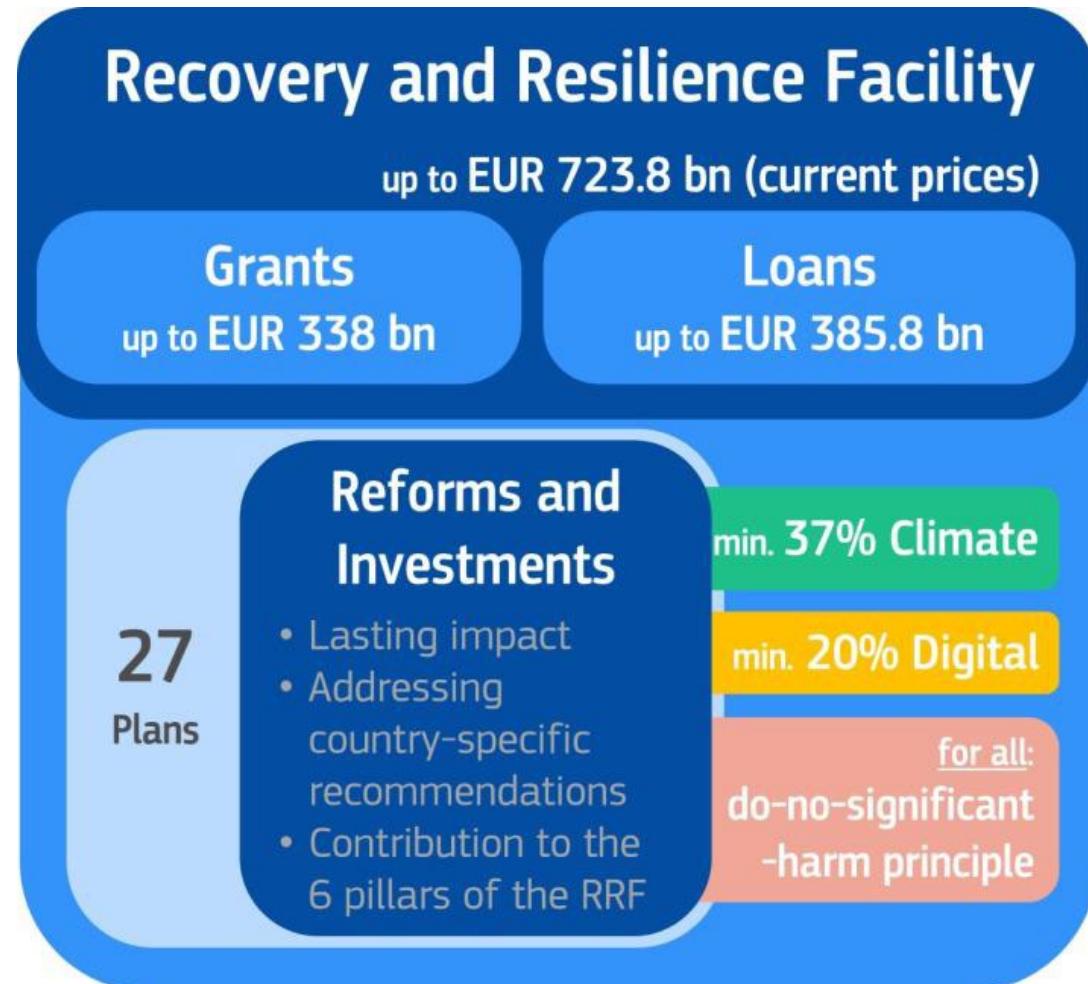


What is the EU doing?

What is the EU doing?



RRF and REPowerEU



NZIA, STEP, CRMA



Net Zero Industry Act (NZIA)

- aims to decarbonize industry by setting legally binding targets to achieve net-zero GHG emissions.
- Proposed 2022; sets ambitious targets to transition industries to cleaner and sustainable practices.



Strategic Transformation Enhanced Programme (STEP)

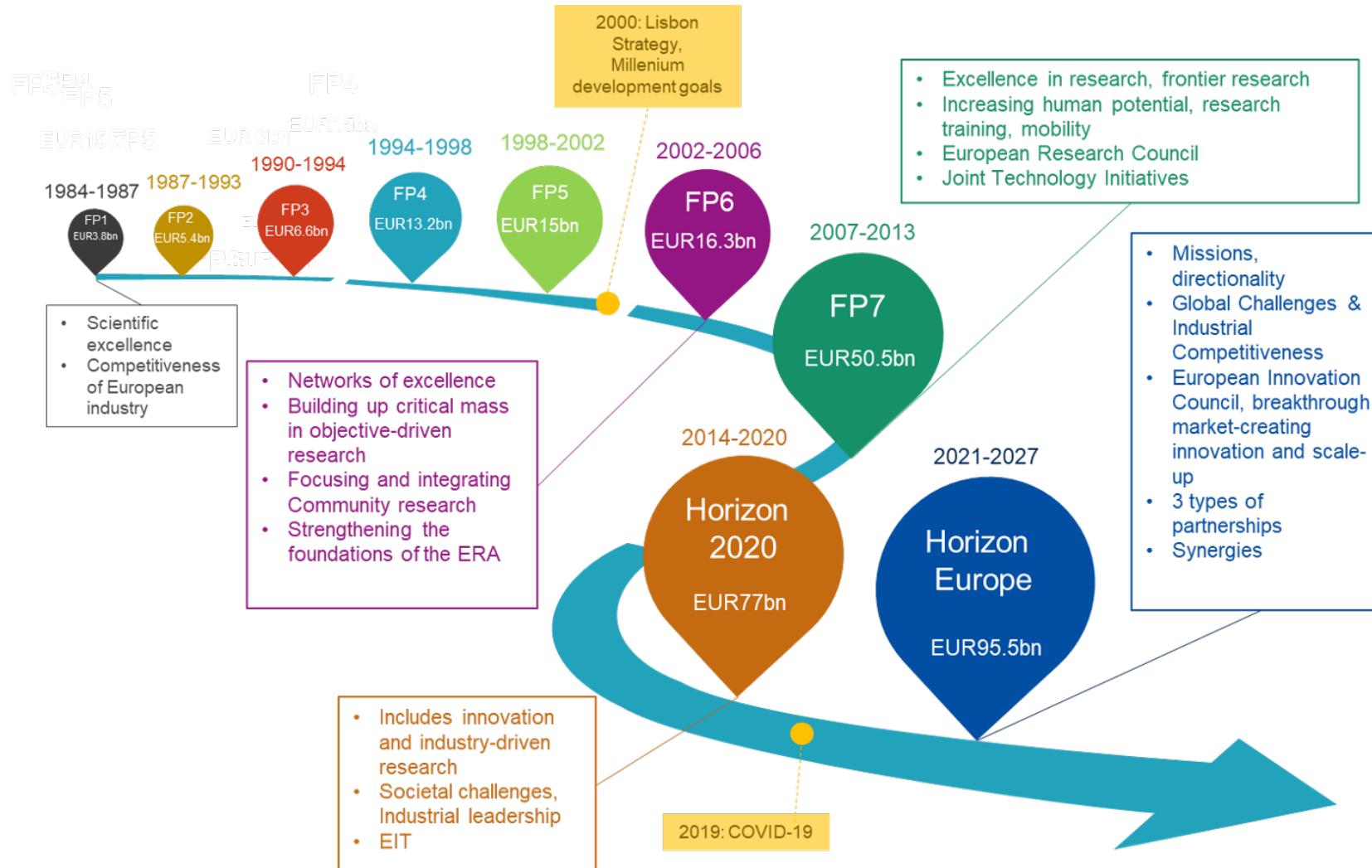
- The Commission's STEP initiative is one-stop shop advisory service
- Launched in 2023, it provides technical guidance and facilitates financial support
- STEP will raise and steer funding across 11 EU programmes to three target investment areas:
 - Digital technologies and deep-tech innovation
 - Clean and resource efficient technologies
 - Biotechnologies



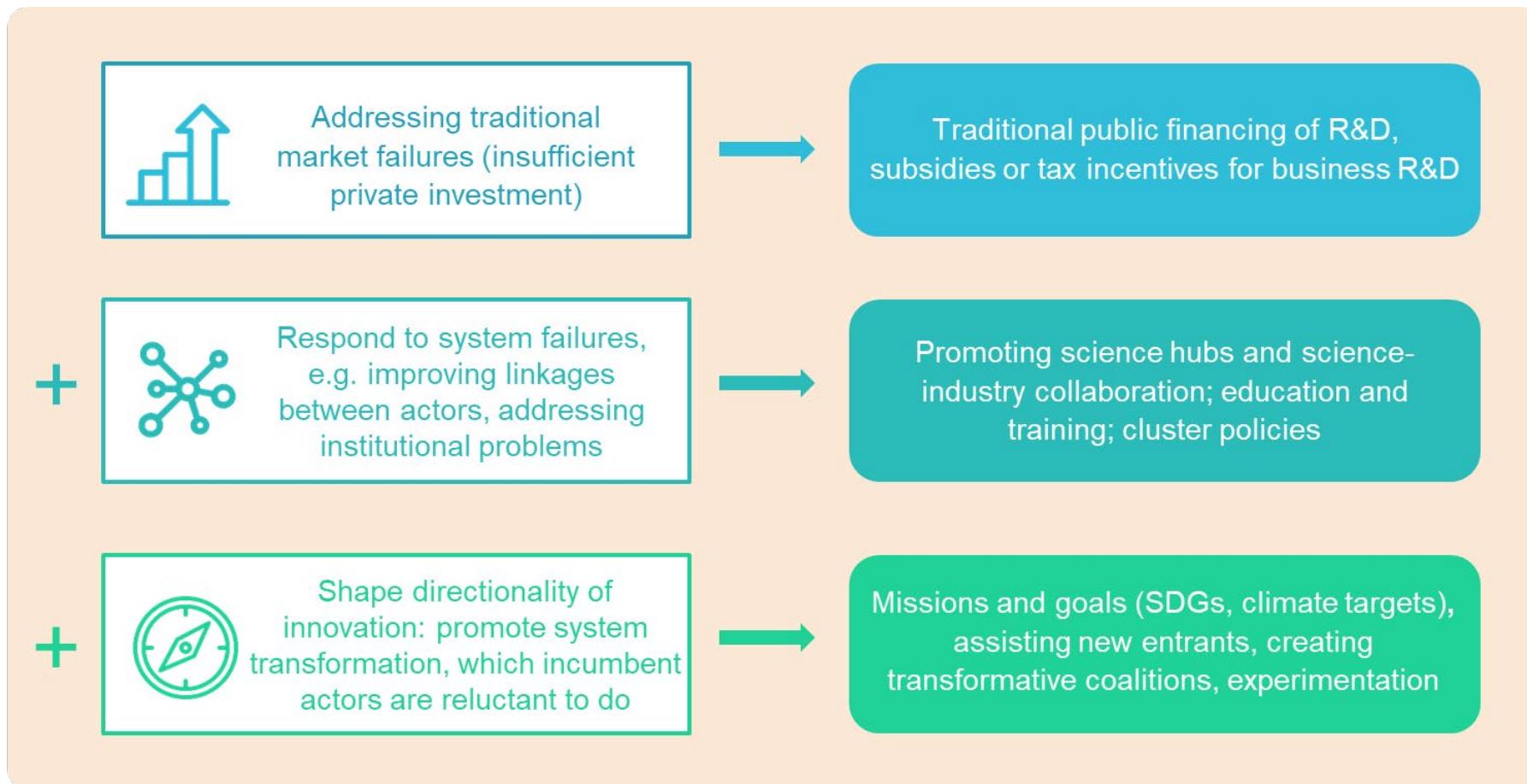
Critical Raw Materials Act (CRMA)

- Enacted in 2020, it aims to secure a stable and sustainable supply chain for critical raw materials.
- The Act focuses on diversifying sources, promoting recycling and substitution, and fostering cooperation with resource-rich countries.

The EU Framework Programme for Research & Innovation (R&I)

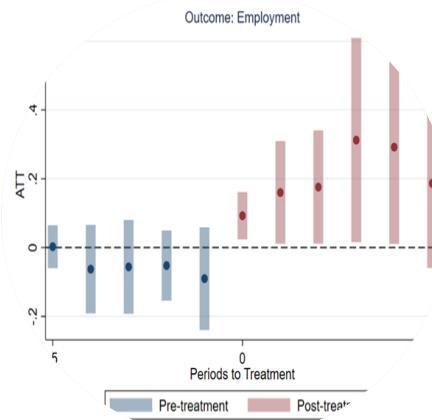


Evolution of the R&I policy



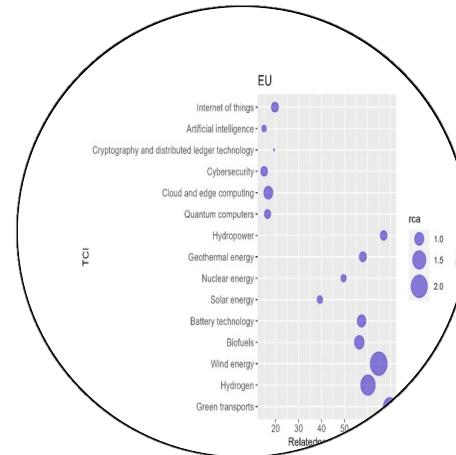
Source: Authors' elaboration based on Geels (2020) in 'Science, Research and Innovation Performance of the EU 2020' and Scott and Steinmueller (2018)

EU R&I in a changing world – The 4 Ds



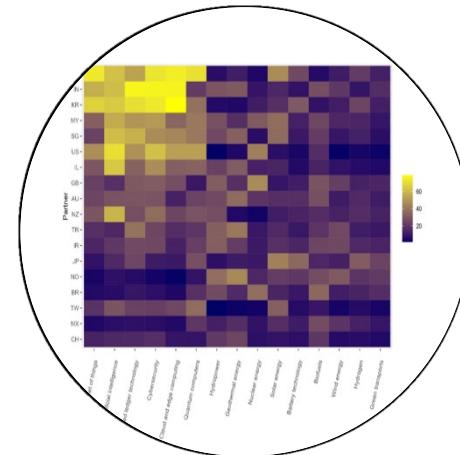
ADditionality

Invest in R&I through policies that deliver EU added value



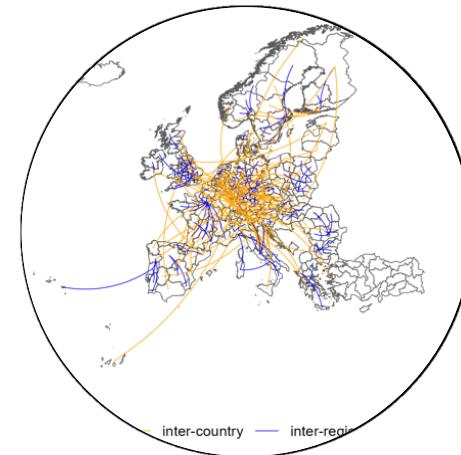
Directing change

Channeling investments toward productivity enhancing technologies



Scientific Diplomacy

Exchange knowledge
with partners based
on technological
complementarities



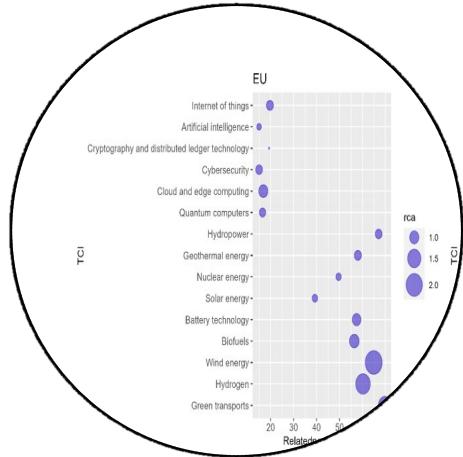
Distributed ecosystem

Break silos by promoting cross country and cross disciplinary innovation

Two complementary approaches for R&I evaluation

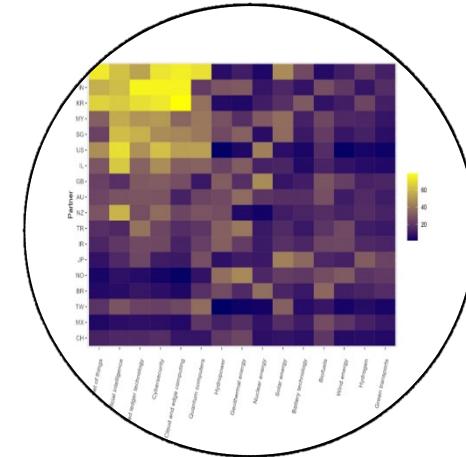


Complexity Economics



Directing change

Channeling investments toward productivity enhancing technologies



Scientific Diplomacy

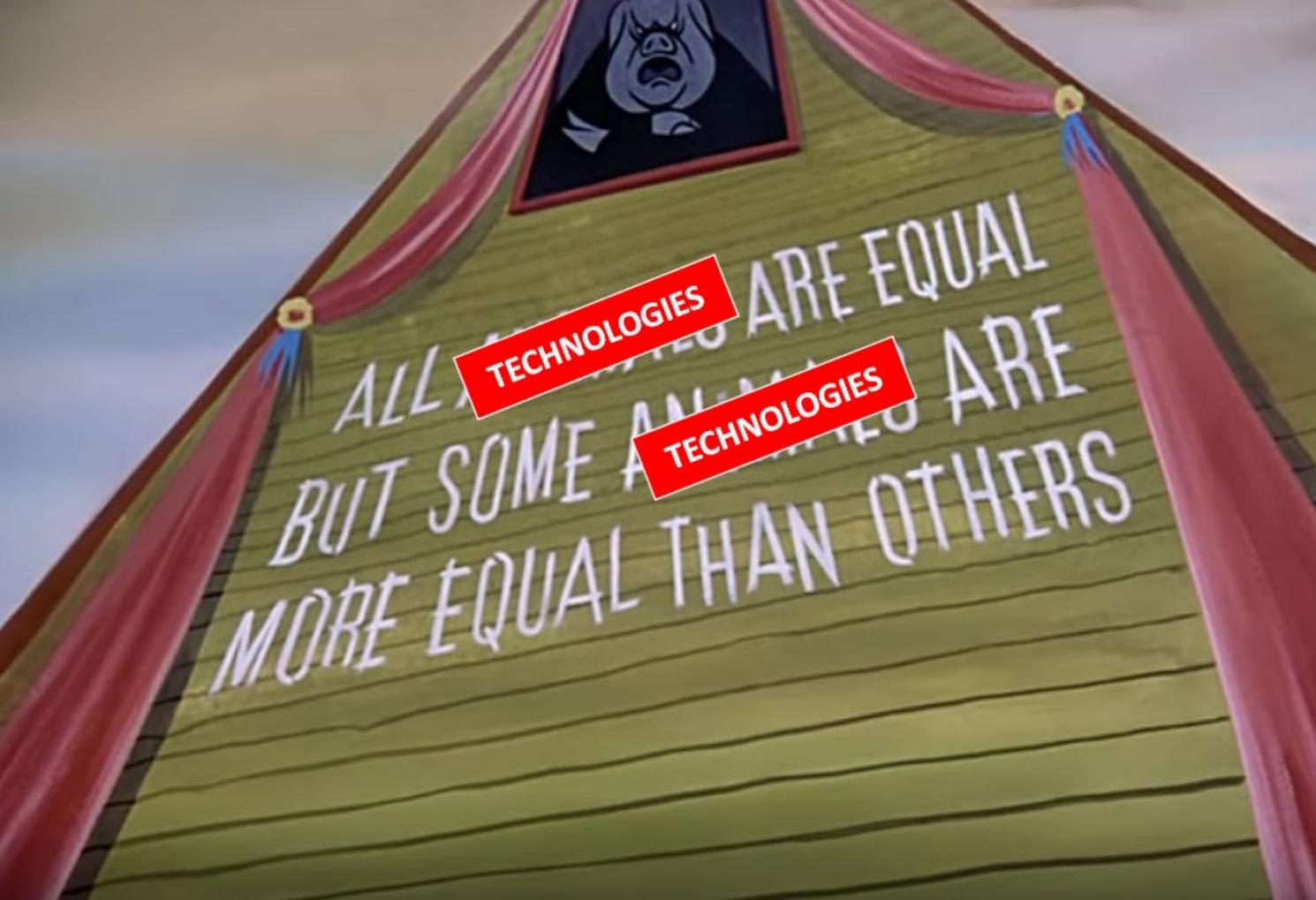
Exchange knowledge with partners based on technological complementarities

Existing literature

- Economic complexity metrics are derived from the work of Hidalgo and Hausmann (2009), which introduced a method to investigate the complexity of individual products and countries, considering their export patterns.
- The underlying idea of economic complexity is that growth, development, technological change, income inequality, spatial disparities, and resilience are the visible outcomes of hidden systemic interactions. (Balland, 2023)

Google's monopoly over internet search goes beyond having the smartest engineers, the largest R&D investments, or the best AI. It is the outcome of a self-reinforcing feedback loop in which slightly better predictions attract more users, which in turn provides more data, leading to better predictions.

An Orwellian approach



Knowledge Complexity in a nutshell

- Technologies easy to replicate are typically associated to lower rents in the long-term.
- Complex technologies (more concentrated in space) are associated to higher growth potential



- Simple technologies require few capabilities; complex technologies require a wider set
- Countries endowed with a stronger knowledge base can more easily access both type of tech

We do not observe capabilities

We do observe innovation output (e.g., patents)

- Use patent data to identify which type of tech is present in a country
- Use complexity metrics to extract information on countries' capabilities and degree of sophistication of a tech
- Predict in which tech a country is likely to diversify into

Methodology – Relative Comparative Advantage

- We follow Balland and Rigby (2017) and identify a two-mode network, represented as $c \times i$ matrix with c denoting the country, and i defining the technological class
- We rely on the concept of **Relative Comparative Advantage (RCA)** to identify whether a country has **Revealed Technology Advantage (RTA)** in a given technology.

$$RCA_{c,i} = \frac{P_{c,i} / \sum_i P_{c,i}}{\sum_c P_{c,i} / \sum_c \sum_i P_{c,i}}$$

- The knowledge complexity index is computed identifying those type of technologies for which a country has RTA in a given period, i.e. for which a country shows $RCA \geq 1$,

Methodology – Knowledge Complexity Index

- Following the method outlined in Hidalgo et al. (2012), we define as $M_{c,i}$ the 2-mode adjacency matrix, with entries equal to 1 if $RCA \geq 1$, and 0 otherwise.
- We row standardize $M_{c,k}$ and its transpose ($M_{c,i}^T$) and calculate $B = M_{c,i} * M_{c,i}^T$ a square matrix with dimension equal to the number of countries considered in the network. The country Knowledge Complexity Index (KCI) is computed as

$$KCI = \frac{\vec{Q} - \langle \vec{Q} \rangle}{\text{stdev}(\vec{Q})}$$

- with \vec{Q} being the second largest eigenvector associated to matrix B , and $\langle \vec{Q} \rangle$ denoting its mean.
- Similarly, the complexity index of individual technologies (TCI) is calculated considering the second largest eigenvectors of matrix $D = M_{c,i}^T * M_{c,i}$, having dimension equal to the number of technologies in the network

Methodology – Relatedness Density

- Closely related to complexity is the concept of **relatedness** (e.g., Hidalgo et al., 2007; Rigby, 2015; Balland and Rigby, 2017).
- Two technologies are considered related when they rely on the same knowledge and competencies to be produced (Hidalgo et al., 2018; Balland et al., 2019).
- Relatedness density ($\omega_{ci,t}$) measures the number of similar activities that are present in a given location
- It is obtained from the technological relatedness (φ_{ij}) of technology i to all other technologies j in which a given country shows a specialisation index greater than 1, divided by the sum of technological relatedness of technology i to all other technologies j in a given period

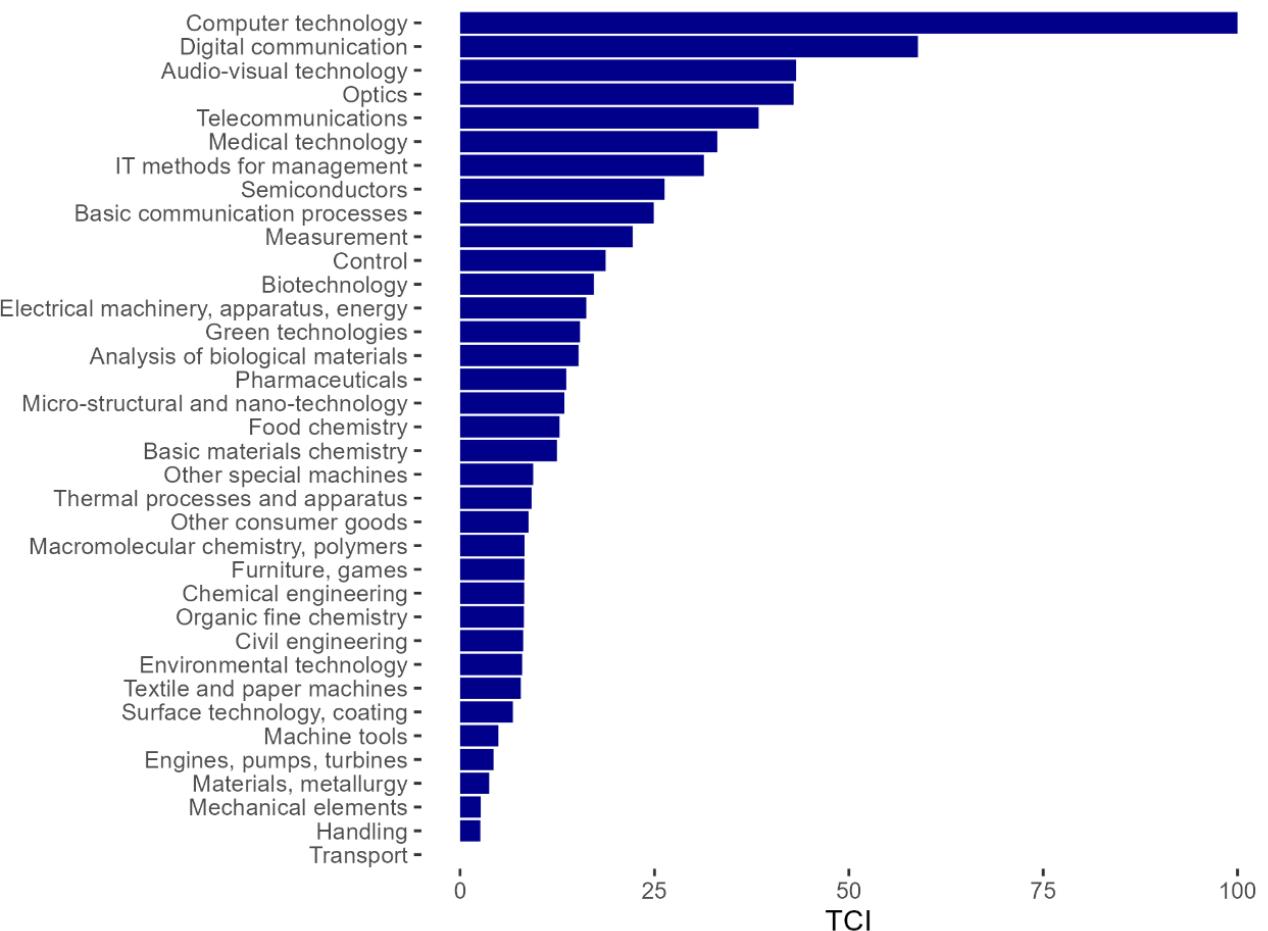
$$\omega_{ci,t} = \frac{\sum_{j \in c, j \neq i} \varphi_{ij}}{\sum_{i \neq j} \varphi_{ij}} \times 100$$

Data

- Google Patents Public Datasets on BigQuery, which is a collection of publicly accessible, connected database tables for empirical analysis of the international patent systems.
- We use information on patent applications filed under the Patent Co-operation Treaty (PCT) and assigned countries to patents based on inventor residence information.
- Overall, we have information on 195 countries, and more than 600 technological classes identified using Cooperative Patent Classification (CPC) at 4-digit level, over the period 2004-2022.
- To avoid noise in the complexity estimation due to the heterogeneity of the CPC classification, we use the more homogeneous classification proposed by Schmoch (2008).
- The complexity index is then calculated over the periods: 2004-2008, 2009-2013, 2014-2018, and 2019-2022.

Results

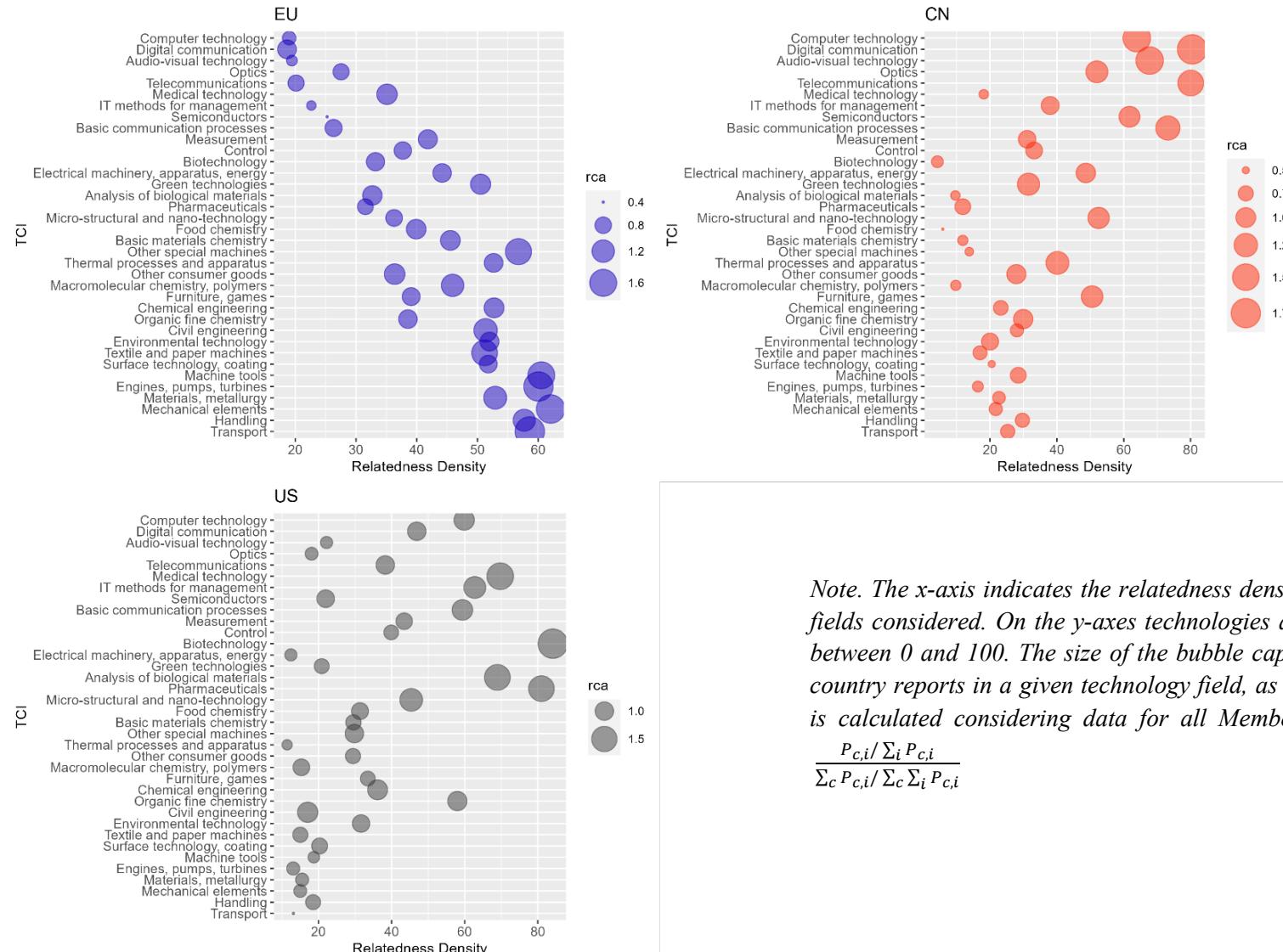
Technology Complexity Index (TCI), 2019-2022



- Technologies associated with the highest TCI values are those in the fields of **computer technologies, digital communication, audio-visual technologies, optics, telecommunications, and medical tech.**
- **Semiconductor, basic communication technologies, IT methods for management** are also found in the upper part of the ranking.
- **Pharmaceuticals, biotechnologies, green technologies and micro-structural and nano-technologies** are found in the middle of the ranking
- In lower positions, we find **environmental technologies, and technologies in the field of engines, pumps and turbines, mechanical elements, machine tools, handling and transport.**

Results

The EU positioning in complex technologies vs US and CN, 2019-2022

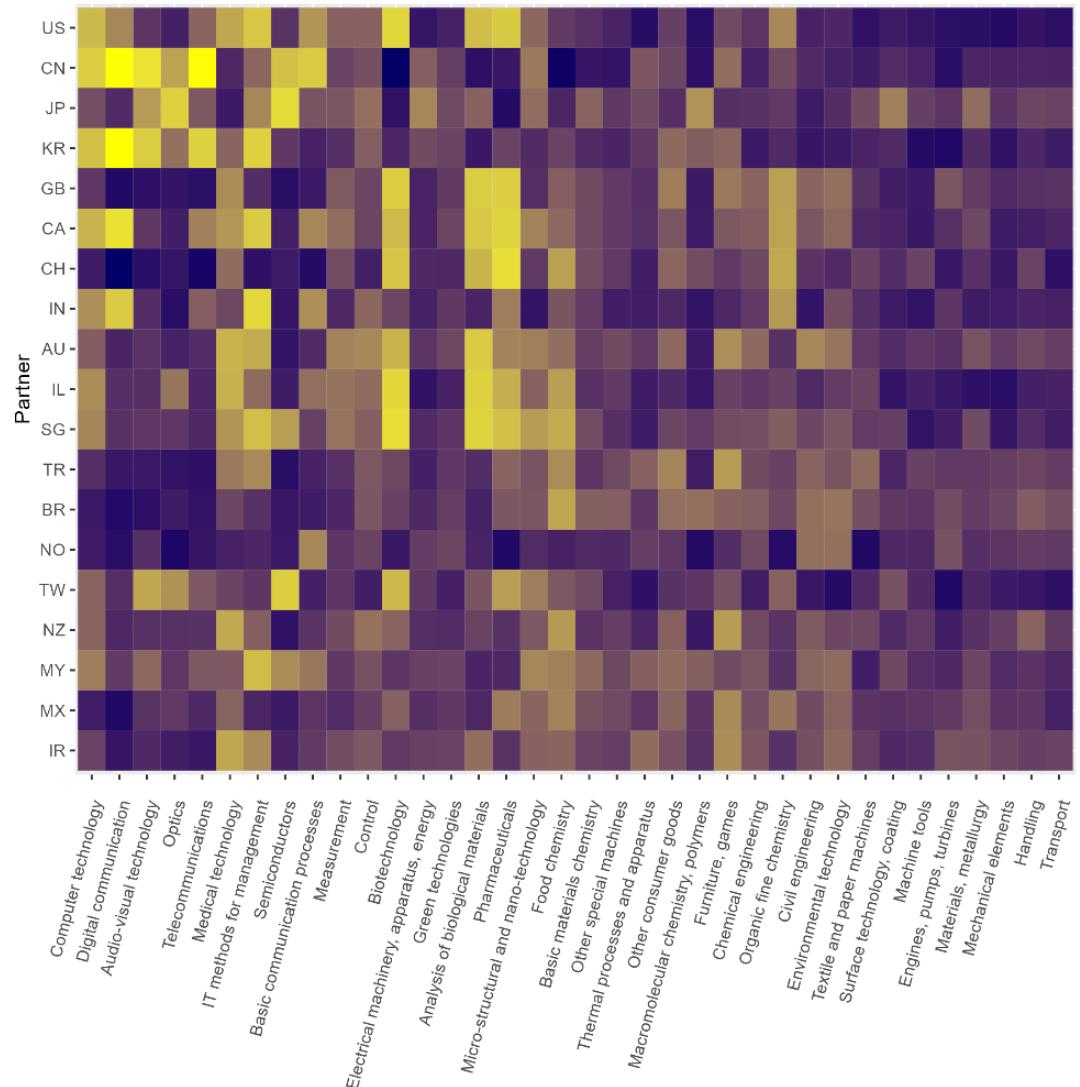


Note. The x-axis indicates the relatedness density of each country in any of the technology fields considered. On the y-axes technologies are ranked by complexity levels, normalized between 0 and 100. The size of the bubble captures the degree of specialisation that each country reports in a given technology field, as measured by the RCA. The RCA for the EU is calculated considering data for all Member States and using the formula $RCA_{c,i} =$

$$\frac{P_{c,i}/\sum_i P_{c,i}}{\sum_c P_{c,i}/\sum_t \sum_i P_{c,i}}$$

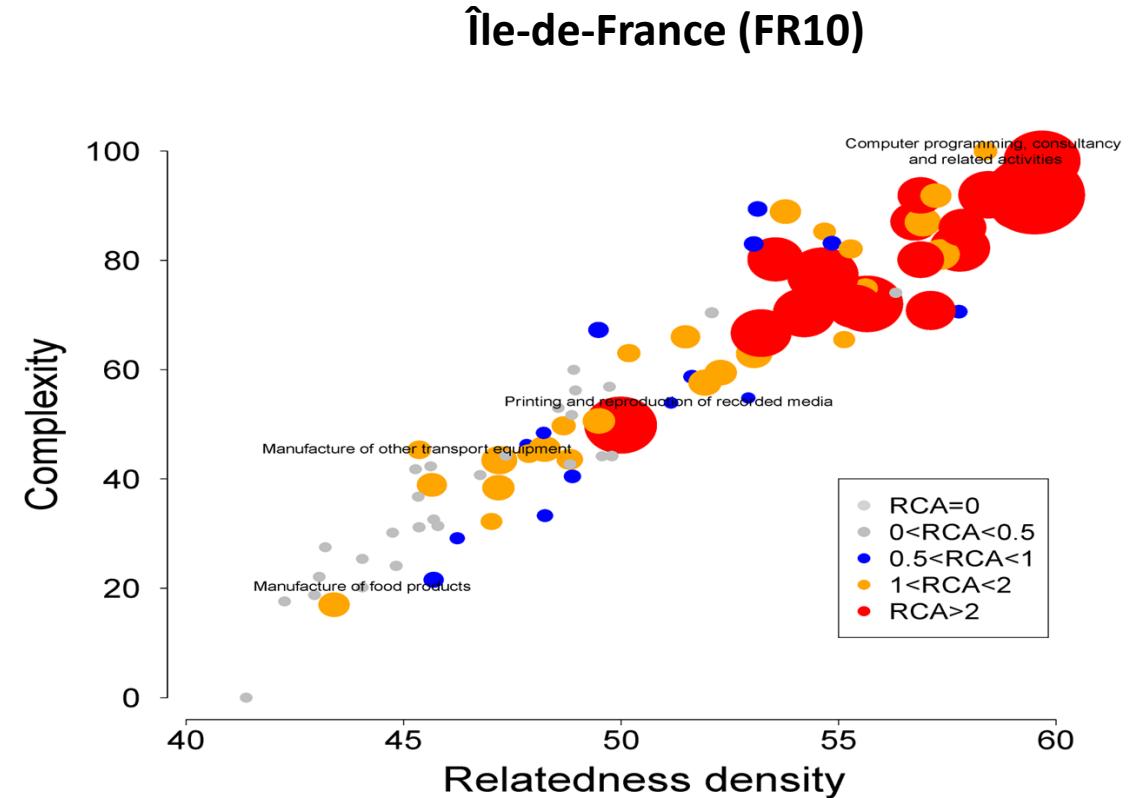
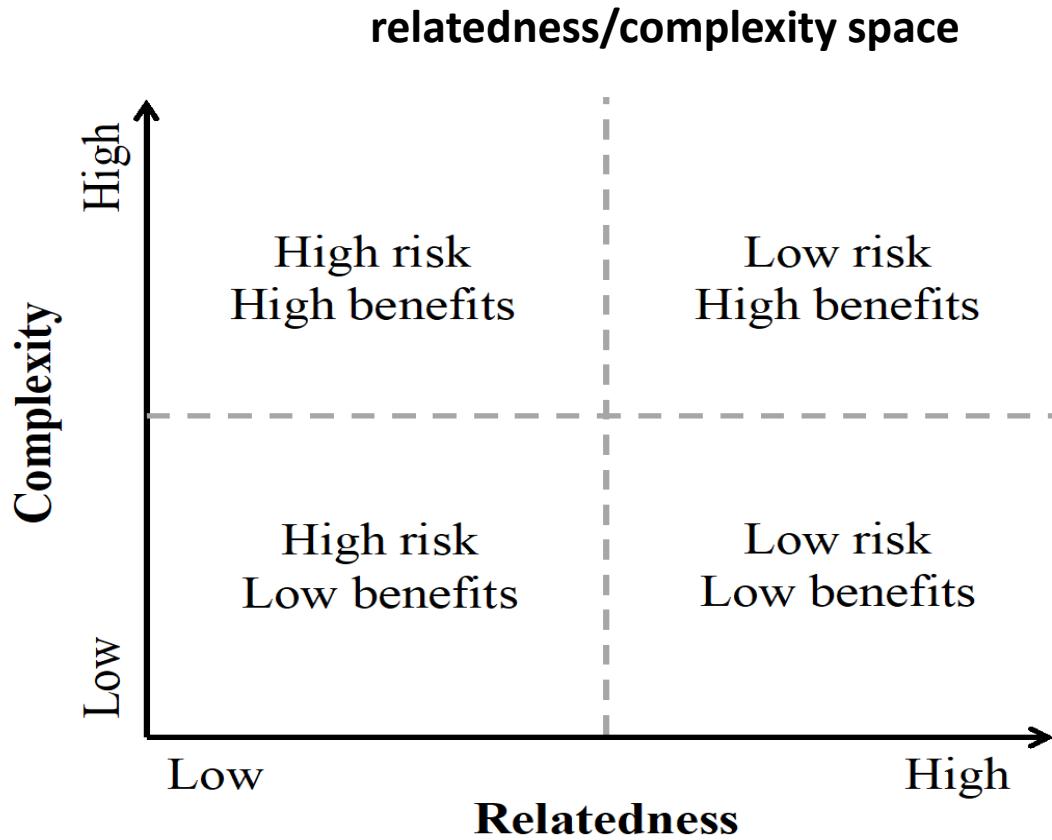
Results

The EU's technological complementarities, 2019-2022



- Significantly **high degree of technological complementarity** is observed in technologies associated with the highest degree of complexity.
- The countries showing the highest degree of complementarity (above 40%) in these fields are China, South Korea, Japan, the US, and India.
- A lower degree of complementarity (between 30% and 40%) is observed for Singapore, Israel, and Taiwan.
- **Biotechnology, medical tech and pharmaceutical** are other areas in which we see high complementarity (around 30%) is observed, mostly with the US, Singapore, Canada and Israel.
- On the contrary, a lower degree of technological complementarity is observed in less complex tech classes in which the EU reports a higher level of specialisation.

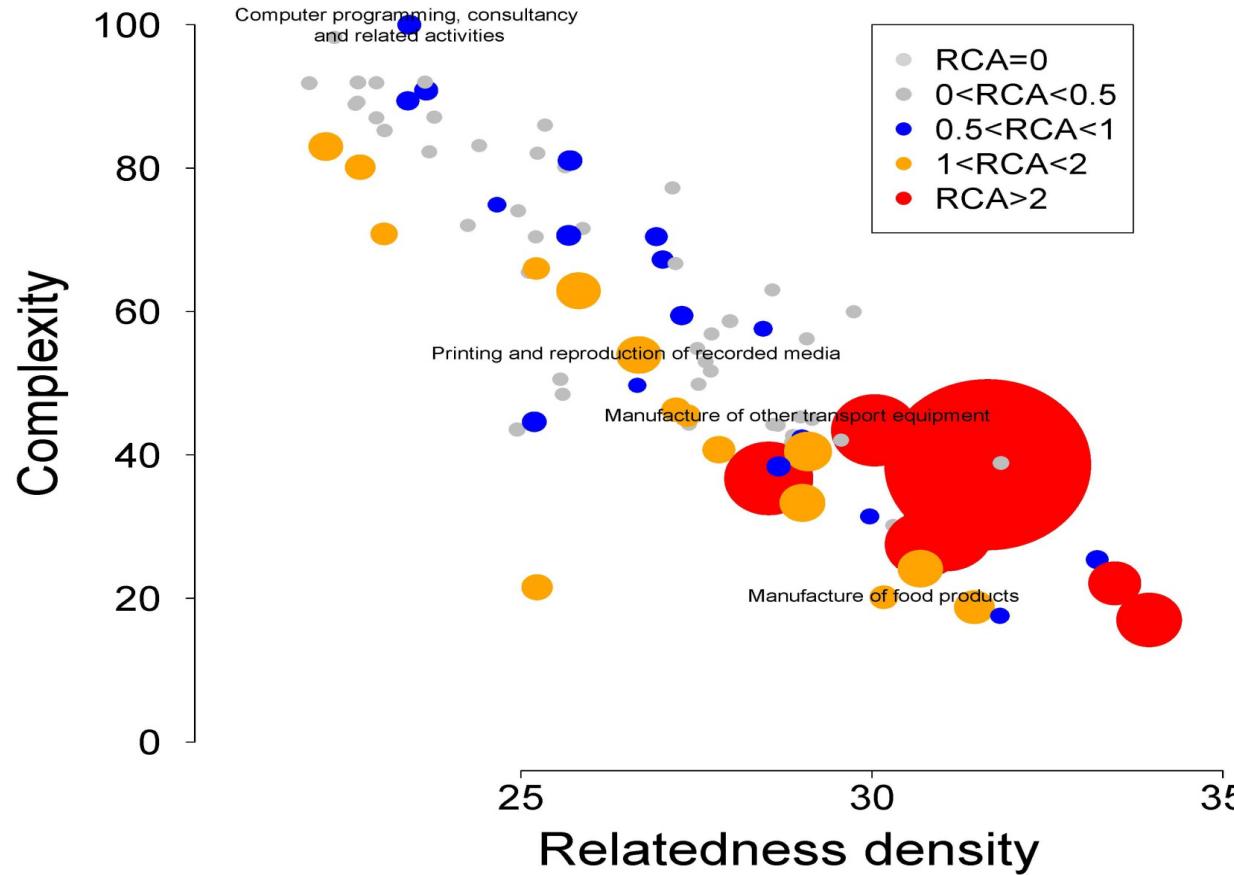
Bonus.. Complexity analysis for smart specialisation



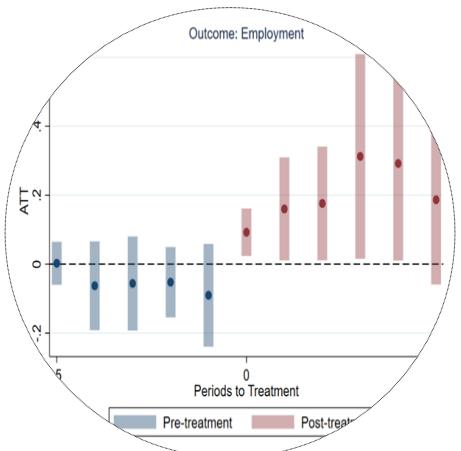
Source: Balland et al. (2019)

Bonus.. Complexity analysis for smart specialisation

Silesia (PL22)

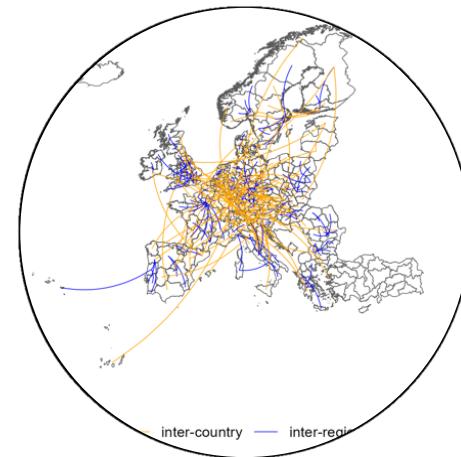


Counterfactual analysis



ADditionality

Invest in R&I through policies that deliver EU added value



Distributed ecosystem

Break silos by promoting cross country and cross disciplinary innovation

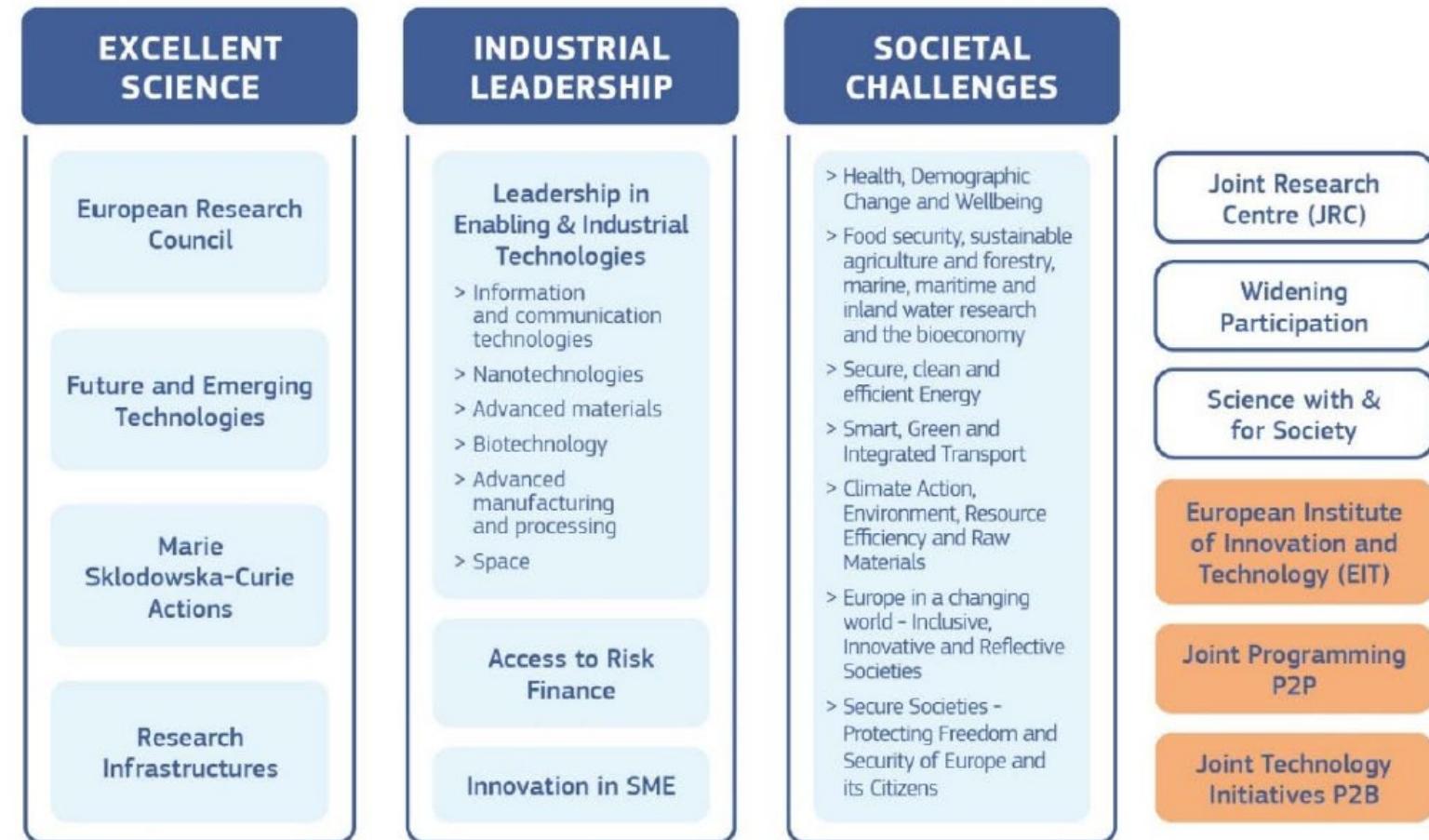
Existing evidence

- Howell (2017) employs a regression discontinuity (RD) design and looks at R&D grants of the U.S. Department of Energy's SBIR grant programme, finding that R&D grants increased beneficiaries companies' revenue and patenting activities
- Using a regression discontinuity design to analyse an Italian R&D grant programme, Bronzini and Iachini (2014) find no overall impact on companies' investment spending, with the positive effects concentrated on small firms.
- Santoleri et al. (2022) looks at a Horizon 2020's "SME instrument" under the Industrial Leadership pillar and using regression discontinuity (RD) design finds positive effects on cite-weighted patents, investment, and firm growth
- Ghirelli et al. (2023) investigate a sub-section of the EU framework programme, focusing on the European Research Council (ERC) grants, employ Difference-in-Differences and do not find any statistically significant effect on research productivity and excellence as a consequence of winning the ERC funding (except for some fields and young researchers).

Horizon 2020's structure

THE FRAMEWORK PROGRAMME FOR RESEARCH AND INNOVATION

HORIZON 2020



Data

- Administrative data on Horizon 2020 successful and unsuccessful proposals and applicants are drawn from CORDA (COmmon Research DAta Warehouse), a database managed by the European Commission Directorate-General for Research and Innovation.
- Firm-level financial data are obtained from the ORBIS company database. Given the absence of harmonized national business register data, ORBIS offers the most reliable source for consistent cross-country company data (Autor et al., 2020).
- Using the VAT identification number and manual disambiguation, 80% of the unique EU beneficiary firms from CORDA were matched to the ORBIS database (118 212 out of 148 226 unique firms). This is in line with the matching precision achieved by previous literature using ORBIS data (e.g., Santoleri et al. 2022)
- To ensure comparability between the unsuccessful and the successful applicants, as defined by the Difference-in-Difference approach used to infer causality, the sample is further restricted to include only applicants with proposals of high quality

Data

Table 2: Tabulation of unique firms by the number of times they applied for grants

N. of times	Freq.	Percent	Cum.	N. of prog. parts	Freq.	Percent	Cum.
1	11023	27.52	27.52	1	19658	49.09	49.09
2	7194	17.96	45.49	2	9863	24.63	73.71
3	4814	12.02	57.51	3	4720	11.79	85.50
4	3565	8.90	66.41	4	2319	5.79	91.29
5	2548	6.36	72.77	5	1330	3.32	94.61
6	1903	4.75	77.52	6	745	1.86	96.47
7	1455	3.63	81.16	7	465	1.16	97.63
8	1164	2.91	84.06	8	286	0.71	98.35
9	930	2.32	86.39	9	223	0.56	98.90
10	672	1.68	88.06	10	121	0.30	99.21
More	4780	11.95	100	More	318	0.79	100
Total	40048	100.00		Total	40048	100.00	

Note: On the left-hand side, the table shows the tabulation of how many times the same companies have applied to different Horizon 2020 grants. On the right-hand side, the table shows the tabulation of to how many different program parts the same companies have applied within Horizon 2020. On average, a unique company applied to 6.1 different grants and 2.2 different program parts.

Data

Table 4: Summary statistics of outcome variables by year

Variables Year	Ln employment		Ln total assets		Ln revenues	
	N	mean	N	mean	N	mean
2010	2161	4.29	4020	15.3	2761	15.603
2011	9659	4.739	15018	16.049	10739	16.474
2012	16441	4.718	25296	16.037	18778	16.469
2013	17734	4.704	27166	15.967	20073	16.383
2014	19158	4.656	28421	15.919	20818	16.329
2015	21518	4.602	30014	15.912	21880	16.312
2016	24266	4.548	31447	15.89	22852	16.248
2017	27577	4.486	33941	15.897	23910	16.26
2018	28121	4.489	34640	15.936	24227	16.295
2019	28180	4.509	34848	16.005	24268	16.346
2020	27934	4.477	33631	16.14	23344	16.363
2021	13081	4.433	15807	16.202	10949	16.59
2022	239	4.452	273	14.835	97	17.041

Note: The table shows the descriptive statistics for all available unique firm level financial information by year. Not all companies reported to ORBIS their financial status every year, hence there are fluctuations on the number of unique firms (N) reporting employment, total assets, and revenues by year.

Method

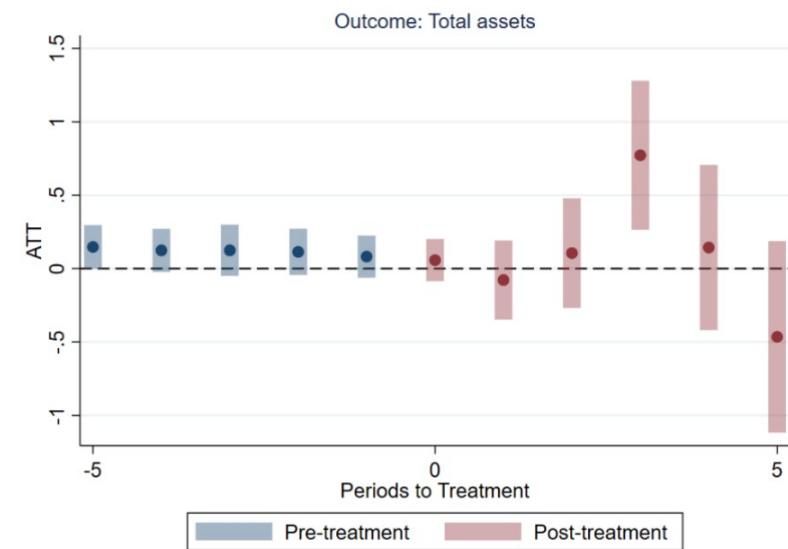
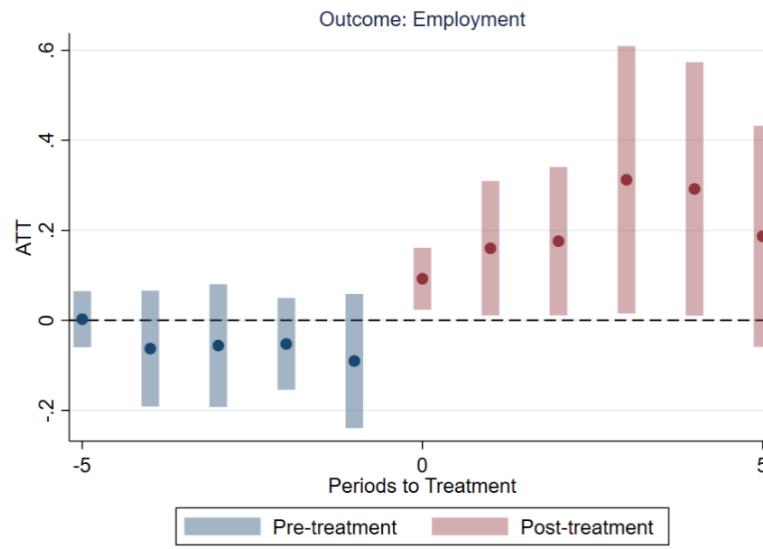
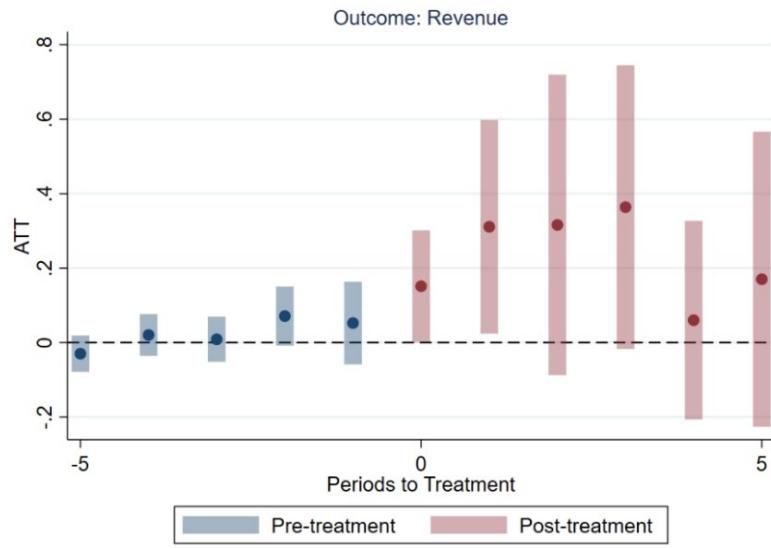
- In recent years, the econometric literature on event-study and Difference-in-Difference approaches has undergone significant development
- These developments are particularly important as these studies showed that even generalised DiD models (such as the Two-way Fixed Effects Model) may not be adequate to identify an ATT when effects are heterogeneous (Goodman-Bacon, 2021).
- We decide to follows the procedure proposed by Callaway and Sant'Anna (2021) for two main reasons:
 - It allows to deal with variations in the treatment timing and heterogeneous treatment effects.
 - It allows to condition on covariates when the parallel trends assumption holds potentially only after conditioning on observed pre-treatment characteristics.

Method

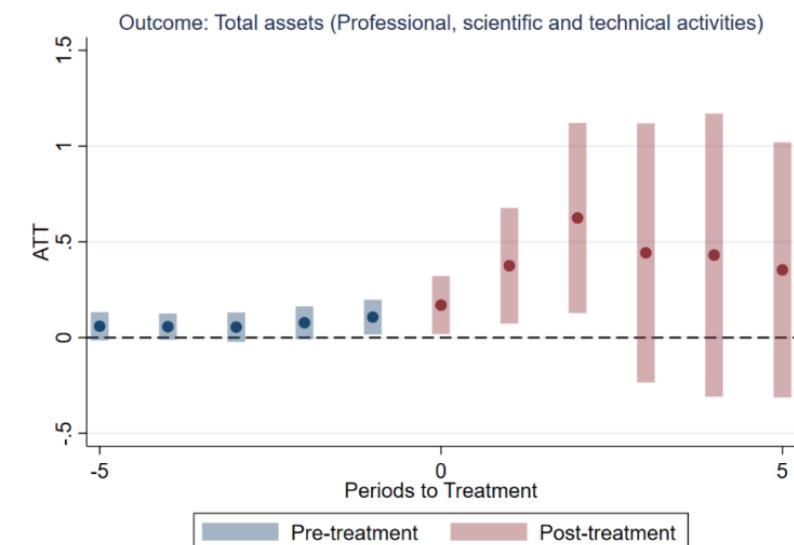
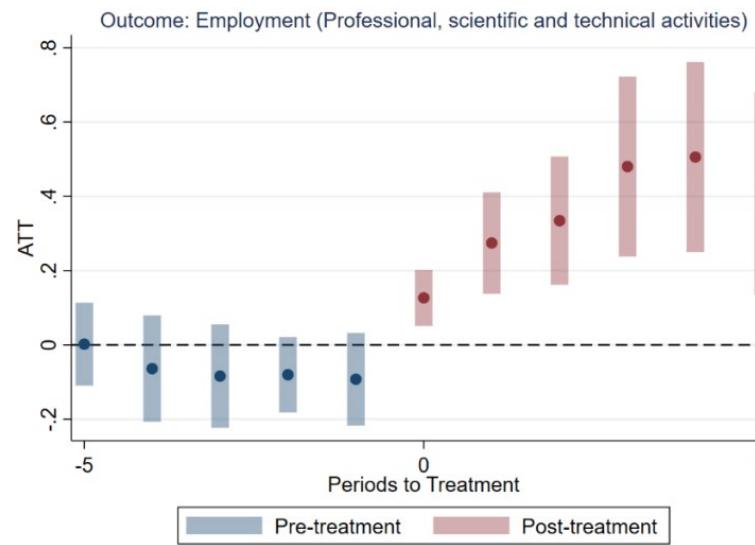
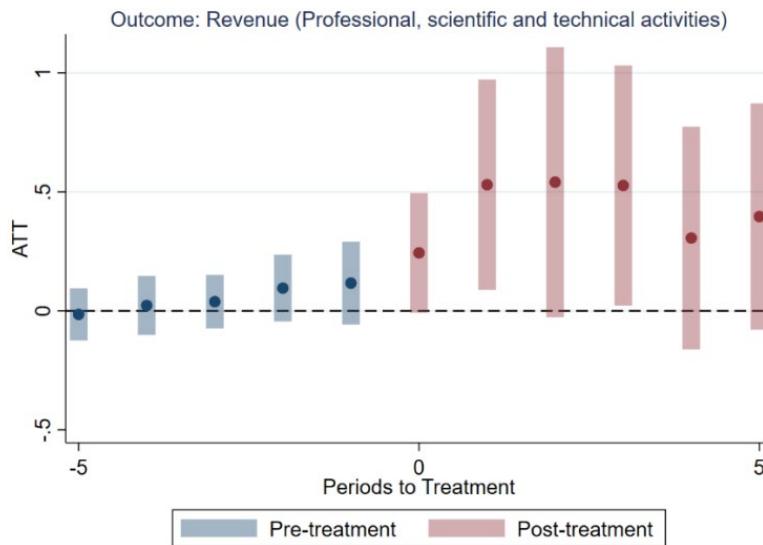
$$y_{i,t,c} = \beta_1 \sum_{-1}^5 T_{i,t,c} \times (c - k) + \beta_2 \sum_0^5 T_{i,t,c} \times (c + k) + \vartheta_i + \gamma_t + \epsilon_{i,t,c}$$

- Where $y_{i,t,c}$ represents our outcome variables of interest for company i , measured in year t , applying in year c .
- As firm-level outcome variables we consider employment, total assets and revenues.
- β_1 is a vector of coefficients capturing the effect of the grant in each year before the call year c .
- The year of reference is $c - 1$, the year prior to the call.
- β_2 is a vector of coefficients estimating the effect of the grant in each year after the call year c
- We control for ϑ_i , firm fixed effects (which capture also call year c) and γ_t calendar year fixed effects.
- We condition the DiD parallel trend assumption on company NACE, country of origin and the number of times it has applied for Horizon 2020 calls.

Results on whole H2020



Results for Professional, scientific, and technical activities



Next steps

Different possible policy counterfactuals:

1. The number of beneficiaries, holding constant the size of grants and the award criteria.
2. The size of individual grants, holding constant the number of beneficiaries and the award criteria.
3. The award criteria or allocation process (choice of reviewers, reviewer incentives, autonomy of program directors, etc.), holding constant the number of beneficiaries and the size of grants.
4. The distribution of funds across different fields or domains, holding constant the total program size.
5. Different combinations of the above, such as for example decreasing grant sizes while increasing the number of beneficiaries, holding constant the program size.
6. Receiving EU grant vs receiving MS grant

Level of analysis:

Investigating knowledge spillovers and crowd out, because of the need of having aggregate causal evidence, not only firm at the level

Different policy objectives:

Other outcomes variables such as publications, patents by technology, venture capital, societal outcomes

What about policy officials' preferences?

Following on what presented by Marco Ottaviani on better grant evaluation and selection processes:

