

Behind on Which Front? Knowledge, Creation and Deployment in Europe's Position Relative to the United States and China in Business, Artificial Intelligence and Renewable Energy

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Abstract

Whether Europe has fallen behind the United States and China is central to European economic policy, yet the debate pools very different activities into one verdict. This study separates three stages of technological competitiveness: knowledge (the science base), creation (turning knowledge into firms, capital, frontier technology and exportable manufacturing) and deployment (adoption and diffusion). It measures the European Union's position in business, artificial intelligence and renewable energy against both rivals with 14 indicators from six public sources. Each indicator is expressed as a log ratio and analysed with HAC-robust trend tests, a pre-specified test for a change after 2020 and leave-one-out pillar indices. In 2023 the EU stood at 1.34 times the United States in knowledge and 1.23 times in deployment, but at 0.33 in creation. Against China it stood at 0.55, 0.29 and 1.52, respectively, and all three ratios declined by 4–12% a year from 2017. The EU's share of R&D among the world's 1,000 largest corporate investors fell from 24.7% to 16.4% between FY2010 and FY2024, and its share of ICT corporate R&D from 16.2% to 6.0%. Europe has fallen behind, but mainly in conversion rather than in science or adoption.

1. Introduction

Few questions have dominated European economic policy since 2024 as much as whether the European Union has fallen behind the United States and China. The report on the future of European competitiveness prepared for the European Commission framed the problem as a widening gap in productivity and innovation, concentrated in the technologies that will shape the next decades (Draghi, 2024). Legal and economic commentary has since examined its diagnosis and that of the parallel report on the single market, which together call for deeper market integration, larger European firms and a stronger industrial policy (López, 2025; Cocconi, 2025). Critics accept the gap but dispute the remedy: Rodríguez-Pose and Dijkstra (2026) argue that chasing parity in the fields where Europe is weakest is the wrong race, and Ábel et al. (2025) point out that human capital is largely missing from the diagnosis.

The difficulty is that “falling behind” is not one thing. A region can lead in scientific output and trail in the firms that commercialise it; it can install renewable capacity faster than its rivals while importing the equipment; it can regulate artificial intelligence (AI) carefully while building few frontier models. Existing studies usually measure one of these dimensions at a time, using patents (Overdiek et al., 2020; Varga & Becsky-Nagy, 2026), digitalisation indicators (Franc et al., 2026), clean-technology trade and patenting (Fankhauser et al., 2013) or the design of AI governance (Birchfield et al., 2022; Bradford, 2024). Because each indicator captures a different stage of the path from ideas to markets, the literature can reach opposite conclusions about the same economy without either being wrong.

A bibliometric screen confirms that this decomposition has not been attempted. A Scopus search (October 2026) for documents published since 2010 that compare the EU, the United States and China in terms of competitiveness, technological gaps or catch-up returned 432 records. Restricting them to AI left 26. Documents on the three economies that combine AI with renewable energy or the energy

transition numbered 17, and only three of them used indicator, index or benchmark terms. The closest contributions map AI patents for the energy transition, an upstream measure whose authors caution that patent concentration is not the same as leadership (Kumar et al., 2026), or compare digitalisation indicators descriptively (Franc et al., 2026). None measures the same economies across business, AI and renewable energy while distinguishing between producing knowledge, converting it into firms and products, and putting technology to use.

This study fills that gap. It proposes a three-pillar framework (knowledge, creation and deployment) and measures the EU-27's position relative to the United States and China on 14 harmonised indicators from public sources covering 2005–2024. Every indicator is expressed as a log ratio, so that one number summarises Europe's position and its trend is directly interpretable as an annual percentage change. The analysis adds HAC-robust trend tests, a pre-specified test for a change in trajectory after 2020, leave-one-out indices, an extended-Europe comparison and a set of explicit measurement safeguards. The main result is an asymmetry. Relative to the United States, Europe produces about a third more science and deploys roughly as much technology or more, but its creation index is only about a third of the American level and has not improved since 2017. Relative to China, Europe still leads in deployment, but its advantages in both knowledge and creation have disappeared within a decade. Europe has fallen behind, but the gap lies mainly in converting knowledge into firms, capital and manufacturing, not in science or adoption.

The rest of the paper proceeds as follows. Section 2 reviews the literature and states the hypotheses. Section 3 describes the data, the aggregation rules and the methods. Section 4 presents the results by pillar and domain. Section 5 reports robustness checks. Section 6 discusses the implications and limitations, and Section 7 concludes.

2. Literature and hypotheses

2.1 The European competitiveness debate

The present debate builds on a decade of concern about Europe's place between two larger economies. After the global financial crisis, Mosconi (2015) asked whether there was room for European manufacturing between an American programme of advanced manufacturing and a China that had become the world's factory, and argued for a new European industrial policy. Aiginger (2021) placed the question in a changing world order: American leadership waning, China rising with an investment strategy steered by the state, and an EU seeking a geopolitical role while becoming more heterogeneous. Gechev (2025) summarises the outcome bluntly: over the last fifteen years the European economy has lagged both rivals in the quantity and in the quality of growth, and new technologies intensify the competition.

Industrial policy has returned to all three economies. Hauge et al. (2025) describe a new economic nationalism in which the United States, China and the EU pursue similar goals of technological

leadership with different instruments. Ninni (2023) contrasts the American Inflation Reduction Act with the European Net Zero Industry Act, and Nicoli and Lappe (2025) document, through conjoint experiments with policy experts, the trade-offs Europeans see between fiscal discipline, competition and climate goals. Other authors stress what the headline reports leave out: foreign direct investment and trade (Csontos et al., 2026), human capital (Ábel et al., 2025) and digital infrastructure and platforms, which Minenna (2025) considers the condition for Europe not to become dependent on non-EU providers. Empirical assessments are mixed. Varnavskii (2025) finds that the EU lost world market share in high-technology products between 2007 and 2021 at a modest 0.6–0.7% a year, before recovering in 2022. Chen et al. (2026) compare total factor productivity across China, the United States and the EU in 27 industries, and multidimensional measures of productivity (Or Rosid et al., 2022) and of national intellectual capital (Vo & Tran, 2023) yield rankings that depend on what is measured.

2.2 Corporate R&D, finance and the scale of firms

A recurring explanation for the European gap concerns the conversion of research into growing firms. Henrekson and Sanandaji (2018) note that Europe lags the United States in venture capital and successful start-ups, and has recently been overtaken by China, despite deep financial markets, strong institutions and high R&D spending. They point to the tax treatment of employee stock options as one reason. Coveri and Zanfei (2023) show that multinationals based in Europe and North America distribute their foreign investments differently across value-chain functions, which affects who captures knowledge-intensive activities. Henderson and Hooper (2021) find that most Chinese investment in Europe has taken the form of acquisitions of European firms rather than new production or research facilities. Banking structures also differ across the three economies (Istudor et al., 2022).

Patent-based studies describe a gradual shift of technological leadership. Over the long run, Chen et al. (2021) see leadership moving from Europe to the United States and possibly to China. Kwon et al. (2017) document substantial catch-up by China, Korea and Taiwan in the quality of patents relative to the United States. Overdiek et al. (2020) track the share of high-value patents in 58 cutting-edge technologies, and Varga and Becsky-Nagy (2026) use revealed technological advantage to compare the United States, Europe and China between 2001 and 2022. Within Europe, Bielig (2023) analyses Germany's position in digital-technology patenting, and Macgregor Pelikánová et al. (2025) examine the first months of the Unitary Patent. Nouveau (2022) frames the European problem as being caught between the two larger economies and asks whether the EU can move its digital transformation away from industrial path dependency. These studies suggest a first hypothesis.

H1 (business). The EU's position relative to the United States and China in corporate R&D and in the technology intensity of its largest firms deteriorated after 2010.

2.3 Artificial intelligence

Research on AI in the three economies has focused on strategy and regulation more than on measurement. Birchfield et al. (2022) examine the EU's ambition to become the world-leading region in “ethical and secure” AI, and Montasari (2023) compares national AI strategies across the United

Kingdom, the EU and the United States. Kaliisa et al. (2025) analyse eleven regulatory documents from the EU, the United States, China and African countries, and Zhang et al. (2022) compare patterns of digital governance in China, the United States and the EU. Whether regulation slows innovation is contested: Bradford (2024) challenges the view that stringent digital regulation necessarily undermines technological progress, while Jørgensen and Ma (2025) review the barriers and benefits that the AI Act, the GDPR and the Data Act create for the adoption of AI in European cities.

Quantitative comparisons remain few. Dong and Meng (2021) build a composite index of AI industry competitiveness for China, the United States, the United Kingdom and Germany. Franc et al. (2026) compare digitalisation indicators and find that the EU performs well in regulation and digital skills but lags in research and development. Earlier work linked digital transformation to output growth (Mičić, 2017). These studies point to the second hypothesis.

H2 (AI). The EU's gap in AI is large in capital, frontier models and patents, but small or absent in the production of AI knowledge and in the diffusion of AI skills.

2.4 Renewable energy and clean-technology manufacturing

The race for green technologies was framed early on by Fankhauser et al. (2013), who combined patent, trade and output data for 110 manufacturing sectors in eight economies to ask who would win the “green race”. Patent studies have compared solar technologies across the United States, the EU and Asia (Fan et al., 2017), renewable versus fossil-fuel technologies in China and developed economies (Zhang et al., 2018) and granted renewable-energy patents across leading countries (Kim & Cho, 2025). Nordensvard et al. (2018) apply a core–semi-periphery framework to wind-energy patents, and Yusta and Lacal-Arántegui (2020) document how wind turbine manufacturing became a global industry as installed capacity grew from under 20 GW in 2000 to 590 GW in 2018.

Manufacturing and trade have become the decisive margin. Qi et al. (2021) map the global trade network in renewable-energy products, and Song et al. (2024) trace the competitiveness of lithium-ion battery exporters between 2012 and 2020. Hemmelder et al. (2025) find that China leads in patent counts across six future battery technologies, while Midler and Alochet (2023) describe Europe and the United States as racing to catch up in high-voltage batteries despite large public funding. Visvizi et al. (2026) treat China's electric-vehicle patenting as both green innovation and industrial policy, and Wang et al. (2025) show how trade in semiconductor manufacturing equipment structures competition among countries. On the deployment side, Zsiros and Kaló (2026) review the falling cost of wind power and the EU's progress towards its 2030 targets. The energy and AI agendas now intersect: Hrynkiv (2026) shows how export controls on semiconductors, AI and critical minerals can slow the energy transition, and Yoo et al. (2026), Jorgensen and Ma (2026) and Singh et al. (2026) examine the electricity demand of AI and the role of renewables in AI competition. These studies suggest the third hypothesis.

H3 (energy). The EU leads the United States in the deployment of renewable electricity but trails China in clean-technology manufacturing and in the absolute scale of the build-out.

Taken together, the literature offers many measurements but few that can be compared. Patent studies capture the production of codified technology, trade studies the sale of manufactured goods, governance studies the rules under which technologies are used, and macroeconomic studies the aggregate outcome. Each stream compares the three economies on its own metric, period and country coverage, and composite indices usually rank countries in a single year rather than track a bilateral gap over time (Dong & Meng, 2021; Vo & Tran, 2023). The question in the title, which asks how the gap is changing and where it lies, requires the same economies to be measured on several stages and domains with a common metric.

2.5 A three-pillar framework

The three hypotheses share a structure. Each domain involves three linked stages. In the first, an economy produces knowledge (scientific articles, AI research). In the second, it converts that knowledge into commercial assets: corporate R&D, firms financed to grow, frontier models, patents, computing infrastructure and exportable manufactured goods. In the third, it puts technology to use: renewable electricity, the diffusion of AI skills. The stages are complementary, but they need not move together. A region with a strong science base and high adoption can still be weak at the intermediate stage if its financial system, firm-size distribution or industrial policy fails to turn ideas into scale (Henrekson & Sanandaji, 2018; Draghi, 2024). The framework therefore implies a testable pattern across domains.

H4 (asymmetry). Europe's lag relative to the United States and China is concentrated in the creation pillar and is smaller, absent or reversed in the knowledge and deployment pillars.

3. Data and methods

3.1 Units of comparison

The unit of analysis is the EU-27 in its current composition, held fixed over the whole period so that changes in membership do not create artificial jumps. The United Kingdom is therefore excluded in every year. The comparators are the United States and China (mainland). A broader "Europe extended" aggregate (EU-27 plus the United Kingdom, Switzerland and Norway) is used as a robustness check. The period runs from 2005 to 2024, but the coverage of each indicator depends on its source (Table 1).

3.2 Indicators and sources

Fourteen indicators were fixed before any data were collected and assigned to the three pillars defined in Section 2.5. Two outcome variables, GDP at purchasing-power parity and GDP per person employed, are reported but excluded from the pillars, because they summarise rather than measure the stages. Table 1 lists the indicators, sources and windows.

Table 1
Indicators, pillars, sources and coverage

Pillar	Indicator	Measure	Source	Coverage
K	Scientific and technical articles	Count	World Bank (WDI)	2005–2023
K	AI publications	Journal and conference papers	Stanford HAI (AI Index)	2017–2024
C	Gross R&D expenditure	% of GDP	World Bank (WDI)	2005–2023
C	Share of R&D, top-1,000 corporate investors	% of R&D of top 1,000	JRC Scoreboard	FY2010–FY2024
C	Share of ICT corporate R&D	% of ICT R&D in top 1,000	JRC Scoreboard	FY2010–FY2024
C	Private AI investment	US\$	Stanford HAI (Quid)	2017–2024; vs US only
C	Newly funded AI companies	Count	Stanford HAI (Quid)	2017–2024; vs US only
C	Notable AI models	Three-year sum	Stanford HAI (Epoch)	2019–2024
C	AI patent grants	Count	Stanford HAI (AI Index)	2017–2024
C	Supercomputing capacity	Rmax (GFLOPS)	Stanford HAI (Top500)	2017–2024; vs US only
C	Exports of wind turbines and Li-ion batteries	US\$; HS 850231 + 850760	Eurostat Comext (EU, extra-EU); UN Comtrade (US, CN)	2012–2024
D	Renewable share of electricity	% of generation	OWID (Ember, Energy Institute)	2005–2024
D	Wind and solar generation per capita	MWh per person	OWID; World Bank (population)	2005–2024
D	AI talent concentration	Share of AI-skilled members	Stanford HAI (LinkedIn)	2017–2024; vs US only
O	GDP, PPP	Constant 2021 international \$	World Bank (WDI)	2005–2024
O	GDP per person employed	Constant 2021 PPP \$	World Bank (WDI)	2005–2024
Note: K = knowledge, C = creation, D = deployment, O = outcome. JRC = European Commission, Joint Research Centre (2024, 2025). Stanford HAI = Stanford Institute for Human-Centered Artificial Intelligence (2025), which compiles data from the AI Index, Epoch, Quid, LinkedIn and Top500. OWID = Our World in Data (2026). FY = financial year.				

Business indicators come from the World Development Indicators (World Bank, 2026) and from the EU Industrial R&D Investment Scoreboard (European Commission, Joint Research Centre, 2024, 2025). The Scoreboard lists the world's largest corporate R&D investors each year. AI indicators come from the public data files of the Global AI Vibrancy Tool (Stanford Institute for Human-Centered Artificial Intelligence [Stanford HAI], 2025), which cover 66 countries from 2017 to 2024, including 26 of the 27 EU members (Slovakia is missing). Energy indicators combine the electricity data compiled by Our World in Data (2026) from Ember and the Energy Institute with trade data. EU exports to non-EU destinations come from Eurostat's Comext database (Eurostat, 2026), and exports of the United States and China to the world come from UN Comtrade (United Nations Statistics Division, 2026). Values in euros are converted at the annual euro-area exchange rate published in the World Development Indicators.

3.3 Aggregation

Count and value indicators (articles, publications, investment, firms, models, patents, computing capacity, generation and exports) are summed over EU members. Shares and intensities are rebuilt from their components where possible: the renewable share of electricity is total renewable generation divided by total generation over the 27 members, and generation per capita divides the sum of wind and solar output by total population. For R&D intensity and GDP per person employed, the published EU-27 aggregate of the World Development Indicators is used. The extended aggregate weights members by GDP at PPP and by labour force, respectively. AI talent concentration is a labour-force-weighted mean over the 24 EU members with data. For the corporate R&D indicators, each Scoreboard edition is ranked by R&D expenditure and restricted to the 1,000 largest investors, because the size of the published sample changes across editions (1,400 to 2,500 companies). Shares computed on the full sample differ from the top-1,000 shares by at most 1.3 percentage points. ICT firms are those classified as software and computer services or technology hardware and equipment; the 2011 edition, which uses four-digit ICB codes, was mapped to the same two sectors.

3.4 Measurement safeguards

Several series contain known measurement problems that, if ignored, would change the conclusions. They were handled as follows before any results were computed. First, the private AI investment and newly funded company series compiled from Quid record venture-type deals and miss state-directed finance, so they understate China. They are used only for the comparison with the United States. Second, China stopped submitting systems to the Top500 list, and its recorded supercomputing capacity falls from 2020 onwards; this indicator is likewise restricted to the comparison with the United States. Third, annual counts of notable AI models are small (five European models in 2024), so they are summed over three-year windows. Fourth, AI citation counts decline mechanically in recent years because recent papers have had little time to be cited, and they are not used. Fifth, Chinese patent counts are dominated by domestic grants, so EU/China patent ratios are interpreted with caution and checked by leave-one-out tests.

Two candidate indicators were excluded after inspection. Stock-market capitalisation in the World Development Indicators is available for only 14 EU members after 2015, so an EU total would be misleading. High-technology exports in the same source include trade within the EU, which inflates the EU/US ratio to more than four; they were replaced by extra-EU exports from Comext. In clean-technology trade, the solar photovoltaic code used up to 2021 (HS 854140) also covered light-emitting diodes and was split in 2022, which produces an artificial collapse in recorded American exports. The export indicator therefore uses only wind generating sets (HS 850231) and lithium-ion accumulators (HS 850760), whose codes were stable throughout 2012–2024. Finally, Comtrade’s public interface did not return data for several large member states. The EU aggregate is therefore taken from Comext, and the 19 members with complete Comtrade data are used as a cross-check (Section 5).

3.5 Log ratios, trends and the 2020 change test

For indicator i , comparator C and year t , Europe’s relative position is the log ratio

$$r_{i,t}^C = \ln(X_{i,t}^{EU} / X_{i,t}^C), C \in \{US, CN\} \quad (1)$$

so that $r = 0$ means parity, $r > 0$ means the EU is ahead, and $\exp(r)$ is the EU’s value as a multiple of the comparator’s.

Log ratios have three useful properties for this purpose. They are symmetric, so that being half of the comparator’s level and being twice it are equidistant from parity; they are invariant to the units and currencies of each indicator; and their linear trend is an exact constant growth rate of the relative position, which makes indicators with very different levels comparable. Because the ratios are taken bloc by bloc, they also remove influences common to all three economies in a given year, such as global price movements or revisions of a source’s methodology.

The trend of each ratio is estimated by ordinary least squares,

$$r_{i,t}^C = \alpha_i + \beta_i \cdot t + \varepsilon_{i,t} \quad (2)$$

and reported as an annual percentage change, $100 \cdot [\exp(\beta_i) - 1]$, with Newey–West standard errors robust to heteroskedasticity and autocorrelation (two lags; Newey & West, 1987). To test whether the trajectory changed with the pandemic, the generative-AI boom and the energy crisis, a break date of 2020 was fixed in advance and the following equation was estimated:

$$r_{i,t}^C = \alpha_i + \beta_i \cdot t + \delta_i \cdot D_t \cdot (t - 2019) + u_{i,t}, D_t = 1 \text{ if } t \geq 2020 \quad (3)$$

where δ_i measures the change in the annual slope from 2020 onwards. The break year is fixed rather than estimated, which avoids searching over possible break dates in short series.

3.6 Pillar indices and leave-one-out tests

For pillar p with K_p indicators observed in every year of a common window, the pillar index is the geometric mean of the ratios:

$$I_{p,t}^C = \exp[(1/K_p) \cdot \sum_{i \in p} r_{i,t}^C] \quad (4)$$

An index of 1 indicates parity on average across the pillar's indicators. The main window is 2017–2023, the longest common period of the AI indicators (the three-year model sums, which start in 2019, are reported separately); a long window, 2010–2023, uses only the indicators available throughout (Section 5). The index is a descriptive, deterministic aggregate: it involves no estimation and its weights are equal by construction. Its sensitivity to composition is assessed by recomputing it after dropping each indicator in turn. The trend of each index is tested with Eq. 2 applied to $\ln I$.

3.7 Data processing and reproducibility

All raw files were downloaded by scripts from the original providers on 9 October 2026 and recorded in download logs with SHA-256 checksums. Each file was checked on arrival for completeness (the expected countries, years and product codes) and for content type, to exclude error pages saved as data. Two of the sources required more than one route. The Stanford HAI data files were located by monitoring the network requests of the interactive tool, and the trade data were completed from Eurostat when the public Comtrade interface stopped returning several reporters. All computations use Python (pandas and statsmodels). A single script builds the panel, the log ratios, the trend tests and the indices from the raw files, and a second script draws the figures. The scripts, the raw files and the derived panel are deposited together (see Data availability), so that every number in the paper can be reproduced on a standard computer in a few minutes.

4. Results

4.1 The three pillars

Figure 1 and Table 2 summarise the main result. Relative to the United States, the EU's knowledge index stood at 1.34 in 2023 and its deployment index at 1.23: Europe produced about a third more science and deployed somewhat more of the technologies measured. Its creation index, in contrast, stood at 0.33, so the EU generated on average a third of the American level of corporate R&D, AI capital, models, patents, computing capacity and clean-technology exports combined. None of the three EU/US indices shows a significant trend between 2017 and 2023, so the asymmetry was stable over the period. Relative to China the picture is one of rapid decline on all fronts. The knowledge index fell from 1.07 to 0.55, the creation index from 0.62 to 0.29 and the deployment index from 1.92 to 1.52, at annual rates of 10.4%, 12.5% and 4.3% (all $p < 0.001$). In 2023 Europe still deployed half as much again as China in relative terms, but it produced half as much knowledge and a little over a quarter as much creation.

Table 2
Pillar indices, 2017 and 2023, and annual trend

Comparison and window	Pillar	k	Start	End	Trend (%/yr)	p
EU/US, 2017–2023	Knowledge	2	1.29	1.34	+ 0.9	0.260
	Creation	8	0.35	0.33	+ 0.2	0.643
	Deployment	3	1.21	1.23	–0.6	0.107
EU/China, 2017–2023	Knowledge	2	1.07	0.55	–10.4	< 0.001
	Creation	5	0.62	0.29	–12.5	< 0.001
	Deployment	2	1.92	1.52	–4.3	< 0.001
EU/US, 2010–2023	Knowledge	1	1.13	1.30	+ 0.8	< 0.001
	Creation	3	0.53	0.33	–4.0	< 0.001
	Deployment	2	1.60	1.29	–2.6	< 0.001
EU/China, 2010–2023	Knowledge	1	1.50	0.60	–7.3	< 0.001
	Creation	3	4.80	0.83	–13.6	< 0.001
	Deployment	2	3.42	1.52	–6.9	< 0.001
Note: Trend is $100 \cdot [\exp(\beta) - 1]$ from Eq. 2 applied to the log of the index; p-values use Newey–West standard errors with two lags. k = number of indicators in the pillar. Long window: knowledge = scientific articles; creation = R&D intensity and the two corporate R&D shares; deployment = renewable share and wind and solar per capita.						

A simple way to express the asymmetry is the ratio of the creation index to the knowledge index. Relative to the United States it was 0.25 in 2023: for every unit of relative scientific output, Europe achieved a quarter of a unit of relative commercial creation. Relative to China the same ratio was 0.52. The comparison with the United States therefore reveals a conversion problem: the EU has the knowledge but does not turn it into firms and products at the American rate. The comparison with China reveals a broader loss of position, in which a conversion gap of similar size is now combined with a smaller science base.

4.2 Indicator-level results

Table 3 reports the trend of each indicator, and Fig. 2 shows its latest value. Every creation indicator is below parity with the United States except one: the EU exported 2.2 times as much in wind turbines and lithium-ion batteries in 2024. The lowest values are in ICT corporate R&D (0.08), notable AI models (0.10), private AI investment (0.13) and AI patent grants (0.15). Against China, the EU is below parity in every creation indicator except the share of corporate R&D among the top 1,000 investors, where it was still marginally ahead in 2024 (1.11), down from fourteen times China's share in 2010.

Table 3
EU-27 relative position by indicator: start and end ratios and annual trend

P.	Indicator	Window	EU/US start → end	Trend	p	EU/China start → end	Trend	p
K	Scientific and technical articles	2005–2023	0.97 → 1.30	+ 1.3	< 0.001	2.26 → 0.60	–6.4	< 0.001
K	AI publications	2017–2024	1.35 → 1.26	+ 0.6	0.583	1.01 → 0.49	–9.9	< 0.001
C	Gross R&D expenditure (% of GDP)	2005–2023	0.71 → 0.66	–0.4	0.276	1.38 → 0.88	–2.3	< 0.001
C	Share of R&D, top-1,000 corporate investors	2010–2024	0.70 → 0.34	–4.6	< 0.001	14.28 → 1.11	–17.4	< 0.001
C	Share of ICT corporate R&D (top-1,000)	2010–2024	0.29 → 0.08	–7.1	< 0.001	6.65 → 0.46	–18.2	< 0.001
C	Private AI investment	2017–2024	0.09 → 0.13	+ 6.3	0.001	–	–	–
C	Newly funded AI companies	2017–2024	0.22 → 0.27	+ 1.7	0.341	–	–	–
C	Notable AI models (3-year sum)	2019–2024	0.09 → 0.10	+ 3.6	0.111	0.63 → 0.33	–12.7	< 0.001
C	AI patent grants	2017–2024	0.09 → 0.15	+ 6.4	0.019	0.08 → 0.02	–18.4	< 0.001
C	Supercomputing capacity (Top500 Rmax)	2017–2024	0.48 → 0.39	+ 0.4	0.825	–	–	–
C	Exports of wind turbines and Li-ion batteries	2012–2024	6.21 → 2.20	–2.1	0.337	0.79 → 0.17	–12.5	< 0.001
D	Renewable share of electricity	2005–2024	1.76 → 2.00	0.0	0.890	0.95 → 1.42	+ 1.7	< 0.001
D	Wind and solar generation per capita	2005–2024	2.57 → 0.80	–5.3	< 0.001	102.54 → 1.36	–19.0	< 0.001
D	AI talent concentration	2017–2024	1.11 → 1.04	–0.6	0.258	–	–	–

Note: Ratio = EU value divided by comparator value. Trend = annual percentage change of the ratio (Eq. 2), with Newey–West p-values. – = not computed by design (Section 3.4). Pillars: K = knowledge, C = creation, D = deployment, O = outcome.

P.	Indicator	Window	EU/US start → end	Trend	p	EU/China start → end	Trend	p
O	GDP, PPP (outcome)	2005– 2024	1.08 → 0.95	–0.7	< 0.001	2.31 → 0.73	–5.8	< 0.001
O	GDP per person employed (outcome)	2005– 2024	0.84 → 0.76	–0.5	< 0.001	8.96 → 2.56	–6.2	< 0.001
Note: Ratio = EU value divided by comparator value. Trend = annual percentage change of the ratio (Eq. 2), with Newey–West p-values. – = not computed by design (Section 3.4). Pillars: K = knowledge, C = creation, D = deployment, O = outcome.								

The trend tests separate stable gaps from widening ones. Relative to the United States, five of the nine creation indicators show no significant trend, two (private AI investment and AI patents) improve from very low levels, and the two corporate R&D shares deteriorate. Relative to China, every comparable indicator in every pillar moves against Europe except the renewable share of electricity. The outcome variables follow the creation pillar rather than the knowledge pillar: GDP at PPP and GDP per person employed decline significantly relative to both rivals, while scientific output relative to the United States rises. This is what the framework would predict if creation, rather than knowledge, is the stage through which technological capacity becomes income.

4.3 Business: corporate R&D and productivity

The clearest evidence for H1 comes from the corporate R&D data (Fig. 3). Among the 1,000 largest corporate R&D investors, the EU's share of R&D fell from 24.7% in FY2010 to 16.4% in FY2024, while the American share rose from 35.0% to 48.3% and the Chinese share from 1.7% to 14.8%. The EU/US ratio of these shares declined by 4.6% a year ($p < 0.001$), and the annual decline steepened by a further 5.8% from 2020 ($p < 0.001$). The fall is concentrated in information and communication technology: the EU's share of the R&D of ICT companies in the top 1,000 fell from 16.2% to 6.0%, while the American share rose from 55.9% to 71.7% and the Chinese share from 2.4% to 13.1%. ICT accounted for about 15% of European corporate R&D in both FY2010 and FY2024 but rose from 39% to 61% of American corporate R&D. The difference therefore reflects the sectoral composition of research, not only its volume.

The macroeconomic indicators are consistent with this pattern. Gross R&D expenditure was 2.26% of GDP in the EU in 2023, against 3.45% in the United States and 2.58% in China. The EU/US ratio shows no significant trend over 2005–2023, but it declined after 2020 ($p < 0.001$), and China overtook the EU around 2020. GDP per person employed fell from 84% to 76% of the American level between 2005 and 2024 (-0.5% a year, $p < 0.001$), and EU GDP at PPP went from 8% above to 5% below that of the United States. Scientific output moved the other way: the EU published 0.97 times as many scientific and technical articles as the United States in 2005 and 1.30 times as many in 2023 ($+1.3\%$ a year, $p < 0.001$). H1 is supported.

4.4 Artificial intelligence

AI shows the same pattern within a single domain. In knowledge, the EU produced 1.26 times as many AI publications as the United States in 2024 and had a slightly higher concentration of AI talent in its labour force (1.04). Neither ratio has a significant trend. In creation, the gap is wide: private AI investment in the EU was US\$14.1 billion in 2024 against US\$109.1 billion in the United States (ratio 0.13), the EU produced 20 notable models over 2022–2024 against 194 in the United States and 60 in China, and its AI patent grants were 15% of the American and 2% of the Chinese level. Some ratios with the United States improved from very low levels: private investment rose from 0.09 to 0.13 (+ 6.3% a year, $p = 0.001$) and patent grants from 0.09 to 0.15 (+ 6.4% a year, $p = 0.019$). The number of newly funded AI companies remained at about a quarter of the American figure, and supercomputing capacity at about 40%. Relative to China, every comparable AI ratio declined significantly, including AI publications, where the EU went from parity in 2017 to less than half of China's output in 2024 (– 9.9% a year). The talent indicator deserves comment. The share of AI-skilled members in the labour force, measured on professional-network data, roughly doubled in both economies between 2017 and 2024 and remained slightly higher in the EU, but its ratio to the United States weakened after 2020 ($p = 0.001$). The skills base is comparable, but it is not growing faster than in the United States. H2 is supported for the United States. The gap is in capital, models and patents, not in research or skills. For China, the gap now extends to knowledge as well.

4.5 Renewable energy and clean-technology manufacturing

The energy results support H3 only in part (Fig. 4). Renewable sources supplied 48.0% of EU electricity in 2024, against 24.1% in the United States and 33.7% in China. The EU led the United States in every year and China in every year from 2009, after the two had been close in 2005–2008; the EU/China ratio rose by 1.7% a year ($p < 0.001$). Deployment measured in wind and solar generation per inhabitant tells a different story. The EU generated 1.77 MWh per person in 2024, against 2.22 MWh in the United States, which overtook Europe during the period (the ratio fell from 2.57 in 2005 to 0.80 in 2024). China, starting from almost nothing, reached 1.30 MWh per person. In absolute terms China's wind and solar output (1,836 TWh) was 2.3 times that of the EU (798 TWh) in 2024. The EU's deployment lead is therefore a lead in the share of renewables in its electricity mix, helped by hydropower and lower demand, rather than in the per-capita build-out of new wind and solar capacity.

Clean-technology manufacturing, measured by exports of wind turbines and lithium-ion batteries, separates the two rivals clearly. The EU exported US\$10.6 billion of these goods outside the EU in 2024, against US\$4.8 billion for the United States and US\$62.3 billion for China. Europe remained more than twice the American level throughout, with no significant trend ($p = 0.34$). Relative to China, however, it fell from 0.79 in 2012 to 0.17 in 2024, a decline of 12.5% a year ($p < 0.001$), as Chinese battery exports rose from US\$4.5 billion to US\$61.1 billion. H3 is therefore supported against China but not against the United States. Europe is not behind the United States in clean-technology manufacturing, and its deployment lead over the United States is confined to the renewable share of electricity.

5. Robustness

Table 4 summarises the robustness checks. The first is a leave-one-out test. Dropping each indicator in turn leaves the EU/US creation index between 0.24 (without clean-technology exports, the only creation indicator above parity) and 0.39 (without private AI investment). The knowledge index stays between 1.30 and 1.38. The EU/US deployment index is the fragile one: it falls to 0.96 when the renewable share is dropped and rises to 1.49 when wind and solar per capita are dropped. Europe's deployment advantage over the United States therefore rests on one indicator, a point the discussion takes up. For China, the creation index ranges from 0.20 to 0.55, with the upper value obtained when AI patents are excluded. It remains well below parity in every variant.

Table 4
Robustness of the 2023 pillar indices

Check	Knowledge	Creation	Deployment
Baseline EU/US, 2023	1.34	0.33	1.23
Leave-one-out EU/US, 2023	1.30–1.38	0.24 (clean-tech exports) – 0.39 (AI investment)	0.96 (renewable share) – 1.49 (wind and solar per capita)
Baseline EU/China, 2023	0.55	0.29	1.52
Leave-one-out EU/China, 2023	0.51–0.60	0.20 (corporate R&D share) – 0.55 (AI patents)	1.48–1.57
Europe extended/US, 2023	1.71	0.30	1.25
Long window EU/US, 2010 → 2023	1.13 → 1.30	0.53 → 0.33	1.60 → 1.29
Long window EU/China, 2010 → 2023	1.50 → 0.60	4.80 → 0.83	3.42 → 1.52
Note: Leave-one-out ranges are the minimum and maximum of the 2023 index after dropping one indicator at a time (indicator dropped in parentheses). Europe extended = EU-27 + United Kingdom, Switzerland and Norway; it excludes clean-technology exports, for which no comparable extra-regional series is available.			

The second check uses the extended European aggregate. Adding the United Kingdom, Switzerland and Norway raises the knowledge index relative to the United States to 1.71 but leaves creation at 0.30 and deployment at 1.25. With these countries included, the creation index declines significantly between 2017 and 2023 (– 1.6% a year, $p < 0.001$). The asymmetry is therefore not an artefact of the EU's borders. The third check uses a long window with the indicators available since 2010. Over 2010–2023 the EU/US creation index fell from 0.53 to 0.33 (– 4.0% a year, $p < 0.001$) while the knowledge index rose from 1.13 to 1.30. Relative to China, creation fell from 4.80 to 0.83 and crossed parity in 2020, and knowledge fell

from 1.50 to 0.60 and crossed parity in 2019. The flat creation index of the short window is therefore the end of a decline that began earlier, not a sign of stability. The fourth check concerns trade data. Summed extra-EU exports of the 19 members with complete Comtrade data account for 36–69% of the Comext total, depending on the year, and the two series have a correlation of 0.94. The shortfall corresponds to the missing members, notably Germany. Finally, the pre-specified 2020 test shows no common break. The EU/US ratios for AI patents and AI publications improved after 2020, while those for the share of corporate R&D, R&D intensity, newly funded AI companies and AI talent concentration worsened. This argues against a single post-pandemic shock and in favour of the structural interpretation developed below.

6. Discussion

6.1 Where Europe has fallen behind

The answer to the question in the title is that Europe has fallen behind, but on one front much more than on the others. Relative to the United States, the EU is not short of science and has not stopped adopting technology. What it lacks is the intermediate stage that turns research into companies, capital, frontier models and patents. This is consistent with explanations that emphasise finance and firm growth, such as the venture-capital gap and the treatment of employee stock options (Henrekson & Sanandaji, 2018), and with the Draghi (2024) diagnosis of a weak transfer from research to scale. The corporate R&D data add a sectoral dimension. The European decline is concentrated in ICT, the sector in which the American corporate research base grew most, which matches the view that Europe's industrial structure locked its research into mature sectors (Nouveau, 2022). Higher R&D spending alone would therefore not close the gap unless it changed the sectors and firms in which research is carried out.

Relative to China the situation is different. China did not overtake Europe by converting a given science base more efficiently; it overtook it on knowledge, creation and the scale of deployment at once, within a decade. The clean-technology trade data illustrate the speed of this process: Europe's exports of wind turbines and batteries nearly tripled between 2012 and 2024, yet its ratio to China fell from 0.79 to 0.17. This agrees with patent-based studies of China's catch-up (Kwon et al., 2017; Chen et al., 2021; Hemmelder et al., 2025) and with descriptions of Chinese clean technology as industrial policy (Visvizi et al., 2026). It also qualifies the view that Europe's main competitor in green manufacturing is the United States: on this evidence Europe remains well ahead of the United States and far behind China.

The framework also helps to reconcile earlier findings. Studies that use patents or trade in a single technology find European positions that range from strong to weak depending on the technology and the period (Fankhauser et al., 2013; Fan et al., 2017; Kim & Cho, 2025). Composite rankings tend to place the EU in a middle position (Franc et al., 2026). In the present terms, these studies measure different mixtures of knowledge and creation. A measure dominated by research output will show Europe close to or ahead of the United States, and a measure dominated by commercial assets will show it far behind. Separating the pillars makes the source of disagreement explicit, and the trend tests show that the

disagreement is growing: the knowledge and creation ratios with the United States moved in opposite directions over 2010–2023.

The erosion of Europe's knowledge advantage over China is the least discussed of the results. In 2017 the EU and China produced the same number of AI publications. By 2024 China produced more than twice as many, and in general scientific output China overtook the EU around 2019. A conversion strategy that assumes a strong science base relative to every rival is therefore no longer sufficient with respect to China, where both the base and the conversion have moved ahead.

6.2 The deployment lead and its fragility

Europe's best-known advantage, its lead in renewable electricity, survives the analysis only in part. The EU's renewable share is twice the American one and well above China's. But the EU has been overtaken by the United States in wind and solar generation per inhabitant and by China in absolute volume. The leave-one-out test shows that the deployment advantage over the United States depends entirely on the renewable-share indicator. This matters for policy because the next phase of the energy transition, including the electricity needed for AI computing, depends on the volume of new generation more than on the share of renewables in an existing mix (Yoo et al., 2026; Jorgensen & Ma, 2026). A high share achieved partly through hydropower and lower demand is a weaker base for an electricity-intensive digital economy than the per-capita figures for the United States suggest.

6.3 Implications

Three implications follow. First, policy should target the conversion stage rather than science or adoption alone. Instruments that act on firm growth and on the sectoral mix of corporate research, such as risk capital for scaling firms, employee ownership, a deeper single market for services and capital, and public procurement of frontier technologies, address the measured gap more directly than further increases in public research spending (Henrekson & Sanandaji, 2018; López, 2025). Second, the comparison with China calls for attention to manufacturing capacity in clean technologies, where industrial policy is already being redesigned in all three economies (Ninni, 2023; Hauge et al., 2025) and where export controls add a security dimension (Hrynkiv, 2026). Third, Europe's relative strengths in science, skills and deployment are assets rather than consolation prizes. Rodríguez-Pose and Dijkstra (2026) warn against pursuing parity only where Europe is weakest. The results support a strategy that builds on the knowledge base and adoption capacity, provided the conversion stage between them is repaired. The debate on whether regulation impedes AI (Bradford, 2024; Jørgensen & Ma, 2025) cannot be settled here. However, the fact that European AI research and skills are on a par with the United States while capital and models are not points to finance and scale as the binding constraints, rather than rules on use.

6.4 Limitations

The study has several limitations. The AI indicators cover only 2017–2024 and depend on third-party compilations whose coverage of China is incomplete; three AI series were therefore used only for the

comparison with the United States, so the EU/China creation index rests on five indicators. The pillar index weights indicators equally and is descriptive. It shows where Europe stands but does not identify why. Deployment is measured mainly through electricity and AI skills; firm-level adoption of AI and the use of clean technologies outside power generation are not covered for lack of comparable data for all three economies. GDP per person employed overstates the productivity gap per hour, because Europeans work fewer hours. Finally, trade data measure exports, not production, and miss output sold in domestic markets, which is particularly large for China. Extending the framework to firm-level data and to measures of the production of clean technology are natural next steps.

7. Conclusion

Has Europe fallen behind the United States and China in business, AI and renewable energy? The evidence assembled here gives a qualified yes. Measured over 14 indicators and three pillars, the EU-27 remains ahead of the United States in producing knowledge and in deploying renewable electricity, but it creates commercial technology at only a third of the American level. In ICT corporate R&D, AI investment, frontier models and AI patents it stands at 8–15% of the American level. This gap is not new: the creation index fell from 0.53 to 0.33 of the American level between 2010 and 2023, and the EU's share of the R&D of the world's largest corporate investors fell by a third. Relative to China, the decline is broader and faster. In about a decade Europe has lost its advantage in scientific output and in commercial creation, and its lead in deployment has halved. In clean-technology exports, Europe went from four-fifths to a sixth of Chinese sales.

The main contribution of the paper is to show that these verdicts are compatible once the stages of competitiveness are separated. Studies that conclude that Europe is holding its ground and studies that conclude that it is falling behind are, in most cases, measuring different stages. Europe's problem is primarily one of conversion: turning a strong science base and a capacity to adopt technology into firms, capital and products at scale. Its deployment lead over the United States is narrower and more fragile than usually assumed, and its main competitor in clean-technology manufacturing is China, not the United States. For policy, the results suggest judging European competitiveness by its weakest stage rather than by averages. A rising share of renewables or a growing volume of publications does not compensate for a creation index that has fallen for more than a decade, because creation is the stage at which technology becomes firms, exports and income. The framework and the replication package can be updated as new data appear, which will make it possible to test whether the policies that followed the 2024 competitiveness reports change the creation index, the indicator on which Europe's position most clearly depends.

Declarations

Data availability

The raw data files, download logs with SHA-256 checksums, the derived indicator panel and all results files are openly available in Zenodo at <https://doi.org/10.5281/zenodo.23289566> under a CC BY 4.0 licence. The underlying sources are public: World Bank World Development Indicators, the EU Industrial R&D Investment Scoreboard, the Stanford HAI Global AI Vibrancy data, Our World in Data (Ember and Energy Institute), Eurostat Comext and UN Comtrade.

Code availability

The Python scripts that download the data, build the panel, run the analysis and draw the figures are included in the same Zenodo record (<https://doi.org/10.5281/zenodo.23289566>).

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Competing interests

The author declares no competing interests.

Author contributions

A.A.M.E. is the sole author and was responsible for conceptualisation, methodology, data collection, analysis, visualisation and writing.

Ethics approval

Not applicable. The study uses only publicly available aggregate data and involves no human participants.

Use of generative AI

The author used Claude Opus 5.5 (Anthropic) in the preparation of this work. In the Introduction and the Literature review, the tool assisted in screening Scopus records selected by the author and in drafting text from their abstracts. In Data and methods, it assisted in writing and debugging the Python scripts for data collection, processing, statistical tests and figures. In Results, Robustness, Discussion and Conclusion, it assisted in drafting and language editing of text based on the outputs of those scripts. The tool was used to speed up drafting, coding and language editing. The author designed the study, chose the indicators and hypotheses, verified every reported number against the outputs of the deposited code and the original sources, checked every reference against its bibliographic record, and takes full responsibility for the content of the manuscript.

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Figures

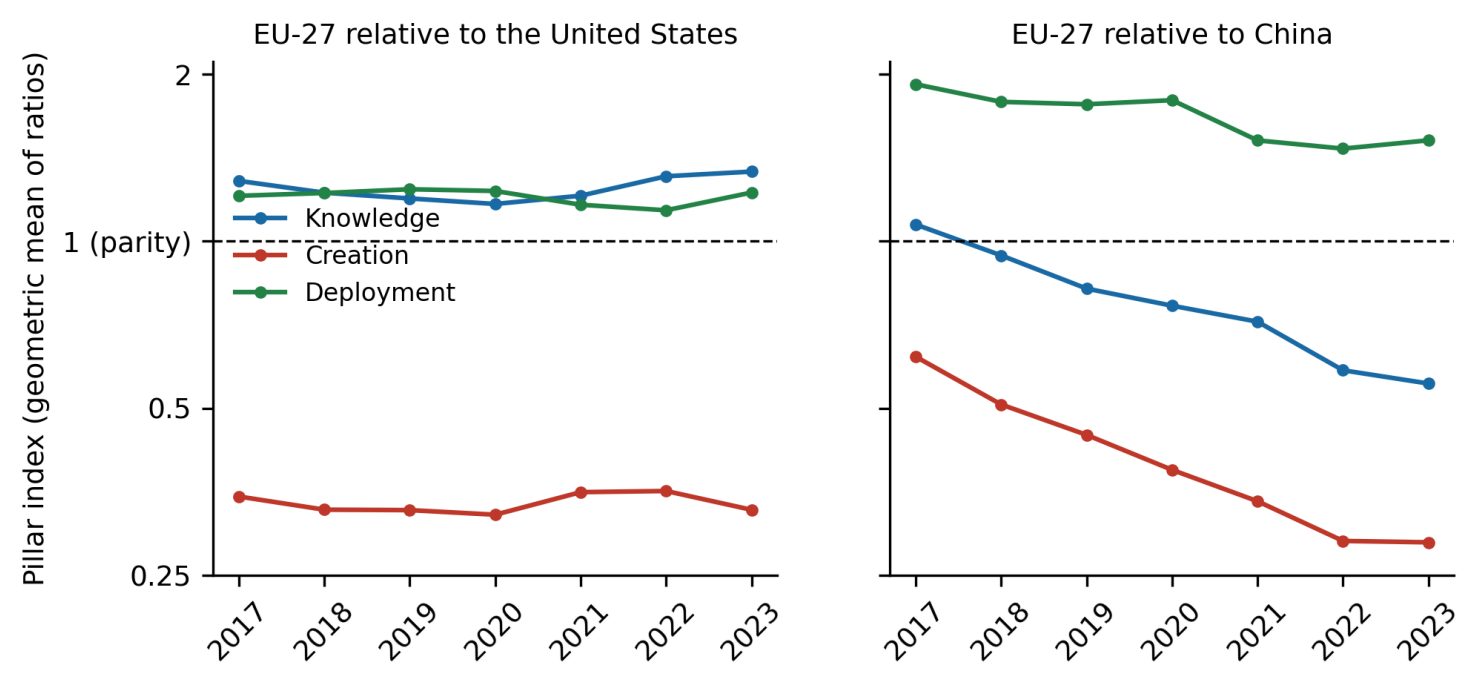


Figure 1

Pillar indices for the EU-27 relative to the United States (left) and China (right), 2017–2023. Each index is the geometric mean of the EU/comparator ratios of the pillar’s indicators (Equation 4); 1 indicates parity. Logarithmic scale.

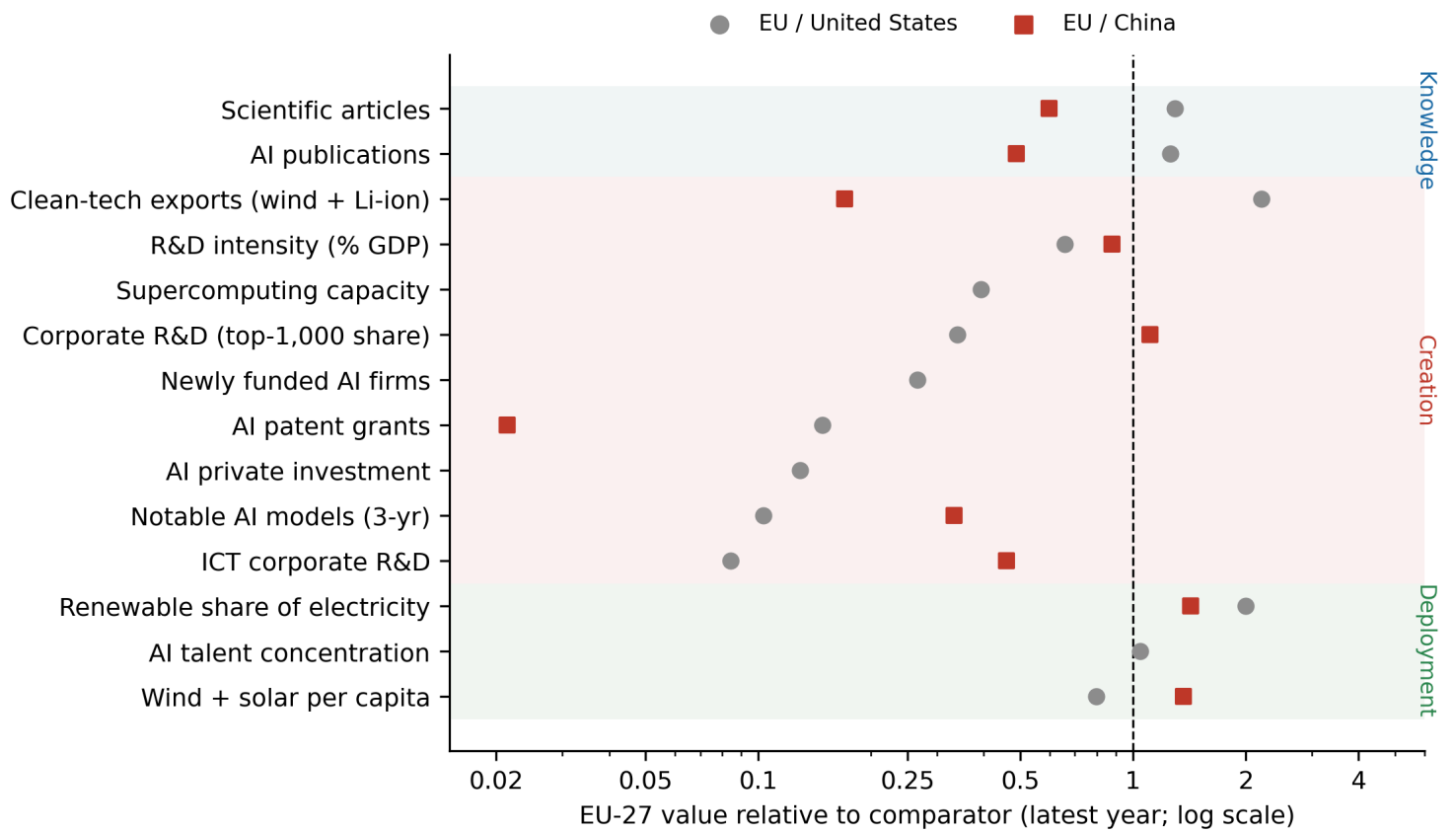


Figure 2

EU-27 values relative to the United States (circles) and China (squares) in the latest year available for each indicator, grouped by pillar. Logarithmic scale; the dashed line marks parity. China is omitted where its data are not comparable (Section 3.4).

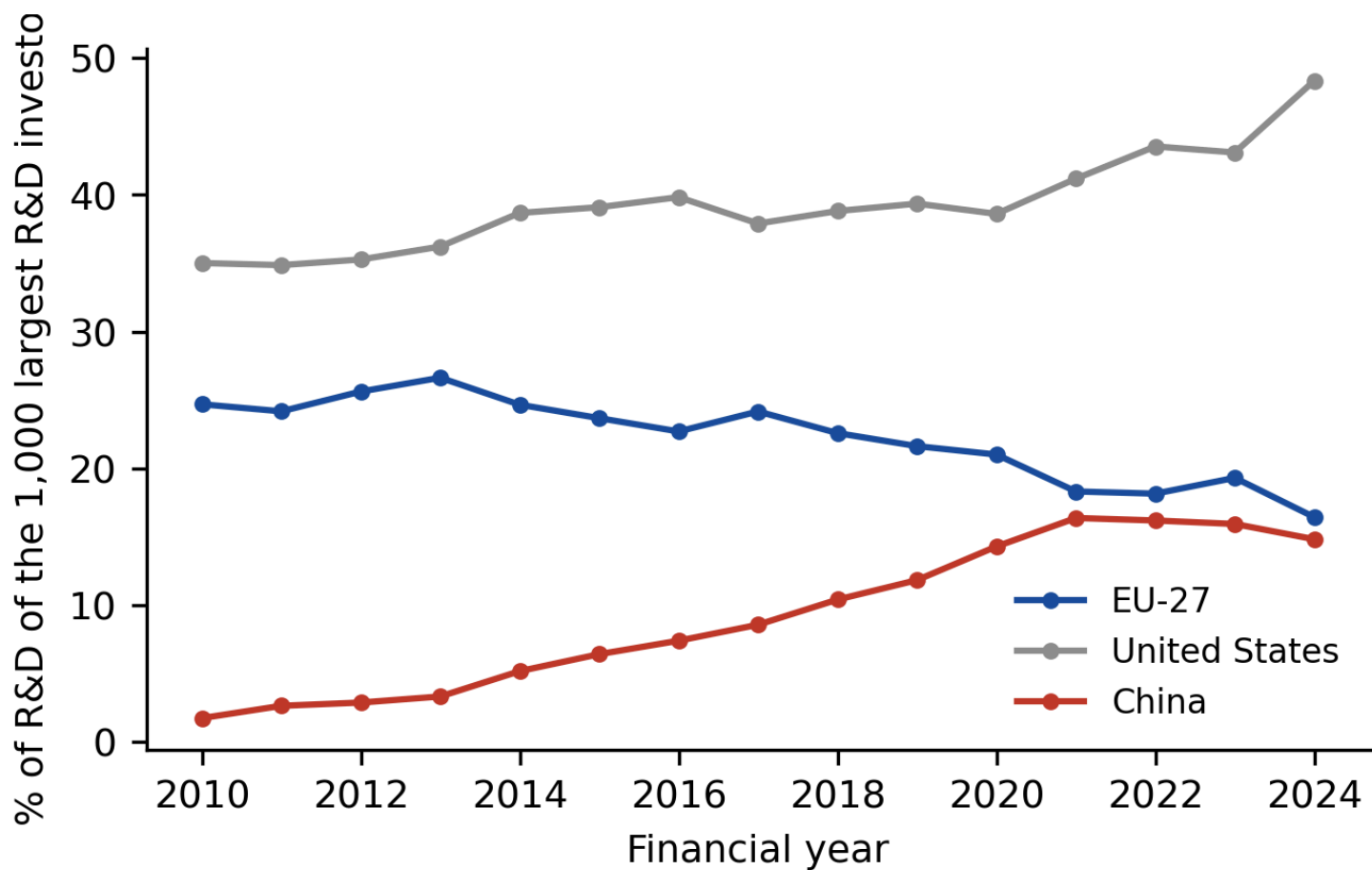


Figure 3

Shares of the EU-27, the United States and China in the R&D expenditure of the world's 1,000 largest corporate R&D investors, FY2010–FY2024. Source: EU Industrial R&D Investment Scoreboard, editions 2011–2025.

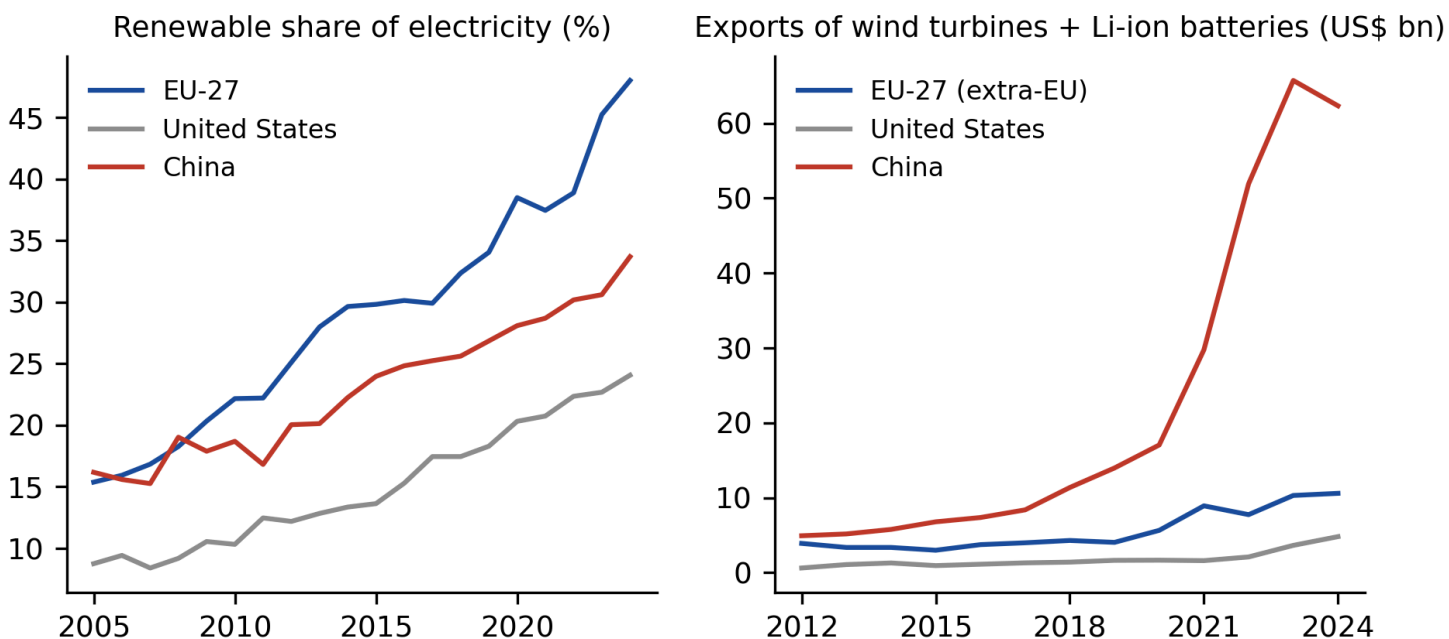


Figure 4

Left: renewable share of electricity generation (%), 2005–2024. Right: exports of wind generating sets and lithium-ion accumulators (HS 850231 + 850760), US\$ billion, 2012–2024; EU-27 exports exclude trade between member states. Sources: Our World in Data/Ember; Eurostat Comext; UN Comtrade.