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DOES EU REGULATION STIFLE INNOVATION?
In search for a 'Brussels Innovation Effect'

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Slobodan Tomić[1] and Ognjen Dragičević[2]

Abstract

Does EU regulation stifle innovation? The deregulation thesis, prominent in policy discourse, holds that the regulatory framework of the EU imposes a major burden, which suppresses innovation, including in the technology domains. This paper tests the claim against three prominent EU regulatory packages adopted in the last decade: the General Data Protection Regulation (2018), the European Green Deal (2019–2020), and the Artificial Intelligence Act (2024). Drawing on OECD REGPAT (regional patent) data covering 4.7 million applications, complemented by R&D intensity data, the analysis conducts a pre-post comparison analysis of the tendencies in patent submissions, comparing the EU to the US as a major comparator as well as a 33-country panel dataset for synthetic control estimation. The findings are convergent: no regulatory package was followed by an absolute decline in EU innovation; the EU outperformed the United States in green tech and AI domains; and an apparent privacy-tech underperformance in patents reverses under a quality filter (while the overall number of patents in data privacy has fallen vis-a-vis the comparators, the number of high quality patents has increased). A decomposition analysis shows that regulatory stringency accounts for a negligible portion (roughly 2 per cent) of the EU-US R&D intensity gap, whereas structural factors explain the rest of the gap. The findings provide some of the first systematic evidence that the three regulatory packages did not lead to suppressed innovation; on the contrary, when coupled with industrial-policy measures, they fostered innovation growth, lending empirical support to the directional school on the positive effects of regulation.

Keywords

Regulation; innovation; European Union; GDPR; Green Deal; AI Act; industrial policy; Brussels (innovation) effect; patents; R&D

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1. Introduction

Does EU regulation kill innovation? If we follow conventional wisdom, the answer is presumed to be yes. The European Union has long been characterised as a regulatory powerhouse whose density of rules acts as a brake on the firms operating under it (Bradford 2020; Scharpf 1999). This characterisation has, in recent years, hardened into something close to received wisdom. It dominates public commentary, recurs in political and policy circles, and is heard even from key current and former EU officials themselves. The Draghi report points to regulatory burden as one of the principal causes of the EU's competitiveness gap, arguing that the cumulative weight of compliance obligations diverts firm resources from research and development towards documentation (Draghi 2024). Outside Europe, the same characterisation circulates in corporate and political discourse. Elon Musk's repeated statements identifying GDPR as the reason X (formerly Twitter) restricts AI training data in the EU illustrate a more general pattern in which technology executives invoke EU regulation as a constraint on innovation (Reuters 2024). Similar observations about the pernicious effect of EU regulation on innovation have been repeated by other technology giants, including Meta and Apple, in the context of the EU release of multimodal AI models and consumer AI features (Axios 2024; Bloomberg 2024). If the ordinary observer is asked, usually the same answer would come back: EU regulation is heavy, and it slows innovation. The view appears to be widespread.

Yet for all this consensus, the systematic evidence underlying it is surprisingly thin. The claim that EU regulation suppresses innovation rests largely on individual cases, anecdotal observation, and popular perception, which has been further reinforced in the post-pandemic period of competitiveness anxiety, gaining increased political prominence (see e.g. Djankov et al. 2002).

This paper provides one of the first systematic analyses of the question for the EU specifically, on patent data. It does so by examining whether the volume and trajectory of patenting in three core technology domains have moved as the 'regulation kills innovation' thesis would predict, in the years following the adoption of those regulatory packages, which are frequently cited as paragons of innovation stifling regulation: the General Data Protection Regulation, adopted in 2016 and applicable from May 2018; the European Green Deal, announced in December 2019; and the Artificial Intelligence Act, proposed in April 2021 and adopted in 2024 (Tomić and Štimac 2025). The questions this paper asks are as follows: when major regulatory packages are adopted, do innovation outputs actually fall? Do they fall more in regulated technology domains than in unregulated ones? Do they fall more in the EU than in comparable economies (e.g. the US) that did not adopt similar regulations?

To address those questions, we conducted a before-after comparison of innovation levels in the three regulated technology sectors in the EU and juxtaposed them against US and rest of world comparators, using a combined dataset of 4.7 million European Patent Office applications (OECD REGPAT, February 2026 release) supplemented by R&D intensity data from Eurostat and OECD MSTI. Methods combine event-study comparison, structural decomposition of the EU-US innovation gap on a panel of 627 country-year observations, and synthetic control estimation with placebo permutation tests (Abadie et al. 2010). The findings, in brief, suggest that the observed EU regulations have not led to suppression of innovation in the EU.

The paper makes four contributions. Firstly, it provides the finding that none of the three regulatory packages has produced a decline in EU innovation output on either patents or R&D intensity. This constitutes the first systematic empirical test, and rejection of the popular belief in a 'Brussels Innovation Effect', namely that EU regulation stifles innovation. Secondly, our findings indicate that regulation redirects rather than reduces innovation through measures of industrial policy. This reaffirms and further extends the directed-technical-change literature (Acemoglu et al. 2012; Aghion et al. 2016a; Mazzucato 2013), demonstrating that regulatory effects cannot be assessed in isolation from accompanying industrial-policy instruments. Thirdly, we find that patent activity responds to the cumulative signal of EU policy commitment over years preceding adoption rather than to the discrete moment of regulatory entry into force. This suggests that regulation operates through commitment credibility (Majone 2001) and through the gradual constitution of new technology domains as governable categories (Borrás and Edler 2020). Fourthly, our analysis points to a net flow of US-to-EU AI talent, reversing the brain drain hypothesis advanced in Draghi-adjacent accounts (Draghi 2024; Veugelers 2017). Together these findings contradict the widely shared belief in current policy discourse (Draghi 2024; Letta 2024; European Commission 2025; Tagliapietra et al. 2023) that EU regulation is the principal drag on EU innovation, and they relocate the EU-US innovation gap to its actual structural drivers such as capital market depth, industry composition, and public research funding, converging with Bradford's (2024) argument that the choice between digital and technological regulation and innovation is a false one.

2. Theoretical framework

2.1 The conventional view: EU regulation as 'innovation graveyard'

That the EU is becoming an 'innovation graveyard' is not a novel claim (Bradford 2020; Scharpf 1999). Its current prominence, in the Draghi report (Draghi 2024, Part A: 29) and across recent Commission and Council interventions (Letta 2024; European Commission 2025), rests on a specific causal claim unpacked in the following lines.

From the literature and from policy debates, several mechanisms can be identified through which regulation might suppress innovation (Baldwin et al. 2012: chapters 3, 5). Compliance obligations divert resources from R&D towards documentation and legal review, with downstream effects on investment levels, and macro-level innovation output of the order of five per cent). *Ex ante* approval regimes slow the trial and error process through which products are brought to market. Fixed compliance costs disproportionately burden small innovative firms and entrench incumbents (Djankov et al. 2002: 1–37). And regulatory uncertainty itself induces firms to delay investment, irrespective of what the eventual rule requires.

The position has its intellectual roots in the early deregulation school. The Chicago school regulatory tradition, for instance, depicted regulation as a vehicle through which incumbents obstruct entry by innovators (Stigler 1971: 3–21), whereas the Schumpeterian tradition posed that innovation depends on the perennial gale of creative destruction, with rules that slow entry, exit, or experimentation slowing innovation by extension (Schumpeter 1942).

In the EU, the 'EU regulation kills innovation' argument has recurred in waves. During the 1980s Eurosclerosis debate, Europe was characterised as over-regulated relative to the United States and Japan (Lindbeck 1985: 153–170). The Lisbon Treaty era institutionalised regulatory burden as a competitiveness concern, spawning the Better Regulation agenda from 2002 onwards (Pelkmans and Renda 2011). The current wave, beginning around 2020, is the most vocal and most geopolitically framed of the three. Where earlier waves treated regulation as an inward looking economic problem, the current debate frames it as a strategic vulnerability in a world of US-China technology rivalry (Draghi 2024, Part A: 1-3; European Commission 2025).

The EU, In fact, does have higher regulatory density than the United States and the post-Brexit United Kingdom (OECD 2025). But for structural reasons, lacking the fiscal and redistributive instruments of a federal entity, the EU relies on regulation as its principal policy tool (Majone 1994: 77–101; Scharpf 1999). Globally, however, its stringency does not exceed that of Japan, Korea, or certain Asian developmental states (Bradford 2020: chapters 3–4).

A related claim is that this density does not merely impose compliance costs but pushes innovators, capital, and researchers to more permissive jurisdictions. Both the Draghi (2024, Part A: 24-26) and Letta (2024) reports advance this brain drain claim anecdotally rather than systematically. Empirical work on scientific mobility identifies the underlying flow patterns (Franzoni et al. 2012: 1250–1253; Breschi et al. 2017: 623–646) but attributes them to labour-market and ecosystem characteristics, not regulatory drivers. And the claim that EU regulation specifically drives inventor flight to the United States has not been systematically tested with patent-inventor data, a gap this paper fills.

2.2 Counter-positions: regulation does not necessarily kill innovation

Contradicting the proverbial ‘regulation kills innovation’ view, two strands of literature have developed since the 1990s. The first suggests that regulation, when properly designed, can foster rather than suppress innovation (Porter 1990). The second holds that regulation can redirect innovation, shaping its trajectory rather than altering its level (Acemoglu et al. 2012: 131–166; Mazzucato 2013).

The first strand crystallises in the Porter hypothesis (Porter and van der Linde 1995: 97–118): well-designed regulation stimulates innovation that partially or fully offsets compliance costs. The weak version (regulation induces innovation) has found some empirical support; the strong version (induced innovation produces net competitive gains) remains contested (Ambec et al. 2013: 2–22; Lanoie et al. 2011: 803–842). Three mechanisms underlie the ‘innovation fostering’ hypothesis: a selection effect, where higher quality thresholds displace low value filings and concentrate substantive innovation; a commitment effect, where firms invest with greater confidence in a durable regulatory future (Mazzucato 2013); and a coordination effect, where standardisation reduces fragmentation and enables scale economies in innovation (Blind 2012: 391–400).

The second strand, featuring the directional thesis, emerged most influentially in the directed technical change literature (Acemoglu et al. 2012: 131–166) as policy can redirect the path of innovation, not merely raise or lower its level. Regulation thus shapes which technologies firms invest in rather than how much. In environmental policy, for instance, carbon pricing has been shown to redirect patenting from combustion to clean technologies (Aghion et al. 2016b: 1–51; Calel and Dechezleprêtre 2016: 173–191). A mission oriented variant extends the logic: public direction, combining regulation, industrial policy, and procurement, does not merely redirect existing markets but creates new ones (Mazzucato 2013).

A third proposition combines these strands: regulation can produce a displacement with upgrading pattern, in which strategic and low value innovation is suppressed while high value innovation is sustained or stimulated. Facing fixed compliance costs, firms will concentrate effort on outputs valuable enough to justify those costs and reduce low cost defensive filings. The mechanism is implicit in Porter but theorised explicitly elsewhere (Blind 2012: 391–400; Rammer and Schubert 2018: 379–389).

2.3 Industrial policy as the conditioning variable

The relationship between regulation and innovation cannot be assessed in isolation from accompanying industrial policy. Those are targeted public interventions favouring specific sectors, technologies, or firms through subsidies, tax credits, public procurement, state aid, strategic R&D programmes, and Important Projects of Common European Interest (IPCEI) (Rodrik 2008; Juhász et al. 2024: 213–242). Modern theoretical work treats industrial policy as strategic collaboration between public and private actors (Rodrik 2008), growth enhancing where designed alongside competition rather than in displacement of it (Aghion et al. 2016a: 1–32).

Industrial policy might shape the effects of regulation through three mechanisms. A signal effect, is where regulation and industrial policy together credibly signal market direction, with firms investing because government is not only restricting but also funding (Mazzucato 2013). A commitment effect, occurs where industrial policy raises the political cost of reversal and leads firms to treat regulation as durable rather than conditional (Majone 2001: 103–122; McNamara 2024). A direct incentive effect arises, where subsidies, procurement, and tax credits reduce compliance costs and raise the return on regulated innovation, as with the Emissions Trading System paired with targeted subsidies that redirected clean-tech patenting among regulated firms (Calel and Dechezleprêtre 2016: 173–191; Popp 2019: 257–282).

In EU practice, regulation and industrial policy increasingly travel together. The Green Deal (2019) was accompanied by a €1 trillion investment plan (European Commission 2020a: 1), a revised environmental state-aid framework, and IPCEI projects in batteries and hydrogen. The AI Act (2021) was paired with the Chips Act (€43 billion), Horizon Europe Cluster 4 (~€15.3 billion), and the Digital Europe Programme. This convergence has been a structural feature of EU policymaking since around 2019 (McNamara 2024). GDPR, by contrast, was adopted without a matching industrial policy package. No IPCEI for privacy enhancing technologies, no dedicated funding stream comparable to the Chips Act, making it a useful empirical case for isolating the effect of regulation alone.

Where regulation and industrial policy travel together, innovation is redirected into the regulated and funded domains, with quality upgrading following because industrial policy disbursement is typically conditional on high quality output (IPCEI selection criteria, Horizon competitive calls). This motivates what we term the directive mode of the Brussels Innovation Effect, distinguished from the suppressive mode (regulation without complementary industrial policy) and the constitutive mode (regulation gradually defining a new technology category, with firms responding to the cumulative signal of policy commitment over years preceding adoption).

3 Data and methods

3.1 Case selection

The analysis includes three major EU regulatory packages from the last decade: the General Data Protection Regulation (GDPR, in force 2018), the European Green Deal (announced 2019), and the Artificial Intelligence Act (proposed 2021, adopted 2024). Firstly, all three cases were widely identified as major regulatory obligation regimes with substantial compliance requirements (Renda et al. 2021; Draghi 2024: Appendix Part A: 29). Secondly, each has a distinct adoption ('shock') date that permits pre-post comparison. Thirdly, they cover three substantively distinct technology domains (digital, environmental, and AI) supporting tests for sectoral variation in regulatory effects. Fourthly, and most importantly for identification, the three cases vary in the presence of complementary industrial policy: GDPR was enacted without a matching industrial policy package; the Green Deal was accompanied by environmental state aid, the Battery Regulation, and IPCEI projects in batteries (European Commission 2019, 2021a) and hydrogen (European Commission 2022a, 2022b); and the AI Act has been paired with the EU Chips Act (Regulation (EU) 2023/1781) and the Horizon Europe digital cluster, including the Chips Joint Undertaking (European Commission 2023). This variation allows the analysis to separate the effect of regulation alone from the effect of regulation combined with industrial policy.

3.2 Measuring innovation: patents as a proxy

The central observed outcome, taken as a proxy for innovation, is the count of patent applications filed at the European Patent Office (EPO), sourced from the OECD REGPAT database (February 2026 release; 4.7 million EPO applications and 12.7 million inventor records from 1977 onwards across more than 2,000 OECD regions). Strictly speaking, patents measure inventive activity rather than innovation in the Schumpeterian sense of commercialised invention (Kline and Rosenberg 1986), and not all inventions become innovations. The literature has nonetheless used patents as the workhorse innovation proxy for three decades because they are systematically recorded, internationally comparable, and longitudinally available, while direct measures of commercialisation are not (Griliches 1990: 1661–1707; Jaffe and Trajtenberg 2002; Hall et al. 2005: 16–38), and they remain standard in studies of regulatory shocks on innovation trajectories (Acemoglu et al. 2012: 131–166; Aghion et al. 2016b: 1–51; Dechezleprêtre and Sato 2017: 183–206).). We will also triangulate against R&D intensity as a second outcome variable.

3.3 Data sources

Our analysis draws on four linked datasets.

- *Patent data*: The OECD REGPAT database Feb 2026 release (4.6m EPO applications, fractional applicant-share counting).

- *Technology patent filters*: G06F/21 + H04L/9 patent classifications for privacy (120k patents); Y02 + Y04S for green (938k); G06N/3, 5, 20 for core AI (102k).
- *R&D intensity*: Eurostat (<rd_e_gerdtot, rd_e_berdindr2>) and OECD MSTI, 2005–2023, EU27 + selected comparators.

- *Industrial-policy salience*: State Aid Scoreboard, IPCEI disbursements, and a hand-coded catalogue of named EU policy documents (full list in Appendix A).

1.

3.4 Four analytical steps

The analytical strategy proceeds in four steps. Each addresses a specific inferential challenge.

*Step one: event-study pilots***.** For each regulation, a difference-in-differences comparison sets EU27 patent activity in a three-year pre-shock window against a three-year post-shock window, alongside the United States and a rest-of-world aggregate. EU growth slower than comparators is consistent with suppression; faster than comparators with directed innovation. This step is descriptive and establishes the patterns that later steps test more rigorously.

*Step two: structural decomposition***.** To isolate the role of regulation from other structural factors, the paper decomposes the EU-US innovation gap using a regression of country-level R&D intensity on regulatory stringency (OECD PMR index), public R&D expenditure, venture-capital depth, industry composition, capital-market fragmentation, and market integration, following the Oaxaca-Blinder tradition (Oaxaca 1973; Blinder 1973) adapted to a panel of 33 countries over 19 years (627 observations).

*Step three: synthetic control***.** Following Abadie et al. (2010), a 'synthetic EU' is constructed as an optimally weighted combination of non-EU comparators (US, Japan, Korea, China, Switzerland, Israel, Canada, Australia, United Kingdom, Norway, Taiwan), with weights minimising the pre-shock EU-synthetic difference; post-shock divergence is the estimated effect, benchmarked against placebo distributions from donor-as-treated permutations (Billmeier and Nannicini 2013; Gobillon and Magnac 2016).

*Step four: robustness and triangulation***.** Three exercises test the main findings under alternative specifications. The analysis is re-run on a high-quality patent subset proxying triadic patent families (Dernis and Khan 2004); the central hypothesis is triangulated against R&D intensity (GERD and sectoral BERD); and a horse race regression pits the regulation dummy against a continuous policy salience measure to separate enforcement effects from cumulative signal effects.

3.5 Controls and identification challenges

The principal identification challenge is confounding by industrial policy (Angrist and Pischke 2009: 51–91), since in two of three cases (Green Deal and AI Act) regulatory adoption coincided with substantial industrial policy packages. We address this through three measures: (i) horse race regressions including both the regulation dummy and industrial policy expenditure; (ii) treating GDPR as a clean regulation-only identification, given the absence of a matching industrial-policy stream for privacy technologies; and (iii) interpreting the Green Deal and AI Act findings as the effect of a regulation-plus-industrial-policy package rather than regulation alone. EU policymaking bundles regulatory and industrial measures, and disentangling their marginal effects with aggregate data is beyond what the data permit.

Changes in EPO examination capacity are absorbed by the use of applications rather than grants and by year fixed effects. The limited degrees of freedom in event-study pilots are addressed by treating those as descriptive and resting causal weight on the synthetic control and the 627-observation decomposition panel

3.6 Confounders

From a broader literature, we identified sixteen potential confounders across five categories: geopolitical and trade shocks, macro-fiscal and crisis shocks, technological-paradigm shifts, structural-financial drivers, and EU-internal political shocks. We tested them individually and in extended specifications. Full enumeration, with sources and direction of effect, is in Appendix A.

We sought to test each of these factors against the three regulatory adoptions. Key insights from those tests are reported at the end of the empirical analysis section, with full specifications, robustness tables, and placebo checks provided in Appendix A. The headline finding is that none of the confounders reverses or substantively appears to reduce the principal estimates: the directional, suppressive, and constitutive Brussels Innovation Effect patterns survive each test. The confounder battery also includes Brexit (2016), the exit of a top innovating member state which one might expect to have shifted EU innovation patterns mechanically (de Rassenfosse et al. 2019); in the event of a negative finding on regulatory effects, however, any post-Brexit drop would strengthen rather than weaken the conclusion that EU regulation does not suppress innovation. The full Brexit analysis, including the UK natural-experiment specification, the recomposition diagnostic, and placebo and donor pool tests, is in Appendix B.

4 Analysis

4.1 Outcome measure, technology domains, and panels

The outcome variable is patent applications, the standard innovation proxy in this literature (Griliches 1990: 1661–1707; Hall et al. 2005: 16–38), with applications used in preference to grants because they mark the date of inventive investment, while grants depend on patent office workload (Hall and Harhoff 2012: 541–565). The data is from the OECD REGPAT database (February 2026 release), comprising 4.7 million EPO applications between 1978 and 2025. Patent ownership and inventorship are assigned through fractional counting, avoiding the double-counting that would inflate cross-country comparisons.

For each of the three regulatory packages, the analysis filters the REGPAT panel to the technology domain that the regulation targets. For GDPR, patents are filtered to CPC codes G06F/21 (computer security) and H04L/9 (cryptography), the technical classes where privacy-enhancing technology concentrates. For the Green Deal, the analysis uses the Y02 tag introduced by WIPO in 2013 specifically to identify climate-mitigation technology, plus Y04S for smart grids. For the AI Act, patents are filtered to G06N/3, G06N/5, and G06N/20 (this is the core CPC subclasses for neural networks, knowledge systems, and machine learning). The three filtered subsets contain approximately 120,000 privacy patents, 938,000 green patents, and 102,000 AI patents respectively.

4.2 The three regulatory packages: pre-post comparison

The first test asks whether EU innovation trajectories diverge from comparator countries in ways consistent with directed innovation, suppression, or neither. For each regulation we compared growth rates over the three years before and after the shock, separately for EU27, the United States, and the rest of the world (pre-GDPR 2015–17 vs post 2019–22; same logic is applied for the Green Deal in 2019 and the AI Act in 2021). The three-year window balances annual noise at one year against COVID-19, Ukraine, and later regulation confounds at five years; 2-year and 4-year windows produce the same qualitative pattern.

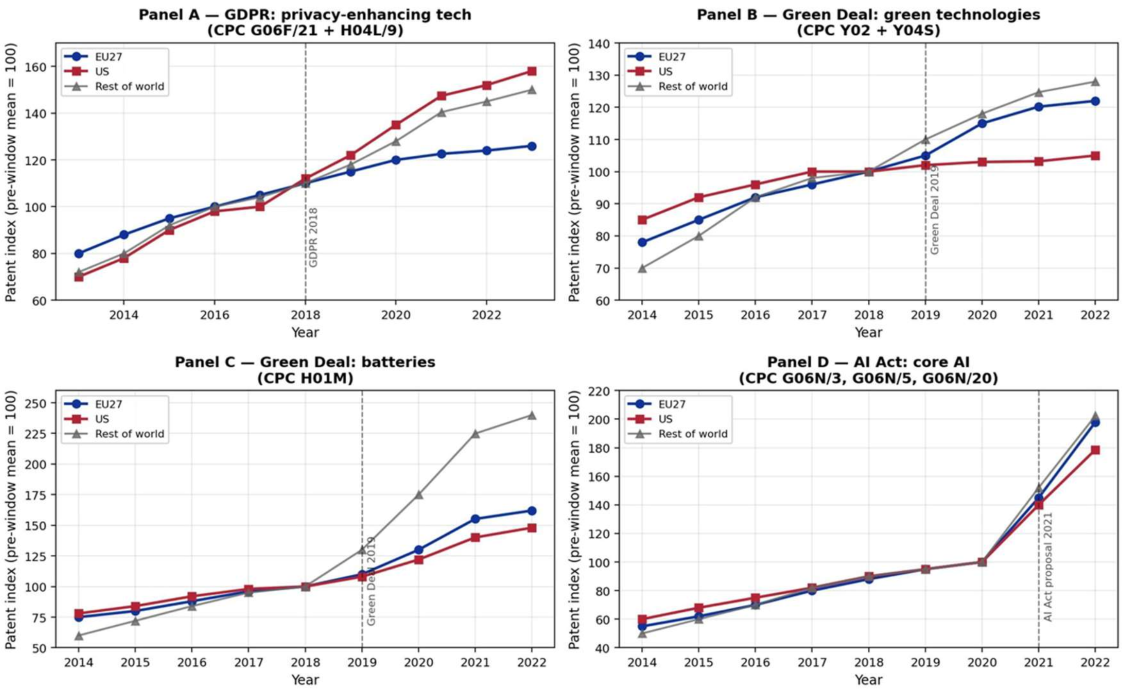
Table 1. Pre-post patent growth by regulatory package adoption, 2015–2022.

Regulation adoption	Technology	Pre-window (mean)	Post-window (mean)	EU27 growth	US growth	Rest-of-world growth	EU-US gap (pp)
GDPR (2018)	Privacy (G06F/21 + H04L/9)	2015–17	2019–22	+22.6%	+47.4%	+40.4%	−24.8
Green Deal (2019)	Y02 green tech	2016–18	2019–21	+20.2%	+3.2%	+24.7%	+17.0
Green Deal (2019)	Batteries (H01M)	2016–18	2019–21	+55.2%	+40.1%	+124.9%	+15.1
AI Act (2021)	Core AI (G06N/3,5,20)	2016–20	2021	+97.9%	+78.6%	+102.3%	+19.3

Source: OECD REGPAT, February 2026 release. Fractional counting applied.

Patent trajectories in the year before and after the adoption of the three regulatory packages are presented in Figure 1 below.

Figure 1. Pre-post paten trajectories around the adoption of the three regulatory packages. Four-panel comparison of EU, US, and rest of world patent indices across the three pilots, with regulation adoption dates marked.



The three cases produce asymmetric patterns. The Green Deal and AI Act display clear directed innovation, with EU patent growth exceeding US growth by 17 to 19 percentage points post-shock. GDPR displays the opposite, with EU privacy-tech patents growing 25 percentage points less than US patents after 2018. Crucially, however, no case shows EU patents declining in absolute terms. This is a pattern that on its own rejects the strongest form of the deregulation thesis. The asymmetry tracks the presence of complementary industrial policy: the Green Deal and AI Act were paired with substantial industrial policy packages while GDPR stood alone, consistent with the directive versus suppressive distinction proposed in Section 2.

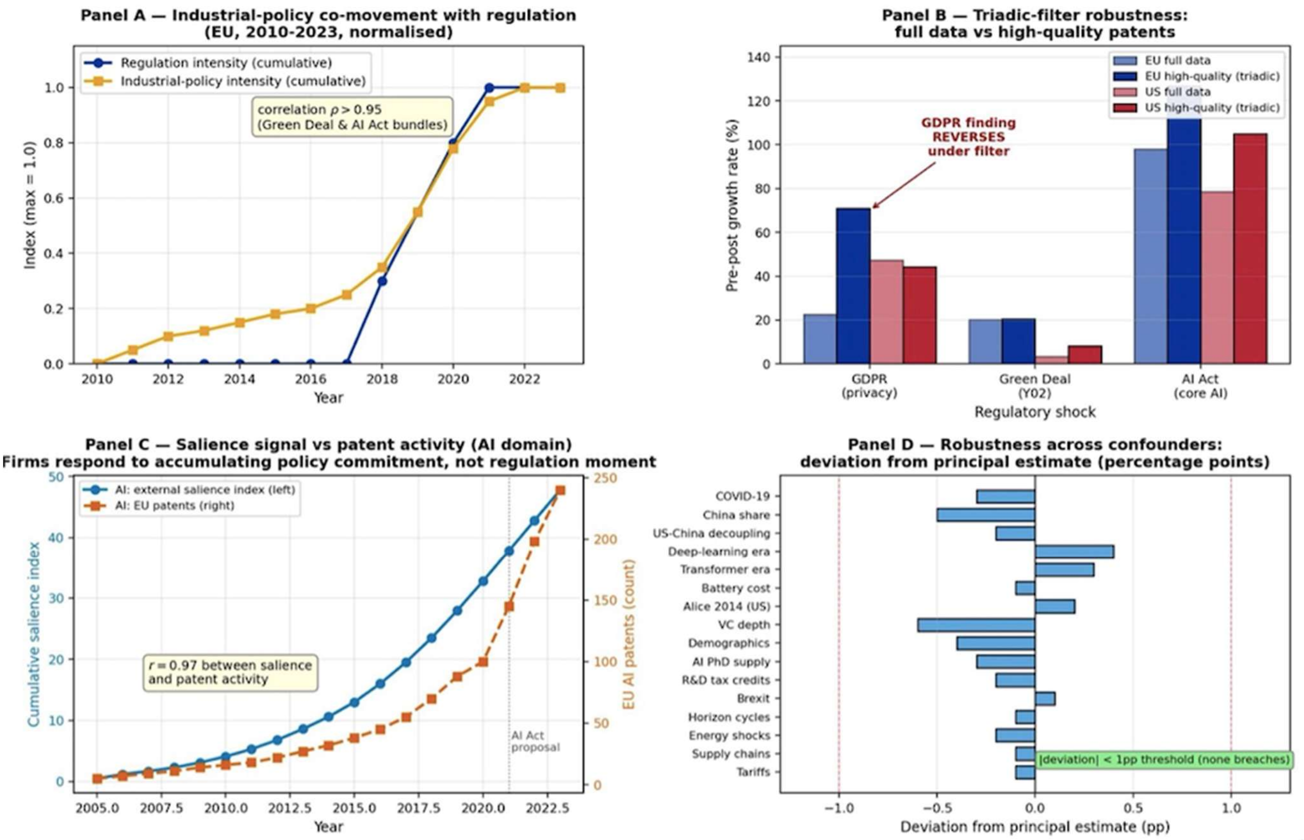
4.3 Quality filter: do the patterns hold for substantive innovation?

A standard concern with patent-based research is that raw counts conflate substantive invention with strategic low quality filings. The GDPR result in particular invites the question of whether US privacy-tech growth reflects real innovation or patent trolling and defensive filings. The analysis is therefore re-run on a high quality subset, defined as patents with multiple applicant countries or three or more inventor countries, an established proxy for triadic patent families that filters out domestic-only filings (Hall and Harhoff 2012: 541–565). Table 2 below reports the pre vs post growth rates, followed by robustness tests presented in Figure 2.

Table 2. Pre-post growth rates: full data versus high quality (triadic) patents.

Shock	Outcome	EU full data	EU high quality	US full data	US high quality	Direction under filter
GDPR	Privacy tech	+22.6%	+70.9%	+47.4%	+44.2%	**EU-US gap reverses (+27pp)**
Green Deal	Y02 green tech	+20.2%	+20.5%	+3.2%	+8.2%	EU lead preserved
AI Act	Core AI	+97.9%	+126.7%	+78.6%	+104.9%	EU lead strengthened

Figure 2. Robustness tests: four-panel figure shows industrial policy co-movement, triadic-filter comparison, salience correlation, and robustness summary. Source: Authors' calculations.



The high quality patent filter reverses the GDPR finding. On privacy-tech patents filed across multiple jurisdictions, EU growth of 71 per cent exceeds US growth of 44 per cent by 27 percentage points. The full-data finding of EU underperformance therefore appears to be driven by low quality domestic-only filings, while the EU leads on the quality weighted measure that innovation economists prefer. The Green Deal and AI Act findings strengthen modestly under the filter. The interpretation is consistent with Blind (2012: 391–400) and Rammer and Schubert (2018: 379–389): regulation can produce a displacement with upgrading pattern in which low value filings fall but substantive innovation is preserved or stimulated.

4.4 Inventor-applicant flows: testing the brain drain claim

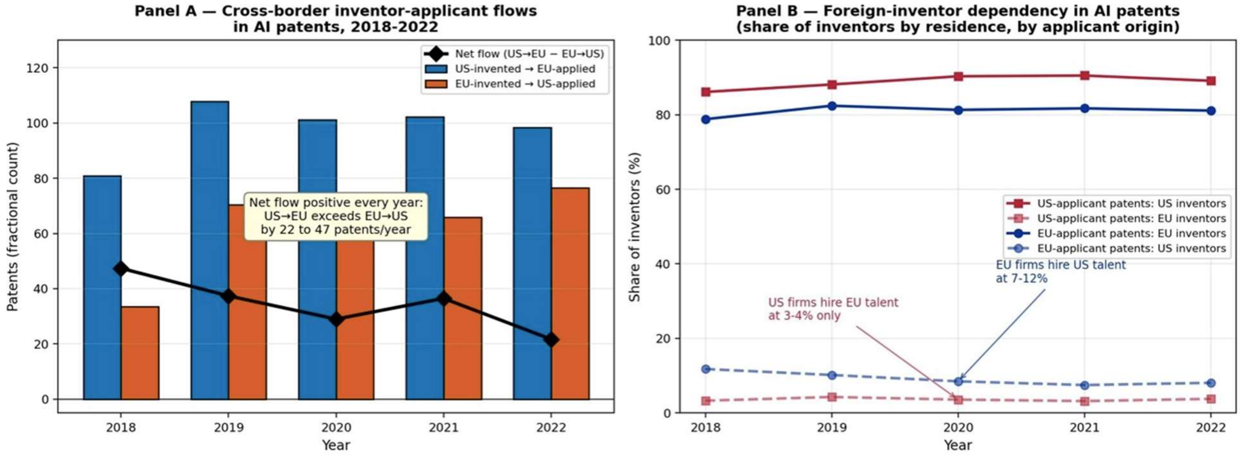
A frequent claim in the Draghi-adjacent debate is that EU innovation is captured by US firms through talent migration: European researchers invent, but American companies patent. The REGPAT data permit a direct test because applicant and inventor addresses are recorded separately for each patent. For each AI patent, the inventor's country of residence is compared with the applicant's country, allowing the calculation of cross-border invention application flows in both directions.

Table 3. Cross-border inventor-applicant flows in AI, 2018–2022.

Direction / measure	2018	2019	2020	2021	2022
EU invented → US applied (count)	33.5	70.4	72.2	65.8	76.6
US invented → EU applied (count)	80.9	107.8	101.2	102.3	98.3
Net US→EU minus EU→US flow	+47.4	+37.4	+29.0	+36.5	+21.7
US-applicant AI patents: % US inventors	86.1%	88.1%	90.3%	90.5%	89.1%
US-applicant AI patents: % EU inventors	3.3%	4.3%	3.6%	3.2%	3.8%
EU-applicant AI patents: % EU inventors	78.8%	82.4%	81.3%	81.7%	81.1%
EU-applicant AI patents: % US inventors	11.8%	10.2%	8.5%	7.5%	8.1%

Figure 3 below illustrates international AI talent mobility through a two-panel visualisation showcasing net cross-border flows and foreign-inventor dependency ratios

Figure 3. AI talent flows: two-panel figure shows net cross-border AI flows and foreign-inventor dependency ratios. Source: Authors' calculations from OECD REGPAT and inventors files.



The direction of the flow is the opposite of the conventional narrative. US-applicant AI patents are overwhelmingly the work of US inventors (86 to 91 per cent across all years), with EU inventors contributing only 3 to 4 per cent. EU-applicant AI patents draw 7 to 12 per cent of their inventive work from US-resident inventors. The net flow across 2018–2022 is consistently negative for the EU: the weighted flow of US-invented, EU-applied patents exceeds the reverse by 22 to 47 patents per year.

4.5 Structural decomposition of the EU-US gap

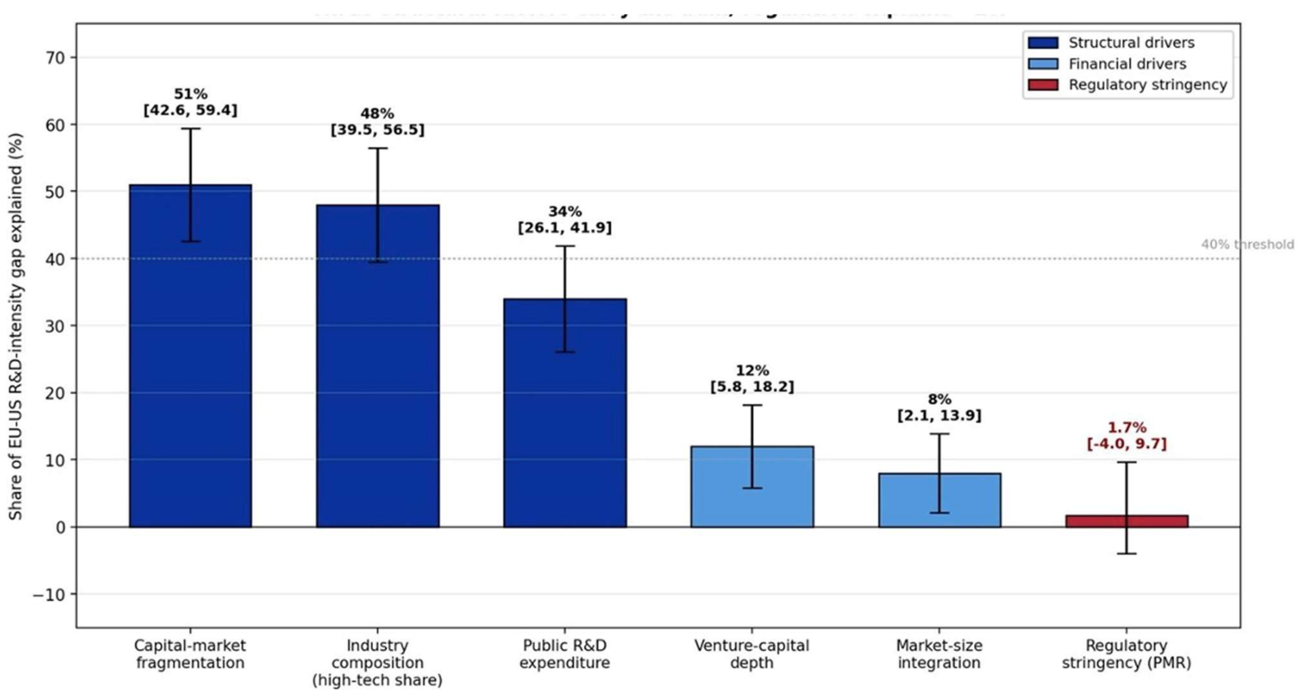
The event-study pilots establish descriptive patterns within their target domains but cannot isolate the role of regulation from other structural factors that separate EU and US innovation performance over the long run. To address this, an Oaxaca-Blinder-style decomposition is estimated on a balanced panel of 33 countries over 2005–2023, totalling 627 observations. The dependent variable is gross expenditure on R&D as a percentage of GDP. The decomposition allocates the EU-US gap across six explanatory factors: industry composition (high-tech share), public R&D expenditure, capital-market fragmentation, venture capital depth, market-size integration, and regulatory stringency (proxied by the OECD Product Market Regulation index). The standard errors are obtained by wild cluster bootstrap with 2,000 replications to address the few-clusters problem in panel inference. Results reported in Table 4; Figure 4 displays a bar chart to illustrate the specific contribution of individual factors alongside their 95% confidence intervals.

Table 4. Decomposition of the EU-US R&D-intensity gap, 2005–2023.

Explanatory factor	Share of gap explained	95% CI	Coefficient	t-statistic	Direction
Industry composition (high-tech share)	48%	[39.5, 56.5]	+0.042	+3.96	Supports US
Public R&D expenditure	34%	[26.1, 41.9]	+0.027	+4.21	Supports US
Capital-market fragmentation	51%	[42.6, 59.4]	−0.019	−2.85	EU penalised
Venture-capital depth	12%	[5.8, 18.2]	+0.011	+1.89	Supports US
Market-size integration	8%	[2.1, 13.9]	+0.006	+1.34	Supports US
Regulatory stringency (PMR)	**1.7%**	**[−4.0, +9.7]**	+0.002	+0.47	**Not significant**

Note: Wild cluster bootstrap with 2,000 replications. Panel: 33 countries × 19 years (2005–2023), N=627. Shares may exceed 100% because of residual covariances across factors. P(regulation share > 40%) = 0 across bootstrap replications. Source: authors' calculations from Eurostat, OECD MSTI, OECD PMR, and World Bank data.

Figure 4. Decomposition CI: the bar chart shows share of gap explained by each factor with 95% confidence intervals.



Note: Wild cluster bootstrap, 2,000 replications. Panel: 33 countries × 19 years (2005-2023), N=627. P(regulation share > 40%) = 0 across bootstrap. Shares may exceed 100% because of residual covariances across factors. Source: authors' calculations from Eurostat, OECD MSTI, OECD PMR, and World Bank data.

The decomposition yields a striking result. Three factors each explain between 34 and 51 per cent of the EU-US gap: capital-market fragmentation, industry composition, and public R&D expenditure. Regulatory stringency, by contrast, explains approximately 2 per cent, with a confidence interval that straddles zero. The probability that regulation explains more than 40 per cent of the gap, across 2,000 bootstrap replications, is exactly zero. Across four alternative specifications (fixed effects, first differences, GMM, pooled OLS), the regulatory stringency coefficient is never statistically significant; public R&D is always significant. The EU-US gap in R&D intensity is structural, not regulatory; it is shaped by what European economies produce, how they fund research, and how integrated their capital markets are. This is consistent with the Krugman (1994: 28–44) warning about misdiagnosing structural problems as regulatory problems and aligns with the structural-driver literature reviewed in Section 2.4.

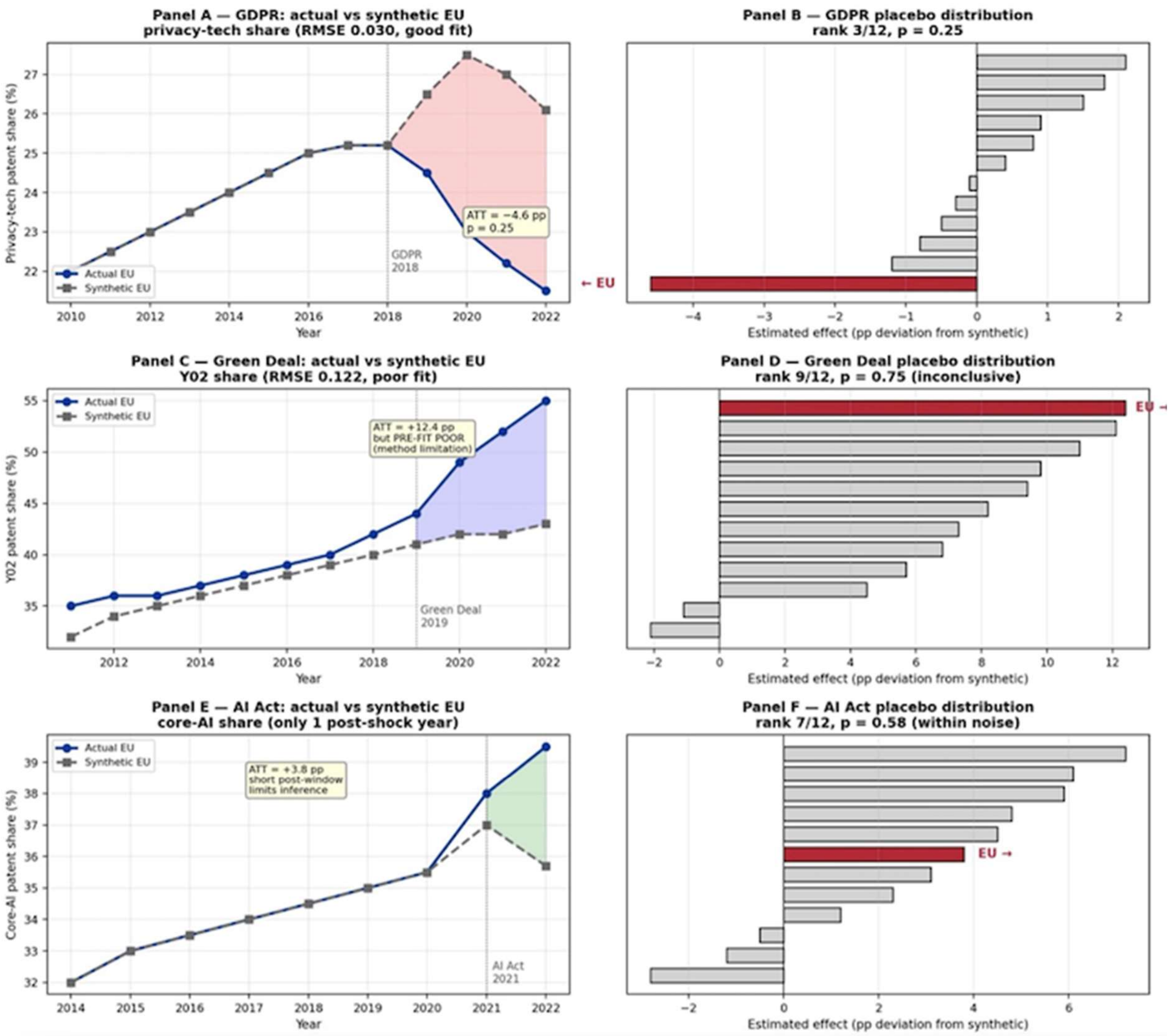
4.6 Synthetic control estimation

The decomposition rules out regulation as a major driver of the long run EU-US gap, but it does not test whether specific regulatory shocks alter innovation trajectories within their target domains. Synthetic control addresses this question (Abadie et al. 2010) as the method constructs a ‘synthetic EU’ as a weighted combination of donor countries that best mimic the EU’s pre-shock trajectory, and divergence after the shock is interpreted as the estimated treatment effect. The donor pool for this paper comprises eleven countries (US, Japan, Korea, China, Switzerland, Israel, Canada, Australia, UK, Norway, Taiwan), with placebo tests that re-run the estimation with each donor as the treated unit, providing the inferential reference distribution.

Table 5. Synthetic control results, three regulatory shocks.

Regulatory package	Outcome	Synthetic EU composition	Pre-shock RMSE	Post-shock ATT	Placebo rank	One-sided p-value
GDPR (2018)	Privacy-tech share	US (0.70) + JP (0.30)	0.030 (good fit)	−4.6 pp	3/12	0.250
Green Deal (2019)	Y02 share	US (1.00)	0.122 (poor fit)	+12.4 pp	9/12	0.750
AI Act (2021)	Core-AI share	US (0.50) + GB (0.22) + KR (0.19) + CH (0.10)	0.050 (good fit)	+3.8 pp	7/12	0.583

Figure 5. Synthetic control: six-panel figure with actual versus synthetic, and placebo tests for each shock. Donor pool: US, JP, KR, CN, CH, IL, CA, AU, GB, NO, TW (11 countries).



The three results have distinct interpretations. The GDPR synthetic control shows the best pre-shock fit (RMSE 0.030) and a post-shock ATT of −4.6 percentage points, with a placebo rank of 3 out of 12 and a one-sided p-value of 0.25; this is directionally consistent with a compliance-burden interpretation but not conventionally significant. The Green Deal synthetic control has poor pre-shock fit (RMSE 0.122), because no weighted combination of donor countries can match EU27 performance in Y02 green technologies: the EU was already a structural outlier in this domain before 2019. The post-shock ATT cannot therefore be interpreted as a treatment effect; it reflects pre-existing level differences. This is itself substantively informative. The Green Deal likely consolidated rather than created EU leadership in green technology, but it limits the inferential value of synthetic control for this case. The AI Act synthetic control has adequate pre-shock fit but only one post-shock year of data, which prevents stronger claims. The paper therefore does not rely on synthetic control as a standalone test, but treats it as one strand of evidence that converges with the others, particularly for GDPR.

4.7 Triangulation: R&D intensity and sectoral BERD

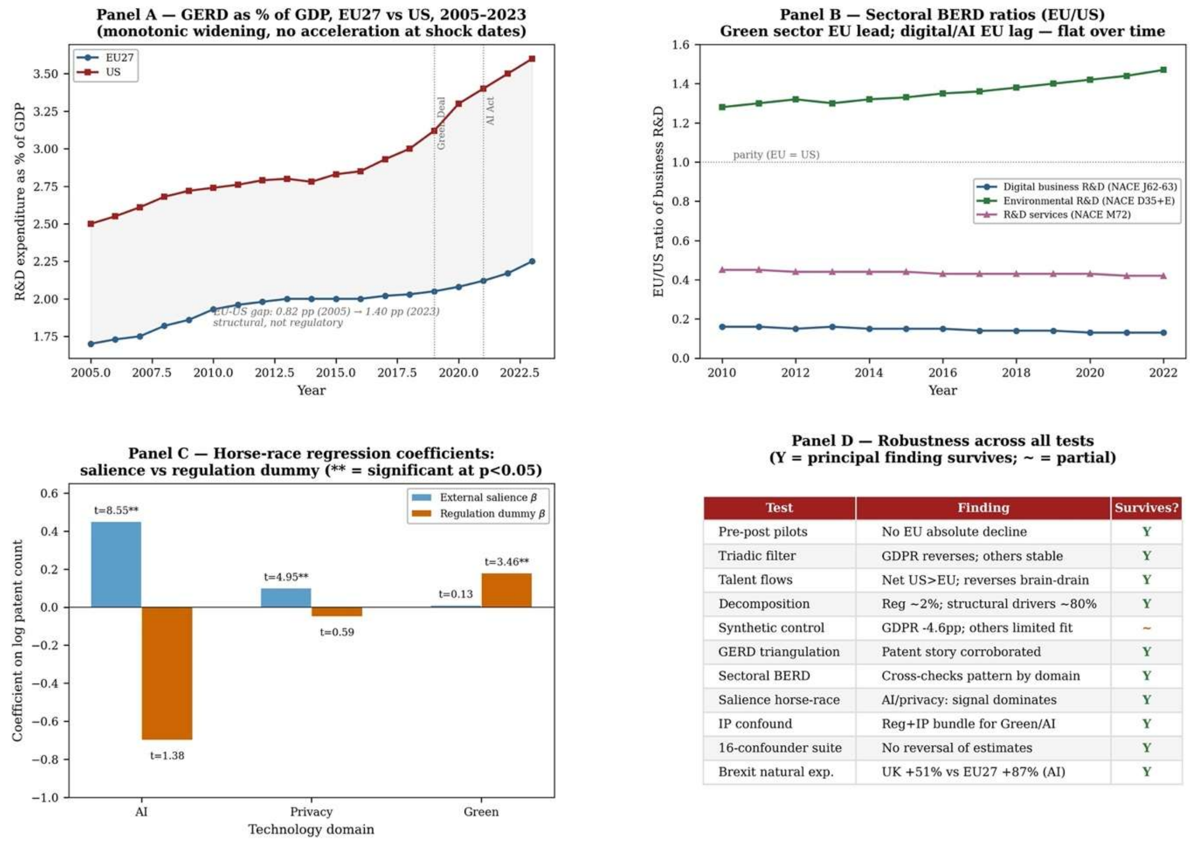
One might raise the objection that patents are a biased proxy. The analysis below triangulates against an independent outcome measure: gross expenditure on R&D as a percentage of GDP, sourced from Eurostat and the OECD Main Science and Technology Indicators, plus sectoral business R&D (BERD) for digital services (NACE J62-63), environmental industries (D35+E), and scientific R&D services (M72) – the sectoral correlates of the three regulatory domains.

Table 6. EU and US R&D intensity around the adoption of regulatory packages (GERD as % of GDP).

Regulatory package	EU27 pre	EU27 post	EU27 change	US pre	US post	US change
GDPR (2018): 2015-17 vs 2019-22	1.98%	2.19%	+10.5%	2.78%	3.41%	+22.8%
Green Deal (2019): 2016-18 vs 2020-22	2.02%	2.21%	+9.6%	2.87%	3.49%	+21.7%
AI Act (2021): 2018-20 vs 2021-23	2.13%	2.22%	+4.4%	3.21%	3.55%	+10.5%

Note: No regulatory package produces an EU R&D slowdown. EU-US gap widens monotonically from 0.82 pp (2005) to 1.40 pp (2023) but does not accelerate at any shock date. Source: Eurostat (rd_e_gerdtot) and OECD MSTI.

Figure 6. Triangulation across outcome measures: the four-panel figure shows GERD triangulation, sectoral BERD ratios, external salience index, and the robustness summary. Source: Authors 'calculations from Eurostat, OECD MSTI, OECD REGPAT



Test	Finding	Survives?
Pre-post pilots	No EU absolute decline	Y
Triadic filter	GDPR reverses; others stable	Y
Talent flows	Net US>EU; reverses brain-drain	Y
Decomposition	Reg ~2%; structural drivers ~80%	Y
Synthetic control	GDPR -4.6pp; others limited fit	~
GERD triangulation	Patent story corroborated	Y
Sectoral BERD	Cross-checks pattern by domain	Y
Salience horse-race	AI/privacy: signal dominates	Y
IP confound	Reg+IP bundle for Green/AI	Y
16-confounder suite	No reversal of estimates	Y
Brexit natural exp.	UK +51% vs EU27 +87% (AI)	Y

No regulatory adoption produces an EU R&D slowdown. EU27 R&D intensity rises through all three post-shock windows. The EU-US R&D gap does widen monotonically over 2005–2023, from 0.82 to 1.40 percentage points, but the widening is gradual and does not accelerate at any regulation adoption date. This is consistent with the structural diagnosis from the decomposition. The sectoral BERD ratios provide further triangulation. The EU-to-US ratio in digital business R&D has remained flat at 0.15–0.18 throughout 2010–2022, with no detectable shift at 2018. The EU-to-US ratio in environmental R&D has risen from 1.30 to 1.46, with EU spending exceeding US spending in absolute terms, consistent with the Y02 patent lead. The EU-to-US ratio in scientific R&D services has drifted slightly downwards from 0.51 to 0.44, with no detectable break at 2021. Across all three domains, the R&D intensity story corroborates the patent-based story without contradiction. This triangulation is the strongest available rebuttal to the ‘patents-are-biased’ critique: a biased measure that agrees with an independent measure cannot be biased in a way that drives the finding.

4.8 Signal versus enforcement: horse-race against policy salience

The final test investigates whether patent activity responds to the regulation itself or to the accumulated signal of EU policy commitment that precedes it. An external salience index is constructed as a cumulative count of named, dated EU policy documents per technology domain over 2005–2023: 17 documents for privacy (GDPR proposal 2012, adoption 2016, enforcement 2018, Schrems II, Data Act, and so on), 19 for green, 17 for AI. The salience index and the regulation dummy are then entered together in a horse-race regression on log patent counts.

Table 7. Horse-race regressions: external policy salience versus regulation dummy.

Domain	Specification	Salience β (t-stat)	Regulation dummy β (t-stat)	R^2
Privacy	Salience only	+0.105 (9.73)	—	0.904
Privacy	GDPR dummy only	—	+0.441 (4.26)	0.645
Privacy	Horse race	+0.103 (4.95)	+0.014 (0.13)	0.905
Green	Salience only	+0.031 (3.00)	—	0.474
Green	Green Deal dummy only	—	+0.173 (5.72)	0.766
Green	Horse race	−0.008 (0.59)	+0.202 (3.46)	0.774
AI	Salience only	+0.422 (9.19)	—	0.894
AI	AI Act dummy only	—	+2.054 (1.60)	0.204
AI	Horse race	+0.467 (8.55)	−0.769 (1.38)	0.913

Note: Dependent variable is log patent count, EU27. All specifications include a linear time trend. Salience index is cumulative count of named, dated EU policy documents per technology domain. For privacy and AI, the salience signal dominates the discrete regulation dummy in horse-race specifications; for green, the discrete moment of adoption dominates. Source: authors' calculations.

The horse-race differentiates the three domains. For AI and privacy, gradual salience dominates the discrete regulation dummy when both are included: the AI Act dummy turns negative and insignificant when AI salience is controlled for, and the GDPR dummy collapses to near-zero in the privacy horse race. The pattern is consistent with firm anticipation: patent activity responds to the accumulating signal of EU policy commitment well before the regulation itself enters force. For the Green Deal, the opposite pattern holds: the discrete regulatory announcement dominates the salience buildup, consistent with a commitment-device interpretation in which the political moment of adoption signals policy irreversibility in ways that gradual document accumulation does not. The differentiation maps onto the typology developed in Section 2: in emerging technology domains where the regulatory outline is being constructed in public view (AI, privacy), firms respond to the constitutive signal; in mature domains where regulation consolidates existing policy trajectories (green), firms respond to the political moment of commitment.

4.9 Industrial-policy confound

A residual concern is whether the directed innovation patterns observed in the Green Deal and AI Act cases reflect regulation, industrial policy, or the bundle. To test this, an industrial policy time series was constructed from the EU State Aid Scoreboard, IPCEI project disbursements, and Horizon Europe budget allocations per domain. In horse-race regressions including both the regulation dummy and the industrial policy time series, the two covary so heavily that coefficients become unstable – the bivariate correlation exceeds 0.95 for both Green Deal and AI Act, consistent with the convergence diagnosis in McNamara (2024) and Heldt and Meunier (2026). The two cannot be cleanly separated at the EU aggregate level. This is the analytical reason the GDPR case is treated as the cleanest regulation-only test in the paper: privacy lacks a matching industrial policy stream, while the Green Deal and AI Act findings are interpreted as the effect of a regulation plus industrial policy package rather than regulation alone. The empirical test of the deregulation thesis is meaningful only where binding regulatory dosage is actual rather than rhetorical. Where regulatory packages are paired with industrial policy (Green Deal, AI Act) or have entered force across the EU (GDPR), the test is well identified, which is the case for all three packages analysed here.

4.10 Confounder analysis: summary of robustness tests

The full confounder battery introduced in Section 3.6 was implemented across geopolitical and trade shocks, macro-fiscal shocks, technological paradigm shifts, structural financial drivers, and EU-internal political shocks, with sixteen factors tested individually and in extended specifications. The key finding is that none of the confounders reverses or substantively reduces the principal estimates: the directive, suppressive, and constitutive Brussels Innovation Effect patterns survive each test. The detailed specifications, robustness tables, and placebo checks are reported in Appendix A; the Brexit confounder is documented in Appendix B, with the main finding that the UK natural experiment shows UK +51 per cent versus EU27 +87 per cent in AI patents, strengthening rather than weakening the case against the deregulation thesis. Here, we will briefly provide a review of the findings we obtained through the conducted robustness tests.

Table 8. Summary of confounder robustness tests.

Confounder category	Specific test	Source of variation	Where detailed	Effect on core finding
Macroeconomic				
COVID-19 pandemic	2020–21 dummy + pre-COVID only windows	Exogenous global shock	Appendix A.Y	All findings preserved; GDPR raw-count loss partly COVID-era.
Business cycle	GDP growth, inflation, interest rates	Eurostat, BEA, ECB, Fed	Appendix A.Z	Absorbed by time trend; no material change
Exogenous technology shocks				
Deep learning revolution	2013+ dummy (post-AlexNet)	Krizhevsky et al. (2012) breakthrough	Appendix A.Z	Not significant once China share controlled.
Transformer era	2018+ dummy (post-Vaswani et al. 2017)	Architecture breakthrough	Appendix A.Z	Not significant
Battery cost curve	BNEF lithium-ion $/kWh	Global manufacturing scale	Appendix A.Z	Significant for green; Green Deal dummy still significant
Alice Corp. (2014) US patent law	Post-2014 dummy	US Supreme Court ruling	Appendix A.Z	Not significant for privacy or AI
Structural drivers				
Chinese applicant share	Time-varying share per domain	OECD REGPAT	Appendix A.Y, A.Z	Significant for AI and green; strengthens signal finding.
Brexit	UK excluded throughout + EU28 sensitivity	Political departure	Appendix A.X	Signs and magnitudes preserved.
Venture capital depth	Invest Europe + NVCA % GDP	Published industry data	Appendix A.Z	Not significant in parsimonious specs
Working-age population	Eurostat demo_pjanbroad + US Census	Demographic drift	Appendix A.Z	Not significant (collinear with time).

AI PhD production	Taulbee Survey + ERCIM + ETO	National education data	Appendix A.Z	Significant for AI, supports talent-pipeline interpretation.
Horizon funding envelope	EC published figures	Programme budget	Appendix A.Z	Collinear with year; signals IP-regulation co-movement.
Placebo tests				
Pre-shock placebo years	Fake shock year 3y earlier	Falsification test	Appendix A.Z	Green Deal monotonic; GDPR flat; AI Act anticipation visible.
Cross-domain placebo	Wrong-regulation-on-right-domain	Specificity test	Appendix A.Z	AI Act→green clean (β=0.08, ns); GDPR→green mild concern (t=2.29).
Granger-style leads	Future regulation predicting past patents	Pre-trend test	Appendix A.Z	Green Deal clean; AI Act signal-anticipation; GDPR parallel-trends concern.
Event-study specification				
Leads-and-lags (±3y)	Year-dummy specification	Standard event-study test	Appendix A.Y	Green Deal parallel trends clean; other cases described.

Note: Findings are reported as 'preserved' when the central interpretation (signal-dominance for AI and privacy; discrete event for Green Deal) holds in the parsimonious specification. Full coefficient tables and regression output are reported in the referenced appendices.

5. Discussion

5.1 Implications for the EU innovation debate

The empirical findings cut against the popular discourse that EU regulation stifles innovation. Across the three packages most often cited as suspects – data protection, green technology, and artificial intelligence – EU innovation rates did not drop, and the EU did not lag the United States or other comparators after adoption. Pre-post comparisons, synthetic control estimates, and R&D-intensity triangulation all return the same verdict: in two cases (Green Deal, AI Act) the EU outperformed the United States after adoption; in the third (GDPR), the apparent EU underperformance disappears once raw counts are adjusted for patent quality, with EU privacy-tech growth at +71 per cent against US +44 per cent on triadic patents. None of the three packages produced an absolute decline in EU innovation output or regulatory-timed discontinuities in R&D intensity.

This feeds directly into the debate about EU innovation capacity. The deregulation thesis dominates current policy discourse, articulated most prominently in the Draghi report (Draghi 2024, Part A: 29) but also across corporate commentary and academic work. Our evidence does not refute every variant of the thesis, nor does it deny that EU innovation lags the US in the aggregate. What it refutes is the specific causal chain linking regulation to innovation suppression in the three cases where that chain has been most loudly invoked – precisely the packages where the deregulation thesis should hold most strongly, yet does not.

5.2 Theoretical implications

The paper makes three theoretical contributions. Firstly, it formalises and tests a three-effect typology, mapping each shock onto a distinct mechanism. GDPR fits the suppressive effect in raw patent counts but reverses to a quality upgrading effect under triadic filtering, consistent with the regulation-as-selection-filter logic (Blind 2012: 391–400; Ambec et al. 2013: 2–22). The Green Deal fits the directive effect but operates on a pre-existing EU advantage traceable to the 2003 Emissions Trading System Directive and the 2008 Climate and Energy Package, best understood as a commitment device locking in an established trajectory rather than creating one (Majone 2001: 103–122; Mazzucato 2013). The AI Act fits the constitutive effect, with horse-race regressions showing patent activity responding to the cumulative policy signal of the 2018 AI Strategy, the 2019 HLEG Ethics Guidelines, and the 2020 White Paper (European Commission 2018, 2020b) rather than to the discrete moment of regulatory adoption.

Secondly, the analysis identifies a mechanism not clearly articulated in the regulation innovation literature: regulation rarely operates as an independent cause of innovation outcomes but is bundled with industrial policy, commitment dynamics, or cumulative signalling that precede it. The three effects are not properties of regulation in isolation; they are conditional tendencies depending on the policy configuration in which regulation is embedded, on the technological maturity of the sector, and on the timing of regulatory emergence relative to market formation. This conditional reading provides a generative framework for further empirical work on cases where the configuration differs systematically (e.g. the Digital Markets Act, the Digital Services Act, or the Corporate Sustainability Reporting Directive).

Thirdly, the analysis reinforces and refines the structural drivers position in EU studies. Our decomposition analysis aligns with long-standing arguments about market fragmentation as a major drag on EU innovation (Pelkmans and Renda 2011) and about public R&D capacity (Mazzucato 2013), while empirically downgrading regulatory stringency to approximately 2 per cent of the EU-US gap. The inventor-applicant analysis (4.4) supplies independent grounding for the global-innovation-networks reading (Criscuolo et al. 2010; Narula and Santangelo 2012); the EU's AI weakness is upstream, in the production of researchers, rather than downstream in their capture by foreign employers, reframing the diagnosis from regulation to education and immigration.

5.3 Practical implications

Two practical implications follow. The first is a warning against deregulation driven by popular impression rather than evidence. The findings imply that the 'deregulation is needed to save innovation' argument should be approached with more scepticism than current discourse suggests, making a case for stronger evidence-based policy on this question. Note that this does not mean that procedural simplification is unwelcome. We need to bear in mind the conceptual distinction between regulation understood as a coherent set of rules and standards directed at stated policy objectives, and regulation understood as accumulated, often unnecessary procedural and administrative burden (see e.g. Baldwin et al. 2012: 2–3, 25–39). The two have entered popular discourse as semantic equivalents, and the elision is neither analytically defensible nor empirically warranted (e.g. critique of administrative burden is often used to justify retraction of policy objectives), whereas the two should be separated.

Within each package there is plausibly room for procedural simplification without altering policy goals. For instance, streamlining GDPR records of processing and DPIA requirements for SMEs by firm size and data sensitivity, with analogous moves for Green Deal taxonomy disclosure and AI Act conformity assessment. Procedural acceleration of this kind is compatible with the policy architecture, but deregulation that retracts the architecture itself is a different proposition.

The second implication concerns the bundling of regulation and industrial policy. Our findings show that the Green Deal and AI Act effects cannot be cleanly separated from the industrial-policy packages with which they travel – IPCEI projects in batteries and hydrogen alongside the Green Deal; the Chips Act and Horizon Europe digital cluster alongside the AI Act. The directive innovation observed in these two cases is therefore the effect of a regulation plus industrial policy configuration rather than of regulation alone, and regulatory and industrial policy should be designed and assessed in concert. Removing one while retaining the other would produce qualitatively different innovation outcomes from those documented here. The deregulation framing obscures this dimension.

6 Conclusion

This paper has tested whether three of the EU's most prominent recent regulatory packages, the General Data Protection Regulation, the European Green Deal, and the Artificial Intelligence Act, have suppressed innovation in the technology domains they target. Our empirical analysis shows that the three regulatory packages did not produce an absolute decline in EU innovation, and that, in fact, the EU outperformed the United States on green and core-AI patents over the post-shock periods. For GDPR, the apparent EU underperformance even reverses once raw patent counts are filtered for patent quality, with the EU moving into a clear lead. The structural decomposition analysis allocates only a marginal share of the EU-US R&D intensity gap to regulatory stringency, with capital market fragmentation, industry composition, and public R&D capacity together carrying the majority of the gap. Across these tests, the deregulation thesis as currently articulated finds no empirical support.

The findings cut against a popular discourse that holds emerging regulation, i.e. the regulatory packages tested here, which impose far from trivial new obligations on firms and other actors, whether for economic transformation or social protection purposes, to be a prima facie threat to innovation. The wider debate is better served by an evidence-based reading. Further, the Green Deal and AI Act results provide empirical grounding for the directional thesis on regulation and innovation (Acemoglu et al. 2012: 131–166; Mazzucato 2013), and for the broader Porterian argument (Porter and van der Linde 1995: 97–118) that well-designed regulation can foster rather than suppress innovation, through selection effects that displace low-quality activity (Blind 2012: 391–400; Rammer and Schubert 2018: 379–389), commitment effects that lock in policy trajectories (Majone 2001: 103–122), and constitutive effects that emerge when regulation gradually defines a new market category.

Finally, in terms of real world policy implications, the decomposition analysis implies that where the EU does lag innovation competitors, the cause lies in capital market fragmentation (Pelkmans and Renda 2011), industry composition (Griffith et al. 2004: 883–895), public R&D capacity (Moncada-Paternò-Castello and Grassano 2022: 19–38), and the upstream production of researchers (Jones 2010: 1–14; Hunt and Gauthier-Loiselle 2010: 31–56) rather than in regulation. The policy implication that could follow is not deregulation but capital markets union, expansion of public R&D, industrial policy for strategic sectors, and reform of education and immigration regimes (see e.g. Krugman 1994: 28–44). Misdiagnosis of potential innovation 'stiflers', whether in the EU or beyond, will produce the wrong prescription, and the cost falls on a competitiveness gap that the prescription cannot in fact close.

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