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Jurisdictional Capital and the Cost of AI Regulation: Evidence from the EU AI Act

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Jurisdictional Capital and the Cost of AI Regulation: Evidence from the EU AI Act
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ABSTRACT: We examine the costs and competitive effects of AI regulation through the EU AI Act. In a cross-sectional event study around the Act's April 2021 proposal, firms with faster prior AI hiring earned lower abnormal returns only when they had EU operations, consistent with markets pricing expected compliance costs. Among EU-exposed firms, however, deeper EU presence attenuated these losses—evidence of jurisdictional capital, whereby regulatory experience reduces adaptation costs. The effect is strongest for high-risk AI and for firms with stable EU presence or prior compliance experience. High-AI, high-EU firms subsequently reallocate revenue toward Europe, suggesting that AI regulation raises aggregate costs while redistributing competitive advantage to locally embedded incumbents.

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WORKING PAPERS

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1 Introduction

Rapid development of artificial intelligence has triggered a global discussion for regulation, highlighting a fundamental tradeoff: addressing AI risks versus causing compliance costs and distorting market competitiveness. How costly is regulating AI, and how is the cost distributed across firms?

We provide a first look at these questions using the EU Artificial Intelligence Act (EU AI Act), the world's first comprehensive AI legislative framework. We document two main results. First, investors price AI regulation as costly on average: firms expanding their AI capabilities lose value after the Act's proposal release. Second, this cost is mitigated by existing EU market footprint. Firms with a large and sustained EU footprint are less negatively affected, and in some cases the offset is large enough to more than neutralize the compliance cost.

We interpret this mitigation effect as the market pricing *jurisdictional capital*: the accumulated experience, routines, and institutional knowledge that firms build through sustained participation in a regulatory jurisdiction. When a new regulation raises compliance costs, this capital can become a *regulatory moat*: a competitive advantage that arises because firms already embedded in the regulator's jurisdiction can adapt at lower cost than less embedded rivals.

The EU AI Act offers a natural setting for studying how technology regulation redistributes competitive advantage. Proposed by the European Commission in April 2021 and finalized in December 2023, the Act establishes *risk-based* compliance obligations that vary by AI use-case risk category, imposing requirements such as conformity assessments, algorithmic audits, and mandatory human oversight. In addition, it has *extraterritorial reach*: any firm using or supplying AI products on the EU market must comply, regardless of where it is headquartered. US firms therefore vary along two dimensions that jointly determine regulatory exposure: reliance on AI technology (regulatory scope) and depth of EU market presence (regulatory jurisdiction). EU market presence could represent two aspects: it determines the Act's jurisdictional reach over the firm, and it proxies for accumulated jurisdictional capital under EU regulation. Whether the jurisdictional reach or the jurisdictional capital aspect dominates is an empirical question that we will test.

Our identification strategy uses predetermined exposure measures constructed from pre-2021 data. We proxy for EU market presence by the average share of revenue earned in the EU, and for AI capability build-up by the growth in AI-related hiring intensity, both computed over 2015–2019 (the pandemic year 2020 is excluded). The valuation impact is measured by cumulative abnormal returns (CARs)—stock returns net of those predicted by aggregate market movements—over a short window around the proposal release date. The key variable is the interaction of EU revenue share and AI hiring growth, which captures the differential market response for firms simultaneously exposed to the Act's substantive scope (AI activity) and its jurisdictional reach or firm's jurisdictional capital (EU market presence).

On the extensive margin, comparing firms with and without material EU operations, we find that the negative valuation effect of the Act is concentrated among firms operating in the EU market. For these firms, a one standard deviation increase in AI hiring growth is associated with a -16 basis point decline in the three day CAR around the proposal announcement. By contrast, AI hiring growth does not predict a comparable loss for firms without material EU operations. This pattern is consistent with markets pricing compliance costs only for firms within the Act's jurisdictional reach.

On the intensive margin, conditional on firms with material EU operations, the results reveal a regulatory moat. AI hiring growth alone remains costly: a one standard deviation increase in AI hiring growth is associated with a -17 basis point decline in the three day CAR, consistent with the extensive margin evidence of compliance costs. However, this cost is mitigated by EU embeddedness. The key coefficient, the interaction between EU revenue share and AI hiring growth, is positive and statistically significant: a one standard deviation increase in EU revenue share offsets the marginal effect of AI hiring growth by approximately 40 basis points.

We interpret this as evidence of jurisdictional capital from EU commitment: firms with deep, sustained presence in EU have built compliance infrastructure, regulator relationships, and interpretive knowledge that could lower the cost of complying with the Act's requirements. This aligns with market view as well, for instance, Fitch notes that firms with mature AI governance can absorb the AI Act's requirements with limited disruption, and Wall Street Journal commentary has warned that the resulting compliance burden disproportionately disadvantages newcomers lacking established compliance infrastructures.[1] Taking account of the offsetting effect of EU commitment, the market prices a net valuation loss $80 billion in the $30 trillion aggregate market capitalization across the US-listed firms in our sample (a 27 bps loss).

We next show that the regulatory moat is not driven by firm size, lobbying, or generic international diversification. High EU revenue share could capture scale or global reach rather than jurisdictional capital, and firms with deep EU roots may also have stronger political access to shape the Act in their favor. The evidence does not support these alternatives.

[1] Fitch: European Insurers Face Emerging AI Governance Standards. Wall Street Journal: The EU Trips Itself Up in the AI Race.

Replacing EU revenue share with absolute EU revenue, firm size, or total foreign revenue share does not generate a comparable AI interaction. Physical capital intensity, if anything, increases the AI compliance cost, suggesting that operational scale can make compliance more costly rather than easier. Direct measures of political access at the EU and member state levels do not absorb the EU×AI coefficient and do not independently predict abnormal returns. These results distinguish the AI Act from the EU General Data Protection Regulation (GDPR) setting, where the regulatory moat is often interpreted as size based. Here, the advantage appears specific to EU jurisdictional commitment.

We then examine which firm characteristics strengthen the regulatory moat. The moat is stronger for firms expanding hiring in *high risk AI* jobs, where the Act imposes the most demanding obligations. It is also stronger among firms with stable EU revenue shares, geographically concentrated EU revenue, and prior EU related compliance experience. These patterns suggest that the valuation advantage comes from durable operating depth in the EU regulatory environment, not from broad or passive foreign exposure.

Beyond valuation effects, we examine whether jurisdictional capital translates into real economic outcomes. If jurisdictional capital lowers compliance costs, EU embedded firms should be better positioned to expand in the EU when less embedded rivals face higher adaptation costs. Consistent with this prediction, among firms with high AI hiring growth and high prior EU exposure, weaker EU embeddedness among AI exposed peers predicts subsequent revenue reallocation toward the EU for the focal firm. Moving from a firm whose peers have median EU embeddedness to one whose peers have no EU embeddedness is associated with about a 21 percent larger expansion of EU revenue relative to non EU revenue. For the median firm within the high EU and high AI sample, this corresponds to a 2.8 percentage point increase in EU revenue share. These patterns suggest that priced jurisdictional capital is reflected not only in valuation, but also in subsequent real reallocation.

The findings have broader implications. For investors, the EU AI Act reveals that capital markets price jurisdiction capital as an intangible asset. For regulators, the results highlight that AI regulation may reshape competition even when it is designed to govern technology risk: compliance costs can strengthen firms already embedded in the regulated market. For firms, the message is that sustained regulatory commitment can pay off, even for small firms. Lastly, our results draw a sharp contrast with the GDPR setting, where regulatory advantage is often viewed as a scale advantage. Under the AI Act, scale alone does not shield firms from compliance costs. The relevant advantage is jurisdictional capital: deep operating experience in the market where the rules are written and enforced. Although GDPR and the AI Act are both recent EU technology regulations, our findings suggest that the competitive effects of one should not be mechanically extrapolated to the other.

Related Literature. A large literature establishes that regulation can redistribute rents toward incumbents (Stigler, 1971; Klapper, Laeven and Rajan, 2006), and that political and relationship capital is priced into firm value (Fisman, 2001; Faccio, 2006). We shift the locus of regulatory capital from political connections to *jurisdictional commitment*: the procedural knowledge and institutional fluency accumulated through sustained market participation, distinct from access to policymakers. Our results provide, in AI regulation, the first empirical evidence of comparative advantages through regulation engagement.

The closest empirical precedent is the EU GDPR literature, which mostly documents a *scale-based* moat: large firms are less negatively affected by the regulation and capture market share, while small players face more severe losses. The leading mechanisms emphasize fixed compliance costs and complementary advantages of large incumbents (e.g., brand strength, organizational capacity), which make compliance easier to absorb at scale (Johnson, Shriver and Goldberg, 2023; Peukert et al., 2022; Goldberg, Johnson and Shriver, 2024). We document a new mechanism under the EU AI Act. Here, the moat operates through *jurisdictional commitment*: EU revenue exposure predicts abnormal returns. This pattern is consistent with the Act imposing product- and use-case-specific requirements that scale with the number of high-risk systems and with the greater interpretive and implementation uncertainty of a new regulatory regime. The relevant advantage, therefore, is not scale, but EU-embedded operational capital—the ability to navigate, implement, and iterate compliance within EU institutions.

Our findings also contribute to the literature on cross-jurisdictional regulation, but the mechanism we identify is distinct. Christensen, Hail and Leuz (2016) show that common EU securities rules have uneven effects because regulatory outcomes depend on country-level prior conditions, implementation, and enforcement. We shift the locus of heterogeneity from regulatory institutions to regulated firms: under a common EU rule, firms differ in their accumulated capacity to operate within the regulator's jurisdiction. Zeume (2017) shows that unilateral anti-bribery regulation penalizes exposed firms and shifts business toward less constrained competitors. In contrast, we show that among firms exposed to the EU AI Act, deeper EU embeddedness mitigates compliance costs and predicts subsequent reallocation toward the regulated market. Klein, Ludwig and Spengel (2022) show that EU digital tax proposals impose larger losses on firms with greater EU exposure, consistent with exposure increasing vulnerability to regulatory burden. We show that under AI regulation, the same jurisdictional footprint can play a second role: it is not only regulatory incidence, but also compliance capability. This turns jurisdictional capital into a regulatory moat.

Lastly, existing work on AI and firm value documents that AI investment is associated with higher growth and market valuations (Babina et al., 2024), that generative-AI workforce exposure generated positive returns after ChatGPT (Eisfeldt, Schubert and Zhang, 2023), and that technical versus ethical AI standards have opposite investment effects (Canayaz and Wang, 2024). We provide, to our knowledge, the first event study of comprehensive AI regulation and the associated compliance cost, providing evidence on both capital market reactions and real economic outcomes.

The remainder of the paper is organized as follows. Section 2 provides institutional background on the EU AI Act. Section 3 describes the data. Section 4 presents the empirical design. Section 5 reports the baseline results. Section 6 and Section 7 test competing mechanisms and amplifiers, respectively. Section 8 explores the implication on within-firm EU market reallocation. Section 9 discusses implications for investors, regulators and practitioners. Section 10 concludes.

2 Institutional Background of EU AI Act

The EU AI Act is the world's first comprehensive legislative framework for artificial intelligence. We describe the features relevant to our identification strategy: the risk-based compliance architecture, the legislative timeline we exploit for event dates, and the Act's extraterritorial reach.

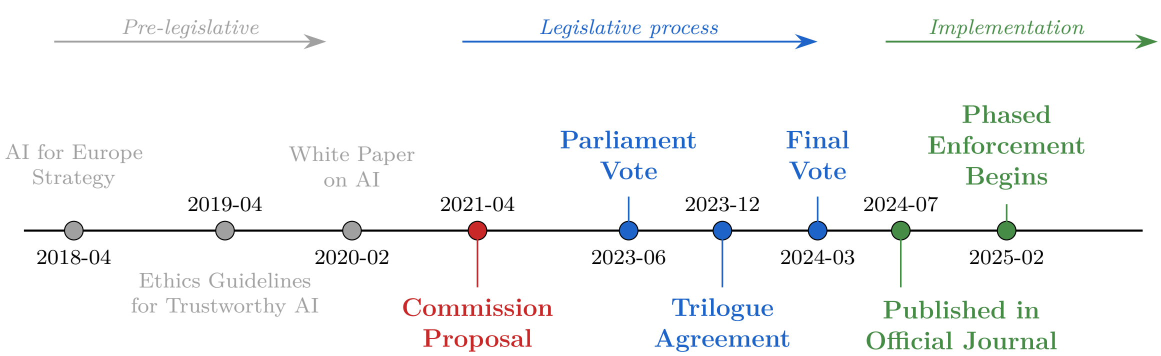

Figure 1: EU AI Act Timeline

Notes: The timeline shows the key milestones in the development of the EU AI Act. Gray markers indicate pre-legislative milestones that established the policy direction. The red marker denotes the European Commission's April 2021 proposal—our primary event date. Blue markers indicate subsequent legislative milestones used in the multi-event analysis. Green markers indicate adoption and the beginning of phased enforcement.

Risk-based compliance architecture. On April 21, 2021, the European Commission published its "Proposal for a Regulation laying down harmonised rules on artificial intelligence" (COM/2021/206).[2] The proposal classifies AI systems into four use-case risk tiers with correspondingly differentiated obligations: *unacceptable-risk* systems (AI use-cases such as manipulative AI, social scoring, "real time" remote biometric identification) are prohibited outright; *high-risk* systems (e.g., AI systems used in critical infrastructure, education, evaluation of creditworthiness) face mandatory conformity assessments, risk-management obligations, data-governance requirements, and human-oversight mechanisms;[3] *limited-risk* systems (e.g., chatbots) face transparency obligations; and *minimal-risk* systems face no additional requirements. Non-compliance penalties reach up to 7% of global annual turnover.[4]

Legislative timeline. The Act's development from proposal to adoption spanned four milestones, which we use as event dates. The *April 21, 2021* Commission proposal introduced the risk-based architecture, the extraterritorial scope, and the enforcement regime. The *June 14, 2023* European Parliament vote expanded the Act's scope to cover foundation models and general-purpose AI—categories absent from the original proposal. The *December 9, 2023* trilogue agreement among the European Parliament, the Council presidency, and the European Commission locked in the final regulatory architecture. The *March 13, 2024* Parliament vote approved the Act, which was published in the Official Journal on July 12, 2024 with phased enforcement beginning in 2025. The April 2021 proposal is our primary event because it was the point at which the Act's cross-sectional incidence on firms was first revealed; subsequent milestones primarily refined an already-disclosed framework.

Extraterritorial reach. The Act applies to any providers or deloyers that place AI systems on the EU market, regardless of where it is established. US firms with EU revenue exposure are therefore directly subject to its requirements, which is the feature that makes our cross-sectional identification strategy feasible.

[2] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52021PC0206

[3] EU AI Act, Article 6: Classification Rules for High-Risk AI Systems

[4] *Generative AI.* The April 2021 EU AI Act proposal predates the public release of ChatGPT and did not contain a separate regime for generative or general purpose AI. In the final Act, generative AI is not automatically classified as high risk. Instead, the Act regulates it through two distinct channels. First, when a generative AI model is incorporated into an AI system used in a high risk domain, the resulting system is subject to the Act's high risk obligations. Second, large generative models are typically treated as general purpose AI models because they can perform a wide range of tasks across contexts. Providers of general purpose AI models must prepare technical documentation, provide information to downstream providers, adopt a policy for compliance with EU copyright law, and publish a sufficiently detailed summary of the content used to train the model. Models that pose systemic risk face additional obligations, including risk assessment, risk mitigation, incident reporting, and cybersecurity. See https://artificialintelligenceact.eu/gpai-guidelines-overview/

3 Sample and Variable Construction

We combine six data sources covering the 771 US-listed firms in our main analysis sample. AI exposure is measured from Lightcast database of job postings that classifies each posting into AI-related categories, linked to Compustat by `gvkey`. EU revenue share is from FactSet's Geographic Revenue (GeoRev) database. Daily stock returns are from CRSP/Compustat Merged; Fama–French factors are from Kenneth French's data library; firm financial controls are from Compustat Annual. Appendix A describes data source, the variable definitions, and the matching procedures in detail.[5]

Our two identifying variables are constructed from predetermined, pre-COVID data. *AI hiring growth* is the annualized change in firm i's AI hiring share between 2015 and 2019, computed as (AI hiring share in 2019 − AI hiring share in 2015)/4, where the AI hiring share in a given year is the share of AI-related postings in total postings (requiring at least five total postings in 2015 and 2019). We use AI hiring growth rather than the level because AI adoption was still at an early stage when the EU AI Act was first proposed in 2021, and both the technology and firms' AI capabilities were evolving rapidly. Since the Act would become binding only several years later, hiring growth better captures the firm's forward looking AI capacity: the growth option that is likely to be exposed to compliance costs when the regulation is ultimately implemented.

EU revenue share is the average share of firm revenue derived from the European Union in total revenue over 2015–2019. For each firm-year, the total revenue from EU region is the summation of disclosed revenue from each EU member country, excluding UK (due to Brexit in 2020). Firms with no disclosure in the window are dropped (we will turn to this extensive margin in Section 5.1), and firms with partial disclosure contribute their mean over disclosed years.

Financial controls (log market capitalization, book-to-market, leverage, R&D intensity, profitability) are averaged over 2015–2019 to match the exposure measurement period; construction details are in Appendix A.2. The analysis sample comprises the 771 US-listed firms that satisfy six sequential filters—CRSP/Compustat match, disclosed EU revenue, sufficient job-posting coverage to compute AI growth, valid Fama–French CARs, non-missing controls, and a pre-event share price of at least \$5—with the attrition waterfall, matching procedure, and the rationale for retaining financial and utility firms documented in Appendix A.3.

Figure 2 plots the time-series evolution of the two exposure variables. The left panel shows that AI hiring was negligible through 2015—median AI share below 2%—before accelerating sharply: the median quadruples from 2% in 2015 to 8% in 2024, and the interquartile

[5] Additional data used in robustness checks and extensions will be described in the corresponding sections.

range widens as firms diverge in their adoption trajectories. The acceleration begins well before the April 2021 proposal, confirming that our 2015–2019 growth measure captures a predetermined trend rather than a response to the Act. The right panel shows that EU revenue share, by contrast, is more persistent: the median declines gradually from roughly 14% in 2005 to 9% in 2024, reflecting the secular growth of US domestic and Asian markets relative to the EU. This persistence is consistent with interpreting EU share as a measure of durable jurisdictional commitment rather than a transient revenue fluctuation.

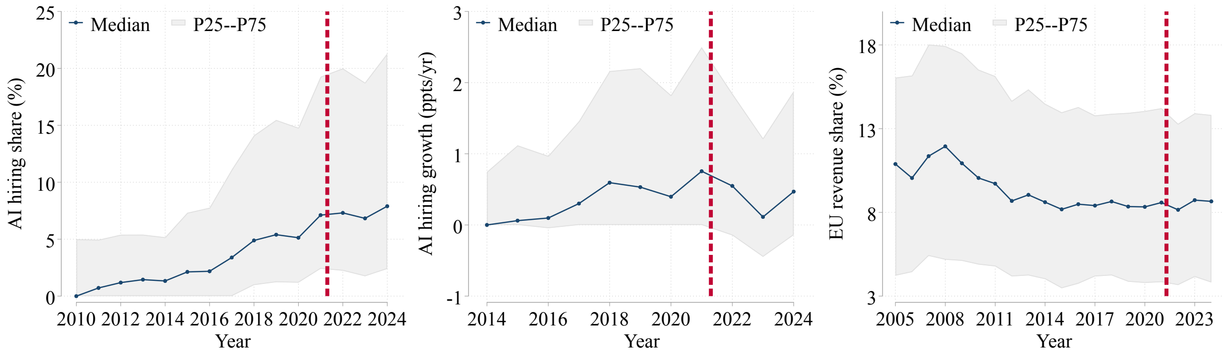

Figure 2: Time Series of Key Exposure Variables

Notes: Left and middle panel plot the median AI job posting share and AI job posting share annualized growth (blue line) with interquartile range (shaded) across the sample 2010–2024, respectively. Right panel plots the median EU revenue share (blue line) with interquartile range, 2005–2024. The dashed red line marks the EU AI Act proposal (April 2021).

Panel a) of Figure 3 displays the cross-sectional joint distribution of the two variables, colored by Fama–French 48 industry groups, while in panel b) and c), each point represents a sector average or a selected large technology firm, respectively. Two features stand out. First, the correlation between EU share and AI hiring growth is very limited ($\rho = -0.04$), so they capture distinct sources of regulatory exposure. Second, the distribution is concentrated in the lower-left quadrant (moderate EU share, low AI growth), with a long right tail of EU-intensive firms (chemicals, pharmaceuticals) and a long upper tail of AI-intensive firms (finance and business services). High-AI-growth firms such as NVIDIA stand in the upper-left, while high-EU-share firms such as Adobe anchor the right side. The orthogonality of the two exposure dimensions provides identifying variation for the interaction specification that follows. Summary statistics are reported in Table A3.

While our main sample is for firms with EU revenue, for the extensive margin analysis (i.e., firms with vs. without EU revenue), we extend our main sample to include firms with no EU revenue disclosure. We define EU presence indicator as a dummy variable of a firm ever having non-missing values of EU revenue share in FactSet's Geographic Revenue

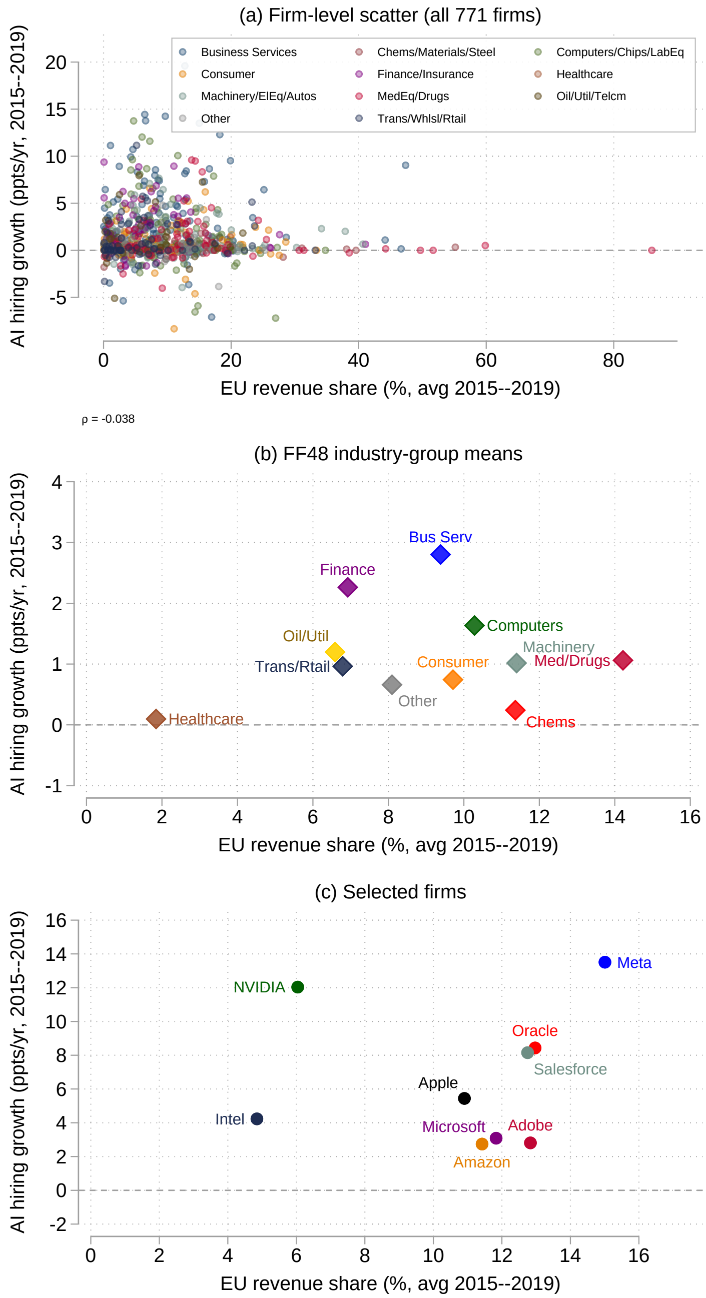

Figure 3: AI Hiring Growth vs. EU Revenue Exposure by FF48 Industry Group

Notes: In panel a, each point represents one of the 771 sample firms, plotted by EU revenue share (avg FY2015–2019, horizontal axis) and AI hiring growth (annualized change CY2015→2019, vertical axis). Colors indicate Fama–French 48 industry groups. The correlation between the two measures is $\rho = -0.038$. In panel b and c, each point represents a sector (labeled) or a selected large technology firm (labeled), respectively.

database between 2015–2019.[6] This expands the analysis sample with EU revenue disclosure from $N = 771$ to $N = 1{,}264$. The 493 additional firms satisfy every other sample filter (Compustat controls, FF48 industry, AI hiring ≥ 5 postings, pre-event price $\geq \$5$, valid FF3 CARs with ≥ 120 estimation-window trading days) but have no EU revenue disclosed over the pre-event window. The sample construction is in Table A2, and summary statistics are in Table A4.

4 Empirical Design

4.1 Estimation Method

Our identification strategy relies on two elements. First, firms' ex ante exposure to the Act is proxied by pre-2021 EU revenue share and AI hiring growth. Second, a narrow event window around the April 2021 proposal isolates announcement-driven repricing. The baseline specification estimates a cross-sectional regression of cumulative abnormal returns on firms' EU revenue share and AI hiring growth.

We test the impact of the Act on both extensive and intensive margins. On the extensive margin, we separately estimate the impact of AI hiring growth on CAR on subsamples of firms with and without EU revenue disclosure.

$$\text{CAR}_i[\tau_1, \tau_2] = \delta_1^{EU} \text{AI}_i + \gamma' \mathbf{X}_i + \delta_s + \varepsilon_i \tag{1}$$

On the intensive margin (i.e., conditional on firms with EU revenue), we add EU revenue share and its interaction term with AI hiring growth.

$$\text{CAR}_i[\tau_1, \tau_2] = \alpha + \beta_1 (\text{EU} \times \text{AI})_i + \beta_2 \text{AI}_i + \beta_3 \text{EU}_i + \Gamma \mathbf{X}_i + \delta_s + \varepsilon_i, \tag{2}$$

where EU (i.e., EU revenue share) and AI (i.e., AI hiring growth) are standardized to mean zero and unit variance within the analysis sample, $\mathbf{X}_i$ denotes the financial controls described in Section 3, and δ_s is an French-French-48 industry fixed effect.

[6] Under SFAS 131 and its international counterpart IFRS 8, publicly listed firms must disclose geographic segments in which they earn more than 10% of revenue or have material interests (Coppola et al., 2021). FactSet's Geographic Revenue database augments these mandated disclosures with narrative footnote and in-text information from 10-K filings, so a firm with material EU exposure is typically captured (see Appendix A.XI of Coppola et al., 2021). Under this data-generating process, a firm with no EU revenue entry in FactSet GeoRev over 2015–2019 is most plausibly a firm whose EU revenue falls below the 10% threshold or is not materially important. That said, we cannot rule out that there are firms with positive EU revenue that FactSet does not capture. Under this measurement error, contamination of the latter kind would attenuate the estimated AI effect for no-EU-revenue firms toward the disclosing-firm value. The estimates therefore bound this contamination from above.

The interaction term of EU and AI capture distinct dimensions of regulatory relevance. EU revenue share measures the historical importance of the EU market to the firm—how deeply committed the firm is to the EU jurisdiction. A high EU share signals that the firm has built its business around the EU market, investing in local operations, regulatory relationships, and compliance infrastructure over time. AI hiring growth captures the firm's accumulation of AI-related growth options. Because the EU AI Act will take years to fully implement, the market should respond most to firms that are actively building AI capabilities for future deployment—not to firms with static AI operations that are already priced in. AI growth thus identifies firms whose future AI deployment options are most directly exposed to the new regulatory regime.

Cumulative abnormal return $\mathrm{CAR}_i[\tau_1, \tau_2] = \sum_{\tau=\tau_1}^{\tau_2} \widehat{\epsilon}_{i\tau}$ is the sum of daily abnormal returns $\widehat{\epsilon}_{i\tau}$ over the event window. Following Fama–French three-factor model (Fama and French, 1993), daily abnormal return $\widehat{\epsilon}_{i\tau}$ is the residual from the following regression

$$r_{it} - r_{ft} = \alpha_i + \eta_{1i}(\text{Mkt-RF})_t + \eta_{2i}\text{SMB}_t + \eta_{3i}\text{HML}_t + \varepsilon_{it},$$

estimated over trading days $[-250, -11]$ relative to the event with a minimum of 120 valid days (median in-sample $R^2 = 0.34$). We report four windows: $[0, +2]$ as primary, $[0, +1]$, $[-1, +1]$, and $[-2, +2]$ as robustness.

For the multi-event analysis, we re-estimate CARs around each subsequent legislative milestone using the same three-factor methodology and hold the exposure measures fixed at their April 2021 values. This predetermined-exposure design ensures that cross-event variation in coefficients reflects differences in the information content of each event, not changes in firm characteristics over the 2021–2024 legislative period.

4.2 Hypothesis

We are interested in three coefficients in Equation (1) and (2).

$\delta_1^{\mathbf{EU}} < 0$: jurisdictional reach based on EU market participation. The AI Act imposes compliance costs on firms with EU operations, not those without. We predict $\delta_1^{EU} < 0$ in Equation (1).

$\beta_2 < 0$: compliance cost of AI activity. The EU AI Act imposes compliance costs on firms actively accumulating AI capabilities captured by AI hiring growth. We predict $\beta_2 < 0$ in Equation (2): AI hiring growth alone predicts negative abnormal returns around the proposal.

$\beta_1 > 0$**: regulatory moat.** The cost is not borne symmetrically. Firms with deep jurisdictional capital from established EU market presence could lower compliance cost. We predict $\beta_1 > 0$: the interaction of EU revenue share and AI hiring growth predicts positive abnormal returns, mitigating the compliance cost effect from β_2.

5 Main Results

5.1 Extensive Margin

To gauge the impact of the Act, our first step is to test this compliance cost is specific to firms subject to EU jurisdiction or whether AI hiring growth carries a cost for all US-listed firms under the new regime. We answer this on the extensive margin estimating Equation (1) on subsamples of firms based on an EU-disclosure indicator.

Table 1: Extensive-Margin: EU Indicator and the AI Cost Channel

	Dependent variable: CAR (bps)			
	(1)	(2)	(3)	(4)
	$[0, +1]$	$[0, +2]$	$[-1, +1]$	$[-2, +2]$
AI Growth, EU_Ind = 0 (non-disclosers)	9.8	51.7	8.9	30.4
	(23.0)	(53.4)	(24.9)	(56.8)
N	488	488	488	488
AI Growth, EU_Ind = 1 (disclosers)	-20.4***	-16.4**	-34.5***	-30.8***
	(6.6)	(6.7)	(9.1)	(8.9)
N	769	769	769	769
Industry FE (FF48)	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes

Notes. This table runs Equation 1 specification on the expanded sample with the binary EU_Indicator in place of EU revenue share and estimates the AI-growth-only regression separately within each EU_Indicator arm. Standard errors clustered at FF48. *, **, *** denote significance at 10%, 5%, 1%.

Table 1 Panel A reports summary statistics across the two groups. EU_Indicator= 0 firms are systematically smaller, have substantially lower foreign-income share, are far less concentrated in technology-oriented industries, and have lower AI hiring growth over the pre-period. The nearly two-fold gap in foreign-income share is direct evidence that the non-disclosing group is a predominantly domestic subset of the US-listed universe, consistent with the materiality-threshold interpretation.

Baseline results. Compliance costs largely disappear for firms outside EU jurisdiction, when re-estimating the AI standalone effect separately within each subsample (Table 1 Panel

B). Among firms with EU revenue, the AI standalone effect is negative and significant across all four CAR windows, ranging from -16 to -31 bps, matching the baseline results in Table 2. Among firms with no material EU revenue, the AI main effect is statistically indistinguishable from zero on every window, indicating that compliance costs associated with the Act largely disappear for firms outside EU jurisdiction.

This is the pattern predicted by the jurisdictional reach of the Act. Firms that do not sell into the EU market are not subject to the Act's conformity assessments, risk-management obligations, post-market monitoring requirements, or any other compliance burden, and their AI hiring growth is therefore not repriced on the April 2021 proposal. Firms with any EU market presence face the cost, and deeper EU commitment unlocks the moat that partly offsets it (which we turn to next in Section 5.2).

5.2 Intensive Margin

Having shown that the effects of the Act applies only to firms with EU operations, now we examine the intensive margin—the effects of the Act conditional on firms with EU operations.

Baseline results. Table 2 reports the full interaction model (Equation 2) across the four event windows. The standalone AI hiring growth effect is significantly negative across the four windows, with one SD increase in AI hiring growth (3 percentage points per year) is associated with -17 bps reduction in our primary window CAR$[0, +2]$. This is consistent with the market pricing compliance costs for firms actively building AI capabilities ($\beta_2 < 0$).

The EU×AI Growth interaction is positive and significant at the 1% level in every window: +40 bps on CAR$[0, +2]$, with comparable magnitudes on CAR$[0, +1]$, CAR$[-1, +1]$, and CAR$[-2, +2]$. The coefficient of +40 bps on CAR$[0, +2]$ means that one SD increase in EU share (9 percentage points) offsets the marginal effect of AI growth on CAR by 40 bps. The positive sign ($\beta_1 > 0$) indicates that EU-committed firms building AI capabilities are *rewarded* by the market: the Act enhances the value of their future AI deployment through a jurisdictional commitment advantage relative to other firms in the market. The standalone EU revenue share effect is economically small and not consistently significant across windows, confirming that the result largely operates through the interaction of EU commitment and AI activity. The regulation reprices the value of future AI activity conditional on EU commitment: among firms building AI, those with deep EU roots enjoy a competitive advantage than those without EU commitment; the latter bear the compliance cost without offset.

Table 2: Baseline: EU×AI and Abnormal Returns

	Dependent variable: CAR (bps)			
	(1)	(2)	(3)	(4)
	$[0, +1]$	$[0, +2]$	$[-1, +1]$	$[-2, +2]$
EU × AI Growth	31.8***	39.7***	43.4***	45.2***
	(9.0)	(10.3)	(7.2)	(8.8)
EU Revenue Share	3.2	2.4	15.1*	22.5**
	(9.4)	(13.9)	(8.5)	(11.1)
AI Growth	-21.9***	-16.7**	-37.1***	-32.2***
	(6.0)	(6.4)	(8.0)	(7.6)
Industry FE (FF48)	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Observations	769	769	769	769
Adjusted R^2	0.018	0.089	0.051	0.079

Notes. OLS regressions of cumulative abnormal returns (CAR, in bps) around the 21 April 2021 EU AI Act proposal, based on Equation 2. Standard errors are clustered at the FF48 industry level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Economic magnitude. Because the baseline specification includes both the AI growth standalone effect and the EU×AI interaction, the predicted effect of AI growth on abnormal returns varies with EU revenue share: $\partial \text{CAR}/\partial \text{AI} = \beta_2 + \beta_1 \times \text{EU}$. Figure 4 plots this marginal effect across the distribution of EU revenue share. For firms with little EU revenue, AI capability building becomes more costly—the marginal effect is -45 bps per SD of AI growth at 25th percentile EU share. As EU revenue share rises, the positive interaction progressively offsets the cost. The zero-crossing occurs at an EU share of approximately 14%, close to the 75th percentile of the sample distribution; above this threshold, AI capability building creates net value. Roughly one quarter of the sample (195 firms) falls in this region.

Aggregate effect accounting. To scale the announcement-day repricing to aggregate market capitalization, we compute the dollar change ($\Delta\text{MktCap} = \text{MktCap}_{\text{Apr20}} \times \text{CAR}[0, +2]$) for each firm and aggregate to the total impact. Across all firms, the regulation destroyed 27 bps of market value ($-\$80$ billion on a \$30 trillion base). The EU AI Act is a cost shock, not a pure transfer: the market as a whole is worse off, not merely redistributed.

The value loss is, however, highly unequal within AI-intensive firms. The high EU × high AI firms (i.e., both above median) lost only 9 bps ($-\$16$ billion loss on a \$17.5 trillion base). while low EU × high AI firms lost 58 bps ($-\$47$ billion on a \$8.1 trillion base). The 49 bps differential illustrates the economic shield: within AI-intensive firms, higher EU jurisdictional commitment mitigated the AI compliance costs effect and preserved shareholder value at

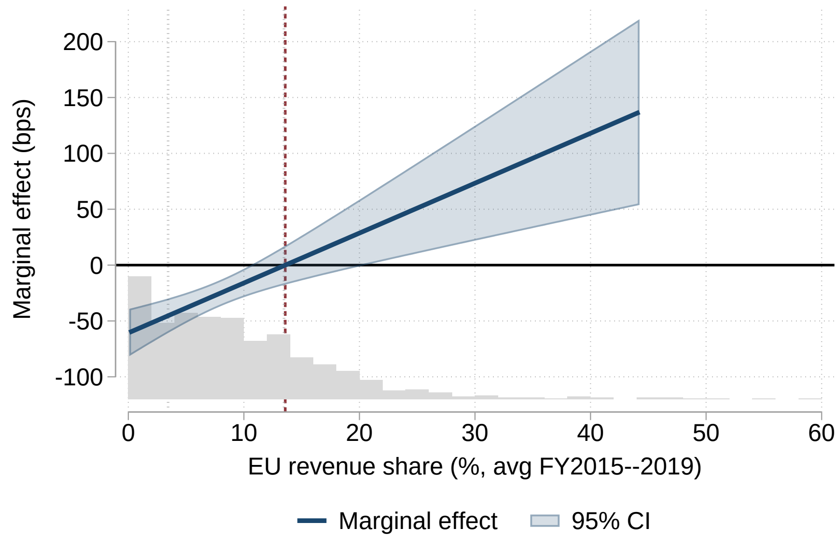

Figure 4: Marginal Effect of AI Capability Building by EU Revenue Share
Notes: The solid line plots $\partial\text{CAR}/\partial\text{AI} = \beta_2 + \beta_1 \times \text{EU}$ from Equation 2, the marginal effect of a 1-SD increase in AI hiring growth on CAR$[0, +2]$ (in basis points), evaluated at each level of EU revenue share (horizontal axis, raw scale). The shaded band is the 95% confidence interval. The dashed red line marks the zero-crossing at EU share $\approx$ 14% (75th percentile). The background histogram shows the sample distribution of EU revenue share.

announcement.

Other legislative events We trace the EU×AI interaction across the four legislative milestones of the AI Act, holding the sample fixed at the April 2021 firms so that cross-event variation in coefficients reflects information content rather than composition. The interaction is large and significant at the 1% level only at the April 2021 Commission proposal—the moment at which the Act's risk-based architecture, extraterritorial scope, and enforcement regime were first revealed—and indistinguishable from zero at every subsequent milestone; the AI growth standalone effect follows the same pattern. Full results are in Appendix A5.

5.3 Pre-Trends Test

The identifying assumption is that, absent the EU AI Act announcement, high EU×AI firms would have experienced abnormal returns similar to other firms. We test this using a symmetric 81-day window $[-40, +40]$ around the event. We shift the abnormal return estimation window back by 40 days relative to the main specification: factor loadings are estimated over $[-291, -41]$ (250 trading days, same minimum 120-day coverage requirement), so the pre-trend window $[-40, -1]$ is fully disjoint from the CAR estimation window and the test is not mechanically contaminated by in-sample fit.

Table 3 reports the EU×AI coefficient across pre-event cumulative windows. The coefficient is economically small and statistically indistinguishable from zero in every pre-event window, in contrast to the significant event-window coefficients post-event. The effect emerges precisely at the event date, not before. Appendix Figure A.1 shows the full cumulative coefficient trajectory from day −40 through day +40: the path is mostly flat and near zero throughout the pre-event period, then rises sharply after day 0 and stabilizes at approximately +100 bps by day +40.

Table 3: Pre-Trend Test: EU×AI Coefficient Across Cumulative Windows

Window	EU × AI (bps)	SE (bps)	t	p-value	N
Pre-event					
CAR[-40,-1]	-25.2	59.5	-0.42	0.674	769
CAR[-40,-21]	-10.9	41.8	-0.26	0.795	769
CAR[-20,-1]	-14.3	23.4	-0.61	0.545	769
CAR[-10,-1]	4.3	18.6	0.23	0.818	769
CAR[-5,-1]	14.6	11.3	1.29	0.205	769
Event / post-event					
CAR[0,+2]	39.7***	10.3	3.87	<0.001	769
CAR[0,+10]	86.7***	32.2	2.70	0.010	769
CAR[0,+40]	174.0***	54.4	3.20	0.003	769

Notes. This table reports the EU×AI coefficient from a separate OLS regression of the indicated cumulative abnormal return window, using the baseline specification Equation 2. Standard errors clustered at the FF48 industry level. *, **, *** denote significance at the 10%, 5%, 1% levels.

5.4 Randomization Inference

Randomization inference provides a distribution-free check on our standard-error computation by comparing the observed coefficient to a placebo distribution built from non-event trading dates. We treat all 483 trading dates between December 2020 and December 2022 as placebo event dates, excluding a ±10-day buffer around April 21, 2021 to avoid mechanical overlap between any placebo window and the actual event window. For each placebo date, we recompute CARs using an estimation window of $[-250, -11]$ trading days relative to the placebo and re-estimate the full interaction model with identical specification.

The observed April 2021 coefficient on the primary CAR$[0, +2]$ window lies in the far right tail of the placebo distribution for the EU×AI interaction (Figure 5, left), and in the far left tail for the AI Growth main effect (Figure 5, right). Both coefficients are rejected by placebo inference at conventional significance levels. In Appendix Table A6 and Appendix

Figures A.2–A.3, we show coefficients for the full set of windows where they are significant on all four windows. The EU revenue share only effect, in contrast, falls well within its placebo distribution, reinforcing that the result operates through the interaction rather than through EU exposure alone.

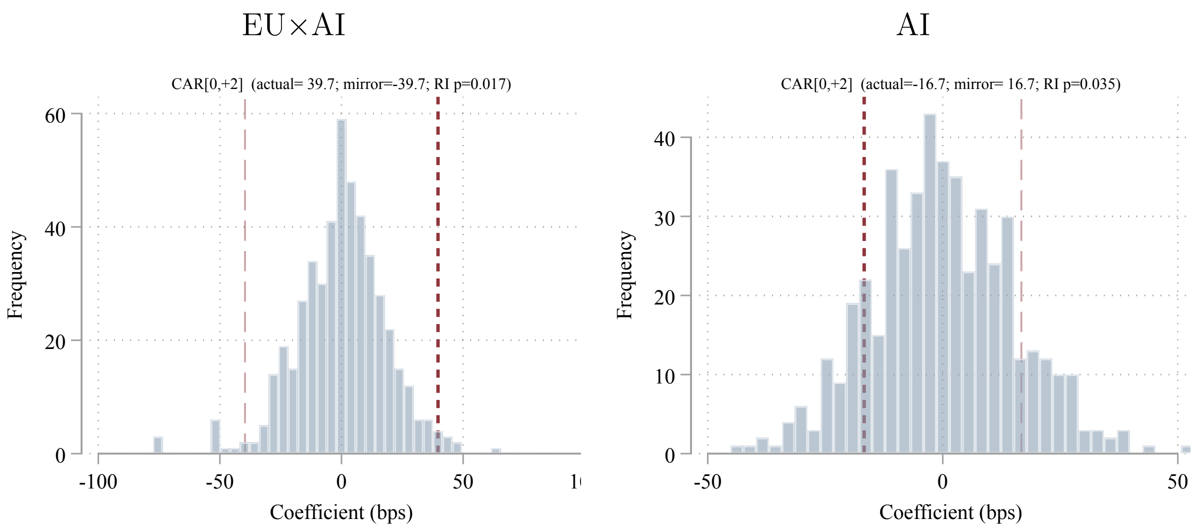

Figure 5: Randomization Inference on CAR$[0,+2]$: Actual Coefficients vs. Placebo Distributions

Notes: Each panel plots (EU×AI in the left panel, and AI in the right panel) the distribution of coefficients from 483 placebo regressions run on non-event trading dates between December 2020 and December 2022, excluding a ±10-day buffer around April 21, 2021. The solid red line marks the actual April 21, 2021 coefficient. Full 2×2 distributions across all four event windows are in Appendix Figures A.2–A.3.

5.5 AI Growth vs. AI Level

A natural question about our specification is if the compliance cost and its mitigating operates through pre-existing AI capability or through the change in capability before the Act's proposal. The level of AI hiring intensity, after all, is a more direct proxy for current AI exposure than the growth rate, and a stock-based reading of the regulatory channel might predict that firms with more AI activity at the time of the proposal incurs more compliance cost. We address this concern through two tests: (i) replacing AI hiring growth with the AI hiring *level* in the baseline specification, and (ii) running a horse race that enters both measures simultaneously.

AI level is not associated with compliance cost or exhibit mitigating effects when interacted with EU share. As show in in Table A11, the coefficient of AI level is not significant in any of the event windows, and the coefficient of EU×AI Level is approximately half the magnitude of the EU×AI growth in Table 2 and not robust.

Table 4: Horse Race: EU×AI Level vs. EU×AI Growth

	Dependent variable: CAR (bps)			
	(1)	(2)	(3)	(4)
	$[0, +1]$	$[0, +2]$	$[-1, +1]$	$[-2, +2]$
EU × AI Level	-9.1	0.2	-14.3	1.2
	(7.7)	(14.4)	(16.2)	(12.8)
EU × AI Growth	37.2**	39.6**	52.0***	44.5*
	(14.7)	(17.8)	(18.1)	(23.7)
AI Level	11.4	4.9	8.6	3.1
	(13.2)	(15.9)	(16.3)	(21.3)
AI Growth	-25.3**	-18.2	-39.6***	-33.2*
	(11.4)	(13.8)	(14.1)	(18.4)
Joint F: EU × (Level+Growth)=0	7.20	9.58	20.60	14.84
	$p = 0.002$	$p \approx 0.000$	$p \approx 0.000$	$p \approx 0.000$
Industry FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
N	769	769	769	769
Adj. R^2	0.017	0.086	0.050	0.077

Notes. This table extends Table 2 by including AI Level and its interaction with EU share. Standard errors clustered at the FF48 industry level are in parentheses. The joint F-test reports the null $\beta(\text{EU} \times \text{AI Level}) + \beta(\text{EU} \times \text{AI Growth}) = 0$. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

A more demanding test enters EU×AI level and EU×AI growth simultaneously, alongside AI main effects (Table 4). The EU×AI growth coefficient is essentially unchanged from the headline (+40 bps on CAR$[0, +2]$) and remains significant on all four event windows. The EU×AI level coefficient is insignificant in every window, with a point estimate of +0 bps on CAR$[0, +2]$. This is not a multicollinearity artifact: the two interactions correlate at $\rho = 0.60$ in the regression sample, well below thresholds at which a real signal would be masked. The AI growth main effect strengthens slightly once AI Level is partialled out, reinforcing that the compliance-cost penalty concentrates among firms actively expanding into AI rather than among AI-intensive firms generally.

Why growth, not level. The horse race confirms that the Act operates through the growth margin: pre-existing AI intensity carries no incremental EU-interactive return reaction or compliance cost once the growth in AI capability is in the model. This pattern is consistent with the Act regulating AI systems placed on the EU market going forward: its compliance obligations bind on future deployment rather than on the firm's existing AI footprint. A firm with high static AI intensity but no further expansion has, in expectation, already amortized its AI investment and faces lower marginal compliance cost from new deployment. A firm scaling its AI capabilities rapidly during the pre-event window has growth options that are repriced when the regulatory regime is announced, because those growth options will be deployed under the new compliance regime. The effects therefore load on growth, not level—the market prices the regulation against firms whose AI investments are still in flight.

5.6 Other Robustness Checks

We test the intensive margin effect persists over longer horizon by extending the window of CAR. The results suggest that the compliance cost offset effect from EU market presence is maintained through several weeks, providing evidence against short-lived overreaction (Appendix B.3 and B.4).

Other robustness checks are replacing the Fama–French three-factor model with the five-factor specification Appendix Table A12, replacing EU revenue share with other pre-2021 years Appendix Table A13, and using the firms whose fiscal year ending in December.[7] They leave all coefficients within small deviations from their baseline values and do not alter any statistical inference.

6 Competing Interpretations

The baseline EU×AI interaction establishes that firms with deeper EU market commitment while growing AI capabilities earned positive abnormal returns around the AI Act proposal. Our story is that the regulatory moat reflects jurisdictional capital—accumulated compliance infrastructure and institutional knowledge from years of operating under EU regulation—that reduces the cost of navigating the AI Act's compliance requirements. However, other competing interpretations could also be consistent with this finding. For instance, the EU×AI interaction may represent other firm characteristics—firm size, international diversification—rather than jurisdictional capital. Or it could reflect lobby effects: firms deeply rooted in the EU may have lobbied to shape the Act in their favor.

This section tests these alternative explanations. Section 6.1 distinguishes jurisdictional commitment from firm scale, separating our finding from the scale-based moat documented under GDPR. Section 6.2 then addresses regulatory capture by testing political-access channels directly using various EU and member state level lobby proxies. Section 6.3 confirms that the effect is specific to EU jurisdiction rather than general international diversification.

[7] Two features of our data construction dilute potential fiscal year and calendar year misalignment ex-ante: we average each input over five years (FY/CY 2015–2019), and we standardize within sample after the average.

6.1 Jurisdictional Commitment, Not Scale

The existing literature on technology regulation emphasizes scale-based moats: large firms are less negatively affected by regulation than small players, because, for instance in the case of GDPR, compliance fixed costs could be amortized over a larger revenue base. Our EU revenue share measure could capture just the scale of the firm's EU operations rather than anything about jurisdictional commitment. To test whether the AI Act's moat operates through the same scale-based mechanism, we modify the baseline specification by replacing EU revenue share with alternative scale proxies as the interaction variable and testing whether each generates a comparable moat.

Table 5: Jurisdictional Commitment vs. Scale

Variable	Dependent variable: CAR (bps)			
	(1) $[0, +1]$	(2) $[0, +2]$	(3) $[-1, +1]$	(4) $[-2, +2]$
Panel A: Alternative scale measures of EU exposure × AI Growth				
EU Share × AI Growth	31.8***	39.7***	43.4***	45.2***
	(9.0)	(10.3)	(7.2)	(8.8)
EU USD × AI Growth	-0.9	-2.8	8.3	5.4
	(4.0)	(4.6)	(7.0)	(7.0)
log(EU USD) × AI Growth	1.4	-4.4	14.2	4.6
	(8.2)	(10.0)	(10.3)	(11.7)
Panel B: Size × AI Growth horse race against the baseline EU × AI moat				
EU × AI Growth	33.5***	41.5***	45.4***	47.6***
	(9.4)	(10.7)	(7.4)	(9.2)
log(Mcap) × AI Growth	-12.8	-13.4	-14.5*	-17.6*
	(7.5)	(9.1)	(8.3)	(11.4)
Industry FE (FF48)	Yes	Yes	Yes	Yes
Firm controls (incl. lower-order interactions)	Yes	Yes	Yes	Yes
Observations	769	769	769	769

Notes. Panel A replaces EU Revenue Share with three alternative scale measures of EU exposure: (i) the baseline EU revenue share; (ii) the corresponding raw EU revenue in USD; and (iii) $\log(1 + \text{EU revenue USD})$. Panel B adds log(Mcap) × AI Growth to the baseline EU × AI specification (all lower-order terms included). All specifications include FF48 industry fixed effects and the five firm controls of Equation (2). FF48-clustered SE in parentheses. *, **, *** denote significance at 10%, 5%, 1%.

Table 5, Panel A replaces EU revenue share with absolute EU revenue in USD and its logarithm, which are direct measures of the absolute size of a firm's EU operations. The interaction between absolute EU revenue and AI growth is economically small and statistically insignificant across all event windows. The moat does not emerge from the absolute size of EU operations; it requires the relative importance of the EU market to the firm's total business. Panel B shows a horse race with both EU share and firm size interacting with AI growth, the coefficient for firm size×AI is small in magnitude and low in significance. Meanwhile, EU×AI remains significant and close to baseline estimates.

Table 6 extends the test in Panel B to three additional firm-level scale proxies, each capturing a distinct dimension along which scale could plausibly operate, estimated on CAR$[0, +2]$. General size—log employment (column 4) alongside log market capitalization (column 2)—carries a negative interaction with AI growth (around -13 bps), suggesting larger firms bearing a modest compliance penalty on their AI operations. Physical capital intensity, measured as PP&E to total assets (column 3), loads strongly negative (-49 bps): firms whose AI systems are embedded in physical capital—e.g., manufacturing, telecom, utilities—face the heaviest compliance costs. It could be that AI embedded in physical production processes is operationally more costly than to modify than software-only deployments. R&D intensity, a proxy for the scale of AI development investment, is essentially zero. In every specification, the EU×AI effect remains significant at the 1% level.

Row 6 of Table 6 enters EU×AI jointly with all three scale interactions. The general-size loading attenuates once physical capital intensity enters, while the physical-capital-intensity penalty remains highly significant; the EU×AI moat holds and the R&D interaction remains null. The EU jurisdictional moat therefore operates through a dimension different from four distinct dimensions of firm scale—absolute EU operations, general size, physical capital intensity, and R&D intensity.

GDPR vs. AI Act. The contrast between GDPR and the AI Act helps explain why scale alone is unlikely to account for the moat. GDPR compliance has a significant firm level fixed cost component. A firm can build a common privacy and consent system, and once users give consent, that consent can often support data use across multiple services offered by the same firm, subject to the stated purposes. Larger user bases can therefore help spread these costs. By contrast, many AI Act obligations apply at the system or use case level, generating more variable compliance costs: a firm with more AI products may face more regulated systems, scaling up the overall compliance burden.

Second, the AI Act may create a more difficult compliance navigation problem than GDPR. GDPR was a major regulatory change, but it revised an existing EU privacy regime, the 1995 Data Protection Directive, giving firms familiar legal and institutional reference points.[8] Regulators, guidance, and compliance advisers were also relatively developed by the time GDPR was introduced. The AI Act is different. As the world's first comprehensive AI regulatory framework, it creates an uncertain and evolving regime, with many practical details to be clarified gradually by regulators, certification bodies, and standard setters. Stable EU presence may therefore matter because it reflects more than market size. Firms with sustained EU operations are more likely to have local legal capacity, experience with

[8] https://eur-lex.europa.eu/legal-content/en/ALL/?uri=CELEX:31995L0046

Table 6: Scale Decomposition: EU Revenue Share vs. Alternative Firm-Level Proxies

	Coefficient on $\cdot\times$ AI Growth (bps), CAR$[0,+2]$					
Variable	(1) Baseline	(2) +log(Mcap)	(3) +PP&E/AT	(4) +log(Employ)	(5) +R&D	(6) Saturated
EU × AI	39.7*** (10.3)	41.5*** (10.7)	34.0*** (9.5)	42.1*** (11.3)	39.7*** (10.3)	35.4*** (9.4)
log(Mcap)	—	-13.4 (9.1)	—	—	—	-10.4 (8.7)
PP&E/AT	—	—	-48.8*** (14.6)	—	—	-47.5*** (15.5)
log(Employ)	—	—	—	-12.8* (7.1)	—	—
R&D Intensity	—	—	—	—	1.5 (8.1)	-4.8 (5.2)
Industry FE (FF48)	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	769	769	769	769	769	769

Notes. Each column reports a regression of CAR$[0,+2]$ on EU × AI Growth plus the cost-structure interaction indicated in the column header, with all five baseline firm controls and FF48 industry fixed effects. log(Mcap) is the natural log of market capitalization in the month prior to the event date. PP&E/AT is net property, plant, and equipment divided by book total assets. log(Employ) is the natural log of total employees, proxy for workforce scale. R&D Intensity is R&D expenditure divided by total assets, proxy for the variable cost of developing AI capabilities. FF48-clustered standard errors in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels on the cluster-robust t-statistic.

EU regulatory processes, and familiarity with how compliance is implemented in practice. Such prior commitment can lower the cost of adapting to a new regime, even when firm size alone does not.

6.2 Political Engagement and Lobby Effect

Another concern is that firms with deeper EU roots shaped the AI Act in their favor, so the positive EU×AI coefficient reflects the payoff from political influence rather than the value of compliance knowledge. Firms with deeper EU roots may be better positioned to influence the Act's design—for example, by engaging with legislative bodies, shaping technical standards, or securing favorable interpretations of vague compliance requirements. Before turning to direct test the lobby effect, it is worth noting that as shown in Table 5 Panel B, the Size×AI Growth interaction is small and mostly insignificant: the moat does not vary with firm size, even though political access is strongly correlated with size.

Table 7: Political Engagement and the Regulatory Moat

	Dependent variable: CAR$[0,+2]$					
	Engagement = Commissioner meetings			*Engagement = Transparency Register*		
	Control	Horse race	Triple interaction	Control	Horse race	Triple interaction
EU × AI Growth	38.6***	40.0***	43.2***	39.4***	39.5***	39.5***
	(9.8)	(9.9)	(10.7)	(9.7)	(10.1)	(10.3)
Engagement	40.2			43.5*		
	(25.7)			(23.3)		
Engagement × AI		-9.1			-5.1	
		(6.5)			(4.8)	
Engagement × EU × AI			10.2			0.3
			(10.1)			(9.5)
	Engagement = AI White Paper consultation			*Engagement = Country-level lobby*		
	Control	Horse race	Triple interaction	Control	Horse race	Triple interaction
EU × AI Growth	39.6***	39.6***	42.1***	42.2***	41.7***	41.4***
	(10.2)	(10.0)	(9.7)	(10.4)	(9.9)	(8.9)
Engagement	61.3			-122.6**		
	(105.2)			(49.0)		
Engagement × AI		3.9			2.6	
		(4.6)			(7.8)	
Engagement × EU × AI			-7.1			2.5
			(9.8)			(11.3)
	Engagement = EU-level trade association			*Any political engagement*		
	Control	Horse race	Triple interaction	Control	Horse race	Triple interaction
EU × AI Growth	39.7***	39.9***	41.1***	39.5***	39.5***	38.5***
	(10.4)	(10.9)	(10.2)	(10.2)	(10.1)	(10.7)
Engagement	-3.9			13.6		
	(49.4)			(33.8)		
Engagement × AI		-20.1			-2.4	
		(13.3)			(13.3)	
Engagement × EU × AI			-17.8			-12.1
			(13.2)			(17.7)
Industry FE (FF48)	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	769	769	769	769	769	769

Notes. This table reports OLS regressions of cumulative abnormal returns (CAR, in bps) around the 21 April 2021 EU AI Act proposal, argumenting baseline specification Equation 2 with political engagement dummy variables as additional control, horse race, and triple interaction. Standard errors are clustered at the FF48 industry level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

We construct various indicators capturing both the intensive and extensive margins of political engagement at EU and member state levels: (i) *Commissioner meetings*, an indicator for any meeting during 2015–2019 (73 of 771 firms); (ii) *Lobby registration*, an indicator for pre-event appearance in the EU Transparency Register (74 firms); (iii) *AI White Paper* *consultation*, an indicator for submitted comments in AI White Paper consultation stage (17 firms); (iv) *Country-level lobby*, an indicator equal to one if the firm appears pre-event in any mandatory member-state political-engagement channels: France, Ireland, and Germany (86 firms); (v) *EU-level trade-association membership*, an indicator if the firm appears on the pre-event member roster of DigitalEurope, DOT Europe, or ITI—the three major EU-level digital-industry trade associations (45 firms); and (vi) *Any political engagement*, equal to one if one of the condition holds. Details of the variable construction is in Appendix A.

We run three progressively demanding tests with each political engagement proxy. *Control* adds political engagement as a control to the baseline specification. Under the lobby effect, as political engagement is positively correlated with EU share and abnormal returns, the coefficient on EU × AI should attenuate once political engagement is absorbed. *Horse race* includes Lobby×AI alongside EU×AI, and *triple interaction* tests whether political access amplifies the moat through Lobby×EU×AI. Under lobby effect, Lobby×AI coefficient and the triple coefficient should be positive, as political engagement should help firms to alleviate the AI compliance cost.

Minimal impact from political engagement variables. Table 7 shows that the EU×AI coefficient is virtually unchanged from its baseline value of +40 bps on CAR$[0, +2]$ when each political engagement indicator is added as a control, as horse race, or as triple interaction. None of the political engagement variables—dummy, interaction term with AI, or triple interaction—show consistent significance. Together, these suggest that political engagement does not substitute for EU presence in generating the moat. Besides the results based on $CAR[0, +2]$, the other outcome variables $CAR[0, +1]$, $CAR[-1, +1]$, $CAR[-2, +2]$ also remain qualitatively unchanged in the three sets of tests.

To complement the analysis on pre-event lobby, we also examine *post*-April-2021 AI-Act lobbying as an outcome. Across EU-level firm lobbying, country-level lobbying, EU trade-association membership, and their union, the EU×AI interaction does not predict additional lobbying (all effects statistically insignificant), while AI hiring growth and firm size strongly do. Appendix C details the construction of the tests and the full regression evidence.

6.3 Foreign Revenue Share vs. EU Revenue Share

Another potential competing explanation is that the EU×AI interaction captures the benefits of general international diversification rather than EU-specific regulatory advantages. If so, the interaction of other foreign revenue share with AI should yield a similar positive coefficient.

Table 8: EU vs. Foreign Revenue Share Interaction with AI Growth

	Dependent variable: CAR (bps)			
	(1)	(2)	(3)	(4)
	$[0, +1]$	$[0, +2]$	$[-1, +1]$	$[-2, +2]$
EU × AI Growth	29.6***	34.0***	44.6***	43.0***
	(10.2)	(12.0)	(7.8)	(7.9)
Foreign Income × AI	1.8	0.3	4.8	2.1
	(7.8)	(10.6)	(8.7)	(13.7)
EU Revenue Share	5.2	16.4*	19.0**	42.8***
	(6.5)	(9.5)	(9.4)	(10.1)
Foreign Income	-12.6	-10.7	-20.3*	-17.7
	(9.2)	(13.5)	(10.8)	(13.0)
AI Growth	-22.4***	-22.4***	-33.4***	-32.8***
	(6.4)	(7.9)	(8.9)	(8.6)
Industry FE (FF48)	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Observations	681	681	681	681
Adjusted R^2	0.023	0.042	0.057	0.021

Notes. This table reports OLS regressions of cumulative abnormal returns (CAR, in bps) around the 21 April 2021 EU AI Act proposal, with foreign-income interaction (non-US, non-EU revenue share). Standard errors are clustered at the FF48 industry level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8 reports the test. We add Foreign×AI Growth to the baseline specification. The EU×AI interaction retains its magnitude and significance across all windows, while the Foreign×AI interaction is economically small and statistically insignificant. General foreign exposure does not generate the moat effect, and only EU-specific regulatory jurisdiction does. This rules out the diversification alternative and confirms that the baseline EU×AI interaction captures a channel specific to the EU AI Act's jurisdictional reach.

7 Amplifiers of the Jurisdictional Capital Effect

The baseline results establish that EU×AI exposure predicts positive returns on average. We now test whether the moat is amplified by observable firm characteristics: high-risk AI capability buildup (Section 7.1), stability of EU market presence (Section 7.2), and geographic concentration of EU operations (Section 7.3). Section 7.4 provides a more direct test of the jurisdictional capital mechanism by asking whether pre-event compliance hiring — an observable proxy for regulatory capital accumulation — amplifies the moat independently of EU revenue share.

7.1 The Moat Is Stronger in High-Risk AI

The Act's heaviest obligations—conformity assessments, Annex IV technical documentation, and post-market monitoring under Articles 16–22—attach specifically to systems listed in Annex III. If the moat reflects jurisdictional capital that lowers compliance cost, it should be largest where the compliance challenge is greatest: firms scaling up into high-risk-AI involvement. We test this using a dictionary-based mapping of Lightcast skills and titles to the Annex III scope.

We construct a high-risk-AI hiring measure by using the skill and title information from Lightcast postings. A posting is classified as high-risk AI if it jointly matches our high-risk-AI skill dictionary and our high-risk-AI title dictionary, constructed by mapping the Lightcast universe to Annex III categories (biometric identification, education and vocational training, employment and worker management, creditworthiness assessment) and Article 6(1) Annex II Section A safety components (robotics and medical-device AI). Deployer-restricted Annex III categories, safety-component carve-outs, and generic HR/recruiting patterns that flag at essentially every firm are excluded. HRAI_i is the 2015–2019 annualised change in firm i's share of postings so classified. A firm scaling into high-risk-AI hiring during the pre-event window is actively building capabilities in the domains Annex III and Annex II Section A target, making it more likely to produce or deploy high-risk AI systems at the time of the proposal and therefore to face the Act's most demanding compliance obligations. Full construction and dictionary listings are in Appendix D.

Panel A of Table 9 shows that the EU×AI moat grows with firm's high-risk-AI hiring: on the CAR$[0, +2]$ window, each additional standard deviation of HRAI_i adds approximately +15 bps to the moat, a pattern that holds across all four event windows. The baseline EU×AI coefficient remains positive, confirming that high-risk-AI exposure amplifies the underlying jurisdictional capital effect. Panel B makes the economic content concrete: splitting the sample by whether firms have any high-risk-AI hiring growth, the moat is large and statistically significant in the high-risk-AI group and economically negligible in its complement, with the contrast widening sharply at longer horizons. EU market presence alone is insufficient to generate the full moat; the compliance-cost offset accrues most to firms simultaneously scaling into high-risk-AI capacities, where Annex III obligations are heaviest and the value of navigating them is greatest.

The results identify where jurisdictional capital is most valuable and why. The moat amplifies with high-risk-AI hiring because high-risk AI carry the Act's heaviest obligations, and these obligations are the most interpretively complex and operationally demanding. Jurisdictional capital is worth most precisely where the regulatory navigation challenge is greatest: firms with deep EU commitment and growing high-risk-AI exposure are best positioned to translate accumulated regulatory capital into a compliance-cost advantage on the specific systems the Act targets most heavily. The binary subsample sharpens this reading in two directions. The large positive moat in the high-risk subsample (+35 bps on CAR$[0, +2]$) shows that EU-committed firms actively building high-risk-AI capabilities were repriced as regulatory-capital beneficiaries at announcement. The insignificant estimate in the zero-HRAI subsample shows that EU presence alone does not generate the moat: without exposure to high-risk-AI, jurisdictional capital has limited compliance burden to offset. Together, the two panels imply that the baseline EU×AI coefficient in Section 5.2 is driven primarily by firms at the intersection of EU commitment and high-risk-AI exposure, and that the compliance-cost offset accrues most where both the jurisdictional and the regulatory requirements bind the most.

Table 9: High-Risk AI

	Dependent variable: CAR (bps)			
	(1)	(2)	(3)	(4)
	$[0, +1]$	$[0, +2]$	$[-1, +1]$	$[-2, +2]$
Panel A: Triple interaction, full sample				
EU × AI × HRAI	10.18***	15.02***	15.82***	20.58***
	(2.95)	(2.81)	(3.08)	(3.33)
EU × AI	25.53*	31.69**	26.57**	23.56
	(1.83)	(2.03)	(2.08)	(1.63)
Panel B: Binary subsample split by HRAI hiring growth				
EU × AI, HRAI > 0 ($N = 202$)	30.76***	34.86***	72.17***	83.65***
	(4.07)	(3.46)	(6.95)	(4.47)
EU × AI, HRAI $= 0$ ($N = 554$)	27.94	27.83	12.55	1.52
	(1.35)	(1.49)	(0.42)	(0.05)
Firm controls	Yes	Yes	Yes	Yes
Industry FE (FF48)	Yes	Yes	Yes	Yes
Cluster	FF48	FF48	FF48	FF48

Notes. Panel A reports the triple-interaction coefficient $\hat{\beta}_1$ on $\text{EU}_i \times \text{AI}_i \times \text{HRAI}_i$ and the EU×AI two-way coefficient $\hat{\beta}_2$ from the same regression; all three continuous variables are in-sample z-scores. Panel B re-estimates the baseline EU×AI specification within subsamples defined by whether the firm has any non-zero high-risk-AI hiring growth over 2015–2019; treatment variables are re-standardised within each subsample. Standard errors clustered on FF48 industry. *, **, *** denote 10%, 5%, 1%, respectively.

7.2 Stable EU Commitment Matters

This section tests if the stability of EU revenue commitment, measured by the coefficient of variation (CV, defined as standard deviation divided by mean) of EU revenue share over time, matters for the magnitude of the moat. Intuitively, stable EU presence—low year-to-year fluctuation in EU share—signals sustained strategic commitment to the EU market, while volatile EU share suggests opportunistic or episodic engagement. This strategic commitment, rather than episodic engagement, would accumulate jurisdictional capital over time.

We split the sample the sample at the median of CV and re-estimate the baseline regression. The prediction under the regulatory moat hypothesis is the coefficient based on the low-CV sample should be larger: firms with more stable EU presence (lower CV) should have a stronger moat effect, because stability reflects accumulated jurisdictional capital rather than transient market participation. Table 10 reports the results. The coefficient of EU×AI for the low-CV sample is significantly positive and close to full sample estimate, however, its high-CV sample counterpart is insignificant across all four event windows.

Table 10: EU Revenue Stability

		Dependent variable: CAR (bps)			
		(1)	(2)	(3)	(4)
		$[0, +1]$	$[0, +2]$	$[-1, +1]$	$[-2, +2]$
Panel A: Low-CV subsample (stable EU presence, below-median CV)					
Low-CV	EU × AI Growth	35.0***	38.0***	58.9***	56.7***
		(10.1)	(8.7)	(8.9)	(9.4)
N				371	
Panel B: High-CV subsample (volatile EU presence, above-median CV)					
High-CV	EU × AI Growth	-4.5	12.9	-13.3	-4.0
		(14.6)	(22.4)	(22.7)	(35.9)
N				368	
Industry FE (FF48)		Yes	Yes	Yes	Yes
Firm controls		Yes	Yes	Yes	Yes

Notes. This table reports OLS regressions of cumulative abnormal returns (CAR, in bps) around the 21 April 2021 EU AI Act proposal, estimated separately on below-median and above-median subsamples of the firm-level coefficient of variation (CV) of the EU revenue share over FY2010–2019. CV is the standard deviation of the firm's annual EU share divided by its mean over the window, winsorized 1%/99% within the analysis sample. Standard errors, clustered at the FF48 industry level, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

7.3 Geographic Concentration of EU Revenue

The regulatory moat hypothesis implies that compliance advantages come from deep jurisdictional capital (e.g., regulatory knowledge, agency relationships, and compliance infrastructure). As the implementation falls at member state level, the jurisdictional capital also crucially depends on tacit, country-specific enforcement knowledge—e.g., how rules are applied in practice and what regulators expect. Holding total EU revenue share fixed, this capital should be larger when revenue is concentrated in a few member states than when it is dispersed. For example, 10% revenue concentrated in Germany builds depth with German enforcement institutions (e.g., *Datenschutzkonferenz*, *BfDI*), whereas 10% spread thinly across many member states is unlikely to generate comparable depth anywhere; under an EU-wide regime like the AI Act, the former converts this depth into advantage. We test this mechanism using within-EU revenue concentration: the Herfindahl index (HHI)[9] across member states and the top-1 member-state revenue share.

Table 11 splits the sample at the median of each measure and re-estimates the baseline regression. Under the HHI measure (Panel A), the high-concentration half shows a strong EU×AI moat across all four event windows, ranging from +47 bps to +86 bps, all significant at the 1% level. The low-concentration half is statistically and economically null on three of the four windows. Panel B (top-1 split) delivers a similar pattern. The magnitude gap between high- and low-concentration subsamples widens from roughly six× on the three-day window (column 2) to 20× on the five-day symmetric window (column 4). This supports the jurisdictional-capital mechanism: depth of engagement, not breadth, converts EU market participation into a regulatory moat. Two firms with identical total EU revenue share can face entirely different event returns depending on whether that revenue is anchored in specific member states or widely dispersed across the union.

A natural follow-up is whether the concentration-based moat reflects broad jurisdictional capital or capital specific to a single national jurisdiction—for example, a Germany-only or Ireland-only effect that happens to load on the HHI measure. Appendix E decomposes each HHI-based subsample by country of EU revenue and shows that major economies in the EU—Germany, France, Italy, and Spain—dominate both halves, and the high-HHI firms simply concentrate more sharply within that same set. The moat is therefore not a single-country artifact.

7.4 Prior Compliance Experience

The mechanism tests so far take EU revenue share as an indirect proxy for jurisdictional capital, we now test the proposition more directly using firms' pre-event scaling of IT, privacy, and data-governance compliance hiring as an observable proxy for jurisdictional-capital accumulation. The intuition is that GDPR's enforcement forced EU-exposed firms to build compliance and actively interact with EU regulators. The accumulated regulatory relation-

[9]For each firm f, define the within-EU share of member state c as $w_{f,c} = s_{f,c}/S_f$, where $s_{f,c}$ is the revenue from member c and S_f is the total EU revenue. The within-EU Herfindahl index $H_f = \sum_c w_{f,c}^2$, which ranges from $1/K$ (perfect diversification across K disclosed countries) to 1 (a single country carries the entire EU exposure).

Table 11: Geographic Concentration of EU Revenue

		Dependent variable: CAR (bps)			
		(1)	(2)	(3)	(4)
		$[0,+1]$	$[0,+2]$	$[-1,+1]$	$[-2,+2]$
Panel A: Split by HHI (within-EU Herfindahl)					
High-concentration (above median)	EU × AI Growth	47.0***	63.9***	75.1***	86.0***
		(13.9)	(19.7)	(12.3)	(15.4)
N		382			
Low-concentration (below median)	EU × AI Growth	21.0**	11.4	13.8	5.9
		(7.8)	(11.5)	(13.1)	(17.1)
N		375			
Panel B: Split by Top-1 within-EU country share					
High-concentration (above median)	EU × AI Growth	47.2***	64.5***	75.3***	87.3***
		(13.3)	(18.7)	(12.1)	(14.6)
N		381			
Low-concentration (below median)	EU × AI Growth	20.9***	9.9	13.0	3.4
		(7.6)	(11.3)	(13.5)	(17.6)
N		376			
Industry FE (FF48)		Yes	Yes	Yes	Yes
Firm controls		Yes	Yes	Yes	Yes

Notes. This table reports OLS regressions of cumulative abnormal returns (CAR, in bps) around the 21 April 2021 EU AI Act proposal, estimated separately on above-median and below-median subsamples of EU concentration. *Panel A* splits the sample at the median of the within-EU HHI. *Panel B* splits the sample at the median of the Top-1 within-EU share. Standard errors, clustered at the FF48 industry level, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

ship and interpretative capability are expected to carry over to AI Act obligations.

We identify compliance-related postings through a text analysis over the Lightcast skills and titles dictionaries, applying a curated screen of 77 patterns across 11 functional categories (documentation in Appendix F.4). For each firm-year, we then compute the share of postings flagged as compliance-related; firm-level compliance hiring growth is the four-year-annualized change in this share over 2015–2019, constructed in parallel with AI hiring growth. We construct two variants of the measure: a *Broader IT/data compliance* measure that includes US-, UK-, and EU-statute hiring patterns, and an *EU IT/data compliance* measure that strips out the US- and UK-statute matches. The Broader measure captures general compliance capacity, and the EU measure isolates the hiring most plausibly driven by GDPR and adjacent EU regulatory exposure.

We split the sample at the median (the results are similar if splitting by terciles), re-estimate the baseline regression within each subsample. The EU×AI moat concentrates among compliance-scaling firms (Table 12): in the top half, the moat is approximately +50 bps on CAR$[0,+2]$ and significant at the 1% level; in the bottom half, the coefficient is largely insignificant. This indicates that jurisdictional capital only exists in firms with active interactions with regulators through prior IT compliance activities, rather than firms investing less EU regulation compliance apparatus (e.g., passive EU sales through distributors).

Table 12: Pre-AI Act Compliance Hiring and the EU×AI Moat

		Dependent variable: CAR (bps)			
		(1)	(2)	(3)	(4)
		$[0,+1]$	$[0,+2]$	$[-1,+1]$	$[-2,+2]$
Panel A: Broader IT/data compliance growth					
Median: Top half	EU × AI Growth	40.9***	49.5***	59.0***	57.5***
	(N =376)	(11.5)	(12.6)	(11.4)	(9.4)
Median: Bottom half	EU × AI Growth	23.6*	15.4	24.6	15.3
	(N =379)	(12.4)	(16.1)	(26.7)	(26.1)
Panel B: EU IT/data compliance growth (excl. US/UK)					
Median: Top half	EU × AI Growth	44.6***	50.4***	63.4***	60.0***
	(N =378)	(13.6)	(13.9)	(12.5)	(9.7)
Median: Bottom half	EU × AI Growth	19.1	14.4	21.2	10.6
	(N =379)	(12.3)	(15.0)	(24.5)	(24.4)
Industry FE (FF48)		Yes	Yes	Yes	Yes
Firm controls		Yes	Yes	Yes	Yes

Notes. This table reports OLS regressions of cumulative abnormal returns (CAR, in bps) around the 21 April 2021 EU AI Act proposal. *Panel A* cuts the analysis sample by the four-year-annualised growth in the share of postings with at least one core-tier match in our IT/data compliance taxonomy ("Broader" = any core-tier compliance match, including US- and UK-statute categories). *Panel B* cuts by the same growth measure restricted to postings whose core matches are not exclusively in US- or UK-statute categories. Standard errors clustered at FF48 in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels.

A natural concern is that compliance growth simply re-labels the EU revenue channel. Table 13 reports a horse race in which EU×AI and Compliance×AI enter simultaneously. The EU×AI coefficient is essentially unchanged from baseline; the Compliance×AI coefficient is statistically indistinguishable from zero on every window. Compliance hiring on its own is not priced as a moat—it requires EU presence to generate the regulatory-capital advantage. The split and the horse race together identify a moderator structure: stable EU presence and pre-event compliance scaling jointly generate the moat, but neither input alone is sufficient.

Instead, the evidence points to a structure active engaging in the compliance of EU regulation—proxied here by prior compliance scaling—jointly important to jurisdictional capital accumulation. The EU×AI moat is present only among firms in the high-compliance-growth group, suggesting that this group captures firms with active EU operations and sustained interaction with EU regulators rather than passive EU sales routed through distributors. In that sense, the null on Compliance×AI is informative rather than puzzling: because the AI Act is a new, product- and use-case-based regime, IT-related GDPR compliance capacity does not carry over mechanically; it becomes valuable only when paired with EU-embedded jurisdictional capital. Appendix F reports the full taxonomy of compliance categories, the article-by-article mapping between GDPR and AI Act obligations.

Table 13: Horse Race: EU×AI vs. Compliance×AI

		Dependent variable: CAR (bps)			
		(1)	(2)	(3)	(4)
		$[0, +1]$	$[0, +2]$	$[-1, +1]$	$[-2, +2]$
Panel A: C = Broader IT/data compliance growth					
(1) Baseline	EU × AI Growth	31.8***	39.7***	43.4***	45.2***
		(9.0)	(10.3)	(7.2)	(8.8)
(2) Replace EU	C × AI Growth	−0.8	−2.5	6.0	−0.1
		(5.0)	(7.7)	(7.0)	(8.7)
(3) Horse race	EU × AI Growth	31.6***	39.5***	43.4***	44.9***
		(8.6)	(9.9)	(7.4)	(9.0)
	C × AI Growth	−0.4	−2.0	6.1	−0.2
		(4.9)	(7.6)	(7.0)	(8.7)
Panel B: C = EU IT/data compliance growth (excl. US/UK)					
(1) Baseline	EU × AI Growth	31.8***	39.7***	43.4***	45.2***
		(9.0)	(10.3)	(7.2)	(8.8)
(2) Replace EU	C × AI Growth	−2.1	−3.7	4.0	−3.3
		(5.7)	(8.8)	(8.0)	(9.9)
(3) Horse race	EU × AI Growth	31.6***	39.6***	43.3***	45.0***
		(8.8)	(10.2)	(7.2)	(9.0)
	C × AI Growth	−2.1	−3.5	3.8	−3.7
		(5.8)	(8.8)	(8.2)	(9.9)
Industry FE (FF48)		Yes	Yes	Yes	Yes
Firm controls		Yes	Yes	Yes	Yes
Observations		769	769	769	769

Notes. This table reports OLS regressions of cumulative abnormal returns (CAR, in bps) around the 21 April 2021 EU AI Act proposal. C is one of two compliance hiring growth measures, z-scored in the analysis sample. *Panel A* uses the Broader measure (any core-tier compliance match, US/UK statutes included). *Panel B* uses the EU measure (core-tier matches restricted to non-US/UK-statute categories). Specification (1) is the baseline EU × AI interaction. Specification (2) replaces EU revenue share with C. Specification (3) includes both interactions simultaneously. Standard errors clustered at FF48 in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels.

8 EU Jurisdictional Capital and Post-Event Market-Share Reallocation

The results so far demonstrate that jurisdictional capital helps to alleviate the compliance cost associated with the Act: firms with deep EU embeddedness absorb the compliance burden more cheaply than peers lacking such exposure. A natural follow-up question is whether this advantage translates into a measurable firm-level benefit beyond the returns reflected in the financial market. One observable margin is EU market revenue relative to non-EU market revenue, or similarly, EU revenue share out of global revenue. If peers find it costlier to comply with the Act and scale back EU AI deployments, one would expect high EU share firms to capture market share. We document a cross-sectional pattern consistent with this mechanism: among high EU and high AI firms, those whose peers are lower in EU share—i.e., those have comparative advantage in complying with the Act—experienced systematically larger post-event reallocation of revenue toward the EU.

8.1 Sample Restriction and Key Variables Construction

We restrict the sample in this test to the subsample: firms for whom both the Act binds meaningfully and the reallocation margin is economically relevant. First, we keep only HighAI firms—those whose AI hiring growth over FY2015–2019 lies above the sample median— because they are most exposed to the AI Act and the related compliance costs. Second, within HighAI sample we focus on HighEU firms: those whose FY2015–2019 average EU revenue share exceeds the sample median. Only a firm with its own deep EU footprint can mechanically capture EU market share that peers may concede. The intersection HighEU $\cap$ HighAI contains 192 firms in the analysis sample.

Defining Peers. For each firm i in this HighEU $\cap$ HighAI subsample, we identify peers via a within-industry leave-one-out design. We assign i to the finest SIC partition that yields at least five total industry peers (firms of any EU or AI type): 4-digit SIC first, then 3-digit, then 2-digit. If no SIC level yields five peers, we fall back unconditionally to i's FF48 industry. Among all industry peers in the assigned peer set $\mathcal{P}_i$, we then count the HighAI firms and compute the fraction of those that are LowEU (EU share below the sample median). We define the continuous variable

$$\text{LowEUPeer}_i \;=\; \frac{\#\{p \in \mathcal{P}_i : p \text{ is LowEU and HighAI}\}}{\#\{p \in \mathcal{P}_i : p \text{ is HighAI}\}},$$

where $\mathcal{P}_i$ denotes i's peer set. The measure is defined for the 634 of $N = 771$ firms whose peer set contains at least three HighAI firms; for the remainder the HighAI denominator is too small to yield a reliable fraction. The variable lies in $[0, 1]$: higher values mean i's AI-Act-affected peer fringe is dominated by LowEU competitors. All HighEU, HighAI, and LowEUPeer constructions use only 2015–2019 data to preserve pre-determination.

Measuring EU Revenue Reallocation. The main outcome variable is the change in the EU-versus-non-EU revenue reallocation measure:

$$\begin{aligned} \text{realloc}_{i,t} &= \log\Big(\text{EU\_Rev}_{i,t}\Big) - \log\Big(\text{nonEU\_Rev}_{i,t}\Big), \\ \Delta\text{realloc}_i &= \overline{\text{realloc}_{i,t\in 2021\text{–}2025}} - \overline{\text{realloc}_{i,t\in 2015\text{–}2020}} \end{aligned}$$

where $\text{EU\_Rev}_{i,t}$ is EU revenue in USD and $\text{nonEU\_Rev}_{i,t} = \text{total\_sale}_{i,t} - \text{EU\_Rev}_{i,t}$ is Compustat sales net of EU revenue, for firm i in year t. The log-difference form compares EU markets to non-EU markets directly, and the transform nets out firm-wide growth that scales both EU and non-EU revenue proportionally.[10]

Equivalently, $\text{realloc}_{i,t} = \log\Big(\text{EU\_Share}_{i,t}/(1-\text{EU\_Share}_{i,t})\Big) = \text{logit}\Big(\text{EU\_Share}_{i,t}\Big)$, the logit of the EU revenue share. For small EU shares this is numerically close to $\log(\text{EU\_Share}_{i,t})$. We use log/logit transforms rather than EU Share in levels because the share variable in levels is mechanically bounded at zero and have many large-share outliers.

8.2 Empirical Specification and Results

On the HighEU $\cap$ HighAI subsample we estimate

$$\Delta\text{realloc}_i = \alpha + \beta \cdot \text{LowEUPeer}_i + \boldsymbol{\gamma}' \mathbf{X}_i + \delta_s + \varepsilon_i, \tag{3}$$

where $\mathbf{X}_i$ contains the same firm controls as in Equation (2), and δ_s denotes FF48 industry fixed effects.

Table 14 reports the baseline results (column 1) alongside two alternative-outcome robustness columns. Both the reallocation outcome (column 1) and the change in log EU share (column 2) show the relative shift in revenue toward EU markets versus non-EU markets. The near-equivalence of the two point estimates (around +0.4) reflect the fact that for firms with small EU shares, i.e., the median 13% EU revenue share, the logit and log transformations are mathematically close approximations of one another. The consistency across these two specifications strengthens the interpretation that firms facing weaker EU-embedded peers systematically reallocate revenue toward the EU post the AI Act announcement, conditional on being HighAI and HighEU themselves. By contrast, the change in log EU revenue (column 3) is far noisier and statistically uninformative. Raw EU revenue growth reflects not only EU-versus-non-EU reallocation but also firm-wide scale changes (e.g., organic growth, acquisitions) that affect both EU and non-EU segments proportionally and are orthogonal

[10] For the HighEU $\cap$ HighAI subsample, the median EU share is 13%, compared with the full sample of 8% (Table A3).

to the peer-displacement channel. It confirms that the relevant margin is the *within-firm* EU-versus-non-EU reallocation, not absolute EU revenue levels.

Table 14: LowEUPeer Effect On Within-Firm EU Reallocation

	(1) Δrealloc	(2) $\Delta\log$(EU_Share)	(3) $\Delta\log$(EU_Rev)
LowEUPeer	$+0.428^{**}$	$+0.386^{*}$	$+0.210$
(t)	(1.80)	(1.76)	(0.58)
Wild-bs p	0.047	0.057	0.586
Industry FE (FF48)	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes
Observations	156	156	156

Notes. This table reports OLS regression of Equation 3. Column (1) reports the baseline results, and columns (2) and (3) replace the outcome with $\Delta\log$(EU_Share) and $\Delta\log$(EU_Rev), respectively. Cluster-robust t-statistics on FF48 industry in parentheses; wild-cluster bootstrap p-values (9,999 Rademacher replications) below. Stars follow the wild-bootstrap p. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Magnitude. The baseline estimate +0.43 log-points means that for moving from a firm whose AI-exposed peers are relatively EU-embedded (median level) to one whose peers are relatively least EU-embedded (zero) maps into about a 21% (= 0.43/2) larger expansion of EU revenue relative to non-EU revenue, or an absolute EU revenue share gain of about 2.8 percentage points ($= e^{(0.39*0.5+\ln(13.2\%))} - 13.2\%$) for the median HighEU $\cap$ HighAI firm with 13.2% pre-event EU share.

8.3 Interpretation and Placebo Tests

The baseline result requires HighAI and HighEU satisfied simultaneously: among HighAI firms, if the firm itself is HighEU, then peer weakness (largely LowEU peers) is associated with significant EU market-share gains for the focal firm. The double requirements point to two testable placebos.

Placebo 1. If the firm is itself not EU-embedded (LowEU $\cap$ HighAI), then market share gain doesn't materialize: a LowEU firm in the same AI sector lacks the EU jurisdictional capital required to pick up EU market share. The prediction: a null effect of LowEUPeer.

Placebo 2. If the firm is not meaningfully exposed to the AI Act (LowAI, regardless of own EU share), then peer competitive weakness in the EU doesn't associate with market share gain, because the Act-driven displacement force is not operative. The prediction: a null effect of LowEUPeer.

Table 15 reports the LowEUPeer coefficient from Equation 3 estimated separately on the LowEU ∩ HighAI cell (row 2, placebo 1), the combined LowAI sample (row 3, placebo 2), and the pooled non HighEU ∩ HighAI sample (row 4). All three placebo coefficients are statistically indistinguishable from zero, consistent the double requirement of HighEU and HighAI for the market share gain channel to work. The LowEU ∩ HighAI cell has a large positive point estimate but is too noisy to distinguish from either zero. The combined LowAI placebo yields a negative point estimate (-0.152), and the pooled non HighEU ∩ HighAI coefficient is essentially zero.

Table 15: Placebo Tests: LowEUPeer Effect On Within-Firm EU Reallocation

Sample	Observations	LowEUPeer coef (t)	Wild-bs p
HighEU ∩ HighAI	156	$+0.428^{**}$ (1.80)	0.047
LowEU ∩ HighAI	147	+0.708 (1.49)	0.153
LowAI	288	−0.152 (−1.10)	0.298
Non HighEU ∩ HighAI	443	−0.001 (0.00)	0.996

Notes. This table reports the placebo tests of LowEUPeer effect on ΔRealloc using different subsamples. Each row reports Equation 3 estimated within the indicated subsample. Row 1 reproduces the baseline from Table 14, column (1). Rows 2–3 are the two placebo subsamples LowEU ∩ HighAI and LowAI. Row 4 reports the pooled non HighEU ∩ HighAI subsample as a combined falsification. Cluster-robust t-statistics on FF48 industry in parentheses. Stars follow the wild-bootstrap p. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Though being descriptive evidence, this cross-sectional reallocation result is consistent with EU jurisdictional capital paying off through market-share gains. We view the evidence as suggestive of a real-economy margin through which the jurisdictional capital mechanism translates into post-event competitive advantage.

9 Implications

The findings have broader implications for investors, regulators, and firms. For investors, the EU AI Act reveals that forward-looking markets price jurisdictional capital as an intangible asset. Firms are not valued only for technological capabilities, market share, or scale. They are also valued for their ability to operate within a regulatory jurisdiction and adapt when that jurisdiction changes the rules. In the context of AI regulation, prior EU embeddedness appears to reduce the expected cost of compliance and preserve the value of AI growth options.

For regulators, the results highlight an important competitive consequence of technology regulation. AI regulation is designed to govern technology risk, but compliance costs can also reshape market structure. When adaptation is easier for firms already embedded in the regulated market, regulation can strengthen incumbents or committed participants relative to firms with weaker local presence. This does not imply that AI regulation is undesirable. It does imply that regulators should recognize the distributional effects of compliance costs: rules written to manage AI risk may also reallocate competitive advantage across firms.

For firms, the message is that sustained regulatory commitment can pay off. A long standing presence in a regulated jurisdiction can become valuable when new rules arrive, not simply because the firm sells more in that market, but because it has accumulated experience with the legal, institutional, and operational environment. This advantage need not belong only to the largest firms. Even smaller firms may benefit if they have invested in durable operating depth in the jurisdiction where the rules are written and enforced.

Lastly, our results draw a sharp contrast with the GDPR setting, where regulatory advantage is often viewed as a scale advantage. Under the AI Act, scale alone does not shield firms from compliance costs. The relevant advantage is jurisdictional capital: deep operating experience in the regulated market. Although GDPR and the AI Act are both recent EU technology regulations, our findings suggest that the competitive effects of one should not be mechanically extrapolated to the other. The GDPR lesson is largely about size-associated advantages; The AI Act lesson is about jurisdictional embeddedness and the ability to navigate a new, evolving regulatory regime.

10 Conclusion

The EU AI Act is the first comprehensive AI regulatory framework and offers a natural setting for studying the cost of AI regulation. Using predetermined exposure measures across about 800 US-listed firms around the April 21, 2021 Commission proposal, we document two key findings. First, financial markets price comprehensive AI regulation as costly on average: AI hiring growth alone predicts negative abnormal returns of roughly -17 bps. Second, this cost is redistributive. Firms with established EU market presence capture a positive announcement return on the EU$\times$AI interaction that more than offsets the compliance penalty—a regulatory moat of approximately $+40$ bps, persisting through day $+40$ without reversal. Together, EU AI Act proposal announcement led to an aggregate loss of approximately \$80 billion over a \$30 trillion market capitalization.

We interpret the moat as the priced value of *jurisdictional capital*: the regulator relationships and interpretive knowledge that firms accumulate through sustained EU market participation, which helps navigating the Act's mandates into compliance practice. Three lines of evidence support this interpretation. The moat operates through EU revenue share rather than firm size or international diversification. Direct measures of political access do not absorb the effect or themselves predict abnormal returns, showing that lobbying is unlikely to drive the moat. The moat is amplified by high-risk AI capacity buildup, stable, geographically concentrated EU presence, and prior compliance experience with EU regulations.

Beyond stock returns, we find suggestive evidence that jurisdictional capital is reflected in real-economy outcomes. Among firms that are both high AI hiring and high EU-embedded, those facing peers with weaker EU presence subsequently reallocate revenue toward EU markets following the Act's proposal. This pattern is consistent with EU-embedded firms capturing market share as less EU-prepared peers retrench, supporting an interpretation of the jurisdictional capital as competitive advantage. Our results show that capital market prices jurisdictional capital as an intangible assets, and they have important implications for both the regulators and firms regarding how AI regulation reshapes firm value and competition.

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A Data Appendix

This appendix documents the data sources, variable construction, and sample-selection procedures summarized in Section 3.

A.1 Data Sources

Job postings. The primary measure of AI exposure is constructed from Lightcast database of job postings covering 8,926 US-listed firms from 2010 to 2026. For each firm-month, we count total job postings and AI-related job postings if the skills in the posting description require AI ethics and governance postings, machine learning, natural language processing, and computer vision. Firms are identified by Compustat `gvkey`, which permits direct linkage to financial data.

Geographic revenue. EU revenue exposure is sourced from FactSet's Geographic Revenue (GeoRev) database, which reports the percentage of total revenue derived from the European Union for 10,382 US-listed firms. Our primary exposure measure is the mean EU revenue share over FY2015–2019, a fully pre-COVID window. Firms are not required to disclose in all five years: a firm with disclosure in $k \leq 5$ years enters with the mean of its k disclosed annual shares.

Stock returns. Daily stock prices and adjustment factors are from the CRSP/Compustat Merged (CCM) database. Daily total returns are computed as

$$r_{it} = \frac{\text{prccd}_{it} \times \text{trfd}_{it}/\text{ajexdi}_{it}}{\text{prccd}_{i,t-1} \times \text{trfd}_{i,t-1}/\text{ajexdi}_{i,t-1}} - 1,$$

where `trfd` is the total return factor for dividends. For firms for which CRSP does not compute `trfd` (approximately 2,200 non-dividend-paying stocks), we set `trfd` = 1 so that price returns equal total returns. We retain only primary securities (`LINKPRIM` $\in$ {'P', 'C'}, `LINKTYPE` starting with 'L', `iid` = 1). All 771 firms have continuous CRSP coverage through June 17, 2021 (day +40 relative to April 21, 2021); no firm is silently truncated from CAR calculations due to mid-window delisting.

Fama–French factors. Daily Fama–French three-factor and five-factor returns are obtained from Kenneth French's data library.

Compustat Annual. Firm-level financial controls are drawn from Compustat Annual, averaged over FY2015–2019, applying standard filters (`indfmt` = 'INDL', `datafmt` = 'STD', `consol` = 'C').

Foreign-income diversification control. Foreign income share (`pifo/pi`) is constructed from Compustat to distinguish EU-specific regulatory effects from general international diversification benefits. The ratio is computed only for firm-years with |`pi`| > 0.01 to avoid division artifacts from near-zero pretax income.

Political access. Several measures of corporate political engagement with EU institutions and member states are constructed. First, following Biguri and Stahl (2025), we download all meetings between corporate representatives and European Commissioners from the Integrity Watch platform (`https://integritywatch.eu`), which aggregates mandatory meeting disclosures across three Commission periods (Juncker 2014–2019, von der Leyen I 2019–2024, von der Leyen II 2024–present; 78,029 total meetings, 25,258 involving companies). We match 73sample firms to Commissioner meetings during 2015–2019. Second, we download the full EU Transparency Register (`https://ec.europa.eu/transparencyregister`; 17,061 organizations)—the mandatory registry for organizations engaging with EU institutions—and match 74sample firms with registration dates before April 21, 2021.

For AI White Paper consultation, we construct an indicator for submitted comments in AI White Paper consultation stage (17 sample firms). In February 2020, the European Commission published a White Paper on Artificial Intelligence and solicited public comments—the consultation that directly informed the April 2021 proposal. We download all 1,216 submissions from the Commission's "Have Your Say" portal and match submitting organizations to our sample by firm name. The consultation ran from February 19 to June 14, 2020, and received 1,216 submissions: 150 from companies, 117 from NGOs, 112 from academic institutions, 111 from business associations, and the remainder from individuals and other organizations. Data downloaded via the Better Regulation API at here. Notable US company submissions include Google, IBM, Microsoft, Intel, Adobe, Cisco, Salesforce, and Qualcomm.

For member-state-level lobby, we check if the firm appears pre-event in any mandatory member-state political-engagement channels: France, Ireland, and Germany (86 firms). France's HATVP répertoire des représentants d'intérêts (mandatory since July 2017), Ireland's SIPO Register of Lobbying (mandatory since September 2015), Germany's §25(3) PartG corporate-donations register (mandatory since July 2002), or pre-event membership in BITKOM, the German trade association for the digital economy and the canonical Berlin lobby vehicle for tech firms. Collectively, these jurisdictions contain ≤ 7 firms with top-1 EU revenue in our sample (Table A16). Italy, Spain, Sweden, Denmark, and the Netherlands had no mandatory pre-event firm-level lobby register over our window.

For EU-level trade-association membership, we construct an indicator if the firm appears on the pre-event member roster of DigitalEurope, DOT Europe, or ITI—the three major EU-level digital-industry trade associations (45 firms). DigitalEurope, DOT Europe, and ITI are the EU-level digital-industry trade associations whose pre-event corporate member rosters are recoverable from archived web snapshots (Internet Archive Wayback Machine captures of 2020-12-04, 2021-01-24, and 2020-04-24 respectively, all strictly pre-event). For member-state-level lobby and EU-level trade-association membership, we include membership of any EU subsidiaries of the firm.

A.2 Financial Controls

Financial controls are constructed from Compustat, averaged across FY2015–2019 to match the exposure measurement period: log market capitalization (log(csho $\times$ prcc_f)), book-to-market ratio (ceq/(csho $\times$ prcc_f)), leverage ((dltt + dlc)/at), R&D intensity (xrd/sale), and profitability (oiadp/at). Book-to-market, leverage, R&D intensity, and profitability are winsorized at the 1st and 99th percentiles within the analysis sample (i.e., after all selection filters). Log market capitalization is not winsorized, since the log transform already compresses the right-skewed distribution. Missing values of long-term debt (`dltt`), short-term debt (`dlc`), and R&D expense (`xrd`) are treated as zero; firm-years with non-positive sales are set to missing for R&D intensity; strictly positive market capitalization is required. For FF48 industry fixed effects, each firm is classified by the SIC code from its most recent Compustat record; firms without a valid match are assigned to the residual "Other" category (FF48 industry 48; 7 firms, 0.9% of the sample).

A.3 Sample-Construction Waterfall

Our sample construction is an inner-join waterfall across five filters, summarized in Table A1. We match FactSet GeoRev firms to CRSP/Compustat using CUSIP and ISIN identifiers in a waterfall merge (ISIN-based CUSIP6, then FactSet CUSIP6): 5,224 of the 10,382 FactSet firms match; the 5,158 unmatched firms are predominantly micro-cap and OTC-listed companies outside CRSP/Compustat coverage.[11] Of the matched firms, 1,739 have non-missing EU revenue data for at least one year in FY2015–2019—the remainder are firms that FactSet lists but for which geographic revenue segments are not disclosed. From the job postings database, we retain firms with at least 5 total postings in both CY2015 and CY2019, which defines AI hiring growth; AI share is computed at the annual level by summing all AI and total postings within each year before dividing. We then require valid Fama–French three-factor CARs around April 21, 2021 (estimation window $[-250, -11]$ with at least 120 trading days), non-missing Compustat controls averaged over FY2015–2019, and a pre-event share price (end of March 2021) of at least \$5. The resulting analysis sample contains **771 firms**.[12]

For the extensive margin sample, we include firms with no EU revenue disclosure and apply the sample filters. The resulted sample size increases to **1,264 firms**.

For the multi-event analysis, we hold the sample and exposure measures fixed at their April 2021 values. This ensures that variation in abnormal returns across events reflects

[11] We verify that the unmatched firms are genuinely absent from CRSP/Compustat rather than lost to identifier mismatches: of the unmatched firms, the majority have US ISINs and valid US-format CUSIPs, yet their CUSIP6 identifiers do not appear in the CRSP/Compustat Merged universe. Ticker-based matching is not used due to the high rate of false matches from ticker reuse (e.g., SPACs recycling tickers of acquired companies). When multiple FactSet firms map to the same `gvkey` via CUSIP, we retain the match from the higher-priority method (ISIN over CUSIP); if tied, both are dropped as ambiguous. The crosswalk is built from the most recent CRSP/Compustat Merged vintage using each `gvkey`'s latest record. We use CUSIP6 (issuer-level) rather than CUSIP9 because FactSet's identifier is issuer-scoped—the 3-digit issue-and-check suffix is immaterial for cross-share-class matching. CUSIP6 values that map to multiple `gvkeys` in CRSP (rare) are excluded from the matchable pool rather than arbitrarily assigned. For the rare FactSet records that disclose revenue under multiple share classes linked to the same `gvkey`, we retain the first occurrence by sort order. All 771 firms in the final sample have a stable `gvkey`–CUSIP6 mapping in Compustat across FY2015–2021, ensuring that Compustat controls and FactSet revenue shares align to the same underlying entity throughout the measurement period.

[12] We do not exclude financial (SIC 6000–6999) or utility (SIC 4900–4999) firms. The EU AI Act's scope is sector-agnostic: Articles 2 and 6 impose obligations on providers and deployers of high-risk AI systems regardless of their industry classification, and both sectors are material AI adopters—banks for credit scoring, fraud detection, and algorithmic trading; utilities for load forecasting, predictive maintenance, and grid optimization. Excluding either sector would narrow the economic interpretation of the regulatory moat without a principled basis.

Table A1: Sample Construction Waterfall: Main Sample

Filter	Remaining	Dropped
FactSet GeoRev universe	10,382	—
Intersection: CRSP/Compustat (CUSIP6 waterfall)	5,224	5,158
Intersection: EU revenue disclosed (FY2015-2019, $\geq$ 1 yr)	1,739	3,485
Intersection: AI hiring growth (CY2015 and CY2019, $\geq$ 5 postings each)	887	852
Intersection: Valid FF3 CARs ($\geq$ 120 estimation trading days)	810	77
Intersection: Compustat controls (non-missing, avg FY2015-2019)	798	12
Intersection: Pre-event share price $\geq$ \$5 (end-March 2021)	771	27
Analysis sample	771	—

Table A2: Sample Construction Waterfall: Extensive Margin Sample

Filter	Remaining	Dropped
FactSet GeoRev universe	10,382	—
Intersection: CRSP/Compustat (CUSIP6 waterfall)	5,224	5,158
Intersection: AI hiring growth (CY2015 and CY2019, $\geq$ 5 postings each)	1,510	3,714
Intersection: Valid FF3 CARs ($\geq$ 120 estimation trading days)	1,339	171
Intersection: Compustat controls (non-missing, avg FY2015-2019)	1,317	22
Intersection: Pre-event share price $\geq$ \$5 (end-March 2021)	1,264	53
Extensive-margin sample	1,264	—
EU revenue disclosed FY2015-2019, $\geq$ 1 yr (EU_Indicator = 1)	771	—
No EU revenue disclosed (EU_Indicator = 0)	493	—

differences in the information content of each legislative milestone, not changes in sample composition or exposure.

A.4 Summary Statistics: Main Sample

Table A3: Summary Statistics

Variable	N	Mean	SD	P25	Median	P75	P99
Panel A: Key Exposure Variables							
AI_Growth (ppts/yr)	771	1.432	2.819	0.000	0.532	2.202	12.035
EU_Share	771	0.098	0.089	0.034	0.081	0.135	0.442
Panel B: Cumulative Abnormal Returns (April 2021, bps)							
CAR[0,+1]	771	16.301	259.957	-102.854	11.428	130.436	668.342
CAR[0,+2]	771	-18.861	326.153	-164.386	-11.787	130.964	875.575
CAR[-1,+1]	771	56.369	326.296	-107.603	72.002	216.598	949.879
CAR[-2,+2]	771	10.668	432.706	-186.424	37.142	208.123	943.127
Panel C: Financial Controls							
Market Cap (USD bn)	771	21.368	57.590	1.391	4.515	14.069	249.742
Book-to-Market	771	0.384	0.303	0.169	0.309	0.535	1.342
Leverage	771	0.259	0.183	0.111	0.248	0.365	0.841
R&D Intensity	771	0.093	0.205	0.000	0.020	0.102	1.405
Profitability	771	0.063	0.120	0.032	0.076	0.119	0.307
Panel D: Diversification							
Foreign Income Share	683	0.305	2.351	0.054	0.309	0.698	3.938

Notes. Descriptive statistics for the N=771 analysis-sample firms. AI_Growth is the annualized change in the AI share of job postings from CY2015 to CY2019 (percentage points per year). EU_Share is the firm mean FactSet GeoRev EU revenue share over FY2015–2019. Market Cap (USD bn) is the antilog of the log market-cap control (firm mean of log market capitalization over FY2015–2019); the regressions use log(market cap). Book-to-market, leverage, R&D intensity, and profitability are reported after 1%/99% within-sample winsorization.

Table A4: Summary Statistics: Extensive Margin Sample

Variable	N	Mean	SD	P25	Median	P75	P99
Panel A: Key Exposure Variables							
AI_Growth (ppts/yr)	1,264	1.145	2.542	0.000	0.317	1.534	11.184
EU Share (0 if non-discloser)	1,264	0.060	0.084	0.000	0.024	0.098	0.383
EU Indicator (1=disclosed)	1,264	0.610	0.488	0.000	1.000	1.000	1.000
Panel B: Cumulative Abnormal Returns (April 2021, bps)							
CAR[0,+1]	1,264	13.961	260.543	-108.495	10.930	129.627	707.486
CAR[0,+2]	1,264	-25.554	379.583	-182.888	-24.980	123.324	894.318
CAR[-1,+1]	1,264	69.719	332.326	-91.251	83.337	227.597	957.213
CAR[-2,+2]	1,264	13.953	452.466	-184.731	29.084	207.729	999.225
Panel C: Financial Controls							
Market Cap (USD bn)	1,264	16.331	47.838	1.073	3.130	11.078	222.056
Book-to-Market	1,264	0.430	0.316	0.193	0.369	0.627	1.430
Leverage	1,264	0.264	0.199	0.094	0.241	0.381	0.866
R&D Intensity	1,264	0.187	0.866	0.000	0.000	0.054	6.938
Profitability	1,264	0.051	0.126	0.023	0.066	0.109	0.309
Panel D: Diversification							
Foreign Income Share	814	0.281	2.169	0.011	0.222	0.663	3.785

Notes. Descriptive statistics for the full sample of N=1,264 firms: the 771 main-analysis firms that disclose EU segment revenue in FactSet GeoRev (EU Indicator = 1) and the 493 additional firms that do not disclose EU segment revenue (EU Indicator = 0). Under SFAS 131, firms report geographic-segment revenues only above a materiality threshold; non-disclosure therefore implies immaterial EU exposure rather than randomly missing data. EU Share is set to zero for the 493 non-disclosers. EU Indicator equals one if the firm discloses positive EU segment revenue in at least one fiscal year during 2015–2019, zero otherwise. AI_Growth is the annualized change in the AI share of job postings, CY2015 to CY2019 (percentage points per year; Lightcast). CARs are market-model cumulative abnormal returns in basis points; day 0 is April 21, 2021 (EU AI Act proposal date). Market Cap (USD bn) is the antilog of the log-market-cap control (firm mean of log market capitalization, FY2015–2019); regressions use log(Market Cap). Book-to-market, leverage, R&D intensity, and profitability are winsorized at the 1st and 99th percentiles within the full 1,264-firm sample. Foreign Income Share is available for N=814 firms.

B Robustness Appendix

B.1 Pre-Trend Trajectory: Cumulative Coefficient

Figure A.1 complements the formal pre-trend tests in Table 3 by plotting the full cumulative trajectory of the EU×AI coefficient from day −40 through day +40.

Table A5: The Interaction Effect Across Legislative Events

	Dependent variable: CAR (bps), event window $[0, +2]$			
	Apr 2021 Proposal	Jun 2023 EP Vote	Dec 2023 Trilogue	Mar 2024 EP Final
EU × AI Growth	39.7***	7.5	6.8	-16.0
	(10.3)	(14.4)	(20.4)	(13.3)
EU Revenue Share	2.4	-7.9	-18.4	-0.9
	(13.9)	(16.8)	(13.6)	(10.1)
AI Growth	-16.7**	24.2	-5.1	-3.5
	(6.4)	(16.8)	(10.2)	(13.9)
Industry FE (FF48)	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Obs. (Apr 2021 Proposal)	769	769	769	769
Obs. (Jun 2023 EP Vote)	767	767	767	767
Obs. (Dec 2023 Trilogue)	766	766	766	766
Obs. (Mar 2024 EP Final)	765	765	765	765

Notes. This table reports OLS regressions of cumulative abnormal returns (CAR, in bps) following Euqation (2) but with four legislative events of the EU AI Act. Standard errors (FF48-clustered) are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Each event is a separate FF3 market-model re-estimation with a pre-event $[-250, -11]$ window.

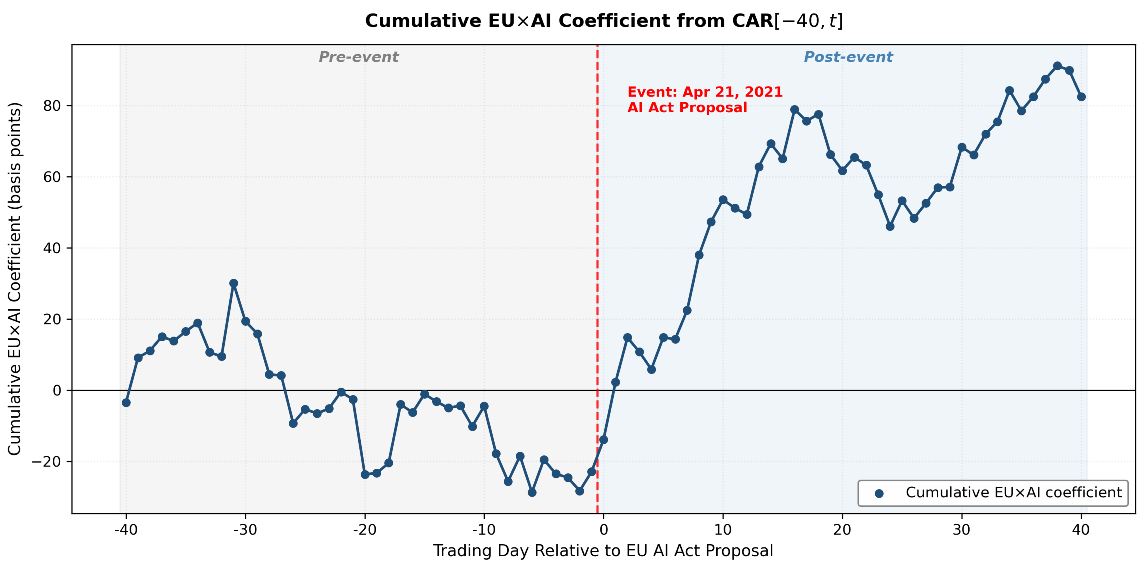

Figure A.1: Cumulative EU×AI Coefficient from CAR$[-40, t]$

Notes: Each point plots the coefficient on EU×AI (standardized) from a regression of CAR$[-40, t]$ based on Equation 2, where t ranges from day -40 to day $+40$. The cumulation anchor is fixed at day -40 throughout. The CAR estimation window $[-291, -41]$ is disjoint from the event window.

B.2 Randomization Inference: Full Distribution

Table A6 reports the full per-window results of the randomization inference procedure described in Section 5.4. Coefficient-based RI p-values for the EU×AI interaction range from 0.019 to 0.054 across the four windows; the corresponding t-statistic-based RI p-values are 0.035 on CAR$[0, +1]$, 0.008 on CAR$[0, +2]$, and 0.004 on the two symmetric windows. The AI Growth main effect yields t-based RI p-values between 0.000 and 0.046 across the four windows. The EU Revenue Share main effect is well within its placebo distribution on every window ($p > 0.50$). Placebo means for all three coefficients are centered near zero with no systematic bias. Figures A.2 and A.3 show the full 2×2 placebo distributions underlying these tests.

Table A6: Randomization Inference: April 21, 2021 Coefficients vs. Placebo Distribution

	[0, +1]	[0, +2]	[−1, +1]	[−2, +2]
EU × AI Growth				
Actual coeff. (bps)	+31.8	+39.7	+43.4	+45.2
Actual t-statistic	+3.54	+3.87	+6.06	+5.15
Placebo mean (bps)	+0.0	−0.0	+0.0	+0.1
Placebo SD (bps)	15.2	18.5	18.5	24.3
Placebo [5, 95] (bps)	[−23.6, +23.2]	[−28.5, +28.4]	[−28.5, +28.4]	[−37.8, +38.7]
RI p-value (coeff.)	0.039	0.041	0.031	0.062
RI p-value (t-stat)	0.012	0.017	0.002	0.000
EU Revenue Share				
Actual coeff. (bps)	+3.2	+2.4	+15.1	+22.5
Actual t-statistic	+0.35	+0.18	+1.78	+2.03
Placebo mean (bps)	−0.1	−0.2	−0.2	−0.4
Placebo SD (bps)	18.5	22.6	22.6	29.9
Placebo [5, 95] (bps)	[−26.5, +28.0]	[−32.5, +32.5]	[−32.6, +32.6]	[−43.7, +47.2]
RI p-value (coeff.)	0.834	0.882	0.447	0.364
RI p-value (t-stat)	0.791	0.886	0.197	0.135
AI Growth				
Actual coeff. (bps)	−21.9	−16.7	−37.1	−32.2
Actual t-statistic	−3.66	−2.60	−4.65	−4.25
Placebo mean (bps)	−0.1	−0.1	−0.2	−0.2
Placebo SD (bps)	12.6	15.2	15.2	20.2
Placebo [5, 95] (bps)	[−19.6, +22.2]	[−24.6, +25.9]	[−24.4, +25.8]	[−31.2, +35.5]
RI p-value (coeff.)	0.091	0.267	0.014	0.116
RI p-value (t-stat)	0.002	0.035	0.000	0.002
Placebo dates		483		

Notes: This table compares the actual April 21, 2021 regression coefficients to a placebo distribution constructed from 483 non-event trading dates (Dec 2020 to Dec 2022, excluding ±10 trading days around April 21, 2021). For each placebo date, CARs are recomputed using a Fama–French three-factor estimation window of [−250, −11] trading days relative to the placebo date, then the full interaction regression with controls and FF48 industry fixed effects is estimated. The actual coefficients and t-statistics are refreshed from the clean-room Stata `reghdfe` Table 2 output. The RI p-value (coeff.) is the fraction of placebo dates where $|\hat{\beta}_{\text{placebo}}| \geq |\hat{\beta}_{\text{actual}}|$. The RI p-value (t-stat) is the analogous fraction based on t-statistics.

B.3 Long-run Effect

Table A7 extends the baseline regression to longer windows. The EU×AI interaction grows monotonically from about +30 bps on CAR[0, +1] to reaching +175 bps on CAR[0, +40]—more than five folds over two calendar months—and is significant at the 1% level at every

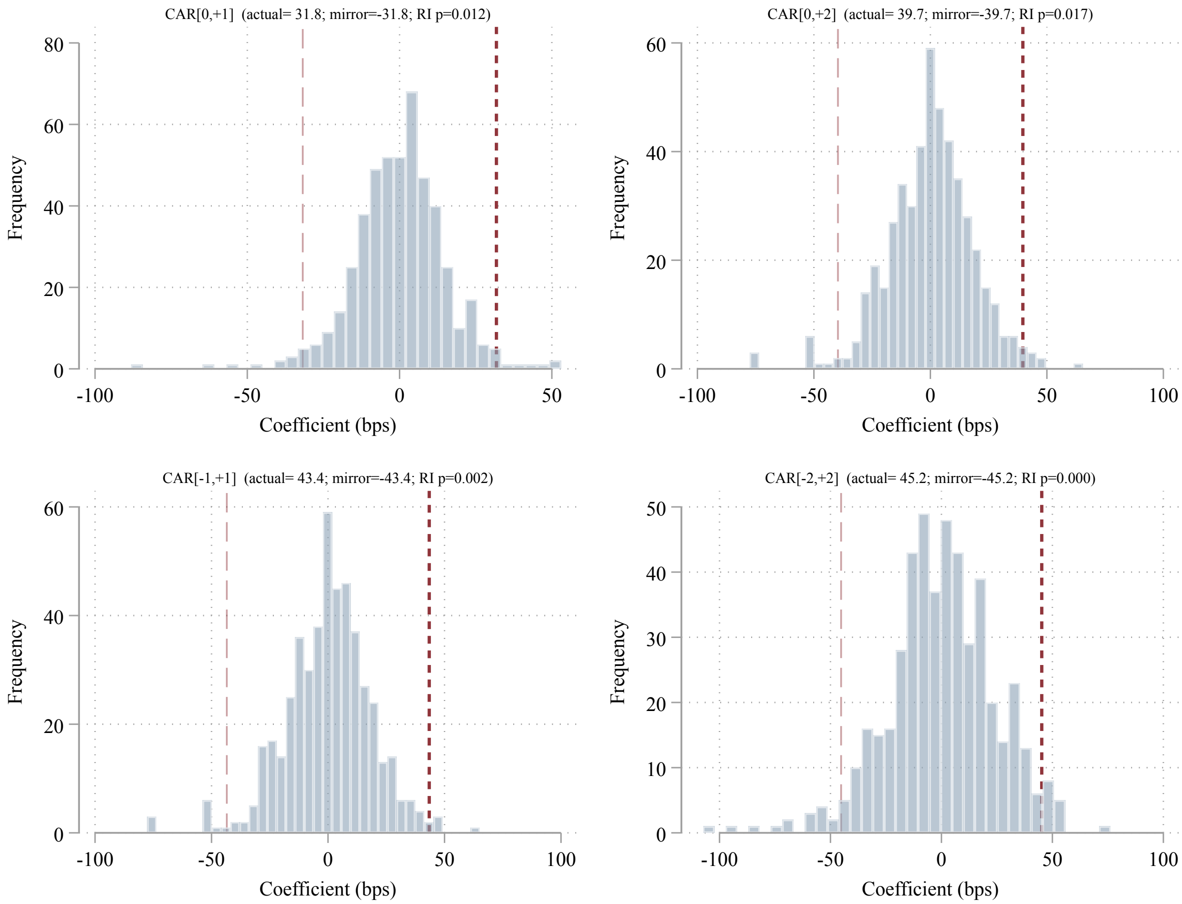

Figure A.2: Randomization Inference: EU×AI Coefficient, All Windows

Notes: Each panel plots the distribution of EU×AI coefficients from 483 placebo regressions (non-event trading dates, December 2020 to December 2022). The solid red line marks the actual April 21, 2021 coefficient; the dashed red line marks its mirror image for two-sided comparison. RI p-values are based on t-statistics.

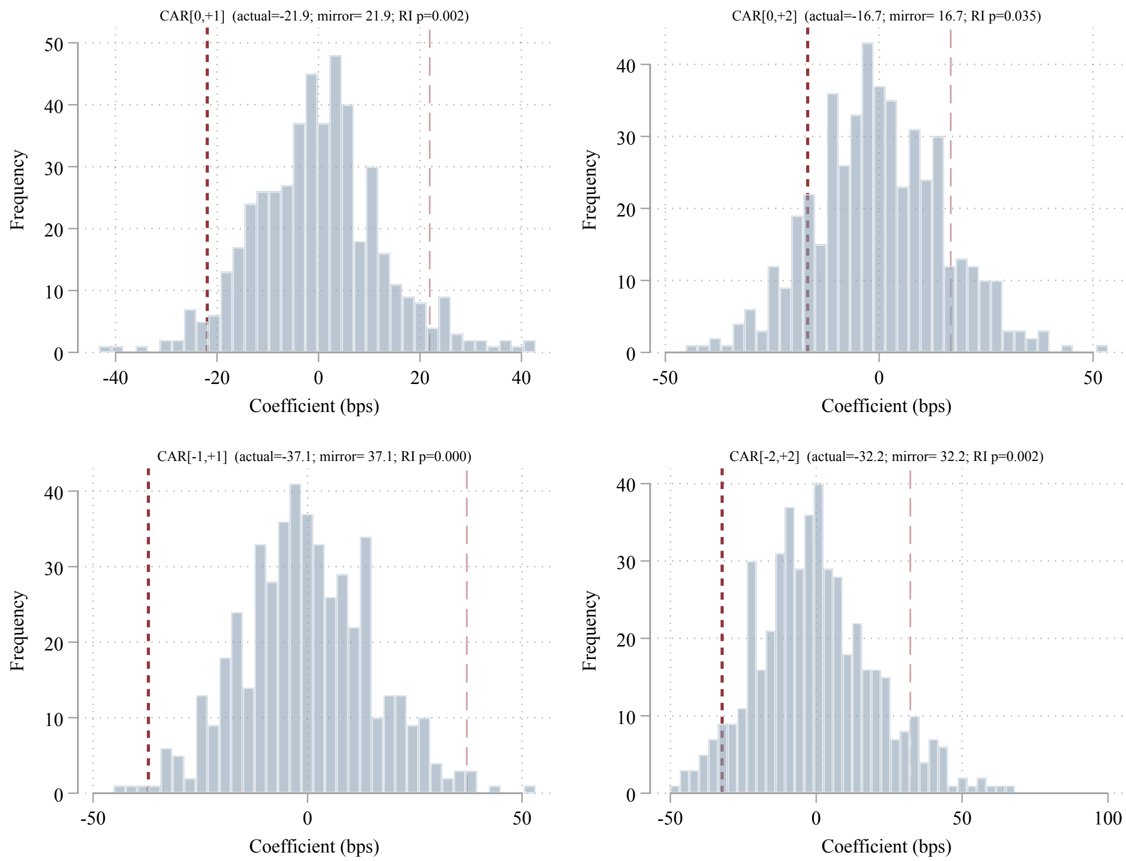

Figure A.3: Randomization Inference: AI Hiring Growth Coefficient, All Windows
Notes: Each panel plots the distribution of AI Growth coefficients from 483 placebo regressions. The solid red line marks the actual April 21, 2021 coefficient. RI p-values are based on t-statistics.

horizon. The absence of reversal provides evidence against short-lived overreaction and is consistent with a permanent repricing of the regulatory moat.

Table A7: Long-Window Persistence: EU×AI Interaction Across Event Windows

	Dependent variable: CAR (bps)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$[0, +1]$	$[0, +2]$	$[0, +5]$	$[0, +10]$	$[0, +20]$	$[0, +30]$	$[0, +40]$
EU × AI Growth	31.8***	39.7***	43.3***	86.7***	113.0***	126.3***	174.0***
	(9.0)	(10.3)	(10.5)	(32.2)	(35.1)	(33.3)	(54.4)
EU Revenue Share	3.2	2.4	-8.6	-14.3	-5.7	17.0	16.8
	(9.4)	(13.9)	(19.0)	(26.9)	(37.1)	(28.2)	(25.2)
AI Growth	-21.9***	-16.7**	-16.4	28.4	60.9**	55.2	-1.6
	(6.0)	(6.4)	(16.6)	(25.2)	(28.1)	(33.8)	(49.5)
Industry FE (FF48)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	769	769	769	769	769	769	769

Notes. This table reports the EU×AI coefficient from a separate OLS regression of the indicated cumulative abnormal return window, using the baseline specification Equation 2. Standard errors clustered at the FF48 industry level. *, **, *** denote significance at the 10%, 5%, 1% levels.

A potential concern about Table A7 is that the long-horizon coefficient growth reflects post-event news correlated with EU×AI rather than persistent repricing of the announcement signal. We address this through a complementary test, in the spirit of local projection, that uses the narrowly identified announcement-window return CAR$[0, +2]$ as the regressor—thereby filtering out post-event news that affects long-horizon CAR but not the main event window—and asks whether longer-window CAR continues to drift in the same direction or mean-revert. We regress the increment CAR$[+3, +h]$ on the main-window return CAR$[0, +2]$, with baseline controls and industry fixed effects.

$$\text{CAR}_i[+3, +h] \;=\; \alpha \;+\; \theta_h\, \text{CAR}_i[0, +2] \;+\; \gamma' \mathbf{X}_i \;+\; \delta_s \;+\; \varepsilon_i, \quad h \in \{5,\ 10,\ 20,\ 30,\ 40\}, \quad (4)$$

where the LHS is the post-main-window increment return $\text{CAR}_i[+3, +h] = \text{CAR}_i[0, +h] - \text{CAR}_i[0, +2]$, the controls $\mathbf{X}_i$ and industry fixed effects δ_s are identical to the baseline specification. A positive θ_h indicates same-sign drift; $\theta_h \approx 0$ indicates the announcement news is fully impounded by day +2; a negative θ_h indicates partial reversal. Local projection tests the long-run effect from a different angle from Table A7. The cumulative EU×AI loading can rise monotonically while $\theta_h \approx 0$.

In Table A8, θ_h is statistically indistinguishable from zero at $h = 5$, mildly negative at $h = 10$ and $h = 20$, and noisy thereafter. This suggests a temporary moderate reversal ($< 20\%$) at intermediate horizons, but no reversal once in the longer-run. This shows that the announcement-window is neither systematically reinforced nor reversed during the post-event period. Combined with Table A7, the two pieces tell a coherent story: EU×AI-treated firms continue to earn positive returns relative to controls during the post-event period, but the size of an individual firm's announcement-window move does not predict whether that

Table A8: Local Projection

CAR[+3,+h]	$h = 5$	$h = 10$	$h = 20$	$h = 30$	$h = 40$
θ	-0.0191	-0.1553**	-0.1811*	-0.0762	+0.1049
	(0.0561)	(0.0753)	(0.1054)	(0.1391)	(0.1592)
N	769	769	769	769	769
Adj R^2	0.111	0.099	0.055	0.055	0.065

Notes: Each column reports the OLS slope θ_h from Equation 4 for the indicated horizon h. Standard errors in parentheses are FF48-clustered. Significance (*, **, ***) refers to the 10%, 5%, and 1% levels.

firm will subsequently drift further or mean-revert.

B.4 Long-run Effect: Earnings-Announcement Contamination Robustness

The April 2021 proposal falls in Q1 earnings season. Earnings news could enter the announcement window CAR through three channels: (i) reporting status—whether the firm released earnings inside the CAR window; (ii) surprise content—size, sign, and forward-guidance implications; and (iii) post-earnings drift (PEAD) (Bernard and Thomas, 1989; Bartov, Givoly and Hayn, 2002; Livnat and Mendenhall, 2006). We address each channel in turn.

Step 1: Correlation diagnostics. We construct firm-level proxies for each channel from I/B/E/S, matched to our sample via the IBES–CRSP–gvkey link (98.8% match rate): $D_t \in \{0, 1\}$ for in-window earnings release, the standardized surprise SUE_z and its absolute value, a centered beat indicator, the 5-day post-release FY1 analyst revision, the PEAD-time exposure $\text{days\_post}_{t,i} = t - \tau_i$, and signed and magnitude PEAD interactions. Table A9 reports Pearson correlations of these eight proxies with the three treatment terms (EU, AI, EU×AI) at three event horizons. The largest correlation with EU×AI is +0.11 (PEAD-time at $[0, +2]$). The strongest correlations involving the FY1 revision at the long horizon (EU: -0.26; EU×AI: +0.17) point in opposite directions and cannot jointly bias the moat coefficient. Low unconditional correlations are necessary but not sufficient for unbiasedness, motivating the regression robustness ladder in Step 2.

Step 2: Regression robustness ladder. We re-estimate the baseline regression under eight nested specifications. Spec (A) is the baseline. Spec (B) adds D_t. Spec (C) adds the four earnings-news measures (with zero imputed for non-window firms). Spec (D) is the union of (B) and (C). Specs (E)–(G) progressively add PEAD-time controls. Spec (H) adds the unrestricted in-window interactions $D_t \times$ EU, $D_t \times$ AI, and $D_t \times$ EU $\times$ AI, identifying EU×AI from out-of-window firms only. All specs retain firm controls and FF48 industry fixed effects.

Table A10 reports the EU×AI coefficient across all eight specifications at $[0, 0]$, $[0, +1]$, and $[0, +2]$. The coefficient is invariant across A–G at every short window. At the headline $[0, +2]$ window, the range across A–G is $[+37, +40]$ bps; at $[0, +1]$, $[+30, +34]$ bps; at $[0, 0]$,

Table A9: Correlation of Earnings-Control Proxies with Treatment Terms

Earnings-control variable	EU	AI	EU × AI
Panel: window $[0, +2]$ *($D_t = 1$ for 73 firms)*			
D_t (in-window indicator, 0/1)	+0.031	+0.056	+0.076*
SUE_z (signed surprise)	+0.007	-0.022	+0.019
$\lvert\text{SUE}\rvert_z$ (magnitude)	-0.040	-0.080*	-0.005
Beat (centered indicator, range $[-0.5, +0.5]$)	+0.065	+0.060	+0.099**
5-day FY1 revision_z (guidance)	+0.008	-0.042	+0.070
days_post (PEAD-time)	+0.047	+0.054	+0.114**
days_post × SUE_z (signed PEAD)	-0.002	-0.026	+0.034
days_post × $\lvert\text{SUE}\rvert_z$ (magnitude PEAD)	-0.038	-0.065	-0.010
Panel: window $[0, +10]$ *($D_t = 1$ for 472 firms)*			
D_t (in-window indicator, 0/1)	+0.014	+0.028	+0.045
SUE_z (signed surprise)	-0.039	+0.032	+0.028
$\lvert\text{SUE}\rvert_z$ (magnitude)	-0.004	-0.041	-0.014
Beat (centered indicator, range $[-0.5, +0.5]$)	+0.048	+0.088*	+0.059
5-day FY1 revision_z (guidance)	-0.056	-0.001	+0.046
days_post (PEAD-time)	+0.031	+0.050	+0.092*
days_post × SUE_z (signed PEAD)	-0.025	-0.014	+0.030
days_post × $\lvert\text{SUE}\rvert_z$ (magnitude PEAD)	-0.053	-0.069	+0.008
Panel: window $[0, +40]$ *($D_t = 1$ for 712 firms)*			
D_t (in-window indicator, 0/1)	+0.047	-0.012	-0.016
SUE_z (signed surprise)	-0.025	-0.015	+0.039
$\lvert\text{SUE}\rvert_z$ (magnitude)	-0.012	-0.054	+0.002
Beat (centered indicator, range $[-0.5, +0.5]$)	+0.061	+0.065	+0.005
5-day FY1 revision_z (guidance)	-0.260***	+0.001	+0.168***
days_post (PEAD-time)	+0.056	-0.007	+0.020
days_post × SUE_z (signed PEAD)	-0.026	-0.007	+0.037
days_post × $\lvert\text{SUE}\rvert_z$ (magnitude PEAD)	-0.014	-0.052	-0.001

Notes: Pearson correlations between standardized treatment terms (EU, AI, EU×AI, z-scored within sample) and earnings-control proxies, computed at three event windows. Earnings-control proxies are zero for firms outside D_t. The Beat (centered) variable is $\mathbf{1}\{\text{SUE} > 0\} - 0.5$. *, **, *** denote significance at 5%, 1%, 0.1%.

[+11, +13] bps. All seven restricted coefficients are significant at the 1% level. Adding PEAD-time controls in (E)–(G) does not attenuate the coefficient. The unrestricted Spec (H) coefficient is somewhat lower (range [+10, +32] bps), as expected since it identifies EU×AI from out-of-window firms; it remains significant at [0, +2] at the 1% level.

Table A10: Earnings-Contamination Robustness Ladder

Spec	Earnings controls included	[0, 0]	[0, +1]	[0, +2]
(A)	Baseline (no earnings controls)	+10.96***	+31.80***	+39.69***
		(3.77)	(8.99)	(10.25)
(B)	D_t only (in-window indicator)	+11.45***	+30.30***	+38.28***
		(3.70)	(10.13)	(11.56)
(C)	Earnings-news controls only (0 imputed)[a]	+12.45***	+31.45***	+36.60***
		(3.50)	(10.04)	(11.37)
(D)	D_t + earnings-news controls (parsimonious)	+12.54***	+32.52***	+36.57***
		(3.48)	(10.51)	(11.26)
(E)	+ days_post (PEAD time, level)	+11.99***	+33.59***	+38.01***
		(3.52)	(11.14)	(11.79)
(F)	+ days_post × SUE_z (signed PEAD)	+11.58***	+33.55***	+38.05***
		(3.46)	(11.15)	(11.76)
(G)	+ days_post × $\lvert\text{SUE}\rvert_z$ (full PEAD)	+11.26***	+33.49***	+38.60***
		(3.39)	(11.28)	(11.56)
(H)	+ D_t interactions (unrestricted)[c]	+10.46*	+21.82**	+32.13***
		(5.57)	(9.28)	(11.43)
Homogeneity F-test (Spec H)[d]		$F = 1.07$ ($p = 0.37$)	$F = 3.15^{**}$ ($p = 0.03$)	$F = 1.35$ ($p = 0.27$)
Industry FE (FF48)		Yes	Yes	Yes
Firm controls[b]		Yes	Yes	Yes
Observations		769	769	769

Notes: OLS regressions of CAR (in bps) for the indicated window on the full interaction model augmented by progressively richer earnings-news controls. Earnings-news controls are SUE_z, $\lvert\text{SUE}\rvert_z$, a centered beat indicator, and the 5-day post-release FY1 analyst revision, all zero for firms outside D_t. Spec (H) adds in-window dummy interactions $D_t\times$ {EU, AI, EU×AI}. The F-test row reports the joint F-statistic for the three Spec (H) interactions equal zero, with FF48-clustered variance. Standard errors clustered at FF48. *, **, *** denote significance at 10%, 5%, 1%.

The Spec (H) joint F-test of $D_t \times \{\text{EU}, \text{AI}, \text{EU} \times \text{AI}\} = 0$ does not reject at the headline $[0, +2]$ window ($F(3, 44) = 1.35$, $p = 0.27$) or at $[0, 0]$ ($p = 0.37$), justifying the homogeneity restriction maintained in Specs (B)–(G). The test marginally rejects at $[0, +1]$ ($p = 0.03$); inspection shows the rejection comes from $D_t \times \text{AI}$ rather than $D_t \times \text{EU} \times \text{AI}$, so the moat itself is not the contaminated channel. Figure A.4 extends the comparison to all horizons through $[0, +40]$ and shows that baseline and PEAD-corrected coefficients track within ~ 10 bps with fully overlapping confidence bands at every horizon.

Step 3: Falsification. If earnings contamination drove the headline coefficient, dropping firms whose Q1 2021 earnings release fell inside the announcement window should substantially attenuate the estimate. Excluding the 73 firms that reported during April 19–23 leaves a 698-firm subsample; the headline $[0, +2]$ coefficient is +34 bps ($t = 3.2$), a 6-bp reduction that remains significant at the 1% level. A complementary cell-level descriptive check goes further: if positive Q1 2021 surprises drove the moat, the High-EU×High-AI cell would have systematically larger surprises than the Low-EU×Low-AI control. The opposite

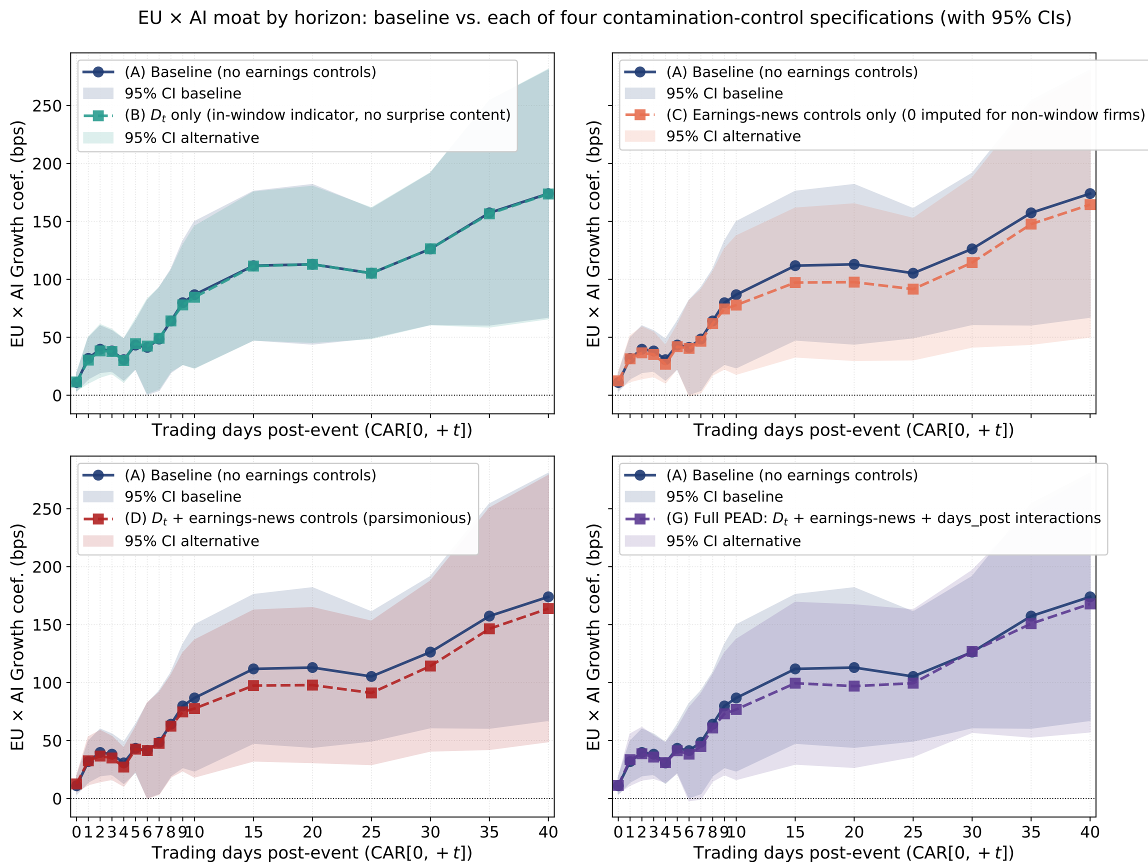

Figure A.4: EU×AI Coefficient by Horizon: Baseline vs. Earnings-Contamination Specifications

Notes: Each panel plots the baseline EU×AI coefficient (solid blue) against one contamination-control specification from Table A10 (dashed), with 95% CIs. Top-left: baseline vs. (B). Top-right: baseline vs. (C). Bottom-left: baseline vs. (D). Bottom-right: baseline vs. (G). All regressions include firm controls and FF48 industry FE with FF48-clustered SE.

is true—mean SUE in the moat cell is +0.20% of pre-event price, versus +0.33% in the Low-EU×Low-AI cell.

Bounding residual bias. The PEAD literature finds typical magnitudes of 30–60 bps over 60 trading days for a 1-SD price-deflated surprise. Applied to our 73-firm in-window subsample and the observed $|r| \leq 0.11$ correlation between PEAD-time and EU×AI, an upper bound on PEAD-driven bias to the long-horizon coefficient is roughly 20–40 bps. The observed gap between baseline and full-PEAD-corrected coefficients at $[0, +40]$ is 9 bps—within this bound and consistent with PEAD operating in the data but orthogonal to the EU×AI dimension. Non-linear contamination outside our specifications (e.g., threshold effects in PEAD correlated with EU×AI) cannot be ruled out, but the convergence of small linear correlations, regression invariance across seven specifications, drop-test stability, and a residual gap within the literature-implied bound makes such hidden contamination an unlikely explanation for the moat.

B.5 AI level

Table A11: AI Level: Baseline Regression with Mean 2015–2019 AI Share

	Dependent variable: CAR (bps)			
	(1)	(2)	(3)	(4)
	$[0, +1]$	$[0, +2]$	$[-1, +1]$	$[-2, +2]$
EU × AI Level	11.4	21.8*	14.4	25.8*
	(7.4)	(12.6)	(17.5)	(14.6)
EU Revenue Share	1.4	0.9	12.2	21.3
	(11.2)	(14.6)	(14.2)	(14.3)
AI Level	0.8	-3.0	-7.9	-10.7
	(15.5)	(18.9)	(24.7)	(26.1)
Industry FE (FF48)	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Observations	769	769	769	769
Adjusted R^2	0.004	0.080	0.031	0.071

Notes. This table reports the baseline Table 2 specification with AI Level (the mean 2015–2019 share of AI postings in firm total postings, averaged over available years) substituted for AI Growth (the annualized change). Standard errors clustered at industry level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

B.6 Fama–French Five-Factor Robustness

Our baseline results use the Fama–French three-factor model to estimate expected returns. To ensure that the findings are not driven by exposure to the profitability (RMW) or investment (CMA) factors, we re-estimate all abnormal returns using the Fama–French five-factor model (Fama and French, 2015) and repeat the full interaction model. Table A12 compares the three key coefficients under FF3 and FF5 across all four event windows. The results are virtually identical: the EU×AI coefficient differs by at most 1.5 bps between factor models on any window, and significance levels are unchanged. On CAR$[0, +2]$, for example, the interaction is +37.6 bps under FF3 and +39.2 bps under FF5. The AI hiring growth and EU revenue share standalone effects are equally insensitive. The stability across factor specifications confirms that the results reflect genuine cross-sectional variation in regulatory exposure, not differences in factor loadings on profitability or investment.

Table A12: Fama–French Five-Factor Robustness: Full Interaction Model

	Dependent variable: CAR (bps)			
	(1)	(2)	(3)	(4)
	$[0, +1]$	$[0, +2]$	$[-1, +1]$	$[-2, +2]$
EU × AI Growth	32.2***	40.8***	42.6***	44.7***
	(8.6)	(10.5)	(6.9)	(8.5)
EU Revenue Share	1.9	1.3	14.1*	21.8*
	(9.4)	(14.2)	(8.1)	(11.1)
AI Growth	-20.7***	-17.2***	-34.5***	-30.3***
	(6.0)	(6.3)	(7.3)	(6.7)
Industry FE (FF48)	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Observations	769	769	769	769
Adjusted R^2	0.020	0.091	0.049	0.080

Notes. OLS regressions of cumulative abnormal returns around the 21 April 2021 EU AI Act proposal, with abnormal returns computed from the Fama–French *five-factor* market model (Mkt–RF, SMB, HML, RMW, CMA) estimated over $[-250, -11]$ trading days. All other variables and conventions match Table 3 (baseline FF3). Standard errors, clustered at the FF48 industry level, are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

B.7 Historical EU Revenue Share Robustness

Table A13: Historical EU Revenue Share and the Regulatory Moat

EU measure	Dependent variable: CAR (bps)				N
	(1) [0, +1]	(2) [0, +2]	(3) [−1, +1]	(4) [−2, +2]	
Panel A					
Avg 2015-2019 (baseline)	31.8***	39.7***	43.4***	45.2***	769
	(9.0)	(10.3)	(7.2)	(8.8)	
Avg 2014-2018	33.1***	40.7***	43.8***	45.1***	758
	(9.3)	(10.3)	(7.3)	(9.5)	
Avg 2012-2016	25.0***	32.4***	36.3***	36.7***	711
	(7.2)	(8.0)	(9.2)	(9.5)	
Avg 2010-2014	11.3*	14.7**	20.2*	20.3	666
	(6.4)	(6.9)	(11.9)	(13.7)	
Avg 2008-2012	11.9*	13.8*	25.3**	22.8	620
	(6.9)	(8.0)	(11.8)	(13.9)	
Panel B					
FY2004	10.7***	11.2***	24.2**	24.7*	430
	(2.8)	(3.7)	(11.3)	(13.9)	
FY2007	5.3	1.9	21.4*	18.3	485
	(6.0)	(5.3)	(11.4)	(12.1)	
FY2012	14.8**	17.2**	30.6***	28.6**	606
	(6.9)	(8.1)	(10.7)	(12.2)	
FY2015	29.6**	35.1**	44.0***	44.3***	674
	(11.2)	(13.0)	(7.5)	(10.9)	
Industry FE (FF48)	Yes	Yes	Yes	Yes	
Firm controls	Yes	Yes	Yes	Yes	

Notes. OLS regressions of cumulative abnormal returns (CAR, in bps) around the 21 April 2021 EU AI Act proposal. Each row re-estimates the CAR$[0, +2]$ specification of Table 2 replacing EU×AI with an alternative historical EU-exposure measure interacted with AI hiring growth. Standard errors are clustered at the FF48 industry level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

C Post-Proposal AI-Act Lobbying

Because post-April-2021 lobbying is realized *after* the proposal event, it cannot enter the event-study regression without look-ahead bias. We therefore treat lobbying as an *outcome* and test whether the April-2021 EU×AI moat predicts subsequent AI-Act lobbying intensity.

Outcomes. We construct four post-2021 firm-level indicators, pooling observable channels into coarse categories. *EU-level firm lobbying* (74 firms) equals one if the firm directly engaged EU institutions on the AI Act via any of: (i) formal feedback on the April 2021 proposal, (ii) a post-event AI-Act entry in the EU Transparency Register, (iii) a post-2021 Commissioner meeting on an AI subject, or (iv) signing the voluntary EU AI Pact / General-Purpose AI Code of Practice. *Country-level lobbying* (18 firms) equals one if the firm (or an EU subsidiary) appears on an AI subject in a member-state lobby register (German Lobbyregister or French HATVP). *EU-level trade-association membership* (84 firms) equals one if the firm is a member of a major EU digital-industry association that lobbied the Act (DigitalEurope, CCIA, BSA, DOT Europe, ITI, or the European Tech Alliance). *Any post-2021 AI lobbying* (115 firms) is the union of the three categories. All channels are dated after April 2021 and are used only as outcomes; we exclude non-EU-directed venues (e.g., U.S. standards bodies).

Specification and findings. We estimate linear probability models of each lobbying indicator on the standardized EU×AI interaction, the standardized EU revenue share and AI hiring growth main effects, log market capitalization, standard firm controls, and FF48 industry fixed effects, with FF48-clustered standard errors; inference for the EU×AI term uses a wild-cluster bootstrap (9,999 replications). The EU×AI interaction does not predict post-proposal lobbying in any category: a one SD increase shifts EU-level firm lobbying by +0.9 pp (wild-bootstrap $p = 0.44$), country-level lobbying by +1.0 pp ($p = 0.73$), trade-association membership by +0.8 pp ($p = 0.25$), and any lobbying by +0.8 pp ($p = 0.59$). Replacing EU×AI with the realized April-2021 abnormal return yields the same null pattern.

These nulls are not driven by low power: in the same regressions, AI hiring growth and firm size strongly predict lobbying (AI hiring growth: +3.3 to +4.3 pp, $p < 0.01$; log market cap: $t \in [2.9, 8.0]$), whereas the EU revenue-share main effect is also flat ($|t| \leq 1.0$). Thus AI-intensive and large firms lobby the AI Act, but moat firms do not lobby more by virtue of the EU×AI combination. The evidence supports an interpretation of the moat as compliance/implementation capability tied to embedded EU operations, rather than political advocacy to shape the Act, with the caveat that our measures capture documented channels and may miss informal engagement or activity shifted to the post-2024 implementation phase.

Table A14: Post-Proposal AI-Act Lobbying

	(1) EU-level firm lobbying	(2) Country-level lobbying	(3) EU-level trade association	(4) Any post-2021 AI lobbying
EU × AI Growth	+0.91	+0.98	+0.80	+0.84
	(0.74)	(1.70)	(0.96)	(0.58)
EU Revenue Share	+0.45	+0.35	−0.12	−0.17
	(0.58)	(0.98)	(−0.19)	(−0.20)
AI Growth	+4.26***	+0.91*	+3.28***	+3.90***
	(3.55)	(1.73)	(2.98)	(4.34)
log Market Cap	+5.85***	+2.10***	+6.81***	+8.36***
	(3.92)	(2.90)	(6.61)	(8.02)
Wild-bootstrap p (EU×AI)	0.44	0.73	0.25	0.59
Controls, FF48 industry FE	Yes	Yes	Yes	Yes
Firms (lobbying = 1)	74	18	84	115
Observations	769	769	769	769

Notes. Each column is a linear probability model of the indicated post-2021 AI-Act lobbying indicator on the standardized EU×AI interaction, the standardized EU revenue share and AI hiring growth main effects, controls, and FF48 industry fixed effects. Coefficients are percentage-point changes in the lobbying probability per one-standard-deviation increase in the regressor; cluster-robust t-statistics (FF48 industry) in parentheses. Stars on the EU×AI row follow the wild-cluster bootstrap (9,999 replications; the bootstrap p is reported in the "Wild-bootstrap p" row); stars on the remaining rows follow the cluster-robust t. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

D High-Risk-AI Hiring Dictionary

A Lightcast job posting is classified as *high-risk AI* if at least one listed skill matches the high-risk-AI skill dictionary *and* its job title matches the high-risk-AI title dictionary (AND-logic). Both dictionaries map the Lightcast universe to the high-risk areas of the April 2021 EU AI Act proposal (COM(2021) 206 final); the rule is dictionary-based rather than topic-model-based to ensure full replicability. Table A15 reports per-category counts and sample entries.

Included scope. Five high-risk areas of the 2021 proposal are mapped: Annex III(1) biometric identification (remote identification and verification systems); Annex III(3) education and vocational training (access determination and student assessment); Annex III(4) employment and worker management (recruitment, evaluation, and performance monitoring, subject to the HR/recruiting exclusions below); Annex III(5)(b) creditworthiness assessment (credit risk modeling and mortgage origination); and Article 6(1) Annex II Section A safety components (robotics and medical-device AI under the Machinery Regulation (2006/42/EC) and the Medical Devices Regulation (2017/745)).

Excluded scope. Three groups are omitted. First, Annex III categories subject to deployer restrictions in the 2021 proposal—public-benefit eligibility, law enforcement, migration, and administration of justice—are excluded because US-listed corporate firms rarely satisfy the deployer condition: a corporate posting does not put an AI system into use by a law-enforcement or judicial authority. Second, Annex III(2) critical infrastructure is excluded because its 2021-proposal scope is narrow and generic industrial postings fail the safety-component test. Third, Annex II Section B safety components (motor vehicles, civil aviation, rail) are excluded because Article 2(2) defers the Act's main high-risk obligations to sectoral type-approval regimes, so the 2021-proposal conformity-assessment burden does not apply.

Excluded HR/recruiting patterns. Within Annex III(4), generic HR/recruiting patterns—talent acquisition, people analytics, automated recruitment, and resume parsing—are excluded because AI co-occurrence in these postings reflects general HR-tech adoption rather than targeted high-risk-AI capability building. Technical performance management variants (network, sales, operational, enterprise, and supplier performance management; Oracle EPM; PeopleSoft EPM) and applicant tracking system skills are retained. The full set of excluded patterns is preserved in a quarantine bucket in the replication package for transparency.

Dictionary summary. After these exclusions, the headline dictionary contains 128 entries (56 skills, 72 titles) across the five Annex categories.

Table A15: High-Risk-AI Hiring Dictionary: Per-Annex-Category Counts and Sample Entries

Annex III category (2021 proposal)	Skills	Titles	Sample dictionary entries
Annex III(1) Biometric identification	10	3	*Skills:* Biometrics; Fingerprint Identification And Classification; Fingerprint Recognition; Biometric Passport; Certified Biometrics Professional. *Titles:* Biometric Health Screeners; Biometrics Technicians; Biometric Screeners.
Annex III(3) Education and vocational training	2	1	*Skills:* Educational Assessment; Admissions Operations. *Titles:* Directors of Admissions Operations.
Annex III(4) Employment, workers' management (post-HR cleanup)	12	5	*Skills (ATS):* Applicant Tracking Systems; CATS Applicant Tracking System. *Skills (technical PM):* Operational/Network/Sales/Enterprise/Supplier Performance Management; Human Performance Evaluation; Oracle EPM; PeopleSoft EPM. *Titles:* Performance Management Analysts/Directors/Consultants/Specialists/Managers.
Annex III(5)(b) Creditworthiness assessment	10	14	*Skills:* Credit Risk Modeling; Credit Risk Analysis; Credit Risk Management; Mortgage Loan Origination; Commercial Mortgage Loan Origination. *Titles:* Credit Risk Managers; Credit Risk Analytics Managers; Credit Risk Underwriters; Credit Risk Associates; Credit Risk Analysts.
Art. 6(1) + Annex II Section A safety components	22	49	*Skills:* Robotic Systems; Advanced Robotics; Industrial Robotics; Robotic Surgery; Computer Aided Diagnosis; Medical Imaging Physics. *Titles:* Biomedical Imaging Technicians; Medical Imaging Technologists; Robotics Coaches; Biomedical Imaging Specialists; Medical Device Territory Managers.
Total (headline)	**56**	**72**	**128 entries**

Notes. A posting is classified as high-risk AI if at least one skill matches the skill dictionary *and* its title matches the title dictionary (AND-logic). Counts are after the HR/recruiting cleanup described in the appendix text. Excluded Annex III categories (2 critical infrastructure, (5)(a) public-benefit eligibility, (5)(c) emergency dispatch, 6 law enforcement, 7 migration, 8 justice) and Annex II Section B safety components under the Article 2(2) carve-out are documented above.

E Country Decomposition of the HHI-Based Subsamples

A natural question about the concentration-based moat reported in Section 7.3 is whether it reflects broad EU regulatory capital (accumulated experience with EU-level rulemaking at the Commission and the European AI Board) or capital specific to a single national jurisdiction (for example, a Germany-only or Ireland-only effect that happens to load on the HHI measure). Table A16 decomposes each HHI-based subsample by the EU member country in which its firms earn revenue. The pattern is unambiguous: both subsamples are

Germany-dominant. Germany carries 33.6% of total EU revenue in the high-HHI half and 21.5% in the low-HHI half, and Germany is the top-1 EU country for 83% of high-HHI firms (320 of 386) and 98% of low-HHI firms (379 of 385). What separates the subsamples is not which countries they operate in but how tightly they concentrate within those countries: the high-HHI subsample concentrates its EU revenue more sharply in Germany, France (20.8% vs. 15.5%), and Italy (10.3% vs. 13.8%), while the low-HHI subsample spreads the same total more evenly. Ireland is slightly over-represented in the high-HHI subsample (11 firms top-1 vs. 2 firms), consistent with a small number of EU tax-domiciled technology firms, but Ireland accounts for only 4.2% of high-HHI EU revenue—too little to drive the +47 to +86 bps moat reported in Section 7.3. The concentration moat therefore operates through depth of engagement with the major continental EU jurisdictions whose national competent authorities will implement and enforce the AI Act, consistent with a regulatory-capital interpretation at the country-authority level rather than at the Brussels-lobbying level.

Table A16: EU Member Country Decomposition of the HHI-Based Subsamples

	High-HHI subsample (concentrated)			**Low-HHI subsample** (diversified)		
Country	Agg. share	Mean share	# top-1	Agg. share	Mean share	# top-1
Germany	33.6%	30.4%	320	21.5%	21.7%	379
France	20.8%	18.9%	24	15.5%	15.7%	4
Italy	10.3%	12.5%	6	13.8%	13.9%	0
Spain	8.1%	9.3%	8	9.7%	9.7%	0
Ireland	4.2%	4.2%	11	2.7%	2.7%	2
Belgium	3.1%	3.2%	2	3.8%	3.8%	0
Sweden	3.1%	3.1%	1	4.0%	4.0%	0
Poland	3.0%	3.9%	5	4.0%	4.0%	0
Austria	2.0%	2.3%	0	3.3%	3.2%	0
Denmark	1.6%	2.0%	2	2.6%	2.6%	0
Czech Republic	1.3%	1.3%	1	2.3%	2.2%	0
Romania	1.2%	1.5%	2	2.1%	2.1%	0
Other (15 countries)	7.9%	7.2%	4	14.7%	14.3%	0
Total	100.0%	–	386	100.0%	–	385

Notes. Decomposition of the EU revenue held by firms in each HHI-based subsample (median split at HHI= 0.1376, $N_{\text{High}} = 386$, $N_{\text{Low}} = 385$, analysis sample restricted to firms with strictly positive bottom-up EU revenue). *Agg. share* is the subsample's total revenue in country c divided by its total bottom-up EU revenue (weighted average of within-EU shares, weighted by each firm's total EU revenue). *Mean share* is the simple cross-firm average of each firm's within-EU share in country c. *# top-1* counts firms whose mean 2015–2019 share is highest in country c. Rows sorted by the high-HHI aggregate share, with the remaining countries collapsed into "Other."

F Compliance Hiring Pre EU AI Act: Detail and Robustness

This appendix provides supporting detail for the compliance-hiring split reported in Section 7.4: the variable construction and the measure's coverage of EU regulations, the article-level mapping from GDPR to AI Act obligations, and bounds on inference under small-cluster conditions.

F.1 Variable Construction

We construct two firm-year compliance hiring measures from a curated regex screen over the Lightcast distinct-skills (31,542) and distinct-titles (72,194) dictionaries. Both measures count the share of a firm's postings whose skill or title list contains at least one core-tier match. The narrower *EU IT/data compliance* measure restricts to postings whose core matches are not exclusively in US-statute or UK-statute categories; the *Broader IT/data compliance* measure includes US- and UK-statute matches as well. For each firm-year in 2015–2019 we count flagged postings, divide by total firm-year postings, and require at least 5 total postings per firm-year (mirroring the AI hiring filter in Section 3). At firm level, the level is the mean over valid years and the growth is the four-year-annualized change.

The Section 7.4 headline uses the EU IT/data compliance measure. The two measures yield quantitatively similar patterns; the EU measure is marginally sharper, consistent with stripping out US- and UK-statute hiring without losing the GDPR-relevant signal.

F.2 Compliance Categories and EU Regulatory Drivers

The categories contributing to both measures cover six functional areas of EU compliance work in force during 2015–2019. We summarize each below.

Privacy and data protection. Data Protection Officers, Chief Privacy Officers, Privacy Counsels and Engineers, privacy-by-design practitioners, DPIA analysts, breach response staff, consent-management implementers, and privacy professional certifications (CIPP/CIPM/CIPT from IAPP, CDPSE from ISACA). The principal driver is the General Data Protection Regulation (applicable from 25 May 2018; entered into force 24 May 2016), together with its predecessor Directive 95/46/EC and the ePrivacy Directive.

Cybersecurity. Security operations (SIEM, SOAR, EDR, DLP), incident response, vulnerability and threat management, network/cloud/endpoint security, cryptography, and certifications including ISO 27001 and the privacy-extended ISO 27701. The principal EU drivers are GDPR Article 32 (security of processing), the NIS Directive, and the EU Cybersecurity Act.

Data governance and lifecycle. Data lineage and mapping, data catalogs and metadata management, data classification, master data management, records management and retention, e-discovery. The principal driver is GDPR Article 30 (records of processing activities) together with Article 5(1).

IT governance, risk, audit, and vendor management. IT general controls, GRC platforms, enterprise and operational risk management, internal IT audit, and vendor and third-party risk management. The principal drivers are GDPR Articles 24, 28, and 39 (controller demonstrability, controller–processor contracting and sub-processor due diligence, DPO compliance monitoring).

AI and algorithmic governance. Explainable AI, algorithmic accountability and fairness, AI bias testing, AI risk and safety management, model validation and monitoring. The principal driver is GDPR Article 22 (right against solely automated decision-making) together with Article 35(3)(a) and the transparency obligations of Articles 13(2)(f) and 14(2)(g). The EC's High-Level Expert Group Ethics Guidelines for Trustworthy AI (April 2019) and the AI White Paper (February 2020) shaped this category in the pre-event window.

Anti-money laundering and financial-crime compliance. AML programs, KYC and customer due diligence, sanctions screening, transaction monitoring. The EU driver is the AML Directive series (4MLD/5MLD/6MLD), although for US-listed firms in our sample, AML hiring is overwhelmingly driven by US and global frameworks (Bank Secrecy Act, FinCEN, OFAC, FATF) rather than AMLD specifically.

Several other EU instruments—eIDAS (electronic identification and trust services), PSD2 (payment services), MiFID II (financial markets), and Council of Europe Convention 108—enter the measure indirectly through adjacent skill patterns. The Broader compliance measure additionally captures core-tier patterns for US privacy and financial statutes (Sarbanes-Oxley, Gramm-Leach-Bliley, FCRA), US bank IT examination guidance (FFIEC), US export controls (ITAR, EAR), and UK transpositions of EU instruments and UK-specific regulation (UK GDPR, Data Protection Act 2018, PECR, UK NIS Regs 2018, ICO, FCA/PRA cyber-resilience, BS 7799, SMCR, UK Open Banking, Cyber Essentials).

Two methodological caveats bound the EU measure: non-EU cybersecurity frameworks (NIST CSF, FedRAMP, FISMA, HITRUST, CMMC; COBIT and ITIL) are categorized under cybersecurity rather than US- or UK-statute and therefore enter the EU measure; and GDPR's cross-border-transfer regime (Articles 44–50, including Standard Contractual Clauses, Binding Corporate Rules, and Schrems II) is substantively important but not captured by the Lightcast vocabulary.

F.3 GDPR-to-AI-Act Article Mapping

The substantive case for compliance carry-over rests on direct mappings between GDPR articles and AI Act articles. The functional layers that GDPR drove firms to build during 2015–2019 carry over as follows:

- Data governance and records of processing under GDPR Article 30 map to the AI Act's data-quality and data-management obligations under Article 10.
- Security of processing under GDPR Article 32 maps to the AI Act's cybersecurity obligations under Article 15.
- Demonstrability under GDPR Article 24 maps to the AI Act's quality-management-system requirement under Article 17 and post-market monitoring under Article 72.

- The DPO function under GDPR Articles 37–39 prefigures organizational structures relevant to the AI Act's risk-management and governance obligations.

Firms that staffed up for GDPR therefore have a plausibly lower marginal cost of complying with these AI Act articles than firms that did not. The horse race shows, however, that this carry-over is not the whole moat: compliance hiring on its own is not priced. The reason, we argue, is that the AI Act is related to but not identical to the prior EU regime. GDPR is a rules-based privacy regulation with a narrow, well-defined compliance perimeter (Voigt and von dem Bussche, 2017), whose obligations can be largely commoditized through standardized infrastructure and consulting playbooks. The AI Act is principles-based and risk-tiered, with materially broader scope and substantial interpretive ambiguity at adoption (Smuha, 2021): what counts as "appropriate" accuracy under Article 15, "adequate" risk management under Article 9, or "sufficient" human oversight under Article 14 was deliberately left to regulatory interpretation. Obligations such as conformity assessments under Article 43, the producer/deployer asymmetry under Articles 16 and 26, and the high-risk classification regime under Article 6 and Annex III have no direct GDPR analogue. What matters for these features is not only the firm's stock of explicit compliance staff but its capacity to anticipate, interpret, and shape implementation-stage decisions made by national competent authorities, notified bodies, and standards organizations—country-specific regulatory know-how that is accumulated through stable EU operations and captured by EU revenue share rather than by hiring data. Neither input is sufficient on its own: explicit compliance has nothing to leverage without jurisdictional embedding (the horse-race null), and jurisdictional embedding without operational compliance scaling delivers a smaller moat than the joint presence of both (the split's bottom half).

F.4 Compliance Category Taxonomy

Table A17 provides the example mapping of each category to its operational scope, principal EU regulation(s), and specific Article-level provisions.

Table A17: Compliance Category Taxonomy and EU Regulatory Drivers

Functional area	**Example Lightcast skills/titles**	**Principal EU regulation**	**Key provisions**
Privacy and data protection	Data Protection Officer; Privacy Engineer; DPIA analyst; CIPP/CIPM/CIPT certifications	GDPR	Articles 37–39 (DPO function); Article 25 (privacy by design); Article 35 (DPIA); Articles 12–22 (data subject rights); Articles 33–34 (breach notification)
Cybersecurity	SIEM/SOAR/EDR/DLP operations; incident response; ISO 27001/27701; CISSP, CISA, CISM	GDPR; NIS Directive; EU Cybersecurity Act	Article 32 (security of processing); Article 5(1)(f) (integrity and confidentiality); Articles 33–34 (breach notification)
Data governance and lifecycle	Data lineage and catalogs; metadata management; records retention; e-discovery	GDPR	Article 30 (records of processing); Article 5(1)(b)–(e) (purpose limitation, data minimization, accuracy, storage limitation)
IT governance, risk, audit, and vendor management	IT general controls; GRC platforms; internal IT audit; third-party risk management	GDPR	Article 24 (demonstrability); Article 28 (processor contracting and sub-processor due diligence); Article 39 (DPO compliance monitoring)
AI and algorithmic governance	Explainable AI; algorithmic accountability; AI bias testing; model validation	GDPR; HLEG Ethics Guidelines (2019); AI White Paper (2020)	Article 22 (automated decision-making safeguards); Article 35(3)(a) (mandatory DPIA for automated profiling); Articles 13(2)(f), 14(2)(g) (transparency on automated-decision logic)
AML and financial-crime compliance	KYC and customer due diligence; sanctions screening; transaction monitoring; CAMS, CAFP	AML Directive series (4MLD - 6MLD)	For US-listed firms, AML hiring is overwhelmingly driven by US frameworks (Bank Secrecy Act, OFAC); GDPR Article 6(1)(c) provides lawful basis for AML processing

Notes. Functional areas captured by the core-tier patterns in the merged Lightcast taxonomy (77 patterns across 11 categories). The example skills/titles column lists representative entries.

PUBLICATIONS

Jurisdictional Capital and the Cost of AI Regulation: Evidence from the EU AI Act

Working Paper No. [WP/YYYY/###]