Supporting Information for:

Industrial policy reshapes venture capital allocation and growth trajectories in climate technologies

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S1 Data Sources and Sample Construction

S1.1 Company Universe

We draw our company universe from the Climate Tech Venture Capital (CTVC) database, which provides comprehensive coverage of venture-backed firms operating in climate-related technologies. The CTVC database tracks 16,474 climate technology companies globally as of our sample extraction date. We restrict our sample to U.S.-based companies, which constitute the majority of the database and are the relevant population for studying the effects of U.S. federal policy.

S1.2 Financing Data

Financing events are sourced from PitchBook, which provides deal-level records of venture capital rounds, corporate investments, debt financing, private equity transactions, and individual investments. Each record includes the deal date, deal type, deal amount (where disclosed), and participating investors. We match PitchBook financing records to CTVC companies using company identifiers and name-matching procedures.

S1.3 Panel Construction

We construct a firm-level panel at the company-quarter frequency spanning Q1 2020 through Q2 2025 (22 quarters). The panel is balanced: each company appears in all quarters from Q1 2020 until either Q2 2025 or its exit event, whichever comes first. Exit events include initial public offerings (IPOs), mergers and acquisitions, and bankruptcies; the panel is truncated after these events to avoid contaminating post-exit observations.

To ensure that our sample captures firms that plausibly could have been affected by the IRA, we apply the following filters:

- **Geographic restriction:** U.S.-based companies only.

- **Age restriction:** Companies must have been founded no more than 10 years before the IRA enactment date (August 16, 2022). This ensures we study relatively young firms for which venture capital financing decisions are most relevant.
- **Exit filtering:** Observations after IPO, M&A, or bankruptcy are excluded.

The resulting panel contains 132,826 firm-quarter observations spanning 22 quarters (Q1 2020–Q2 2025). Table S4 presents summary statistics for the key outcome and control variables.

S1.4 Variable Definitions

Outcome variables. We construct three primary outcome variables from the PitchBook financing data:

- *AnyVC*: Binary indicator equal to 1 if the firm received at least one venture capital deal in a given quarter, and 0 otherwise.
- *VC_Deal_Count*: Count of venture capital deals received by the firm in a given quarter.
- *VC_Amount_Sum*: Total venture capital investment amount (in millions of USD) received by the firm in a given quarter. Set to zero for quarters with no VC activity.

Control variables. All models include the following controls:

- *CompanyAge*: Years since founding, computed dynamically for each quarter.
- *Ownership indicators*: Dummy variables for company ownership status (e.g., privately held, subsidiary, etc.), with one category dropped as the reference.
- *Region indicators*: Dummy variables for U.S. Census regions (Northeast, Midwest, South, West), constructed from state-level USPS codes using standard Census mappings.

S2 Technology Classification Methodology

S2.1 CTVC Taxonomy

The Climate Tech Venture Capital (CTVC) database classifies climate technology firms into seven mutually exclusive primary categories based on their core technological focus:

1. **Energy** (39.8% of sample): Clean power generation, distributed energy resources, hydrogen, energy storage, and grid management.
2. **Industrial** (23.2%): Decarbonization of industrial processes, green steel and cement, circular economy, metals and mining.

3. **Built Environment** (13.8%): Sustainable buildings, construction materials, heating and cooling, energy efficiency.

4. **Food & Land Use** (6.4%): Sustainable agriculture, alternative protein, regenerative agriculture, food waste.

5. **Climate Management** (6.1%): Climate data, earth observation, climate risk, emissions tracking, ESG investing.

6. **Transportation** (5.3%): Electric vehicles, batteries, micromobility, zero-emission aviation and shipping.

7. **Carbon** (5.0%): Carbon capture, removal, utilization, offsets and marketplaces, MRV.

Each primary category contains multiple subcategories (see Table S5 for the full taxonomy). Companies are assigned to their primary category based on a combination of business description analysis, keyword matching, and manual review.

S2.2 Semantic Classification

For our primary classification, we employ a large language model (LLM)-based semantic classifier. The classifier takes as input each company's business description, product information, and keywords, and assigns it to one of the seven CTVC primary categories along with a specific subcategory. The classification prompt includes detailed descriptions and examples for each category to ensure consistency.

We validate the semantic classifier against expert-labeled ground truth data. Expert labels were obtained through manual review of a stratified random sample of companies by research assistants with domain expertise in climate technology. The semantic classifier achieves high agreement with expert labels across all primary categories.

S2.3 Alternative Classification Approaches

To ensure robustness, we implement two alternative classification approaches:

Keyword matching. A rule-based classifier that assigns companies to categories based on the presence of category-specific keywords in their business descriptions. The keyword lexicon was developed iteratively through domain expert review and includes terms specific to each technology category and subcategory.

BERTopic classification. An unsupervised topic modeling approach using BERTopic [1] that clusters companies based on the semantic content of their business descriptions. Topic clusters are then mapped to the CTVC taxonomy categories. This approach provides an independent validation of the category structure and identifies companies whose business descriptions are semantically ambiguous.

S3 Policy Exposure Measurement

We construct three complementary measures of firm-level exposure to the Inflation Reduction Act.

S3.1 Binary Treatment (CTVC-Based)

Our simplest measure classifies firms as treated if their primary CTVC category is *Energy* or *Carbon*, and as control if they belong to any other climate technology category. This distinction reflects the IRA's core incentive structure: the production tax credit (PTC), investment tax credit (ITC), manufacturing production credits, and carbon capture credits (Section 45Q) most directly benefit firms developing energy generation, energy storage, and carbon capture technologies.

The remaining categories—*Climate Management*, *Industrial*, *Food & Land Use*, *Built Environment*, and *Transportation*—receive comparatively less direct statutory support. While some provisions (e.g., clean vehicle credits, energy efficiency rebates) touch these sectors, the incentive linkage is typically indirect, limited in scope, or contingent on downstream adoption.

S3.2 Continuous IRA Exposure Index

To capture finer-grained variation in policy alignment, we construct a continuous IRA exposure index (IRA_Index) using a supervised text-based classification approach. The index is constructed as follows:

1. We extract the text of IRA provisions related to climate technology from the Congressional Research Service analysis (CRS Report R47262), which provides section-by-section summaries of the IRA's climate and energy provisions.

2. For each company, we score the alignment between the company's business description and each IRA provision using a large language model prompted to evaluate relevance on a 0–7 scale.

3. The final IRA_Index for each company is the maximum alignment score across all evaluated provisions.

This approach captures within-category variation in policy alignment. For example, within the Energy category, a solar panel manufacturer receives a higher score than an energy management software company, reflecting the former's more direct access to production tax credits.

S3.3 Text-Based Exposure Score (S_c)

Our third measure uses a continuous semantic similarity score to capture alignment between firm descriptions and IRA statutory language. The score is constructed as follows:

1. We extract and preprocess the full text of relevant IRA provisions, combining section numbers, titles, overviews, sectors, and types of assistance.

2. We compute term frequency–inverse document frequency (TF-IDF) representations of both company descriptions and IRA provision texts.

3. For each company, we calculate the cosine similarity between its TF-IDF representation and each IRA provision, retaining the top-k most relevant provisions ($k = 7$).

4. The raw exposure score S_z is computed as the weighted average of these top-k similarity scores, where weights are based on the normalized CBO revenue effect and appropriation amount of each provision.

5. We winsorize S_z at the 1st and 99th percentiles and standardize to obtain the centered score S_c.

Importantly, S_c is determined by pre-existing firm characteristics (business descriptions and technological focus) that are fixed prior to the IRA, ruling out concerns about reverse causality.

S4 Empirical Strategy

S4.1 Difference-in-Differences Specification

Our baseline difference-in-differences specification [2] takes the form:

$$Y_{it} = \alpha + \beta(\text{Post}_t \times \text{Treated}_i) + \gamma\text{Post}_t + \delta\text{Treated}_i + \mathbf{X}_{it}'\boldsymbol{\theta} + \varepsilon_{it} \tag{S1}$$

where Y_{it} is the outcome variable for firm i in quarter t, Post_t is an indicator for quarters after August 2022, Treated_i indicates whether the firm is in a policy-exposed technology category (Energy or Carbon), $\mathbf{X}_{it}$ is a vector of controls, and ε_{it} is the error term. Standard errors are clustered at the firm level throughout.

For the continuous treatment designs, we replace Treated_i with either IRA_Index_i or $S_{c,i}$ and interact these with Post_t:

$$Y_{it} = \alpha + \beta(\text{Post}_t \times \text{Exposure}_i) + \gamma\text{Post}_t + \delta\text{Exposure}_i + \mathbf{X}_{it}'\boldsymbol{\theta} + \varepsilon_{it} \tag{S2}$$

We progressively add fixed effects to absorb unobserved heterogeneity:

- **Specification 1:** Controls only (no fixed effects).
- **Specification 2:** Controls + time (quarter) fixed effects.
- **Specification 3:** Controls + time fixed effects + firm fixed effects (two-way FE).

In the two-way fixed effects specification [3], the main effects of Post_t and Treated_i are absorbed by the time and firm fixed effects, respectively. The coefficient of interest β identifies the differential change in outcomes for treated firms relative to control firms after the IRA, beyond any aggregate time trends or firm-specific levels.

S4.2 Event-Study Specification

To examine dynamic treatment effects and test for differential pre-trends [4, 5], we estimate event-study specifications:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{k \neq -1} \beta_k (\mathbf{1}[t = k] \times \text{Treated}_i) + \mathbf{X}'_{it}\boldsymbol{\theta} + \varepsilon_{it} \tag{S3}$$

where k indexes quarters relative to the IRA enactment date, α_i and λ_t are firm and time fixed effects, and the omitted baseline period is $k = -1$ (the quarter immediately before enactment). The coefficients $\{\beta_k\}$ trace out the dynamic treatment effect. Pre-period coefficients ($k < -1$) close to zero and statistically insignificant support the parallel trends assumption. The default event window spans ± 8 quarters (2 years before and after the IRA).

S4.3 Robustness Specifications

We implement several alternative estimators to address potential concerns with our baseline linear specifications:

Poisson pseudo-maximum likelihood (PPML). For the count outcome (VC_Deal_Count), we estimate Poisson models with high-dimensional fixed effects. This approach accommodates the non-negative integer nature of the outcome and is consistent under weaker distributional assumptions than negative binomial models. Firms with zero deals across the entire sample are excluded to avoid separation.

Log-linear specification. For the amount outcome (VC_Amount_Sum), we estimate log-linear models using $\log(1 + Y_{it})$ as the dependent variable with two-way fixed effects. This specification addresses the right-skewness of investment amounts.

Logit specification. For the binary outcome (AnyVC), we estimate logit models with clustered standard errors. Firms with constant outcomes across the sample (all zeros or all ones) are dropped to avoid separation. We report average marginal effects (AMEs) for interpretability.

Alternative clustering. In addition to our baseline firm-level clustering (CRV1), we implement more conservative clustering using CRV3 (cluster-robust variance estimator 3), which provides valid inference under fewer assumptions about within-cluster dependence.

S5 Latent State Model for Financing Trajectories

S5.1 Model Specification

To characterize the dynamic structure of firm financing, we estimate a Hidden Markov Model (HMM) [6, 7] with the following components:

Observed variables. The emission variable at each time step is the deal class observed for a given firm-event: venture capital (VC), debt, corporate investment, private equity (PE), individual investment, or non-dilutive capital (a pooled category combining accelerator/incubator participation, federal and state grants, and direct public-sector investment). Three event types are excluded from the emission space: bankruptcy and "out of business" events (96% of which are terminal in the firm's sequence and therefore reflect firm exit rather than a financing decision), secondary-transaction events (investor-side liquidity, not firm financing), and hedge-fund deals ($n = 8$, too rare to support a stable emission probability). After these exclusions the analytic sample comprises 14,357 financing events across 3,786 firms with at least two events.

Latent states. We specify four latent states ($K = 4$). The number of states was selected based on a combination of information criteria (AIC, BIC), bootstrap stability, and interpretability of the resulting state characterizations. We fit models for $K \in \{2, 3, 4, 5, 6\}$ using random initializations and EM iteration; Table S1 reports the resulting log-likelihoods and information criteria. The BIC declines sharply from $K = 3$ to $K = 4$ (ΔBIC = 1,407, a large improvement), reaches its minimum at $K = 4$, and then increases at $K = 5$ and $K = 6$ (ΔBIC = −81 and −257, respectively, both worse than $K = 4$). AIC marginally favors $K = 5$ over $K = 4$ (ΔAIC = 25), but the AIC→BIC disagreement for the additional state is itself a signal that the $K = 5$ improvement does not survive penalization for parameters in proportion to sample size. Bootstrap diagnostics for $K = 5$ on the original specification show substantial instability in the additional state (mean bootstrap standard deviation on self-transition probabilities of 0.40–0.44); we expect similar behavior on the cleaned specification. Together with the interpretability of the four recovered regimes (described in Section S5.2), these diagnostics support $K = 4$ as the preferred specification.

Table S1: HMM Model Selection

K	Log-likelihood	AIC	BIC	Parameters
2	−18,438.31	36,902.62	37,001.06	13
3	−18,388.92	36,823.85	36,998.00	23
4	**−17,628.05**	**35,326.10**	**35,591.12**	**35**
5	−17,601.78	35,301.56	35,672.59	49
6	−17,653.63	35,437.26	35,929.44	65

Note. Log-likelihood, AIC, and BIC for Categorical HMM specifications with $K \in \{2, 3, 4, 5, 6\}$ latent states on the cleaned emission space (six categories: Corporate, Debt, Individual, Non-Dilutive, Private Equity, Venture Capital; terminal events and secondary transactions excluded). Each model is the best of three random initializations over 60 EM iterations. Sample comprises 3,786 firms with at least two financing events and 14,357 total events. BIC is minimized at $K = 4$ (bolded); $K = 5$ marginally improves AIC (ΔAIC = 25) but worsens BIC (ΔBIC = −81, i.e. $K = 4$ better), and bootstrap diagnostics for $K = 5$ on the original specification indicate poor stability of the fifth state. $K = 4$ is the preferred specification.

Parameters. The model estimates:

- Initial state probabilities $\boldsymbol{\pi} = (\pi_1, \ldots, \pi_K)$.
- Transition matrix $\mathbf{A}$, where $a_{jk} = P(z_t = k \mid z_{t-1} = j)$.
- Emission probabilities $\mathbf{B}$, where $b_k(o)$ gives the probability of observing deal type o conditional

on occupying state k.

S5.2 State Characterization

The four recovered states correspond to distinct financing regimes, reported here with states indexed in descending order of venture-capital share:

- **State 0 (VC-Pure):** venture capital accounts for 71% of financing activity, with small contributions from individual investors (11%) and non-dilutive sources (12%). This state is the purest venture regime in the panel.
- **State 1 (VC-Debt-Mixed):** a hybrid regime in which venture capital (56%) is paired with significant debt financing (20%) and individual investment (11%). This state captures capital-intensive climate-technology firms that combine equity rounds with project- or working-capital debt.
- **State 2 (Non-Dilutive-Led):** non-dilutive capital—accelerator and incubator participation, grants, and direct public-sector investment—accounts for 69% of activity, with venture capital contributing a further 26%. This state is a mixed regime in which venture capital plays a meaningful but non-modal role alongside ecosystem and policy-driven capital sources.
- **State 3 (Debt-Mature):** debt accounts for 49% of financing, with corporate investment (27%) and private-equity participation (17%). This state is characteristic of firms that have progressed beyond pure equity financing toward capital structures typical of mature operations.

Stability across initializations. The EM algorithm for HMMs is non-convex and converges to local optima that differ across initializations. Re-fitting the $K = 4$ HMM across 30 random initializations reveals two structurally distinct families of solutions with comparable log-likelihoods. The first family treats venture capital as a single latent regime and yields a partition (VC, Non-Dilutive, Corporate, Debt) in which the smaller corporate and debt states are recovered less reliably across seeds. The second family separates venture-capital events into two regimes—a *pure* VC state and a *mixed* VC–debt state—and groups corporate and private-equity events into a debt-mature regime. We adopt the second specification because the explicit separation of pure and debt-paired venture capital provides additional interpretive resolution for analyzing the post-IRA trajectory shift, given the simultaneous monetary-policy-driven repricing of debt over the same window. Under the single-VC-state specification, the qualitative direction of the post-IRA shift (away from VC-paired toward non-dilutive trajectories) is preserved.

S5.3 Pre- and Post-IRA State Distributions

We compare the distribution of firm-event observations across latent states before and after the IRA, using Q3 2022 (the IRA enactment quarter) as the boundary. Prior to the IRA (Q1 2020–Q2 2022), firm-events are distributed across all four regimes: Non-Dilutive-Led (State 2, 48.2%),

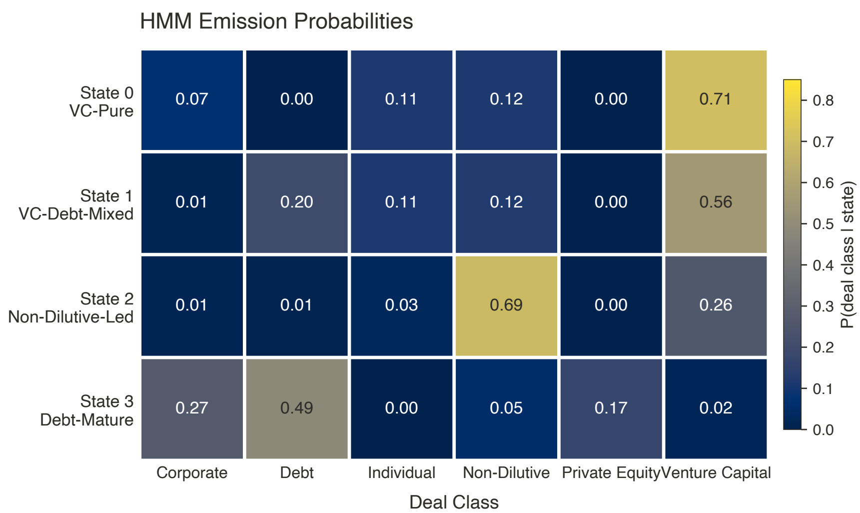

Figure S1: Emission probabilities from the four-state hidden Markov model estimated on 14,357 financing events across 3,786 climate technology companies (2020–2025). Each row represents a latent financing regime; columns indicate the probability of observing each deal class (Corporate, Debt, Individual, Non-Dilutive, Private Equity, Venture Capital) conditional on occupying that regime; darker cells indicate higher probability. The Non-Dilutive category pools accelerator and incubator participation, federal and state grants, and direct public-sector investment. Terminal events and secondary transactions are excluded from the emission space. State selection ($K = 4$) is based on BIC minimization (Table S1).

VC-Debt-Mixed (State 1, 19.3%), VC-Pure (State 0, 16.9%), and Debt-Mature (State 3, 15.6%). Following the IRA (Q3 2022–Q2 2025), the distribution shifts along an equity-versus-debt axis: VC-Pure expands by 8.8 percentage points (to 25.7%), Non-Dilutive-Led expands by 7.1 points (to 55.4%), the VC-Debt-Mixed regime contracts by 13.9 points (to 5.5%), and the Debt-Mature regime contracts modestly by 2.1 points (to 13.5%). This pattern (Figure S2) indicates that the IRA did not simply deepen venture-capital intensity uniformly: rather, it accelerated a reallocation away from VC–debt mixed structures and toward both purer venture-capital trajectories and policy-supported non-dilutive capital. The pattern is consistent with two complementary mechanisms: the IRA's tax credits and grants partially substituting for project- and working-capital debt, and the post-2022 monetary-policy environment raising the cost of debt for capital-intensive climate firms. The latent-state shifts mirror, and are recovered without imposing, the observable financing-phase partition reported in the main text.

S5.4 State Transition Diagram

Figure S3 presents the estimated transition probabilities between the four latent financing regimes. Arrow widths and opacities are proportional to transition probabilities; only transitions exceeding 3% are shown. Self-transition probabilities (shown as labels outside each node) indicate strong state persistence: all four regimes have self-transition rates above 70%, consistent with financing regimes being sticky over adjacent deal events.

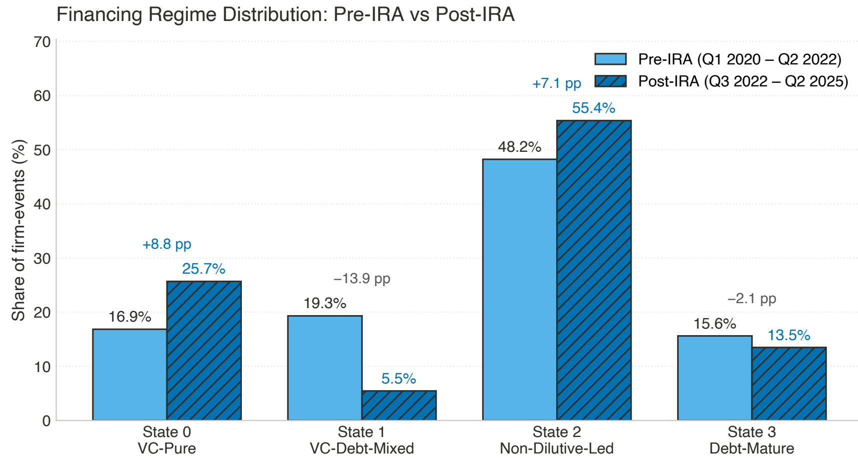

Figure S2: Distribution of financing events across four latent regimes before the IRA (Q1 2020–Q2 2022, light blue) and after (Q3 2022–Q2 2025, dark blue with hatching). The IRA was signed in August 2022 (Q3); Q3 2022 is included in the post-IRA window. Percentage labels indicate each regime's share of total events; signed annotations denote shifts ≥ 2 percentage points. Sample: 14,357 events across 3,786 firms.

S6 Climate Policy Uncertainty Analysis (Triangulation)

The credibility-channel identification in the main text rests on the statutory-text-based Policy Credibility Index and the OBBBA stress test. As an external triangulation, we additionally construct a news-based Climate Policy Uncertainty (CPU) index and report its co-movement with venture capital activity. We treat the patterns documented here as supporting evidence rather than primary identification.

S6.1 Index Construction

We follow the newspaper-based methodology of Baker, Bloom, and Davis [8]. The CPU index captures the monthly share of climate-policy news articles containing uncertainty language—terms indicating delays, reversals, litigation, funding freezes, or regulatory ambiguity—across eight major news outlets indexed by LexisNexis (*Financial Times*, *Wall Street Journal*, *New York Times*, *Washington Post*, *Reuters*, *Bloomberg*, *Politico*, and *The Economist*). Construction follows the standard four-step BBD normalization: scale by outlet volume, standardize per outlet, average across outlets, and normalize so that the sample mean equals 100. The CPU news series covers January 2021 through June 2025 (54 months); June 2025 is imputed as the three-month trailing mean of March–May 2025 because LexisNexis access expired prior to collection of June. The imputed observation is flagged as such in figures and excluded from every correlation calculation.

We correlate this index with deal-level venture financing outcomes from PitchBook—deal count, deal size, and unique-firm count per sector-month—using actual deal dates and venture-class financing events (Seed, Early-Stage VC, Later-Stage VC, and Angel rounds; corporate and private-equity rounds are excluded). The correlation analysis covers the 53 observed months from January 2021

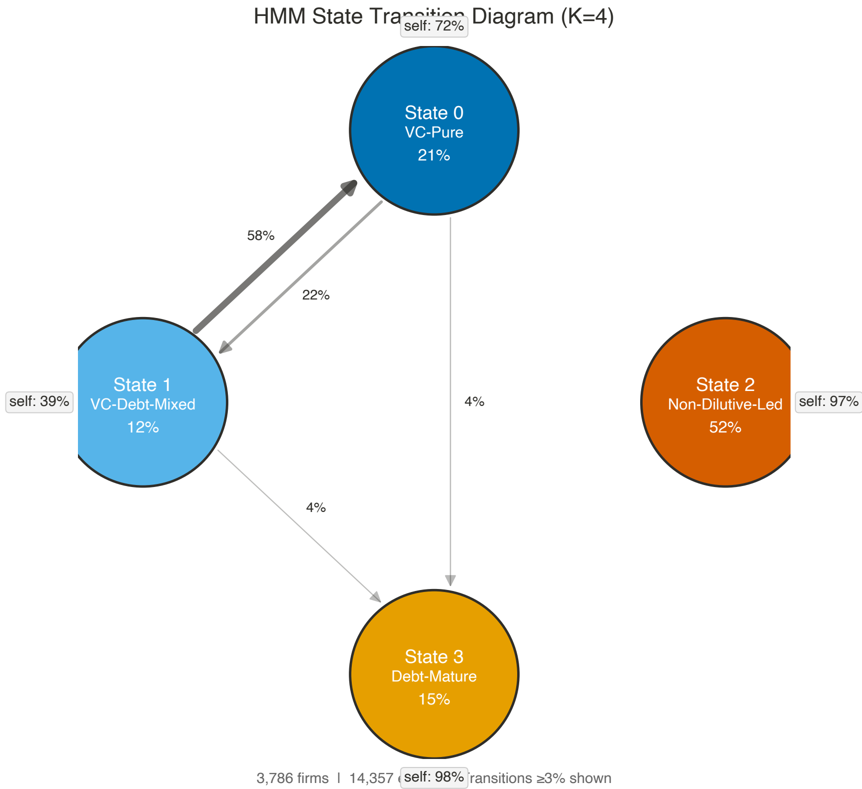

Figure S3: State transition diagram for the four-state hidden Markov model. Nodes represent latent financing regimes, colored by their dominant capital source. Node labels show the regime name and percentage of total events assigned to each state. Directed arrows indicate transition probabilities exceeding 3%; arrow width is proportional to probability. Self-transition probabilities are shown as italic labels outside each node. Sample: 3,786 firms with at least two financing events, 14,357 total events.

through May 2025 (the deal-data export ends 2025-05-31), encompassing 5,363 venture financing events across 3,135 climate technology companies.

S6.2 Decomposition into Implementation and Reversal Uncertainty

We decompose the aggregate CPU index into two components. **Implementation uncertainty** captures news about delays or ambiguity in policy implementation (Treasury guidance, rulemaking, administrative procedures, implementation timeline, regulatory delay, rule finalization, compliance deadline). **Reversal uncertainty** captures news about potential policy repeal or rollback (repeal, rollback, executive-order reversal, legislative challenge, defund, phase out, policy reversal, political opposition). The decomposition is conceptually important because the two types of uncertainty generate opposing predictions: implementation uncertainty may temporarily delay investment while firms await operational clarity but does not threaten the long-run value of policy incentives, whereas reversal uncertainty directly undermines the present value of future policy benefits and should disproportionately affect long-horizon investments.

S6.3 Aggregate Co-Movement

Figure S4 presents the CPU index alongside aggregate VC deal counts. The two series display visible co-movement around major political events: the IRA signing in August 2022 is followed by a sustained increase in deal flow, while subsequent political events that raised doubts about policy durability—most prominently the months surrounding the 2024 presidential election and the 2025 OBBBA legislative proposals—coincide with contractions in deal activity. We report this as a descriptive co-movement pattern; we do not interpret it as a clean causal estimate.

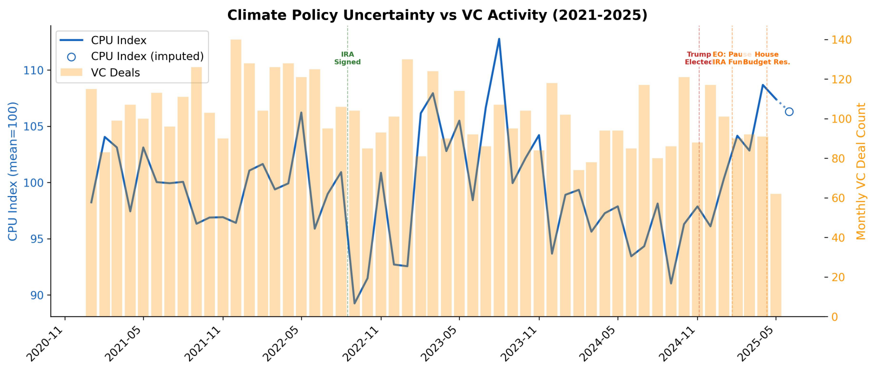

Figure S4: Climate Policy Uncertainty (CPU) index and aggregate VC deal counts, 2021–2025. June 2025 is imputed (open-circle marker) and excluded from every correlation. Key political events annotated.

S6.4 Sector Heterogeneity

We compute CPU–VC correlations across all seven climate technology sectors and three funding metrics (deal count, deal size, unique-firm count). Figure S5 reports the deal-count correlations; full results across all three metrics appear in Table S2 and Figure S8. Two sectors are consistently suppressed across all three metrics: Food & Land Use ($r = -0.41$ on deal count) and Built Environment ($r = -0.27$); Transportation is suppressed on deal count and unique-firm count but mixed on deal size. Carbon is consistently attracted across all three metrics ($r = +0.28$ on deal count, $r = +0.45$ on deal size). The remaining sectors—Energy, Industrial, and Climate Management—exhibit mixed patterns whose sign depends on the metric examined. The mixed patterns are difficult to reconcile with any single mechanism and most likely reflect within-sector heterogeneity in the technologies driving aggregate deal flow over a short observation window.

S6.5 Cross-Correlation Analysis

We compute cross-correlation functions (CCFs) between the CPU index and monthly VC deal counts at integer lags from -12 to $+12$ months:

$$\mathrm{CCF}(\ell) = \mathrm{Corr}(\mathrm{CPU}_t, \mathrm{VC}_{t+\ell}). \tag{S4}$$

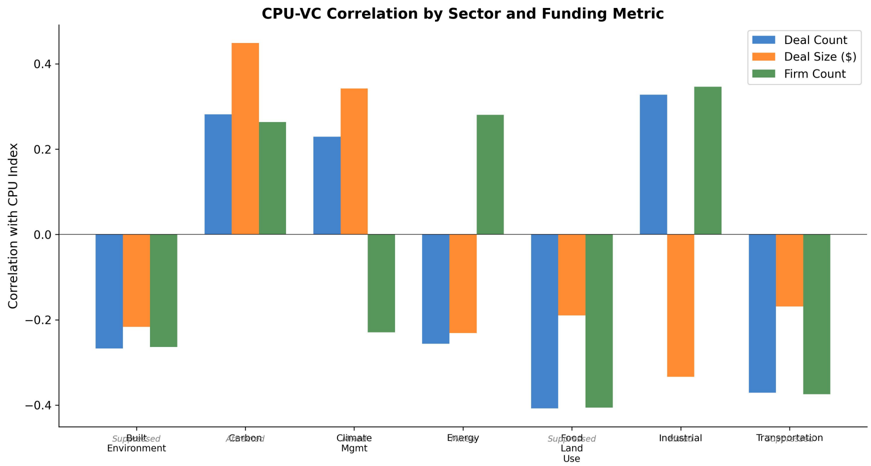

Figure S5: Sector-specific correlation between CPU and three VC funding metrics (deal count, deal size, unique-firm count), 2021–2025, $N = 53$ months. Sample: 3,135 companies, 5,363 venture-class deals.

Negative lags ($\ell < 0$) indicate CPU *leads* VC; positive lags indicate CPU *follows* VC. The lead-lag structure is itself heterogeneous across sectors and metrics rather than reflecting a single common lag (Figure S6): Built Environment exhibits a contemporaneous correlation, Food & Land Use peaks at long negative lags, and Carbon peaks at lags of 7–11 months. Because the optimal lag varies meaningfully and not all signs are consistent with a uniform CPU-leads-VC structure, we interpret these correlograms as descriptive timing evidence rather than identifying any uniform causal lag.

S6.6 Dose-Response by IRA Exposure

If policy dependence drives uncertainty sensitivity, companies with higher IRA exposure should exhibit stronger negative CPU correlations. Companies with high IRA exposure (text-based score ≥ 6; $n = 1{,}784$ companies, 3,053 deals) show a deal-count correlation of $r = -0.31$ with CPU; low-exposure companies (score ≤ 3; $n = 504$ companies, 862 deals) show $r = -0.29$. Both groups are negatively correlated, with the high-exposure group only marginally more sensitive. This pattern is consistent with CPU acting as a broad-based dampener on venture activity in the post-IRA period rather than producing a sign reversal across exposure groups, and is consistent with—but does not independently identify—the credibility channel.

S6.7 Triangulation with PCI

Figure S9 cross-validates the news-based CPU measure against the statutory-text-based PCI. Sectors aligned with high-PCI provisions (e.g., Carbon's reliance on §45Q) tend to exhibit implementation-sensitive CPU correlations, while sectors reliant on lower-PCI discretionary provisions (e.g., LPO funding for parts of Built Environment) tend to exhibit reversal-sensitive correlations. We treat the

Table S2: Sector-Specific CPU–VC Correlations Across Funding Metrics (2021–2025)

Sector	Deal Count	Deal Size ($)	Firm Count	Pattern
Food & Land Use	−0.41	−0.20	−0.41	Suppressed
Built Environment	−0.27	−0.22	−0.27	Suppressed
Carbon	+0.28	+0.45	+0.27	Attracted
Transportation	−0.37	−0.17	−0.37	Mixed (suppressed-leaning)
Industrial	+0.33	−0.34	+0.34	Mixed
Climate Management	+0.23	+0.34	−0.23	Mixed
Energy	−0.26	−0.23	+0.28	Mixed

Note. Pearson correlations between monthly CPU index and sector-specific VC funding metrics, January 2021–May 2025 ($N = 53$ months). Sample: 3,135 companies, 5,363 venture-class deal events (Seed, Early-Stage VC, Later-Stage VC, Angel; corporate and private-equity rounds excluded). June 2025 imputed and excluded from correlations.

agreement between the two measures as supporting evidence consistent with the credibility-channel identification in the main text.

S6.8 Caveats

The political events generating policy uncertainty are not exogenous to broader economic conditions, and we cannot isolate uncertainty effects from contemporaneous macroeconomic factors (notably the 2022–2024 monetary-policy tightening cycle). The 53-month window is short. Two sub-claims weakened relative to a prior company-level specification once we re-ran the analysis on deal-level events with VC-only deal types: a stronger sign-reversal between high- and low-IRA exposure groups, and a clean "flight-to-quality" interpretation in Energy, are not supported in the deal-level analysis and have been removed. We therefore position these patterns as triangulating co-movement evidence rather than primary identification of the credibility channel.

S7 Policy Credibility Index Construction

S7.1 Conceptual Framework

The Policy Credibility Index (PCI) operationalizes credible commitment theory [9, 10] by measuring institutional design features of individual policy provisions. Unlike news-based uncertainty indices that capture market sentiment, PCI scores properties of the statutory and regulatory text itself. This approach follows the policy-mix credibility literature [11, 12], which treats credibility as a measurable design characteristic rather than a latent perception.

S7.2 Dimension Definitions and Scoring Rubric

PCI is constructed from three dimensions, each scored on a 1–5 integer scale:

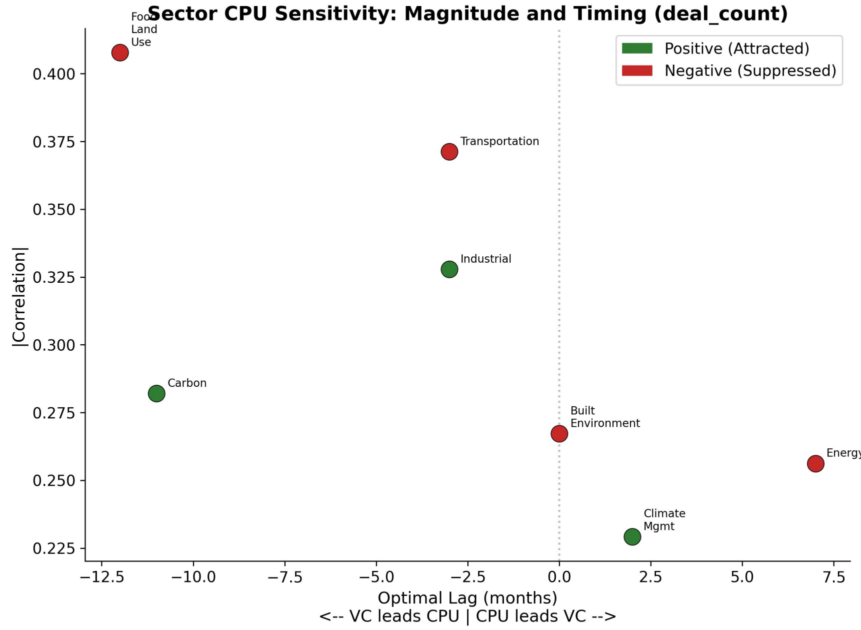

Figure S6: Magnitude and timing of sector-level CPU–VC correlations. Left panel: peak correlation magnitude by sector. Right panel: lead-lag structure (months at which the cross-correlation magnitude is maximized).

Specificity measures the degree to which eligibility criteria and incentive parameters are rule-based versus discretionary.

- 5: Eligibility criteria fully codified in statute with quantitative thresholds; no agency discretion in determining qualification.
- 4: Criteria largely codified but with some parameters delegated to implementing guidance.
- 3: Mix of statutory criteria and agency-determined requirements.
- 2: Broad statutory authorization with substantial agency discretion in eligibility.
- 1: Fully discretionary allocation with no statutory eligibility criteria.

Durability measures the temporal horizon and insulation from political revision.

- 5: Permanent authorization with no sunset provision; embedded in tax code.
- 4: Multi-year statutory horizon ($\geq$10 years) with insulation from annual appropriations.
- 3: Medium-term horizon (5–10 years) or subject to periodic reauthorization.
- 2: Short-term authorization ($<$5 years) or dependent on annual appropriations.
- 1: Single-year funding or subject to annual discretionary allocation.

Enforceability measures the clarity of agency assignment and procedural specification.

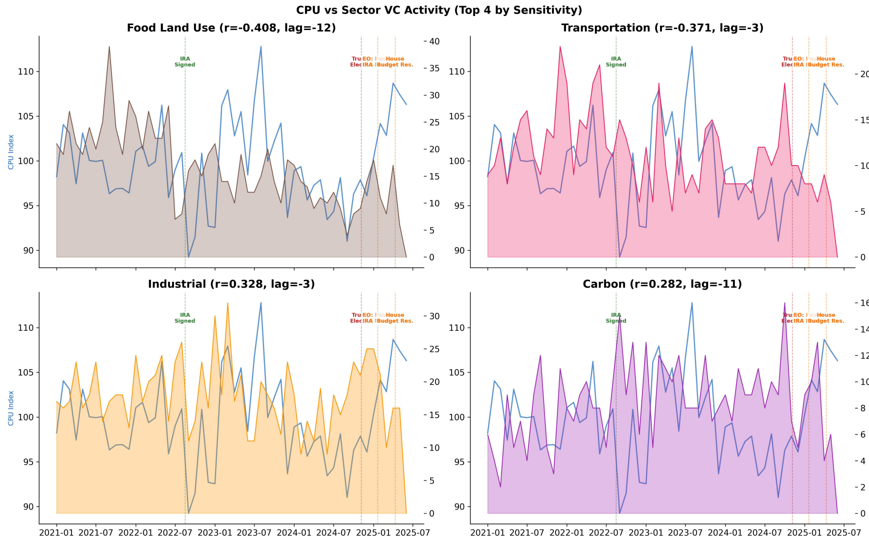

Figure S7: CPU index (rescaled) and sector-level VC deal counts for the most uncertainty-sensitive sectors, 2021–2025.

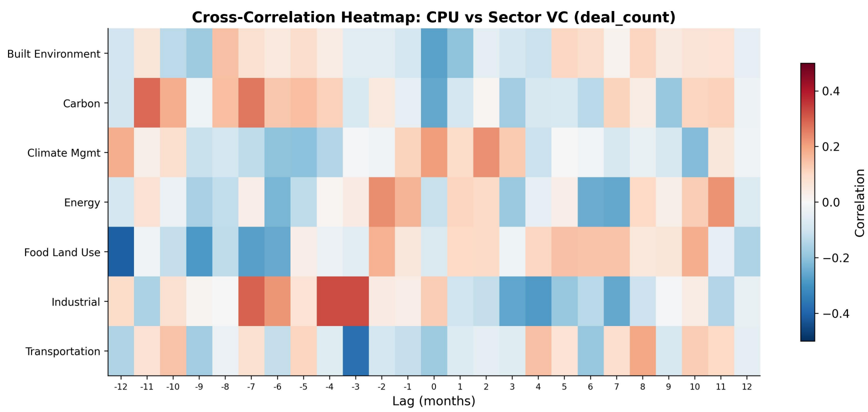

Figure S8: Heatmap of CPU–VC correlations across sectors (rows) and three funding metrics (columns), 2021–2025.

- 5: Single agency with specified procedures; implementation is automatic (e.g., tax credits claimed on returns).
- 4: Clear agency assignment with published guidance; standard administrative process.
- 3: Agency assignment clear but procedures involve multi-step review or interagency coordination.
- 2: Multiple agencies with overlapping jurisdiction; procedures subject to revision.
- 1: No clear agency assignment; implementation depends on executive discretion.

The final PCI for each provision is the simple average of the three dimension scores.

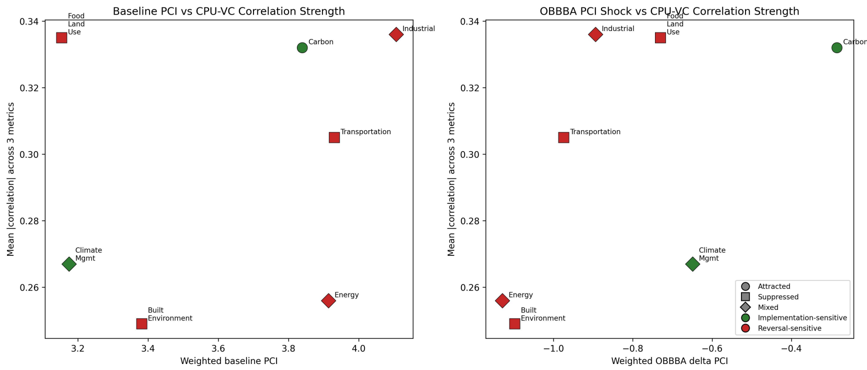

Figure S9: Cross-validation of news-based CPU and statutory-text-based PCI. Sector-average baseline PCI (x-axis) plotted against the absolute CPU–VC correlation magnitude (y-axis).

S7.3 Provision Selection

We score six IRA provisions that collectively span the policy's climate technology incentive structure:

1. **Section 45X** (Advanced Manufacturing Production Credit): Tax credit for domestic production of clean energy components.
2. **Section 45V** (Clean Hydrogen Production Credit): Production tax credit for clean hydrogen based on lifecycle emissions intensity.
3. **Section 45Q** (Carbon Oxide Sequestration Credit): Tax credit for carbon capture, utilization, and storage.
4. **Section 30D** (Clean Vehicle Credit): Consumer tax credit for purchase of qualifying electric vehicles.
5. **Section 50144** (Energy Infrastructure Reinvestment): DOE Loan Programs Office authority for energy infrastructure projects.
6. **Section 50141** (Loan Programs Office Funding): Appropriations for DOE loan guarantee programs.

These provisions were selected because they represent the IRA's primary channels for supporting climate technology development and deployment, spanning tax-based credits (45X, 45V, 45Q, 30D) and appropriations-based programs (50141, 50144).

S7.4 Scoring Protocol

Each provision is scored based on three source categories: (1) the statutory text of the IRA as enacted (Public Law 117-169); (2) implementing guidance issued by the relevant agency (IRS for tax credits; DOE for loan programs); and (3) the regulatory structure governing implementation.

Scoring is performed independently by two researchers and reconciled through discussion. Inter-rater agreement exceeded 85% before reconciliation.

S7.5 OBBBA Credibility Shock Scoring

The 2025 "One Big Beautiful Bill Act" (OBBBA) proposals introduced provision-specific amendments that altered PCI scores. We score each affected dimension based on the proposed legislative text:

- **Section 45X**: Wind component elimination and stricter domestic content requirements reduce Specificity (narrower eligibility) and Durability (conditional on new requirements). ΔPCI $= -1.00$.
- **Section 45V**: Accelerated construction deadline (2027 vs. indefinite) directly reduces Durability. ΔPCI $= -1.00$.
- **Section 30D**: Early termination (September 2025 vs. 2032 sunset) eliminates Durability. ΔPCI $= -1.00$.
- **Section 45Q**: No proposed changes. ΔPCI $= 0.00$.
- **Section 50141**: Rescission of unobligated balances reduces Enforceability. ΔPCI $= -0.67$.
- **Section 50144**: Mission rebranding and revised selection criteria under heightened executive discretion reduce all three dimensions. ΔPCI $= -1.33$.

S7.6 Validation

We assess PCI validity through two checks. First, *internal consistency*: provisions with similar institutional structures receive similar scores (e.g., tax-based production credits 45X, 45V, and 45Q cluster at PCI ≥ 4.33, while appropriations-based LPO programs cluster at PCI ≤ 3.33). Second, *event sensitivity*: PCI scores respond meaningfully to major policy events—the OBBBA proposals produce heterogeneous ΔPCI values that align with the specific statutory changes proposed for each provision, rather than applying uniform changes.

S7.7 Blind LLM Re-Scoring

As an external check on the hand-coded scores, we re-scored all six provisions with large-language-model judges under a blind protocol. Two models of different scale (Claude Sonnet 4.6 and Claude Haiku 4.5) each scored every provision three times at provider-default sampling settings; we aggregate by the median across runs and judges. The judges received only the scoring rubric reproduced above and neutral provision descriptions drawn from Congressional Research Service Report R47262, supplemented with statutory facts (citation, mechanism, duration, implementing agency, appropriations status). Prompts did not mention this study, its hypotheses, venture capital, the term "credibility," or the hand-coded scores, and the judges ran in an isolated environment with no access to project materials. Each judge scored each provision under two conditions: as enacted, and as it would stand under the 2025 OBBBA amendments, described factually. The difference between conditions yields a within-judge Δ for each provision, and the unamended 45Q provision serves as a placebo.

Agreement with the hand-coded scores is high. At the dimension level, all 18 LLM median scores fall within one point of the hand-coded values (exact agreement 39%; mean absolute difference 0.56). At the provision level, the LLM-implied index reproduces the hand-coded ranking (Spearman $\rho = 0.86$) and places all four tax-credit provisions above both Loan Programs Office provisions, the qualitative hierarchy on which the credibility analysis relies. In the OBBBA condition the judges recover the direction of every shock: all five amended provisions receive negative Δ and the 45Q placebo receives $\Delta = 0.00$. The ranking of shock magnitudes aligns with the hand-coded ΔPCI (Spearman $\rho = 0.83$), with the judges assigning uniformly smaller magnitudes (medians between -0.17 and -0.67, versus -0.67 to -1.33 hand-coded). The empirical analyses use ΔPCI for classification and ordering rather than as a cardinal regressor, so the agreement in direction and ranking is the relevant standard. Prompts, scripts, and raw judge outputs are included in the replication archive.

S8 Additional Results

S8.1 Event-Study Estimates Across Designs

We estimate event-study specifications following equation (S3) for all three outcome variables (AnyVC, VC_Deal_Count, VC_Amount_Sum) under the binary treatment design. Across all outcomes, pre-trend coefficients are small and statistically insignificant, supporting the parallel trends assumption; the continuous IRA-Index event study reported in the main text (Figure 1) is representative of the full set. Full coefficient estimates are available in the replication archive.

S8.2 Cash-Flow Channel: Text-Based Exposure S_c (Moved from Main Text)

S8.3 Alternative Exposure Designs

We additionally report results using the BERTopic-based cosine similarity measure, which provides an independent and fully unsupervised measure of policy alignment. The BERTopic-based results yield qualitatively similar patterns: higher topic-level alignment with IRA focus areas is associated with stronger post-IRA increases in VC financing.

S8.4 Heterogeneity by Firm Age

We examine whether the IRA's effects vary with firm age by interacting the treatment variable with firm age at the time of enactment. Younger firms (those founded more recently) exhibit stronger

Table S3: Difference-in-Differences Estimates: Cash-Flow Channel (Text-Based Policy Alignment S_c)

	AnyVC			*VC Deal Count*			*VC Amount Sum*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post$\times S_c$	0.002***	0.002***	0.003***	0.002***	0.002***	0.003***	0.137***	0.147***	0.122**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.037)	(0.038)	(0.057)
Post	0.001			0.001			-0.308***		
	(0.001)			(0.001)			(0.093)		
S_c	-0.004***	-0.004***		-0.004***	-0.004***		-0.023	-0.025	
	(0.001)	(0.001)		(0.001)	(0.001)		(0.063)	(0.063)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes
R^2	0.056	0.038	0.000	0.055	0.038	0.000	0.004	0.002	0.000
Obs.	132,826	132,826	132,826	132,826	132,826	132,826	132,826	132,826	132,826

Note. Text-based exposure score S_c measures semantic alignment between firm descriptions and IRA statutory language. Higher values indicate technologies more directly targeted by IRA incentive provisions. Standard errors clustered at firm level. *, **, *** denote significance at 10%, 5%, 1% levels.

treatment effects, consistent with the interpretation that policy incentives are most consequential for firms in earlier stages of development, where external financing constraints are more binding.

S8.5 Heterogeneity by Energy Sector

Among treated firms, we test whether effects differ for the Energy sector (which benefits from the broadest set of IRA provisions) relative to the Carbon sector. Energy firms show somewhat larger and more precisely estimated effects, consistent with the broader scope of production and investment tax credits available to clean energy technologies compared to the more targeted carbon capture provisions.

S8.6 Matched-Sample Difference-in-Differences (Coarsened Exact Matching)

To address the possibility that treated and control firms differ on observable baseline characteristics, we re-estimate the main specifications on a matched sample constructed via coarsened exact matching (CEM). Firms are matched within strata defined by (i) firm age at IRA enactment (coarsened into bins of 0, 1–5, 6–10, 11–20, 21+ years), (ii) a hardware indicator derived from the semantic classification (Energy, Carbon, Industrial, and Built Environment coded as hardware), and (iii) pre-IRA cumulative VC financing (binned as 0, \$0–1M, \$1–10M, \$10–100M, >\$100M). This procedure yields 5,780 matched firms (79.5% of the full sample) across 20 valid strata with common support on all three dimensions.

Re-estimating the binary and TF-IDF exposure specifications on the matched sample yields coefficients of the same sign and similar order of magnitude as the full-sample estimates, though attenuated in the binary specification. The attenuation is consistent with CEM removing comparisons across firms whose baseline characteristics differ substantially—a set for which the binary treatment absorbs compositional differences in addition to the policy effect. The continuous TF-IDF specification, which exploits within-category variation in policy alignment, shows very modest attenuation. This pattern is consistent with the interpretation that continuous exposure measures are more informative about the underlying treatment effect than binary sector assignments, and it motivates our decision to lead with the continuous specifications in the main text.

S8.7 SUTVA and Control-Group Trends

A standard concern in difference-in-differences designs is the Stable Unit Treatment Value Assumption (SUTVA): the outcome for a control firm should not depend on the treatment status of other firms. Although SUTVA is not directly testable, differential pre-trends or contamination can be probed by examining the quarterly evolution of outcomes for treated and control firms separately.

Examining the quarterly share of firms in each group that receive venture capital from Q1 2020 through Q2 2025, we find that pre-IRA both groups exhibit similar variation around their respective means without systematic divergence. Post-IRA, treated firms' quarterly VC rate stabilizes around 3.3–4.0%, while the control group declines modestly from its 2021 peak but remains within its pre-IRA range. During the OBBBA quarters (Q1–Q2 2025), treated firms drop from 3.9% to 2.5% (a 36% decline), while control firms decline from 4.5% to 3.6% (a 20% decline). The larger contraction among treated firms during OBBBA provides a descriptive counterpart to the DiD estimates reported in the Credibility section and is not explained by aggregate trends in the control group.

S8.8 Horizon-Dependence and Capital Intensity

The credibility channel predicts that firms with longer commercialization horizons—typically capital-intensive hardware firms—should exhibit stronger responses to changes in policy credibility. We test this prediction by interacting the TF-IDF exposure measure S_c with a capital-intensity indicator (equal to one for firms classified as Energy, Carbon, Industrial, or Built Environment, and zero otherwise; this group comprises 71% of the sample).

Contrary to the simple horizon prediction, the triple interaction Post $\times$ S_c $\times$ CapitalIntensive is *negative* and statistically significant ($\hat{\beta} = -0.0061$, SE $= 0.0024$, $p < 0.05$ for AnyVC; -0.0066, SE $= 0.0025$, $p < 0.05$ for VC deal count), implying that capital-intensive firms exhibit a *smaller* post-IRA VC response per unit of exposure than lighter asset-class firms. We interpret this pattern cautiously. One interpretation is that policy incentives first translate into VC flows through firms whose commercialization pathways are shorter and whose teams can respond quickly to new market signals (e.g., software-enabled climate solutions, analytics platforms, distributed energy resources), with capital-intensive hardware firms responding with longer lags that are partially outside our observation window. A second interpretation is that capital-intensive firms already receive a larger share of their financing through non-venture channels (project finance, debt, government loan programs), so IRA-driven changes in the venture margin are mechanically smaller for this group.

Both interpretations are consistent with the broader evidence in the paper; distinguishing them requires longer time series and is left to future work.

S8.9 Within-Credibility Provision Comparison

The PCI framework predicts that provisions with higher institutional credibility should mobilize more venture capital, holding incentive levels constant. We test this by mapping each firm to its closest IRA provision using BERTopic–provision cosine similarity, grouping provisions into credibility tiers, and interacting each tier with the Post-IRA indicator.

The high-credibility tier includes tax-based production credits (45X Advanced Manufacturing, 45V Clean Hydrogen) and investment credits with well-defined eligibility (45Q Carbon Capture, 48C Advanced Energy Project). The medium-credibility tier includes consumer-facing credits with simpler compliance but greater political exposure (30D Clean Vehicle). The low-credibility tier includes programs dependent on discretionary appropriations or grant allocation (Loan Programs Office, agricultural and environmental programs).

Across 6,891 firms with provision assignments, production credits (45X, 45V, and renewable electricity credits in 13101/13302) are associated with a positive post-IRA increase in VC investment amounts ($\hat{\beta} = 0.27$, SE = 0.16, $p < 0.10$), while firms aligned with carbon capture (45Q) exhibit a negative extensive-margin effect ($\hat{\beta} = -0.011$, SE = 0.006, $p < 0.10$ for AnyVC), consistent with 45Q's longer commercialization timelines and political contestation relative to more-established renewable energy credits. Differences across provision types are imprecisely estimated given the short observation window, but the ordering—production credits above carbon capture—aligns with the credibility ordering implied by PCI scores.

S9 Summary Statistics

Table S4 reports summary statistics for the key outcome and control variables in the analysis panel, stratified by treatment status.

Table S4: Summary Statistics

	Treated (Energy & Carbon)			Control (Other Climate Tech)		
Variable	Mean	SD	N	Mean	SD	N
AnyVC	0.033	0.179	57,518	0.042	0.201	75,308
VC_Deal_Count	0.034	0.183	57,518	0.043	0.206	75,308
VC_Amount_Sum ($M)	0.565	12.204	57,518	0.678	14.288	75,308
CompanyAge (years)	4.691	3.293	57,518	4.694	3.173	75,308
IRA_Index	6.214	1.336	57,518	4.547	1.665	75,308
S_c	0.514	0.893	57,518	−0.331	0.930	75,308
Panel dimensions						
Firms		3,207			4,064	
Quarters		22			22	
Firm-quarters		57,518			75,308	

Note. Summary statistics for treated (Energy and Carbon categories) and control (remaining climate technology categories) firms. Sample spans Q1 2020–Q2 2025 (22 quarters). VC_Amount_Sum reported in millions of USD. IRA_Index ranges from 0–7 (higher indicates stronger policy alignment). S_c is the standardized text-based exposure score centered at zero. Total sample: 7,271 firms, 132,826 firm-quarter observations.

S10 Climate Technology Taxonomy

Table S5 presents the full CTVC taxonomy used to classify climate technology firms. The seven primary categories and their subcategories are listed below.

Table S5: Climate Technology Taxonomy (CTVC)

Primary Category	Subcategory	IRA Exposure
Energy	Clean Power Generation	Direct
	Distributed Energy Resources	Direct
	Hydrogen	Direct
	Energy Storage	Direct
	Grid Management	Direct
Carbon	Carbon Removal & Storage	Direct
	Carbon Utilization	Direct
	Point-source Carbon Capture	Direct
	Carbon Offsets/Marketplaces	Indirect
	MRV and Ratings	Indirect
Industrial	Steel, Cement, Chemicals	Indirect
	Efficient Manufacturing	Indirect
	Metals and Mining	Indirect
	Circular Economy	Minimal
	Waste and Recycling	Minimal
Built Environment	Building Materials	Indirect
	Heating and Cooling	Indirect
	Energy Efficiency	Indirect
	Construction	Minimal
Transportation	Electric Autos	Indirect
	Batteries	Indirect
	Micromobility	Minimal
	Zero-emission Aviation & Shipping	Indirect
	Low-carbon Fuels	Indirect
Food & Land Use	Alternative Protein	Minimal
	Regenerative Agriculture	Indirect
	Sustainable Fertilizers	Minimal
	Nature Restoration	Minimal
	Food Waste	Minimal
Climate Management	Earth Observation	Minimal
	Climate Risk	Minimal
	Emissions Tracking	Minimal
	Emissions Accounting	Minimal
	ESG Investing & Fintech	Minimal

Note. Primary categories and subcategories from the CTVC taxonomy. IRA Exposure indicates the degree of direct statutory support: "Direct" denotes explicit eligibility for major tax credits or subsidies; "Indirect" denotes partial or conditional support; "Minimal" denotes limited or no direct IRA targeting.

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