

# Whether industrial policy mobilizes private capital depends on the credibility of its commitments

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Governments struggle to make long-term commitments. Because today's policy can be revised by future legislatures and administrations, private investors may discount even generous public incentives, and the investment those incentives target may never materialize. We study this commitment problem in the U.S. Inflation Reduction Act (IRA), which directed approximately \$369 billion toward climate and energy. Using financing histories for 7,271 climate-technology firms across 132,826 firm-quarter observations (Q1 2020–Q2 2025), we find that the IRA shifted venture investment toward firms whose technologies align most directly with statutory incentives and changed how firms finance growth: reliance on mixed venture–debt structures declined, while venture-only and non-dilutive financing expanded. To examine why, we introduce a Policy Credibility Index that scores each IRA provision on the specificity, durability, and enforceability of its commitment. Investment responds to both the size of incentives and the credibility of the commitment behind them. The 2025 “One Big Beautiful Bill” proposals offer a sharper test, because they threatened the durability of some provisions while leaving enacted incentives in force; venture activity contracted most in the sectors that depend on the threatened provisions. The results point to a market channel of policy feedback operating alongside the electoral one. Whether public commitments draw in private capital, and with it a constituency for the policy's survival, depends on how the commitment is built.

industrial policy | policy credibility | policy feedback | venture capital | climate technology

Democratic governments face a familiar commitment problem: policies adopted today can be revised by the next coalition, so promises of long-term support may fail to move the investment they are meant to attract (1–4). The problem is acute in climate policy. Decarbonization requires private capital committed over horizons longer than electoral cycles (5, 6), and U.S. federal climate commitments have repeatedly been contested and revised across administrations (7, 8). Commercializing new climate technologies depends heavily on early-stage investors who supply patient capital under deep uncertainty (9, 10), and the value of their investments often rests on policy holding for a decade or more. When the United States enacted the Inflation Reduction Act (IRA), directing approximately \$369 billion toward climate and energy, it was therefore not obvious that investors would treat those commitments as durable.

## Significance

Governments promise long-term support to steer private investment, but those promises can be revised by future legislatures and administrations. Studying the Inflation Reduction Act, we show that where private capital moved depended on the credibility of each provision: its specificity, durability, and enforceability. When 2025 legislative proposals threatened to roll back particular provisions, investment fell in the sectors that relied on them, even though the enacted benefits were still in force. Recent work finds that clean-energy investments win policymakers little credit from voters. We identify a second feedback channel: credible commitments recruit investors whose capital is staked on a policy's survival. Durable design, as much as spending, is what mobilizes private capital.

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123 Political scientists have long argued that major statutes  
124 can entrench themselves by creating constituencies in-  
125 vested in their survival (11). Recent evidence suggests  
126 the electoral version of this mechanism is weak for clean-  
127 energy policy: voters notice IRA-funded projects but  
128 do not credit the policymakers responsible (12). We  
129 examine a different channel. Investors, unlike voters,  
130 price policy durability directly, and institutional design is  
131 known to shape support for climate commitments among  
132 mass publics (13). Whether design shapes the behavior  
133 of capital has not been measured. A large literature  
134 documents industrial policy's effects on innovation and  
135 sectoral growth (14–19), and separate work shows how  
136 venture capital responds to market opportunities and  
137 institutional uncertainty (20–23). What neither literature  
138 provides is a measure of commitment credibility at the  
139 level where it operates, the individual statutory provision,  
140 or evidence on which provisions investors believe and what  
141 happens when a commitment comes under threat.

142 The IRA offers an unusually sharp setting in which to  
143 measure this. One of the largest climate-related industrial  
144 policy initiatives globally (24, 25), it introduced a compre-  
145 hensive set of tax credits, subsidies, and incentives target-  
146 ing a broad range of climate technologies, including clean  
147 energy generation, energy storage, electrification, and  
148 industrial decarbonization. By linking financial incentives  
149 to specific technological activities, the IRA altered the  
150 expected returns and risk profiles of private investments  
151 in these domains. Compared with similar programs in the  
152 EU, South Korea, and Japan, the IRA relies more heavily  
153 on technology-specific tax credits with long statutory  
154 horizons and automatic implementation through the tax  
155 code. These features generate sharp variation in how  
156 directly different technologies are supported, and they  
157 make policy commitments empirically tractable. The scale,  
158 scope, and institutional design of the IRA thus create a  
159 rare opportunity to examine how a large, clearly defined  
160 policy intervention reshapes venture capital decisions in a  
161 high-uncertainty technological environment.

162 Using firm-level venture capital financing data covering  
163 7,271 climate technology companies across 132,826 firm-  
164 quarter observations spanning 22 quarters (Q1 2020–  
165 Q2 2025), we examine how the IRA affected venture  
166 investment across three dimensions. First, we study  
167 whether policy increased the likelihood that firms receive  
168 venture funding—the initial decision to invest. Second,  
169 we examine how investment shifts across technologies and  
170 investor types, revealing changes in the composition of  
171 capital rather than only its aggregate level. Third, we  
172 analyze firms' financing trajectories over time, assessing  
173 whether policy alters the mix of capital sources that fund  
174 climate firms across successive financing events. This  
175 dynamic perspective captures how policy shapes longer-  
176 run growth pathways. We make three contributions.  
177 First, we introduce the Policy Credibility Index (PCI),  
178 which scores IRA provisions on specificity, durability,  
179 and enforceability. The index operationalizes credible-  
180 commitment theory at the level of the individual provision.  
181 Second, we use the 2025 legislative proposals to roll back  
182 IRA provisions as a commitment-reversal test. Those  
183 proposals shifted credibility while enacted incentives  
184 remained in force, and investment contracted in the sectors  
185 that depend on the threatened provisions, a pattern  
186 consistent with a credibility channel distinct from cash

187 flow. Third, we show that policy reshaped the structure  
188 of climate finance: which technologies and investors  
189 capital reaches, and the mix of venture, debt, and non-  
190 dilutive funding that firms rely on. We read this as a  
191 market channel of policy feedback operating alongside the  
192 electoral channel.

## 193 Results

194 **IRA and venture capital entry.** To measure policy exposure at  
195 the technology level, we use the Climate Tech Venture  
196 Capital (CTVC) taxonomy, which classifies climate tech-  
197 nology firms into seven mutually exclusive subfields based  
198 on their primary technological focus. We classify a subfield  
199 as *directly targeted* by the IRA when at least one of the  
200 six focal provisions (45X, 45V, 45Q, 30D, 50141, 50144)  
201 designates the subfield's core technology development as  
202 the primary eligible activity. By this rule, two subfields  
203 are directly targeted. *Energy* captures the production-side  
204 credits that anchor the IRA's manufacturing push (45X  
205 for solar, wind, and battery components; 45V for clean  
206 hydrogen) together with Loan Programs Office authorities  
207 for energy infrastructure (50141, 50144), and *Carbon*  
208 captures the 45Q carbon-capture credit. The remaining  
209 five subfields (*Climate Management, Industrial, Food*  
210 *and Land Use, Built Environment, and Transportation*)  
211 are comparatively less exposed: IRA support for these  
212 technologies is absent, indirect, or channeled through  
213 downstream adoption rather than core-technology devel-  
214 opment.

215 The Transportation subfield warrants explicit treat-  
216 ment because it is home to the IRA's most visible  
217 provision, the Section 30D clean-vehicle tax credit. We  
218 classify Transportation as less-exposed for two reasons.  
219 First, 30D is an *adoption-side* rebate: it subsidizes end-  
220 user purchases of already-commercial electric vehicles and  
221 does not directly reduce the venture-stage technology  
222 risk that shapes early-stage investment decisions. This  
223 distinguishes it from 45X and 45V, which are *production-*  
224 *side* credits that change per-unit unit economics for  
225 upstream manufacturers. Second, upstream EV-relevant  
226 firms (battery manufacturers, advanced materials, power  
227 electronics, charging infrastructure) are classified as  
228 Energy in the CTVC taxonomy and are therefore already  
229 in the treated group; the Transportation residual in our  
230 panel consists primarily of mobility software, logistics,  
231 and autonomous-vehicle firms whose core technologies  
232 are not IRA-eligible. To verify that this classification  
233 choice does not drive our results, we re-estimate the main  
234 specification reclassifying Transportation as treated (*SI*  
235 *Appendix, Section S8*); the estimated treatment effects  
236 attenuate modestly (AnyVC: 0.0086 → 0.0079; VC deal  
237 count: 0.0090 → 0.0081; VC amount sum: 0.385 →  
238 0.298) but remain statistically significant, consistent with  
239 Transportation being, on balance, a less-exposed subfield  
240 diluted by a small number of upstream-EV firms.

241 We use this distinction to construct a binary policy  
242 exposure design, classifying firms in the Energy and  
243 Carbon subfields as treated and firms in the remaining  
244 climate technology categories as controls. This approach  
245 exploits systematic variation in statutory targeting across  
246 climate technologies while holding constant broader sec-  
247 toral trends, enabling a transparent comparison between  
248 policy-aligned and less-aligned technologies within the  
249  
250

climate tech ecosystem. We note that treated and control categories may differ in baseline VC affinity, available capital pools, and investor familiarity; our specifications address this through firm fixed effects that absorb time-invariant differences across categories, and we verify robustness using the continuous exposure measures that exploit within-category variation (Table 2 and *SI Appendix*).

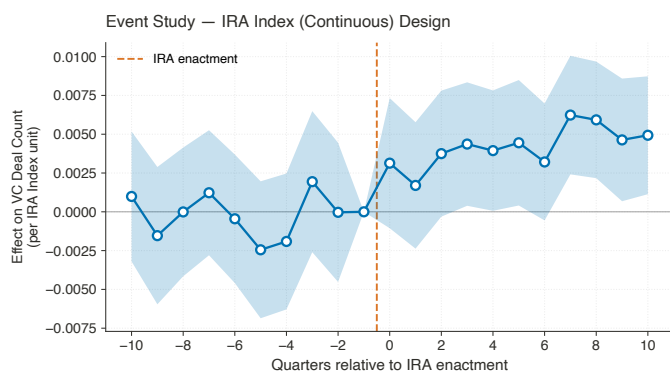
Our empirical approach compares changes in venture capital activity for technologies directly targeted by IRA incentives against changes for technologies in the same climate sector that were less directly supported. By examining both groups over the same time period, this design isolates the effect of policy targeting from broader trends, such as macroeconomic shifts or the post-pandemic venture capital cycle, that affected all climate technologies simultaneously.

We begin by examining how the IRA affected venture capital entry into U.S. climate technology firms. Focusing on the extensive margin (whether a firm receives any venture capital in a given quarter), we ask whether firms in technologies directly exposed to IRA incentives became more likely to receive venture financing after enactment. This margin captures the initial decision to invest, which is particularly consequential for early-stage and high-uncertainty technologies (26, 27).

Figure 1 presents event-study estimates under the continuous IRA-Index design, comparing venture deal activity for firms in policy-exposed technologies with those in less-exposed climate technology categories. Prior to the IRA, estimated coefficients are small and statistically indistinguishable from zero, providing no evidence of differential pre-trends between the two groups and supporting the validity of the identification strategy. Following the enactment of the IRA, however, firms in exposed technologies experience a sustained increase in venture deal activity. The effect emerges within one to two quarters after enactment and persists over subsequent periods, indicating a durable shift in investment behavior rather than a transitory response. The approximately three-to-six-month lag is consistent with the time required for investors to evaluate new policy provisions, adjust due diligence processes, and advance deals through funding pipelines, and aligns with prior evidence that corporate investment responds to policy-uncertainty shocks with a one- to two-quarter delay (28, 29). The corresponding binary-treatment event study yields a quantitatively similar pattern (*SI Appendix*, Section S8).

Table 1 corroborates these dynamic patterns using difference-in-differences specifications (30, 31). Across multiple model specifications with progressively richer fixed effects, exposure to the IRA is associated with a higher likelihood of receiving venture capital, an increase in the number of venture deals, and higher total investment amounts. These effects remain stable when firm and time fixed effects are included. Time fixed effects absorb aggregate investment trends, including the deployment of capital raised by the wave of new VC firms entering between 2018 and 2023. Such pent-up dry powder would flow to treated and control technologies alike, so the exposure-based design differences it out rather than confounding the policy effect.

The increase in venture capital entry is not uniform across the climate technology sector. The estimated effects



**Fig. 1.** Event-study estimates of the IRA’s effect on venture deal activity (VC\_Deal\_Count) under the continuous IRA Index design. Each coefficient represents the interaction of an event-time indicator with the firm’s IRA alignment score, relative to the omitted baseline period ( $t = -1$ ). Vertical bars indicate 95% confidence intervals. The dashed vertical line marks the policy enactment quarter.

are concentrated in technologies most closely aligned with the IRA’s incentive structure, particularly capital-intensive applications such as clean energy generation and carbon capture. We observe little change in entry rates for firms in adjacent or weakly exposed technologies. In one sense this validates the policy’s targeting: investors responded to the incentives as intended. The selectivity is also informative in its own right, because it indicates that the IRA changed investors’ screening and selection decisions rather than producing a broad expansion of venture investment.

Together, these findings provide causal evidence that large-scale industrial policy influences the likelihood that firms attract venture capital financing. The IRA did not simply raise overall investment activity; it reshaped the economics of targeted technologies. In some cases it lowered venture-stage entry barriers, in others it reduced lifecycle capital requirements or improved after-tax unit economics. These shifts set the stage for the reallocation and dynamic effects examined below.

**Policy intensity and graded investment responses.** The binary estimates establish that venture capital entry increased following the IRA for technologies directly exposed to policy incentives. We next examine whether these effects vary with the *intensity* of policy exposure. Rather than treating exposure as a discrete classification, we construct a continuous IRA exposure index that captures the degree to which a firm’s technological focus aligns with the policy’s incentive provisions.

The IRA exposure index is constructed using a supervised text-based classification approach (32). For each company, the index scores the alignment between the firm’s business description and each IRA provision on a 0–7 scale, using a large language model prompted against the statutory language of the IRA (see *SI Appendix*, Section S3.2 for full construction details). The final index is the maximum alignment score across all evaluated provisions. This continuous measure captures within-category heterogeneity that the binary classification cannot: 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.

**Table 1. Difference-in-Differences Estimates for Venture Financing Outcomes (Binary Treatment)**

	AnyVC			VC Deal Count			VC Amount Sum		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post×Treated	0.007*** (0.001)	0.010*** (0.002)	0.009*** (0.002)	0.007*** (0.001)	0.011*** (0.002)	0.009*** (0.002)	-0.038 (0.079)	0.336*** (0.099)	0.385*** (0.128)
Post	-0.003* (0.002)			-0.003** (0.002)			-0.461*** (0.126)		
Treated	-0.009*** (0.002)	-0.011*** (0.002)		-0.010*** (0.002)	-0.012*** (0.002)		-0.295* (0.161)	-0.280* (0.162)	
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 <sup>2</sup>	0.056	0.034	0.003	0.055	0.034	0.003	0.004	0.003	0.000
Obs.	132,826	132,826	132,826	132,826	132,826	132,826	132,826	132,826	132,826

**Note.** Columns (1)–(3), (4)–(6), and (7)–(9) report estimates for *AnyVC*, *VC Deal Count*, and *VC Amount Sum*, respectively. Specification (1)/(4)/(7) includes controls only; (2)/(5)/(8) adds time fixed effects; (3)/(6)/(9) further adds firm fixed effects. Controls include firm age and indicator controls for ownership and region categories (as constructed in the panel). Models are estimated using `PanelOLS`. Standard errors clustered at the firm level are reported in parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 2. Difference-in-Differences Estimates for Venture Financing Outcomes (IRA Index Intensity)**

	AnyVC			VC Deal Count			VC Amount Sum		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post×IRA_Index	0.001*** (0.000)	0.004*** (0.000)	0.004*** (0.001)	0.001*** (0.000)	0.004*** (0.000)	0.004*** (0.001)	-0.022* (0.012)	0.138*** (0.029)	0.066* (0.038)
Post	-0.014*** (0.004)			-0.015*** (0.004)			-0.986*** (0.217)		
IRA_Index	-0.002*** (0.000)	-0.004*** (0.001)		-0.002*** (0.000)	-0.004*** (0.001)		0.005 (0.038)	0.041 (0.057)	
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 <sup>2</sup>	0.056	0.021	0.018	0.055	0.020	0.018	0.004	-0.003	0.001
Obs.	132,826	132,826	132,826	132,826	132,826	132,826	132,826	132,826	132,826

**Note.** Columns (1)–(3), (4)–(6), and (7)–(9) report estimates for *AnyVC*, *VC Deal Count*, and *VC Amount Sum*, respectively. The treatment intensity is the continuous IRA exposure index. Specification (1)/(4)/(7) includes controls only; (2)/(5)/(8) adds time fixed effects; (3)/(6)/(9) further adds firm fixed effects. Controls include firm age and indicator controls for ownership and region categories (as constructed in the panel). Models are estimated using `PanelOLS`. Standard errors clustered at the firm level are reported in parentheses. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

To quantify how closely each company’s technological focus aligns with IRA incentive provisions, we measure the semantic similarity between each firm’s business description and the statutory language of each IRA provision. This computational approach weighs words by how distinctive they are across documents (common words receive low weight, technology-specific terms high weight), producing a continuous alignment score that captures finer-grained variation than the binary treated/control classification alone.

Table 2 reports difference-in-differences estimates using this continuous exposure measure. Across specifications, higher IRA exposure is associated with a larger post-policy increase in venture capital entry, deal counts, and investment amounts. The estimated coefficients remain positive and statistically significant after the inclusion of time and firm fixed effects, indicating that the results are not driven by aggregate investment cycles or time-invariant firm characteristics.

The presence of a graded response strengthens the causal interpretation of the policy effects. Rather than a

uniform shift affecting all exposed firms equally, venture investment increases more strongly for firms whose technologies are more closely aligned with the IRA’s incentive structure. This pattern is difficult to reconcile with explanations based solely on broad macroeconomic trends, contemporaneous shocks such as interest rate changes, or the post-pandemic technology investment cycle. If these aggregate factors were driving the results, we would expect uniform effects across technology categories rather than a dose-response relationship tied to policy alignment. The graded pattern instead suggests that investors respond to economically meaningful variation in the degree of policy support, consistent with a direct policy mechanism.

The continuous treatment results are also consistent with the binary treatment estimates in Table 1. Both approaches identify a selective policy effect concentrated in technologies most directly aligned with IRA incentives. The continuous measure adds that, even within treated categories, firms with stronger policy alignment respond more. This reinforces the causal reading and gives finer-grained evidence on how policy affects capital allocation.

**Dynamic financing trajectories.** The preceding analyses focus on whether and how much capital flows to policy-exposed firms. We now ask how the policy changed the way firms finance growth: the mix of instruments behind their financing events. We classify every financing event in the sample into observable phases using PitchBook deal classifications: accelerator and grant support, angel investment, seed rounds, early- and later-stage venture rounds, growth and private-equity investment, corporate investment, and debt (17,765 events across 7,194 firms; *Materials and Methods*).

Table 3 (panel A) compares the composition of financing events before and after the IRA. Venture rounds rise from 30.6% to 38.1% of events, with gains at every stage: seed (10.0% to 11.9%), early-stage (8.1% to 10.4%), and later-stage (12.5% to 15.8%). Accelerator and grant support rises from 32.8% to 35.6%. Debt moves the other way, falling from 17.6% to 8.3% of events, while corporate and growth-equity shares are roughly flat.

The same shift appears at the firm level (Table 3, panel B), where it speaks directly to how firms combine instruments. Among firms with at least one venture round in a given window, the share financing exclusively through venture rounds rose from 48.2% to 56.9%, while the share that also used debt fell from 16.2% to 5.5%. The share combining venture rounds with accelerator or grant support was essentially unchanged (32.1% to 32.2%). The contraction is therefore specific to the venture–debt combination rather than to hybrid financing in general.

Transitions between consecutive events tell the same story. The probability that a later-stage venture round is followed by a debt deal halved after the IRA (14.9% to 7.7%). Stage progression strengthened: the probability that an early-stage round is followed by a later-stage round rose from 11.9% to 18.6%, while seed-to-early progression was little changed (21.2% to 19.4%). Debt became increasingly confined to debt-reliant firms, with the probability that a debt event is followed by another debt event rising from 24.0% to 54.7%.

This reallocation is consistent with two complementary mechanisms. First, the IRA’s tax credits (Sections 45X, 45V, 45Q, 30D) and grant programs reduce policy-aligned firms’ need for debt complementarity: the present value of statutory incentives partially substitutes for project- and working-capital debt, allowing firms to finance growth through equity rounds alone. Second, the IRA’s grant and loan-program authorities (Sections 50141 and 50144) directly expand the pool of non-dilutive capital available to climate-technology firms. Two caveats apply. Shares are computed over deal counts rather than dollars, and debt deals are larger on average, so the dollar composition shifts less sharply than the event composition. And the post-2022 rise in interest rates raised the cost of debt for all firms; the time pattern alone cannot separate the policy contribution from the rate environment, which is one reason we read these shifts alongside the exposure-based designs above.

The partition into financing phases is imposed by us rather than estimated. As a check, a four-state hidden Markov model fitted to the same event sequences recovers the same structure from the data alone: a pure-venture regime that expands after the IRA (16.9% to 25.7% of firm-events), a mixed venture–debt regime that contracts to 5.5%, and a non-dilutive-led regime that expands (48.2%

**Table 3. Composition of Climate-Technology Financing Before and After the IRA**

	Pre-IRA (%)	Post-IRA (%)	Change (pp)
<i>A. Share of all financing events</i>			
Accelerator/grant	32.8	35.6	+2.8
Angel	5.7	6.1	+0.4
Seed	10.0	11.9	+1.9
Early-stage venture	8.1	10.4	+2.3
Later-stage venture	12.5	15.8	+3.3
Growth/PE	3.6	3.5	−0.1
Corporate	9.4	8.3	−1.2
<b>Debt</b>	<b>17.6</b>	<b>8.3</b>	<b>−9.3</b>
<i>B. Instrument mix among venture-backed firms</i>			
Venture only	48.2	56.9	+8.7
Venture + accel./grant	32.1	32.2	+0.1
<b>Venture + debt</b>	<b>16.2</b>	<b>5.5</b>	<b>−10.7</b>

**Note.** Pre-IRA = Q1 2020–Q2 2022; Post-IRA = Q3 2022–Q2 2025. Panel A shares are over deal counts (may not sum to 100 due to rounding and a negligible uncategorized-venture share); Panel B is over venture-backed firms (those with  $\geq 1$  venture round in the window), where “+ accel./grant” and “+ debt” are not mutually exclusive. Phases are classified from PitchBook deal classes and types; terminal events, secondary transactions, and hedge-fund deals are excluded. Sample: 17,765 events across 7,194 firms. Bold rows mark the venture–debt substitution.

to 55.4%). Model details, state characterizations, and transition estimates appear in *SI Appendix*, Section S5.

## Mechanisms

### Financial incentive channel: policy alignment and incentive capture.

If policy operates primarily through direct financial incentives, firms whose technologies more directly match IRA provisions should exhibit stronger investment responses. These firms are better positioned to capture tax credits and subsidies that improve their economic profile: reduced tax liability on the income statement, transferable credits that can be monetized directly, or production incentives that improve unit economics. A hydrogen producer can claim production tax credits that directly improve per-unit profitability, while a software platform for carbon accounting cannot. Investors recognizing this heterogeneity should direct capital toward firms with greater incentive capture potential.

We test this prediction using a text-based exposure score,  $S_c$ , that measures semantic alignment between firm business descriptions and IRA statutory language describing eligible activities (32, 33). This approach captures policy alignment at a granular level: firms developing technologies explicitly named in IRA provisions (e.g., clean hydrogen, carbon capture, battery manufacturing) receive higher scores than firms in adjacent but less directly supported areas.

Difference-in-differences estimates using  $S_c$  as the treatment intensity (*SI Appendix*, Table S3) confirm that higher text-based policy alignment is associated with larger post-IRA increases in VC financing: a one-standard-deviation increase in  $S_c$  corresponds to a 0.3 percentage-point increase in the probability of receiving VC ( $p < 0.01$ ) and approximately \$122,000–\$147,000 in additional VC investment per firm-quarter (lower bound: controls plus

635 firm and time fixed effects; upper bound: controls plus  
636 time fixed effects). The graded response strengthens  
637 the causal interpretation: firms cannot select into higher  
638  $S_c$  scores after observing the policy, ruling out reverse  
639 causality.

641 **Credibility channel: policy durability and long-horizon investment.**

642 While the cash-flow channel explains cross-sectional variation  
643 in policy response, it does not fully account for how  
644 investors evaluate long-horizon climate investments. Venture  
645 capital in climate technologies requires commitments  
646 spanning 7–10 years or longer (34, 35), during which  
647 policy regimes may shift. If investors doubt whether  
648 IRA incentives will persist, the present value of expected  
649 subsidies declines even if current policy remains unchanged  
650 (3, 36). This credibility channel generates predictions  
651 distinct from the cash-flow mechanism: investment should  
652 be sensitive not only to policy levels but also to signals  
653 about policy durability and the political economy of  
654 commitment.

655 We conceptualize policy credibility as the degree to  
656 which investors believe that enacted incentives will remain  
657 in force over the time horizons relevant to their investment  
658 decisions. Several features of the IRA’s design bear on  
659 credibility: the use of uncapped tax credits with ten-year  
660 statutory horizons, automatic implementation through  
661 the tax code rather than annual appropriations, and  
662 transferability provisions that create broad constituencies  
663 for policy preservation. These design features are  
664 intended to make policy reversal politically costly, thereby  
665 enhancing credible commitment (1, 2). The logic parallels  
666 credibility effects documented in other policy domains,  
667 from monetary rules that anchor inflation expectations  
668 to constitutional commitments that enable long-run  
669 public finance, and echoes empirical work showing that  
670 perceived durability, as well as the scale of support, shapes  
671 renewable-energy investment responses to policy mixes  
672 (37, 38).

673 **Measuring policy credibility: the Policy Credibility Index.**  
674 A direct test of the credibility channel  
675 requires measuring institutional design features that  
676 underpin credible commitment, independent of market  
677 sentiment. Drawing on the policy-mix credibility literature  
678 (37, 39), we construct a Policy Credibility Index (PCI)  
679 that scores individual IRA provisions along three  
680 dimensions: *specificity* (rule-based eligibility criteria  
681 versus discretionary delegation), *durability* (multi-year  
682 statutory horizons versus annual reauthorization), and  
683 *enforceability* (clear agency assignment with specified  
684 procedures versus discretionary funding allocation). Each  
685 dimension is scored on a 1–5 scale, and the PCI is the  
686 simple average of the three dimensions. The index is  
687 conceptually analogous to institutional quality indices  
688 used in political science and development economics,  
689 but applied at the level of individual policy provisions  
690 rather than countries. The three dimensions capture  
691 the institutional architecture that determines whether  
692 a commitment is likely to persist over the multi-year  
693 horizons relevant to venture investment. Because the  
694 PCI is built from the statutory and regulatory text itself,  
695 rather than from media coverage or investor sentiment,  
696 it provides a lens that is complementary to news-based  
697 measures of policy uncertainty. Provisions are scored  
698 independently by two researchers and reconciled through

699 discussion, with inter-rater agreement above 85% before  
700 reconciliation, and the resulting scores are cross-validated  
701 against an independent news-based measure of climate  
702 policy uncertainty (*SI Appendix*, Section S6). A blind  
703 re-scoring of all six provisions by large-language-model  
704 judges, given only the rubric and neutral provision  
705 descriptions, reproduces the provision ranking ( $\rho = 0.86$ )  
706 and the direction of every OBBBA shock, including  
707 a null for the unamended 45Q placebo (*SI Appendix*,  
708 Section S7.7). Full construction details appear in *SI*  
709 *Appendix*, Section S7.

710 Table 4 reports baseline PCI scores at IRA enactment  
711 (August 2022) for six focal provisions spanning the IRA’s  
712 climate technology incentive structure. Tax-based production  
713 credits, Advanced Manufacturing (Section 45X, PCI  
714 = 4.67) and Clean Hydrogen (Section 45V, PCI = 4.33),  
715 score highest because they are self-executing through  
716 the Internal Revenue Service: eligibility criteria are  
717 codified in statute, credit values are formula-determined,  
718 and implementation requires no annual appropriation or  
719 agency discretion. Carbon Capture (Section 45Q, PCI  
720 = 4.33) and Clean Vehicles (Section 30D, PCI = 4.00)  
721 also score highly, though with slightly lower enforceability  
722 due to more complex compliance requirements. By  
723 contrast, Department of Energy Loan Programs Office  
724 authorities (Sections 50141 and 50144, PCI = 3.00–3.33)  
725 score substantially lower: loan approvals are discretionary,  
726 funding depends on congressional appropriations, and  
727 program priorities can shift with changes in agency  
728 leadership. This heterogeneity in institutional design  
729 quality implies that not all IRA incentives are equally  
730 credible, and investors attuned to policy risk should  
731 differentiate accordingly.

732 **Stress test: the OBBBA credibility shock.** The  
733 2025 legislative proposals under the “One Big Beautiful  
734 Bill Act” (OBBBA) framework provide a natural stress  
735 test of the credibility channel. These proposals introduced  
736 specific statutory amendments that degraded the institutional  
737 design quality of several IRA provisions without  
738 immediately changing enacted incentives, which created  
739 variation in credibility shocks across provisions. We distinguish  
740 two types of shocks. *Design shocks* directly altered  
741 statutory parameters: the Advanced Manufacturing credit  
742 (45X) faced elimination of wind energy components and  
743 stricter domestic content requirements ( $\Delta\text{PCI} = -1.00$ );  
744 the Clean Hydrogen credit (45V) faced an accelerated  
745 construction deadline from indefinite eligibility to 2027  
746 ( $\Delta\text{PCI} = -1.00$ ); and the Clean Vehicle credit (30D) faced  
747 early termination in September 2025, seven years ahead of  
748 its original 2032 sunset ( $\Delta\text{PCI} = -1.00$ ). *Political shocks*  
749 targeted program operations rather than statutory text:  
750 the Loan Programs Office saw rescission of unobligated  
751 balances (Section 50141,  $\Delta\text{PCI} = -0.67$ ) and mission  
752 rebranding with revised selection criteria under heightened  
753 executive discretion (Section 50144,  $\Delta\text{PCI} = -1.33$ ). The  
754 Carbon Capture credit (45Q) was unaffected by OBBBA  
755 proposals ( $\Delta\text{PCI} = 0.00$ ) and provides a within-provision  
756 comparison.

757 This variation in credibility shocks generates testable  
758 predictions: technologies aligned with provisions experiencing  
759 larger PCI declines should exhibit stronger investment  
760 contractions, holding current incentive levels constant.  
761 We test this prediction using a difference-in-differences  
762 design restricted to the post-IRA period (Q4

**Table 4. Policy Credibility Index: Baseline Scores at IRA Enactment (August 2022)**

IRA Provision	Description	Specificity	Durability	Enforceability	PCI
Section 45X	Advanced Manufacturing Production Credit	5	4	5	4.67
Section 45V	Clean Hydrogen Production Credit	5	4	4	4.33
Section 45Q	Carbon Capture Credit	5	4	4	4.33
Section 30D	Clean Vehicle Credit	4	4	4	4.00
Section 50144	Energy Infrastructure Reinvestment (LPO)	4	3	3	3.33
Section 50141	Loan Programs Office Funding	3	3	3	3.00

**Note.** PCI is the simple average of three dimensions, each scored 1–5. **Specificity:** rule-based eligibility (5) versus discretionary allocation (1). **Durability:** multi-year statutory horizon with insulation from annual reauthorization (5) versus short-term or annually reauthorized (1). **Enforceability:** clear agency assignment with specified procedures (5) versus discretionary selection with flexible criteria (1). Scores reflect institutional design at enactment (August 2022); subsequent OBBBA changes are captured separately as  $\Delta$ PCI in the stress-test analysis below. See *SI Appendix, Section S7* for scoring protocol.

2022–Q2 2025), in which the two OBBBA quarters (Q1–Q2 2025) serve as the treatment period and earlier post-IRA quarters as the comparison period. Two specifications probe the intensive margin of exposure: a continuous IRA-index interaction and a text-based exposure interaction.

Consistent with the credibility channel, firms with higher IRA alignment exhibit significant declines in venture activity during the OBBBA window. The IRA-index specification yields a negative interaction coefficient ( $IRA\_Index \times OBBBA = -0.0020$ ,  $SE = 0.0009$ ,  $p < 0.05$ ) for both the probability of receiving venture capital and the number of venture deals: each one-unit increase in IRA alignment corresponds to a 0.20 percentage-point reduction in the quarterly probability of receiving VC during OBBBA. The text-based exposure specification yields comparable results ( $S_c \times OBBBA = -0.0035$ ,  $SE = 0.0016$ ,  $p < 0.05$  for AnyVC;  $-0.0037$ ,  $SE = 0.0016$ ,  $p < 0.05$  for VC deal count). Firm-level trends reinforce this pattern: during the OBBBA quarters, the share of treated firms receiving venture capital fell from 3.9% to 2.5%, a 36% decline, while control firms contracted by 20% (4.5% to 3.6%) over the same window. The observation window is short and these estimates should be interpreted with caution, but the concentration of the contraction among policy-aligned firms and the dose-response pattern in the continuous specifications are jointly consistent with the credibility channel. The distinction between design shocks (which reduce durability and specificity) and political shocks (which reduce enforceability) further suggests that different dimensions of institutional credibility may affect investor behavior through distinct channels. As an external triangulation, a complementary news-based Climate Policy Uncertainty analysis (*SI Appendix, Section S6*) yields directional patterns broadly consistent with the credibility channel; we report it as supporting co-movement evidence rather than primary identification.

## Discussion

Our contribution can be read as a construct, its measurement, and its identification. The construct is policy credibility: the believability that a statutory commitment will persist, which we separate from both the magnitude of incentives and the choice of instrument that prior work has emphasized. The measurement is the Policy Credibility Index, which reads credibility off statutory text at the level of the individual provision, scoring specificity, durability,

and enforceability. The identification comes from treating the enactment of the Inflation Reduction Act and its attempted 2025 rollback as paired natural experiments, the rollback a shock to credibility while enacted incentives still stood, traced through venture capital, a forward-looking form of finance whose returns depend on a policy regime persisting for a decade.

These contributions organize what we find. The IRA raised the likelihood that firms in targeted clean energy and carbon technologies received venture financing, but selectively: the response concentrated in technologies most directly aligned with statutory incentives rather than expanding investment across the sector. It also changed how firms finance growth, as venture-only and non-dilutive financing expanded while mixed venture-debt funding contracted, consistent with the IRA’s tax credits and grants substituting for the project- and working-capital debt that capital-intensive climate firms had relied on. Prior work on optimal staging (26) and on R&D-grant spillovers into later venture financing (17) shows that grant awards, investor learning, and cohort effects can reshape a firm’s path through funding stages; we extend that logic to a large-scale industrial-policy shock that reweights the financing ecosystem along an equity-versus-debt dimension.

The credibility channel rests on two design-based analyses. The Policy Credibility Index shows that IRA provisions vary widely in institutional design quality, with self-executing tax credits scoring highest and discretionary loan programs lowest. The OBBBA stress test shows that the 2025 proposals degraded credibility unevenly across provisions, and that venture activity contracted most where credibility fell most, even as enacted incentive levels held. A news-based Climate Policy Uncertainty index co-moves with sector-level venture activity in the same direction, with deal activity persistently lower under elevated uncertainty in policy-dependent sectors such as Food & Land Use and Built Environment (*SI Appendix, Section S6*); we read it as descriptive corroboration rather than identification.

**Alternative explanations and limitations.** Several alternative explanations merit consideration. First, the period 2020–2025 coincided with a broader venture capital cycle, including rapid entry of new firms between 2018 and 2023 driven by limited-partner capital availability. As noted in the Results section, time fixed effects absorb

891 such aggregate cycles, including pent-up deployment of  
892 capital raised in earlier vintages. The selective nature  
893 of the trajectory shifts, concentrated in policy-aligned  
894 technologies, further supports a policy mechanism rather  
895 than a uniform cyclical pattern.

896 Second, our identification strategy relies on differential  
897 exposure across climate technology categories, which may  
898 not fully capture heterogeneity within each category  
899 in policy alignment, baseline venture capital affinity,  
900 or available capital pools. We address this concern  
901 through the continuous exposure measures (Table 2 and  
902 *SI Appendix*), which exploit within-category variation and  
903 yield consistent results.

904 Third, observable team quality and founder experi-  
905 ence may correlate with both selection into IRA-aligned  
906 technologies and venture capital outcomes. The en-  
907 trepreneurship literature consistently emphasizes founder  
908 characteristics as a determinant of commercialization  
909 success in capital-intensive sectors. Although our firm  
910 fixed effects absorb time-invariant team characteristics and  
911 the OBBBA stress test exploits political shocks orthogonal  
912 to founder formation, we cannot rule out that experienced  
913 teams disproportionately pivoted toward policy-aligned  
914 categories around enactment. Direct evidence on team  
915 formation, capability matching, and founder mobility  
916 under industrial-policy regimes is a productive direction  
917 for future qualitative work.

918 Fourth, the mechanism analysis drawing on insti-  
919 tutional design measures and market-level uncertainty  
920 correlations characterizes co-movement patterns rather  
921 than identifying causal effects; we cannot definitively rule  
922 out alternative explanations for the observed patterns,  
923 and the OBBBA observation window is too short for  
924 conclusive inference.

925 Finally, our findings are set in the U.S. context, where  
926 the IRA represents one of the largest national-level  
927 industrial policies for climate technology to date. Whether  
928 similar credibility-mediated dynamics arise in other insti-  
929 tutional settings, such as the EU's Green Deal, China's  
930 coordinated industrial subsidies, or appropriations-driven  
931 public investment programs in other developed economies,  
932 is an empirical question we leave to future work, alongside  
933 the longer-run effects on technology commercialization  
934 and emissions outcomes.

935  
936 **Implications for policy design.** These limitations notwithstand-  
937 ing, our findings carry direct implications for the design of  
938 climate industrial policy. The central finding is that the  
939 institutional architecture of policy commitments shapes  
940 their effectiveness in mobilizing private capital, over and  
941 above their financial magnitude. Large incentive packages  
942 may fail to mobilize private capital if investors doubt their  
943 durability, while design features such as long statutory  
944 horizons, automatic implementation through the tax code,  
945 and insulation from annual appropriations may amplify  
946 policy effectiveness.

947 Our findings extend a literature linking renewable-  
948 energy investment to policy design and instrument choice  
949 (37, 38), but we differ from that work on three dimensions.  
950 First, the construct: prior studies operationalize policy as  
951 design features or instrument type, measuring the balance  
952 and evolution of national policy mixes (37) or the presence  
953 of feed-in tariffs, quotas, and tax incentives (38). Neither  
954 isolates credibility, the believability that a commitment

955 will persist. The IRA-to-OBBBA sequence illustrates why  
956 the distinction matters: much of the statutory design  
957 remained intact on paper while credibility was the margin  
958 that moved. Second, the measurement: where prior work  
959 relies on expert coding or categorical variables drawn  
960 from secondary sources, we extract credibility proper-  
961 ties directly from statutory text at the provision level,  
962 capturing sunset clauses, contingency triggers, claw-back  
963 conditions, and phase-down schedules that no instrument-  
964 type label records. Third, identification and outcome: the  
965 cross-country evidence is observational panel variation  
966 in aggregate renewable-energy asset finance, whereas we  
967 exploit the enactment and subsequent modification of a  
968 single statute as natural experiments, with the OBBBA  
969 functioning as a credibility shock to an otherwise-standing  
970 policy, and we study venture capital, a forward-looking  
971 form of innovation finance whose returns depend on a  
972 policy regime persisting over a decade.

973 This design trades breadth for identification. The  
974 cross-country literature spans many economies over long  
975 horizons (37, 38); ours is a within-country design centered  
976 on one statute in one institutional context, and external  
977 validity to other polities is an open question for future  
978 work. The tradeoff is deliberate: only within a single legal  
979 system, with provision-level text and identifiable political  
980 shocks, can credibility be separated from instrument  
981 design and tied causally to firm-level investment.

982 The Policy Credibility Index offers policymakers a  
983 practical tool for evaluating the credibility properties of  
984 proposed legislation along the dimensions of specificity,  
985 durability, and enforceability before enactment. As  
986 governments worldwide design industrial policy packages  
987 to accelerate the energy transition, these findings suggest  
988 that attention to institutional design features deserves  
989 at least as much consideration as the scale of financial  
990 incentives.

## 991 Materials and Methods

992  
993 **Data.** We construct a firm-level panel of climate technology compa-  
994 nies using the Climate Tech Venture Capital (CTVC) database, which  
995 provides comprehensive coverage of venture-backed firms operating in  
996 climate-related technologies. The sample includes 132,826 firm-quarter  
997 observations spanning Q1 2020–Q2 2025. Financing events are sourced  
998 from PitchBook and include venture capital rounds, corporate investments,  
999 debt financing, and private equity transactions. Full details of data sources,  
1000 sample construction, and variable definitions appear in *SI Appendix*,  
1001 Section S1.

1002 **Policy Exposure.** We measure policy exposure using three comple-  
1003 mentary approaches. First, we construct a binary treatment indicator  
1004 based on the CTVC taxonomy, classifying firms in the Energy and Carbon  
1005 subfields as directly exposed to IRA incentives (*SI Appendix*, Section S3.1).  
1006 Second, we develop a continuous IRA exposure index using supervised  
1007 text classification that scores firm descriptions against statutory language  
1008 (*SI Appendix*, Section S3.2). Third, we compute a text-based exposure  
1009 score ( $S_c$ ) using TF-IDF cosine similarity to capture semantic alignment  
1010 with policy provisions (*SI Appendix*, Section S3.3). Details of the technology  
1011 classification methodology appear in *SI Appendix*, Section S2.

1012 **Empirical Strategy.** We estimate difference-in-differences specifica-  
1013 tions (30, 40) comparing outcomes for policy-exposed and less-exposed  
1014 firms before and after IRA enactment (August 2022). Event-study  
1015 specifications allow for dynamic effects and test for differential pre-trends.  
1016 All models include firm and time fixed effects and cluster standard errors  
1017 at the firm level. Robustness checks using Poisson PPML, log-linear, and  
1018 logit specifications are reported in *SI Appendix*, Section S4.3.

1019 **Financing Trajectories.** We classify each financing event into observ-  
1020 able phases from PitchBook deal classes and types (accelerator/grant,  
1021 angel, seed, early-stage venture, later-stage venture, growth/private equity,  
1022 corporate, debt), excluding terminal events, secondary transactions, and  
1023 hedge-fund deals. We compare the composition of events, firm-level

1019 instrument combinations, and next-event transition rates before and after  
1020 IRA enactment (boundary: Q3 2022). As corroboration, a four-state  
1021 Hidden Markov Model estimated on the same deal sequences recovers an  
1022 equivalent partition without imposing the phase classification; model details  
1023 and state characterizations appear in *SI Appendix*, Section S5.

1024 **Data, Materials, and Software Availability.** The Climate Policy Uncertainty  
1025 index, Policy Credibility Index scores, IRA exposure scores, and all  
1026 replication code are publicly available at [https://github.com/Yikai-Cao/  
1027 climate-tech-vc-paper](https://github.com/Yikai-Cao/climate-tech-vc-paper). Company-level data from the Climate Tech Venture  
1028 Capital (CTVC) database and PitchBook are available under institutional

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identified analytical dataset containing all constructed variables sufficient  
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