Why Clean Energy Investments Had Limited Political Returns

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Abstract

The Inflation Reduction Act (IRA), now partially repealed, is the largest federal investment in climate policy in U.S. history. We examine whether its clean energy projects generated political support for the policymakers behind the law. Using geolocated survey data linked to investment records and a new database of company and politician statements, we assess investment visibility, perceived benefits, and credit attribution. Residents living near IRA projects were more likely to notice investments but not perceive economic gains or credit the Biden Administration. Instead, they credited their governors, who actively claimed credit, while companies spread recognition broadly. This fragmented information environment helps explain why federal officials gained little political benefit from the IRA's investments and underscores the difficulty of using green spending alone to build support for climate policy.

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AG led the research design with input from NJ and DT. NJ collected the initial company announcement data, which was expanded by AG. AG analyzed the data. AG wrote the paper with support from NJ and DT. Corresponding author: agaz@umich.edu

Significance Statement

The Inflation Reduction Act made historic climate investments in clean energy and manufacturing. Policymakers had expected that by delivering material economic benefits to constituents, the reform would generate a political return. Using geolocated survey and investment data, along with a new dataset of company and politician statements, we assess whether the law changed public opinion and business behavior among groups that benefited. While people living closest to new projects were more likely to notice them, this visibility did not translate into perceived local economic benefits or greater credit for federal leaders. Instead, Americans credited governors, and companies spread recognition across multiple actors. These findings suggest that green spending alone may not deliver significant political support. Policy durability is more likely to depend on firms defending their own interests than on broad public backing.

Introduction

The Inflation Reduction Act (IRA), now partially repealed, made historic investments in clean energy and manufacturing. Beyond its economic goals, the law was designed to build political support for climate policy through visible economic benefits, often in swing states (Meckling et al., 2015; Cullenward and Victor, 2021; Ross, 2025). This strategy sought to create allies both in business, by giving firms a stake in the clean energy transition, and among voters, whose views shape politicians' electoral incentives. This paper focuses on the latter, examining whether these investments shifted public opinion in ways that could help defend and expand the IRA.

There are three necessary conditions for federal climate policy to generate political returns. Residents must notice projects, view them as beneficial, and link them to the responsible policymakers (Arnold, 1990). Attribution, however, isn't guaranteed. Governors and local officials often step in to claim responsibility (Jensen and Malesky, 2018), while partisan polarization shapes how the public receives and interprets information (Hopkins, 2023; Mettler, 2011). These dynamics could make it challenging for federal policymakers to receive a political reward from green spending.

Systematic evidence about the IRA's effect on public opinion is limited due to the IRA's recency. Few surveys capture whether people notice or attribute credit for local investments, and statements by companies and politicians are scattered across thousands of announcements. We use three geolocated national surveys from 2024 and a database of statements covering every green manufacturing investment announced between 2022 and 2024 to examine how people, businesses, and politicians responded to these projects.

We test three hypotheses about how clean energy investments affect public opinion. First, residents living closest to projects should be more likely to recognize them and view them as beneficial, essential first steps for investments to shape political attitudes. Second, if recognition translates into attribution, then communities with projects should be more likely to credit the Biden Administration as the architect of federal incentives. Third, attribution is likely to be contested, since politicians across multiple levels of government have incentives to claim responsibility, while businesses spread credit across actors, producing a mixed information environment that could weaken recognition of federal responsibility.

We find modest evidence that proximity makes projects more visible, but no evidence that it causes people to credit the Biden Administration. Instead, Americans view governors as more responsible, a pattern consistent with our analysis of statements showing that governors are far more active in claiming credit than federal officials. These dynamics illustrate challenges the IRA faces in generating durable constituencies.

Research Design

Project Proximity, Visibility, and Credit Attribution

We conducted three national online surveys of U.S. adults in 2024 (total $N = 5026$) to examine whether clean energy investments influenced public opinion. Respondents reported whether they had seen a new project in their community, assessed its economic effects, and rated the responsibility of political actors for new investments (Materials and Methods).

Geographic proximity is central because those living nearest to new facilities are the IRA's intended beneficiaries. We measure proximity using geocoded ZIP-level coordinates for respondents and project sites, avoiding bias from self-reports (Egan and Mullin, 2012). Respondents are grouped into national distance quintiles by project type, with the most distant 20% serving as the reference group; results are robust to using continuous measures (SI S3.5). The investment data cover utility-scale solar and wind facilities under construction, and operational clean energy manufacturing sites. Although these investments accelerated after the IRA (Bistline et al., 2023), individual projects reflect multiple policy and market factors, so any single project cannot be attributed solely to the law.

Fig. 1 shows the distribution of survey respondents and clean energy projects. There is substantial geographic overlap, which enables the identification strategy comparing people living near projects versus those far away within the same state.

We estimate the effect of proximity by comparing respondents to others in the same state, holding constant state-level political and economic conditions. Project siting is not random, so we adjust for observable differences, such as infrastructure and local workforce capacity, that could also shape opinions. Models include state and survey-wave fixed effects and controls for county- and individual-level characteristics. A causal interpretation relies on the assumption that, after these adjustments, proximity is as-if random within states. Sensitivity and power analyses (SI S3) indicate the design can detect meaningful effects and is robust to plausible unobserved confounding.

Company and Politician Statements

We compiled a comprehensive database of company and politician statements on all clean energy manufacturing projects from August 2022 to December 2024 (327 projects). These large, high-profile investments often attract local media coverage and are prime opportunities for politicians to claim credit (Jensen and Malesky, 2018; Walters and Walters, 1992).

The dataset covers statements by companies, governors, U.S. Senators, Representatives, and the president (including senior administration officials). We used large language models

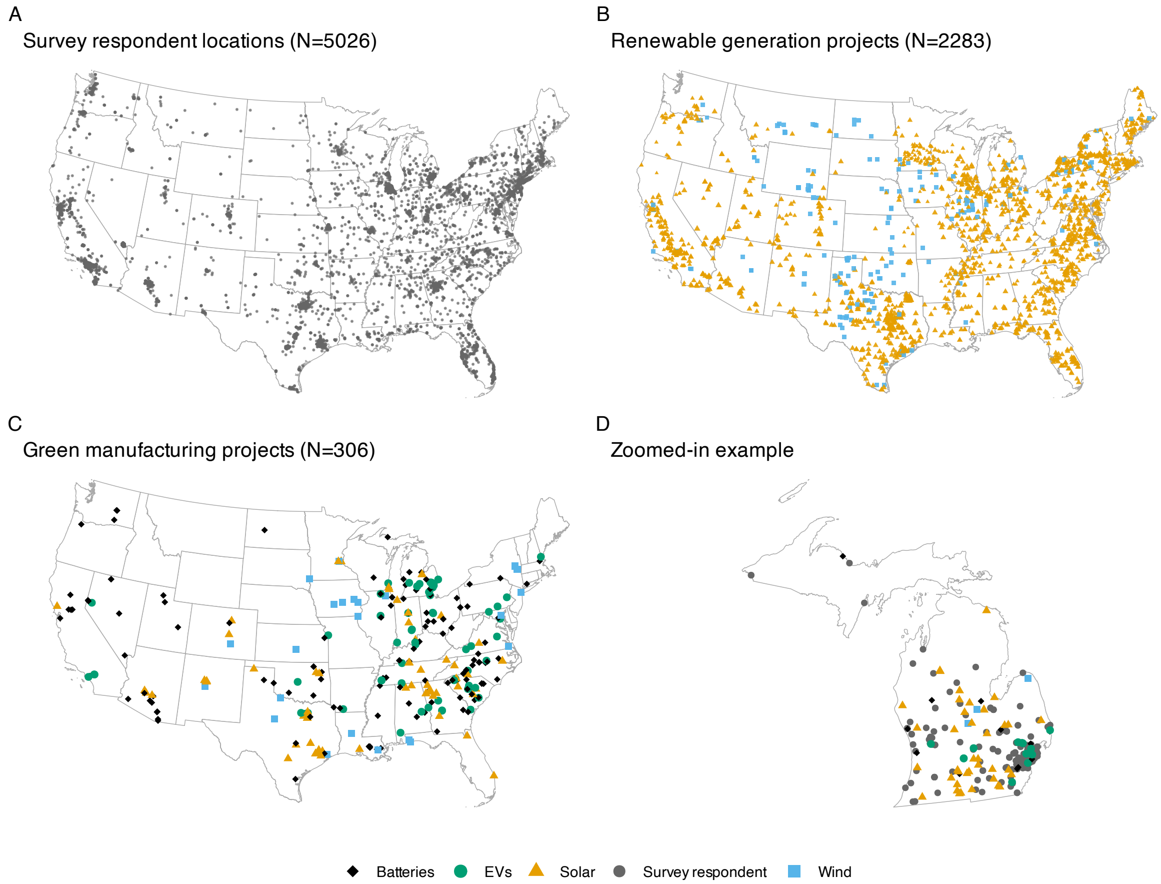

Fig. 1. Geographic distribution of survey respondents and clean energy investments, 2022–2024. Alaska and Hawaii not shown.

to classify whether each statement credited specific actors or policies, capturing both explicit claims and implicit actions (e.g., ribbon-cutting events). Materials and Methods describes coding procedures and validation steps. This dataset enables a systematic analysis of how credit is allocated across political and business actors.

Results

Effect of Proximity on Political Attitudes

Visibility

About 27% of Americans reported seeing a new clean energy project in the last year. Proximity increases visibility. Relative to those farthest away in the same state, respondents in the nearest quintile are 6.3 (manufacturing) and 6.6 (renewables) percentage points more likely to report seeing a project; effects extend into the second quintile for renewables (Fig. 2A).

Project visibility varies with timing. Manufacturing projects (especially EV and wind

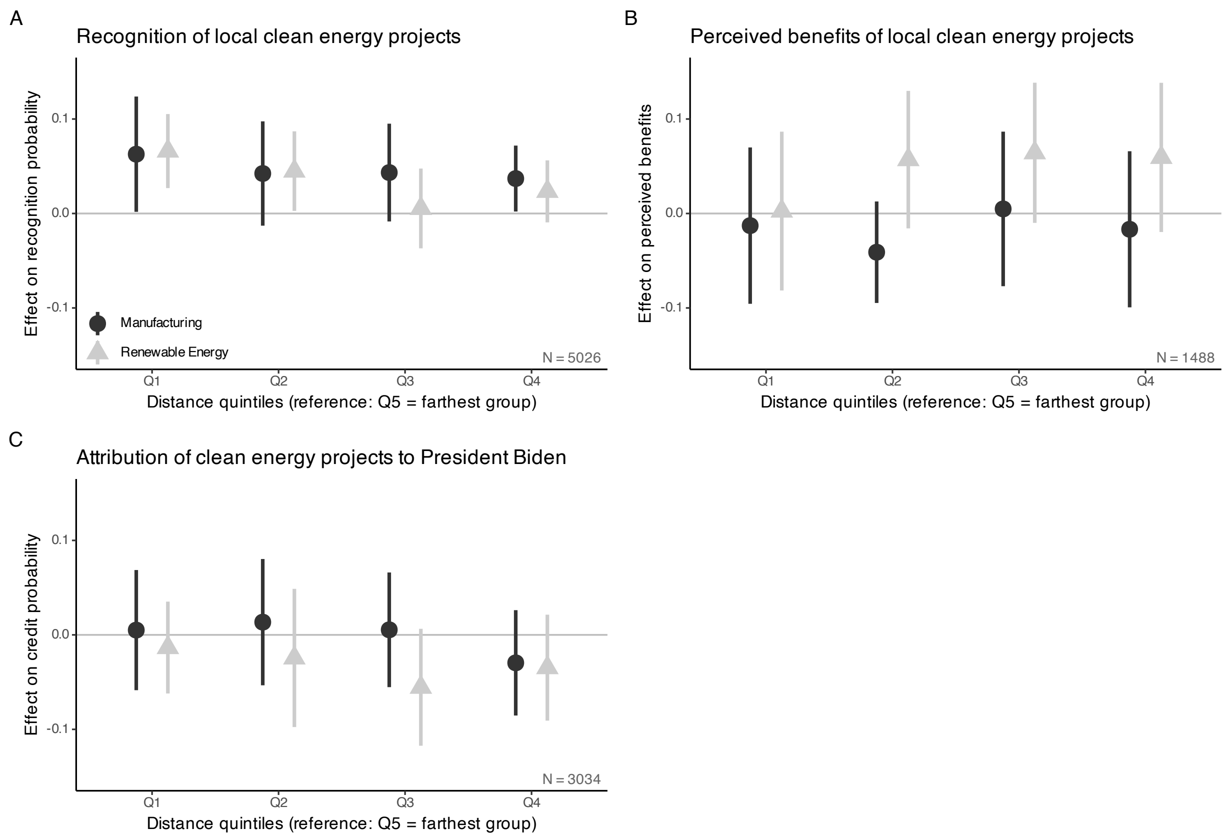

Fig. 2. Effects of proximity to clean energy projects on perceptions. **(A)** Recognition of nearby projects. **(B)** Credit to President Biden for new investments. **(C)** Perceived economic benefits by proximity. Points are coefficients from a linear regression of the given outcome on proximity quintile indicators, state fixed effects, and covariates. Outcomes are on a 0–1 scale. Bars denote 95% confidence intervals.

plants) tend to attract attention only once they are at least partially operational, with little recognition during planning or construction. Renewable projects, in contrast, are often most visible before construction begins, possibly due to publicity around siting decisions or local news coverage.

Partisanship has a modest moderating effect on proximity's relationship with visibility. Republicans closer to renewable projects are slightly more likely to report seeing them compared to Democrats, while independents near manufacturing projects are more likely to notice them. We also examine income and education, as these characteristics often predict political awareness, but find no clear heterogeneity (SI S3.6).

Perceived Benefits

Perceived economic gains are a necessary link for climate policy to increase public support. Yet benefits are not guaranteed since projects can generate local conflict as seen with debates over wind siting (Stokes et al., 2023).

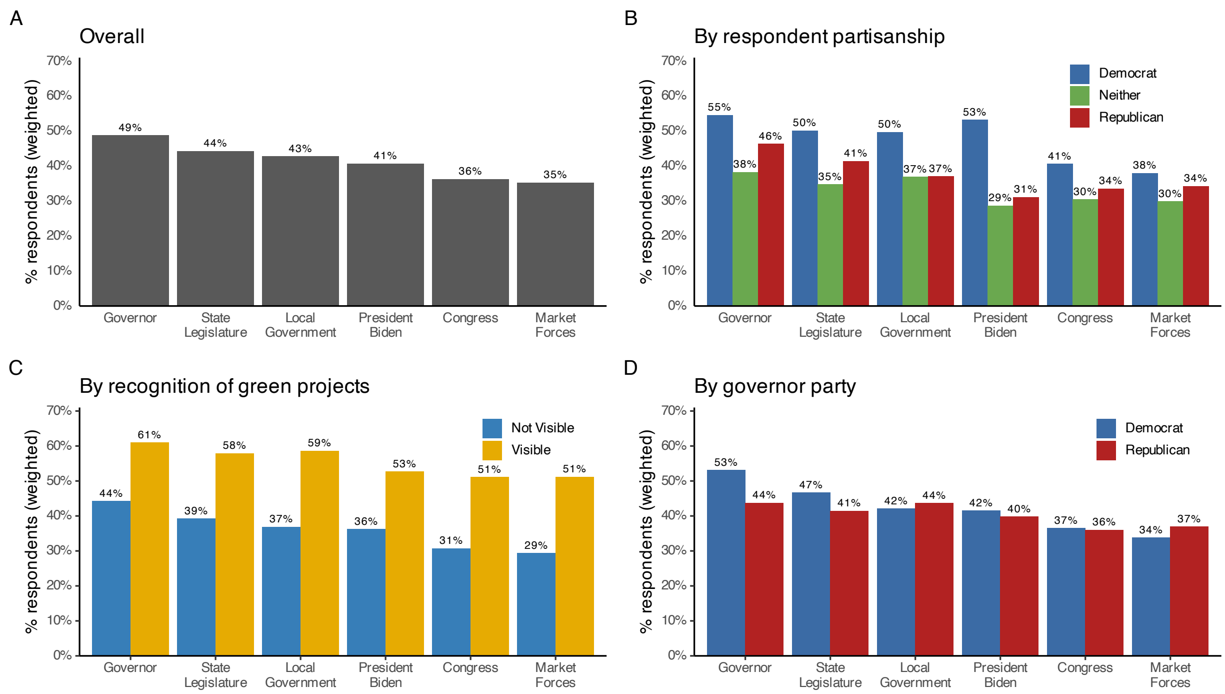

Fig. 3. Perceived responsibility for clean energy investments. Values use survey weights. Two independent cross-sectional waves in 2024 (pooled $N = 3{,}034$). **(A)** Overall. **(B)** By party ID. **(C)** By self-reported recognition. **(D)** By governor's party.

Overall, a majority of Americans (66%), including Republicans and Democrats, view local clean energy investments as economically beneficial. However, proximity does not increase perceived benefits. Relative to those farthest away in the same state, respondents in nearer proximity quintiles are no more likely to report economic benefits (Fig. 2C). There are no consistent differences by project status or sector, nor by respondents' income or education, although Democrats are relatively more likely than Republicans to see proximate clean energy projects as beneficial (SI S3.6).

The limited effect of proximity on perceived economic benefits is likely due to already favorable baseline views. Perceived benefits appear broadly positive regardless of distance, though these estimates are less precise given smaller samples and limited within-state variation.

Credit Attribution

There is no evidence that people closer to new projects were more likely to credit President Biden for these investments (Fig. 2B). The design had 80% power ($\alpha = 0.05$) to detect a 10–percentage-point effect (SI S3). Two one-sided equivalence tests further bound any proximity effect to be small; effects larger than 5.9 pp for manufacturing and 5.5 pp for renewables are rejected since the 90% confidence intervals lie entirely within these margins.

There is also no detectable heterogeneity in proximity's effects across partisans, nor clear heterogeneity by education, income, project status, or sector (SI S3.6). Proximity makes projects more visible, but it does not make the Biden Administration's role traceable.

Overall, governors receive the most credit for new clean energy investments. President Biden trails by about eight percentage points. Congress and market forces receive the least credit (Fig. 3A). Patterns are broadly bipartisan. Even among Democrats, credit to Biden is comparable to credit to the governor (Fig. 3B).

Respondents who report a nearby project credit all actors more rather than reallocating credit toward federal policymakers (Fig. 3C). Attribution also varies with the governor's party, and credit is higher when respondents and governors share a party (Fig. 3D; SI S5).

Business and Politician Credit Claiming Patterns

We argue that a complex information environment helps explain why clean energy projects were visible but not easily attributed to federal policymakers. State and local officials have strong incentives to claim credit for attracting investments (Jensen and Malesky, 2018), while companies often avoid overt partisanship to maintain relationships across administrations. To test this mechanism, we analyze project-related statements from elected officials and companies, assessing both their frequency and credit allocation. We expect state officials to be active credit-claimers, while companies will distribute credit broadly across political actors.

Who Speaks

Companies issued statements for 97% of projects (Fig. 4A). Among political actors, governors "spoke" most often (65%), followed by President Biden (48%), a U.S. senator (40%), and the district's U.S. representative (34%). Shares are calculated as the percent of projects with at least one statement by the actor.

Statement rates vary by the speaker's partisanship (Fig. 4B). Democratic governors, senators, and representatives speak more often than Republican counterparts. The partisan gap is largest for members of Congress, although Republican governors still comment on most projects in their states (59%). These partisan differences appear even when controlling for variables including project type, economic conditions, and political factors (SI S6).

Politicians issued more statements about projects that have specific investment amounts, which is consistent with elected officials having incentives to claim credit for good economic outcomes. For context, about three-quarters of projects report a capital investment target. This association persists with covariate adjustment (Fig. 4C; SI S6).

Presidential statements were most frequent immediately after the IRA's passage, then declined through mid-2024 and remained below governor levels despite a pre-election uptick (Fig. 4D). Governor statement rates were comparatively stable.

Who Credits Whom

Fig. 5A shows the share of projects in which a speaker's statement credited each recipient. Companies spread credit broadly, but especially for local actors; they most often credited governors and local actors, followed by the IRA (28%) and President Biden (14%).

Across elected officials, self-credit is, unsurprisingly, common. When President Biden and his delegates spoke, references to the Bipartisan Infrastructure Law occurred in 71%

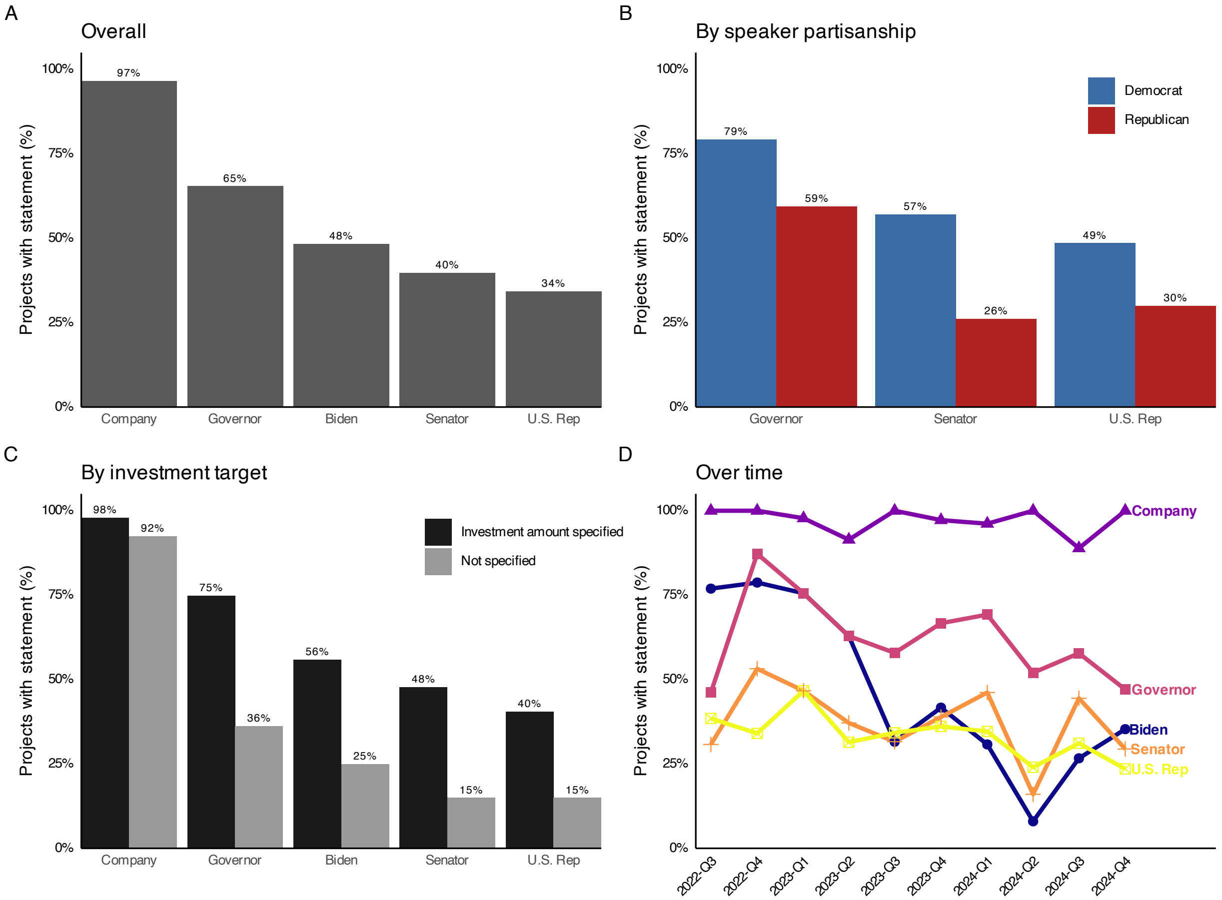

Fig. 4. Share of clean energy manufacturing projects with at least one public statement by companies and elected officials after the IRA (327 projects; Aug. 16, 2022–Dec. 2024). **(A)** By actor. **(B)** By actor party. **(C)** By whether the investment amount is specified. **(D)** Quarterly trend. Percentages are relative to the number of projects in each quarter.

of projects and to the IRA in 47%. Biden and his administration's officials would also occasionally credit governors and local officials.

Senators and representatives did not issue as many statements as governors, but when they did, they credited the White House in 17% and 19% of projects. These speakers also sometimes acknowledged governors and local politicians.

Fig. 5B visualizes project-level credit networks varying with the partisanship of the speaker. Governors from both political parties credit local actors. Democratic governors occasionally credit President Biden while Republican governors never do. Overall, Republican speakers are less likely to credit the White House, which holds with covariate adjustment (SI S6).

Discussion

Policymakers intended for the IRA to not only address climate change but to generate political rewards from voters in communities receiving investments. While proximity modestly makes

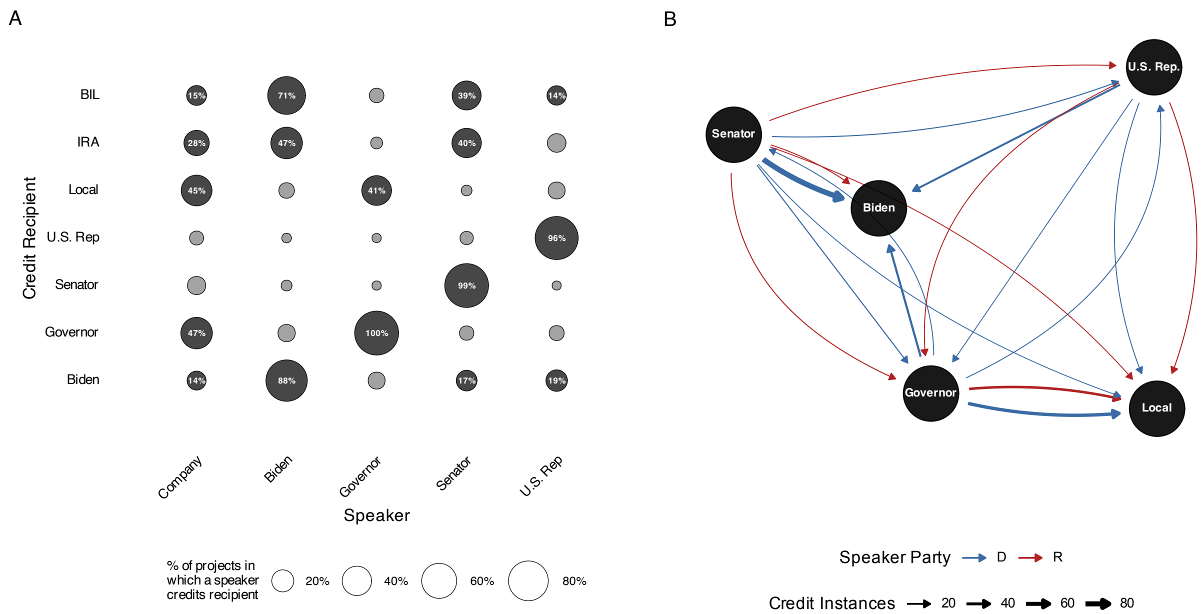

Fig. 5. Credit giving for clean energy manufacturing projects after the IRA (327 projects; Aug. 16, 2022–Dec. 2024). **(A)** Share of projects in which each speaker credited each recipient. **(B)** Project-level credit network by speaker partisanship. Edge thickness denotes the share of projects. Blue lines denote Democratic speakers and red Republicans.

projects more visible, it does not increase credit to the Biden Administration. Fewer than half of Americans (41%) view the president as responsible, while governors receive the most credit across parties. The IRA was visible, but not traceable.

The mixed information environment provides a plausible mechanism for the IRA's limited political effects. The statements data reveal that companies spread credit across multiple actors, highlighting governors and local partners more often than President Biden or the IRA. Governors, for their part, also issued more statements about green investments than the White House. This supply of competing messages emphasizes subnational actors over federal ones. Visibility without traceability could prevent green spending from generating political rewards for the IRA's architects.

The findings align with political science research on policy feedback, which shows that the inability of voters to connect policies and outcomes can contribute to policy retrenchment (Arnold, 1990; Mettler, 2011). Clean energy investments may face particular barriers to reshaping public opinion compared to other programs thought to generate policy feedbacks. First, economic benefits from green investments materialize indirectly through private firms rather than directly through contact with government agencies as with Social Security, which could make traceability hinge more on political messaging (Campbell, 2012; Hamel, 2025). Second, national, state, and local policies influence clean energy projects, complicating attributions in federal systems (Arceneaux, 2006).

While we cannot observe the internal strategies of firms, two considerations may help interpret why companies distribute credit broadly. First, firms manage political risk over long horizons, so broad credit can preserve relationships with multiple governments (Gazmararian and Tingley, 2023). Second, state and local governments provide tangible support for projects such as incentives, infrastructure, and permitting, so credit is often warranted (Bartik, 2019).

While traceability is a necessary condition for shifting public opinion, the results do not imply that it is a sufficient condition for generating political returns. While we do not have access to internal White House deliberations, we speculate that the administration was constrained by the concern that presidential branding could risk polarizing projects in purple and red states. There appears to be a trade-off between building projects and receiving political credit. The White House was also at a structural disadvantage in messaging compared to governors who have more time to visit projects in their states.

Several limits qualify our conclusions. First, the surveys are cross-sectional rather than repeated panels, which would be useful to learn about opinion change as projects advance or are canceled. Second, while the national samples had adequate coverage near projects, it is possible that feedback effects would be stronger if over-sampling communities immediately around project investments. Third, the responsibility item is framed at the state level, which may favor governors, but it improves comparability and matches how projects were presented locally. Fourth, the research design cannot estimate the causal effect of message supply on attribution because statements aren't random but follow political strategy. Finally, LLM-assisted annotation carries risks of misclassification, although we attempt to mitigate this through reliability checks.

These findings suggest that policy feedback from climate policy is likely to flow more through firms that can link policy changes to their economic interests than through voters, who face higher barriers to political mobilization (Meckling et al., 2015). The IRA's partial repeal reflects multiple forces beyond public opinion, including intense partisan polarization, which likely constrained lawmakers' willingness to break party ranks. Still, Republican legislators might have faced stronger pressure to resist repeal had constituents been more aware of the law's local economic benefits. Notably, several provisions survived, underscoring that material self-interest—when coupled with effective mobilization by voters or firms—could help entrench policy gains.

While our findings indicate that the IRA's passage did not yield clear political rewards, its repeal could carry significant political costs. This dynamic reflects the politics of loss aversion. Threatened cuts and canceled projects may be more effective at mobilizing beneficiaries to defend green projects (Béland, Campbell, and Weaver, 2022). Yet the core challenge remains. For voters to defend climate reforms, the public needs to be able to trace green investments to the actions of federal policymakers.

Materials and Methods

Survey Data and Measurement

Sampling

Three independent national online surveys of U.S. adults were administered via Qualtrics in 2024. Surveys were available in English. Fieldwork periods were March 14–April 9 (N = 1,500), May 13–June 6 (N = 1,992), and August 6–November 11 (N = 1,534). After applying the data quality protocol (attention checks; speeding; duplicate IP/device;

invisible reCAPTCHA), the combined sample includes 5,026 respondents. Samples used nonprobability quotas to approximate the U.S. adult population by age, sex, race/ethnicity, education, income, and region, based on the 2023 5-year ACS.

Measures

Recognition. All waves included a recognition item: "In the last year, have there been any clean energy investments in your community? Examples include wind and solar farms, and plants to build electric cars or batteries." Response options were "Yes," "No," or "Not sure." Analyses coded recognition as a binary indicator 1 for Yes, and 0 otherwise.

Credit attribution. Waves 1 and 3 included an attribution battery: "Thinking about your state, who or what has played a significant role in bringing clean energy investments? For each option, please rate how responsible you believe they are." Respondents rated President Biden, the U.S. Congress, their governor, state legislature, community leaders, and market forces (randomized order) on a five-point scale: "Extremely, Very, Moderately, Not too, or Not at all responsible." We used the term responsibility rather than credit to maximize construct validity, since "credit" can have a positive normative valence. Analyses use a binary indicator coded 1 for "Extremely" or "Very" and 0 otherwise. The question did not query about party brands (Egan, 2013), although diagnostic checks show that the question captured the principal perceived sources of responsibility and engaged respondents similarly across partisan groups (SI S2.4). The state-level frame ensured that the item was meaningful for all respondents and reflected how the IRA's design emphasized place-based benefits.

Perceived benefits. Wave 1 measured perceived local economic effects by asking: "How much do you think green investments have benefited or harmed your community's economy?" If the respondent reported not having a local project, the question stem branched to say "would benefit or harm." The five-point outcome scale included: "Greatly benefit, Somewhat benefit, No effect, Somewhat harm, Greatly harm." Analyses use a dichotomized outcome where "Greatly benefit" or "Somewhat benefit" was coded 1, and 0 otherwise.

Question order. The recognition item always preceded the attribution battery to minimize priming of recognition by political responsibility. Other survey content varied by wave. Items analyzed generally followed batteries measuring climate beliefs, international climate aid, and trade.

Geolocation & Linkage

Respondents were geocoded to ZIP centroids and linked to the nearest eligible project of the relevant type. ZIP Codes were self-reported and mapped to longitude and latitude coordinates using the Google Maps API. When a reliable ZIP was unavailable (<1%), we used IP-based city-level geolocation. The results are robust to restricting the sample to respondents whose ZIP Code coordinates matched those implied by IP addresses (SI S3.5).

Distance was aligned to interview date as follows: utility-scale solar and wind generators under construction in the prior two years (EIA-860M) and clean energy manufacturing facilities that were at least partially operational in that window (Big Green Machine). Distances were binned into national quintiles by project type, although they are robust using a continuous measure (SI S3.5).

Weights

Descriptive estimates use survey weights. Proximity regressions do not, but weighted regressions are similar (SI S3.5). Validation checks show that the weights improve representativeness (SI S2.2).

Clean Energy Project Data

Clean energy generation. Utility-scale solar and wind generation projects were identified from the U.S. Energy Information Administration's EIA-860M monthly generator updates. Project locations were defined using the EIA plant address point. A plant is included if at least one solar or wind generator at the facility was reported as pre-construction or under construction, with a start time within the two years preceding the respondent's interview date. Records with invalid or out-of-bounds coordinates were excluded.

Clean energy manufacturing. Manufacturing facilities information comes from Jay Turner's Big Green Machine dataset (April 19, 2025 version). These data were compiled from public sources and track technologies including EVs, batteries, solar, and wind. The sample excludes rumored, closed, or canceled projects, as well as records lacking an announcement date or valid geo-coordinates. The proximity analysis includes facilities operational or partially operational within two years preceding the respondent's interview date and prior to the IRA's passage, whereas the statements analysis considers all manufacturing projects regardless of status.

Company and Politician Statements

Collection

The statements dataset covers 327 manufacturing projects. It tracks public statements by companies, state governors, U.S. Senators, U.S. Representatives, and President Biden. The collection window spans August 16, 2022, to December 31, 2024. The research team located 992 statements out of 1962 potential statements.

A statement is defined broadly to minimize false negatives. It includes (i) official communications (press releases, newsletters, transcripts, reports) published on government or corporate websites; (ii) posts on verified social media accounts including Facebook, X, Instagram, and LinkedIn; and (iii) direct quotes attributable to the actor in credible news articles or in another actor's press release. If no official statement exists, a single attributable quote from a news article is retained and linked. Multiple distinct statements by the same actor about the same project were consolidated into one record; the canonical record retained the earliest statement date, the source URL, and the channel type. When a company press release contained a politician's quote and no separate official statement existed, that quote was used as the politician's statement and the company release was cited. All source URLs and statement texts were archived.

Annotation

Statements were annotated to identify (i) whether they contained a credit claim and (ii) the recipient(s) of credit. Potential recipients included President Biden, the state's U.S. senator(s), the district's U.S. representative, the governor, local officials, the Inflation Reduction Act (IRA), and the Bipartisan Infrastructure Law (BIL/IIJA); party brands were also checked but were almost never credited.

A two-stage LLM-assisted procedure was used. Stage 1 (policy targeting) applied gpt-3.5-turbo-0125 at temperature 0 to classify whether the statement explicitly indicated that the IRA or BIL/IIJA funded, financed, or enabled the specific project. Stage 2 (general credit) applied gpt-4o-mini at temperature 0 using the full codebook to identify credit claims and assign recipients. The Stage-2 prompt included: (a) the statement text; (b) statement metadata (speaker/company, role, state/district, channel, release type); and (c) Stage-1 outputs as features.

The codebook distinguished explicit credit (e.g., causal verbs, attributions of decision-making, financial involvement) from implicit credit (e.g., attending or hosting a project ceremony, framing an announcement as an achievement, public association with a specific project using active language) and separated descriptive mentions without credit (Mayhew, 2004). Post-processing enforced explicit-mention rules: a statement could be coded as crediting the IRA/BIL/President only if a corresponding synonym appeared in text. Human coders and the LLMs jointly annotated a calibration subset of two statements for every actor to refine instructions.

LLM-assisted annotation is well validated for political text. GPT-class models can match or exceed crowd workers on common text-as-data tasks, often with higher inter-coder agreement and lower cost (Gilardi, Alizadeh, and Kubli, 2023). In political science, few-shot prompting can achieve expert-level performance across topic tasks (Chew et al., 2023; Ornstein, Blasingame, and Truscott, 2025). The annotation protocol followed emerging best-practice guidelines, including codebook prompts, temperature control, model disclosure, human calibration, and post-processing, which increase reproducibility (Törnberg, 2024).

Analyses

Causal Identification

The analysis estimates the effect of project proximity on outcomes such as visibility. The causal inference challenge is that project location could be confounded by political and economic factors that independently affect political attitudes. Therefore, the research design leverages within-state variation in proximity. It assumes that the within-state deviation in a survey-taker's distance to clean energy projects is as-if random after controlling for individual and county-level covariates that predict site selection within a state. The centrality of state-level factors for project site selection, which the state fixed effects address, increases the credibility of this assumption.

The analysis further includes pre-treatment county and individual-level covariates because factors within states could affect distance to new projects. County-level controls include the unemployment rate, labor force size, county domestic product, median income per capita, highway access, share of college-educated residents, share of residents under the federal poverty line, share of foreign-born residents, median housing costs, population density, broadband access, and 2020 Biden vote share. Where applicable, controls are lagged by a year to avoid post-treatment bias. Individual-level controls include age, sex, race, education, labor force participation, income, party identification, and global warming beliefs.

To account for spatial spillovers, such as from shared local news markets, a robustness check re-estimates the models including fixed effects for Nielsen Designated Market Areas (DMAs). These fixed effects hold constant any unobserved shocks or common information environments at the media-market level. The estimates remain substantively unchanged (SI S3.5).

Estimation

The main specification for the proximity analyses is a linear probability model:

$$Y_i = \sum_{q=1}^{4} \mathbb{1}\{Distance_i \in Q_q\}\beta_q + X_i^\top \gamma + State_{s(i)} + Wave_{t(i)} + \epsilon_i, \tag{1}$$

where Q_5 (farthest quintile) is the reference. The primary analysis operationalizes distance with quintiles to ensure there is common support and captures non-linear effects (Hainmueller, Mummolo, and Xu, 2019). Outcomes are indicators for recognition, credit to President Biden or the IRA, or belief that green investments are beneficial. X_i includes individual- and county-level covariates; $State_s$ and $Wave_t$ denote state and wave fixed effects.

An omnibus Wald test assesses the joint null that the first two distance quintile indicators equal zero. Q1-Q2 capture the individuals closest to projects. For the visibility outcome, the joint Wald test rejects the null of no proximity effect for renewables ($p = 0.0039$), indicating a consistent signal beyond any single bin, whereas the pooled contrast for manufacturing is smaller and not statistically distinguishable from zero ($p = 0.12$).

Inference

Spatial HAC (Conley) standard errors were computed using respondents' ZIP-centroid latitude/longitude (decimal degrees), a uniform kernel with a hard 400 km cutoff, the default triangular distance metric, and no grid pooling. Results are robust to computing great-circle distances, to alternative cutoffs (e.g., 300 and 500 km), and to clustering by state (SI S3.5).

Sensitivity

Sensitivity to unobserved confounding was assessed using the partial R^2–based bias formulas of Cinelli and Hazlett (2020). This procedure quantifies the strength of a hypothetical unobserved confounder required to reduce the Q1 proximity coefficient to statistical insignificance at the 5% level. For the manufacturing and renewable energy distance measures, an unobserved confounder would need to explain approximately 0.1% and 1.9% of the residual variation in both the treatment and the recognition outcome. These values are substantially larger than the correlations of strong observed predictors of proximity and outcomes, such as labor force size and income (SI S3.5).

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Competing Interests

The authors declare no competing interests.

Data, Materials, and Code Availability

All data, replication code, and materials will be archived at the Harvard Dataverse.

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SI Appendix

S1 Data Sources

Variable	Source and Description	Access Link
Clean Energy Data		
Clean energy: generation	EIA-860M (monthly). Reports existing and proposed generating units $\geq$1 MW; required reporting for new generators scheduled within 12 months of operation.	EIA-860M
Clean energy: manufacturing	The Big Green Machine dataset (Wellesley College) covering North American clean-energy supply chains from extraction to manufacturing.	Big Green Machine
Electricity prices (industrial)	State-level average industrial electricity price, 2023 (EIA Table 5C), cents per kWh.	EIA: Sales/Revenue/Price
Political Actors & Elections		
Democratic vote share (2020)	David Leip's Atlas of U.S. Presidential Elections. Alaska reports by state house district; converted to counties via population-weighted harmonization using district and county shapefiles.	US Election Atlas
Governor party	Ballotpedia state executive data (incumbent party at survey reference date).	Ballotpedia
Lawmaker parties	Official rosters from the Senate and House Clerks (used to assign party of state's federal delegation).	Senate Clerk House Clerk
Congressional elections	MIT Election Data + Science Lab.	Dataverse
Economic Context		
Unionization rates (private sector)	State-level union coverage/intensity, 2023; series based on Hirsch and MacPherson (2003).	UnionStats
Broadband access	FCC Form 477 county-level Internet Access Services (Tier 4: residential fixed $\geq$100 Mbps downstream).	FCC Form 477
Socioeconomic & Infrastructure		
Unemployment rate	Annual average county-level unemployment (BLS Local Area Unemployment Statistics).	BLS LAU Tables
Labor force size	Annual average county-level labor force (BLS LAU).	BLS LAU Tables
Gross domestic product	County real GDP, chained dollars, all industries (BEA CAGDP9).	BEA: GDP by County
Per capita income	County personal income per capita (BEA CAINC30).	BEA Regional Data
Highway access	TIGER/Line shapefiles (U.S. Primary Roads, 2023). Interstate access coded as a binary based on county–interstate intersection.	TIGER/Line: Primary Roads

Variable	Source and Description	Access Link
College degree share	ACS 2023 5-year estimate, share of residents with BA+ (table B06009_005).	Census API (ACS 5-year)
Poverty rate	ACS 2023 5-year estimate, below poverty (table B06012_002).	Census API (ACS 5-year)
Median housing costs	ACS 2023 5-year estimate, median monthly housing costs (table B25105_001).	Census API (ACS 5-year)
Foreign-born share	ACS 2023 5-year estimate, foreign-born (table B06012_017).	Census API (ACS 5-year)
Population density	Derived from 1 km WorldPop raster aggregated to 25 km circles around each respondent's lat–lon (analysis code documented in SI).	WorldPop Hub

S2 Survey

S2.1 Sample Summary Statistics

Table S2: Survey sample summaries, showing means of respondent-level characteristics

	2024 Field Date		
	3/14–4/9	5/13–6/6	8/6–11/11
Age	47	49	49
Female	0.54	0.52	0.52
Black	0.14	0.14	0.13
Asian	0.043	0.057	0.055
Other race	0.072	0.087	0.067
Hispanic/Latino	0.19	0.18	0.18
College	0.37	0.35	0.35
Employed	0.58	0.53	0.53
Income Q1	0.22	0.22	0.22
Income Q2	0.26	0.24	0.24
Income Q3	0.27	0.28	0.27
Income Q4	0.16	0.16	0.17
Income Q5	0.091	0.098	0.093
Democrat	0.44	0.45	0.47
Republican	0.39	0.37	0.37
Global Warming Index	0.76	0.75	0.76
N	1500	1992	1534

S2.2 Weight Diagnostics

Survey weights were constructed for the pooled sample and separately for questions only on specific waves. Iterative proportional fitting (raking) was used to align the sample to population benchmarks from the 2023 ACS 5-year release. The raking targets included the joint distribution of gender × age × education, and the marginal distributions of race/ethnicity, household income, and Census region (4 categories). Weights were trimmed to the interval [0.3, 3.0] to limit the influence of extreme values and were normalized to have mean 1 within each analysis sample.

Table S3. Comparison of Survey Distributions with ACS Population Benchmarks

Demographic Category	Unweighted	Weighted	ACS Target	Abs Diff (W-ACS)	Abs Diff (U-ACS)
Race: Asian Alone	0.05	0.06	0.06	0.00	0.01
Race: Black or African American Alone	0.13	0.12	0.12	0.00	0.01
Race: Other	0.08	0.15	0.16	0.02	0.08
Race: White Alone	0.74	0.67	0.66	0.02	0.08
Income: Q1	0.22	0.19	0.18	0.01	0.04
Income: Q2	0.25	0.21	0.20	0.01	0.04
Income: Q3	0.27	0.23	0.22	0.01	0.05
Income: Q4	0.16	0.18	0.17	0.00	0.01
Income: Q5	0.09	0.19	0.22	0.02	0.12
Region: Midwest	0.21	0.21	0.20	0.00	0.00
Region: Northeast	0.18	0.17	0.17	0.00	0.01
Region: South	0.38	0.39	0.39	0.00	0.01
Region: West	0.23	0.23	0.23	0.00	0.00
18-24 × No College × Female	0.05	0.05	0.05	0.00	0.00
25-34 × No College × Female	0.08	0.05	0.05	0.00	0.03
35-44 × No College × Female	0.04	0.05	0.05	0.00	0.00
45-64 × No College × Female	0.10	0.11	0.11	0.00	0.00
65+ × No College × Female	0.09	0.09	0.09	0.00	0.00
18-24 × College × Female	0.01	0.01	0.01	0.00	0.00
25-34 × College × Female	0.03	0.04	0.04	0.00	0.01
35-44 × College × Female	0.02	0.03	0.04	0.00	0.01
45-64 × College × Female	0.04	0.06	0.06	0.00	0.01
65+ × College × Female	0.06	0.03	0.03	0.00	0.03
18-24 × No College × Male	0.03	0.05	0.05	0.00	0.02
25-34 × No College × Male	0.06	0.06	0.06	0.00	0.00
35-44 × No College × Male	0.05	0.05	0.05	0.00	0.00
45-64 × No College × Male	0.07	0.10	0.11	0.00	0.04
65+ × No College × Male	0.06	0.06	0.06	0.00	0.01
18-24 × College × Male	0.00	0.01	0.01	0.00	0.00
25-34 × College × Male	0.04	0.03	0.03	0.00	0.01
35-44 × College × Male	0.05	0.03	0.03	0.00	0.02
45-64 × College × Male	0.04	0.05	0.05	0.00	0.01
65+ × College × Male	0.06	0.03	0.03	0.00	0.02

S2.3 Survey Instrument

The questions below were used in the analysis and were not already described in the article's Materials and Methods section. The question order varies slightly across the samples.

S2.3.1 Background Characteristics

1. Are you male or female?

   Male; Female

2. Are you Spanish, Hispanic, or Latino or none of these?

   Yes; None of these

3. Choose one or more races that you consider yourself to be:

   White; Black or African American; American Indian or Alaska Native; Asian; Native Hawaiian or Pacific Islander; Other

4. In what year were you born? (text entry)

5. What is your state? (drop-down list)

6. What is the highest level of education you have completed?

   No high school; Some high school; High school diploma or GED; Some college course work but non-degree certificate; Technical certificate; Associate degree; Bachelor's degree; Advanced degree (post college, such as JD or MBA)

7. What is your 5 digit ZIP code? (text entry)

S2.3.2 Climate Change Beliefs

8. Climate change refers to the claim that the world's average temperature has been increasing over the past 150 years, may be increasing more in the future, and that the world's climate may change as a result.

   What do you think? Do you think that climate change is happening?

   Climate change is happening; Climate change is not happening

9. How sure are you that [pipe in answer from the previous question]?

   Very sure; Somewhat sure; Not sure

10. Which of the following statements comes closest to your own opinion?

    Humans are causing climate change; Humans are not causing climate change

11. How sure are you that [pipe in answer from the previous question]?

    Very sure; Somewhat sure; Not sure

12. Which of the following do you think best describes your view about global warming?

    This is not a serious problem; More research is needed before action is taken; We should take some action now; Immediate and drastic action is necessary

13. How would you describe your current employment status?

    Employed full-time; Employed part-time; Work in the home (not paid); Not employed, but looking for work; Not employed, and not looking for work

14. Thinking back over the last year, what was your family's annual income?

    Less than $10,000; $10,000 - $19,999; $20,000 - $29,999; $30,000 - $39,999; $40,000 - $49,999; $50,000 - $59,999; $60,000 - $69,999; $70,000 - $79,999; $80,000 - $99,999; $100,000 - $119,999; $120,000 - $149,999; $150,000 - $199,999; $200,000 - $249,999; $250,000 - $349,999; $350,000 - $499,999; $500,000 or more; Prefer not to say

S2.3.3 Political Background

15. Generally speaking, do you think of yourself as a...?

    Democrat; Republican; Independent; Other (text entry)

16. (If Democrat/Republican) Would you call yourself a strong [Democrat/Republican] or not so strong [Democrat/Republican]?

    Strong [Democrat/Republican]; Not so strong [Democrat/Republican]

17. (If Independent or Other) Do you think of yourself as closer to the Democratic or Republican party?

    The Democratic Party; The Republican Party; Neither; Not sure

S2.4 Credit Attribution Internal Validity

First, to minimize partisan differences in response patterns, the question described green investments neutrally, without specifying whether projects were good or bad. Partisan expressive responding is an inherent risk, but we focus here on whether the wording disengaged or primed partisans differently. Response times do not differ across partisan identification or ideology (Table S4), suggesting the question was equally engaging across groups.

Table S4: Linear probability model of credit attribution question time latency by political affiliation

	(1)	(2)	(3)	(4)
Intercept	36.4***	37.1***	33.17***	33.9***
	(2.6)	(3.4)	(0.99)	(1.6)
Republican	-2.0	-2.0		
	(2.8)	(2.9)		
Neither party	-3.3	-3.3		
	(3.1)	(3.2)		
Ideology: Conservative			3.1	3.2
			(2.3)	(2.3)
Ideology: Not sure			-3.6	-3.7
			(2.2)	(2.2)
Ideology: Liberal			4.0	4.1
			(4.1)	(4.1)
N	3034	3034	3034	3034
Adjusted R^2	-0.000	-0.001	-0.000	-0.000
Sample Fixed Effects	No	Yes	No	Yes

Notes: Heteroskedasticity-robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Second, the question asked respondents to evaluate multiple actors independently. This approach avoids forcing trade-offs, as in a bipolar scale (e.g., Biden vs. governor), or imposing unrealistic quantitative judgments, as in a "divide-the-dollar" measure. Nearly all respondents found at least one actor responsible: only 1.2% rated every listed factor as "not at all responsible," suggesting good coverage of perceived sources of responsibility.

Third, we examined potential satisficing through straight-lining (e.g., rating all actors as "extremely responsible"). Such patterns were rare: only 3.2% of respondents did so. This indicates that indiscriminate responding was infrequent.

Taken together, these checks provide evidence consistent with the internal validity and reliability of the credit attribution battery.

S3 Proximity Effects on Recognition, Benefits, and Attribution

S3.1 Summary Statistics

Table S5: Proximity analysis summary statistics

	Mean	SD	Min	Max	NA
Sees clean energy project	0.26	0.44	0	1	0
Credits Biden	0.42	0.49	0	1	1992
Credits State	0.44	0.5	0	1	1992
Credits Congress	0.36	0.48	0	1	1992
Credits Local Officials	0.42	0.49	0	1	1992
Credits Markets	0.35	0.48	0	1	1992
Age	48	18	18	97	0
Female	0.53	0.5	0	1	0
Black	0.14	0.35	0	1	0
Asian	0.052	0.22	0	1	0
Other race	0.077	0.27	0	1	0
Hispanic/Latino	0.18	0.39	0	1	0
College	0.36	0.48	0	1	0
Employed	0.55	0.5	0	1	0
Income Q1	0.22	0.41	0	1	0
Income Q2	0.25	0.43	0	1	0
Income Q3	0.27	0.45	0	1	0
Income Q4	0.16	0.37	0	1	0
Income Q5	0.094	0.29	0	1	0
Democrat	0.46	0.5	0	1	0
Republican	0.38	0.48	0	1	0
Global warming index	0.75	0.3	0	1	0
Unemployment rate	3.8	1	1.7	18	0
Labor force (log) $(t-1)$	12	1.6	6.8	15	0
County GDP (log) $(t-1)$	17	1.8	11	21	0
County income pc $(t-1)$	42349	17735	12744	131902	0
Highway access	0.87	0.34	0	1	0
County college share $(t-1)$	0.34	0.11	0.057	0.66	0
County poverty share $(t-1)$	0.18	0.066	0.03	0.6	0
Median county housing costs $(t-1)$	1414	478	393	3049	0
County foreign-born share $(t-1)$	0.2	0.15	0	0.75	0
Population density	734	1073	0.21	5632	0
Faster broadband access	0.74	0.44	0	1	0
County 2020 Biden vote share	52	17	8.6	92	0

Notes: Summary statistics across all survey samples. Analyses standardize continuous county-level measures with the within-state variance. $N = 5026$

S3.2 Within-State Variation in Distance

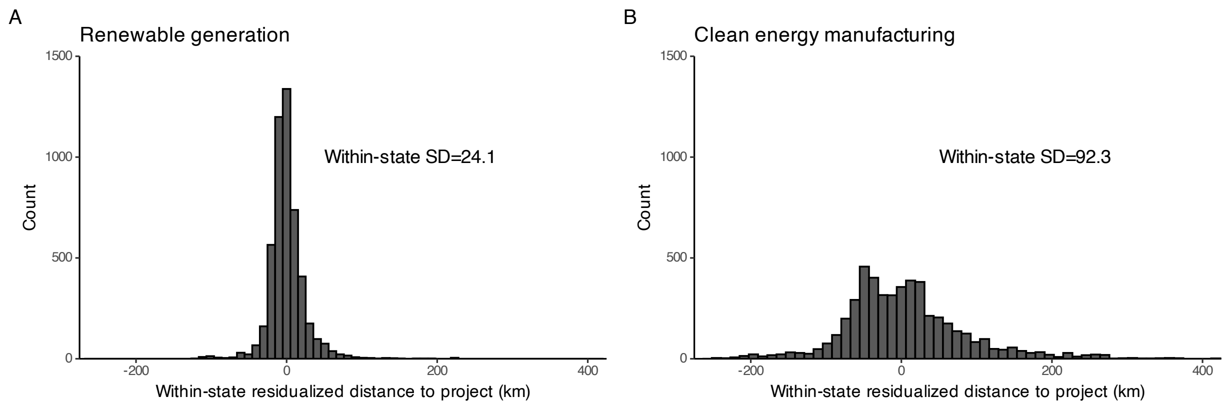

Fig. S1. Within-state variation in survey respondent proximity to clean energy investments

S3.3 Main Regression Table

Table S6: Linear probability models of project recognition, credit attribution, and perceived benefits

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewable Energy	Manufacturing	Renewable Energy	Manufacturing	Renewable Energy	Manufacturing
Q1 proximity	0.066***	0.063*	-0.013	0.0051	0.0025	-0.013
	(0.020)	(0.031)	(0.025)	(0.0324)	(0.0428)	(0.042)
Q2 proximity	0.045*	0.042	-0.024	0.013	0.057	-0.041
	(0.021)	(0.028)	(0.037)	(0.034)	(0.037)	(0.027)
Q3 proximity	0.0053	0.043	-0.055	0.0054	0.064	0.0048
	(0.0215)	(0.026)	(0.032)	(0.0310)	(0.038)	(0.0417)
Q4 proximity	0.023	0.037*	-0.035	-0.030	0.059	-0.017
	(0.017)	(0.018)	(0.029)	(0.028)	(0.040)	(0.042)
Age	-0.00123***	-0.00126***	0.00059	0.00056	0.00029	0.00026
	(0.00032)	(0.00032)	(0.00052)	(0.00052)	(0.00102)	(0.00103)
Female	-0.063***	-0.062***	-0.060***	-0.060***	-0.036*	-0.036*
	(0.013)	(0.012)	(0.017)	(0.017)	(0.017)	(0.017)
Black	0.023	0.022	0.042	0.041	-0.044	-0.045
	(0.018)	(0.019)	(0.034)	(0.035)	(0.031)	(0.033)
Asian	-0.043	-0.041	0.027	0.026	-0.034	-0.039
	(0.024)	(0.023)	(0.050)	(0.049)	(0.088)	(0.088)
Other race	-0.023	-0.026	-0.036	-0.035	0.065*	0.064*
	(0.022)	(0.022)	(0.031)	(0.030)	(0.029)	(0.029)
Hispanic/Latino	0.0252**	0.0276**	0.0077	0.0077	-0.090**	-0.085**
	(0.0094)	(0.0096)	(0.0221)	(0.0216)	(0.033)	(0.033)
College	0.072***	0.070***	0.050**	0.049*	0.0016	0.0011
	(0.016)	(0.015)	(0.019)	(0.020)	(0.0278)	(0.0292)
Employed	0.066***	0.067***	0.035*	0.034	0.050	0.049
	(0.014)	(0.014)	(0.018)	(0.018)	(0.031)	(0.031)
Income Q2	0.017	0.016	-0.014	-0.012	0.031	0.028
	(0.016)	(0.016)	(0.027)	(0.028)	(0.030)	(0.031)
Income Q3	0.007	0.0067	-0.045*	-0.044	0.013	0.014
	(0.015)	(0.0143)	(0.023)	(0.024)	(0.032)	(0.033)
Income Q4	0.056***	0.057***	-0.021	-0.020	0.048	0.048
	(0.016)	(0.016)	(0.024)	(0.024)	(0.045)	(0.045)
Income Q5	0.074**	0.076**	-0.034	-0.031	0.077	0.075
	(0.024)	(0.025)	(0.021)	(0.021)	(0.048)	(0.048)
Republican	-0.009	-0.0093	-0.169***	-0.170***	-0.147***	-0.147***
	(0.017)	(0.0175)	(0.017)	(0.018)	(0.034)	(0.032)
Neither party	-0.069***	-0.070***	-0.221***	-0.223***	-0.105**	-0.105**
	(0.013)	(0.013)	(0.024)	(0.025)	(0.033)	(0.035)
Global warming index	0.128***	0.128***	0.074*	0.074*	0.566***	0.566***
	(0.013)	(0.014)	(0.032)	(0.033)	(0.048)	(0.048)
Population density	-0.0049	-0.0097	0.0150	0.015	0.013	0.0188*
	(0.0064)	(0.0062)	(0.0087)	(0.008)	(0.010)	(0.0086)
County college share $(t-1)$	0.0045	0.004	-0.00034	-0.0015	0.015	0.018
	(0.0131)	(0.013)	(0.01827)	(0.0176)	(0.028)	(0.027)
County poverty share $(t-1)$	0.0085	0.0097	-0.0041	-0.0031	-0.0072	-0.0035
	(0.0141)	(0.0147)	(0.0145)	(0.0148)	(0.0190)	(0.0189)
County foreign-born share $(t-1)$	-0.00038	-0.0033	-0.00035	-0.0012	-0.012	-0.013
	(0.00716)	(0.0061)	(0.01378)	(0.0127)	(0.017)	(0.017)
Median county housing costs $(t-1)$	-0.038**	-0.041**	0.006	0.0068	0.00039	0.0075
	(0.013)	(0.013)	(0.016)	(0.0159)	(0.01883)	(0.0203)
Faster broadband access $(t-1)$	0.013	0.017	-0.043	-0.044*	0.053	0.054
	(0.016)	(0.015)	(0.023)	(0.022)	(0.037)	(0.036)
County GDP (log) $(t-1)$	0.059	0.051	0.049	0.051	0.040	0.039
	(0.041)	(0.042)	(0.043)	(0.041)	(0.065)	(0.064)
Labor force (log) $(t-1)$	-0.071	-0.063	-0.045	-0.048	-0.051	-0.052
	(0.040)	(0.042)	(0.037)	(0.036)	(0.057)	(0.052)
County unemployment rate $(t-1)$	-0.0086	-0.0061	0.0243***	0.0259***	0.022*	0.0245*
	(0.0065)	(0.0057)	(0.0064)	(0.0059)	(0.011)	(0.0099)
Highway access	0.015	0.016	0.076	0.074	0.0021	0.011
	(0.024)	(0.024)	(0.040)	(0.039)	(0.0295)	(0.029)
County income pc $(t-1)$	0.024*	0.0283**	-0.0027	-0.0012	-0.0099	-0.012
	(0.010)	(0.0096)	(0.0147)	(0.0142)	(0.0237)	(0.023)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.075	0.074	0.069	0.068	0.182	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model. Models 1–2: outcome = 1 if the respondent reports a local green project, 0 otherwise. Models 3–4: outcome = 1 if the respondent credits the Biden Administration for local green investments. Models 5–6: outcome = 1 if the respondent perceives a benefit from local green projects. Unit of analysis: individual. Estimates are OLS with Conley SEs (400 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S3.4 Power Analyses

The main text analysis relies on a categorical measure of distance quintiles from new clean energy projects. To assess statistical power, we focus on the contrast between individuals in the nearest quintile and those in the farthest quintile. This contrast is the most likely case for an effect of proximity on credit attribution or recognition, so any other comparisons necessarily have less statistical power for the same minimally detectable effect.

Three binary outcomes were considered: (i) whether respondents indicated that President Biden was "extremely" or "very" responsible for new clean energy investments in their state, (ii) whether respondents recognized the presence of a new clean energy project in their community, and (iii) whether respondents thought green investments were economically beneficial.

Power was calculated analytically using the following procedure. First, for each proximity measure, the outcome mean was estimated from the control group (respondents in the farthest quintile). A minimum detectable effect (MDE) was then specified. Next, 1,000 datasets were simulated, each with the same number of respondent–state observations as in the observed data. In each simulation, the outcome variable was drawn from a binomial distribution with the probability parameter determined by the control group mean and the assumed MDE. The treatment effect was modeled as decaying with distance for the intermediate quintiles of the categorical proximity measure.

For each assumed MDE, the simulated outcome was regressed on the treatment indicator, including the same state fixed effects and covariates as in the main specification. The proportion of estimates that were correctly signed and statistically significant at the 5% level was recorded as the analytical power.

Figures S2–S4 present power analyses for the three main outcomes. The horizontal blue line indicates the MDE for which the design has 80% power ($\alpha = 0.05$). Since each outcome ranges from 0-1, multiply the MDE by 100 for interpretation in percentage point shifts.

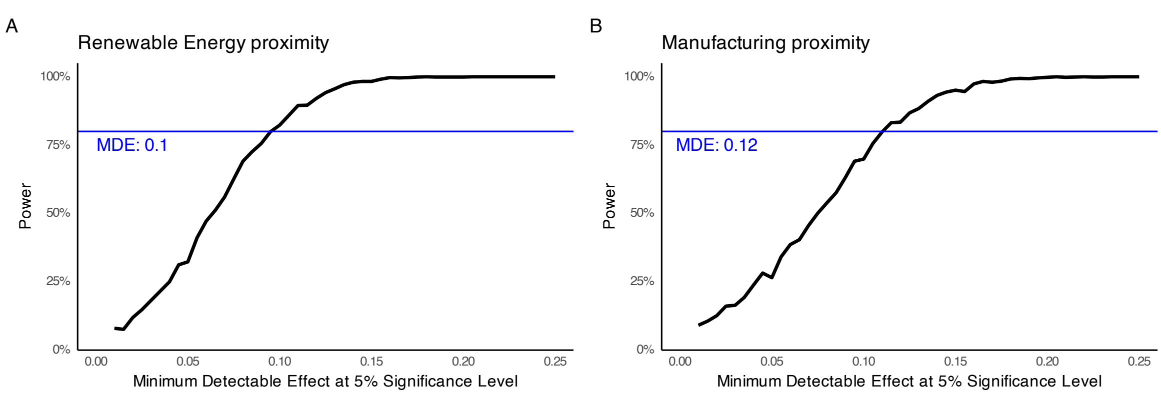

Fig. S2. Analytical power analysis, credit attribution outcome.

It is reasonable to imagine that reformers behind the IRA anticipated that individuals living near projects would be noticeably more likely to recognize their presence—on the order of an 8 percentage point increase—and, in turn, roughly 10 percentage points more likely to attribute credit to the Biden Administration. While partisan polarization constrains belief

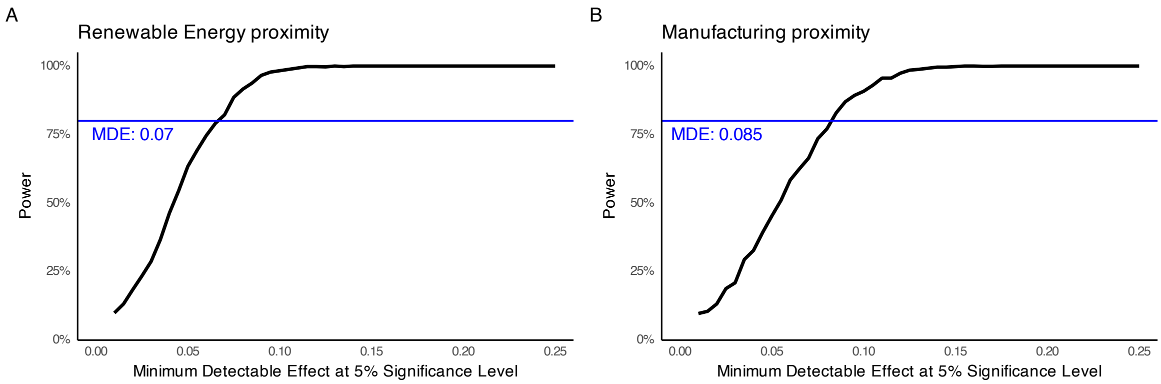

Fig. S3. Analytical power analysis, recognition outcome

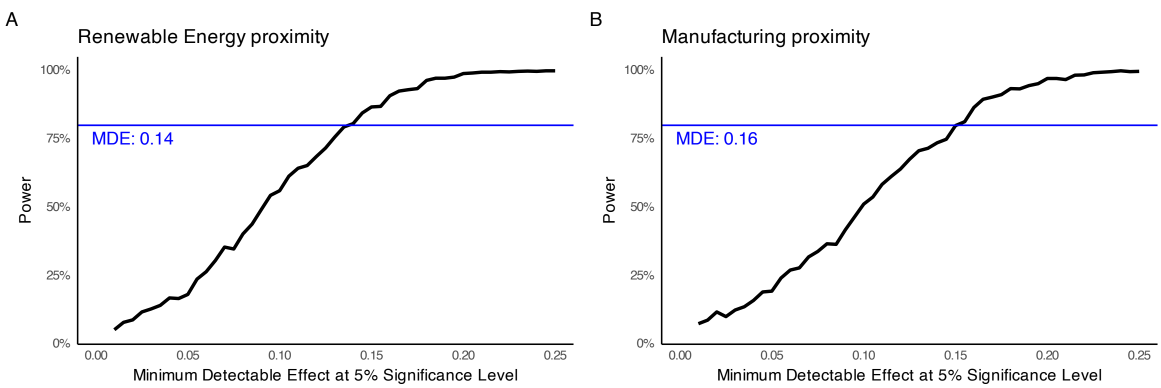

Fig. S4. Analytical power analysis, benefit outcome

change among Democrats and Republicans, a substantial share of the public identifies as independent, and at least some of these respondents may be open to updating their views if exposed to local projects. We therefore treat shifts of this magnitude as substantively meaningful benchmarks. Although our design cannot reliably detect smaller effects, such effects would be more difficult to interpret as politically consequential, even if they existed.

There are limits to the analytic power calculation. First, the procedure assumes independent binomial draws and a decay of treatment effects across distance bins, which may not fully reflect real-world correlation structures or alternative functional forms. Second, because simulated outcomes are generated without reference to covariates, the role of covariate adjustment is limited to variance reduction, which could result in under-estimating power.

S3.5 Robustness Checks

S3.5.1 Sensitivity to Omitted Variable Bias

Table S7. Sensitivity analysis for recognition outcome, manufacturing proximity (q1) model

Outcome: *Recognition (=1)*						
Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Manufacturing proximity (Q1)	0.063	0.031	2.016	0.1%	2.8%	0.1%
df = 4942	*Bound (1 x County Labor Force (log))*: $R^2_{Y\sim Z\|\mathbf{X},D} = 0.3\%$, $R^2_{D\sim Z\|\mathbf{X}} = 0\%$					

Table S8. Sensitivity analysis for recognition outcome, renewable energy proximity (q1) model

Outcome: *Recognition (=1)*						
Treatment:	Est.	S.E.	t-value	$R^2_{Y\sim D\|\mathbf{X}}$	$RV_{q=1}$	$RV_{q=1,\alpha=0.05}$
Renewable energy proximity (Q1)	0.066	0.02	3.305	0.2%	4.6%	1.9%
df = 4942	*Bound (1 x County Labor Force (log))*: $R^2_{Y\sim Z\|\mathbf{X},D} = 0.1\%$, $R^2_{D\sim Z\|\mathbf{X}} = 0.3\%$					

S3.5.2 Alternative Specifications of Spatial Standard Errors

Table S9: Robustness to 300 km Conley standard error cutoff: Linear probability models of project recognition and credit attribution.

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Q1 proximity	0.066**	0.063*	-0.013	0.0051	0.0025	-0.013
	(0.021)	(0.028)	(0.033)	(0.0334)	(0.0437)	(0.046)
Q2 proximity	0.045*	0.042	-0.024	0.013	0.057	-0.041
	(0.022)	(0.024)	(0.038)	(0.031)	(0.036)	(0.044)
Q3 proximity	0.0053	0.043	-0.055	0.0054	0.064	0.0048
	(0.0218)	(0.025)	(0.032)	(0.0265)	(0.038)	(0.0396)
Q4 proximity	0.023	0.037*	-0.035	-0.030	0.059	-0.017
	(0.023)	(0.018)	(0.035)	(0.018)	(0.041)	(0.041)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.075	0.074	0.069	0.068	0.182	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model. Models 1–2: outcome = 1 if the respondent reports a local green project, 0 otherwise. Models 3–4: outcome = 1 if the respondent credits the Biden Administration for local green investments. Models 5–6: outcome = 1 if the respondent perceives a benefit from local green projects. Unit of analysis: individual. Estimates are OLS with Conley SEs (300 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S10: Robustness to 500 km Conley standard error cutoff: Linear probability models of project recognition and credit attribution.

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Q1 proximity	0.066***	0.063*	-0.013	0.0051	0.0025	-0.013
	(0.016)	(0.032)	(0.033)	(0.0341)	(0.0372)	(0.047)
Q2 proximity	0.045*	0.042	-0.024	0.013	0.057*	-0.041
	(0.021)	(0.029)	(0.040)	(0.034)	(0.026)	(0.042)
Q3 proximity	0.0053	0.043	-0.055	0.0054	0.064*	0.0048
	(0.0203)	(0.027)	(0.035)	(0.0397)	(0.028)	(0.0430)
Q4 proximity	0.023	0.037*	-0.035	-0.030	0.059	-0.017
	(0.016)	(0.015)	(0.029)	(0.028)	(0.039)	(0.041)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.075	0.074	0.069	0.068	0.182	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model. Models 1–2: outcome = 1 if the respondent reports a local green project, 0 otherwise. Models 3–4: outcome = 1 if the respondent credits the Biden Administration for local green investments. Models 5–6: outcome = 1 if the respondent perceives a benefit from local green projects. Unit of analysis: individual. Estimates are OLS with Conley SEs (500 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S11: Robustness to state-clustered standard errors: Linear probability models of project recognition and credit attribution.

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Q1 proximity	0.066**	0.063*	-0.013	0.0051	0.0025	-0.013
	(0.020)	(0.030)	(0.026)	(0.0376)	(0.0382)	(0.037)
Q2 proximity	0.045	0.042	-0.024	0.013	0.057	-0.041
	(0.026)	(0.024)	(0.036)	(0.031)	(0.030)	(0.036)
Q3 proximity	0.0053	0.043	-0.055	0.0054	0.064	0.0048
	(0.0205)	(0.023)	(0.030)	(0.0361)	(0.037)	(0.0404)
Q4 proximity	0.023	0.037	-0.035	-0.030	0.059	-0.017
	(0.018)	(0.020)	(0.032)	(0.028)	(0.034)	(0.048)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.075	0.074	0.069	0.068	0.182	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model. Models 1–2: outcome = 1 if the respondent reports a local green project, 0 otherwise. Models 3–4: outcome = 1 if the respondent credits the Biden Administration for local green investments. Models 5–6: outcome = 1 if the respondent perceives a benefit from local green projects. Unit of analysis: individual. Estimates are OLS with robust standard errors clustered at the state level. Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S3.5.3 Alternative Geocoordinate and Distance Measures

Table S12: Robustness to precise geo-coordinates: Linear probability models of project recognition and credit attribution.

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Q1 proximity	0.056**	0.06*	-0.012	-0.00096	0.00015	-0.018
	(0.020)	(0.03)	(0.028)	(0.03406)	(0.04210)	(0.042)
Q2 proximity	0.040	0.039	-0.036	0.016	0.054	-0.042
	(0.022)	(0.028)	(0.041)	(0.036)	(0.038)	(0.029)
Q3 proximity	-0.002	0.044	-0.060	-0.0028	0.058	0.0059
	(0.021)	(0.027)	(0.034)	(0.0338)	(0.038)	(0.0411)
Q4 proximity	0.018	0.038*	-0.041	-0.029	0.064	-0.0074
	(0.017)	(0.016)	(0.029)	(0.031)	(0.038)	(0.0414)
N	4856	4856	2931	2931	1452	1452
Adjusted R^2	0.065	0.064	0.062	0.061	0.177	0.174
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This analysis is performed on the subset of respondents whose IP addresses and ZIP codes imply similar longitude-latitude geo-coordinates. Each column reports a separate linear probability model. Models 1–2: outcome = 1 if the respondent reports a local green project, 0 otherwise. Models 3–4: outcome = 1 if the respondent credits the Biden Administration for local green investments. Models 5–6: outcome = 1 if the respondent perceives a benefit from local green projects. Unit of analysis: individual. Estimates are OLS with Conley SEs (400 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S13: Robustness to spherical distance metric: Linear probability models of project recognition and credit attribution.

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Q1 proximity	0.066**	0.063*	-0.013	0.0051	0.0025	-0.013
	(0.020)	(0.032)	(0.024)	(0.0336)	(0.0429)	(0.043)
Q2 proximity	0.045*	0.042	-0.024	0.013	0.057	-0.041
	(0.021)	(0.029)	(0.037)	(0.034)	(0.038)	(0.029)
Q3 proximity	0.0053	0.043	-0.055	0.0054	0.064	0.0048
	(0.0216)	(0.026)	(0.031)	(0.0318)	(0.038)	(0.0420)
Q4 proximity	0.023	0.037*	-0.035	-0.030	0.059	-0.017
	(0.016)	(0.018)	(0.028)	(0.029)	(0.042)	(0.041)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.075	0.074	0.069	0.068	0.182	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model. Models 1–2: outcome = 1 if the respondent reports a local green project, 0 otherwise. Models 3–4: outcome = 1 if the respondent credits the Biden Administration for local green investments. Models 5–6: outcome = 1 if the respondent perceives a benefit from local green projects. Unit of analysis: individual. Estimates are OLS with Conley SEs (400 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S3.5.4 Continuous Distance Measure

Table S14: Robustness to continuous distance specification: Linear probability models of project recognition, credit attribution, and perceived benefits.

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Distance to renewables (log)	-0.0309***		0.0013		0.0034	
	(0.0083)		(0.0079)		(0.0223)	
Distance to manufacturing (log)		-0.0171*		0.00017		-0.0064
		(0.0075)		(0.00859)		(0.0142)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.076	0.074	0.068	0.068	0.181	0.181
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model. Models 1–2: outcome = 1 if the respondent reports a local green project, 0 otherwise. Models 3–4: outcome = 1 if the respondent credits the Biden Administration for local green investments. Models 5–6: outcome = 1 if the respondent perceives a benefit from local green projects. Unit of analysis: individual. Estimates are OLS with Conley SEs (400 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S3.5.5 Survey Weights

Table S15: Robustness to survey weights: Linear probability models of project recognition, credit attribution, and perceived benefits.

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Q1 proximity	0.064**	0.082**	-0.034	0.0007	0.0025	-0.013
	(0.022)	(0.030)	(0.028)	(0.0368)	(0.0428)	(0.042)
Q2 proximity	0.039	0.061*	-0.0084	0.0024	0.057	-0.041
	(0.025)	(0.030)	(0.0353)	(0.0373)	(0.037)	(0.027)
Q3 proximity	-0.0017	0.054	-0.065*	-0.0042	0.064	0.0048
	(0.0263)	(0.029)	(0.028)	(0.0360)	(0.038)	(0.0417)
Q4 proximity	0.022	0.068***	-0.029	-0.058*	0.059	-0.017
	(0.020)	(0.016)	(0.020)	(0.027)	(0.040)	(0.042)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.074	0.073	0.075	0.074	0.182	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model. Models 1–2: outcome = 1 if the respondent reports a local green project, 0 otherwise. Models 3–4: outcome = 1 if the respondent credits the Biden Administration for local green investments. Models 5–6: outcome = 1 if the respondent perceives a benefit from local green projects. Unit of analysis: individual. Estimates are OLS with Conley SEs (400 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S3.5.6 Additional Credit Recipients

Table S16: Robustness to different credit attribution outcomes: Linear probability models of credit attribution.

	Governor (=1)		State lawmakers (=1)		Congress (=1)		Local officials (=1)		Markets (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Q1 proximity	0.011	-0.032	-0.020	0.017	-0.018	0.049	-0.050	0.056	-0.017	-0.0057
	(0.031)	(0.042)	(0.037)	(0.040)	(0.023)	(0.027)	(0.041)	(0.034)	(0.039)	(0.0396)
Q2 proximity	-0.023	-0.046	0.0011	0.035	-0.017	0.036	-0.0065	0.014	-0.023	-0.042
	(0.033)	(0.031)	(0.0316)	(0.034)	(0.034)	(0.025)	(0.0338)	(0.030)	(0.036)	(0.028)
Q3 proximity	-0.023	-0.029	-0.052	0.036	-0.045*	0.015	-0.052	0.051*	-0.039	0.025
	(0.035)	(0.034)	(0.036)	(0.040)	(0.021)	(0.030)	(0.033)	(0.024)	(0.029)	(0.033)
Q4 proximity	-0.053	-0.030	-0.048	0.014	-0.011	0.00086	-0.074	0.011	-0.05	-0.038
	(0.036)	(0.037)	(0.037)	(0.039)	(0.022)	(0.01995)	(0.038)	(0.028)	(0.03)	(0.028)
N	3034	3034	3034	3034	3034	3034	3034	3034	3034	3034
Adjusted R^2	0.042	0.041	0.047	0.045	0.079	0.079	0.048	0.046	0.055	0.056
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model. Unit of analysis: individual. Estimates are OLS with Conley SEs (400 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S3.6 Treatment Effect Heterogeneity

We assess whether the effect of proximity varies with a moderator M_i. The specification extends Eq. 1 by interacting M_i with proximity quintile indicators:

$$Y_i = M_i\lambda + M_i \times \sum_{q=1}^{4} \mathbb{1}[Distance_i \in Q_q]\beta_q + X_i^\top\gamma + State_{s(i)} + Wave_{t(i)} + \epsilon_i, \qquad \text{(S1)}$$

where Q_5 (farthest quintile) is the omitted category. Models are estimated using OLS on the full sample for which the outcome is observed. Standard errors are spatial heteroskedasticity- and autocorrelation-consistent (Conley) with a 400 km cutoff. No weights are applied. All subsequent subsections apply this specification to a single moderator.

S3.6.1 Project Heterogeneity

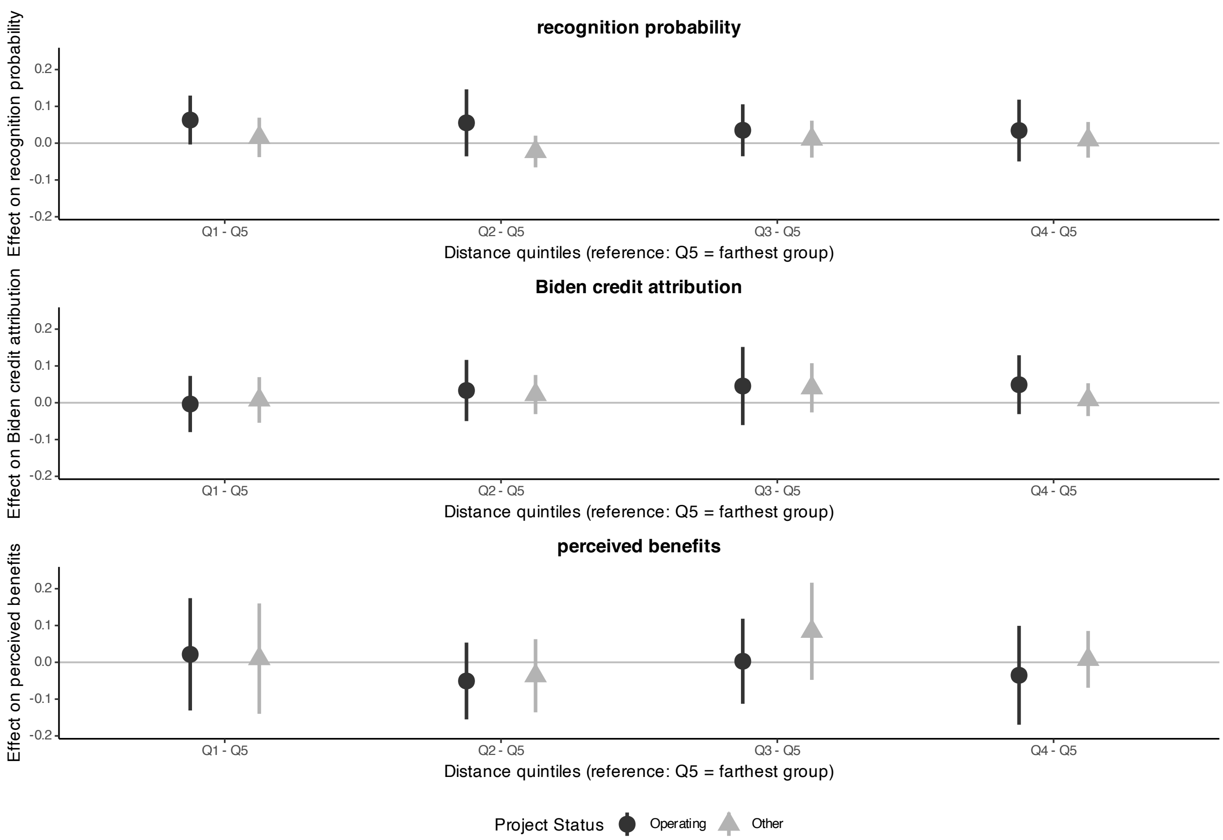

Fig. S5. Heterogeneous effects of clean energy manufacturing proximity on recognition by project status

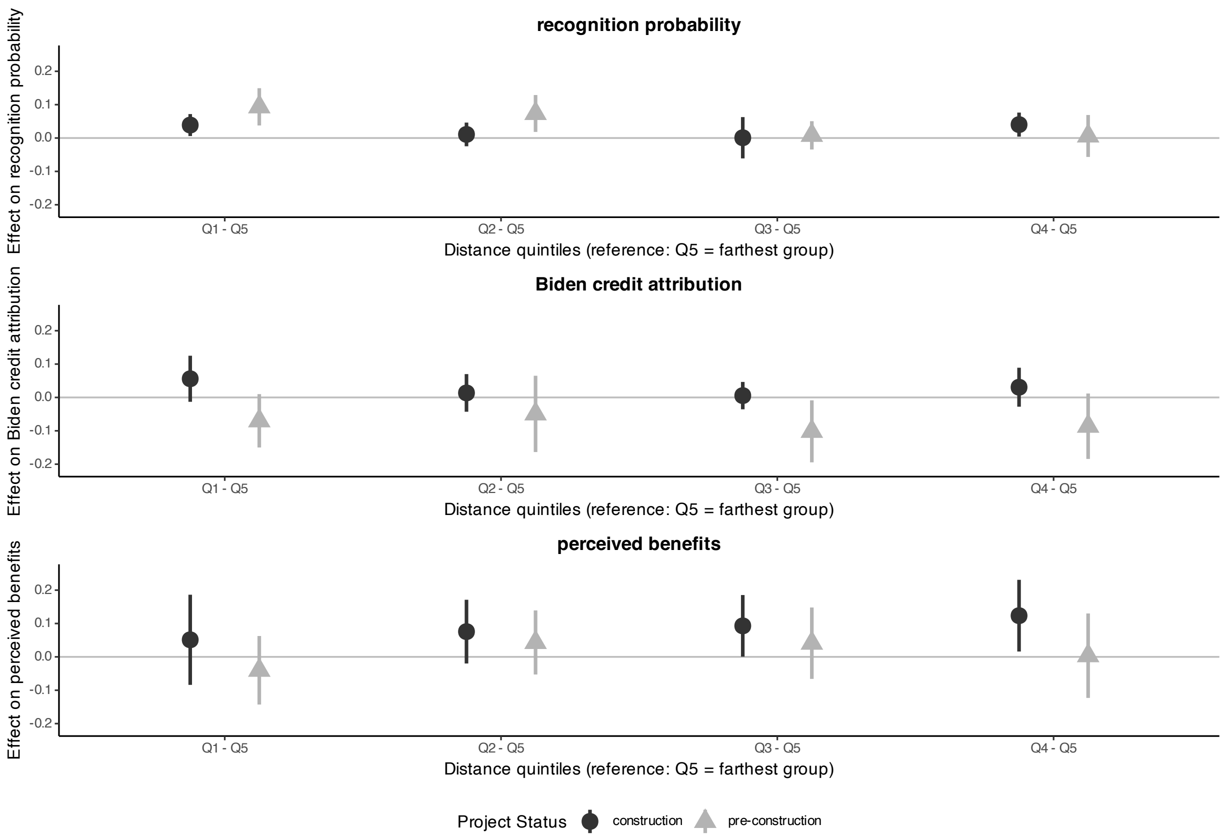

Fig. S6. Heterogeneous effects of renewable generation proximity by project status

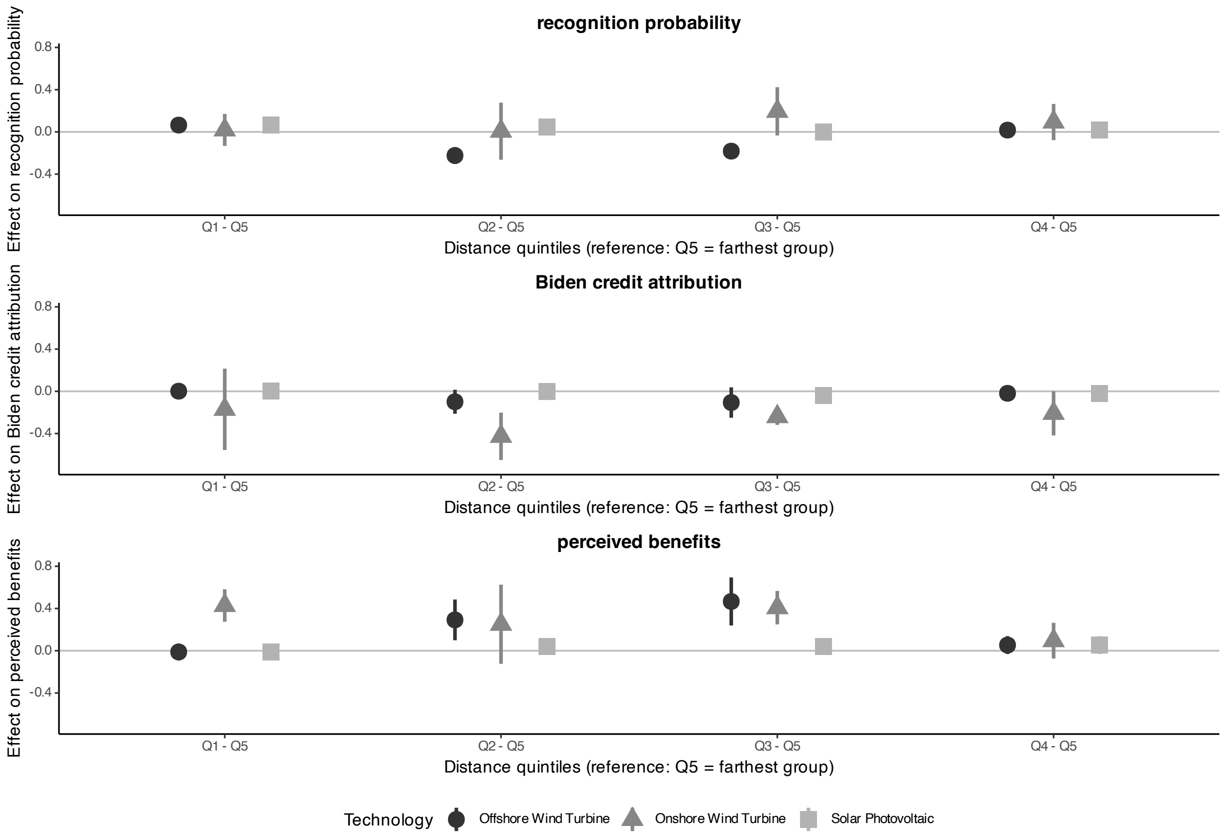

Fig. S7. Heterogeneous effects of renewable generation proximity by technology

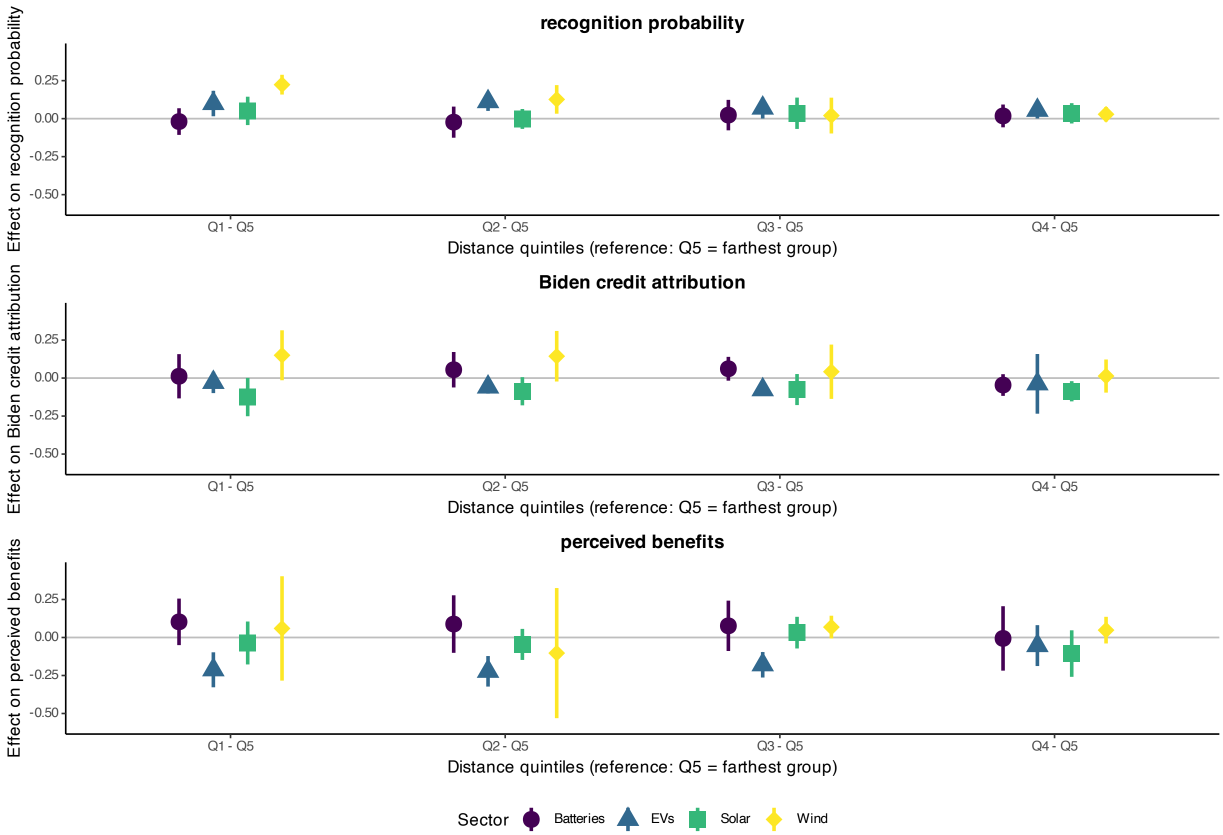

Fig. S8. Heterogeneous effects of clean energy manufacturing proximity by project sector

S3.6.2 Individual-Level Heterogeneity

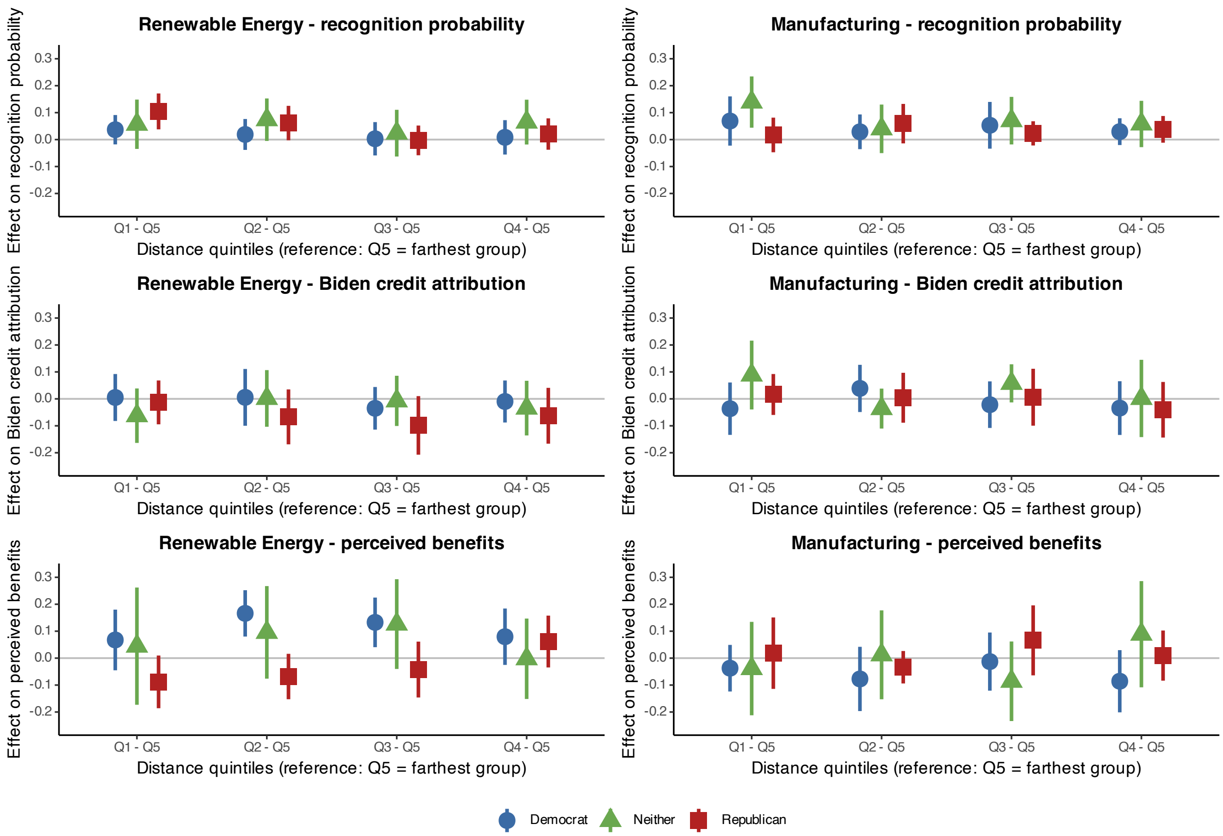

Fig. S9. Heterogeneous effects of proximity by respondent partisan identification

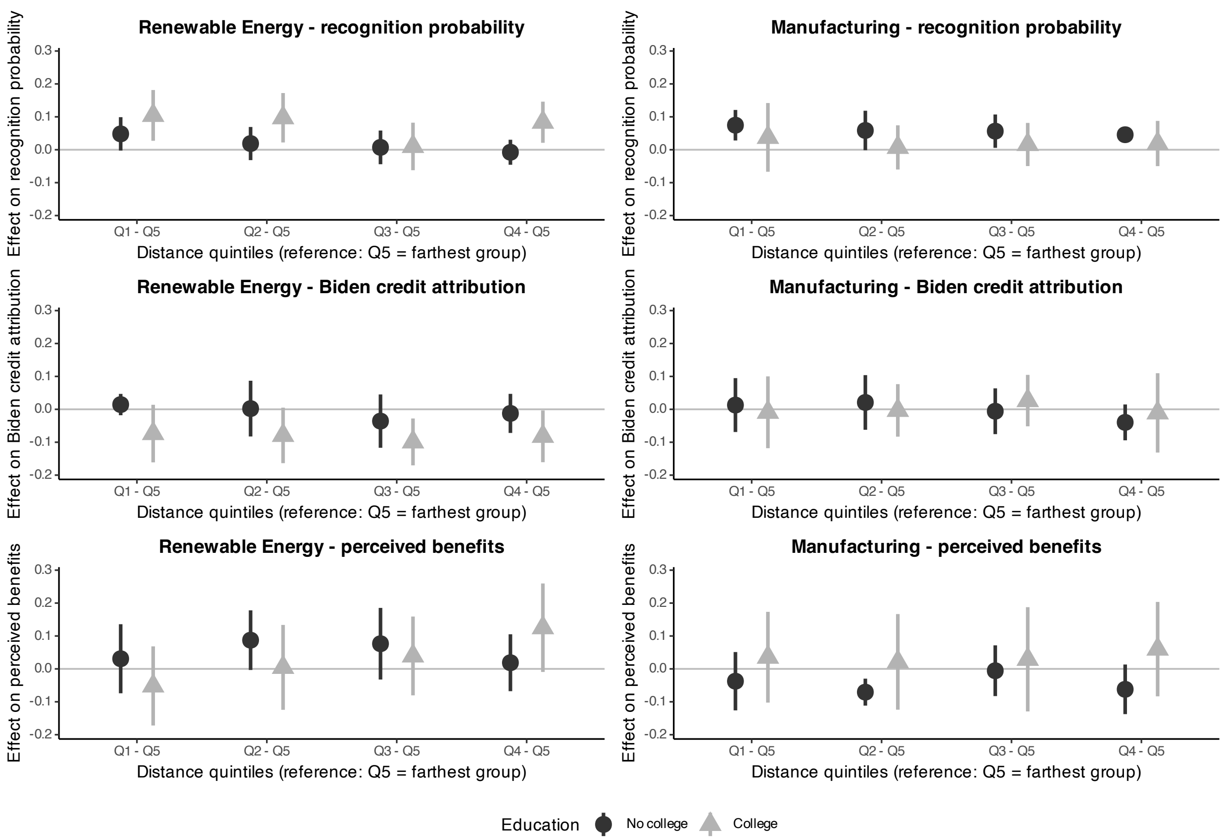

Fig. S10. Heterogeneous effects of proximity by respondent education

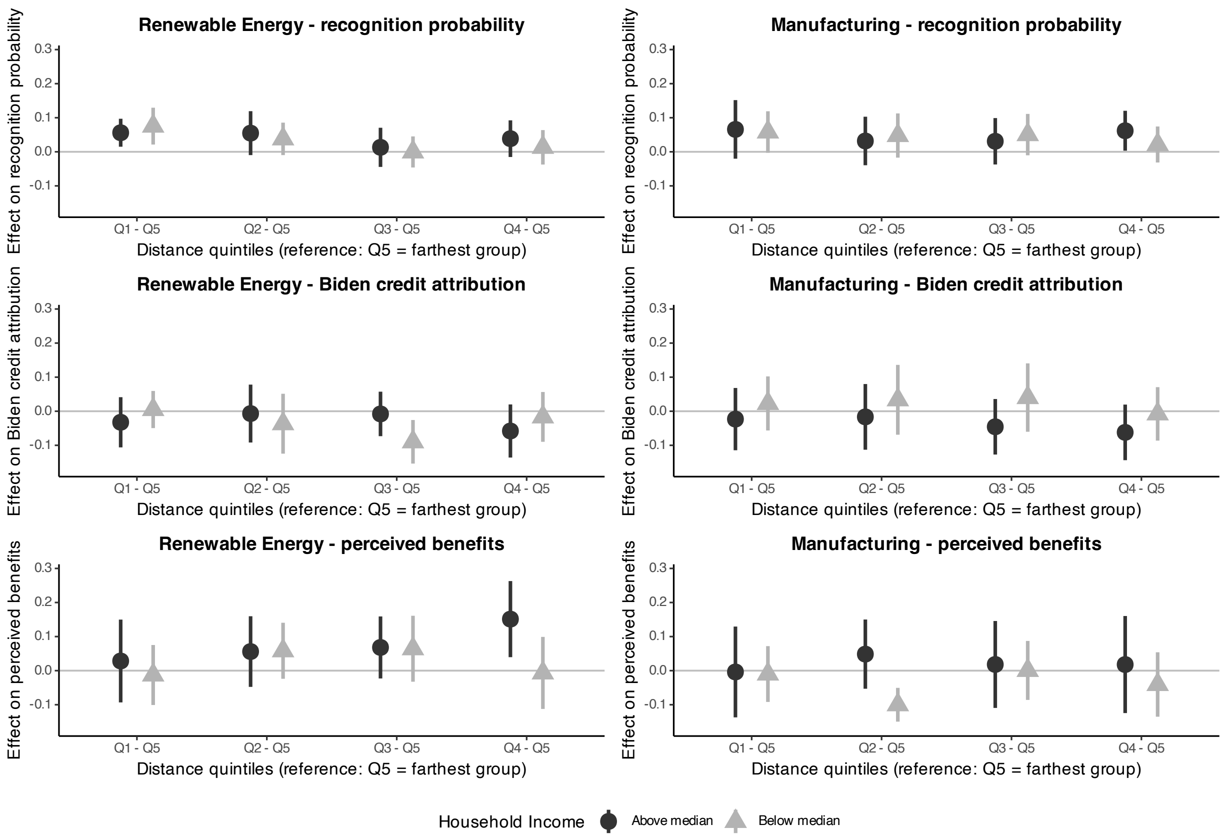

Fig. S11. Heterogeneous effects of proximity by respondent income

S4 Model of Perceived Benefits

Table S17: Linear probability model of perceived project benefits

	(1)	(2)	(3)
Intercept	0.12	0.17	0.11
	(0.19)	(0.20)	(0.19)
Age	0.00026	0.00033	0.00023
	(0.00105)	(0.00105)	(0.00106)
Female	-0.042*	-0.042*	-0.042*
	(0.020)	(0.020)	(0.020)
Black	-0.033	-0.036	-0.034
	(0.032)	(0.032)	(0.031)
Asian	-0.038	-0.033	-0.038
	(0.064)	(0.063)	(0.064)
Other race	0.060	0.061	0.059
	(0.043)	(0.045)	(0.044)
Hispanic/Latino	-0.080*	-0.082*	-0.079*
	(0.034)	(0.035)	(0.034)
College	0.010	0.011	0.010
	(0.023)	(0.024)	(0.023)
Employed	0.051	0.053	0.050
	(0.034)	(0.034)	(0.034)
Income Q2	0.031	0.030	0.030
	(0.026)	(0.026)	(0.026)
Income Q3	0.004	0.002	0.0026
	(0.031)	(0.030)	(0.0313)
Income Q4	0.044	0.043	0.042
	(0.035)	(0.034)	(0.035)
Income Q5	0.065	0.069	0.065
	(0.040)	(0.040)	(0.040)
Republican	-0.141***	-0.188***	-0.141***
	(0.033)	(0.039)	(0.033)
Neither party	-0.100**	-0.119**	-0.099**
	(0.036)	(0.044)	(0.036)
Global warming index	0.588***	0.575***	0.587***
	(0.045)	(0.049)	(0.046)
Population density	0.0019	0.00056	0.0023
	(0.0133)	(0.01390)	(0.0135)
County college share ($t-1$)	0.022	0.024	0.024
	(0.023)	(0.022)	(0.023)
County poverty share ($t-1$)	0.0029	0.0063	0.0038
	(0.0161)	(0.0162)	(0.0161)
County foreign-born share ($t-1$)	0.006	0.0062	0.0058
	(0.012)	(0.0124)	(0.0125)
Median county housing costs ($t-1$)	-0.0019	-0.0022	-0.0017
	(0.0105)	(0.0106)	(0.0106)
Faster broadband access ($t-1$)	0.050	0.050	0.049
	(0.027)	(0.027)	(0.028)
County GDP (log) ($t-1$)	0.036	0.025	0.036
	(0.055)	(0.057)	(0.055)
Labor force (log) ($t-1$)	-0.043	-0.033	-0.043
	(0.046)	(0.048)	(0.046)
County unemployment rate ($t-1$)	0.013	0.011	0.013
	(0.012)	(0.012)	(0.012)
Highway access	-0.014	-0.018	-0.015
	(0.032)	(0.033)	(0.032)
County income pc ($t-1$)	-0.014	-0.011	-0.014
	(0.021)	(0.021)	(0.022)
Recognition (=1)	-0.039	-0.105**	0.027
	(0.025)	(0.033)	(0.096)
Recognition x Neither party		0.056	
		(0.075)	
Recognition x Republican		0.165*	
		(0.063)	
Recognition x 2020 county Biden share			-0.017
			(0.025)
N	1488	1488	1488
Adjusted R^2	0.193	0.196	0.192
Sample Fixed Effects	No	No	No
State Fixed Effects	No	No	No

Notes: Unit of analysis: individual. Estimates are OLS with cluster-robust standard errors by state. Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S5 Model of Credit Attribution

Table S18: Linear probability models of credit attribution

	Credit Recipient:					
	Biden	Congress	Governor	State	Local	Markets
Intercept	0.10	0.11	0.24	0.34*	0.16	0.11
	(0.19)	(0.16)	(0.19)	(0.15)	(0.13)	(0.16)
Age	0.00069	-0.00289***	0.00041	-0.00066	-0.00102	-0.00034
	(0.00058)	(0.00053)	(0.00059)	(0.00054)	(0.00053)	(0.00050)
Female	-0.053**	-0.089***	-0.024	-0.041*	-0.012	-0.101***
	(0.018)	(0.015)	(0.024)	(0.018)	(0.021)	(0.018)
Black	0.037	0.075**	0.042	0.054	0.026	0.060*
	(0.028)	(0.027)	(0.031)	(0.030)	(0.031)	(0.027)
Asian	0.024	0.052	0.012	0.052	-0.075	-0.079*
	(0.044)	(0.049)	(0.041)	(0.055)	(0.049)	(0.035)
Other race	-0.031	0.027	0.042	0.021	0.070*	-0.017
	(0.029)	(0.039)	(0.036)	(0.030)	(0.033)	(0.030)
Hispanic/Latino	-0.0033	-0.0065	-0.016	-0.043*	-0.005	0.0082
	(0.0180)	(0.0211)	(0.025)	(0.019)	(0.019)	(0.0205)
College	0.038	0.035	-0.0089	-0.0072	-0.0013	0.058***
	(0.021)	(0.022)	(0.0270)	(0.0156)	(0.0164)	(0.016)
Employed	0.029	0.042	0.021	0.04*	0.031	0.055*
	(0.018)	(0.022)	(0.021)	(0.02)	(0.021)	(0.025)
Income Q2	-0.014	-0.021	-0.0055	-0.028	0.034	-0.0054
	(0.026)	(0.030)	(0.0229)	(0.024)	(0.023)	(0.0297)
Income Q3	-0.044	-0.0069	0.028	0.047*	0.034	-0.023
	(0.027)	(0.0277)	(0.022)	(0.023)	(0.022)	(0.029)
Income Q4	-0.028	-0.0048	0.039	0.014	0.041	-0.027
	(0.028)	(0.0289)	(0.030)	(0.021)	(0.027)	(0.031)
Income Q5	-0.040	-0.015	0.123***	0.085**	0.098*	0.039
	(0.033)	(0.034)	(0.032)	(0.027)	(0.039)	(0.038)
Republican	-0.168***	0.0029	-0.021	-0.023	-0.052*	0.011
	(0.019)	(0.0184)	(0.033)	(0.027)	(0.025)	(0.025)
Neither party	-0.213***	-0.078**	-0.112***	-0.103***	-0.099***	-0.044
	(0.026)	(0.027)	(0.029)	(0.025)	(0.023)	(0.026)
Global warming index	0.054	0.077	0.129***	0.093*	0.148***	0.051
	(0.037)	(0.039)	(0.032)	(0.041)	(0.039)	(0.037)
Population density	0.012	0.0164	-0.0058	0.0011	0.0074	0.0224**
	(0.007)	(0.0088)	(0.0111)	(0.0137)	(0.0132)	(0.0079)
County college share $(t-1)$	-0.016	-0.019	0.003	0.017	0.014	-6.6e-06
	(0.019)	(0.020)	(0.020)	(0.024)	(0.017)	(2.0e-02)
County poverty share $(t-1)$	-0.0039	0.0059	-0.0068	0.013	0.0099	0.0099
	(0.0123)	(0.0099)	(0.0149)	(0.012)	(0.0105)	(0.0100)
County foreign-born share $(t-1)$	-0.0044	0.0178	0.019	0.0197*	0.013	-0.0054
	(0.0116)	(0.0096)	(0.011)	(0.0085)	(0.011)	(0.0119)
Median county housing costs $(t-1)$	0.017	0.0067	-0.008	-0.020	-0.00039	-0.012
	(0.012)	(0.0147)	(0.019)	(0.013)	(0.01871)	(0.012)
Faster broadband access $(t-1)$	-0.04	-0.042	-0.024	0.031	-0.0038	0.009
	(0.02)	(0.025)	(0.023)	(0.032)	(0.0233)	(0.020)
County GDP (log) $(t-1)$	0.055	0.131**	0.029	-0.021	0.024	-0.0073
	(0.039)	(0.046)	(0.051)	(0.036)	(0.046)	(0.0513)
Labor force (log) $(t-1)$	-0.048	-0.126**	-0.035	-0.0016	-0.032	0.012
	(0.037)	(0.045)	(0.044)	(0.0338)	(0.046)	(0.045)
County unemployment rate $(t-1)$	0.0163*	0.0047	0.0139	0.0085	0.0043	0.0138
	(0.0075)	(0.0076)	(0.0078)	(0.0086)	(0.0088)	(0.0082)
Highway access	0.069	0.0027	-0.013	-0.011	0.038	0.015
	(0.041)	(0.0315)	(0.036)	(0.032)	(0.035)	(0.030)
County income pc $(t-1)$	-0.0088	-0.016	0.0093	0.031	-0.0017	0.025
	(0.0132)	(0.014)	(0.0171)	(0.025)	(0.0150)	(0.019)
N	3034	3034	3034	3034	3034	3034
Adjusted R^2	0.084	0.098	0.054	0.062	0.071	0.073
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model. Robust standard errors clustered at the state level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S19: Linear probability models of within-subject credit attribution

	Credit Biden but not the...	
	Governor	State
Intercept	0.13	0.16
	(0.12)	(0.15)
Age	0.00082	0.00085
	(0.00058)	(0.00061)
Female	-0.013	-0.017
	(0.015)	(0.011)
Black	-0.0036	-0.0098
	(0.0192)	(0.0229)
Asian	0.0076	-0.029
	(0.0200)	(0.022)
Other race	-0.012	-0.016
	(0.020)	(0.021)
Hispanic/Latino	-0.0035	0.0067
	(0.0186)	(0.0164)
College	0.013	0.018
	(0.014)	(0.010)
Employed	0.00079	-0.0042
	(0.01306)	(0.0163)
Income Q2	0.0063	-0.0032
	(0.0186)	(0.0243)
Income Q3	-0.0058	-0.033
	(0.0160)	(0.020)
Income Q4	-0.025	-0.021
	(0.025)	(0.022)
Income Q5	-0.081**	-0.081**
	(0.027)	(0.027)
Republican	-0.076***	-0.086***
	(0.015)	(0.015)
Neither party	-0.091***	-0.099***
	(0.016)	(0.020)
Global warming index	-0.018	-0.0099
	(0.023)	(0.0344)
Population density	0.0097	0.0020
	(0.0077)	(0.0097)
County college share ($t-1$)	-0.0074	-0.015
	(0.0116)	(0.012)
County poverty share ($t-1$)	-0.0035	-0.0087
	(0.0112)	(0.0100)
County foreign-born share ($t-1$)	-0.012	-0.0077
	(0.012)	(0.0077)
Median county housing costs ($t-1$)	0.013	0.023
	(0.011)	(0.011)
Faster broadband access ($t-1$)	-0.0019	-0.026
	(0.0157)	(0.017)
County GDP (log) ($t-1$)	-0.02	-0.0022
	(0.03)	(0.0281)
Labor force (log) ($t-1$)	0.021	0.015
	(0.028)	(0.024)
County unemployment rate ($t-1$)	0.0034	0.0028
	(0.0060)	(0.0065)
Highway access	0.045	0.044
	(0.023)	(0.025)
County income pc ($t-1$)	-0.0024	-0.020
	(0.0099)	(0.013)
N	3034	3034
Adjusted R^2	0.033	0.024
Sample Fixed Effects	Yes	Yes

Notes: Each column reports a separate linear probability model. Robust standard errors clustered at the state level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S6 Company and Politician Statements

S6.1 Statement Type Description

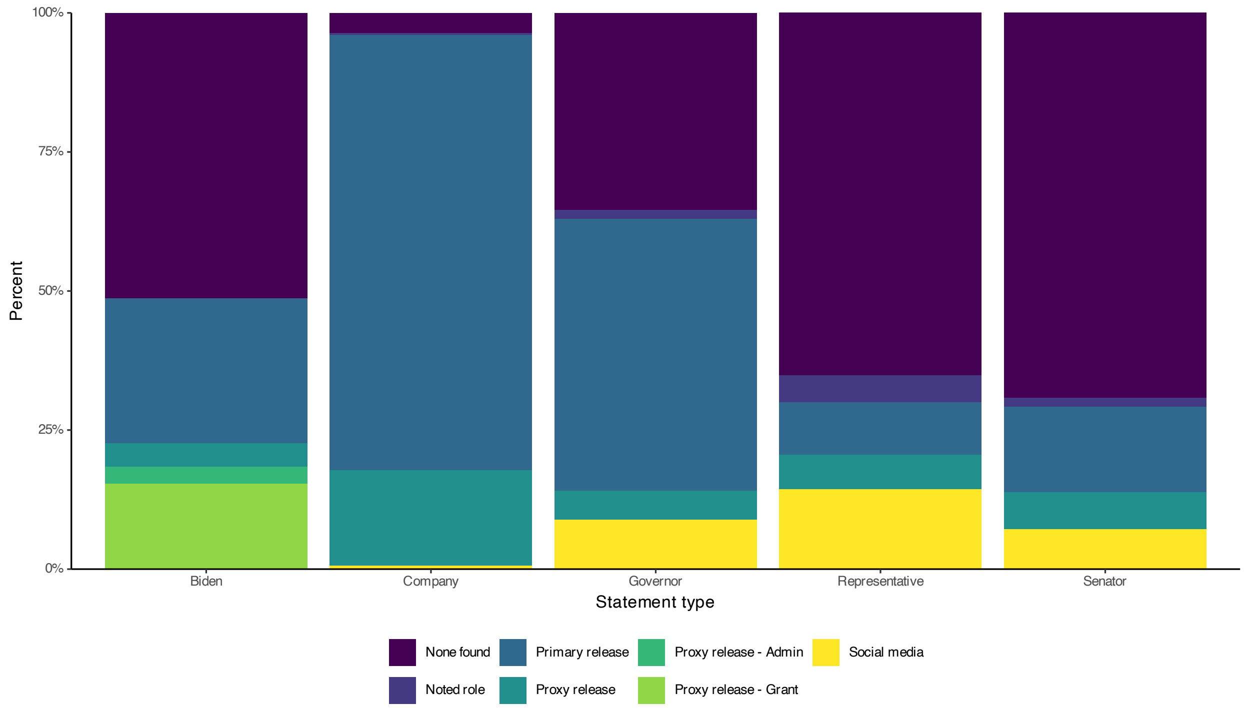

Fig. S12. Types of statements by actor. Categories are mutually exclusive and indicate the highest-quality source found for each actor–project pair. *None found*: No statement located. *Primary release*: Official communication (press release, newsletter, transcript, or report) issued on the actor's website. *Social media*: Posts on X, Facebook, Instagram, or LinkedIn, used only if no primary release exists. *Proxy release*: Statements about the project appearing only in a news article or another actor's release. For Biden, proxy releases are subdivided into *Grant* (project appears in a grant-specific administration release) and *Admin* (statement by a senior official speaking for the administration). *Noted role*: No direct statement found, but actor involvement is documented (e.g., groundbreaking attendance, executive meeting, or mention in a grant application).

S6.2 Summary Statistics

Table S20: Summary statistics for statement analysis covariates

	Mean	SD	Min	Max	Missing
Party: Democrat	0.426	0.495	0	1	710
Party: Republican	0.574	0.495	0	1	710
Sector: EVs	0.193	0.394	0	1	0
Sector: Wind	0.086	0.28	0	1	0
Sector: Solar	0.235	0.424	0	1	0
Sector: Batteries	0.486	0.5	0	1	0
Target jobs specified	0.737	0.44	0	1	0
Capital investment	0.755	0.43	0	1	0
Status: Cancelled/Closed/Paused/Sold/Rumored	0.165	0.371	0	1	0
Status: Pilot/Planned/Construction	0.599	0.49	0	1	0
Status: Operating	0.235	0.424	0	1	0
Manufacturing project	0.804	0.397	0	1	0
Highway access	0.824	0.381	0	1	84
Broadband 100+ Mbps	0.479	0.5	0	1	84
U.S. Rep. Party: Democrat	0.349	0.477	0	1	120
U.S. Rep. Party: Republican	0.651	0.477	0	1	120
Governor Party: Democrat	0.429	0.495	0	1	72
Governor Party: Republican	0.571	0.495	0	1	72
Swing state	0.242	0.428	0	1	0
Competitive district	0.075	0.263	0	1	120
College education (z)	-0.001	0.969	-1.958	2.617	84
Poverty rate (z)	0.014	0.958	-1.915	3.271	84
GDP log (z)	0.121	1.035	-2.511	2.413	84
Unemployment rate (z)	0.045	0.97	-1.713	6.507	84
Labor force log (z)	0.11	1.041	-3.104	2.333	84
Income per capita (z)	-0.002	0.909	-1.221	9.1	84
Democratic vote share (z)	0.063	0.977	-2.23	2.803	84
Foreign-born population (z)	0.09	1.029	-1.02	3.784	84
Housing costs (z)	0.041	0.962	-2.055	3.753	84
Electricity price (z)	-0.04	0.925	-1.005	4.397	0
Union membership (z)	-0.015	1.025	-1.244	2.752	0

Notes: Summary statistics for covariates used in statement regression models. Continuous and dummy variables show mean, standard deviation, minimum, maximum, and missing values. Categorical variables are split into dummy variables (0/1) for each category. Standardized variables (suffix 'z') have mean 0 and standard deviation 1 in the full sample. Missingness largely due to certain variables not being available for certain statements, such as companies not having political parties. $N = 1962$

S6.3 LLM Annotation

S6.3.1 Stage 1 Prompt

You are a binary classifier. Output `YES` or `NO` only.

Answer `YES` only if the statement **explicitly** indicates that *the Inflation Reduction Act / the Bipartisan Infrastructure Law*:

1. Directly funded or financed the specific project being discussed, **OR**
2. Directly enabled or made possible the specific project through incentives, **OR**
3. Is explicitly cited as contributing to the investment decision, including when:
   - The law's economic impact is cited as a factor in the decision
   - The law's industry growth effects influenced the choice
   - The law's broader benefits are linked to this specific investment

The statement must show a **causal link** between the law and **this specific project**.

Do *not* answer `YES` if:

- The law is only mentioned as a goal or target
- The project helps meet the law's goals
- The law is mentioned only as background without influencing decisions
- The statement only discusses eligibility without confirming use
- The speaker only mentions helping to write the law

S6.3.2 Stage 2 Prompt

Credit Attribution Codebook

1. First Check: Is there any credit claim? (`gives_credit`)
Decision tree for `gives_credit`:

1. Explicit credit:
   a) Causal verbs (enabled, secured, funded), OR
   b) Attribution of decision-making ("contributes to our decision", "influenced by"), OR
   c) Economic environment claims ("thanks to", "because of", "due to")
   → If YES to any, set `gives_credit=1` and continue to Step 2
   → If NO, continue to Question 2
2. Implicit credit (check all):
   - Actor attends/hosts ceremony for project

- Actor announces project and frames it as achievement
- Actor publicly associates with project success

→ If YES to any, set `gives_credit=1` and continue to Step 2
→ If NO, continue to Question 3

3. Merely descriptive/informative (check all):
   - Technical specifications or equipment lists
   - Routine business updates
   - Factual job numbers without attribution
   - Boilerplate text

   → If YES to any, set all variables to 0 and STOP

Key distinction: Credit includes both direct causation ("funded by") *and* attribution of influence ("contributed to our decision").
Examples of NO credit:

- "New factory will create 500 jobs" (just reporting)
- "Company X announced plans to expand" (passive description)
- "The IRA sets ambitious goals" (mere mention)

Examples of YES credit:

- "Our state attracted this investment" (active role)
- "Thanks to our business climate..." (explicit attribution)
- "The IRA's impact on industrial growth contributed to our decision" (policy impact attribution)

2. Who Gets Credit? (if `gives_credit=1`)
Social media rules:

- Credit if @mention in success/achievement context
- Credit for "partnership with @Actor", "working with @Actor", "thanks to @Actor"
- No credit for cc's, FYIs, requests, or complaints

Federal actors:

- `credit_biden=1` if President/White House named or tagged with credit
- `credit_senate=1` if specific U.S. Senator credited
- `credit_us_rep=1` if specific U.S. Representative credited

State & local actors:

- `credit_governor=1` if Governor named/quoted with credit
- `credit_local=1` if local government credited (support, recruitment, incentives)

Party & laws:

- `credit_dem/credit_gop=1` if explicit partisan attribution
- `credit_ira/credit_bil=1` if laws explicitly cited as enabling or influencing project

3. Credit Attribution Language Guide

- *Direct causation:* enable, secure, fund, finance, deliver
- *Decision influence:* contributes to, influenced by, thanks to, because of
- *Partnership:* partnership with, working with, collaboration
- *Ceremonies:* announce, unveil, celebrate, ribbon-cut, host

4. Calibration Examples

1. "Thanks to President Biden's leadership, we secured two billion dollars..." → `gives_credit=1`, `credit_biden=1`
2. "This project meets IRA ten percent bonus criteria." → all zeros
3. "Our city council worked for years to land this plant." → `gives_credit=1`, `credit_local=1`

5. Metadata Usage
Metadata keys:

- `speaker`, `role`, `state`, `district`, `city`
- `release_type`, `ira_funding`, `bil_funding`

Rules: self-credit if role matches speaker + first person; proxy releases only count quoted text; laws require explicit funding language unless metadata = YES.

6. Output Format

```
{
 "gives_credit":0,
 "credit_biden":0,
 "credit_senate":0,
 "credit_us_rep":0,
 "credit_governor":0,
 "credit_local":0,
 "credit_dem":0,
 "credit_gop":0,
 "credit_ira":0,
 "credit_bil":0
}
```

S6.4 Regression Models of Statement Giving

Table S21: Linear probability models of statement giving, by speaker

	Company	Governor	Senator	Rep	President
Intercept	0.996***	0.54**	0.27	0.11	0.62**
	(0.055)	(0.17)	(0.14)	(0.16)	(0.18)
Sector: EVs	-0.019	-0.011	0.0056	0.102	0.065
	(0.028)	(0.090)	(0.0748)	(0.085)	(0.085)
Sector: Solar	-0.044	-0.068	-0.00059	-0.118	0.084
	(0.033)	(0.063)	(0.07145)	(0.073)	(0.097)
Sector: Wind	-0.031	-0.209*	-0.065	-0.00052	0.11
	(0.030)	(0.088)	(0.067)	(0.09682)	(0.12)
Investment amount specified	0.018	0.181	0.216***	0.178*	0.155*
	(0.029)	(0.095)	(0.057)	(0.071)	(0.064)
Target jobs specified	-0.019	0.100	-0.041	-0.034	0.061
	(0.023)	(0.062)	(0.069)	(0.065)	(0.068)
Manufacturing investment	-0.0062	0.146	0.065	0.111	0.00087
	(0.0193)	(0.076)	(0.076)	(0.077)	(0.07761)
Status: Operating	0.041	-0.044	-0.022	-0.071	-0.099
	(0.043)	(0.098)	(0.084)	(0.111)	(0.098)
Status: Pilot/Planned/Construction	0.037	0.116	0.075	0.041	-0.031
	(0.036)	(0.097)	(0.080)	(0.093)	(0.092)
County college share $(t-1)$	-0.0012	-0.059	-0.017	-0.048	-0.102*
	(0.0227)	(0.053)	(0.034)	(0.059)	(0.049)
County poverty share $(t-1)$	0.032**	0.051	-0.044	-0.019	-0.093**
	(0.010)	(0.036)	(0.028)	(0.046)	(0.033)
County foreign-born share $(t-1)$	-0.0096	-0.060	0.034	0.057	0.028
	(0.0147)	(0.054)	(0.034)	(0.046)	(0.041)
Median county housing costs $(t-1)$	0.022	0.077	-0.051	-0.089	-0.023
	(0.018)	(0.067)	(0.051)	(0.078)	(0.063)
Faster broadband access $(t-1)$	0.045	-0.050	0.033	0.118*	-0.147*
	(0.032)	(0.065)	(0.049)	(0.053)	(0.069)
County GDP (log) $(t-1)$	-0.013	0.113	0.13	0.047	0.12
	(0.041)	(0.095)	(0.10)	(0.148)	(0.12)
Labor force (log) $(t-1)$	-0.014	-0.202*	-0.20	-0.07	-0.16
	(0.035)	(0.095)	(0.11)	(0.15)	(0.12)
County unemployment rate $(t-1)$	-0.0053	-0.037	0.024	0.051	-0.013
	(0.0109)	(0.031)	(0.028)	(0.038)	(0.039)
Highway access	0.037	0.042	0.054	0.056	0.12
	(0.028)	(0.062)	(0.066)	(0.075)	(0.11)
County income pc $(t-1)$	0.014	0.029	-0.023	-0.0035	-0.074
	(0.014)	(0.033)	(0.031)	(0.0380)	(0.041)
Republican speaker		-0.296***	-0.418***	-0.172*	
		(0.072)	(0.068)	(0.082)	
County 2020 Biden vote share	-0.0038	0.116*	0.012	0.044	0.107**
	(0.0076)	(0.057)	(0.046)	(0.066)	(0.036)
Republican Representative	-0.033	0.087	0.028		0.089
	(0.017)	(0.073)	(0.044)		(0.052)
Republican Governor	-0.040		-0.0021	0.029	-0.187**
	(0.027)		(0.0663)	(0.075)	(0.067)
Swing state	0.0073	0.039	-0.077	0.022	0.152*
	(0.0219)	(0.068)	(0.063)	(0.085)	(0.059)
Competitive congressional district	-0.021	0.013	0.152*	0.15	-0.100
	(0.059)	(0.090)	(0.075)	(0.12)	(0.095)
State electricity price $(t-1)$	-0.0101	-0.107**	-0.038	-0.024	-0.032
	(0.0098)	(0.035)	(0.042)	(0.047)	(0.032)
State unionization rate $(t-1)$	-0.0037	-0.0087	-0.026	-0.012	-0.070
	(0.0065)	(0.0237)	(0.026)	(0.037)	(0.039)
2023	-0.040	-0.114	-0.019	0.077	-0.270***
	(0.022)	(0.066)	(0.082)	(0.063)	(0.066)
2024	-0.068**	-0.178*	-0.058	-0.027	-0.478***
	(0.020)	(0.078)	(0.078)	(0.082)	(0.052)
N	307	307	614	307	307
Adjusted R^2	-0.006	0.271	0.193	0.090	0.267

Notes: Each column reports a separate linear probability model for a speaker. The dependent variable equals 1 if the speaker issued a public project statement, 0 otherwise. Unit of analysis is the project–actor pair. Senators have higher observation counts (two per state). Some covariates are missing for projects without announced locations. Estimates are OLS with state-clustered SEs. Continuous covariates are county-standardized. Coefficients are percentage-point changes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S6.5 Regression Models of Credit Attribution in Statements

Table S22: Linear probability models of Biden/IRA credit, by speaker

	Outcome: Credited Biden/IRA (=1)				
	Company	Governor	Senator	Rep	President
Intercept	0.22	-0.063	0.79**	0.27	0.79***
	(0.12)	(0.111)	(0.23)	(0.15)	(0.22)
Sector: EVs	-0.054	0.076	0.091	-0.074	0.131
	(0.057)	(0.048)	(0.057)	(0.097)	(0.095)
Sector: Solar	0.349***	0.128	-0.075	0.085	0.076
	(0.088)	(0.064)	(0.099)	(0.190)	(0.126)
Sector: Wind	0.19	0.058	0.173	0.32	-0.22
	(0.11)	(0.107)	(0.095)	(0.19)	(0.15)
Investment amount specified	-0.036	-0.074	0.092	-0.14	0.06
	(0.069)	(0.069)	(0.109)	(0.14)	(0.16)
Target jobs specified	0.038	0.048	0.040	-0.04	-0.048
	(0.057)	(0.047)	(0.084)	(0.10)	(0.094)
Manufacturing investment	-0.099	-0.089	-0.19	0.044	-0.037
	(0.062)	(0.075)	(0.10)	(0.069)	(0.110)
Status: Operating	0.152	0.147	-0.14	0.065	-0.25
	(0.082)	(0.073)	(0.16)	(0.098)	(0.16)
Status: Pilot/Planned/Construction	0.116	0.087	0.087	0.051	-0.105
	(0.067)	(0.051)	(0.124)	(0.107)	(0.099)
County college share ($t-1$)	0.021	0.0085	-0.194**	0.123	-0.035
	(0.053)	(0.0518)	(0.057)	(0.077)	(0.079)
County poverty share ($t-1$)	-0.0052	-0.011	0.072	-0.011	-0.153**
	(0.0424)	(0.035)	(0.047)	(0.037)	(0.055)
County foreign-born share ($t-1$)	0.022	-0.076*	-0.177***	-0.015	0.076
	(0.044)	(0.036)	(0.037)	(0.054)	(0.052)
Median county housing costs ($t-1$)	0.097	-0.042	0.21	-0.032	-0.074
	(0.061)	(0.039)	(0.11)	(0.079)	(0.105)
Faster broadband access ($t-1$)	0.094	-0.019	0.099	-0.053	0.013
	(0.062)	(0.031)	(0.099)	(0.099)	(0.077)
County GDP (log) ($t-1$)	-0.068	-0.177	0.045	-0.12	0.19
	(0.097)	(0.089)	(0.139)	(0.18)	(0.20)
Labor force (log) ($t-1$)	-0.022	0.189*	0.075	0.089	-0.27
	(0.093)	(0.078)	(0.113)	(0.186)	(0.18)
County unemployment rate ($t-1$)	-0.067	0.047	-0.043	0.030	-0.079
	(0.035)	(0.033)	(0.030)	(0.036)	(0.056)
Highway access	-0.061	0.070	-0.067	0.093	-0.14
	(0.076)	(0.047)	(0.083)	(0.093)	(0.11)
County income pc ($t-1$)	-0.079*	0.052	-0.041	-0.17	-0.075
	(0.034)	(0.110)	(0.126)	(0.09)	(0.131)
Republican speaker		-0.12	-0.70***	-0.38**	
		(0.06)	(0.12)	(0.13)	
County 2020 Biden vote share	0.0061	0.019	-0.031	-0.018	0.043
	(0.0468)	(0.035)	(0.065)	(0.064)	(0.067)
Republican Representative	0.061	0.061	-0.249**		0.10
	(0.058)	(0.068)	(0.084)		(0.12)
Republican Governor	-0.026		0.096	0.19	-0.11
	(0.073)		(0.087)	(0.10)	(0.11)
Swing state	0.038	0.089*	-0.073	-0.090	-0.037
	(0.050)	(0.042)	(0.083)	(0.074)	(0.095)
Competitive congressional district	0.041	0.207*	-0.088	-0.091	0.21
	(0.101)	(0.099)	(0.092)	(0.139)	(0.16)
State electricity price ($t-1$)	-0.025	0.032	0.103	0.042	-0.135*
	(0.036)	(0.043)	(0.067)	(0.059)	(0.054)
State unionization rate ($t-1$)	0.021	0.042	-0.073*	0.061	0.028
	(0.032)	(0.023)	(0.033)	(0.045)	(0.050)
2023	-0.180*	0.044	-0.036	0.053	0.031
	(0.087)	(0.041)	(0.068)	(0.069)	(0.109)
2024	-0.145	0.12	-0.013	-0.037	0.27
	(0.081)	(0.10)	(0.093)	(0.084)	(0.14)
N	297	212	191	112	156
Adjusted R^2	0.132	0.195	0.398	0.266	0.073

Notes: Each column reports a separate linear probability model for a speaker, conditional on the speaker making a project-related statement. The dependent variable equals 1 if the speaker credited the Biden Administration or IRA, 0 otherwise. Unit of analysis is the project–actor pair. Estimates are OLS with state-clustered SEs. Continuous covariates are county-standardized. Coefficients are percentage-point changes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S23: Linear probability models of Governor credit, by speaker

	Outcome: Credited Governor (=1)				
	Company	Governor	Senator	Rep	President
Intercept	-0.042	0.87***	-0.15	0.017	-0.0096
	(0.159)	(0.09)	(0.12)	(0.124)	(0.1559)
Sector: EVs	0.0082	0.11**	0.128	0.019	-0.0073
	(0.0717)	(0.04)	(0.065)	(0.062)	(0.0564)
Sector: Solar	0.047	0.065	0.140*	0.067	0.0063
	(0.081)	(0.046)	(0.062)	(0.068)	(0.0714)
Sector: Wind	-0.13	-0.0021	-0.065	-0.045	-0.024
	(0.14)	(0.1097)	(0.042)	(0.054)	(0.127)
Investment amount specified	0.073	0.113	0.0011	-0.045	-0.043
	(0.070)	(0.084)	(0.0397)	(0.090)	(0.110)
Target jobs specified	0.108	0.115	0.085*	-0.059	0.020
	(0.064)	(0.079)	(0.037)	(0.058)	(0.064)
Manufacturing investment	0.167*	-0.016	0.012	-0.0082	0.093
	(0.073)	(0.057)	(0.035)	(0.0427)	(0.069)
Status: Operating	0.077	-0.058	0.0081	-0.031	0.14
	(0.087)	(0.042)	(0.0441)	(0.040)	(0.11)
Status: Pilot/Planned/Construction	0.286***	-0.119*	-0.017	0.081	0.078
	(0.075)	(0.052)	(0.049)	(0.057)	(0.115)
County college share $(t-1)$	-0.025	0.036	-0.042	-0.052	0.12
	(0.052)	(0.037)	(0.039)	(0.071)	(0.07)
County poverty share $(t-1)$	-0.059	-0.041	-0.0055	-0.022	0.152**
	(0.044)	(0.038)	(0.0210)	(0.037)	(0.052)
County foreign-born share $(t-1)$	-0.026	-0.078	-0.059*	0.022	-0.063*
	(0.040)	(0.046)	(0.025)	(0.026)	(0.028)
Median county housing costs $(t-1)$	-0.064	-0.027	-0.022	-0.006	0.047
	(0.076)	(0.067)	(0.043)	(0.060)	(0.069)
Faster broadband access $(t-1)$	-0.057	-0.019	0.010	0.016	-0.043
	(0.075)	(0.069)	(0.046)	(0.046)	(0.064)
County GDP (log) $(t-1)$	-0.13	1.9e-05	-0.22	-0.048	-0.24
	(0.14)	(7.6e-02)	(0.11)	(0.170)	(0.14)
Labor force (log) $(t-1)$	0.072	-0.030	0.133	0.01	0.17
	(0.133)	(0.067)	(0.087)	(0.19)	(0.11)
County unemployment rate $(t-1)$	-0.018	0.016	0.042	-0.034	0.040
	(0.041)	(0.031)	(0.026)	(0.026)	(0.035)
Highway access	-0.091	-0.034	0.088	0.081	0.124
	(0.068)	(0.054)	(0.055)	(0.059)	(0.082)
County income pc $(t-1)$	-0.016	-0.053	0.147*	0.043	0.11
	(0.036)	(0.067)	(0.068)	(0.099)	(0.11)
Republican speaker		-0.023	0.0074	0.068	
		(0.064)	(0.0467)	(0.043)	
County 2020 Biden vote share	0.14*	0.093	0.118	0.079	-0.075
	(0.06)	(0.052)	(0.063)	(0.061)	(0.057)
Republican Representative	0.083	-0.037	0.093		0.066
	(0.070)	(0.049)	(0.073)		(0.086)
Republican Governor	-0.037		-0.054	0.0043	-0.226**
	(0.063)		(0.050)	(0.0391)	(0.066)
Swing state	-0.028	0.035	-0.022	-0.0035	-0.042
	(0.077)	(0.052)	(0.052)	(0.0496)	(0.065)
Competitive congressional district	0.1	0.042	-0.066	-0.039	-0.048
	(0.1)	(0.037)	(0.057)	(0.049)	(0.077)
State electricity price $(t-1)$	0.015	0.050	-0.063	0.037	0.019
	(0.044)	(0.043)	(0.036)	(0.064)	(0.060)
State unionization rate $(t-1)$	-0.073*	-0.037	0.010	0.012	-0.036
	(0.030)	(0.045)	(0.023)	(0.023)	(0.036)
2023	0.031	-0.022	0.0066	-0.044	0.045
	(0.095)	(0.051)	(0.0692)	(0.077)	(0.076)
2024	-0.069	-0.0043	-0.071	-0.123	-0.045
	(0.109)	(0.0674)	(0.057)	(0.081)	(0.063)
N	297	212	191	112	156
Adjusted R^2	0.155	0.087	0.098	-0.086	0.061

Notes: Each column reports a separate linear probability model for a speaker, conditional on the speaker making a project-related statement. The dependent variable equals 1 if the speaker credited the Governor, 0 otherwise. Unit of analysis is the project–actor pair. Estimates are OLS with state-clustered SEs. Continuous covariates are county-standardized. Coefficients are percentage-point changes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S24: Linear probability models of Senator credit, by speaker

	Outcome: Credited Senator (=1)				
	Company	Governor	Senator	Rep	President
Intercept	-0.21*	0.0008	0.84**	0.011	-0.076
	(0.10)	(0.0313)	(0.24)	(0.039)	(0.057)
Sector: EVs	-0.091	5.7e-05	0.085	0.0015	0.00016
	(0.052)	(1.3e-02)	(0.070)	(0.0128)	(0.02049)
Sector: Solar	0.041	0.021	0.29***	-0.025	0.054
	(0.054)	(0.025)	(0.08)	(0.024)	(0.047)
Sector: Wind	0.0054	0.023	0.269**	0.092	0.085
	(0.0898)	(0.023)	(0.093)	(0.088)	(0.071)
Investment amount specified	0.012	0.017	0.08	0.0062	0.044
	(0.051)	(0.020)	(0.11)	(0.0234)	(0.036)
Target jobs specified	0.028	0.018	0.016	0.012	0.0012
	(0.029)	(0.015)	(0.090)	(0.014)	(0.0183)
Manufacturing investment	0.080	-0.013	0.0074	-0.018	0.023
	(0.046)	(0.017)	(0.1177)	(0.018)	(0.030)
Status: Operating	0.100*	-0.0028	0.18	0.041	-0.019
	(0.048)	(0.0295)	(0.13)	(0.043)	(0.046)
Status: Pilot/Planned/Construction	0.117**	-0.024	0.075	-0.0085	-0.024
	(0.039)	(0.016)	(0.118)	(0.0199)	(0.049)
County college share $(t-1)$	-0.019	0.0011	-0.165**	0.0053	0.034
	(0.029)	(0.0155)	(0.048)	(0.0154)	(0.035)
County poverty share $(t-1)$	-0.065*	-0.030	0.030	0.016	0.018
	(0.032)	(0.017)	(0.039)	(0.017)	(0.021)
County foreign-born share $(t-1)$	0.032	0.0014	-0.062	0.0056	-0.012
	(0.021)	(0.0105)	(0.035)	(0.0092)	(0.018)
Median county housing costs $(t-1)$	-0.071	-0.054*	-0.046	-0.019	0.051
	(0.039)	(0.021)	(0.065)	(0.021)	(0.033)
Faster broadband access $(t-1)$	0.0026	0.0019	-0.042	-0.0064	-0.0041
	(0.0364)	(0.0199)	(0.068)	(0.0146)	(0.0170)
County GDP (log) $(t-1)$	-0.119	-0.037	-0.24	-0.099	-0.016
	(0.064)	(0.028)	(0.14)	(0.087)	(0.044)
Labor force (log) $(t-1)$	0.114	0.053	0.26	0.101	0.0021
	(0.059)	(0.038)	(0.14)	(0.087)	(0.0280)
County unemployment rate $(t-1)$	0.011	0.053	-0.016	-0.00031	0.0071
	(0.030)	(0.029)	(0.022)	(0.00460)	(0.0117)
Highway access	0.017	-0.015	-0.096	0.011	0.038
	(0.061)	(0.043)	(0.069)	(0.017)	(0.028)
County income pc $(t-1)$	0.0061	0.034	0.25**	0.0064	-0.044
	(0.0241)	(0.023)	(0.08)	(0.0199)	(0.048)
Republican speaker		-0.026	-0.38***	-0.027	
		(0.018)	(0.10)	(0.027)	
County 2020 Biden vote share	0.044	0.0036	0.075	-0.022	-0.036
	(0.033)	(0.0137)	(0.061)	(0.024)	(0.023)
Republican Representative	0.113**	0.015	-0.050		0.0003
	(0.036)	(0.025)	(0.062)		(0.0306)
Republican Governor	-0.058		0.068	-0.0082	-0.019
	(0.050)		(0.079)	(0.0206)	(0.025)
Swing state	-0.036	0.031**	-0.056	-0.031	0.011
	(0.038)	(0.010)	(0.051)	(0.027)	(0.015)
Competitive congressional district	-0.012	0.057	-0.117	0.090	0.027
	(0.089)	(0.054)	(0.065)	(0.068)	(0.087)
State electricity price $(t-1)$	0.013	0.0068	-0.0096	0.0071	0.001
	(0.027)	(0.0113)	(0.0394)	(0.0093)	(0.024)
State unionization rate $(t-1)$	-0.011	-0.0262**	0.054	-0.009	-0.0060
	(0.016)	(0.0087)	(0.035)	(0.014)	(0.0097)
2023	0.088	0.011	-0.083	0.017	0.022
	(0.044)	(0.035)	(0.090)	(0.020)	(0.017)
2024	0.076	0.015	-0.039	0.0018	0.013
	(0.052)	(0.040)	(0.101)	(0.0194)	(0.020)
N	297	212	191	112	156
Adjusted R^2	0.035	0.101	0.262	0.093	-0.060

Notes: Each column reports a separate linear probability model for a speaker, conditional on the speaker making a project-related statement. The dependent variable equals 1 if the speaker credited the U.S. Senator, 0 otherwise. Unit of analysis is the project–actor pair. Estimates are OLS with state-clustered SEs. Continuous covariates are county-standardized. Coefficients are percentage-point changes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S25: Linear probability models of Representative credit, by speaker

	Outcome: Credited Representative (=1)				
	Company	Governor	Senator	Rep	President
Intercept	-0.0064	0.013	0.029	0.44	0.021
	(0.0463)	(0.016)	(0.065)	(0.36)	(0.074)
Sector: EVs	0.00009	-0.0077	0.059	-0.029	0.034
	(0.03439)	(0.0104)	(0.048)	(0.099)	(0.047)
Sector: Solar	0.0012	0.019	0.0099	0.238*	-0.010
	(0.0315)	(0.029)	(0.0299)	(0.094)	(0.021)
Sector: Wind	0.131	0.0038	0.15	0.27	0.046
	(0.086)	(0.0135)	(0.13)	(0.14)	(0.065)
Investment amount specified	-0.020	0.011	-0.010	-0.17	0.020
	(0.046)	(0.019)	(0.037)	(0.15)	(0.033)
Target jobs specified	0.0087	0.014	0.012	0.138	0.0094
	(0.0236)	(0.011)	(0.027)	(0.097)	(0.0233)
Manufacturing investment	0.020	0.0081	-0.010	-0.21	0.0046
	(0.033)	(0.0080)	(0.025)	(0.15)	(0.0341)
Status: Operating	0.055	0.024	-0.0047	0.39**	0.017
	(0.034)	(0.026)	(0.0262)	(0.11)	(0.034)
Status: Pilot/Planned/Construction	0.073*	-0.00011	0.015	0.303**	-0.016
	(0.027)	(0.00724)	(0.030)	(0.093)	(0.021)
County college share $(t-1)$	0.00095	-0.00056	-0.024	0.11	-0.012
	(0.02390)	(0.01288)	(0.029)	(0.11)	(0.016)
County poverty share $(t-1)$	0.023	-0.0097	0.015	0.206**	0.004
	(0.023)	(0.0144)	(0.017)	(0.069)	(0.019)
County foreign-born share $(t-1)$	-0.038	-0.0106	-0.039*	-0.172*	0.0013
	(0.022)	(0.0086)	(0.019)	(0.065)	(0.0087)
Median county housing costs $(t-1)$	0.057*	-0.027	0.031	0.47***	-0.0064
	(0.027)	(0.018)	(0.050)	(0.11)	(0.0228)
Faster broadband access $(t-1)$	0.0089	0.014	0.015	-0.27	-0.016
	(0.0243)	(0.017)	(0.016)	(0.15)	(0.019)
County GDP (log) $(t-1)$	-0.012	-0.0037	-0.038	0.53	-0.019
	(0.046)	(0.0118)	(0.053)	(0.28)	(0.041)
Labor force (log) $(t-1)$	0.0053	0.004	0.024	-0.49	0.010
	(0.0420)	(0.010)	(0.037)	(0.30)	(0.025)
County unemployment rate $(t-1)$	0.020	0.0099	0.035**	0.019	-0.0061
	(0.017)	(0.0102)	(0.010)	(0.047)	(0.0072)
Highway access	-0.040	-0.023	0.029	0.043	0.026
	(0.059)	(0.041)	(0.036)	(0.162)	(0.024)
County income pc $(t-1)$	0.0083	0.020	0.035	-0.30*	0.016
	(0.0132)	(0.015)	(0.041)	(0.11)	(0.019)
Republican speaker		-0.030	-0.017	-0.26*	
		(0.016)	(0.033)	(0.11)	
County 2020 Biden vote share	0.0093	0.004	0.032	-0.14	-0.013
	(0.0272)	(0.010)	(0.040)	(0.10)	(0.018)
Republican Representative	0.072	-0.0025	0.029		-0.054
	(0.044)	(0.0192)	(0.041)		(0.043)
Republican Governor	-0.110*		0.0081	0.131	-0.019
	(0.042)		(0.0322)	(0.093)	(0.017)
Swing state	-0.021	0.0172*	-0.082*	-0.029	-0.029
	(0.021)	(0.0064)	(0.031)	(0.099)	(0.027)
Competitive congressional district	-0.047	0.049	-0.0049	0.11	0.065
	(0.049)	(0.054)	(0.0587)	(0.11)	(0.064)
State electricity price $(t-1)$	-0.0099	0.0026	0.154***	0.115	0.018
	(0.0148)	(0.0068)	(0.028)	(0.061)	(0.040)
State unionization rate $(t-1)$	-0.032*	-0.0103	-0.039*	0.025	-0.0036
	(0.016)	(0.0064)	(0.017)	(0.047)	(0.0105)
2023	0.0075	-0.025	-0.056*	0.218*	-0.0083
	(0.0225)	(0.019)	(0.026)	(0.088)	(0.0223)
2024	0.064	-0.013	0.0025	0.30*	0.027
	(0.040)	(0.028)	(0.0312)	(0.13)	(0.019)
N	297	212	191	112	156
Adjusted R^2	0.053	-0.027	0.320	0.296	-0.004

Notes: Each column reports a separate linear probability model for a speaker, conditional on the speaker making a project-related statement. The dependent variable equals 1 if the speaker credited the U.S. Representative, 0 otherwise. Unit of analysis is the project–actor pair. Estimates are OLS with state-clustered SEs. Continuous covariates are county-standardized. Coefficients are percentage-point changes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

References for SI Appendix

Hirsch, Barry T. and David A. MacPherson (2003). "Union Membership and Coverage Database from the Current Population Survey: Note." *ILR Review* 56(2): 349–354.