Why Clean Energy Investments Had Limited Political Returns

Alexander F. Gazmararian[1], Nathan M. Jensen[2] and Dustin Tingley[3]

[1] *Department of Political Science, University of Michigan, Ann Arbor, MI 48109, USA*
[2] *Department of Government, University of Texas at Austin, Austin, TX 78712, USA*
[3] *Department of Government, Harvard University, Cambridge, MA 02138, USA*

September 21, 2025

Abstract

The Inflation Reduction Act (IRA) is the largest federal investment in climate policy in U.S. history. We examine whether its clean energy projects shifted the public's attitudes. 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 closer to IRA projects were more likely to notice investments but not perceive economic gains or credit the Biden Administration. Instead, they were more likely to credit their governors, who actively claimed responsibility, while companies spread recognition broadly. This fragmented information environment underscores the challenges of using green spending to achieve electoral gains and build public support for climate policy. (114 words)

Significance: 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 the intended beneficiaries. While people living closer to new projects were more likely to notice them, this visibility did not translate into perceived local economic benefits or greater credit for the Biden Administration. Instead, Americans credited governors. These patterns are consistent with political messaging about investments, where governors claimed more credit than the White House, and companies spread credit across multiple political actors. These findings suggest that green spending alone may not deliver significant political support. Policy durability is more likely to depend on firms lobbying to defend their interests than on broad public backing. (154 words)

Word count: 4889 (excluding references)

Keywords: Climate change; Public opinion; Firm behavior; Green industrial policy; Credit claiming; Policy feedback

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

Introduction

The Inflation Reduction Act (IRA) 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 material benefits such as new jobs and tax revenue (Cullenward and Victor, 2021; Meckling et al., 2015; 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 examines whether green investments shifted public opinion in ways that could help defend and expand the IRA.

There are three necessary conditions for federal green investments to generate public support where they're built. Voters must notice projects, view them as beneficial, and link them to the responsible policymakers (Arnold, 1990). These steps aren't guaranteed. Projects could generate local conflict over siting (Stokes et al., 2023). Attribution could be challenging, since governors and local officials often claim responsibility (Jensen and Malesky, 2018), while partisanship shapes how the public receives and interprets information (Druckman, Peterson, and Slothuus, 2013). These dynamics could make it challenging for federal policymakers to receive an electoral return from green spending.

Systematic evidence about the IRA's effects on public opinion is limited due to the law'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 closer to projects, compared to those farther away, are more likely to recognize green investments and view them as beneficial, a necessary first step for policy to shape political attitudes. Second, if visibility translates into attribution, people closer to projects are more likely to credit the Biden Administration.

Third, we examine an information mechanism that could shape how the public interprets green spending. We expect a mixed messaging environment: state politicians have electoral incentives to claim responsibility (Jensen and Malesky, 2018), businesses strategically diffuse credit across multiple actors to avoid appearing partisan and to maintain broad support, while federal policymakers have limited capacity to claim credit for every project. Together, these dynamics could dilute the public's recognition of federal responsibility.

We find modest evidence that the IRA's investments were visible, but no sign that people closer to these projects were more likely to credit the Biden Administration. Although many green projects are not fully built yet, residents still notice them but do not credit federal policymakers, even when facilities become operational. Instead, Americans view governors as more responsible. This pattern is consistent with our analysis of statements showing that governors are far more active in claiming credit than the White House, and that companies spread recognition and emphasize local actors. The IRA was visible but not traceable, which limited its ability to create public 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

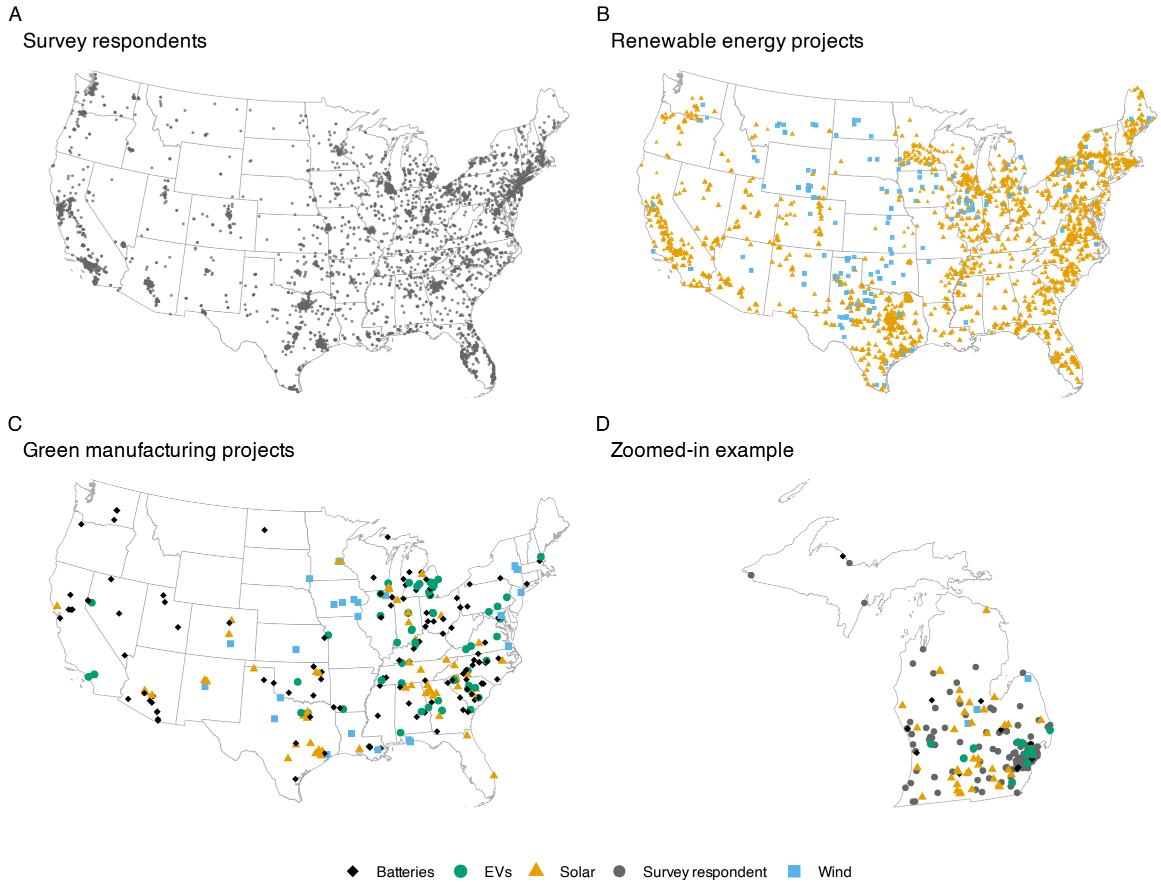

Fig. 1: Geographic distribution of survey respondents and clean energy investments, 2022–2024. Alaska and Hawaii not shown.

had seen a new project in their community, assessed its economic effects, and rated the responsibility of political actors. Materials and Methods describes question wording and validation.

Our research design uses geographic proximity to new facilities to evaluate effects on visibility, perceived benefits, and credit attribution. Because many projects remain under construction two years after passage, proximity is an imperfect proxy for realized benefits. We therefore also examine differences by project status. Still, proximity captures potential visibility and salience, since nearby residents are more likely to observe construction, media coverage, and political claims, even before permanent jobs materialize.

Proximity is measured using geo-coordinates for respondents and project sites, which avoids bias from self-reports (Egan and Mullin, 2012). Respondents are grouped into national distance quintiles by project type, although results are robust to using continuous measures (SI Appendix, 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 closer projects versus those farther away within the same state.

We estimate the effect of proximity by comparing respondents to others in the same state, which holds 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 sample 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 indicate the design can detect meaningful effects and is robust to plausible unobserved confounding (SI Appendix, S3).

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 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 political and business actors allocate credit.

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, with effects extending into the second quintile for renewables (Fig. 2A). The gradient is strongest close to projects and tapers with distance, but limited precision makes it difficult to separate the intermediate quintiles from one another.

The effect of proximity on visibility varies slightly with project phase. For manufacturing, proximity increases recognition only once facilities are at least partially operational; estimates for the planning/permitting or under-construction phases are near zero, although the operational-non-operational difference is not statistically distinguishable and is imprecisely estimated. For renewable projects, proximity only has a detectable positive effect on visibility before construction begins, possibly due to publicity around siting decisions or local news coverage (SI Appendix, S3.6).

Partisanship shows no consistent moderation of the proximity–recognition relationship. Among Republicans, closer proximity to renewable projects causes higher recognition, but the Republican–Democrat contrast is imprecisely estimated and not statistically distinguishable from zero. Among Independents, closer proximity to manufacturing projects causes higher recognition, yet the party interaction is only weakly distinguishable from zero. Income and education, which could predict political awareness, also show no consistent moderating effects (SI Appendix, S3.6).

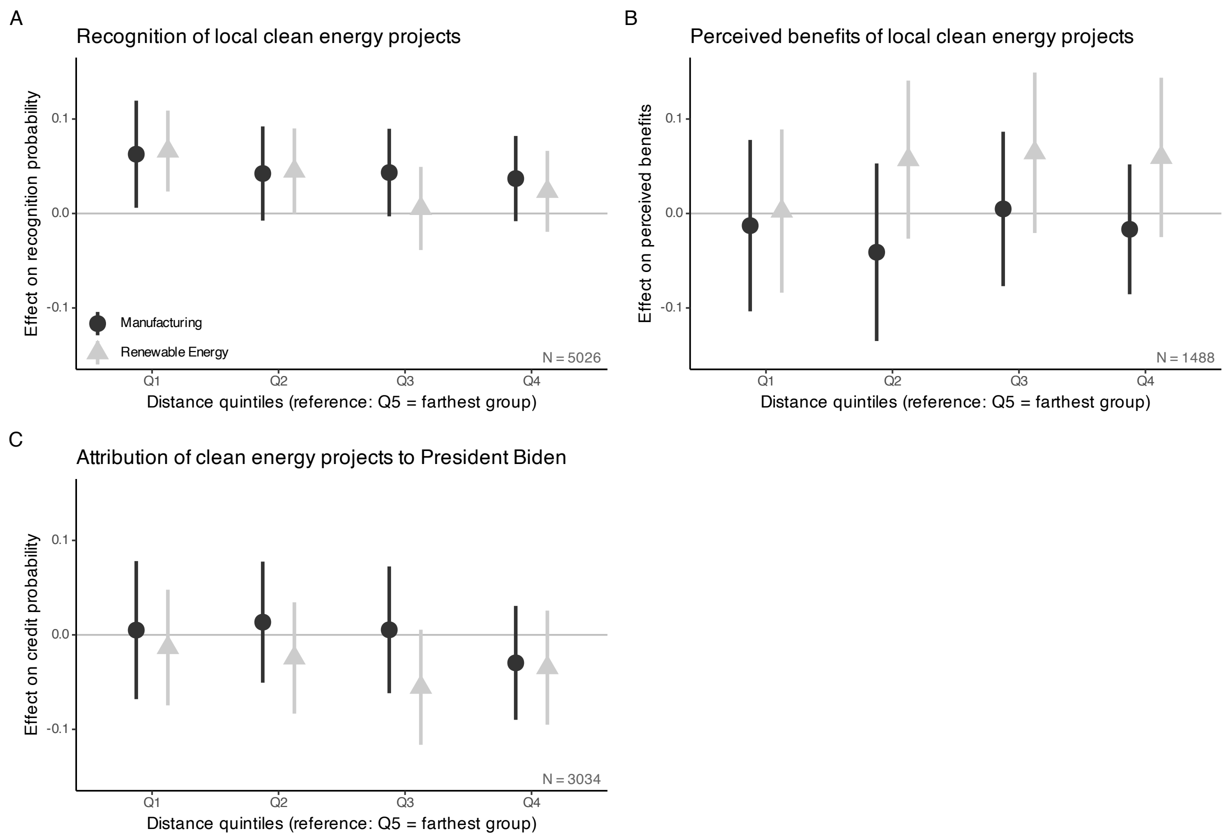

Fig. 2: Effects of proximity to clean energy projects on public attitudes and beliefs. Points are coefficients from a linear regression of the given outcome on proximity quintile indicators, state and sample fixed effects, and covariates. Outcomes are on a 0–1 scale. Bars denote 95% confidence intervals from Conley-adjusted standard errors.

Perceived Benefits

Overall, a majority of Americans (66%), including Republicans (50%) and Democrats (81%), 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 or harms (Fig. 2C). There are no consistent differences by project status, nor by respondents' income or education. Democrats closer to renewable energy projects, but not manufacturing, are more likely than Republicans to see green investments as economically beneficial.

Finally, proximity's effect on perceived benefits varies by project type; people closer to wind energy are more likely to report benefits compared to solar, whereas those nearer to electric vehicle manufacturing are less likely to perceive benefits compared to battery facilities (SI Appendix, S3.6).

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 Appendix, S3.4). Two one-sided equivalence tests further bound any proximity effect to

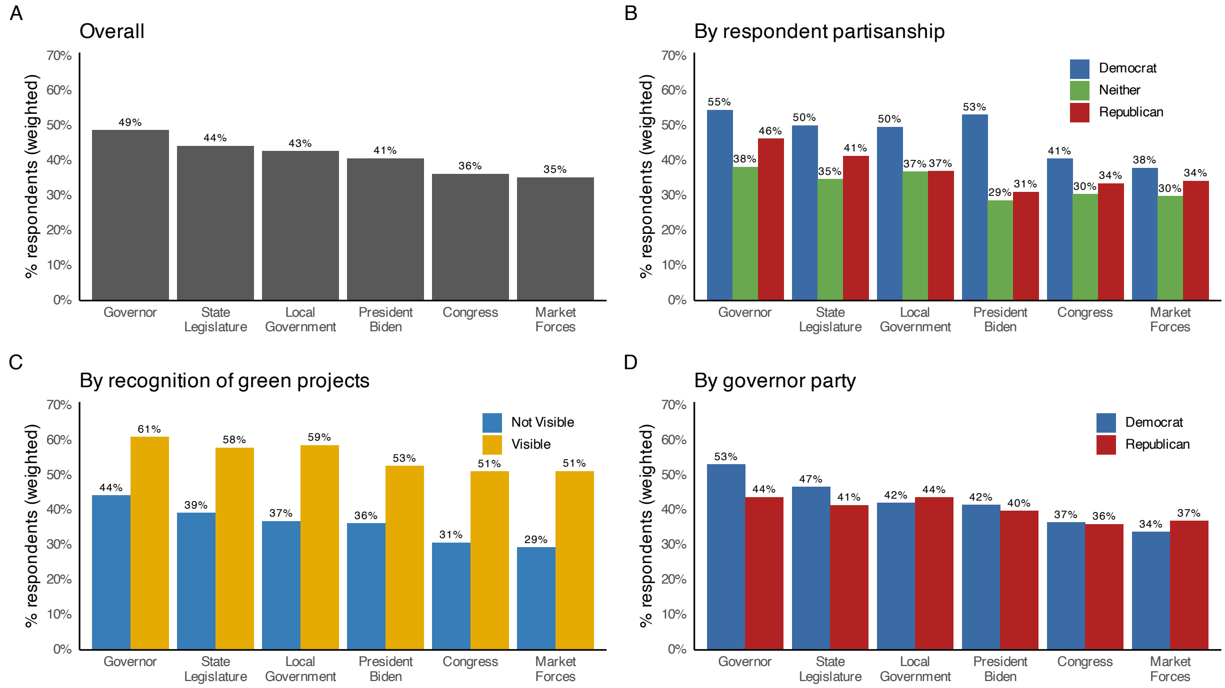

Fig. 3: Perceived responsibility for clean energy investments. Values use survey weights. Two national samples in 2024 (pooled $N = 3{,}034$).

be small; effects larger than 6.7 pp for manufacturing and 6.6 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 by respondent partisanship. There is also no clear heterogeneity by education, income, project status, or sector (SI Appendix, S3.6).

Fig. 3A shows that, 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. Patterns are broadly bipartisan. Even among Democrats, credit to Biden is comparable to credit to the governor.

Respondents who report a nearby project credit all actors more rather than reallocating credit toward federal policymakers (Fig. 3C). Credit for the governor isn't driven by Republicans not acknowledging Biden's role, but is higher among Democrats (Fig. 3D). Respondents are more likely to credit the governor when they share the same party (SI Appendix, S5).

Business and Politician Credit Claiming Patterns

Who "Speaks"

Companies issued statements for nearly all projects (Fig. 4A). Among political actors, governors "spoke" most often, followed by President Biden, a U.S. senator, and the district's U.S. representative. Governors issued statements on 17% more projects than the White House did.

Statement rates varied 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 comment on 59% of projects in their states. These partisan differences appear even when controlling for project type, construction status, and

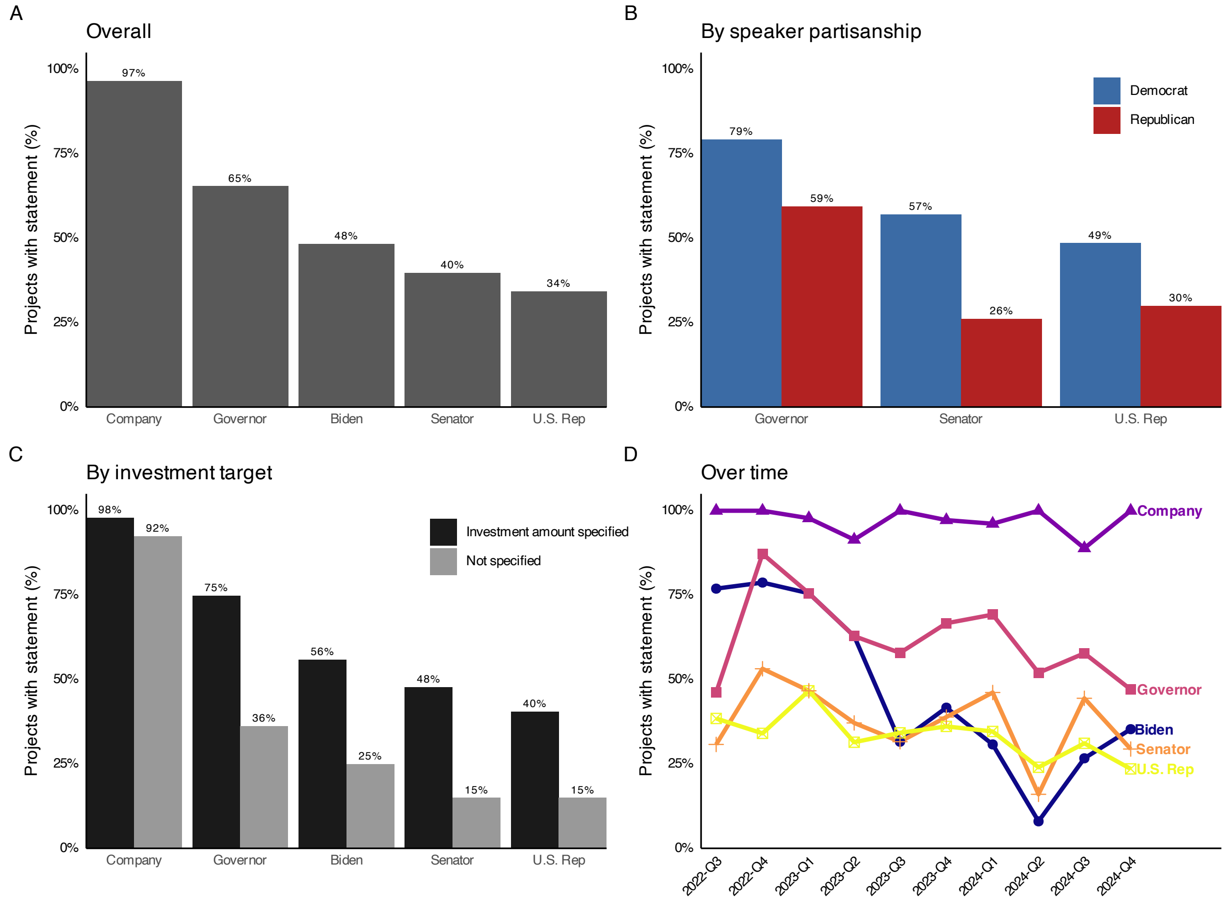

Fig. 4: Share of clean energy manufacturing projects with at least one public statement by companies and elected officials after the IRA (327 projects; Aug. 16, 2022–Dec. 2024).

local economic and political factors (SI Appendix, S6).

Politicians issued more statements about projects that have specific investment amounts (Fig. 4C), 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 (SI Appendix, S6).

Presidential statements were most frequent immediately after the IRA's passage in the third quarter of 2022, then declined through mid-2024 and remained below governor levels despite a pre-election uptick (Fig. 4D). Governor statement rates were comparatively stable. Politicians claimed credit for projects even before the IRA was implemented.

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 acknowledge local actors. Businesses most often credited governors and local actors, followed by the IRA and President Biden.

Across elected officials, self-credit is common. When President Biden and his delegates spoke, they referenced the Bipartisan Infrastructure Law (BIL) in 71% of projects and the IRA in 47%. Biden and his administration's officials occasionally credited governors and local officials.

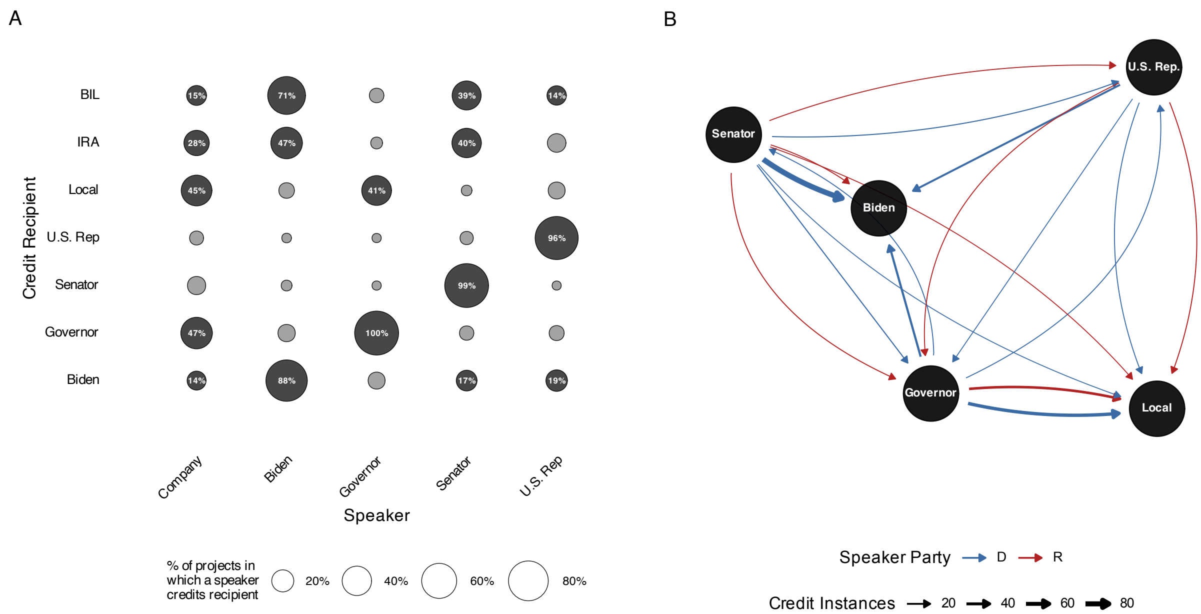

Fig. 5: Credit giving for clean energy manufacturing projects after the IRA (327 projects; Aug. 16, 2022–Dec. 2024). **(A)** Share of projects in which each speaker credited each recipient. BIL refers to the Bipartisan Infrastructure Law. **(B)** Project-level credit network by speaker partisanship.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

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 speaker's partisanship. Governors from both parties recognized local actors. Democratic governors occasionally credited President Biden while Republican governors never did. Republican speakers, compared to Democrats, were overall less likely to credit the White House, which holds with covariate adjustment (SI Appendix, 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 projects more visible, it does not increase credit to the Biden Administration. Less than half of Americans (41%) view the president as responsible for new green projects, while governors receive the most credit, including from people identifying with both political parties. The IRA was visible, but not traceable.

The mixed information environment provides a plausible mechanism for the IRA's limited effect on public opinion. Governors from both parties issued more statements about green investments than the White House. Companies spread credit across multiple actors, highlighting state and local partners more often than President Biden and the IRA. The supply of competing messages emphasized subnational actors over federal ones, diluting policy traceability.

The bipartisan belief that green investments are beneficial suggests that the IRA had the potential to shift public opinion. Although proximity doesn't change beliefs about benefits, we interpret this null result as likely the consequence of already favorable baseline views of clean energy, which is consistent with prior research (Ansolabehere and Konisky, 2014).

The findings align with political science research on how visibility and traceability shape whether policies affect mass attitudes (Campbell, 2012; Soss and Schram, 2007; Mettler, 2011). Clean energy investments may face particular barriers compared to other government programs. 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 (Hamel, 2025). Second, national, state, and local policies influence clean energy projects, complicating attributions in federal systems (Arceneaux, 2006). Politicians cannot count on "good" policy alone to deliver political returns (Galvin and Thurston, 2017).

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 spreading credit could 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 sufficient 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 polarize 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.

Although the national samples had adequate coverage near projects, it is possible that feedback effects would be stronger in communities immediately around project investments. Qualitative work in communities receiving new green investments show that workers and the public often fail to identify the IRA's role (Bergquist and Shepherd, 2025), which is consistent with our systematic surveys. Future work should also conduct targeted samples.

Additional 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, the responsibility survey question is framed at the state level, which may favor governors, but this wording improves comparability and matches how projects were presented locally. Third, 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.

Our findings suggest that climate policy is more likely to create feedback effects through organized interest groups than voters (Meckling et al., 2015; Skocpol, 1992; Pierson, 1993). Businesses can better link policy changes to their economic interests and when benefits are concentrated have strong incentives to lobby. Future research should study how green investments affected both lawmakers and interest groups, whose strategies may also be constrained by public opinion (Gazmararian, Mildenberger, and Tingley, 2025).

Challenges to the IRA will evolve over time. The law's limited ability to create public supporters among voters poses a serious hurdle. The IRA's partial repeal in 2025 resulted from multiple forces beyond public opinion, including partisan polarization (Patashnik and Zelizer, 2013; Hopkins, 2023). Still, Republican legislators might have faced stronger pressure to resist cutbacks had constituents been more aware of the IRA's role in creating local benefits. At the same time, cuts to green investments could carry political costs, as canceled projects may prove more effective at mobilizing beneficiaries (Béland, Campbell, and Weaver, 2022). Yet the core challenge remains. For climate spending to create political returns, the public must be able to trace material benefits back to federal policymakers.

Materials and Methods

Survey Data and Measurement

Sampling

Three nonprobability 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 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 samples 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. Samples 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 connotation. Analyses use a binary indicator coded 1 for "Extremely" or "Very" and 0 otherwise. 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. Sample 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" are coded 1, and 0 otherwise.

Question order. The recognition item always preceded the attribution battery to minimize priming of recognition by political responsibility. The location of other survey content, such as demographics, varied by sample.

Geolocation & Linkage

Respondents were geocoded to ZIP Code centroids, the most granular geographic identifier available, and linked to the nearest project in the two years before the survey date. ZIP Codes were self-reported and mapped to longitude and latitude coordinates using the Google Maps API. When a reliable ZIP Code 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 Appendix, S3.5).

Weights

Descriptive estimates use survey weights. Proximity regressions do not, but weighted regressions are similar (SI S3.5). Although the raw samples generally approximated the national population, 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 coordinates were excluded.

Clean energy manufacturing. Manufacturing plant 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 before the respondent's interview date and after the IRA's passage. The statements analysis considers all post-IRA manufacturing projects regardless of operational 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. Multiple distinct statements by one actor about the same project were consolidated into one record. 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); party brands (e.g., Democratic Party) 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 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 captured explicit credit (e.g., causal verbs, attributions of decision-making, financial involvement) and 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). Post-processing ensured that 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. Results are qualitatively similar with an alternative codebook.

LLM-assisted annotation is 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 visibility, perceived benefits, and credit attribution. Since project location could be confounded by political and economic factors, the research design leverages within-state variation in proximity. The assumption is that the within-state deviation in distance to 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, bolsters the credibility of this assumption.

The analysis includes pre-treatment county and individual-level covariates. 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. Controls are lagged by a year where applicable. Individual-level controls include age, sex, race, education, labor force participation, income, party identification, and global warming beliefs.

Estimation

The analysis uses a linear probability model with the following specification:

$$Y_i = \sum_{q=1}^{4} \mathbb{1}\{Distance_i \in Q_q\}\beta_q + X_i^\top \gamma + State_i + Sample_i + \epsilon_i, \tag{1}$$

where Q_5 (farthest quintile) is the reference. The primary analysis operationalizes distance with quintiles to ensure that it captures non-linear effects. Outcomes are indicators for recognition, credit to President Biden, or belief that green investments are beneficial. X_i includes individual- and county-level covariates; *State* and *Sample* denote state and sample fixed effects.

An omnibus Wald test assesses the joint null that the first two distance quintile indicators equal zero. For the visibility outcome, the test rejects the null of no proximity effect for renewables ($p = 0.01$), whereas the pooled contrast for manufacturing is smaller and not distinguishable from zero ($p = 0.095$).

Inference

Spatial HAC (Conley) standard errors were computed using respondents' ZIP-centroid latitude/longitude (decimal degrees), a uniform kernel with a hard 50 km cutoff, the default triangular distance metric, and no grid pooling. Results are robust to computing great-circle distances, to alternative cutoffs (e.g., 100 and 200 km), and to clustering by state (SI Appendix, S3.5).

Sensitivity

The sensitivity analysis quantifies the strength of a hypothetical unobserved confounder required to reduce the Q1 proximity coefficient to insignificance at the 5% level (Cinelli and Hazlett, 2020). A hypothetical omitted variable would need to be more than ten times larger than the correlations of strong observed predictors of proximity and the visibility outcome (SI Appendix, S3.5).

Acknowledgments

The paper received helpful comments from Jim Bisbee, Patrick Egan, Daniel Hopkins, Matto Mildenberger, and participants at the Princeton University Conference on "The Politics of Clean Energy Abundance Under Federalism" and the 2025 American Political Science Association Annual Meeting. Thank you to Branden Bohrnsen, Pranav Moudgalya, Ahmed Shareef, and especially Dylan Carlson Sirvent León for excellent research assistance.

Funding

Financial support came from the Harvard University Salata Institute Strengthening Communities research cluster and the University of Michigan.

Competing Interests

The authors declare no competing interests.

Data, Materials, and Code Availability

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

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SI Appendix

Why Clean Energy Investments Had Limited Political Returns

S1 Data Sources

Variable	Source and Description	Access Link
Clean Energy Data		
Clean energy: generation	EIA-860M (monthly). Reports existing and proposed generating units ≥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 ≥100 Mbps downstream).	FCC Form 477
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
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.	WorldPop Hub

S2 Survey

S2.1 Sample Summary Statistics

Table S2: Survey sample summaries

	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

Notes: Prefer not to say income answers imputed with median household income. Column header shows month/day of survey wave start and end dates. Global warming index ranges from 0 to 1, where larger values indicate greater concern.

S2.2 Weight Diagnostics

Survey weights were constructed for the pooled sample and separately for questions only on specific samples. 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 Materials and Methods. 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 Item Internal Validity

We took three steps to validate the credit attribution item's accuracy and reliability. First, to minimize partisan differences in response patterns, the question used neutral language to describe green investments; it didn't presume that projects were good or bad. Partisan expressive responding is an inherent risk. As a test, we assess 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

	(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
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 Effect Analyses

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	737	1079	0.21	5677	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

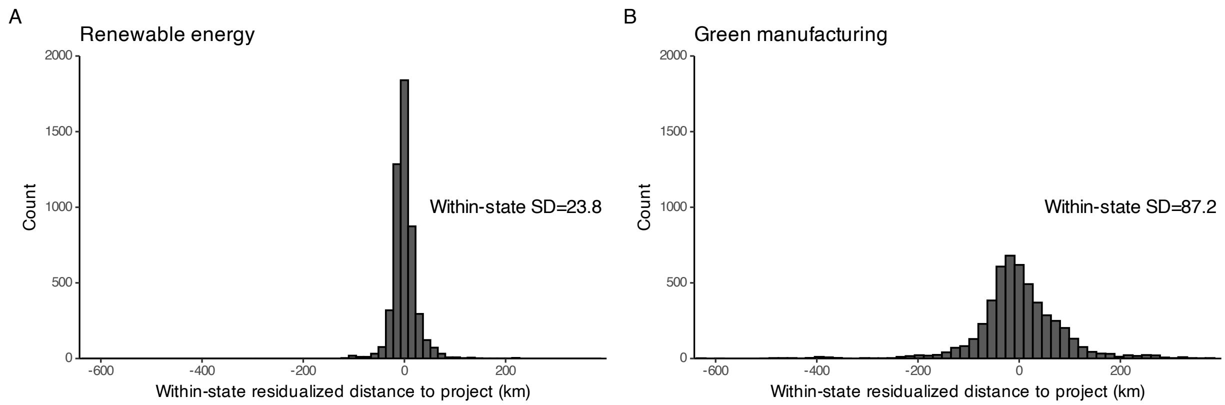

Fig. S1: Within-state variation in survey respondent proximity to clean energy investments. Histograms plot the residual variation in continuous (logged) distance to renewable energy and green manufacturing projects after regressing the distance measures on the state fixed effects, sample fixed effects, and covariates in the main model specification.

S3.3 Main Regression Table

Table S6: Linear probability models of proximity's effect on project visibility, 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	0.005	0.0026	-0.013
	(0.022)	(0.029)	(0.031)	(0.037)	(0.0441)	(0.046)
Q2 proximity	0.045	0.042	-0.024	0.013	0.057	-0.041
	(0.023)	(0.025)	(0.030)	(0.033)	(0.043)	(0.048)
Q3 proximity	0.0053	0.043	-0.055	0.0054	0.064	0.0048
	(0.0225)	(0.024)	(0.031)	(0.0342)	(0.043)	(0.0417)
Q4 proximity	0.023	0.037	-0.035	-0.030	0.059	-0.017
	(0.022)	(0.023)	(0.031)	(0.031)	(0.043)	(0.035)
Age	-0.00123**	-0.00126**	0.00059	0.00056	0.00029	0.00026
	(0.00042)	(0.00042)	(0.00061)	(0.00065)	(0.00076)	(0.00076)
Female	-0.063***	-0.062***	-0.060***	-0.060***	-0.036	-0.036
	(0.013)	(0.013)	(0.018)	(0.018)	(0.022)	(0.022)
Black	0.023	0.022	0.042	0.041	-0.044	-0.045
	(0.022)	(0.022)	(0.028)	(0.028)	(0.037)	(0.038)
Asian	-0.043	-0.041	0.027	0.026	-0.034	-0.039
	(0.032)	(0.032)	(0.050)	(0.050)	(0.058)	(0.058)
Other race	-0.023	-0.026	-0.036	-0.035	0.065	0.064
	(0.024)	(0.024)	(0.035)	(0.035)	(0.052)	(0.053)
Hispanic/Latino	0.025	0.028	0.0077	0.0077	-0.090*	-0.085*
	(0.020)	(0.020)	(0.0249)	(0.0248)	(0.036)	(0.036)
College	0.072***	0.070***	0.050*	0.049*	0.0016	0.0011
	(0.013)	(0.014)	(0.023)	(0.023)	(0.0247)	(0.0251)
Employed	0.066***	0.067***	0.035	0.034	0.050	0.049
	(0.014)	(0.014)	(0.021)	(0.021)	(0.029)	(0.029)
Income Q2	0.017	0.016	-0.014	-0.012	0.031	0.028
	(0.016)	(0.016)	(0.028)	(0.028)	(0.035)	(0.035)
Income Q3	0.007	0.0067	-0.045	-0.044	0.013	0.014
	(0.018)	(0.0175)	(0.030)	(0.030)	(0.036)	(0.036)
Income Q4	0.056*	0.058**	-0.021	-0.020	0.048	0.048
	(0.022)	(0.022)	(0.036)	(0.036)	(0.037)	(0.037)
Income Q5	0.074**	0.076**	-0.034	-0.031	0.077	0.075
	(0.026)	(0.026)	(0.041)	(0.041)	(0.049)	(0.049)
Republican	-0.009	-0.0093	-0.169***	-0.170***	-0.15***	-0.15***
	(0.015)	(0.0151)	(0.022)	(0.022)	(0.03)	(0.03)
Neither party	-0.069***	-0.070***	-0.221***	-0.223***	-0.105**	-0.105**
	(0.017)	(0.017)	(0.025)	(0.025)	(0.038)	(0.038)
Global warming index	0.128***	0.128***	0.074*	0.074*	0.566***	0.566***
	(0.021)	(0.021)	(0.035)	(0.035)	(0.044)	(0.044)
Population density	-0.0048	-0.0097	0.0150	0.0151	0.013	0.019
	(0.0072)	(0.0076)	(0.0092)	(0.0092)	(0.015)	(0.015)
County college share $(t-1)$	0.0045	0.004	-0.00032	-0.0015	0.015	0.018
	(0.0139)	(0.014)	(0.01979)	(0.0202)	(0.025)	(0.025)
County poverty share $(t-1)$	0.0085	0.0097	-0.0041	-0.0031	-0.0072	-0.0035
	(0.0104)	(0.0102)	(0.0145)	(0.0145)	(0.0185)	(0.0184)
County foreign-born share $(t-1)$	-0.0004	-0.0034	-0.00038	-0.0012	-0.012	-0.013
	(0.0093)	(0.0093)	(0.01211)	(0.0123)	(0.019)	(0.019)
Median county housing costs $(t-1)$	-0.038**	-0.041**	0.006	0.0069	0.00041	0.0075
	(0.014)	(0.014)	(0.018)	(0.0181)	(0.02192)	(0.0214)
Faster broadband access $(t-1)$	0.013	0.017	-0.043	-0.044	0.053	0.054
	(0.021)	(0.021)	(0.028)	(0.028)	(0.030)	(0.030)
County GDP (log) $(t-1)$	0.059	0.051	0.049	0.051	0.040	0.039
	(0.039)	(0.039)	(0.050)	(0.050)	(0.063)	(0.063)
Labor force (log) $(t-1)$	-0.071	-0.063	-0.045	-0.048	-0.051	-0.052
	(0.038)	(0.038)	(0.048)	(0.048)	(0.059)	(0.059)
County unemployment rate $(t-1)$	-0.0086	-0.0061	0.0243*	0.0259**	0.022	0.025*
	(0.0079)	(0.0078)	(0.0095)	(0.0099)	(0.012)	(0.012)
Highway access	0.015	0.016	0.076*	0.074*	0.0021	0.011
	(0.020)	(0.020)	(0.033)	(0.032)	(0.0412)	(0.041)
County income pc $(t-1)$	0.024	0.028	-0.0027	-0.0012	-0.0099	-0.012
	(0.015)	(0.016)	(0.0159)	(0.0159)	(0.0234)	(0.023)
N	5026	5026	3034	3034	1487	1487
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. Estimates are OLS with Conley SEs (50 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.

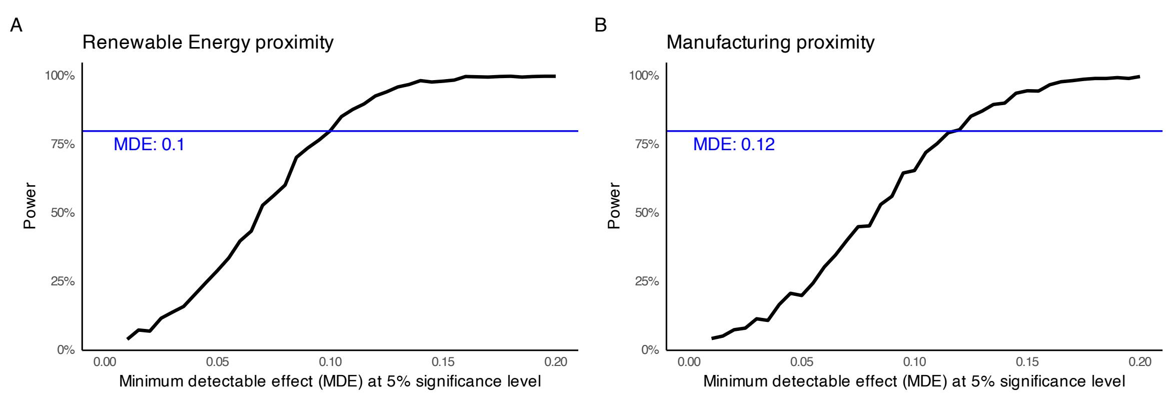

Fig. S2: Analytical power analysis, credit attribution outcome.

It is reasonable to imagine that reformers behind the IRA had anticipated that people living near projects would be at least 10 percentage points more likely to notice them and, in turn, credit the Biden Administration. While partisan polarization constrains belief change among Democrats and Republicans, a substantial share of the public identifies as independent, so at least some of these respondents could update their views if benefiting from investments. 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 if

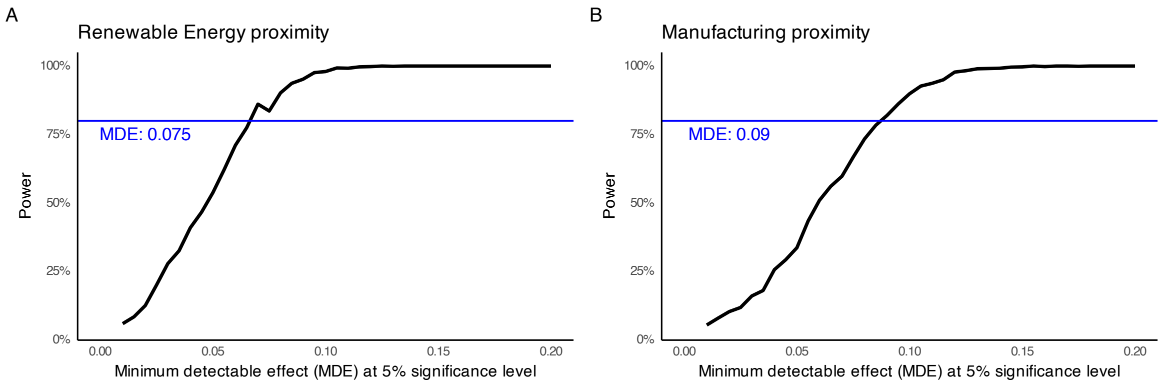

Fig. S3: Analytical power analysis, recognition outcome.

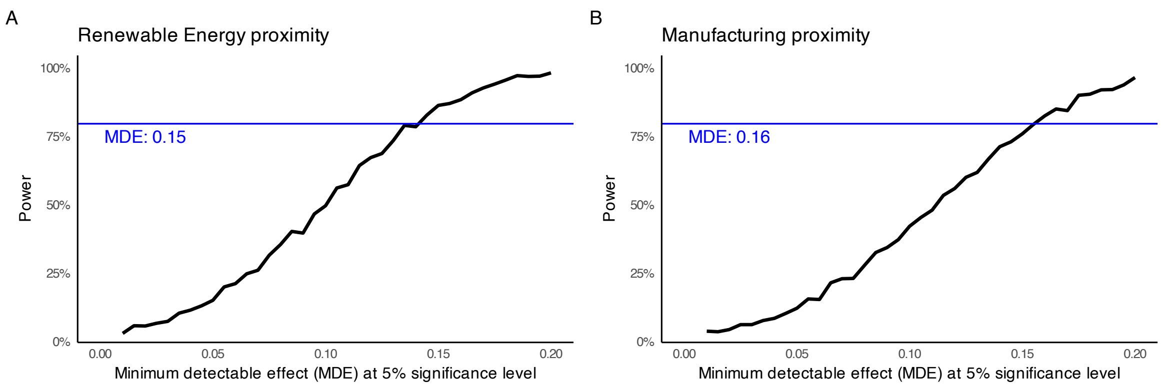

Fig. S4: Analytical power analysis, benefit outcome.

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

Tables S8 and S7 report sensitivity analysis diagnostics following Cinelli and Hazlett (2020). For the first proximity quintile, the robustness value $RV_{q=1}$ is 2.8% for manufacturing and 4.6% for renewables. In other words, an unobserved confounder would need to explain at least 2.8% and 4.6% of the residual variance of both the treatment and the outcome to fully eliminate the estimated effects.

The robustness values for statistical significance, $RV_{q=1,\alpha=0.05}$, are 0.1% for manufacturing and 1.9% for renewables. These values indicate the strength an unobserved confounder would need to reduce the lower bound of the 95% confidence interval to zero.

Finally, the partial R^2 ($R^2_{Y\sim D|\mathbf{X}}$) shows that even if we assume an extreme scenario where unobserved confounders explain all of the remaining variance in the outcome, such a confounder would need to account for at least 0.1% (manufacturing) or 0.2% (renewables) of the residual variance in the treatment to eliminate the observed effect.

Interpreting these values requires domain knowledge. Using the strongest observed covariates as benchmarks—labor force participation for manufacturing and household income for renewables—any plausible unobserved confounder would need to be more than ten times stronger than these variables to overturn our conclusions.

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	0.029	2.17	0.1%	3%	0.3%
df = 4942	*Bound (1 x Labor force (log) (t − 1))*: $R^2_{Y\sim Z\|\mathbf{X},D} = 0.3\%$, $R^2_{D\sim Z\|\mathbf{X}} = 0\%$					

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	0.022	3.024	0.2%	4.2%	1.5%
df = 4942	*Bound (1 x Income Q4)*: $R^2_{Y\sim Z\|\mathbf{X},D} = 0.1\%$, $R^2_{D\sim Z\|\mathbf{X}} = 0.4\%$					

S3.5.2 Alternative Standard Errors

Table S9: Robustness to 100 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	0.005	0.0026	-0.013
	(0.021)	(0.029)	(0.032)	(0.037)	(0.0462)	(0.044)
Q2 proximity	0.045	0.042	-0.024	0.013	0.057	-0.041
	(0.024)	(0.024)	(0.032)	(0.035)	(0.042)	(0.042)
Q3 proximity	0.0053	0.043	-0.055	0.0054	0.064	0.0048
	(0.0227)	(0.022)	(0.032)	(0.0329)	(0.042)	(0.0388)
Q4 proximity	0.023	0.037	-0.035	-0.03	0.059	-0.017
	(0.021)	(0.021)	(0.035)	(0.03)	(0.043)	(0.035)
N	5026	5026	3034	3034	1487	1487
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. Estimates are OLS with Conley SEs (100 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table S10: Robustness to 200 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	0.005	0.0026	-0.013
	(0.022)	(0.028)	(0.035)	(0.030)	(0.0404)	(0.043)
Q2 proximity	0.045	0.042	-0.024	0.013	0.057	-0.041
	(0.025)	(0.024)	(0.038)	(0.030)	(0.035)	(0.037)
Q3 proximity	0.0053	0.043	-0.055	0.0054	0.064	0.0048
	(0.0238)	(0.023)	(0.036)	(0.0280)	(0.041)	(0.0351)
Q4 proximity	0.023	0.037	-0.035	-0.030	0.059	-0.017
	(0.021)	(0.019)	(0.040)	(0.026)	(0.036)	(0.038)
N	5026	5026	3034	3034	1487	1487
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. Estimates are OLS with Conley SEs (200 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	0.005	0.0026	-0.013
	(0.020)	(0.030)	(0.026)	(0.038)	(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	1487	1487
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. 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 Geocoordinates

Table S12: Robustness to alternative geocoordinates: 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*	0.060*	-0.012	-0.00097	0.00016	-0.018
	(0.022)	(0.029)	(0.032)	(0.03866)	(0.04503)	(0.046)
Q2 proximity	0.040	0.039	-0.036	0.016	0.054	-0.042
	(0.023)	(0.026)	(0.031)	(0.035)	(0.043)	(0.048)
Q3 proximity	-0.002	0.044	-0.060	-0.0028	0.058	0.0059
	(0.023)	(0.024)	(0.032)	(0.0359)	(0.044)	(0.0424)
Q4 proximity	0.018	0.038	-0.041	-0.029	0.064	-0.0074
	(0.022)	(0.023)	(0.031)	(0.032)	(0.042)	(0.0346)
N	4856	4856	2931	2931	1451	1451
Adjusted R^2	0.065	0.064	0.062	0.061	0.176	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. Estimates are OLS with Conley SEs (50 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	0.005	0.0026	-0.013
	(0.022)	(0.029)	(0.031)	(0.038)	(0.0442)	(0.046)
Q2 proximity	0.045	0.042	-0.024	0.013	0.057	-0.041
	(0.023)	(0.025)	(0.030)	(0.033)	(0.043)	(0.047)
Q3 proximity	0.0053	0.043	-0.055	0.0054	0.064	0.0048
	(0.0224)	(0.024)	(0.031)	(0.0345)	(0.043)	(0.0413)
Q4 proximity	0.023	0.037	-0.035	-0.030	0.059	-0.017
	(0.022)	(0.023)	(0.031)	(0.031)	(0.043)	(0.034)
N	5026	5026	3034	3034	1487	1487
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. Estimates are OLS with Conley SEs (50 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	
	(0.0081)		(0.0120)		(0.0170)	
Distance to manufacturing (log)		-0.0171*		0.00017		-0.0064
		(0.0074)		(0.01105)		(0.0151)
N	5026	5026	3034	3034	1487	1487
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. Estimates are OLS with Conley SEs (50 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S3.5.5 Weighted Regressions

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	0.00067	0.0026	-0.013
	(0.024)	(0.031)	(0.035)	(0.04199)	(0.0441)	(0.046)
Q2 proximity	0.039	0.061*	-0.0084	0.0023	0.057	-0.041
	(0.026)	(0.028)	(0.0341)	(0.0372)	(0.043)	(0.048)
Q3 proximity	-0.0017	0.054*	-0.065	-0.0042	0.064	0.0048
	(0.0251)	(0.026)	(0.035)	(0.0352)	(0.043)	(0.0417)
Q4 proximity	0.022	0.068**	-0.029	-0.058	0.059	-0.017
	(0.023)	(0.026)	(0.033)	(0.033)	(0.043)	(0.035)
N	5026	5026	3034	3034	1487	1487
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. Estimates are OLS with Conley SEs (50 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S3.5.6 Media Market Fixed Effects

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.

Table S16: Robustness to DMA fixed effects: Linear probability models of project recognition and credit attribution.

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Q1 proximity	0.088***	0.018	-0.045	0.0057	-0.035	-0.13
	(0.025)	(0.046)	(0.035)	(0.0508)	(0.057)	(0.10)
Q2 proximity	0.057*	0.014	-0.043	0.063	0.017	-0.125
	(0.026)	(0.041)	(0.035)	(0.050)	(0.056)	(0.096)
Q3 proximity	0.021	0.055	-0.076*	0.091*	0.019	-0.013
	(0.025)	(0.037)	(0.036)	(0.042)	(0.056)	(0.068)
Q4 proximity	0.043	0.035	-0.045	0.0058	0.038	-0.014
	(0.024)	(0.027)	(0.036)	(0.0352)	(0.053)	(0.043)
N	5012	5012	3017	3017	1455	1455
Adjusted R^2	0.074	0.072	0.071	0.072	0.178	0.178
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
DMA 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. Estimates are OLS with Conley SEs (50 km threshold). Continuous covariates are standardized. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S3.5.7 Additional Credit Recipients

Table S17: 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	0.018	-0.018	0.048	-0.050	0.056	-0.017	-0.0056
	(0.034)	(0.044)	(0.033)	(0.044)	(0.029)	(0.036)	(0.033)	(0.037)	(0.033)	(0.0367)
Q2 proximity	-0.023	-0.046	0.0011	0.035	-0.017	0.036	-0.0065	0.014	-0.023	-0.042
	(0.034)	(0.036)	(0.0311)	(0.037)	(0.030)	(0.032)	(0.0306)	(0.033)	(0.032)	(0.033)
Q3 proximity	-0.023	-0.029	-0.052	0.036	-0.045	0.015	-0.052	0.051	-0.039	0.025
	(0.033)	(0.039)	(0.032)	(0.037)	(0.029)	(0.032)	(0.031)	(0.034)	(0.029)	(0.035)
Q4 proximity	-0.053	-0.030	-0.048	0.014	-0.011	8e-04	-0.074*	0.011	-0.05	-0.038
	(0.035)	(0.031)	(0.030)	(0.033)	(0.027)	(3e-02)	(0.031)	(0.032)	(0.03)	(0.032)
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. Estimates are OLS with Conley SEs (50 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:

$$Y_i = M_i\lambda + M_i \times \sum_{q=1}^{4} \mathbb{1}[Distance_i \in Q_q]\beta_q + X_i^\top\gamma + State_i + Sample_i + \epsilon_i, \tag{S1}$$

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 clustered by state since diagnostic tests found these to be more reliable than the Conley estimator given the more saturated model specification. No weights are applied. All subsequent subsections apply this specification to a given moderator.

S3.6.1 Manufacturing Operational Status

We assess whether the effect of proximity varies by project status. For manufacturing projects, the moderator distinguishes between "operating" (projects categorized by Big Green Machine as "Operating" or Operating Partially; Under Construction") and "other" (projects categorized as "Paused," "Pilot," "Planned," "Sold," or "Under Construction").

Fig. S5 reports the average marginal effect of proximity (relative to Q5) for each status category. The visibility effect at Q1 appears only for projects that are fully or partially operational. The interaction term is negative but imprecisely estimated, so we cannot conclude that the visibility effect differs by project status (Table S18).

There is no moderating effect of manufacturing project status on proximity for the credit attribution and perceived benefit outcomes.

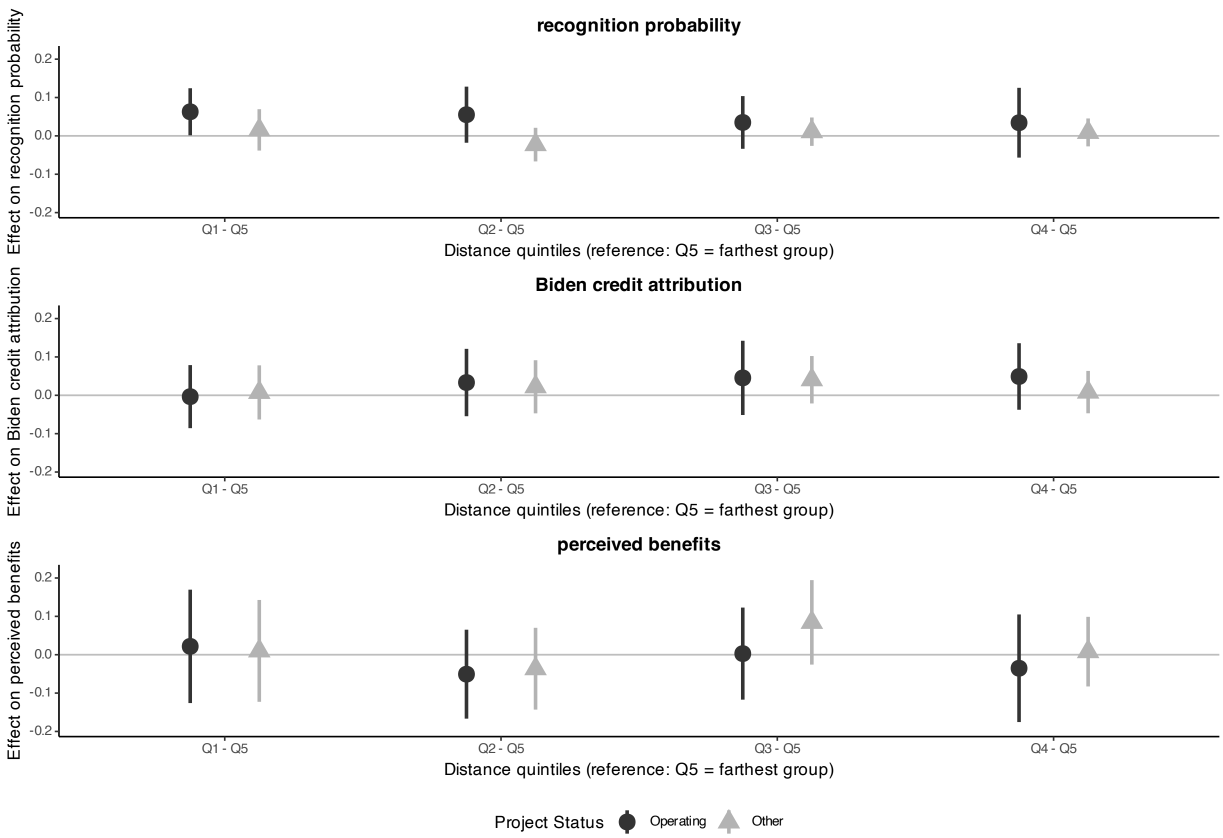

Fig. S5: Heterogeneous effects of clean energy manufacturing proximity on recognition by project status. Plot depicts the average marginal effect of a proximity quintile (relative to Q5) across moderator values. Bars denote 95% confidence intervals with cluster-robust standard errors by state. Equation S1 describes the model specification. Table S18 reports interaction terms and sample sizes.

Table S18: Heterogeneous proximity effects by manufacturing project status

	Manufacturing		
	Recognition	Credit	Benefit
Q1 proximity	0.063	-0.0035	0.022
	(0.031)	(0.0419)	(0.075)
Q2 proximity	0.055	0.033	-0.051
	(0.037)	(0.045)	(0.059)
Q3 proximity	0.035	0.045	0.0029
	(0.035)	(0.049)	(0.0612)
Q4 proximity	0.034	0.049	-0.035
	(0.046)	(0.044)	(0.072)
Other	0.017	-0.0028	-0.053
	(0.030)	(0.0374)	(0.053)
Q1 $\times$ Other	-0.047	0.011	-0.012
	(0.046)	(0.050)	(0.090)
Q2 $\times$ Other	-0.078	-0.011	0.014
	(0.043)	(0.052)	(0.067)
Q3 $\times$ Other	-0.024	-0.0048	0.081
	(0.045)	(0.0670)	(0.089)
Q4 $\times$ Other	-0.025	-0.041	0.043
	(0.051)	(0.050)	(0.071)
N	5026	3034	1487
Adjusted R^2	0.073	0.067	0.182
Covariates	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model with interactions between proximity and manufacturing project status. Recognition = 1 if respondent reports a local green project, 0 otherwise. Credit = 1 if respondent credits the Biden Administration for local green investments. Benefit = 1 if respondent perceives a benefit from local green projects. OLS coefficient estimates with cluster-robust standard errors by state in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

S3.6.2 Renewable Energy Operational Status

For renewable energy projects, the status moderator has two levels: "construction" and "pre-construction." Construction refers to plants that are not yet fully operational but have active building underway. Pre-construction refers to projects that are planned or have received approvals but where building has not yet begun, although site preparation may be underway.

Figure S6 shows the average marginal effects of proximity across these categories. Patterns vary by outcome, but the only reliably detectable difference is that the proximity coefficient for pre-construction projects is smaller than for projects under construction (Table S19). For example, proximity to pre-construction projects causes higher recognition but lower attribution of credit to the Biden Administration, while proximity to projects under construction shows positive effects on perceived benefits.

Although the mechanism behind the negative attribution effect near pre-construction projects is unclear, the result is consistent with our broader finding that the intended beneficiaries of IRA investments are not systematically more likely to credit federal policymakers.

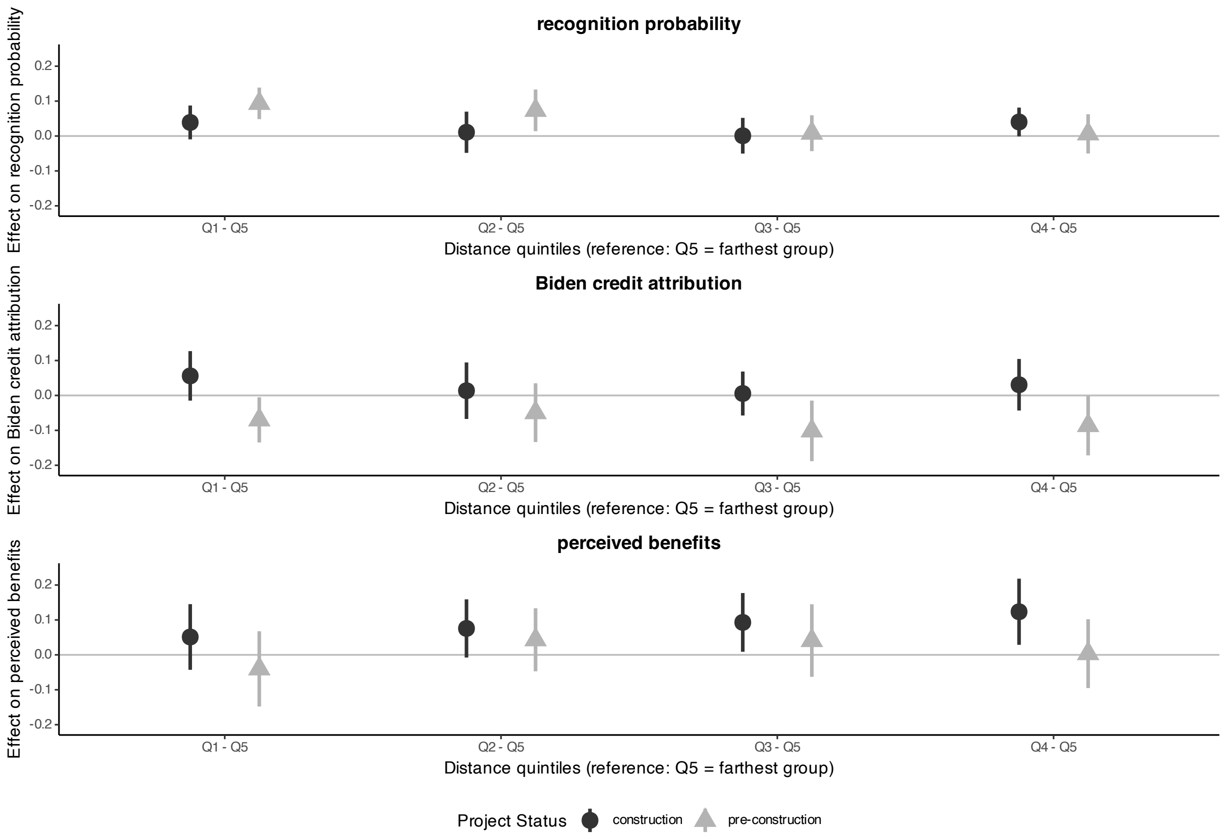

Fig. S6: Heterogeneous effects of renewable generation proximity by project status

Table S19: Heterogeneous proximity effects by renewable energy project status

	Renewable Energy		
	Recognition	Credit	Benefit
Q1 proximity	0.039	0.056	0.051
	(0.025)	(0.036)	(0.048)
Q2 proximity	0.011	0.014	0.076
	(0.030)	(0.041)	(0.043)
Q3 proximity	0.00083	0.0055	0.093*
	(0.02608)	(0.0321)	(0.043)
Q4 proximity	0.040	0.031	0.123*
	(0.021)	(0.038)	(0.048)
pre-construction	-0.012	0.105**	0.052
	(0.024)	(0.033)	(0.050)
Q1 × pre-construction	0.055	-0.126**	-0.091
	(0.029)	(0.046)	(0.072)
Q2 × pre-construction	0.063	-0.063	-0.032
	(0.033)	(0.043)	(0.068)
Q3 × pre-construction	0.0072	-0.107*	-0.052
	(0.0336)	(0.052)	(0.064)
Q4 × pre-construction	-0.034	-0.117*	-0.12
	(0.036)	(0.052)	(0.07)
N	5026	3034	1487
Adjusted R^2	0.076	0.069	0.181
Covariates	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model with interactions between proximity and renewable energy project status. Recognition = 1 if respondent reports a local green project, 0 otherwise. Credit = 1 if respondent credits the Biden Administration for local green investments. Benefit = 1 if respondent perceives a benefit from local green projects. OLS coefficient estimates with cluster-robust standard errors by state in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

S3.6.3 Renewable Energy Technology

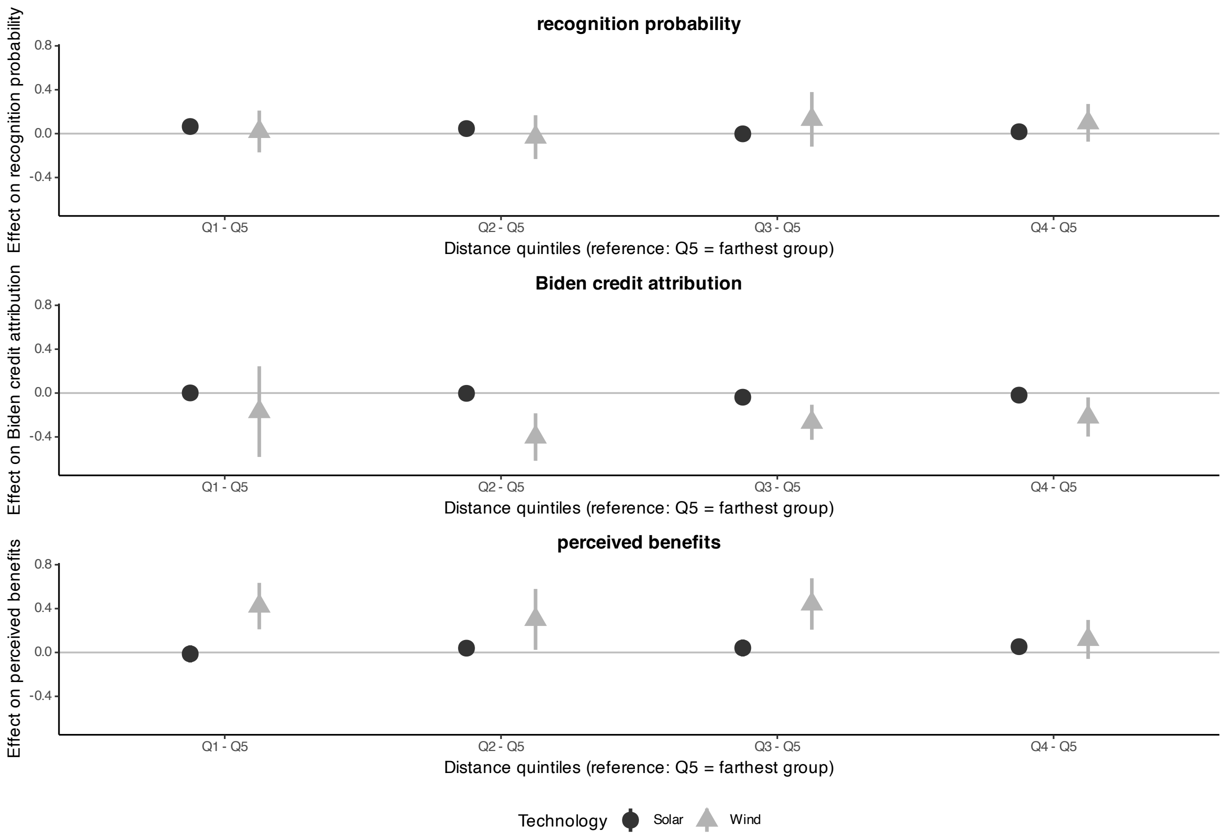

Fig. S7: Heterogeneous effects of renewable generation proximity by technology. Plot depicts the average marginal effect of a proximity quintile (relative to Q5) across moderator values. Bars denote 95% confidence intervals with cluster-robust standard errors by state. Equation S1 describes the model specification. Table S19 reports interaction terms and sample sizes.

Table S20: Heterogeneous proximity effects by renewable energy technology

	Renewable Energy		
	Recognition	Credit	Benefit
Q1 proximity	0.065***	0.0012	-0.013
	(0.019)	(0.0261)	(0.040)
Q2 proximity	0.046	-0.0028	0.039
	(0.026)	(0.0344)	(0.031)
Q3 proximity	-0.002	-0.038	0.041
	(0.019)	(0.031)	(0.039)
Q4 proximity	0.017	-0.019	0.053
	(0.017)	(0.032)	(0.037)
Wind	-0.027	0.172*	-0.187
	(0.063)	(0.066)	(0.098)
Q1 $\times$ Wind	-0.045	-0.17	0.44***
	(0.100)	(0.22)	(0.11)
Q2 $\times$ Wind	-0.078	-0.40***	0.26
	(0.108)	(0.11)	(0.14)
Q3 $\times$ Wind	0.13	-0.229*	0.40**
	(0.13)	(0.093)	(0.13)
Q4 $\times$ Wind	0.081	-0.199*	0.066
	(0.090)	(0.091)	(0.100)
N	5026	3034	1487
Adjusted R^2	0.075	0.070	0.184
Covariates	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model with interactions between proximity and renewable energy technology. Recognition = 1 if respondent reports a local green project, 0 otherwise. Credit = 1 if respondent credits the Biden Administration for local green investments. Benefit = 1 if respondent perceives a benefit from local green projects. OLS coefficient estimates with cluster-robust standard errors by state in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

S3.6.4 Manufacturing Sector

Fig.S8 plots average marginal effects of proximity to manufacturing projects by sector: batteries, EVs, solar, and wind. For recognition, Q1 proximity is positive for EV and wind, but only the wind estimate is statistically distinguishable from the battery baseline (TableS21).

For credit attribution, proximity effects do not differ consistently across sectors, and none are statistically distinguishable.

For perceived benefits, people nearer to EV facilities (Q1–Q3 vs. Q5) are less likely than those farther away in the same state to view green investments as economically beneficial.

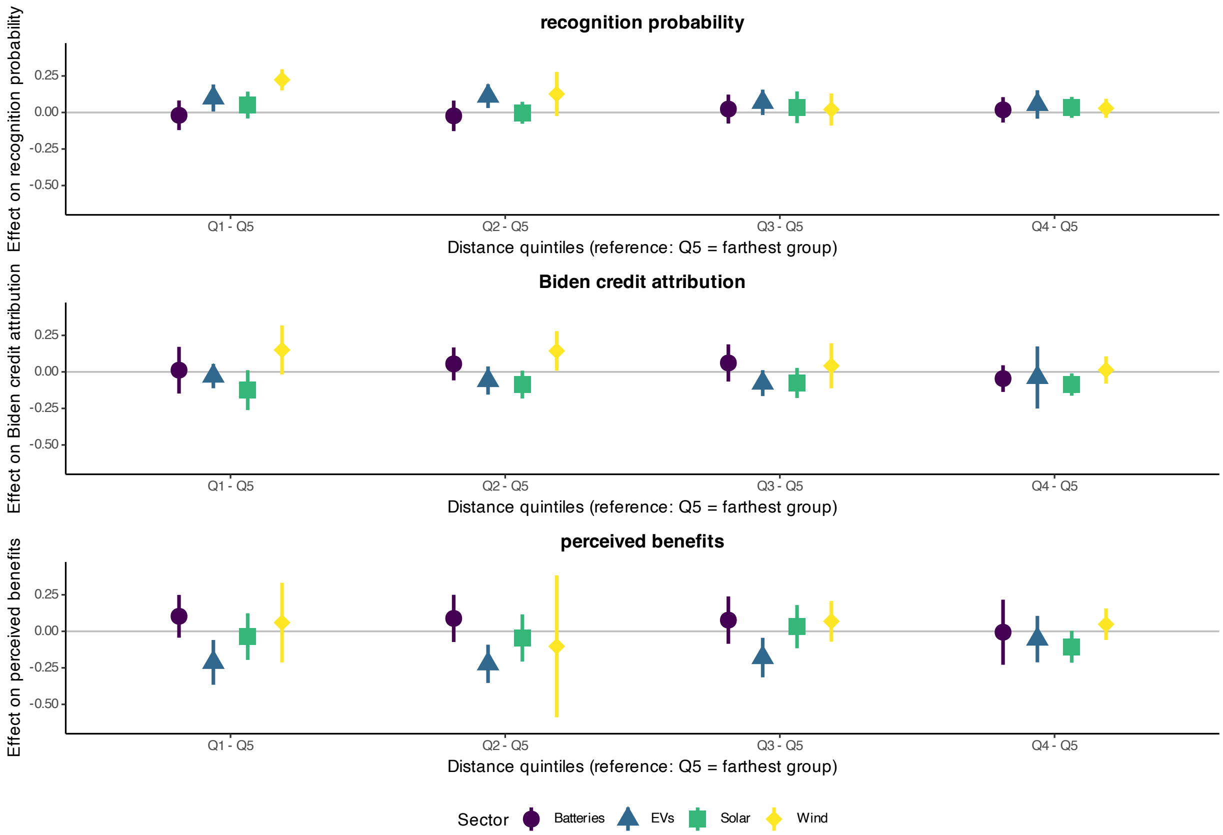

Fig. S8: Heterogeneous effects of clean energy manufacturing proximity by project sector. Plot depicts the average marginal effect of a proximity quintile (relative to Q5) across moderator values. Bars denote 95% confidence intervals with cluster-robust standard errors by state. Equation S1 describes the model specification. Table S21 reports interaction terms and sample sizes.

Table S21: Heterogeneous proximity effects by manufacturing sector

	Manufacturing		
	Recognition	Credit	Benefit
Q1 proximity	-0.019	0.012	0.103
	(0.052)	(0.082)	(0.075)
Q2 proximity	-0.023	0.055	0.088
	(0.053)	(0.058)	(0.082)
Q3 proximity	0.023	0.061	0.077
	(0.051)	(0.065)	(0.083)
Q4 proximity	0.018	-0.046	-0.0062
	(0.044)	(0.047)	(0.1137)
EVs	-0.081	0.047	0.166
	(0.052)	(0.051)	(0.096)
Solar	-0.043	0.056	-0.021
	(0.052)	(0.071)	(0.096)
Wind	-0.037	-0.013	0.015
	(0.057)	(0.065)	(0.071)
Q1 × EVs	0.119	-0.041	-0.315**
	(0.068)	(0.086)	(0.099)
Q1 × Solar	0.070	-0.14	-0.14
	(0.064)	(0.10)	(0.10)
Q1 × Wind	0.243**	0.14	-0.043
	(0.072)	(0.12)	(0.153)
Q2 × EVs	0.135	-0.114	-0.31*
	(0.074)	(0.073)	(0.12)
Q2 × Solar	0.021	-0.142	-0.13
	(0.068)	(0.078)	(0.11)
Q2 × Wind	0.150	0.089	-0.19
	(0.088)	(0.092)	(0.25)
Q3 × EVs	0.046	-0.138	-0.26*
	(0.061)	(0.077)	(0.11)
Q3 × Solar	0.012	-0.14	-0.045
	(0.068)	(0.09)	(0.100)
Q3 × Wind	-0.0031	-0.019	-0.0085
	(0.0898)	(0.101)	(0.1113)
Q4 × EVs	0.037	0.0078	-0.047
	(0.066)	(0.1203)	(0.126)
Q4 × Solar	0.017	-0.041	-0.10
	(0.057)	(0.066)	(0.11)
Q4 × Wind	0.011	0.059	0.055
	(0.062)	(0.063)	(0.125)
N	5026	3034	1487
Adjusted R^2	0.074	0.067	0.182
Covariates	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model with interactions between proximity and manufacturing sector. Recognition = 1 if respondent reports a local green project, 0 otherwise. Credit = 1 if respondent credits the Biden Administration for local green investments. Benefit = 1 if respondent perceives a benefit from local green projects. OLS coefficient estimates with cluster-robust standard errors by state in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

S3.6.5 Partisanship

Fig.S9 plots average marginal effects (AMEs) of proximity quintiles by partisanship. For recognition, Republicans show a positive Q1 effect for renewable energy projects but not for manufacturing, whereas Independents show a positive Q1 effect for manufacturing with null effects for renewables. TableS22 reports the underlying estimates. These subgroup AMEs are positive in the cases noted, but cross-party differences are imprecisely estimated and cannot rule out zero difference.

For credit attribution to President Biden, there is no consistent proximity gradient within any partisan group.

For perceived economic benefits, Republicans living nearer to projects report lower benefits than Democrats at similar distances. Within Republicans, however, proximity itself shows no detectable gradient; the Q1–Q4 contrasts relative to Q5 are near zero and not precisely estimated.

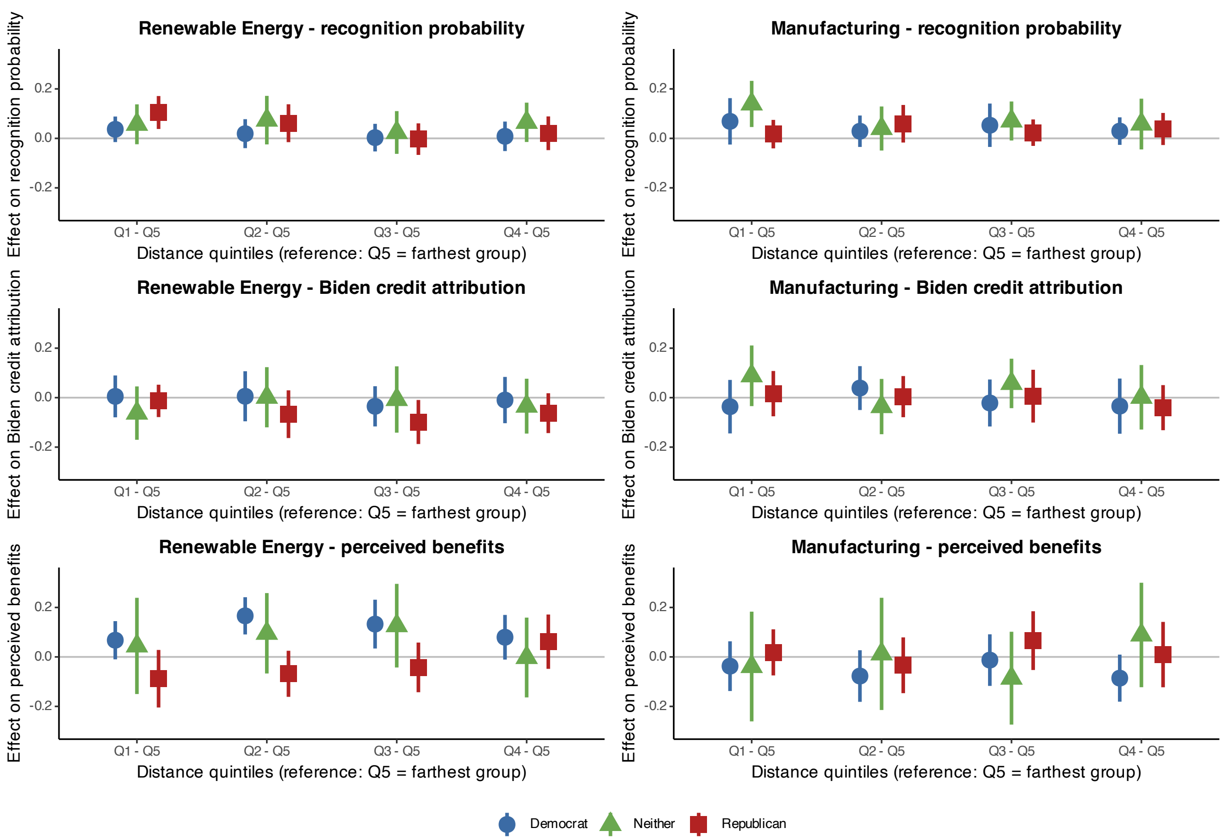

Fig. S9: Heterogeneous effects of proximity by respondent partisan identification. Plot depicts the average marginal effect of a proximity quintile (relative to Q5) across moderator values. Bars denote 95% confidence intervals with cluster-robust standard errors by state. Equation S1 describes the model specification. Table S22 reports interaction terms and sample sizes.

Table S22: Heterogeneous proximity effects by partisanship

	Renewable Energy			Manufacturing		
	Recognition	Credit	Benefit	Recognition	Credit	Benefit
Q1 proximity	0.037	0.0051	0.067	0.069	-0.036	-0.037
	(0.026)	(0.0432)	(0.039)	(0.048)	(0.055)	(0.051)
Q2 proximity	0.019	0.0055	0.166***	0.029	0.039	-0.077
	(0.030)	(0.0516)	(0.038)	(0.032)	(0.045)	(0.053)
Q3 proximity	0.003	-0.035	0.13*	0.053	-0.022	-0.013
	(0.028)	(0.041)	(0.05)	(0.045)	(0.048)	(0.053)
Q4 proximity	0.0083	-0.0098	0.079	0.029	-0.034	-0.086
	(0.0304)	(0.0477)	(0.046)	(0.028)	(0.057)	(0.049)
Neither	-0.100*	-0.208***	-0.06	-0.096*	-0.259***	-0.140
	(0.046)	(0.047)	(0.07)	(0.038)	(0.059)	(0.081)
Republican	-0.033	-0.127**	-0.030	-0.0014	-0.179***	-0.200**
	(0.029)	(0.037)	(0.048)	(0.0337)	(0.042)	(0.057)
Q1 × Neither	0.020	-0.068	-0.023	0.07	0.125	-0.0014
	(0.052)	(0.059)	(0.100)	(0.06)	(0.082)	(0.1143)
Q1 × Republican	0.068	-0.018	-0.156*	-0.052	0.053	0.056
	(0.039)	(0.054)	(0.069)	(0.050)	(0.057)	(0.065)
Q2 × Neither	0.055	-0.0039	-0.071	0.011	-0.075	0.09
	(0.056)	(0.0676)	(0.084)	(0.051)	(0.079)	(0.12)
Q2 × Republican	0.042	-0.072	-0.234***	0.030	-0.035	0.044
	(0.039)	(0.069)	(0.061)	(0.045)	(0.054)	(0.087)
Q3 × Neither	0.021	0.028	-0.0063	0.017	0.079	-0.073
	(0.045)	(0.070)	(0.0879)	(0.045)	(0.072)	(0.094)
Q3 × Republican	-0.006	-0.063	-0.175*	-0.030	0.028	0.079
	(0.043)	(0.058)	(0.068)	(0.056)	(0.054)	(0.079)
Q4 × Neither	0.057	-0.025	-0.082	0.028	0.036	0.175
	(0.058)	(0.062)	(0.093)	(0.052)	(0.101)	(0.098)
Q4 × Republican	0.012	-0.053	-0.018	0.0086	-0.0061	0.095
	(0.048)	(0.060)	(0.072)	(0.0442)	(0.0777)	(0.071)
N	5026	3034	1487	5026	3034	1487
Adjusted R^2	0.075	0.067	0.187	0.074	0.068	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model with interactions between proximity and partisanship. Recognition = 1 if respondent reports a local green project, 0 otherwise. Credit = 1 if respondent credits the Biden Administration for local green investments. Benefit = 1 if respondent perceives a benefit from local green projects. OLS coefficient estimates with cluster-robust standard errors by state in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

S3.6.6 Education

Fig. S10 reports the effects of proximity for respondents with and without a 4-year college degree. Table S23 contains the interaction terms. There are no consistent differences in proximity's effects by respondent education level.

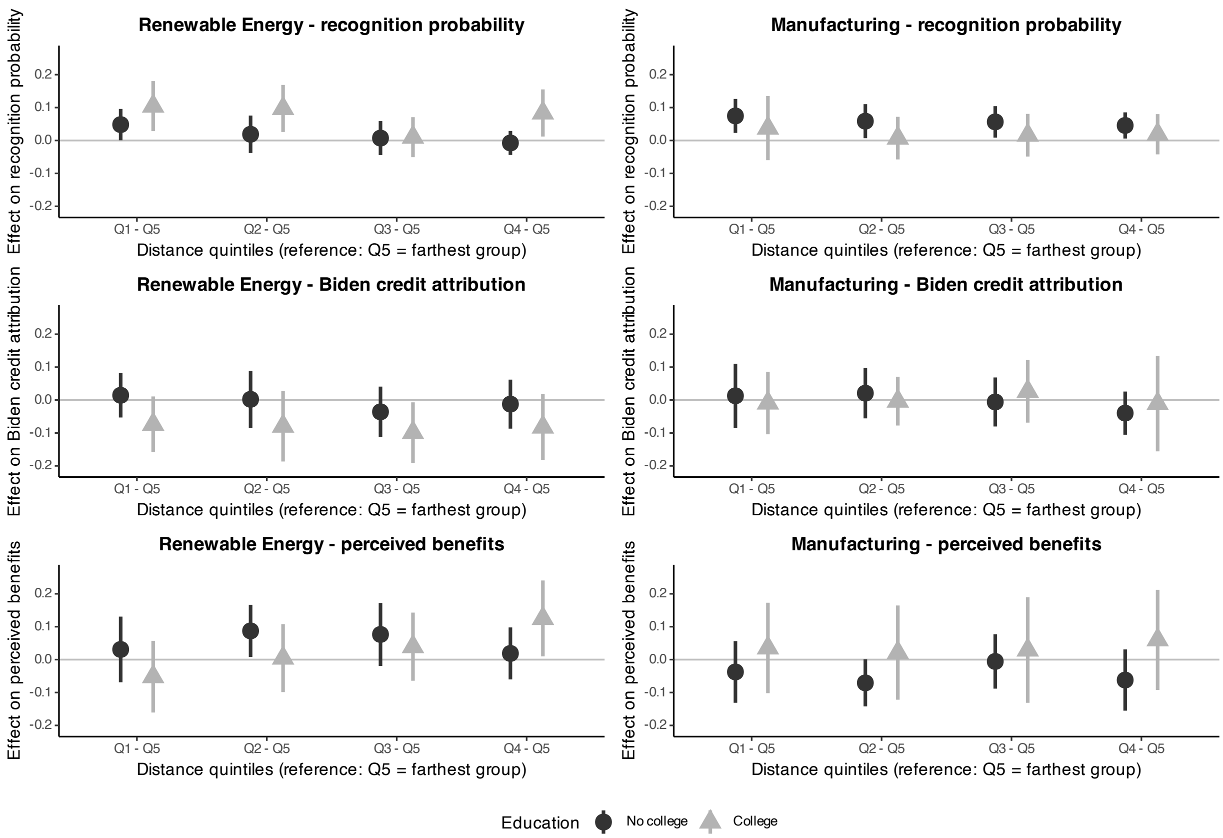

Fig. S10: Heterogeneous effects of proximity by respondent education. Plot depicts the average marginal effect of a proximity quintile (relative to Q5) across moderator values. Bars denote 95% confidence intervals with cluster-robust standard errors by state. Equation S1 describes the model specification. Table S23 reports interaction terms and sample sizes.

Table S23: Heterogeneous proximity effects by no college vs. college

	Renewable Energy			Manufacturing		
	Recognition	Credit	Benefit	Recognition	Credit	Benefit
Q1 proximity	0.048	0.014	0.031	0.075**	0.013	-0.037
	(0.024)	(0.034)	(0.051)	(0.026)	(0.050)	(0.048)
Q2 proximity	0.019	0.0022	0.087*	0.059*	0.021	-0.071
	(0.029)	(0.0443)	(0.040)	(0.026)	(0.039)	(0.037)
Q3 proximity	0.0072	-0.036	0.077	0.056*	-0.0059	-0.0056
	(0.0263)	(0.039)	(0.049)	(0.024)	(0.0380)	(0.0422)
Q4 proximity	-0.0076	-0.012	0.019	0.046*	-0.040	-0.062
	(0.0186)	(0.038)	(0.040)	(0.020)	(0.033)	(0.047)
College	0.026	0.110*	0.015	0.101***	0.046	-0.062
	(0.032)	(0.049)	(0.054)	(0.026)	(0.039)	(0.058)
Q1 × College	0.056	-0.088	-0.083	-0.037	-0.022	0.073
	(0.048)	(0.058)	(0.076)	(0.043)	(0.066)	(0.084)
Q2 × College	0.078	-0.081	-0.083	-0.051	-0.024	0.092
	(0.040)	(0.067)	(0.071)	(0.033)	(0.049)	(0.077)
Q3 × College	0.0028	-0.063	-0.037	-0.041	0.032	0.035
	(0.0407)	(0.062)	(0.072)	(0.033)	(0.045)	(0.088)
Q4 × College	0.091*	-0.070	0.106	-0.027	0.029	0.122
	(0.041)	(0.061)	(0.069)	(0.029)	(0.092)	(0.071)
N	5026	3034	1487	5026	3034	1487
Adjusted R^2	0.076	0.068	0.185	0.073	0.067	0.179
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model with interactions between proximity and no college vs. college. Recognition = 1 if respondent reports a local green project, 0 otherwise. Credit = 1 if respondent credits the Biden Administration for local green investments. Benefit = 1 if respondent perceives a benefit from local green projects. OLS coefficient estimates with cluster-robust standard errors by state in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

S3.6.7 Household Income

Fig. S11 reports the average marginal effect of proximity on the outcomes depending on whether the respondent's household income is above or below the national median. Table S24 contains the interaction terms. There are no consistent differences in proximity's effect on the outcomes across income levels.

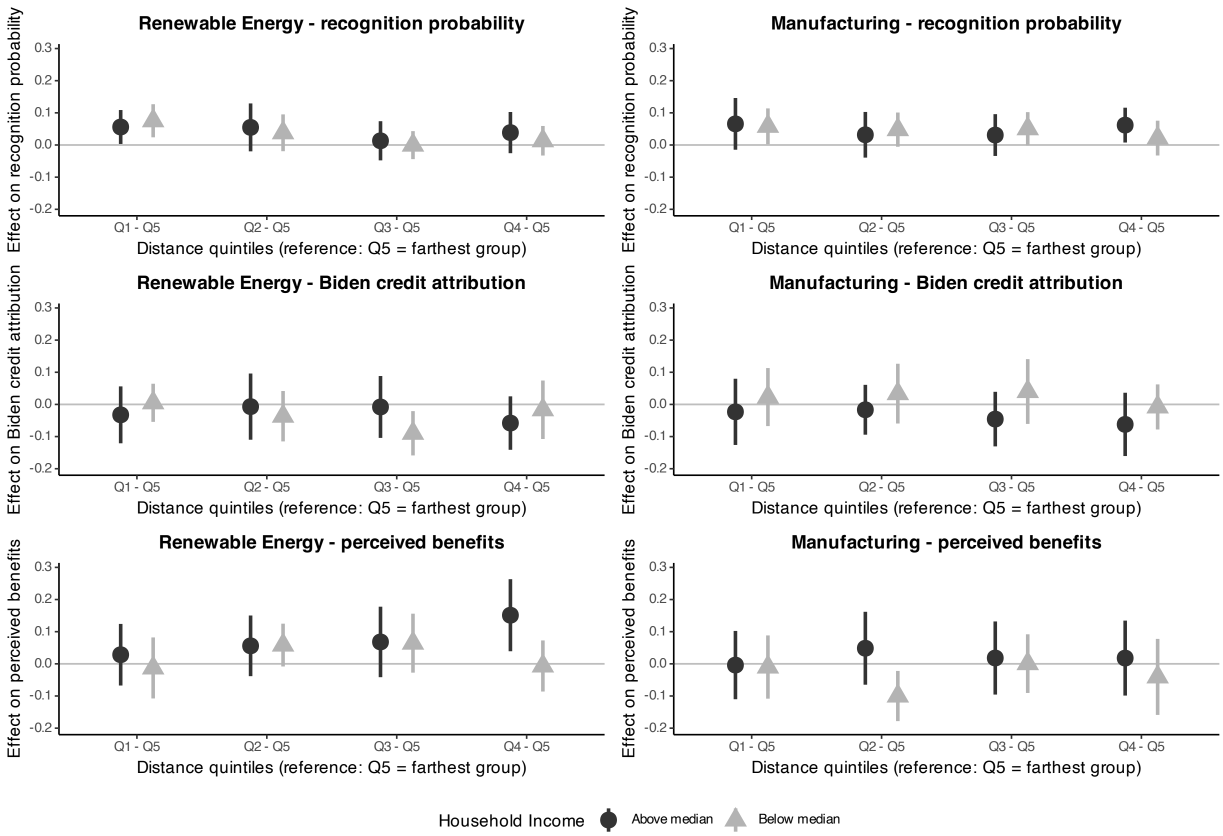

Fig. S11: Heterogeneous effects of proximity by respondent income. Plot depicts the average marginal effect of a proximity quintile (relative to Q5) across moderator values. Bars denote 95% confidence intervals with cluster-robust standard errors by state. Equation S1 describes the model specification. Table S24 reports interaction terms and sample sizes.

Table S24: Heterogeneous proximity effects by household income

	Renewable Energy			Manufacturing		
	Recognition	Credit	Benefit	Recognition	Credit	Benefit
Q1 proximity	0.056*	-0.032	0.028	0.066	-0.023	-0.0039
	(0.027)	(0.045)	(0.049)	(0.041)	(0.053)	(0.0542)
Q2 proximity	0.055	-0.0069	0.056	0.032	-0.017	0.048
	(0.038)	(0.0525)	(0.048)	(0.036)	(0.040)	(0.058)
Q3 proximity	0.013	-0.0079	0.068	0.031	-0.046	0.018
	(0.031)	(0.0491)	(0.056)	(0.033)	(0.043)	(0.058)
Q4 proximity	0.039	-0.058	0.151*	0.062*	-0.062	0.018
	(0.033)	(0.042)	(0.057)	(0.028)	(0.050)	(0.059)
Below median	-0.030	0.015	0.075	-0.036	-0.035	0.079
	(0.034)	(0.055)	(0.063)	(0.029)	(0.058)	(0.060)
Q1 × Below median	0.019	0.037	-0.041	-0.0076	0.046	-0.0061
	(0.036)	(0.053)	(0.061)	(0.0345)	(0.064)	(0.0699)
Q2 × Below median	-0.017	-0.030	0.0023	0.016	0.050	-0.149*
	(0.043)	(0.057)	(0.0559)	(0.041)	(0.065)	(0.065)
Q3 × Below median	-0.014	-0.082	-0.0038	0.020	0.086	-0.017
	(0.034)	(0.058)	(0.0704)	(0.038)	(0.065)	(0.064)
Q4 × Below median	-0.025	0.041	-0.16*	-0.040	0.054	-0.059
	(0.042)	(0.065)	(0.07)	(0.038)	(0.064)	(0.078)
N	5026	3034	1487	5026	3034	1487
Adjusted R^2	0.075	0.069	0.184	0.074	0.067	0.181
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports a separate linear probability model with interactions between proximity and household income. Recognition = 1 if respondent reports a local green project, 0 otherwise. Credit = 1 if respondent credits the Biden Administration for local green investments. Benefit = 1 if respondent perceives a benefit from local green projects. OLS coefficient estimates with cluster-robust standard errors by state in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

S4 Regression of Perceived Benefits on Covariates

Table S25 reports the results from a linear regression of the perceived benefits indicator on covariates. Model 1 includes the covariates from the primary model specification in addition to the recognition indicator. Model 2 interacts the recognition indicator with respondent partisanship. Model 3 interacts the recognition indicator with the 2020 Biden two-party vote share for the respondent's county. The intention of Models 2-3 is to see if visibility's correlation with perceived benefits varies with measures of individual partisanship and local political context.

Table S25: 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	0.002	0.00063	0.0023
	(0.013)	(0.01391)	(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 $(t-1)$	0.0059	0.0061	0.0057
	(0.0125)	(0.0124)	(0.0125)
Median county housing costs $(t-1)$	-0.0019	-0.0022	-0.0016
	(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 Regression of Credit Attribution on Covariates

Table S26: 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	0.0165	-0.006	0.00092	0.0075	0.0224**
	(0.007)	(0.0088)	(0.011)	(0.01364)	(0.0132)	(0.0079)
County college share $(t-1)$	-0.016	-0.019	0.003	0.017	0.014	8.4e-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	0.0098	0.0099
	(0.0123)	(0.0099)	(0.0149)	(0.012)	(0.0105)	(0.0100)
County foreign-born share $(t-1)$	-0.0045	0.0177	0.019	0.0198*	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	-0.0074
	(0.039)	(0.046)	(0.051)	(0.036)	(0.046)	(0.0513)
Labor force (log) $(t-1)$	-0.048	-0.126**	-0.034	-0.0015	-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 $(t-1)$	-0.0089	-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 S27: 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	-0.0057	-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	0.0098	0.0021
	(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)	(0.0076)
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 $(t-1)$	-0.0025	-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 Statement Analyses

S6.1 Statement Type Description

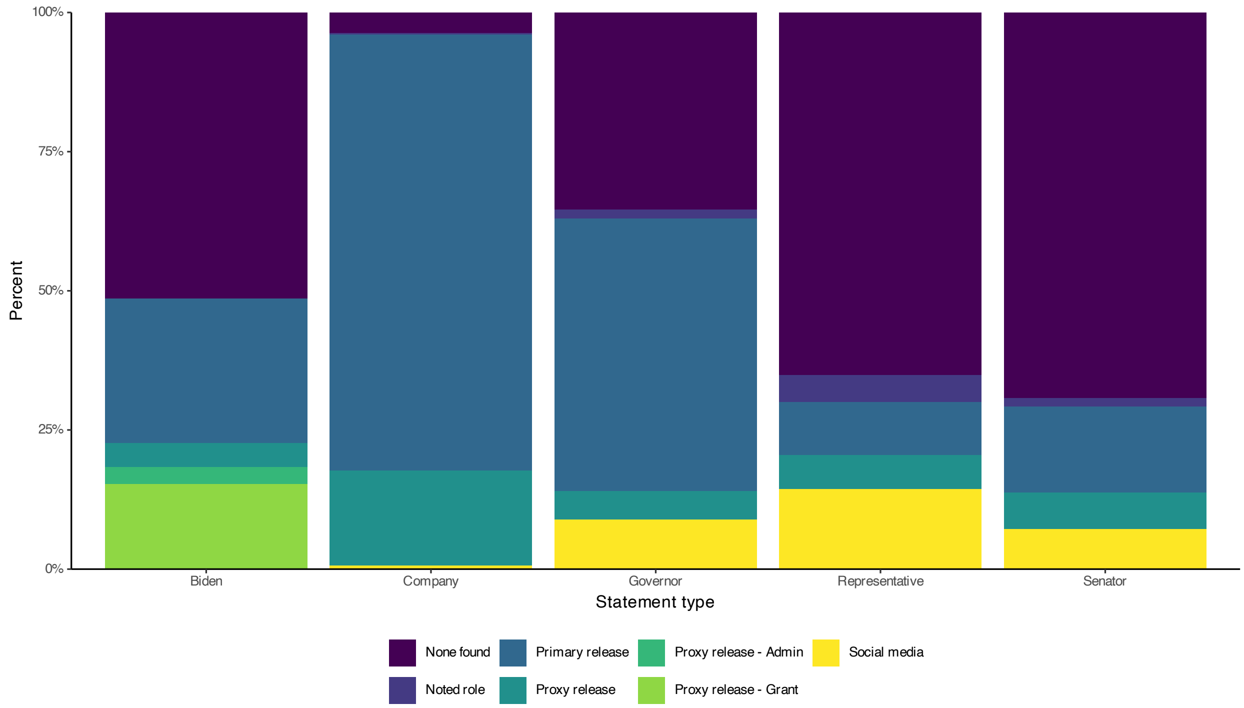

Fig. S12: Types of statements by actor. Categories are mutually exclusive and indicate the highest-quality source found for each actor–project pair. *None found*: No statement located. *Primary release*: Official communication (press release, newsletter, transcript, or report) issued on the actor's website. *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 S28: 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 Robustness to Alternative Codebook

The LLM annotation prompt in SI Appendix, S6.3, adopts a strict definition of credit in stage 1, saying that the IRA or BIL can only be credited if there's an explicit connection between these policies and the project. A possible concern is that these criteria under-count the frequency with which the IRA is credited.

As a robustness check, Fig. S13 reports results for an updated codebook that allows credit to be given in the following cases: the law is only mentioned as a goal or target, the project helps meet the law's goal, the law is mentioned only as background, the statement only discusses eligibility without confirming use, or the speaker only mentions helping to write the law. The results are qualitatively consistent.

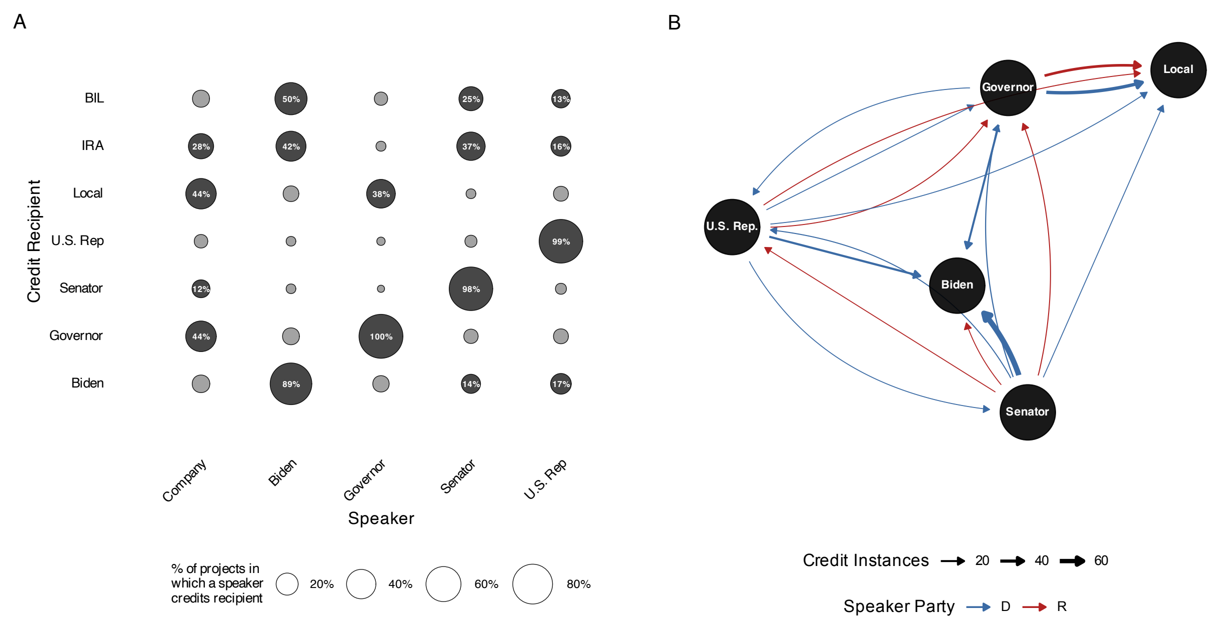

Fig. S13: Robustness to alternative codebook that counts any mention of the IRA, even if the speaker doesn't make a causal claim. Plot shows credit giving for clean energy manufacturing projects after the IRA (327 projects; Aug. 16, 2022–Dec. 2024). **(A)** Share of projects in which each speaker credited 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.

S6.5 Regression Models of Statement Giving

Table S29: 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

S6.6 Regression Models of Statement Credit Attribution

Table S30: 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 S31: 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 S32: 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 S33: 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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