Why Clean Energy Investments Did Not Create New Political Constituencies

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Abstract

Why didn't new clean energy investments create constituencies that could help defend the Inflation Reduction Act (IRA) against repeal efforts? This paper analyzes the mechanisms behind such policy feedback effects by examining whether the public noticed new clean energy projects, whom they credited, and how businesses and politicians attributed responsibility for new investments. We combine geolocated survey and investment data, and construct an original dataset of company and politician statements. Results show that while people living closer to new investments are modestly more likely to notice projects, this recognition does not translate into perceived economic benefits or credit for the Biden Administration. Instead, Americans assign more responsibility to their governors. Statement data reveal that governors more actively claimed credit than President Biden, while companies spread credit across multiple actors. This fragmented information environment provides a plausible explanation for why federal officials received little credit from people and businesses that benefited from the IRA. In the short run, policymakers cannot rely on investment flows alone to build supportive constituencies for durable climate policy. (163 words)

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

Significance Statement

The recent partial repeal of the Inflation Reduction Act highlights the challenge of sustaining ambitious climate policy. Policymakers intended that the law's historical investment into clean energy and manufacturing would create constituencies that would defend the reform. Using geolocated survey and investment data, along with a new dataset of company and politician statements, we assess whether the law changed public opinion and business behavior among groups that benefited. While people living closest to new projects are more likely to notice them, this recognition does not translate into perceived local economic benefits nor greater credit for federal leaders. Instead, Americans credit governors, and companies spread recognition across multiple actors. These findings emphasize that federal policymakers in the short run cannot rely on investment flows alone to build political support for climate policy.

Introduction

In 2025, Congress partially repealed the Inflation Reduction Act (IRA). This retrenchment occurred despite historic levels of investment in clean energy and manufacturing (Congressional Budget Office, 2024). Policymakers had designed the IRA to channel these economic benefits into visible local projects, often in electoral swing states, with the goal of fostering durable public and political support (Meckling et al., 2015; Cullenward and Victor, 2021; Ross, 2025). The intention was that such a climate coalition could help protect the law and lay the groundwork for stronger future policies.

For investments to generate durable support, several conditions must be met. People need to notice new projects in their communities, view them as beneficial, and connect them to the policies that enabled them (Arnold, 1990). Only then can material benefits translate into political behavior.

But these steps are far from automatic. Credit attribution is the crucial link. It connects material benefits to political support, ensuring that policymakers are rewarded for their actions and that coalitions form to defend policies from retrenchment. The IRA's role may not be traceable, since governors and local officials often step in to claim responsibility (Jensen and Malesky, 2018), while partisan polarization shapes how information about projects is shared and received (Hopkins, 2023; Mettler, 2011). As a result, federal policymakers may struggle to convert investments into political coalitions.

To study these dynamics, we need fine-grained evidence on how both citizens and elites perceive investments. Yet such data are scarce. Surveys have not captured project recognition and attribution, and public statements from firms and politicians are dispersed across thousands of press releases and announcements. This paper addresses these challenges with three original geolocated surveys fielded in 2024 and a comprehensive database of company and politician statements covering all green manufacturing investments from 2022 to 2024.

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

We find modest evidence that proximity increases recognition of projects but no evidence that it makes people see more economic benefits from clean energy nor increases credit to the Biden Administration. Instead, Americans view governors as more responsible, a pattern consistent with our analysis of statements showing that governors are far more active in claiming credit than federal officials. These dynamics illustrate challenges the IRA faces in generating durable constituencies.

Research Design

Project Proximity, Recognition, and Credit Attribution

We fielded three online surveys of American adults in 2024 (total $N = 5026$) with questions designed to assess how green investments incentivized by the IRA influence public opinion. To test Hypothesis 1, the survey asked whether respondents had seen a new clean energy project in their communities in the last year. Another item on one wave measured whether respondents thought new clean energy projects were economically beneficial or harmful. To evaluate Hypothesis 2, two survey waves asked respondents to rank how responsible different political actors were for new investments in their state (Material and Methods).

Proximity to clean energy investments is measured with the geographic coordinates of respondents and projects, which avoids bias from self-reporting (Egan and Mullin, 2012). The project data include (1) post-IRA utility-scale solar and wind construction recorded by the EIA and (2) newly operational clean energy manufacturing tracked by the Big Green Machine database (Materials and Methods). Although such investments expanded after the IRA's passage (Bistline et al., 2023), we make no claim about whether specific projects were caused by the law.

The analysis compares respondents in each quintile of distance, with the most distant 20% serving as the reference group. Results are robust with a continuous distance measure. Fig. 1 shows that survey respondents overlap with project locations, enabling comparison of those living near versus far from projects (see SI for further validation).

The research design accounts for the potential confounding of distance to investments by factors such as household income that could also influence political attitudes. The model estimates the effect of within-state variation in project proximity. This removes confounding from state-level factors that predict investment, such as tax incentives, labor laws, and comparative advantage (Bartik, 2019). It further controls for county- and individual-level factors (e.g., unemployment, broadband, household income) that could shape project siting and attitudes. To interpret the estimates as causal, we assume that proximity to a new project, relative to the state average, is as-if random after accounting for these within-state and individual-level factors. Sensitivity analyses indicate robustness to hypothetical unobserved confounding, while power analyses show that for most analyses the research

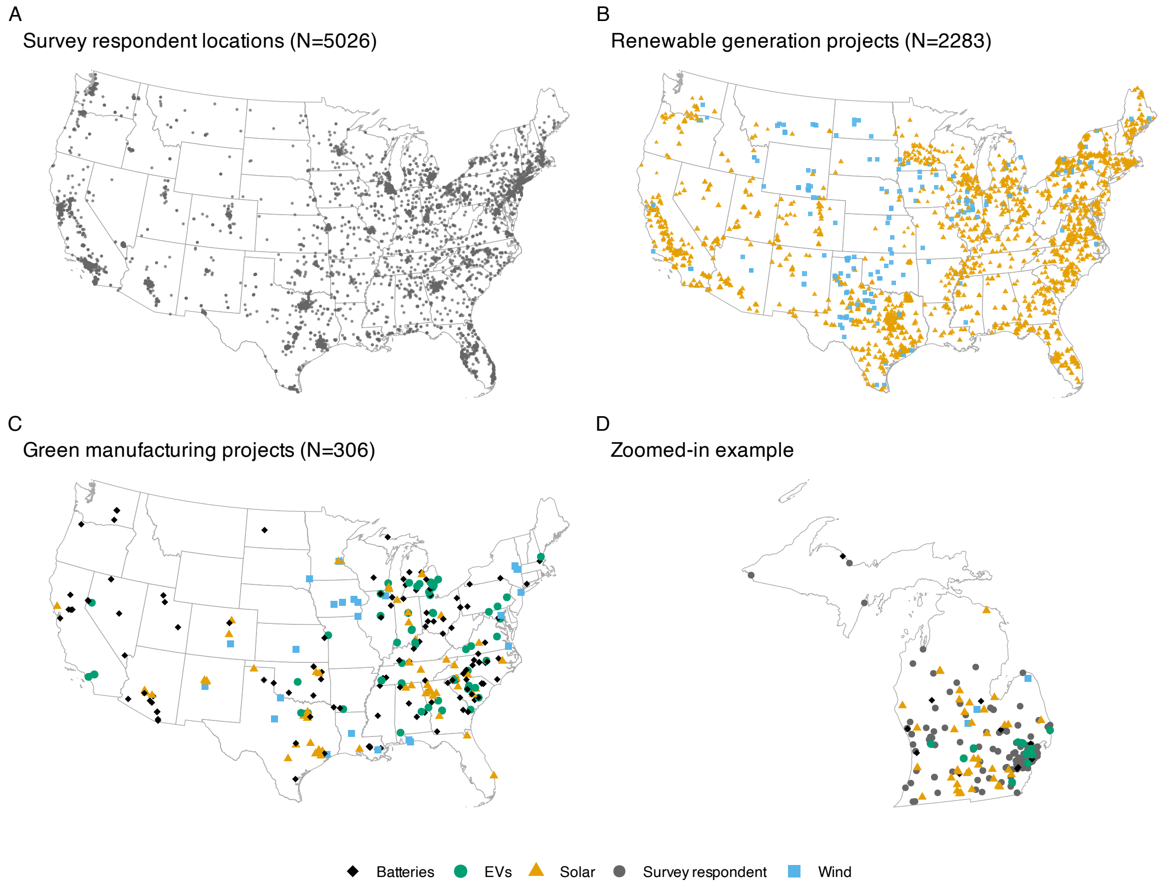

Figure 1: Geographic distribution of survey respondents and new clean energy investments, 2022–2024. Alaska and Hawaii not displayed. (B) Dot size for renewable generation projects is scaled by logged nameplate capacity. (C) Sample size visualized is slightly smaller than the statement analysis due to unavailable geo-coordinates for projects that haven't selected a site yet (6%).

design can reliably identify a meaningful effect (see Materials and Methods).

Company and Politician Statements

To understand how the information environment shapes policy feedback, we built a new database of company and politician statements about clean energy manufacturing projects. These projects often have substantial local economic effects and generate media coverage, making them natural credit-claiming opportunities (Jensen and Malesky, 2018; Walters and Walters, 1992). Credit-claiming is a common re-election strategy that is persuasive to voters, even when politicians aren't actually responsible for beneficial projects (Mayhew, 2004; Grimmer, Messing, and Westwood, 2012; Grimmer, Westwood, and Messing, 2015; Cruz and Schneider, 2017).

Our dataset's inclusion of business messaging moves beyond the standard focus on politicians. Firms matter because their decisions to acknowledge (or not) federal support could shape whether policymakers gain political returns. Since companies have their business interests on the line, their signals may be especially credible.

The database covers 327projects announced between passage of the IRA and the end of 2024. Materials and Methods describes how for each project we located statements from companies, governors, U.S. Senators, U.S. Representatives, and President Biden. Statements for the Biden Administration also included those from his delegates, such as the Secretary of Energy.

We then used large language models to code whether each statement contained a credit claim and, if so, which actors or policies were credited. Credit claims include explicit statements (e.g., "I was responsible for X") and implicit activities (e.g., attending a ribbon cutting ceremony), which encompasses the range of strategies politicians employ (Mayhew, 2004). This systematic dataset of credit-claiming and credit allocation around "green" industrial policy on a national scale allows us to examine who "speaks," how credit is distributed across actors, and why federal leaders may struggle to secure recognition.

Results

Effect of Proximity on Political Attitudes

Recognition

We first analyze whether people living closer to new clean energy projects—the IRA's intended beneficiaries—recognize these investments. The mechanism behind how proximity could make these investments visible is beyond our scope, but it could operate through people directly seeing projects, hearing about them in the local news, or learning through social networks (Gazmararian, 2025).

Overall, 27% of Americans reported seeing a new clean energy project in their area in the last year. Recognition varies across communities within the same state, which is critical for our analysis that compares people to others in their state. After accounting for state differences, the standard deviation of recognition is 0.43 on a 0-1 scale, meaning some individuals in a state report widespread recognition while others report almost none. While we lack comparable pre-IRA measures, these figures suggest that projects are visible to a meaningful share of the public, though recognition is highly uneven across space.

Fig. 2A shows that the immediate beneficiaries of clean energy manufacturing and renewable generation projects are 6.3 and 6.6 percentage points more likely to notice them, compared with people farthest away in the same state. This change accounts for approximately 14 and 15 percent of the within-state variation in project recognition. The effect extends into the second distance quintile for renewables but is weaker for manufacturing. To assess whether these patterns reflect a genuine signal rather than noise in any single bin, we pool the two nearest quintiles and conduct a Wald test. This test shows a robust proximity effect for renewables ($p = 0.0039$), while the manufacturing contrast is smaller and less precise ($p = 0.12$). Taken together, recognition rises with proximity, though the strength of this effect varies across generation and manufacturing projects.

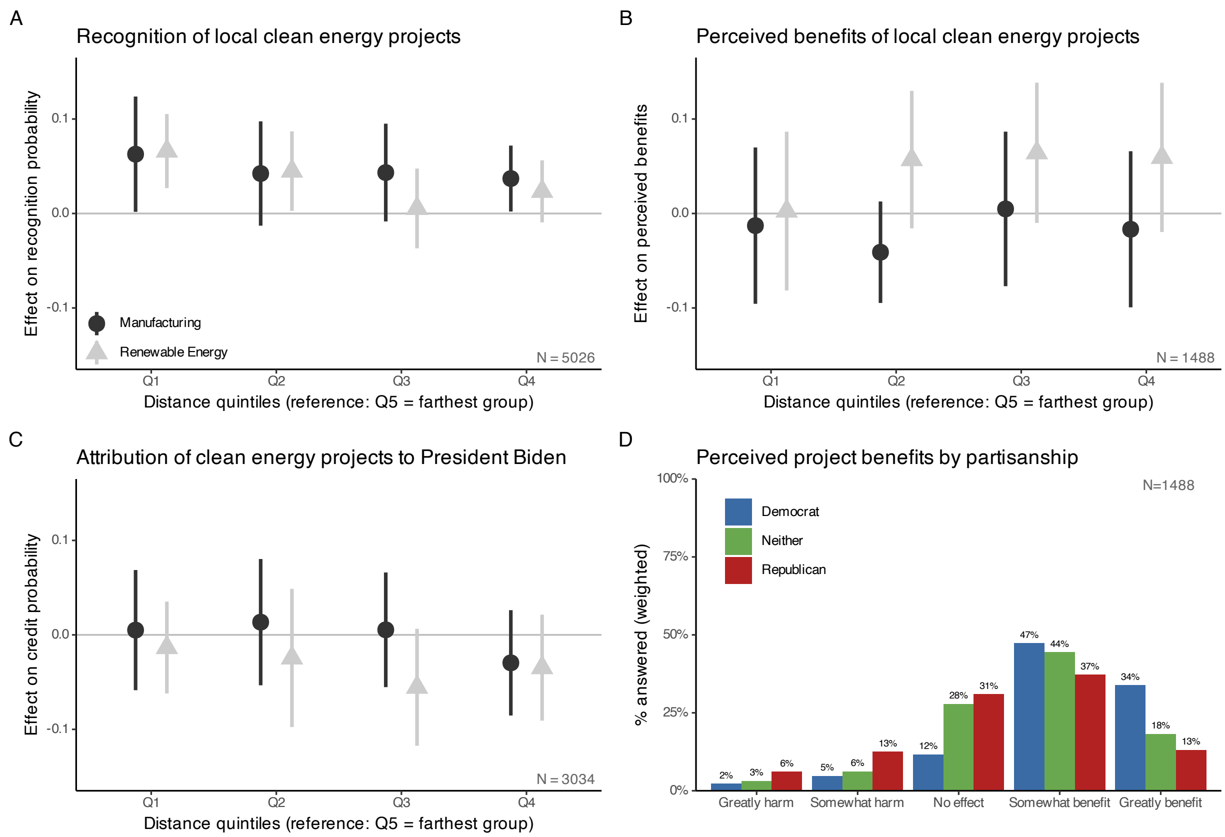

Figure 2: Effect of project proximity on **(A)** recognition of clean energy projects and **(B)** credit to President Biden. Bars denote 95% confidence intervals. **(C)** Perceived economic effects of projects by proximity and **(D)** by partisanship.

Recognition also differs with project status and sector. For manufacturing, effects appear only once plants are partially operational, especially for facilities making electric vehicles. There is no effect during planning, pilot, or construction phases. For renewables, pre-construction projects are more likely to be noticed than those already underway, possibly reflecting publicity during siting debates. Recognition effects are more precisely estimated for solar than wind, since there are more states with solar generators (SI).

At the individual level, partisanship modestly shapes recognition. For renewables, Republicans are slightly more likely to notice nearby projects; for manufacturing, there are no detectable partisan differences, although these tests necessarily have more limited statistical power. For other respondent characteristics, there are also no statistically distinguishable differences in proximity's effects across income and education levels (SI).

Perceived Benefits

For policy feedback to occur, people must view clean energy projects as beneficial. This is not guaranteed. Development of projects, such as wind turbines, sometimes spurs contentious local land-use conflicts (Stokes, Franzblau, et al., 2023).

In overall terms, a majority of Americans (Weighted mean of perceived benefits: 66%) view local clean energy investments as economically beneficial in their communities. This is consistent with previous research about a public preference for cheap, clean energy (Ansolabehere and Konisky, 2014). Fig. 2D shows these attitudes are largely bipartisan, though Republicans and Independents are less optimistic than Democrats. The positive valence of clean energy investments—across partisans—suggests that who gets credit could matter politically.

People with green investments close to them, however, are not more likely to view clean energy projects as beneficial compared to people at other distances in the same state (Fig. 2B). There are limited to no robust statistically distinguishable differences in proximity's effect when looking at the project's status or sector, nor by a respondent's income or education. There may be slight partisan differences, with Republican respondents who are closer to renewable energy projects being less likely to see benefits than Democrats, but these differences are in marginal not absolute terms.

These results suggest that new projects do not change perceptions of economic benefits from the clean energy transition. Since most members of the public already had favorable views, this result does not imply that people do not perceive local economic gains. We caution that these results are less reliable than the others because of the more limited sample size, resulting in less statistical power and within-state variation (SI).

Credit Attribution

Fig. 2C shows no effect of proximity on crediting President Biden. This null finding is unlikely due to limited statistical power, given that the design had 80% power ($\alpha = 0.05$) to detect a 9.5 percentage point effect of proximity on credit for renewable energy and a 12 percentage point effect for manufacturing projects (SI), enough to rule out any sizable increase in attribution to federal policymakers. Further, equivalence tests show that any true proximity effect on credit attribution is smaller than 5.9 and 5.5 percentage points for renewable energy and manufacturing, respectively, with the 90% confidence interval lying entirely within these bounds.

This null effect is also not explained by partisan differences in credit to Biden. Proximity to projects does not make Republicans, Democrats, nor Independents more likely to credit the Biden Administration for new green investments (SI). There are also limited to no robust differences by respondent education or income, nor the project's operating status or sector. Proximity makes projects more visible, but does not make them more attributable to the IRA.

Public Credit Attribution Patterns

Fig. 3A summarizes whom the public thinks is most responsible for new green investments in their states. Governors receive the most credit. 49% of American adults say their governor is very or extremely responsible for new green projects in their state. By comparison, 41% credit President Biden—eight points less than the governor. Congress (36%) and market forces (35%) receive the least credit.

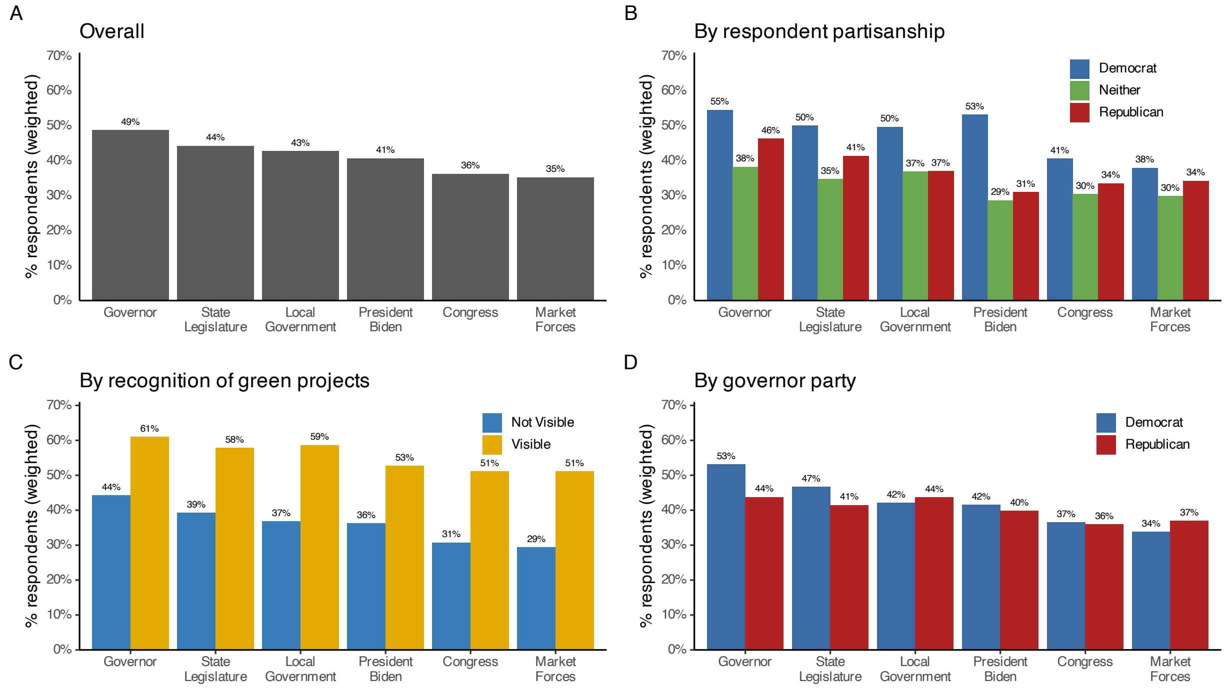

Figure 3: Perceived responsibility for clean energy investments. Weighted percentage rating each actor as "very" or "extremely" responsible for clean energy projects in their state (two waves; N = 3,034). **(A)** Overall distribution across the full sample. **(B)** By respondent partisan identification. **(C)** By whether respondents report a new clean energy project in their community. **(D)** By the political party of the respondent's governor.

Credit to governors is broadly bipartisan, with 55% of Democrats, 47% of Republicans, and 38% of Independents crediting their governor (Fig. 3B). Democrats credit both their governor and President Biden more than Republicans or Independents do. Yet even among Democrats, credit to Biden is roughly equal to credit to the governor (pattern holds with covariate adjustments; see SI).

Recognition of new clean energy projects is associated with more credit across all actors, rather than shifting specifically toward policymakers responsible for the IRA (Fig. 3C). This finding mirrors the proximity result, where greater visibility increases recognition but not federal attribution in particular.

Attribution also varies with the governor's party (Fig. 3D). On average, respondents view Democratic governors as more responsible for new clean energy investments than Republican governors. Partisan congruence matters as well. Republicans are likelier to credit Republican governors, and Democrats to credit Democratic governors (see SI).

Business and Politician Credit Claiming Patterns

We next examine how often companies and elected officials comment on projects and how they allocate credit in those statements.

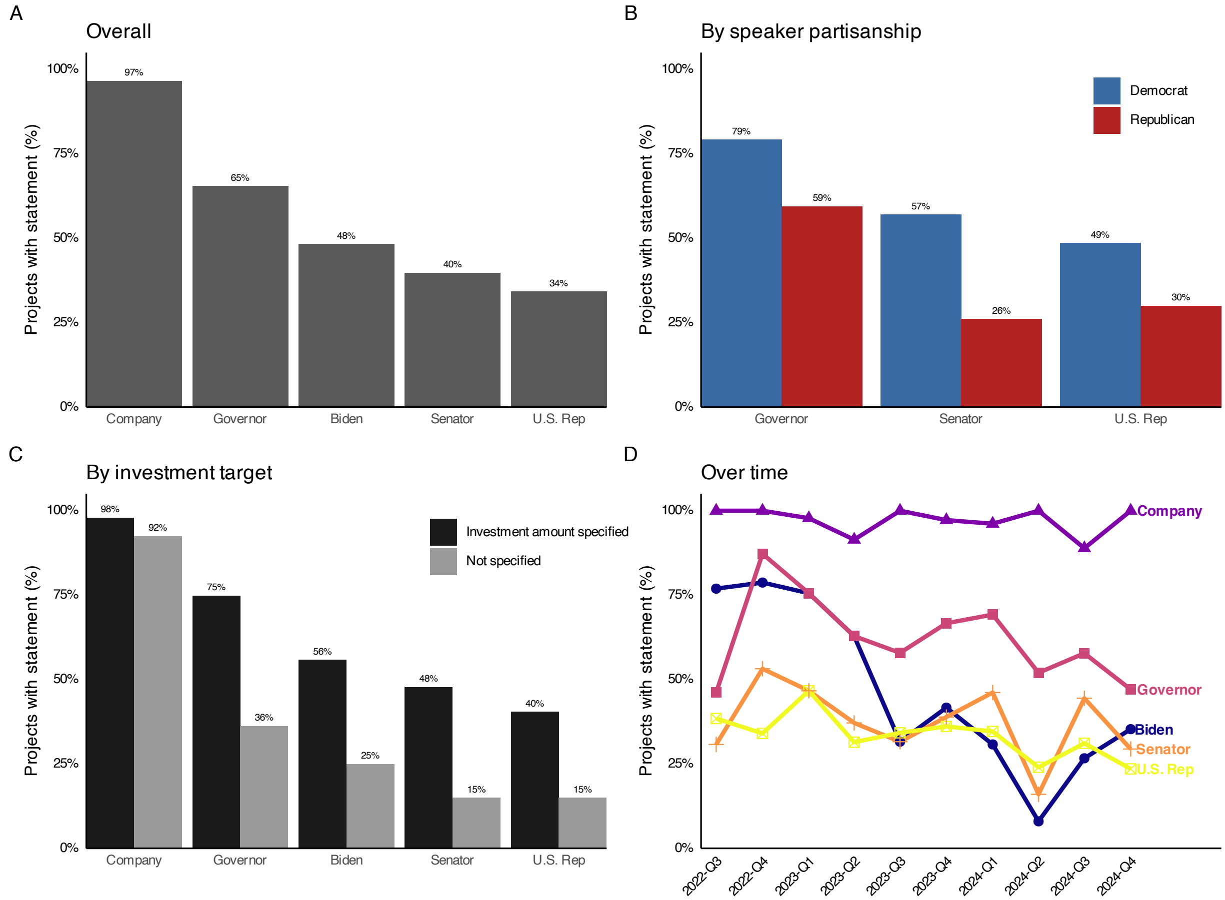

Figure 4: Share of clean energy projects with public statements by companies and elected officials after passage of the IRA (327 projects; Aug. 16, 2022–Dec. 2024). **(A)** Share of projects with a statement by the company, President Biden, Governor, U.S. Senators, or U.S. Representative. **(B)** Share of projects with statements by speaker partisan affiliation. **(C)** Share of projects with statements by whether the investment amount was specified. **(D)** Quarterly trend in the share of projects with at least one statement, 2022Q3–2024Q4. Percentages are relative to the number of projects in each category or quarter.

Who Speaks

Companies issued statements for 97% of projects (Fig. 4A). Among political actors, governors speak most frequently (65% of projects), followed by the president (48%), a U.S. senator from the state (40%), and the district's U.S. representative (34%).

Statement rates vary by party (Fig. 4B). Democratic governors, senators, and representatives issue statements more often than their Republican counterparts. These differences by speaker partisanship appear both in raw averages and with covariate adjustment (SI). Even with this partisan gap, Republican governors still commented on most projects in their states (59%). By contrast, Republican senators (26%) and representatives (30%) issued statements far less often than Democrats.

Politicians are more likely to issue statements when companies specify the investment amount (Fig. 4C). Approximately three-quarters of projects have such a target. The higher statement frequency likely reflects the greater news value and clearer economic stakes of projects with explicit dollar figures, which incentivize politicians to speak.

President Biden was most active in issuing statements immediately after the IRA's 2022 passage, at levels comparable to governors (Fig. 4D). His statement rate then declined steadily from early 2023 through mid-2024, eventually falling below that of governors. Although there was a modest uptick in President Biden's speaking about green projects before the 2024 election, the rate remained well below initial levels. In contrast, governors' statement rates stayed comparatively stable across quarters.

Who Credits Whom

We next examine whom speakers credit. Fig. 5A reports, by speaker, the share of projects in which their statement credited a given recipient. Companies credited governors or local actors in roughly half of projects, followed by the IRA in 14% and President Biden in 28%. Across elected officials, self-credit is common. When President Biden spoke, he referenced the Bipartisan Infrastructure Law in about 71% of projects and the IRA in 47%. Governors tended to credit local partners (e.g., county officials) and rarely credited federal officials. Senators and representatives credited the White House in 17% and 19% of projects, respectively, when they spoke.

Credit allocation varies with some political factors but not others (Fig. 5B). The most consistent pattern are partisan differences, where Republican speakers are substantially less likely than Democratic speakers to credit President Biden or the IRA. Looking at credit allocation in electoral swing states, governors there are somewhat more likely to credit the Biden Administration, but other political actors are not. Whether the project is closer to the 2024 election generally does not matter, although companies may be slightly less likely to credit the White House in 2024 and 2023 compared to 2022. Finally, whether the place receiving a manufacturing project voted for Biden in 2020 has no correlation with credit allocation to the White House across all political actors.

The networks in Fig. 5C-D visualize who credits whom at the project level and by the speaker's party. Companies disperse credit across the governor, local officials, and the president for the same project. Businesses spread credit rather than concentrating it. The president is most often credited by senators, especially Democrats. Democratic governors occasionally credit the president, while Republican governors rarely do.

Discussion

Policymakers designed the IRA with the intent of harnessing material self-interest, aiming for visible investments to create beneficiaries who support the law. Our surveys show that Americans near new green projects are modestly more likely to notice them and, on the whole, view clean energy projects as beneficial. However, people in places directly benefiting from new clean energy investments are not more likely to credit the Biden Administration. Overall, fewer than half of Americans (41%) view President Biden as responsible. Instead, nearly half of voters, across party lines, credit governors as the primary actors behind green

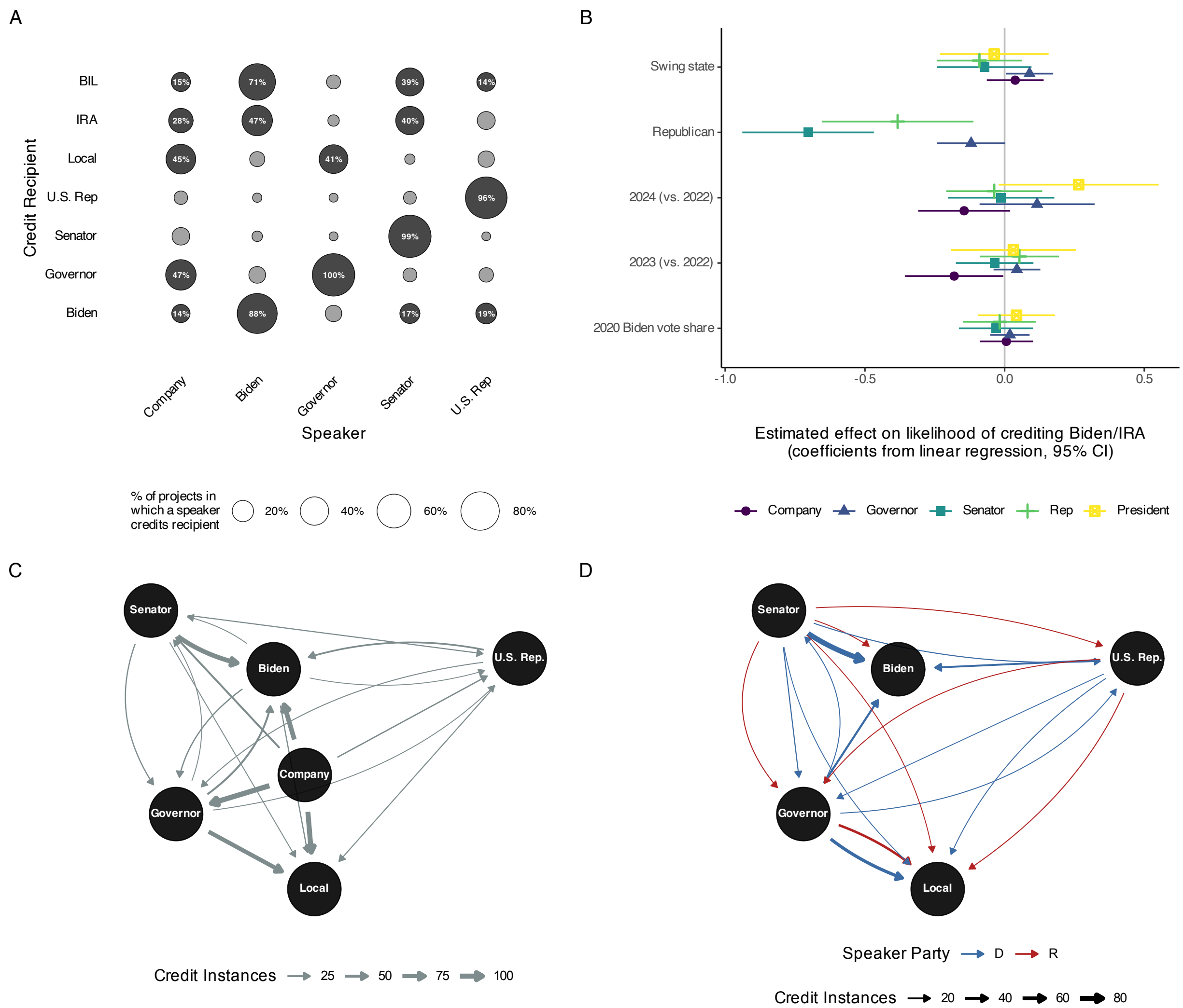

Figure 5: Credit-giving patterns for clean energy manufacturing projects after the IRA (327 projects; Aug 16, 2022–Dec 2024). **(A)** Share of projects in which each speaker (x-axis) credited each recipient (y-axis). Dot area is proportional to the share of projects; darker shading indicates values above the median. **(B)** Linear probability model estimates of whether a speaker credited President Biden/IRA or not. **(C)** Project-level network of credit, with arrows from credit-giver to credit recipient; thicker edges indicate higher frequency. **(D)** Network by speaker partisanship; edge colors denote the party of the credit-giver.

projects.

Our analysis suggests that the mixed information environment, created by competing credit claims from politicians and dispersed credit by companies, helps explain why Americans did not view the Biden Administration as more responsible. In our statements database, companies credit governors and local partners in nearly half of projects—far more often than they credit President Biden (14%) or the IRA (28%). This pattern, combined with sharp partisan asymmetries in messaging, further weakens federal visibility. Democratic officials frequently highlight federal actors, whereas Republican governors rarely do. These patterns are consistent with the idea that visibility without traceability limits the ability of industrial policy to create new climate coalitions.

Could clearer attribution signals have increased support for defending the IRA? While we hypothesize that it would have, it's possible that many voters' limited political knowledge would have muted any effect, though research shows politician statements can be persuasive (Grimmer, Messing, and Westwood, 2012). Another consideration is that green investments' material benefits, like job creation, were insufficient to shift voters' priorities. Yet prior work finds that when stakes are salient, self-interest can shape behavior (Citrin and Green, 1990). Because political messaging is not random, we cannot conclusively estimate its effect with our data, although we are pursuing this question in ongoing work.

The findings align with political science work on traceability. When voters cannot see the connection between policy and outcomes, they struggle to reward responsible officials, which can lead to policy retrenchment (Arnold, 1990; Mettler, 2011). Clean energy investments compound the problem in two ways compared to other government policies. First, the immediate policy beneficiaries are private firms, unlike programs targeting the public directly such as Social Security, which could reduce the traceability of benefits (Campbell, 2012; Hamel, 2025). Second, national, state, and local policies influence clean energy projects, complicating attributions in federal systems (Arceneaux, 2006).

While research on policy retrenchment often focuses on organized interests mobilizing to block losses (Stokes, 2020; Patashnik, 2008), our results underscore the underappreciated role of beneficiaries in sustaining reforms. Despite receiving substantial subsidies, firms seldom credited federal actors, instead highlighting governors and local partners. This behavior is striking because businesses, with their resources and close knowledge of policy design, are well positioned to advocate for preserving beneficial programs. It is possible that they did so in private, but publicly they did not give clear credit to federal policy.

There are three plausible reasons why companies distribute credit broadly rather than emphasizing federal policy. First, firms hedge to manage political risk. With long investment horizons, partisan turnover, and regulatory exposure, companies have incentives to avoid alienating potential allies by spreading credit widely. Second, state and local governments play meaningful roles in shaping clean energy investments through tax incentives, infrastructure support, and permitting (Bartik, 2019), giving firms genuine reasons to highlight subnational partners. Finally, some projects would likely have proceeded even without the IRA's incentives, meaning subsidies primarily influenced marginal investments—the "free rider" limitation of subsidies (Jaffe, Newell, and Stavins, 2005). Together, these factors help explain why even clear beneficiaries of federal subsidies might not amplify the IRA's role, weakening one of the intended feedback mechanisms for building political support.

Two explanations may help account for why federal officials issued relatively few credit-claiming statements. The first is polarization risk. The White House may have worried that explicitly branding projects with presidential credit would mobilize partisan backlash, particularly in Republican-leaning districts. The second is project prematurity. Many IRA-funded projects were still in early planning or construction phases and lacked concrete numbers on job creation or total investment, which might have made federal policymakers hesitant to draw attention to projects before benefits were tangible. Both factors suggest that federal officials may have chosen strategic restraint, though this caution likely limited opportunities to build recognition of the IRA's role.

Several limitations qualify these findings. Most importantly, although our surveys are national and include adequate coverage of communities near clean energy investments, future work should oversample these areas where policy feedback effects should be strongest. The attribution question's state-level framing may also have modestly favored governors, but this choice improves validity by ensuring all respondents could meaningfully evaluate responsibility. It also reflects the IRA's place-based political strategy, which emphasized state- and community-level benefits over national branding. Randomized answer order, the clear gap between governor and state legislature credit, and partisan asymmetries suggest this bias is unlikely to alter our conclusions.

Other constraints are less consequential but worth noting. Because our surveys are cross-sectional, they capture attribution at one point in time rather than opinion change as projects progress from announcement to operation. Finally, our large-scale, LLM-assisted coding of company and politician statements introduces the possibility of measurement error.

While this study focuses on statement-making and explicit credit-claiming, future work should analyze a broader range of messaging strategies, including the frequency, tone, and framing of company and politician communications around clean energy investments. Researchers should also examine other tactics policymakers use to protect climate reforms, such as targeted outreach, coalition-building, or behind-the-scenes advocacy, to capture the full repertoire of strategies that shape policy durability beyond public credit attribution.

These findings contribute to debates on political communication, climate policy design, and the IRA's retrenchment. Reformers shifted from carbon pricing to industrial policy partly to obscure costs and highlight visible benefits (Ross, 2025; Meckling et al., 2015). Prior work shows that framing climate reforms in economic terms can increase support (Stokes and Warshaw, 2017; Gazmararian, Mildenberger, and Tingley, 2025) and that voters reward federal spending (Kriner and Reeves, 2015). Our evidence is consistent with the argument that message supply also matters. Credit-claiming provides information that can influence voters (Mayhew, 2004; Grimmer, Messing, and Westwood, 2012; Grimmer, Westwood, and Messing, 2015). Building durable feedback effects from climate investments therefore requires not only material benefits and strategic framing but clear traceability to policymakers.

Following the IRA's partial repeal, the politics of clean energy investment are shifting toward loss aversion. Research shows that threatened benefit cuts can mobilize beneficiaries (Béland, Campbell, and Weaver, 2022), and repealed or delayed projects may prompt communities and firms to organize in ways they did not at the law's passage. Yet the core political challenge remains. Creating climate coalitions requires more than material benefits. To secure lasting support, reforms must make those benefits traceable to the policymakers who delivered them.

Materials and Methods

Survey Data and Measurement

Sampling

Three independent national online surveys of U.S. adults were administered via Qualtrics in 2024. Surveys were available in English. Fieldwork periods were March 14–April 9

(N = 1,500), May 13–June 6 (N = 1,992), and August 6–November 11 (N = 1,534). After applying the data quality protocol (attention checks; speeding; duplicate IP/device; invisible reCAPTCHA), the combined sample includes 5,026 respondents. Samples used nonprobability quotas to approximate the U.S. adult population by age, sex, race/ethnicity, education, income, and region, based on the 2023 5-year ACS.

Measures

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

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

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

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

Geolocation & Linkage

Respondent location was assigned using centroid coordinates of the self-reported five-digit ZIP Code, retrieved via the Google Maps API. When a reliable ZIP was unavailable (<1%), we used IP-based city-level geolocation. The results are robust to restricting the sample to respondents whose ZIP Code coordinates matched those implied by IP addresses (see SI).

Project locations are defined at the facility street address. Proximity is defined as the minimum distance from a respondent's ZIP centroid to the nearest eligible project of the specified type. Distances were computed as planar Euclidean distances in meters after transforming both layers to ESRI:102003. Eligibility was aligned to each respondent's interview date: renewable generation projects with construction start dates in the prior two years, and clean energy manufacturing facilities at least partially operational during that window. Distances were binned into national quintiles by project type (Q1=closest...Q5=farthest).

Weights

Survey weights were constructed for the pooled sample and separately for questions only on specific waves. Iterative proportional fitting (raking) was used to align the sample to population benchmarks from the 2023 ACS 5-year release. The raking targets included the joint distribution of gender $\times$ age $\times$ 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. Validation checks show that the weights improve representativeness (SI).

Weights were not applied in the proximity regressions (identification relies on within-state comparisons), but they were applied to all descriptive estimates and figures. Weighted regression specifications yield substantively similar results (SI).

Clean Energy Project Data

Clean energy generation. Utility-scale generation projects were identified from the U.S. Energy Information Administration's EIA-860M monthly generator updates, which supplement the annual EIA-860 census of generators $\geq$1 MW. Solar and wind plants were selected because the IRA expanded investment and production tax credits for these technologies. Project locations were defined using the EIA plant address point. Eligibility for the proximity analysis is based on construction activity. A plant was considered eligible if at least one solar or wind generator at the facility was reported as pre-construction or under construction, with a start month/year within the two years preceding the respondent's interview date. Monthly EIA-860M status/date fields were used to align project timing directly to interviews. Records with invalid or out-of-bounds coordinates were excluded.

Clean energy manufacturing. Manufacturing facilities were drawn from the Big Green Machine dataset from Jay Turner, Wellesley College (archived April 19, 2025). These data were compiled from public sources (e.g., company press releases and news articles). Technologies covered include EVs, batteries, solar, and wind. The analytic sample excluded rumored, closed, or canceled projects, as well as records lacking an announcement date or valid latitude/longitude. Facility coordinates were defined at the street-address point. The proximity analysis included facilities operational or partially operational within two years preceding the respondent's interview date and prior to the IRA's passage, whereas the statements analysis considers all manufacturing projects regardless of status.

Company and Politician Statements

Collection

The statements dataset covers 327 projects listed in the Big Green Machine archive (see Clean Energy Project Data) and 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 (formerly Twitter), Instagram, and LinkedIn; and (iii) direct quotes attributable to the actor in credible news articles or in another actor's press release (e.g., a company release quoting a governor). Statements from advocacy organizations and op-eds by third parties are excluded. When both official and media sources exist, sources are prioritized in the following order: official website > verified social account > campaign or legislative page > news quote. If no official statement exists, a single attributable quote from a news article is retained and linked. The SI provides descriptive information about the types of statements for each actor.

For each project, coders verified the identities of companies and politicians, along with project details. Statements were retained only if the speaker held the relevant office at the time. The unit of analysis was the project–actor pair. Multiple distinct statements by the same actor about the same project were consolidated into one record; the canonical record retained the earliest statement date, the source URL, and the channel type (press, social, news). When a company press release contained a politician's quote and no separate official statement existed, that quote was used as the politician's statement and the company release was cited. All source URLs and statement texts were archived.

Annotation

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

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

The codebook distinguished explicit credit (e.g., causal verbs, attributions of decision-making, financial involvement) from implicit credit (e.g., attending or hosting a project ceremony, framing an announcement as an achievement, public association with a specific project using active language) and separated descriptive mentions without credit. Post-processing enforced explicit-mention rules: a statement could be coded as crediting the IRA/BIL/President only if a corresponding synonym appeared in text. This convention yields conservative estimates of credit.

Human coders and the LLMs jointly annotated a calibration subset of two statements for every actor to refine instructions. The unit of analysis is the project–actor pair.

LLM-assisted annotation is well validated for political text. Multiple studies find that GPT-class models match or exceed crowd workers and conventional supervised methods on common text-as-data tasks, often with higher inter-coder agreement and far lower cost (Gilardi, Alizadeh, and Kubli, 2023). In political science specifically, few-shot prompting can outperform standard classifiers and achieve expert-level performance across sentiment, scaling, and topic tasks (Chew et al., 2023; Ornstein, Blasingame, and Truscott, 2025). The annotation protocol follows emerging best-practice guidelines, including codebook prompts, temperature control, model disclosure, human calibration, and conservative post-processing, which increase reproducibility and guard against over-attribution (Törnberg, 2024).

Analyses

Causal Identification

The analysis aims to estimate the effect of project proximity on recognition and credit attribution. The causal inference challenge is that project location is related to political and economic factors that could independently affect political attitudes. Tax credits could target swing states with distinct political dynamics or go to places with a more college-educated workforce. The analysis would be confounded if it failed to account for project site selection.

The research design leverages within-state variation in project proximity. It assumes that the within-state deviation in a survey-taker's distance to clean energy projects is as-if random after controlling for individual and county-level covariates that predict site selection within a state. The centrality of state-level factors for project site selection, which the state fixed effects address, increases the credibility of this assumption. States vary in the governor's partisanship, electoral college importance, economic incentive programs, electricity costs, presence of pre-existing green industries, and unionization rates, all of which influence investment decisions.

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

A possible concern is that the estimated proximity effects might partly reflect spillovers such as shared local news markets. To address this, we re-estimated our models including fixed effects for Nielsen Designated Market Areas (DMAs), which hold constant any unobserved shocks or common information environments at the media-market level. The proximity estimates remain substantively unchanged with DMA fixed effects included (SI).

Estimation

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

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

where Q_5 (farthest quintile) is the reference. Outcomes are indicators for recognition, credit to President Biden or the IRA, or belief that green investments are beneficial. X_i includes individual- and county-level covariates; $State_s$ and $Wave_t$ denote state and wave fixed effects.

The analysis operationalizes distance with quintiles to ensure there is common support and captures non-linear effects (Hainmueller, Mummolo, and Xu, 2019). A continuous measure would miss non-linearities because it assumes that there is a linear functional relationship between distance and exposure, treating a 10 km shift for a respondent next to a project as equivalent to the same shift for a respondent 100 km away. Results are robust when using logged distance (SI).

An omnibus Wald test assesses the joint null that the first two distance quintile indicators equal zero. The focus is on Q1-Q2 to identify any proximity effect that should be most relevant for individuals closest to projects.

Inference

Spatial HAC (Conley) standard errors were computed using respondents' ZIP-centroid latitude/longitude (decimal degrees), a uniform kernel with a hard 400 km cutoff, the default triangular distance metric, and no grid pooling. Results are robust to computing great-circle distances, to alternative cutoffs (e.g., 300 and 500 km), and to clustering by state (SI). Conley errors are preferred to state clustering because projects can fall near state borders and spatial correlation in residuals can extend across jurisdictions.

Sensitivity

Sensitivity to unobserved confounding was assessed using the partial R^2–based bias formulas of Cinelli and Hazlett (2020). This procedure quantifies the strength of a hypothetical unobserved confounder required to reduce the Q1 proximity coefficient to statistical insignificance at the 5% level. For the manufacturing and renewable energy distance measures, an unobserved confounder would need to explain approximately 0.25% and 0.56% of the residual variation in both the treatment and the recognition outcome, respectively. These values are substantially larger than the correlations of strong observed predictors of treatments and outcomes, such as labor force size and income (SI).

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Competing Interests

The authors declare no competing interests.

Data, Materials, and Code Availability

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

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Supplemental Information: Why Clean Energy Investments Did Not Create New Political Constituencies

A 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
Socioeconomic & Infrastructure		
Unemployment rate	Annual average county-level unemployment (BLS Local Area Unemployment Statistics).	BLS LAU Tables
Labor force size	Annual average county-level labor force (BLS LAU).	BLS LAU Tables
Gross domestic product	County real GDP, chained dollars, all industries (BEA CAGDP9).	BEA: GDP by County
Per capita income	County personal income per capita (BEA CAINC30).	BEA Regional Data
Highway access	TIGER/Line shapefiles (U.S. Primary Roads, 2023). Interstate access coded as a binary based on county–interstate intersection.	TIGER/Line: Primary Roads

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

B Survey

B.1 Sample Summary Statistics

Table B2: Survey sample summaries, showing means of respondent-level characteristics

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

B.2 Weight Diagnostics

Table B3: 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

B.3 Survey Instrument

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

B.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)

B.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

B.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

B.4 Credit Attribution Internal Validity

First, to minimize partisan differences in response patterns, the question described green investments neutrally, without specifying whether projects were good or bad. Partisan expressive responding is an inherent risk, but we focus here on whether the wording disengaged or primed partisans differently. Response times do not differ across partisan identification or ideology (Table B4), suggesting the question was equally engaging across groups.

Table B4: Linear probability model of credit attribution question time latency by political affiliation

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

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

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

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

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

C Proximity Effects on Recognition, Benefits, and Attribution

C.1 Summary Statistics

Table C5: Proximity analysis summary statistics

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

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

C.2 Within-State Variation in Distance

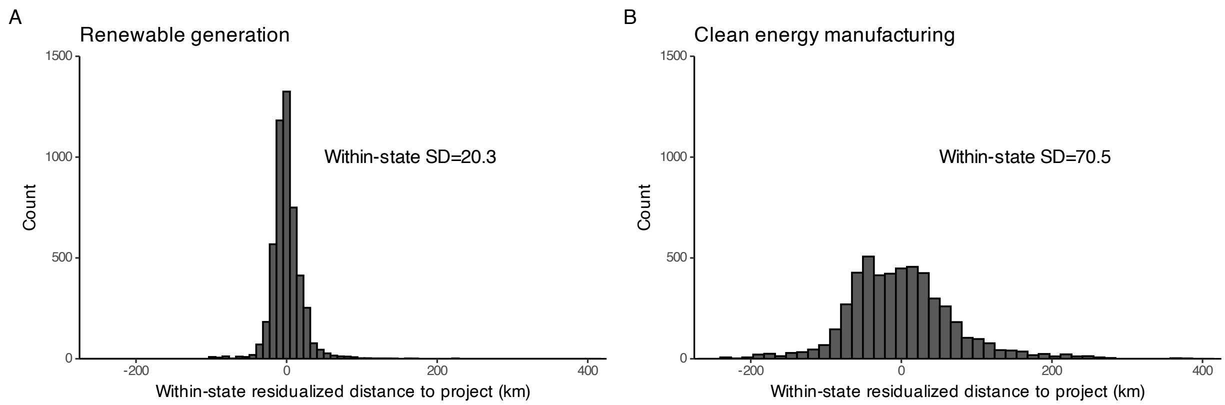

Figure C6: Within-state variation in survey respondent proximity to clean energy investments

C.3 Main Regression Table

Table C6: 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	0.053*	0.054*	-0.013	-0.030	-0.028	0.039
	(0.022)	(0.025)	(0.023)	(0.032)	(0.036)	(0.038)
Q2 proximity	0.055**	0.031	-0.018	-0.031	0.020	0.00077
	(0.021)	(0.023)	(0.027)	(0.028)	(0.041)	(0.01532)
Q3 proximity	0.021	0.026	-0.038	-0.039	0.034	0.025
	(0.021)	(0.022)	(0.026)	(0.025)	(0.038)	(0.033)
Q4 proximity	0.019	0.027	-0.031	-0.080**	0.0019	0.037
	(0.020)	(0.029)	(0.027)	(0.026)	(0.0331)	(0.027)
Age	-0.00124***	-0.00125***	0.00058	0.00058	3e-04	0.00023
	(0.00032)	(0.00032)	(0.00053)	(0.00053)	(1e-03)	(0.00104)
Female	-0.063***	-0.062***	-0.060***	-0.060***	-0.037*	-0.037*
	(0.013)	(0.012)	(0.017)	(0.017)	(0.017)	(0.017)
Black	0.023	0.022	0.042	0.041	-0.045	-0.045
	(0.018)	(0.019)	(0.035)	(0.035)	(0.031)	(0.033)
Asian	-0.041	-0.041	0.028	0.028	-0.033	-0.040
	(0.023)	(0.023)	(0.049)	(0.049)	(0.088)	(0.087)
Other race	-0.022	-0.025	-0.037	-0.033	0.066*	0.062*
	(0.022)	(0.022)	(0.031)	(0.029)	(0.028)	(0.030)
Hispanic/Latino	0.0255**	0.0274**	0.0078	0.0069	-0.087**	-0.087*
	(0.0096)	(0.0099)	(0.0216)	(0.0213)	(0.033)	(0.034)
College	0.072***	0.070***	0.049*	0.050**	0.0021	0.00059
	(0.015)	(0.015)	(0.020)	(0.019)	(0.0280)	(0.02829)
Employed	0.066***	0.067***	0.035	0.034*	0.050	0.049
	(0.015)	(0.014)	(0.018)	(0.017)	(0.032)	(0.031)
Income Q2	0.017	0.016	-0.013	-0.013	0.029	0.029
	(0.015)	(0.016)	(0.027)	(0.027)	(0.030)	(0.031)
Income Q3	0.0063	0.0062	-0.045*	-0.045	0.013	0.012
	(0.0142)	(0.0144)	(0.023)	(0.023)	(0.032)	(0.033)
Income Q4	0.057***	0.057***	-0.021	-0.020	0.049	0.048
	(0.015)	(0.016)	(0.024)	(0.024)	(0.044)	(0.046)
Income Q5	0.074**	0.076**	-0.033	-0.032	0.074	0.074
	(0.024)	(0.025)	(0.020)	(0.021)	(0.048)	(0.048)
Republican	-0.0093	-0.0092	-0.169***	-0.168***	-0.146***	-0.147***
	(0.0173)	(0.0175)	(0.017)	(0.018)	(0.033)	(0.033)
Neither party	-0.069***	-0.069***	-0.221***	-0.222***	-0.106**	-0.106**
	(0.013)	(0.013)	(0.024)	(0.024)	(0.033)	(0.034)
Global warming index	0.128***	0.127***	0.074*	0.074*	0.566***	0.566***
	(0.013)	(0.013)	(0.033)	(0.033)	(0.048)	(0.048)
Population density	-0.0066	-0.0095	0.0145	0.0157*	0.014	0.015*
	(0.0061)	(0.0062)	(0.0076)	(0.0077)	(0.011)	(0.007)
County college share $(t-1)$	0.0052	0.0027	-0.00098	-0.0029	0.017	0.019
	(0.0135)	(0.0128)	(0.01848)	(0.0183)	(0.029)	(0.027)
County poverty share $(t-1)$	0.0078	0.011	-0.0053	-0.0032	-0.0056	-0.0041
	(0.0141)	(0.015)	(0.0144)	(0.0152)	(0.0191)	(0.0186)
County foreign-born share $(t-1)$	0.00063	-0.0030	-0.001	0.0037	-0.012	-0.014
	(0.00723)	(0.0063)	(0.013)	(0.0134)	(0.017)	(0.017)
Median county housing costs $(t-1)$	-0.038**	-0.038**	0.005	0.0031	0.0033	0.0077
	(0.014)	(0.013)	(0.016)	(0.0155)	(0.0191)	(0.0204)
Faster broadband access $(t-1)$	0.015	0.016	-0.043	-0.041	0.054	0.055
	(0.015)	(0.015)	(0.023)	(0.023)	(0.038)	(0.036)
County GDP (log) $(t-1)$	0.059	0.054	0.048	0.048	0.039	0.039
	(0.042)	(0.041)	(0.042)	(0.037)	(0.064)	(0.064)
Labor force (log) $(t-1)$	-0.071	-0.067	-0.044	-0.049	-0.050	-0.052
	(0.041)	(0.040)	(0.037)	(0.033)	(0.055)	(0.052)
County unemployment rate $(t-1)$	-0.0085	-0.0066	0.0244***	0.0245***	0.022	0.026*
	(0.0064)	(0.0060)	(0.0063)	(0.0062)	(0.012)	(0.010)
Highway access	0.015	0.017	0.076	0.076*	0.0061	0.0095
	(0.023)	(0.025)	(0.039)	(0.039)	(0.0280)	(0.0278)
County income pc $(t-1)$	0.023*	0.0276**	-0.0022	0.0021	-0.010	-0.012
	(0.011)	(0.0098)	(0.0148)	(0.0135)	(0.023)	(0.022)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.074	0.073	0.068	0.069	0.181	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

C.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 C7–C9 present power analyses for the three main outcomes. The design had 80% power ($\alpha = 0.05$) to detect increases in credit attribution of 9.5 and 12 percentage points for proximity to renewable generation projects and clean energy manufacturing, respectively; increases in recognition of local investments of 7 and 8.5 percentage points; and increases in perceived benefits of 13 and 15 percentage points.

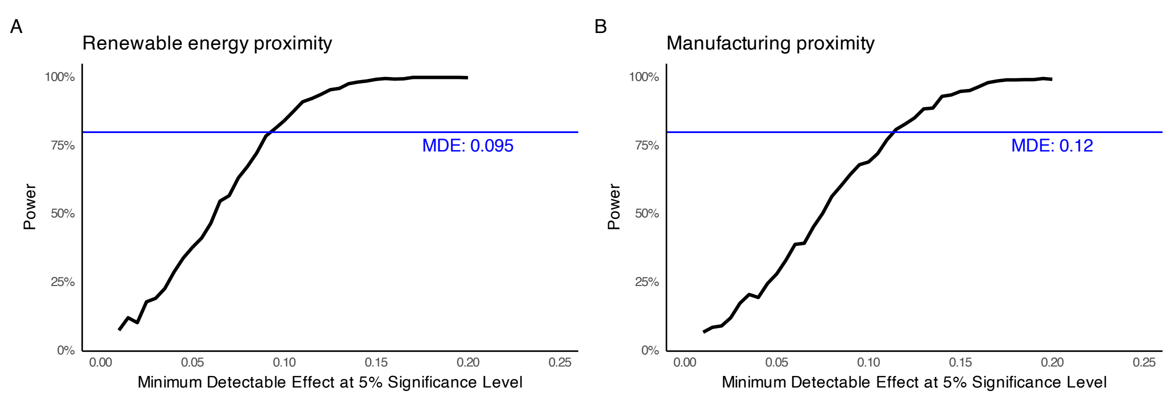

Figure C7: Analytical power analysis, credit attribution outcome.

It is reasonable to imagine that reformers behind the IRA anticipated that individuals living near projects would be noticeably more likely to recognize their presence—on the order

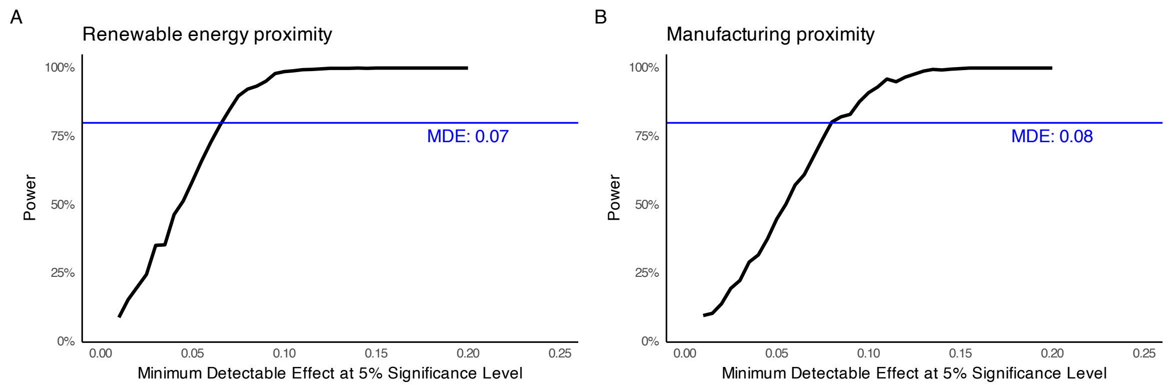

Figure C8: Analytical power analysis, recognition outcome

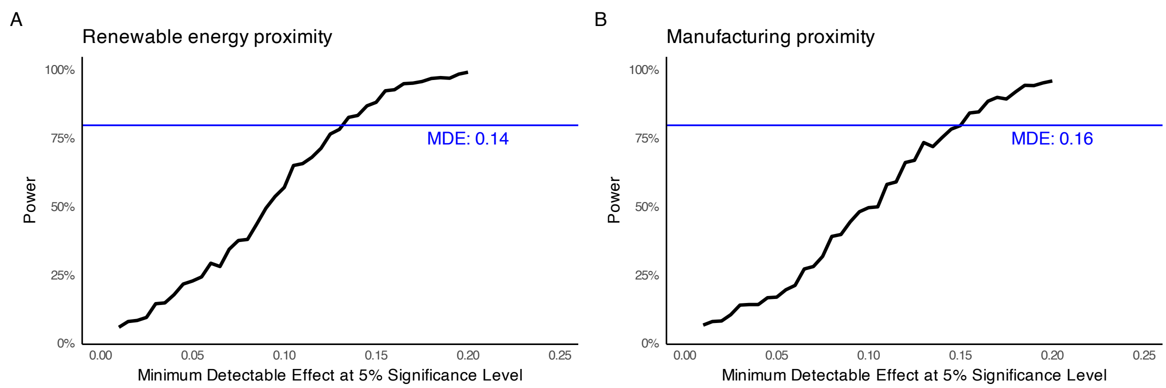

Figure C9: Analytical power analysis, benefit outcome

of an 8 percentage point increase—and, in turn, roughly 10 percentage points more likely to attribute credit to the Biden Administration. While partisan polarization constrains belief change among Democrats and Republicans, a substantial share of the public identifies as independent, and at least some of these respondents may be open to updating their views if exposed to local projects. We therefore treat shifts of this magnitude as substantively meaningful benchmarks. Although our design cannot reliably detect smaller effects, such effects would be more difficult to interpret as politically consequential, even if they existed.

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

C.5 Robustness Checks

C.5.1 Sensitivity to Omitted Variable Bias

Table C7: Sensitivity analysis for recognition outcome, manufacturing proximity 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)	0.054	0.025	2.136	0.1%	3%	0.2%
df = 4942	*Bound (1 x County Labor Force (log))*: $R^2_{Y\sim Z\|\mathbf{X},D} = 0.2\%$, $R^2_{D\sim Z\|\mathbf{X}} = 0.6\%$					

Table C8: Sensitivity analysis for recognition outcome, renewable energy proximity 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)	0.053	0.022	2.359	0.1%	3.3%	0.6%
df = 4942	*Bound (1 x County Labor Force (log))*: $R^2_{Y\sim Z\|\mathbf{X},D} = 0.1\%$, $R^2_{D\sim Z\|\mathbf{X}} = 0.2\%$					

C.5.2 Alternative Specifications of Spatial Standard Errors

Table C9: Robustness to 300 km Conley standard error cutoff: Linear probability models of project recognition and credit attribution.

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Q1 proximity	0.053*	0.054*	-0.013	-0.030	-0.028	0.039
	(0.021)	(0.025)	(0.032)	(0.028)	(0.037)	(0.042)
Q2 proximity	0.055*	0.031	-0.018	-0.031	0.020	0.00077
	(0.022)	(0.022)	(0.029)	(0.025)	(0.037)	(0.03506)
Q3 proximity	0.021	0.026	-0.038	-0.039	0.034	0.025
	(0.024)	(0.023)	(0.025)	(0.028)	(0.040)	(0.031)
Q4 proximity	0.019	0.027	-0.031	-0.080***	0.0019	0.037
	(0.022)	(0.029)	(0.032)	(0.018)	(0.0315)	(0.037)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.074	0.073	0.068	0.069	0.181	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Table C10: Robustness to 500 km Conley standard error cutoff: Linear probability models of project recognition and credit attribution.

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Q1 proximity	0.053*	0.054*	-0.013	-0.03	-0.028	0.039
	(0.023)	(0.026)	(0.030)	(0.03)	(0.041)	(0.040)
Q2 proximity	0.055*	0.031	-0.018	-0.031	0.020	0.00077
	(0.022)	(0.023)	(0.034)	(0.023)	(0.039)	(0.03280)
Q3 proximity	0.021	0.026	-0.038	-0.039	0.034	0.025
	(0.022)	(0.020)	(0.032)	(0.029)	(0.036)	(0.033)
Q4 proximity	0.019	0.027	-0.031	-0.080**	0.0019	0.037
	(0.016)	(0.029)	(0.027)	(0.029)	(0.0303)	(0.022)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.074	0.073	0.068	0.069	0.181	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Table C11: 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	0.053*	0.054	-0.013	-0.030	-0.028	0.039
	(0.021)	(0.028)	(0.024)	(0.043)	(0.050)	(0.039)
Q2 proximity	0.055*	0.031	-0.018	-0.031	0.020	0.00077
	(0.025)	(0.022)	(0.031)	(0.032)	(0.044)	(0.03155)
Q3 proximity	0.021	0.026	-0.038	-0.039	0.034	0.025
	(0.021)	(0.022)	(0.030)	(0.038)	(0.049)	(0.036)
Q4 proximity	0.019	0.027	-0.031	-0.080*	0.0019	0.037
	(0.018)	(0.028)	(0.027)	(0.038)	(0.0358)	(0.038)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.074	0.073	0.068	0.069	0.181	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

C.5.3 Alternative Geocoordinate and Distance Measures

Table C12: Robustness to precise geo-coordinates: Linear probability models of project recognition and credit attribution.

	Recognition (=1)		Credit Biden (=1)		Benefits (=1)	
	Renewables	Manufacturing	Renewables	Manufacturing	Renewables	Manufacturing
Q1 proximity	0.048*	0.049*	-0.015	-0.040	-0.036	0.032
	(0.023)	(0.024)	(0.026)	(0.032)	(0.036)	(0.037)
Q2 proximity	0.052*	0.027	-0.023	-0.030	0.013	-0.0044
	(0.021)	(0.023)	(0.030)	(0.029)	(0.043)	(0.0182)
Q3 proximity	0.021	0.026	-0.038	-0.048	0.023	0.022
	(0.020)	(0.023)	(0.027)	(0.025)	(0.041)	(0.034)
Q4 proximity	0.018	0.030	-0.032	-0.077**	0.0033	0.040
	(0.020)	(0.029)	(0.027)	(0.026)	(0.0351)	(0.028)
N	4856	4856	2931	2931	1452	1452
Adjusted R^2	0.064	0.063	0.061	0.062	0.175	0.175
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

Table C13: 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	0.053*	0.054*	-0.013	-0.030	-0.028	0.039
	(0.022)	(0.026)	(0.023)	(0.033)	(0.036)	(0.038)
Q2 proximity	0.055**	0.031	-0.018	-0.031	0.020	0.00077
	(0.021)	(0.023)	(0.028)	(0.028)	(0.041)	(0.01729)
Q3 proximity	0.021	0.026	-0.038	-0.039	0.034	0.025
	(0.021)	(0.022)	(0.026)	(0.026)	(0.039)	(0.032)
Q4 proximity	0.019	0.027	-0.031	-0.080**	0.0019	0.037
	(0.020)	(0.030)	(0.026)	(0.027)	(0.0330)	(0.025)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.074	0.073	0.068	0.069	0.181	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

C.5.4 Continuous Distance Measure

Table C14: 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)	-0.0252*		0.0084		0.0052	
	(0.0098)		(0.0109)		(0.0171)	
Distance to manufacturing (log)		-0.0180*		0.0041		-0.015
		(0.0081)		(0.0085)		(0.015)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.075	0.074	0.068	0.068	0.181	0.182
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

C.5.5 Survey Weights

Table C15: 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	0.050*	0.058*	-0.025	-0.017	-0.028	0.039
	(0.025)	(0.023)	(0.025)	(0.039)	(0.036)	(0.038)
Q2 proximity	0.059*	0.036	-0.017	-0.029	0.020	0.00077
	(0.025)	(0.023)	(0.030)	(0.030)	(0.041)	(0.01532)
Q3 proximity	0.023	0.019	-0.047	-0.026	0.034	0.025
	(0.024)	(0.025)	(0.035)	(0.029)	(0.038)	(0.033)
Q4 proximity	0.032	0.024	-0.021	-0.095***	0.0019	0.037
	(0.024)	(0.034)	(0.024)	(0.024)	(0.0331)	(0.027)
N	5026	5026	3034	3034	1488	1488
Adjusted R^2	0.073	0.072	0.074	0.076	0.181	0.180
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

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

C.5.6 Additional Credit Recipients

Table C16: 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	0.021	-0.013	0.021	0.033	-0.029	0.035	-0.044	0.059	-0.0086	-0.010
	(0.029)	(0.047)	(0.033)	(0.035)	(0.025)	(0.032)	(0.035)	(0.047)	(0.0304)	(0.035)
Q2 proximity	-0.027	-0.030	0.015	0.047	-0.039	0.018	-0.021	0.012	-0.011	-0.038
	(0.031)	(0.034)	(0.024)	(0.032)	(0.036)	(0.029)	(0.030)	(0.045)	(0.036)	(0.026)
Q3 proximity	-0.020	-0.026	0.014	0.045	-0.03	0.012	-0.021	0.054	-0.0096	-0.00016
	(0.034)	(0.036)	(0.022)	(0.030)	(0.02)	(0.026)	(0.023)	(0.035)	(0.0303)	(0.02848)
Q4 proximity	-0.022	-0.031	-0.021	0.0061	-0.019	-0.035	-0.052*	0.001	-0.0011	-0.026
	(0.035)	(0.045)	(0.026)	(0.0304)	(0.029)	(0.026)	(0.027)	(0.039)	(0.0278)	(0.030)
N	3034	3034	3034	3034	3034	3034	3034	3034	3034	3034
Adjusted R^2	0.042	0.041	0.046	0.046	0.079	0.079	0.046	0.047	0.054	0.055
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

C.6 Treatment Effect Heterogeneity

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

$$Y_i = M_i\lambda + M_i \times \sum_{q=1}^{4} \mathbb{1}[Distance_i \in Q_q]\beta_q + X_i^\top\gamma + State_{s(i)} + Wave_{t(i)} + \epsilon_i, \qquad (2)$$

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

C.6.1 Project Heterogeneity

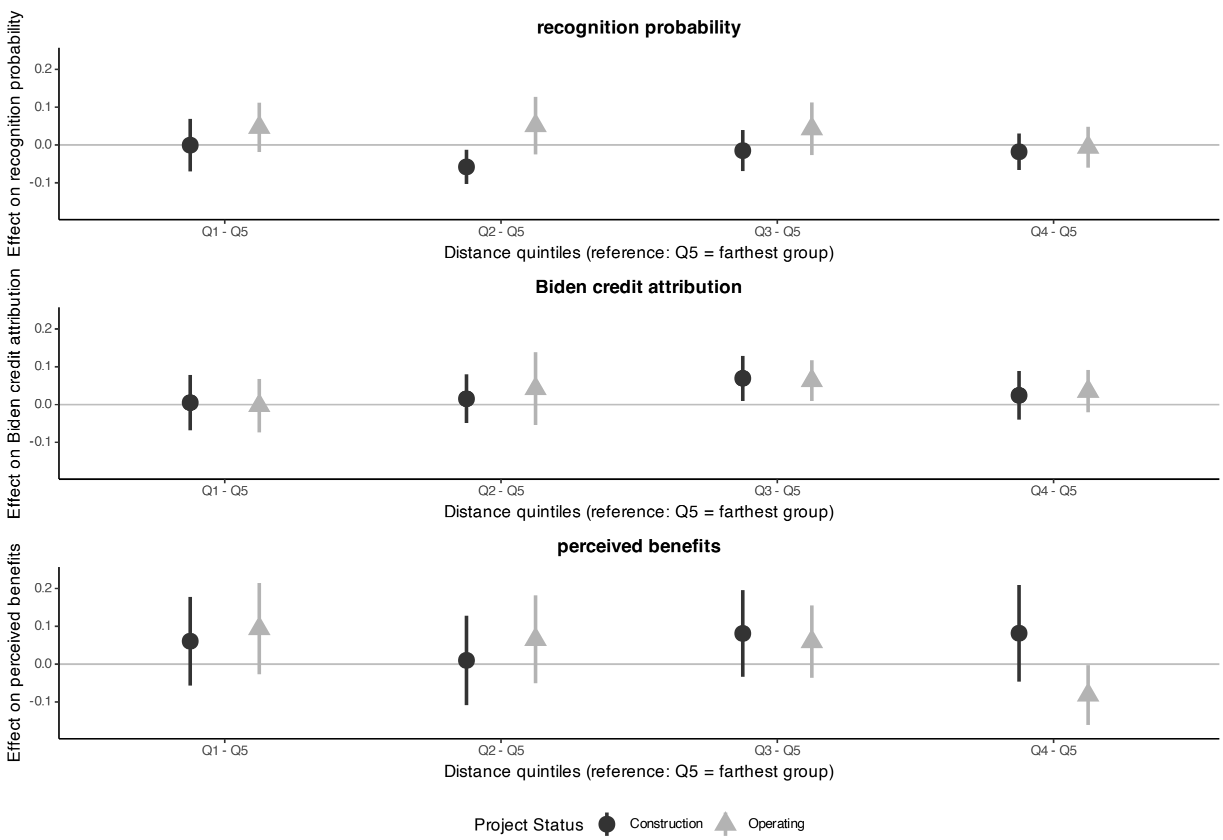

Figure C10: Heterogeneous effects of clean energy manufacturing proximity on recognition by project status

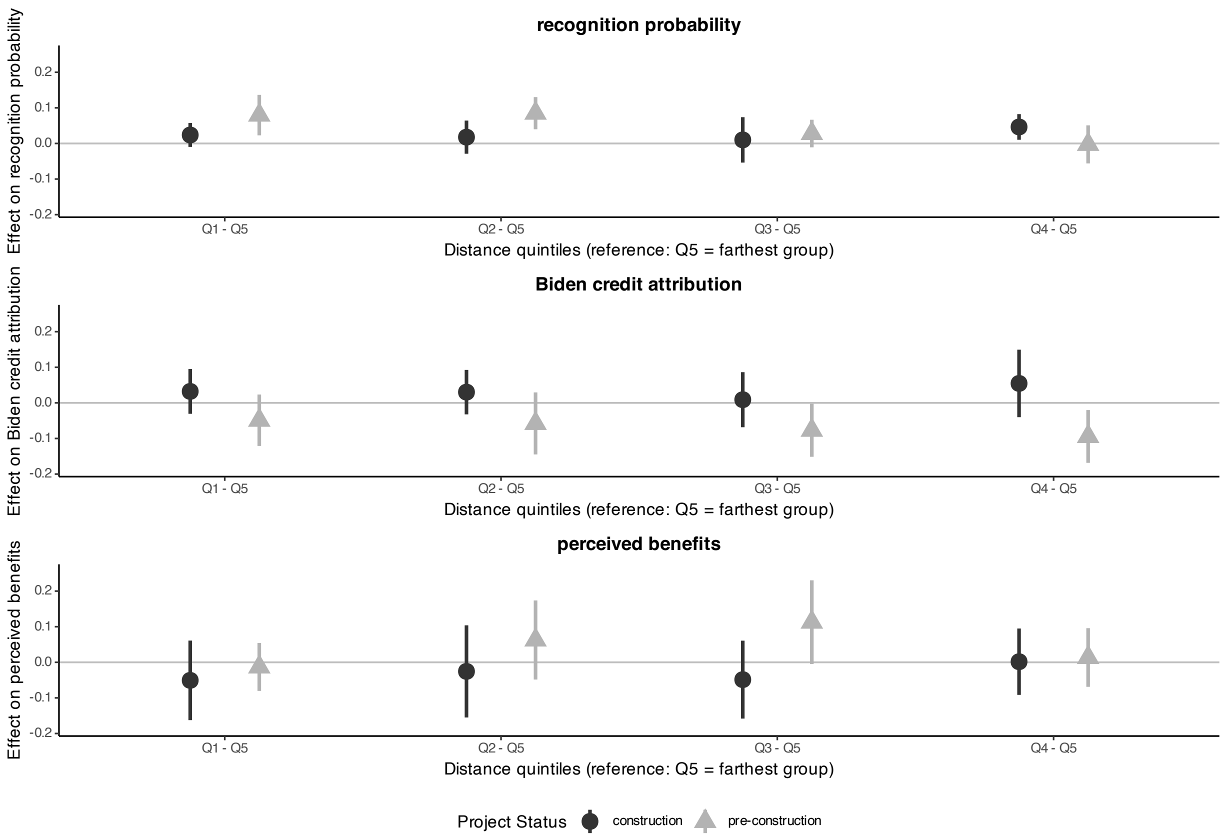

Figure C11: Heterogeneous effects of renewable generation proximity by project status

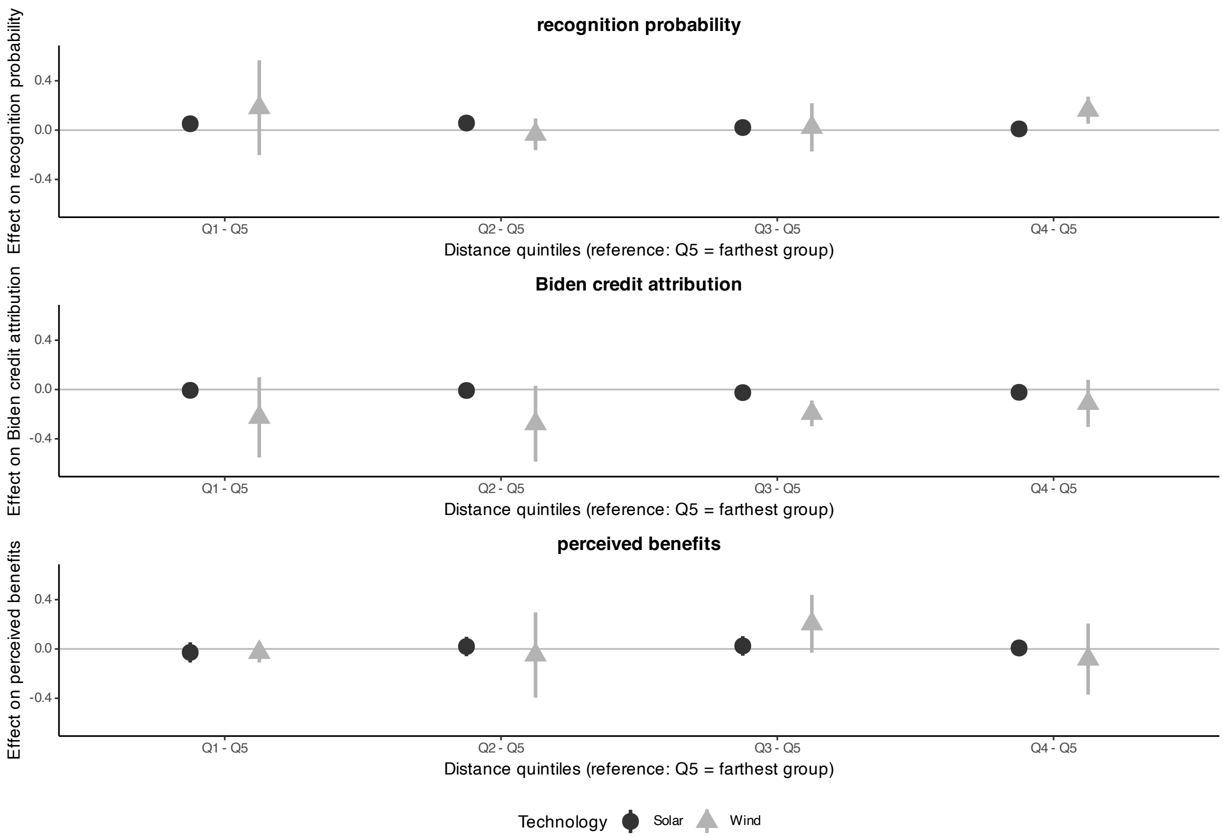

Figure C12: Heterogeneous effects of renewable generation proximity by technology

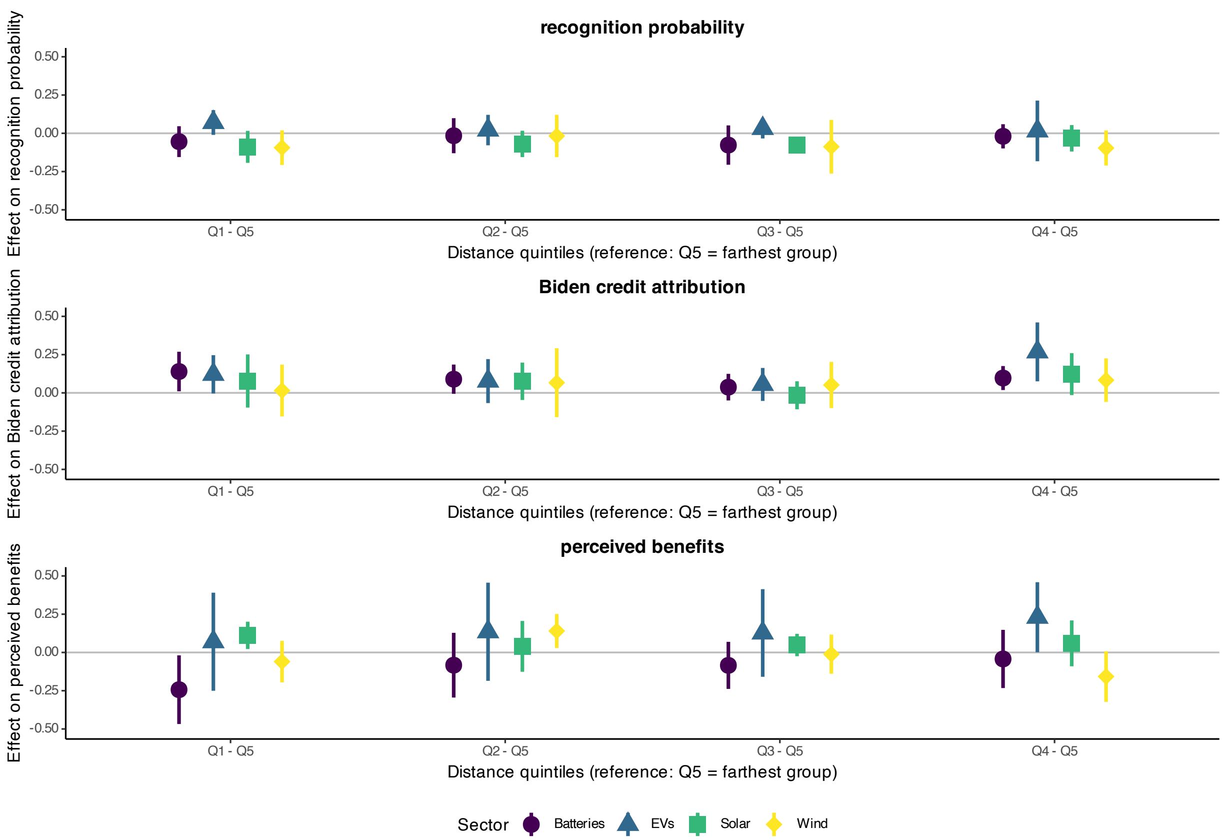

Figure C13: Heterogeneous effects of clean energy manufacturing proximity by project sector

C.6.2 Contextual Heterogeneity

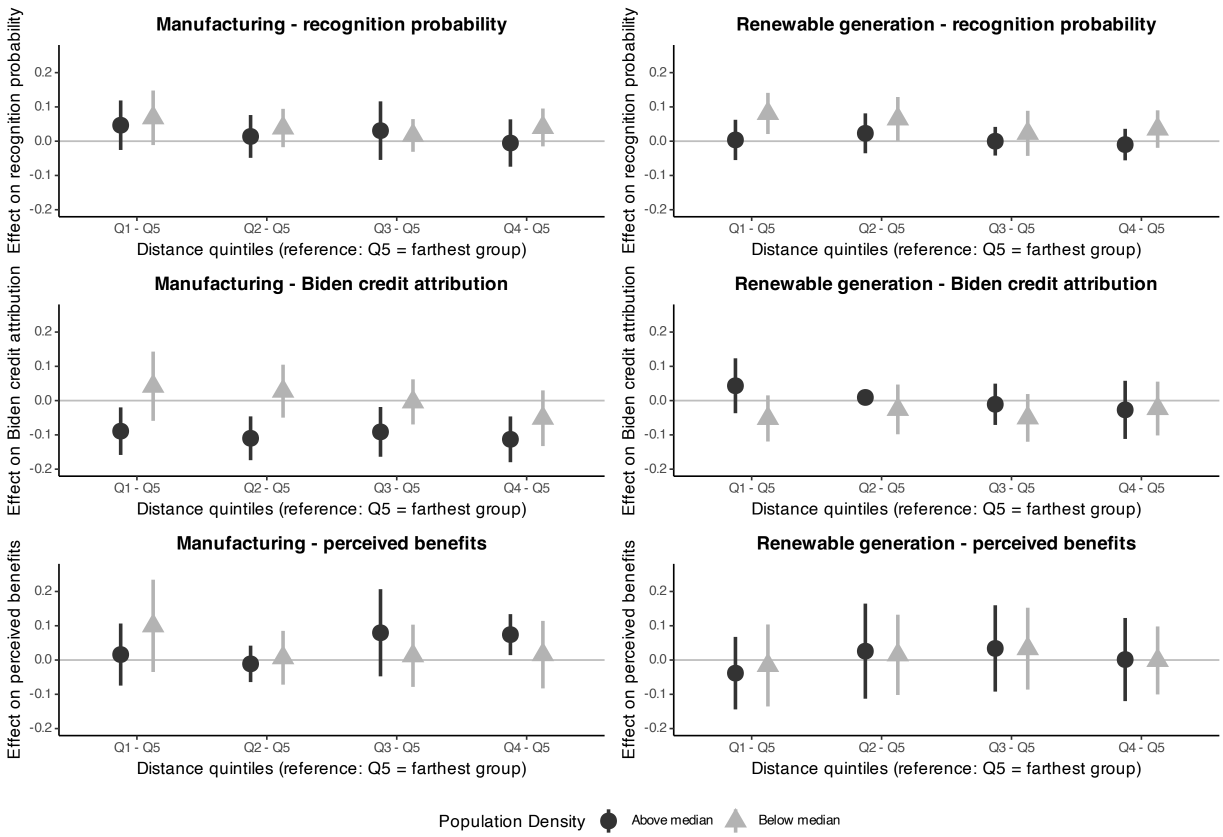

Figure C14: Heterogeneous effects of proximity on recognition by local population density. Projects should be more noticeable in less population-dense areas.

C.6.3 Individual-Level Heterogeneity

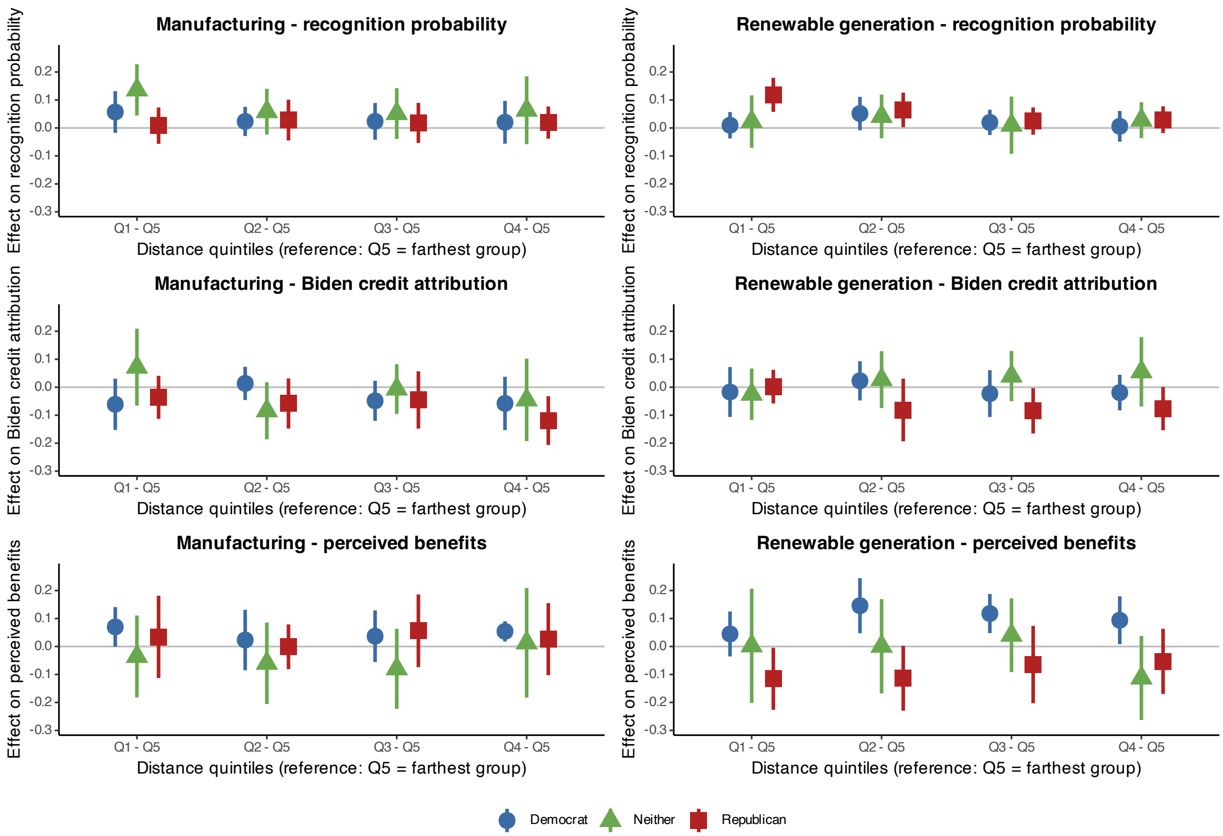

Figure C15: Heterogeneous effects of proximity by respondent partisan identification

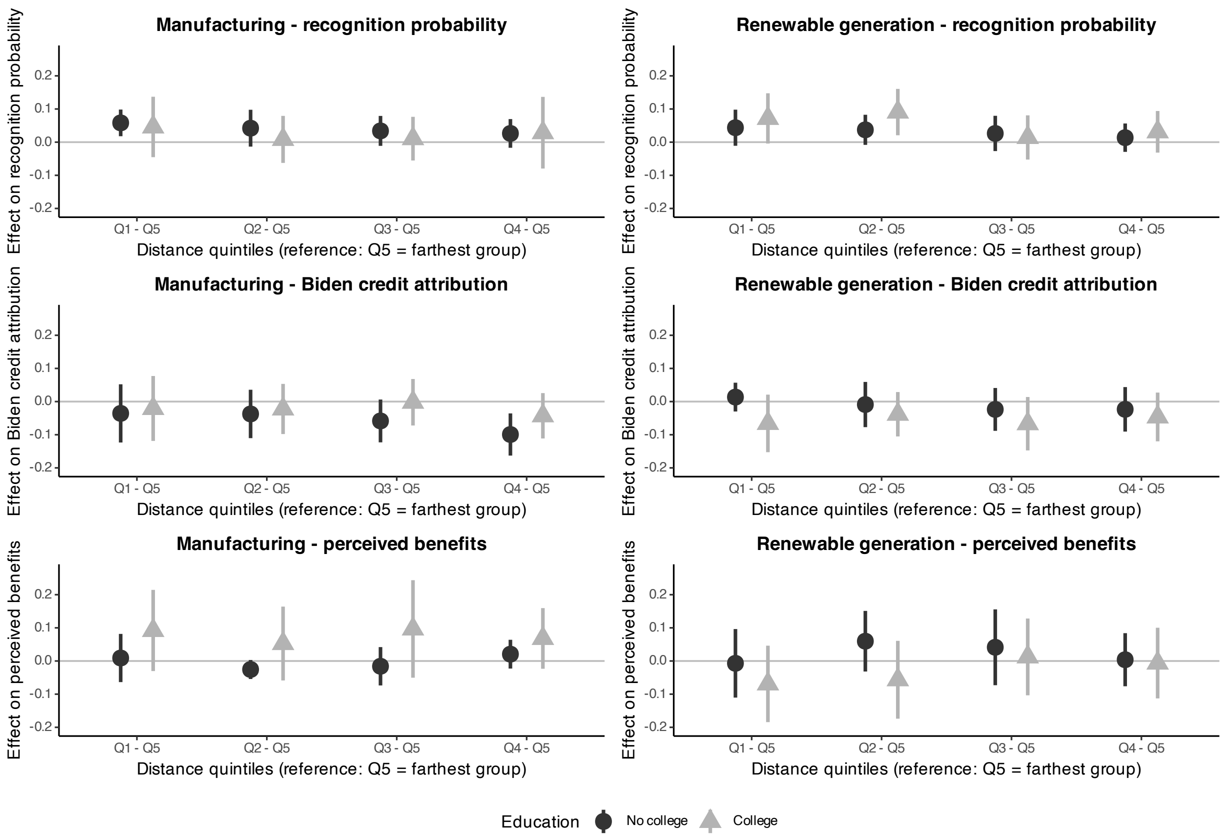

Figure C16: Heterogeneous effects of proximity by respondent education

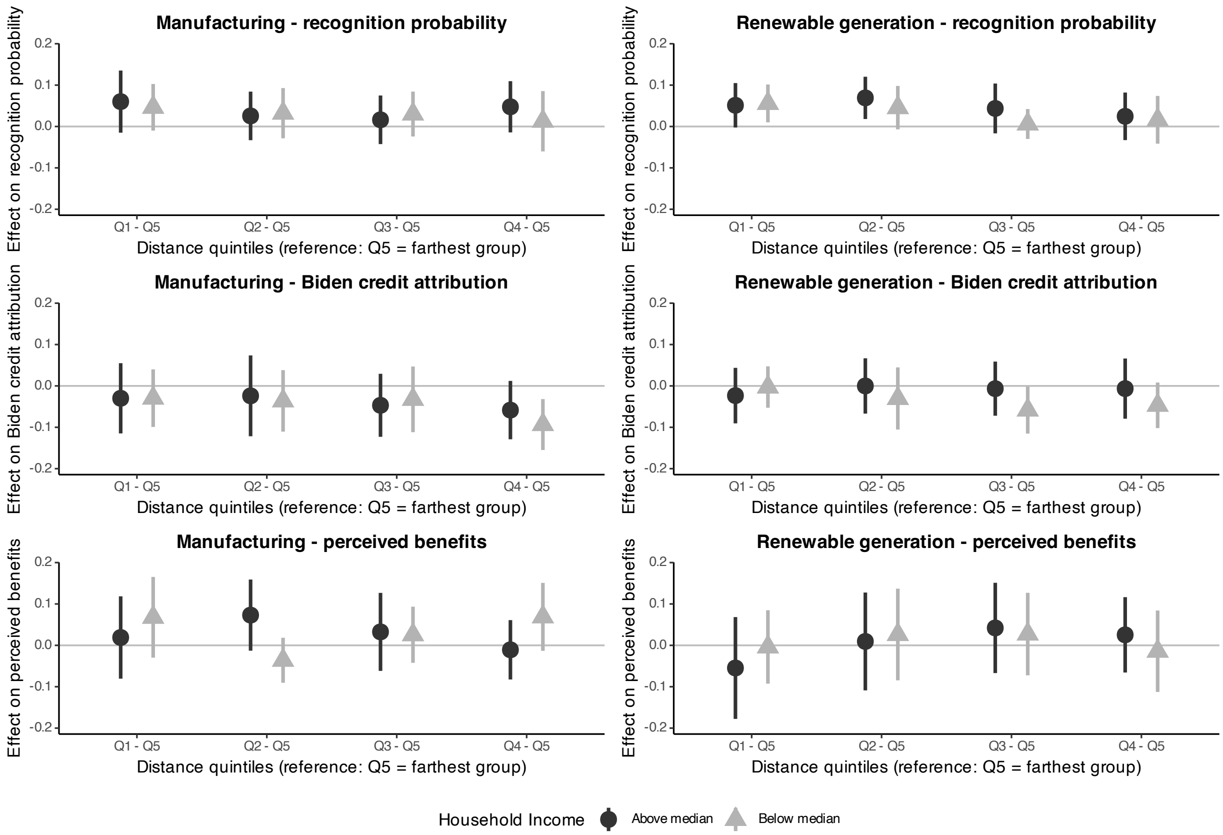

Figure C17: Heterogeneous effects of proximity by respondent income

D Model of Perceived Benefits

Table D17: Linear probability model of perceived project benefits

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

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

E Model of Credit Attribution

Table E18: Linear probability models of credit attribution

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

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

Table E19: Linear probability models of within-subject credit attribution

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

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

F Company and Politician Statements

F.1 Statement Type Description

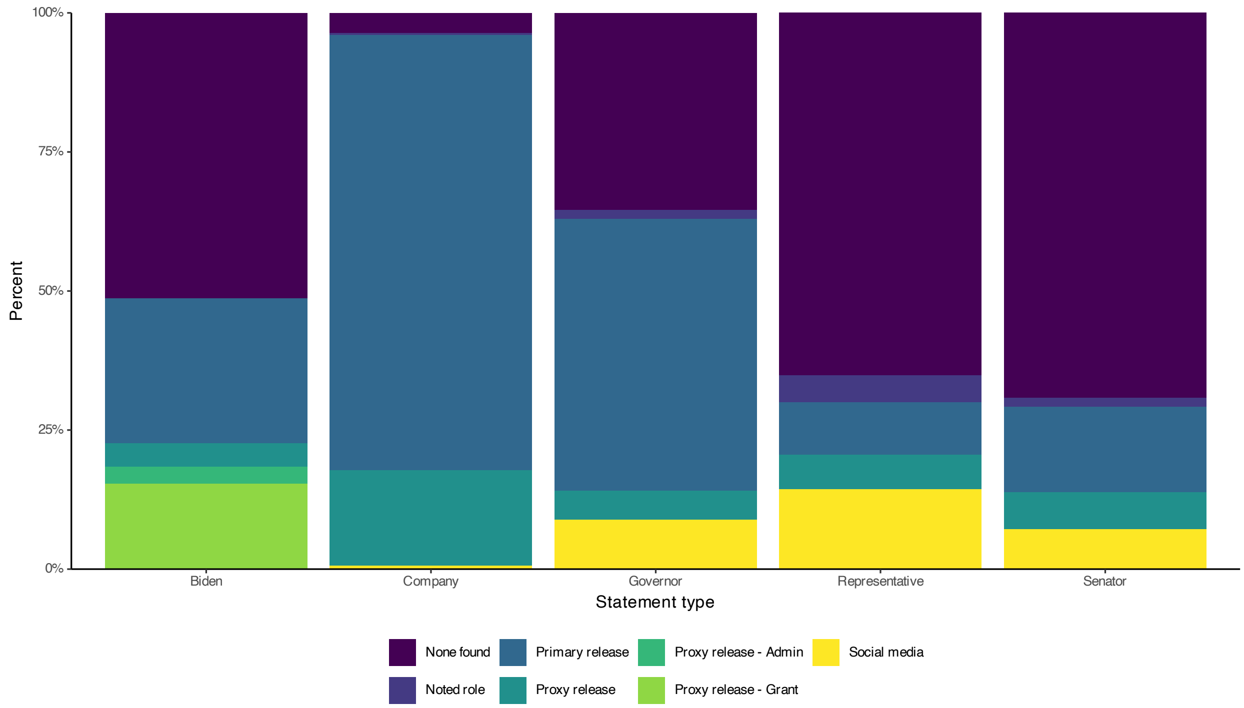

Figure F18: Types of statements by actor. Categories are mutually exclusive and indicate the highest-quality source found for each actor–project pair. *None found*: No statement located. *Primary release*: Official communication (press release, newsletter, transcript, or report) issued on the actor's 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).

F.2 Summary Statistics

Table F20: 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. $N = 1962$

F.3 LLM Annotation

F.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

F.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
}
```

F.4 Regression Models of Statement Giving

Table F21: 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

F.5 Regression Models of Credit Attribution in Statements

Table F22: 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 F23: 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 F24: 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 F25: Linear probability models of Representative credit, by speaker

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

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

References

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