Who Gets Credit for Green Industrial Policy?*

Alexander F. Gazmararian† Nathan Jensen‡ Dustin Tingley§

March 6, 2025

Abstract

The United States government passed a climate law in 2022 that is estimated to spend over half a trillion dollars to incentivize clean energy production and manufacturing. Policymakers intend for these new green projects to create political constituencies that support the clean energy transition. This paper tests this hypothesis using geolocated survey and investment data. We find that while the public sometimes recognizes visible green projects in their community, this proximity does not affect credit attribution. Overall, Americans view their governors as more responsible than the federal government for green investments. Using an original database of project announcements, we find that governors are more active in claiming credit than federal politicians. This mixed information environment provides one reason why the public does not do more to credit the federal government for green investments. When it is challenging for people to trace economic outcomes back to public policies, reforms are unlikely to affect mass opinion.

Significance Statement: Countries are making substantial green investments to stop climate change. The political logic behind these reforms is that the investments will create coalitions that support the energy transition. However, our analysis in the United States shows that while the public recognizes certain green projects, this does not translate into credit for federal investments. These limited policy feedback effects appear due to the information environment, where federal, state, and local politicians compete for credit. Green investments do not automatically create green coalitions due to causal complexity. These results can guide energy system modelers who increasingly seek to incorporate political dynamics into decarbonization pathways. Policymakers should also rethink strategies attempting to mobilize mass support for the energy transition.

*Thanks to Jim Bisbee for comments, Dylan Carlson Sirvent León for research assistance, and the Harvard University Salata Institute Strengthening Communities research cluster for financial support.

†Ph.D. Candidate, Department of Politics, Princeton University.

‡Professor, Department of Government, University of Texas-Austin.

§Professor, Department of Government, Harvard University.

Recent legislation in the United States makes sweeping green investments to fight climate change. The Inflation Reduction Act will spend more than half a trillion dollars over the next decade to incentivize clean energy and manufacturing [1]. This industrial policy approach breaks from previous market-based proposals [2, 3]. There is a political logic behind this transformation. Reformers intend for the economic benefits from green projects, many located in swing states, to shift public opinion in favor of the clean energy transition [4]. This public support, in turn, could protect the law from repeal and create a basis to ratchet up climate policy [5–8].

Policy feedback effects, where government policy seeks to remake political coalitions, are not automatic. On the one hand, some green projects will create substantial economic benefits, such as battery plants that employ hundreds and contribute to local tax revenue. People who benefit could come to see the clean energy transition as in their self-interest and credit the Democratic Party because of its association with climate policy [9]. On the other hand, the IRA's incentives are one of many factors driving green investments; governors and local politicians also provide tax incentives and think claiming credit can help win re-election [10, 11]. Moreover, partisan polarization may limit the messages the public receives and how much their views could change [12–14]. Indeed, there is initial evidence that the IRA did not affect presidential voting [15].

It is challenging to systematically learn about how green investments affect public attitudes for two reasons. First, such an analysis would require large-scale surveys that measure perceptions of new projects and beliefs about attribution, but these are questions not typically included in political polls. Second, understanding the mechanism behind policy feedback would require data on the local political information that voters consume, which is an input into their political attitudes [16, 17]. This paper addresses these barriers with original surveys and data collection on credit claiming.

We collected geolocated data to test three hypotheses about policy feedback effects. First, we hypothesize that people closer to green projects are more likely to recognize these developments compared to people who are farther away. This may seem obvious, but it is a critical assumption. People do not always connect changes in their community to political attitudes [18, 19]. Recognition can vary depending on whether projects have characteristics that make them more visible and associated with green energy, such as the size of their capital investment, job creation, and company branding [5, 20, 21].

The second hypothesis implied by policy feedback theories is that people in communities that receive green investments will be more likely to credit the federal government for these projects. Credit matters because it is part of the political logic of green industrial policy. The assumption is that elected officials supporting green reforms are rewarded at the polls for their efforts, which depends on them being viewed as responsible.

Since we find no evidence to support Hypothesis 2, we propose and test an informational mechanism to explain why. We argue that conflicting messages make it challenging for the public to trace green investments back to federal policies [21–25]. State and local politicians, in particular, have electoral incentives to claim credit for investments that create jobs [10]. The observable implication is that multiple political actors will claim credit for green investments. The mixed information environment could explain why voters do not assign the most credit to the federal government.

Research Design

Measuring the public's recognition of credit for green investments requires surveys. We fielded three online surveys of American adults in 2024 (N = 5,026) with questions tailored to study policy feedback effects. The item measuring recognition asked whether the respondent had seen a

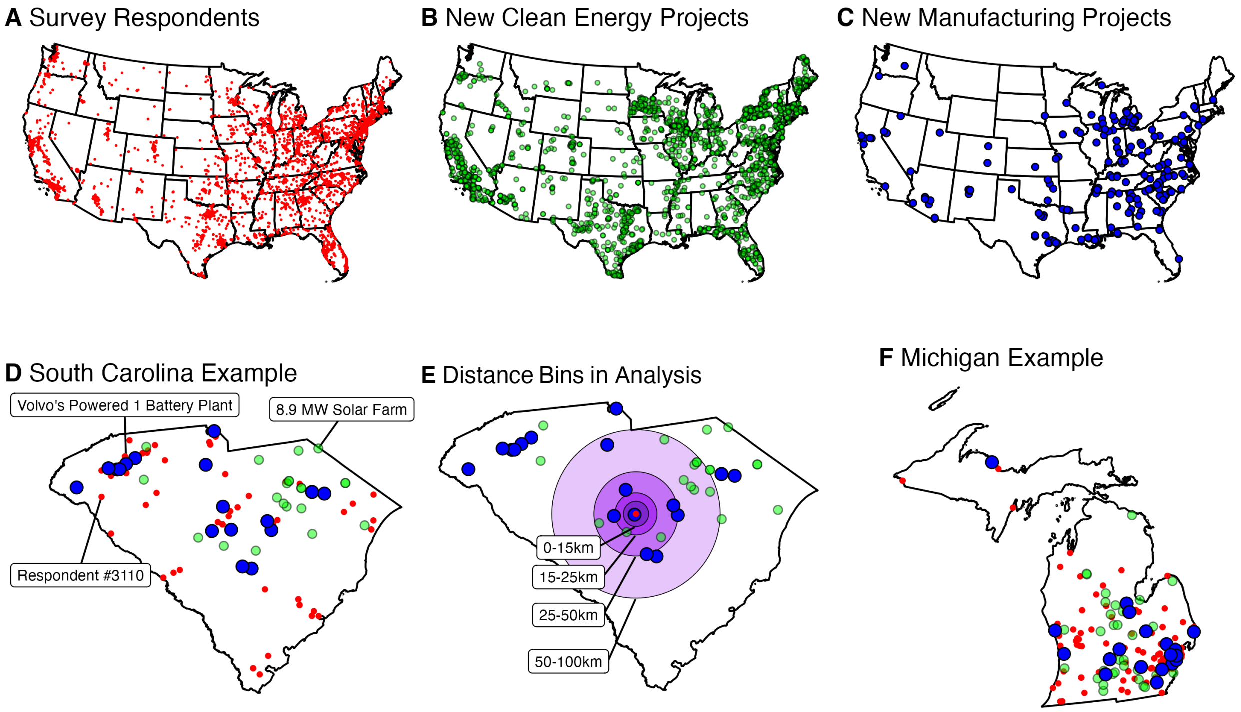

Figure 1: **Survey respondent and clean energy project locations, 2023–2024.** The period covers time after IRA's passage. Panel A shows the distribution of survey respondents. Panel B shows the distribution of new clean energy projects that include wind, solar, and battery generation projects. Panel C shows the distribution of new green manufacturing projects, such as electric vehicle and wind turbine plants. Panels D-F show zoomed-in examples of the data, while E depicts the distance bins employed in the analysis.

new green energy project in her community. People have varying definitions of community, but it typically connotes one's immediate physical surroundings. The answer options include yes, no, and not sure. About 26% of the sample reported seeing a new green project in their community.

Two of the surveys measured credit attribution by asking respondents to rank how responsible the following people, institutions, or other factors are for new green investments in their state: President Joe Biden, the US Congress, the governor, state legislature, community leaders, and the free market (Materials and Methods discusses construct validity). The analyses examine a binary indicator for whether the respondent said the factor was "very" or "extremely" responsible for new clean energy projects.

Proximity to green investments is measured by calculating each survey respondent's distance to the nearest new green project. The objective data on project location avoids bias from self-reported experience that could be clouded by political predispositions [26]. The geolocated investment data include electricity generation by solar, wind, and batteries, along with clean energy manufacturing projects such as electric vehicle and battery plants. The analysis focuses on green investments that had begun construction two years before each respondent began the survey, corresponding to the post-IRA period. The main analysis examines a variable that categorizes respondents based on whether they are 0-15km, 15-25km, 25-50km, and 50-100km from new projects and compares these survey-takers to those who are more than 100km away (see Material and Methods).

Figure 1 shows that the sample has sufficient overlap with the spatial distribution of clean energy projects. This overlap is necessary to study the effect of project proximity on political attitudes. Such an analysis must be able to compare people who live close and far away from green projects but who are otherwise similar except for their proximity.

A post-hoc power analysis indicates that the research design for most green project types would be able to detect a minimum effect of proximity of recognition between 0.11 and 0.19 and of proximity of credit attribution between 0.08 and 0.21 with 80% probability at the 5% significance level (see SI Appendix). The research design is less well-powered for wind turbine proximity, but better-powered for solar. What is a large effect size can be subjective, but one could imagine that reformers behind the IRA had intended for the majority of people near projects to notice them and credit the Biden Administration.

A respondent's distance to new green investments is not random, so an analysis that correlated proximity and political attitudes could be confounded. The research design takes several steps to approach this challenge. First, the model estimates the effect of within-state variation in green project proximity. This removes confounding from state-level factors, which are strong predictors of where investments occur and, therefore, also predict how close a respondent is to new green projects. States influence investment through tax incentive programs, labor laws, and comparative advantage for green industries [11].

Since certain locations within a state may be more suited for investment, the analysis further controls for individual and county-level factors that could affect project location within states and proximity to new investments, such as the unemployment rate, broadband connectivity, and a respondent's household income. The assumption to interpret the estimates as causal is that a survey-taker's distance to a new project, relative to the state average, is exogenous after conditioning for factors within the state and at the individual level that influence proximity. Consistent with this assumption, there is no correlation between the individual covariates in the analysis and distance to green projects after residualizing state fixed effects and conditioning for the other controls (see Materials and Methods).

Results

Mixed Visibility of Green Projects

Figure 2 reports the effect of proximity to new green investments on the probability that a survey-taker says she's seen a new project in her community. Overall, whether proximity to new investments causes recognition depends on the type of project. Panel A shows the effect of distance to clean electricity generation projects. People who live within 0-15km of new solar farms are 8.1 percentage points more likely than those over 100km away to say that there is a new green project in their community. Very few people in the sample live close to wind farms, but among those who are 25-50km away, they are 7.1 percentage points more likely to believe there is a new green project in their area compared to people over 100km away. There is no effect for proximity battery generators, which have smaller visual footprints than wind and solar farms.

Panel B shows that proximity to battery plants and solar manufacturing facilities does not affect individual recognition of clean energy projects. In contrast, electric vehicle manufacturing plants increase belief in new green projects by up to 9 percentage points compared to people over 100km away. People closer to wind turbine manufacturing projects are 11 percentage points more likely to recognize these projects compared to more distant residents.

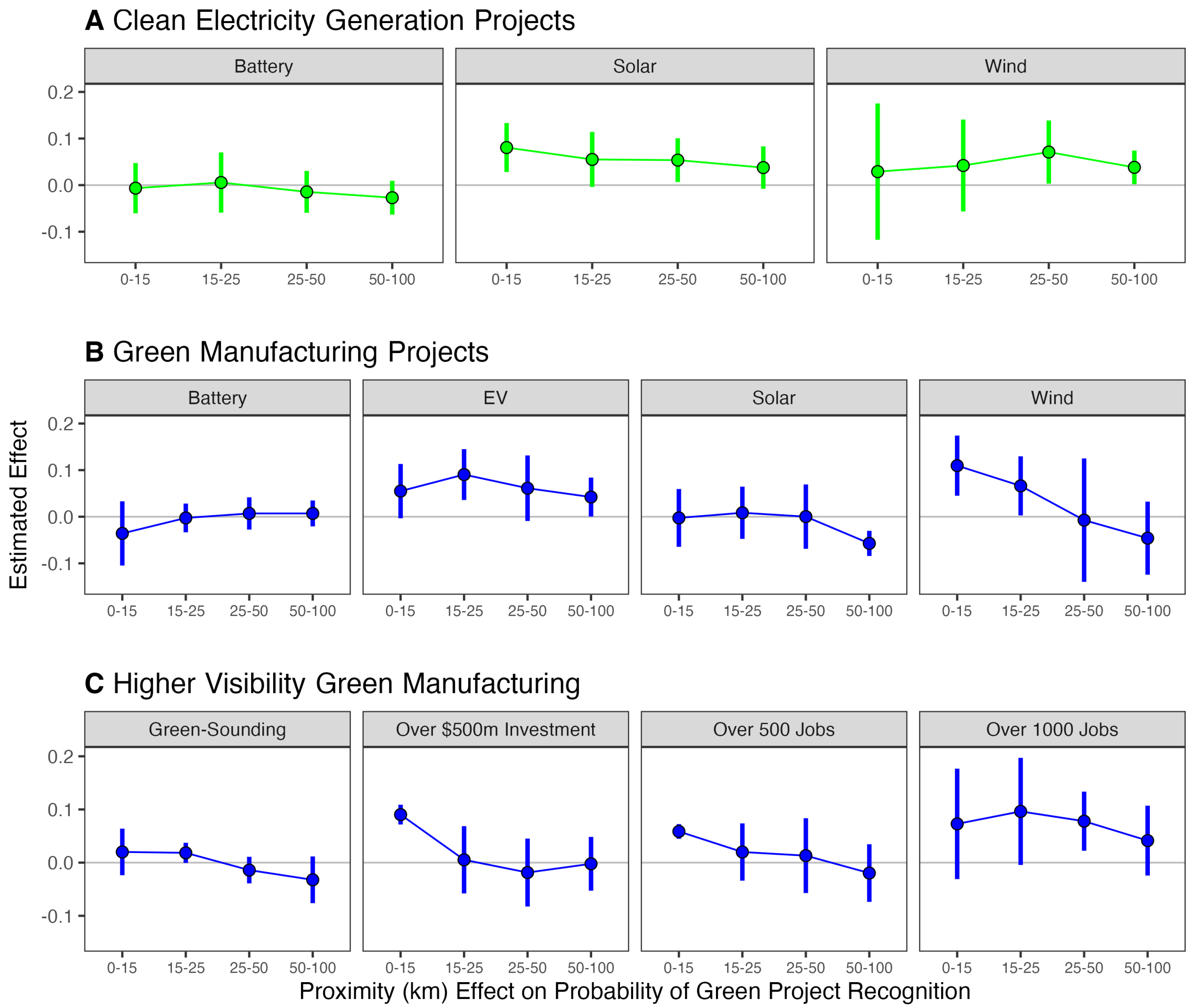

Figure 2: **Proximity effect on green investment recognition.** Estimates are relative to respondents who live +100km from new projects. Bars denote 95% confidence intervals. Estimates come from a linear regression of the recognition indicator on the respondent's distance to new green projects, state fixed effects, and political and economic controls that predict project location. Conley standard errors with a 400km cutoff account for spatial correlation. Panel A reports the effect of proximity to electricity generation projects. Panel B reports the effect of proximity to clean energy manufacturing projects. Panel C reports the effect of proximity to projects with characteristics hypothesized to make investments more visible and associated with green energy.

Visibility Mechanism

Visibility is one potential mechanism behind how proximity increases recognition. We hypothesize that people closer to new green projects are more likely to see them in daily life, such as their commutes, or hear about the investments through local news. This mechanism implies that proximity is more likely to lead to recognition when projects are more noticeable and associated with the clean energy transition. Further, visibility could vary at the individual level. For example, people with stronger incentives to pay attention to economic changes in their community may be more likely to recognize proximate green projects.

We employ various tests of the visibility mechanism. First, we expect that projects with more extensive economic benefits are more visible [5, 20, 21]. Economic benefits could increase visibility through several channels. Politicians might be more likely to call attention to and claim credit for projects that promise to create substantial jobs. Larger investments may also involve more construction that people notice and invite local news coverage. Panel C shows that proximity has a stronger effect on recognition for manufacturing projects with more than $500 million in capital investment and over 500 jobs promised. For projects that promise over 1,000 jobs, proximity increases recognition even for people 15-50km away, a sign of these projects' wider economic footprint.

Second, we hypothesize that recognition is more likely when people see projects with green-sounding names (see Materials and Methods for measurement). These investments may be more associated with clean energy in a respondent's mind, so when she see a project in her community, it is more likely to come to mind when asked about green investments in the survey. "Microvast Battery Manufacturing," for example, sounds more related to the clean energy transition than the "Ford Kansas City Assembly Plant." The first facet of Panel C shows that proximity may have a stronger effect on recognition when people are within 15-25km of projects with green-sounding names.

Third, the visibility mechanism implies that people are more likely to recognize projects in places where their construction is more distinctive relative to the existing economic landscape. Fewer people are likely to notice a new investment in a dense urban place, whereas new developments could be more noticeable in a rural area [19, 27]. We proxy for this facet of investment distinctiveness using population density. People in more population dense areas are less likely to recognize most types of green projects when they are 25-50km away compared to people in more rural areas. This moderating effect holds except for in the case of solar, batteries, green-sounding manufacturing, and projects creating over 1000 jobs. In other words, people in more rural areas do not need to be as close to certain green projects to recognize them (see SI Appendix).

Fourth, green investments could be more visible when built in places with a robust local media presence. Local reporters provide information about these developments to community members, facilitating recognition. Local news is a critical intermediary that informs residents of changes in their community and their connection to national politics [28, 29]. The media also shapes how the public assigns responsibility for economic news in general [30]. Indeed, we find that proximity has weaker effects on green project recognition in places with limited local news. This weaker effect occurs for wind energy, battery manufacturing, solar manufacturing, wind manufacturing, and projects with large capital investments and job creation (SI Appendix).

Lastly, green projects are likely most visible to people with more motivation to pay attention to the local labor market because these investments could be a source of employment. Aligning with this hypothesis, proximity sometimes has a stronger effect on recognition for people who are in the workforce, especially for projects that create numerous jobs (SI Appendix). Together, these five findings are generally consistent with visibility as the mechanism behind proximity's relationship with the public's recognition of green projects. There are several instances where the hypothesized interaction effect doesn't appear, though it is often for green projects that the public was unlikely to recognize because of their low profile, such as battery generators.

Political Heterogeneity

Attitudes about climate change polarize along partisan lines in the United States [31], so there could be differences in how project proximity affects whether Democrats, Republicans, and Independents recognize green investments [32]. However, the respondent's partisanship has no consistent moderating effect on proximity's relationship with recognition. For example, proximity to wind turbines

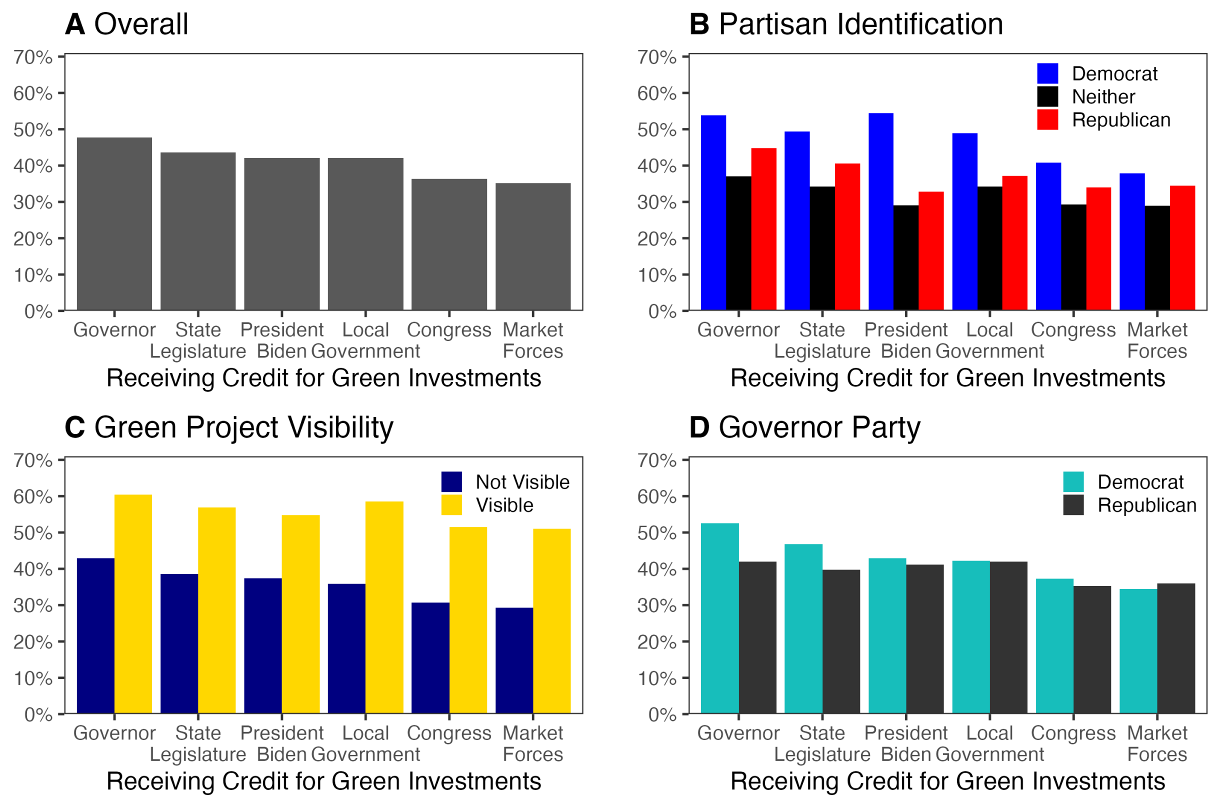

Figure 3: **Credit attribution for new green investments in respondent's state.** The y-axis shows the percent of respondents who thought that the credit recipient on the x-axis is "very" or "extremely" responsible for new green investments in the state. Samples collected March 14–April 9 and August 6-November 11, 2024 ($N = 3{,}034$). Panel A shows credit attribution across the entire sample. Panel B shows how credit attribution varies by the respondent's partisan identification. Panel C shows how responses vary depending on whether respondents believe there is a new green project in their communities or not. Panel D shows how credit attribution varies depending on the political party of the respondent's governor.

and battery manufacturing is more likely to lead Independents to recognize green projects compared to Democrats. For Republicans, proximity to solar manufacturing has weaker effects on attitudes, whereas proximity to wind manufacturing and high job-creating projects has stronger effects compared to Democrats.

Governor partisanship also does not consistently moderate the effect of proximity. When it does, it appears that respondents in Republican-led states may be less likely to recognize wind turbines but more likely to notice battery manufacturing, EV manufacturing, wind manufacturing, green-sounding projects, and job-creating projects. Governor partisanship does not inhibit the public from seeing new clean energy projects (SI Appendix).

Mixed Credit Attribution

Recognition of new projects matters for politics if it affects beliefs about who is responsible for new investments. We find that proximity to green investments has no consistent relationship with credit attribution. Proximity to new battery generators, solar panels, or wind turbines has no effect on crediting President Biden for green investments. The same is true for battery manufacturing, electric vehicle manufacturing, and solar manufacturing. The only exception is wind manufacturing, where closer respondents are more likely to credit President Biden, the US Congress, and local politicians. The overall pattern, however, is no relationship between proximity and credit attribution (SI Appendix contains results). Visibility does not imply traceability. People can see economic changes from green investments but generally do not give more credit to the federal government.

One explanation for the absence of a relationship between proximity and credit attribution is that most people, regardless of distance, see the federal government and Democratic Party as responsible for these investments because of their issue ownership over the environment [9, 26].

Credit attribution, however, varies across the national public, irrespective of their proximity to new green investments. Figure 3 shows that the state governor receives the most credit, with 48% of American adults saying that the governor is very or extremely responsible for new green investments. In contrast, 42% say that President Biden is responsible, 6 percentage points less than the governor ($p < .001$). Congress and market forces receive the least credit.

Respondents of all political backgrounds—Democrats, Republicans, and Independents—all give the most credit to the governor. There are differences in credit attribution across partisans once accounting for the political party of their governor. Democrats are 24% less likely than Republicans to credit the governor when the governor is Republican (SI Appendix contains results).

Democratic respondents are 17% more likely to credit Biden than Republicans ($p < .001$). However, only 54% of Democrats say that Biden is very or extremely responsible for new green investments in their state.

Mixed Credit Signals

We examine causal complexity as one reason why the public does not credit federal government officials for green investments. For credit-claiming to work as envisioned by policy feedback theory, the public must be able to trace the local changes back to specific federal policies. If there are competing claims to credit, voters may struggle to attribute responsibility for new investments. We predict that there will be a mixed information environment because state and local politicians also claim credit for projects [10].

We test whether political actors send conflicting messages by collecting new data on investment announcements. While this analysis does not directly evaluate the effect of conflicting messages on the public's attitudes, existing research in political science provides a firm foundation to predict that in the presence of a mixed information environment, voters struggle to allocate credit. Multiple studies show how the "traceability" of government policy [19, 21–24] and the "clarity of responsibility" influence when policies affect political attitudes, candidate evaluations and voting [33–38].

To measure the information environment, we construct a database of press releases accompanying new green investments. These press releases come primarily from companies. There are also some statements from state and local economic development officials. The data cover investments made as part of the electric vehicle assembly and the supply chain, which was a focus of the IRA. These manufacturing projects often have a sizable economic effect and are, therefore, the most likely cases for politicians to attempt to claim credit [10]. The local media often reports on the announcements, so they are also more visible to the public [39]. Credit statements in business press releases may be particularly influential in political attitudes because companies could be seen as relatively less political than elected leaders, so the public is more receptive to these messages [40]. Our research team coded who or what, if anything, received credit in these statements (see Materials and Methods).

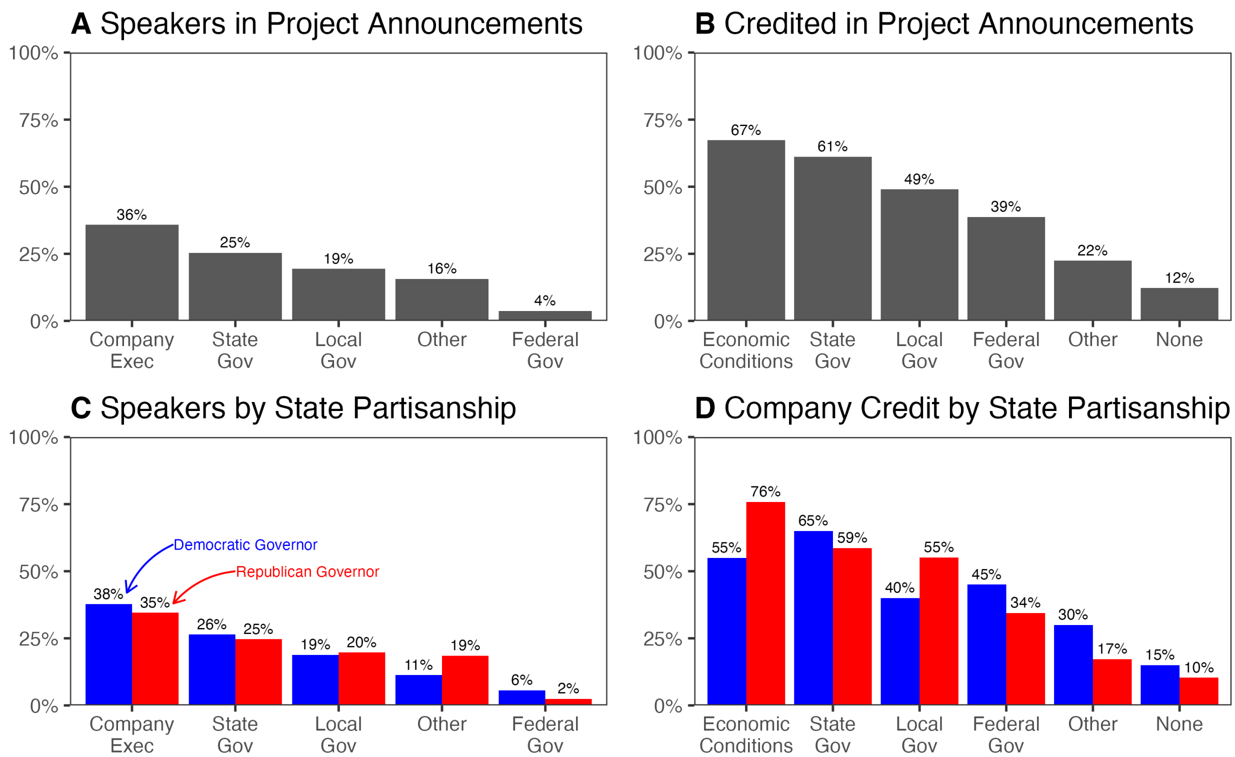

Figure 4: **Credit attribution in electric vehicle supply chain project announcements, 2022–2024.** Data cover 66 unique projects after the IRA's passage on August 16, 2024. Panel A shows the frequency with which a political actor appears in press releases accompanying a new investment. Panel B shows the frequency with which a political actor or factor receives credit for a project. Panel C shows the speaker frequency for projects in Democrat- and Republican-led states. Panel D shows the credit frequency in Democrat- and Republican-led states.

Figure 4 first shows the frequency with which specific speakers, such as state officials like the governor or federal officials like a Senator, appear in project announcements. If someone's name appears in a project announcement, that typically means they were at the groundbreaking ceremony for the event or made a statement to be included in the company's press release. Panel A shows that the most frequently mentioned speaker in project announcements is the company executive. The second most frequent is a representative from the state government, who typically is the governor. Only 4% of press releases mention federal government officials, such as the President. Panel C shows there are no significant differences in what political actors appear in a press release across Republican and Democratic-led states. Regardless of state partisanship, voters in places with new electric vehicle investments are more likely to see or read about the involvement of state rather than federal politicians.

Figure 4 also shows the frequency with which investment announcements offer an explicit reason for why the project happened. Over half of the projects mentioned an area's economic conditions, such as workforce quality and manufacturing comparative advantages. A majority of the statements (61%) also name the state government's policies as an influential factor in causing the investment. In contrast, only 39% of statements credit federal government policies.

There are not large partisan differences in credit allocation across Democrat- and Republican-governed states. There is no detectable difference in credit allocated to the federal government.

Press releases in Republican-led states are 21 percentage points more likely to mention economic conditions, but this difference isn't precise ($t = 1.46$). In general, credit allocation is similar regardless of the governor's partisanship.

Discussion

The results show that people recognize new green investments, but this recognition does not affect whether they credit federal government policy. Instead, the public primarily credits state officials such as the governor and state legislature. Simultaneously, it is also these political actors who are most likely to appear in project announcements and receive credit from the businesses making green investments.

How the public attributes credit matters for the political shift to green industrial policy. These reforms aim to provide an electoral incentive for politicians to back green investments and sustain these policies. If elected officials do not receive credit, they will be less likely to find it in their interest to pass climate policies. The lack of credit also means that local communities that benefit from these projects could be less likely to mobilize to protect these industries against the threat of repeal of federal policies.

Credit claiming by state and local officials may contribute to the limited public acknowledgment of the federal government's role in incentivizing green investments. While this analysis does not directly link individual beliefs to business messages, we find that companies, are more likely to credit state and local officials. These company statements may be influential in individual opinion formation because businesses could be seen as more apolitical, and thus, their messages are more likely to be received than those sent by partisan politicians [40]. A barrier to policy feedback effects from complex green investments is that businesses and local politicians often do not credit national policies. They take credit for themselves.

While some scholars question whether voters have the capacity to incorporate information [41], we interpret these results as consistent with a model where voters are competent within constraints [19]. Economists, let alone voters, face challenges in beginning to quantify the contribution of the IRA to new green investments. These projects depend on a host of actors and forces, including state and local tax incentives. Therefore, it is not automatic to expect that ordinary people would credit federal investments, even if they had complete information. These results are consistent with voters responding based on readily accessible information from their surroundings, including what they can see for themselves and read in the local news.

While the survey data allow us to explore the recognition of and credit for green projects, future research should collect panel data. Repeated observations of the same respondents would allow an analysis of how opinions evolve in response to green projects. While we collected large national samples of the public, follow-on studies should also consider over-sampling respondents who live next to new green projects. This would allow for a more robust examination of heterogeneity by the type of clean energy project. For example, our analysis of the effects of proximity to wind turbines is more limited because there are fewer respondents in the sample near these installations, unlike other project types in the data.

Our findings have implications for the design of durable climate policies. Green investments involve multiple political actors, all of which have incentives to claim credit for economic benefits. While green investments can lead the public to notice these projects, the political benefits of the reforms are unlikely to flow back to those responsible. Still, policymakers could attempt to find ways to enhance the traceability of their involvement, such as signs and attendance at ribbon cuttings, but whether these strategies work is an empirical question, and there's a risk they could backfire.

The results could also help understand decarbonization pathways. Energy system modelers have begun to incorporate politics and human behavior into models to better capture the relationship between politics and the clean energy transition [42]. These endeavors require micro-founded models of political dynamics, such as policy feedback effects. The results here indicate that when energy models attempt to represent the public, they should also consider policy traceability, which may influence whether feedback effects take root. Alternatively, political representations in models could emphasize interest group dynamics, institutions [43], or clean technology adoption.

The findings also speak to the political prospects of the IRA's green investments under changing political administrations. Policy opponents often seek to reverse reforms [44–47], and the IRA is no exception [48]. Reformers cannot count on public opinion to lock in the IRA.

The results also point to the need for studies on alternative ways green reforms could deter repeal attempts. Reformers could rely on businesses to defend their economic stake in the clean energy transition. This was already part of the logic of green industrial policy and should receive renewed focus. Scholars should study whether and when businesses lobby to defend green tax credits if the federal government tries to shut down existing projects. In the scenario where companies face losses, they may be more willing to publicly credit the government's policies, despite not doing so before when the investment did not appear under threat.

The same loss aversion logic could apply to public opinion. While the mass public did not initially credit the federal government's investments, attempts to block projects could spark blowback. If investments come under threat, people could receive new information and mobilize. Indeed, the threat of loss is one mechanism for how political reforms can affect mass opinions [23]. Overall, our findings point to the urgent need to rethink political strategies to mobilize mass support for the clean energy transition.

Materials and Methods

Data and Measurement

Sampling

We fielded three national online surveys of American adults in 2024 with Qualtrics. The surveys ran from March 14–April 9 (N = 1,500), May 13–June 6 (N = 1,992), and August 6–November 11 (N = 1,534). There are 5,026 respondents in total after applying the data quality protocol described in the SI Appendix. The survey employed nationally representative quotas for age, sex, race, education, income, and region.

Geolocating Respondents

The respondent's location is inferred from the longitude and latitude coordinates associated with self-reported ZIP codes. For respondents without reliable ZIP codes ($< 1\%$), geo-coordinates come from their Internet Protocol (IP) address. The results are robust when including only respondents whose ZIP code geo-coordinates match those implied by IP addresses (SI Appendix).

Green Investment

The analysis employs multiple sources of green project-level data with longitude and latitude coordinates. The projects include clean electricity and manufacturing. The projects analyzed have begun construction in the two years before the survey date to align with the post-IRA period and because construction is more visible. It is challenging to determine whether a specific project would have happened without the IRA, but such investments became more likely after the policy [49].

Clean electricity data comes from EIA-860M company disclosures required under federal regulations. The dataset is a complete census of generators that produce at least 1 megawatt of electricity. These projects include solar, wind, and batteries. The IRA expanded investment and production tax credits for clean electricity resources, which is projected to result in 31 GW/year more solar and wind deployment compared to a scenario with no new policy [49].

Clean energy manufacturing projects come from the Big Green Machine dataset created by James Turner at Wellesley College. These data are compiled from public sources, such as company press releases and news articles. The analysis excludes rumored, closed, and canceled projects, along with those lacking a project announcement date. Several provisions in the IRA, such as the Advanced Manufacturing Production Credit and Advanced Energy Project Credit, incentivized solar, wind, battery, and critical mineral manufacturing projects.

We used large language models to classify the "green-soundingness" of manufacturing projects. This concept refers to whether a typical person would consider the project and company name as related to clean energy. SI Appendix describes the coding protocol and validation checks.[1]

Credit Claiming

We collected a database of company press releases about electric vehicle and battery manufacturing projects identified in the Big Green Machine Database. This comprehensive database covers the universe of EV supply chain investments in the United States. Of 122 unique projects, our research assistants found press releases for 111 (91%). The text of the press releases was processed with automated web scrapers and manual extraction. A research assistant annotated each press release, coding who spoke, whether the speaker gave credit for the project, and, if so, whom they credited (SI Appendix describes the coding protocol).

Proximity Analysis

The primary analysis estimates the effect of proximity to green projects 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.

Our approach leverages within-state variation in proximity to green projects. The assumption is that the within-state deviation in a survey-taker's distance to clean energy projects is plausibly random after controlling for individual and county-level covariates that predict site selection. 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, median housing costs, population density, broadband access, and 2024

[1]We are still refining this annotation protocol to reduce prediction error.

Democratic vote share. Individual-level controls include age, sex, race, education, labor force participation, income, party identification, and global warming beliefs.

We estimate the following linear regression model:

$$Y_i = Distance_i\beta_1 + \boldsymbol{X}'\boldsymbol{\beta} + State_i + \epsilon_i.$$

Y is the outcome, a binary indicator for whether a respondent says there is a new green energy project in her community.

Distance is a categorical variable that records whether the respondent is between 0-15km, 15-25km, 25-50km, 50-100km, or over 100km away from a new clean energy project. Figure 1 illustrates these bandwidths, which were selected to correspond with how far people typically travel and allow for non-linearities in the relationship between distance and political attitudes.

$\boldsymbol{X}$ contains the covariates described above. The regression models control for the sample wave to account for survey design artifacts or information environment changes. *State* represents the fixed effects.

Conley standard errors adjust for spatial dependence in respondent distance to new green projects [50]. The results are robust to using various distance cutoffs (SI Appendix).

Credit Attribution

The question measuring credit attribution asks respondents to assess each factor independently. This is because there are multiple factors that could cause green investments, which could not be adequately captured in a bipolar where, for example, the survey-taker was asked whether Biden or the governor was most responsible. We also preferred the independent items to a "divide the dollar" measure because people do not have accessible numerical quantities corresponding with credit. The analysis at the individual level allows us to retrieve relative credit assessments. The SI Appendix describes several checks of the question's internal validity.

Data Availability

Scripts and data for analysis will be made available on the Harvard Dataverse.

References

[1] Congressional Budget Office. *The Budget and Economic Outlook: 2024 to 2034*. Tech. rep. 2024.

[2] Danny Cullenward and David G. Victor. *Making Climate Policy Work*. Polity Press, 2021.

[3] James Meadowcroft and Daniel Rosenbloom. "Governing the Net-Zero Transition: Strategy, Policy, and Politics." In: *Proceedings of the National Academy of Sciences* 120.47 (2023), e2207727120.

[4] Alexander F. Gazmararian, Matto Mildenberger, and Dustin Tingley. "Public Opinion Foundations of the Clean Energy Transition." Unpublished Manuscript. Princeton University, 2023.

[5] Paul Pierson. "When Effect Becomes Cause: Policy Feedback and Political Change." In: *World Politics* 45.4 (1993), pp. 595–628.

[6] Jonas Meckling and Jonas Nahm. “Strategic State Capacity: How States Counter Opposition to Climate Policy.” In: *Comparative Political Studies* 55.3 (2022), pp. 493–523.

[7] Leah Stokes. *Short Circuiting Policy: Interest Groups and the Battle Over Clean Energy and Climate Policy in the American States*. Oxford University Press, 2020.

[8] Jonas Meckling, Thomas Sterner, and Gernot Wagner. “Policy Sequencing toward Decarbonization.” In: *Nature Energy* 2.12 (2017), pp. 918–922.

[9] David Karol. *Red, Green, and Blue: The Partisan Divide on Environmental Issues*. Elements. Cambridge University Press, 2019.

[10] Nathan M. Jensen and Edmund Malesky. *Incentives to Pander: How Politicians Use Corporate Welfare for Political Gain*. Cambridge University Press, 2018.

[11] Timothy J. Bartik. *Making Sense Of Incentives: Taming Business Incentives to Promote Prosperity*. Upjohn Institute, 2019.

[12] Daniel J. Hopkins. *Stable Condition: Elites' Limited Influence on Health Care Attitudes*. New York: Russell Sage Foundation, 2023.

[13] Sarah F. Anzia, Jake Alton Jares, and Neil Malhotra. “Does Receiving Government Assistance Shape Political Attitudes? Evidence from Agricultural Producers.” In: *American Political Science Review* 116.4 (2022), pp. 1389–1406.

[14] Douglas L. Kriner and Andrew Reeves. “The Influence of Federal Spending on Presidential Elections.” In: *American Political Science Review* 106.2 (2012), pp. 348–366.

[15] Karl Magnus Møller. *Big Investments, No Electoral Reward: The Inflation Reduction Act, Low-Carbon Investments, and the 2024 US Presidential Election*. 2025.

[16] Stephen Ansolabehere, Marc Meredith, and Erik Snowberg. “Mecro-Economic Voting: Local Information and Micro-Perceptions of the Macro-Economy.” In: *Economics & Politics* 26 (2014), pp. 380–410.

[17] Andrew Reeves and James G. Gimpel. “Ecologies of Unease: Geographic Context and National Economic Evaluations.” In: *Political Behavior* 34.3 (2012), pp. 507–534.

[18] Daniel J. Hopkins. “Politicized Places: Explaining Where and When Immigrants Provoke Local Opposition.” In: *American Political Science Review* 104.1 (2010), pp. 40–60.

[19] Alexander F. Gazmararian. “Sources of Partisan Change: Evidence from the Shale Gas Shock in American Coal Country.” In: *The Journal of Politics* Forthcoming (2024).

[20] Hunter E. Rendleman and Jesse Yoder. “Do Government Benefits Affect Officeholders' Electoral Fortunes? Evidence from State Earned Income Tax Credits.” In: *American Political Science Review* (2024), pp. 1–18.

[21] Andrea Louise Campbell. “Policy Makes Mass Politics.” In: *Annual Review of Political Science* 15.1 (2012), pp. 333–351.

[22] R. Douglas Arnold. *The Logic of Congressional Action*. Yale University Press, 1990.

[23] Daniel Béland, Andrea Louise Campbell, and R. Kent Weaver. “Policy Feedback: How Policies Shape Politics.” In: *Elements in Public Policy* (2022).

[24] Brian T. Hamel. “Traceability and Mass Policy Feedback Effects.” In: *American Political Science Review* (2024), pp. 1–16.

[25] Suzanne Mettler. *The Submerged State: How Invisible Government Policies Undermine American Democracy*. University of Chicago Press, 2011.

[26] Patrick Egan and Megan Mullin. “Turning Personal Experience into Political Attitudes: The Effect of Local Weather on Americans’ Perceptions about Global Warming.” In: *Journal of Politics* 74.3 (2012), pp. 796–809.

[27] James Bisbee. “What You See Out Your Front Door: How Political Beliefs Respond to Local Trade Shocks.” Unpublished Manuscript. 2024.

[28] Megan Mullin and Katy Hansen. “Local News and the Electoral Incentive to Invest in Infrastructure.” In: *American Political Science Review* 117.3 (2023), pp. 1145–1150.

[29] Danny Hayes and Jennifer L. Lawless. *News Hole: The Demise of Local Journalism and Political Engagement*. Cambridge University Press, 2021.

[30] Diana Mutz. “Contextualizing Personal Experience: The Role of Mass Media.” In: *Journal of Politics* 56.3 (1994), pp. 689–714.

[31] Patrick Egan and Megan Mullin. “Climate Change: US Public Opinion.” In: *Annual Review of Political Science* 20.1 (2017), pp. 209–227.

[32] Thomas J. Rudolph. “Triangulating Political Responsibility: The Motivated Formation of Responsibility Judgments.” In: *Political Psychology* 27.1 (2006), pp. 99–122.

[33] Kevin Arceneaux. “The Federal Face of Voting: Are Elected Officials Held Accountable for the Functions Relevant to Their Office?” In: *Political Psychology* 27.5 (2006), pp. 731–754.

[34] G. Bingham Powell and Guy D. Whitten. “A Cross-National Analysis of Economic Voting.” In: *American Journal of Political Science* 37.2 (1993), pp. 391–414.

[35] Thomas J. Rudolph. “Institutional Context and the Assignment of Political Responsibility.” In: *The Journal of Politics* 65.1 (2003), pp. 190–215.

[36] Thomas J. Rudolph. “Who’s Responsible for the Economy? The Formation and Consequences of Responsibility Attributions.” In: *American Journal of Political Science* 47.4 (2003), pp. 698–713.

[37] Michael W. Sances. "Attribution Errors in Federalist Systems: When Voters Punish the President for Local Tax Increases." In: *Journal of Politics* 79.4 (2017), pp. 1286–1301.

[38] Timothy Hellwig and David Samuels. "Voting in Open Economies: The Electoral Consequences of Globalization." In: *Comparative Political Studies* 40.3 (2007), pp. 283–306.

[39] Lynne Masel Walters and Timothy N. Walters. "Environment of Confidence: Daily Newspaper Use of Press Releases." In: *Public Relations Review* 18.1 (1992), pp. 31–46.

[40] James N Druckman. "A Framework for the Study of Persuasion." In: *Annual Review of Political Science* (2022).

[41] Larry M. Bartels. *Unequal Democracy: The Political Economy of the New Gilded Age*. 2nd. Princeton University Press, 2016.

[42] Wei Peng et al. "Climate Policy Models Need to Get Real about People — Here's How." In: *Nature* 594.7862 (2021), pp. 174–176.

[43] Gokul C. Iyer et al. "Improved Representation of Investment Decisions in Assessments of CO2 Mitigation." In: *Nature Climate Change* 5.5 (2015), pp. 436–440.

[44] Eric Patashnik and Julian Zelizer. "The Struggle to Remake Politics: Liberal Reform and the Limits of Policy Feedback in the Contemporary American State." In: *Perspectives on Politics* 11.4 (2013), pp. 1071–1087.

[45] Alan M. Jacobs and R. Kent Weaver. "When Policies Undo Themselves: Self-Undermining Feedback as a Source of Policy Change." In: *Governance* 28.4 (2015), pp. 441–457.

[46] Eric Patashnik. *Countermobilization: Policy Feedback and Backlash in a Polarized Age*. University of Chicago Press, 2023.

[47] Barry George Rabe. *Can We Price Carbon?* American and Comparative Environmental Policy. Cambridge, MA: MIT Press, 2018.

[48] Alexander F. Gazmararian and Dustin Tingley. *Uncertain Futures: How to Unlock the Climate Impasse*. Cambridge University Press, 2023.

[49] John Bistline et al. "Emissions and Energy Impacts of the Inflation Reduction Act." In: *Science* 380.6652 (2023), pp. 1324–1327.

[50] T. G. Conley. "GMM Estimation with Cross Sectional Dependence." In: *Journal of Econometrics* 92.1 (1999), pp. 1–45.

Supplemental Information:
Who Gets Credit for Green Industrial Policy?

A Data and Measurement

A.1 Summary Statistics

Table A1: Summary Statistics

	Mean	SD	Min	Max	NA
Sees New Green 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	0.18	0.39	0	1	0
High school or less	0.27	0.44	0	1	0
Some college	0.38	0.48	0	1	0
Bachelor's or more	0.36	0.48	0	1	0
Employed or looking for work	0.65	0.48	0	1	0
Income Q1	0.18	0.39	0	1	0
Income Q2	0.18	0.39	0	1	0
Income Q3	0.21	0.41	0	1	0
Income Q4	0.12	0.33	0	1	0
Income Q5	0.3	0.46	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	1.6	17	0
Labor force (log)	12	1.6	6.9	15	0
GDP (log)	17	1.8	11	21	0
Income per capita	42332	17664	12744	131902	0
Highway access	0.93	0.26	0	1	0
College share	0.34	0.11	0.057	0.66	0
Poverty share	0.18	0.066	0.03	0.6	0
Median monthly housing cost	1414	479	393	3049	0
Population density	734	1072	0.73	5630	0
Broadband: 0-400	0.046	0.21	0	1	0
Broadband: 600-800	0.63	0.48	0	1	0
Broadband: >800	0.13	0.34	0	1	0
Democratic presidential vote share	0.5	0.16	0.08	0.93	0

Notes: Summary statistics across all survey samples. Analyses standardize continuous county-level measures with the within-state variance. $N = 5{,}026$

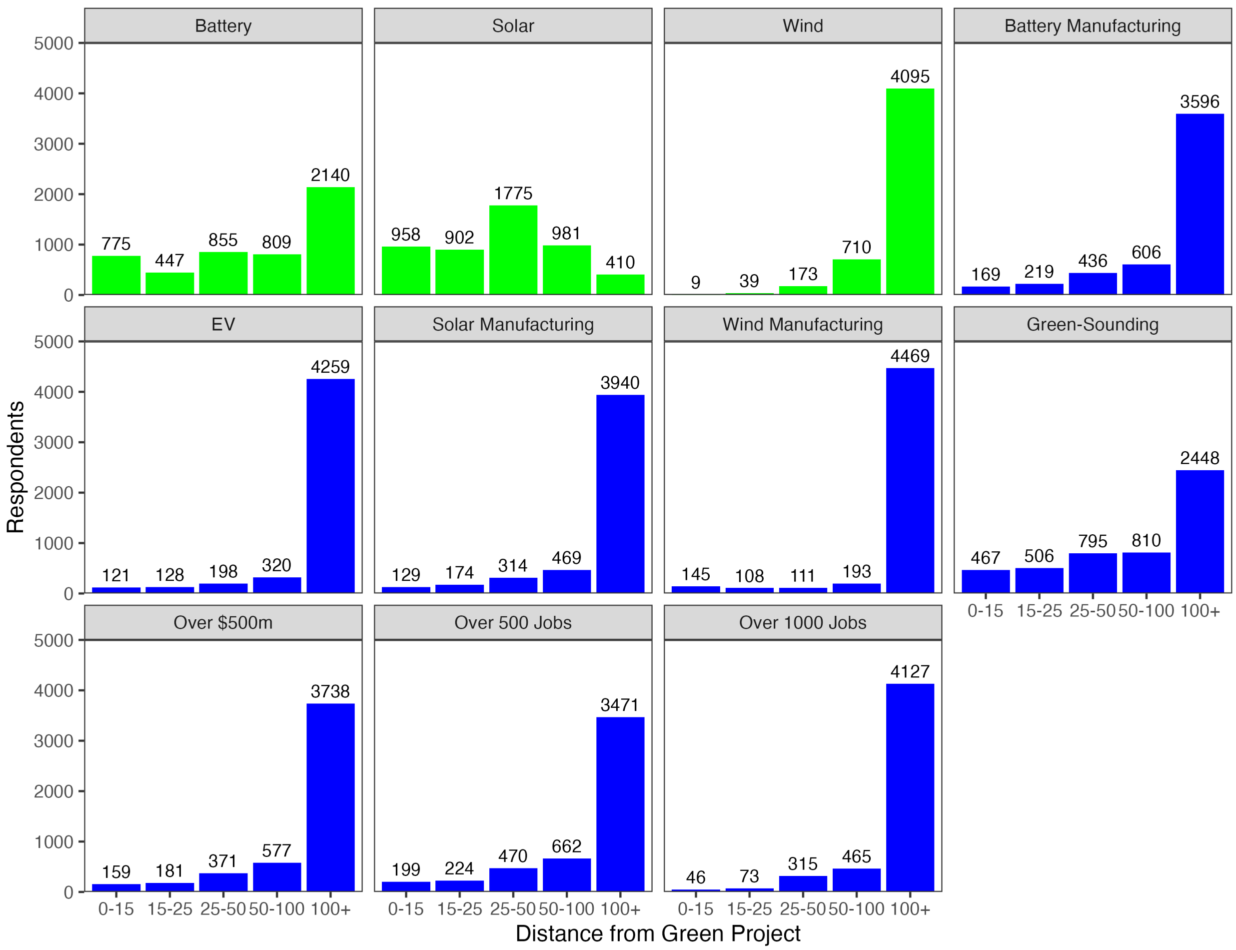

Figure A5: Survey-Respondent Proximity to Green Projects with Analysis Cutoffs

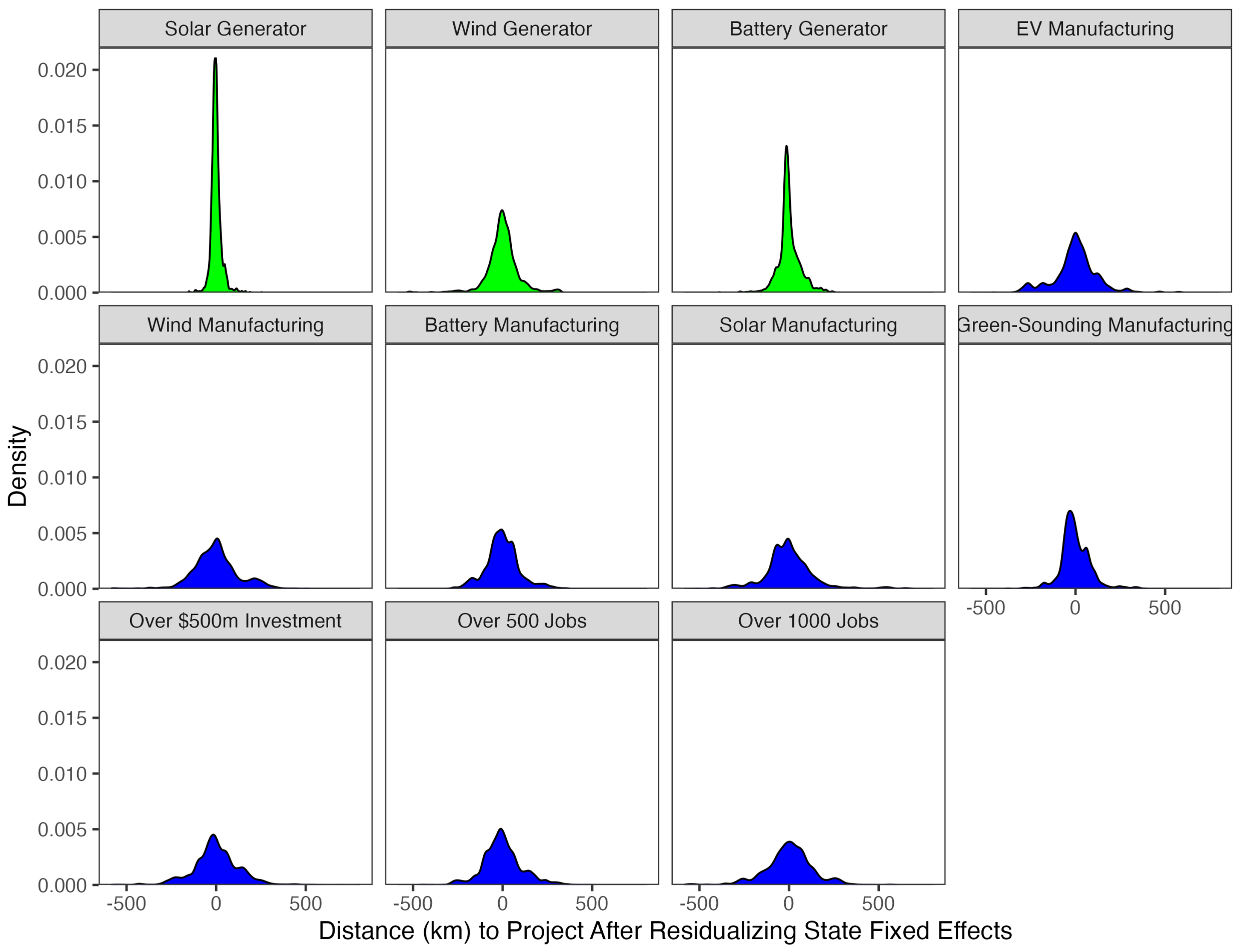

Figure A6: Within-State Variation in Green Project Proximity

A.2 Data Sources

Variable	Source and Description	URL
Clean energy generation	Monthly EIA-860M form. This form reports the status of existing and proposed generating units with 1mw or greater combined nameplate capacity. Reporting is required for proposed new generators that are scheduled to begin commercial operation within the next 12 months. Timely reporting is required by law and sanctioned by civil penalties.	https://www.eia.gov/electricity/data/eia860m/
Clean energy manufacturing	The Big Green Machine dataset maintained by Jay Turner at Wellesley College. The dataset covers the North American clean energy supply chain from mine to factory.	https://www.the-big-green-machine.com
Democratic vote share	David Leip's Atlas of U.S. Presidential Elections. Data cover the 2024 election. Alaska reports election results at the district rather than county level, so we calculate the population-weighted county vote share, merging across the district and county shapefiles.	https://uselectionatlas.org
Governor party	Ballotpedia	https://ballotpedia.org/Governor_%28state_executive_office%29
County newspapers	The State of Local News Project dataset as of 1/21/2025.	https://localnewsinitiative.northwestern.edu/projects/state-of-local-news/
Unemployment	2023 annual average county-level data from the Bureau of Labor Statistics. 2024 annual data was not available at the time of analysis.	https://www.bls.gov/lau/tables.htm#mcounty
Labor force size	2023 annual average county-level data from the Bureau of Labor Statistics.	https://www.bls.gov/lau/tables.htm#mcounty
Gross domestic product	County-level real GDP in chained dollars for 2023 across all industries from the Bureau of Economic Analysis (CAGDP9).	https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas
Per capita income	County-level personal income per capita in 2023 from the Bureau of Economic Analysis (CAINC30).	https://apps.bea.gov/regional/downloadzip.htm
Highway access	Highway data from the TIGER/Line shapefiles for U.S. Primary Roads. Data are subset to interstate highways. Intersection is calculated with county boundaries and a binary indicator constructed for whether a county intersects with an interstate or not.	https://catalog.data.gov/dataset/tiger-line-shapefile-2023-nation-u-s-primary-roads
Share of county residents with college degree or more	2023 5-Year American Community Survey (B06009_005)	Census API
Share of county residents under poverty line	2023 5-Year American Community Survey (B06012_002)	Census API

Variable	Source and Description	URL
Median housing costs	2023 5-Year American Community Survey (B25105_001).	Census API
Population density	Calculated by aggregating 1km gridded population data to 25km circles around each survey respondent's longitude-latitude location. Population data from WorldPop.	https://hub.worldpop.org
Broadband access	County-level data from the FCC Form 477. Internet Access Services Speed Tier Data From June 30, 2014 to December 31, 2023. Variable uses Tier 4, which is residential fixed broadband connections with a downstream speed of at least 100 Mbps because this is most relevant for businesses. We combine the 0-200 and 200-400 categories into 0-400.	https://www.fcc.gov/form-477-county-data-internet-access-services
Electricity prices	State-level. EIA Table 5C, covering 2023 prices for industrial users. Average price in cents per kilowatt hour.	https://www.eia.gov/electricity/sales_revenue_price/
Unionization rates	State-level. 2023 data covering private sector unions [1].	https://www.unionstats.com

A.3 Project Greenness Coding

Project name annotation was done using LLMs. LLMs can perform deductive coding with inter-coder agreement comparable to human coders [2, 3], and can outperform humans in certain tasks [4].

We used the gpt-4o-mini model from OpenAI. This is currently OpenAI's most cost-efficient small model, scoring 82% on MMLU. The temperature parameter was 0.5.

ChatGPT received the following codebook instructions:

> You are a research assistant who is annotating clean energy project names.
>
> To code a project, do the following. First, read the codebook and the project name with its company. Next, decide which code is most applicable.
>
> Codebook:
>
> Green sounding: The project and company name would sound to an ordinary person like it is related to clean technology or the green energy transition.
>
> Here are examples:
>
> Ohio I, First Solar: Yes;
>
> Flender Corporation Manufacturing Facility, Flender Corporation: No;
>
> EBOS Facility, Shoals Technologies: No;
>
> Lake Mead Facility, Lithion Battery Inc: Yes;
>
> GTI Goodyear Facility, GTI Fabrication: No;
>
> Golden Eagle, Maxeon: No.
>
> Here is the project and company name to code: [insert project and company name]
>
> Answer only 'Yes' or 'No'.

The input text included both the name of the project and the company.

A.3.1 Validation

To assess the reliability of the results, we ran 30 independent iterations. The Fleiss' Kappa for interrater agreement is .922 across the runs, which indicates almost perfect agreement [5]. This suggests that the LLM predictions are internally reliable despite the temperature parameter allowing for non-deterministic outcomes. Although the predictions are consistent in this limited test, this does not rule out the possibility of prediction errors.

A.3.2 Summary Statistics

Table A3 describes the frequency with which different projects are labeled as green-sounding.

Table A3: Project Green–Soundingness

Sector	N	Green	%
Batteries	134	113	84
EVs	56	25	45
Solar	60	46	77
Wind	24	18	75

Table A4: 20 Randomly Selected Annotations

Project Name	Company	Green
Kia West Point Assembly Plant	Kia	No
Raymond Binghamton Facility	The Raymond Corporation	No
TMEIC Brookshire Facility	TMEIC	No
Staubl California Facility Expansion	Staubli	No
Sewon Manufacturing	Sewon America	No
GTI Goodyear Facility	GTI Fabrication	No
Greenville Bus Manufacturing Facility	Phoenix Motor	No
Mack Trucks Roanoke Facility	Mack Trucks	No
Golden Eagle	Maxeon	No
NVH Korea	NVH Korea	No
Trina Solar Texas PV Plant	Freyr Battery	Yes
Skanska South Brooklyn Marine Wind Port	Skanska	Yes
Forge Nano North Carolina Battery Facility	Forge Nano	Yes
Electrovaya US Gigafactory	Electrovaya	Yes
Envision AESC South Carolina Plant	Envision AESC	Yes
Silfab South Carolina	Silfab Solar	Yes
Enel USA Gigafactory	Enel North America	Yes
Hyundai SK Battery Facility	Hyundai, SK	Yes
Solar Components Manufacturing Facility	Hemlock Semiconductor Operations	Yes
LiCAP Technologies California Battery Factory (Expansion?)	LiCAP Technologies	Yes

B Survey

B.1 Sample Summaries

Table B5: Survey Sample Summaries

	2024 Field Date		
	3/14–4/9	5/13–6/6	8/6–11/11
Age	47	49	49
Female	0.54	0.52	0.52
Black	0.14	0.14	0.13
Asian	0.043	0.057	0.055
Other race	0.072	0.087	0.067
Hispanic	0.19	0.18	0.18
High school or less	0.24	0.27	0.28
Some college	0.38	0.37	0.37
Bachelor's or more	0.37	0.35	0.35
Employed or looking for work	0.68	0.64	0.63
Income Q1	0.18	0.18	0.18
Income Q2	0.19	0.18	0.18
Income Q3	0.2	0.21	0.21
Income Q4	0.12	0.12	0.12
Income Q5	0.31	0.3	0.3
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 Survey Instrument

The survey instrument below groups questions thematically. The question order varies slightly across the samples. The question about recognition always came before the credit question to avoid priming respondents to think there were green projects in their communities.

B.2.1 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.2.2 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.2.3 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.2.4 Recognition

18. In the last year, have there been any green investments in your community? Examples include wind and solar farms, and plants to build electric cars or batteries.

    Yes; No; Not sure

B.2.5 Credit

19. Your state has seen an increase in green investments. Examples include wind and solar farms, and plants to build electric cars. Who or what do you think has played a significant role in bringing these investments to your state? For each option, please rate how responsible you believe they are for attracting these green investments.

    - President Joe Biden [Programming: randomize row order]
    - The US Congress
    - Your Governor
    - Your state legislature
    - Community leaders
    - The free market

    Extremely responsible; Very responsible; Moderately responsible; Not too responsible; Not at all responsible

B.3 Geo-Locating Respondents

Respondent longitude and latitude coordinates are inferred from self-reported ZIP codes. While there is IP address information, initial testing suggested that some respondents were using virtual private networks. A few respondents did not report valid ZIP codes, so for these, IP address-implied geo-coordinates were employed.

For the majority of observations the ZIP code geo-coordinates are similar to those implied by the IP addresses. The results are robust when trimming to the subset of respondents whose IP addresses and ZIP codes imply similar locations.

C Proximity, Visibility, and Recognition

C.1 Covariate Balance

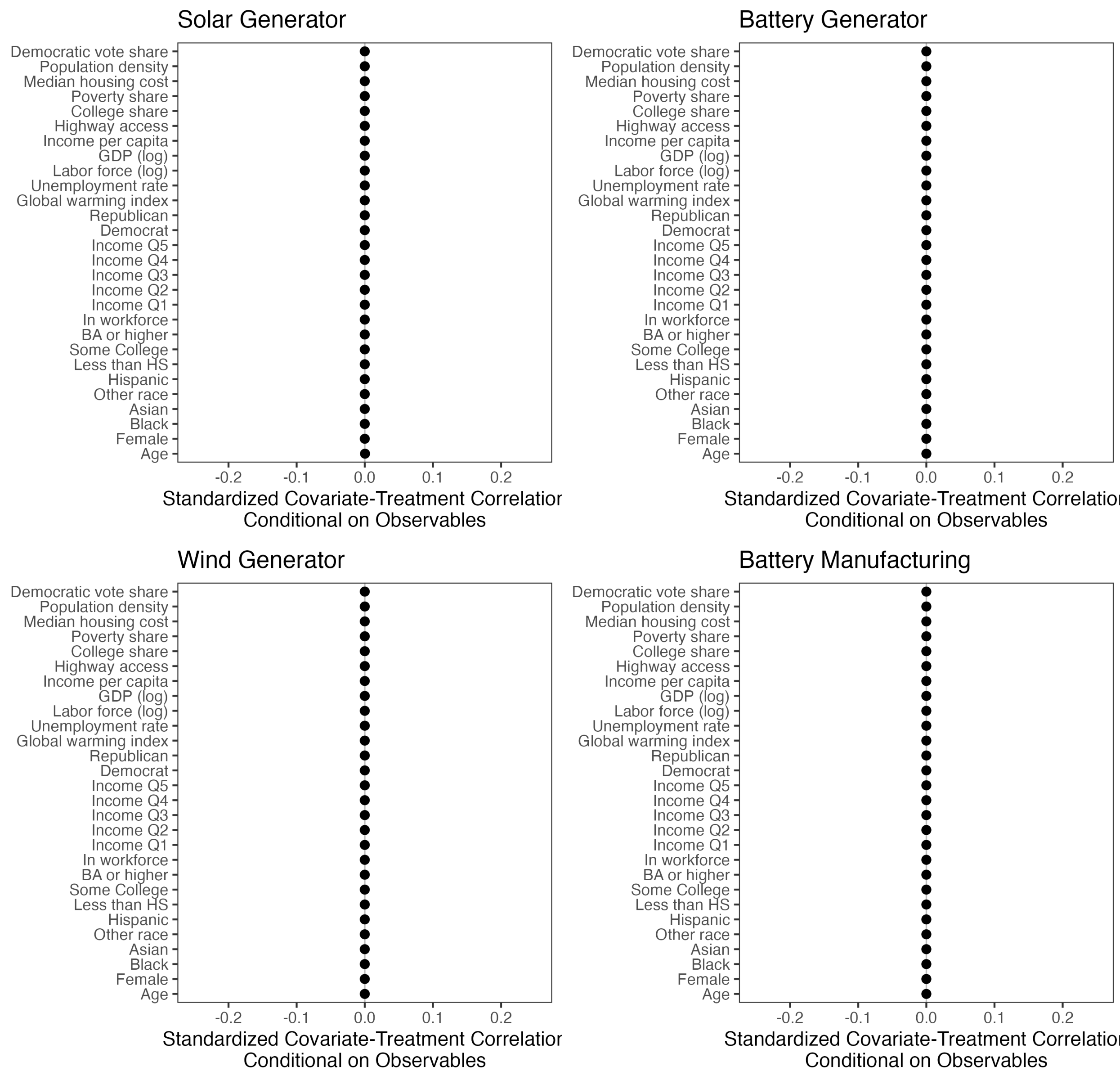

Figure C7: Covariate balance (1/3). Estimates from a regression of the standardized covariate on a continuous distance measure, observed covariates, and state fixed effects. Some of the estimates are statistically significant at the 5% level but are precisely estimated as 0. Bars denote 95% confidence intervals, but are not visible because of the estimate precision.

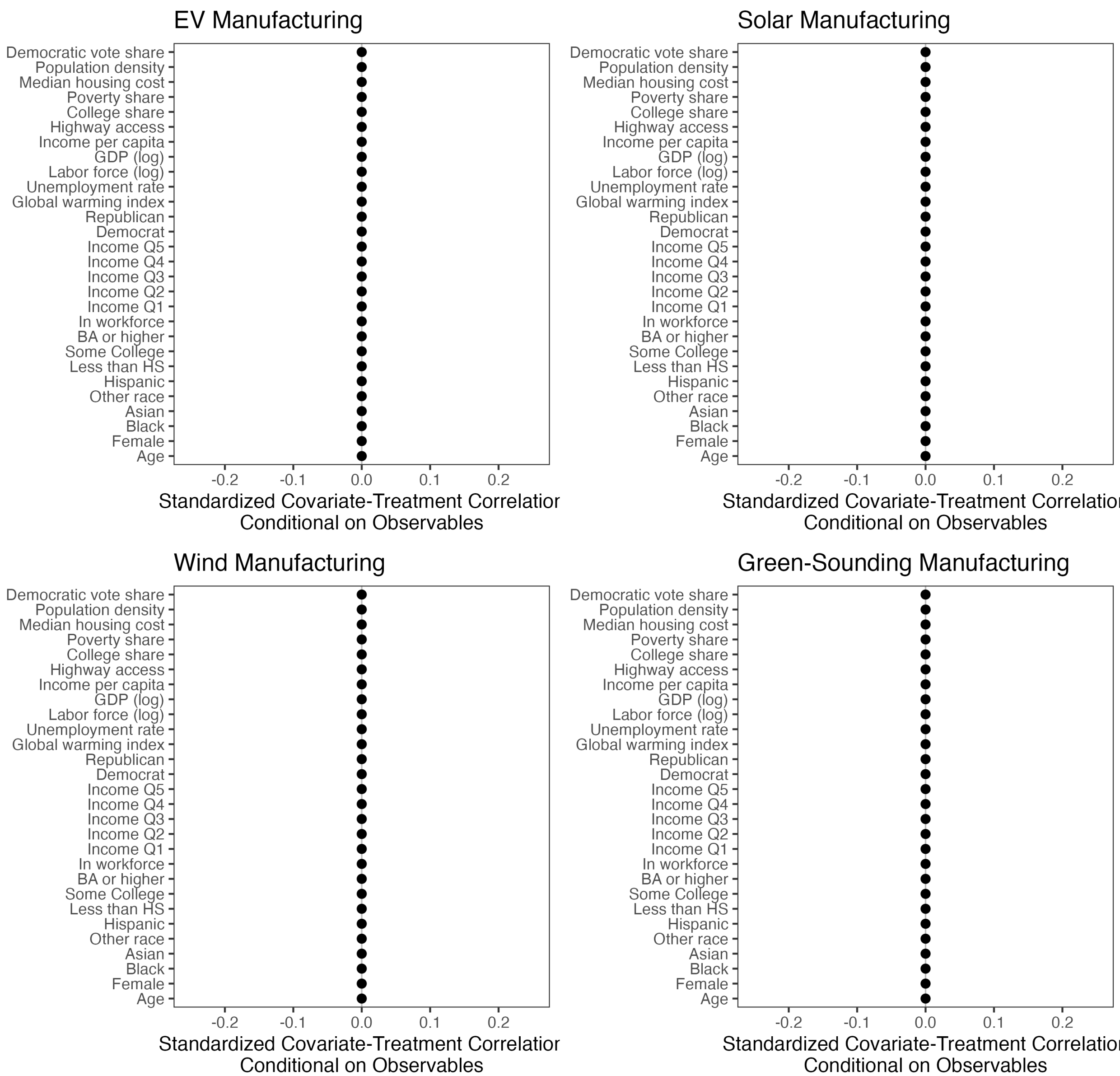

Figure C8: Covariate balance (2/3). Estimates from a regression of the standardized covariate on a continuous distance measure, observed covariates, and state fixed effects. Some of the estimates are statistically significant at the 5% level, but precisely estimated as 0. Bars denote 95% confidence intervals, but are not visible because of the estimate precision.

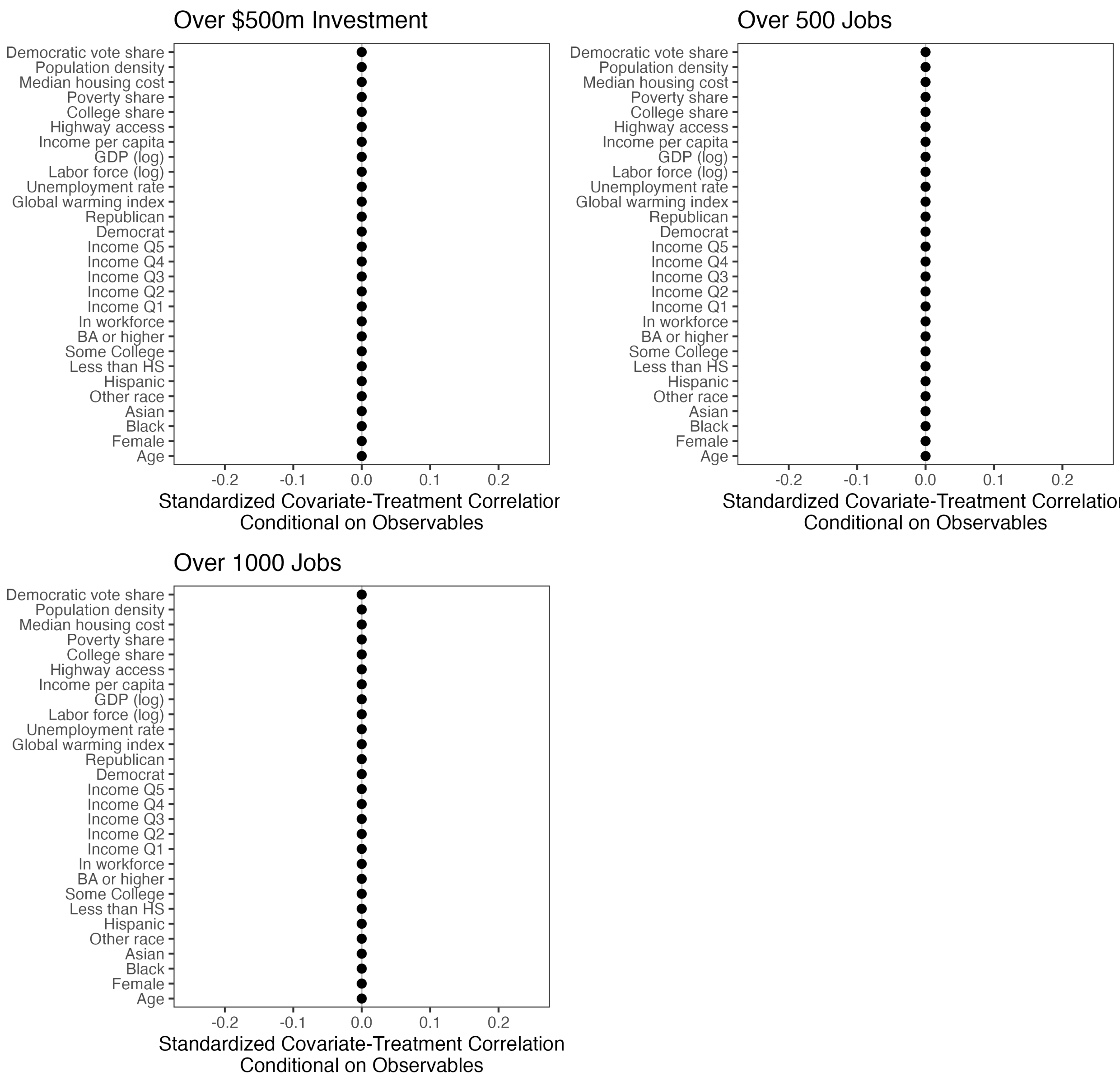

Figure C9: Covariate balance (3/3). Estimates from a regression of the standardized covariate on a continuous distance measure, observed covariates, and state fixed effects. Some of the estimates are statistically significant at the 5% level, but precisely estimated as 0. Bars denote 95% confidence intervals, but are not visible because of the estimate precision.

C.2 Robustness of Main Results

C.2.1 Alternative Conley Standard Errors Cutoff

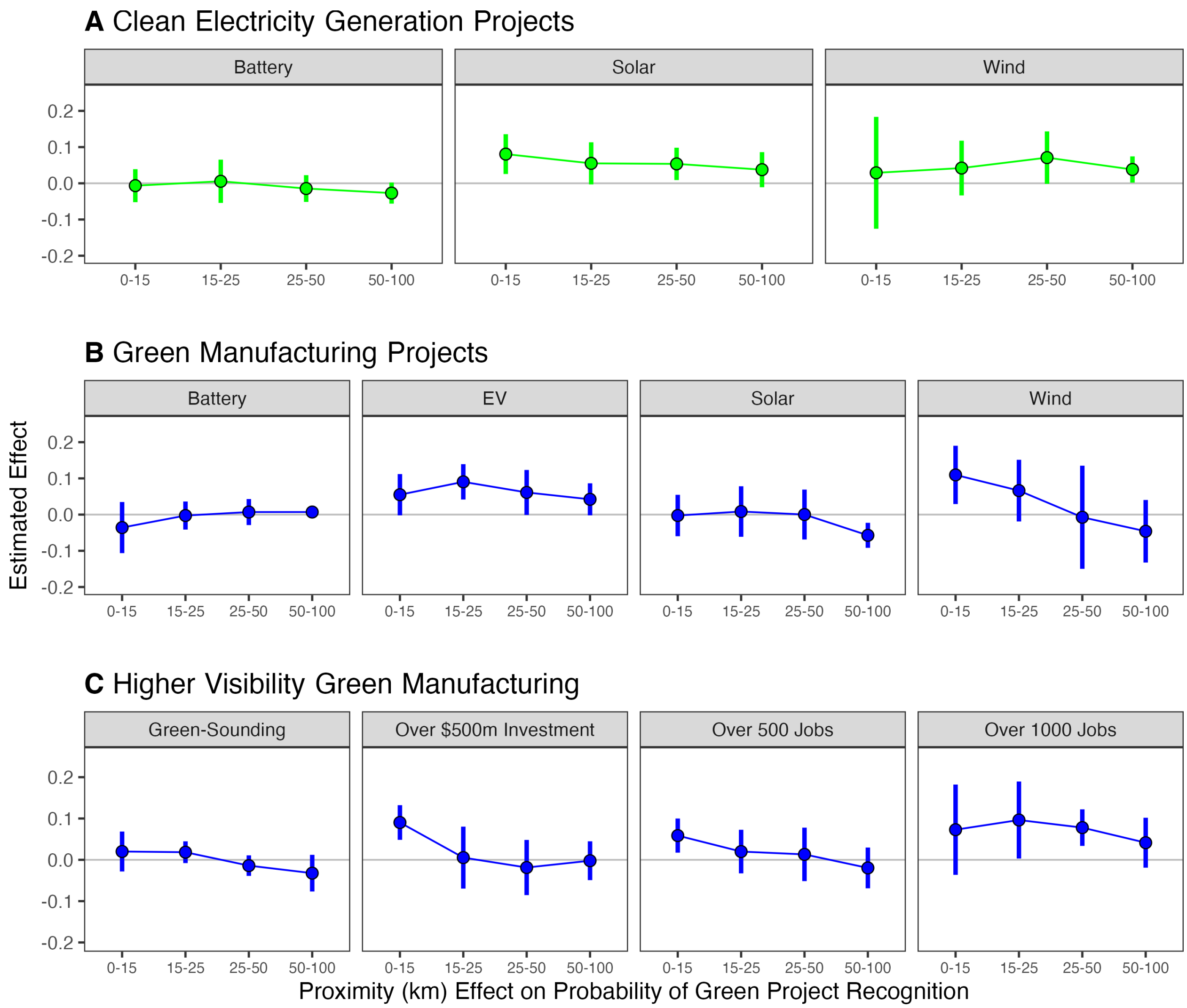

Figure C10: 500km Cutoff for Conley Standard Errors

Notes: Estimates from a linear regression of the green project recognition indicator on the respondent's distance to new green projects. The reference category is > 100km. State fixed effects mean that the estimates are the effect of distance relative to the average green project proximity in a state. The model controls for political and economic variables at the individual and county levels. Bars denote 95% confidence intervals. $N = 5{,}026$.

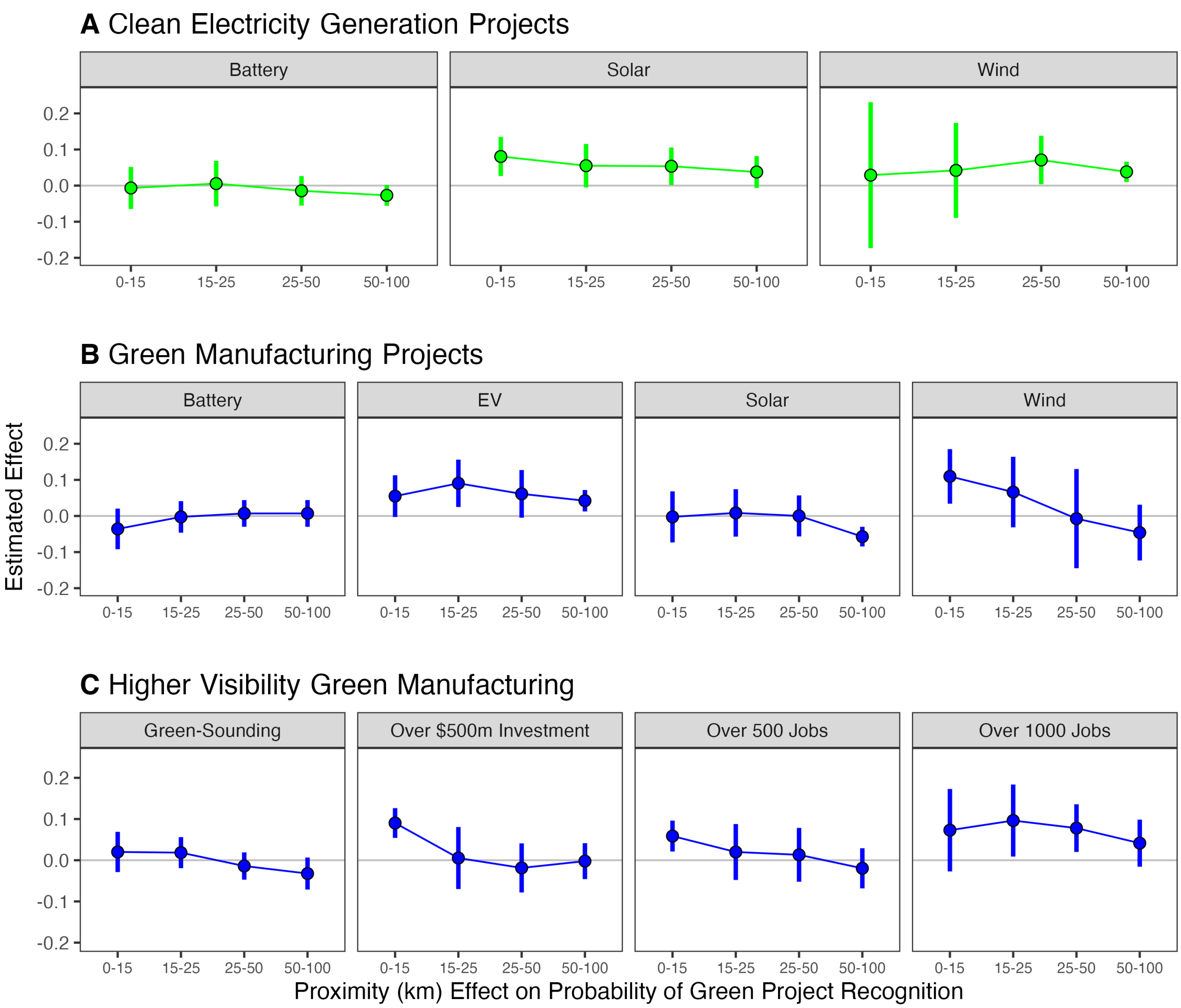

Figure C11: 300km Cutoff for Conley Standard Errors

Notes: Estimates from a linear regression of the green project recognition indicator on the respondent's distance to new green projects. The reference category is $>$ 100km. State fixed effects mean that the estimates are the effect of distance relative to the average green project proximity in a state. The model controls for political and economic variables at the individual and county levels. Bars denote 95% confidence intervals. $N = 5{,}026$.

C.2.2 Alternative Geo-Coordinates

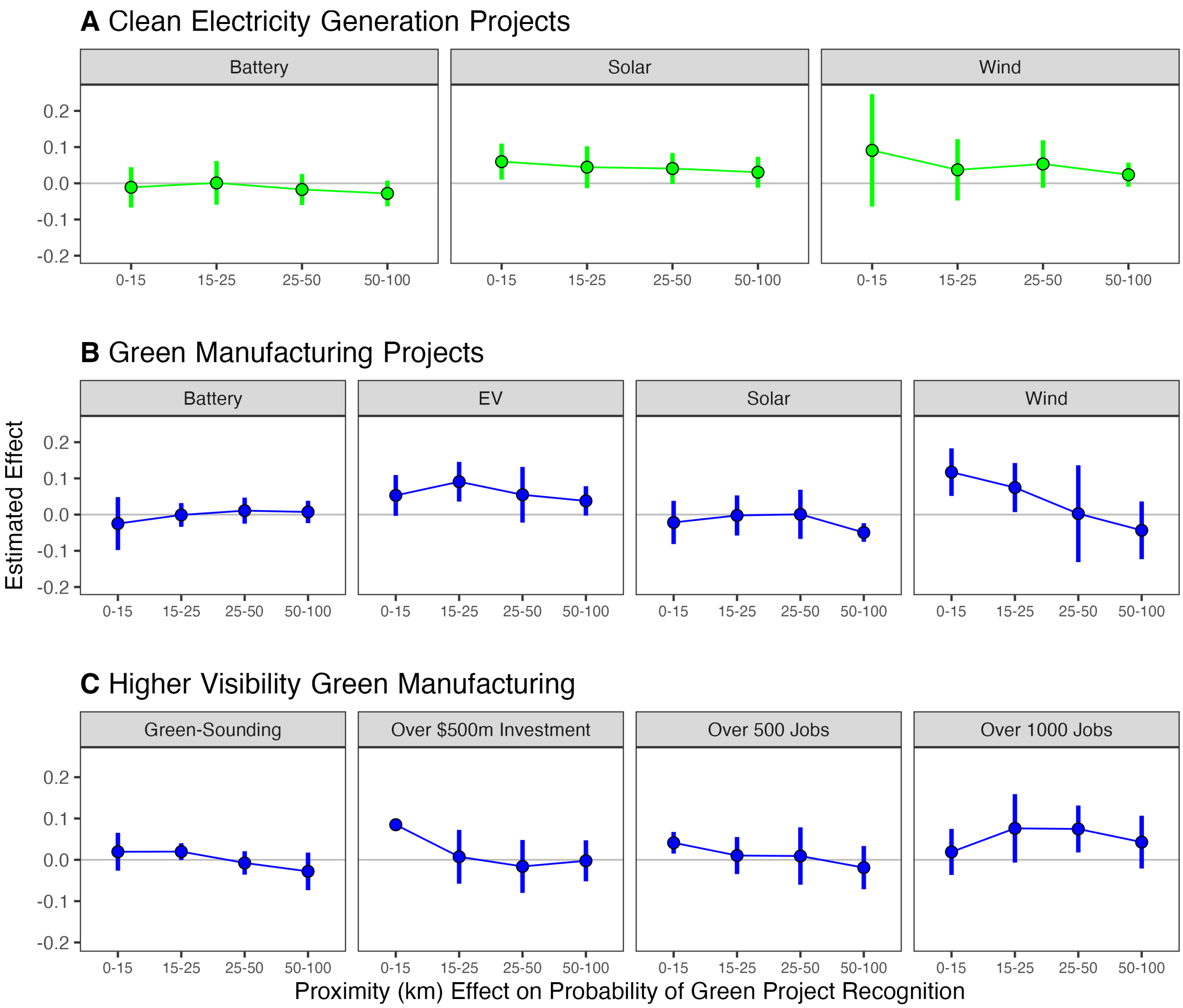

Figure C12: Robustness to Using Only Consistent Geo-Coordinates

Notes: This analysis is performed on the subset of respondents whose IP addresses and ZIP codes imply similar longitude-latitude geo-coordinates (N = 4,859). Consistency is determined by regressing the geo-coordinates derived from IP addresses on those implied by ZIP codes and trimming observations whose residuals are more than twice the standard deviation of the residuals. Estimates from a linear regression of the green project recognition indicator on the respondent's distance to new green projects. The reference category is $>$ 100km. State fixed effects mean that the estimates are the effect of distance relative to the average green project proximity in a state. The model controls for political and economic variables at the individual and county-levels. Conley standard errors with a 400km cutoff. Bars denote 95% confidence intervals.

C.2.3 Online Data Quality

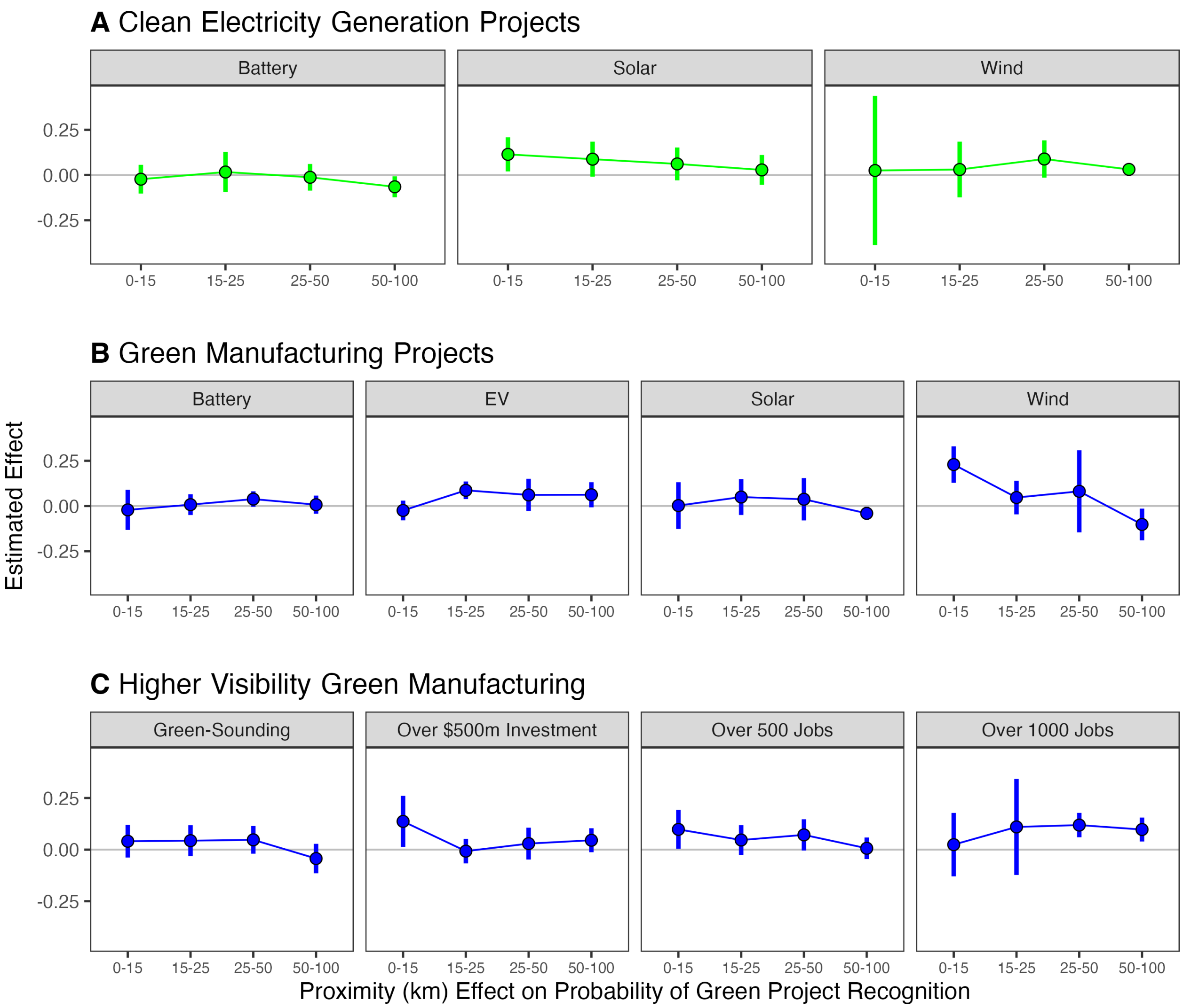

Figure C13: Robustness to Only Including Respondents with Perfect Invisible reCAPTCHA Scores

Notes: Estimates from a linear regression of the green project recognition indicator on the respondent's distance to new green projects. The reference category is $>$ 100km. State fixed effects mean that the estimates are the effect of distance relative to the average green project proximity in a state. The model controls for political and economic variables at the individual and county levels. Conley standard errors with a 400km cutoff. Bars denote 95% confidence intervals. $N = 2{,}120$.

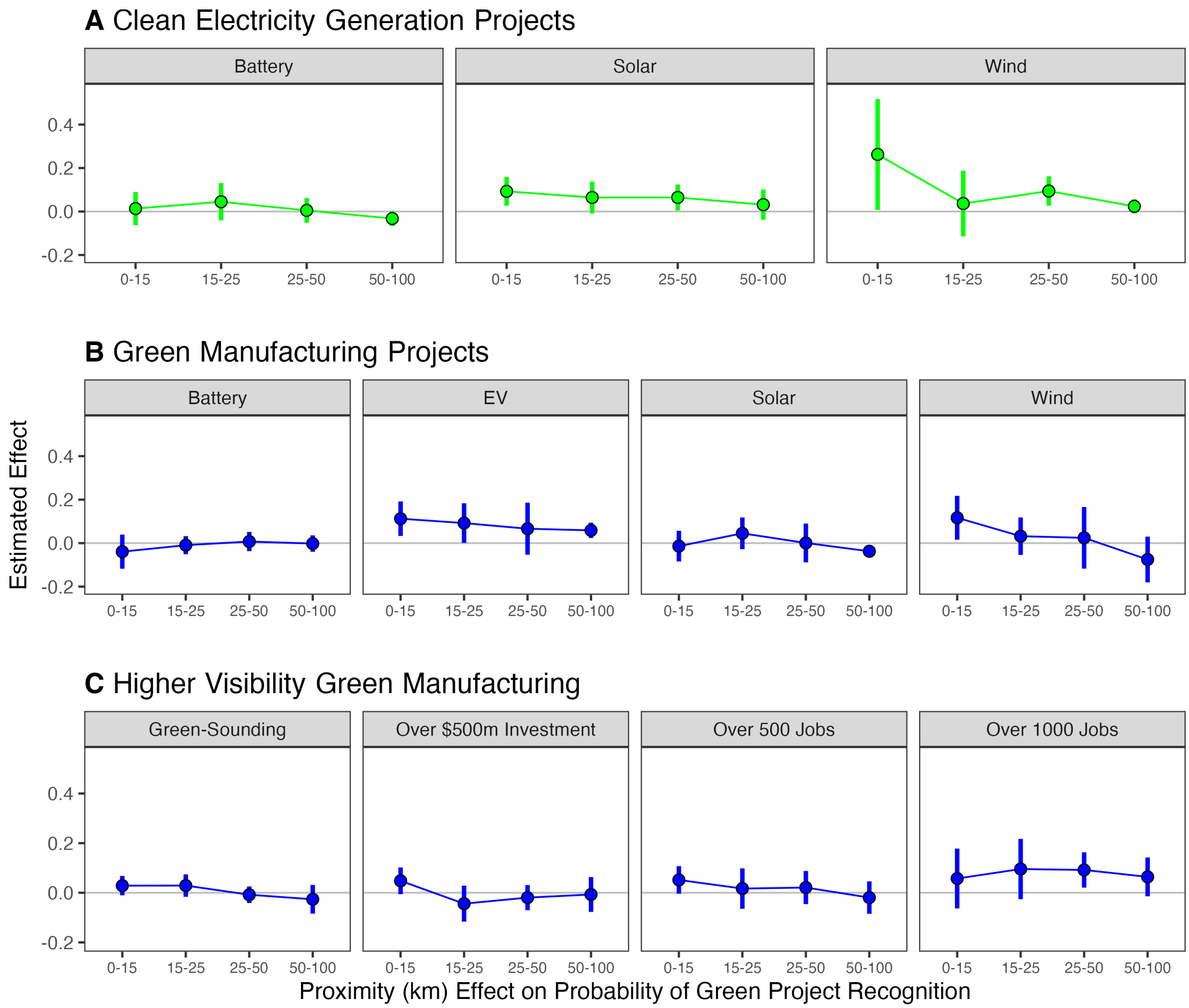

Figure C14: Robustness to Only Including Respondents Who Spent at Least 2/3rd the Median Time on the Outcome Question

Notes: Estimates from a linear regression of the green project recognition indicator on the respondent's distance to new green projects. The reference category is $>$ 100km. State fixed effects mean that the estimates are the effect of distance relative to the average green project proximity in a state. The model controls for political and economic variables at the individual and county levels. Conley standard errors with a 400km cutoff. Bars denote 95% confidence intervals. $N = 2{,}120$.

C.2.4 Alternative Proximity Measure

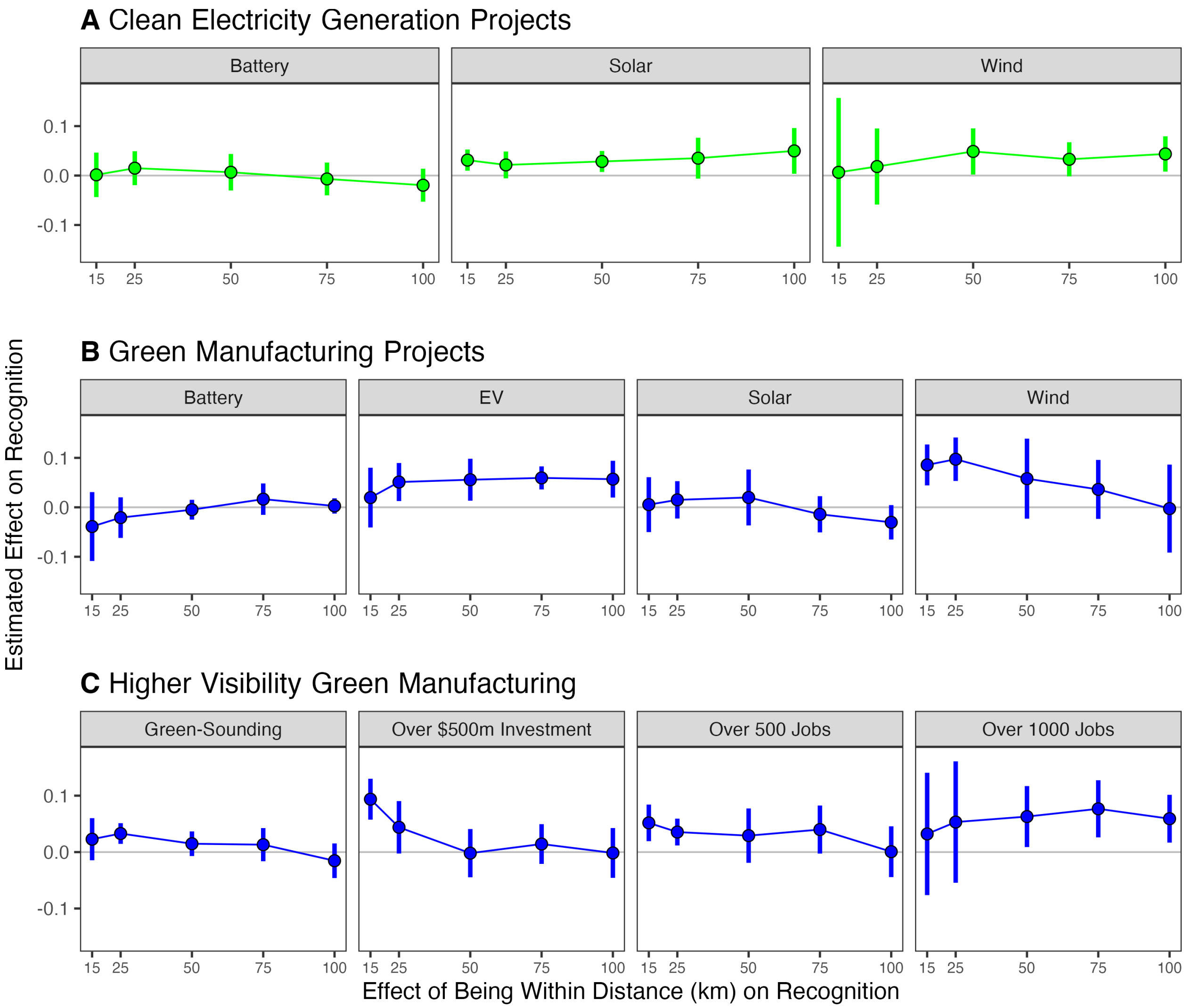

Figure C15: Proximity effect with alternative distance measure. Distance measure here is a binary indicator for whether a respondent is within the threshold. Each estimate comes from a separate linear regression. This approach follows [6].

C.3 Regression Tables

Table C6: Effect of Green Project Distance on Recognition

	Outcome: Recognize Green Project										
	Generation			Manufacturing							
	Solar	Battery	Wind	Battery	EV	Solar	Wind	Green	Over $500m	500 Jobs	1000 Jobs
0-15km	0.08**	-0.01	0.03	-0.04	0.05	0.00	0.11***	0.05*	0.09***	0.06***	0.07
	(0.03)	(0.03)	(0.07)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)	(0.05)
15-25km	0.06	0.01	0.04	0.00	0.09**	0.01	0.07*	0.03	0.01	0.02	0.10
	(0.03)	(0.03)	(0.05)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.05)
25-50km	0.05*	-0.01	0.07*	0.01	0.06	0.00	-0.01	0.07**	-0.02	0.01	0.08**
	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.04)	(0.07)	(0.02)	(0.03)	(0.04)	(0.03)
50-100km	0.04	-0.03	0.04*	0.01	0.04*	-0.06***	-0.05	0.00	0.00	-0.02	0.04
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)
Age	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Black	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Asian	-0.04*	-0.04*	-0.05*	-0.04*	-0.04*	-0.04*	-0.04*	-0.04*	-0.04*	-0.04*	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Other race	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Hispanic	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03***	0.03**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Some College	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income Q2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Income Q3	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Income Q4	0.02	0.03	0.02	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Income Q5	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Republican	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Neither Party	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Global warming index	0.13***	0.13***	0.13***	0.13***	0.13***	0.13***	0.13***	0.13***	0.13***	0.13***	0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Unemployment rate	-0.01	-0.01	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Labor force (log)	-0.10	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
GDP (log)	0.09	0.08	0.09	0.08	0.09	0.08	0.09	0.08	0.08	0.08	0.08
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Income per capita	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Highway access	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.01	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
College share	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Poverty share	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Median housing cost	-0.03**	-0.03*	-0.03*	-0.03**	-0.03*	-0.02**	-0.02	-0.03*	-0.02*	-0.03*	-0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Population density	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02*	-0.01	-0.02*	-0.02*	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Broadband: >800	-0.09	-0.08	-0.09*	-0.09*	-0.08	-0.09*	-0.09	-0.08	-0.09*	-0.09	-0.08
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Broadband: 600-800	-0.03	-0.03	-0.03	-0.03	-0.02	-0.03	-0.03	-0.02	-0.03	-0.03	-0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Broadband: 400-600	-0.04	-0.04	-0.04	-0.04	-0.03	-0.04	-0.04	-0.03	-0.04	-0.04	-0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Democratic vote share	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	5026	5026	5026	5026	5026	5026	5026	5026	5026	5026	5026
Adjusted R^2	0.071	0.070	0.071	0.070	0.071	0.071	0.071	0.071	0.071	0.070	0.071
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Linear regression model estimates. Conley standard errors (400km cutoff). Continuous county-level measures standardized by within-state variance. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

C.4 Visibility Mechanism

C.4.1 Population Density

Table C7: Proximity Effect on Recognition Moderated by Population Density

	Outcome: Recognize Green Project										
	Generation			Manufacturing							
	Solar	Battery	Wind	Battery	EV	Solar	Wind	Green	Over \$500m	500 Jobs	1000 Jobs
0-15km	0.073	-0.028	-0.13	-0.052	-0.051	-0.008	0.032	0.054	0.068	0.0081	0.0047
	(0.042)	(0.029)	(0.18)	(0.031)	(0.087)	(0.056)	(0.082)	(0.041)	(0.056)	(0.0321)	(0.0204)
15-25km	0.052	-0.017	0.131	0.020	0.185*	0.0037	0.22***	0.034	0.024	0.046	-0.017
	(0.045)	(0.038)	(0.069)	(0.036)	(0.086)	(0.0393)	(0.05)	(0.048)	(0.058)	(0.039)	(0.084)
25-50km	0.043	0.0024	0.142***	0.016	0.128**	-0.071***	0.088	0.051	0.019	0.060	0.137**
	(0.040)	(0.0286)	(0.037)	(0.037)	(0.044)	(0.014)	(0.079)	(0.033)	(0.031)	(0.037)	(0.042)
50-100km	0.032	-0.059	0.046*	0.0072	0.071***	-0.068***	-0.035	0.0026	-0.013	-0.034	0.038
	(0.034)	(0.035)	(0.018)	(0.0218)	(0.018)	(0.015)	(0.065)	(0.0257)	(0.041)	(0.044)	(0.064)
0-15km x Density	0.038	0.031	1.2	0.011	0.103	0.017	-0.0055	-0.0082	-0.0051	0.0073	0.115
	(0.115)	(0.019)	(0.9)	(0.013)	(0.058)	(0.051)	(0.0171)	(0.0319)	(0.0170)	(0.0137)	(0.092)
15-25km x Density	0.033	0.033	-0.74	-0.026	-0.112	0.013	-0.057**	-0.0077	-0.016	-0.017	0.149*
	(0.116)	(0.022)	(0.39)	(0.031)	(0.072)	(0.035)	(0.018)	(0.0475)	(0.017)	(0.016)	(0.072)
25-50km x Density	**0.042**	**-0.016**	**-0.274*** **	**-0.014**	**-0.142*** *	**0.091*** *	**-0.062*** *	**0.025**	**-0.035***	**-0.043*** *	**-0.064**
	(0.114)	**(0.036)**	**(0.073)**	**(0.054)**	**(0.045)**	**(0.033)**	**(0.020)**	**(0.024)**	**(0.014)**	**(0.015)**	**(0.033)**
50-100km x Density	0.033	0.068	-0.013	-0.00028	-0.096	0.017	-0.030	0.001	0.025	0.034	0.0071
	(0.114)	(0.045)	(0.024)	(0.04915)	(0.056)	(0.021)	(0.087)	(0.032)	(0.047)	(0.054)	(0.0753)
N	5026	5026	5026	5026	5026	5026	5026	5026	5026	5026	5026
Adjusted R^2	0.070	0.071	0.071	0.069	0.072	0.071	0.072	0.070	0.070	0.071	0.072
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Linear regression model estimates. Conley standard errors (400km cutoff). Continuous county-level measures standardized by within-state variance.
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

C.4.2 Local News

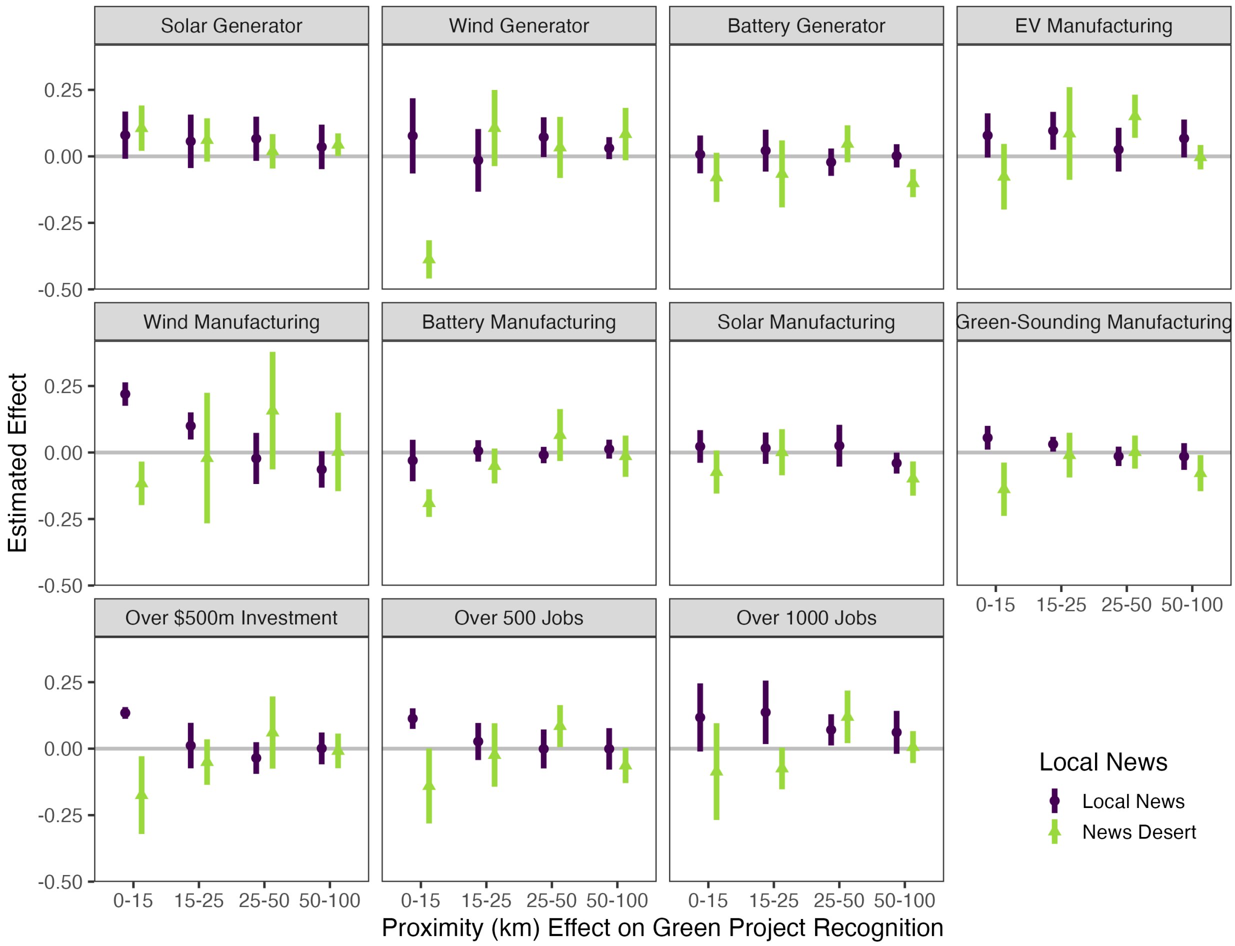

Figure C16: Proximity Effect Heterogeneity by Local News

Notes: Estimates from a linear regression of the green project recognition indicator on the respondent's distance to new green projects. The reference category is > 100km. State fixed effects mean that the estimates are the effect of distance relative to the average green project proximity in a state. The model controls for political and economic variables at the individual and county-levels. Conley standard errors with a 400km cutoff. Bars denote 95% confidence intervals. $N = 5{,}026$.

C.4.3 Labor Force Participation

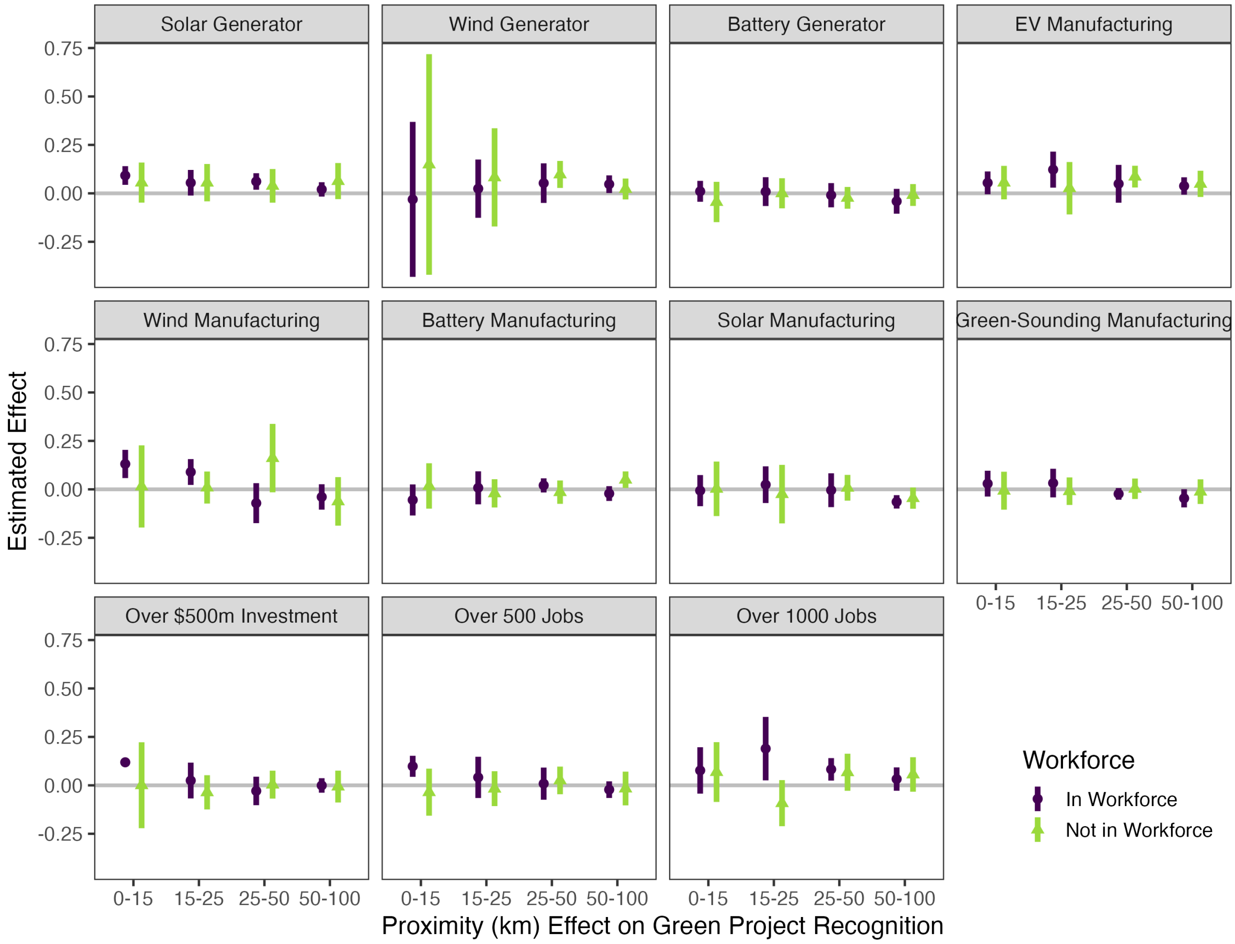

Figure C17: Proximity Effect Heterogeneity by Workforce Participation

Notes: Estimates from a linear regression of the green project recognition indicator on the respondent's distance to new green projects. The reference category is $>$ 100km. State fixed effects mean that the estimates are the effect of distance relative to the average green project proximity in a state. The model controls for political and economic variables at the individual and county-levels. Conley standard errors with a 400km cutoff. Bars denote 95% confidence intervals. $N = 5{,}026$.

C.5 Political Heterogeneity

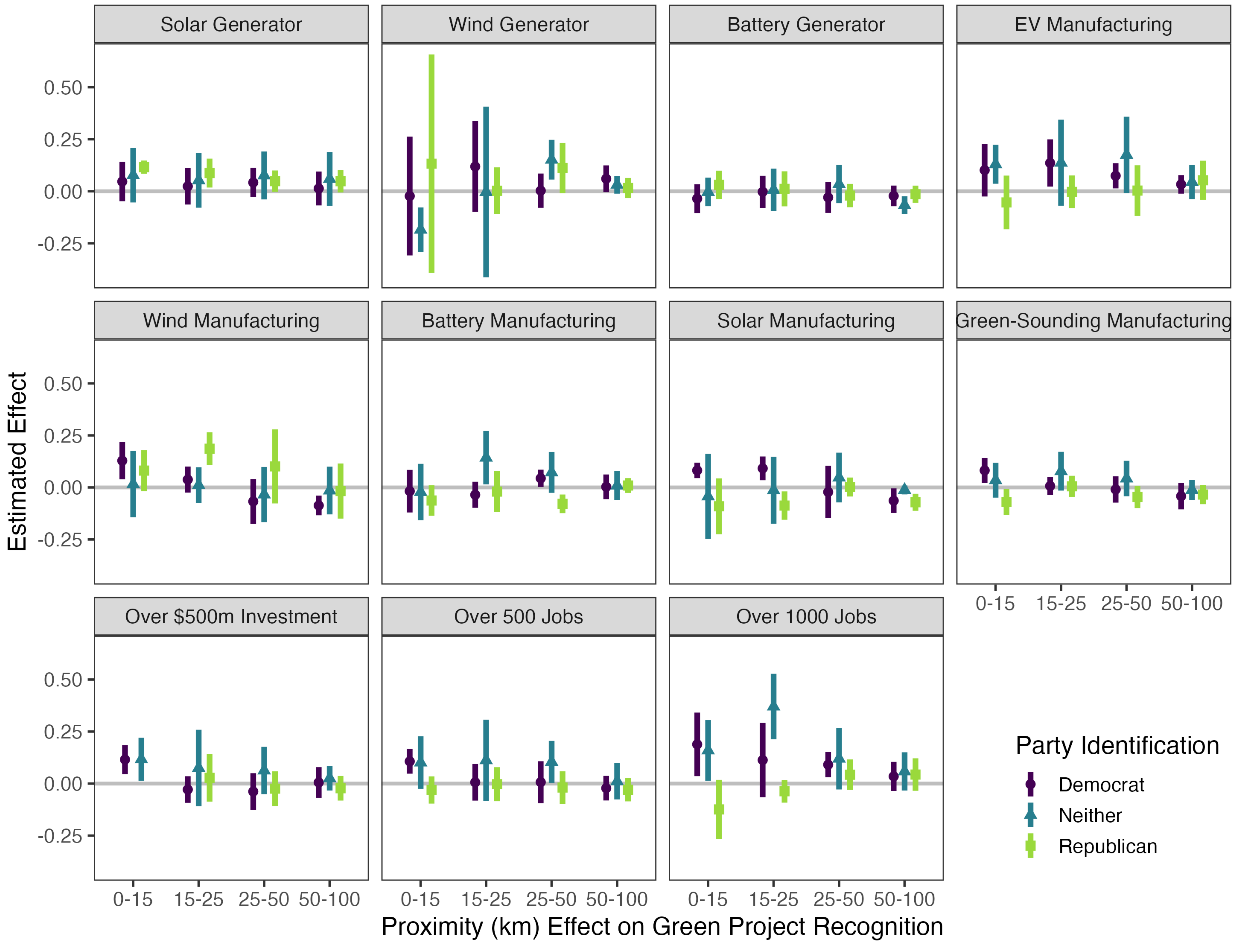

Figure C18: Proximity Effect Heterogeneity by Respondent Partisanship

Notes: Estimates from a linear regression of the green project recognition indicator on the respondent's distance to new green projects. The reference category is > 100km. State fixed effects mean that the estimates are the effect of distance relative to the average green project proximity in a state. The model controls for political and economic variables at the individual and county-levels. Conley standard errors with a 400km cutoff. Bars denote 95% confidence intervals. $N = 5{,}026$.

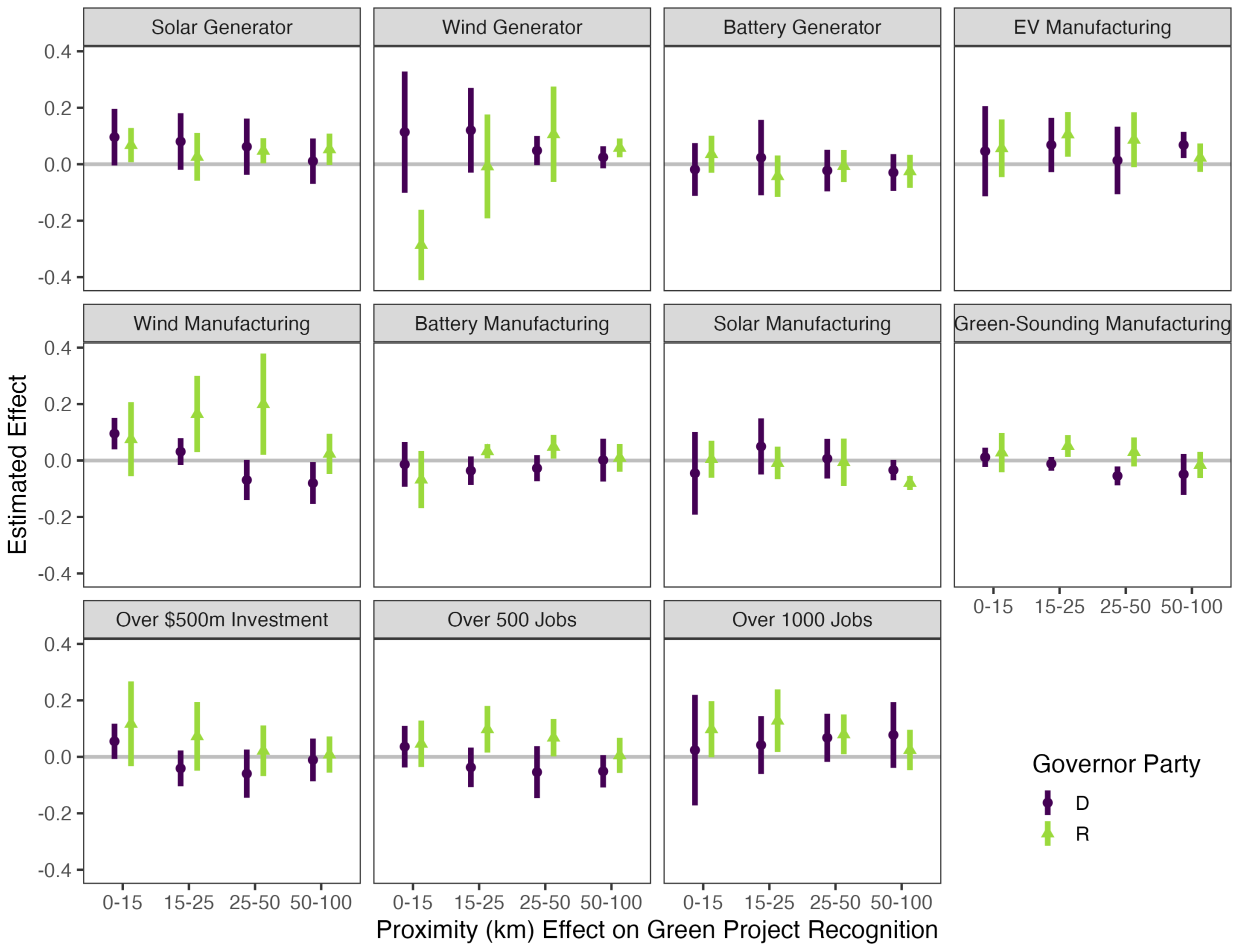

Figure C19: Proximity Effect Heterogeneity by Governor Partisanship

Notes: Estimates from a linear regression of the green project recognition indicator on the respondent's distance to new green projects. The reference category is $>$ 100km. State fixed effects mean that the estimates are the effect of distance relative to the average green project proximity in a state. The model controls for political and economic variables at the individual and county-levels. Conley standard errors with a 400km cutoff. Bars denote 95% confidence intervals. $N = 5{,}026$.

C.6 Power Analysis

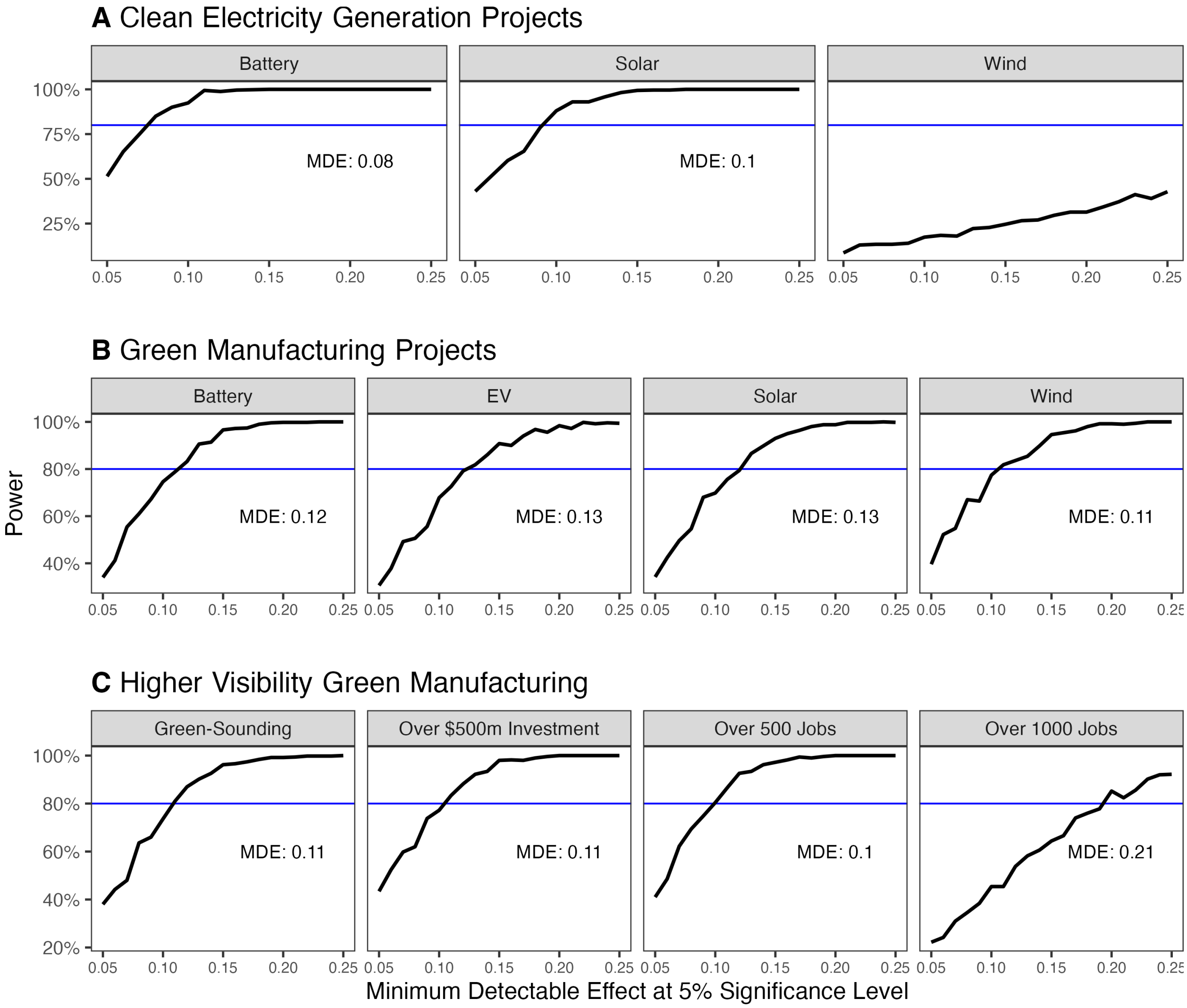

Figure C20: Analytical Power Analysis for Effect of Proximity on Recognition

D Credit Attribution

D.1 Question Internal Validity

We take several steps to assess the question's construct validity and reliability:

- To minimize partisan differences in response patterns, the question described green investments with neutral wording, not specifying whether the projects were good or bad, only that they had happened. There is no difference in answer speed across partisans, which suggests that the question wording did not disengage respondents.

- We checked to make sure that the list captured the primary factors that could be responsible. Indeed, only 1.15% of respondents said that all of the listed factors were "not at all responsible" for green investments.

- We examined whether respondents were satisficing by giving credit to all options. But this was infrequent. Only 3.2% said that all of the options were "extremely responsible" for investments. These tests support the internal validity of the credit attribution battery.

D.2 Proximity and Credit Attribution

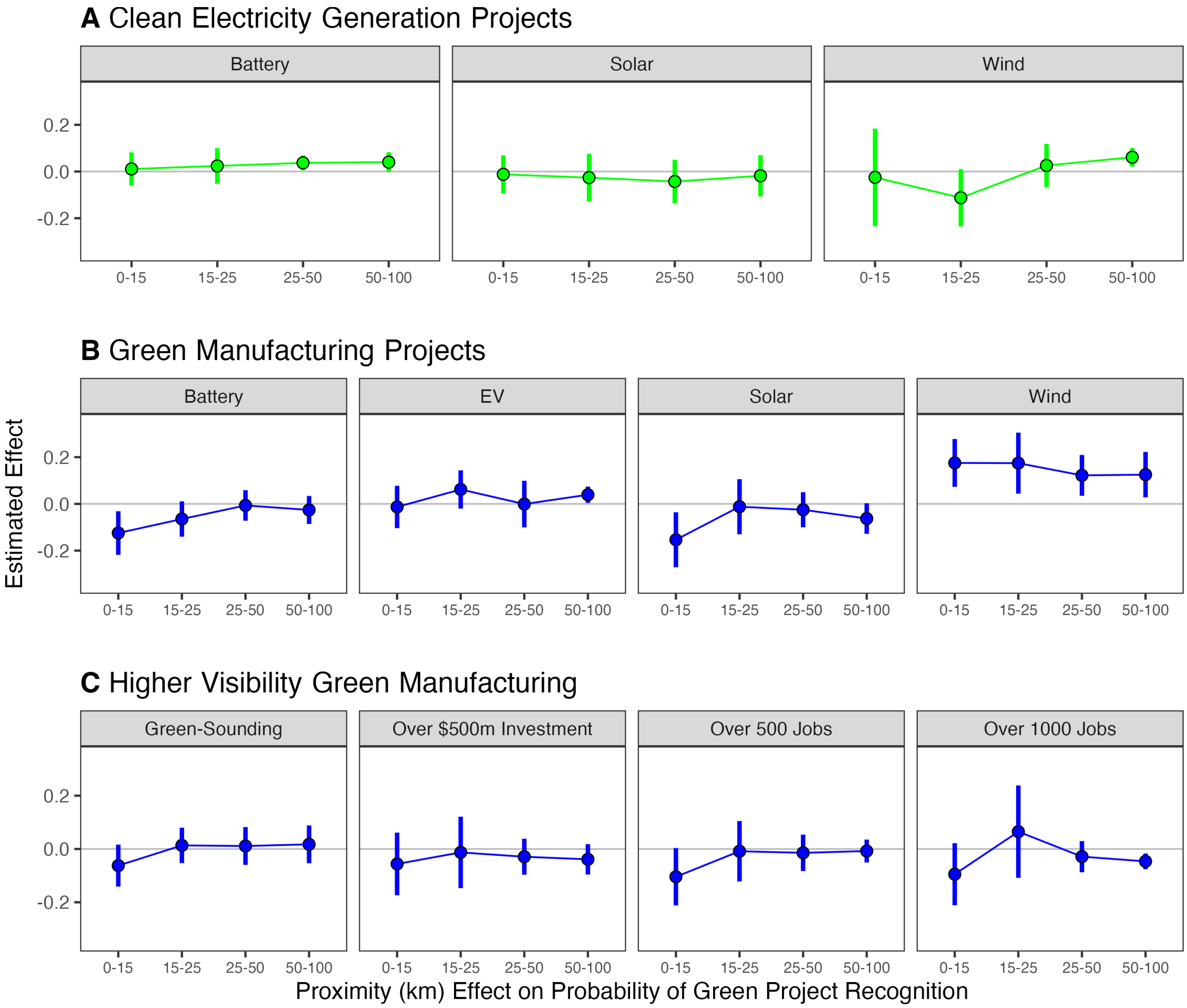

Figure D21: Proximity and Crediting President Biden

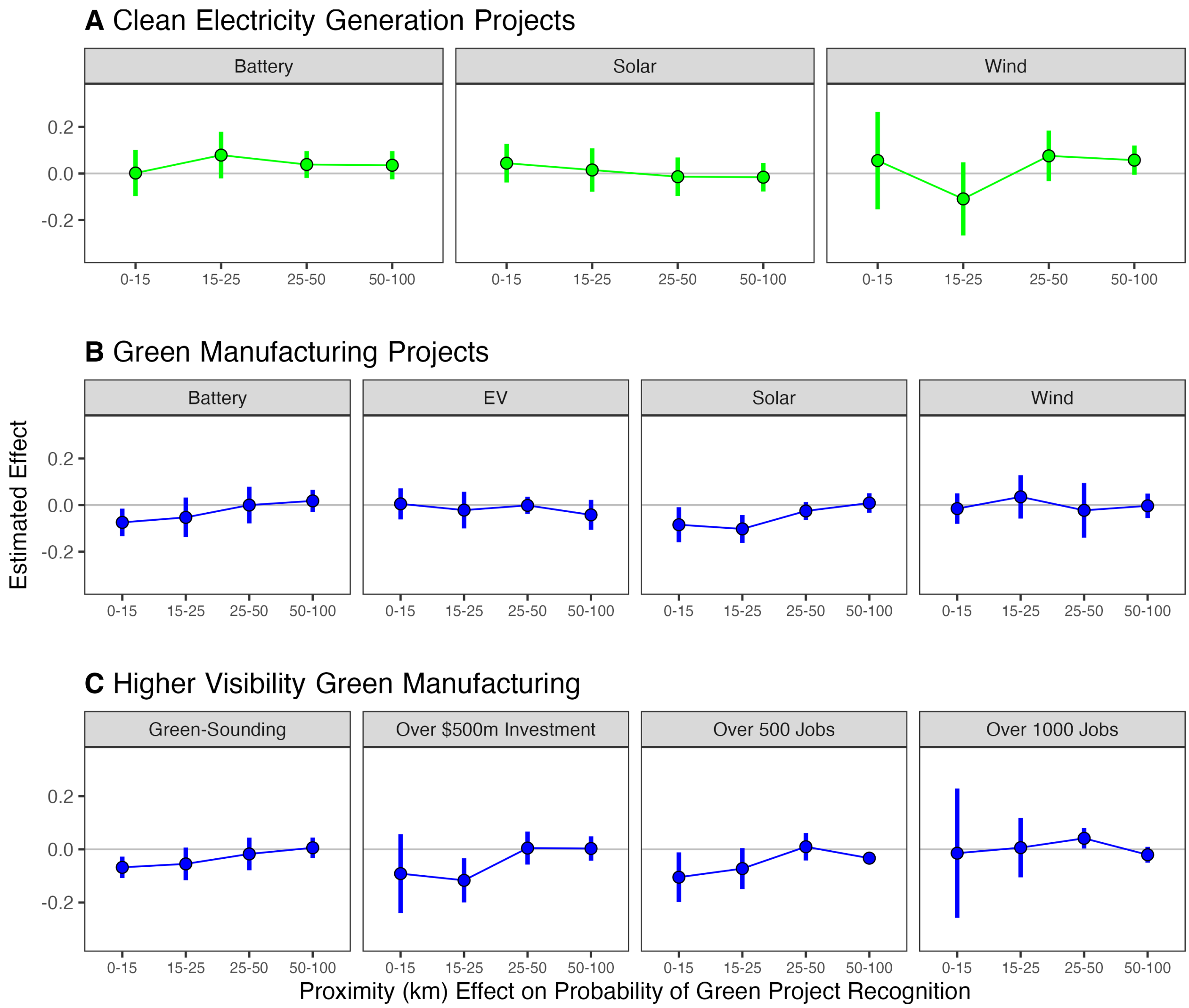

Figure D22: Proximity and Crediting the Governor

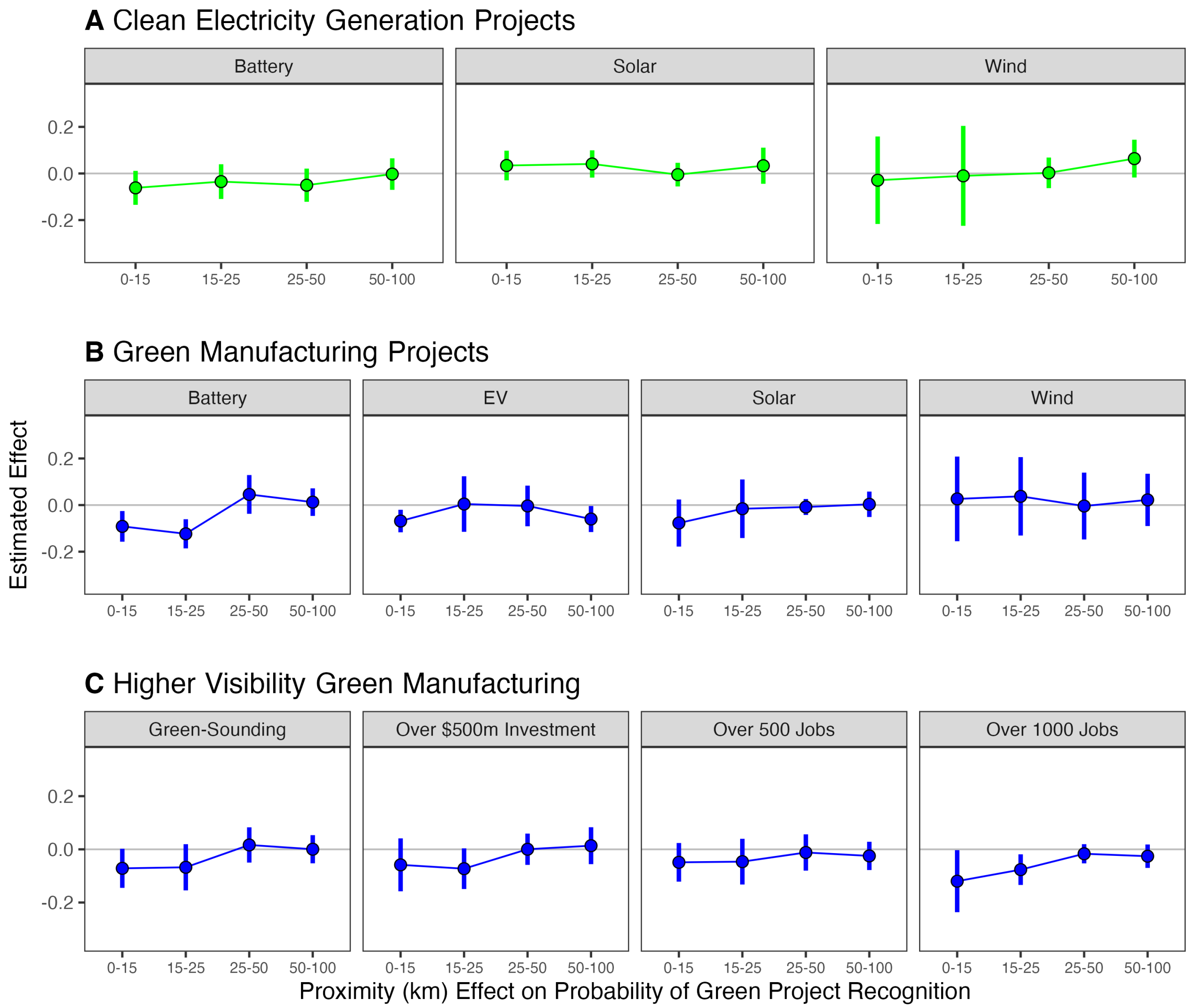

Figure D23: Proximity and Crediting the State Legislature

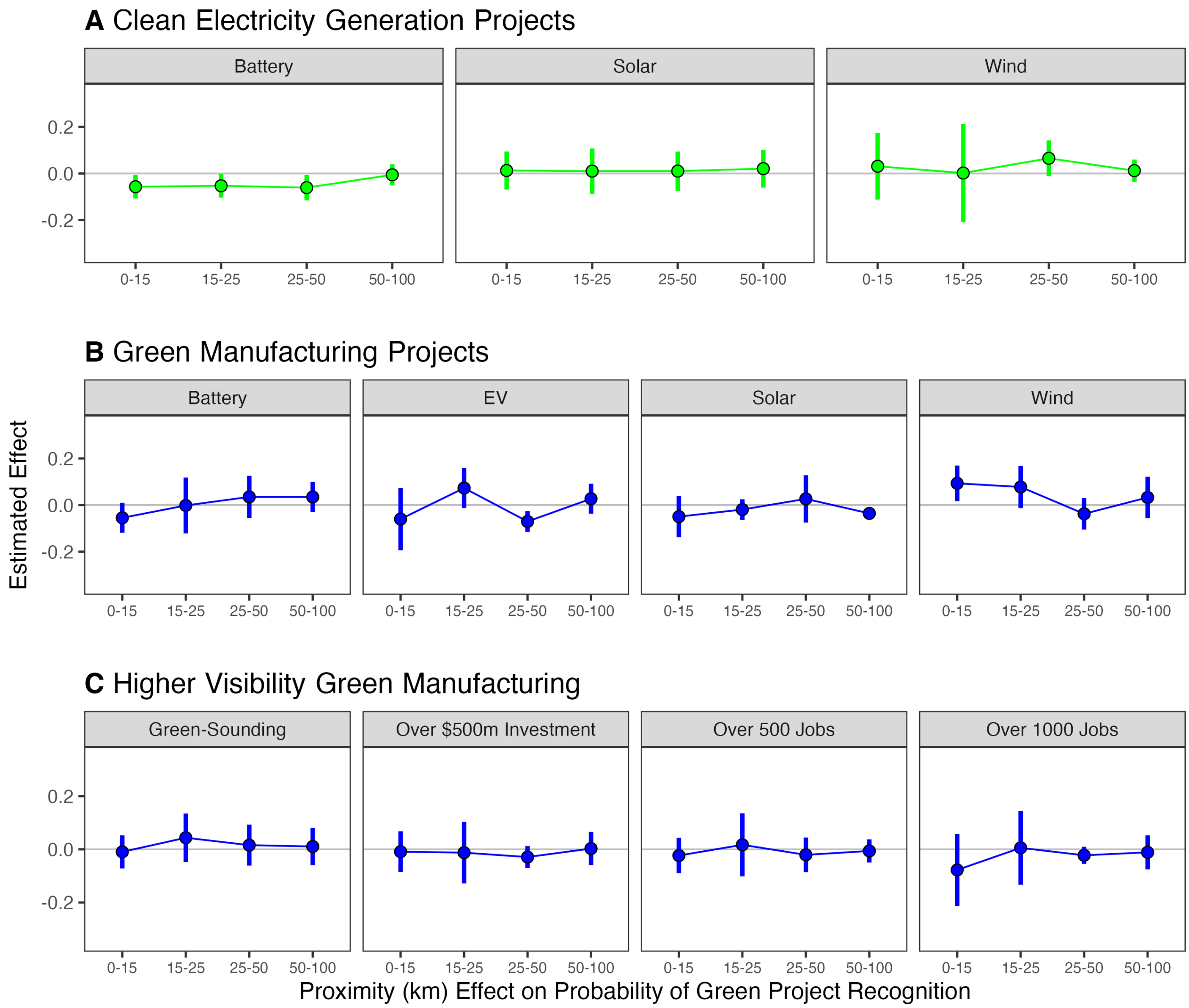

Figure D24: Proximity and Crediting Congress

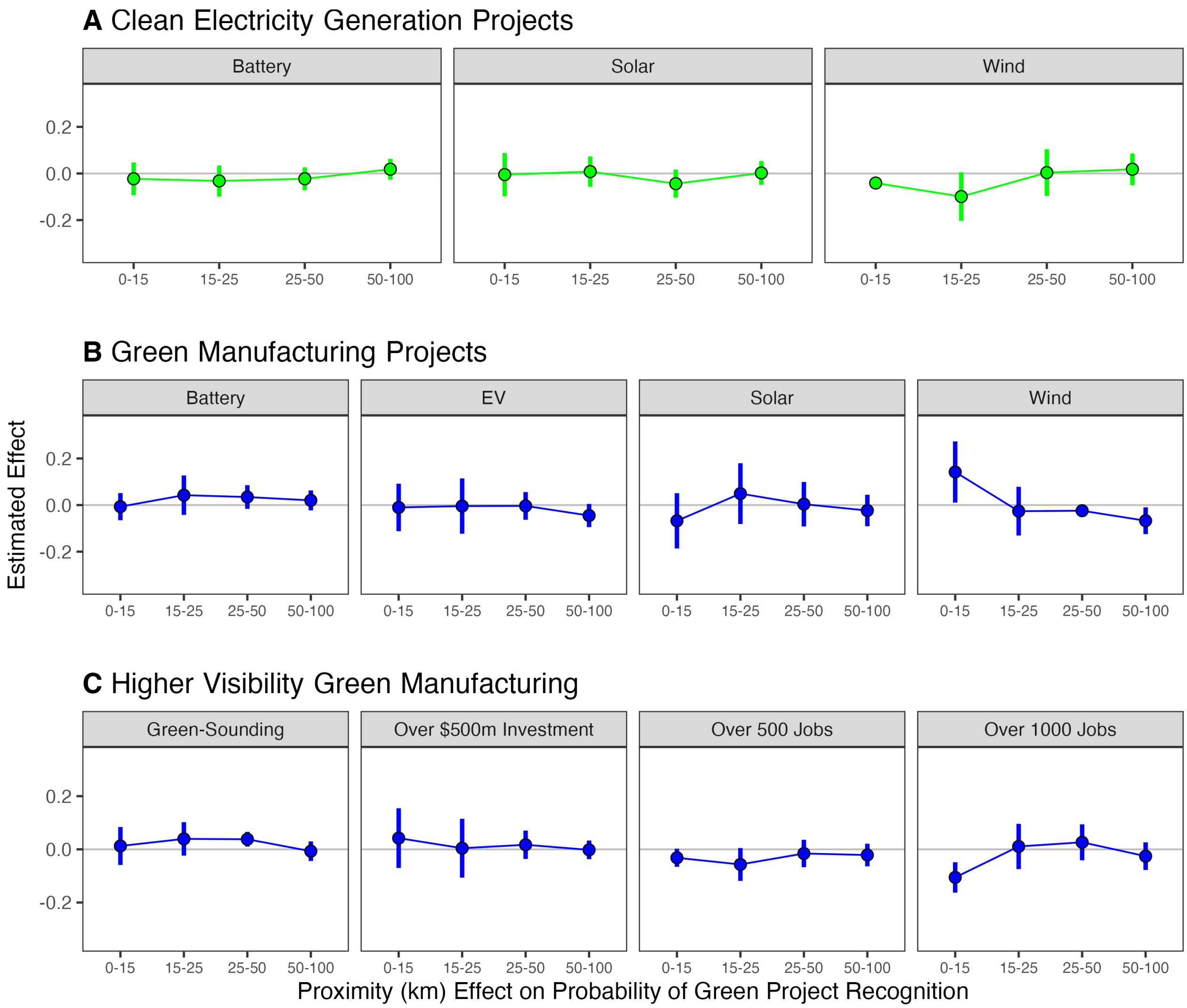

Figure D25: Proximity and Crediting Local Officials

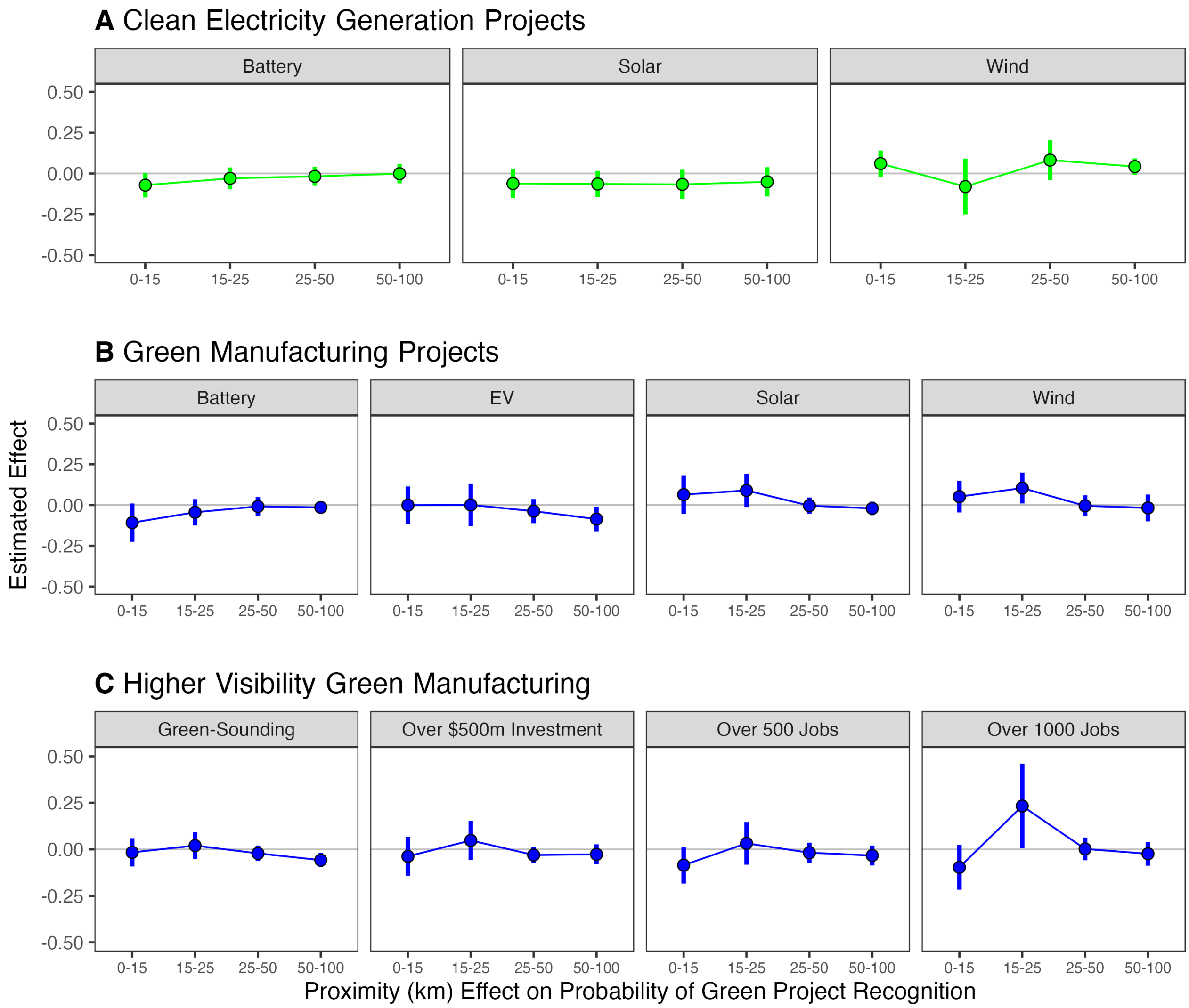

Figure D26: Proximity and Crediting Market Forces

D.3 Regression Tables

Table D8: Credit Allocation Predictors

	Credit Recipient:					
	Biden	Congress	Governor	State	Local	Markets
Age	0.00	0.00***	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.05**	-0.09***	-0.04	-0.05**	-0.02	-0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Black	0.04	0.08**	0.04	0.05	0.02	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Asian	0.02	0.05	0.01	0.05	-0.08	-0.08*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Other race	-0.04	0.02	0.03	0.02	0.06	-0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Hispanic	0.00	-0.01	-0.02	-0.04	-0.01	0.01
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Some College	-0.02	-0.04	-0.04	-0.03	-0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Not in workforce	-0.03	-0.06**	-0.03	-0.03	-0.03	-0.06**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Income Q2	-0.01	-0.01	0.02	-0.03	-0.01	0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Income Q3	0.01	0.03	0.03	-0.02	0.00	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Income Q4	-0.01	0.00	0.00	0.00	-0.05	-0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Income Q5	-0.01	0.01	0.02	-0.04	-0.02	-0.02
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Republican	-0.17***	0.00	-0.02	-0.02	-0.05*	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Neither Party	-0.22***	-0.08***	-0.12***	-0.11***	-0.10***	-0.05
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
Global warming index	0.06	0.08*	0.13***	0.10**	0.15***	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Visible green project	0.13***	0.15***	0.13***	0.14***	0.19***	0.18***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Republican governor	0.06*	0.03	-0.04	0.01	0.05*	0.05*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	3034	3034	3034	3034	3034	3034
Adjusted R^2	0.082	0.098	0.050	0.057	0.069	0.072
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Linear regression of credit indicator on individual and geographic covariates. Heteroskedasticity-robust standard errors in parentheses. Additional controls include county unemployment rate, labor force, GDP, income per capita, highway access, college share, poverty share, housing costs, population density, broadband access, Democratic vote share, state union membership, and state industrial electricity prices. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table D9: Credit Allocation Predictors: Governor Interaction

	Credit Recipient:					
	Biden	Congress	Governor	State	Local	Markets
Age	0.00	0.00***	0.00	0.00*	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.06***	-0.10***	-0.05**	-0.06***	-0.04*	-0.12***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Black	0.04	0.08**	0.04	0.05	0.03	0.06*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Asian	0.02	0.05	0.01	0.05	-0.08	-0.08*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Other race	-0.05	0.01	0.02	0.01	0.04	-0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Hispanic	0.01	0.00	-0.01	-0.03	0.01	0.02
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
Some College	-0.03	-0.04	-0.04	-0.03	-0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Not in workforce	-0.03	-0.06**	-0.03	-0.04	-0.04	-0.07**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Income Q2	-0.01	-0.01	0.02	-0.03	-0.01	0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Income Q3	0.01	0.02	0.02	-0.03	-0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Income Q4	-0.01	0.00	0.00	0.00	-0.05	-0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Income Q5	-0.01	0.02	0.03	-0.04	-0.01	-0.02
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Republican	-0.18***	-0.01	-0.13***	-0.08**	-0.08**	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Neither Party	-0.22***	-0.12***	-0.20***	-0.16***	-0.14***	-0.04
	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
Global warming index	0.08*	0.10**	0.15***	0.12***	0.18***	0.08*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Republican Governor	0.05	0.01	-0.16***	-0.06	0.01	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Neither Party x Republican Governor	-0.01	0.05	0.16**	0.08	0.05	-0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Republican x Republican Governor	0.02	0.02	0.24***	0.13***	0.07	-0.02
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
N	3034	3034	3034	3034	3034	3034
Adjusted R^2	0.070	0.081	0.048	0.046	0.043	0.046
Sample Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Linear regression of credit indicator on individual and geographic covariates. Heteroskedasticity-robust standard errors in parentheses. Additional controls include county unemployment rate, labor force, GDP, income per capita, highway access, college share, poverty share, housing costs, population density, broadband access, Democratic vote share, state union membership, and state industrial electricity prices. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table D10: Credit Allocation Predictors: Within Subject

	Credit Biden but Not the...			
	Governor		State Legislature	
	(1)	(2)	(3)	(4)
Age	0.00*	0.00*	0.00*	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.00	0.00	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Black	0.00	0.00	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)
Asian	0.00	0.00	-0.03	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)
Other race	-0.01	-0.01	-0.02	-0.02
	(0.02)	(0.02)	(0.03)	(0.03)
Hispanic	0.00	0.00	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Some College	0.01	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Not in workforce	-0.01	-0.01	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)
Income Q2	0.00	0.00	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)
Income Q3	-0.03	-0.03	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Income Q4	-0.01	-0.02	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Income Q5	-0.03	-0.03	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)
Republican	-0.08***	-0.05**	-0.09***	-0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
Neither Party	-0.09***	-0.04*	-0.10***	-0.07**
	(0.02)	(0.02)	(0.02)	(0.02)
Global warming index	-0.02	-0.02	-0.01	-0.01
	(0.02)	(0.02)	(0.03)	(0.03)
Visible green project	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.02)	(0.02)
Republican Governor	0.11***	0.15***	0.05*	0.06*
	(0.02)	(0.02)	(0.02)	(0.03)
Neither Party x Republican Governor		-0.10**		-0.05
		(0.03)		(0.04)
Republican x Republican Governor		-0.05		-0.02
		(0.03)		(0.03)
N	3034	3034	3034	3034
Adjusted R^2	0.029	0.031	0.022	0.022
Sample Fixed Effects	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes

Notes: Linear regression of credit indicator on individual and geographic covariates. Heteroskedasticity-robust standard errors in parentheses. Additional controls include county unemployment rate, labor force, GDP, income per capita, highway access, college share, poverty share, housing costs, population density, broadband access, Democratic vote share, state union membership, and state industrial electricity prices. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

E Credit Claiming

E.1 Coding Protocol

Research assistants used the following protocol to code the press releases accompanying green projects:

First, the press releases were separated into individual lines. These lines are referred to as "text entries" in this section, and they ranged in length from a sentence to a long paragraph. This separation was partially by default because of the web scraping employed, but it also served a purpose of identifying the location in each press release where an inference was being made about the speaker and credit claiming. Blank text entries, headers, text under 150 characters, or extraneous text were trimmed.

Second, the research assistant sorted each text entry into one of four mutually exclusive categories:

- Quote: A text entry is categorized as a "quote" if it is a quoted statement.
- Statement: Statement refers to a statement that was not quoted but is part of the press release.
- Announcement: A text entry is categorized as an "announcement" if it is a statement that relates to the unveiling of a project.
- Visit: A text entry is categorized as a "visit" if it is a statement that describes a tour of the facility.

Text entries in the "announcement" and "visit" categories are not considered in the analysis of credit attribution. Only text entries in the "quote" or "statement" categories are considered in the analysis of credit attribution.

Third, each text entry is annotated to indicate if the following sources received credit. The speaker giving the credit was also recorded.

- **Economic Conditions:** A text entry was coded as a credit to economic conditions if the "quote" or "statement" appealed to any of the following factors as the reason for investment: a comparative advantage for electric vehicle manufacturing, the growing demand for electric vehicles, a hospitable environment for business, or the quality of the workforce pool.
- **Federal Government:** A text entry was coded as a credit to the federal government if the "quote" or "statement" appealed to any of the following factors as the reason for investment: electoral branches and its members (e.g., White House, Congress, U.S. President, U.S. Senator, U.S. Representative, etc.), federal agencies and its functionaries (e.g., Environmental Protection Agency, Secretary of the Department of Energy, etc.), or federal legislation (e.g., the Inflation Reduction Act, the Bipartisan Infrastructure Law, the CHIPS Act, etc.).
- **State Government:** A text entry was coded as a credit to the state government if the "quote" or "statement" appealed to any of the following factors as the reason for investment: state electoral branches and its members (e.g., the Governor, the State House, the State Senate, state senator, state representative, etc.), state agencies and its functionaries (e.g., the state Department of Commerce, the Secretary of the state Department of Commerce, etc.), or state initiatives (e.g., state clean energy plan, state regulation, state grants, etc.).

- **Local Government:** A text entry was coded as a credit to the local government if the "quote" or "statement" appealed to any of the following factors as the reason for investment: local electoral branches and its members (e.g., the mayor, county executive, city manager, the local council, council member, etc.) or local initiatives led by the local government.
- Development Groups
  - **Federal Public-Private Development:** A text entry was coded as a credit to a federal public-private development group if the "quote" or "statement" cited the Tennessee Valley Authority (TVA) or a TVA official as the reason for investment.
  - **State Public-Private Development:** A text entry was coded as a credit to a state public-private development group if the "quote" or "statement" cited a state development corporation (e.g., Michigan Economic Development Corporation, etc.) or other state development agencies that are considered public-private partnerships.
  - **State Private Development:** A text entry was coded as a credit to a state private development group if the "quote" or "statement" cited a private entity dedicated to state development, typically a Chamber of Commerce.
  - **Local Public-Private Development:** A text entry was coded as a credit to a local public-private development group if the "quote" or "statement" cited a local development authority (e.g., Shoals Economic Development Authority, etc.) or other local development agencies that are considered public-private partnerships.
  - **Local Private Development:** A text entry was coded as a credit to a local private development group if the "quote" or "statement" cited a private entity dedicated to local development, typically a Chamber of Commerce.

Text entries determined to not allocate credit are coded as either "descriptive statement" or "investment benefit". A text entry is considered as a "descriptive statement" if it does not provide an explanation for what caused the investment. A text entry is recorded as an "investment benefit" if it is a descriptive statement that discusses job creation.

E.2 LLM Annotation

As a check, we provided the ChatGPT API with the following prompt:

> You are a research assistant. Read this announcement on a new investment. First, determine what type of statement it is. If the statement describes who or what is responsible for the investment, it is a statement with credit. If the statement gives credit, answer 'Yes' and categorize the credit as follows. Credit means that the statement has a clear description of who or what is responsible for the investment.
>
> Economic Conditions: If the statement credits abstract or generalized economic factors (such as growing market demand, regional workforce strength, local supply chain advantages, industry growth trends, economic development drivers, or economic forecasts) as the primary reason for the investment, answer 'Yes' and cite 'Economic Conditions'; this category is for statements that emphasize broader economic or market forces driving the decision. Because statements that credit Economic Conditions generally appeal to abstract or generalized economic factors, you can be more permissive in coding what counts as a credit statement, but this applies only to this category. For Federal Government, State Government, and Local Government, maintain the condition defined earlier

— that is, Credit means that the statement has a clear description of who or what is responsible for the investment.

Federal Government: If the statement credits federal officials, such as the President of the United States, U.S. Senators, U.S. Representatives, or references federal legislation (e.g., Inflation Reduction Act (IRA), Bipartisan Infrastructure Law (BIL), National Electric Vehicle Infrastructure (NEVI) Program), or mentions federal agencies like the EPA, DOE, or TVA, answer 'Yes' and cite 'Federal Government'.

State Government: If the statement credits state officials, such as governors, state senators, state representatives, or mentions state development corporations (e.g., Michigan Economic Development Corporation (MEDC), Empire State Development (ESD)), state legislative initiatives, or state-specific clean energy plans (e.g., Maryland's clean energy plan), answer 'Yes' and cite 'State Government'.

Local Government: If the statement credits local officials, such as mayors, county executives, town managers, or mentions local development authorities (e.g., Shoals Economic Development Authority (SEDA), Joint Development Authority of Stanton Springs), answer 'Yes' and cite 'Local Government'.

Other: If the statement gives credit to any other entity, such as international organizations, non-profits, regional entities, or any other identifiable party not mentioned in the above categories, answer 'Yes' and cite 'Other'.

Company Credit: Do not credit companies (such as Hyundai, Toyota, Form Energy, etc.) for the investment. If a company is mentioned as the source of credit, do not attribute credit to it. If the statement credits a company or includes a company name as the reason for investment, answer 'No'.

For all other cases that do not clearly describe who or what is responsible for the investment (i.e., statements that do not provide a clear attribution or describe abstract economic factors as the cause), answer 'No'.

We used OpenAI's gpt-4o-mini model. The temperature parameter was 0.5.

The model assessed all text entries that passed the initial text quality check. We then assessed the consistency of the coding between the human coder and the LLM coder. Agreement over the whole sample was 74.3%. However, at least 158 instances of disagreement occur due to the LLM's systematic inability to identify appeals to abstract or generalized economic factors as credit statements. Excluding these disagreements, interrater agreement increases to 82.6%. Below, we include a table listing the level of interrater agreement per credit group (which is based on the human coder's grouping).

Credit Group	**#**	**% of Agreement**
Not a credit statement	625	89.5
State government	133	81.1
Federal government	32	55.2
Development groups	47	53.4
Local government	14	41.2
Economic conditions	70	35.0

Table E11: Interrater Agreement

Despite varying levels of interrater agreement, interrater agreement on what should not be considered a credit statement stands at 89.5%.

E.3 Power Analysis

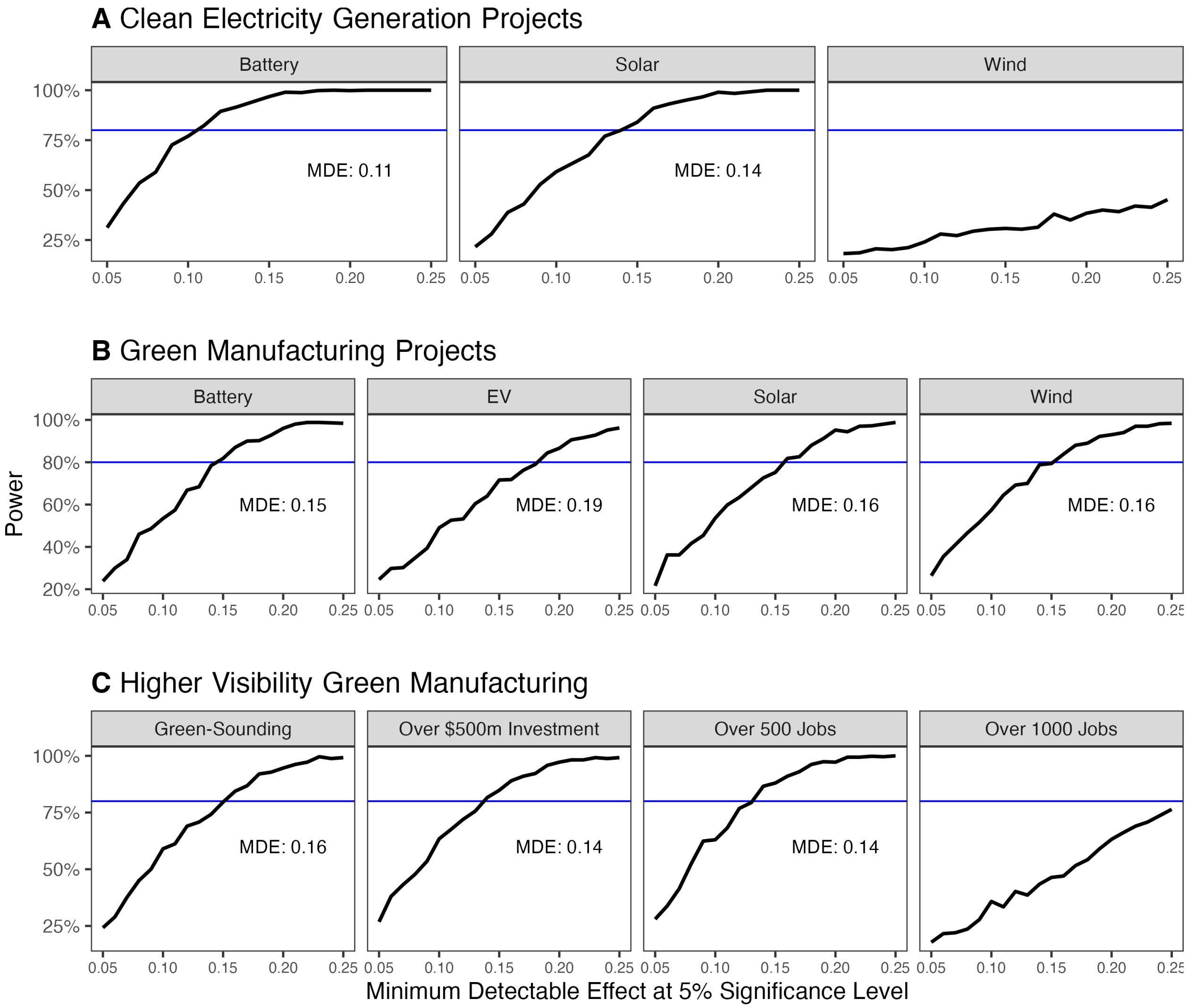

Figure E27: Analytical Power Analysis for Effect of Proximity on Credit Attribution

References

[1] Barry T. Hirsch and David A. MacPherson. "Union Membership and Coverage Database from the Current Population Survey: Note." In: *ILR Review* 56.2 (2003), pp. 349–354.

[2] Robert Chew et al. *LLM-Assisted Content Analysis: Using Large Language Models to Support Deductive Coding*. 2023. arXiv: 2306.14924 [cs].

[3] Joseph T. Ornstein, Elise N. Blasingame, and Jake S. Truscott. "How to Train Your Stochastic Parrot: Large Language Models for Political Texts." In: *Political Science Research and Methods* (2025), pp. 1–18.

[4] Fabrizio Gilardi, Meysam Alizadeh, and Maël Kubli. "ChatGPT Outperforms Crowd-Workers for Text-Annotation Tasks." In: *Proceedings of the National Academy of Sciences* 120.30 (2023), e2305016120. arXiv: 2303.15056 [cs].

[5] Joseph L. Fleiss. "Measuring Nominal Scale Agreement among Many Raters." In: *Psychological Bulletin* 76.5 (1971), pp. 378–382.

[6] Ryan D. Enos. "What the Demolition of Public Housing Teaches Us about the Impact of Racial Threat on Political Behavior." In: *American Journal of Political Science* 60.1 (2016), pp. 123–142.