Pathway to Zero Natural Gas

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DEPARTMENT OF
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Executive Summary

The Los Alamos Department of Public Utilities (LADPU) has set a goal of eliminating natural gas service in Los Alamos County by 2070. Reaching it depends on residential customers replacing gas furnaces, water heaters, and stoves with electric alternatives, largely through voluntary decisions over the coming decades. This white paper combines a survey of LADPU customers, a discrete choice experiment, and household-level metered electricity and natural gas data from 2022 through 2025 to assess how willing households are to switch, what it would cost them, and how the transition would reshape electricity demand.

Our key findings are:

1. **Households are receptive in principle but highly cost-sensitive, and few are planning to switch.** Nearly all surveyed households use natural gas, and most are satisfied with their gas appliances. About three-quarters report no near-term intention to electrify. Asked what would change their decision, respondents rank cost savings and appliance efficiency far above environmental benefits, and most would face hardship from a bill increase of \$50–\$100 per month. Stated support for the 2070 goal is currently low.

2. **Households value efficiency and bill savings over emissions, and the electrical-panel upgrade is a major barrier.** In the choice experiment, households are willing to pay the most for appliance efficiency, somewhat less for carbon reductions, and least for one-time rebates. The roughly three-quarters of homes that would need a 200-amp electrical-panel upgrade are markedly less willing to electrify. Offsetting that barrier would take about \$800 per year in lower energy bills or incentives. Pro-environmental attitudes, more than current energy bills, explain who is willing to pay for emissions reductions, and an informational message about the health and climate effects of gas had little measurable effect.

3. **Rooftop solar lowers grid purchases but raises total energy use (a rebound effect).** Among solar adopters, grid electricity purchases fall sharply, yet total electricity use rises and natural gas use is essentially unchanged, so total household energy consumption increases by roughly 7% after adoption. This rebound offsets a meaningful share of the emissions reductions that solar would otherwise deliver, and it varies by season and time of day.

4. **What drives consumption differs by fuel.** Persistent natural gas use is governed mostly by the building envelope (home size, age, and structure), whereas persistent electricity use reflects the building, the appliance stock, and household characteristics together. The two fuels therefore call for different policy levers.

5. **Meeting the 2070 goal would sharply raise electricity demand and reshape it toward a winter peak, and households' stated plans fall well short of it.** Eliminating residential natural gas on LADPU's schedule would raise annual residential electricity use by about 61% by 2070. Because electric heating concentrates the new load in winter, the seasonal peak grows even faster (about 74%), so sizing the distribution system to the winter peak, rather than to annual energy, becomes the binding planning constraint. Voluntary switching at the pace households say they intend would stall well short of the goal, leaving roughly 60% of today's gas use still burning in 2070. Closing that gap depends on electric becoming the default choice when gas equipment is replaced. Rooftop solar lowers the grid load the utility must serve, but only modestly, about 5% by 2070 even if it reaches 40% of homes.

These findings carry several policy implications. First, because households weigh efficiency, comfort, and bill savings far above emissions, and an informational message about the climate and health effects of gas changed willingness to pay very little, outreach that highlights bill savings and performance is likely to reach more households than climate framing. Second, the largest near-term gains come from lowering the cost and friction of getting homes ready, through streamlining electrical-panel permitting, helping households find and stack the federal and state incentives already available, offering loans to financially constrained households, and reaching households at the moment their gas equipment fails. Third, the two fuels respond to different levers, so the largest gas reductions come from the older, larger homes where gas use is concentrated and from sequencing weatherization, run through county and state programs, ahead of electric heating, while space and water heating, not cooking, are the high-load end uses worth prioritizing. Fourth, rooftop solar offsets only a small share of the added load and the rebound erodes its carbon benefit, so solar compensation that rewards self-consumption and load-shifting, especially toward the winter-evening peak, would raise its grid value. Fifth, the added load is large, about a 61% rise in annual residential electricity use and a steeper winter peak by 2070, so capacity planning that carries the rebound into load forecasts and builds affordability and equity into program design is central to the transition.

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1 Introduction

Residential buildings account for roughly one-fifth of greenhouse gas emissions in the United States, and the largest share of that footprint comes from burning natural gas on-site for space heating, water heating, and cooking (U.S. EPA, 2024). Decarbonizing the residential sector therefore requires replacing natural gas appliances with electric alternatives, such as heat pumps, electric water heaters, and induction cooktops, and supplying the additional electricity from an increasingly clean grid. Eliminating in-home gas combustion also removes a source of indoor air pollutants, including carbon monoxide, nitrogen dioxide, and fine particulate matter, that have been linked to respiratory illness (Lin et al., 2013).

The Los Alamos Department of Public Utilities (LADPU), the municipal utility serving Los Alamos County, New Mexico, has adopted the goal of eliminating natural gas service by 2070 as part of the county's long-term sustainability plan. Because the target lies decades away, it functions as an active planning horizon rather than an imminent mandate. To meet the goal, the utility must understand whether, and how quickly, its residential customers are willing to move away from natural gas, what that transition will cost households, and how it will reshape electricity demand on the local grid.

Yet the environmental and health case for electrification does not by itself determine whether, or how fast, the county will reach the goal. Whether a household replaces a working gas furnace or water heater with an electric system depends on upfront and operating costs, the perceived reliability of electric appliances, the condition of the home's electrical service, and the household's own attitudes and circumstances. The transition also raises distributional concerns. If higher-income households electrify first, the fixed costs of the legacy gas system may fall on a shrinking and lower-income set of remaining customers (L. Davis and C. Hausman, 2022). It raises engineering concerns as well, about how shifting a large heating load from gas to electricity will affect peak demand and system planning.

This report assembles several sources of evidence to inform LADPU's pathway to zero natural gas. It combines a survey of LADPU residential customers, a discrete choice experiment (DCE) that elicits households' willingness to pay for the attributes of an electrification decision, and hourly metered electricity and natural gas consumption data from January 2022 through June 2025, linked to households at the meter level. Together these allow us to describe who LADPU's customers are and what appliances they own, to quantify how they trade off cost, efficiency, incentives, and emissions when considering switching, and to project how electricity load would evolve under alternative switching scenarios.

The report is organized into five parts. Part I summarizes the resident survey, covering demographics, billing and housing characteristics, the household appliance stock, and stated preferences toward switching from natural gas to electric appliances. Part II presents the discrete choice experiment and uses it to estimate households' willingness to pay for electrification attributes. Part III examines rooftop solar adoption and its rebound effect on household energy consumption. Part IV analyzes the household characteristics that drive natural gas and electricity use and projects residential electricity load under a range of appliance-switching scenarios. Part V synthesizes the findings, centering on the gap between households' stated willingness and their observed switching, and sets out the resulting policy recommendations.

2 Background

2.1 Los Alamos County

Los Alamos County is an atypical utility service territory. Los Alamos National Laboratory (LANL) is the dominant employer, accounting for an estimated 60 to 70% of county employment, and the resulting population is highly educated and affluent. Roughly half of adults hold a graduate degree and median household income is approximately $143,000 (U.S. Census Bureau, 2023), more than double the New Mexico median of about $62,000 and well above the national median of about $79,000. LADPU is a municipally owned utility that provides electricity, natural gas, water, and sewer service to the community, including approximately 8,500 residential customers.

Los Alamos County comprises two neighboring communities, Los Alamos and White Rock, about ten miles apart. Los Alamos sits at an elevation of 7,425 feet, while White Rock lies lower, at 6,548 feet, and has a warmer, drier climate (Bruggeman and Waight, 2021). White Rock's population is roughly half that of Los Alamos. At these elevations the county has a high-desert climate, with cold winters, mild summers, large day-to-night temperature swings, and low humidity. Space heating is therefore the dominant seasonal load and natural gas use is heavily concentrated in winter, a pattern central to how electrification would reshape the county's electricity demand.

Much of the county's housing stock dates to LANL's expansion between the 1940s and the 1970s. These older homes were not built for whole-home electrification. Many are served by 100- or 150-amp electrical panels that cannot accommodate the combined load of a heat pump, a heat pump water heater, and an induction cooktop without an upgrade to 200-amp service.

2.2 Zero natural gas policies

Los Alamos County has adopted a target of eliminating natural gas service by 2070 as part of the county's sustainability plan. Unlike a near-term regulatory mandate, a 2070 horizon gives the utility and its customers decades to plan, but it also means the transition will unfold gradually and largely through voluntary household decisions about when to replace aging equipment.

Understanding the drivers of those decisions today is therefore central to whether the long-run goal is met.

The local goal sits within a broader policy environment that increasingly favors electrification, from state-level standards that phase out fossil-fuel appliances in new construction (California Air Resources Board, 2023; New York State Legislature, 2023) to federal incentives. At the federal level, the home energy rebate and tax-credit provisions of the Inflation Reduction Act of 2022 subsidized heat pumps, electric appliances, and in some cases the electrical-panel upgrades that enable them, lowering the upfront cost of switching during the period of this study.[1] The case for moving away from residential natural gas rests on two pillars. The first is climate. On-site combustion of natural gas for heating and cooking is a substantial source of household greenhouse gas emissions, and switching to efficient electric appliances reduces those emissions to the extent that the electricity grid is clean. The second is indoor air quality and health. Gas appliances emit carbon monoxide, nitrogen dioxide, fine particulate matter ($PM_{2.5}$), and formaldehyde indoors, and these pollutants are linked to elevated rates of childhood asthma and respiratory illness, particularly where gas stoves are used. Eliminating in-home combustion removes these exposures regardless of the grid mix.

[1] The federal incentive landscape shifted during the study. When the survey was fielded (July to September 2025), the Inflation Reduction Act's Section 25C Energy Efficient Home Improvement Credit (covering heat pumps, electric appliances, and electrical-panel upgrades) and Section 25D Residential Clean Energy Credit (covering rooftop solar) were both in effect. The One Big Beautiful Bill Act (Public Law 119-21, signed July 4, 2025) subsequently terminated both credits for property placed in service after December 31, 2025, roughly seven years earlier than the Inflation Reduction Act had scheduled. The Act did not rescind the $8.8 billion in Inflation Reduction Act Home Energy Rebates (the HOMES and Home Electrification and Appliance Rebate programs), which had already been obligated to the states; New Mexico's rebate program launched in September 2024 and remains available, but is limited to income-qualified households (broadly, those below 80% of area median income). The analysis in this report reflects the incentive environment at the time of the survey.

Part I
Resident Survey

3 Overview

In collaboration with LADPU, we surveyed the utility's residential customers from July to September 2025 to learn how they use natural gas today and how they view switching to electric appliances. The survey had two parts, a questionnaire on demographics, housing, billing, and the household appliance stock, and a discrete choice experiment. We received 912 responses, of which 582 were complete. The survey was distributed through several channels, namely the utility's customer email list, a paper billing insert, the county newsletter, and community social media, so a single conventional response rate is not well defined. As a rough gauge, the 912 responses represent about 11% of LADPU's roughly 8,500 residential customers, and the 582 complete responses about 7%.

The respondents are broadly representative of Los Alamos County. About 78% report household incomes above \$100,000 and 55% above \$150,000, 60% hold a graduate degree, and nearly half are employed full-time while about 40% are retired (Figure 1). The sample nonetheless departs from the county demographics in several dimensions. It under-represents Hispanic or Latino residents (about 8% of the sample versus 17% county-wide) and skews towards older and more male (Table A.1).

The difference between the survey sample and the county demographics can be corrected with calibrated post-stratification weighting on age, sex, ethnicity, and education, after which the weighted sample matches county benchmarks. Full demographic breakdowns, the weighting procedure, and the formal representativeness tests are reported in Appendix A.1, with housing characteristics in Appendix A.3 and billing in Appendix A.2. The remainder of this part focuses on the three survey findings that bear most directly on the transition. These are the natural gas appliances households own, how sensitive they are to energy costs, and their stated attitudes toward switching.

4 Natural Gas Appliance Stock

Los Alamos households rely heavily on natural gas. Nearly all (96%) use gas appliances, and gas is the primary heating fuel for 90% of homes, against just 8% for electricity. Heating is delivered mostly by central furnaces (59%) and steam or hot-water systems (32%), with heat pumps a marginal 5%. Gas is also the main fuel source for water heating, where 90% of homes use gas and only 9% electric. Cooking is more mixed. Gas powers about 63% of ranges and

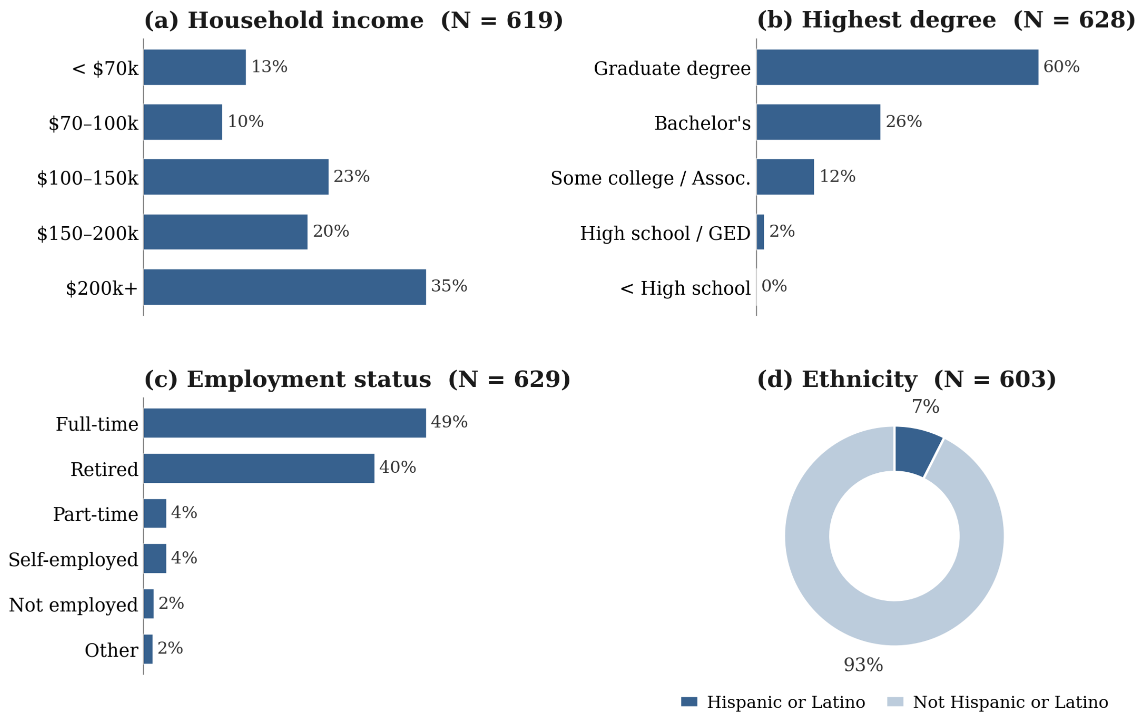


Figure 1: Survey respondents at a glance

59% of cooktops, but wall ovens (83%) and clothes dryers (74%) are predominantly electric, indicating that households already accept electric versions of some appliances more readily than others. Much of the heating stock is also aging, with about a third of primary heating systems at least 20 years old, so a large share of homes will face a replace-or-switch decision within the planning horizon. Detailed appliance counts, fuels, ages, and usage patterns are reported in Appendix A.4.

5 Cost Sensitivity

Households are sensitive to energy bill changes. Modest bill increases of $10–$25 per month cause no hardship for most households (77% and 63%, respectively), but sensitivity rises sharply beyond that. At $50 per month, 61% would face some or great hardship, and at $100 per month, 82% would, with over half (52%) reporting great hardship. The affordability threshold for most households therefore lies between $25 and $50 per month. Households also perceive electricity as already the larger cost burden, with 47% putting their peak electricity bill at $150 or more, against 28% for gas (Table 1, with full bill estimates in Appendix A.2).

Table 1: Hardship of a Net Monthly Out-of-pocket Increase for all Energy-Related Costs

Increase ($/month)	No hardship (%)	Some hardship (%)	Great hardship (%)	N
$10	77.0	12.9	10.1	435
$25	62.7	24.3	13.0	437
$50	39.2	35.1	25.7	436
$75	24.3	34.3	41.4	437
$100	17.8	30.6	51.5	454

Note: Most households report no hardship at $10/month (77%) and still a majority at $25 (63%), but the response shifts sharply by $50, where 61% say they would face hardship (35% "some," 26% "great"). Hardship grows at higher amounts: at $75, three in four report hardship, and by $100 a clear majority (82%) say it would cause hardship.

6 Attitudes Toward Switching

Households' stated attitudes are the most direct survey evidence on the transition, and they are consistently cautious. Most (88%) are satisfied with their current gas appliances and only 4% are dissatisfied. A majority (54%) believe electric appliances are less reliable than gas, while only 11% think they are more reliable. Consistent with this, about three-quarters (74%) are not planning to switch to electric appliances at all (Figure 2).

The factors households weigh in a switching decision are practical rather than environmental. Cost savings, performance, efficiency, and incentives rank highest, while environmental and health benefits rank lowest, and 16% report that no factor would lead them to switch. The perceived obstacles are financial and infrastructural (Figure 3). The most-cited obstacle is the upfront installation cost (73%), followed by higher ongoing energy bills (65%) and grid reliability (65%). About half (51%) cite insufficient electrical-panel capacity, a barrier specific to this older housing stock in which roughly three-quarters of homes would need a 200-amp panel upgrade to electrify. Part II quantifies how much this panel requirement lowers willingness to pay. Concerns about the carbon content of electricity (25%) or poor home insulation (16%) are far less common, and only 5% report none at all.

The appliance-by-appliance question drew far fewer responses than the general attitude items (175 respondents) and from a more self-selected group, so it indicates which equipment the more engaged households would switch first rather than any softening of overall reluctance. Among those who sorted individual appliances into "very likely to switch," "no intention to switch," and "already electric," the predominantly gas-powered appliances, water heaters, space heaters, and ranges, were most often marked as switch candidates (Figure 4). This points to the equipment a voluntary transition would most plausibly begin with, consistent with framing it as a sequence of concrete replacements rather than an all-at-once decision.

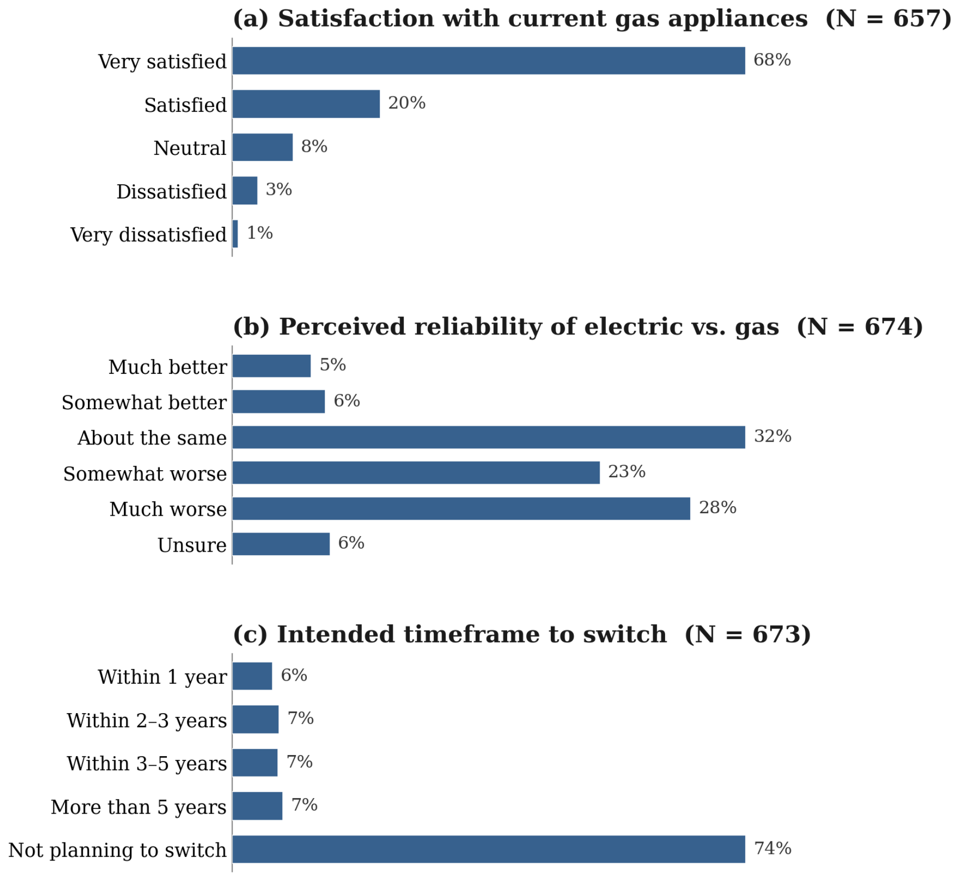


Figure 2: Household attitudes toward switching to electric appliances

Notes: Likert-scale responses on satisfaction with current gas appliances, the perceived reliability of electric appliances relative to gas, and how soon respondents would consider switching.

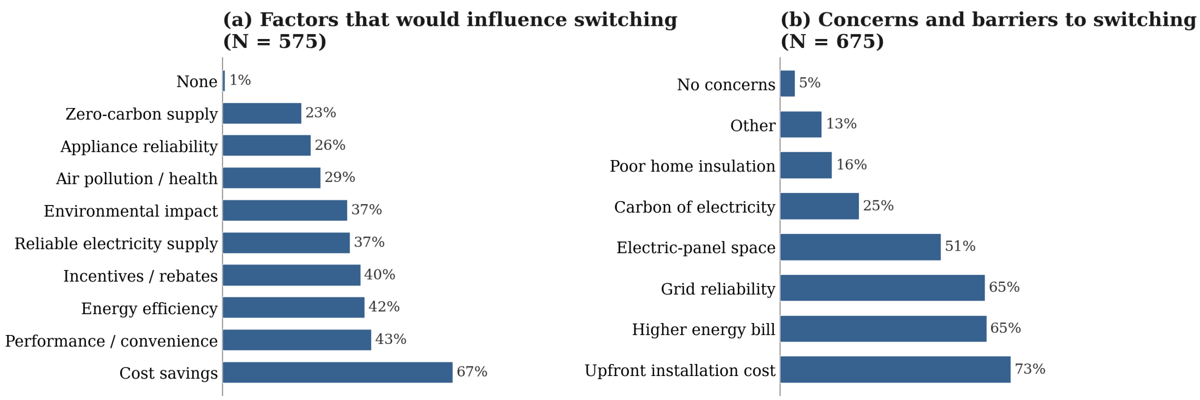


Figure 3: Drivers of and barriers to switching to electric appliances

Notes: Respondents could select all options that apply, so shares do not sum to 100%.

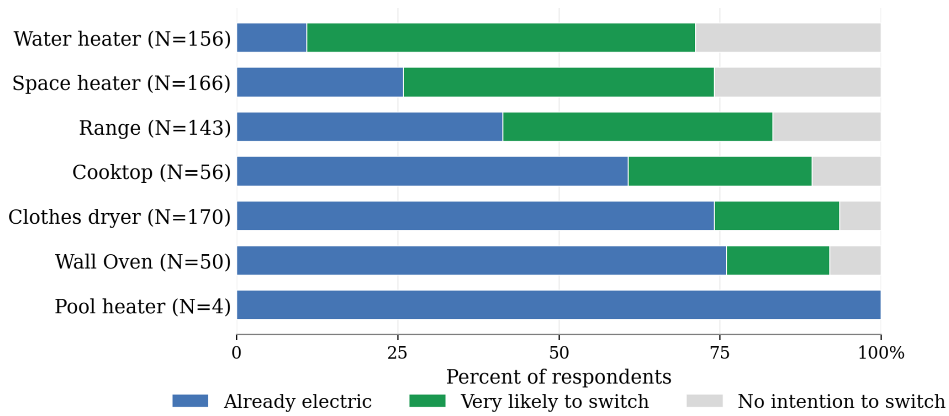


Figure 4: Intentions to switch a given appliance to electric

Notes: Respondents sorted each appliance into "very likely to switch," "no intention to switch," or "already electric." They were not required to classify every appliance.

7 Environmental Attitudes

We also measured environmental attitudes with six items from the New Ecological Paradigm (NEP) scale (Dunlap, Van Liere, et al., 2000), a standard measure of pro-environmental worldview. Respondents express moderate environmental concern on average. Most respondents acknowledge ecological limits and human responsibility for the environment, while agreement with the reverse-coded items is relatively low. As the attitudes above make clear, however, this concern is not the primary driver of their appliance decisions (Figure 5). Item-level summary statistics are reported in Appendix A.5.

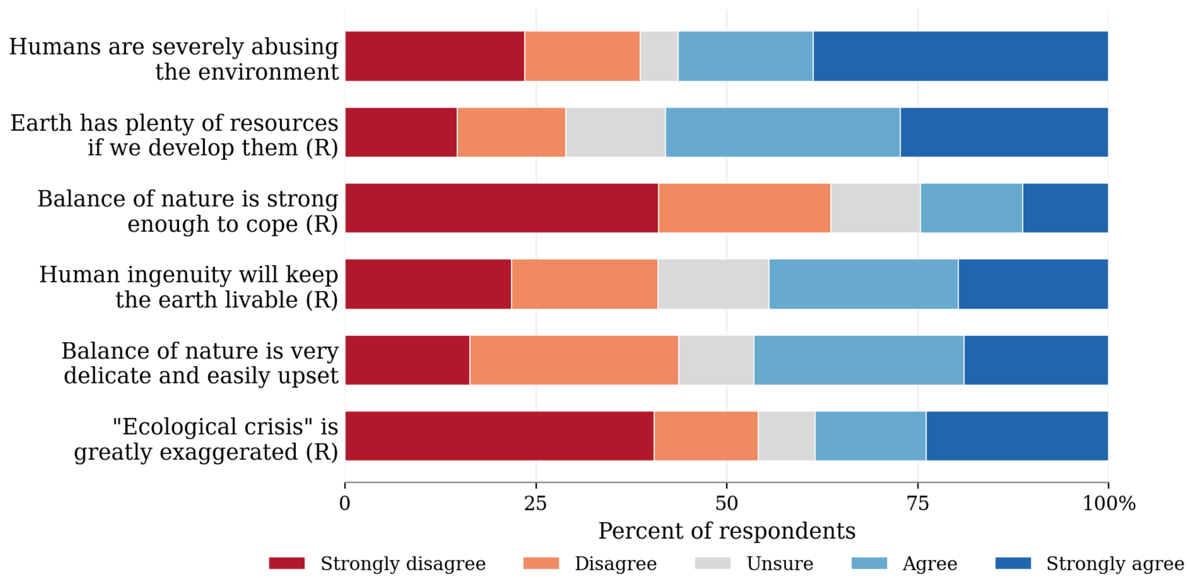


Figure 5: Attitudes Toward NEP Questions

Notes: Responses to six New Ecological Paradigm items, each rated on a five-point scale from strongly disagree to strongly agree. Items marked with "(R)" are reverse-coded statements, where higher scores indicate lower environmental concern.

Part II

Household Willingness to Switch

8 Overview

To quantify how households trade off the costs and benefits of switching to electric appliances, we fielded a discrete choice experiment (DCE) in which respondents repeatedly chose among hypothetical electrification options that varied in carbon reduction, appliance efficiency, financial incentive, and net monthly cost. This part estimates how much households are willing to pay (WTP) for each attribute, how the prospect of a required electrical-panel upgrade changes those valuations, and how preferences vary with environmental attitudes.

9 Data and Methods

9.1 Survey Design and Sample

The survey and its administration are described in Part I. The analysis sample for the DCE is the 403 respondents who completed all six choice tasks. Because this analysis subsample is more selective than the full survey, Table 2 reports its characteristics against Los Alamos County census figures. The full-survey demographics and the formal representativeness analysis are in Part I and Appendix A.1.

Table 2: Sample Demographics and Census Comparison

Variable	Sample (N = 403)	Los Alamos County
	Panel A: Demographics	
Age (mean years, SD)	51.8 (15.0)	42.5[a]
Age 65+ (%)	18.2	26.7
Female (%)	35.4	49.7
Hispanic or Latino (%)	10.1	16.5
	Panel B: Education	
Graduate degree (%)	42.1	50.5
Bachelor's degree (%)	18.8	22.0
Some college or less (%)	26.9	21.6
	Panel C: Household Income	
< $35,000 (%)	2.7	15.9
$35,000–$70,000 (%)	7.8	17.4

Continued on next page

Table 2 continued

Variable	Sample (N = 403)	Los Alamos County
\$70,000–\$150,000 (%)	8.3	32.0
> \$150,000 (%)	81.2	34.7
	Panel D: Housing and Energy	
Homeowner (%)	84.6	77.2
Panel upgrade required (%)	78.7	–
Solar adoption (%)	14.1	–
	Panel E: Survey Design	
NEP score (mean; range 6–30)	18.8	–
Protesters, all opt-out (%)	31.1	–
Information treatment (%)	20.8	–
Effective N (Kish)	318	–

Notes: Los Alamos County figures from U.S. Census Bureau, American Community Survey 2023 five-year estimates (U.S. Census Bureau, 2023). [a]Census reports median age; survey reports mean age. Sample statistics are computed using the age × education post-stratification (raking) weights described in Part I, whose design effect gives the Kish effective N of 318 reported in Panel E; unweighted analysis-sample values therefore differ (for example, unweighted mean age is 55.9, and the unweighted protester share is 29.3%, i.e. 118 of 403; Table B.5 reports unweighted values). "Protesters" are respondents who selected the status-quo (opt-out) alternative on all six choice tasks; they are retained in estimation through a separate constant rather than dropped (see Appendix B.1). The sample overrepresents older, male, White, and high-income residents relative to the county population. The sample's high-income skew reflects the Los Alamos labor market, where LANL is the dominant employer. Of the 607 matched households in the broader survey, 403 provided complete responses for all variables required in the analysis (demographics, NEP items, and all six DCE choice tasks). The remaining 204 were excluded due to incomplete NEP responses (N = 89), incomplete choice tasks (N = 74), or missing demographic fields (N = 41). Comparing the analysis sample with all 204 excluded respondents, attrition was not selective on gender (p = 0.34), homeownership (p = 0.51), or solar adoption (p = 0.67), but completers were slightly younger (mean 51.8 vs. 54.2, p = 0.04) and had higher incomes (81% vs. 73% above \$150K, p = 0.03). Table B.5 reports a complementary, unweighted comparison against the subset of excluded respondents who began the choice experiment but did not complete it; that subset is markedly older than the analysis sample, and the difference between the two comparisons reflects their different bases, not conflicting data.

9.2 Environmental Attitudes: New Ecological Paradigm Scale

Part I introduced the six-item NEP scale (Dunlap, Van Liere, et al., 2000) and the distribution of responses. Here we use those items to construct the environmental-attitude measure that enters the choice model.

Exploratory factor analysis confirms a single underlying factor (eigenvalue = 3.54, KMO = 0.88, Cronbach's α = 0.89). We compute factor scores using regression scoring. Results are stable under Bartlett scoring and simple averages (Table B.6).

The NEP scale may function differently in a population dominated by scientists and engineers. High NEP scores in Los Alamos may reflect climate-science knowledge as much as the affective environmental concern the scale captures in more representative samples. We therefore interpret the NEP–WTP gradient as an association specific to this population rather than a transferable behavioral primitive, and its magnitude may not carry over to other populations even if the qualitative pattern persists.

9.3 DCE Attribute Development

We identified four attributes based on a literature review and three focus groups with 10 Los Alamos residents in May 2025. Focus group participants discussed their current energy use, attitudes toward electrification, concerns about switching, and the factors that would most influence their decisions. Below we describe each attribute in detail.

The first attribute, annual reduction in household carbon footprint, captures preferences for the environmental benefits of electrification. Households switching from natural gas to electric appliances can reduce on-site carbon emissions by varying degrees depending on the local electricity generation mix (Tarroja et al., 2018; Waite and Modi, 2020). We specified four levels of 0% (status quo), 33%, 66%, and 100% reduction. The 100% level represents complete elimination of on-site fossil fuel combustion.

The second attribute, energy efficiency of electric appliances, captures preferences for appliance performance improvements. The DCE literature on heating systems consistently finds that operating cost and efficiency are primary drivers of technology choice, often exceeding environmental considerations (Achtnicht, 2011; Michelsen and Madlener, 2012; Michelsen and Madlener, 2016). In the survey, this attribute was defined as the percentage improvement in energy efficiency of electric appliances over current gas appliances, with levels of 0% (status quo), 10%, 25%, and 50%. Respondents were informed that electric stoves, water heaters, and furnaces can be approximately 20 to 50% more efficient than their gas counterparts, and that higher efficiency can lead to lower operating costs.

The third attribute, financial incentives (rebates/subsidies), reflects the role of upfront cost subsidies in adoption decisions. The Inflation Reduction Act of 2022 allocated $8.8 billion in home energy rebates, and state and local programs offer additional incentives. This attribute represents the percentage of electrification costs covered by rebates or subsidies, with levels of 0% (status quo), 30%, 50%, and 75%.

The fourth attribute, net monthly out-of-pocket cost, serves as the payment vehicle. This attribute captures the change in monthly household energy costs over the first decade after switching, with levels of $0 (status quo), –$50, +$50, +$150, and +$200. The negative value represents potential savings, while positive values represent net cost increases. These levels were informed by engineering estimates of the cost differential between gas and electric systems at current LADPU rates.

In addition to these four attributes, electrical panel upgrade status emerged from the focus groups as a critical household-specific factor. Because panel upgrade requirements vary by household (78.7% of respondents indicated they would need an upgrade), we did not include panel status as a DCE attribute with varying levels. Instead, each respondent was reminded of their self-reported panel status before beginning the choice tasks: "Earlier you indicated your property [needs / does not need] an electrical panel upgrade. Please remember this while you make your choices." Panel upgrade status enters the model as a fixed interaction term (Equation B.3) rather than a choice attribute.

Table 3 summarizes the four attributes and their levels and Figure 6 shows an example DCE choice question for the respondents.

Table 3: DCE Attributes and Levels

Attribute	Definition	Levels	Variable
Financial Incentives (Rebates/Subsidies)	Percentage of electrification costs covered by utility rebates or government subsidies	**0%**, 30%, 50%, 75%	Rebate
Energy Efficiency of Electric Appliances	Percentage improvement in energy efficiency of electric appliances over current gas appliances	**0%**, 10%, 25%, 50%	Efficiency
Annual Reduction in Household Carbon Footprint	Percentage reduction in household carbon emissions from switching to electric appliances	**0%**, 33%, 66%, 100%	Carbon
Net Monthly Out-of-Pocket Cost (First 10 Years)	Change in monthly household energy costs over the first decade after switching	−\$50, **\$0**, +\$50, +\$150, +\$200	Cost

Notes: Levels in bold are status quo levels. Attributes were identified through three focus groups with 10 Los Alamos residents. The cost attribute is framed as the net change in monthly costs, with negative values indicating savings. Each choice task presented two electrification alternatives with varying attribute levels plus an opt-out (status quo) option. Figure 6 shows an example choice question as presented to respondents.

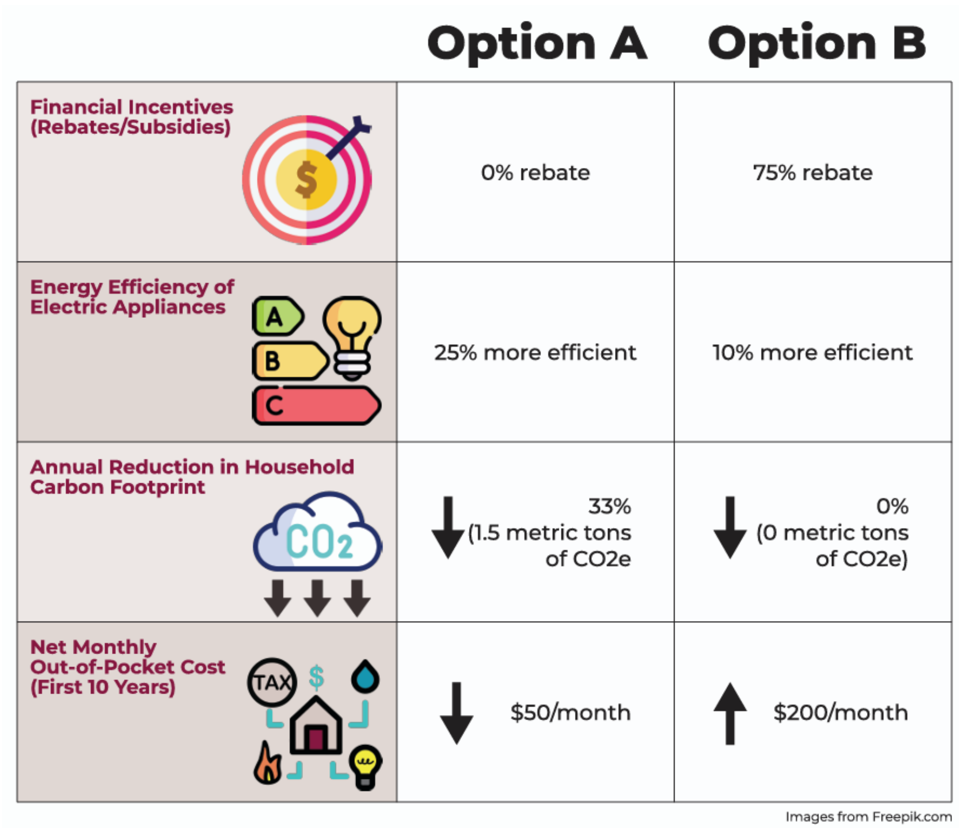


Figure 6: Example DCE choice question as presented to survey respondents. Each task presented two electrification alternatives (Option A, Option B) with varying levels of the four attributes, plus the option to choose neither (status quo).

The DCE employed a Bayesian D-efficient experimental design (Hensher et al., 2015) optimized using priors from a separate pilot sample (N = 45, not included in the main analytical sample), achieving a D-error of 0.0082. Each respondent completed six choice tasks, yielding 2,418 choice observations across 403 respondents. We tested for order effects across the six tasks and found no evidence of systematic fatigue or learning effects (Table B.7).

9.4 Information Treatment

We randomly assigned respondents to a control or information treatment group. Before completing the choice tasks, the treatment group received the following informational nudge, reproduced verbatim from the survey instrument:

> **Natural Gas Use in Homes in Los Alamos County.** Natural gas is commonly used for heating, water heating, cooking, and drying clothes. The main ingredient in natural gas is methane, a powerful greenhouse gas. Most emissions from natural gas come from burning it, which releases CO_2, but small methane leaks during extraction and transportation also

> contribute significantly to climate change. In Los Alamos County, the average household uses about 743 therms of natural gas per year, resulting in about 4.5 metric tons of greenhouse gas emissions, mostly from home heating. Burning natural gas indoors, for example using a gas stove, also creates indoor air pollutants such as carbon monoxide, nitrogen dioxide, fine particulate matter ($PM_{2.5}$), and formaldehyde. Poor ventilation can cause these pollutants to build up inside the home, increasing health risks like asthma, respiratory infections, dizziness, and headaches. Children and people with asthma or allergies are especially vulnerable. Studies have found that gas cooking can worsen asthma symptoms and reduce lung function, particularly in children. Frequent use of gas stoves without proper ventilation can significantly increase cancer risks, often exceeding WHO safety limits. Children are especially vulnerable, facing 1.85 times higher cancer risk than adults. Using a high-efficiency vented hood can greatly reduce harmful exposure. In rare cases, leaks inside the home can also create risks of suffocation or explosion if not properly managed. Lastly, using fuel-burning appliances at home also impacts the environment. The report showed that residential and commercial emissions made up 13% of total U.S. global warming emissions in 2020. Petroleum-based fuels, including natural gas, propane, fuel oil and kerosene are the primary driver of these emissions.

We verified randomization ex-post: treatment and control groups are balanced on NEP, income, education, and all other observables except age (Table B.8). The treatment effect disappears when NEP is included not because of differential assignment, but because NEP mediates the treatment pathway.

Balance tests confirm that treatment ($N = 84$) and control ($N = 319$) groups are statistically indistinguishable on NEP score, graduate education, female share, panel upgrade status, solar adoption, and all income brackets. Age shows a statistically significant imbalance, which we address by including age as a covariate in all specifications. The correlation between treatment assignment and NEP is negligible, confirming that the null treatment effect conditional on NEP is not an artifact of differential assignment.

We estimate willingness to pay with a mixed-logit model specified directly in willingness-to-pay space, with environmental attitudes (the NEP score), self-reported panel-upgrade status, and the information treatment entering as interactions, and with respondents who always chose the status quo ("protesters") handled through a separate constant rather than dropped. Full estimation details, covering the utility specification, distributional assumptions, model selection, recovery of household-level WTP, and protester handling, are reported in Appendix B.1.

9.5 Administrative Data Linkage

We matched survey respondents to LADPU administrative billing records (January 2022 through June 2025, the roughly three and a half years of metered consumption leading up to the survey) using fuzzy matching algorithms on name and address fields, followed by manual verification. Of the 403 analysis-sample respondents, 376 (93.3%) were successfully linked to monthly electricity and natural gas billing histories. Among matched respondents, 350 have complete natural gas records and 362 have complete electricity records. The remainder have billing gaps due to account changes or service interruptions.

Mean monthly electricity consumption is 621 kWh (SD = 341, median = 525), and mean monthly natural gas consumption is 80 hundred cubic feet (CCF) (SD = 40, median = 72). At current LADPU rates of approximately $1.10 per CCF, the median monthly gas bill is $79 and the mean is $88. Gas expenditure varies widely, with the interquartile range spanning $58 to $111 per month. The 90th percentile household spends $149 per month on natural gas, while the 10th percentile spends only $41. This variation in gas expenditure creates heterogeneous financial incentives for electrification.

Figure 7 displays the seasonal profile of household energy consumption. Electricity peaks in both winter and summer (reaching approximately 790 kWh in January and July), reflecting combined heating and cooling loads in this high-desert climate. Natural gas consumption is heavily winter-concentrated. January averages 185 CCF, roughly ten times the June–August baseline of 18 CCF. This seasonal concentration means that electrification through heat pump adoption would primarily displace winter gas loads, with the largest bill impacts falling in December through February.

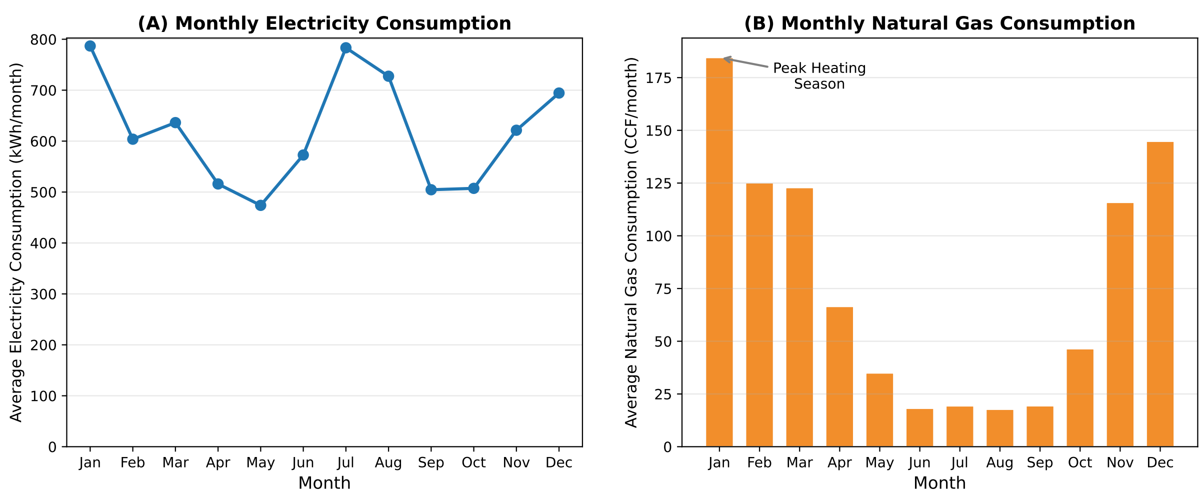


Figure 7: Average monthly energy consumption for matched LADPU households (N = 362 electricity, N = 350 gas). Panel A: Monthly electricity consumption (kWh). Panel B: Monthly natural gas consumption (CCF). Consumption records span January 2022 through June 2025.

The average electricity share of total household energy expenditure is 0.45, indicating that these households already derive roughly half their energy services from electricity. 14% of matched respondents have rooftop solar installations.

10 Discrete Choice Experiment Results

10.1 Population-Level WTP Estimates

Table 4 reports the headline WTP estimates. The full mixed-logit specification, with all interaction terms and model diagnostics, is reported in Appendix Table B.1. Because the model is estimated directly in the WTP space, the attribute coefficients are marginal WTP in dollars per month per percentage point of each attribute, denominated over the first decade after switching to match the payment vehicle framing described above.

Table 4: Headline Willingness to Pay Estimates

Electrification attribute	WTP ($/month per %-point)	Implied value ($/year)
Energy efficiency	2.31***	1,385 (at +50%)
Carbon reduction	1.49***	1,788 (at 100%)
Financial rebate (upfront)	1.10***	988 (at 75%)
Key adoption barrier		
Electrical-panel upgrade (resistance cost)	$813 per year	

Notes: Mean WTP from a WTP-space mixed-logit model (N = 403 respondents, 2,418 choice observations). All figures are expressed over the first decade (the first 10 years) after switching, consistent with the survey's payment-vehicle framing. WTP is in dollars per month per percentage-point improvement in each attribute, and the implied annual value applies that WTP to the attribute's maximum level (efficiency +50%, carbon 100%, rebate 75%) over twelve months (for example, energy efficiency: $2.31 × 50 points × 12 months ≈ $1,385 per year). The electrical-panel-upgrade figure is the resistance cost, the additional annual benefit a panel-needing household requires to choose electrification. It is a stated-preference measure of the barrier, not the physical upgrade cost ($2,000–$5,000 one-time). The full mixed-logit specification, with all interaction terms (panel upgrade, NEP, information treatment, sociodemographics) and diagnostics, is reported in Appendix B.1 (Table B.1). *** $p < 0.01$.

Energy efficiency commands the highest WTP at $2.31 per month per percentage point, followed by carbon reduction ($1.49) and rebates ($1.10). The ordering indicates that performance and operating cost savings matter more to households than either environmental benefits or upfront cost reductions. For the maximum efficiency improvement of 50%, the implied WTP is $115.40 per month ($1,385 annually).

The efficiency WTP estimate reflects bundled performance expectations. Respondents likely value reliability, comfort, and modernization alongside energy savings. A heat pump operating at a coefficient of performance of 3.5 replacing an 80% efficient gas furnace saves approximately $38 per month at Los Alamos energy prices, and the percentage-point framing generates large aggregate values. Applying the Penn and Hu (2018) trimmed-sample mean calibration factor of 1.94, the ratio of hypothetical to real willingness to pay in their meta-analysis, scales the headline efficiency estimate of $2.31 per month per percentage point to about $1.19 ($2.31 ÷ 1.94), or roughly $59 per month at a 50% efficiency improvement, moving the stated value toward revealed-preference benchmarks.

Carbon reduction WTP of $1.49 per month per percentage point translates to $149 per month for complete decarbonization from natural gas use ($1,788 annually). The ordering, where efficiency exceeds carbon exceeds rebates, is consistent with a population that values electrification primarily for private rather than social benefits.

The rebate coefficient of $1.10 per month per percentage point implies that households value a 75% rebate at $82.35 per month ($988 annually). The low standard deviation (CV = 0.09) indicates homogeneous rebate preferences. A two-class latent class model (Table B.11) identifies Class 1 (59%) with significant WTP similar to the main model and Class 2 (41%) with imprecise estimates and a large status-quo alternative-specific constant (ASC, the model's baseline pull toward the no-switch option), consistent with protesters and disengaged respondents rather than attribute-specific non-attendance.[2] Design-based non-attendance diagnostics show 37.7% of respondents with choice sequences consistent with rebate non-attendance, comparable to 37.0% for carbon and 39.5% for efficiency. The similarity of these rates alone would not rule out non-attendance as the source of rebate's low variance; the more direct evidence is that non-attendance rates do not track WTP dispersion across the attributes. Efficiency has the highest non-attendance rate (39.5%) yet a CV of 0.54, six times rebate's 0.09, so the attribute with the most apparent non-attendance shows wide dispersion while rebate shows almost none. If non-attendance were compressing rebate's variance, the same mechanism should compress efficiency's variance at least as much. The low rebate variance therefore reflects genuine preference homogeneity rather than attribute non-attendance.

Standard deviations are large relative to means (carbon CV = 0.70, efficiency CV = 0.54), indicating wide preference variation that motivates the individual-level analysis in Section B.4. Average shrinkage factors (posterior SD / population SD)[3] are 0.54 for carbon, 0.57 for efficiency, and 0.16 for rebate. Read consistently against the definition, all three values indicate posteriors concentrated relative to their population spreads, confirming that six choice tasks provide adequate individual-level identification. For rebate, however, the population distribution is itself nearly degenerate (CV = 0.09), so its very low shrinkage means individual rebate WTPs are precisely located within an extremely narrow band: households are both well identified and nearly identical. The rebate value should therefore be read together with the homogeneity documented above, not as evidence of wide, well-measured individual differences.

We test the maintained independence assumption by computing individual-level posterior

[2]Attribute non-attendance refers to respondents ignoring one or more attributes when making their choices, rather than trading them all off as the standard model assumes. It is common in stated-preference studies, and if left unmodeled it can bias willingness-to-pay estimates (Hensher et al., 2005; Scarpa, Gilbride, et al., 2009).

[3]The shrinkage factor is the ratio of the posterior standard deviation of an individual's parameter estimate to the standard deviation of the estimated population distribution. Values near zero indicate that an individual's choices are highly informative and the posterior is tightly concentrated, while values near one indicate that the posterior remains diffuse and largely reflects the population distribution, implying that individual-level data add little information beyond the population mean (Revelt and K. Train, 2000).

WTP correlations from the M4A_NEP1 specification (Table B.13). Among 360 non-protester respondents, the posterior correlations are modest, with carbon-efficiency $r = 0.226$ ($p < 0.001$), carbon-rebate $r = 0.156$ ($p = 0.009$), and efficiency-rebate $r = 0.071$ ($p = 0.234$). The largest correlation implies shared variance of only 5.1%. A correlated specification allowing the full variance-covariance matrix was estimated but encountered numerical instability in the Cholesky decomposition before convergence, consistent with the weak correlations providing insufficient signal to identify the off-diagonal elements. The low posterior correlations support the independent specification, which we retain for parsimony (Hess and K. Train, 2017).

The NEP interaction effects are all statistically significant (Table B.1) and are interpreted in the Environmental Attitudes subsection below. A one-standard-deviation increase in NEP is associated with $0.76 higher carbon WTP (51% of the $1.49 baseline), $0.66 higher efficiency WTP, and $0.35 higher rebate WTP. Panel upgrade interactions are also significant, reducing carbon and efficiency WTP by $0.89 and $0.80 per month, respectively. These magnitudes are large relative to the base attribute WTP values. Krinsky-Robb confidence intervals are reported in Table B.2.

10.2 Electrical-Panel Upgrade

Panel upgrade requirements reduce WTP for both carbon and efficiency while increasing responsiveness to financial rebates (Table B.1). The panel interaction for carbon is –$0.89, meaning households expecting panel upgrades value carbon reduction at only $0.60 per month per percentage point (versus $1.49 for households not needing upgrades). The panel interaction for efficiency is –$0.80, reducing efficiency WTP to $1.51 (versus $2.31). The rebate-panel interaction is positive (+$0.32) though not statistically significant. Panel-needing households may be somewhat more responsive to upfront financial incentives.

The panel upgrade coefficient on the ASC ($67.73 per month) represents the additional monthly amount a panel-needing household requires to choose electrification over the status quo. This is a stated preference measure of the additional hurdle, not an engineering cost estimate. It captures the combined financial, logistical, and psychological burden that panel upgrades impose on the electrification decision. We refer to it as a "resistance cost" for brevity. With 78.7% of surveyed households indicating panel upgrade needs, this barrier affects roughly four in five potential adopters and translates to approximately $813 annually. Programs that directly address panel upgrade costs through subsidies, financing, or streamlined permitting would reduce the single largest adoption obstacle.

10.3 Environmental Attitudes

NEP interactions demonstrate strong positive associations with all attribute valuations. A one-standard-deviation increase in NEP is associated with \$0.76 (= $\$0.794 \times 0.954\,(\mathrm{SD})$) per month higher carbon WTP (+51% relative to baseline), \$0.66 higher efficiency WTP (+29%), and \$0.35 higher rebate WTP (+32%). These effects are captured in the fixed portion of the model, meaning the systematic NEP-WTP relationship is controlled when examining residual heterogeneity through the random parameters.

To illustrate the policy segmentation potential of NEP interactions, Table 5 reports predicted WTP at NEP percentiles (10th, 25th, 50th, 75th, 90th), showing how carbon, efficiency, and rebate WTP vary across the environmental attitude distribution.

Table 5: Predicted WTP at NEP Percentiles (\$/month per percentage point)

NEP Percentile	NEP factor score	Carbon WTP	Efficiency WTP	Rebate WTP
10th	−1.462	\$0.33	\$1.30	\$0.56
25th	−0.867	\$0.81	\$1.71	\$0.78
50th	0.160	\$1.62	\$2.42	\$1.16
75th	0.911	\$2.22	\$2.94	\$1.43
90th	1.111	\$2.38	\$3.08	\$1.51

Notes: The NEP factor score is the standardized regression factor score (mean 0, standard deviation 1) from the exploratory factor analysis, not the raw 6–30 summed scale reported in Table 2; negative values indicate below-average environmental concern. Predicted WTP computed from individual-level posterior WTP scores regressed on NEP factor scores. The NEP-carbon gradient is \$0.794 per unit NEP, implying that moving from the 10th to the 90th percentile of environmental attitudes is associated with \$2.05 higher carbon WTP. The NEP-efficiency gradient (\$0.693 per unit) produces a \$1.78 increase over the same range. Rebate WTP increases by \$0.95 across the NEP distribution (slope = \$0.368), consistent with financial incentive preferences being partly associated with environmental attitudes. The posterior gradient reflects the population-level NEP interaction coefficient (\$0.794 in Table B.1), which captures the systematic NEP-WTP relationship in the fixed interaction terms.

10.4 Information Treatment

The information treatment effects are not statistically significant for any attribute once NEP is included (Table B.1). In models without NEP controls, the treatment shows significant positive effects on carbon WTP, confirming that the treatment effect is absorbed by the NEP variable. This pattern indicates a “ceiling” rather than a “null.” The information works, but its effect is captured by the NEP variable with which it correlates. While information interventions reduce energy consumption in other settings (Allcott, 2011) and shift conservation behavior (Ferraro and Price, 2013), our results indicate that health and environmental risk information primarily activates pre-existing environmental concern rather than creating it. With only 84 treated respondents, the study had limited statistical power to detect interaction effects. The standard errors on the treatment interaction terms are large relative to the coefficients (Table B.1), meaning that effects up to $0.30 per percentage point could not be ruled out. A further caveat is differential attrition: respondents assigned to the treatment were about twice as likely as controls to start but not complete the choice experiment (40.0% of the dropped group in Table B.5 was treated, versus 20.8% of the analysis sample, $p = 0.003$), which we take up in the Limitations below. Programs targeting households with low environmental concern may need to lead with cost savings and comfort rather than environmental or health information.

10.5 Sociodemographic Patterns

Education shows the largest sociodemographic effect on the status-quo constant. Graduate degree holders have a $179.69 lower ASC than those without college education, about $2,156 less resistance annually, exceeding the NEP, income, and panel-status effects on the ASC. This outsized effect may capture several mechanisms, including knowledge about electrification technology, trust in the survey instrument, openness to change, or familiarity with the scientific rationale for electrification. In a community where about half of adults hold graduate degrees and most work in scientific or technical fields, education likely proxies for a constellation of traits associated with technology adoption rather than education per se.

Age and income, by contrast, raise status-quo preference. Age increases opt-out propensity by $1.45 per year, so a 60-year-old has about $58 per month higher status-quo preference than a 20-year-old. Higher-income groups likewise show greater status-quo preference ($94 to $101 per month versus the under-$35,000 baseline), consistent with satisfaction with existing high-quality gas appliances in expensive homes, higher absolute switching costs in larger residences, and lower marginal utility of the environmental benefits electrification offers. An alternative interpretation is that higher-income respondents were more sensitive to the hypothetical nature of the exercise and more likely to treat the opt-out as a default when uncertain. Either pattern is consistent with the status-quo-bias literature, in which households with greater investment in existing systems show stronger default preferences.

Retirement status deserves separate attention, because retired households make up about a third of the analysis sample (33% unweighted, and 29% after the age-by-education post-stratification weighting) and might be expected to resist large discretionary expenditures while on a fixed income. Two pieces of evidence bear on this. First, their recovered attribute WTP is statistically indistinguishable from that of non-retired households (carbon $1.53 versus $1.52, efficiency $2.30 versus $2.32, and rebate $1.10 versus $1.09, all $p > 0.5$). Second, we re-estimated the choice model with an explicit retirement interaction on both the attribute valuations and the status-quo constant. Retirement leaves attribute WTP unchanged (all interactions $p > 0.6$), and it raises the status-quo constant by about $34 per month, in the direction of a fixed-income resistance to switching, but this effect is not statistically significant once age and income are controlled ($p = 0.14$). Because retirement in this sample is almost entirely a function of age, with retired respondents averaging 71 years against 49 for the non-retired, the fixed-income channel operates largely through the age and income terms already in the status-quo constant, where both older age and higher income raise status-quo preference.

Beyond these population averages, the household-level WTP estimates show that environmental attitudes explain most of the variation in carbon and efficiency valuations, whereas WTP for rebates rises with a household's actual natural gas use. Private financial interest surfaces mainly in responsiveness to incentives. These individual-level distributions, and the relationship between stated WTP and metered consumption, are reported in Appendix B.4.

11 Discussion

11.1 Key Findings and Interpretation

Three patterns in our estimates inform electrification program design. Efficiency leads attribute valuations, followed by carbon reduction and then rebates. This ordering, with private benefits exceeding social benefits exceeding upfront cost reductions, suggests that communication strategies should lead with performance and operating cost messaging.

Environmental worldview co-varies systematically with preferences through the NEP interaction terms. After controlling for these systematic effects, very few respondents have negative residual carbon WTP (Table B.12). Panel upgrade requirements impose a substantial annual barrier affecting most households. The individual-level analysis reveals residual heterogeneity even after controlling for observables.

The consumption data linkage (Section B.5) is consistent with the interpretation that this heterogeneity is associated primarily with attitudes rather than energy expenditure. Carbon and efficiency WTP are not significantly correlated with actual gas consumption, while rebate WTP increases significantly with gas bills (Table B.16). The WTP-to-expenditure ratio declines from 7.11 for the lowest gas quartile to 1.89 for the highest, indicating that stated preferences are better calibrated to financial reality among households with the largest gas expenditures.

11.2 Comparison to Existing Literature

Our findings can be situated within the DCE literature on heating system preferences. The dominance of efficiency over environmental attributes aligns with Achtnicht (2011), who finds that investment cost is the primary driver of fuel-type preferences in German heating choices, and with Michelsen and Madlener (2012), who reach a similar conclusion. That the efficiency-over-environment ordering appears in both the German heating market (with different gas prices, climate, and policy frameworks) and a U.S. municipal utility planning gas elimination suggests a broader behavioral pattern. Our efficiency WTP estimates, however, exceed the 5 to 15% premiums typically found for efficient appliances (Galarraga et al., 2011). Applying the Penn and Hu (2018) trimmed-sample mean hypothetical-bias calibration factor of 1.94 brings the estimates closer to the expected range. Contributing factors also include our high-income sample, the percentage-point framing, and possible conflation of efficiency with cost savings despite the separate cost attribute.

The NEP-WTP-space integration approach speaks to the broader environmental valuation literature beyond heating-system DCEs. WTP-space estimation has been applied to recreation demand (Scarpa, Thiene, and Train, 2008), health valuation (Hole and Kolstad, 2012), and transportation choice (W. H. Greene and Hensher, 2010), but we are not aware of published work combining attitudinal scale interactions in the fixed portion of a WTP-space random parameter logit with individual-level posterior estimation. Mariel et al. (2021), in their review of environmental valuation with discrete choice experiments, do not document this specific combination. The approach is applicable wherever researchers suspect that observable attitudes or beliefs drive a large share of preference heterogeneity that would otherwise be absorbed into random parameters.

The null information treatment result is consistent with recent evidence that information interventions interact with pre-existing attitudes. Allcott (2011) and Ferraro and Price (2013) demonstrate information effects in energy conservation, but these studies use social comparison or norm-based messaging rather than environmental risk information. Our result suggests that environmental and health risk information faces diminishing returns when targeting populations with well-formed environmental attitudes. Information campaigns should be paired with tangible incentives and streamlined adoption pathways rather than relied upon as standalone interventions.

The panel upgrade barrier ($813 per year) is consistent with Lane et al. (2024), who identify hassle costs as major obstacles. Our quantification provides specific program design guidance. Panel upgrade subsidies or financing equivalent to approximately $800 to $1,000 annually would offset this barrier.

11.3 Limitations

Several limitations bear on interpretation. First, the Los Alamos sample's unusual demographics limit generalizability. WTP magnitudes may exceed those in more typical communities, though the efficiency-over-carbon ordering aligns with cross-country evidence that private benefits motivate adoption more than social benefits (Achtnicht, 2011; Michelsen and Madlener, 2012). The methodological approach transfers to any population. Replication in lower-income communities is a priority. An unweighted specification produces qualitatively similar WTP estimates and identical sign patterns (Table B.9), confirming that the post-stratification weights do not drive the main results.

Second, the 31.1% protest rate is comparable to the 15 to 30% range common in DCE studies of environmental goods (Meyerhoff and Liebe, 2006). Because low-NEP respondents disproportionately protest (Table B.10), the non-protester subsample skews toward higher environmental concern. A Heckman selection correction yields insignificant inverse Mills ratios for all three WTP attributes (carbon $p = 0.97$, efficiency $p = 0.89$, rebate $p = 0.54$), indicating that selection on NEP does not materially bias the WTP estimates.

Third, the unbalanced treatment allocation ($N = 84$ treated, 20.8%) limits power to detect information treatment effects, and attrition from the choice experiment was differential by treatment arm: treated respondents were about twice as likely as controls to begin the choice tasks without completing them (40.0% of the dropped group versus 20.8% of the analysis sample, $p = 0.003$; Table B.5). This is a more direct threat to the null information-treatment finding than limited power alone. If the information script itself discouraged completion among the respondents least receptive to it, the surviving treated sample would be selected toward those already sympathetic to the message, which works in the same direction as the NEP-mediation interpretation and could contribute to the null conditional effect. The lengthy treatment script placed immediately before the choice tasks is the most likely mechanism, since the dropped group is also much older. More intensive interventions with balanced allocation, and a shorter treatment placed earlier in the instrument, may yield detectable differences.

Part III

Solar Rebound

12 Overview

Many LADPU customers have installed rooftop solar, and more are expected to as the county electrifies. A natural question is whether solar adoption actually lowers a household's total energy use and emissions, or simply changes where its energy comes from. Prior studies find that solar adopters tend to consume more electricity afterward, a "rebound" effect, but they examine electricity alone and so cannot tell whether that extra electricity displaces natural gas or adds to total energy demand.

This part uses LADPU's household-level hourly electricity and natural gas data (2022–2025) to estimate the causal effect of solar adoption on both fuels, using a staggered difference-in-differences design that compares adopters with matched non-adopters before and after installation.

13 Data and Descriptive Patterns

In collaboration with LADPU, we assemble a household-level dataset for Los Alamos County that combines hourly electricity consumption, natural gas consumption, and system-level solar installation information.

13.1 Data description

Our main dataset is the household hourly electricity and natural gas consumption data covering all households served by LADPU for the period January 2022 to June 2025. The data include household identifiers, meter identifiers, household addresses, geographic coordinates, hourly consumption timestamps, electricity drawn from the grid, electricity exported to the grid, adjusted total electricity consumption, and natural gas consumption.

The second dataset contains solar installation information from LADPU, which we matched to households using service addresses. This dataset includes system-level information on installed capacity and installation date.

The third dataset is simulated hourly solar generation data from the Photovoltaic Geographical Information System (PVGIS). Because solar generation is not directly observed in the utility data, we use PVGIS to simulate hourly PV output for each solar household from 2022 to 2023, based on each system's geographic coordinates. The simulation period is limited to 2022–2023 due to PVGIS data availability. In the simulation, we allow PVGIS to optimize the system slope and azimuth,[4] and use its default assumption of 14% overall system losses.

The fourth dataset is hourly weather and solar irradiance data from the National Solar Radiation Database (NSRDB), which we use to project household-level solar generation for 2024–2025. We combine PVGIS simulated solar generation for 2022–2023 with NSRDB weather and irradiance variables to train a two-stage random forest model, then apply the trained model to NSRDB weather and irradiance data for 2024–2025 to project hourly household-level solar output. The two sources together provide uninterrupted coverage of the study period: the PVGIS series runs through December 2023, and the random-forest projection covers January 2024 through June 2025, so there is no gap year between them. Should PVGIS later extend its public time series beyond 2023, the projected years could be replaced with, or validated against, the extended simulations.

We combine these data sources to construct a unique household-level hourly panel dataset. To form a control group to the solar households, we match each solar household to its five nearest non-solar neighbors by straight-line distance, so the panel pairs 447 solar adopters with 1,729 matched non-solar controls. We match on geography because nearby households face the same weather, neighborhood characteristics, and utility-pricing environment, which makes the

[4] PVGIS calculates the slope and azimuth of the PV modules that yield the highest annual energy output.

controls a credible counterfactual for the difference-in-differences and absorbs local confounders that could otherwise be mistaken for an effect of solar adoption. The staggered difference-in-differences identifies the rebound from the 198 households that adopt within the study window, compared with the never-adopting controls, excluding the 249 households that already had solar before the window for lack of a pre-adoption period. To study heterogeneity across different time horizons, we further aggregate the hourly data to the daily and monthly levels according to the corresponding model specifications. The detailed data construction process is described in Appendix C.1 and C.2.

13.2 Electricity and Natural Gas Consumption Patterns

Table C.4 presents summary statistics for the full sample. Among solar households, the average installed capacity is 5.52 kW. Average hourly solar generation is 2.28 kWh per generating hour. Average hourly electricity consumption is 1.05 kWh, of which 0.96 kWh is drawn from the grid. Average hourly natural gas consumption is approximately 0.01 MMBtu. There is substantial variation across solar households, especially in installed solar capacity, solar generation, and electricity consumption.

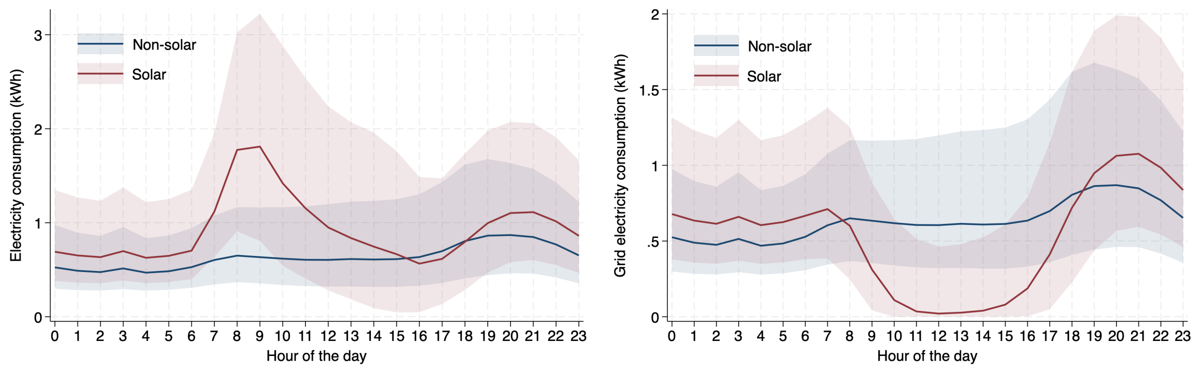
Solar and non-solar households exhibit different electricity consumption patterns (Table C.18). Grid electricity use is initially higher among future solar households than non-solar households, but after installation the pattern reverses, with solar households drawing less electricity from the grid while maintaining higher total electricity consumption.

Figure 8 compares the hourly dynamics of electricity consumption over the full study period, distinguishing between solar and non-solar households. Panel (a) shows a pronounced morning peak for solar households, with usage rising sharply and reaching its maximum around 8–9 AM, suggesting a shift in consumption toward anticipated solar-generation hours. Panel (b) reveals a duck-curve pattern for solar households, where grid electricity use declines during daylight hours as on-site solar generation displaces grid demand. Appendix C.3 reports additional figures on consumption dynamics within the calendar year and over the monthly cycle, which display pronounced temporal variation.

Natural gas consumption does not differ meaningfully between future solar and non-solar households before installation, but after installation non-solar households consume more natural gas than solar households. This pattern suggests a substitution away from natural gas toward electricity use following solar adoption.

13.3 Solar Installations and Solar Generation

Figure 9 illustrates the temporal distribution of solar installations and installed capacity over the study period. The figures show that solar adoption is dispersed across months and years, with



(a) Total electricity consumption **(b)** Grid electricity consumption

Figure 8: Hourly electricity consumption patterns of solar and non-solar households

Notes: The figure plots hourly electricity consumption patterns for solar and non-solar households. Panel (a) shows total electricity consumption, and Panel (b) shows grid electricity consumption. Solid lines represent the median hourly consumption for each group, and shaded bands indicate the 25th–75th percentile range. Consumption is measured in kWh.

noticeable variation in both the number of installations and total installed capacity. While there are relatively more installations in late 2023, installations are not concentrated within a narrow time window. Instead, adoption occurs gradually over time, generating meaningful variation in treatment timing across households.

This staggered pattern of adoption motivates our empirical strategy. In particular, the variation in installation timing allows us to exploit a staggered difference-in-differences framework, which leverages differences in treatment timing to identify causal effects while accounting for heterogeneous treatment effects across cohorts and over time.

Figure 10 compares monthly electricity consumption and solar generation relative to the pre-adoption electricity consumption baseline among solar-adopting households. Total electricity consumption rises above the pre-solar baseline after adoption, providing descriptive evidence of a rebound response. At the same time, monthly solar generation fluctuates around the pre-adoption consumption baseline after installation. This pattern suggests that households install solar systems with generation capacity roughly aligned with their historical electricity demand on average. This is also consistent with LADPU's interconnection requirement that residential solar systems be sized to offset actual electricity consumption over the immediately preceding 12 months.[5] Therefore, the observed post-adoption increase in electricity consumption is unlikely to be driven by households installing excessively large systems in anticipation of future demand growth. Instead, it is more consistent with a post-adoption behavioral response, where households increase electricity use after gaining access to self-generated solar electricity.

[5]Details on LADPU's solar installation and system-sizing requirements can be found at https://www.losalamosnm.gov/Business/Apply-for-a-permit/Solar-Power-Installation.

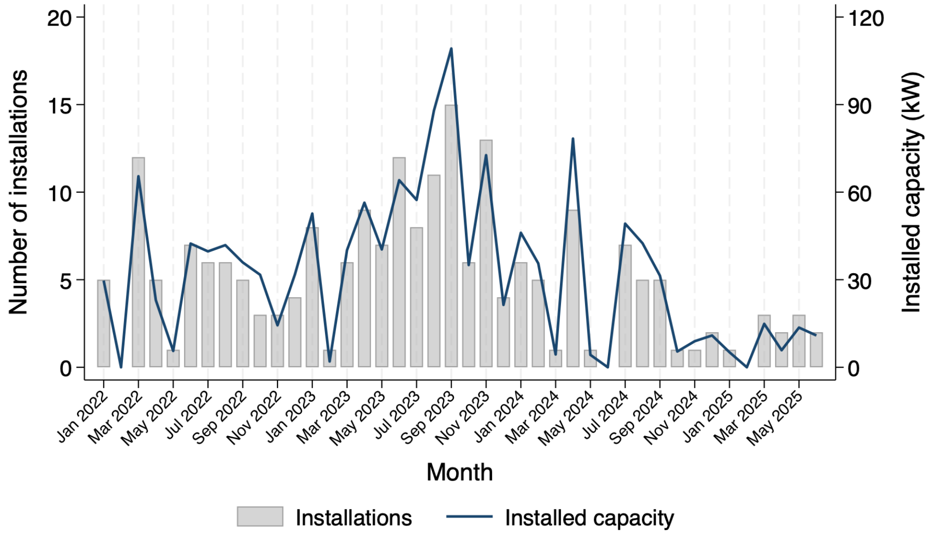


Figure 9: Monthly solar installations and installed capacity

Notes: The figure summarizes monthly solar adoption from January 2022 to June 2025. Grey bars show the number of solar installations in each installation month, measured on the left y-axis. The navy line shows total installed solar capacity in kW among households installed in each month, measured on the right y-axis. Each household is counted once in its installation month.

We estimate the causal effect of solar adoption with a staggered difference-in-differences design (Callaway and Sant'Anna, 2021) that compares adopting households with matched non-adopters before and after installation. The estimator and its identifying assumptions are detailed in Appendix C.4.

14 Main Results

14.1 Average Effects

Table 6 reports the estimated average treatment effect on the treated (ATT) of solar adoption on household monthly energy consumption. Treatment timing is defined by the year-month of solar installation, and we use households that never adopt solar as the control group. Standard errors are clustered at the household level. The parallel trend assumption holds in our analysis and the event study plots are reported in Section C.5.

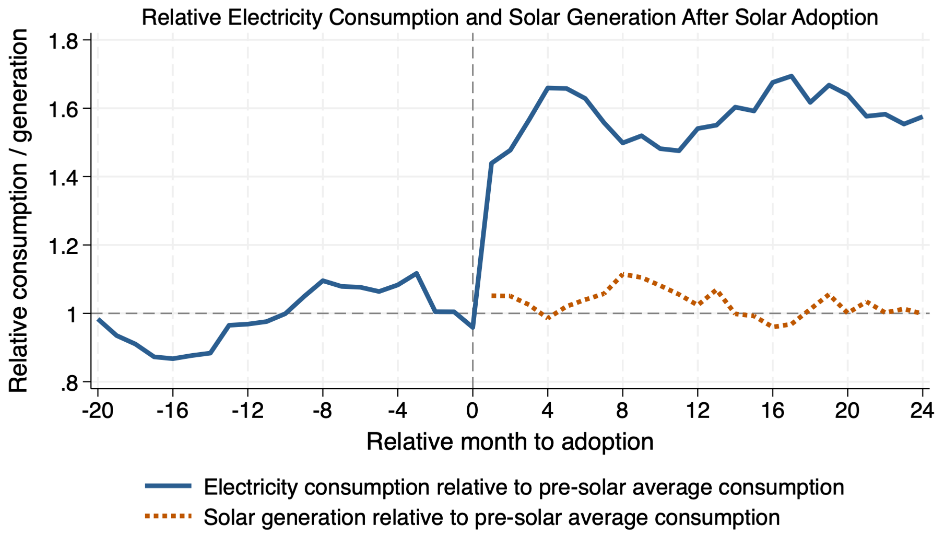


Figure 10: Relative electricity consumption and solar generation after solar adoption

Notes: The sample includes all households that adopted solar within the study period. The monthly electricity consumption and solar generation are normalized by the same pre-solar electricity consumption baseline. The horizontal dashed line represents the pre-solar baseline, and the vertical dashed line marks the month of solar adoption. Solar generation in the installation month is omitted because installation may occur at any point within the month and the generation in that month may reflect only partial-month production and may not be comparable to full-month solar generation in subsequent months.

Table 6: Effects of solar adoption on monthly household energy consumption

	Electricity consumption	Grid electricity consumption	Natural gas consumption
ATT	118.696***	-131.117***	-0.345
	(44.088)	(41.573)	(0.266)
Pre-treatment Mean	631.794	631.782	6.541
% change	+18.79%	-20.75%	-
Unit	kWh	kWh	MMBtu

*Note: This table reports the ATT of solar adoption on household monthly energy consumption. Treatment timing is defined by the year-month of solar installation, and we use households that never adopt solar as the control group. Standard errors, reported in parentheses, are clustered at the household level. Pre-treatment means are calculated using observations prior to solar adoption for treated households. Percentage changes are computed relative to pre-treatment means and are not reported when the ATT estimate is statistically insignificant. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.*

The results show a substantial increase in total electricity consumption following solar adoption. On average, electricity use increases by 118.70 kWh per month (18.79%). Grid electricity consumption falls by 131.12 kWh (20.75%), which provides direct evidence that self-generated solar power is substituting for grid-supplied electricity. Natural gas consumption does not exhibit a statistically significant response to solar adoption. The final column of Table 6 standardizes electricity and natural gas into a common energy unit (MMBtu) to gauge the net effect across fuels, converting electricity at 1 kWh = 0.003412 MMBtu and summing it with metered natural gas at the household-month level. On average, solar adoption increases total energy consumption by 7.29% relative to the pre-treatment mean.[6]

These estimates show that solar adoption increases both total electricity and total household energy consumption, with part of the additional electricity use possibly substituting for other fuels. Although the average ATT on natural gas consumption is statistically insignificant, this aggregate estimate may mask substantial temporal heterogeneity in household energy use. Electricity is used for a broad range of end uses, including cooling, lighting, appliances, and small electric heating equipment, whereas natural gas in our household sample is primarily used for space heating and cooking. As a result, the substitution relationship between electricity and natural gas is likely to depend on heating demand and may vary across seasons and hours of the day. The following subsections examine this heterogeneity across seasons, days of the week, and hours of the day.

14.2 Seasonal Heterogeneity

The rebound effect varies sharply across seasons. Figure 11 reports the seasonal ATT for total electricity, grid electricity, natural gas, and total energy. Within each panel, the top plot shows the ATT with its 95% confidence interval and the bottom plot the implied rebound as a percentage of the pre-adoption seasonal mean. Total-electricity use (panel a) rises by 175 kWh per month in Spring, a 31% rebound, and by 459 kWh per month in Winter, a 65% rebound, both precisely estimated. The Summer and Fall estimates are statistically indistinguishable from zero. The rebound is thus absent in the high-generation cooling seasons and concentrated in the low-generation heating seasons, the opposite of what self-consumption of midday solar output alone would predict. The full seasonal ATT tables, in native units (Table C.19) and in MMBtu (Table C.20), are reported in Appendix C.8.

The grid-electricity panel (panel b) shows how households source this additional consumption. In Spring, Summer, and Fall, grid consumption falls sharply, by 18%, 36%, and 60% respectively, as self-generated solar displaces electricity that would otherwise have been bought from the grid. In winter it does not fall, and the point estimate is a statistically insignificant +152 kWh. The additional winter consumption is large enough to offset the grid-displacement effect of solar entirely, so grid consumption shows no decline even as households consume their own generation. This is the first indication that the winter rebound is not a consumption timing

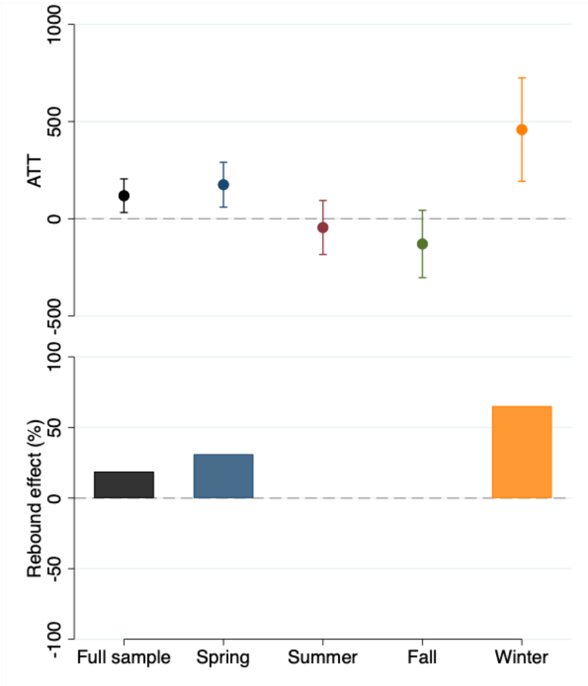
[6] The total-energy ATT is estimated directly on this summed household-month outcome, not computed by adding the electricity and natural-gas ATTs. Because each outcome's group-time effects are estimated and aggregated separately, the total-energy estimate need not equal the sum of the component estimates, and its standard error reflects the covariance between the two fuels rather than treating them as independent.

shift to absorb on-site generation but a genuine increase in the level of demand.

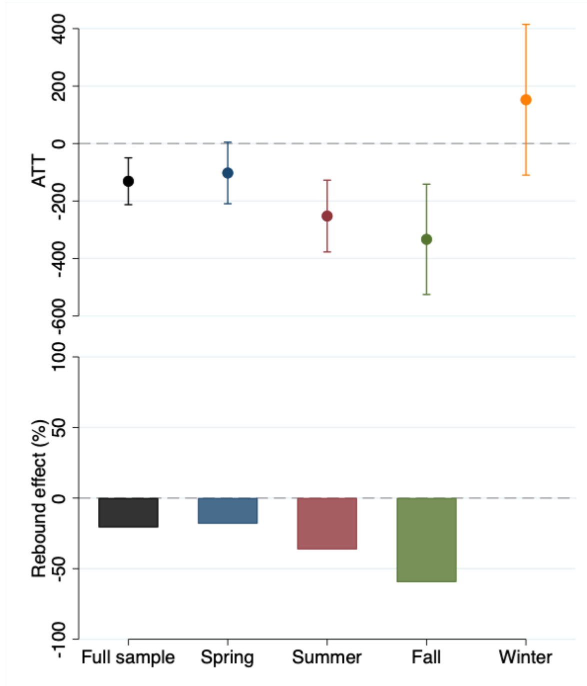
Sorrell (Sorrell, 2009) distinguishes between conventional rebound effects and backfire, which represents the more extreme case in which behavioral responses more than offset the expected engineering energy savings, leading to energy consumption that ultimately exceeds the level that would have occurred without the efficiency improvement. Although Sorrell's discussion is developed in the context of energy efficiency improvements, similar behavioral responses can also arise when distributed generation changes the perceived marginal cost of electricity consumption. Our empirical design does not estimate engineering energy savings and therefore cannot directly quantify rebound rates or determine whether backfire occurs in the strict sense. Nevertheless, the winter results suggest that the additional electricity generated by rooftop PV is largely absorbed by higher household electricity demand rather than displacing electricity purchased from the grid. Although these findings do not establish backfire as formally defined in the literature, they are qualitatively consistent with the behavioral response described by Sorrell (Sorrell, 2009). Under winter heating conditions, residential solar adoption induce sufficiently large increases in electricity demand to offset a substantial share of the potential reduction in conventional energy use.

Natural gas (panel c) responds only in Spring, where it falls by 0.95 MMBtu per month (14%). No other season shows a significant change. The all-fuel total in panel (d) combines these outcomes in common energy units. Averaged over the year, solar adoption raises total household energy use by 7.3%. The net increase is statistically significant in Summer and Winter, and largest in absolute terms in Winter (+1.6 MMBtu per month).[7] Spring is the exception, because there the rise in electricity is matched by the fall in gas, so the net energy effect is indistinguishable from zero. The seasonal evidence therefore distinguishes two mechanisms. In spring, households substitute electricity for gas, which leaves total energy roughly unchanged. In winter, total energy use rises, and the next subsection identifies the within-day source of that increase.

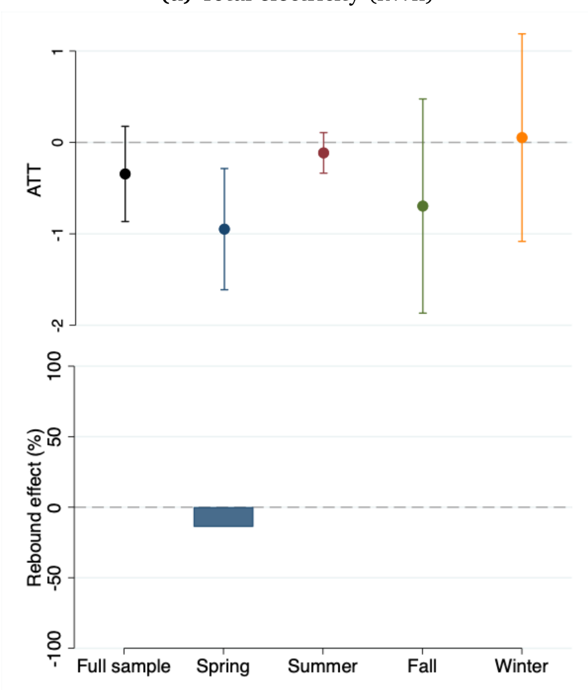
[7] As with the annual estimate, each seasonal total-energy ATT is estimated directly on the summed outcome rather than by adding the fuel-specific seasonal estimates, so a season in which neither fuel-specific estimate is individually significant can still show a statistically significant total: the summed outcome is estimated with its own precision, which incorporates the covariance between the two fuels.



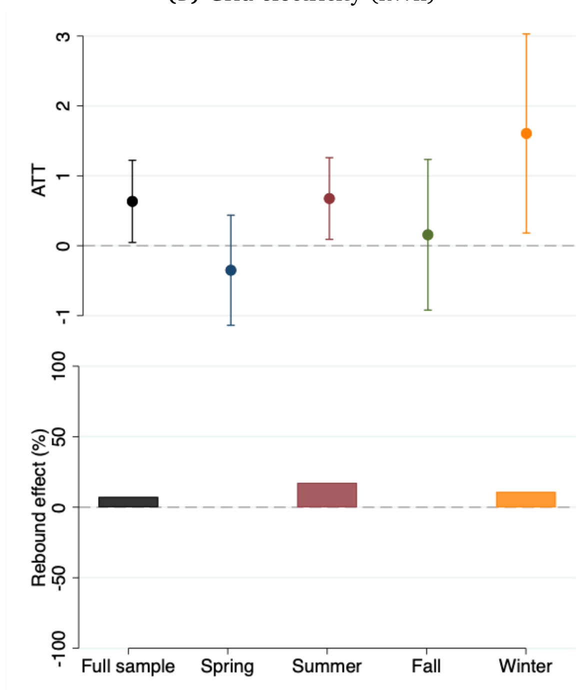
(a) Total electricity (kWh)



(b) Grid electricity (kWh)



(c) Natural gas (MMBtu)



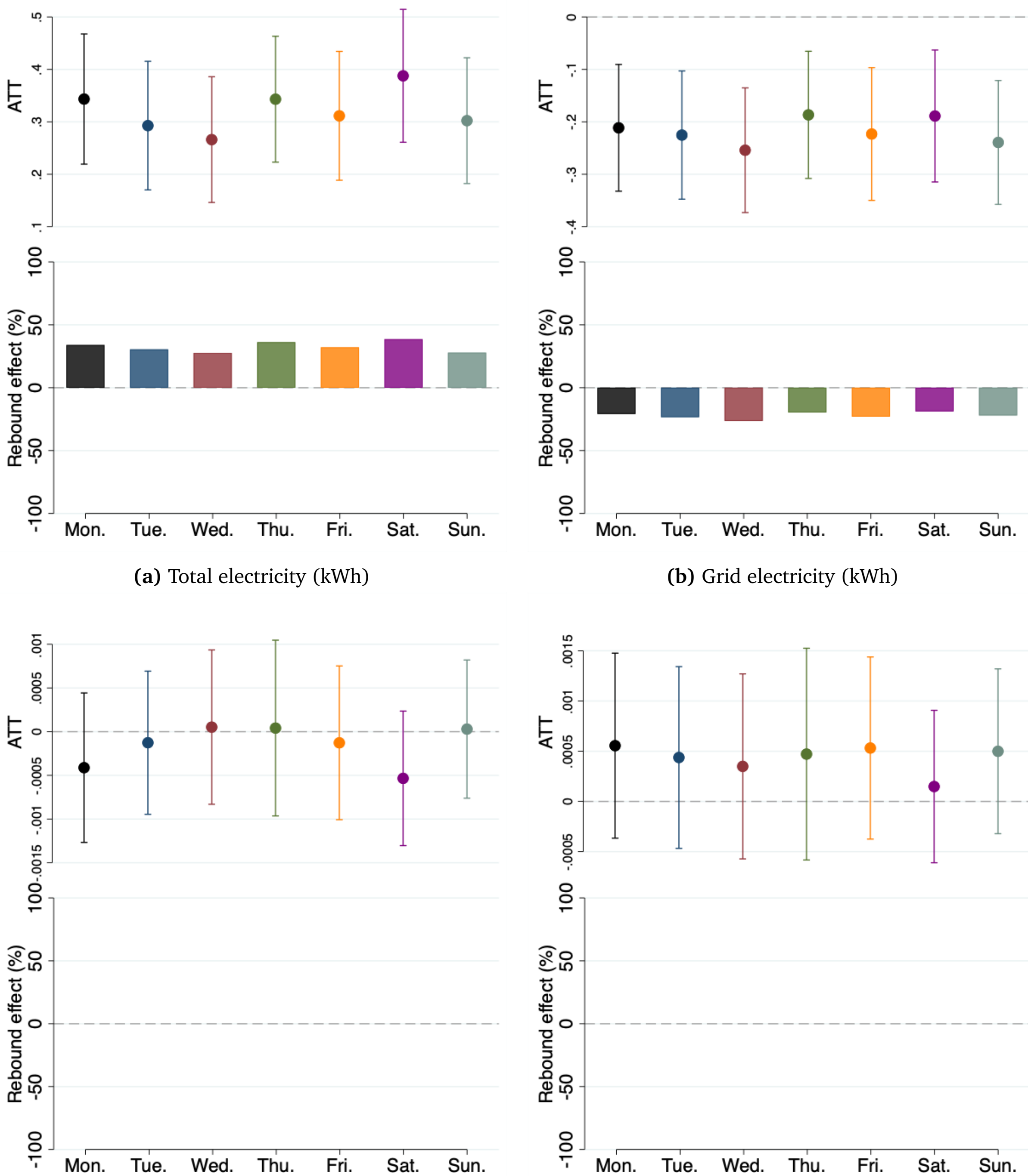
(d) Total energy (MMBtu)

Figure 11: Seasonal treatment effects by energy outcome

Notes: Each panel plots the ATT with 95% confidence intervals (top) and the implied rebound as a percentage of the pre-adoption mean (bottom), for the full sample and by season.

14.3 Day-of-Week and Within-Day Patterns

We next examine the effect by day of the week (Figure 12). The rebound in total electricity is positive and stable across the week. The daily-average rebound ranges from 28% on Wednesdays and Sundays to 39% on Saturdays, every estimate is significant at the 1% level, and the confidence intervals overlap across all seven days. Grid electricity falls by a comparable 19–26% on every day. The absence of a weekday–weekend gap is informative. If the rebound reflected households spending more time at home after adopting solar, it would concentrate on weekends. Its stability across days instead indicates a uniform change in the level of consumption, consistent with always-on heating and baseload uses rather than greater weekend occupancy. The day-of-week ATT table is reported in Appendix C.8.



(a) Total electricity (kWh)

(b) Grid electricity (kWh)

(c) Natural gas (MMBtu)

(d) Total energy (MMBtu)

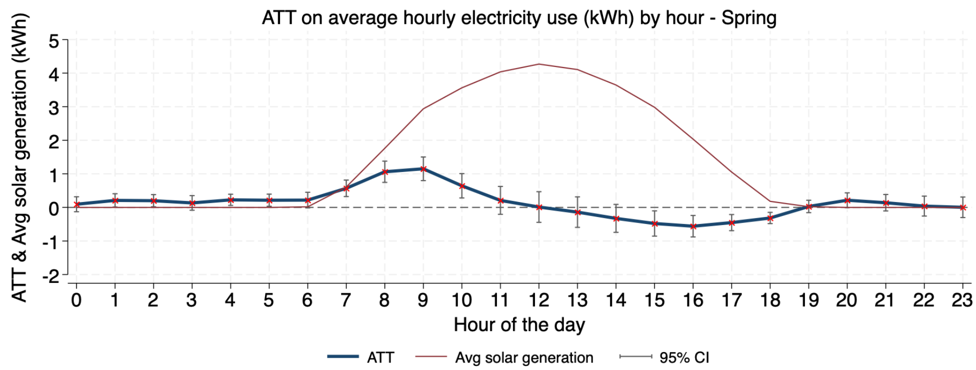
Figure 12: Day-of-week treatment effects by energy outcome

Notes: ATT with 95% confidence intervals (top) and implied rebound (bottom) by day of the week, for each energy outcome.

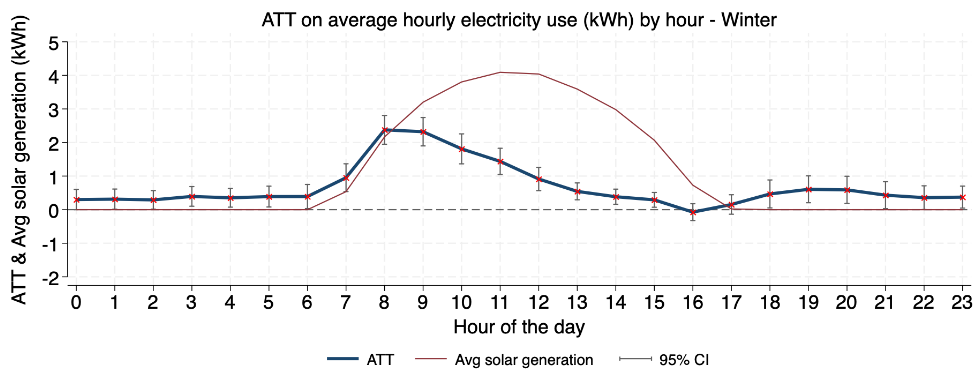
We next estimate the effect on electricity consumption by hour of the day. Figure 13 plots the hourly ATT on electricity use against the average solar-generation profile shown for reference. In Spring (panel a) the additional electricity use rises with the morning increase in generation, but it peaks earlier in the day than generation does. It reaches about +1.1 kWh near 9 a.m., a few hours before solar output peaks at midday, then declines to approximately zero by midday and to a small negative value in the afternoon. The increase is concentrated in the hours when the panels are producing. Because LADPU adopts the net billing structure for solar generation where the buy-back price of excess solar power sent back to the grid is low, on-site consumption during solar-generating hours is worth more than exporting. Total electricity in spring nonetheless rises by 31% (Table C.19), so the response is a genuine increase rather than a consumption timing shift within the day. Because the spring decline in gas offsets this increase in energy terms, total household energy is roughly unchanged, and the spring rebound reflects substitution of electricity for gas rather than a rise in total energy. This gas reduction is identified at the seasonal level, where the monthly ATT is significant, and the hourly gas estimates are too imprecise to localize it within the day (Figure C.11).

The response in winter (panel b) differs. The ATT is both larger and more persistent. It rises to about +2.4 kWh in the early morning, remains elevated through the generation hours, declines to near zero only briefly in the late afternoon, and then rises again in the evening and stays positive overnight, when the panels produce nothing. An effect that persists well past sunset cannot reflect self-consumption of contemporaneous solar output. It is instead consistent with an income effect, in which the bill savings from solar raise the budget available for additional heating and comfort, in addition to the daytime self-consumption channel. The cold high-desert winter, at elevations of 6,500–7,400 feet, makes this additional heating demand substantial.

Table C.22 summarizes the rebound effect difference between spring and winter hours. The spring rebound occurs during solar hours and substitutes for gas, whereas the larger winter rebound extends throughout the day and reflects both self-consumption and income effects. The hourly grid-electricity and natural-gas figures and the remaining seasons are reported in Appendix C.6.



(a) Spring



(b) Winter

Figure 13: ATT on hourly electricity use (kWh) by hour of day, Spring vs. Winter

Notes: Each panel plots the ATT on hourly electricity use (kWh) with 95% confidence intervals against hour of the day; the lighter line shows average hourly solar generation for reference. Spring (top) and Winter (bottom) are shown; the remaining seasons and the grid-electricity and natural-gas analogues are reported in Appendix C.6.

15 Carbon Reduction Analysis

A central rationale for supporting residential solar is its climate benefit. Because photovoltaic output is carbon-free, each kWh a household generates is expected to displace a kWh of grid electricity and to avoid the emissions of the fossil-fueled generation that would otherwise have supplied it. The environmental case for distributed solar, and much of the public support for it, rests on this displacement. The rebound effect documented above complicates the accounting. When a household raises its electricity use after adopting solar, part of the clean generation meets the additional demand rather than displacing grid purchases, and any consumption drawn from the grid is supplied at the grid's emission factor. The realized carbon offset is therefore smaller than the household's gross solar output would imply, and the size of the shortfall depends on how large the rebound is and when it occurs.

We next translate the consumption effects into carbon emissions, combining each household's ATT on grid electricity and natural gas with hourly carbon emission factors for the Public Service Company of New Mexico (PNM) grid. We use this factor because LADPU, a municipal utility, generates or procures part of its supply and purchases the remainder from the surrounding grid, which lies in the PNM balancing authority area. Marginal changes in a household's grid electricity are therefore served by generation dispatched within PNM. The grid factor is the marginal emission factor implied by a merit-order dispatch of generation. The method and the full by-hour, by-season calculations are in Appendix C.8.

Figure 14 summarizes the result. Reduced grid purchases lower CO_2 emissions by 332, 329, and 240 kg per household per year in Spring, Summer, and Fall, but by essentially nothing in Winter (a slight 1.6 kg increase), when the rebound is strongest (panel a). Reduced natural gas use adds a further 78 kg per year, concentrated in Spring. Summing both channels, observed solar adoption avoids about 978 kg of CO_2 per household per year, just under one metric tonne (1 tonne = 1,000 kg). Valued at the U.S. Environmental Protection Agency's updated central social cost of carbon of roughly \$190 per metric tonne (U.S. Environmental Protection Agency, 2023), each adopting household generates about \$185 per year in avoided climate damages, compared with roughly \$745 under the no-rebound counterfactual of 3,915 kg discussed below.

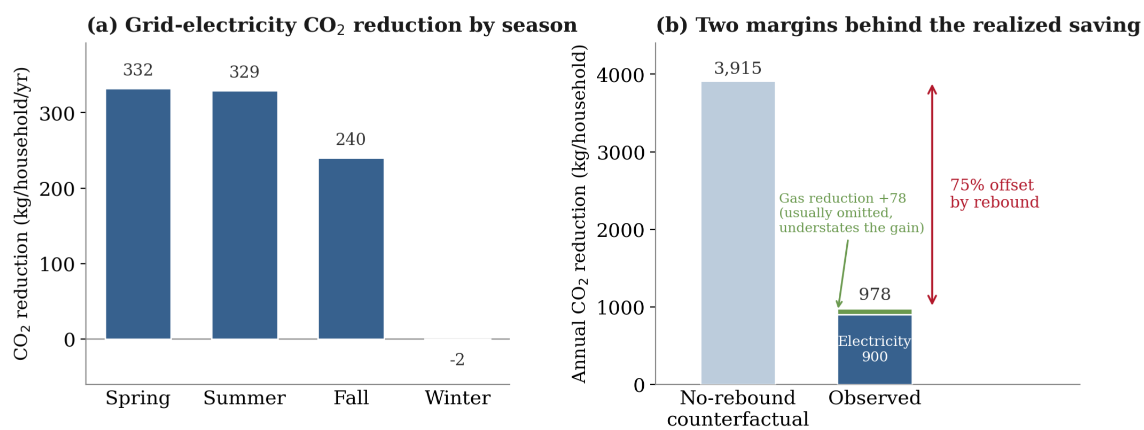


Figure 14: Carbon reduction from solar adoption, the rebound offset and the omitted gas margin

Notes: Panel (a) shows the annual CO_2 reduction from reduced grid-electricity purchases, by season. Panel (b) decomposes the observed reduction of 978 kg CO_2 per household per year into the grid-electricity channel (about 900 kg, which the literature typically counts) and the natural-gas channel (about 78 kg, usually omitted), and compares the total with a no-rebound counterfactual of 3,915 kg that credits each household's hourly solar generation at the marginal emission factor with no behavioral response; the gap between the two bars is the roughly 75% of potential savings forgone to the rebound.

That observed reduction reflects two offsetting margins (panel b). On one side, the realized saving of 978 kg falls far below the no-rebound counterfactual of 3,915 kg per household per year, so the rebound effect offsets roughly 75% of the carbon savings solar would otherwise deliver. On the other side, most studies of distributed solar count only the electricity channel and ignore the accompanying reduction in natural-gas use. That gas channel adds about 78 kg per household per year here, so an electricity-only accounting understates the true emissions benefit of adoption. Because both the rebound and the grid's emission intensity vary by season and hour, the net figure is also sensitive to how emission factors are applied. A comparison across emission-factor specifications is reported in Appendix C.8.

16 Discussion

16.1 Key Findings and Interpretation

Residential solar adoption raises total household electricity use by 18.8% on average, even as metered grid purchases fall by about 21% (Table 6). The difference is self-consumed solar generation. Because the accompanying change in natural gas offsets only part of the higher electricity use, total household energy use rises by 7.29%. The headline result is a net increase in the energy a household consumes, not only a substitution of self-generated power for purchased power.

The rebound is heterogeneous across seasons and hours, and two mechanisms drive it. In spring the additional electricity use is concentrated in solar-generation hours, consistent with a self-consumption response to net billing, and total energy is roughly unchanged because a seasonal decline in natural gas offsets the higher electricity use. In winter the rebound is larger, a 65% increase in electricity, and is spread throughout the day, including evening and overnight hours when the panels generate nothing, consistent with an income effect and added heating demand rather than self-consumption alone. Observing natural gas alongside electricity is what separates these cases, because it distinguishes a net increase in energy demand from a reallocation across fuels.

These responses do not change how much clean power the panels produce, but they reduce the grid emissions that this production displaces. Counting both the grid-electricity and natural-gas channels, solar adoption avoids about 978 kg of CO_2 per household per year, far below the 3,915 kg that a no-rebound counterfactual credits to the same generation, so the rebound forgoes roughly three-quarters of the grid-emission reduction solar would otherwise deliver. The natural-gas channel adds about 78 kg per year, which an electricity-only accounting would miss. This shortfall is not a fixed property of the technology. Because both the rebound and the grid's emission intensity vary across seasons and hours, the timing of the rebound governs its emissions cost, and a single average emission factor can materially misstate the carbon benefit of distributed solar.

16.2 Comparison to Existing Literature

Our estimates can be situated within the literature on residential solar rebound. Quasi-experimental studies typically report rebound effects of roughly 8 to 18% (Aydın et al., 2023; Bigler, 2025; Havas et al., 2015; Qiu et al., 2019; Spiller, Sopher, et al., 2017). Our average electricity rebound of 18.8% is at the upper end of that range, consistent with the strong self-consumption incentive of LADPU's net-billing tariff, under which a low export price makes on-site use more valuable than export (Gautier, Hoet, et al., 2019). The rebound concept originates in the energy-efficiency literature, where a lower effective price of energy services induces additional consumption that offsets part of the intended savings (Gillingham et al., 2014; Sorrell and Dimitropoulos, 2008). That literature reserves a stronger term, "backfire," for cases in which the induced consumption more than exhausts the expected savings, the household-scale analogue of the economy-wide Jevons paradox (Sorrell, 2009). Our winter estimates fit that stronger description for the season: total electricity use rises 65% above the pre-adoption baseline while grid purchases show no statistically detectable decline, so during the heating season the behavioral response absorbs the entire grid-displacement benefit of the panels rather than a fraction of it. Averaged over the year the response remains a partial rebound, but the winter result is better described as seasonal backfire than as a partial offset.

Most of this literature measures electricity alone. By observing electricity and natural gas together, we connect the solar-rebound question to the literature on cross-fuel substitution in the home (Alberini et al., 2011; Dubin and McFadden, 1984; Mansur et al., 2008). The distinction matters for interpretation. The spring pattern, in which higher electricity use accompanies lower gas use with little change in total energy, is substitution across fuels, whereas the winter pattern is a net increase in energy demand. An electricity-only design cannot separate the two and would read the spring response as pure rebound when it is partly a move away from gas.

Our results also bear on whether distributed solar delivers its expected emissions reduction. Several studies argue that rebound and grid carbon intensity can erode the emissions benefit of rooftop PV (Deng and Newton, 2017; Toroghi and Matthew E. Oliver, 2019). We quantify that erosion in one setting with hourly data and find it large, about three-quarters of the potential grid-emission reduction, which shows that the gap between solar's engineering potential and its realized climate benefit can be first-order rather than marginal.

16.3 Limitations

The central finding of a positive, seasonally varying rebound is robust, but the data and setting bound how well it can be measured and how far it generalizes. First, the total-electricity outcome combines metered consumption with imputed solar generation, since household self-generation is not separately metered. The imputation is validated out of sample (Appendix C.2), but the total-electricity and total-energy estimates inherit its uncertainty. Two features limit how much this matters. The grid-electricity estimate uses only metered data and is independent of the imputation, so the core displacement result does not rest on the imputed series. In addition, because the same imputation is applied to every solar household, a bias common to all of them would change the magnitude of the rebound but not its qualitative features, including the seasonal heterogeneity and the within-day concentration on which the interpretation rests.

Second, the causal interpretation relies on the Stable Unit Treatment Value Assumption. A placebo test that assigns adoption timing to nearby non-adopters yields no significant effect, which provides no evidence of neighborhood spillovers, although we cannot rule out small or indirect interference or heterogeneity in treatment intensity across systems.

Third, the event-study estimates suggest the rebound is strongest shortly after adoption and attenuates beyond about two years, consistent with households learning to balance self-consumption and export over time, so a single average effect understates the initial response and overstates the long-run one.

Fourth, the setting is a high-income, high-altitude community with cold winters and a specific net-billing tariff, and both the size of the rebound and its carbon cost depend on the local tariff and grid mix, so the external validity of the point estimates is limited even where the mechanisms are general.

Finally, we quantify the rebound but do not take a welfare stance on it. By revealed preference, the additional consumption is worth more to the household than its private cost, so part of what the carbon accounting records as forgone emissions savings is welfare-enhancing comfort. Quantifying that consumer-surplus gain would require estimating a household demand function, and LADPU's residential tariff offers no cross-household price variation with which to identify one: every household faces the same flat volumetric rate in any given month, so average price paid does not vary across customers the way it does under the increasing block rates exploited in, for example, the municipal water-demand literature. Estimating the welfare value of the rebound from tariff changes over time, or across neighboring utilities with different rate structures, is a natural direction for future research.

Part IV

Household Factors and Load Projection

17 Overview

Los Alamos has committed to phasing out residential natural gas, which moves space heating, water heating, cooking, and drying onto the electric system. For the utility, the first-order question is how this switch will reshape electricity demand. Answering this question requires knowing what factors govern household energy use.

This part studies how much household and housing characteristics explain persistent electricity and natural gas use, combining the resident survey (appliance stock, demographics, and housing characteristics) with daily metered consumption (2022–2025) and a two-step estimator that removes weather and calendar effects to recover each household's persistent (baseload) demand. Using the estimated coefficients, we project the electricity load that gas-to-electric conversion would add under alternative switching pathways.

18 Data and Empirical Approach

The analysis links five household-level data sources for Los Alamos County, New Mexico. LADPU provides daily smart-meter records of electricity and natural gas consumption, observed from January 2022 through June 2025. These are merged with the resident survey (appliance stock, housing characteristics, and demographics), property records scraped from online real-estate platforms (home size, age, structure), PRISM gridded daily weather, and vehicle-registration and Census benchmarks. After trimming physically implausible reads, the estimation panel covers about 580 surveyed households for electricity, of which 562 also have a gas meter, with roughly 1,080 daily observations per household. The full data description and weather summary are in Appendix D.2, and expanded descriptive statistics in Appendix D.5.

Because the characteristics of interest (home structure, appliance stock, and demographics) are fixed over the study period, a conventional household fixed-effects regression cannot recover their association with consumption, since the fixed effect absorbs everything time-invariant. We therefore use the two-step fixed-effects-filtered (FEF) estimator of Pesaran and Zhou (2018), run separately for each fuel. Step 1 regresses daily consumption on a flexible temperature response (interacted with each home's primary heating fuel), other weather controls, and calendar effects, then removes them to recover each household's persistent (baseload) consumption. Step 2 then regresses that persistent component on housing structure, appliance portfolio, and demographic characteristics, in a progression of nested models (M1–M3). The estimator, the

Step 1 specification and equations, and the temperature-binning approach are detailed in Appendix D.3.

19 Results

The household characteristics that explain persistent consumption differ sharply by energy carrier. Step 1 strips weather and calendar variation from daily consumption. The residual is a household's stable demand level, and what explains it depends on whether the carrier is electricity or natural gas. Electricity baseload is shaped by household characteristics. Appliances, housing structure, tenure, and time-at-home behaviors each leave a detectable mark. Natural gas baseload is shaped by the physical characteristics of the home. The pattern is not an artifact of how weather is modeled. It survives all six Step 1 specifications.

The Step 1 filter itself reveals a first asymmetry. Weather and calendar variation account for 63.5% of the daily variation in a household's natural gas use but only 9.3% for electricity. Daily natural gas use is therefore tightly governed by thermal conditions and seasonal timing, whereas electricity use contains a much larger non-weather component that reflects appliances, occupancy, and the number and type of electric devices in the home. Substantial household heterogeneity remains after filtering, which motivates the household-level decomposition below. The Step 1 temperature-response estimates, the remaining weather and calendar coefficients, and the distribution of the persistent component are reported in Appendix D.

Step 2 explains the household-level persistent component $\bar{u}_i$, defined as the average Step 1 residual for each household. The regressors fall into three groups, namely housing structure, appliance portfolio, and demographic covariates.

Table 7 reports the preferred specification (M3).[8] It is estimated separately for electricity and natural gas. Each coefficient is a difference in average daily consumption after weather and calendar variation have been filtered out. The estimates are persistent-component associations and not causal effects on total consumption. The percentage columns express each coefficient as a share of mean daily consumption in the estimation sample.

Table 7: Persistent-Component Decomposition (Step 2)

	Electricity		Natural gas	
	Coef. (kWh/d)	% of mean	Coef. (therms/d)	% of mean
Panel A: Housing Characteristics				
Home size (1,000 Sqft)	4.897*** (0.736)	24.5%	0.683*** (0.073)	32.6%
Residence type (ref: single-family detached)				

continued on next page

[8] Appendix D.7 reports the full M1 through M3 progression.

Table 7 – continued

	Electricity		Natural gas	
	Coef. (kWh/d)	% of mean	Coef. (therms/d)	% of mean
Mobile/manufactured	-2.115* (1.089)	-10.6%	-0.099 (0.118)	-4.7%
Multi-family	-2.013 (1.659)	-10.0%	-0.043 (0.154)	-2.1%
Residence age (decades)	0.280 (0.258)	1.4%	0.048** (0.023)	2.3%
Stories	0.386 (0.829)	1.9%	-0.157* (0.085)	-7.5%
Rooftop solar	-3.723** (1.489)	-18.6%	-0.219* (0.122)	-10.5%
Panel B: Appliance Portfolio & Usage				
Electric primary cooking†	1.471* (0.893)	7.3%	-0.061 (0.082)	-2.9%
Electric primary water heating†	4.278** (1.718)	21.4%	-0.249 (0.155)	-11.9%
Electric clothes dryer†	1.428 (0.969)	7.1%	-0.157* (0.089)	-7.5%
Clothes dryer use (times/week)	1.587*** (0.282)	7.9%	0.065*** (0.024)	3.1%
Primary heating appliance age (yrs)	0.007 (0.057)	0.0%	0.015*** (0.005)	0.7%
Panel C: Demographics & Occupancy				
High income ($100k+)	1.709* (1.056)	8.5%	0.123 (0.106)	5.9%
Graduate degree	-1.098 (0.860)	-5.5%	-0.019 (0.077)	-0.9%
Works from home	0.970 (1.037)	4.8%	-0.131 (0.090)	-6.3%
Respondent age	-0.068* (0.038)	-0.3%	0.003 (0.004)	0.1%
Renter	-4.587*** (1.539)	-23.0%	-0.417* (0.246)	-19.9%
Retired	3.306*** (1.261)	16.5%	-0.027 (0.124)	-1.3%
Intercept	4.920 (3.326)	—	1.081 (0.297)	—
Observations	418		406	
R^2	0.328		0.440	
Adjusted R^2	0.300		0.415	
Mean daily load	20.030 kWh/d		2.094 therms/d	

Notes: Pesaran-Zhou (2018) estimator standard errors in parentheses. The "% of mean" column expresses each coefficient as a share of the observed mean daily consumption (20.030 kWh/d for electricity, 2.094 therms/d for gas). Estimation sample is restricted to households heating with electricity or NG. Primary heating fuel enters Step 1 as an interaction. It is excluded from Step 2 since heating demand is mainly weather-driven. †Binary indicators with the reference category being natural gas appliances. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The main result is that persistent natural gas consumption is mainly tied to housing structure, while persistent electricity consumption is explained by a wider set of household characteristics. Panel A shows that home size is the largest predictor for both energy carriers. An additional 1,000 square feet is associated with 4.90 kWh/day higher electricity use and 0.68 therms/day higher gas use. Relative to mean consumption, the association is larger for gas, at 32.6% compared with 24.5% for electricity. Residence age and number of stories are also statistically significant only for natural gas. This pattern is consistent with gas use being tied to the home's thermal characteristics. Rooftop solar is associated with lower consumption of both energy carriers. The electricity result is expected because solar generation reduces metered grid use. The negative natural gas association should not be interpreted as a direct effect of solar panels on gas consumption. It likely reflects unobserved differences between solar and non-solar households, such as conservation preferences, efficiency investments, or other home upgrades. Appliance fuel matters more clearly for electricity.

The appliance-fuel indicators in Panel B use natural gas as the reference category for each type of end use (i.e., cooking, water heating, and clothes drying). This allows the same appliance contrast to be read across electricity and natural gas consumption. For cooking, electric appliances are associated with higher electricity use, about 7.3% of mean electricity consumption, and lower natural gas use, about 2.9% of mean gas consumption. The signs are consistent with fuel substitution, though only the electricity-side estimate is statistically significant at conventional levels. Electric dryers are associated with 7.5% lower natural gas use and 7.1% higher electricity use, the former significant. Electric water heating is associated with 21.4% higher electricity use, while the natural gas estimate is negative but imprecise.

Panel C shows that demographic and tenure covariates matter mainly for electricity. Retired households and higher-income households consume more electricity, while older respondents consume less. Renter status is negative for both energy carriers. Because the model already controls for housing structure and primary appliance fuel, this coefficient likely proxies for unobserved energy-related capital such as appliance efficiency, insulation, window quality, or heating-system maintenance. For natural gas, most demographic coefficients are small and statistically insignificant.

The Step 2 estimates reinforce the contrast from Step 1. Natural gas consumption is more tightly linked to weather in the daily panel and more tightly linked to housing and heating-related characteristics in the household-level regression. Electricity consumption is different. After weather and calendar variation are removed, its persistent component is associated with a wider set of margins (e.g., home size, appliance fuel, rooftop solar, tenure, and some demographic characteristics). Persistent natural gas consumption is mainly a building and heating-stock outcome, while persistent electricity consumption is distributed across the building, appliances, and household routines. Robustness checks, covering re-estimation of the decomposition under alternative temperature-response filters, verification of specification stability across the progressive models, and confirmation of the absence of multicollinearity, are reported in Appendix D.13.

20 Electricity Load Projection under Various Switching Scenarios

This section translates the household-level estimates from the preceding parts into a utility-scale projection of residential electricity load through 2070, the horizon of LADPU's gas-elimination goal. It combines the household characteristic estimates, the stated switching intentions of the resident survey (Part I), and the solar-rebound estimates of Part III. The projection can be reproduced in the fully interactive workbook (`LADPU_load_projection_tool.xlsx`) in which the milestones, willingness ceilings, appliance lifetimes, solar path, and growth rate are editable inputs.

20.1 Projection methodology

We use the 8,646 residential meters' real 2024 monthly electricity and gas use to aggregate the baseline load profile with about 62,400 MWh of electricity and 5.76 million therms of gas, of which 6,906 homes heat with gas. Electrifying a gas end-use in a home adds the Part-IV per-home electricity effect, a weather-weighted space-heating load concentrated in winter plus flat appliance increments for water heating, cooking, and clothes drying, and removes that home's actual gas for that end-use, so a fully converted home's gas use falls to zero. Each scenario detailed below specifies how fast homes convert each end-use, and both the baseline and the conversions grow with the housing stock at 0.4% per year. Bands are 95% confidence intervals propagated from the regression standard errors. The full construction, covering the actual-2024 per-home baseline, the machine-learning inference of each home's appliance fuels, the gas apportionment, and the conversion arithmetic, is detailed in Appendix D.14.

20.2 Scenarios

We project the annual electricity load and natural gas demand change under three scenarios. Scenario 1 (S1) is a top-down planning path built to achieve the 2070 zero-natural gas goal. Scenarios 2a and 2b are bottom-up scenarios based on the survey responses we gathered. Table 8 summarizes the assumptions of each scenario, and the paragraphs below detail each.

S1: Top-down (the 2070 goal). S1 is backward-induced from LADPU's target and answers a planning question: if the utility eliminates residential gas by 2070, what load must it serve along the way? Each converting home goes all-electric at once, with space heating, water heating, cooking, and drying together, and the share of gas homes fully converted rises on fixed decadal milestones (10% by 2030, 30% by 2040, 50% by 2050, 75% by 2060, 100% by 2070), interpolated linearly between them. The pace is imposed, not behavioral. S1 deliberately sets willingness aside to trace the demand consistent with hitting the goal on schedule. By construction it ends gas service in 2070.

S2a: Bottom-up, stated intentions only. S2a replaces the forced schedule with what households told us they will do, and converts each appliance independently rather than whole homes. Only the willing switch, at the "very likely to switch" shares from the survey (48% of gas space

Table 8: Switching-scenario assumptions

Scenario	Conversion rule	Households that switch, and timing	Elec. 2070	Gas 2070
S1: Top-down	Whole-home all-electric switch on a schedule set by the 2070 goal.	Every gas home, paced to decadal milestones: 10/30/50/75/100% all-electric by 2030/40/50/60/70.	100%	0%
S2a: Stated only	Per-appliance; only survey-willing homes ever switch.	Willing households switch on the survey's stated timing (saturating ∼2034); the 74% with no plan never switch. Willing ceilings: space heating 48%, water heater 60%, range 42%, dryer 19%.	48%	60%
S2b: Replace-on-burnout	Per-appliance; same as S2a and the reluctant majority switch at equipment end-of-life.	Willing on the stated timing; the rest replace gas with electric at one over the appliance lifetime per year. Lifetimes (year): space heating 18, water heater 12, range 15, dryer 13.	96%	4%

Notes: "% elec." is the share of gas homes that have electrified space heating in 2070, and "Gas left" is the share of 2024 residential gas still consumed in 2070 (grown with the housing stock). Willing ceilings and stated timing are from the resident survey (Part I), and appliance lifetimes are standard engineering values. All parameters are editable in the delivered workbook. The table reports only the 2070 endpoints; the full decadal trajectories under each scenario are reported in Table 9 and Figures 15 and 16.

heating, 60% of water heating, 42% of ranges, and 19% of dryers), and they convert on the survey's stated timing, which fills the willing pool over roughly a decade (saturating near 2034). The 74% who report no plan to switch never do. Adoption therefore plateaus at each appliance's willing ceiling, leaving about 60% of 2024 gas use still flowing in 2070. S2a is the lower, "intentions-only" bound on voluntary adoption.

S2b: Bottom-up, replace-on-burnout. S2b keeps S2a's willing adopters but adds the mechanism most likely to electrify the reluctant majority, namely equipment turnover. A household that would never scrap a working furnace will still face a choice when it fails, and S2b assumes that at replacement the gas unit is swapped for electric. Reluctant homes therefore convert each appliance at a rate of one over its expected lifetime per year (space heating 18 years, water heating 12, ranges 15, dryers 13). This drives electrification to about 96% of gas homes by 2070, close to the goal, without anyone replacing equipment early. S2b is the "natural replacement" path, the outcome if electric simply becomes the default at end-of-life.

20.3 Projected Load Growth

Figure 15 and Table 9 report the trajectories. Meeting the 2070 goal (S1) raises residential load from about 62,400 MWh in 2024 to roughly 100,600 MWh in 2070 (95% CI 97,300–103,800), a 61% increase. About 20 percentage points of that is housing growth alone, and the remaining 41 points, some 25,500 MWh, is the electrification add-on. The bottom-up paths fall short of the goal by differing margins. Under stated intentions alone (S2a), adoption plateaus once the willing households convert. About 48% of gas homes electrify space heating, roughly 60% of 2024 gas use is still burning in 2070, and load reaches only about 88,300 MWh. Allowing the reluctant majority to switch at equipment failure (S2b) lifts electrification to about 96% of gas homes by 2070 and load to about 100,000 MWh, close to the goal, but reached through organic turnover rather than on the milestone schedule. Both bottom-up paths rise faster than S1 in the near term because the 2070 milestones are back-loaded (only 10% by 2030), whereas willing and replacement-driven adoption begin immediately. S1 overtakes them only as it accelerates toward full conversion after 2050. The gap between the goal and stated intentions, about 12,300 MWh in 2070, with the majority of gas use still unconverted, is the willingness–action gap of Parts I–II expressed in load terms.

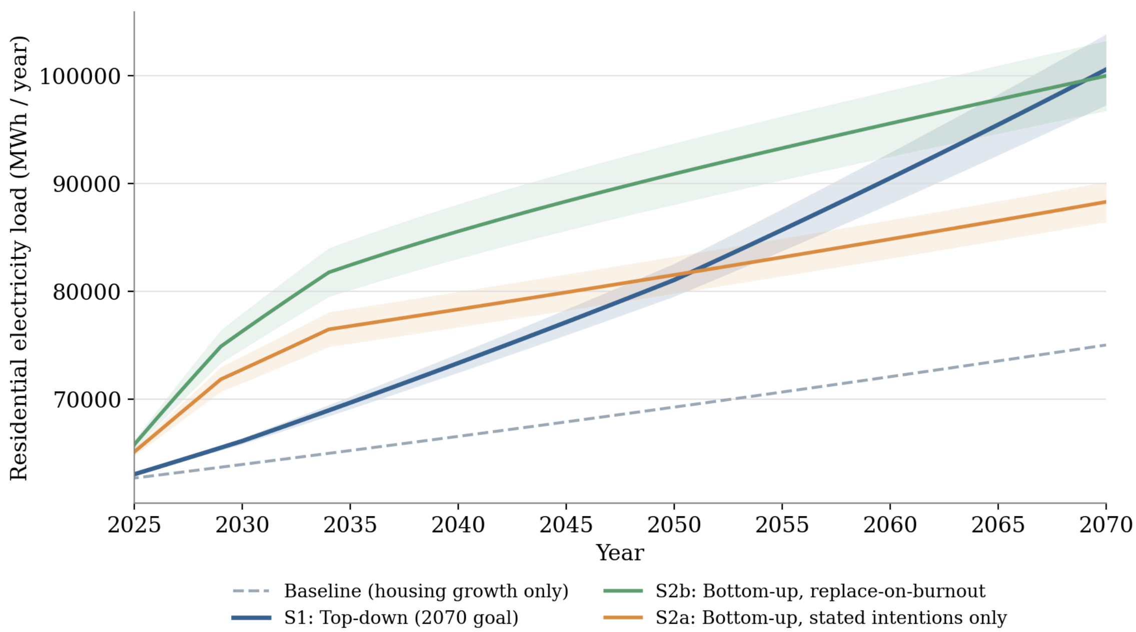


Figure 15: Projected residential electricity load by switching scenario, 2024–2070

Notes: Annual residential electricity load (MWh) for Los Alamos under the top-down 2070-goal path (S1), the bottom-up survey paths (S2a stated-intentions-only, S2b replace-on-burnout), and the baseline of housing growth alone, anchored to actual 2024 metered consumption. Each scenario path carries a shaded 95% confidence interval propagated from the Part-IV coefficient standard errors. The effect of rooftop solar on grid load is shown separately in Figure 18.

Table 9: Residential electricity-load projections by switching scenario

	Total electricity load (MWh/yr)				In 2070	
Scenario	2030	2040	2050	2070	% elec.	Gas left
Baseline (growth only)	63,949	66,553	69,264	75,021	0%	100%
S1: Top-down	66,126	73,350	81,054	100,560	100%	0%
95% CI, 2070				[97,273, 103,848]		
S2a: Stated only	72,756	78,326	81,516	88,291	48%	60%
S2b: Replace-on-burnout	76,304	85,561	90,887	99,974	96%	4%

Notes: Total residential electricity load (MWh/year) at decadal milestones, anchored to actual 2024 metered consumption. “% elec.” is the share of gas homes that have electrified space heating and “Gas left” the share of 2024 residential gas still consumed (which grows with the housing stock), both in 2070. The 95% CI propagates the Part-IV coefficient standard errors. The net grid load after the rooftop-solar overlay is reported separately in Table 10. Reproduced by the delivered standalone workbook `LADPU_load_projection_tool.xlsx`.

The mirror image of that load growth is the decline in gas use (Figure 16). Under S1, residential gas falls from 5.76 million therms in 2024 to zero in 2070 by construction. Under stated intentions (S2a) it falls only to about 3.4 million therms, roughly 60% of today’s use, and plateaus there once the willing pool is exhausted. Replace-on-burnout (S2b) drives gas down to about 0.2 million therms (4%) by 2070 through equipment turnover alone. The vertical distance between S1 and S2a is the same willingness–action gap, now measured in unburned gas rather than added electricity.

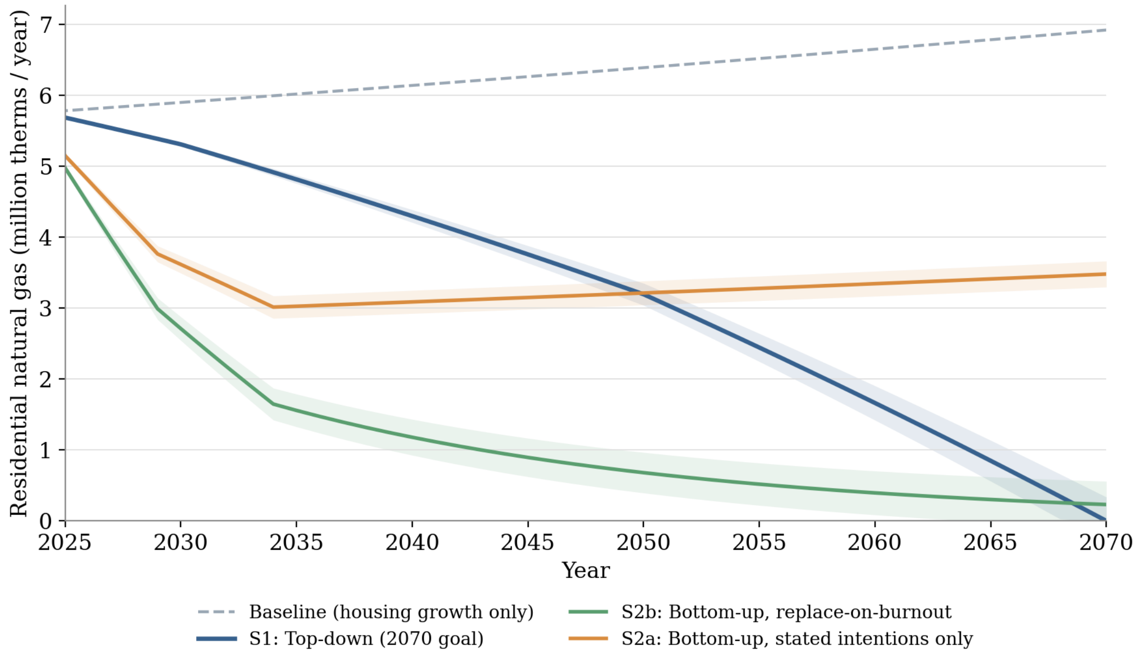


Figure 16: Projected residential natural gas consumption by switching scenario, 2024–2070

Notes: Annual residential natural gas use (million therms) under each scenario, anchored to actual 2024 metered consumption. S1 eliminates gas by 2070 by construction. S2a plateaus as the survey-willing pool is exhausted, leaving about 60% of today's gas, while S2b approaches zero through equipment turnover. The baseline rises with the housing stock. Shaded bands are 95% confidence intervals constructed exactly as for the load projection, propagated from the gas-coefficient standard errors and clipped at zero, so S1's band is one-sided as the central path reaches zero. Rooftop solar also reduces gas. Part III estimates a statistically significant spring reduction (−0.948 MMBtu/month, −13.85%, with the annual average smaller and not significant). The projection applies this as a small solar-gas overlay, scaled by the gas a home still uses so it does not double-count electrified homes. It lowers remaining gas by about 1% and is reported separately ("gas net of solar") in the delivered workbook.

20.4 Seasonal Pattern

Because electric space heating concentrates the added load in winter, the seasonal peak grows faster than the annual total. January load, the monthly proxy for the winter peak, rises from about 5,900 MWh in 2024 to about 10,300 MWh in 2070 under S1, a 74% increase that far outpaces the 61% growth in annual energy. Figure 17 shows the reshaping directly. Today's mild seasonal profile gives way, under full electrification, to a pronounced winter peak. Sizing distribution capacity to that winter peak, rather than to annual energy, is therefore the binding planning constraint.

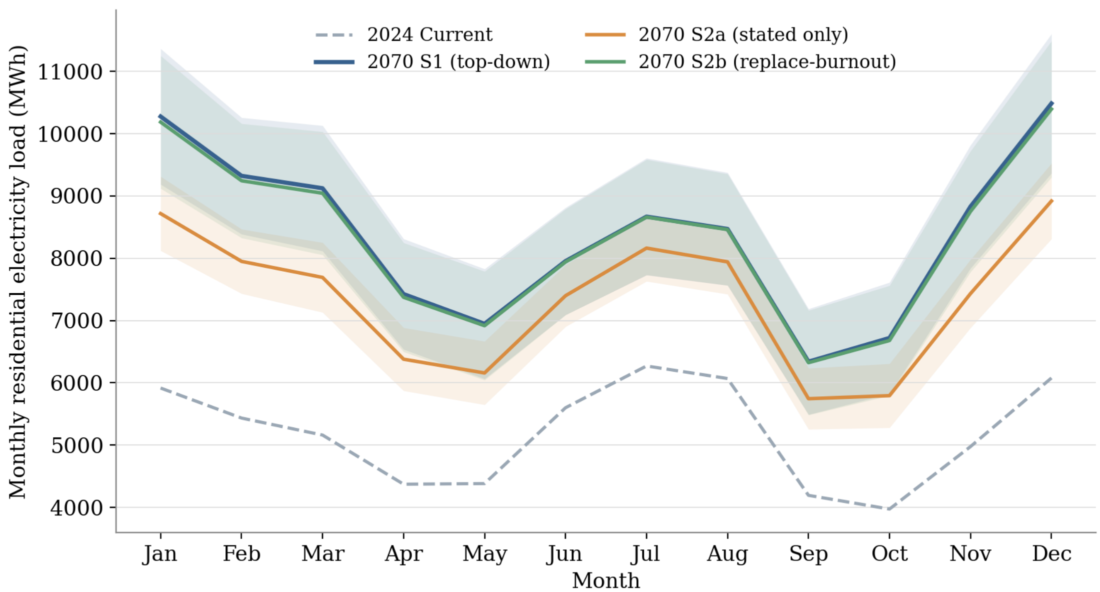


Figure 17: Monthly residential electricity load shape, 2024 versus 2070 by scenario

Notes: Monthly residential electricity load (MWh) for actual 2024 and for 2070 under each electrification scenario, with shaded 95% confidence intervals on the 2070 paths (the 2024 line is metered actuals). Electrifying space heating concentrates the new load in the winter months, turning today's mild seasonal profile into a pronounced winter peak, while the shoulder and summer months rise far less.

20.5 Rooftop Solar

Rooftop solar lowers the load LADPU must serve but does not close the electrification gap. Growing solar to 40% of homes by 2050 trims the S1 2070 grid load from about 100,600 to about 95,900 MWh, a reduction of roughly 4,700 MWh (about 5%). The offset is modest both because solar reaches a minority of homes and because, as Part III shows, the rebound returns part of the would-be grid reduction to consumption, so each adopter's measured grid saving is already net of an 18.8% rise in total use. Solar also trims gas. Part III finds a statistically significant spring reduction (about −14% of spring gas, though the annual average is not significant), which the projection carries through as a roughly 1% further cut in whatever gas remains under each scenario. Figure 18 shows the top-down path with and without solar for each fuel, Table 10 reports the net grid load for all three scenarios, and the bottom-up panels are in Appendix D.14. Solar is a useful but partial hedge against the new winter load, and compensation that rewards self-consumption and load-shifting would raise its value to the grid.

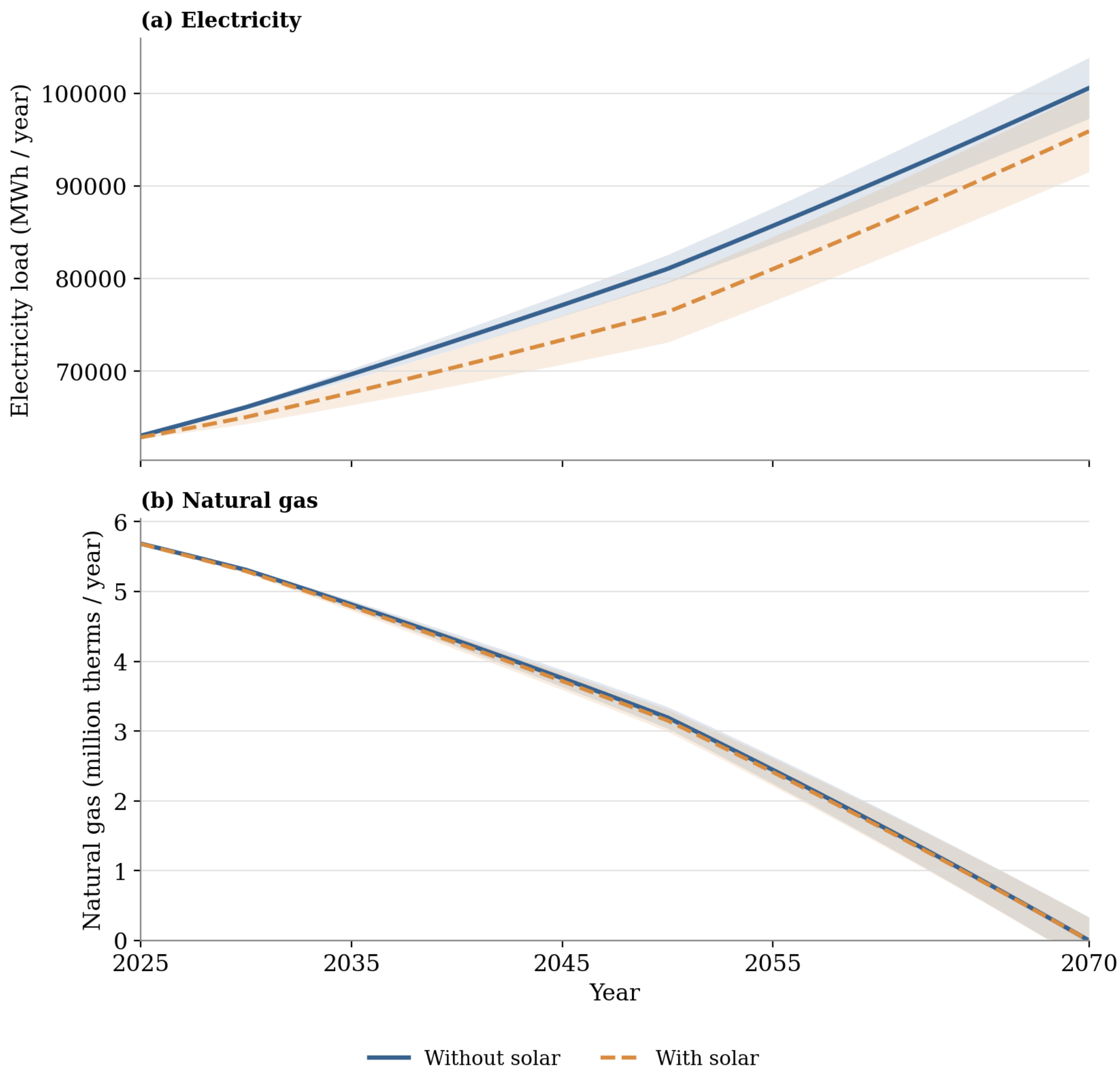


Figure 18: Rooftop solar's effect on projected residential electricity and gas under S1, 2024–2070

Notes: The top-down scenario (S1) with and without the rooftop-solar overlay (growing to 40% of homes by 2050), with 95% confidence intervals on both paths. In Panel (a), solar lowers the electricity grid load LADPU must serve by the Part-III grid ATT (−131 kWh per month per adopting home), about 4,700 MWh (5%) by 2070. In Panel (b), because S1 eliminates residential gas by 2070, little gas remains for solar to displace, so the with- and without-solar gas paths nearly coincide. The corresponding panels for the bottom-up scenarios (S2a, S2b), where gas persists, are in Appendix D.14 (Figure D.9).

Table 10: Residential electricity-load projections net of rooftop solar

Scenario	Net grid load (MWh/yr) 2030	2040	2050	2070	Solar saving, 2070
S1: Top-down	65,051	70,483	76,394	95,901	4,659 (4.6%)
S2a: Stated only	71,680	75,458	76,856	83,632	4,659 (5.3%)
S2b: Replace-on-burnout	75,229	82,694	86,227	95,314	4,660 (4.7%)

Notes: Net grid load (MWh/year) after the rooftop-solar overlay, for the three switching scenarios. Gross loads are in Table 9. Solar grows to 40% of homes by 2050 and reduces grid purchases by the Part-III grid ATT (−131 kWh per month per adopting home). Because the solar path is the same across scenarios, the 2070 saving is nearly identical in level (about 4,700 MWh) and differs in percentage only with each scenario's total load. Reproduced by the delivered standalone workbook `LADPU_load_projection_tool.xlsx`.

21 Discussion

21.1 Key Findings and Interpretation

This part combines two analyses. The first decomposes what drives persistent household energy use. Persistent natural gas consumption is concentrated in the building envelope, with home size, age, and number of stories its main predictors, whereas persistent electricity consumption is spread across a wider set of margins, namely appliances, structure, tenure, and demographics. Weather and the calendar explain 63.5% of the daily variation in gas use but only 9.3% for electricity, so once weather is removed gas baseload is a building-stock outcome while electricity baseload reflects the household. The levers therefore differ by fuel. Envelope measures such as insulation, sealing, and windows are the primary instrument for reducing gas, while appliances, efficiency, and behavior are what move electricity.

The second analysis carries these household relationships, the survey's stated switching intentions, and the solar rebound effect we identified into a utility-scale load projection to 2070. Meeting LADPU's gas-elimination goal (S1) raises residential electricity load by about 61%, from roughly 62,400 to 100,600 MWh, of which about 20 percentage points is housing growth and the remainder the electrification add-on. The seasonal reshaping is sharper than the annual total, because electrifying space heating concentrates the new load in winter. The January peak rises about 74%, so distribution capacity sized to the winter peak rather than to annual energy is the binding constraint. The bottom-up paths express the willingness–action gap in load terms. Stated intentions alone (S2a) leave about 60% of today's gas still burning in 2070 and fall roughly 12,300 MWh short of the goal, whereas allowing the reluctant majority to convert at equipment failure (S2b) reaches about 96% electrification through turnover alone. Rooftop solar trims the grid load by about 5% but does not close the gap.

21.2 Comparison to Existing Literature

Our household-level decomposition is the consumption-side counterpart to the literature on household fuel choice and appliance adoption, which has emphasized why households switch more than what governs their use once the stock is fixed. That work finds adoption shaped by income, infrastructure, and social context (Alem et al., 2016; Edwards et al., 2024; Lane et al., 2024), with Lane et al. (2024) finding hassle and reliability concerns to outweigh equipment cost. Our estimates add that, conditional on the existing stock, gas use is governed by the building and electricity by the household, which is why a given retrofit changes the two fuels by different amounts.

The load projection connects to work on the grid consequences of electrification. Studies of heat-pump uptake and feeder limits show that electrification concentrates new load where hosting capacity is already strained (Brockway et al., 2021; Edwards et al., 2024), and techno-economic analyses warn that under high volumetric rates a retrofit can raise winter bills (Borenstein et al., 2022). Our metered, winter-peaked 74% growth in the seasonal maximum is the local analogue of those concerns, and it quantifies a gap the adoption literature describes qualitatively, namely that stated intent falls well short of the conversion a public target requires, so the binding question for planners is the pace of replacement rather than willingness.

The contrast between a goal-driven and a turnover-driven path also speaks to the equity literature on transition sequencing. Distributional analyses warn that if higher-income homes electrify first, the fixed costs of the legacy gas system fall on a shrinking, lower-income remainder (L. Davis and C. Hausman, 2022; Hill, 2025; Waite and Modi, 2020). Because our bottom-up paths electrify the willing first and the reluctant only at burnout, they trace the ordering those studies flag, which is why the drawdown of gas infrastructure and the protection of remaining customers, taken up in Part V, are part of a credible pathway.

21.3 Limitations

The two findings are robust to the checks we run, but several features of the data and method bound their interpretation. First, the household-level estimates are conditional associations rather than causal effects. They locate where persistent consumption differences sit, in the building stock for gas and across a broader set of margins for electricity, but they do not identify the effect of changing any single characteristic.

Second, the projection is monthly, so it bounds winter energy rather than the hourly megawatt peak that ultimately drives distribution upgrades, and a full hourly peak analysis is left for future work. Relatedly, the household demand model contains no price term. LADPU's residential tariff is a flat volumetric rate plus a fixed service charge, identical for every residential customer at any point in time, so there is no cross-household variation in marginal or average price with which to identify a price response, and the common month-to-month rate changes are absorbed by the Step 1 calendar effects. A demand elasticity could be identified only from tariff variation the setting does not provide, such as the increasing block rates used in municipal water-demand studies.

Third, the solar-rebound effect carried into the projection was estimated on today's largely gas-heated stock, so its application to future all-electric homes is an approximation. Finally, the confidence bands propagate only the regression estimation uncertainty and treat the end-use coefficients as independent. They do not capture the larger uncertainty in the pace of adoption, which the scenarios are designed to bracket rather than to estimate.

Part V

Synthesis and Policy Recommendations

22 From Analysis to a Transition Roadmap

The four part analyses point to a sequence of steps for LADPU to transition away from natural gas use under the current policy goal. The transition will be voluntary and gradual, and what governs it is the cost and friction of replacing working gas equipment more than households' awareness or attitudes. The survey and choice experiment show that customers weigh efficiency and bill savings far above emissions and that most are not planning to switch (Figure 4 and Table 4). The metered-consumption analyses describe how the transition will impact the grid, namely a winter-peaked rise in electricity demand (Figure 17) and a solar rebound that limits the reduction of grid electricity demand (Figure 14). The implications below are organized by horizon, from the near-term measures that lower the cost of switching to the long-run planning the new load will require.

22.1 Near-term steps to lower the cost of switching

The barriers customers name are financial and infrastructural, not informational. The most common is the upfront installation cost, cited by about three-quarters of households, followed by concern about higher ongoing bills and grid reliability (each about two-thirds) and insufficient electrical-panel capacity (about half) (Figure 3). Each of these has a corresponding lever. Upfront cost is what federal and state rebates and low-interest financing are designed to offset. The concern about higher bills is met by the efficiency of modern heat pumps and by rate design. The panel constraint is a one-time upgrade that incentives and streamlined permitting can cover. The reliability concern is largely a perception of older electric equipment, which targeted information and the utility's own grid investment can address. The steps below take these barriers in turn, starting with the ones that bind for the most households.

Outreach that highlights bill savings and performance might work better than one that focuses on climate benefits. Households weigh efficiency, comfort, and bill savings above emissions, and an informational message about the climate and health effects of gas moved willingness to pay very little (Table B.1). Modern heat pumps deliver two to three times the efficiency of a gas furnace, add summer cooling, and can lower or stabilize bills where the rate structure supports it. Climate and air-quality benefits are real and worth stating, but the evidence suggests they work better in support of that case than as the lead, since the pro-environmental minority adopts early in any event while the cost-focused majority responds to savings.

The largest near-term barrier is the cost and hassle of getting homes physically ready. About three-quarters of homes would need a 200-amp electrical-panel upgrade, typically $2,000–$5,000, before they could run electric heating, water heating, and cooking together, and the choice experiment implies that roughly $800–$1,000 per year in lower bills or incentives, or support that directly covers the panel, is about what it takes to move a panel-needing household (Table 4). Streamlining permitting for panel upgrades and appliance swaps, helping households become aware of the federal and state incentives already available, and offering infrastructure loans to financially constrained households could each lower that cost and friction.

Programs that target fuel switching when appliances reach the end of their life are likely to be the most effective. Switching is cheapest at equipment failure, when a household faces only the incremental cost of going electric rather than the cost of scrapping a working appliance. About a third of primary heating systems in the sample are already at least twenty years old (Appendix A.4), and the projection shows that conversion at natural replacement alone would electrify most homes over the coming decades (Table 9). Reaching households at that moment, with a ready electric option and incentives lined up, is where near-term effort pays off most. Solar adopters are a natural place to start, since they are more likely to have already electrified heating and water heating (Yang and Mamkhezri, 2026), so bundling outreach or a panel upgrade with a solar installation concentrates effort where uptake is most likely.

22.2 Medium-term steps to target and sequence conversions

As the transition broadens, focusing first on the homes that use the most gas could deliver the largest reductions. What governs persistent consumption differs sharply between the two fuels. Persistent gas use is concentrated in the building envelope, in larger, older, multi-story homes, while persistent electricity use is spread across appliances, occupancy, and household characteristics (Table 7). The homes that burn the most gas today are therefore both the largest source of gas reductions and the largest future electric load once they convert, and they can be identified directly from meter and property records. Weatherizing those homes before they electrify would lower both their current gas use and the load they later add. The utility can coordinate its electrification outreach with the county and state programs that can would capture that envelope-first benefit for the grid as well as the household.

Concentrating on space and water heating, rather than spreading effort across all appliances, could do more for both the goal and the grid. These two end uses remain almost entirely gas and account for most of both the gas use and the new electric load (Appendix A.4), and they are also among the appliances households are most willing to switch (Figure 4). Clothes drying is already largely electric. Cooking is the harder case. A substantial share of households prefer gas cooking, and although measures like LADPU's induction-cooktop rental program help them try the electric alternative, cooking is unlikely to be a first-order source of gas reductions or new load.

Solar compensation structure is the medium-run lever most under the utility's control. Rooftop solar lowers a household's grid purchases but raises its total energy use, offsetting roughly three-quarters of the carbon reduction it would otherwise deliver (Figure 14), and the rate structure shapes when households consume. The effect matters most in winter, where the new electric load and the solar rebound fall in the same hours. Electrification raises the January peak by about 74% (Figure 17), and the solar rebound is largest in winter and extends into the evening, after the panels stop generating (Figures 11 and 13). Both push load increases into the winter evening hours, when rooftop solar provides no offset. Rate structure that rewards self-consumption and load-shifting, through time-varying export and retail prices and support for on-site storage that moves midday solar toward the evening, would raise solar's grid value rather than simply maximizing exports.

22.3 Long-run steps to plan for load and affordability

The transition's largest long-run consequence is the load it adds. Meeting the 2070 goal would raise annual residential electricity use by about 61% and the winter peak by about 74%, so distribution capacity sized to the winter peak, not to annual energy, becomes the binding planning constraint (Table 9 and Figure 17). The load projection, under the goal-driven, stated-intention, and replacement-driven paths, gives the utility a range to plan against, and it can be revisited as adoption unfolds. The rebound belongs in those forecasts as well, since solar adopters reduce their grid purchases by less than their panels generate, so treating solar generation as a one-for-one reduction in grid load would overstate the relief it provides (Table 6).

Building affordability and equity into the program design could keep the transition's costs from falling on the households least able to bear them. A bill increase of $50–$100 per month would impose hardship on a majority of households (Table 1), and if higher-income homes electrify first, the fixed costs of the legacy gas system fall on a shrinking, lower-income set of remaining customers. Planning the drawdown of the gas system in step with conversions, and attending to who is left on it, belongs in the transition plan from the start rather than at the end. The most direct counter to that dynamic is to aim subsidy at the constraint that binds hardest for lower-income households, namely the one-time cost of getting the home electric-ready. Income-qualified support for electrical-panel upgrades and pre-wiring, of the kind New Mexico's Home Energy Rebate program now reserves for households below 80% of area median income, would move the households least able to pay the $2,000–$5,000 upgrade cost into the electrification pool early, rather than leaving them to carry the fixed costs of a shrinking gas system at the end.

23 Conclusion

Los Alamos County has set out to eliminate natural gas service by 2070. For the residential sector, that means converting the county's homes to all-electric heating, water heating, and cooking over the coming decades, largely through the voluntary decisions of individual households. This report finds the goal feasible on a natural-replacement timeline but well out of reach on stated intent alone. What households say about switching runs far ahead of what they do, and the binding constraint is the cost and friction of replacing working gas equipment rather than awareness or attitudes. The switch will also reshape the electric system, raising annual residential load by about 61% and the winter peak more steeply still, while rooftop solar offsets only a modest share of that load and returns part of its carbon benefit to consumption through the rebound. Reaching the goal will therefore take coordinated action rather than any single lever. The utility can lower the cost and friction of switching and plan for the load it adds, but closing the gap will also depend on the federal and state incentives, financing, and weatherization programs that reach homes the utility cannot serve directly, and on managing the affordability of the transition so that its costs do not fall on the households least able to bear them.

List of Abbreviations

Abbreviation	Definition
ACS	American Community Survey
AIC	Akaike Information Criterion
ASC	Alternative-specific constant
ATT	Average treatment effect on the treated
BIC	Bayesian Information Criterion
CCF	Hundred cubic feet (natural gas volume)
CDD	Cooling degree days
CO_2	Carbon dioxide
CV	Coefficient of variation
DCE	Discrete choice experiment
DiD	Difference-in-differences
EF	Emission factor
EV	Electric vehicle
FEF	Fixed-effects filtered (estimator)
HDD	Heating degree days
IRA	Inflation Reduction Act of 2022
KMO	Kaiser–Meyer–Olkin measure of sampling adequacy
kWh	Kilowatt-hour
LADPU	Los Alamos Department of Public Utilities
LANL	Los Alamos National Laboratory
LPG	Liquefied petroleum gas
MEF	Marginal emission factor
MMBtu	Million British thermal units
NEP	New Ecological Paradigm (environmental-attitude scale)
NSRDB	National Solar Radiation Database
OLS	Ordinary least squares
PHEV	Plug-in hybrid electric vehicle
$PM_{2.5}$	Fine particulate matter (diameter $\leq 2.5\,\mu$m)
PNM	Public Service Company of New Mexico
PRISM	Parameter-elevation Regressions on Independent Slopes Model (climate data)
PV	Photovoltaic
PVGIS	Photovoltaic Geographical Information System
RMSE	Root mean squared error
SD	Standard deviation
SE	Standard error
SUTVA	Stable Unit Treatment Value Assumption
TWFE	Two-way fixed effects
VIF	Variance inflation factor
WTP	Willingness to pay

A Appendix to Part I: Resident Survey

This appendix collects the full descriptive detail behind Part I, namely respondent demographics and the representativeness analysis, billing preferences, housing characteristics, the detailed appliance stock, and the environmental-attitude items.

A.1 Respondent Demographics and Representativeness

Figure A.1 summarizes additional respondent and household characteristics. Among respondents who reported sex at birth, 64% identified as male, and White respondents accounted for 89% of the sample. About 80% live in homes at least 30 years old, and 15% have rooftop solar.

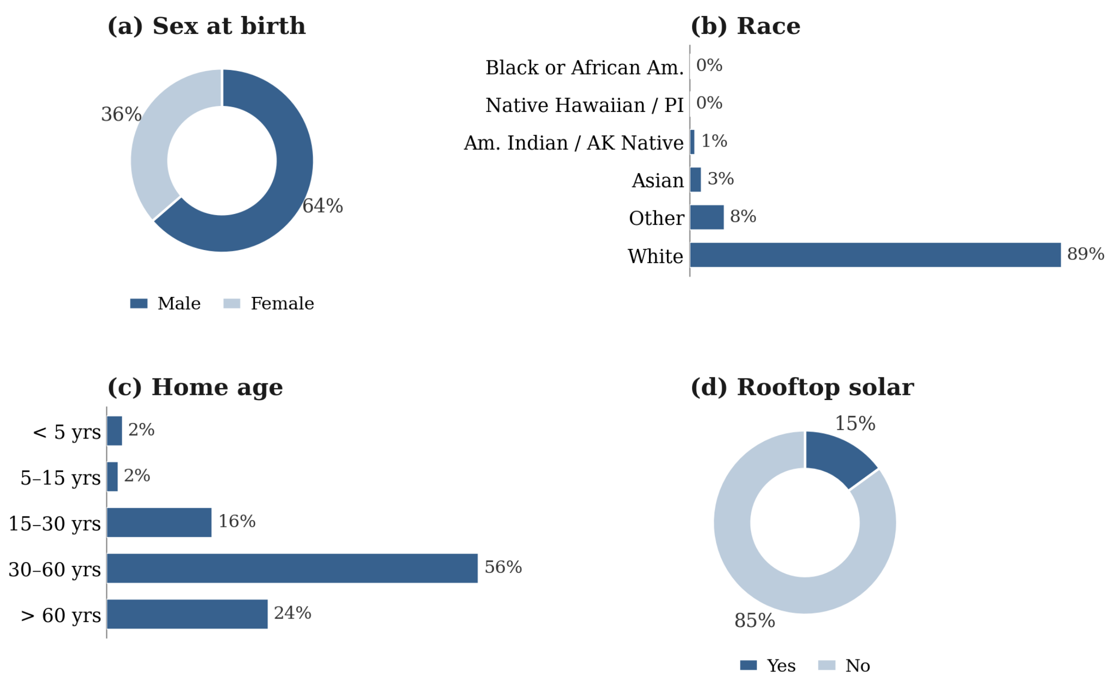


Figure A.1: Survey respondents: additional respondent and household characteristics

To check whether the survey respondents are representative of the broader LADPU customer base, we compare the sample to U.S. Census Bureau benchmarks for Los Alamos County (U.S. Census Bureau, 2023) and reweight it to match them. We apply a multi-stage post-stratification and raking procedure to generate respondent-specific weights (Battaglia et al., 2009; Kolenikov, 2014). Each weight begins at 1 (set to 0 when all key demographic variables are missing) and is iteratively adjusted so that the weighted sample matches county benchmarks on sex, Hispanic origin, housing tenure, and educational attainment, with an additional exponential-tilting step (Kim, 2010; Wu and Lu, 2016) that calibrates the resident age distribution. All weights are bounded between 0 and 10.

Table A.1 compares the survey sample to the county census benchmarks before and after weighting. The unweighted sample over-represents older, more-educated, non-Hispanic homeowners, while the weighted shares match the census targets across sex, Hispanic origin, tenure, education, and age. Table A.2 summarizes the resulting weight distribution, which carries a design effect of 2.43 (a Kish effective sample size of 273).

Table A.1: Los Alamos County Demographics: Census Benchmark and Survey Sample

	Census benchmark	Survey (unweighted)	Survey (weighted)
% Male	51.6	64.0	51.6
% Hispanic or Latino	17.9	7.4	17.9
% Homeowner	77.5	95.3	77.5
% High school or higher	98.3	99.8	98.5
% Bachelor's degree or higher	68.2	86.2	68.2
Resident age distribution (%)			
Under 18	21.4	21.6	21.4
18 to 64	60.4	49.3	60.4
65 or older	18.2	29.1	18.2
Mean household income ($)	143,728	146,400	137,717

Notes: Census benchmarks are U.S. Census Bureau (American Community Survey) estimates for Los Alamos County. Survey columns are response shares among respondents answering each item, before and after post-stratification weighting (Table A.2). The unweighted sample over-represents older, more-educated, non-Hispanic homeowners; the weighted shares match the census targets on the calibration margins. Household income is not a calibration margin and is shown for reference.

Table A.2: Survey Raking-Weight Distribution

Statistic	Value
Respondents with positive weight	663
Mean weight	1.00
Weight range (min–max)	0.12–10.00
Effective sample size (Kish)	273
Design effect	2.43

Notes: Weights are constructed by iterative proportional fitting (raking) on sex, Hispanic origin, housing tenure, and education (high-school-or-higher and bachelor's-or-higher), with an exponential-tilt calibration of the resident age distribution, and are bounded to $[0, 10]$. The Kish effective sample size is $(\sum w)^2 / \sum w^2$; the design effect is the ratio of nominal to effective N. The achieved calibration is shown in Table A.1.

Table A.3: Survey Summary Statistics for Demographic Variables

Variables	Mean	S.D.	Min	Max	N
Number of current residents in each of the following age categories					
0 to 17 years old	0.82	1.08	0	5	427
18 to 64 years old	1.53	0.92	0	5	524
65 years or older	0.93	0.93	0	5	509
Age of the survey respondent					
Age	58.3	16.99	18	120	650
Sex at birth					
Male	0.64	–	–	–	642
Female	0.36	–	–	–	642
Hispanic or Latino					
Yes/No	0.07	–	–	–	625
Race (Multi-select)					
White	0.88	–	–	–	623
Black or African American	0.00	–	–	–	623
American Indian or Alaska Native	0.01	–	–	–	623
Asian	0.02	–	–	–	623
Native Hawaiian or Pacific Islander	0.00	–	–	–	623
Other	0.08	–	–	–	623
Highest degree or level of school of the survey respondent					
Less than high school diploma or GED	0.00	–	–	–	653
High school diploma or GED	0.02	–	–	–	653
Some college or Associate's degree	0.12	–	–	–	653
Bachelor's degree	0.26	–	–	–	653
Master's, Professional, or Doctoral degree	0.60	–	–	–	653
Total combined income of all household members for the past year					
Less than $20,000 per year	0.04	–	–	–	627
$20,000 to $34,999	0.02	–	–	–	637
$35,000 to $49,999	0.02	–	–	–	637
$50,000 to $64,999	0.03	–	–	–	637
$65,000 to $69,999	0.02	–	–	–	637
$70,000 to $84,999	0.04	–	–	–	637
$85,000 to $99,999	0.06	–	–	–	637
$100,000 to $149,999	0.23	–	–	–	637
$150,000 to $199,999	0.21	–	–	–	637
$200,000 or more	0.34	–	–	–	637
Current employment status of the survey respondent					
Employed full-time	0.49	–	–	–	637
Employed part-time	0.04	–	–	–	637
Self-employed	0.04	–	–	–	637
Retired	0.40	–	–	–	637
Not employed	0.02	–	–	–	637
Other	0.02	–	–	–	637
Having residents work from home more than three days per week?					
Yes/No	0.28	–	–	–	637

Note: Standard deviation, minimum, and maximum values are not reported for dummy variables. The mean values can capture the spread in the dataset, while the minimum and maximum are always 0 and 1, respectively, and therefore omitted for brevity.

A.2 Billing Preferences

Most households still receive paper bills (73%), but the majority use electronic payment options, with 42% enrolled in autopay and 41% paying online. Only a small share pays by check (12%) or in person (4%). Customer-portal use is almost evenly split, and a small share (6%) is unaware the portal exists (Figure A.2).

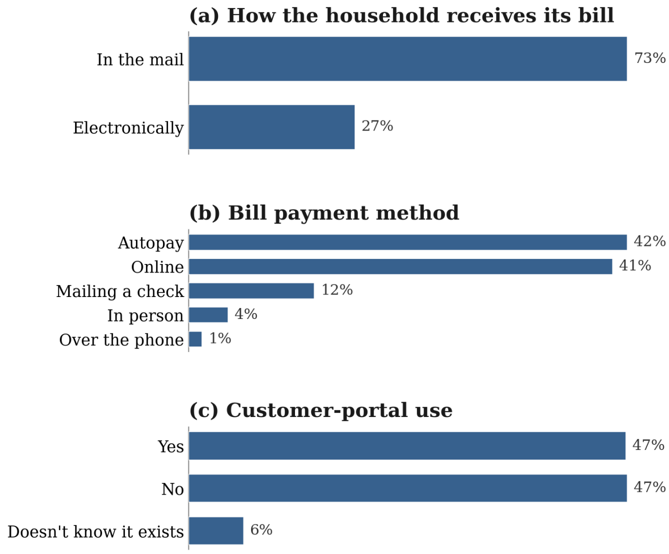


Figure A.2: Survey Respondents Billing Preferences

Table A.4: Survey Summary Statistics for Billing Variables

Variables	Mean	N
How does your household receive the monthly utility bill from LAC-DPU?		
Electronically	0.27	713
In the mail	0.73	713
How do you pay your utility bill?		
Autopay	0.42	712
In person	0.04	712
Mailing a check	0.12	712
Online (credit/debit/checking account)	0.41	712
Over the phone	0.01	712
Do you use the LAC-DPU customer portal to see your bill and usage?		
No	0.47	713
Yes	0.47	713
I do not know what this is	0.06	713
How often do you examine your utility usage in the LAC-DPU customer portal? (only recorded for the portal users.)		
Never	0.01	334
Sometimes (1 to 2 times per year)	0.22	334
Often (3 to 6 times per year)	0.22	334
Regularly (7 to 12 times per year)	0.55	334
Which of the following best explains why you do not track your utility usage in the LAC-DPU customer portal?		
I do not have an account in the customer portal	0.08	333
I prefer receiving utility information through traditional methods	0.43	333
I find the customer portal difficult to navigate or use	0.12	333
I don't see a need to track my utility usage online	0.20	333
I don't have reliable internet/computer access	0.01	333
I don't pay attention to how much my energy bill is	0.03	333
Other	0.14	333
Are you enrolled in the LAC-DPU Utilities Assistance Program?		
No	0.97	705
Yes	0.01	705
Not sure	0.01	705
Are you enrolled in the Budget Billing Program?		
No	0.93	708
Yes	0.05	708
Not sure	0.02	708

Note: Standard deviation, minimum, and maximum values are not reported for dummy variables. The mean values can capture the spread in the dataset, while the minimum and maximum are always 0 and 1, respectively, and therefore omitted for brevity.

A.3 Housing Characteristics

The majority of respondents are homeowners, and 82% live in single-family detached homes. More than half (56%) reside in homes built between 30 and 60 years ago. The most common sizes are 1,000–2,000 square feet (43%) and 2,000–3,000 square feet (36%) (Figure A.3). Home age and rooftop-solar adoption are shown in the main text (Figure 1).

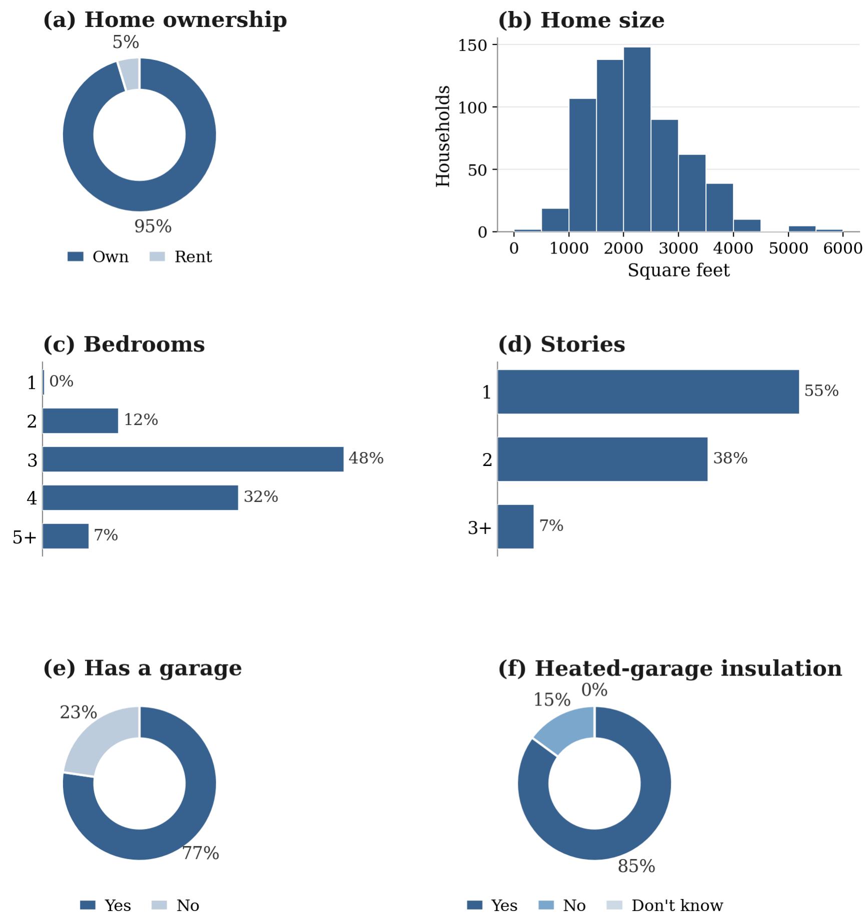


Figure A.3: Additional Housing Characteristics

Table A.5: Survey Summary Statistics for Residence Variables

Variables	Mean	S.D.	Min	Max	N
Type of Residence					
Single-family detached house	0.82	–	–	–	708
Single-family attached house	0.12	–	–	–	708
Apartment/condominium	0.04	–	–	–	708
Mobile home	0.02	–	–	–	708
Other	0.004	–	–	–	708
Do you own or rent your primary residence?					
Rent	0.05	–	–	–	642
Own	0.95	–	–	–	642
Is your utility bill included in your rent? (only recorded for renters).					
Yes/No	0.03	–	–	–	30
Approximately how old is your primary residence?					
Less than 5 years old	0.02	–	–	–	639
5 to 15 years old	0.02	–	–	–	639
15 to 30 years old	0.16	–	–	–	639
30 to 60 years old	0.56	–	–	–	639
Older than 60 years	0.24	–	–	–	639
What is the square footage of your home?					
Size	2175.50	875.81	0	6000	628
How many bedrooms does your primary residence have?					
1	0.00	–	–	–	631
2	0.12	–	–	–	631
3	0.48	–	–	–	631
4	0.32	–	–	–	631
5+	0.07	–	–	–	631
Excluding basements and attics, how many stories does your primary residence have?					
1	0.55	–	–	–	633
2	0.38	–	–	–	633
3+	0.07	–	–	–	633
Does your primary residence have a garage?					
Yes/No	0.77	–	–	–	635
What size is the garage at your primary residence? (only recorded if having garage).					
1	0.19	–	–	–	484
2	0.72	–	–	–	484
3+	0.08	–	–	–	484
Which of these describes your garage? (only recorded if having garage).					
Attached and heated	0.14	–	–	–	490
Attached and not heated	0.76	–	–	–	490
Detached and heated	0.02	–	–	–	490
Detached and not heated	0.09	–	–	–	490
Is your heated garage insulated? (only recorded if having heated garage).					
No	0.15	–	–	–	67
Yes	0.85	–	–	–	67
I don't know	0.00	–	–	–	67
Do you have rooftop solar system on your primary residence?					
Yes/No	0.15	–	–	–	634

Note: Standard deviation, minimum, and maximum values are not reported for dummy variables. The mean values can capture the spread in the dataset, while the minimum and maximum are always 0 and 1, respectively, and therefore omitted for brevity.

A.4 Appliance Stock Detail

The following tables report the full appliance stock summarized in the main text, covering primary and secondary space heating, temperature control, cooking appliances, and water heating and laundry. The final table reports respondents' estimated highest monthly electricity and gas bills.

Table A.6: Survey Summary Statistics for Household & Primary Space Heating.

Variables	Mean	N
Natural Gas Usage		
Natural gas appliance use	0.96	708
Main Heating Equipment		
Central furnace	0.59	693
Steam or hot water system	0.32	693
Central heat pump	0.02	693
Ductless heat pump	0.03	693
Other	0.04	693
Main Equipment's Fuel		
Electricity	0.08	690
Natural gas (underground pipes)	0.90	690
Other	0.02	690
Main Equipment's Age		
Less than 2 years old	0.12	670
2 to 4 years old	0.11	670
5 to 9 years old	0.18	670
10 to 14 years old	0.16	670
15 to 19 years old	0.10	670
20 or more years old	0.33	670
Main Equipment's Use		
Use all or almost all of the time	0.91	690
Use at least once per week	0.05	690
Use a few times per month	0.001	690
Use only when it is very cold	0.04	690
Use only in rare situations	0.001	690

Table A.7: Survey Summary Statistics for Secondary Space Heating.

Variables	**Mean**	**N**
Secondary Heating Equipment		
No other equipment used	0.32	689
Portable electric heaters	0.16	689
Fireplace	0.16	689
Wood/pellet stove	0.11	689
Built-in electric units	0.04	689
Ductless heat pump	0.11	689
Other	0.10	689
Secondary Equipment's Fuel		
Electricity	0.46	469
Natural gas (underground pipes)	0.22	469
Wood or pellets	0.29	469
Other	0.03	469
Secondary Equipment's Age		
Less than 2 years old	0.16	449
2 to 4 years old	0.19	449
5 to 9 years old	0.20	449
10 to 14 years old	0.11	449
15 to 19 years old	0.08	449
20 or more years old	0.27	449
Secondary Equipment's Use		
Use all or almost all of the time	0.28	471
Use at least once per week	0.25	471
Use a few times per month	0.15	471
Use only when it is very cold	0.21	471
Use only in rare situations	0.11	471

Table A.8: Survey Summary Statistics for Controls & Setpoints.

Variables	**Mean**	**S.D.**	**Min**	**Max**	**N**
Thermostat Type					
Manual/non-programmable	0.31	–	–	–	476
Programmable	0.54	–	–	–	476
Smart (internet-connected)	0.13	–	–	–	476
No Thermostat	0.02	–	–	–	476
Winter indoor temperature (F)					
During the day- Someone home	68.75	3.06	58	78	476
During the day- No one home	65.18	4.66	45	76	467
At night	65.21	4.59	45	78	473

Table A.9: Survey Summary Statistics for Cooking Appliances: Stock & Fuels.

Variables	Mean	N
Number of Ranges		
0	0.21	692
1	0.76	692
2	0.02	692
3+	0.01	692
Fuel for Ranges		
Electricity	0.34	547
Natural gas from pipes	0.63	547
Other	0.03	547
Number of Cooktops		
0	0.64	692
1	0.34	692
2+	0.01	692
Fuel for Cooktops		
Electricity	0.40	250
Natural gas from pipes	0.59	250
Propane (bottled gas)	0.02	250
Number of Wall Ovens		
0	0.70	692
1	0.19	692
2+	0.11	692
Fuel for Wall Ovens		
Electricity	0.83	207
Natural gas from pipes	0.17	207
Propane (bottled gas)	0.00	207

Table A.10: Survey Summary Statistics for Water Heating & Laundry.

Variables	Mean	N
Main Water Heater Size- house		
Small (30 gallons or less)	0.05	534
Medium (31 to 49 gallons)	0.43	534
Large (50 gallons or more)	0.41	534
Tankless or on-demand	0.11	534
Main Water Heater Fuel- house		
Electricity	0.09	580
Natural gas from pipes	0.90	580
Other	0.01	580
Main Water Heater Age- house		
Less than 2 years old	0.13	566
2 to 4 years old	0.14	566
5 to 9 years old	0.26	566
10 to 14 years old	0.19	566
15 to 19 years old	0.11	566
20 or more years old	0.17	566
At-Home Clothes Dryer		
Yes/No	0.99	690
At-Home Dryer Fuel		
Electricity	0.74	678
Natural gas from pipes	0.26	678
Propane (bottled gas)	0.00	678
Pool Heater at home		
Yes/No	0.03	609

Table A.11: Survey Summary Statistics for Bills' Guesstimates

Variables	Mean	N
Highest electricity bill guesstimate		
Less than $50	0.04	457
$50-$99	0.18	457
$100-$149	0.31	457
$150-$200	0.18	457
More than $200	0.29	457
Highest natural gas bill guesstimate		
Less than $50	0.11	457
$50-$99	0.26	457
$100-$149	0.35	457
$150-$200	0.18	457
More than $200	0.10	457

Note: Electricity bills tend to be higher than natural gas bills: 47% of households report electricity bills ≥ $150 (including 29% over $200), compared with 28% for natural gas (10% over $200). The most common bracket for both utilities is $100-$149 (electricity 31%, gas 35%), while lower bills are more common for gas, with 37% under $100 versus 22% for electricity.

A.5 Environmental Attitudes (NEP)

Table A.12 summarizes household responses to the six New Ecological Paradigm (NEP) items. The distribution of responses to each statement is shown in the main text (Figure 5). Respondents exhibit a moderate level of environmental concern. Most recognize human responsibility for environmental stewardship and the fragility of ecological systems, while agreement with the reverse-coded items is relatively low.

Table A.12: Survey Summary Statistics for NEP Variables

How strongly do you agree with the following statement?	**Mean**	**S.D.**	**Min**	**Max**	**N**
Humans are severely abusing the environment.	3.35	1.64	1	5	480
The earth has plenty of natural resources if we just learn how to develop them. **(R)**	3.38	1.40	1	5	480
The balance of nature is strong enough to cope with the impacts of modern industrial nations. **(R)**	2.31	1.41	1	5	477
Human ingenuity will ensure that we do NOT make the earth unlivable. **(R)**	2.99	1.45	1	5	478
The balance of nature is very delicate and easily upset.	3.06	1.40	1	5	479
The so-called “ecological crisis” facing humankind has been greatly exaggerated. **(R)**	2.68	1.66	1	5	478

Note: Responses were coded on a scale ranging from 1 = “Strongly disagree”, 3 = “Unsure”, to 5 = “Strongly agree”. Items marked with “(R)” are reverse-coded statements, where higher scores indicate lower environmental concern. For the non-reverse statements, higher scores instead reflect greater environmental concern.

B Appendix to Part II: Discrete Choice Experiment

This appendix collects the estimation detail and supplementary tables behind Part II, namely the full mixed-logit specification and model selection, the recovery of individual-level willingness to pay, the handling of protest responses, and the linkage between stated willingness to pay and metered consumption.

B.1 Econometric Specification

We estimate WTP using a random parameter logit in WTP-space (K. E. Train and Weeks, 2005). For respondent i, alternative j, and choice occasion t, indirect utility takes the standard additive form:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \tag{B.1}$$

where V_{ijt} is the systematic component and ε_{ijt} is an i.i.d. type I extreme value error term. Following K. E. Train and Weeks (2005), we decompose systematic utility in WTP-space by factoring out the cost coefficient:

$$V_{ijt} = -\alpha_i \cdot p_{jt} + \alpha_i \sum_k \beta_{ik} x_{kjt} \tag{B.2}$$

where α_i is the respondent-specific cost coefficient and the β_{ik} are WTP coefficients, directly interpretable as marginal WTP in dollars per month per percentage point of attribute k. Because the alternative-specific constant (ASC) enters multiplied by α_i, it too is expressed in WTP-space units and represents the WTP for choosing any electrification alternative over the status quo, already denominated in dollars per month. The WTP coefficients incorporate observed heterogeneity through interactions:

$$\beta_{ik} = \bar{\beta}_k + \sigma_k \nu_{ik} + \gamma_k^{NEP} \cdot NEP_i + \gamma_k^{Panel} \cdot Panel_i + \gamma_k^{Info} \cdot Info_i \tag{B.3}$$

where $\bar{\beta}_k$ is the population mean WTP for attribute k, σ_k is the standard deviation of unobserved preference heterogeneity, ν_{ik} is a respondent-specific random draw, NEP_i is respondent i's standardized NEP factor score (mean 0, standard deviation 1, from the exploratory factor analysis), $Panel_i$ is an indicator equal to one if the respondent reported that their home requires an electrical-panel upgrade, $Info_i$ is an indicator equal to one if the respondent was randomly assigned to the information treatment, and γ_k^{NEP}, γ_k^{Panel}, and γ_k^{Info} capture the corresponding systematic preference variation. The same variable names are used in the model-selection schematic (Figure B.1), where the panel-upgrade interaction appears under its estimation-code label `elect_upgrade`. NEP enters linearly. We tested a quadratic specification (NEP-squared interaction) and found the squared term non-significant for all three attributes ($p > 0.25$), which supports the linear functional form over the observed range of NEP scores. The ASC enters with sociodemographic and protester interactions:

$$ASC_i = \delta_0 + \mathbf{Z}_i'\boldsymbol{\delta} + \delta^{Protest} \cdot Protest_i \tag{B.4}$$

where $\mathbf{Z}_i$ includes age, income, education, and homeownership, and $Protest_i$ identifies respondents who selected the opt-out on all six choice tasks. The distributional assumptions are:

$$\ln(\alpha_i) \sim N(\mu_\alpha, \sigma_\alpha^2), \qquad \beta_{ik} \mid NEP_i, Panel_i, Info_i \sim N(\cdot, \sigma_k^2) \tag{B.5}$$

The lognormal specification for the cost coefficient ensures $\alpha_i > 0$, while the normal specification for β_{ik} permits both positive and negative WTP for the non-cost attributes.

We specify the three WTP coefficients (β_{ik} for carbon, efficiency, and rebate) as independent random draws, while all interaction terms (γ) enter as fixed parameters. We also tested lognormal distributions for efficiency (which is entirely positive in individual estimates) and triangular distributions. The results are presented in Table B.3.

The lognormal specification for the cost coefficient implies a right-skewed distribution (median 0.028, mean 0.131), meaning some respondents have near-zero price sensitivity and correspondingly large WTP.[9] Trimming the top and bottom 2.5% of posterior WTP scores has negligible effects on mean WTP (less than 0.5% change for all three attributes), confirming that population-level estimates are not driven by extreme cost sensitivities.

All models use 10,000 scrambled Sobol draws. Simulation stability was verified at 1,000, 2,500, and 5,000 draws (Table B.4).

We tested over 150 specifications drawn from a design space of twelve base model structures crossed with three protester-handling approaches (no adjustment, ASC interaction, and dropping protesters) and nine weighting schemes, a space of $12 \times 3 \times 9 = 324$ candidate combinations. The full weighting grid was not estimated for every combination of base structure and protester handling, which is why the number of estimated specifications (over 150) is smaller than the number of possible combinations. Figure B.1 summarizes the selection structure. The final specification was selected based on AIC/n (1.1014), theoretical consistency, and policy relevance (Table B.2). No pre-registration or holdout validation was employed.

[9] The estimated underlying normal distribution for $\ln(\alpha_i)$ has mean -3.573 and SD 1.756, so the 5th and 95th percentiles of the cost coefficient α_i are 0.002 and 0.504 (both positive, consistent with $\alpha_i > 0$). The price term in Equation B.2 enters as $-\alpha_i$ and therefore ranges from -0.504 to -0.002 across the same percentiles; the positive values in the text describe α_i itself, and the negative values describe the utility weight on cost, $-\alpha_i$. Mean and median WTP at the attribute level are close (e.g., carbon mean \$1.49 versus median \$1.47), indicating that the skewness does not substantially distort population-level estimates.

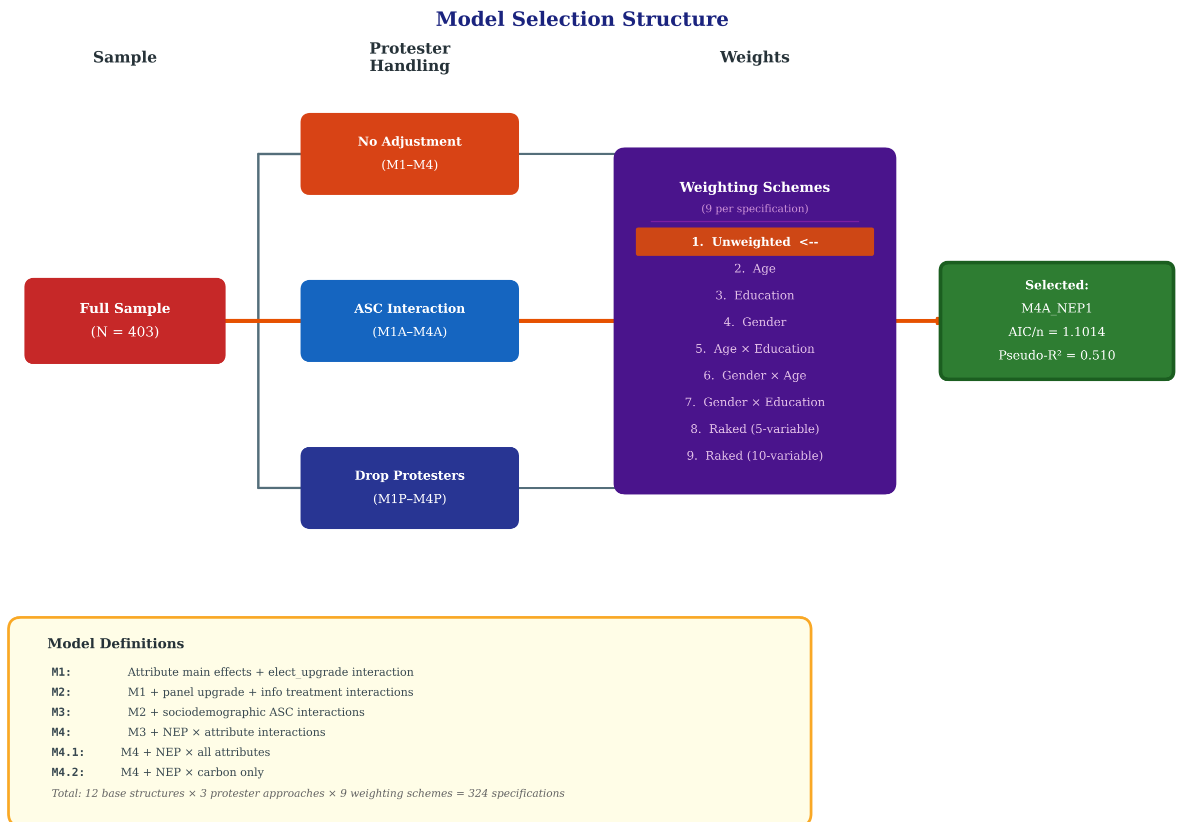


Figure B.1: Model selection schematic. Twelve base model structures were crossed with three protester-handling approaches (no adjustment, M1–M4; ASC interaction, M1A–M4A; drop protesters, M1P–M4P) and nine weighting schemes; over 150 of the 324 candidate combinations were estimated (the weighting grid was not run for every branch). The interaction labelled `elect_upgrade` in the schematic is the panel-upgrade interaction $Panel_i$ (γ^{Panel}) of Equations B.3–B.4. The selected model (M4A_NEP1) achieves the lowest AIC/n among all estimated specifications.

Table B.1 reports the full WTP-space mixed-logit specification summarized in Part II, including all interaction terms and model diagnostics.

Table B.1: Mixed Logit Results in WTP-Space, Selected Model (M4A_NEP1)

	Mean		SD	
Variable	Coeff.	SE	Coeff.	SE
Random parameters				
Carbon reduction	1.494***	(0.188)	1.051***	(0.071)
Energy efficiency	2.308***	(0.230)	1.243***	(0.074)
Financial rebate	1.098***	(0.197)	0.611***	(0.058)
Panel upgrade interactions				

Continued on next page

Table B.1 continued

	Mean		SD	
Variable	Coeff.	SE	Coeff.	SE
Carbon × Panel	−0.894***	(0.165)	–	
Efficiency × Panel	−0.800***	(0.201)	–	
Rebate × Panel	0.323	(0.198)	–	
ASC × Panel	67.731***	(9.362)	–	
Information treatment interactions				
Carbon × Info	0.034	(0.152)	–	
Efficiency × Info	0.257	(0.243)	–	
Rebate × Info	−0.224	(0.177)	–	
ASC × Info	−3.079	(9.458)	–	
NEP interactions				
Carbon × NEP	0.794***	(0.096)	–	
Efficiency × NEP	0.693***	(0.113)	–	
Rebate × NEP	0.368***	(0.082)	–	
ASC × NEP	0.842	(4.236)	–	
Sociodemographic ASC interactions				
ASC × Age	1.447***	(0.243)	–	
ASC × BA degree	−174.901***	(13.503)	–	
ASC × Some college	−153.399***	(10.924)	–	
ASC × Graduate degree	−179.686***	(11.670)	–	
ASC × Female	34.849***	(4.694)	–	
ASC × Income $35–70K	94.379***	(10.789)	–	
ASC × Income $70–150K	95.248***	(10.189)	–	
ASC × Income >$150K	101.161***	(10.409)	–	
Protester and cost				
Protester ASC†	2,184,388	(2,770,055)	–	
–Price (lognormal)	−3.573***	(0.200)	1.756***	(0.300)
ASC (constant)	−25.564	(24.423)	–	
Model diagnostics				
Log-likelihood	−1,301.61			
McFadden pseudo-R^2	0.510			
AIC/n	1.101			
Observations	2,418			
Respondents	403			

Parameters	30

Notes: Mixed logit estimated in WTP-space with 10,000 scrambled Sobol draws and age × education post-stratification weights. Mean coefficients for the three random parameters (carbon, efficiency, rebate) represent WTP in \$/month per percentage point. Interaction terms are fixed. Carbon, efficiency, and rebate are normally distributed, and price is lognormally distributed. Robust standard errors clustered at the respondent level to account for the panel structure of six choice tasks per respondent. †The Protester ASC is constrained to a large positive value that functions as a binary switch ensuring opt-out dominance for protester-classified respondents; its striking magnitude and standard error are expected and not economically interpretable (see Section 9). The effective sample for attribute WTP identification is approximately 285 non-protester respondents (1,710 choice observations). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B.2: Model Comparison, Mixed Logit in WTP-Space

	Model A (Full)		Model B (No NEP)		Model C (Non-prot.)		Model D (Main eff.)	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Random parameters (means)								
Carbon	1.494***	1.051***	1.708***	1.345***	1.530***	1.027***	−0.068	2.864***
	(0.188)	(0.071)	(0.041)	(0.021)	(0.086)	(0.055)	(0.072)	(0.308)
Efficiency	2.308***	1.243***	2.376***	1.371***	2.347***	1.197***	1.276***	2.588***
	(0.230)	(0.074)	(0.043)	(0.035)	(0.173)	(0.072)	(0.213)	(0.146)
Rebate	1.098***	0.611***	1.120***	0.726***	1.121***	0.682***	1.080***	1.526***
	(0.197)	(0.058)	(0.040)	(0.021)	(0.120)	(0.060)	(0.137)	(0.128)
ASC	−25.564		−151.6***		−38.576		87.149***	
	(24.423)		(35.524)		(36.606)		(12.562)	
Panel upgrade interactions								
Carbon × Panel	−0.894***		−1.032***		−0.920***			
	(0.165)		(0.046)		(0.090)			
Efficiency × Panel	−0.800***		−0.723***		−0.794***			
	(0.201)		(0.047)		(0.185)			
Rebate × Panel	0.323		0.184***		0.240*			
	(0.198)		(0.047)		(0.138)			
ASC × Panel	67.731***		88.379***		67.241***			
	(9.362)		(4.195)		(8.435)			
Information treatment interactions								
Carbon × Info	0.034		0.221***		0.070			
	(0.152)		(0.021)		(0.075)			
Efficiency × Info	0.257		0.546***		0.231*			
	(0.243)		(0.082)		(0.128)			
Rebate × Info	−0.224		0.069		−0.178**			
	(0.177)		(0.067)		(0.082)			
ASC × Info	−3.079		−3.736		−2.462			
	(9.458)		(3.883)		(8.163)			
NEP interactions								
Carbon × NEP	0.794***				0.816***			
	(0.096)				(0.047)			
Efficiency × NEP	0.693***				0.613***			

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Table B.2 continued

	Model A (Full)		Model B (No NEP)		Model C (Non-prot.)		Model D (Main eff.)	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	(0.113)				(0.096)			
Rebate × NEP	0.368***				0.365***			
	(0.082)				(0.078)			
ASC × NEP	0.843				0.690			
	(4.236)				(4.992)			
Sociodemographic ASC interactions								
ASC × Age	1.447***		1.663***		1.464***			
	(0.243)		(0.111)		(0.257)			
ASC × BA degree	−174.9***		−341.7***		−169.8***			
	(13.503)		(5.225)		(22.554)			
ASC × Some college	−153.4***		−310.6***		−147.5***			
	(10.924)		(5.794)		(28.199)			
ASC × Graduate	−179.7***		−349.9***		−175.6***			
	(11.670)		(5.098)		(21.694)			
ASC × Female	34.849***		24.321***		35.538***			
	(4.694)		(2.977)		(8.547)			
ASC × Inc. \$35–70K	94.379***		346.4***		103.9***			
	(10.789)		(34.391)		(15.864)			
ASC × Inc. \$70–150K	95.248***		353.7***		101.0***			
	(10.189)		(35.207)		(17.969)			
ASC × Inc. >\$150K	101.2***		366.2***		108.9***			
	(10.409)		(34.345)		(15.158)			
Protester and cost								
Protester ASC	2,184,388		4,894,019					
	(2,770,055)		(7,292,746)					
−Price (lognormal)	−3.573***	1.756***	−3.464***	2.102***	−3.564***	1.775***	−3.414***	1.307***
	(0.200)	(0.300)	(0.233)	(0.382)	(0.203)	(0.304)	(0.194)	(0.241)
Model diagnostics								
Log-likelihood	−1,301.61		−1,358.10		−1,318.03		−1,777.32	
McFadden pseudo-R^2	0.510		0.489		0.298		0.331	
AIC/n	1.101		1.145		1.575		1.478	
BIC/n	1.173		1.207		1.668		1.499	
Observations	2,418		2,418		1,710		2,418	
Respondents	403		403		285		403	
Parameters	30		26		29		9	

Notes: Standard errors in parentheses (robust sandwich). SD = standard deviation of random parameter distribution. All models estimated with 10,000 Sobol draws and age × education post-stratification weights. Model A: full specification with NEP interactions. Model B: no NEP interactions. Model C: non-protester subsample ($N = 285$). Model D: main effects only (no interactions). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B.3: Sensitivity of WTP Estimates to Distributional Assumptions

Distribution	Attribute	Mean WTP	SD	Log-likelihood	AIC/n	Note
Normal (baseline)	Carbon	1.494	1.051	−1,301.61	1.1014	Selected
	Efficiency	2.308	1.243			
	Rebate	1.098	0.611			
Lognormal	Carbon	1.781	1.263	−1,321.47	1.1178	
	Efficiency	2.334	1.398			
	Rebate	1.236	1.258			
Triangular	Carbon	1.457	1.030	−1,321.57	1.1179	
	Efficiency	1.985	1.404			
	Rebate	1.107	0.783			

Notes: Distributional assumption sensitivity for random parameters. Compares WTP estimates under normal, lognormal, and triangular mixing distributions for carbon, efficiency, and rebate coefficients. Reports log-likelihood and AIC/n for each specification.

Table B.4: Sobol Draw Stability Analysis

Draws	Carbon WTP	Efficiency WTP	Rebate WTP	Log-likelihood
1,000	1.692	2.433	1.124	−1,313.68
2,500	1.712	2.349	1.186	−1,316.47
5,000	1.571	2.379	1.213	−1,319.64
10,000	1.494	2.308	1.098	−1,301.61

Notes: Sobol draw stability analysis. Reports WTP estimates at 1,000, 2,500, 5,000, and 10,000 Sobol draws to verify convergence. The selected model uses 10,000 draws, and estimates should stabilize by 5,000.

Table B.5: Comparison of Analysis Sample and Excluded Respondents

Variable	Analysis ($N = 403$)	Dropped ($N = 70$)	t-statistic	p-value
Age (years)	55.93	73.31	−4.597	0.000
Female (%)	34.49	31.58	0.260	0.798
NEP factor score	−0.00	0.01	−0.130	0.897
Panel upgrade (%)	76.67	72.86	0.663	0.509
Information treatment (%)	20.84	40.00	−3.072	0.003
Graduate degree (%)	60.79	14.29	9.558	0.000

Notes: Unweighted comparison of the 403 respondents in the analysis sample with the “Dropped” group, defined as the subset of excluded respondents who began the choice experiment but did not complete it ($N = 70$); the dropped group is a subset of the 204 excluded respondents described in the notes to Table 2, which compares the analysis sample against all 204 exclusions using the post-stratification weights. The two comparisons therefore differ by construction: respondents who started the choice tasks and quit are markedly older than the analysis sample (73.3 vs. 55.9 years here), whereas the full excluded group, most of whom never reached the choice tasks, is close in age to completers (54.2 vs. 51.8 weighted). Percentages are computed over respondents with non-missing values for each row item. Differences are assessed with t-tests (chi-squared for categorical variables).

Table B.6: Sensitivity of Posterior WTP–NEP Correlations to NEP Scoring Method

NEP Scoring Method	Carbon WTP	Efficiency WTP	Rebate WTP	w/ Baseline
Factor analysis (baseline)	0.086	0.033	−0.051	1.000
Simple mean	0.084	0.023	−0.052	0.992
Sum score	0.084	0.023	−0.052	0.992
Bartlett scoring	0.084	0.024	−0.051	0.994

Notes: Sensitivity of WTP estimates to alternative NEP scoring methods: (1) baseline factor analysis score, (2) simple mean of 6 NEP items, (3) sum score, (4) Bartlett scoring. w/ Baseline is the Pearson correlation between the alternative score and the baseline factor score. Shows that WTP estimates are robust to the NEP operationalization.

Table B.7: Test for Choice Task Order Effects

Metric	Early tasks (1–3)	Late tasks (4–6)	p-value
Program choice rate	0.549	0.532	0.375
N tasks	1,419	1,407	
N observations	4,257	4,221	
N respondents	473	473	

Notes: Test for choice task order effects. Compares WTP estimates from early choice tasks (1-3) vs. late choice tasks (4-6) to check for learning or fatigue effects. Includes Hausman test for parameter stability across task blocks.

Table B.8: Randomization Balance Check for Information Treatment

Variable	Treatment (N = 84)	Control (N = 319)	t-statistic	p-value
Age (years)	60.99	54.60	3.201	0.002
Female (%)	35.71	34.17	0.262	0.794
NEP factor score	–0.03	0.01	–0.355	0.723
Panel upgrade (%)	80.95	75.55	1.094	0.276
Graduate degree (%)	61.90	60.50	0.234	0.815

Notes: Randomization balance check for the information treatment. Comparison of treatment (N = 84) and control (N = 319) groups in the 403-respondent analysis sample. t-statistics from two-sample t-tests (continuous) or tests of proportions (binary). Randomization is balanced on all observables except age: treated respondents are significantly older ($p = 0.002$). NEP scores, gender, panel upgrade status, and education do not differ significantly between groups.

Table B.9: Unweighted vs. Weighted Mixed Logit Estimates

	Unweighted		Weighted	
Parameter	Coeff.	SE	Coeff.	SE
Random parameters (means)				
Carbon	0.564***	(0.159)	0.862***	(0.016)
Efficiency	1.330	(0.809)	2.425***	(0.054)
Rebate	0.705**	(0.320)	1.106***	(0.038)
ASC	156.694***	(43.699)	545.176***	(7.973)
Panel upgrade interactions				
Carbon × Panel	–0.484**	(0.200)	–0.590***	(0.027)
Efficiency × Panel	–0.179	(0.894)	–0.885***	(0.056)
Rebate × Panel	0.645	(0.406)	0.414***	(0.046)
ASC × Panel	63.740***	(23.171)	87.686***	(3.657)
Information treatment interactions				
Carbon × Info	–0.012	(0.155)	–0.516***	(0.040)
Efficiency × Info	0.600**	(0.252)	–0.041	(0.042)
Rebate × Info	–0.268*	(0.142)	–0.390***	(0.030)
ASC × Info	–17.060	(12.309)	–37.232***	(4.236)
NEP interactions				
Carbon × NEP	1.534***	(0.146)	1.409***	(0.020)
Efficiency × NEP	0.874***	(0.099)	0.517***	(0.034)
Rebate × NEP	0.313*	(0.162)	0.291***	(0.023)
ASC × NEP	–38.467***	(9.073)	–47.186***	(2.582)
Sociodemographic ASC interactions				
ASC × Age	1.253***	(0.383)	3.207***	(0.051)
ASC × BA degree	–10.892	(17.323)	–148.258***	(5.781)

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Table B.9 continued

	Unweighted		Weighted	
Parameter	Coeff.	SE	Coeff.	SE
ASC × Some college	2.940	(20.203)	−131.459***	(6.035)
ASC × Graduate	−51.917**	(23.518)	−189.278***	(4.993)
ASC × Female	33.032***	(6.349)	23.464***	(1.553)
ASC × Inc. $35–70K	−114.304**	(57.998)	−413.495***	(5.360)
ASC × Inc. $70–150K	−170.593***	(36.434)	−514.997***	(6.027)
ASC × Inc. >$150K	−165.752***	(35.003)	−513.764***	(5.125)
Cost				
−Price (lognormal)	−3.352***	(0.188)	−3.203***	(0.253)
Standard deviations				
SD: Carbon	1.991***	(0.198)	2.128***	(0.022)
SD: Efficiency	1.961***	(0.232)	1.681***	(0.017)
SD: Rebate	1.209***	(0.070)	1.176***	(0.013)
SD: −Price	1.675***	(0.296)	2.187***	(0.376)
Model diagnostics				
Log-likelihood	−1,616.71		−1,593.20	
AIC/n	1.361		1.342	
BIC/n	1.431		1.411	
Pseudo-R^2	0.561		0.595	
Parameters	29		29	
Observations	2,418		2,418	
Respondents	403		403	
Sobol draws	10,000		10,000	

Notes: Weighting sensitivity check. Reports unweighted and weighted mixed logit estimates side by side using the same specification with NEP interactions, 10,000 Sobol draws, and 403 respondents. Weighted specification uses age × education post-stratification weights. Sign patterns are identical across specifications, and magnitude differences reflect the reweighting of older and less-educated respondents. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B.2 Individual-Level WTP Estimation

Following Revelt and K. Train (2000), we derive individual-level WTP from posterior scores of the random parameter distributions. The posterior mean for each respondent is computed as the expected value of the random parameters weighted by the likelihood of their choice sequence, conditioning on observed choices via Bayes' theorem.

Because the model includes NEP interactions in the fixed portion, the individual scores represent residual heterogeneity after controlling for environmental attitudes. The individual carbon WTP scores do not reflect the systematic NEP-carbon relationship, which is captured in the fixed interaction term. The individual scores instead capture unexplained variation in preferences not attributable to NEP, panel upgrade status, or other observable characteristics in the model.

B.3 Protester Handling

Approximately 29% of respondents (118 of 403) selected the opt-out on all six choice tasks, a rate at the upper end of the 15 to 30% range typical for environmental goods DCEs (Meyerhoff and Liebe, 2006).[10] Following Meyerhoff and Liebe (2006) and Lancsar and Louviere (2006), we retain protesters in estimation using an ASC interaction term rather than deleting them. The protester ASC absorbs the additional status quo preference, whether motivated by format rejection or genuine satisfaction with natural gas, allowing remaining coefficients to reflect attribute preferences among engaged respondents. The effective sample for attribute WTP identification is approximately 285 non-protester households providing 1,710 choice observations. We report WTP estimates from a non-protester-only subsample in Table B.2 Model C. The differences from the full-sample estimates are small (less than 1.3% for all attributes).

Table B.10: Probit Model of Protest Response Determinants

Variable	Coefficient	SE	z	p-value	ME
Intercept	−0.689	(0.403)	−1.71	0.087	
Age	0.010**	(0.005)	2.17	0.030	0.003
NEP	−0.753***	(0.085)	−8.86	0.000	−0.229
Graduate degree	−0.431***	(0.153)	−2.81	0.005	−0.131
Panel upgrade	−0.013	(0.191)	−0.07	0.944	−0.004
Solar	−0.325	(0.239)	−1.36	0.174	−0.099
Female	0.060	(0.163)	0.36	0.716	0.018
High income	−0.407**	(0.192)	−2.12	0.034	−0.123

Notes: Probit model of protest response ($N = 473$). Dependent variable: 1 if respondent always chose status quo. Independent variables: age, income, education, homeownership, NEP score, information treatment, gas consumption quartile. Reports marginal effects at means. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

[10] Protesters are older (mean age 60 versus 55, $p = 0.002$), have lower NEP scores (mean −0.67 versus 0.28, $p < 0.001$), and are less likely to hold graduate degrees (42 versus 59%, $p < 0.001$). Table B.10 reports full protester determinants. The Protester ASC coefficient (approximately $2.2 million/month in WTP-space units) functions as a binary switch ensuring opt-out dominance for protest-classified respondents. Its precise magnitude is not economically interpretable.

Table B.11: Two-Class Latent Class Model (WTP-Space)

	Class 1 (58.6%)		Class 2 (41.4%)	
Variable	Coeff.	SE	Coeff.	SE
Carbon	1.075***	(0.165)	−0.296	(1.301)
Efficiency	2.075***	(0.295)	3.352	(2.991)
Rebate	1.645***	(0.195)	3.934**	(1.984)
ASC	37.375***	(13.897)	843.124*	(490.193)
−Price	0.012***	(0.001)	0.005**	(0.002)
Model diagnostics				
LL at convergence	−1,765.00			
McFadden pseudo-R^2	0.335			
AIC/n	1.469			
BIC/n	1.495			
Observations	2,418			
Parameters	11			

Notes: Two-class latent class model estimated in WTP-space with 1,000 Sobol draws. Class probabilities are average posterior probabilities. Class 1 (58.6%) shows well-identified WTP for all three attributes. Class 2 (41.4%) exhibits imprecisely estimated WTP across all attributes and a very large status-quo ASC, consistent with protesters and disengaged respondents rather than attribute-specific non-attendance. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B.4 Individual-Level WTP Analysis

B.4.1 Distribution of Individual WTP

Table B.12 presents individual-level WTP distributions. Carbon WTP has a mean of $1.52, efficiency $2.31, and rebate $1.09. Only 1.2% of non-protester respondents have negative carbon WTP.

Table B.12: Individual-Level WTP Distribution ($/month per percentage point)

Attribute	Mean	SD	P5	P25	Median	P75	P95	% Neg.
Carbon reduction	1.524	0.569	0.534	1.280	1.494	1.815	2.569	1.2%
Energy efficiency	2.315	0.712	1.193	2.045	2.308	2.437	3.828	0.0%
Financial rebate	1.093	0.096	0.916	1.065	1.098	1.131	1.251	0.0%

Notes: Individual-level posterior means from the M4A_NEP1 specification. $N = 403$ respondents. Percentiles computed across individual posterior WTP scores. % Negative is the share of respondents with negative individual WTP.

The rate of negative individual carbon WTP requires careful interpretation. In the model with NEP interactions, 5 non-protester respondents (1.2%) have negative carbon WTP. If one conservatively assumes all 118 protesters have negative carbon preferences, the upper-bound rate is 31%.

A decomposition (Table B.14) traces the negative carbon WTP rate from 10.2% (population parametric from the no-NEP model) to 3.0% (Bayesian shrinkage alone) to 1.2% (shrinkage plus NEP conditioning). Shrinkage accounts for most of the reduction, with NEP conditioning providing additional compression.

Three caveats apply. The 1.2% is conditional on the normal mixing distribution (a bimodal distribution would produce higher rates), on the model specification (omitting NEP interactions yields 3.0%), and on the non-protester subsample.

The 10.2% represents unconditional heterogeneity relevant to population-level policy, while the 1.2% represents residual heterogeneity after conditioning on attitudes and choice histories. The gap between them quantifies the information value of measuring environmental attitudes.

The five respondents with negative carbon WTP do not form a single archetype. NEP scores range from -0.93 to $+0.86$, ages from 31 to 53, and all hold graduate degrees. Their negative WTP likely reflects idiosyncratic preference patterns rather than a coherent anti-carbon stance.

Efficiency WTP is entirely positive. No respondent has negative efficiency WTP. This result is consistent with the interpretation that households universally value the performance and cost-saving aspects of efficient appliances, even as they disagree about the value of environmental benefits.

Figure B.2 presents the distribution of individual WTP. Panel A shows carbon WTP by NEP status (above and below median), revealing that the low-NEP group shows greater dispersion with a small mass in the negative range. Panel B shows the entirely positive efficiency WTP distribution. Panel C presents violin plots across all three attributes. Panel D presents a scatter plot of individual carbon versus efficiency WTP colored by NEP score, showing the positive but weak correlation.

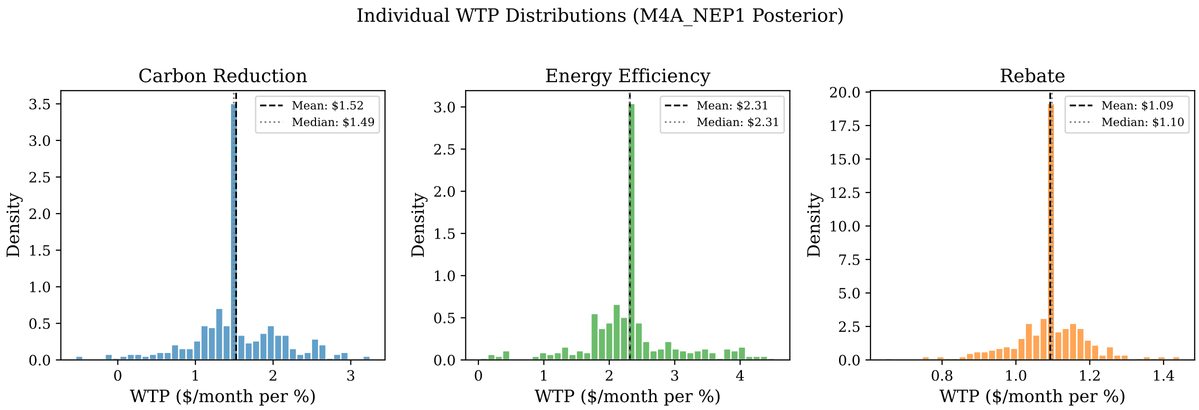


Figure B.2: Individual-level WTP distributions from Bayesian posterior scores ($N = 403$). Panel A: Carbon WTP kernel densities by NEP median split. Panel B: Efficiency WTP histogram. Panel C: Violin plots for carbon, efficiency, and rebate WTP. Panel D: Scatter plot of carbon vs. efficiency WTP colored by NEP factor score.

Table B.13: Posterior WTP Correlations

	Carbon	Efficiency	Rebate
Carbon	1.000		
Efficiency	0.226***	1.000	
Rebate	0.156***	0.071	1.000

Notes: Pearson correlations of individual posterior WTP scores from the M4A_NEP1 specification ($N = 360$ non-protester respondents). The largest correlation (carbon–efficiency, $r = 0.226$) implies shared variance of 5.1%. A correlated random parameters specification was estimated but encountered numerical instability before convergence, consistent with weak off-diagonal elements. The low correlations support the maintained independence assumption. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B.14: Decomposition of Negative Carbon WTP Rates

Metric	Value
Population parameters (no-NEP model)	
Mean carbon WTP ($/mo/pp)	1.708
SD carbon WTP	1.345
$P(\text{WTP} < 0)$ parametric	10.2%
Individual posteriors (no-NEP model)	
N	402
Mean posterior carbon WTP	1.852
SD posterior carbon WTP	0.951
N with negative WTP	12
% with negative WTP	3.0%
Individual posteriors (NEP model)	
N	403
Mean posterior carbon WTP	1.524
SD posterior carbon WTP	0.573
N with negative WTP	5
% with negative WTP	1.2%
Non-protester subsample	
N non-protesters	285
N with negative WTP	5
% with negative WTP	1.8%
Decomposition path	10.2% → 3.0% → 1.2%

Notes: The no-NEP model drops the four NEP interaction terms from the M4A_NEP1 specification, and all other covariates remain. LL (no-NEP) = −1,358.1, LL (NEP) = −1,301.6. Bayesian shrinkage reduces the negative rate from 10.2% to 3.0% by compressing individual posteriors toward the conditional mean. NEP conditioning provides further compression from 3.0% to 1.2%.

B.4.2 Heterogeneity by Panel Upgrade Status

In contrast to the strong panel effects in the fixed interactions, individual-level estimates show no significant differences by panel status. Households requiring upgrades have mean individual carbon WTP of $1.52 versus $1.55 without upgrades, a difference that is not statistically significant. Efficiency WTP is $2.33 versus $2.26 (also not significant), and rebate WTP is essentially identical at $1.09 for both groups. These null results confirm that panel effects are properly captured in the fixed interactions rather than leaking into the random parameters. Programs can use the fixed effects to predict systematic differences (e.g., panel-needing households require larger incentives) while the individual scores capture remaining uncertainty.

B.4.3 Residual Heterogeneity by NEP Quartile

Table B.15 presents individual-level WTP by NEP quartile.

Table B.15: Individual-Level WTP by NEP Quartile ($/month per percentage point)

NEP Quartile	*N*	NEP Mean	Carbon WTP	Efficiency WTP	Rebate WTP
Q1 (lowest)	101	−1.336	1.516 (0.361)	2.254 (0.430)	1.092 (0.062)
Q2	101	−0.324	1.419 (0.559)	2.301 (0.727)	1.099 (0.095)
Q3	100	0.577	1.568 (0.704)	2.461 (0.826)	1.103 (0.102)
Q4 (highest)	101	1.080	1.593 (0.590)	2.244 (0.789)	1.077 (0.117)

Notes: Individual-level posterior means from the M4A_NEP1 specification. NEP quartiles defined within the 403-respondent analysis sample. Standard deviations in parentheses reflect within-quartile dispersion. The lower within-quartile SD for Q1 (e.g., 0.361 for carbon versus 0.559–0.704 for Q2–Q4) may reflect stronger Bayesian shrinkage for low-NEP respondents whose choice patterns are less informative, compressing their posterior estimates toward the conditional mean. Mean carbon WTP ranges from $1.42 (Q2) to $1.59 (Q4), a spread of just $0.17. Efficiency WTP ranges from $2.24 (Q4) to $2.46 (Q3), and rebate WTP shows minimal variation from $1.08 to $1.10. The weak residual correlation between NEP and individual WTP confirms that the NEP interactions capture the systematic relationship, with remaining variation representing genuine unobserved heterogeneity. This residual heterogeneity might reflect personal experience with electric appliances, social network effects, aesthetic preferences, or unmeasured aspects of household circumstances.

Figure B.3 visualizes the NEP quartile analysis. Panel A shows mean WTP by quartile for all three attributes with 95% confidence intervals, demonstrating the relatively flat relationship after controlling for NEP. Panel B shows within-quartile standard deviations, which are similar across quartiles, suggesting homogeneous residual heterogeneity. Panel C shows the distribution of respondents across quartiles with mean NEP scores.

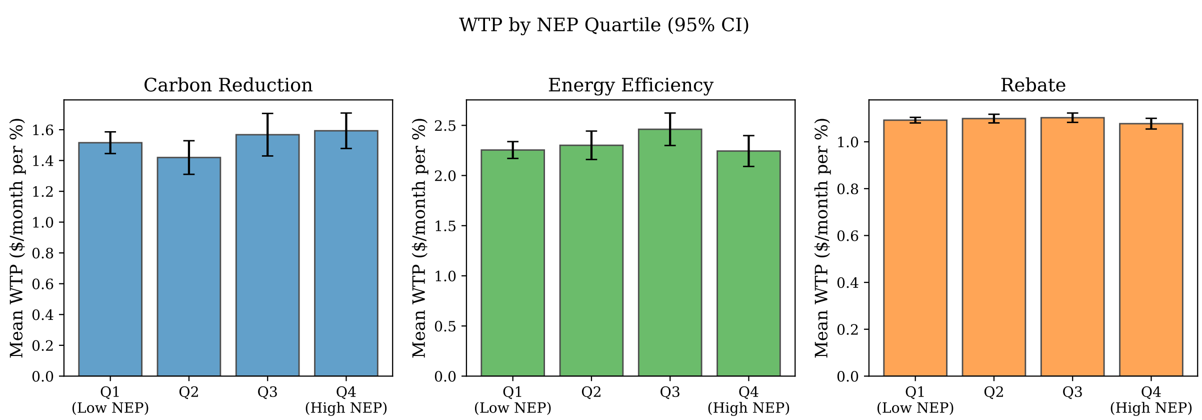


Figure B.3: Individual-level WTP by NEP quartile (N = 403). Panel A: Mean WTP ($/month per percentage point) for carbon, efficiency, and rebate by NEP quartile with 95% confidence intervals. Panel B: Within-quartile standard deviations. Panel C: Respondent counts per quartile with mean NEP factor scores.

The correlation between individual carbon and efficiency WTP is positive but modest, indicating some commonality in pro-electrification attitudes, though with considerable independent variation in how households value environmental versus performance attributes.

Correlations between rebate WTP and the other attributes are weak, indicating modest positive associations that do not suggest strong common drivers of financial and non-financial attribute preferences. This independence has practical implications. Households that value carbon reduction do not necessarily respond more to rebates, and those most responsive to financial incentives are not systematically more or less environmentally motivated. Multi-attribute programs combining incentives with performance messaging may reach broader audiences than single-attribute approaches.

B.5 Consumption and Stated Preference Linkage

B.5.1 Consumption Patterns and Individual WTP

Linking administrative consumption records to individual-level posterior WTP estimates enables a direct test of whether stated electrification preferences covary with economic self-interest (proxied by actual energy expenditure) or with attitudinal factors. Table B.16 reports Pearson correlations and mean WTP by natural gas consumption quartile.

Table B.16: Individual WTP by Natural Gas Consumption Quartile ($/month per percentage point)

Gas Quartile	Gas (CCF/mo)	N	Carbon WTP	Efficiency WTP	Rebate WTP
Q1 (lowest)	35	93	1.593	2.295	1.082
Q2	57	91	1.537	2.210	1.087
Q3	81	94	1.578	2.438	1.098
Q4 (highest)	130	98	1.403	2.305	1.097
Pearson r			−0.079	+0.064	+0.132**
p-value			0.138	0.229	0.013
Linear trend			−0.104**	+0.039	+0.064

Notes: WTP values are individual-level posterior means from the M4A_NEP1 specification. Gas consumption is average monthly CCF from LADPU billing records. Quartiles defined within the matched sample (N = 376 with complete gas records). Pearson r is the bivariate correlation between gas consumption and WTP. Linear trend is the OLS slope of WTP on standardized gas consumption. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The pattern across gas quartiles reveals an economically coherent but statistically modest relationship. Carbon WTP declines from $1.59 in the lowest gas quartile to $1.40 in the highest, a difference of $0.19 per month per percentage point. In an OLS regression controlling for NEP, panel status, and solar adoption, the highest-consumption quartile is associated with lower carbon WTP, though the difference is not statistically significant (Table B.16). This negative gradient is consistent with high-gas households perceiving greater switching costs or valuing the status quo more highly. Alternatively, it may reflect compositional differences in environmental attitudes across gas consumption levels, though the regression controls for NEP.

The negative but statistically insignificant correlation between carbon WTP and gas consumption (Table B.16) deserves attention for program targeting. If high-gas users, who stand to produce the largest carbon reductions from switching, have somewhat lower carbon WTP, then carbon-framed messaging may be least effective for the households with the greatest abatement potential. This suggestive pattern, though not statistically significant, indicates that programs seeking maximum emissions reductions should pair carbon messaging with financial incentives for high-consumption households. A formal power calculation indicates that with $N = 376$ matched observations, the minimum detectable effect at 80% power is \$0.27 per month, while the observed Q1–Q4 difference is \$0.19. The analysis is thus underpowered for detecting consumption-carbon WTP effects of this magnitude (ex-post power of 43%). The absence of a significant consumption-carbon WTP relationship may therefore reflect insufficient sample size rather than a true null effect.

Efficiency WTP shows no monotonic trend, peaking in Q3 at \$2.44 and declining to \$2.31 in Q4. The absence of a strong consumption-efficiency relationship suggests that efficiency valuations are driven more by general preferences for performance than by household-specific energy bills.

Rebate WTP, in contrast, shows a positive and statistically significant linear trend across gas quartiles (Table B.16). OLS regression of rebate WTP on standardized gas consumption with controls confirms this relationship. High-gas users (above-median consumption) value rebates at \$1.097 per month per percentage point compared to \$1.078 for low-gas users, a difference that is marginally significant. This pattern is economically intuitive. Households facing larger gas bills are more sensitive to financial incentives because the absolute dollar stakes of switching are greater.

B.5.2 Consumption, Attitudes, and the Decomposition of WTP

The weak and statistically insignificant consumption-WTP correlations for carbon and efficiency contrast sharply with the strong NEP-WTP relationships documented in Section B.4. In multivariate regressions of carbon WTP on standardized gas consumption, NEP, panel status, and solar adoption, the model explains very little variation. Adding a gas-by-NEP interaction does not improve fit. NEP remains the only consistent predictor of carbon and efficiency WTP, and consumption enters significantly only for rebate preferences.

A methodological caveat applies to this finding. Because the individual posterior scores condition on NEP through the fixed effects, any consumption variable correlated with NEP is partly controlled by construction, which could mechanically attenuate the consumption-WTP correlation for attitudinal attributes. Two observations mitigate this concern. First, the NEP-consumption correlation in the matched sample is modest, which limits the scope for mechanical attenuation. Second, the rebate-consumption correlation is significant and in the expected direction, and it would also be attenuated if the mechanism were purely mechanical. The selective significance pattern (rebate responds to consumption, while carbon and efficiency do not) is more consistent with a substantive interpretation than with a purely mechanical one.

With this caveat, the finding carries a specific interpretation. Stated environmental valuations in this population are associated primarily with attitudes and worldview rather than with the financial scale of each household's gas dependency. High-gas and low-gas users express similar willingness to pay for carbon reduction conditional on their environmental attitudes. The consumption-rebate link, the one significant relationship, is precisely the channel where financial self-interest should operate most directly.

Comparing respondents at the tails of the carbon WTP distribution reinforces this conclusion. The bottom decile of carbon WTP consumes 85 CCF of gas per month on average, while the top decile consumes 77 CCF. The difference is not statistically significant. NEP scores differ modestly between tails (0.26 versus 0.44), but the variation within each tail is large. What separates high and low carbon valuers is not their gas bills but their residual preference heterogeneity after NEP is accounted for.

B.5.3 Stated WTP and Actual Energy Expenditure

A central concern in stated preference research is whether hypothetical WTP is calibrated to actual financial magnitudes. We construct a benchmark by comparing individual-level aggregate WTP for a representative electrification scenario (66% carbon reduction, 50% efficiency improvement, 50% rebate) against actual monthly gas expenditure.

The mean aggregate WTP for this scenario is $270 per month, roughly three times the mean gas bill of $88. The ratio of stated WTP to actual gas expenditure varies systematically across the consumption distribution. For the highest gas quartile (mean bill $143 per month), the ratio is 1.89. For the lowest quartile (mean bill $38), it is 7.11. The declining ratio suggests that stated WTP is more closely anchored to real financial stakes among high-consumption households, where the economic consequences of fuel switching are most tangible. For low-consumption households, the gap between stated WTP and actual expenditure is consistent with the well-documented hypothetical bias in stated preference studies (Penn and Hu, 2018), compounded by the fact that low-gas households face smaller absolute switching costs and may therefore treat the WTP question as more abstract.

Engineering cost estimates provide an additional calibration. At a heat pump coefficient of performance of 3.5 and 80% gas furnace efficiency, full fuel switching would save the median household approximately \$19 per month in net energy costs (gas savings of \$79 minus incremental electricity cost of approximately \$60). Stated efficiency WTP for a 50% improvement (\$115 per month at the mean) exceeds plausible realized savings by a factor of roughly six, consistent with the Penn and Hu (2018) trimmed-sample mean hypothetical-bias calibration factor of 1.94 and suggesting additional sources of inflation (percentage-point framing effects, high-income sample effects, and possible conflation of efficiency with broader performance benefits).

The consumption data thus serve two functions. First, they provide suggestive evidence for the economic coherence of WTP estimates. The consumption-rebate link is significant in the expected direction, the WTP-to-expenditure ratio declines with consumption as expected if respondents anchor partly to real costs, and consumption does not predict carbon or efficiency WTP once attitudes are controlled, consistent with the model's decomposition. The WTP-to-expenditure ratio is not a standard measure of hypothetical bias, which is conventionally defined as the ratio of hypothetical to real WTP for the same good. The ratio of stated electrification WTP to current gas expenditure conflates hypothetical bias with genuine consumer surplus, since households may value electrification above their current gas spending if they value carbon reduction, efficiency improvements, and comfort gains. Second, the consumption data provide quantitative benchmarks for calibrating stated preferences to revealed financial magnitudes, which is necessary for translating DCE estimates into program cost-benefit calculations.

C Appendix to Part III: Solar Rebound

C.1 Data Construction

Hourly Solar Generation To impute unobserved hourly solar generation and recover gross household electricity consumption, we use a two-stage random forest model (Breiman, 2001). The model is trained by combining PVGIS simulated hourly solar generation for 2022–2023 with NSRDB hourly weather and irradiance variables.

We then apply the trained model to NSRDB weather and irradiance data for 2024–2025 to project hourly solar generation for each solar household. The predicted solar output is added to metered net electricity consumption to construct hourly gross electricity consumption, which serves as one of the main electricity outcomes in the rebound analysis. Additional details on the imputation procedure, validation designs, and diagnostic results are reported in Appendix C.2.

Standardizing Electricity and Natural Gas Consumption To quantify the rebound effect on total energy consumption, we convert electricity and natural gas usage into a standardized energy unit, million British thermal units (MMBtu). Specifically, electricity consumption measured in kilowatt-hours (kWh) is converted using the standard conversion factor[11] , while natural gas consumption measured in hundred cubic feet (CCF) is converted based on its elevation factor and a time-varying heat content obtained from LADPU [12]. For White Rock, the elevation factor is 0.81, and 0.78 for the Los Alamos townsite.

Formally, total energy consumption for household i in period t is constructed as

$$\text{TotalEnergy}_{it} = \text{Elec}_{it} \times \kappa^E + \text{Gas}_{it} \times \hbar_i \times \kappa_t^G,$$

where κ^E is the constant kWh-to-MMBtu conversion factor, $\hbar_i$ is the elevation adjustment factor for the city in which household i is located, and κ_t^G is the time-varying heat content factor for natural gas. All components are expressed in MMBtu.

Treatment and control group construction To construct a comparable control group, we restrict the sample of non-solar households to the five geographically closest neighbors (based on straight-line distance) to each solar-adopting household. This spatial matching approach helps ensure similarity in local conditions, including exposure to weather patterns (e.g., temperature, solar irradiance), neighborhood characteristics (such as housing density, building age, and infrastructure), and local energy environments (including utility pricing, grid conditions, and policy exposure). The geographic proximity may also capture localized social interactions and information spillovers, such as peer effects in solar adoption and energy use behavior. While matching on nearby households does not fully eliminate concerns about unobserved heterogeneity or selection, it helps reduce these concerns by limiting comparisons to geographically proximate households that are more likely to share similar environmental and neighborhood conditions.

The final dataset includes 447 treated households with solar installations and 1,729 unique control households without solar installations, yielding 66,370,003 household-hour observations. The 447 treated households are those among the 487 solar sites with imputed generation that also meet the panel-coverage and control-matching requirements of the staggered design. Table C.2 reports the number of households in each treatment group.

C.2 Solar Generation Imputation

To recover solar output, the imputation procedure combines two primary data sources at the household-hour level for 2022–2023. The first source is the historical hourly simulations for

[11]Electricity consumption is converted from kilowatt-hours to British thermal units using the standard conversion factor 1 kWh = 3,412 Btu.

[12]Natural gas consumption is converted from CCF to MMBtu using the elevation adjustment factor and time-varying heat content reported by LADPU. See https://www.losalamosnm.us/files/sharedassets/public/v/30/departments/utilities/documents/regularly-updating-files/dpu-cost-of-gas-sched.pdf.

487 solar households in the LADPU service territory from PVGIS, which includes hourly AC power output, plane-of-array irradiance, and PV system capacity, yielding more than 8,453,833 household-hour observations after non-missing screens. The second source is the NSRDB, which provides hourly weather and irradiance variables on an approximately 4 km spatial grid, including global horizontal irradiance (GHI), diffuse horizontal irradiance (DHI), direct-normal irradiance (DNI), solar zenith angle, ambient temperature, and wind speed. Each solar household is matched to its nearest NSRDB grid cell by great-circle distance. While PVGIS hourly generation data end in 2023, NSRDB extends through 2025, allowing the model to project household-level solar generation beyond the PVGIS coverage period.

We use a two-stage random forest framework (Breiman, 2001) to impute hourly solar generation. In the first stage, household-level plane-of-array irradiance is predicted using NSRDB weather and irradiance variables, hour of day, and month of year. In the second stage, the predicted plane-of-array irradiance is combined with PV system characteristics, including installed capacity, household location, and long-run average daily temperature and precipitation, to estimate hourly solar power generation. Both stages are estimated using random forests with 120 trees and a minimum leaf size of five.

We evaluate the model using four out-of-sample validation designs, including a chronological 80/20 holdout that trains on the earlier 80% of the panel and tests on the remaining later 20% of observations, a year-ahead holdout that trains on 2022 and tests on 2023, a household holdout that excludes entire solar households from training, and five-fold cross-validation. The two-stage random forest demonstrates strong predictive performance across all specifications. Under the year-ahead validation design, which most closely resembles the deployment setting, the model achieves an R^2 of 0.949, while the chronological holdout yields an R^2 of 0.961. The normalized mean absolute error remains below 4% of peak generation, and the prediction bias is negligible relative to productive-hour solar output. Validation results also indicate strong cross-household transferability, with an R^2 of 0.998 when entire households are excluded from the training sample. Because the irradiance input in stage-2 is itself a model output rather than a measurement, these diagnostics establish that the NSRDB-driven random forest reliably reproduces PVGIS-style projections. PVGIS's own validation against measured systems is documented in Huld et al. (2012). The full table and diagnostics are in Table C.1, and we summarize the two-stage performance visually in Figure C.1. The trained two-stage model is then deployed on NSRDB weather observations for 2024–2025 to project hourly household-level solar generation, and the predicted output is added back to metered electricity consumption to recover gross household electricity demand.

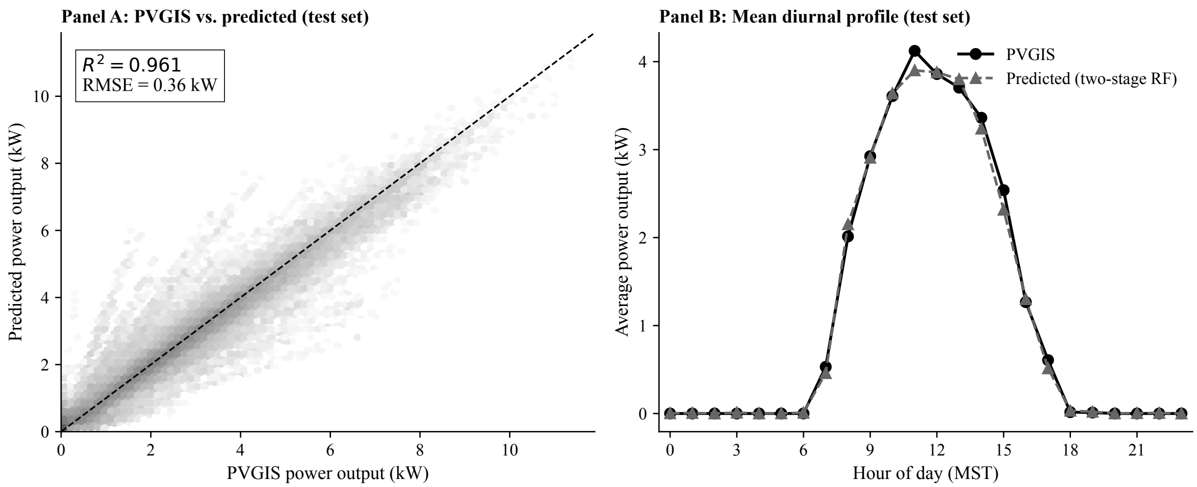


Figure C.1: Main model validation - chronological 80/20 test

Notes. Panel A shows the hexagonal-bin density of test-set household-hour observations, PVGIS versus model prediction. The dashed line is the 45-degree reference. Panel B shows average power output by hour of day (mountain standard time) on the test set, where black is PVGIS and dashed grey is the two-stage random-forest prediction.

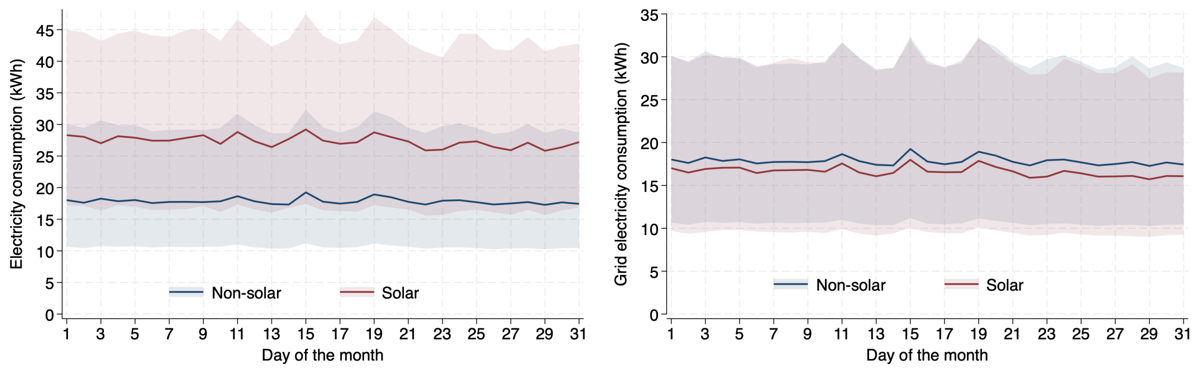
Table C.1: Out-of-sample performance of the household solar-generation model

Validation design	R^2	RMSE (W)	nMAE (%)
Time-ordered (80/20)	0.961	365	2.94
Train 2022 / Test 2023	0.949	428	3.71
Household hold-out (20%)	0.998	99	0.82
5-fold CV (mean)	0.998	80	0.61

Note: Two-stage random forest, with stage-1 mapping NSRDB grid variables to plane-of-array irradiance and stage-2 mapping the stage-1 prediction together with PV system characteristics to power output. R^2 *is the coefficient of determination against the PVGIS target on the held-out fold; RMSE is in watts; nMAE is the mean absolute error normalised by the 95th-percentile site-hour power output. Five-fold cross-validation reports the cross-fold mean.*

C.3 Temporal Patterns in Household Energy Consumption

Figures C.2 and C.3 plot daily and monthly electricity consumption for solar and non-solar households, separately for total and grid electricity.

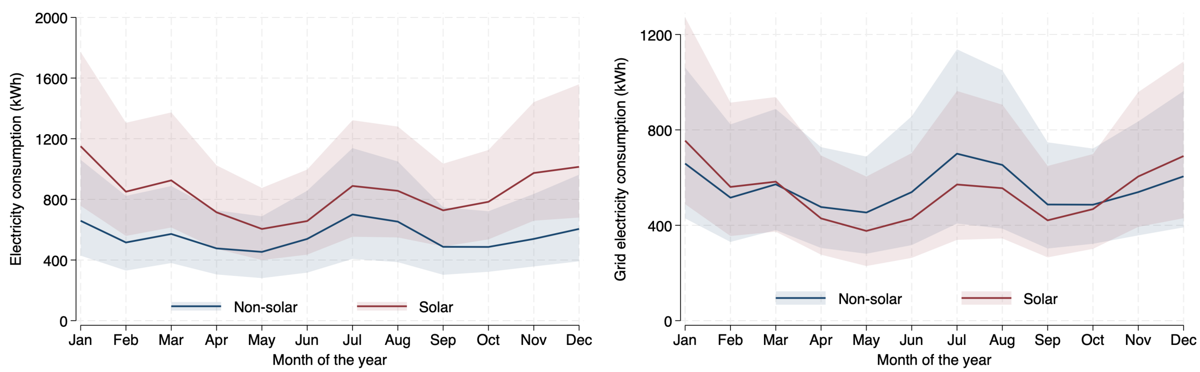


(a) Median total electricity consumption

(b) Median grid electricity consumption

Figure C.2: Daily electricity consumption patterns for solar vs. non-solar households

Notes: The figure plots daily electricity consumption patterns for solar and non-solar households. Panel (a) shows total electricity consumption, and Panel (b) shows grid electricity consumption. Solid lines represent the median hourly consumption for each group, and shaded bands indicate the 25th–75th percentile range. Consumption is measured in kWh.



(a) Median total electricity consumption

(b) Median grid electricity consumption

Figure C.3: Monthly electricity consumption patterns for solar vs. non-solar households

Notes: The figure plots monthly electricity consumption patterns for solar and non-solar households. Panel (a) shows total electricity consumption, and Panel (b) shows grid electricity consumption. Solid lines represent the median hourly consumption for each group, and shaded bands indicate the 25th–75th percentile range. Consumption is measured in kWh.

C.4 Energy Rebound Analysis

We employ a staggered difference-in-differences approach to estimate the solar rebound effect in the residential sector. This framework allows us to exploit variation in the timing of solar adoption across households and to account for heterogeneous treatment effects. Our objective is to identify the causal impact of solar adoption on electricity consumption and natural gas consumption. To provide a unified measure of energy use, we convert both electricity and natural gas consumption into million British thermal units (MMBtu) to estimate the rebound effect on total energy consumption. Detailed model specifications and estimation procedures are presented below.

C.4.1 Methodology

We estimate the dynamic effects of solar adoption using the staggered difference-in-differences framework developed by Callaway and Sant'Anna (2021). To improve computational tractability, we conduct our baseline analysis at the monthly level. We aggregate household-level hourly energy consumption data to monthly frequency and define treatment timing based on the month-year of solar adoption.

$$Y_{it} = \gamma_{-K^-} D_{it}^{<-K} + \sum_{k=-K}^{-2} \gamma_k D_{it}^k + \sum_{k=0}^{L} \gamma_k D_{it}^k + \gamma_{L^+} D_{it}^{>L} + \alpha_i + \alpha_t + \varepsilon_{it} \tag{C.1}$$

where $D_{it}^k = \mathbf{1}\{t - G_i = k\}$ is an event-time indicator equal to one when household i is k months from its adoption month G_i, the period immediately before adoption ($k = -1$) is the omitted reference, and $D_{it}^{<-K} = \mathbf{1}\{t - G_i < -K\}$ and $D_{it}^{>L} = \mathbf{1}\{t - G_i > L\}$ bin any event times beyond the endpoints into single indicators with one coefficient each (γ_{-K^-} and γ_{L^+}). K and L are set to the longest lead and lag observable in the January 2022–June 2025 monthly panel, so the estimation uses the full event window and the endpoint bins are included for generality; the event-study figures display event times −20 to +40 for visual clarity.

As specified in Equation C.1, this approach allows us to estimate group-time average treatment effects on the treated group (ATT) by comparing households that adopt solar in a given period to never-treated households.

$$ATT(g,t) = \mathbb{E}[\, Y_{it}(1) - Y_{it}(0) \mid G_i = g\,], \qquad t \geq g \tag{C.2}$$

$$ATT = \sum_{g \leq t} w_g \, ATT(g,t) \tag{C.3}$$

where the aggregation weights w_g follow the "simple" aggregation of Callaway and Sant'Anna (2021): each post-treatment group-time cell (g,t) with $t \geq g$ receives a weight proportional to the size of adoption cohort g, so the overall ATT is the cohort-size-weighted average of all post-treatment group-time effects.

In our application, Y_{it} denotes the outcome of interest for household i in month-year t. Let G_i denote the first month in which household i adopts solar. For never-treated households, $G_i = 0$. Following Callaway and Sant'Anna (2021), we first estimate the group-time average treatment effect, $ATT(g,t)$, which measures the average effect of solar adoption in month-year t for the cohort of households that first adopt in month-year g. Formally, $ATT(g,t)$ is defined as the expected difference between the treated potential outcome, $Y_{it}(D = 1)$, and the untreated potential outcome, $Y_{it}(D = 0)$, conditional on belonging to treatment cohort g. We then aggregate these group-time effects across treatment cohorts to obtain overall time-specific treatment effects, ATT, and event-time treatment effects, $ATT(e)$, where $e = t - g$ denotes months relative to adoption. Insignificant lead coefficients (i.e., $e < 0$) support the validity of the identification strategy. The lag coefficients (i.e., $e \geq 0$) capture the magnitude and persistence of the rebound effect following adoption.

C.4.2 Identification strategy

A central identification concern in estimating the causal effect of solar adoption on energy consumption is self-selection. Households voluntarily choose whether and when to install solar panels, and the factors driving adoption may also be correlated with subsequent energy consumption behavior. While household fixed effects account for time-invariant unobserved heterogeneity, they do not address the possibility that households adopt solar in response to evolving consumption preferences or expectations.

More broadly, the identification concern is whether solar adoption is driven by time-varying household-level factors that also affect energy consumption. These factors could operate in either direction. For example, households may adopt solar because they anticipate a future increase in electricity demand, such as adding electric appliances, working more from home, or planning other lifestyle changes. Conversely, households with increasing environmental awareness may adopt solar while also becoming more attentive to energy conservation. Their electricity consumption may decline after adoption. However, not all post-adoption changes represent a threat to identification.

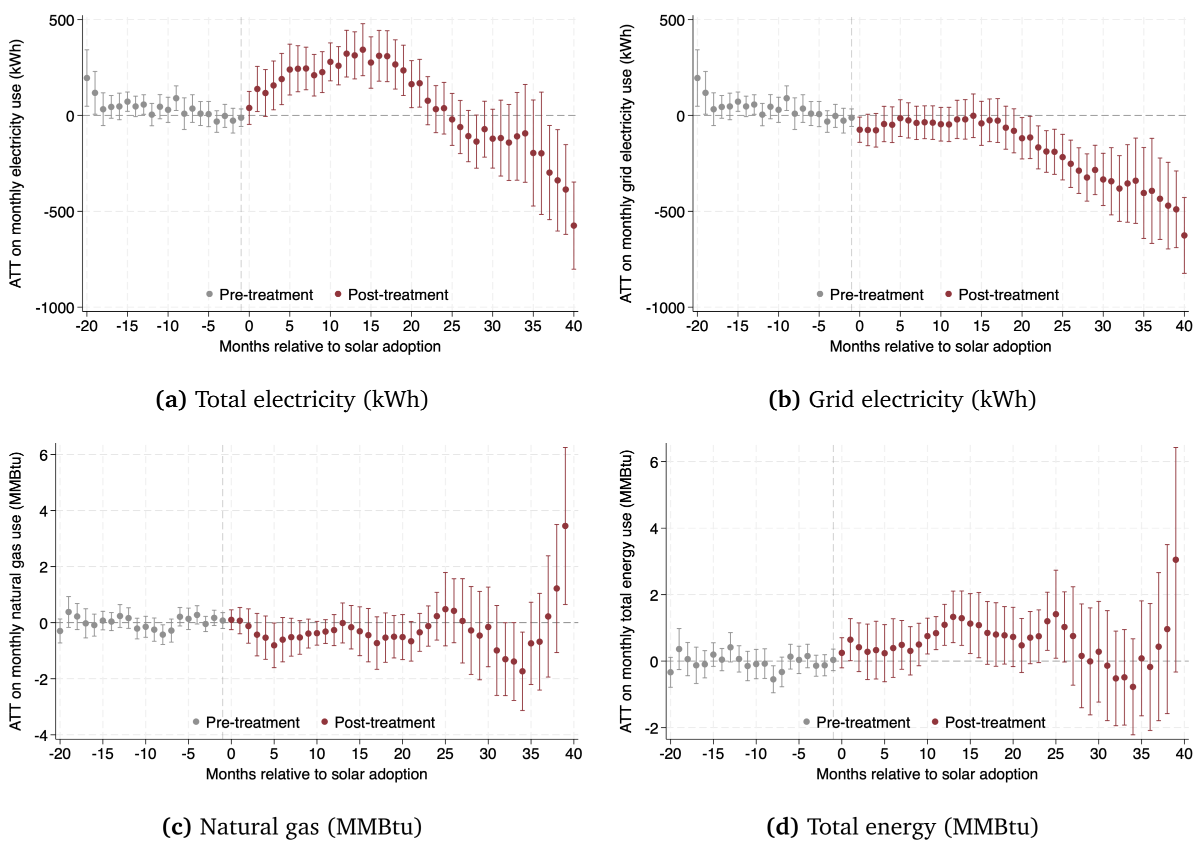
For example, if households increase electricity consumption only after adoption because self-generated electricity lowers the effective cost of electricity or enables additional electricity services, then this behavioral adjustment is precisely the rebound effect of interest. Similarly, if households reduce electricity consumption only after adoption because they learn to manage energy use more efficiently, or respond to limited compensation for exporting excess generation back to the grid, then this post-adoption adjustment is also a treatment-induced behavioral response. In both cases, the change in energy consumption is part of the causal effect of solar adoption as long as the behavioral response is induced by adoption itself and would not have occurred otherwise. The identification threat arises only if the same consumption trajectory would have emerged even in the absence of treatment because of underlying time-varying factors correlated with adoption timing.

To assess this concern, we examine pre-treatment trends using the event-study specification.

If solar adopters were systematically on different energy consumption trajectories before installation, we would expect to observe significant pre-treatment effects. The parallel pre-treatment trends provide supportive evidence that households followed similar trends before adoption, making it more plausible that the post-adoption change reflects the causal effect of solar adoption rather than pre-existing demand growth or conservation trends.

C.5 Parallel Trend Tests

Figures C.4 and C.5 report the monthly event-study estimates for the full sample and the restricted surveyed sample, respectively. In both, the pre-adoption coefficients are flat, supporting the parallel-trends assumption.



(a) Total electricity (kWh)

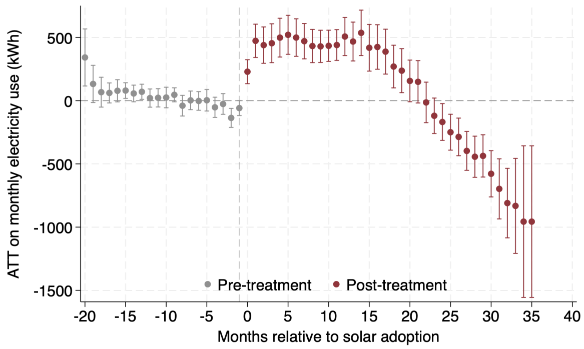
(b) Grid electricity (kWh)

(c) Natural gas (MMBtu)

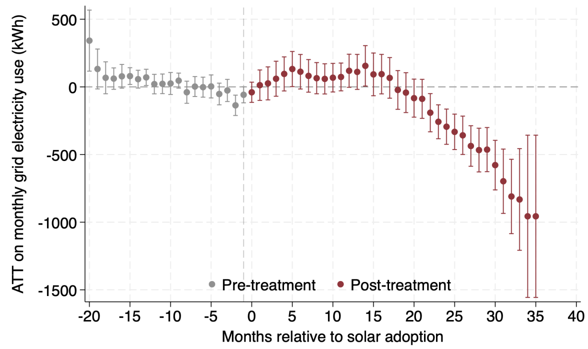
(d) Total energy (MMBtu)

Figure C.4: Event study estimates for monthly energy consumption (full sample)

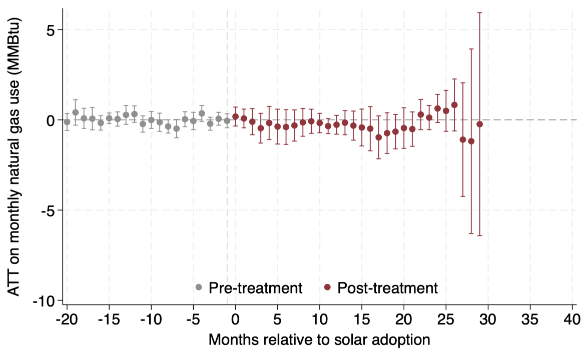
Notes: The figure displays event-study estimates for 20 periods before and 40 periods after solar adoption for visual clarity, while the regression specification includes the full event window.



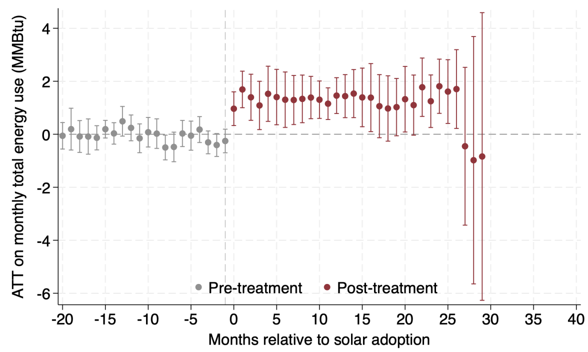
(a) Total electricity (kWh)



(b) Grid electricity (kWh)



(c) Natural gas (MMBtu)



(d) Total energy (MMBtu)

Figure C.5: Event study estimates for monthly energy consumption (restricted sample)

C.6 Supplementary Figures

This subsection collects supporting figures for the solar-rebound analysis. Figure C.6 relates monthly electricity consumption to average installed capacity by installation month. Figures C.7 and C.8 report the ATT on hourly grid-electricity and natural-gas use by day type, and Figure C.12 plots the hourly solar-generation profile against the grid emission factor.

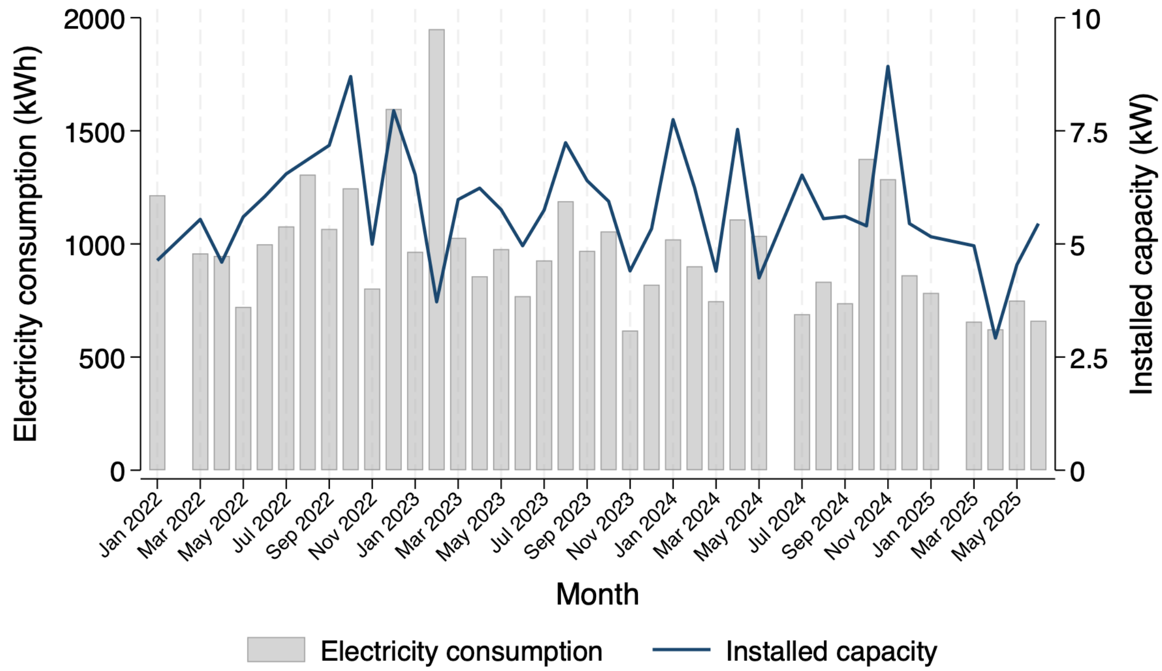
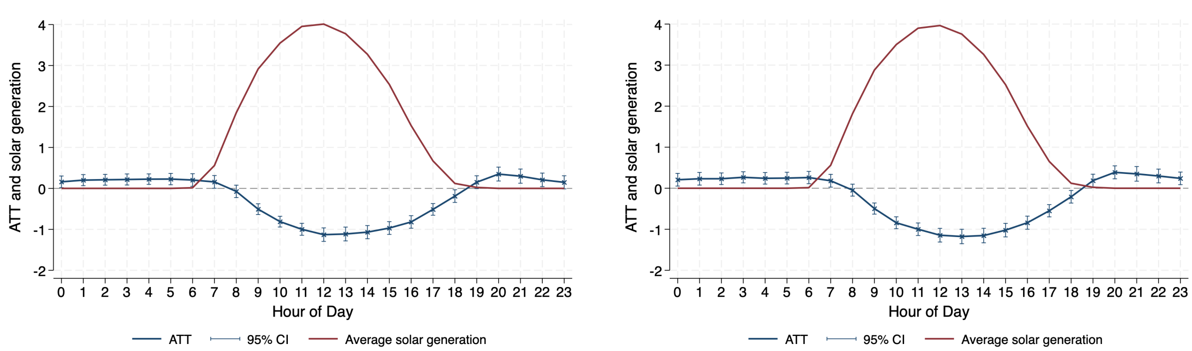


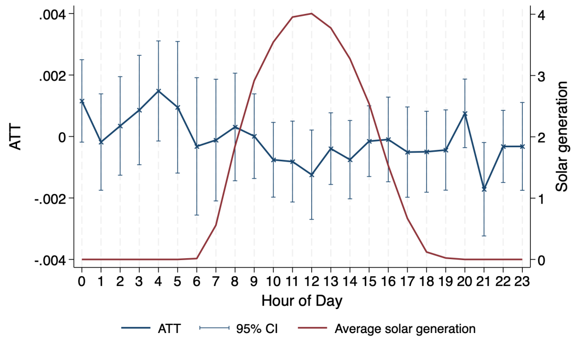
Figure C.6: Monthly electricity consumption and average installed capacity

Notes: The figure is based on solar households only. Grey bars show average monthly household electricity consumption in kWh, calculated at the household-month level and averaged by installation month. The navy line shows average installed solar capacity in kW for households installed in each month. The x-axis reports the month of solar installation. (the outlier in 2023m2 is for only 1 household)

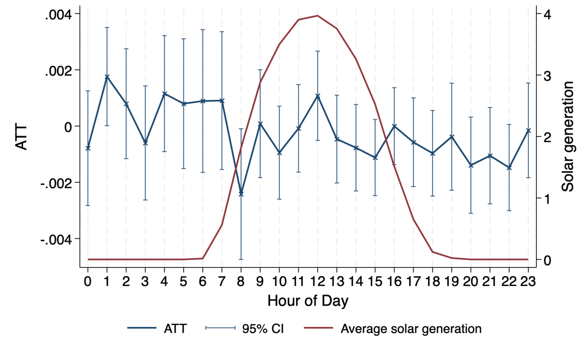


(a) Weekdays **(b)** Weekends

Figure C.7: ATT on hourly grid electricity use (kWh) by day type

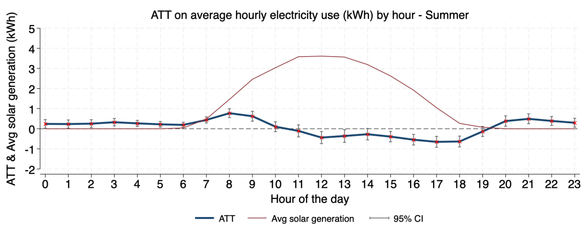


(a) Weekdays

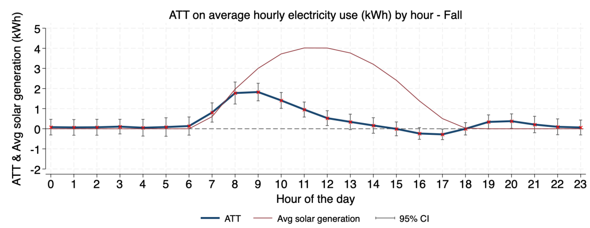


(b) Weekends

Figure C.8: ATT on hourly natural gas use (MMBtu) by day type

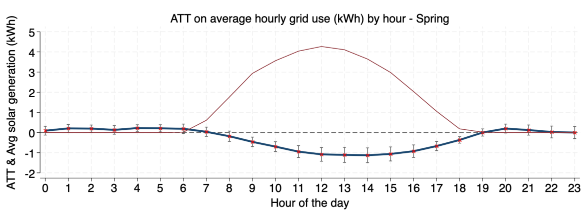


(a) Summer

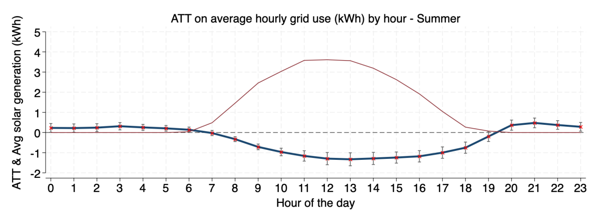


(b) Fall

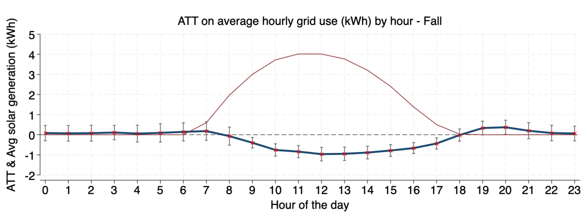
Figure C.9: ATT on hourly electricity use (kWh) by season



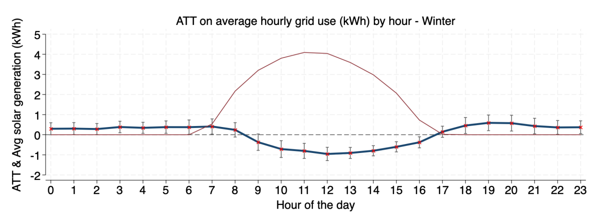
(a) Spring



(b) Summer

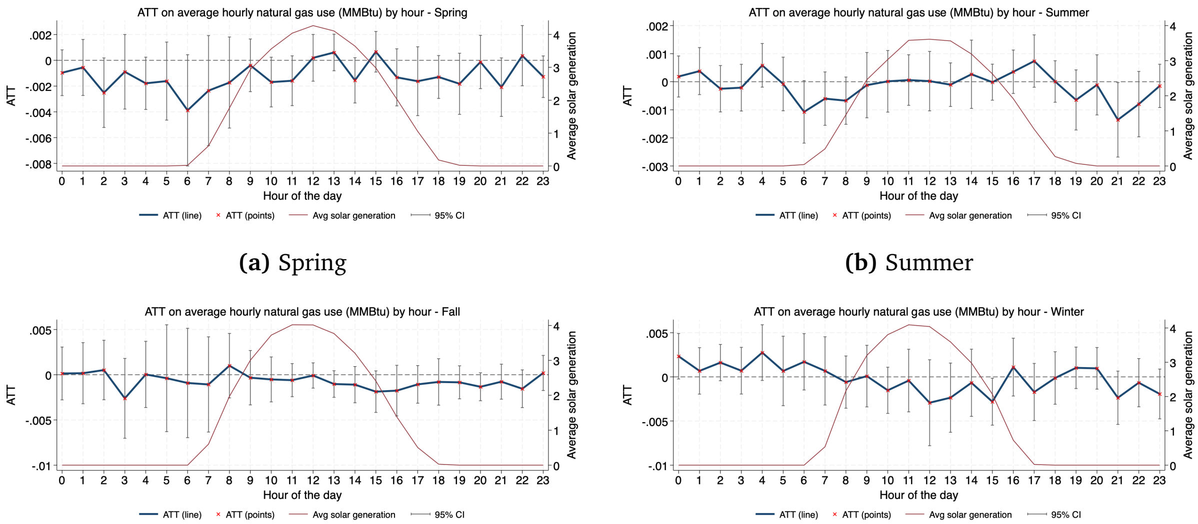


(c) Fall



(d) Winter

Figure C.10: ATT on hourly grid electricity use (kWh) by season



(a) Spring

(b) Summer

(c) Fall

(d) Winter

Figure C.11: ATT on hourly natural gas use (MMBtu) by season

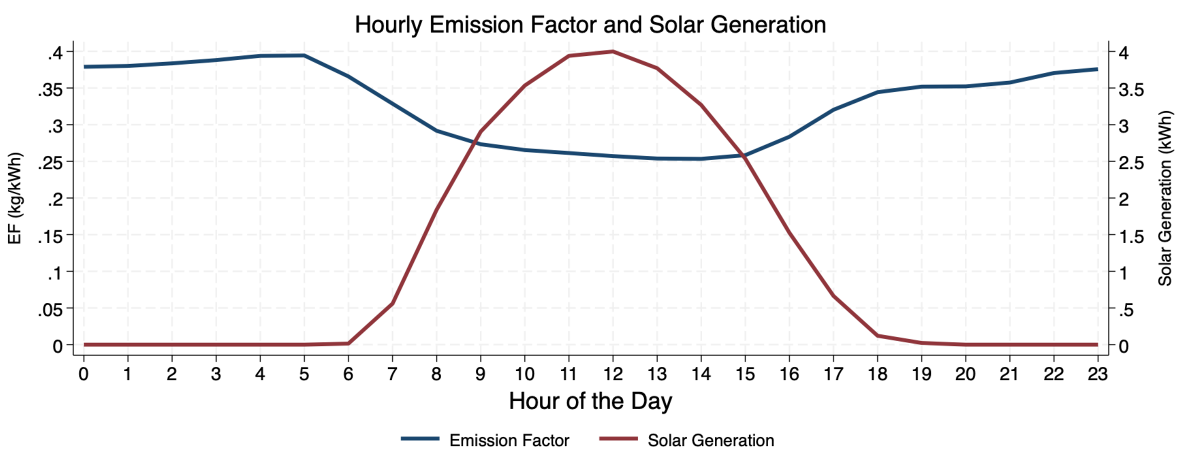


Figure C.12: Hourly solar generation and emission factor

C.7 Supplementary Tables

This subsection collects supporting tables for the solar-rebound analysis. Table C.3 reports the staggered-adoption data structure for the restricted sample. Tables C.5 and C.6 report the seasonal ATT for the restricted sample in native units and in MMBtu. The grid- and gas-channel CO_2 reductions by hour and season are reported in Tables C.9 and C.12. Tables C.13, C.14, C.15, and C.16 compare natural-gas and electricity consumption across surveyed versus non-surveyed and solar versus non-solar households, and Table C.17 reports Kolmogorov–Smirnov tests of the corresponding distributions.

Table C.2: Number of households in each solar adoption group (Full sample)

Never treated	Always treated	Treated within the period	Total
1,729	249	198	2,176

Table C.3: Number of households in each solar adoption group (Restricted sample)

Never treated	Always treated	Treated within the period	Total
1,729	0	110	1,839

Table C.4: Summary Statistics

	Full Sample (N = 2,176)			
	Mean	**S.D.**	**Min**	**Max**
Solar adoption	0.21	0.40	0	1
Solar capacity (kW)	5.52	2.09	1.23	10.00
Hourly solar generation (kWh) - all hours	1.16	0.44	0.26	2.10
Hourly solar generation (kWh) - with positive generation	2.28	0.87	0.5	4.19
Hourly grid electricity consumption (kWh)	0.96	0.57	0	5.79
Hourly electricity consumption (kWh)	1.05	0.62	0	5.79
Hourly gas consumption (MMBtu)	0.01	0.01	0	0.16
Hourly total energy consumption (MMBtu)	0.01	0.01	0	0.16

Notes: This table reports summary statistics based on household-level averages. We first average hourly consumption and generation outcomes within each household over the study period, and then summarize the distribution of these household-level means across households. This approach gives each household equal weight in the summary statistics and avoids giving more weight to households with more observed hourly records. Average solar generation is reported both over all observed hours and conditional on positive generation hours.

Table C.5: Rebound effect heterogeneity: ATT by season - Restricted sample

		(1) Full sample	(2) Spring	(3) Summer	(4) Fall	(5) Winter
Panel A: Total electricity (kWh)	ATT	238.697***	247.946***	94.208	39.093	458.526***
	Std. Err	(56.8526)	(80.7660)	(105.4202)	(77.7122)	(142.6081)
	Pre-treatment mean	631.0236	564.4052	692.6547	558.9326	705.9960
	% change	+37.827%	+43.930%	-	-	+64.947%
Panel B: Grid electricity (kWh)	ATT	-50.368***	-41.627	-130.836	-155.584**	79.500
	Std. Err	(53.0038)	(77.6366)	(88.8329)	(71.7170)	(145.7907)
	Pre-treatment mean	631.0119	564.4052	692.6547	558.9326	705.9516
	% change	-7.982%	-	-	-27.836%	-
Panel C: Natural gas (MMBtu)	ATT	-0.266	-0.500	-0.125	-0.401	0.830*
	Std. Err	(0.2907)	(0.3517)	(0.2150)	(0.3813)	(0.4327)
	Pre-treatment mean	6.55737	6.1827	1.5424	5.3487	12.4711
	% change	-	-	-	-	+6.658%
	N	77,622	21,382	17,804	15,958	19,706
	Sample period	All	Mar. - May.	Jun. - Aug.	Sept. - Nov.	Dec. - Feb

*Note: This table reports the ATT of solar adoption on household energy consumption. Treatment timing is defined by the year-month of solar installation, and we use households that never adopt solar as the control group. Standard errors, reported in parentheses, are clustered at the household level. Pre-treatment means are calculated using observations prior to solar adoption for treated households. Percentage changes are computed relative to pre-treatment means and are not reported when the ATT estimate is statistically insignificant. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.*

Table C.6: Rebound effect heterogeneity: ATT by season (in MMBtu) - Restricted sample

		(1) Full sample	(2) Spring	(3) Summer	(4) Fall	(5) Winter
Panel A: Total electricity (MMBtu)	ATT	0.814***	0.845***	0.321	0.133	1.564***
	Std. Err	(0.1940)	(0.2756)	(0.3597)	(0.2652)	(0.4866)
	Pre-treatment mean	2.1531	1.9258	2.3633	1.9071	2.4089
	% change	+37.826%	+43.929%	-	-	+64.946%
Panel B: Grid electricity (MMBtu)	ATT	-0.172	-0.142	-0.446	-0.531**	0.271
	Std. Err	(0.1808)	(0.2649)	(0.3031)	(0.2447)	(0.4974)
	Pre-treatment mean	2.1530	1.9258	2.3633	1.9071	2.4087
	% change	-7.982%	-	-	-27.836%	-
Panel C: Natural gas (MMBtu)	ATT	-0.266	-0.500	-0.125	-0.401	0.830*
	Std. Err	(0.2907)	(0.3517)	(0.2150)	(0.3813)	(0.4327)
	Pre-treatment mean	6.55737	6.1827	1.5424	5.3487	12.4711
	% change	-	-	-	-	+6.658%
Panel D: Total energy (MMBtu)	ATT	1.307***	0.346	1.201***	1.027**	3.083***
	Std. Err	(0.3508)	(0.4592)	(0.4497)	(0.4862)	(0.7328)
	Pre-treatment mean	8.7118	8.1096	3.9073	7.2573	14.8816
	% change	+15.008%	-	+30.738%	+14.154%	+20.719%
	N	77,622	21,382	17,804	15,958	19,706
	Sample period	All	Mar. - May.	Jun. - Aug.	Sept. - Nov.	Dec. - Feb

*Note: This table reports the ATT of solar adoption on household energy consumption. Treatment timing is defined by the year-month of solar installation, and we use households that never adopt solar as the control group. Standard errors, reported in parentheses, are clustered at the household level. Pre-treatment means are calculated using observations prior to solar adoption for treated households. Percentage changes are computed relative to pre-treatment means and are not reported when the ATT estimate is statistically insignificant. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.*

Table C.7: CO_2 Reduction from Grid Electricity with Rebound (Seasonal Aggregation)

Season	Marginal EF (kg/kWh)	ATT	Reduction (kg)
Spring	0.465	-102.309*	-47.574
Summer	0.441	-252.238***	-111.346
Fall	0.442	-333.309***	-147.196
Winter	0.443	insignificant	-
Spring total			-142.723
Summer total			-334.039
Fall total			-441.588
Winter total			-
Annual total			-918.351

Table C.8: CO_2 Reduction from Grid Electricity with Rebound: Hourly ATT Estimates

Hour	Marginal EF (kg/kWh)	ATT_fmt	Hourly effect (kg)
0	0.445	0.175**	0.078
1	0.445	0.211***	0.094
2	0.445	0.216***	0.096
3	0.445	0.232***	0.103
4	0.445	0.230***	0.102
5	0.444	0.233***	0.104
6	0.445	0.222***	0.099
7	0.453	0.167**	0.076
8	0.456	-0.065	0.000
9	0.456	-0.504***	-0.230
10	0.455	-0.820***	-0.373
11	0.454	-1.000***	-0.454
12	0.454	-1.134***	-0.515
13	0.455	-1.133***	-0.515
14	0.455	-1.093***	-0.497
15	0.454	-0.983***	-0.446
16	0.453	-0.824***	-0.373
17	0.449	-0.524***	-0.235
18	0.443	-0.193**	-0.086
19	0.443	0.161**	0.071
20	0.443	0.357***	0.158
21	0.444	0.312***	0.138
22	0.444	0.232***	0.103
23	0.445	0.176**	0.078
Daily reduction			-2.423
Annual reduction			-884.296

Table C.9: CO_2 Reduction from Grid Electricity with Rebound: Hour–Season ATT Estimates

Season	Hr	EF(kg/kWh)	ATT	Reduction(kg)
Spring	0	0.451	0.092	0.000
Spring	1	0.452	0.205**	0.093
Spring	2	0.451	0.195**	0.088
Spring	3	0.451	0.131	0.000
Spring	4	0.451	0.221***	0.100
Spring	5	0.450	0.208**	0.094
Spring	6	0.452	0.187	0.000
Spring	7	0.481	0.037	0.000
Spring	8	0.487	-0.184	0.000
Spring	9	0.487	-0.462***	-0.225
Spring	10	0.486	-0.699***	-0.340
Spring	11	0.485	-0.946***	-0.458
Spring	12	0.485	-1.084***	-0.525
Spring	13	0.486	-1.108***	-0.539
Spring	14	0.487	-1.127***	-0.548
Spring	15	0.483	-1.063***	-0.514
Spring	16	0.480	-0.925***	-0.444
Spring	17	0.467	-0.671***	-0.313
Spring	18	0.447	-0.368***	-0.165
Spring	19	0.447	0.002	0.000
Spring	20	0.447	0.197*	0.088
Spring	21	0.449	0.123	0.000
Spring	22	0.449	0.026	0.000
Spring	23	0.451	0	0.000
Summer	0	0.442	0.229**	0.101
Summer	1	0.442	0.221**	0.098
Summer	2	0.442	0.244**	0.108
Summer	3	0.442	0.313***	0.138
Summer	4	0.442	0.256***	0.113
Summer	5	0.442	0.208***	0.092
Summer	6	0.442	0.139**	0.061
Summer	7	0.442	-0.025	0.000
Summer	8	0.442	-0.328***	-0.145
Summer	9	0.441	-0.712***	-0.314
Summer	10	0.441	-0.965***	-0.426
Summer	11	0.441	-1.161***	-0.512
Summer	12	0.441	-1.295***	-0.571
Summer	13	0.441	-1.327***	-0.585
Summer	14	0.441	-1.286***	-0.567
Summer	15	0.440	-1.241***	-0.547
Summer	16	0.440	-1.179***	-0.519
Summer	17	0.441	-0.997***	-0.439
Summer	18	0.441	-0.751***	-0.331
Summer	19	0.441	-0.194	0.000
Summer	20	0.441	0.366***	0.161
Summer	21	0.441	0.477***	0.211
Summer	22	0.442	0.374***	0.165
Summer	23	0.442	0.285***	0.126
Spring daily reduction: 3.610kg				
Summer daily reduction: 3.580kg				

Season	Hr	EF(kg/kWh)	ATT	Reduction(kg)
Fall	0	0.442	0.083	0.000
Fall	1	0.442	0.07	0.000
Fall	2	0.442	0.078	0.000
Fall	3	0.442	0.11	0.000
Fall	4	0.442	0.057	0.000
Fall	5	0.442	0.093	0.000
Fall	6	0.442	0.142	0.000
Fall	7	0.441	0.183	0.000
Fall	8	0.441	-0.07	0.000
Fall	9	0.442	-0.399***	-0.176
Fall	10	0.442	-0.757***	-0.334
Fall	11	0.442	-0.839***	-0.370
Fall	12	0.442	-0.965***	-0.426
Fall	13	0.442	-0.947***	-0.418
Fall	14	0.442	-0.888***	-0.392
Fall	15	0.441	-0.786***	-0.347
Fall	16	0.441	-0.664***	-0.293
Fall	17	0.441	-0.435***	-0.192
Fall	18	0.441	-0.017	0.000
Fall	19	0.441	0.332*	0.147
Fall	20	0.441	0.372**	0.164
Fall	21	0.441	0.199	0.000
Fall	22	0.442	0.086	0.000
Fall	23	0.442	0.063	0.000
Winter	0	0.444	0.297*	0.132
Winter	1	0.443	0.305**	0.135
Winter	2	0.443	0.283**	0.125
Winter	3	0.443	0.385***	0.171
Winter	4	0.443	0.344**	0.152
Winter	5	0.443	0.379**	0.168
Winter	6	0.444	0.376**	0.167
Winter	7	0.444	0.409**	0.181
Winter	8	0.445	0.243	0.000
Winter	9	0.445	-0.370*	-0.165
Winter	10	0.444	-0.713***	-0.316
Winter	11	0.442	-0.804***	-0.356
Winter	12	0.443	-0.955***	-0.423
Winter	13	0.443	-0.906***	-0.401
Winter	14	0.443	-0.796***	-0.353
Winter	15	0.443	-0.602***	-0.267
Winter	16	0.443	-0.377***	-0.167
Winter	17	0.443	0.147	0.000
Winter	18	0.443	0.457**	0.202
Winter	19	0.443	0.591***	0.262
Winter	20	0.442	0.575***	0.254
Winter	21	0.442	0.432**	0.191
Winter	22	0.442	0.363**	0.161
Winter	23	0.443	0.373**	0.165
Fall daily reduction: 2.639kg				
Winter daily reduction: -0.018kg				

Table C.10: CO_2 Reduction from Natural Gas with Rebound (Seasonal Aggregation)

Season	Emissions Coefficients (kg/MMBtu)	ATT	Reduction (kg)
Spring	52.91	-0.948***	-50.183
Summer	52.91	insignificant	-
Fall	52.91	insignificant	-
Winter	52.91	insignificant	-
Spring total			-150.550
Summer total			-
Fall total			-
Winter total			-
Annual total			-150.550

Table C.11: CO_2 Reduction from Natural Gas with Rebound: Hourly ATT Estimates

Hour	Emissions Coefficients (kg/MMBtu)	ATT_fmt	Hourly effect (kg)
0	52.91	0.001	0.000
1	52.91	0	0.000
2	52.91	0	0.000
3	52.91	0	0.000
4	52.91	0.001*	0.053
5	52.91	0.001	0.000
6	52.91	0	0.000
7	52.91	0	0.000
8	52.91	0	0.000
9	52.91	0	0.000
10	52.91	-0.001	0.000
11	52.91	-0.001	0.000
12	52.91	-0.001	0.000
13	52.91	0	0.000
14	52.91	-0.001	0.000
15	52.91	0	0.000
16	52.91	0	0.000
17	52.91	-0.001	0.000
18	52.91	-0.001	0.000
19	52.91	0	0.000
20	52.91	0	0.000
21	52.91	-0.002**	-0.106
22	52.91	-0.001	0.000
23	52.91	0	0.000
Daily total			-0.053
Annual total			-19.312

Table C.12: CO_2 Reduction from Natural Gas with Rebound: Hour–Season ATT Estimates

Season	Hr	EC (kg/MMBtu))	ATT	Reduction(kg)
Spring	0	52.91	-0.001	0.000
Spring	1	52.91	-0.001	0.000
Spring	2	52.91	-0.003*	-0.159
Spring	3	52.91	-0.001	0.000
Spring	4	52.91	-0.002*	-0.106
Spring	5	52.91	-0.002	0.000
Spring	6	52.91	-0.004*	-0.212
Spring	7	52.91	-0.002	0.000
Spring	8	52.91	-0.002	0.000
Spring	9	52.91	0	0.000
Spring	10	52.91	-0.002*	-0.106
Spring	11	52.91	-0.002	0.000
Spring	12	52.91	0	0.000
Spring	13	52.91	0.001	0.000
Spring	14	52.91	-0.002*	-0.106
Spring	15	52.91	0.001	0.000
Spring	16	52.91	-0.001	0.000
Spring	17	52.91	-0.002	0.000
Spring	18	52.91	-0.001	0.000
Spring	19	52.91	-0.002	0.000
Spring	20	52.91	0	0.000
Spring	21	52.91	-0.002*	-0.106
Spring	22	52.91	0	0.000
Spring	23	52.91	-0.001	0.000
Summer	0	52.91	0	0.000
Summer	1	52.91	0	0.000
Summer	2	52.91	0	0.000
Summer	3	52.91	0	0.000
Summer	4	52.91	0.001	0.000
Summer	5	52.91	0	0.000
Summer	6	52.91	-0.001*	-0.053
Summer	7	52.91	-0.001	0.000
Summer	8	52.91	-0.001	0.000
Summer	9	52.91	0	0.000
Summer	10	52.91	0	0.000
Summer	11	52.91	0	0.000
Summer	12	52.91	0	0.000
Summer	13	52.91	0	0.000
Summer	14	52.91	0	0.000
Summer	15	52.91	0	0.000
Summer	16	52.91	0	0.000
Summer	17	52.91	0.001	0.000
Summer	18	52.91	0	0.000
Summer	19	52.91	-0.001	0.000
Summer	20	52.91	0	0.000
Summer	21	52.91	-0.001**	-0.053
Summer	22	52.91	-0.001	0.000
Summer	23	52.91	0	0.000
Spring daily reduction: 0.794kg				
Summer daily reduction: 0.106kg				

Season	Hr	EC (kg/MMBtu))	ATT	Reduction(kg)
Fall	0	52.91	0	0.000
Fall	1	52.91	0	0.000
Fall	2	52.91	0.001	0.000
Fall	3	52.91	-0.003	0.000
Fall	4	52.91	0	0.000
Fall	5	52.91	0	0.000
Fall	6	52.91	-0.001	0.000
Fall	7	52.91	-0.001	0.000
Fall	8	52.91	0.001	0.000
Fall	9	52.91	0	0.000
Fall	10	52.91	-0.001	0.000
Fall	11	52.91	-0.001	0.000
Fall	12	52.91	0	0.000
Fall	13	52.91	-0.001	0.000
Fall	14	52.91	-0.001	0.000
Fall	15	52.91	-0.002	0.000
Fall	16	52.91	-0.002	0.000
Fall	17	52.91	-0.001	0.000
Fall	18	52.91	-0.001	0.000
Fall	19	52.91	-0.001	0.000
Fall	20	52.91	-0.001*	-0.053
Fall	21	52.91	-0.001	0.000
Fall	22	52.91	-0.002	0.000
Fall	23	52.91	0	0.000
Winter	0	52.91	0.002*	0.106
Winter	1	52.91	0.001	0.000
Winter	2	52.91	0.002	0.000
Winter	3	52.91	0.001	0.000
Winter	4	52.91	0.003*	0.159
Winter	5	52.91	0.001	0.000
Winter	6	52.91	0.002	0.000
Winter	7	52.91	0.001	0.000
Winter	8	52.91	-0.001	0.000
Winter	9	52.91	0	0.000
Winter	10	52.91	-0.002	0.000
Winter	11	52.91	0	0.000
Winter	12	52.91	-0.003	0.000
Winter	13	52.91	-0.002	0.000
Winter	14	52.91	-0.001	0.000
Winter	15	52.91	-0.003**	-0.159
Winter	16	52.91	0.001	0.000
Winter	17	52.91	-0.002	0.000
Winter	18	52.91	0	0.000
Winter	19	52.91	0.001	0.000
Winter	20	52.91	0.001	0.000
Winter	21	52.91	-0.002	0.000
Winter	22	52.91	-0.001	0.000
Winter	23	52.91	-0.002	0.000
Fall daily reduction: 0.053kg				
Winter daily reduction: -0.106kg				

Table C.13: Gas Consumption: Survey (N=588) vs. Non-Survey (N=7,268)

	Survey (N=588)		Non-Survey (N=7,268)		
	Consumption (CCF)	**S.D.**	**Consumption (CCF)**	**S.D.**	**T-Test**
Year					
2023	913.68	1092.19	990.54	1906.66	0.97
2024	955.37	1231.62	1058.91	2265.43	1.11
2025 (Incomplete)	555.45	746.6	626.98	1485.43	1.16
Month					
1	198.61	210.61	215.33	372.69	1.09
2	135.17	150.15	147.9	263.22	1.17
3	132.59	155.09	149.38	308.83	1.32
4	71.68	92.58	82.36	211.47	1.23
5	37.67	56.1	45.66	171.59	1.14
6	20.45	37.5	25.34	123.29	0.97
7	22.06	56.33	23.37	118.76	0.26
8	20.37	40.46	24.03	120.14	0.73
9	22.15	39.63	26.03	110.08	0.84
10	50.83	65.17	57.38	155.42	1.00
11	124.52	139.23	135.55	236.69	1.09
12	156.09	166.72	170.32	316.3	1.06
Day of Week					
Sunday	3.17	3.6	3.57	8.16	1.2
Monday	3.19	3.61	3.6	8.02	1.25
Tuesday	3.22	3.66	3.62	7.92	1.24
Wednesday	3.12	3.54	3.52	7.73	1.24
Thursday	3.02	3.44	3.41	7.51	1.27
Friday	3.3	3.8	3.66	8.13	1.05
Saturday	3.27	3.79	3.64	8.16	1.1

Notes: A t-value with an absolute magnitude greater than 1.96 indicates statistical significance at the 5% level.

Table C.14: Electricity Consumption: Survey (N=536) vs. Non-Survey (N=7,746)

	Survey (N=536)		Non-Survey (N=7,746)		
	Consumption (KWH)	**S.D.**	**Consumption (KWH)**	**S.D.**	**T-Test**
Year					
2023	6267.3	3791.82	6547.96	4622.61	-1.39
2024	7296.39	4621.66	7925.67	5618.25	-2.55
2025 (Incomplete)	3532.71	2319.47	3901.11	2798.9	-2.98
Month					
1	727.04	623.08	758.78	492.62	-1.17
2	559.92	468.52	587.15	367.01	-1.34
3	608.63	491.89	646.36	384.41	-1.77
4	490.41	381.66	527.66	302.74	-2.25
5	445.92	342.77	489.5	287.08	-2.92
6	533.05	412.48	585.64	372.94	-2.92
7	741.57	576.2	799.08	542.43	-2.27
8	705.66	553.56	755.11	504.65	-2.04
9	481.91	374.94	513.4	328.31	-1.92
10	482.92	370.03	517.51	296.51	-2.14
11	557.07	458.75	605.37	371.11	-2.41
12	621.03	530.18	668.89	434.62	-2.06
Day of Week					
Sunday	20.45	15.06	22.1	12.73	-2.52
Monday	19.74	15.01	21.28	12.28	-2.36
Tuesday	19.69	20.1	21.38	12.38	-1.95
Wednesday	19.56	14.77	21.15	12.22	-2.48
Thursday	19.89	14.86	21.52	12.28	-2.53
Friday	20.8	15.16	22.54	12.7	-2.65
Saturday	22.43	15.98	24.2	13.52	-2.54

Notes: A t-value with an absolute magnitude greater than 1.96 indicates statistical significance at the 5% level.

Table C.15: Gas Consumption: Solar (N=74) vs. Non-Solar (N=588)

	Solar (N=74)		Non-Solar (N=588)		
	Consumption (CCF)	**S.D.**	**Consumption (CCF)**	**S.D.**	**T-Test**
Year					
2023	894.91	739.4	770.33	428.27	1.41
2024	937.18	829.71	774.12	497.82	1.65
2025 (Incomplete)	544.83	525.32	447.79	320.05	1.54
Month					
1	195.25	142.44	169.74	95.18	1.49
2	132.97	103.2	113.56	64.39	1.57
3	130.24	108.22	111.28	66.74	1.47
4	70.58	66.44	57.13	31.45	1.71
5	37.21	42.56	28	16.06	1.84
6	19.86	24.54	14.88	9.49	1.71
7	21.6	49.99	15	11.07	1.12
8	19.6	24.4	14.7	10.76	1.68
9	21.77	26.67	14.55	9.95	2.26
10	50.58	49.37	37.07	22.88	2.24
11	122.3	92.43	103.78	64.58	1.61
12	153.92	112.41	128.22	76.63	1.84
Day of Week					
Sunday	3.14	2.61	2.59	1.38	1.78
Monday	3.14	2.51	2.61	1.4	1.77
Tuesday	3.17	2.52	2.67	1.48	1.65
Wednesday	3.08	2.44	2.56	1.44	1.77
Thursday	2.97	2.36	2.48	1.32	1.75
Friday	3.26	2.61	2.71	1.47	1.77
Saturday	3.22	2.62	2.67	1.44	1.78

Notes: A t-value with an absolute magnitude greater than 1.96 indicates statistical significance at the 5% level.

Table C.16: Electricity Consumption: Solar (N=82) vs. Non-Solar (N=536)

	Solar (N=82)		Non-Solar (N=536)		
	Consumption (KWH)	**S.D.**	**Consumption (KWH)**	**S.D.**	**T-Test**
Year					
2023	6547.96	3791.82	9461.36	5333	-5.74
2024	7925.67	4621.66	10745.14	5861.21	-4.93
2025 (Incomplete)	3901.11	2319.48	6100.99	3240.91	-7.54
Month					
1	758.78	492.62	1034.18	697.41	-4.43
2	587.15	367.01	885.37	502.79	-6.51
3	646.36	384.41	891.11	456.98	-5.24
4	527.66	302.74	962.92	467.64	-11.2
5	489.5	287.08	937.02	436.93	-12.19
6	585.64	372.94	953.03	451.9	-8.13
7	799.08	542.43	1037.08	477.65	-3.63
8	755.11	504.65	888.67	404.39	-2.22
9	513.4	328.31	922.3	448.24	-9.88
10	517.51	296.51	862.07	418.68	-9.15
11	605.37	371.11	918.23	540.15	-6.62
12	668.89	434.62	962.86	609.92	-5.36
Day of Week					
Sunday	22.1	12.73	35.8	17.57	-8.7
Monday	21.28	12.28	36.44	17.77	-9.82
Tuesday	21.38	12.38	36.6	17.81	-9.79
Wednesday	21.15	12.22	37.33	18.42	-10.43
Thursday	21.52	12.28	37.38	19.22	-10.12
Friday	22.54	12.7	36.05	17.32	-8.61
Saturday	24.2	13.52	36.74	17.71	-7.58

Notes: A t-value with an absolute magnitude greater than 1.96 indicates statistical significance at the 5% level.

Table C.17: KS Test P-Values for Electricity and Gas Comparisons

	Electricity		Gas	
	Survey vs. Non-Survey	**Solar vs. Non-Solar**	**Survey vs. Non-Survey**	**Solar vs. Non-Solar**
Year				
2023	0.004	<0.0001	0.199	0.124
2024	<0.0001	<0.0001	0.466	0.267
2025 (Incomplete)	<0.0001	<0.0001	0.803	0.197
Month				
1	<0.0001	0.001	0.132	0.162
2	<0.0001	<0.0001	0.154	0.093
3	<0.0001	<0.0001	0.436	0.208
4	<0.0001	<0.0001	0.475	0.147
5	<0.0001	<0.0001	0.307	0.088
6	<0.0001	<0.0001	0.634	0.255
7	0.008	<0.0001	0.418	0.198
8	0.014	<0.0001	0.217	0.223
9	0.001	<0.0001	0.26	0.016
10	<0.0001	<0.0001	0.539	0.109
11	<0.0001	<0.0001	0.148	0.254
12	<0.0001	<0.0001	0.07	0.089
Day of Week				
Sunday	<0.0001	<0.0001	0.058	0.172
Monday	<0.0001	<0.0001	0.177	0.153
Tuesday	<0.0001	<0.0001	0.161	0.188
Wednesday	<0.0001	<0.0001	0.117	0.152
Thursday	<0.0001	<0.0001	0.148	0.129
Friday	<0.0001	<0.0001	0.096	0.074
Saturday	<0.0001	<0.0001	0.13	0.168

Notes: Kolmogorov–Smirnov (KS) test p-values comparing electricity and gas consumption distributions across household groups. A p-value below 0.05 indicates a statistically significant difference between the two distributions.

C.8 Supplementary Solar-Rebound Results

This subsection collects the detailed tables, the carbon-accounting method, and the robustness analyses summarized in Part III.

Consumption summary and treatment effects. Table C.18 compares consumption across solar and non-solar households before and after adoption. The seasonal ATT is reported in native units (Table C.19) and in MMBtu (Table C.20), the day-of-week ATT in Table C.21, and the Spring/Winter mechanism decomposition in Table C.22. These underlie Figures 11 and 12.

Table C.18: Summary Statistics: Solar households vs. Non-solar households

		Non-Solar		**Non-Solar**			**Solar**				
		Mean	**S.D.**	**Min**	**Max**	**Max**	**Mean**	**S.D.**	**Min**	**Max**	**Diff**
Pre-solar periods	Grid consumption (kWh)	0.97	0.59	0	5.79		1.07	0.51	0.18	3.03	-0.1**
	Total electricity consumption (kWh)	0.97	0.59	0	5.79		1.38	0.61	0.36	3.89	-0.41***
	Gas consumption (MMBtu)	0.01	0.01	0	0.16		0.01	0.01	0	0.03	0
	Total energy consumption (MMBtu)	0.01	0.01	0	0.16		0.01	0.00	0	0.04	0.002***
Post-solar periods	Grid consumption (kWh)	0.97	0.59	0	5.79		0.82	0.45	0.04	2.82	0.15***
	Total electricity consumption (kWh)	0.97	0.59	0	5.79		1.37	0.66	0.31	3.62	-0.4***
	Gas consumption (MMBtu)	0.01	0.01	0	0.16		0.01	0.00	0	0.03	0.003***
	Total energy consumption (MMBtu)	0.01	0.01	0	0.16		0.01	0.00	0	0.03	0.003***
All periods	Grid consumption (kWh)	0.97	0.59	0	5.79		0.93	0.49	0.04	3.03	0.04
	Total electricity consumption (kWh)	0.97	0.59	0	5.79		1.37	0.64	0.31	3.89	-0.4***
	Gas consumption (MMBtu)	0.01	0.01	0	0.16		0.01	0.00	0	0.03	0.003***
	Total energy consumption (MMBtu)	0.01	0.01	0	0.16		0.01	0.00	0	0.04	0.003***

Notes: Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table C.19: Rebound effect heterogeneity: ATT by season

		(1) Full sample	(2) Spring	(3) Summer	(4) Fall	(5) Winter
Panel A: Total electricity (kWh)	ATT	118.696***	175.249***	-44.947	-129.493	458.764***
	Std. Err	44.088	58.842	70.957	88.464	135.764
	Pre-treatment mean	631.794	565.872	694.249	560.092	704.418
	% change	+18.78%	+30.97%	-	-	+65.13%
Panel B: Grid electricity (kWh)	ATT	-131.117***	-102.309*	-252.238***	-333.309***	152.401
	Std. Err	(41.573)	(54.608)	(63.669)	(97.907)	(133.837)
	Pre-treatment mean	631.782	565.872	694.249	560.092	704.375
	% change	-20.76%	-18.08%	-36.33%	-59.51%	-
Panel C: Natural gas (MMBtu)	ATT	-0.345	-0.948***	-0.115	-0.696	0.052
	Std. Err	(0.266)	(0.338)	(0.113)	(0.598)	(0.579)
	Pre-treatment mean	6.542	6.847	1.538	5.343	12.395
	% change	-	-13.85%	-	-	-
	N	82,219	21,997	18,485	16,408	20,435
	Sample period	All	Mar. - May.	Jun. - Aug.	Sept. - Nov.	Dec. - Feb

*Note: This table reports the ATT of solar adoption on household energy consumption. Treatment timing is defined by the year-month of solar installation, and we use households that never adopt solar as the control group. Standard errors, reported in parentheses, are clustered at the household level. Pre-treatment means are calculated using observations prior to solar adoption for treated households. Percentage changes are computed relative to pre-treatment means and are not reported when the ATT estimate is statistically insignificant. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.*

Table C.20: Rebound effect heterogeneity: ATT by season (in standard units)

		(1) Full sample	(2) Spring	(3) Summer	(4) Fall	(5) Winter
Panel A: Total electricity (MMBtu)	ATT	0.405***	0.598***	-0.153	-0.442	1.565***
	Std. Err	(0.150)	(0.201)	(0.242)	(0.302)	(0.463)
	Pre-treatment mean	2.156	1.931	2.369	1.911	2.404
	% change	+18.79%	+30.97%	-	-	+65.13%
Panel B: Grid electricity (MMBtu)	ATT	-0.447***	-0.349*	-0.861***	-1.137***	0.520
	Std. Err	(0.142)	(0.186)	(0.217)	(0.334)	(0.457)
	Pre-treatment mean	2.156	1.931	2.369	1.911	2.403
	% change	-20.75%	-18.08%	-36.33%	-59.51%	-
Panel C: Natural gas (MMBtu)	ATT	-0.345	-0.948***	-0.115	-0.696	0.052
	Std. Err	(0.266)	(0.338)	(0.113)	(0.598)	(0.579)
	Pre-treatment mean	6.542	6.847	1.538	5.343	12.395
	% change	-	-13.85%	-	-	-
Panel D: Total energy (MMBtu)	ATT	0.634**	-0.351	0.675**	0.156	1.606**
	Std. Err	(0.300)	(0.402)	(0.298)	(0.550)	(0.727)
	Pre-treatment mean	8.699	8.104	3.908	7.256	14.800
	% change	+7.29%	-	+17.27%	-	+10.86%
	N	82,219	21,997	18,485	16,408	20,435
	Sample period	All	Mar. - May.	Jun. - Aug.	Sept. - Nov.	Dec. - Feb

*Note: This table reports the ATT of solar adoption on household energy consumption. Treatment timing is defined by the year-month of solar installation, and we use households that never adopt solar as the control group. Standard errors, reported in parentheses, are clustered at the household level. Pre-treatment means are calculated using observations prior to solar adoption for treated households. Percentage changes are computed relative to pre-treatment means and are not reported when the ATT estimate is statistically insignificant. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.*

Table C.21: Rebound effect heterogeneity: ATT on daily average consumption by day of the week

		(1) Monday	(2) Tuesday	(3) Wednesday	(4) Thursday	(5) Friday	(6) Saturday	(7) Sunday
Panel A: Total electricity (kWh)	ATT	0.343***	0.293***	0.266***	0.343***	0.311***	0.388***	0.302***
	Std. Err	(0.063)	(0.063)	(0.061)	(0.061)	(0.063)	(0.065)	(0.061)
	Pre-treatment mean	1.011	0.961	0.962	0.948	0.969	1.006	1.084
	% change	33.93%	+30.49%	+27.65%	+36.18%	+32.09%	+38.57%	+27.86%
Panel B: Grid electricity (kWh)	ATT	-0.211***	-0.225***	-0.254***	-0.187***	-0.223***	-0.189***	-0.239***
	Std. Err	(0.062)	(0.062)	(0.061)	(0.062)	(0.065)	(0.064)	(0.060)
	Pre-treatment mean	1.011	0.961	0.962	0.948	0.969	1.006	1.084
	% change	-20.87%	-23.41%	-26.40%	-19.73%	-23.01%	-18.79%	-22.05%
Panel C: Natural gas (MMBtu)	ATT	-0.000	-0.000	0.000	0.000	-0.000	-0.001	0.000
	Std. Err	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
	Pre-treatment mean	0.011	0.011	0.011	0.011	0.01	0.011	0.011
	% change	-	-	-	-	-	-	-
Panel D: Total energy (MMBtu)	ATT	0.000	0.000	0.000	0.000	0.001	0.000	0.000
	Std. Err	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
	Pre-treatment mean	0.014	0.014	0.014	0.014	0.014	0.015	0.014
	% change	-	-	-	-	-	-	-
	N	70,325	70,328	70,328	70,291	70,327	70,325	70,327

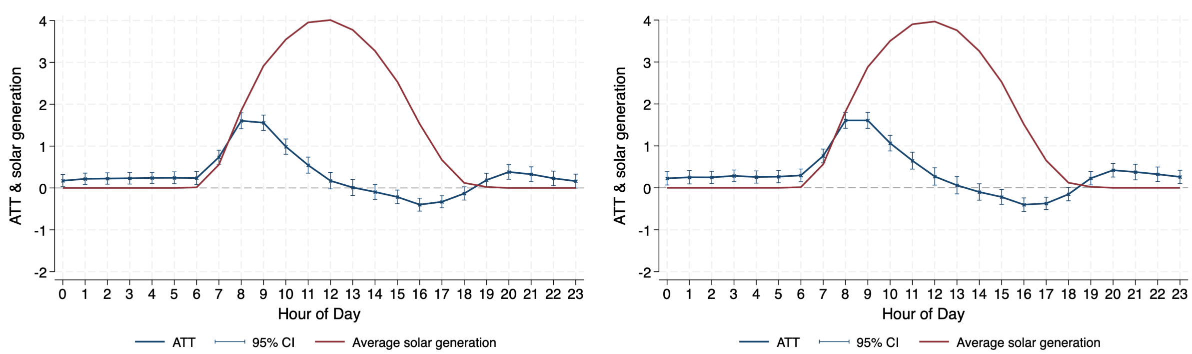
*Note: This table reports the ATT of solar adoption on household average daily energy consumption. Treatment timing is defined by the year-month of solar installation, and we use households that never adopt solar as the control group. Standard errors, reported in parentheses, are clustered at the household level. Pre-treatment means are calculated using observations prior to solar adoption for treated households. Percentage changes are computed relative to pre-treatment means and are not reported when the ATT estimate is statistically insignificant. Significance levels are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.*

Table C.22: Heterogeneous rebound effects in spring and winter

	Spring	Winter
Total electricity consumption	+31%	+65%
Grid electricity consumption	-18%	–
Natural gas consumption	-13%	–
When is the rebound	Solar hours	Throughout the day
Possible drivers	Solar generation, substitution	Solar generation, income effects

Note: This table summarizes the key results from Table C.19 and Figure **??**, *reporting seasonal and within-day patterns in rebound effects.*

The within-day mechanism is shown by the hourly ATT estimates, which track solar-generation hours. The main text (Figure 13) reports electricity use by hour for Spring and Winter. The weekday–weekend split is shown below (Figure C.13), and the remaining seasons together with the grid-electricity and natural-gas analogues appear among the supplementary figures (Figures C.9, C.10, and C.11).



(a) Weekdays **(b)** Weekends

Figure C.13: ATT on hourly electricity use (kWh) by day type

Carbon-accounting method. The grid marginal emission factor (MEF) is the emission intensity of the marginal generator under a merit-order dispatch (solar, wind, hydro, nuclear, coal, natural gas, petroleum):

$$\text{MEF}_t = e_{i^*(t)}, \quad \text{where } i^*(t) = \min\left\{ i : D_t \leq \sum_{j=1}^{i} K_j \right\}, \tag{C.4}$$

where i indexes technologies ordered by increasing marginal cost, K_j is generated capacity by technology j, and D_t is total demand at time t. The CO_2 reduction from reduced grid purchases is the sum over time of the hourly grid-electricity ATT times the MEF, and the reduction from reduced natural gas use applies the gas emission coefficient (52.91 kg CO_2 per MMBtu):

$$\Delta CO_2^{grid} = \sum_t ATT_t^{grid} \times MEF_t, \qquad \Delta CO_2^{gas} = \sum_t ATT_t^{gas} \times EC_t. \tag{C.5}$$

Tables C.23 and C.24 report the CO_2 reductions by hour and season for the grid and gas channels, and Table C.25 compares the observed reduction with the no-rebound counterfactual across alternative emission-factor specifications.

Table C.23: CO_2 Reduction from Grid Electricity with Rebound: Hour–Season ATT Estimates

Season	Number of days	Daily reduction	Seasonal reduction	Total reduction
Spring	92	3.610	332.09	899.87 kg
Summer	92	3.580	329.32	
Fall	91	1.544	240.11	
Winter	90	-0.018	-1.64	

Table C.24: CO_2 Reduction from Natural Gas with Rebound: Hour–Season ATT Estimates

Season	Number of days	Daily reduction	Seasonal reduction	Total effect
Spring	92	0.794	73.016	78.042 kg
Summer	92	0.106	9.735	
Fall	91	0.053	4.815	
Winter	90	-0.106	-9.524	

Table C.25: Comparison of Theoretical and Estimated CO_2 Reductions

Theoretical reduction		Estimated reduction by ATT and emission factors				
		(1)	(2)	(3)	(4)	(5)
3915.17	CO_2 reduction_Electricity (kg)	705.99	918.35	884.30	899.87	899.87
	CO_2 reduction_NG (kg)	-	150.55	19.31	78.04	×
	Total CO_2 reduction (kg)	705.99	1,068.90	903.61	977.91	899.87
	Offset	81.97%	72.70%	76.92%	75.02%	77.02%
	Seasonal variation in EF	×	✓	×	✓	✓
	Within-day variation in EF	×	×	✓	✓	✓
	Detailed calculation in	×	Table C.7, C.10	Table C.8, C.11	Table C.23, C.24	Table C.23

Notes: This table compares the theoretical CO_2 reduction with estimated reductions based on the ATT on grid electricity consumption. When no variation in emission factors (EF) is incorporated, the estimated reduction is computed using the ATT on average monthly grid electricity consumption multiplied by the average EF over the study period and scaled to an annual basis. Specifically, the estimate is given by
$-131.117 \text{ kWh/month} \times 0.4487 \text{ kg/kWh} \times 12 \text{ months} = 705.99 \text{ kg}$.

The deviation across specifications reflects the temporal alignment between grid-use reductions and emission factors: reductions are larger in mid-summer to fall months when emission factors are high (Figure C.14), but concentrated in solar-generation hours when emission factors are low.

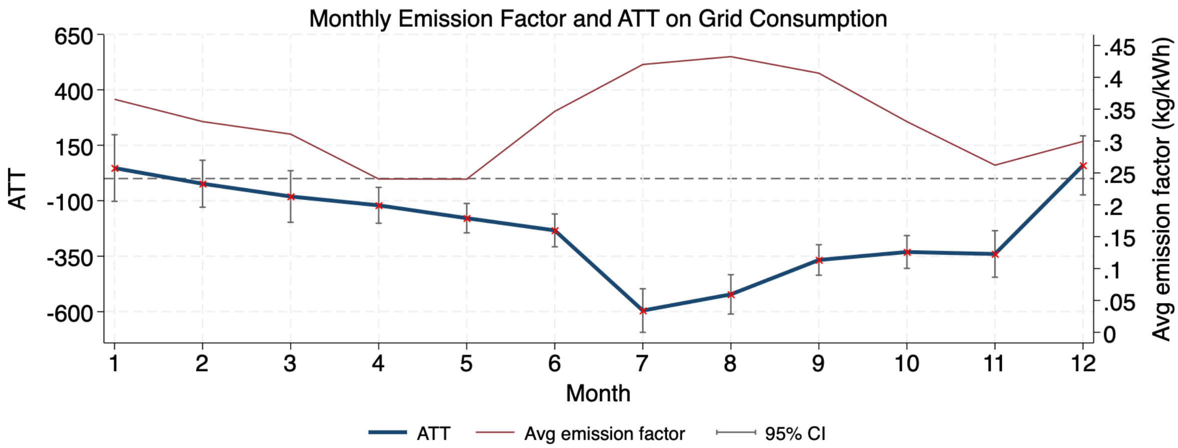
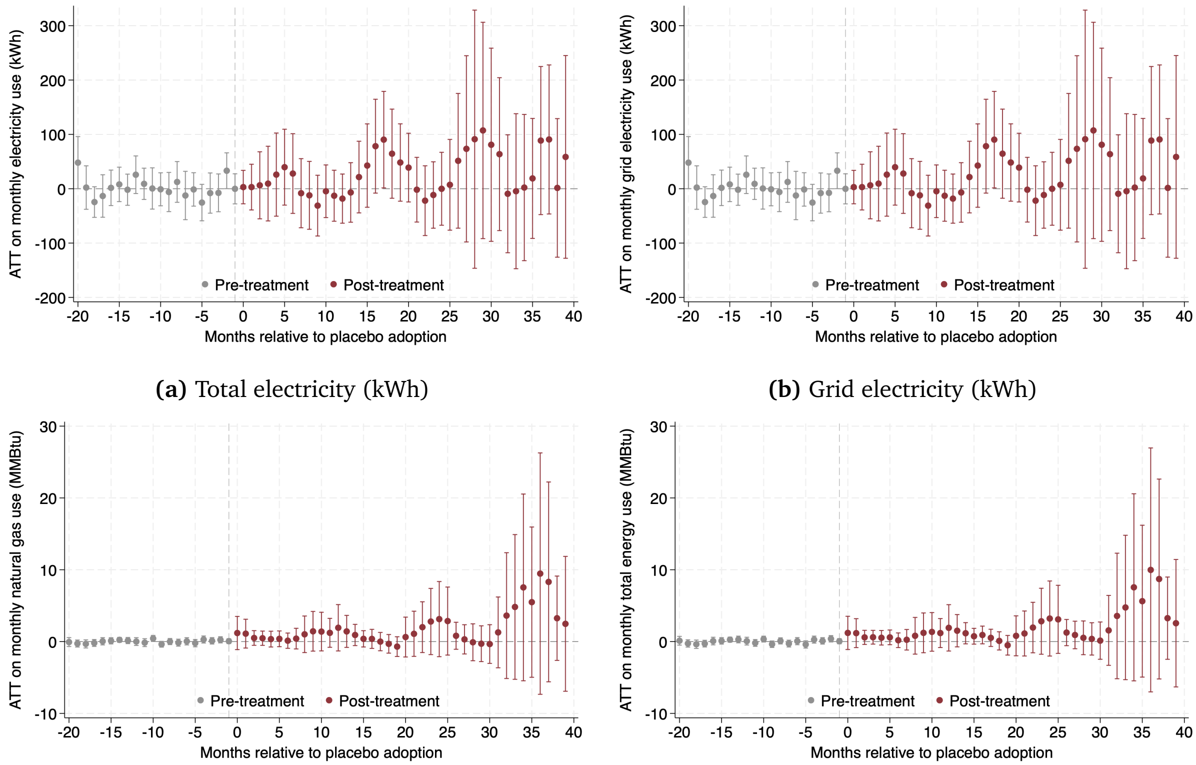


Figure C.14: Monthly ATT and emission factor

SUTVA and placebo test. Identification relies on the Stable Unit Treatment Value Assumption (SUTVA), under which each household's potential consumption depends only on its own adoption status and timing, not on others' adoption. To probe spillovers, we assign each solar household's adoption timing to one randomly chosen nearby non-solar household (the placebo treatment), removing actual adopters from the sample. The placebo ATT estimates are statistically insignificant throughout the event window (Figure C.15), providing no evidence of strong local spillovers. Two caveats remain. We cannot rule out small or indirect interference outside geographic proximity, and residential solar is not a uniform treatment (systems differ in capacity, orientation, tilt, shading, and compensation), so the estimates are the average effect of adoption under the observed system characteristics.



(a) Total electricity (kWh)

(b) Grid electricity (kWh)

(c) Natural gas (MMBtu)

(d) Total energy (MMBtu)

Figure C.15: Event-study estimates for monthly energy consumption (placebo treatment sample)

Finally, the full-sample event study (Figure C.4) shows an inverted-U pattern. The monthly electricity rebound rises after adoption and then attenuates beyond about two years, consistent with households learning over time to balance self-consumption, grid exports, and overall use rather than with rising consumption among nearby non-adopters.

D Appendix to Part IV: Household Factors and Consumption

This appendix collects the background, data, and methodological detail relocated from the Part IV body, followed by the supplementary tables and figures that complement the main results.

D.1 Background and Motivation

Decomposing persistent consumption by fuel matters for policy because efficiency programs deliver value only when they reach the households where savings are largest, and because the answer shapes electrification planning. The gap between projected and realized savings is well documented, and one source is misallocation. Programs do not consistently reach the homes where reductions would be greatest (Allcott and Greenstone, 2012; Burlig et al., 2020; Fowlie et al., 2018). When a household switches from gas to electric heating, its heating load moves from a fuel governed mainly by the building envelope to one that also reflects appliances and occupant behavior, so the new electricity load a switch adds depends on which household switches. A utility that knows which characteristics drive each fuel can direct envelope measures, appliance programs, or behavioral tools to the households where each will do the most.

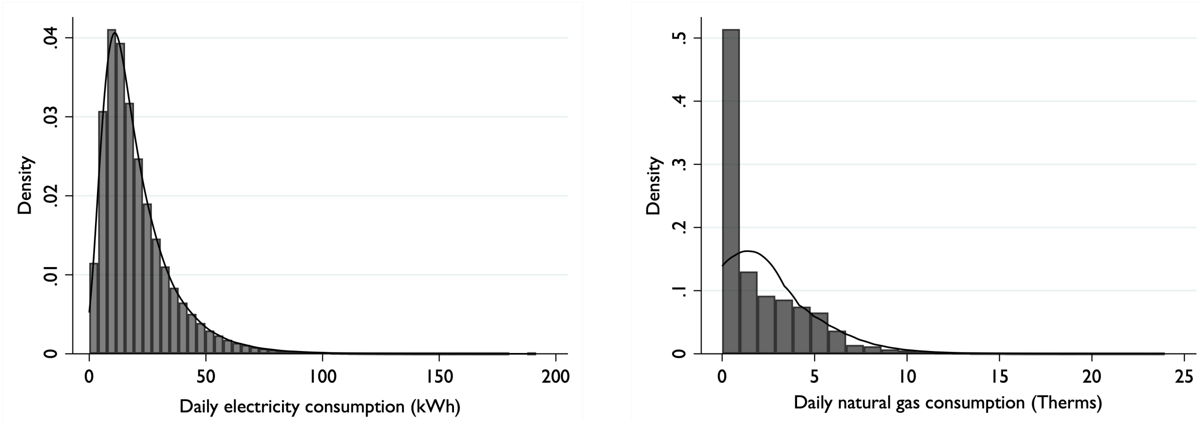
D.2 Data

This part draws on five linked data sources for Los Alamos County, New Mexico, spanning January 2022 through June 2025.

D.2.1 Smart Meter Consumption Data

The Los Alamos Department of Public Utilities (LADPU) provided household-level daily electricity and natural gas consumption records for about 8,500 residential accounts. Observations that violate physical limits are dropped: daily electricity readings above 200 kWh or 35 kWh per thousand square feet of home size, and daily gas readings above 25 therms[13] or 4 therms per thousand square feet. Negative reads, which indicate meter errors or manual adjustments, are also dropped. After trimming, the estimation panel contains approximately 695,000 household-days. Figure D.1 plots the post-trimming distribution of daily consumption for both fuels.

[13] Natural gas consumption is reported in therms throughout. One therm equals one CCF multiplied by an elevation factor (0.78 for Los Alamos, 0.81 for White Rock) and a monthly heat-content value from the LADPU cost-of-gas schedule. The mean conversion factor is approximately 0.81.



(a) Electricity **(b)** Natural gas

Figure D.1: Distribution of daily household consumption

Notes: Post-trimming distribution. Electricity consumption (kWh/day) is right-skewed with a mode near 10–15 kWh/day and a long upper tail. Natural gas consumption (therms/day) is mainly concentrated near zero with a heavy right tail. Most household-days fall below 2 therms/day, but cold winter days exceed 10 therms/day.

D.2.2 Household Survey

LADPU fielded a discrete choice experiment (DCE) survey to its residential customers via mail and email. The survey collected appliance portfolios, demographics, self-reported housing characteristics, behavioral measures, and perceptions about electrification from 631 households. Data collection ran from July to September 2025. The survey collects information about the primary fuels used for space heating, water heating, cooking, and clothes drying. It also records heating equipment type and age, rooftop solar ownership, and standard demographics including income, education, retirement status, work-from-home arrangements, ethnicity, and respondent age. Some data recoding is applied to a set of ordinal variables to make them suitable for regression analysis. The recoding details are documented in the notes to Table D.2.

D.2.3 Property Characteristics

Property records were manually collected from online real estate platforms and linked to survey respondents via street-address matching. We replace survey-stated square footage, house age, and bedroom counts with scraped values. Figure D.2 plots survey-reported home size against scraped values. The close alignment along the 45-degree line, with no systematic over- or under-reporting, speaks to the quality of the survey responses more broadly.[14] Residence type is consolidated into three categories: single-family detached, mobile or manufactured homes, and multi-family structures.

[14] Table D.9 in the appendix confirms that gaps between survey-reported and scraped measures are not systematically related to household demographics.

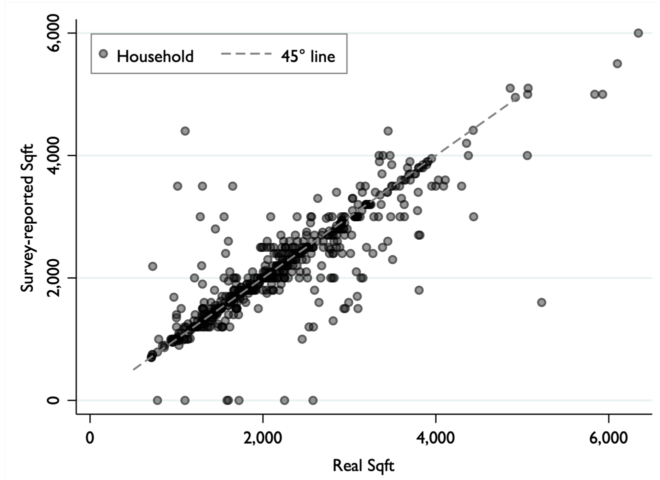


Figure D.2: Survey-reported versus scraped home size

Notes: The 45-degree line indicates perfect agreement. The close alignment, with no evidence of systematic misreporting, supports the reliability of the survey data.

D.2.4 Weather Data

We collect weather variables from the PRISM Climate Group's 800 m daily gridded product, extracted at the centroids of Los Alamos and White Rock. The variables include daily mean temperature, dewpoint temperature, vapor pressure deficit, diurnal temperature range, and total precipitation. Table D.1 summarizes the weather characteristics of the estimation window. The high-desert environment at about 7,300 feet elevation produces large diurnal temperature swings and low humidity. The mean daily temperature is 11.0°C, ranging from −13.4°C to 30.7°C, and precipitation falls on about a quarter of the year. Typical-weather profiles, used to construct the baseline expected loads, are computed from day-of-year PRISM averages weighted by the observed calendar composition of each energy carrier's Step 2 sample.

Table D.1: PRISM Weather Summary (Jan 2023– Dec 2025)

	Mean	SD	Min	Max
Daily mean temperature (°C)	10.97	9.02	−13.40	30.70
Dewpoint temperature (°C)	−3.01	7.98	−24.20	16.00
Vapor pressure deficit (hPa)	11.04	7.42	0.40	40.10
Diurnal temperature range (°C)	13.77	3.72	1.90	27.10
Daily precipitation (mm)	1.03	2.88	0.00	39.40

Notes: Data for the daily panel across the estimation window (2023–2025; N = 695,244 household-days). Dewpoint and vapor pressure deficit capture the high-desert environment. The diurnal range reflects the large day–night temperature swings at 7,300 ft elevation. Rain falls on 26.0% of days.

D.2.5 Additional Data Sources

Electric vehicle registrations were matched to survey respondents using address-level records from the New Mexico Motor Vehicle Division. Active battery-electric and plug-in hybrid registrations in Los Alamos and White Rock were linked to survey street addresses, yielding 15 matched households out of 214 active registrations. The matched share, 2.4% of survey households (15 of 631), aligns closely with the county-wide EV/PHEV ownership rate of 2.6% (214 of 8,247 occupied housing units from the ACS).

The American Community Survey (ACS) 2024 five-year estimates for Los Alamos County report 8,247 occupied housing units, of which 81.6% use natural gas as the primary heating fuel and 15.0% use electricity. These proportions align closely with the survey sample (90.0% using natural gas and 8.0% using electricity), supporting its representativeness on heating-fuel composition.

Table D.2: Descriptive Statistics: Step 2 Model Variables

	Mean	SD	*N*
Panel A: Housing Structure			
Home size (1,000 Sqft)	2.17	0.89	566
Stories	1.51	0.61	569
Residence age (decades)	3.99	0.82	573
Residence type			
Single-family detached	0.82	—	625
Mobile / manufactured	0.13	—	625
Multi-family	0.03	—	625
Has garage	0.77	—	571
Panel B: Appliance Portfolio			
Primary heating fuel			
Electric	0.08	—	610
Natural gas	0.90	—	610
Cooking fuel			
Electric	0.37	—	607
Natural gas	0.61	—	607
Water heating fuel			
Electric	0.09	—	510
Natural gas	0.90	—	510
Dryer fuel			
Electric	0.75	—	600
Natural gas	0.25	—	600
Has rooftop solar	0.13	—	631
Has EV or PHEV	0.02	—	631
Panel C: Demographics			
High income ($100k+)	0.78	—	565
Graduate degree	0.60	—	582
Works from home	0.28	—	572
Respondent age (years)	57.97	16.74	581
Hispanic	0.08	—	560
Renter	0.04	—	575
Retired	0.39	—	572
Panel D: Usage & Equipment			
Dryer: Uses ≥2 times/week (share)	0.70	—	602
Heating equipment ≥10 years old (share)	0.59	—	595

Notes: Statistics use one observation per survey respondent household. Proportions are reported for binary and categorical indicators (SD omitted as fully determined by the mean). Dryer use and heating equipment age are self-reported on ordinal scales and recoded to continuous measures for the regression analysis: dryer use is mapped to approximate times per week (1→0, 2→0.5, 3→1, 4→2.5, 5→5), and heating equipment age is mapped to year midpoints (1→1, 2→3, 3→7, 4→12, 5→17, 6→22). The shares reported in Panel D use the recoded continuous measures. *N* reports non-missing household observations for each variable. The complete descriptive table (reporting raw survey scales) is in Appendix Table D.4.

D.3 Empirical Strategy

A household's daily electricity and natural gas consumption depends not only on housing structure, appliances, and demographics, but also on factors that vary frequently, namely weather and calendar effects (Hor et al., 2005; Kang and Reiner, 2022; Zhang and Zhou, 2019). On cold winter days, households use more electricity or natural gas, depending on their appliances, to heat their home. Electricity consumption likewise increases on hot summer days to cool homes. On weekends, people are more likely to stay at home and consume more energy.

We use the fixed-effects filtered (FEF) estimator of Pesaran and Zhou (2018) to recover how time-invariant household characteristics relate to energy use. The challenge this estimator addresses is that the characteristics of interest (home structure, appliances, and demographics) are stable over time. A standard two-way fixed effects (TWFE) regression cannot identify the relationship between time-invariant covariates and energy use, because the fixed-effect term absorbs everything constant within a household that weather and calendar cannot explain statistically. FEF instead proceeds in two steps. A first step uses the daily panel to estimate the common weather and calendar response and filters it from consumption. The remaining component bundles households' time-invariant traits, observed and unobserved. A second step then takes this household-specific component and regresses it on the observed characteristics using ordinary least squares (OLS).

The estimation panels comprise 580 surveyed households for electricity, of which 562 also have a natural gas smart meter. Each household is observed daily from January 2022 through June 2025. Each household has an average of 1,080 daily observations for electricity and 1,073 for natural gas, with a minimum of six months. Both steps are estimated separately for each energy carrier.

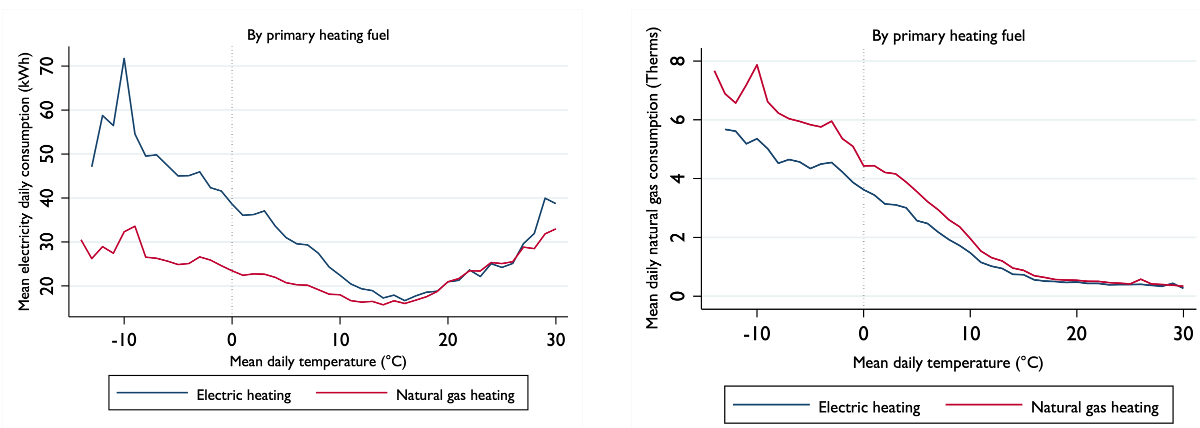
D.3.1 Step 1: Time-Varying Demand Filter

Daily consumption is dominated by two components that are unrelated to persistent household differences. The first component is weather, which includes ambient air temperature, humidity, and precipitation. Temperature is the primary driver behind daily fluctuations because it determines both heating and cooling usage. Humidity adds to the cooling load by making air feel hotter and by forcing air conditioners to work harder at a given temperature. Precipitation matters indirectly by keeping people indoors.

Figure D.3 plots mean daily consumption against daily mean temperature in 1°C bins, separated by each household's primary heating appliance fuel. The figure shows electricity consumption following a U-shape. It rises with cooling load in summer for all households and rises again with heating in winter. The cold-side response is steeper among households that heat primarily with electricity than among those that heat with natural gas. The figure shows that natural gas consumption declines monotonically with temperature for both heating groups. Consumption does not rise on the warm range since natural gas serves no cooling load. Both groups consume more natural gas as temperature falls, but homes that are primarily gas-heated sit consistently above electrically-heated homes throughout the cold range. The temperature response differs by heating fuel, which motivates interacting primary heating fuel with temperature in Step 1.

The second component is the calendar. Energy consumption behavior depends on the month of the year (seasons) and on the day of the week. The former factor captures changes related to holidays, school breaks, and day length which shift consumption independently of weather patterns. Similarly, the latter factor mainly captures the effect of people spending more time at home during weekends than during weekdays. Our sample displays expected behavior. Electricity consumption peaks during winter months that are both colder and coincide with the holiday season spanning November and January. It peaks again during summer months, which are both hotter and coincide with the school break (see Appendix Figure D.7). Natural gas consumption mostly peaks during fall and winter and falls to the baseline level during the rest of the year. This pattern can be mostly explained by space heating being the heaviest use for natural gas.

Temperature and calendar effects are entangled, so we include both in the Step 1 filtering specification. Step 1 removes these two components from each household's daily consumption so that the remaining part can be interpreted as a household-level baseload.



(a) Electricity **(b)** Natural gas

Figure D.3: Mean daily consumption versus daily mean temperature, by primary heating fuel

Notes: Mean daily consumption by 1°C temperature bin, separated by primary heating fuel. Bins with fewer than five household-day observations are excluded.

For each energy carrier we estimate a household fixed-effects regression of the form

$$y_{it} = f(T_{it};\theta) + \mathbf{W}_{it}'\psi + \delta_t + \alpha_i + \varepsilon_{it}, \tag{D.1}$$

where y_{it} is daily consumption for household i on date t. The temperature-response function

$f(T_{it};\theta)$ captures how daily mean temperature (°C) maps to consumption. The vector $\mathbf{W}_{it}$ contains the remaining weather covariates. Humidity enters through dewpoint temperature (°C) and vapor pressure deficit (hPa). The weather vector also includes total daily precipitation (mm) and a rainy-day indicator. Within-day temperature variation is captured through the diurnal range (°C). The term δ_t collects the calendar controls, namely day-of-week, month-of-year, and year indicators. The household fixed effect α_i absorbs every time-invariant household characteristic (during the study period), including those captured in our data (housing structure, appliance portfolios, and demographics).

The main specification models $f(T_{it};\theta)$ semiparametrically. Daily mean temperature is divided into 5°C bins, with a separate coefficient estimated for each:

$$f(T_{it};\theta) = \sum_{b=1}^{B} \theta_b \cdot \mathbf{1}[T_{it} \in \text{bin}_b] + \sum_{b=1}^{B} \tau_b \cdot \mathbf{1}[T_{it} \in \text{bin}_b] \cdot h_i, \tag{D.2}$$

where the 15–20°C bin serves as the omitted reference category and h_i is a binary indicator for primary heating fuel (i.e., electricity or natural gas). The semiparametric form does not restrict the temperature response to any given shape, making it the most flexible option to absorb the time-varying signal among the specifications we consider. A disadvantage is that it produces parameters that are less interpretable than a polynomial or HDD/CDD parameterization. [15]

Binned temperature specifications originate with Schlenker and Roberts (2006) and Schlenker and Roberts (2009) in the climate-yield literature and have since become common for estimating weather effects across environmental and energy economics applications (Aroonruengsawat and Auffhammer, 2011; Auffhammer, 2022; Auffhammer et al., 2017; L. W. Davis and Gertler, 2015; Deschênes and Greenstone, 2011).

Electric and natural gas heating systems have fundamentally different thermal response mechanisms. Therefore, equation (D.2) includes the heating-fuel interaction τ_b. This is the only household-level interaction with temperature we allow in Step 1. Adding further interactions (e.g., home size, residence age, or appliance ownership) would risk absorbing baseload household signal that belongs in Step 2 estimation.

D.3.2 Step 2: Baseload Decomposition

Step 2 explains the household baseload component $\bar{\hat{u}}_i \equiv T_i^{-1} \sum_{t=1}^{T_i} \hat{u}_{it}$, the within-household time average of the Step 1 residual $\hat{u}_{it} = y_{it} - \hat{f}(T_{it}) - \mathbf{W}'_{it}\hat{\psi} - \hat{\delta}_t$. Following Pesaran and Zhou (2018), this residual subtracts only the time-varying components of equation (D.1), so it retains the

[15] Appendix Table D.5 compares this specification against four parametric families (polynomials, restricted cubic splines, heating- and cooling-degree days, and piecewise linear splines) on within-R^2 and holdout RMSE. All considered specifications perform similarly, so the semiparametric choice carries no fit cost.

household-specific level that the fixed effect α_i absorbs in Step 1. It is therefore on the scale of the household's typical daily consumption.

The following progressive sequence of cross-sectional regressions is estimated:

$$\bar{u}_i = \beta_0 + \mathbf{Z}_i^{\text{housing}}\beta_1 + \mathbf{Z}_i^{\text{appliance}}\beta_2 + \mathbf{Z}_i^{\text{demo}}\beta_3 + \eta_i, \tag{D.3}$$

This paper estimates three specifications, each nesting the previous one and adding a group of characteristics.

The first model (M1) captures the home's physical capacity to consume energy. This includes house size (SqFt) and age, number of stories, and residence type (single-family, multi-family, mobile). These characteristics capture the home's geometry and proxy for its thermal envelope. Larger and older homes require more energy to heat in winter and to cool in summer. This model also conditions on whether the house has a solar rooftop system, which offsets metered electricity use.

The second model (M2) adds the appliance and technology stock, which converts energy into services. The type of appliance a household uses determines which carrier they use for a given service (electricity or natural gas). For instance, a household with electric water heating is expected to draw more persistent electricity and less natural gas than one with gas water heating. Observing consumption in both energy carriers allows us to study the cross-fuel tradeoff of using different types of appliances.

The third model (M3) adds household demographic characteristics such as income, education, ethnicity, and retirement status. Income and education proxy for both the quality and quantity of appliances and devices used at home. Higher-earning households are more likely to own more devices and therefore use more electricity. They are also more likely to purchase costly but efficient appliances and devices. Retirement and working from home proxy for more time spent at home using energy.

Los Alamos county is a high-income, highly educated national laboratory community. Therefore, income and education enter the model as indicators rather than continuous measures. We use a high-income indicator for households earning over $100,000 and a graduate-degree indicator. The models progress from the house's structure, to the equipment within it, to the characteristics of its occupants.

Each coefficient gives the change in the household-level persistent component $\bar{\hat{u}}_i$ associated with a unit change in the corresponding characteristic, conditional on other covariates in the model. The coefficients for electricity and natural gas are in kWh/day and therms/day, respectively.

The dual energy carrier feature of our data allows us to compare how each characteristic relates to electricity and to natural gas for the same households. This can reveal whether a factor shifts demand between the two carriers or relates to only one.

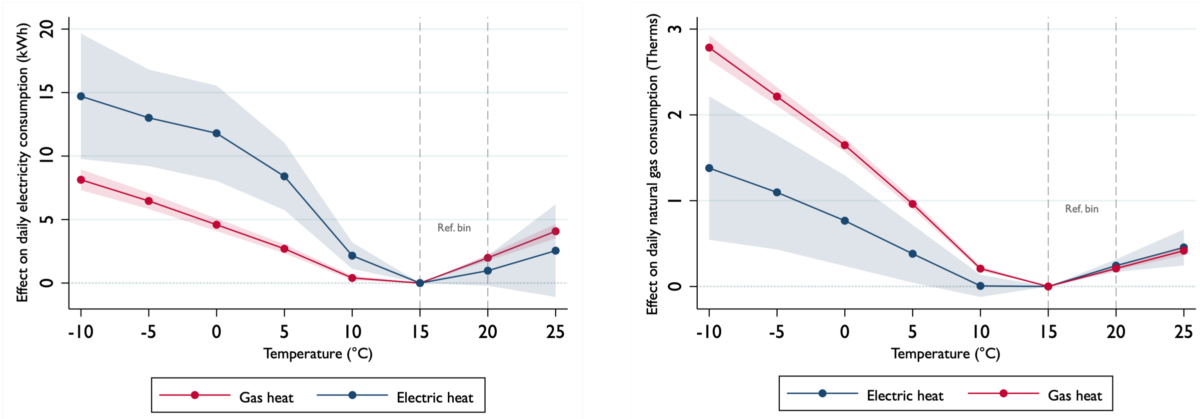
D.4 Step 1 Estimates: Temperature Response and Model Fit

Figures D.4a and D.4b plot the semi-parametric Step 1 temperature-response estimates for each energy carrier, with households grouped by primary heating fuel. Each point is a bin-level coefficient relative to the 15–20°C reference comfort bin.

For electricity, both heating-fuel groups consume more than their reference level as temperature falls (Figure D.4a). On the cold side, the response splits by heating fuel: in the −5 to 0°C level, homes that are primarily electrically heated consume about 13.2 kWh per day above their reference level, twice the 6.5 kWh response of primarily gas-heated homes. This gap persists through colder temperature levels. On the warm side, the two groups' responses are statistically indistinguishable. Consumption rises with temperature, but more modestly compared to the sharp response to cold weather. The cold side splits by heating fuel and the warm side does not because the two sides activate different end uses. Cold weather activates space heating, whose primary fuel differs across households, while warm weather activates cooling, which is delivered by electric air conditioning regardless of how a home is heated.

The natural gas response mirrors that of electricity, except that it is the primarily gas-heated homes whose consumption rises most sharply as temperature falls (Figure D.4b). On the cold side, the response again splits by heating fuel. At the −5 to 0°C level, gas-heated homes consume 2.2 therms per day above their reference level, twice the response of primarily electrically heated homes (1.1 therms). Unlike the electricity gap that persists at a stable size, this gap widens as temperature falls. It reaches about 2.8 therms at the −10 to −5°C level. Primarily electrically heated homes respond on the gas meter as well, although more weakly. This is because not all of them are fully electric in heating. 64.7% of them have gas water heaters which draw more gas on colder days. Some may also operate secondary gas heating. On the warm side, both groups show a nearly flat response.

For both carriers, estimates show wider 95% confidence intervals closer to the end tails of the temperature range where the panel contains fewer days with such levels (see Appendix D.6). The 95% C.I. band for primarily electrically heated homes is wider at every temperature level, since the group makes up only 8% of the sample. Nonetheless, the heating-fuel interaction remains statistically significant at the 95% level.



(a) Electricity

(b) Natural Gas

Figure D.4: Semiparametric Step 1 temperature-response estimates

Notes: Each point is a bin-level coefficient relative to the 15–20°C reference bin (vertical dashed lines). Shaded ribbons give 95% confidence intervals. Household fixed effects and calendar controls are included. Bins with fewer than five observations are omitted.

Table D.3 reports the remaining weather covariates and calendar blocks from the preferred specification. Households consume more of both electricity and natural gas on days with precipitation. Relative to average daily use (20.03 kWh/d for electricity, 2.09 therms/d for gas), a rainy day is associated with 10.6% higher natural gas use, against only a 2.0% effect for electricity use. This is expected considering people are more likely to stay indoors. A wider diurnal temperature range is associated with lower consumption of both carriers (−0.13% per °C for electricity and −0.33% per °C for natural gas). Large temperature swings allow for natural night cooling, which reduces the need for air conditioning during the day. Similarly, sunnier days deliver solar gain, which offsets the need for heating. For calendar effects, results show that month-of-year and day-of-week coefficients are jointly significant ($p < 0.0001$). This confirms that calendar variation also explains day-to-day consumption beyond the variation in weather that is controlled for.

The most important Step 1 result is the contrast in the regression's explanatory power across carriers. Weather and calendar variables account for 63.5% of the daily variation in a household's daily consumption in natural gas, but only 9.3% for electricity. Daily natural gas use is therefore tightly governed by thermal conditions and seasonal timing. Electricity use contains a larger non-weather component, which likely reflects appliance use, occupancy, and the number and type of electric devices used in the home. Step 2 investigates this contrast even further using the cross-sectional household (survey) and housing characteristics. [16]

[16] The lower electricity within-R^2 does not undermine the second step. The purpose of Step 1 is to remove time-varying variation before explaining the remaining household-level component.

Table D.3: Step 1 Weather and Calendar Controls (Semiparametric 5°C Bin Specification)

	Electricity		Natural Gas	
Dep. variable: daily consumption	kWh/day		therms/day	
	Coef.	t	Coef.	t
Weather covariates				
Precipitation (mm)	0.063***	11.37	0.004***	6.14
Dewpoint (°C)	0.021**	2.12	−0.035***	−21.73
Vapor pressure deficit (hPa)	0.145***	9.28	−0.038***	−20.87
Diurnal temperature range (°C)	−0.026***	−2.93	−0.007***	−6.25
Rainy day (0/1)	0.405***	9.56	0.222***	27.90
Calendar fixed effects (joint F-test)				
Day-of-week (6)	$F(6, 592) = 60.78$		$F(6, 576) = 95.34$	
Month-of-year (11)	$F(11, 592) = 78.54$		$F(11, 576) = 189.19$	
Year (3)	$F(3, 592) = 46.48$		$F(3, 576) = 40.51$	
Households	580		562	
Household-days	626,536		602,918	
Within-R^2	0.093		0.635	

Notes: Standard errors clustered by household. All specifications include household fixed effects and 5°C temperature bins interacted with primary heating fuel. Temperature-response coefficients are shown in Figure D.4. Calendar coefficients are not reported for brevity. Joint F-tests against zero are reported instead. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure D.5 shows the cross-household distribution of the persistent component for electricity and natural gas. The figure shows that substantial household heterogeneity remains after the Step 1 filter. The remaining variation further motivates the Step 2 decomposition.

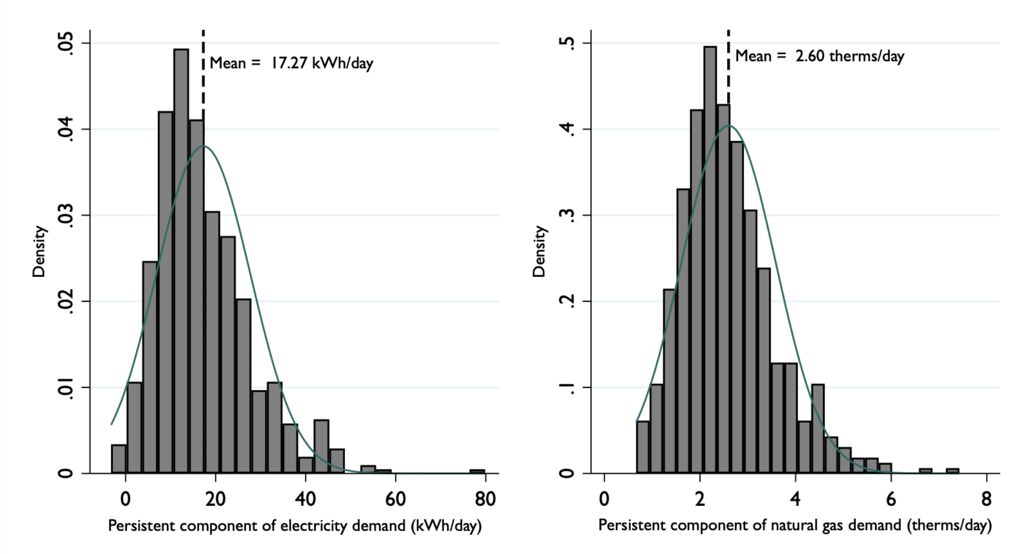


Figure D.5: Distribution of the household persistent component, by energy carrier.

Notes: The persistent component of energy demand $\bar{u}_i$ is the household-level average of the Step 1 residual $\hat{u}_{it}$. Vertical lines mark sample means.

D.5 Expanded Descriptive Statistics

Table D.4: Expanded Survey Respondent Descriptive Statistics

	Mean/share	SD	Range	*N*
Panel A: Housing Structure				
Home size (1,000 Sqft)	2.17	0.89	[0.00, 6.00]	566
Bedrooms	3.34	0.81	[1.00, 5.00]	567
Stories	1.51	0.61	[1.00, 3.00]	569
Residence age (decades)	3.99	0.82	[1.00, 5.00]	573
Residence type				
Single-family detached	0.82	—	—	625
Mobile/manufactured	0.13	—	—	625
Multi-family	0.03	—	—	625
Renter	0.04	—	—	575
Has garage	0.77	—	—	571
Conditional on having a garage				
Garage heated	0.14	—	—	438
Garage insulated	0.85	—	—	60
Panel B: Primary Space Heating				

Continued on next page

Table D.4 – continued

	Mean/share	SD	Range	*N*
Equipment type				
Central furnace	0.58	—	—	613
Steam/hot water	0.32	—	—	613
Heat pump (central or ductless)	0.06	—	—	613
Other (built-in elec/gas, wood, fireplace, etc.)	0.05	—	—	613
Primary heating fuel				
Electric	0.08	—	—	610
Natural gas	0.90	—	—	610
Propane (bottled gas)	0.00	—	—	610
Wood or pellets	0.01	—	—	610
Other (fuel oil, other)	0.01	—	—	610
Heating equipment age (1–6)	4.01	1.76	[1.00, 6.00]	595
Has secondary heating system	0.68	—	—	610
Main heating use frequency (1–5)	1.17	0.63	[1.00, 4.00]	610
Panel C: Appliance Portfolio				
Cooking appliance ownership				
Has range	0.77	—	—	631
Has cooktop	0.35	—	—	631
Has wall oven	0.29	—	—	631
Range fuel (conditional on having range)				
Electric	0.34	—	—	486
Natural gas	0.63	—	—	486
Other (propane, dual-fuel)	0.03	—	—	486
Cooktop fuel (conditional on having cooktop)				
Electric	0.42	—	—	219
Natural gas	0.57	—	—	219
Propane	0.01	—	—	219
Wall oven fuel (conditional on having wall oven)				
Electric	0.83	—	—	183
Natural gas	0.17	—	—	183
Has outdoor grill	0.58	—	—	611
Water heating fuel				
Electric	0.09	—	—	510
Natural gas	0.90	—	—	510
Has second water heater	0.11	—	—	606
Water heater age (1–6)	3.53	1.61	[1.00, 6.00]	499
Dryer				
Has dryer	0.99	—	—	610
Dryer fuel: Electric	0.75	—	—	600
Dryer fuel: Natural gas	0.25	—	—	600
Dryer age (1–6)	3.06	1.48	[1.00, 6.00]	594

Continued on next page

Table D.4 – continued

	Mean/share	SD	Range	*N*
Has pool heater	0.03	—	—	610
Has rooftop solar	0.13	—	—	631
EV / PHEV ownership				
Has EV or PHEV	0.02	—	—	631
Has more than one EV	0.00	—	—	631
Panel D: Demographics				
Household size	2.52	1.50	[0.00, 15.00]	317
Respondent age	57.97	16.74	[18.00, 120.00]	581
Female	0.37	—	—	574
Hispanic	0.08	—	—	560
Graduate degree	0.60	—	—	582
High income (100k+)	0.78	—	—	565
Respondent is retired	0.39	—	—	572
Works from home	0.28	—	—	572
Panel E: Usage & Behavior				
Dryer use frequency (1–5)	3.89	0.98	[1.00, 5.00]	602
Cooktop use frequency (1–5)	2.17	0.82	[1.00, 5.00]	485
Oven use frequency (1–6)	3.58	1.03	[1.00, 6.00]	484
Indoor temperature, day (°F)	68.74	3.09	[58.00, 78.00]	420
Indoor temperature, evening (°F)	65.14	4.77	[45.00, 76.00]	411
Indoor temperature, night (°F)	65.13	4.62	[45.00, 78.00]	417
Gas appliance satisfaction (1–5)	1.52	0.87	[1.00, 5.00]	578
Equipment age (1–6 scale)				
Main heating	4.01	1.76	[1.00, 6.00]	595
Water heater	3.53	1.61	[1.00, 6.00]	499
Dryer	3.06	1.48	[1.00, 6.00]	594
Panel F: Billing, Engagement & Attitudes				
Has usage dashboard	0.48	—	—	629
Tracks usage regularly	0.77	—	—	301
Receives energy assistance	0.01	—	—	623
Utilities included in rent	0.04	—	—	25
Perceived need for panel upgrade	0.74	—	—	419

Supports 2070 carbon-free goal	0.28	—	—	419

Notes: Statistics are computed using one observation per survey respondent household. For binary variables and mutually exclusive categories, the Mean/share column reports the proportion equal to one; SD and range are omitted (–) because the support is $\{0,1\}$. Range is shown as [minimum, maximum] for non-binary variables. N reports non-missing household observations for each row. Fuel shares may not sum exactly to one due to small other-fuel categories and item nonresponse. Table reports raw survey scales. For the regression analysis, heating equipment age and dryer use frequency are recoded to continuous measures (see main-text Table D.2 notes for the mapping). Water heater age, dryer age, cooktop/oven use frequency, and heating use frequency remain on their original ordinal scales. Shared-row variables are computed on the conditional sample (e.g., garage characteristics on garage-owning households).

D.6 Step 1 Model Comparison

Table D.5 reports Step 1 comparison metrics across candidate temperature specifications for both energy carriers. We report within-R^2 (filtering quality) and holdout RMSE from a 20% random validation split. The semiparametric 5°C bin model is the main specification. All other entries are robustness checks. RMSE is reported on the original scale and is not comparable across energy carriers.

Table D.5: Step 1 Model Comparison

	Electricity			Natural Gas		
Model	d.f.	R^2_w	RMSE_{out}	d.f.	R^2_w	RMSE_{out}
Semiparametric						
5°C bins (main)	18	0.095	10.14	18	0.632	1.503
Restricted cubic splines						
RCS (4 knots)	6	0.098	10.11	6	0.636	1.493
Polynomials						
Cubic	6	0.097	10.12	6	0.635	1.495
Quadratic	4	0.092	10.14	4	0.633	1.497
Heating / cooling degree days						
Quadratic HDD/CDD	8	0.096	10.13	8	0.636	1.493
Piecewise linear						
Knots at 0°C, 18°C	6	0.097	10.12	6	0.635	1.495

Notes: R^2_w = within-R^2 from the household fixed-effects regression. RMSE_{out} = root mean squared error on a 20% holdout split. d.f. = degrees of freedom consumed by the temperature specification. All models share the same calendar controls.

D.7 Progressive Step 2 Decomposition

Tables D.6 and D.7 report the specifications' progression M1 through M3, namely housing structure alone (M1), adding appliance portfolios (M2), and the full specification with demographics and behavioral controls (M3).

Table D.6: Progressive Step 2 Decomposition: Electricity

	M1: Housing	M2: +Appliances	M3: +Demo+Beh
Electric cooking		1.841**	1.471
		(0.931)	(0.893)
Electric water heating		3.539**	4.278**
		(1.595)	(1.718)
Electric dryer		0.627	1.428
		(1.008)	(0.969)
Rooftop solar		-3.444**	-3.723**
		(1.585)	(1.489)
Home size (1,000 sq ft)	4.439***	5.460***	4.897***
	(0.646)	(0.673)	(0.736)
Mobile/manufactured	-1.760	-2.324**	-2.115*
	(1.080)	(1.179)	(1.089)
Multi-family	-1.765	-2.778*	-2.013
	(1.711)	(1.589)	(1.659)
Residence age (decades)	-0.189	0.166	0.280
	(0.245)	(0.249)	(0.258)
Stories	-0.073	-0.309	0.386
	(0.748)	(0.765)	(0.829)
Renter	-3.574***	-3.589**	-4.587***
	(1.329)	(1.484)	(1.539)
High income ($100k+)			1.709
			(1.056)
Graduate degree			-1.098
			(0.860)
Works from home			0.970
			(1.037)
Respondent age			-0.068*
			(0.038)
Retired			3.306***
			(1.261)

Continued on next page

Table D.6 continued

	M1: Housing	M2: +Appliances	M3: +Demo+Beh
Dryer use (times/week)			1.587***
			(0.282)
Main heating age (yrs)			0.007
			(0.057)
Observations	533	438	418
R^2	0.197	0.250	0.328
Adjusted R^2	0.188	0.233	0.300
Mean persistent component (kWh/day)	17.080	17.159	17.215
Predicted persistent baseline	.	16.091	15.660

Notes: Standard errors in parentheses. Residence-type coefficients are relative to single-family detached homes. is unobserved in the electricity M3 sample and omitted. * pi0.10, ** pi0.05, *** pi0.01.

Table D.7: Progressive Step 2 Decomposition: Natural Gas

	M1: Housing	M2: +Appliances	M3: +Demo+Beh
Electric cooking		-0.089	-0.061
		(0.080)	(0.082)
Electric water heating		-0.300**	-0.249
		(0.141)	(0.155)
Electric dryer		-0.182*	-0.157*
		(0.093)	(0.089)
Rooftop solar		-0.367***	-0.219*
		(0.117)	(0.122)
Home size (1,000 sq ft)	0.664***	0.677***	0.683***
	(0.059)	(0.067)	(0.073)
Mobile/manufactured	-0.081	-0.114	-0.099
	(0.112)	(0.117)	(0.118)
Multi-family	-0.175	-0.114	-0.043
	(0.135)	(0.139)	(0.154)
Residence age (decades)	0.033	0.039*	0.048**

Continued on next page

Table D.7 continued

	M1: Housing	M2: +Appliances	M3: +Demo+Beh
	(0.022)	(0.023)	(0.023)
Stories	-0.096	-0.097	-0.157*
	(0.077)	(0.082)	(0.085)
Renter	-0.282	-0.280	-0.417*
	(0.185)	(0.213)	(0.246)
High income ($100k+)			0.123
			(0.106)
Graduate degree			-0.019
			(0.077)
Works from home			-0.131
			(0.090)
Respondent age			0.003
			(0.004)
Retired			-0.027
			(0.124)
Dryer use (times/week)			0.065***
			(0.024)
Main heating age (yrs)			0.015***
			(0.005)
Observations	520	427	406
R^2	0.366	0.396	0.440
Adjusted R^2	0.358	0.381	0.415
Mean persistent component (therms/day)	2.605	2.586	2.592
Predicted persistent baseline	.	2.826	2.778

Notes: Standard errors in parentheses. Residence-type coefficients are relative to single-family detached homes. * pi0.10, ** pi0.05, *** pi0.01.

D.8 Typical-Weather Expected-Load Decomposition

Table D.8 reports the expected-load decomposition that translates the Step 2 persistent-component coefficients into shares of typical daily consumption, evaluated under day-of-year PRISM averages for Los Alamos and White Rock. Total expected daily load is the sum of the household persistent component and the Step 1 weather component. These totals serve as the denominators for the % of typical calculations in the main results table.

Table D.8: Expected Daily Load Under Typical Weather

	Electricity (kWh/day)	Natural Gas (therms/day)
Step 1 typical-weather component	2.523	−0.899
Step 2 persistent baseline ($\hat{\alpha}_0$)	17.397	2.597
Total expected daily load	19.920	1.698
Observed mean daily load	19.920	2.096
Typical vs actual weather effect	−0.000	−0.398
Model fit gap (actual weather)	0.030	0.015
Weather variation (typical − actual)	−0.030	−0.413

Notes: The persistent baseline $\hat{\alpha}_0$ is $\hat{\alpha}_0 \equiv \bar{y} - \bar{\mathbf{X}}'\hat{\boldsymbol{\beta}}$, the sample average of the household fixed effect recovered from the Step 1 semiparametric bins specification (the intercept of the Pesaran–Zhou cross-sectional regression). It represents expected consumption at the Step 1 reference category (January, Sunday, 15–20°C, no precipitation). The Step 1 weather component is the average deviation from this reference under PRISM day-of-year typical weather, evaluated with a 365-day unweighted grid at the sample-average household. The gap decomposition isolates model fit error (near zero by OLS identity) from the effect of replacing realized 2023–2025 weather with long-run PRISM climatology. The negative weather gap for gas indicates that 2023–2025 weather was, on net, more conducive to gas heating demand than the PRISM climatology. The observed mean daily load (19.920 kWh/d for electricity, 2.096 therms/d for gas) serves as the denominator for all % of mean calculations in Table 7.

D.9 Survey Misreporting Diagnostics

Some housing controls used in Step 2 are self-reported. Table D.9 examines whether the gap between survey-reported and scraped property measures is systematically related to demographics by regressing the signed error in square footage and bedroom count on household characteristics. The coefficients are uniformly small and mostly imprecise. Survey-scraped gaps are not systematically related to demographics, supporting the use of scraped values when available.

Table D.9: Survey-Scraped Misreporting: OLS Diagnostics

	Square footage error (%)	Bedroom count error
High income ($100k+)	-0.154**	-0.119
	(0.062)	(0.108)
Graduate degree	-0.018	0.002
	(0.034)	(0.079)
Household size	0.012	0.014
	(0.010)	(0.027)
Single-family detached	0.010	0.176*
	(0.034)	(0.093)
Renter	-0.099	0.071
	(0.136)	(0.197)
Works from home	0.009	-0.006
	(0.031)	(0.077)
Constant	0.112**	-0.035
	(0.056)	(0.121)
Observations	306	306
R^2	0.053	0.013

Notes: Signed error between survey-reported and scraped property characteristics. Square footage error (%) = $100 \times (\text{survey} - \text{scraped})/\text{scraped}$; bedroom count error = survey – scraped. Positive values indicate survey over-reporting. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.10 Temperature Distribution

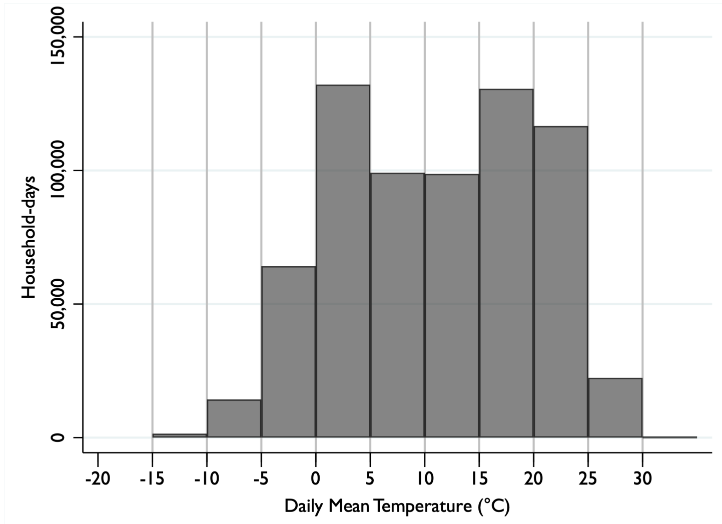
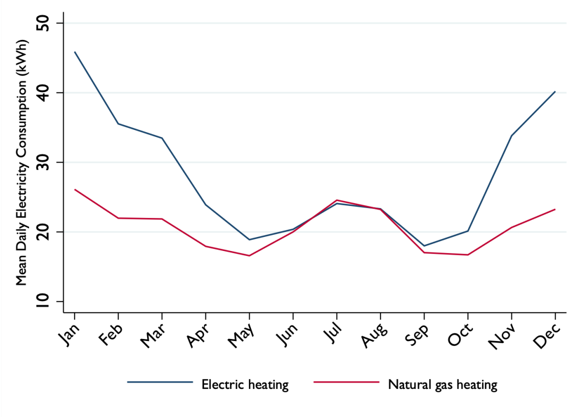


Figure D.6: Distribution of daily mean temperature

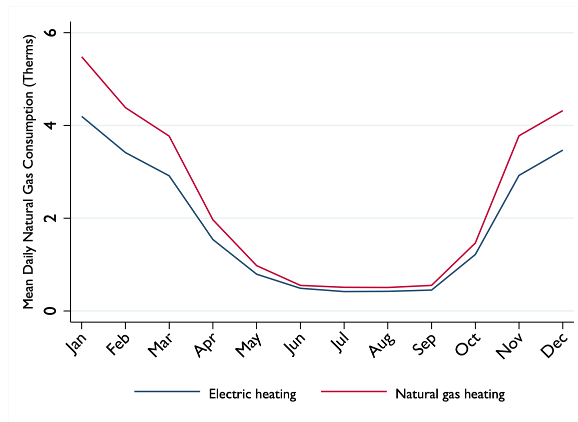
Notes: Estimation window covers January 2022 through June 2025.

D.11 Seasonal Consumption Patterns

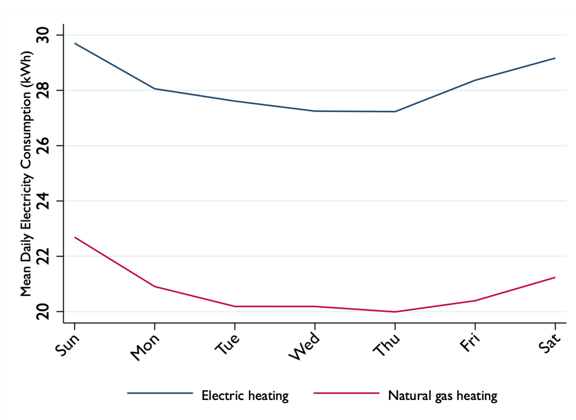
Figure D.7 reports mean daily consumption by month for each carrier, separated by primary heating fuel. Electricity displays two seasonal peaks, a summer peak driven by cooling load (common to both heating-fuel groups) and a winter peak driven by heating load (concentrated in households whose primary heating fuel is electric). Natural gas shows the expected winter-bowl shape, with the strongest winter rise among households whose primary heating fuel is gas. The calendar fixed effects in Step 1 (month-of-sample, day-of-week, and holiday indicators) absorb this systematic seasonal cycle so that the recovered household persistent component is not contaminated by the timing of when each household happened to be observed.



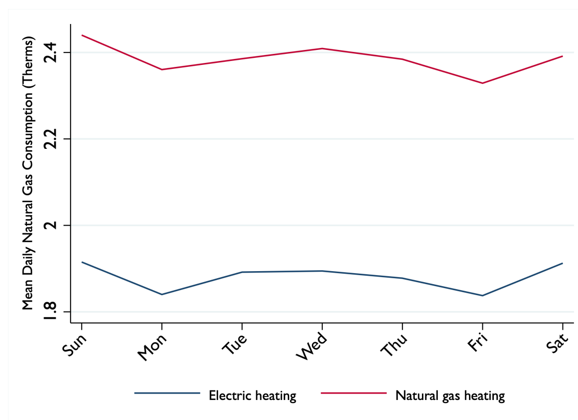
(a) Electricity, by month



(b) Natural gas, by month



(c) Electricity, by day of week



(d) Natural gas, by day of week

Figure D.7: Mean daily consumption by calendar cycle, by primary heating fuel

D.12 Step 2 (FEF) versus OLS on Mean Daily Consumption

This subsection compares the two-step FEF estimates with OLS on mean daily consumption. Figure D.8 shows the cross-sectional dispersion of daily mean temperature across households on a given day, which is small relative to the seasonal swing that Step 1 removes. Tables D.10 and D.11 report the natural-gas and electricity coefficients under both estimators.

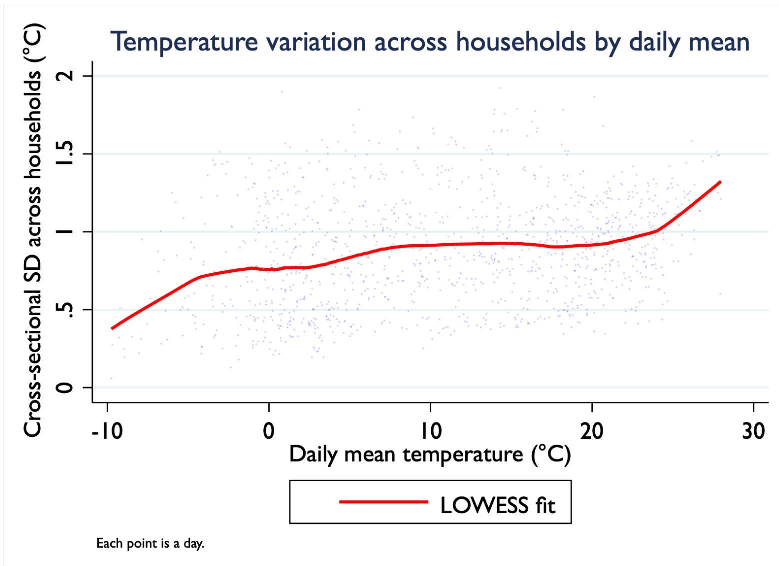


Figure D.8: Cross-sectional temperature variation across households by daily mean temperature

Notes: Each point is a day. The vertical axis reports the cross-sectional standard deviation of daily mean temperature across all households on that day.

Table D.10: Step 2 (FEF) versus OLS on mean daily consumption: Natural Gas

	FEF (persistent)		OLS (mean)	
	Coef.	SE	Coef.	SE
Housing structure				
Home size (1,000 sqft)	0.683***	(0.073)	0.683***	(0.068)
Residence type (ref: single-family detached)				
Mobile/manufactured	−0.099	(0.118)	−0.105	(0.119)
Multi-family	−0.043	(0.154)	−0.037	(0.155)
Residence age (decades)	0.048**	(0.023)	0.049**	(0.022)
Stories	−0.157*	(0.085)	−0.149*	(0.086)
Renter	−0.417*	(0.246)	−0.422*	(0.244)
Appliance portfolio				
Electric cooking	−0.061	(0.082)	−0.059	(0.076)
Electric water heating	−0.249	(0.155)	−0.262*	(0.142)
Electric dryer	−0.157*	(0.089)	−0.155*	(0.082)
Rooftop solar	−0.219*	(0.122)	−0.210*	(0.111)

Table D.10 – continued

	FEF (persistent)		OLS (mean)	
	Coef.	SE	Coef.	SE
Demographics & occupancy				
High income ($100k+)	0.123	(0.106)	0.095	(0.101)
Graduate degree	–0.019	(0.077)	–0.016	(0.071)
Works from home	–0.131	(0.090)	–0.117	(0.084)
Respondent age	0.003	(0.004)	0.002	(0.004)
Retired	–0.027	(0.124)	–0.011	(0.116)
Dryer use (times/week)	0.065***	(0.024)	0.064***	(0.023)
Heating equip. age (yrs)	0.015***	(0.005)	0.015***	(0.005)
Observations	406		406	
R^2	0.440		0.511	

Notes: Robust standard errors in parentheses. Both columns estimate the same M3 specification. The FEF dependent variable is the household persistent component. The OLS dependent variable is mean daily consumption. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.11: Step 2 (FEF) versus OLS on mean daily consumption: Electricity

	FEF (persistent)		OLS (mean)	
	Coef.	SE	Coef.	SE
Housing structure				
Home size (1,000 sqft)	4.897***	(0.736)	4.897***	(0.735)
Residence type (ref: single-family detached)				
Mobile/manufactured	–2.115*	(1.089)	–2.214**	(1.065)
Multi-family	–2.013	(1.659)	–2.086	(1.641)
Residence age (decades)	0.280	(0.258)	0.270	(0.256)
Stories	0.386	(0.829)	0.361	(0.831)
Renter	–4.587***	(1.539)	–4.364***	(1.512)
Appliance portfolio				
Electric cooking	1.471*	(0.893)	1.422	(0.893)
Electric water heating	4.278**	(1.718)	4.302**	(1.716)
Electric dryer	1.428	(0.969)	1.455	(0.965)
Rooftop solar	–3.723**	(1.489)	–3.557**	(1.474)
Demographics & occupancy				
High income ($100k+)	1.709*	(1.056)	1.738*	(1.052)
Graduate degree	–1.098	(0.860)	–1.051	(0.857)
Works from home	0.970	(1.037)	1.044	(1.035)
Respondent age	–0.068*	(0.038)	–0.071*	(0.038)
Retired	3.306***	(1.261)	3.345***	(1.255)
Dryer use (times/week)	1.587***	(0.282)	1.558***	(0.281)
Heating equip. age (yrs)	0.007	(0.057)	0.009	(0.056)
Observations	418		418	
R^2	0.328		0.331	

Notes: Robust standard errors in parentheses. Both columns estimate the same M3 specification. The FEF dependent variable is the household persistent component. The OLS dependent variable is mean daily consumption. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D.13 Robustness

The main findings rest on two modeling choices, the Step 1 weather filter and the Step 2 specification sequence. This section documents that neither drives the cross-carrier asymmetry.

D.13.1 Step 1 Filter Sensitivity

The Step 2 baseload estimates could in principle depend on which weather model is used to strip time-varying variation in Step 1. Table D.12 re-estimates a common five-predictor Step 2 specification under each of the six Step 1 filters. The home-size coefficient varies by less than 5% across all specifications for either energy carrier. The cross-carrier asymmetry is not an artifact of filter choice.

Table D.12: Step 2 Coefficient Stability Across Step 1 Filters

Step 1 filter	Home size	Rooftop solar	Renter	Retired	Dryer use
Electricity (kWh/day)					
5°C bins (main)	5.043	-3.561	-4.705	3.371	1.548
RCS (4 knots)	4.960	-3.126	-4.528	3.737	1.587
Cubic polynomial	4.957	-3.100	-4.518	3.757	1.589
Quadratic polynomial	4.956	-3.142	-4.507	3.734	1.586
Quadratic HDD/CDD	5.062	-3.608	-4.735	3.319	1.544
Piecewise linear (0, 18°C)	4.944	-3.063	-4.493	3.793	1.592
Natural Gas (therms/day)					
5°C bins (main)	0.640	-0.224	-0.390	0.001	0.067
RCS (4 knots)	0.655	-0.310	-0.429	-0.047	0.062
Cubic polynomial	0.655	-0.310	-0.429	-0.046	0.062
Quadratic polynomial	0.653	-0.309	-0.429	-0.045	0.062
Quadratic HDD/CDD	0.640	-0.218	-0.389	0.006	0.067
Piecewise linear (0, 18°C)	0.654	-0.308	-0.428	-0.045	0.062

Notes: Five-predictor Step 2 specification (home size, rooftop solar, renter, retired, dryer use) re-estimated under each Step 1 filter; differences across rows reflect filter choice only. Home size per 1,000 Sqft; dryer use in times per week.

The natural gas heating coefficient in Step 2 provides the clearest illustration of why the filter matters. Under the semiparametric bins, that coefficient is near zero, because the filter absorbs the differential cold-weather response of gas-heated homes into Step 1. Under every smooth parametric alternative, the same coefficient is large and precisely estimated. The smooth models, with only four to six temperature parameters, cannot fully separate the heating-fuel level shift from its weather response. The unabsorbed load enters Step 2 as a spurious baseload effect. The quadratic HDD/CDD model, which includes a dedicated heating-degree-day term, is intermediate, consistent with partial but incomplete absorption. This pattern is not evidence of fragility in the semiparametric filter. It is the expected signature of a filter flexible enough to do its job.

D.13.2 Step 2 Specification Stability

The progressive M1 through M3 sequence in Appendix Tables D.6 and D.7 shows that the key structural coefficients are stable as thematic tiers are added. For natural gas, the home-size coefficient is nearly flat across all three specifications, confirming that it is orthogonal to the appliance portfolio and occupant characteristics added in M2 and M3. For electricity, the home-size path is non-monotonic. Adding appliance controls initially increases the gradient before demographics pull it back toward the M1 value, consistent with a negative correlation between home size and electric appliance holdings. M1 and M2 retain more households than M3 and serve as larger-sample structural robustness checks. The cross-carrier asymmetry is present and similarly sized in all three specifications.

D.13.3 Multicollinearity

Table D.13 reports the largest variable-level VIFs by fuel and specification. All specifications show uniformly low VIFs, confirming that multicollinearity does not inflate the standard errors of the focal housing and appliance regressors.

Table D.13: Variance Inflation Factors, Step 2 M3 Specification

Variable	VIF
Housing structure	
Home size	1.60
Stories	1.57
Has garage	1.51
Residence age	1.50
Multi-family (vs. single-family detached)	1.44
Mobile/manufactured (vs. single-family detached)	1.44
Renter	1.13
Appliance portfolio	
Electric heating	1.84
Electric water heating	1.30
Electric dryer	1.17
Electric cooking	1.14
Rooftop solar	1.13
Demographics & behavior	
Dryer use (times/week)	4.33
Retired	2.27
Respondent age	2.18
Heating equipment age (years)	1.28
High income	1.25
Works from home	1.22
Graduate degree	1.11
Hispanic	1.10
EV/PHEV ownership	1.08

Notes: VIFs from the M3 main specification ($N = 430$). All values are well below the conventional threshold of 10. Interaction terms are omitted, and their component VIFs are listed individually.

D.14 Load-Projection Methodology

This appendix documents the household-anchored load projection summarized in Section 20. The projection is a microsimulation. It begins from each residential meter's actual 2024 monthly consumption and layers regression-based fuel switching on top, so the baseline requires no representativeness assumption and is exact by construction. The model is implemented in Python (which generates the figures and table in the body) and delivered to LADPU as a standalone, formula-driven spreadsheet (`LADPU_load_projection_tool.xlsx`) that reproduces the same numbers from editable inputs.

(1) Actual-2024 per-home baseline. We aggregate the LADPU monthly meter file to one row per electric meter for calendar year 2024, linked to its natural-gas meter where present. We retain meters with at least ten months of electricity coverage and trim physically implausible reads (negative or extreme meter-months, and the top and bottom 0.5% of annual electricity). Metered gas is converted from hundred-cubic-feet (CCF) to therms as therms = CCF $\times \phi_\ell \times h_m$, where ϕ_ℓ is the location elevation factor (0.78 for the Los Alamos townsite, 0.81 for White Rock, assigned from the meter's service city) and $h_m \in [1.02, 1.05]$ is the month-specific heat content from the utility's gas-rate schedule. The resulting baseline comprises 8,646 residential meters with about 62,400 MWh of electricity and 5.76 million therms of gas in 2024. Of these homes, 6,906 heat with gas. Forward years scale this baseline by the 0.4% annual housing-stock growth. Because the baseline is the literal 2024 system load, no calibration or re-basing factor is applied.

(2) Appliance-fuel inference. Switching must be applied to the homes that actually own each gas appliance, which is observed only for the roughly 470 survey-matched homes. We tested whether each meter's appliance fuels can be inferred from its consumption pattern (a fuel-type non-intrusive load-disaggregation problem), training gradient-boosted classifiers (`HistGradientBoosting`, five-fold stratified cross-validation) on the labeled homes using electricity winter/summer and baseload ratios and gas seasonality features. Space heating carries a strong, near-deterministic signature and is identified per home directly from gas seasonality (see step 3). The data-driven flag classifies 79.9% of homes as gas-heated, closely matching the ACS estimate of 81.6%. The minor gas appliances, however, do not separate from consumption alone. Cross-validated AUCs of 0.68 (water), 0.57 (cooking), and 0.54 (dryer) do not beat the majority-class baseline. We therefore assign water heating, cooking, and drying by their survey ownership shares (0.903, 0.634, and 0.251 of gas customers, respectively) applied as expected fractions, rather than per home. This is the source of the minor-appliance caveat in the body.

(3) Gas seasonality split and apportionment. Each home's annual gas is split into a non-space component (its summer baseload, taken as twelve times the mean of June–August gas) and a space-heating component (the winter excess above that baseload). Summed over gas-heated homes, the space component is 4.29 million therms and the non-space component 1.47 million therms, together reconciling to the 5.76 million-therm metered total. The non-space pool is divided across water heating, cooking, and drying in proportion to each end-use's ownership count times its electricity switching effect. Removing an end-use from a home eliminates exactly its share of that home's actual gas, so a fully converted home reaches zero gas and the aggregate gas removed reconciles to the metered total at full electrification. This avoids the bias of using the small estimated gas coefficients directly, which would leave a large gas residual even at 100% conversion.

(4) Conversion arithmetic. Electrifying end-use k in a converting home adds the Part-IV per-home electricity effect and removes the apportioned gas. For the minor appliances the added electricity is the Step-2 (M3) coefficient applied flat across months (+4.278, +1.471, and +1.428 kWh/day for water heating, cooking, and drying). For space heating it is the Step-1 temperature response evaluated against each month's temperature distribution, so the added electric-heating load is concentrated in the cold months. This is what drives the winter-peak growth. Aggregate added load in year y is $\sum_k p_k(y) N_k \Delta E_k$, where $p_k(y)$ is the scenario's cumulative conversion share for end-use k, N_k the gas-appliance count, and ΔE_k the per-home monthly increment. This quantity is added to the growth-scaled baseline.

(5) Scenario pace and targeting. Scenarios differ only in $p_k(y)$. S1 sets p_k equal across end-uses to the whole-home milestone schedule (10/30/50/75/100% by 2030/40/50/60/70). S2a fills only the willing pool, with $p_k(y) = c_k f(t)$, where c_k is the survey "very likely" ceiling and $f(t)$ the stated-timing curve (saturating about a decade out), so adoption plateaus at c_k. S2b adds replace-on-burnout turnover for the reluctant remainder, $p_k(y) = c_k f(t) + (1 - c_k)[1 - e^{-t/L_k}]$, with L_k the appliance lifetime, so conversion approaches one as the stock turns over. Within a pace, the highest-gas (oldest-equipment) homes are taken first.

(6) Solar overlay and confidence intervals. Rooftop solar grows from the installed base (about 500 homes) to 40% of meters by 2050. Each adopting home reduces grid load by the Part-III grid-electricity ATT (−131 kWh per month per home, which already nets out the rebound). Confidence intervals propagate the regression standard errors. An effect with standard error s_k applied to N_k homes at pace p_k contributes variance $(p_k N_k s_k)^2$, summed across independent end-uses and months, with the 95% band at ±1.96 times the resulting standard error. The bands therefore capture estimation uncertainty in the switching coefficients, not uncertainty in the adoption pace, which the three scenarios are designed to bracket.

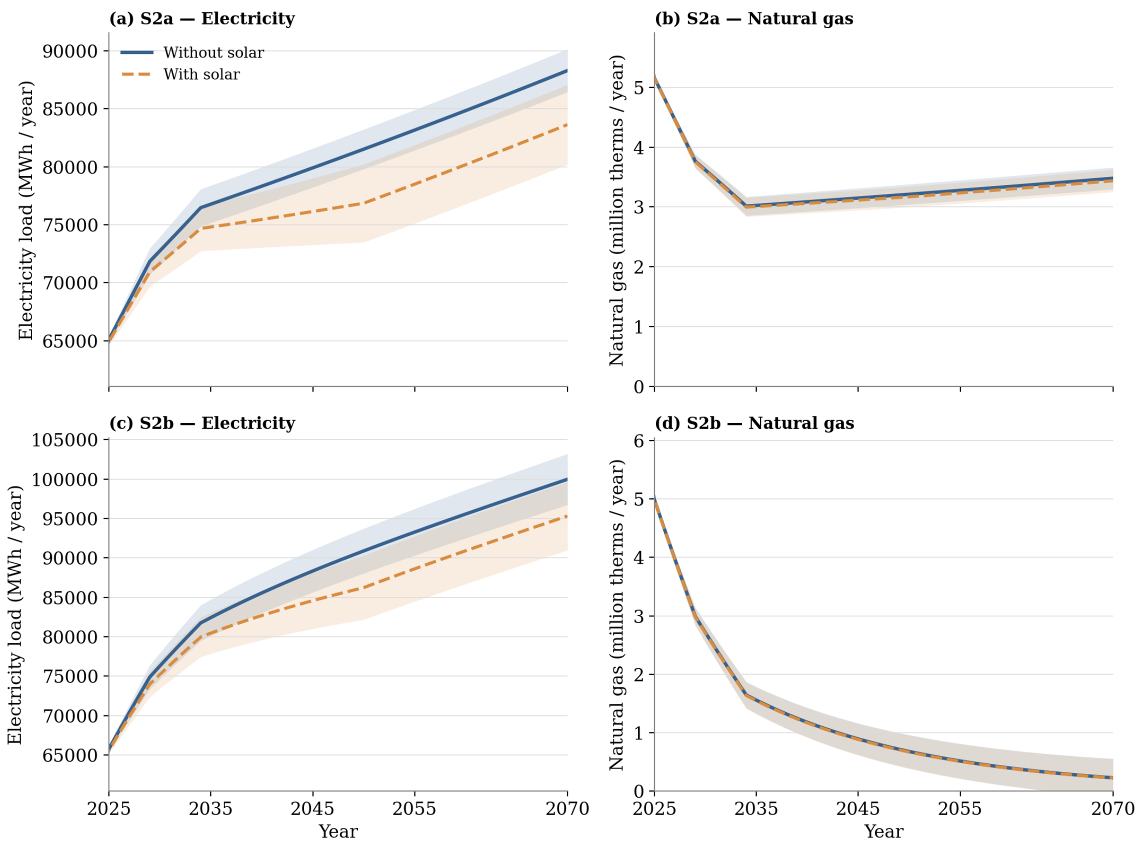


Figure D.9: Rooftop solar's effect on projected electricity and gas under the bottom-up scenarios

Notes: The bottom-up scenarios S2a (stated-only; panels a, b) and S2b (replace-on-burnout; panels c, d), each shown with and without the rooftop-solar overlay (40% of homes by 2050), with 95% confidence intervals on both paths. The electricity panels show the grid offset from the Part-III grid ATT. The gas panels show the smaller spring gas reduction, which is visible here, unlike the top-down path of Figure 18, because these scenarios leave natural gas in service.

E Related Literature

E.1 Tariff design, incentives and the economics of electrification

Work in energy-economics journals shows that price signals (i.e., volumetric tariffs and up-front subsidies) remain the dominant levers for appliance switching. In Colombia, McRae and Wolak (2021) demonstrate that a two-part tariff calibrated to income elasticities can recover network costs while shielding low-income users, a design later encouraged for Chicago by Spiller, Esparza, et al. (2023), who find time-differentiated prices cut peak demand and improve the private payback of rooftop PV and batteries. Complementary techno-economic simulations confirm that tariff structure often matters more than equipment efficiency, because under high volumetric rates a heat-pump retrofit can raise winter bills (Borenstein et al., 2022). Studies in emerging markets underline the same point from the opposite angle. Subsidizing Liquefied Petroleum Gas (LPG) or grid electricity crowds out clean-burn cookstoves when tariffs fail to internalize health costs (Behnia et al., 2024; Bouaguel and Alsulimani, 2022). The literature converges on tariff reform plus targeted incentives as the cost-effective path to large-scale electrification, but it also warns that bill outcomes would depend on local load shapes that few papers measure with smart-meter data.

E.2 Household fuel choice and appliance adoption

Socio-economic status, infrastructure access and cultural practice together shape which fuels households use and when they switch. Panel data from Ethiopia (Alem et al., 2016) and rural China (Hou et al., 2017) show evidence for an “energy ladder” in which higher income and education raise the probability of adopting LPG or electricity, yet later studies complicate that ladder. Beauchampet and Walsh (2021) introduce the idea of energy citizenship, showing that pro-environmental norms can override economic constraints, while Goswami et al. (2023) demonstrate that caste and gender roles override income in rural India. In high-income contexts the frontier issue is whole-home electrification. Edwards et al. (2024) map the United States' (US) heat-pump uptake and reveal stark climate-zone and racial disparities, and Brockway et al. (2021) link those disparities to feeder-level hosting limits. Lane et al. (2024) add qualitative depth to the switching decision, finding that New York City renters perceive upfront hassle and reliability concerns as larger obstacles than equipment cost. One major implication of this literature is that policies that ignore local infrastructure and social context will hinder switching and adoption even where tariffs are favorable.

E.3 Equity and distributional outcomes

Distributional analyses cut across the previous themes by asking who pays during and after the transition. Using customer-level billing data, L. Davis and C. Hausman (2022) project that if richer households electrify first, legacy gas costs could triple for the lowest-income decile. Similar dynamics appear in California feeder-studies (Waite and Modi, 2020) and in a national model of appliance mandates (Hill, 2025), both concluding that uncoordinated roll-outs risk regressive bill impacts that swamp climate benefits. Equity research also flags infrastructure barriers. Montañés et al. (2025) show that past blackout experience depresses electric-appliance adoption in vulnerable neighborhoods, while Das et al. (2021) document how high first costs of improved cook-stoves exclude the poorest quintile in Bangladesh even when lifetime savings are positive. This literature shows why electrification programs must retire gas infrastructure in tandem with low-income conversions and pair rebates with low-interest finance.

E.4 Consumer preferences, willingness-to-pay (WTP) and information interventions

Stated-preference studies improve our understanding of how much value households place on cleaner energy services. Meta-evidence across Europe and Asia finds average WTP premiums of 5 to 15 % for green electricity (Hojnik et al., 2021) and for high-efficiency appliances (Galarraga et al., 2011), but only when respondents trust the label. Risk and loss-aversion experiments with Chinese farmers reveal that higher risk tolerance reduces uptake of energy-efficient fridges and lamps (He et al., 2019). Information interventions amplify or mute those premiums, and carefully framed environmental messages elevate WTP for efficient appliances by up to one-third (Li et al., 2024; Wang et al., 2021).

E.5 System-level environmental and health effects

Finally, engineering and public-health research connect household choices to aggregate emissions and exposure. Stoner et al. (2021) trace global cooking-fuel trends and show that the drop in biomass reliance since 1990 cut population-weighted $PM_{2.5}$ exposure approximately by one-fifth, although rural biomass use remains stubbornly high. Applied Energy simulations for California indicate that space-heating electrification can lower state residential CO_2 by more than 60 % if accompanied by a 75 % renewable grid (Tarroja et al., 2018), but it could shift the system peak to winter (Elmallah et al., 2022). Health-oriented work underlines that partial 'fuel stacking' leaves most of the indoor-air benefit unrealized (Tumwesige et al., 2017). The consensus is clear on direction, in that electrification cuts emissions and health burdens. The size of those benefits depends on grid cleanliness and the pace at which households fully abandon polluting fuels.

E.6 Solar rebound and distributed generation

Residential solar adoption turns households into prosumers who both consume and export electricity (Boccard and Gautier, 2021; Gautier, Jacqmin, and Poudou, 2018; Green and Staffell, 2017), creating scope for a rebound effect through the lower effective cost of self-generated power (Matthew E Oliver et al., 2025), moral licensing (Beppler et al., 2023), and pro-environmental spillovers (Truelove et al., 2014). The rebound idea originates in the energy-efficiency literature, where cheaper energy services induce additional consumption that offsets part of the intended savings (Binswanger, 2001; Gillingham et al., 2014; Liang et al., 2018; Sorrell and Dimitropoulos, 2008). Classic examples include vehicle fuel economy (D. L. Greene et al., 1999) and home heating (Haas and Biermayr, 2000). Applied to rooftop PV, households shift or increase use during solar-generation hours when self-consumption is more valuable than export under net metering (Gautier, Hoet, et al., 2019), and recent quasi-experimental studies estimate residential solar rebound effects of roughly 8 to 18% (Aydın et al., 2023; Bigler, 2025; Havas et al., 2015; Qiu et al., 2019; Spiller, Sopher, et al., 2017). Because the additional demand may be met by carbon-intensive grid generation, the rebound can erode solar's emissions benefits (D'Agosti and Danza, 2025; Deng and Newton, 2017; Toroghi and Matthew E. Oliver, 2019). A related literature shows that household electricity and natural gas use are jointly determined, so cross-fuel substitution shapes the net energy and emissions impact (Alberini et al., 2011; Bernard et al., 2011; Dubin and McFadden, 1984; Mansur et al., 2008).

E.7 Discrete choice experiments for heating and fuel choice

A substantial discrete-choice-experiment (DCE) literature examines household heating-system and fuel choices. In Germany, Achtnicht (2011) finds that investment cost dominates heating-system replacement, with households paying modest premiums for carbon reductions but requiring large subsidies to leave natural gas. Michelsen and Madlener (2012) and Michelsen and Madlener (2016) reach similar conclusions, with operating-cost savings and energy independence outweighing environmental motives. Zemo et al. (2019) integrate environmental attitudes into a fuel-switching DCE, Park and Kwon (2011) show that subsidy design interacts with household characteristics to determine adoption, and Bersisa et al. (2021) model scale and preference heterogeneity in rural energy choices. The recurring finding that private economic benefits outweigh environmental ones motivates the cost- and efficiency-led framing of our choice experiment.

E.8 Environmental attitudes and willingness to pay

The New Ecological Paradigm (NEP) scale (Dunlap and Van Liere, 1978; Dunlap, Van Liere, et al., 2000) is the standard measure of pro-environmental worldview in environmental valuation. Kotchen and Reiling (2000) show that NEP scores predict stated valuations, and Hoyos et al. (2015) find that environmental attitudes explain substantial preference heterogeneity in DCEs and that omitting them inflates random-parameter variances. Mamkhezri (2025), Mamkhezri (2026), and Mamkhezri et al. (2020) and Scarpa and Willis (2010) document attitude–willingness-to-pay links for renewable energy, while Faccioli et al. (2020) and Mariel et al. (2021) discuss capturing such heterogeneity through observable covariates. A parallel literature emphasizes that the attitude–behavior gap is context-dependent (Diekmann and Preisendörfer, 2003; Whitmarsh, 2009). This is consistent with our finding that attitudes predict stated willingness more strongly than metered behavior.

E.9 Hypothetical bias, stated–revealed preference consistency, and WTP-space estimation

Because choice-experiment estimates are hypothetical, a long literature asks how well they track real behavior (J. Hausman, 2012; Kling et al., 2012; Penn and Hu, 2018). Meta-analyses document systematic hypothetical–real divergence (List and Gallet, 2001; Murphy et al., 2005), while within-subject stated–revealed preference comparisons (Bishop and Heberlein, 1979; Johnston et al., 2017; Loomis, 2011) show that the gap varies by context and elicitation format. Best-practice guidance stresses consequentiality and careful design (Carson, Flores, and Meade, 2001; Carson and Groves, 2007; Vossler et al., 2012), attention to protest responses (Meyerhoff and Liebe, 2006), and attribute non-attendance (Scarpa, Gilbride, et al., 2009). We estimate the model directly in willingness-to-pay space (K. E. Train and Weeks, 2005) and recover individual-level posterior estimates (Revelt and K. Train, 2000), linking stated values to metered consumption.

E.10 Household factors and persistent energy consumption

A growing literature uses household smart-meter data to ask what drives residential energy demand, linking the two fuels' records or comparing their load shapes, but rarely asks, for each fuel separately, which household and housing characteristics explain persistent (weather- and calendar-adjusted) consumption (Matsumoto, 2022; McKenna et al., 2022; Pullinger et al., 2024). The question matters for policy because efficiency and electrification programs deliver value only when they reach the homes where savings are largest, and a well-documented gap between projected and realized savings is partly one of misallocation, because programs do not consistently reach those homes (Allcott and Greenstone, 2012; Burlig et al., 2020; Fowlie et al., 2018). Identifying the cross-fuel asymmetry in persistent consumption tells a utility where to aim envelope measures versus appliance and behavioral tools, and which households will add the most electric load when they switch. Methodologically, recovering the association between time-invariant household characteristics and consumption is not possible with a standard household fixed-effects regression, because the fixed effect absorbs everything constant within a household. We use the two-step fixed-effects-filtered estimator of Pesaran and Zhou (2018), which first removes the common weather and calendar response and then explains the residual household component. Zhang and Zhou (2019) develop a related two-step estimator of time-invariant effects in dynamic panels. The first step follows the energy-demand tradition of controlling flexibly for weather and the calendar (Hor et al., 2005; Kang and Reiner, 2022) and of modeling the temperature response with binned indicators, an approach that originates in the climate-yield literature (Schlenker and Roberts, 2006; Schlenker and Roberts, 2009) and is now standard across environmental and energy economics (Aroonruengsawat and Auffhammer, 2011; Auffhammer, 2022; Auffhammer et al., 2017; L. W. Davis and Gertler, 2015; Deschênes and Greenstone, 2011).

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