On the Back Burner: Experimental Evidence For Energy Transitions *

Meera Mahadevan[a] Adrian Martinez[a] Ryan McCord[b]
Robyn C. Meeks[b] Manisha Pradhananga[c]

March 26, 2026

Abstract

Governments promoting clean energy transitions must not only overcome household barriers to adopting new technologies, but also ensure that adoption translates into sustained demand shifts that justify public investment. Cooking, one of the largest sources of household energy demand, is a natural place to study these tradeoffs. We conduct an RCT with 3,521 households in Kathmandu Valley, Nepal, where hydropower makes electrification feasible but LPG dominates cooking. Households were randomly assigned subsidy vouchers redeemable toward an induction stove or compatible cookware, information treatments on cost savings or health benefits, and a combination of these treatments. Subsidies increased stove adoption by 23 percentage points and cookware purchases by 41 percentage points; information alone had little impact. Using 29 months of billing data, we show that adopters in subsidy-only arms revert toward control-group electricity consumption levels, while the combined subsidy-and-information arms produce 15% higher long-run usage, with gains emerging after roughly a year. The explanation is compositional: combined arms induced more households to invest in both the stove and complementary cookware. These "complete" adopters learn through sustained use and increase electricity consumption over time; adopters with only a stove or only cookware revert. We embed these behavioral responses in a structural model of a social planner who maximizes sustained electricity usage subject to grid capacity and fiscal constraints. Counterfactual simulations show that concentrating the budget into subsidies deep enough to induce this complementary investment generates nearly twice the consumer welfare of spreading it thinly as universal discounts.

JEL Codes: C93, O1, O33, Q48, Q56

Keywords: Energy transition, Technology adoption, Policy design, Development, Energy

*We thank Pankaj Kumar and Udbodh Rijal for data collection assistance. We are grateful to participants at the CESifo Conference on Energy and Climate Economics, UCSD, Triangle Resources and Environmental Economics Seminar, Princeton Development Seminar, and the AERE Annual Conference for helpful comments and feedback. This project is covered by IRB at Duke University (2023-0241) and University of California, San Diego (810846). The experiment was registered in the AEA RCT Registry (AEARCTR-0014027). This project was funded by the Asian Development Bank (Technical Assistance 9940 and 6585). All errors are our own.

[a]UC San Diego. [b]Duke University. [c]Asian Development Bank. Corresponding author: mmahadevan@ucsd.edu.

1 Introduction

Energy security – countries' uninterrupted access to energy at affordable prices – is a critical driver of the global economy. With armed conflict and climate change inducing additional uncertainty in global energy supplies and prices, many governments are rethinking their approaches to achieving energy security (IEA, 2022). By coupling electricity generation via renewable energy sources with electrification of end uses, such as transportation and cooking, countries may both reduce dependence on imported fossil fuels and decarbonize their economies. Such a strategy requires economy-wide changes in fuel consumption. Yet the private incentives to shift fuels may fall short of a social planner's goal, because households and firms do not privately capture the full benefits from cleaner fuel use, given the benefits from energy security and positive externalities, including reduced emissions and improved public health, accrue more broadly (Holland et al., 2016; Rapson and Muehlegger, 2023).

Government policy is often necessary to promote technologies to realize both private and social gains.[1] Promoting adoption alone, however, is insufficient to achieve the social planner's goal of shifting fuel consumption at scale, as adoption of a technology need not translate into sustained use. Evidence from other sectors illustrates that even when adoption does translate into use, scaling adoption can impose costs that require calibration. For instance, scaling up agronomy training can increase input competition (Duflo et al., 2025), over-irrigation can deplete groundwater (Fishman et al., 2023; Pfeiffer and Lin, 2014), and simultaneous charging of electric vehicles can overload grids (Bailey et al., 2025b). Clean energy transitions exemplify this tension between household and planner objectives.

We study this energy transition challenge through a ubiquitous household activity with significant potential for transformation: cooking. We focus on the transition from liquefied petroleum gas (LPG) to electric cooking, an application of end-use electrification with new and different challenges than those that are faced when promoting efficiency improvements

[1] This is not uncommon in sectors where private and aggregate returns often diverge. For instance, water (Dupas et al., 2023; Kremer et al., 2011), sanitation (Deutschmann et al., 2024; Geruso and Spears, 2018), and health technologies (Dupas, 2014) all reduce individuals' exposure to disease, as well as community transmission of those diseases. Agricultural trainings, fertilizer use, and irrigation raise individual farm productivity and, in the aggregate, can improve regional food security (Duflo and Pande, 2007; Duflo et al., 2008). Electric vehicles lower individual drivers' operating costs while also reducing local pollution and global greenhouse gas emissions (Holland et al., 2016; Rapson and Muehlegger, 2023).

within fossil fuel based cooking.[2]. We tackle the first challenge to this problem: sufficient and cleanly generated electricity by studying this question in the context of Nepal. The setting is ideal for studying energy transitions: abundant, domestically-produced hydropower makes electricity both cleaner and cheaper than imported LPG and recent improvements in electricity generation and grid reliability (Acharya et al., 2024; Mahadevan et al., 2026) removed the most commonly cited barriers to this energy transition. However, even with clean electricity generation capacity, governments must navigate this transition carefully: boosting electricity demand without overloading grids or straining fiscal budgets, and allocating incentives efficiently across households facing heterogeneous barriers to adoption and sustained use. Given past import supply shocks, the Government of Nepal has tried to promote electric cooking (Acharya and Adhikari, 2021), but LPG remains the dominant cooking fuel used in urban Nepal.

We combine a randomized experiment with a structural model of adoption and post-adoption usage to evaluate subsidy designs available to a government planner. The randomized controlled trial was carried out in Kathmandu Valley with 3,521 LPG-using households. Our interventions mirror policy tools available to alleviate the existing adoption constraints: subsidies to relax liquidity constraints and information to address cost and health misperceptions. Designed in partnership with the Nepal Electricity Authority, the experiment randomly assigned households to nine groups combining two subsidy levels (approximately USD 7.5 and 22.5), two information treatments (cost and health), their interactions, and a control group.[3] Subsidies were delivered as vouchers redeemable at the country's largest retail chain, embedding the experiment in the population and delivery channels a planner would actually use (List, 2022). We track outcomes using both follow-up survey data and 29 months of monthly administrative electricity billing records from the national utility. We then develop a structural model that embeds household behavior within planner constraints,

[2]Prior evidence on improved or efficient fossil-fuel cookstoves suggests that adoption is constrained by liquidity (Berkouwer and Dean, 2022), depends on how interventions are targeted and to whom (Mobarak et al., 2012), and that usage may decline even after adoption (Hanna et al., 2016a). For a deeper discussion of the drivers of electronic appliances and use, see (Meeks and Mahadevan, 2025).

[3]Finally, the subsidy levels substantially mitigate upfront costs, with the higher subsidy constituting an approximately 50% discount off the price of a single electric stove, and almost the full cost of compatible cookware. The cost treatment explained that electric cooking is typically cheaper than LPG, while the health treatment highlighted indoor air-pollution risks from LPG (Daouda et al., 2024; Lebel et al., 2022). An intervention correcting misperceptions about operating costs may boost adoption, especially among price-sensitive households who may underestimate the savings from switching (Allcott and Taubinsky, 2015; Bensch and Peters, 2015).

using the experimental variation to recover behavioral parameters and evaluate counterfactual subsidy designs that a government could implement.

The randomized experiment yields three main results. First, subsidies had large and economically meaningful effects on adoption, while information alone did not. Households offered the high subsidy were 53 percentage points more likely to adopt electric cooking (defined as acquiring either an induction stove or compatible cookware) relative to a control mean of 15 percent. The low subsidy increased adoption by 27 percentage points, though much of this effect operated through cookware rather than stove purchases. Treatments that combined subsidy and information yielded similar adoption results to subsidies alone. In contrast, standalone cost and health information treatments generated negligible changes in adoption. These findings indicate that liquidity constraints, rather than misperceptions, were the primary barrier to adoption in this context.

Second, using follow-up survey data, we examine short-run cooking behavior. Subsidy recipients shifted meaningfully toward electric cooking, increasing the share of meals prepared with induction stoves by 7 to 9 percentage points and reallocating 14 to 17 minutes of daily cooking time toward electricity. LPG use declined modestly but remained substantial, consistent with fuel-stacking behavior documented in prior work (Guta et al., 2022; Masera et al., 2000; Shankar et al., 2020). Information treatments alone did not significantly alter cooking behavior. Thus, while adoption translated into real changes in household fuel use, substitution was partial rather than complete.

Third, we study how adoption translates into long-run electricity consumption using detailed administrative billing data spanning eighteen months after the intervention. Here, the patterns differ from the short-run adoption results. Sustained increases in electricity consumption are not observed for subsidy-only arms. Instead, durable and gradually emerging consumption gains are concentrated in the combined high subsidy and information treatment arms, suggesting electricity consumption went up by 6-8% by month 18. Event study estimates reveal that usage effects ramp up over time rather than appearing immediately at treatment onset.[4] This dynamic pattern indicates that adoption does not mechanically

[4]In rural South Africa, electricity usage lags e-stove adoption by 3 years (Dinkelman et al., 2026).

translate into persistent increases in electricity demand. Rather, sustained usage appears to depend on both substantial financial incentives and complementary information.

Taken together, the results highlight an important distinction between adoption and durable usage. While subsidies successfully induced technology uptake, long-run increases in electricity demand emerged only when adoption was paired with information and unfolded gradually over time. For policymakers concerned with energy transitions, the relevant outcome is not merely whether households acquire new technologies, but whether they incorporate them into sustained patterns of electricity use.

Finally, we embed these findings in a structural model of adoption and post-adoption electricity usage to evaluate counterfactual subsidy designs. The model captures the mechanisms that the reduced-form results identify as central to the adoption-to-usage gap. Adoption depends on perceived electricity costs, reliability beliefs, and liquidity constraints. These parameters determine not only whether a household adopts, but what it adopts: both stove and cookware, or only one component. This distinction matters because post-adoption usage evolves through experiential learning, and learning trajectories differ by adopter type. Complete adopters (cookware and stove) follow positive usage paths, while partial adopters revert toward baseline. A subsidy design that only maximizes adoption may therefore induce a composition of adopter types that fails to generate sustained demand. The model embeds these behavioral responses within a social planner's problem that internalizes grid capacity constraints and fiscal costs, allowing us to compare alternative subsidy designs under the same budget. Counterfactual simulations show that concentrating full subsidies on fewer households, inducing deep adoption of complete technology bundles, dominates spreading small discounts widely, generating 50-66% more welfare than the experimental design. Sophisticated machine-learning-based targeting offers only modest gains beyond simpler observable rules such as targeting based on LPG purchase records.

This paper makes three main contributions. First, we contribute to a thin but growing literature on energy transitions. Energy transitions are inherently macro processes: fuel generation, grid infrastructure, and policy planning require governments and social planners. Yet, transitions ultimately depend on decentralized decisions to adopt and use new

technologies, highlighting the importance of micro-founded demand parameters to inform macro-level planning. This is especially true for end-use electrification, where replacing fossil fuels with electricity depends not only on household demand, but also on grid capacity and the broader generation mix.[5] A growing literature studies these issues in the context of electric vehicles, including the role of subsidies, charging infrastructure, and the strain that widespread electrification can place on electricity systems (Bailey et al., 2025a,b; Gallagher and Muehlegger, 2011; Holland et al., 2016; Li, 2023; Li et al., 2017, 2022; Springel, 2021; Xing et al., 2021). We bring this end-use electrification perspective to household cooking, where adoption frictions differ but the planner's problem is closely related. Our contribution is to use experimentally identified adoption decisions and usage behavior into a structural model to evaluate counterfactual subsidy policies under planner constraints, bridging macro-oriented work on energy transitions with micro evidence. This complements recent work such as Fried et al. (2025), which models household equipment choice in a policy context.

Second, we contribute to the emerging literature on electric cooking within the transitions literature. Previous studies have examined shifts from biomass to improved stoves or to LPG (Abubakari et al., 2024b; Afridi et al., 2021, 2023; Kar et al., 2024; Meeks et al., 2019; Pattanayak et al., 2019), but evidence on the demand for electric stoves (Pattanayak et al., 2019) and on the transition from LPG to electric cooking remains limited (Gould et al., 2024, 2023). We contribute in particular to the literature on fuel shifting, which is underpinned by the well-established practice of fuel stacking, whereby the extent to which households shift from using an old fuel to a new one is critical for characterizing cooking transitions (Kar et al., 2024; Shankar et al., 2020). We extend this literature in two ways. First, by combining experimental variation with monthly electricity consumption data, we trace how usage evolves after adoption, documenting that increases in use emerge gradually and are not mechanically implied by take-up. Second, we observe complementary investments in stoves and cookware, moving beyond binary measures of adoption and capturing how households adopt cooking technology bundles in practice. Together, these results highlight the importance of understanding not only whether households adopt electric cooking, but also how they incorporate it into their cooking portfolio over time.

[5]Existing work examines the evolution of household adoption of electricity-using assets (Gertler et al., 2016).

Finally, we contribute to the literature on the relationship between technology adoption, sustained use, and policy targeting. Adoption does not always translate into sustained use, with previous work typically attributing this to post-adoption frictions such as maintenance failures, behavioral biases, or habit persistence (Ashraf et al., 2013; Cohen et al., 2015; Dupas, 2014; Dupas et al., 2024; Hanna et al., 2016b; Tarozzi et al., 2014). A related literature shows mixed evidence on the effectiveness of pricing and non-monetary costs in targeting households more likely to use a technology (Ashraf et al., 2013; Dupas et al., 2023). We show new evidence that the gap between adoption and sustained use can also arise through the composition of adopters induced by the intervention. In our setting, the households most likely to adopt are not the same households that are most likely to increase their long-run electricity demand. This compositional channel has first-order implications for targeting and subsidy design (Abubakari et al., 2024a; Burlig and Sudarshan, Forthcoming; Hanna and Olken, eds, 2026). Our counterfactual simulations show that deep subsidies that induce complete adoption among fewer households generate more persistent use and higher welfare than broad subsidies that maximize adoption rates.

The paper proceeds as follows. Section 2 discusses the local context in Nepal, while Section 3 develops the structural model of household adoption, post-adoption electricity usage, and the social planner's problem. Section 4 describes the randomized experiment on electric cookstoves. Section 5 presents the data and summary statistics. Section 6 outlines the empirical strategy, and Section 7 reports the experimental results and analysis of long-run electricity usage. Section 8 estimates the structural parameters, Section 9 decomposes the adoption-to-usage gap by adopter type, and Section 10 evaluates counterfactual subsidy designs. Section 11 concludes.

2 Study Setting: Urban Nepal

Nepal's energy landscape makes it a natural laboratory for studying cooking transitions. The country's generation, transmission, and distribution of electricity are the responsibility of the Nepal Electricity Authority (NEA), which is a vertically-integrated government entity. With improvements in electricity access as a core component of the country's development

strategy, Nepal attained substantial gains over the past 3 decades, increasing from 14.1 % in 1995/96 to 94% of households as of 2022/23 (National Statistics Office, 2025). Even with access improvements, the quality of those service lagged behind, meaning – until relatively recently – poor electricity reliability and frequent load-shedding plagued electricity provision in Nepal (Timilsina and Steinbuks, 2021).

In recent years electricity reliability and quality of services have improved substantially (Sharma and Shrestha, 2023), as the country increased electricity generation capacity. Expanded generation, particularly since 2015/16 (National Statistics Office, 2025) and including through new independent power producer contracts, greatly contributed to reliability improvements (Ghising, 2022; Kathmandu Post, 2023; Open Data Nepal, 2022). Hydropower now supplies nearly 99 percent of electricity with minimal carbon emissions (Bhandari and Subedi, 2023), making electricity increasingly viable for cooking.

The study was implemented in Bagmati, one of the country's seven provinces, which is the location of Kathmandu Valley and home to 6.1 million people. Bagmati Province is the country's economic center and represents 21% of the its total population. Across the province's 13 districts, 62% of the province lives in urban areas (National Statistics Office, 2025).

There is much heterogeneity across the country – particularly across rural and urban populations – in the types of fuels used for cooking; however, in Bagmati Province LPG is the cooking fuel used by the majority of households. As of the 2021 census, within the province 29% of households cooked with firewood, 69.8% with LP gas, and 0.6% with electricity (National Statistics Office, 2025). This dependence on LPG for cooking is the result of the country's subsidies provided for the fuel, with petroluem accounting for 20% of the Nepal's total imports and are greater than all of the country's exports (Koirala, 2023). This reliance on imports, particularly those from India, induces both national security and financial stability concerns. In 2019-2020 alone, Nepal imported approximately 4,51,000 metric tons of LPG, all of which cam from India (Gautam, 2021); however, the dependability of the LPG supply from India is regularly of concern. A 2015 Indian blockade exposed the country's vulnerability to fuel supply disruptions and catalyzed a policy shift toward

electricity (Acharya and Adhikari, 2021; Giri, 2015). As a result, in its recent planning exercise, the Government of Nepal indicated to promote electric cooking while gradually reducing the existing LPG subsidies (National Planning Commission, 2024).

At the time of this study, NEA's domestic electricity customers faced and increasing block price, which varied by both the ampere of the customers' connection and the kWh per month used (NepalEnergyForum, 2023). The government reduced electricity tariffs just prior to the study implementation, in efforts to encourage increased electricity consumption including through electric cooking adoption (Acharya et al., 2025).

3 Model

We develop a tractable structural model to discipline our policy analysis and connect experimental variation to behavioral parameters. The model captures the frictions households face in adopting and using electric cooking technology: upfront liquidity constraints, misperceptions about relative operating costs, and heterogeneity in preferences. Importantly, the model also allows adoption to generate broader changes in electricity use over time through learning and experience. In this setting, technology adoption is not merely a discrete purchase decision, but a path into sustained electrification.

At the same time, the framework incorporates the constraints faced by a social planner. While higher electricity consumption is socially desirable because it reduces dependence on imported LPG and improves health, additional load is not costless when generation or distribution capacity is tight. The planner therefore weighs household welfare gains against the marginal cost of serving additional electricity demand under capacity constraints, as well as the fiscal cost of subsidies.

The model generates empirically estimable equations that allow us to map structural parameters to reduced form treatment effects observed in the RCT. We preserve a clean adoption equation that directly corresponds to our experimental variation. We then extend the framework to connect adoption to long-run billed electricity consumption, which is the key outcome of interest for utilities and policymakers.

Although we calibrate the model to Nepal, the structure is intentionally simple and portable. The household adoption margin can be estimated wherever quasi experimental variation in incentives is available, while the planner's shadow values for fiscal resources, capacity constrained supply costs, and LPG dependence can be reparameterized for other contexts. In this way, the framework provides a general tool for identifying the optimal mix of subsidies and information policies in energy transitions.

3.1 Adoption

Households choose between cooking with LPG or electricity based on perceived costs, subsidies, and idiosyncratic preferences. The key economic forces are: (i) lower perceived electricity costs raise adoption; (ii) subsidies enter concavely, so each additional dollar has diminishing effect; and (iii) subsidies are more effective when perceived electricity costs are high. This third force, the interaction between subsidies and perceived cost, is quantitatively important.

Taking log-odds of the adoption probability and substituting for indirect utilities (see Appendix A for derivation) yields:

$$\log \frac{\pi_{Eg}}{1-\pi_{Eg}} = \underbrace{-\frac{\eta\theta}{1-\eta}\log P_{Eg}}_{\text{perceived cost}} + \underbrace{\theta\, s_{Eg}^{\rho}}_{\text{subsidy}} + \underbrace{\theta\gamma_P\left(s_{Eg}^{\rho} P_{Eg}\right)}_{\text{subsidy}\times\text{cost interaction}}, \tag{1}$$

where π_{Eg} is the probability of adopting electric cooking, P_{Eg} is perceived electricity cost (shifted downward by information treatments), s_{Eg} is the subsidy normalized by stove price, ρ governs subsidy concavity, η is the price sensitivity of cooking demand, and θ scales taste heterogeneity. The interaction $\gamma_P > 0$ means subsidies work best for households who perceive electricity as expensive, precisely the group where a subsidy relaxes the binding constraint.

Four treatment arms from the RCT (control, info-only, high subsidy, high subsidy + info) exactly identify the four parameters $\{\eta, \theta, \rho, \gamma_P\}$, with the remaining two arms (low subsidy, low subsidy + info) serving as out-of-sample validation. The model reproduces

observed adoption across all six arms within 1.5 percentage points (Figure G1; Appendix Table 7).

3.2 Electricity usage conditional on adoption

Adopting a stove does not guarantee a change in cooking behavior. The model decomposes post-adoption electricity usage into channels that each imply a different policy response. Among adopters, optimal cooking time is $T_{it}^{*} = (\eta/\tilde{P}_{it})^{1/(1-\eta)}$, where the effective perceived cost $\tilde{P}_{it}$ depends on:

$$\log \tilde{P}_{it} = \underbrace{\delta_r R_i}_{\text{reliability}} + \underbrace{\delta_L \, g(t)}_{\text{learning}} + X_i'\beta + \nu_i, \tag{2}$$

where R_i is baseline beliefs about grid reliability, $g(t) = 1 - e^{-\kappa t}$ is a learning curve that rises from zero toward one as households gain experience with electric cooking, X_i includes household characteristics, and ν_i is a residual preference term. Billed electricity captures total household consumption, not just cooking, so the learning channel may also reflect broader changes in electricity use patterns.

Each channel maps to a different policy lever. *Reliability* (δ_r): if outage beliefs raise the perceived cost of committing to electric cooking, grid investment helps. *Learning* (δ_L): the sign reveals whether households integrate electric cooking into their routines ($\delta_L \approx 0$, stable usage) or revert after initial experimentation ($\delta_L < 0$); follow-up support such as cooking demonstrations could sustain households in the latter group. *Preference heterogeneity* (ν_i): a household-level residual capturing intrinsic cooking cost after accounting for the first two channels and observables. Households with high ν_i face high perceived cost and have low electric cooking demand; those with low ν_i have strong revealed preference for electric cooking. Identifying high-ν_i households helps avoid subsidizing stoves that will not be used.

3.3 Targeting

A social planner maximizes total electricity usage for cooking, subject to a subsidy budget B, grid capacity $\bar{G}$ (at per-unit cost δ), and a shadow value λ on LPG displacement:

$$\max_{s_i, I_i} \sum_i \pi_{Ei}(s_i, I_i) \cdot \mathbb{E}\big[kWh_{it}^{\text{cook}} \mid \text{adopt}\big] \tag{3}$$

$$\text{s.t.} \quad \sum_i s_i + c_{\text{info}} I_i \leq B, \quad \sum_i \pi_{Ei} \cdot \mathbb{E}[kWh_i \mid \text{adopt}] \leq \bar{G}/\delta, \quad \lambda \sum_i \pi_{Ei} \cdot \Delta LPG_i \geq 0.$$

The grid constraint matters because each additional electric cook draws on the network; δ is calibrated from Nepal Electricity Authority data, $\bar{G}$ from regional transformer capacity, and λ from LPG import prices. Taken together, this formulation highlights the planner's tradeoff: raising subsidies or shifting perceived prices boosts household welfare through higher adoption, but it also risks higher grid costs, fiscal burdens, or continued exposure to LPG dependence. Our RCT provides the variation needed to estimate the behavioral parameters in (1) and (2), which then discipline the decomposition in Section 9 and the counterfactual simulations in Section 10.

4 Randomized Experiment on Electric Cookstoves

We conduct a randomized experiment in the Kathmandu Valley, which is located within the Bagmati Province of Nepal. The experiment randomly varies interventions designed to alleviate constraints to the adoption of electric stoves. The following sub-sections detail the sampling procedures employed, the experimental design, and the intervention.

4.1 Study Area Selection and Sampling Process

In June and July 2023, the research team surveyed 3,521 households in the Kathmandu Valley. Our selection procedure to attain this sample was comprised of two steps, as described in the paragraphs below.

First, we start with 2,190 households that were previously surveyed by our research team in 2021. These households are situated along the Bisnumati River, which runs north-south along the western side of Kathmandu, and were part of an earlier study on the effects of smart meters. All of those households were within 1 km of the river, with approximately half located to the western side of the river and the other half to the eastern side. These households are located in a relatively consolidated area, and serve by approximately 60 transformers (half on the east and half on the western part of the river). We can match households with smart meters (on the eastern side) to the transformers through which electricity is distributed.

Second, to systematically extend the sampled area to include additional households that would be less densely concentrated, but still similar to those selected in the first step, we used NEA data on transformer locations within a 2 km distance to the east of the Bisnumati River. We select transformers on the eastern side of the river, and went north of the sample selected in the first step, as these are the neighborhoods in which households had smart meters installed during the same intervention mentioned above. We extend the study area up to the Tokha Municipality, as this is within Kathmandu District, urban/peri-urban like the areas included in the first step, and also proximate to Bhat Bhateni store locations.

Limiting to this area, there are 172 transformers. The locations of these transformers selected in the second step – and their proximity to transformers in the first step – are mapped in Figure C1.[6]

From the utility records of all households served by these 172 transformers, we randomly sampled 7 to 8 households per transformer.[7] This results in 1,331 additional households selected within the second step. From the two steps, the 3,521 household sample results. When surveyed in summer 2023, these households were asked if they consented to participate in a future study on electric cooking. Of the households surveyed, 2,894 consented to participate in the study going forward.

[6]The map does not show transformers on the western side of the river from the first step, as the distribution system on the western side is not connected to smart meters and therefore we do not have GPS location data.

[7]We created a list of 40 randomly selected households per transformers. The list was given to the survey company, which proceeded to survey down the list as with replacements.

4.2 Experimental Design

Using this sample of households, which covers 3 of NEA's DCs (Ratnapark, Maharajgunj, and Kuleshor), households are randomly assigned by computer through a cross-randomization design. Households are randomly assigned to receive one of three electric cooking subsidy treatments – a higher subsidy of 3,000 NPR (≈ USD 22.5), a lower subsidy of 1,000 NPR (≈ USD 7.5), or no subsidy – that can be used to purchase electric cookstoves (or the pots/pans specific to electric induction stoves). The low and high subsidies offset a substantial share of upfront costs, including an induction stove (USD 30–45 for one burner, roughly double for two) and compatible cookware (USD 10–22). Based on the project budget, approximately 600 households were intended to be assigned to the high and low subsidy groups, and 1800 households assigned to no subsidy group.[8] The locations of households randomly assigned to the subsidy treatments are mapped in Figure 2.

We randomize the subsidy assignments along with three information treatments, with information provided on the operating costs of electric stoves, the health benefits from electric cooking, or no information. Households were intended to be assigned in approximately equal numbers (1000 households per treatment) to each of the information treatment groups. The locations of households assigned to the subsidy treatments are mapped in Figure 3.

This randomization led to 9 different groups to which households could potentially be assigned.[9] The 9 groups and actual numbers of households assigned to each are depicted in Table 2. Randomization was done on a computer, finding balance on seven baseline characteristics that were collected via the 2023 household survey.[10] Due to this approach, there are slightly different numbers of households assigned to the treatment groups.

[8]Numbers were a bit lower across all three groups, as we are randomized across 2,894 households rather than the 3,000 households we estimated prior to the study.

[9]The 8 different treatment combinations include high subsidy-cost info, low subsidy-cost info, no subsidy-cost info, high subsidy-health info, low subsidy-health info, no subsidy-health info, high subsidy-no info, low subsidy-no info. The pure control group is assigned to no subsidy-no info. For ease of viewing, we do not display all 9 groups in one map.

[10]The baseline variables on which balance was forced in randomization are: household size, household head education (both if they have less than 1 year of schooling and if they bachelor's degree or more), if the house is connected via a smart meter, if the household already owns an induction cookstove, and an income proxy based on appliances (increasing in the number of appliances owned including microwave, AC and washing machine).

4.3 Intervention

The intervention occurred in January and February 2024 and was comprised of delivering the combinations of information and subsidy coupons to households based on the randomized assignment. The timeline depicting the intervention relative to the survey implementation is shown in Figure 1. The actual treatment assignment is described in Table 2.

The intervention proceeded as follows. All 2,894 households were visited by project staff during these two month period. They were thanked for consenting to participate in the study and received a small mobile phone re-charge credit in thanks for their continued participation in the study.[11] The full script for this interaction is in Appendix 1. For the pure control households, the interaction ended there. The households assigned to other combinations of treatments received additional documentation, per their random assignment.[12]

Households randomly assigned to receive either of the information treatments received a paper on which their respective messages – cost or pollution – were printed. Images of these information texts, printed in Nepali, are in the appendix (Figure D2). The full English translations of the information on the cost of electric cooking and the pollution reduction from electric cooking, are in Appendices 2 and 3, respectively.

Households randomly assigned to receive either the high or low subsidy treatments received a paper explaining that they had been randomly selected to receive a voucher for a subsidy of NPR 3000 or NPR 1000 (these amounts are approximately 165% and 55% of an average monthly bill payment, respectively) that could be used on either an induction stove or cookware compatible with an induction stove. This printed information detailed the logistics of using the subsidy vouchers. Full information on these message – both the pamphlets printed in Nepali (Figure D4 and the English translations of the messages – are in Appendix 4.)

These households also received a physical voucher card marked as "Subsidy to buy induction appliance". The card stated the amount of subsidy, a household unique id assigned

[11] The credit was for 100 Nepali Rupees, which was approximately 0.75 USD at the time.

[12] There were 57 households for which the intervention was unable to be delivered, either because they had moved since the 2023 survey or they were not home to receive the treatment during the multiple attempts made by the research team. We show the breakdown of the undeliverable treatments by assignment in Appendix Table D1.

by project staff, and the logo of Bhat Bhateni super store, which is the largest chain store in Nepal with 27 store locations throughout the country.[13] The mega store is well known in the country and sells most household goods, from food to appliances, cookware, and furniture, as well as clothes.

To use the subsidy, a household member had to bring the voucher to the customer service desk in the Bhat Bhateni store. Households had to be a Bhat Bhateni Club Card member or register to become one if they were not already. It costs nothing to become a member and is essentially a system through which shoppers earn points and rewards based on their prior purchases, like one would find in many major retailers in the United States.[14] The households were then directed towards the induction stoves and induction-related cookware within the store. The subsidy coupons were eligible to be redeemed from the date that the households received them through April 30, 2024.

The subsidy vouchers could be used in Bhat Bhateni locations throughout Kathmandu Valley. There are 9 super store locations throughout Kathmandu Valley (mapped in Figure D5). Prior to the intervention Bhat Bhateni had provided the research team with a list of all induction stoves and related cookware sold in their stores. The voucher card could only be used towards these designated induction related cooking items.

5 Data

We use two main sets of data for this study: data from a household survey conducted by our research team and data collected by Nepal Electricity Authority. We describe both in the sections below, as well as test for baseline balance following the randomization.

5.1 Survey Data

We have two rounds of households survey data. The baseline survey conducted in June and July 2023. The follow-up survey was conducted June and July 2024.

[13] Pictures of the subsidy voucher are shown in the Appendix (Figure D3).

[14] Given the coverage of the super store many people in the study were already Club Card members. Because of their own club card system and their store's system of giving annual "rewards" to their customers, Bhat Bhateni already had a voucher system set up with employees trained to receive vouchers.

The timing of the follow-up survey was selected as it one year after the baseline survey was implemented and approximately 6 months after the onset of the intervention. Of the 2,894 households randomly assigned to treatment, we were able to re-survey 95% (2,740 households) at the follow-up mid-2024. As a check, the survey data are matched with the information on voucher use from Bhat Bhateni.

Responses to the 2023 baseline survey provide help us better understand the study sample (Appendix Table 1). We see that approximately one-third of households pay for their electricity bills by cash/cheque, where the other two-thirds pay by credit. Respondent report, on average, that their prior month electricity bill was 2,090 Nepali rupees. Although almost all household respondents report knowing their most recent electricity expenses (97%), only 54% report know what their monthly electricity consumption (in kWh) was. More than two-third of households have a smart meter installed, which is indicative of the study's sampling strategy. In "normal months", respondents report just over 1 electricity outage per week on average; this increases to 5.5 outages per week in the "bad" months when electricity reliability substantially worsens.

Reports on appliances and other electricity-related and cooking practices provide important insights for this study. Approximately one-third of respondents report heating their houses in the winter, whereas almost no households (3%) report cooling with air conditioners. Households have a substantial number of electric appliances, with most respondents having a refrigerator (89%), fan (84%), and a kettle (64%). On average, approximately 2 hours per day are spent on cooking (13.5 hours in the last week).

5.2 Administrative Billing Data

We examine usage patterns using a large confidential electricity billing dataset obtained from the Nepal Electricity Authority (NEA). The dataset is matched to the subjects of the RCT, and we are able to track their electricity consumption records from January 2023 to May 2025, a full year before the RCT began and 18 months after the experiment concluded. This administrative panel provides a direct and objective measure of sustained changes in electricity demand, enabling us to evaluate whether the experimental treatments led to

durable shifts in household energy use.

The dataset consists of monthly data for the 3500 consumers in the 2023 survey starting from January 2023 and going through May 2025. These data include information on the type of bill, the units consumed (kWh), amount due on bill (NPR), amount payable, and date the bill was due. Additionally, there are data on the date the bill was actually paid, the monetary amount that was paid at that time, and the method through which the payment was made.

Together, these two data sources allow us to study both the adoption of electric cooking technologies and subsequent patterns of electricity consumption. We next describe how we use the randomized assignment and the panel structure of the administrative data to estimate treatment effects.

5.3 Randomization Balance

Using data from the baseline survey, we check for balance on key variables that might affect either adoption and use of electric cookstoves: household size, the education of the household head (both if they have no formal education and if they have higher education), if the house has a smart meter installed, the number of electric cooking appliances owned, and whether the household owns and induction stove. Table 3 presents results from these balance tests and shows that none of the 8 treatment groups are statistically significantly different from the control group (column 9).

6 Empirical Strategy

In this section, we describe how we leverage the experimental variation in treatment assigned to estimate the effects of the intervention.

6.1 Intent to Treat

First, we estimate the effect of being randomly assigned to a particular treatment (or combination of treatments). Given the baseline balance shown in the prior section, we estimate

the impact of the intervention's treatment arms using a simple specification:

$$\begin{aligned} Y_i = \alpha &+ \beta_1 \text{HighSubsidy}_i + \beta_2 \text{LowSubsidy}_i + \beta_3 \text{CostInfo}_i + \beta_4 \text{HealthInfo}_i \\ &+ \beta_5(\text{HighSubsidy}_i \& \text{CostInfo}_i) + \beta_6(\text{HighSubsidy}_i \& \text{HealthInfo}_i) \\ &+ \beta_7(\text{LowSubsidy}_i \& \text{CostInfo}_i) + \beta_8(\text{LowSubsidy}_i \& \text{HealthInfo}_i) + \varepsilon_i \end{aligned} \tag{4}$$

HighSubsidy_i, LowSubsidy_i, CostInfo_i, and HealthInfo_i are indicator variables corresponding to the distinct experimental arms. Households were randomly assigned into one of nine mutually exclusive treatment cells. The omitted category consists of households assigned to the pure control group, that is, those who received neither a subsidy nor an information treatment. The constant term α therefore represents the mean outcome for the pure control group.

Each coefficient β_k represents the difference in mean outcomes between households assigned to that specific treatment cell and households in the pure control group. For example, β_1 captures the effect of assignment to the high subsidy arm, β_3 captures the effect of assignment to the cost information arm, and β_5 captures the effect of assignment to the combined high subsidy and cost information arm.

Because treatment cells are mutually exclusive, the coefficients do not represent incremental interaction effects in a factorial sense. Rather, they reflect the average treatment effect of each experimental arm relative to the pure control group. Finally, ε_i denotes the idiosyncratic error term.

Our empirical analysis distinguishes clearly between adoption and usage outcomes. The experimental design was designed to affect the adoption of induction stoves and associated cookware. Accordingly, we first examine outcomes at the extensive margin, focusing on whether households adopt induction cookstoves and compatible cookware as a result of the intervention.

However, from the perspective of the Nepal Electricity Authority (NEA), the ultimate policy question concerns electricity usage, particularly whether the intervention translates into sustained increases in electricity consumption. The motivation behind the experiment

was always to understand what factors could propel the energy transition in Nepal towards greater electricity consumption.

We therefore study intensive margin outcomes in two complementary ways. First, we examine short-run impacts on usage using self-reported measures collected in our endline survey. These include reported usage of electric stoves and LPG stoves for cooking meals, as well as amount of time spent cooking with an electricity stove versus an LPG stove. These measures allow us to assess substitution patterns between fuels and the extent to which adoption translates into behavioral change.

However, self-reported measures may of course be subject to various biases. We therefore proceed to a dynamic analysis using the panel structure of the billing dataset from NEA.

6.2 Event Study Design

To assess the validity of the parallel trends assumption and to examine the dynamic effects of the treatments over time, we estimate an event study specification. For each treatment arm $T \in \{1, \ldots, 8\}$, we estimate the following equation using the sample restricted to households in treatment group T and the control group:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{k=-6, k\neq -1}^{17} \beta_k \times \mathbb{1}\{\text{Month}_t = k\} \times \mathbb{1}\{\text{Treatment}_i = T\} + \epsilon_{it} \tag{5}$$

where Y_{it} represents the log electricity consumption for household i in month t. The termsα_i and λ_t denote household and time fixed effects, respectively.

The index k represents the month relative to the reference period, where $k = -1$ corresponds to December 2023 (the month prior to the start of the intervention). The summation creates a set of coefficients β_k for the pre-treatment period ($k \in \{-6, \ldots, -2\}$) and the post-treatment period ($k \in \{1, \ldots, 17\}$).

The coefficients β_k capture the differential change in consumption for the treated group relative to the control group in month k, compared to the base period of December 2023.

We cluster standard errors at the household level.

The pre-treatment coefficients provide a direct test of the parallel trends assumption underlying the difference-in-differences framework. Under valid identification, the estimates for $k < 0$ should be statistically indistinguishable from zero, indicating that treated and control households were on similar consumption trajectories prior to the intervention.

The post-treatment coefficients trace out the dynamic treatment effects over time. This allows us to examine whether electricity consumption responds immediately following treatment, whether effects grow gradually as households integrate electric cooking into daily routines, and whether any observed changes persist over the longer run. In this way, the event study complements the average post-treatment estimates by providing a flexible, non-parametric view of treatment dynamics.

6.3 Difference-in-differences Strategy

To estimate the effect of the treatments on electricity consumption, we employ a DD specification with a linear TWFE. The estimation equation is defined as follows:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{T=1}^{8} \beta_T \left(Post_t \times \mathbb{1}\{\text{Treatment}_i = T\} \right) + \epsilon_{it} \tag{6}$$

where Y_{it} denotes the electricity consumption for household i at time t. As in the event study, α_i and λ_t represent household and time fixed effects, respectively. The household fixed effects absorb time-invariant heterogeneity across households, while the time fixed effects account for common shocks affecting all units simultaneously.

The interaction term captures the treatment effect. $Post_t$ is a binary variable equal to one during the intervention period (2024 and 2025) and zero otherwise. The term $\mathbb{1}\{\text{Treatment}_i = T\}$ is an indicator function that equals one if household i was assigned to treatment arm T. The coefficients of interest are β_T, which estimate the differential impact of each treatment T relative to the control group during the post-treatment period. Finally, ϵ_{it} represents the error term. Standard errors are clustered at the household level to

allow for serial correlation within households over time.

This framework provides three main advantages in our setting. First, while random assignment ensures treated and control households are comparable in expectation, electricity consumption is noisy and highly seasonal. By differencing within household over time and netting out common time shocks, the two-way fixed effects DD improves precision relative to a purely cross-sectional post-treatment comparison.

Second, the availability of a long pre-treatment panel allows us to examine whether consumption trends were similar across experimental arms prior to treatment exposure. We implement event study specifications in the next subsection to visualize and test for pre-treatment trend differences, which provides a transparent diagnostic for the identifying assumptions underlying the DD design.

Third, the administrative panel allows us to study dynamic and long-run outcomes. Adoption of a new cooking technology may not translate into immediate, stable changes in electricity demand. Usage may evolve gradually as households learn, adjust cooking practices, or spread use across household members. The panel structure lets us estimate whether treatment effects emerge slowly, persist, or fade out over an extended horizon, which is central to the policy question faced by the NEA.

7 Results

7.1 Survey-based outcomes

7.1.1 Adoption at the extensive margin

Table 4 documents strong impacts of subsidies on adoption of electric cooking. Households offered the high subsidy were 53 percentage points more likely to adopt (defined as acquiring either an induction stove or compatible cookware), relative to the control group mean of 15 percent. The low subsidy also increased adoption by 27 percentage points, though most of this effect came from cookware rather than stove purchases. Indeed, while the high subsidy raised stove ownership by 23 percentage points, the low subsidy increased stove ownership

by only 4 percentage points and instead shifted households toward cookware adoption. We observe large effects in the adoption of induction-compatible cookware, with high and low subsidy groups adopting at rates of 41% and 25%. Both the information treatments had negligible standalone effects, and their combinations with subsidies produced results similar in magnitude to subsidies alone. We follow these results in estimating our parameters in Section 8. These findings indicate that liquidity constraints, rather than misperceptions, are the primary barrier to adoption specifically in the Nepal context.

Table B2 breaks up the above finding by the study sample that already owned stoves at baseline versus those that did not. As may be expected, the group that already owned electric stoves, use their subsidies to purchase cookware at higher rates (50 % for high subsidy and 29% for low subsidy), while a very low percentage (statistically indistinguishable from 0) adopted new induction stoves.

7.1.2 Intensive margin: cooking behavior and self reported consumption

Table 5 presents reduced-form estimates of self-reported cooking behavior by treatment arm. The control group cooks 16 percent of meals using induction stoves and 89 percent using LPG, consistent with widespread fuel stacking at baseline.

Subsidy treatments lead to economically meaningful shifts toward electric cooking. Households assigned to the high subsidy arm increase the share of meals cooked with induction stoves by 6.9 percentage points, while those assigned to the low subsidy arm increase this share by 8.5 percentage points. These represent increases of roughly 40 to 50 percent relative to the control mean. Consistent with substitution, the share of meals cooked with LPG declines by 4.6 percentage points in the high subsidy arm and by 2.5 percentage points in the low subsidy arm, though the latter is not statistically significant.

Time-use measures tell a similar story. Electric cooking time increases by approximately 17 minutes in the high subsidy arm and 14 minutes in the low subsidy arm. Reductions in LPG cooking time are more modest and imprecisely estimated for the high subsidy group, though the low subsidy arm shows a statistically significant decline of roughly 10 minutes.

In contrast, information treatments alone generate small and statistically insignificant changes in cooking behavior across all outcomes. Neither cost information nor health information meaningfully shifts the share of meals cooked with electricity or LPG, nor do they significantly affect time allocation across fuels.

The combined treatment arms generally exhibit patterns similar to the subsidy-only arms. For example, the high subsidy combined with health information increases the share of meals cooked with induction stoves by 9.5 percentage points and reduces the LPG share by 6.6 percentage points, alongside a 16-minute increase in electric cooking time. However, these effects are broadly comparable in magnitude to the subsidy-only arms, suggesting that subsidies, rather than information, are the primary driver of behavioral change.

Taken together, these results indicate that financial incentives translate into meaningful but partial substitution toward electricity. Households increase electric cooking and reduce LPG use, yet LPG remains an important fuel, consistent with fuel-stacking behavior observed in other settings.

7.2 Effects on billed electricity consumption

Next, we turn to examining the billing data obtained from the Nepal Electricity Authority to examine long-run usage patterns as a result of the intervention. Figure **??** presents event study estimates of monthly log electricity consumption (December 2023 is the omitted month). Several patterns emerge.

First, across all treatment arms, the pre-treatment coefficients are tightly centered around zero and statistically insignificant. There is no evidence of differential pre-trends or anticipatory effects prior to the intervention, lending support to the identifying assumptions underlying the difference-in-differences framework.

Second, sustained increases in electricity consumption are concentrated in the combined treatment arms rather than in the subsidy-only arms. Households assigned to high subsidy alone do not exhibit a clear and persistent divergence from the control group over the full post-treatment horizon. In contrast, the combinations of high subsidy with information

treatments display a gradual and sustained upward trajectory in electricity consumption beginning several months after treatment exposure. These effects persist through the end of the eighteen-month window.

Importantly, the divergence does not appear immediately at the onset of the intervention. Instead, consumption increases gradually over time, suggesting that households integrate electric cooking progressively rather than instantaneously.

Yet the long-run administrative consumption effects reveal that usage responses are not mechanically determined by adoption alone. As shown in Table **??**, subsidy treatments generated very large increases in adoption, which we do not observe to translate into long-run usage.

The dynamic patterns reveal that durable increases in electricity consumption emerge gradually and are driven primarily by a combination of substantial financial incentives and relevant information interventions. In fact, Column 1 in Table B3 presents aggregate difference-in-difference estimates and also demonstrates the advantage of exploiting the panel nature of the dataset. When studied in aggregate, effect sizes appear small and often statistically insignificant. This is partly due to the delayed increase in usage patterns we observe in the event studies. However, even when studied in aggregate, with short-run and long-run effects averaged out, we observe large and significant impacts particularly for the sub-group of our sample who adopt both a stove and cookware. The delayed ramp-up in usage underscores the importance of long-run administrative data: short-run adoption measures would not fully capture the evolving nature of household electricity demand following technology adoption.

Table 6 breaks up the post-period for the DiD analysis into a short-run (12 months after the intervention) and a long-run (12-18 months after the intervention), and we clearly observe large and statistically significant impacts in the long-run for the combination treatment of cost information and high subsidy.

Taken together, these results highlight a central contribution of the paper. Much of the adoption literature focuses on whether households acquire new technologies. Our results

show that adoption and sustained usage can diverge, and that long-run administrative consumption data provide a critical complement to short-run survey measures. In the context of energy transitions, what ultimately matters for utilities and policymakers is not merely technology uptake but persistent changes in electricity demand. The administrative panel allows us to observe precisely these longer-run adjustments.

7.2.1 Heterogeneity by baseline ownership and adopter type

We next turn to heterogeneity in long-run usage patterns for households that adopted either a stove, cookware or both, post-intervention. Figure 5 presents event study estimates of treatment effects on log electricity consumption, disaggregated by adopter type. Three patterns emerge. First, increases in long-run electricity use are concentrated among households that adopt both the induction stove and compatible cookware, with effects that are larger in magnitude and more persistent than for stove-only or cookware-only adopters. This suggests that complementary capital, namely the joint ownership of stove and cookware, is critical for translating adoption into meaningful and sustained usage. Notably, these patterns appear across nearly all treatment arms for the subgroup that adopts both components. We emphasize, however, that these heterogeneity results are suggestive, as adoption is endogenous and reflects selection into take-up.

Second, high-subsidy arms generate earlier and more sustained increases in consumption than low-subsidy or information-only treatments, consistent with liquidity constraints limiting both adoption and subsequent intensity of use. Third, households that adopt only one component exhibit smaller and less stable effects, often characterized by short-lived spikes rather than durable shifts in consumption. Taken together, the heterogeneity patterns indicate that full technology adoption, rather than partial take-up, drives persistent changes in electricity demand, and that financial support plays a central role in enabling sustained behavioral transition.

8 Estimation of Structural Parameters

The reduced-form results in Section 7 establish three patterns: subsidies sharply increase adoption, information alone does not, and sustained electricity gains are concentrated in the combined subsidy-plus-information arms. We now discipline the structural model using these experimental moments. The adoption equation is identified from variation across RCT treatment arms; the usage equation is estimated on administrative billing data for adopters. Full identification arguments and estimation procedures are in Appendix G; here we summarize the approach and interpret the key estimates (Table 7).

8.1 Adoption

The adoption equation (1) has four parameters: ρ (subsidy concavity), θ (taste heterogeneity), η (price sensitivity of cooking demand), and γ_P (the subsidy–cost interaction). We identify them from four treatment arms through a system of moment conditions. The control group pins down baseline adoption. The information-only arm, which shifts perceived electricity cost without offering a subsidy, identifies the price sensitivity η. The high-subsidy arm and the high-subsidy-plus-information arm jointly identify θ and γ_P from the difference in adoption responses with and without information. Finally, a grid search over ρ selects the concavity that minimizes out-of-sample prediction error on the two held-out arms (low subsidy and low subsidy + info).

Three features of the estimates are worth highlighting. First, subsidies enter concavely ($\hat{\rho} = 0.55$): the first NPR 1,000 of discount matters substantially more than the next 2,000. This has direct implications for subsidy design, because it means that concentrating larger subsidies on fewer households generates more adoption per rupee than spreading small discounts widely. Second, the subsidy–cost interaction is large and positive ($\hat{\gamma}_P = 2.289$), meaning subsidies are roughly three times more effective for households that perceive electricity as expensive, precisely those who have not received cost information. This interaction rationalizes the reduced-form finding that combining subsidies with information does not produce adoption rates much higher than subsidies alone: information lowers perceived cost, which simultaneously raises the baseline adoption probability but weakens the marginal ef-

fect of the subsidy. Third, the model fits the data well. Predicted adoption rates match observed rates across all six treatment arms within 1.5 percentage points, including the two out-of-sample validation arms (Figure G1). This close fit provides confidence that the estimated parameters capture the key behavioral margins driving adoption decisions.

8.2 Post-adoption electricity usage

We estimate the usage equation (2) on 16,457 adopter-month observations from Nepal Electricity Authority billing records, covering 836 adopters across all nine treatment arms over 14 months post-intervention. The estimation uses cluster fixed effects (169 clusters) and standard errors clustered at the household level. For the learning curve, we perform a grid search over $\kappa \in [0.01, 2.0]$ and select the rate that minimizes the sum of squared residuals.

The vector X_i includes nine baseline characteristics: household size, head age, education, homeownership, LPG consumption (kg/month), cooking time, number of electric appliances, meals cooked on LPG, and baseline stove ownership. These controls serve a specific purpose in interpreting the preference residual $\hat{\nu}_i$. By conditioning on household size and head age, the residual does not simply reflect larger families cooking more. Controlling for LPG consumption and meals on LPG rules out that heavy baseline cooks mechanically use more electricity. Number of appliances and homeownership absorb wealth differences in baseline electricity demand. Baseline stove ownership accounts for prior familiarity with induction cooking. Cooking time nets out general cooking intensity, and education controls for openness to new technology. What remains in $\hat{\nu}_i$ after these controls is genuine taste, or taste-adjacent unobservables, for electric cooking.

Two results stand out from the pooled estimation. First, baseline reliability beliefs have no detectable effect on post-adoption electricity usage ($\hat{\delta}_r = +0.001$, not statistically significant). This is a substantively important null: it means that households who express greater concern about power outages do not use less electricity after adopting an electric stove. The gap between households who adopt and increase electricity usage versus those who do not is driven by preferences and learning, not by grid concerns. This suggests that grid reliability investments, while valuable for other reasons, would not by themselves close

the adoption-to-usage gap.

Second, the pooled learning coefficient is modestly negative ($\hat{\delta}_L = -0.058$), suggesting that on average, adopters' electricity usage drifts slightly downward over time. But this pooled estimate masks sharply different dynamics by adopter type, which turn out to be central to understanding why some treatment arms produce persistent electricity gains while others do not. We defer the by-type estimates to Section 9, where they form the core of the composition mechanism.

8.3 Treatment effect heterogeneity

The pooled estimates recover average parameters, but the γ_X term in the adoption equation allows household characteristics to moderate subsidy effectiveness. A planner needs to know which households respond most on the adoption margin and, separately, which translate adoption into sustained electricity usage. These need not be the same households. We estimate both dimensions using machine learning methods, with details in Appendix H.

For adoption, we estimate a causal forest (Athey et al., 2019; Wager and Athey, 2018) that leverages RCT randomization to recover each household's conditional average treatment effect $\hat{\tau}_i$.[15] A best linear projection of the forest onto standardized covariates yields the γ_X coefficients used in the counterfactual targeting exercise (Section 10). For usage, a separate regression forest predicts each household's kWh growth $\hat{y}_i$ from baseline characteristics. This second estimate is predictive, not causal, since there is no experimental variation in usage intensity conditional on adoption. Splitting at the median of each dimension yields four household types.

The central finding is that these two margins are nearly orthogonal. The correlation between $\hat{\tau}_i$ and $\hat{y}_i$ is only 0.17: household characteristics predicting strong adoption responses are largely distinct from those predicting sustained electricity gains (Appendix Table H5). A program that looks successful by take-up may look quite different by long-run electricity demand.

[15] We use the `grf` package in R (Athey et al., 2019), estimating the causal forest with 4,000 trees and honesty splitting on N = 1,617 households in subsidy and control arms. The regression forest for electricity usage uses the same package and settings, trained on 574 treated adopters. See Appendix H for details.

Figures 8 and 9 characterize the four cells. "Fuel switchers" (High Adopt, High Use) respond to subsidies and increase consumption (+0.14 log points). They have low prior stove ownership (18%), higher LPG use (11.6 kg/month), and lower reliability concerns (6.9/10); 81% are first-time electric cookers (Appendix Table H4). At the other extreme, Low Adopt, Low Use households have high prior stove ownership (56%) and negative kWh growth, consistent with equipment replacement. The off-diagonal cells underscore the independence of the two margins: "equipment replacers" (High Adopt, Low Use) are subsidy-responsive but do not change cooking behavior, while Low Adopt, High Use households would increase usage if induced to adopt.

Note that "High/Low Adopt" refers to predicted *marginal response* to a subsidy ($\hat{\tau}_i$), not adoption level. A household with high baseline adoption propensity may respond little on the margin, and vice versa. Realized adoption rates in Table H4 therefore do not monotonically follow the labels (see Appendix H).

These results carry a clear lesson: fuel switchers offer the highest return per subsidy dollar for genuine fuel switching, because they both respond to incentives and change behavior. Equipment replacers respond but do not increase usage, so targeting on take-up alone overstates program impact. The near-orthogonality means that evaluating subsidy programs solely on adoption can be misleading. We return to these tradeoffs in Sections 9 and 10, where the γ_X coefficients estimated here become central inputs.

9 Decomposition and Mechanisms

The near-orthogonality in Section 8.3 poses a puzzle: if subsidy-responsive households are not the same ones who increase electricity usage, what determines which side a given adopter falls on? The answer traces to the *type* of adoption each arm induces. Households purchasing the complete stove-and-cookware bundle follow a fundamentally different trajectory than those purchasing only one component, and treatment arms differ sharply in the composition of types they produce.[16]

[16]The analyses in this section use all 836 adopters across all nine treatment arms (16,457 adopter-months of billing data). The CATE analysis in Section 8.3 uses a restricted sample of 1,617 households in subsidy and control arms.

9.1 Treatment arms induce different adopter types

Treatment arms differ not only in how many households adopt but in the *kind* of adoption they generate (Table 8). The information-plus-high-subsidy arm produces the highest rate of complete adoption: 19.6% of households purchase both stove and cookware, versus 11.4% for subsidy-only and 3.1% for info-only. Among adopters, nearly a third (30.3%) chose the complete bundle versus roughly a fifth (20.8%) for subsidy-only. Information combined with a generous subsidy does not merely push more households over the adoption threshold; it shifts the margin toward a qualitatively different form of adoption.

This matters because usage responses diverge by type. Most complete adopters increase electricity usage after adoption, while most cookware-only adopters decrease it (Figure 6), consistent with experimentation that does not persist. Arms producing more complete adopters generate larger gains not because they produce more adopters, but because those adopters behave differently.

9.2 Learning curves differ by adopter type

The pooled estimates in Section 8 showed a modest downward drift in usage ($\hat{\delta}_L = -0.058$). Disaggregating by type reveals sharply different trajectories (Table 7, Panel C; Figure 7). Complete adopters are the only group whose usage *grows* with experience ($\hat{\delta}_L = +0.087$), gradually integrating electric cooking over a slow adjustment ($\hat{\kappa} = 0.07$) still unfolding at 14 months. Cookware-only adopters show rapid reversion ($\hat{\delta}_L = -0.101$, $\hat{\kappa} = 0.95$), consistent with trying new cookware and falling back on LPG. Stove-only adopters show no detectable trend.

9.3 Connecting household types to learning trajectories

The CATE analysis identified fuel switchers as the highest-return type. The composition results explain why: 37% purchased the full bundle versus 18% among equipment replacers (Figure 10). Fuel switchers also have the lowest prior stove ownership (18% vs. 43%) and 81% are first-time electric cookers (Appendix Table H4). Because complete adopters are the only type with a positive learning curve, this composition difference accounts for their

sustained electricity gains.

Decomposing predicted usage confirms that composition is the dominant channel. Reliability beliefs contribute nothing ($\hat{\delta}_r \approx 0$, not significant). The preference residual $\hat{\nu}_i$ varies modestly across types. What separates fuel switchers from equipment replacers is not unobserved preferences but the type of adoption and the learning trajectory that follows.

A single mechanism traces from treatment design to long-run impact. Information and high subsidies shift adopter composition toward the complete bundle ($\hat{\gamma}_P > 0$), and complete adopters are the only group on a positive learning trajectory. This chain from policy design to composition to learning to sustained demand determines whether a cookstove subsidy produces lasting fuel switching.

10 Counterfactual Policy Simulations

The decomposition identifies a mechanism from treatment design to long-run impact through adopter composition. Can a planner who understands this mechanism allocate the same budget more effectively? We explore this through counterfactual simulations varying the subsidy level, targeting rule, and intervention form, holding spending fixed at the RCT budget ($B = 2{,}180{,}000$ NPR). All counterfactuals bundle cost information with the subsidy. The planner chooses a target set $N_t \subseteq N$ and subsidy level $s \in [0, 1]$, optimizing the welfare function in equation (3). Adoption heterogeneity enters through the γ_X coefficients from the CATE best linear projection (Section 8.3).[17] The expected usage conditional on adoption, $\mathbb{E}[kWh_i \mid \text{adopt}]$, is evaluated at a 24-month horizon using the type-specific learning curves from Panel C of Table 7, weighted by the adopter-type composition each policy induces. This means the planner values a complete adopter (who integrates electric cooking) more than a cookware-only adopter (who reverts toward baseline). Figure 11 reports welfare gains from eleven policies, normalized to the RCT.

Concentration dominates partial discounts: The budget funds 311 free stoves or an 11% discount for all 2,740 households. The blanket discount achieves only 0.83× the RCT

[17] The adoption equation implies a θ multiplier on γ_X, but since θ is a scalar it does not affect household rankings; we absorb it into γ_X.

welfare, because 11% barely moves adoption from baseline. Giving free stoves to 311 randomly chosen households achieves 1.51×. Concavity ($\hat{\rho} = 0.55$) means small discounts fall on the flat part of the response curve while full subsidies push adoption above 85%. The RCT performed well because it already concentrated high subsidies on a subset of arms.

Observable targeting rules: We consider six rules a government could implement without a baseline survey or machine learning: targeting households without a prior electric stove (0.80×), those reporting high grid reliability (0.82×), above-median cooking time (0.89×), stable grid areas with few outages (0.87×), households with a bachelor's degree or higher (1.04×), and top LPG users from administrative records (1.42×). Most of these rules select large groups (950–1,800 households), forcing the budget to spread thinly and landing on the flat part of the concave response curve. Only top LPG users and, marginally, education-based targeting select groups small enough for meaningful concentration. The lesson is that targeting on observables helps only when it also concentrates.

CATE targeting: CATE-ranked selection of the 300 most responsive households achieves 1.66×, 10% above the random stove lottery. Targeting top LPG users performs nearly as well (1.42×). But CATE targeting requires a baseline survey and machine learning infrastructure, while LPG targeting uses existing administrative data. The incremental gain may not justify the cost, though the broader lesson that concentration dominates uniform subsidies is robust across all rules we consider.

Bundle restriction: The stove-plus-cookware package costs more per unit ($K_{\text{bundle}} =$ 10,000 vs. $K_{\text{stove}} =$ 7,000 NPR), so the same budget funds free bundles for 218 randomly chosen households instead of 311 free stoves. But every bundle adopter follows the positive learning trajectory ($\hat{\delta}_L = +0.087$), whereas unrestricted subsidies produce only about 25% complete adopters, the rest of whom revert toward baseline (Table 8). The free bundle lottery achieves 1.21× the RCT welfare. At a two-year horizon the usage multiplier for bundle adopters (1.07) exceeds that for the default composition (0.96). The free stove lottery still dominates (1.51×) because it serves 50% more households, but the bundle comparison shows that the quality of adoption matters: the gap between stove and bundle lotteries is smaller than the difference in headcount.

Cost-benefit: The free stove lottery provides a concrete benchmark: 311 stoves at NPR 7,000 each, 87% adoption, 272 new electric cooks, program cost NPR 2.18 million (USD 16,400). Nepal's government values this program through two strategic channels. First, reduced LPG import dependence: Nepal imports virtually all LPG from India, and each adopter who displaces even half a cylinder per month saves roughly NPR 11,000 per year in foreign exchange.[18] Second, increased utilization of surplus hydropower: the Nepal Electricity Authority gains revenue from incremental cooking load at near-zero marginal cost on existing infrastructure. Under conservative assumptions about partial displacement, combined import savings and electricity revenue approach break-even within approximately one year, even before counting the roughly 130 tonnes of CO_2 avoided annually. Two caveats apply in opposite directions. Our RCT's low treatment intensity could not measure adoption spillovers, which could amplify impacts at scale. Conversely, a large rollout may face supply-side constraints such as stove shortages or price increases, and fully subsidized recipients may value and use their stoves less intensively than households that invest their own resources.

11 Conclusion

Electrification of household end uses is increasingly central to strategies for reducing carbon dioxide emissions, improving indoor air quality, and enhancing energy security. In contexts where households rely on imported gas for cooking, shifting to electricity offers the dual benefits of cutting CO_2 emissions and mitigating health risks, while also reducing vulnerability to supply shocks. Nepal provides a particularly compelling case: nearly all of its electricity is generated from renewable hydropower, and recent investments have alleviated the chronic load-shedding that once constrained adoption. As the government seeks both to expand electricity consumption and to reduce dependence on imported LPG, the key policy question becomes how best to spur adoption and sustained use of electric cooking.

Using a large-scale randomized controlled trial, we show that the binding constraint for adoption is upfront cost, consistent with a broad literature on technology subsidies. A 50%

[18] Based on Nepal Oil Corporation import prices of approximately NPR 130 per kg for LPG. A standard 14.2 kg cylinder at 50% displacement yields 85 kg per year in avoided imports.

subsidy increases stove adoption by 53 percentage points, while information treatments alone have no effect. Second, adoption and sustained use are governed by different mechanisms. The households most responsive to subsidies are not the same ones who translate adoption into lasting increases in electricity demand. The structural model reveals why: only households purchasing both the stove and compatible cookware follow a positive learning trajectory. Treatment arms that combine information with subsidies produce disproportionately more of these complete adopters, which is why they alone generate sustained electricity gains. Third, concentrating large or full subsidies on fewer households dominates spreading thin discounts widely, raising welfare by 51% over the experimental design.

These findings carry a concrete policy implication. Nepal's government aims for 25% of households to adopt electric cooking by 2030. Our estimates suggest this goal is achievable with concentrated subsidies at modest fiscal cost, but only if programs are designed to induce complete adoption rather than piecemeal equipment purchases. A blanket subsidy program that maximizes adoption counts will look successful on paper while failing to shift long-run electricity demand.

There are several avenues for future work to explore. Our 14-month post-intervention billing panel cannot determine whether the positive learning trajectory of complete adopters eventually levels off or continues to grow. The welfare simulations hold macro parameters fixed while in practice, large-scale adoption could strain grid capacity. Finally, our sample is urban and peri-urban, and bounds the extent to which we can generalize these findings to rural areas.

References

Abubakari, Sulemana, K P Asante, Misbath Daouda, B Kelsey Jack, Darby Jack, Flavio Malagutti, and Paulina Oliva, "Menu design and evidence from clean fuels," *Working Paper*, 2024.

_ , _ , _ , _ , _ , _ , and _ , "Targeting subsidies through price menus: Menu design and evidence from clean fuels," *Working Paper*, 2024.

Acharya, Bikram and Santosh Adhikari, "Household energy consumption and adaptation behavior during crisis: Evidence from Indian economic blockade on Nepal," *Energy Policy*, 2021, *148*, 111998.

_ , Dipendra Prasad Pant, and Mukunda Raj Kattel, "Household clean cooking in Nepal: Policies, practice and prospects," *Energy Policy*, November 2025, *206*, 114758.

Acharya, J., P. Manandhar, G. Shah, B. S. Khadka, and R. D. Sharma, *Powering Nepal: 5 Decades of ADB–Nepal Partnership in the Energy Sector*, Asian Development Bank, June 6 2024.

Afridi, Farzana, Sisir Debnath, and E. Somanathan, "A Breath of Fresh Air: Raising Awareness for Clean Fuel Adoption," *Journal of Development Economics*, 2021, *151*, 102674.

_ , _ , Taryn Dinkelman, and Komal Sareen, "Time for Clean Energy? Cleaner Fuels and Women's Time in Home Production," *The World Bank Economic Review*, 2023, *37* (2), 283–304.

Allcott, Hunt and Dmitry Taubinsky, "Behavior and Energy Policy," *Science*, 2015, *347* (6224), 208–210.

Ashraf, Nava, B. Kelsey Jack, and Emir Kamenica, "Information and subsidies: Complements or substitutes?," *Journal of Economic Behavior & Organization*, 2013, *88*, 133–139. Asian Institutional Economics.

Athey, Susan, Julie Tibshirani, and Stefan Wager, "Generalized Random Forests," *Annals of Statistics*, 2019, *47* (2), 1148–1178.

Bailey, Megan R., David P. Brown, Blake Shaffer, and Frank A. Wolak, "Show Me the Money! A Field Experiment on Electric Vehicle Charge Timing," *American Economic Journal: Economic Policy*, May 2025, *17* (2), 259–284.

_ , _ , Erica Myers, Blake Shaffer, and Frank A. Wolak, "Electric Vehicles and the Energy Transition: Unintended Consequences of Time-of-Use Pricing," *American Economic Review: Insights*, 2025, *7* (4), 550–566.

Bensch, Gunther and Jörg Peters, "The intensive margin of technology adoption – Experimental evidence on improved cooking stoves in rural Senegal," *Journal of Health Economics*, 2015, *42*, 44–63.

Berkouwer, Susanna B. and Joshua T. Dean, "Credit, Attention, and Externalities in the Adoption of Energy Efficient Technologies by Low-Income Households," *American Economic Review*, 2022, *112* (10), 3291–3330.

Bhandari, Ramchandra and Subodh Subedi, "Evaluation of surplus hydroelectricity potential in Nepal until 2040 and its use for hydrogen production via electrolysis," *Renewable Energy*, 2023, *212*, 403–414.

Burlig, Fiona and Anant Sudarshan, "Reforming energy subsidies," in Rema Hanna and Benjamin Olken, eds., *Handbook of Social Protection in the Developing World*, MIT Press, Forthcoming. Forthcoming.

Cohen, Jessica, Pascaline Dupas, and Simone Schaner, "Price Subsidies, Diagnostic Tests, and Targeting of Malaria Treatment: Evidence from a Randomized Controlled Trial," *American Economic Review*, 2015, *105* (2), 609–645.

Daouda, Misbath, Annie Carforo, Heather Miller, Jennifer Ventrella, Yu Ann Tan, Michelle Feliciano, Jessica Tryner, Andrew Hallward-Driemeier, Steve Chillrud, Roisin Commane, Diana Hernández, Michael Johnson, and Darby Jack, "Out of Gas, In with Justice: Findings from a Gas-to-Induction Pilot in Low-Income Housing," *Energy Research & Social Science*, 2024, *116*, 103662.

Deutschmann, Joshua W., Molly Lipscomb, Laura Schechter, and Jessica Zhu, "Spillovers without Social Interactions in Urban Sanitation," *American Economic Journal: Applied Economics*, July 2024, *16* (3), 482–515.

Dinkelman, Taryn, Mark Collinson, Wayne Twine, and Martin Wittenberg, "Appliance Adoption Dynamics Following Electri cation: Evidence from Rural South Africa," *Working Paper*, 2026.

Duflo, Esther and Rohini Pande, "Dams," *The Quarterly Journal of Economics*, May 2007, *122* (2), 601–646.

_ , Daniel Keniston, Tavneet Suri, and Céline Zipfel, "Chat Over Coffee? Diffusion of Agronomic Practices and Market Spillovers in Rwanda," Technical Report w31368, National Bureau of Economic Research, Cambridge, MA 2025.

_ , Michael Kremer, and Jonathan Robinson, "How High Are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya," *American Economic Review*, April 2008, *98* (2), 482–488.

Dupas, Pascaline, "Getting essential health products to their end users: Subsidize, but how much?," *Science*, 2014, *345* (6202), 1279–1281.

_ , Basimenye Nhlema, Zachary Wagner, Aaron Wolf, and Emily Wroe, "Expanding Access to Clean Water for the Rural Poor: Experimental Evidence from Malawi," *American Economic Journal: Economic Policy*, February 2023, *15* (1), 272–305.

_ , Seema Jayachandran, Adriana Lleras-Muney, and Pauline Rossi, "The Negligible Effect of Free Contraception on Fertility: Experimental Evidence from Burkina Faso," 2024.

Fishman, Ram, Xavier Giné, and Hanan G. Jacoby, "Efficient irrigation and water conservation: Evidence from South India," *Journal of Development Economics*, May 2023, *162*, 103051.

Fried, Stephie, David Lagakos, and Hannah Rhodenhiser, "Homework in Climate Economics: Household Production, Environmental Preferences, and Climate Policy," *Review of Economics and Statistics*, February 2025. Revision requested.

Gallagher, Kelly Sims and Erich Muehlegger, "Giving green to get green? Incentives and consumer adoption of hybrid vehicle technology," *Journal of Environmental Economics and Management*, 2011, *61* (1), 1–15.

Gautam, Biraj, "Nepal e-Cookbook: Electric Cooking vs. Other Fuels," Technical Report, People, Energy & Environment Development Association (PEEDA) December 2021.

Gertler, Paul J., Orie Shelef, Catherine D. Wolfram, and Alan Fuchs, "The Demand for Energy-using Assets among the World's Rising Middle Classes," *American Economic Review*, 2016, *106* (6), 1366–1401.

Geruso, Michael and Dean Spears, "Neighborhood Sanitation and Infant Mortality," *American Economic Journal: Applied Economics*, April 2018, *10* (2), 125–162.

Ghising, M.D., "Kathmandu Valley To See Uninterrupted And Qualitative Electricity Supply: MD Ghising," January 6 2022.

Giri, Sanjeev, "Blockade, Energy Shortages Goad Country into Looking for Solutions," *The Kathmandu Post*, October 2015.

Gould, Carlos F., Lissete Davila, M. Lorena Bejarano, Marshall Burke, Darby W. Jack, Samuel B. Schlesinger, José R. Mora, and Alfredo Valarezo, "Exposure to Nitrogen Dioxide and Fine Particulate Matter When Cooking with Electricity Compared to Gas, a Randomized Crossover Study in Quito, Ecuador," *Environmental Health Perspectives*, January 2024, *132* (1), 017702.

_ , M. Lorena Bejarano, Brandon De La Cuesta, Darby W. Jack, Samuel B. Schlesinger, Alfredo Valarezo, and Marshall Burke, "Climate and health benefits of a transition from gas to electric cooking," *Proceedings of the National Academy of Sciences*, August 2023, *120* (34), e2301061120.

Guta, Dawit, Jill Baumgartner, Darby Jack, Ellison Carter, Guofeng Shen, Jennifer Orgill-Meyer, Joshua Rosenthal, Katherine Dickinson, Rob Bailis, Yuta Masuda, and Hisham Zerriffi, "A systematic review of household energy transition in low and middle income countries," *Energy Research & Social Science*, 2022, *86*, 102463.

Hanna, Rema and Benjamin A. Olken, eds, *The Handbook of Social Protection: Evidence and New Directions for Low- and Middle-Income Countries*, Cambridge, MA: MIT Press, 2026.

_ , Esther Duflo, and Michael Greenstone, "Up in Smoke: The Influence of Household Behavior on the Long-Run Impact of Improved Cooking Stoves," *American Economic Journal: Economic Policy*, February 2016, *8* (1), 80–114.

_ , _ , and _ , "Up in Smoke: The Influence of Household Behavior on the Long-Run Impact of Improved Cooking Stoves," *American Economic Journal: Economic Policy*, February 2016, *8* (1), 80–114.

Holland, Stephen P., Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates, "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors," *American Economic Review*, December 2016, *106* (12), 3700–3729.

IEA, "World Energy Outlook 2022," 2022.

Kar, Abhishek, Theresa Tawiah, Linnea Graham, Georgette Owusu-Amankwah, Misbath Daouda, Flavio Malagutti, Steve Chillrud, Erin E. Harned, Seidu Iddrisu, Edward A. Apraku, Richard Tetteh, Sule Awuni, Kelsey Jack, Sulemana W. Abubakari, Darby Jack, and Kwaku P. Asante, "Factors associated with the use of liquefied petroleum gas in Ghana vary at different stages of transition," *Nature Energy*, 2024, *9*, 434–445.

Kathmandu Post, "Behind the Mega Electricity Deal," *Kathmandu Post*, January 2023.

Koirala, Yugottam, "Nepal's energy policy in 2023 and beyond," *Nepali Times*, January 2023. Section: News.

Kremer, Michael, Jessica Leino, Edward Miguel, and Alix Peterson Zwane, "Spring Cleaning: Rural Water Impacts, Valuation, and Property Rights Institutions*," *The Quarterly Journal of Economics*, February 2011, *126* (1), 145–205.

Lebel, Eric D., Colin J. Finnegan, Zutao Ouyang, and Robert B. Jackson, "Methane and NOx emissions from natural gas stoves, cooktops, and ovens in residential homes," *Environmental Science & Technology*, 2022, *56* (4), 2529–2539.

Li, Jing, "Compatibility and Investment in the U.S. Electric Vehicle Market," *Working Paper*, 2023.

Li, Shanjun, Lang Tong, Jianwei Xing, and Yiyi Zhou, "The Market for Electric Vehicles: Indirect Network Effects and Policy Design," *Journal of the Association of Environmental and Resource Economists*, 2017, *4* (1), 89–133.

_ , Xianglei Zhu, Yiding Ma, Fan Zhang, and Hui Zhou, "The Role of Government in the Market for Electric Vehicles: Evidence from China," *Journal of Policy Analysis and Management*, 2022, *41* (2), 450–485.

List, John A., *The Voltage Effect: How to Make Good Ideas Great and Great Ideas Scale*, Crown Currency, 2022.

Mahadevan, Meera, Ryan McCord, Robyn C. Meeks, and Manisha Pradhananga, "Growing Pains: Infrastructure Upgrades for Energy Transitions," March 2026. Working paper.

Masera, Omar R., Barbara D. Saatkamp, and Daniel M. Kammen, "From linear fuel switching to multiple cooking strategies: a critique and alternative to the energy ladder model," *World Development*, 2000, *28* (12), 2083–2103.

Meeks, Robyn and Meera Mahadevan, "Electricity Infrastructure," VoxDevLit May 2025. VoxDevLit.

_ , Katharine R. E. Sims, and Hope Thompson, "Waste Not: Can Household Biogas Deliver Sustainable Development?," *Environmental and Resource Economics*, March 2019, *72* (3), 763–794.

Mobarak, Ahmed Mushfiq, Puneet Dwivedi, Robert Bailis, Lynn Hildemann, and Grant Miller, "Low Demand for Nontraditional Cookstove Technologies," *Proceedings of the National Academy of Sciences*, 2012, *109* (27), 10815–10820.

National Statistics Office, *Statistical Pocket Book, Nepal 2024*, Vol. 23, Kathmandu, Nepal: Government of Nepal, National Statistics Office, July 2025.

NepalEnergyForum, "NEA Electricity tariff rates," July 2023.

Open Data Nepal, "List of Currently Operating IPPs' Hydro Power Projects - Nepal Electricity Authority," 2022.

Pattanayak, S. K., M. Jeuland, J. J. Lewis, F. Usmani, N. Brooks, V. Bhojvaid, A. Kar, L. Lipinski, L. Morrison, O. Patange, N. Ramanathan, I. H. Rehman, R. Thadani, M. Vora, and V. Ramanathan, "Experimental evidence on promotion of electric and improved biomass cookstoves," *Proceedings of the National Academy of Sciences*, July 2019, *116* (27), 13282–13287.

Pfeiffer, Lisa and C.-Y. Cynthia Lin, "Does efficient irrigation technology lead to reduced groundwater extraction? Empirical evidence," *Journal of Environmental Economics and Management*, March 2014, *67* (2), 189–208.

Rapson, David and Erich Muehlegger, "Global Transportation Decarbonization," *Journal of Economic Perspectives*, August 2023, *37* (3), 163–188.

Shankar, Anita V., Ashlinn K. Quinn, Katherine L. Dickinson, Kendra N. Williams, Omar Masera, Dana Charron, Darby Jack et al., "Everybody stacks: Lessons from household energy case studies to inform design principles for clean energy transitions," *Energy Policy*, 2020, *141*, 111468.

Sharma, Binod and Ashish Shrestha, "Petroleum dependence in developing countries with an emphasis on Nepal and potential keys," *Energy Strategy Reviews*, January 2023, *45*, 101053.

Springel, Katalin, "Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives," *American Economic Journal: Economic Policy*, 2021, *13* (4), 393–432.

Sweeney, Micah, Jeff Dols, Brian Fortenbery, and Frank Sharp, "Induction Cooking Technology Design and Assessment," in "in" 2014.

Tarozzi, Alessandro, Aprajit Mahajan, Brian Blackburn, Dan Kopf, Lakshmi Krishnan, and Joanne Yoong, "Micro-Loans, Insecticide-Treated Bednets, and Malaria: Evidence from a Randomized Controlled Trial in Orissa, India," *American Economic Review*, July 2014, *104* (7), 1909–1941.

Timilsina, Govinda and Jevgenijs Steinbuks, "Economic costs of electricity load shedding in Nepal," *Renewable and Sustainable Energy Reviews*, 2021, *146*, 111112.

Wager, Stefan and Susan Athey, "Estimation and Inference of Heterogeneous Treatment Effects using Random Forests," *Journal of the American Statistical Association*, 2018, *113* (523), 1228–1242.

Xing, Jianwei, Benjamin Leard, and Shanjun Li, "What does an electric vehicle replace?," *Journal of Environmental Economics and Management*, 2021, *107*, 102432.

Figures and Tables

Figures

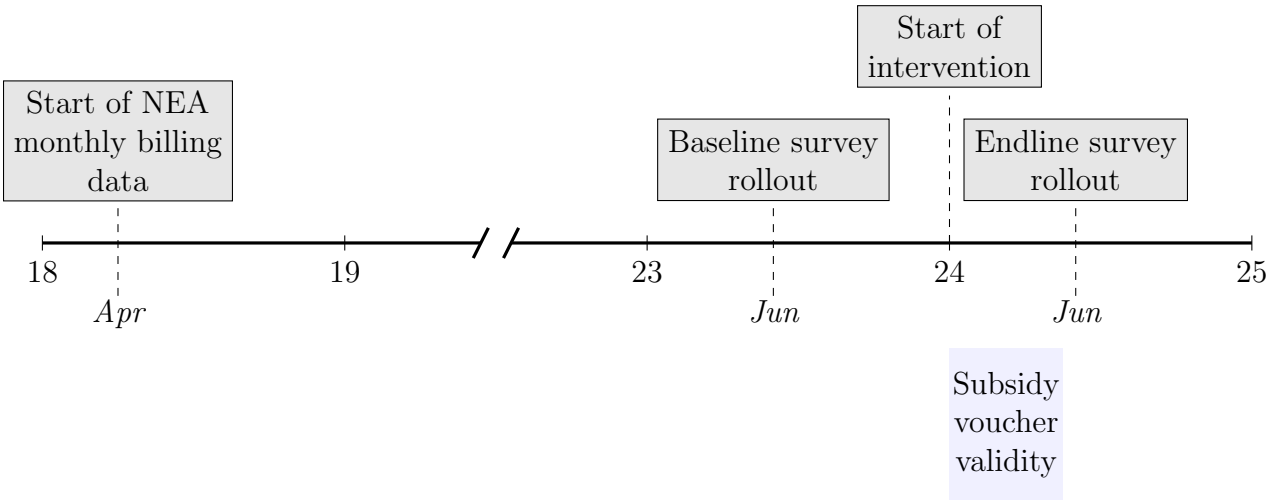
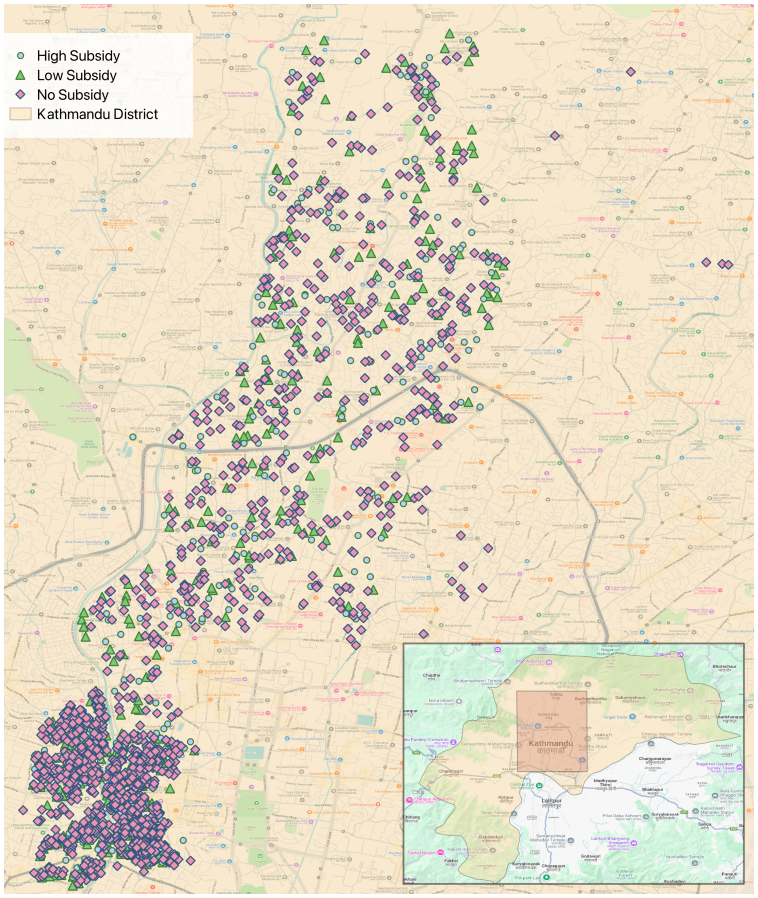


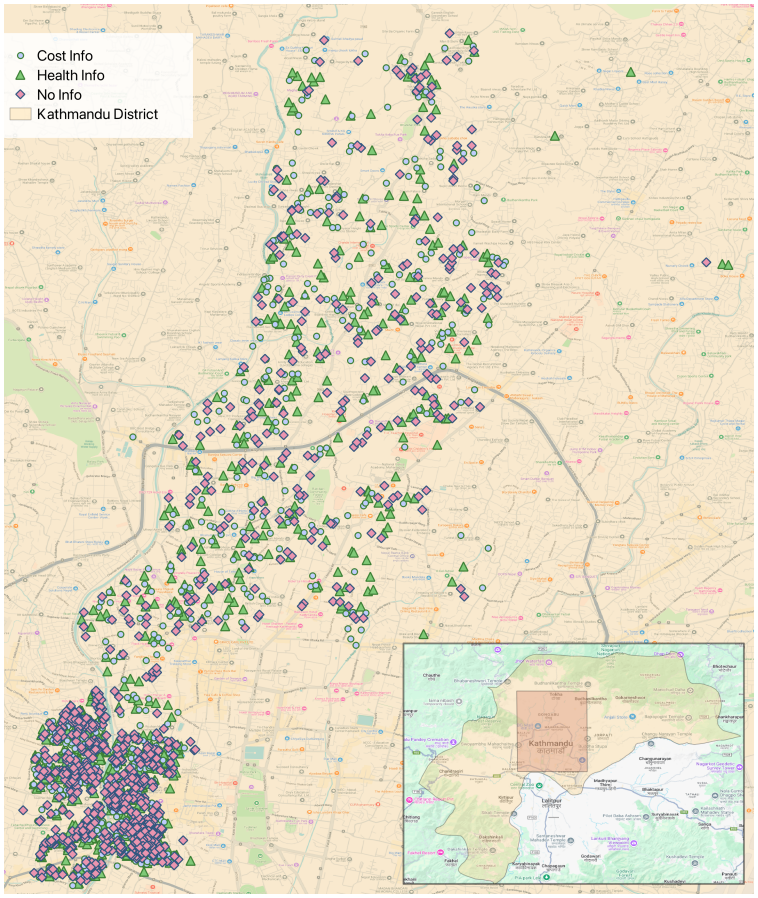
Figure 1: Timeline of surveys and key activities

Figure 2: Spatial spread of households by subsidy treatment group



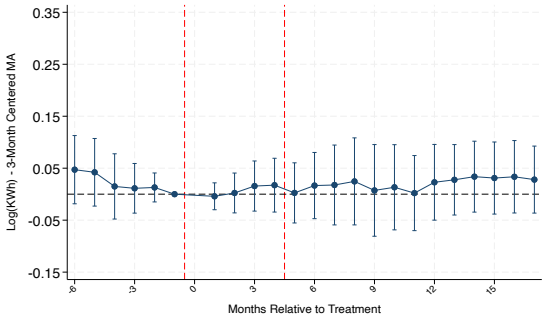
Source: Kathmandu district boundary is from 2015 and was obtained from Code for Nepal.

Figure 3: Spatial spread of households by information treatment group

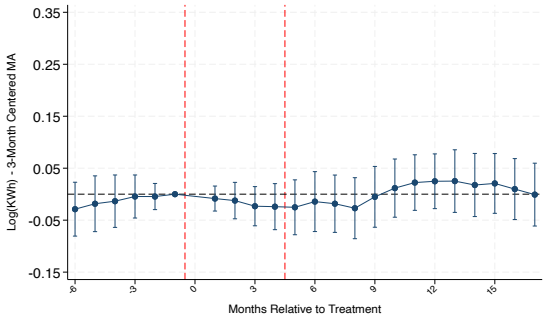


Source: Kathmandu district boundary is from 2015 and was obtained from Code for Nepal.

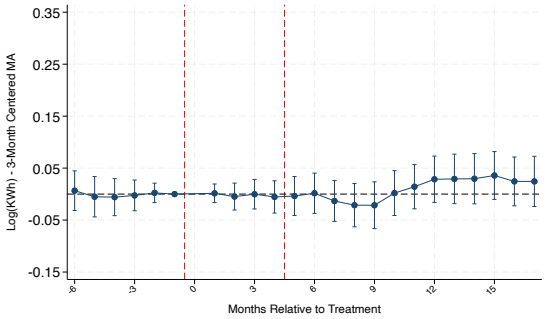
Figure 4: Event Study Estimates of Treatment Effects on Log Electricity Consumption



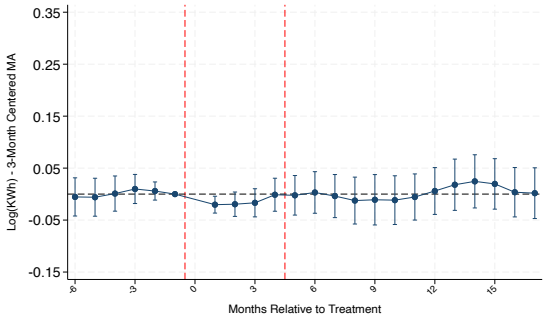
(a) High Subsidy Only



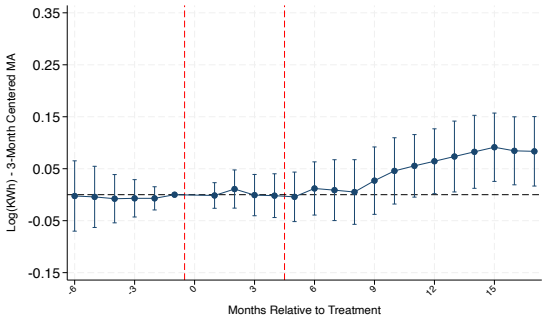
(b) Low Subsidy Only



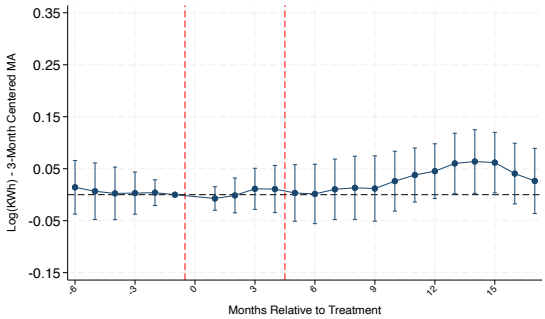
(c) Cost Information Only



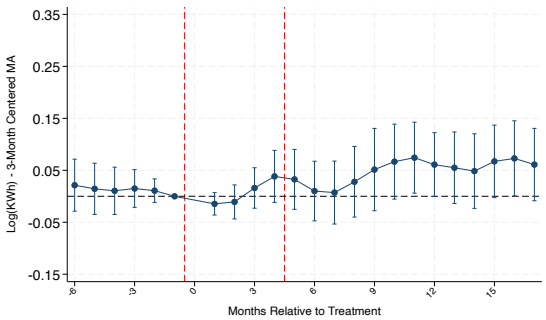
(d) Health Information Only



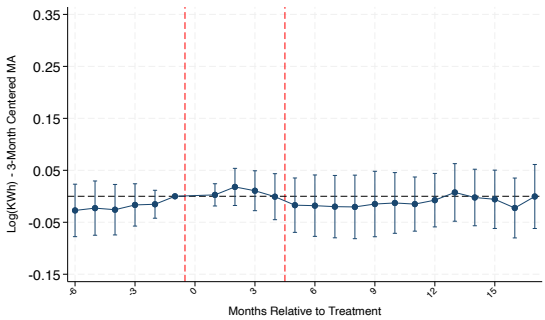
(e) Cost Information & High Subsidy



(f) Cost Information & Low Subsidy



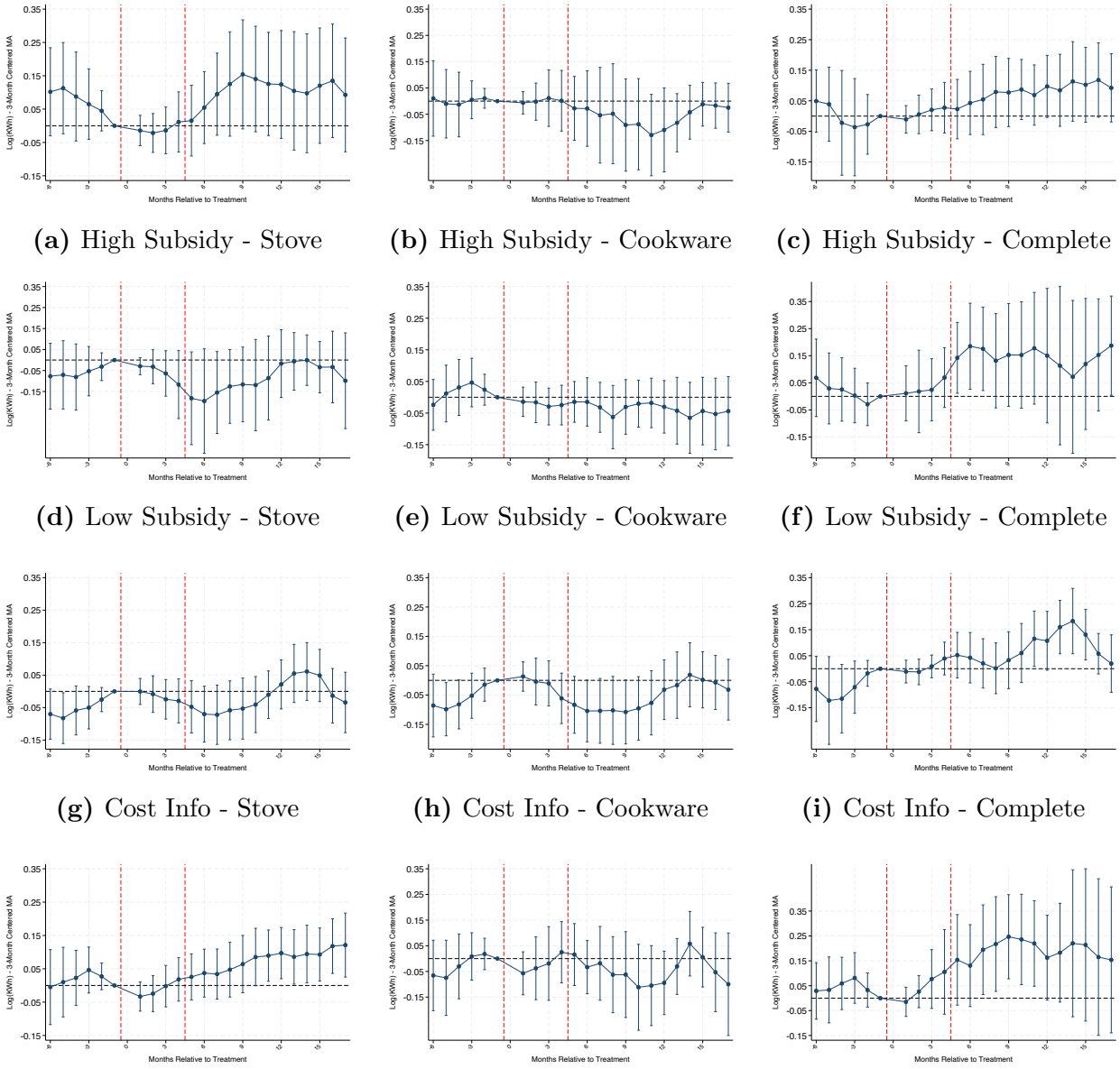
(g) Health Information & High Subsidy



(h) Health Information & Low Subsidy

Notes: This figure plots event study estimates of the effect of treatment arms on log electricity consumption (three-month centered moving average), based on Equation (5). Each panel compares a specific treatment arm relative to the control group. The reference period (omitted category) is December 2023. Vertical red dotted lines indicate the intervention window. Standard errors are clustered at the household level. Whiskers represent 95% confidence intervals.

Figure 5: Event Study Estimates on Log Electricity Consumption by Adopter Type



(a) High Subsidy - Stove **(b)** High Subsidy - Cookware **(c)** High Subsidy - Complete

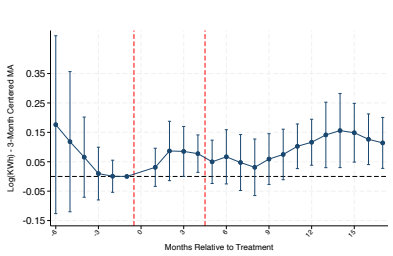
(d) Low Subsidy - Stove **(e)** Low Subsidy - Cookware **(f)** Low Subsidy - Complete

(g) Cost Info - Stove **(h)** Cost Info - Cookware **(i)** Cost Info - Complete

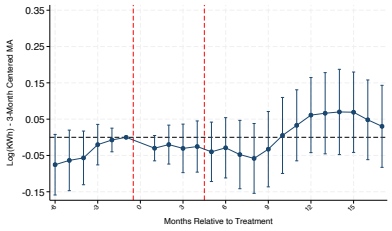
(j) Health Info - Stove **(k)** Health Info - Cookware **(l)** Health Info - Complete

Notes: This figure plots event study estimates of the effect of treatment on log electricity consumption (three-month centered moving average), based on Equation (5). The columns display heterogeneity by adoption type relative to the control group: Column 1 includes treated households who adopted only electric stoves; Column 2, those who adopted only compatible cookware; and Column 3, those who adopted both. The reference period is December 2023. Vertical red dotted lines indicate the intervention deployment period. Standard errors are clustered at the household level. Whiskers represent 95% confidence intervals.

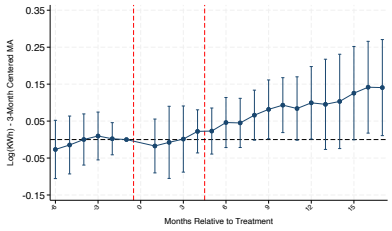
Figure 5: Event Study Estimates on Log Electricity Consumption by Adopter Type (continued...)



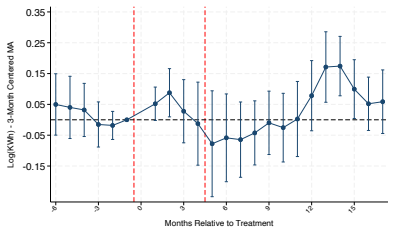
(m) High Sub. & Cost - Stove



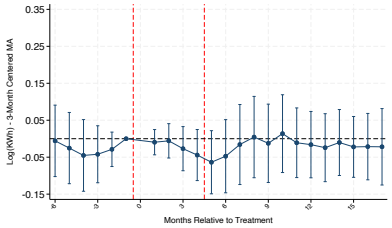
(n) High Sub. & Cost - Cookware



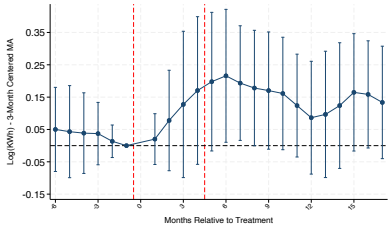
(o) High Sub. & Cost - Complete



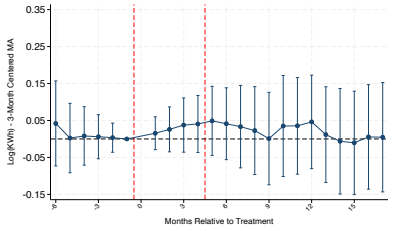
(p) Low Sub. & Cost - Stove



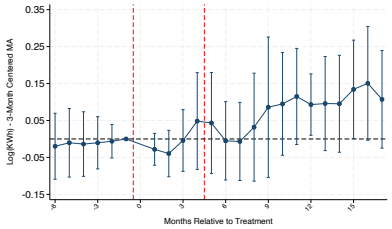
(q) Low Sub. & Cost - Cookware



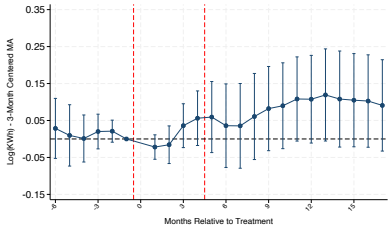
(r) Low Sub. & Cost - Complete



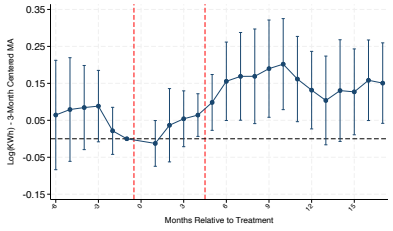
(s) High Sub. & Health - Stove



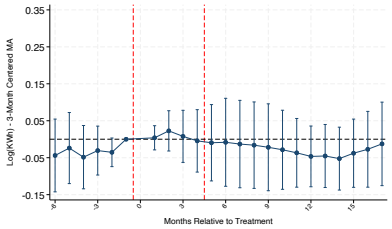
(t) High Sub. & Health - Cookware



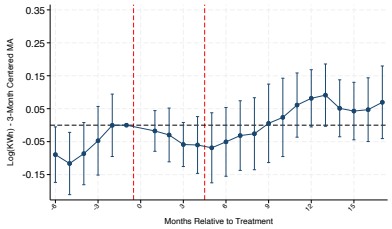
(u) High Sub. & Health - Complete



(v) Low Sub. & Health - Stove



(w) Low Sub. & Health - Cookware



(x) Low Sub. & Health - Complete

Notes: This figure plots event study estimates of the effect of treatment on log electricity consumption (three-month centered moving average), based on Equation (5). The columns display heterogeneity by adoption type relative to the control group: Column 1 includes treated households who adopted only electric stoves; Column 2, those who adopted only compatible cookware; and Column 3, those who adopted both. The reference period is December 2023. Vertical red dotted lines indicate the intervention deployment period. Standard errors are clustered at the household level. Whiskers represent 95% confidence intervals.

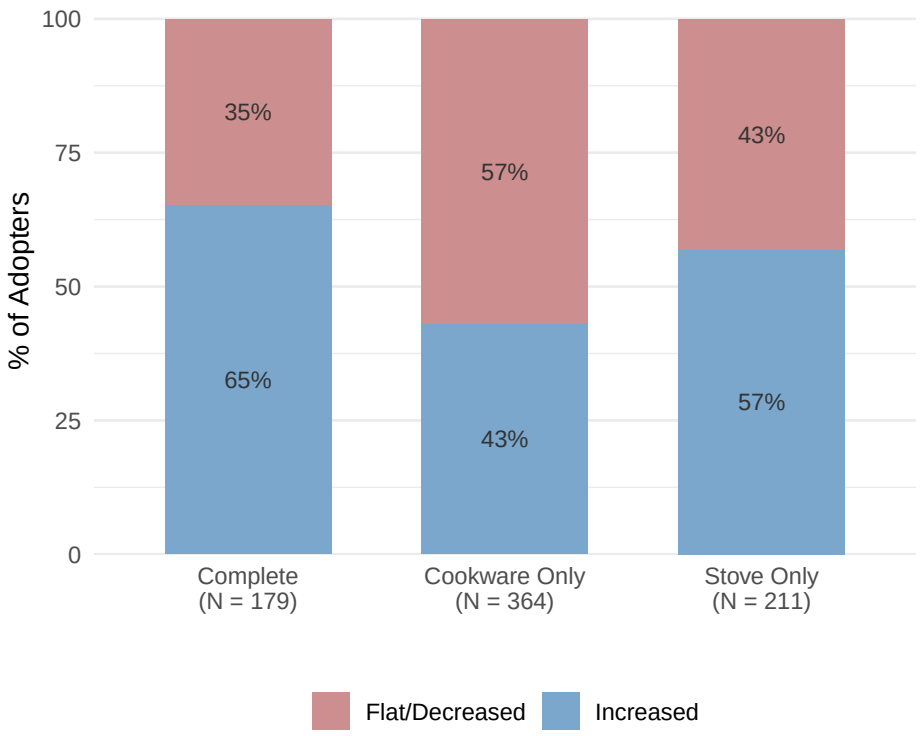


Figure 6: Change in Post-Adoption Electricity Usage by Adopter Type

Notes: Stacked bars show the percentage of adopters in each type who increased versus decreased or maintained their total billed electricity usage, measured as Δ log(kWh) between months 0–2 and months 12–14 post-intervention. Electricity data are from Nepal Electricity Authority administrative billing records and capture total household consumption, not cooking alone. Complete = purchased both stove and induction-compatible cookware; Cookware Only = cookware without stove; Stove Only = stove without cookware. $N = 754$ adopters with matched billing data across all treatment arms (control excluded).

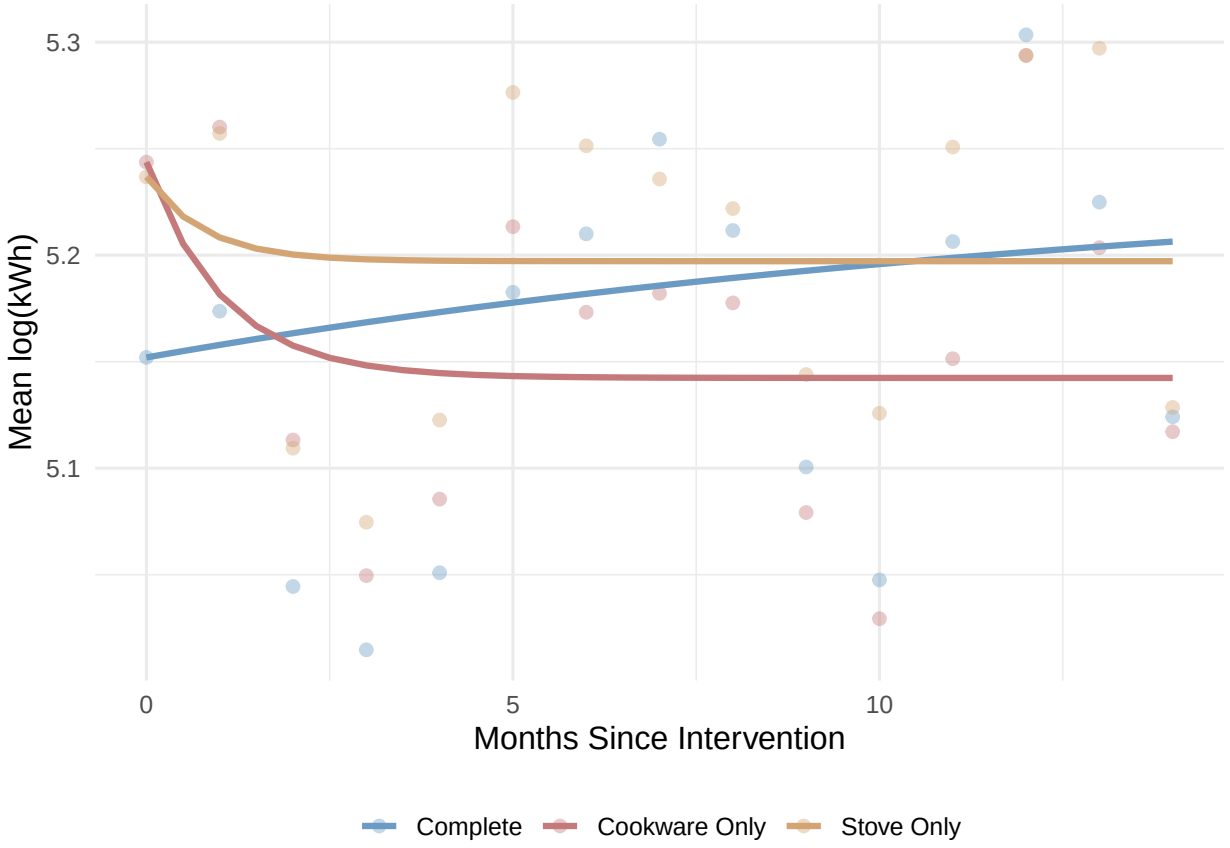


Figure 7: Post-Adoption Electricity Trajectories by Adopter Type

Notes: Points show monthly mean log(kWh) by months since intervention, separately for each adopter type. Solid lines show fitted values from the usage equation (2), estimated separately by type via OLS with cluster fixed effects (169 clusters) and standard errors clustered at the household level. The learning curve $g(t) = 1 - e^{-\hat{\kappa}t}$ is estimated by grid search over $\kappa \in [0.01, 2.0]$. Electricity data are from Nepal Electricity Authority billing records and capture total household consumption, not cooking alone. Complete = stove + cookware ($N = 196$); Cookware Only = cookware without stove ($N = 394$); Stove Only = stove without cookware ($N = 246$). Total: 836 adopters, 16,457 adopter-months.

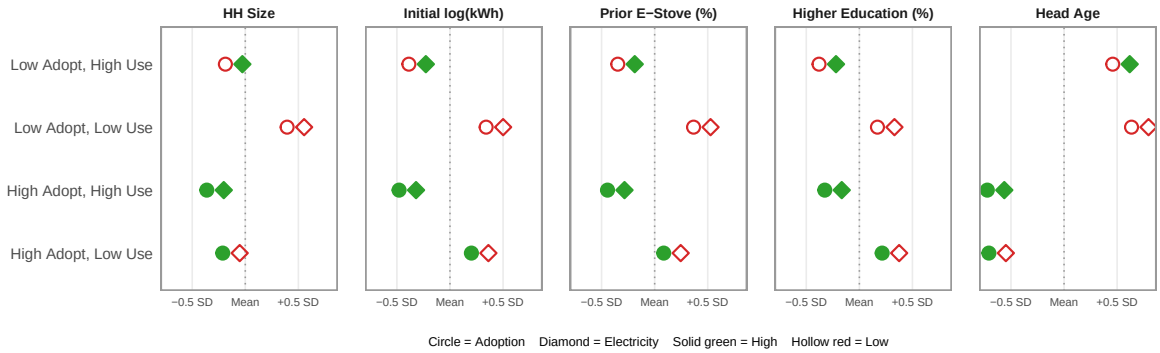


Figure 8: Baseline Household Characteristics by Predicted Household Type

Notes: Each point shows the cell-level mean for the indicated baseline characteristic, normalized to the sample mean and standard deviation. Household types are defined by median splits on the causally estimated adoption treatment effect $\hat{\tau}_i$ (causal forest) and predicted kWh growth $\hat{y}_i$ (regression forest) across $N = 1{,}617$ households in subsidy and control arms. Circles denote the adoption response dimension; diamonds denote the electricity usage growth dimension. Green indicates above-median and red indicates below-median predicted response. The vertical dotted line marks the sample mean. All covariates are from the baseline household survey.

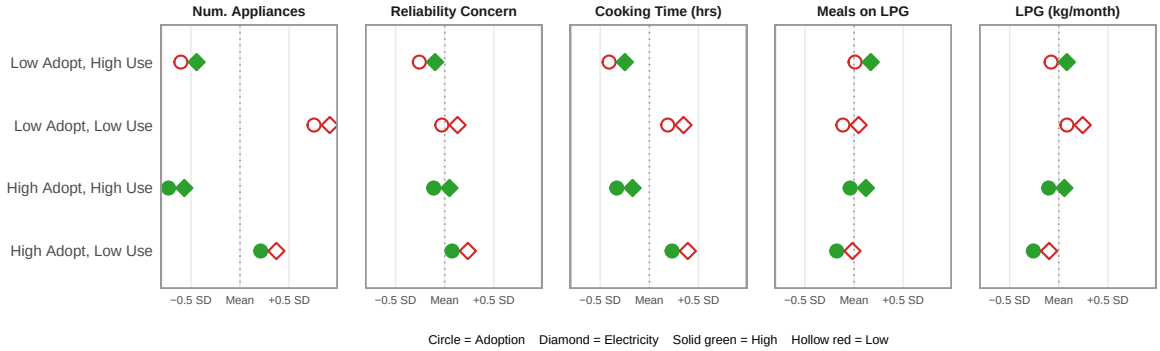


Figure 9: Energy and Targeting Covariates by Predicted Household Type

Notes: Each point shows the cell-level mean for the indicated energy or targeting variable, normalized to the sample mean and standard deviation. Household types are defined by median splits on the causally estimated adoption treatment effect $\hat{\tau}_i$ (causal forest) and predicted kWh growth $\hat{y}_i$ (regression forest) across $N = 1{,}617$ households in subsidy and control arms. Circles denote the adoption response dimension; diamonds denote the electricity usage growth dimension. Green indicates above-median and red indicates below-median predicted response. The vertical dotted line marks the sample mean. All variables are from the baseline household survey.

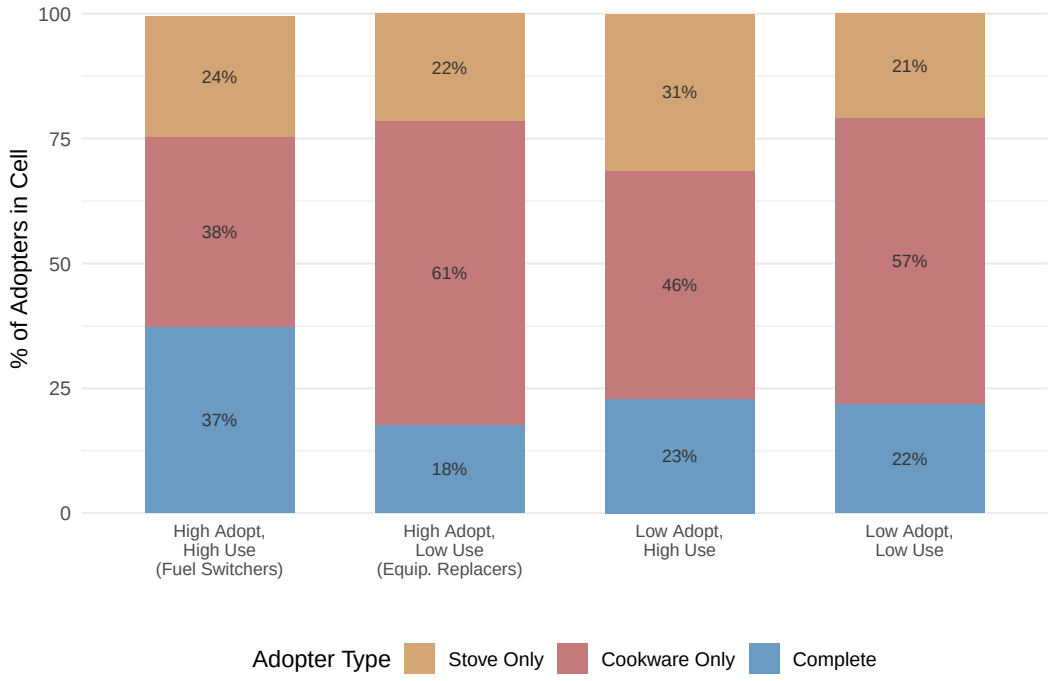


Figure 10: Adopter Composition by Predicted Household Type

Notes: Stacked bars show the share of adopters in each predicted household type who purchased the complete bundle (stove + cookware), cookware only, or stove only. Household types are defined by median splits on the causally estimated adoption treatment effect $\hat{\tau}_i$ (causal forest) and predicted kWh growth $\hat{y}_i$ (regression forest). Adoption type is from the endline survey. $N = 656$ adopters with matched billing data in subsidy and control arms ($N = 1{,}617$ households).

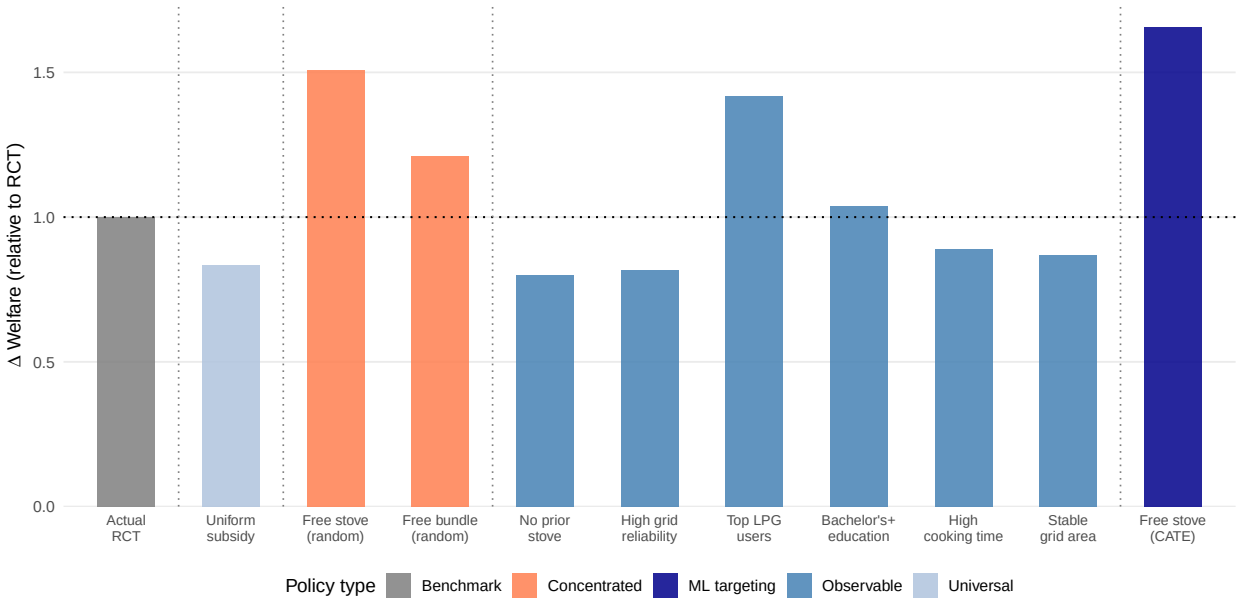


Figure 11: Counterfactual Welfare Gains under Alternative Subsidy Designs

Notes: Each bar shows the welfare gain from the planner's objective (3), relative to the RCT design (normalized to 1), across $N = 2{,}740$ households. The budget equals actual RCT subsidy spending ($B = 2{,}180{,}000$ NPR). All counterfactual policies bundle cost information with the subsidy ($P = 0.85$). Adoption probabilities are from the structural equation (1) with household-level heterogeneity from causal forest BLP coefficients (γ_X). "Free stove (CATE)" gives free stoves to the 300 households with the highest predicted adoption response. "Free stove (random)" and "Free bundle (random)" are lotteries: divide the budget by the unit cost, randomly select that many households, and give them the item free. The "stove" is the induction stove alone ($K_{\text{stove}} = 7{,}000$ NPR, 311 winners); the "bundle" is the stove plus compatible cookware ($K_{\text{bundle}} = 10{,}000$ NPR, 218 winners), which guarantees all adopters are complete adopters with positive learning trajectories. Observable rules target on baseline characteristics: no prior stove ownership, high grid reliability (below-median outage worry), top LPG users (administrative data), bachelor's degree or higher, above-median cooking time, and below-median monthly outage frequency. For each targeting rule, the planner optimizes the subsidy level s (and for LPG, CATE, and random, also the number of recipients). Each adopter's contribution is weighted by expected electricity usage at a 24-month horizon, based on the adopter-type composition each policy induces and the type-specific learning curves from Panel C of Table 7. Planner parameters: $\delta = 5{,}000$, $\lambda = 2{,}000$, $\psi = 1.0$.

Tables

Table 1: Summary Statistics

	Mean	S.D.	Min	Max	N
Prop. with smart meter	0.69	0.46	0	1	2740
Cash/Cheque for Elec. Bill	0.37	0.48	0	1	2740
Credit for Elec. Bill	0.63	0.48	0	1	2740
Know Most Recent Elec. Expense	0.97	0.18	0	1	2740
Recent Elec. Expense (NPR)	2090.24	2816.51	14	60000	2652
Know Most Recent Elec. Consumption	0.54	0.50	0	1	2740
Recent Elec. Consumption (KWh)	203.91	268.47	0	7189	1479
Avg. Elec. Outages (per week, Normal Months)	1.26	2.33	0	21	2685
Avg. Elec. Outages (per week, Bad Months)	5.52	4.58	0	30	1803
Voltage Fluctuation in 12 Months	0.33	0.47	0	1	2740
Elec. Fluctuation $\geq$ Once/Week	0.08	0.26	0	1	836
Appliance for Voltage Fluctuation	0.20	0.40	0	1	2740
Prop. that heat house	0.33	0.47	0	1	2740
Prop. with AC	0.03	0.16	0	1	2740
# of light bulbs per HH	21.78	15.23	1	223	2740
# of EE bulbs per HH	20.83	15.04	0	223	2740
# of Elec. appliances per HH	16.95	7.29	1	65	2740
Prop. with fan	0.84	0.37	0	1	2740
Prop. with fridge	0.89	0.32	0	1	2740
Prop. with rice cooker	0.42	0.49	0	1	2740
Prop. with pressure cooker	0.01	0.08	0	1	2740
Prop. with induction stove	0.35	0.48	0	1	2740
Prop. with microwave	0.31	0.46	0	1	2740
Prop. with washing machine	0.48	0.50	0	1	2740
Prop. with AC	0.03	0.17	0	1	2740
Prop. with kettle/pot	0.64	0.48	0	1	2740
Prop. with an EV	0.03	0.16	0	1	2740
Hours spent on cooking (last week)	13.50	5.41	0	44	2716

Notes: The variables used to generate this table are from the baseline survey.

Table 2: Household Random Assignment by Treatment

	Subsidy Treatments			
Info Treatments	High (3000 NPR)	Low (1000 NPR)	No subsidy	Info treatment totals
Induction Cooking Costs	195	181	576	952
Induction Cooking Health	191	201	585	977
No Info	184	196	585	965
Column totals	570	578	1746	2894

Notes: The information treatments and the subsidy treatments wee cross randomized. Each cell depicts the number of households randomly assigned to that combination of treatments. A total of 2,894 households were randomized across groups. This is from the 2,985 households surveyed in 2023 that consented to participate in the RCT.

Table 3: Baseline balance across treatment groups

	(1) High Subs-Cost Info	(2) Low Subs-Cost Info	(3) No Subs-Cost Info	(4) High Subs-Health Info	(5) Low Subs-Health Info	(6) No Subs-Health Info	(7) High Subs-No Info	(8) Low Subs-No Info	(9) No Subs-No Info
Household size	4.61	4.28	4.34	4.31	4.24	4.35	4.26	4.49	4.42
	(.1572)	(.1353)	(.0878)	(.1431)	(.1394)	(.0876)	(.1375)	(.151)	(.0875)
	[0.29]	[0.39]	[0.55]	[0.54]	[0.29]	[0.56]	[0.34]	[0.69]	
HH head has no education	0.20	0.16	0.20	0.19	0.18	0.20	0.20	0.20	0.20
	(.0296)	(.0282)	(.0174)	(.0294)	(.0281)	(.0169)	(.03)	(.0296)	(.017)
	[0.92]	[0.25]	[0.91]	[0.82]	[0.54]	[0.96]	[1.00]	[0.92]	
HH head has higher education	0.17	0.20	0.20	0.17	0.18	0.19	0.19	0.20	0.19
	(.0274)	(.0308)	(.0174)	(.0281)	(.0278)	(.0167)	(.0294)	(.0296)	(.0166)
	[0.46]	[0.71]	[0.63]	[0.56]	[0.65]	[0.91]	[0.99]	[0.83]	
House has smart meter installed	0.70	0.69	0.70	0.69	0.67	0.69	0.69	0.69	0.68
	(.0336)	(.0353)	(.0198)	(.0345)	(.0344)	(.0196)	(.0348)	(.0343)	(.0198)
	[0.51]	[0.74]	[0.39]	[0.76]	[0.83]	[0.75]	[0.83]	[0.73]	
Electric cooking appliances #	0.55	0.53	0.54	0.52	0.61	0.52	0.55	0.53	0.58
	(.0575)	(.0608)	(.032)	(.0568)	(.0586)	(.0304)	(.0572)	(.0544)	(.0334)
	[0.69]	[0.46]	[0.37]	[0.40]	[0.69]	[0.17]	[0.63]	[0.41]	
Owns induction cookstove	0.27	0.28	0.27	0.30	0.31	0.29	0.27	0.26	0.31
	(.0328)	(.0343)	(.0193)	(.0341)	(.0338)	(.0191)	(.0332)	(.0328)	(.0196)
	[0.39]	[0.48]	[0.24]	[0.83]	[0.97]	[0.48]	[0.31]	[0.26]	
Houses #	186	172	535	181	188	560	179	182	557

Notes: The standard errors are in parentheses and p-values of the difference between the treatment and control in square brackets. Column 9 is the pure control group.

Table 4: Treatment Effect on Extensive Margin

	(1) Adoption	(2) Bought Ind. Compatible Cookware	(3) Induction Stove
High Subsidy	0.529***	0.413***	0.230***
	(0.0358)	(0.0324)	(0.0301)
Low Subsidy	0.270***	0.245***	0.0439
	(0.0356)	(0.0322)	(0.0300)
Cost Info.	0.0210	0.00347	0.0279
	(0.0252)	(0.0228)	(0.0212)
Health Info.	0.0153	-0.000452	0.0174
	(0.0249)	(0.0225)	(0.0210)
High Subsidy & Cost Info.	0.471***	0.394***	0.192***
	(0.0353)	(0.0319)	(0.0297)
Low Subsidy & Cost Info.	0.237***	0.259***	0.0399
	(0.0364)	(0.0329)	(0.0306)
High Subsidy & Health Info.	0.532***	0.413***	0.321***
	(0.0357)	(0.0322)	(0.0300)
Low Subsidy & Health Info.	0.273***	0.277***	0.0610**
	(0.0351)	(0.0318)	(0.0296)
Constant	0.147***	0.0844***	0.0880***
	(0.0177)	(0.0160)	(0.0149)
Observations	2740	2740	2740

Notes: All dependent variables are dummies. Bought induction compatible cookware indicates if the household reported buying induction compatible cookware in the last 6 months before the endline interview. Induction stove indicates if the household reported buying an induction stove. The variable adoption combines both of the previous variables (i.e. indicates adoption of either cookware or induction stove). Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

Table 5: Treatment Effect on Cooking Behavior (OLS)

	(1) % of Meals with induction stove	(2) % of Meals with LPG stove	(3) Elec. Time Cooking	(4) LPG Time Cooking
High Subsidy	0.0694**	-0.0461**	17.39***	-7.340
	(0.0292)	(0.0210)	(5.038)	(4.703)
Low Subsidy	0.0853***	-0.0247	14.27***	-9.978**
	(0.0290)	(0.0209)	(5.006)	(4.674)
Cost Info.	0.0145	-0.0160	3.852	-0.758
	(0.0206)	(0.0148)	(3.550)	(3.319)
Health Info.	0.0310	-0.0241	0.207	-3.152
	(0.0203)	(0.0147)	(3.509)	(3.278)
High Subsidy & Cost Info.	0.0922***	-0.0406*	13.72***	-6.416
	(0.0288)	(0.0207)	(4.966)	(4.645)
Low Subsidy & Cost Info.	0.0385	-0.0511**	7.393	-7.595
	(0.0296)	(0.0214)	(5.115)	(4.786)
High Subsidy & Health Info.	0.0954***	-0.0655***	16.06***	-8.226*
	(0.0291)	(0.0209)	(5.017)	(4.683)
Low Subsidy & Health Info.	0.0403	-0.0248	10.24**	-6.339
	(0.0287)	(0.0207)	(4.946)	(4.636)
Constant	0.159***	0.887***	47.72***	120.0***
	(0.0144)	(0.0104)	(2.485)	(2.321)
Observations	2740	2740	2740	2731

Notes: The table presents OLS estimates of treatment effects on cooking behavior outcomes. The outcome variables are (1) percentage of meals cooked with an induction stove, (2) percentage of meals cooked with a LPG stove, (3) time spent cooking in minutes on an average day using electric appliances, (4) time spent cooking in minutes on an average day using a LPG stove. Significance: $***$ p < 0.01, $**$ p < 0.05, $*$ p < 0.10.

Table 6: Treatment Effects on Log(kWh) by Adopter Type - Short-run vs Long-run

	(1) Log(kWh)	(2) Log(kWh)	(3) Log(kWh)	(4) Log(kWh)	(5) Log(kWh)	(6) Log(kWh)	(7) Log(kWh)	(8) Log(kWh)
High Subsidy	-0.0295	-0.000868	-0.0509	0.00211	-0.0772	-0.0515	0.0610	0.125*
	(0.0246)	(0.0307)	(0.0326)	(0.0633)	(0.0528)	(0.0468)	(0.0616)	(0.0669)
Low Subsidy	0.00240	0.0315	-0.0552	0.0313	-0.0369	-0.0613	0.141***	0.137
	(0.0202)	(0.0278)	(0.0847)	(0.0728)	(0.0326)	(0.0435)	(0.0533)	(0.0864)
Cost Information	-0.0182	0.0143	0.000741	0.0522	-0.0404	0.0248	0.111**	0.173***
	(0.0138)	(0.0210)	(0.0271)	(0.0407)	(0.0427)	(0.0493)	(0.0467)	(0.0607)
Health Information	-0.0161	0.00879	0.0458	0.117**	0.00807	0.0455	0.122	0.141
	(0.0147)	(0.0228)	(0.0417)	(0.0474)	(0.0491)	(0.0622)	(0.0811)	(0.137)
Cost Info & High Subsidy	0.00471	0.0744**	-0.0453	0.0279	0.0142	0.0959*	0.0637**	0.154**
	(0.0263)	(0.0358)	(0.103)	(0.110)	(0.0363)	(0.0521)	(0.0298)	(0.0609)
Cost Info & Low Subsidy	-0.00860	0.0239	-0.0143	0.113**	-0.0135	-0.0129	0.0881	0.0794
	(0.0190)	(0.0281)	(0.0340)	(0.0518)	(0.0297)	(0.0423)	(0.0721)	(0.0882)
Health Info & High Subsidy	0.0118	0.0418	0.0125	-0.0214	0.0320	0.113*	0.0338	0.0820
	(0.0220)	(0.0321)	(0.0423)	(0.0672)	(0.0511)	(0.0607)	(0.0371)	(0.0604)
Health Info & Low Subsidy	0.00580	0.0149	0.103**	0.129**	0.0150	-0.00283	0.0408	0.121**
	(0.0182)	(0.0247)	(0.0406)	(0.0654)	(0.0377)	(0.0413)	(0.0382)	(0.0480)
Observations	63894	45163	18730	13245	21611	15278	17169	12141
Period	Short-run	Long-run	Short-run	Long-run	Short-run	Long-run	Short-run	Long-run
Adopter Type	Full Sample	Full Sample	Stove	Stove	Cookware	Cookware	Complete	Complete
Num. Households	2698	2698	791	791	913	913	725	725
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The pre-treatment period spans January–December 2023. Short-run and long-run post-treatment periods cover January–December 2024 (12 months) and January–May 2025 (5 months), respectively. The outcome variable is winsorized log electricity consumption (kWh). Columns 1–2, 3–4, 5–6, and 7–8 present estimates for the full sample, stove-only adopters, cookware-only adopters, and complete adopters, respectively. Within each pair, odd columns report short-run effects and even columns report long-run effects. A common pure control group is included across all specifications. All regressions include household and month-year fixed effects. Standard errors are cluster at the household level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Structural Parameter Estimates

Panel A: Adoption equation (1) — *identified from RCT*			
Parameter	Description	Estimate	Identification
ρ	Subsidy concavity	0.55	Grid search (min. OOS error)
θ	Taste heterogeneity	1.207	Sub. × info system
η	Price sensitivity	0.412	Info-only arm
γ_P	Sub. × cost interaction	2.289	Sub. × info system
Model fit		Observed	Predicted
	Control	0.147	0.147
	Low subsidy†	0.418	0.403
	High subsidy	0.676	0.676
	Info only	0.165	0.165
	High sub. + info	0.648	0.648
	Low sub. + info†	0.403	0.401
Panel B: Usage equation (2) — *from billing panel*			
		Estimate	Identification
$\hat{\delta}_r$	Reliability	+0.001 (0.009)	Cross-sectional
$\hat{\kappa}$	Learning rate (pooled)	1.26	Grid search
$\hat{\delta}_L$	Learning coeff. (pooled)	−0.058 (0.014)	Within-HH time path
Panel C: Learning curve by adopter type			
		$\hat{\kappa}$	$\hat{\delta}_L$ (SE)
	Complete (stove + cookware), $N = 196$	0.07	+0.087 (0.043)**
	Cookware only, $N = 394$	0.95	−0.101 (0.021)***
	Stove only, $N = 246$	1.27	−0.040 (0.028)

Notes: Panel A: $N = 2{,}740$; subsidy normalized by $K =$ NPR 7,000; info shifts P: $1 \to 0.85$. † = out-of-sample. Panel B: 16,457 adopter-month obs. (836 HHs), cluster FE (169 clusters), SEs clustered at HH level. $g(t) = 1 - e^{-\kappa t}$; κ from grid search over $[0.01, 2.0]$. Panel C: separate estimation by adopter type. Complete = purchased both stove and induction cookware; Cookware only = cookware without stove; Stove only = stove without cookware. $^{**}p < 0.05$; $^{***}p < 0.001$. Billing data is total household electricity.

Table 8: Adopter Composition by Treatment Arm

	Info Only	Sub Only	Info + Low Sub	**Info + High Sub**
Total HHs	1,095	361	360	**367**
Adopters	181	197	145	**238**
Adoption rates (% of HHs)				
Adoption (stove or cookware or both)	16.5	54.6	40.3	**64.9**
Complete adoption (stove + cookware)	3.1	11.4	9.4	**19.6**
Among adopters (%)				
Complete adoption (stove + cookware)	18.8	20.8	23.4	**30.3**
Cookware only	33.1	54.8	64.1	**45.0**
Stove only	48.1	24.4	12.4	**24.8**

Notes: Adoption is defined as purchasing an electric induction stove, cookware, or both by the endline survey. Complete = purchased both stove and induction-compatible cookware. Adopter type shares (among adopters) sum to 100% within each arm. Each column pools across cost- and health-information variants of the corresponding treatment. Sample: all treatment arms excluding control ($N = 2{,}183$ households).

Appendix

A Additional Details on Structural Model

This appendix provides additional derivations and assumptions underlying the structural model presented in Section 3 of the main text. We expand on the household problem, the adoption equation, and the social planner's problem to make clear how each functional form arises.

A.1 Household Problem

Each household i in group g chooses between two cooking modes, LPG ($m = L$) and electricity ($m = E$), and an intensity of use T_{mg}. Utility has three components: (i) consumption utility net of perceived costs, (ii) transfers from subsidies if applicable, and (iii) idiosyncratic taste shocks:

$$\log U_{img} = \log C_{mg} + \log S_{mg} + \log \varepsilon_i. \tag{1}$$

Consumption utility. We assume consumption utility is

$$C_{mg} = T_{mg}^{\eta} - P_{mg}\, T_{mg}, \tag{2}$$

where P_{mg} is the perceived unit cost of cooking (monetary cost plus any perceived health costs) and $\eta \in (0, 1)$ governs the curvature.

The household chooses T_{mg} to maximize C_{mg}. Taking the FOC:

$$\frac{\partial C_{mg}}{\partial T_{mg}} = \eta T_{mg}^{\eta-1} - P_{mg} = 0. \tag{3}$$

Solving gives the optimal intensity of use:

$$T_{mg}^{*} = \left(\frac{\eta}{P_{mg}}\right)^{\frac{1}{1-\eta}}. \tag{4}$$

Indirect consumption utility. Plugging T_{mg}^{*} back into C_{mg} yields indirect consumption utility:

$$C_{mg}^{*} = \eta \left(\frac{\eta}{P_{mg}}\right)^{\frac{\eta}{1-\eta}} - P_{mg} \left(\frac{\eta}{P_{mg}}\right)^{\frac{1}{1-\eta}}. \tag{5}$$

This simplifies to

$$C_{mg}^{*} = \bar{\eta}\, P_{mg}^{\frac{-\eta}{1-\eta}}, \tag{6}$$

where $\bar{\eta} \equiv \eta^{\frac{\eta}{1-\eta}} - \eta^{\frac{1}{1-\eta}}$ is a positive constant that normalizes consumption utility.

Transfers Transfers from subsidies are denoted S_{mg}. For LPG, $S_{Lg} = 1$. For electricity, subsidies enter concavely and may interact with household and group characteristics:

$$\log S_{Eg} = s_{Eg}^{\rho}(1 + \gamma_P P_{Eg} + \gamma_X X_g + \gamma_A A_{-i,g}), \tag{7}$$

with $\rho \in (0, 1)$ capturing concavity of subsidy value.

Indirect utility Indirect utility for household i from choosing mode m is then

$$V_{mg} = \bar{\eta} P_{mg}^{\frac{-\eta}{1-\eta}} S_{mg}. \tag{8}$$

The full utility is $U_{img} = V_{mg}\varepsilon_i$.

A.2 Adoption Equation

Distributional assumption We assume the idiosyncratic shocks ε_i are drawn from a Fréchet distribution with shape parameter $\theta > 0$. This is a standard assumption in random utility models because it yields tractable choice probabilities. In particular, the "logit trick" implies:

$$\Pr(m = E) = \frac{V_{Eg}^{\theta}}{V_{Eg}^{\theta} + V_{Lg}^{\theta}}, \qquad \Pr(m = L) = \frac{V_{Lg}^{\theta}}{V_{Eg}^{\theta} + V_{Lg}^{\theta}}. \tag{9}$$

Adoption share Thus the adoption share of electricity is

$$\pi_{Eg} = \frac{V_{Eg}^{\theta}}{V_{Eg}^{\theta} + V_{Lg}^{\theta}}. \tag{10}$$

Taking the odds ratio:

$$\frac{\pi_{Eg}}{1 - \pi_{Eg}} = \left(\frac{V_{Eg}}{V_{Lg}}\right)^{\theta}. \tag{11}$$

Since $V_{Lg} = \bar{\eta}$ and $V_{Eg} = \bar{\eta} P_{Eg}^{\frac{-\eta}{1-\eta}} S_{Eg}$, the ratio simplifies to

$$\frac{\pi_{Eg}}{1 - \pi_{Eg}} = \left(P_{Eg}^{\frac{-\eta}{1-\eta}} S_{Eg}\right)^{\theta}. \tag{12}$$

Log-odds form Taking logs, we obtain the estimating equation for adoption:

$$\log \frac{\pi_{Eg}}{1 - \pi_{Eg}} = -\frac{\eta\theta}{1-\eta} \log P_{Eg} + \theta s_{Eg}^{\rho} + \theta\gamma_P(s_{Eg}^{\rho} P_{Eg}) + \theta\gamma_X(s_{Eg}^{\rho} X_g) + \theta\gamma_A(s_{Eg}^{\rho} A_{-i,g}). \tag{13}$$

Equation (13) highlights the roles of perceived costs, subsidies, and heterogeneity in determining adoption probabilities.

A.3 Electricity Usage Decomposition

The adoption equation determines which households take up the stove. Among adopters, what matters for policy is whether and how much electricity usage changes. This subsection details the decomposition of post-adoption usage introduced in equation (2).

From adoption to usage. Among adopters, electricity usage for cooking is governed by optimal cooking time $T_{it}^* = (\eta/\tilde{P}_{it})^{1/(1-\eta)}$, where $\tilde{P}_{it}$ is the effective perceived cost of electric cooking. Total billed electricity for cooking is $kWh_{it}^{\text{cook}} = \alpha\, T_{it}^*$, with α converting cooking hours to kilowatt-hours.

Estimating equation. The reduced-form estimating equation for electricity usage among adopters is:

$$\log kWh_{it} = \alpha + \delta_r R_i + \delta_L\, g(t) + X_i'\gamma + \mu_c + \epsilon_{it}, \tag{14}$$

where R_i is baseline reliability belief (Likert 1–10), $g(t) = 1 - e^{-\kappa t}$ is the learning curve with t months since intervention, X_i includes nine baseline household characteristics (household size, head age, higher education, homeownership, LPG consumption, cooking time, number of electric appliances, meals cooked on LPG, and baseline stove ownership), and μ_c is a cluster fixed effect (169 clusters). Standard errors are clustered at the household level. Billing data captures *total* household electricity, not just cooking kWh.

Estimation proceeds in two steps. First, a grid search over $\kappa \in [0.01, 2.0]$ (step 0.01) computes $g_\kappa(t) = 1 - e^{-\kappa t}$ for each candidate and estimates equation (14) by OLS with cluster fixed effects; the κ minimizing SSR is selected. Second, we report the coefficients at the optimal κ.

Identification. Each parameter draws on a distinct source of variation. The reliability coefficient δ_r comes from cross-sectional variation in baseline beliefs among adopters: comparing two households observed at the same month since adoption, one with high outage concern and one with low, the difference in electricity usage after controlling for observables identifies δ_r. Because the RCT randomizes subsidy receipt independently of baseline beliefs, adoption timing does not confound this comparison.

The learning parameters κ and δ_L are identified from the within-household time path of billed electricity. With monthly observations from month 0 through 14, the trajectory shape pins down κ (convergence speed) and δ_L (direction and magnitude). The sign of δ_L is unrestricted: $\delta_L > 0$ indicates usage grows with experience, $\delta_L < 0$ indicates reversion after initial experimentation.

Preference residual. The residual $\hat{\nu}_i^{\text{reg}} = T_i^{-1} \sum_t \hat{\epsilon}_{it}$ is the time-averaged residual from equation (14), capturing household-level electricity demand after accounting for reliability,

learning, and observables. Because X_i controls for income, appliance ownership, and household size, a large positive $\hat{\nu}_i^{\text{reg}}$ reflects genuinely high intrinsic demand rather than economic constraints. Note the sign convention: in the cost equation (2), high ν_i means high perceived cost (low demand), while in the kWh regression a positive residual means high usage. We follow the cost-equation convention in the main text, where low ν_i indicates strong demand for electric cooking.

A.4 Social Planner's Problem

The social planner chooses subsidy levels s_{Eg} and information treatments I_{Eg}^c, I_{Eg}^h to maximize aggregate welfare. Higher electricity use reduces reliance on LPG and improves health, but additional electricity demand is not costless when generation or distribution capacity is constrained. The planner therefore internalizes the marginal social cost of supplying electricity as well as the fiscal cost of subsidies.

The planner's objective is:

$$\max_{s_{Eg}, I_{Eg}^c, I_{Eg}^h} \sum_i U_{ig} - \delta KWh_{Eg} - \lambda(1 - \pi_{Eg}) - (s_{Eg} + \psi s_{Eg}^2), \tag{15}$$

where δ is the marginal social cost of supplying electricity when capacity is constrained, λ captures the social cost of continued LPG reliance, and ψ reflects the marginal cost of public funds.

Billed electricity consumption. Total long-run billed electricity consumption is:

$$KWh_{Eg} = K_g^0 + \pi_{Eg}\alpha T_{Eg}^* + \pi_{Eg}(H_g - 1)K_g^0, \tag{16}$$

where K_g^0 is baseline electricity demand and H_g is the post-adoption electrification factor defined in the main text.

Expanded formulation. Substituting the expressions for indirect utility and billed electricity, the planner's problem can be written as:

$$\max_{s_{Eg}, I_{Eg}^c, I_{Eg}^h} \quad \underbrace{\bar{\eta}\left[\left(P_{Eg}^{\frac{-\eta}{1-\eta}} S_{Eg}\right)^{\theta} + 1\right]^{1/\theta}}_{\text{(i) Household option value}} \tag{17}$$

$$- \underbrace{\delta\, KWh_{Eg}}_{\text{(ii) Capacity-constrained supply cost}} \tag{18}$$

$$- \underbrace{\lambda(1 - \pi_{Eg})\bar{\eta}}_{\text{(iii) LPG dependence}} \tag{19}$$

$$- \underbrace{(s_{Eg} + \psi s_{Eg}^2)}_{\text{(iv) Subsidy cost}}. \tag{20}$$

First-order condition with respect to s_{Eg}. Differentiating with respect to s_{Eg}:

$$\frac{\partial W}{\partial s_{Eg}} = \frac{\partial \pi_{Eg}}{\partial s_{Eg}} \left[\bar{\eta} P_{Eg}^{\frac{-\eta}{1-\eta}} - \delta \left(\alpha T_{Eg}^{*} + (H_g - 1) K_g^0 \right) + \lambda \bar{\eta} \right] - (1 + 2\psi s_{Eg}). \tag{21}$$

The optimal subsidy balances three forces: the welfare gain from increasing adoption, the marginal social cost of additional electricity demand under capacity constraints, and the fiscal cost of public funds.

ONLINE APPENDIX

B Additional Tables

Table B1: Treatment Effect by Type of Intervention

	(1) Adoption	(2) Bought Ind. Compatible Cookware	(3) Induction Stove
Only Subsidy	0.398***	0.328***	0.136***
	(0.0286)	(0.0256)	(0.0241)
Only Subsidy & Information	0.380***	0.337***	0.154***
	(0.0239)	(0.0214)	(0.0201)
Only Information	0.0181	0.00146	0.0225
	(0.0221)	(0.0197)	(0.0186)
Constant	0.147***	0.0844***	0.0880***
	(0.0180)	(0.0161)	(0.0151)
Observations	2740	2740	2740

Notes: This table presents estimates of the treatment effects on adoption variables using reduced-form regressions with compressed treatment arms. "Subsidy" indicates treatment groups that received subsidies (both high and low subsidy arms combined). "Subsidy & Information" indicates treatment groups that received both subsidies and information treatments (cost or health information combined with subsidies). "Information" indicates treatment groups that received only information treatments without subsidies. The dependent variables are dummies that indicate: (1) purchase of an induction stove or induction compatible cookware, (2) purchase of induction-compatible cookware, and (3) purchase of an induction stove. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: Treatment Effect on Extensive Margin by Baseline E-Stove Ownership

	(1) Adoption	(2) Bought Ind. Compatible Cookware	(3) Induction Stove	(4) Adoption	(5) Bought Ind. Compatible Cookware	(6) Induction Stove
High Subsidy	0.534***	0.372***	0.326***	0.520***	0.506***	0.0205
	(0.0428)	(0.0366)	(0.0403)	(0.0646)	(0.0619)	(0.0370)
Low Subsidy	0.241***	0.204***	0.0690	0.305***	0.286***	0.0220
	(0.0449)	(0.0384)	(0.0422)	(0.0587)	(0.0562)	(0.0336)
Cost Info.	0.0429	0.0255	0.0385	-0.0210	-0.0448	0.0182
	(0.0309)	(0.0264)	(0.0291)	(0.0435)	(0.0417)	(0.0249)
Health Info.	0.0199	0.0150	0.0140	0.00411	-0.0348	0.0282
	(0.0303)	(0.0259)	(0.0285)	(0.0435)	(0.0417)	(0.0249)
High Subsidy & Cost Info.	0.474***	0.395***	0.253***	0.458***	0.373***	0.115***
	(0.0444)	(0.0379)	(0.0417)	(0.0584)	(0.0559)	(0.0334)
Low Subsidy & Cost Info.	0.227***	0.258***	0.0534	0.252***	0.256***	0.0179
	(0.0442)	(0.0378)	(0.0416)	(0.0634)	(0.0607)	(0.0363)
High Subsidy & Health Info.	0.550***	0.407***	0.392***	0.497***	0.443***	0.138***
	(0.0421)	(0.0360)	(0.0395)	(0.0665)	(0.0637)	(0.0380)
Low Subsidy & Health Info.	0.232***	0.240***	0.0771*	0.340***	0.332***	0.0404
	(0.0432)	(0.0370)	(0.0406)	(0.0602)	(0.0577)	(0.0344)
Constant	0.130***	0.0459**	0.116***	0.182***	0.160***	0.0321*
	(0.0213)	(0.0182)	(0.0200)	(0.0312)	(0.0299)	(0.0179)
Observations	1767	1767	1767	973	973	973
Owned estove at baseline	No	No	No	Yes	Yes	Yes

Notes: The dependent variables are dummies that indicate: (1) purchase of an induction stove or induction compatible cookware, (2) purchase of induction-compatible cookware, and (3) purchase of an induction stove. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3: Treatment Effects on Log(kWh) by Adopter Type

	(1) Log(kWh)	(2) Log(kWh)	(3) Log(kWh)	(4) Log(kWh)
High Subsidy	-0.0212	-0.0352	-0.0695	0.0793
	(0.0245)	(0.0369)	(0.0482)	(0.0606)
Low Subsidy	0.0109	-0.0299	-0.0440	0.139**
	(0.0207)	(0.0797)	(0.0321)	(0.0551)
Cost Information	-0.00863	0.0162	-0.0213	0.128***
	(0.0144)	(0.0290)	(0.0409)	(0.0493)
Health Information	-0.00902	0.0665	0.0190	0.129
	(0.0159)	(0.0419)	(0.0482)	(0.0862)
Cost Info & High Subsidy	0.0246	-0.0238	0.0370	0.0899**
	(0.0279)	(0.104)	(0.0386)	(0.0349)
Cost Info & Low Subsidy	0.00154	0.0231	-0.0132	0.0857
	(0.0199)	(0.0339)	(0.0315)	(0.0755)
Health Info & High Subsidy	0.0203	0.00204	0.0555	0.0479
	(0.0237)	(0.0461)	(0.0522)	(0.0427)
Health Info & Low Subsidy	0.00837	0.110***	0.00950	0.0641*
	(0.0183)	(0.0416)	(0.0359)	(0.0367)
Observations	77097	22607	26076	20718
Adopter Type	Full Sample	Stove	Cookware	Complete
Num. Households	2698	791	913	725
Household FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes

Notes: The pre-treatment period spans January–December 2023, and the post-treatment period covers January 2024–May 2025. The outcome variable is winsorized log electricity consumption (kWh). Columns 1–4 present estimates for the full sample, stove-only adopters, cookware-only adopters, and complete adopters (stove and cookware), respectively. A common pure control group is included across all specifications. All regressions include household and month-year fixed effects. Standard errors are cluster at the household level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Treatment Effects on kWh Levels by Adopter Type

	(1) kWh	(2) kWh	(3) kWh	(4) kWh
High Subsidy	-5.843*	-2.049	-12.43*	1.998
	(3.423)	(4.631)	(6.340)	(7.478)
Low Subsidy	8.163*	15.04	6.474	22.04*
	(4.678)	(15.44)	(6.810)	(12.06)
Cost Information	-2.771	1.723	-7.182	9.861
	(2.699)	(7.932)	(12.20)	(7.721)
Health Information	-1.550	10.27	2.739	13.97
	(2.945)	(7.068)	(12.34)	(16.40)
Cost Info & High Subsidy	8.800**	16.06**	11.61*	14.83*
	(4.194)	(7.599)	(6.898)	(7.647)
Cost Info & Low Subsidy	-1.304	6.933	-0.146	-5.705
	(4.329)	(7.393)	(6.888)	(13.84)
Health Info & High Subsidy	-2.339	-8.598	6.394	-1.714
	(3.886)	(10.52)	(5.700)	(7.162)
Health Info & Low Subsidy	-0.0796	24.72**	-4.245	26.26**
	(4.054)	(10.71)	(6.766)	(12.27)
Observations	77097	22607	26076	20718
Adopter Type	Full Sample	Stove	Cookware	Complete
Num. Households	2698	791	913	725
Household FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes

Notes: The pre-treatment period spans January–December 2023, and the post-treatment period covers January 2024–May 2025. The outcome variable is winsorized electricity consumption (kWh). Columns 1–4 present estimates for the full sample, stove-only adopters, cookware-only adopters, and complete adopters (stove and cookware), respectively. A common pure control group is included across all specifications. All regressions include household and month-year fixed effects. Standard errors are cluster at the household level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Treatment Effects on kWh Levels by Adopter Type - Short-run vs Long-run

	(1) kWh	(2) kWh	(3) kWh	(4) kWh	(5) kWh	(6) kWh	(7) kWh	(8) kWh
High Subsidy	-6.225*	-4.908	-2.703	-0.461	-12.24*	-12.97*	-0.0393	7.022
	(3.342)	(4.670)	(3.908)	(8.091)	(6.724)	(7.498)	(6.789)	(10.81)
Low Subsidy	6.735	11.49*	7.584	32.82	8.789	0.712	22.87*	19.93
	(4.419)	(6.540)	(11.38)	(27.28)	(7.470)	(9.834)	(12.01)	(13.74)
Cost Information	-2.032	-4.713	0.494	4.425	-9.102	-2.639	10.73	7.280
	(2.549)	(3.854)	(6.614)	(12.71)	(12.28)	(13.75)	(6.759)	(13.14)
Health Information	-1.993	-0.407	8.489	14.59	-0.501	10.72	14.40	12.59
	(2.745)	(4.211)	(6.995)	(9.257)	(10.60)	(18.49)	(14.86)	(22.35)
Cost Info & High Subsidy	6.145	15.27**	11.71	26.38**	7.898	20.82**	11.26*	23.35*
	(3.886)	(5.977)	(7.195)	(12.19)	(6.400)	(10.04)	(6.399)	(12.49)
Cost Info & Low Subsidy	-1.300	-1.417	1.310	20.37*	0.107	-1.038	-7.208	-2.416
	(4.239)	(5.793)	(6.791)	(10.40)	(6.738)	(8.525)	(13.89)	(19.34)
Health Info & High Subsidy	-2.413	-2.236	-6.593	-13.45	3.746	12.75	-1.008	-3.595
	(3.532)	(5.622)	(9.994)	(13.63)	(5.156)	(8.832)	(6.056)	(10.72)
Health Info & Low Subsidy	0.708	-2.085	24.32**	25.65	-1.977	-9.744	22.90*	34.35**
	(3.920)	(5.260)	(10.92)	(15.92)	(7.228)	(7.565)	(11.92)	(15.03)
Observations	63894	45163	18730	13245	21611	15278	17169	12141
Period	Short-run	Long-run	Short-run	Long-run	Short-run	Long-run	Short-run	Long-run
Adopter Type	Full Sample	Full Sample	Stove	Stove	Cookware	Cookware	Complete	Complete
Num. Households	2698	2698	791	791	913	913	725	725
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The pre-treatment period spans January–December 2023. Short-run and long-run post-treatment periods cover January–December 2024 (12 months) and January–May 2025 (5 months), respectively. The outcome variable is winsorized electricity consumption (kWh). Columns 1–2, 3–4, 5–6, and 7–8 present estimates for the full sample, stove-only adopters, cookware-only adopters, and complete adopters, respectively. Within each pair, odd columns report short-run effects and even columns report long-run effects. A common pure control group is included across all specifications. All regressions include household and month-year fixed effects. Standard errors are cluster at the household level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B1: Mean Electricity Consumption (KwH) by treatment arm

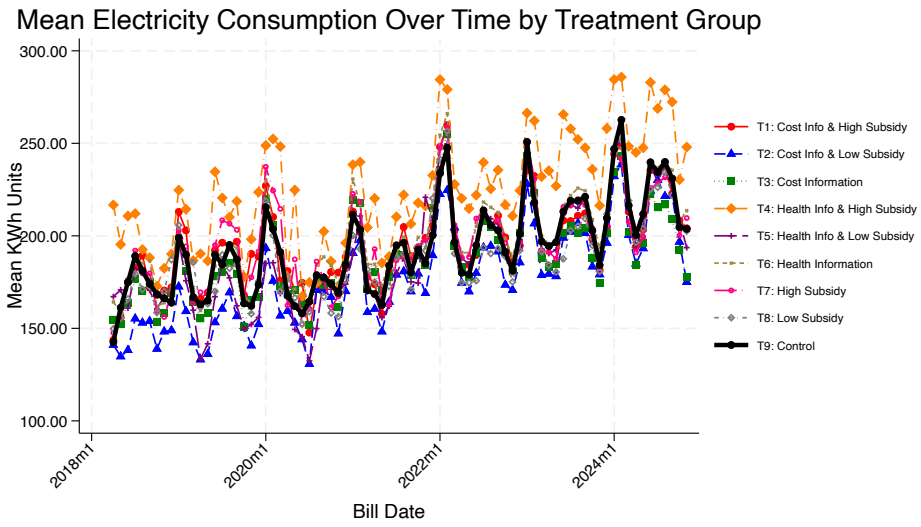


Table B6: Spillovers on Log(KWh) for pure control group, based on intensity of treatment within area)

	(1) Log(KWh)	(2) Log(KWh)	(3) Log(KWh)
Post x High Subsidy Intensity	-0.175*	-0.254	-0.187
	(0.100)	(0.162)	(0.126)
Post x Low Subsidy Intensity	0.171**	0.214*	0.159*
	(0.0676)	(0.119)	(0.0825)
Post x Any Information Intensity	0.0640**	-0.0513	0.141***
	(0.0270)	(0.0368)	(0.0374)
Post x High Subsidy x Any Info Intensity	0.225*	0.431**	0.166
	(0.117)	(0.188)	(0.149)
Post x Low Subsidy x Any Info Intensity	0.0296	0.294*	-0.119
	(0.0986)	(0.165)	(0.123)
Constant	5.057***	5.312***	4.929***
	(0.00269)	(0.00404)	(0.00350)
Observations	18158	6084	12074
Owned estove at baseline	Full sample	Yes	No
HH FE	Yes	Yes	Yes
Standard errors in parentheses			
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$			

Notes: This table presents the DiD spillover analysis for the control group, estimating the impact of treatment intensity in neighboring locations on log-transformed electricity consumption. Geographic units are defined by municipality, ward, area, and tole. The interaction terms measure the spillover effects of treatment intensity for subsidies and information treatments, both individually and combined. The analysis includes household fixed effects to control for unobserved household characteristics. Results are shown for the full sample, households with an electric stove at baseline, and households without an electric stove at baseline. Significance levels are denoted by p ¡ 0.10 (*), p ¡ 0.05 (**), and p ¡ 0.01 (***).

Table B7: Spillovers on intensive margin fuel use for pure control group, based on intensity of treatment within area)

	(1) Time cooking past wk (hrs)	(2) Use Elec. Cooking	(3) Use LPG Cooking	(4) Kg LPG Used	(5) Count of Ind. stoves
Post x High Subsidy Intensity	-0.210	-0.0257	0.0411***	-8.430***	0.189***
	(0.957)	(0.0650)	(0.0115)	(0.724)	(0.0509)
Post x Low Subsidy Intensity	3.752***	0.0541	0.0305***	-4.304***	0.0233
	(0.660)	(0.0446)	(0.00786)	(0.497)	(0.0350)
Post x Any Information Intensity	-2.974***	0.0801***	-0.00702**	-0.428**	-0.0596***
	(0.279)	(0.0191)	(0.00335)	(0.212)	(0.0149)
Post x High Subsidy x Any Info Intensity	2.590**	-0.132*	-0.0113	10.47***	-0.164***
	(1.124)	(0.0763)	(0.0135)	(0.854)	(0.0598)
Post x Low Subsidy x Any Info Intensity	-4.379***	0.173***	-0.0951***	0.798	-0.0192
	(0.953)	(0.0646)	(0.0114)	(0.719)	(0.0506)
Post	2.187***	-0.0181***	-0.00630***	-0.623***	0.0337***
	(0.0673)	(0.00456)	(0.000804)	(0.0508)	(0.00357)
Constant	13.56***	0.442***	1.000***	11.76***	0.354***
	(0.0285)	(0.00194)	(0.000341)	(0.0215)	(0.00151)
Observations	17994	18088	18046	18046	18158
Owned estove at baseline	Full sample	Full sample	Full sample	Full sample	Full sample
HH FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

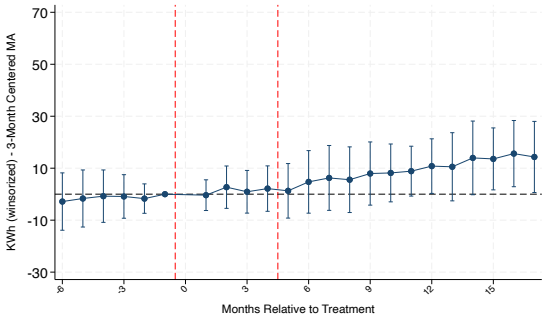
Notes: This table presents the DiD intensive margin analysis for the control group, examining the effects of treatment intensity on cooking behavior and appliance usage. The regressions measure outcomes related to time spent cooking, the use of electric and LPG stoves, LPG usage (in kilograms), and the number of induction stoves. The interaction terms capture the intensity of subsidies and information treatments in neighboring locations during the post-period. All regressions include household fixed effects to control for unobserved heterogeneity. Results are reported for the full sample of control households. Significance levels are denoted by p ¡ 0.10 (*), p ¡ 0.05 (**), and p ¡ 0.01 (***).

Table B8: Spillovers: Effects of transformer treatment intensity and household treatment status

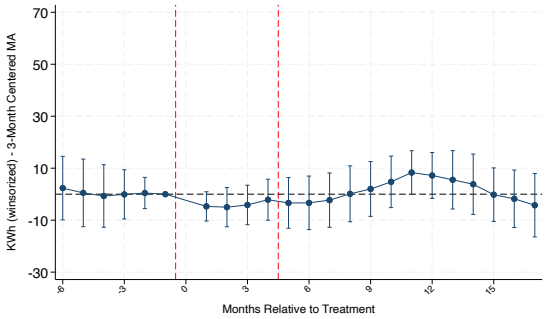
	(1) Adoption (v2)	(2) Bought Ind. Compatible Cookware (v2)	(3) Induction Stove (v2)
control_PropTG_mid	-0.0801	-0.0739	-0.0493
	(0.141)	(0.133)	(0.284)
control_PropTG_high	-0.105	-0.0633	-0.0472
	(0.051)	(0.191)	(0.297)
subsidy_high_PropTG_low	0.385***	0.340***	0.132
	(0.000)	(0.000)	(0.106)
subsidy_high_PropTG_mid	0.449***	0.362***	0.198***
	(0.000)	(0.000)	(0.001)
subsidy_high_PropTG_high	0.542***	0.437***	0.254***
	(0.000)	(0.000)	(0.000)
subsidy_low_PropTG_low	0.165	0.140	-0.0182
	(0.124)	(0.148)	(0.840)
subsidy_low_PropTG_mid	0.261***	0.256***	-0.00810
	(0.000)	(0.000)	(0.883)
subsidy_low_PropTG_high	0.157*	0.148*	0.0374
	(0.039)	(0.032)	(0.561)
only_info_PropTG_low	-0.0206	-0.0362	0.00343
	(0.669)	(0.407)	(0.933)
only_info_PropTG_mid	-0.0660	-0.0510	-0.0305
	(0.163)	(0.234)	(0.446)
only_info_PropTG_high	-0.0371	-0.0444	-0.00341
	(0.427)	(0.293)	(0.931)
high_subsidy_info_PropTG_low	0.389***	0.362***	0.143*
	(0.000)	(0.000)	(0.023)
high_subsidy_info_PropTG_mid	0.499***	0.391***	0.266***
	(0.000)	(0.000)	(0.000)
high_subsidy_info_PropTG_high	0.374***	0.297***	0.175***
	(0.000)	(0.000)	(0.000)
low_subsidy_info_PropTG_low	0.362***	0.414***	-0.0603
	(0.000)	(0.000)	(0.415)
low_subsidy_info_PropTG_mid	0.214***	0.250***	0.0194
	(0.000)	(0.000)	(0.675)
low_subsidy_info_PropTG_high	0.0877	0.142**	-0.0110
	(0.136)	(0.008)	(0.824)
Constant	0.224***	0.138***	0.129***
	(0.000)	(0.000)	(0.000)
Observations	1878	1878	1878

Notes: This is the spillovers extension to Table 4 in the manuscript. The omitted group in these regressions is the pure control households in `PropTG_low`, which is the households assigned to control status locates within the transformers with the lowest proportion treated. Transformer (abbreviated as "TG") treatment intensity is found by diving the total number of households randomly assigned to any of the subsidy treatments within a transformer, by the total number of NEA customers served by that transformer. We create 3 binary indicators to represent bins of treatment intensity: `PropTG_low`, which equals 1 if the transformer treatment intensity is less than 0.01 and zero otherwise; `PropTG_mid` which equals 1 if the intensity is between 0.01 and 0.05 and zero otherwise; and `PropTG_high`, which equals 1 if the treatment intensity is greater than 0.05 and zero otherwise. We then interact the six households treatment status variables used in Table 4 (`control`, `subsidy_high`, `subsidy_low`, `only_info`, `high_subsidy_info`, `low_subsidy_info`) with each of these three binary indicators of transformer treatment intensity. These interactions are used as the independent variables in the regressions displayed in this table. For each independent variable the first term is the household's own treatment status and the second term is the treatment intensity of the transformer in which the household is located. For example, `subsidy_high_PropTG_low` is a household that was assigned to high subsidy treatment and is located in a transformer with a low treatment intensity (i.e., less than 0.01 (1%) of the NEA customers in the transformers were assigned to one of the subsidy treatments). These analyses are performed for the households on the eastern side of the Bishnumati River, as that is the region of Kathmandu Valley for which we have data on the transformers to which households are served.

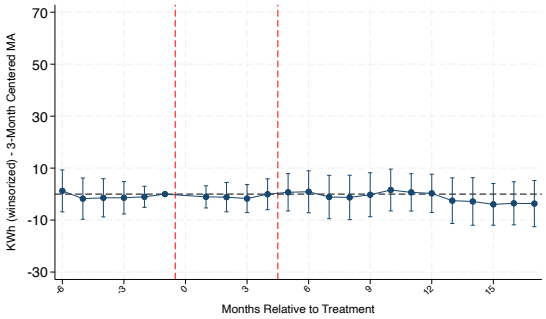
Figure B2: Event Study Estimates on Electricity Consumption



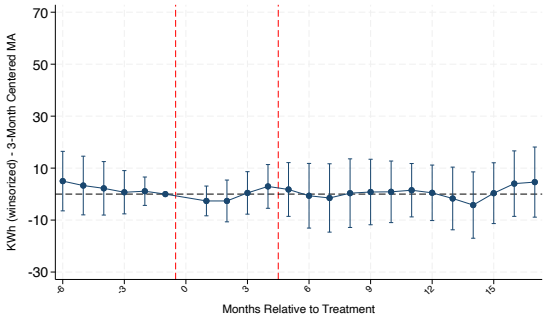
(a) Cost Information & High Subsidy



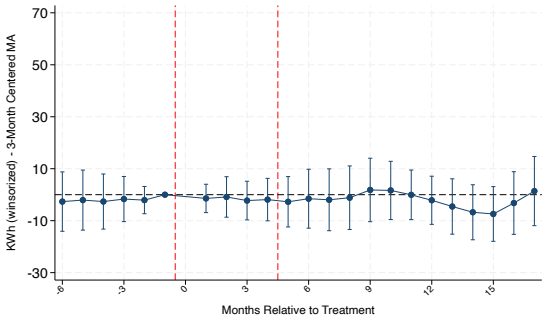
(b) Cost Information & Low Subsidy



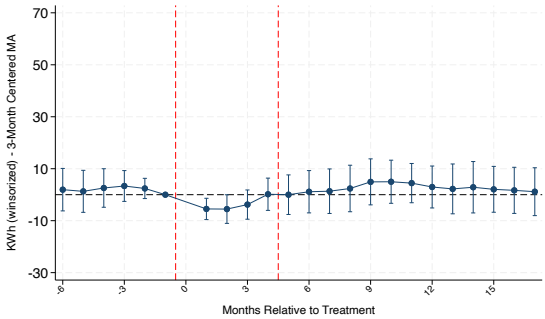
(c) Cost Information Only



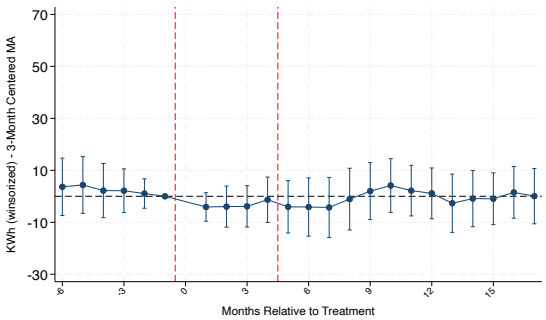
(d) Health Information & High Subsidy



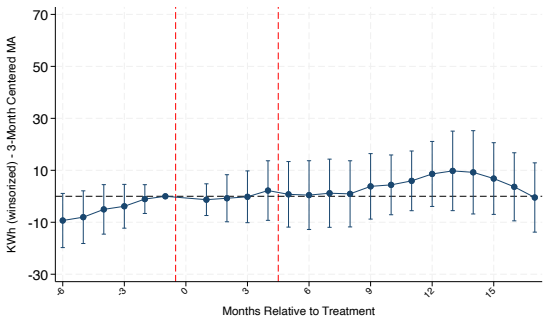
(e) Health Information & Low Subsidy



(f) Health Information Only



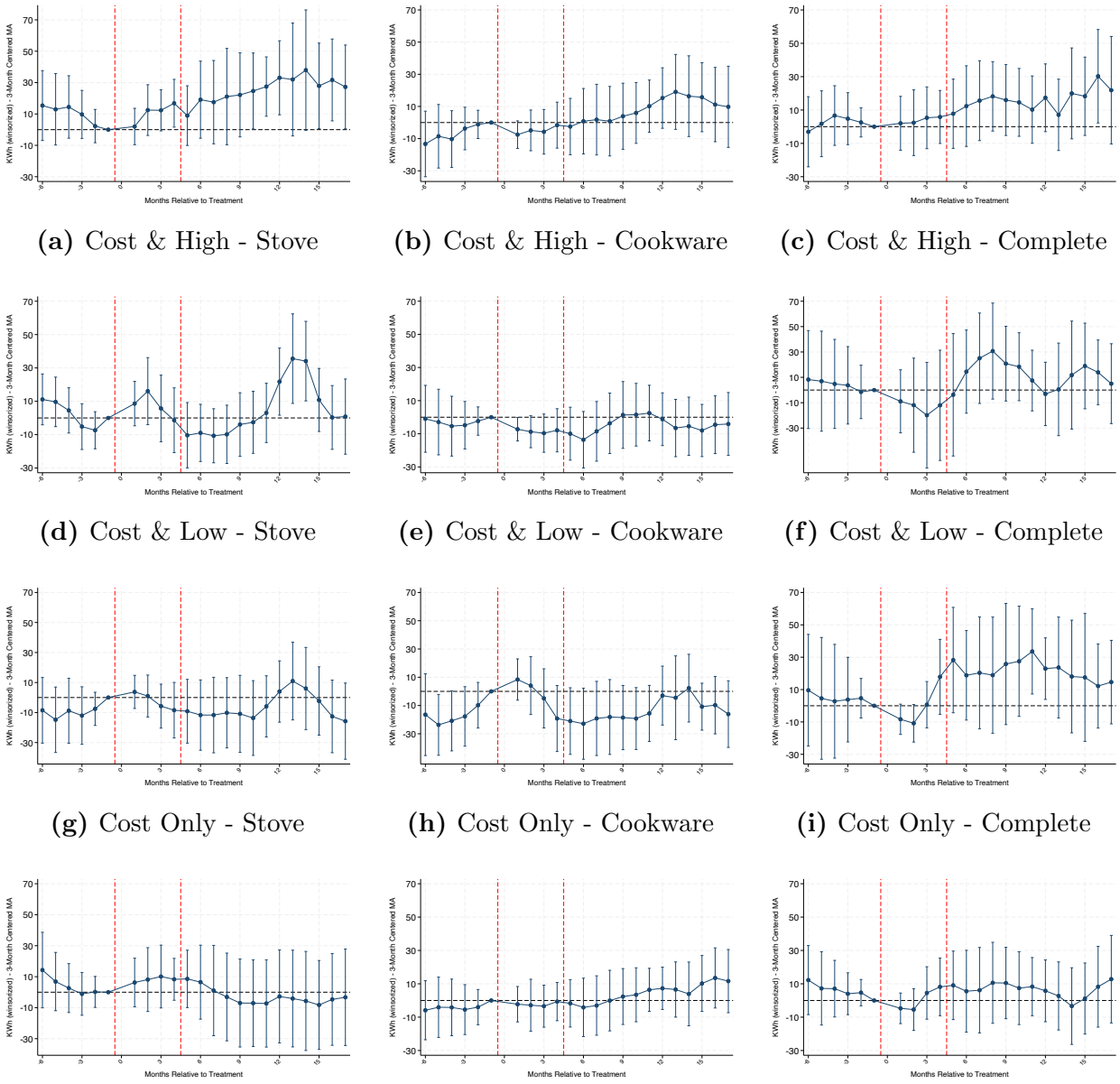
(g) High Subsidy Only



(h) Low Subsidy Only

Notes: This figure plots event study estimates of the effect of treatment arms on electricity consumption (three-month centered moving average), based on Equation (5). Each panel compares a specific treatment arm relative to the control group. The reference period (omitted category) is December 2023. Vertical red dotted lines indicate the intervention window. Standard errors are clustered at the household level. Whiskers represent 95% confidence intervals.

Figure B3: Event Study Estimates on Electricity Consumption by Adopter Type



(a) Cost & High - Stove **(b)** Cost & High - Cookware **(c)** Cost & High - Complete

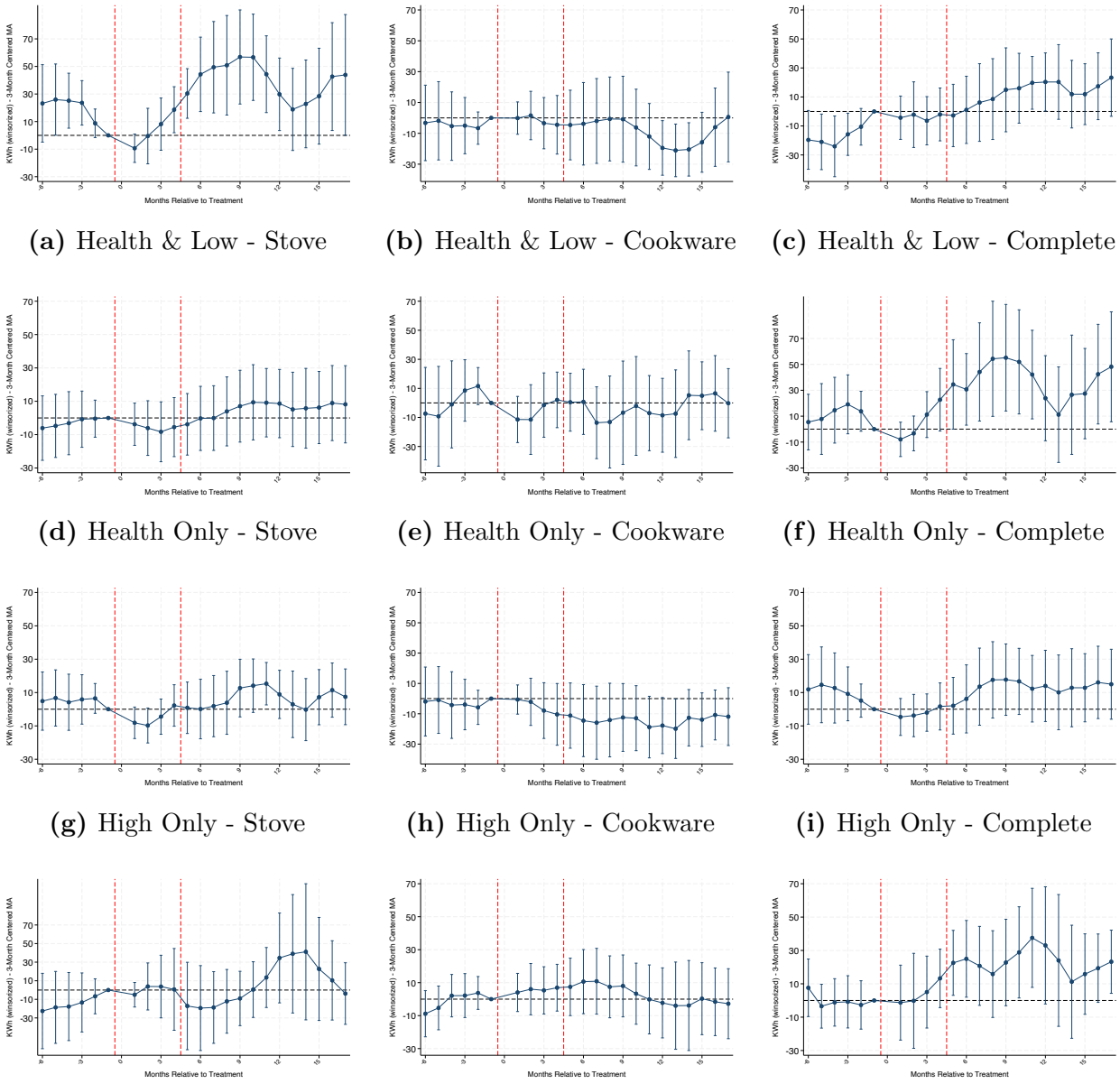
(d) Cost & Low - Stove **(e)** Cost & Low - Cookware **(f)** Cost & Low - Complete

(g) Cost Only - Stove **(h)** Cost Only - Cookware **(i)** Cost Only - Complete

(j) Health & High - Stove **(k)** Health & High - Cookware **(l)** Health & High - Complete

Notes: This figures plots event study estimates of the effect of treatment on electricity consumption (three-month centered moving average), based on Equation (5). The columns display heterogeneity by adoption type relative to the control group: Column 1 includes treated households who adopted only electric stoves; Column 2, those who adopted only compatible cookware; and Column 3, those who adopted both. The reference period is December 2023. Vertical red dotted lines indicate the intervention deployment period. Standard errors are clustered at the household level. Whiskers represent 95% confidence intervals.

Figure B4: Event Study Estimates of Electricity Consumption by Adopter Type



(a) Health & Low - Stove **(b)** Health & Low - Cookware **(c)** Health & Low - Complete

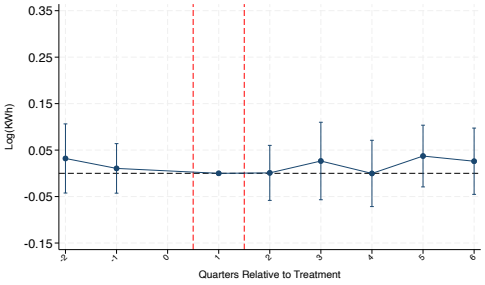
(d) Health Only - Stove **(e)** Health Only - Cookware **(f)** Health Only - Complete

(g) High Only - Stove **(h)** High Only - Cookware **(i)** High Only - Complete

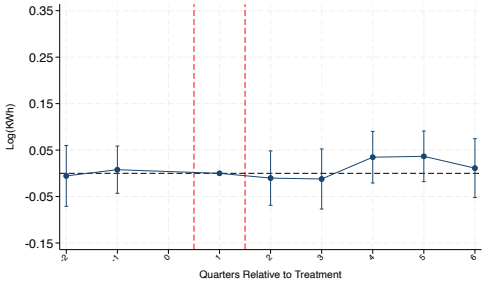
(j) Low Only - Stove **(k)** Low Only - Cookware **(l)** Low Only - Complete

Notes: This figures plots event study estimates of the effect of treatment on electricity consumption (three-month centered moving average), based on Equation (5). The columns display heterogeneity by adoption type relative to the control group: Column 1 includes treated households who adopted only electric stoves; Column 2, those who adopted only compatible cookware; and Column 3, those who adopted both. The reference period is December 2023. Vertical red dotted lines indicate the intervention deployment period. Standard errors are clustered at the household level. Whiskers represent 95% confidence intervals.

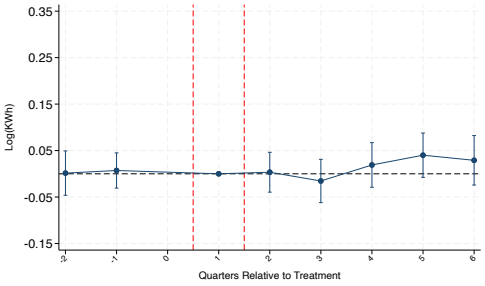
Figure B5: Quarterly Event Study Estimates of Treatment Effects on Log Electricity Consumption



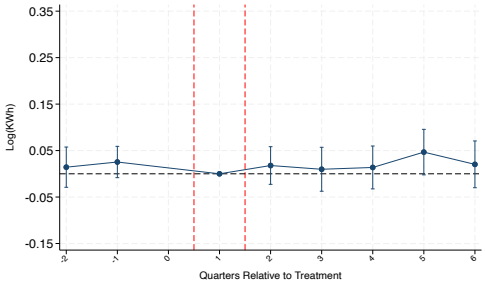
(a) High Subsidy Only



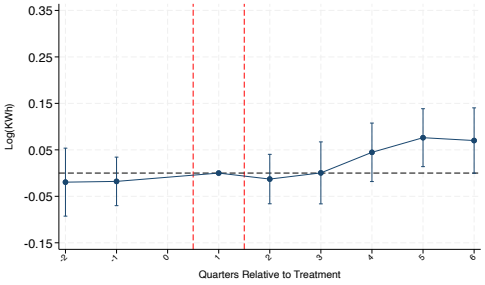
(b) Low Subsidy Only



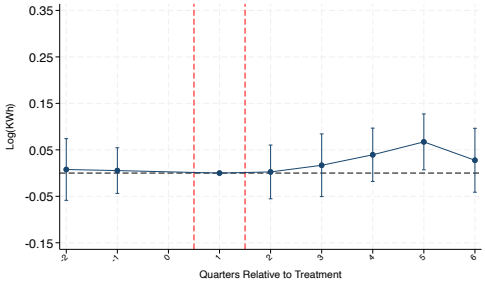
(c) Cost Information Only



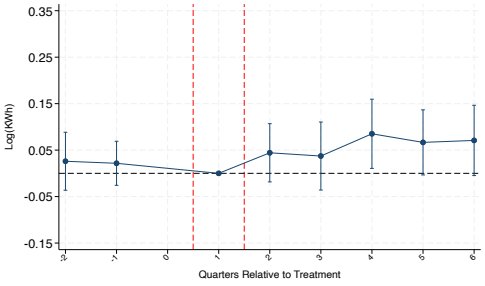
(d) Health Information Only



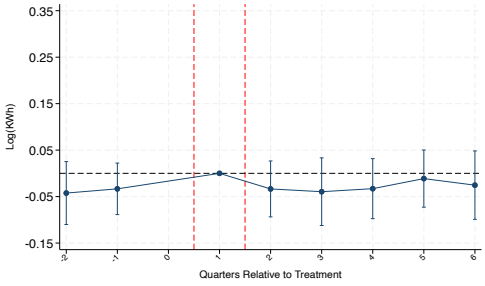
(e) Cost Info & High Subsidy



(f) Cost Info & Low Subsidy



(g) Health Info & High Subsidy



(h) Health Info & Low Subsidy

Notes: This figure plots quarterly event study estimates of the effect of treatment on log electricity consumption, based on Equation (5). Data are aggregated to the quarterly level. The reference period is the first quarter of 2024 (January–March). Vertical red dotted lines demarcate the intervention deployment period. Standard errors are clustered at the household level. Whiskers represent 95% confidence intervals.

C Additional Maps

1 For Sampling Strategy Using Transformers

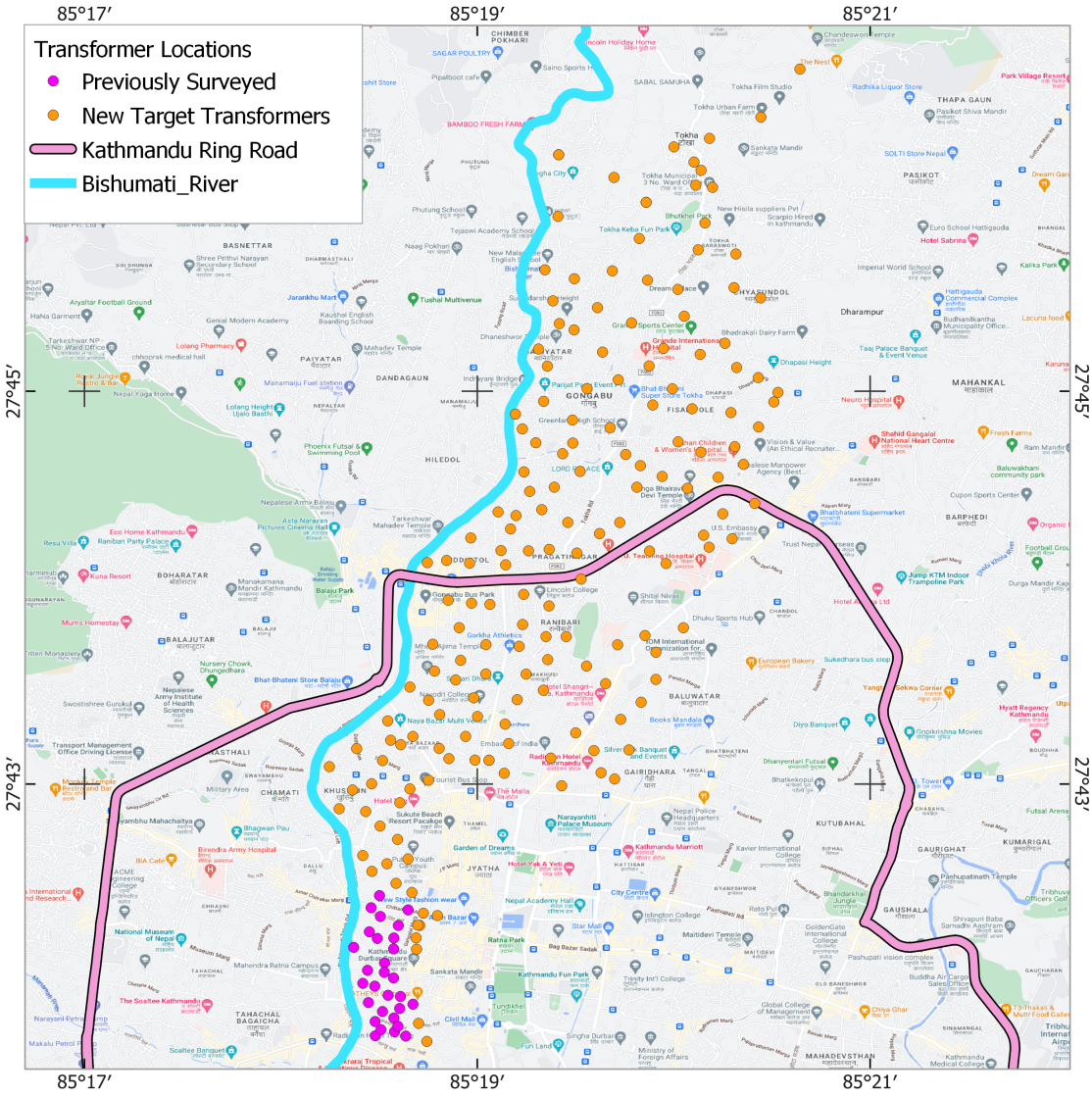


Figure C1: Map of Transformers Used in the Sampling Strategy

Notes: This map shows the locations of transformers located with 1000 m to the east of the Bishnumati River.

D The Intervention

1 Text Regarding Phone Credit for Continued Study Participation

The following message was read to all study participants (including those assigned to the control group) approached in January through February 2024 during the intervention:

"Namaste, my name is XXXXXX and I am from New ERA, which is a Kathmandu based research organization. I am here to thank you again for your continued support in the study conducted by Asian Development Bank in collaboration with Nepal Electricity Authority and New ERA. The study is being conducted to understand electricity use including electric cooking by the households and too understand electricity related needs and concerns of the households, as well as to support Nepal in improving its electricity transmission and distribution system. Also, we would like to provide you with a token of appreciation in the form of a recharge card worth Rs 100 on behalf of Asian Development Bank for giving us your valuable time in the previous survey and for your support in the next round of survey to be conducted around June/July, 2024."

2 Regarding Cost of Electric Cooking

The cost message, which was printed on the pamphlets given to study participants randomly assigned to received them, states: "CAN YOUR COOKING NEEDS BE MET FOR LESS MONEY? Did you know that induction and electric cooking could result in savings for your household? Find out if electric cooking is suited to your household needs and you could save hundreds of rupees ! With a one-time investment into an electric or induction cookstove, you can easily transition your cooking needs to electric. If you have an existing connection with the NEA (15 amp connection or above), and purchase an electric cookstove with over 66% efficiency, shifting your cooking medium could result in hundreds of rupees of savings per month!"

An image of the message provided through the intervention regarding the cost of electric cooking is on the left side of Figure D2.

3 Regarding Pollution from Electric Cooking

The health message, which was printed on the pamphlets given to study participants randomly assigned to received them, states: "DID YOU KNOW THAT ELECTRIC COOKING IS THE "CLEANEST" WAY TO COOK IN NEPAL? Studies in Nepal have shown that electric cooking creates less household air pollution (fine particulate matter, PM2.5) than cooking with the other currently available fuels, including kerosene, biomass (dung, firewood, etc), and even LPG. This is important as studies show that burning fuels is harmful to health and associated with increased risk of disease."

An image of the message provided through the intervention regarding the pollution and

health effects of cooking is on the right side of Figure D2.



Figure D2: Messages Regarding Cost (left) and Health (right) of E-Cooking

Notes: These graphics depict information pamphlets provided to study participants randomly assigned to receive them. The cost message is on the left and the health message is on the right.

4 Subsidy Treatments

Households that were randomly assigned to the subsidy treatment, received a coupon card, as shown in Figure D3.

4.1 Regarding Lower Subsidy

The lower subsidy message, which was printed on the pamphlets given to study participants randomly assigned to received them, states: "Your household has been randomly selected to receive a 1000 NPR subsidy to purchase an induction stove!!!!! If you already have an induction stove, you can use this voucher to purchase a second stove or new pots and pans that are appropriate for and compatible with an induction stove. These vouchers can be used at your local Bhat Bhateni store in Kathmandu Valley. To use the subsidy, you must bring this voucher to the customer service desk in the Bhat Bhateni store. This voucher is for your house and should not be given to others. To use this voucher, the customer from your household will need to be a member of BBSM Clubcard. If your household is not already a Clubcard member, that is ok! You can sign up at the Customer Service Desk of any BBSM

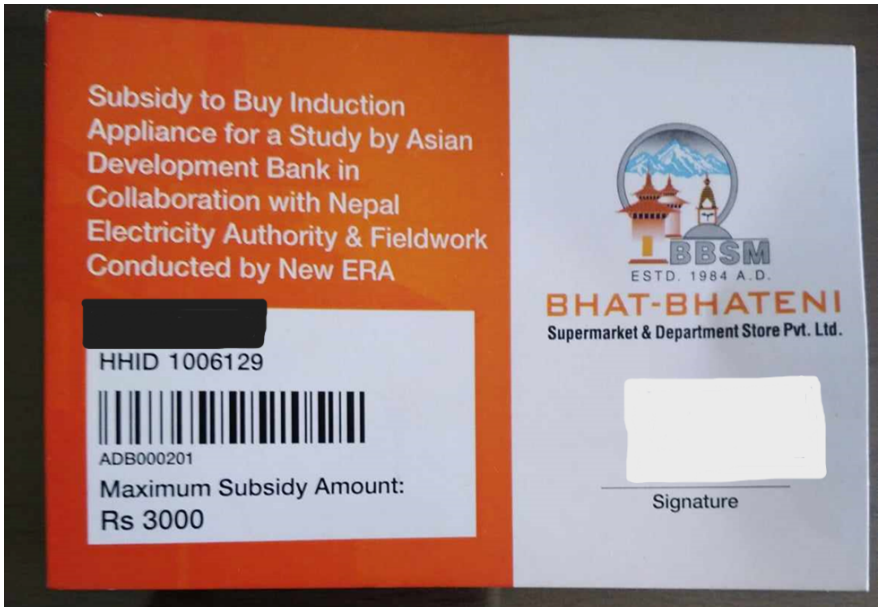


Figure D3: Example of Subsidy Card Provided

Notes: This is an example of the actual subsidy card received by those households randomly assigned to receive one. The name of the household member that was the survey respondent is printed in the rectangle marked in black. The signature of that person is in the rectangle marked in white.

branch. This voucher subsidy is valid until April 30th, 2024. All details are printed on the voucher."

An image of the voucher for this lower subsidy is on the left side of Figure D4.

4.2 Regarding Higher Subsidy

The higher subsidy message, which was printed on the pamphlets given to study participants randomly assigned to received them, states: "Your household has been randomly selected to receive a 3000 NPR subsidy to purchase an induction stove!!!!! If you already have an induction stove, you can use this voucher to purchase a second stove or new pots and pans that are appropriate for and compatible with an induction stove. These vouchers can be used at your local Bhat Bhateni store in Kathmandu Valley. To use the subsidy, you must bring this voucher to the customer service desk in the Bhat Bhateni store. This voucher is for your house and should not be given to others. To use this voucher, the customer from your household will need to be a member of BBSM Clubcard. If your household is not already a Clubcard member, that is ok! You can sign up at the Customer Service Desk of any BBSM branch. This voucher subsidy is valid until April 30th, 2024. All details are printed on the voucher."

An image of the voucher for this higher subsidy is on the right side of Figure D4.

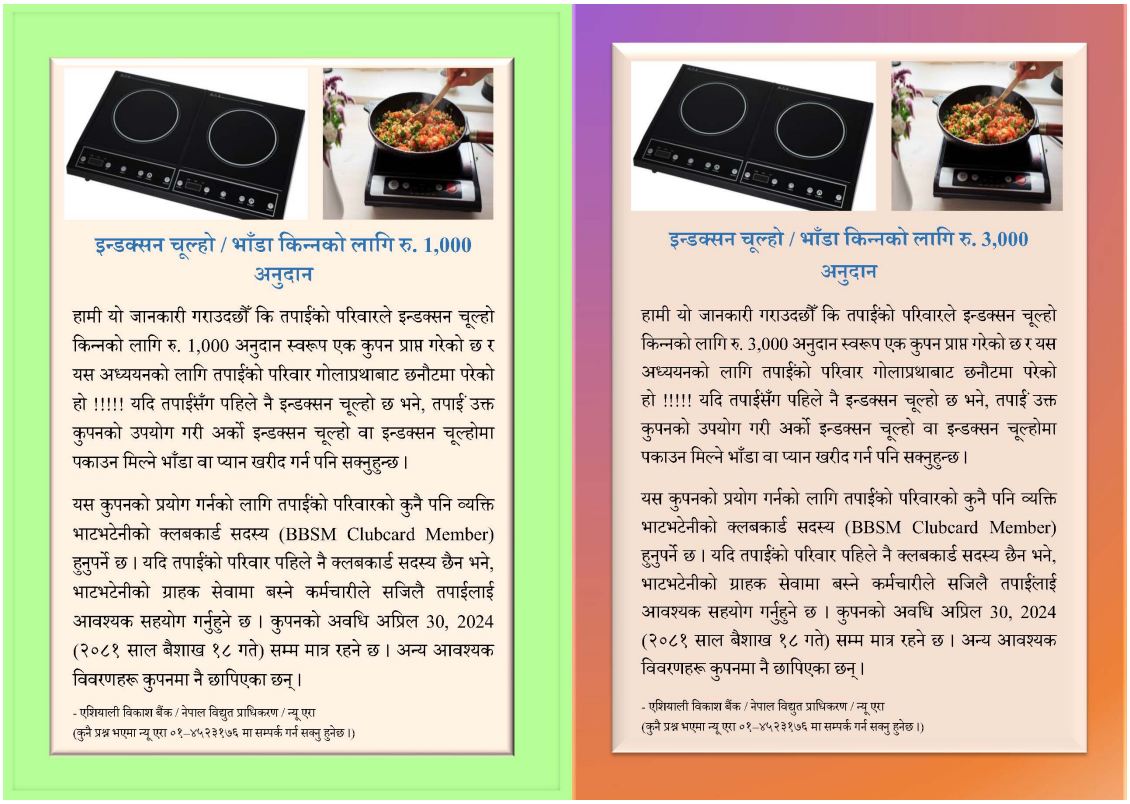


Figure D4: Messages Regarding Subsidies

Notes: These graphics depict pamphlets on the subsidies for electric cooking provided to study participants randomly assigned to receive them. The lower subsidy (1000 NPR) message is on the left and the higher subsidy (3000 NPR) message is on the right.

5 Treatments Not Delivered

Despite consenting to future participation, 57 households were not reachable at the time of the intervention. We show the breakdown of these by treatment group in the table that follows.

Table D1: Intervention Undelivered, by Treatment Group

Treatment	Frequency	Percent
High subsidy-cost info	3	5.26
low subsidy-cost info	5	8.77
no subsidy-cost info	20	35.09
High subsidy-health info	2	3.51
low subsidy-health info	4	7.02
no subsidy-health info	15	26.32
low subsidy-no info	8	14.04
Totals	57	100.00

Notes: A total of 2,894 households were randomized across groups these are the only households to which the treatment was unable to be delivered.

6 Bhat Bhateni Super Store Locations in Kathmandu Valley

Bhat Bhateni stores are spread out across the region under study (see Figure D5), providing easy access to participating households. Subsidy vouchers could be used at any of these stores to purchase an induction stove or induction-related cookware.

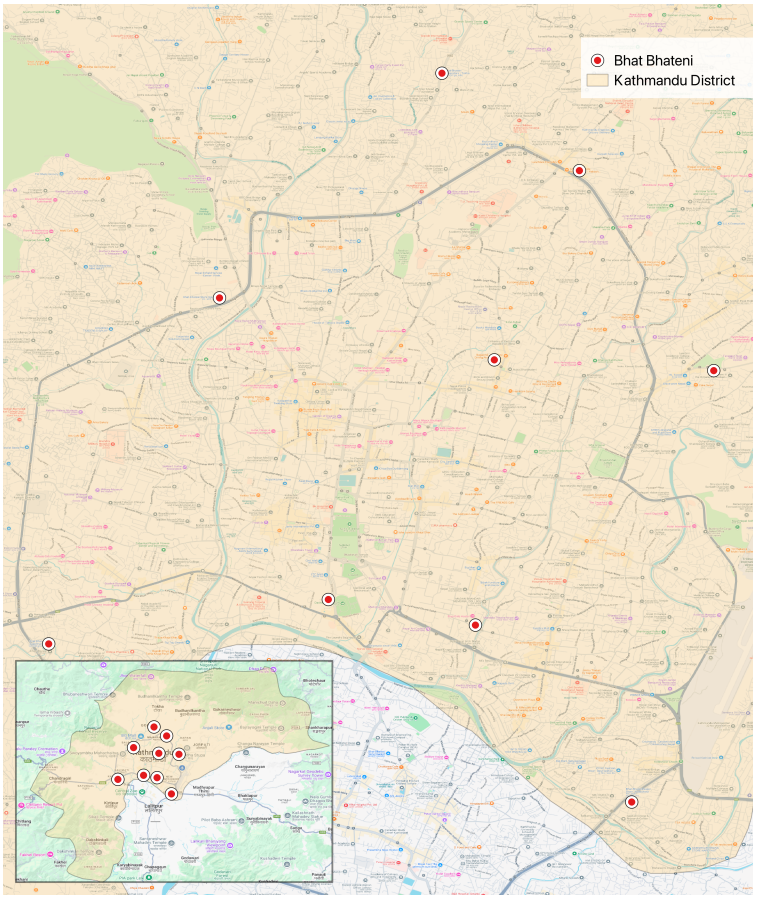


Figure D5: Locations of Bhat Bhateni stores in Kathmandu

Source: Store names from Bhat Bhateni's website were used to search their locations on Google Maps.

E Cost Comparison between LPG and Electric Cooking

Given that an LPG cylinder costs NRs. 1,895 in Nepal, it is cheaper for all consumer types, irrespective of their current monthly electricity consumption, to switch to electric cooking. Detailed calculations are provided in Table E1 and Table E2 using heat values of 51 MJ/kg for LPG[19] and 3.6 MJ/kWh for electricity. According to Nepal Gas, a big cylinder contains 14.2 kg of LPG[20], which means a cylinder holds 724.2 MJ of heat energy in it. Using an efficiency of 90%[21] for Induction Heat stoves and a conservative estimate of 55%[22] for gas stoves, it was found that one cylinder of LPG is equivalent to 122.9 kWh of electricity.

Initial Monthly Consumption (kWh)	Min Charge (NRs.)	Energy Charge (NRs.)	Initial Bill (NRs.)	One Cylinder Equivalent Additional Consumption (kWh)	Min Charge (NRs.)	Energy Charge (NRs.)	Revised Bill (NRs.)	Marginal Cost of One Cylinder Equivalent (NRs.)
20	50	80	130	142.9	125	1187.9	1312.9	1182.9
30	75	145	220	152.9	125	1282.9	1407.9	1187.9
50	75	305	380	172.9	125	1472.9	1597.9	1217.9
100	100	780	880	222.9	125	1947.9	2072.9	1192.9
250	125	2205	2330	372.9	175	3557.3	3732.3	1402.3
400	175	3855	4030	522.9	175	5207.3	5382.3	1352.3
650	175	6605	6780	772.9	175	7957.3	8132.3	1352.3

Table E1: Cost calculations of shifting one cylinder equivalent cooking from LPG stove to Induction Heat stove with a 15 amp electricity connection

Initial Monthly Consumption (kWh)	Min Charge (NRs.)	Energy Charge (NRs.)	Initial Bill (NRs.)	One Cylinder Equivalent Additional Consumption (kWh)	Min Charge (NRs.)	Energy Charge (NRs.)	Revised Bill (NRs.)	Marginal Cost of One Cylinder Equivalent (NRs.)
20	75	100	175	142.9	150	1207.9	1357.9	1182.9
30	100	165	265	152.9	150	1302.9	1452.9	1187.9
50	100	325	425	172.9	150	1492.9	1642.9	1217.9
100	125	800	925	222.9	150	1967.9	2117.9	1192.9
250	150	2225	2375	372.9	200	3577.3	3777.3	1402.3
400	200	3875	4075	522.9	200	5227.3	5427.3	1352.3
650	200	6625	6825	772.9	200	7977.3	8177.3	1352.3

Table E2: Cost calculations of shifting one cylinder equivalent cooking from LPG stove to Induction Heat stove with a 30 amp electricity connection

[19] A heat value of LPG represents the energy released when one kilogram of LPG is combusted. A heat valye of 51 MJ/kg is a conservative estimate taken from the World Nuclear Association and corroborated from the International Energy Agency.

[20] The cylinder capacity is reported on the Nepal Gas website.

[21] This statistic on efficiency was taken from Sweeney et al. (2014).

[22] This is a conservative estimate taken from: https://tcdorji.wordpress.com/2022/01/19/electric-stove-vs-lpg-stove-which-cooking-technology-is-more-cost-effective/.

F Nepal's Electricity Tariff Schedule

Table F1: Tariff for Residential Consumers, Single Phase

Units (kWh) per month	5 Ampere Minimum charge	5 Ampere Per kWh	15 Ampere Minimum charge	15 Ampere Per kWh	30 Ampere Minimum charge	30 Ampere Per kWh	60 Ampere Minimum charge	60 Ampere Per kWh
Panel A: Tariff in effect FY 2022/23 – FY 2023/24								
0–20	30	0.00	50	4.00	75	5.00	125	6.00
21–30	50	6.50	75	6.50	100	6.50	125	6.50
31–50	50	8.00	75	8.00	100	8.00	125	8.00
51–100	75	9.50	100	9.50	125	9.50	150	9.50
101–250	100	9.50	125	9.50	150	9.50	200	9.50
Above 251	150	11.00	175	11.00	200	11.00	250	11.00
Panel B: Tariff in effect FY 2024/25								
0–20	30	0.00	50	4.00	75	5.00	125	6.00
21–30	50	6.50	75	6.50	100	6.50	125	6.50
31–50	30	8.00	75	8.00	100	8.00	125	8.00
51–100	30	9.50	100	9.50	125	9.50	150	9.50
101–250	100	9.50	125	9.50	150	9.50	200	9.50
Above 251	100	11.00	110	11.00	200	11.00	250	11.00

Notes: Monetary values are expressed in Nepalese rupees (NRs.). Panel A corresponds to the tariff schedule in effect during FY 2022/23–FY 2023/24. Panel B corresponds to the revised tariff schedule in effect during FY 2024/25. Beginning in FY 2021/22, domestic consumers with a 5 Ampere connection receive the first 20 kWh at zero marginal charge, subject to the condition that if monthly consumption exceeds 20 kWh, the first 20 units are charged at NRs. 3.00 per kWh.

G Estimation Procedure and Parameter Estimates

This appendix details how we identify and estimate the structural parameters in Section 3.

1 Adoption: Identification and Estimation

The adoption equation (1) has four parameters $\{\rho, \theta, \eta, \gamma_P\}$, identified from four RCT treatment arms through a simultaneous system.

Step 1: Intercept and price sensitivity. The control group ($s = 0$, $P = 1$) pins down $\beta_0 = \text{logit}(\pi_{\text{control}})$. The information-only arm ($s = 0$, $P = 0.85$) shifts only perceived cost, identifying η through $\beta_P = (\text{logit}(\pi_{\text{info}}) - \beta_0)/\log(0.85)$, where $\beta_P = -\eta\theta/(1-\eta)$.

Step 2: Subsidy and interaction. The high-subsidy arm ($s = 3000/7000$, $P = 1$) and high-subsidy-plus-info arm ($s = 3000/7000$, $P = 0.85$) jointly identify θ and γ_P from:

$$\gamma_P = \frac{d_{HI} - d_H}{d_H \cdot P_{\text{info}} - d_{HI}}, \qquad \theta = \frac{d_H}{s_H^{\rho}(1+\gamma_P)},$$

where $d_H = \text{logit}(\pi_H) - \beta_0$ and $d_{HI} = \text{logit}(\pi_{HI}) - \beta_0 - \beta_P \log(P_{\text{info}})$.

Step 3: Grid search over ρ. For each $\rho \in [0.10, 1.00]$ (step 0.01), we solve the system above and compute out-of-sample prediction error on the two arms not used in identification: low subsidy and low subsidy + info. The ρ minimizing this error is selected ($\hat{\rho} = 0.55$).

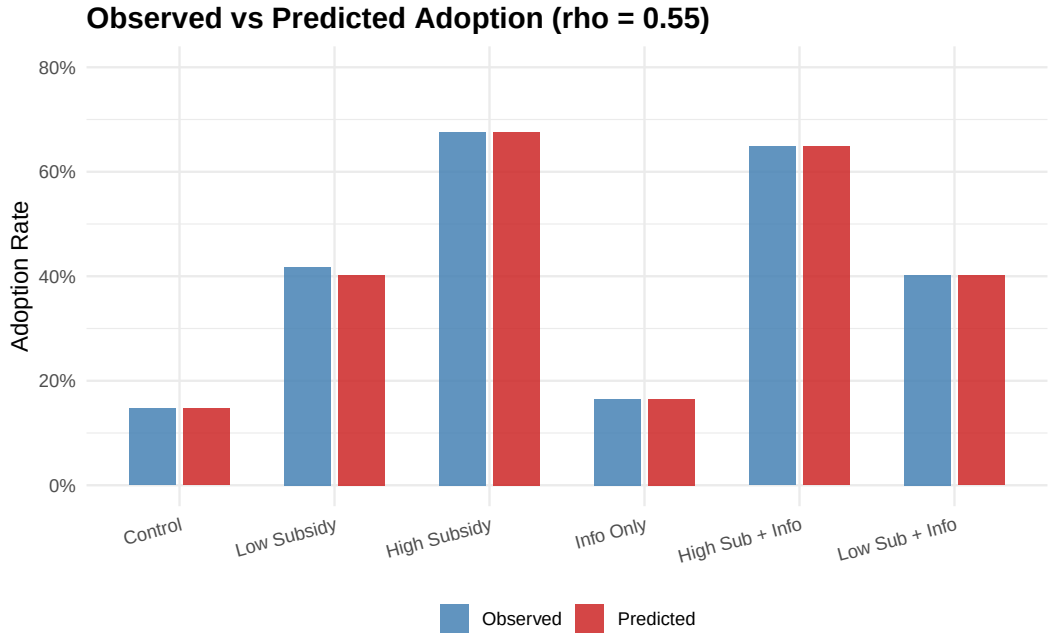


Figure G1: Model Fit: Observed and Predicted Adoption Rates by Treatment Arm

Notes: Bars show observed and model-predicted adoption rates for each of the six RCT treatment arms ($N = 2{,}740$ households). Observed rates are from the endline survey. Predicted rates are from the structural adoption equation (1) with parameters $\{\rho, \theta, \eta, \gamma_P\}$ identified from four arms (control, info-only, high subsidy, high subsidy + info). Low subsidy and low subsidy + info are out-of-sample validation arms. Maximum out-of-sample prediction error is 1.5 percentage points at $\hat{\rho} = 0.55$.

Table G2: Adopter Composition by Treatment Arm

	Control	Info Only	Subsidy Only	Info + Low Sub	Info + High Sub
Adoption					
Total HHs	557	1095	361	360	367
Any adoption (%)	14.7	16.5	54.6	40.3	64.9
Complete adoption (%)	3.1	3.1	11.4	9.4	19.6
Among adopters					
% complete (stove + cookware)	20.7	18.8	20.8	23.4	30.3
% first-time (among complete)	70.6	97.1	80.5	82.4	84.7
Revealed demand ($\hat{\nu}_i$)					
All adopters	0.098	0.071	-0.093	0.057	-0.052
Complete adopters	0.216	0.102	-0.085	0.136	-0.024

Notes: Adoption is defined as purchasing an electric induction stove, cookware, or both by the endline survey. Complete = purchased both stove and induction-compatible cookware. First-time = did not own an electric stove at baseline. $\hat{\nu}_i$ is the household-level time-averaged residual from the usage equation (2), estimated on Nepal Electricity Authority billing data with cluster fixed effects and standard errors clustered at the household level; higher values indicate stronger revealed demand for electric cooking. Info Only pools cost-information and health-information arms; Info + Low Sub and Info + High Sub similarly pool across information type.Sample: $N = 2{,}740$ households.

Table G3: Learning Curve Estimates by Adopter Type

Adopter Type	N HHs	$\hat{\kappa}$	$\hat{\delta}_L$	SE	p-value
Pooled	836	1.26	-0.058	(0.014)	0.000
Stove Only	246	1.27	-0.040	(0.028)	0.164
Cookware Only	394	0.95	-0.101	(0.021)	0.000
Complete	196	0.07	0.087	(0.043)	0.043

Notes: Learning curve $g(t) = 1 - e^{-\kappa t}$; κ from grid search over $[0.01, 2.0]$. Estimating equation: $\log kWh_{it} = \alpha + \delta_r R_i + \delta_L g(t) + X_i'\gamma + \mu_c + \epsilon_{it}$, with cluster FE and SEs clustered at HH level. Complete = stove + cookware; Stove Only = stove without cookware; Cookware Only = cookware without stove.

2 Post-Adoption Electricity Usage: Identification and Estimation

We estimate the usage equation (14) on 16,457 adopter-month observations from Nepal Electricity Authority billing records, covering 836 adopters across all nine treatment arms over 14 months post-intervention. The estimation uses cluster fixed effects (169 clusters) to absorb group-level heterogeneity, with standard errors clustered at the household level. Because billing data captures total household electricity consumption rather than cooking alone, the learning coefficient δ_L reflects changes in overall electricity use patterns following stove adoption, not cooking kWh specifically.

The learning curve introduces a nonlinearity that prevents standard OLS from estimating all parameters simultaneously. We therefore proceed in two steps. First, for each candidate $\kappa \in [0.01, 2.0]$ (step size 0.01), we compute the learning curve $g_\kappa(t) = 1 - e^{-\kappa t}$

and estimate equation (14) by OLS, selecting the κ that minimizes the sum of squared residuals. Second, we report the coefficients from the regression at this optimal κ. The grid search is necessary because κ enters nonlinearly through the exponential; conditional on κ, all remaining parameters are linear and estimated by OLS in a single pass.

We then split the sample by adopter type (complete, cookware only, stove only) and re-estimate, allowing separate κ and δ_L for each type. This is the decomposition that reveals the sharply divergent learning trajectories discussed in Section 9. The identification of each parameter and the construction of the preference residual $\hat{\nu}_i$ are detailed in Appendix A.

H Heterogeneous Treatment Effects: Estimation Details

Section 8.3 summarizes our approach to estimating household-level heterogeneity in both the adoption response to subsidies and post-adoption electricity usage growth. This appendix provides the full estimation details, sample construction, and additional results.

1 Data and Definitions

Adoption: We define adoption as a binary indicator equal to one if the household purchased or received an electric induction stove by the endline survey, corresponding to the `true_adoption` variable used throughout the paper.

Electricity usage: We measure long-run electricity usage from administrative billing data provided by the Nepal Electricity Authority. For each household we compute the change in mean log(kWh) between the first three months after the intervention (months 0–2) and a long-run window 12 to 14 months post-intervention. We refer to this difference as *kWh growth*. This measure captures which households increased their billed electricity consumption over time, the behavioral margin that distinguishes genuine fuel switching from a one-time equipment purchase.

Sample: The analysis sample includes all households assigned to any subsidy arm (treatment groups 1, 2, 4, 5, 7, 8) or the pure control group (group 9), conditional on having matched billing data, yielding $N = 1{,}617$ households (656 adopters: 574 in subsidy arms, 82 in the control group). We exclude info-only groups (3 and 6) because the causal forest estimates a binary treatment effect and these households fit neither side of the subsidy contrast: they received an intervention that shifted perceived cost ($P = 0.85$ vs. $P = 1$) but no subsidy. Including them as controls would pool two different counterfactuals; including them as treated would conflate the subsidy and information margins. The structural model identifies the information effect separately through η (Section G). Since all counterfactual policies bundle information at negligible cost, the planner needs to know which households respond most to the subsidy, which is what the CATE isolates.

Covariates: Both models use the same 15 baseline covariates: household size, head age, higher education (bachelor's degree or above), homeownership, monthly LPG consumption (kg), reliability beliefs (Likert 1–10 response to "I am worried about the reliability of

electricity supply"), whether unplanned outages are reported as the main electricity service problem, voltage fluctuation reported as a problem, whether the household reduced non-essential spending due to electricity costs, weekly cooking time (hours), number of electricity outages in a normal month, number of electric appliances, access to credit from a commercial or government bank, number of meals cooked on an LPG stove (out of 12 meal-slots over three days), and whether the household owned an electric stove at baseline. All covariates are from the baseline survey to avoid contamination by treatment effects. Missing values are median-imputed; all variables are standardized to mean zero and unit variance.

2 Estimation

Adoption CATE (causal): We estimate the conditional average treatment effect of subsidies on adoption using a causal forest (Athey et al., 2019; Wager and Athey, 2018), which leverages experimental randomization to estimate individual-level treatment effects $\hat{\tau}_i = \mathbb{E}[Y_i(1) - Y_i(0) \mid X_i]$, where Y_i is adoption and W_i indicates assignment to any subsidy arm. The forest uses all 1,617 households (both treated and control), since the control group provides the counterfactual adoption rate at each point in covariate space. We use 4,000 trees with honesty splitting. This estimate is **causal**: the RCT randomization ensures that, within any region of covariate space, subsidy assignment is independent of potential outcomes.

Predicted electricity usage (predictive): Because there is no experimental variation in electricity usage intensity conditional on adoption, we cannot estimate a causal effect of treatment on usage among adopters. Instead, a regression forest trained on 574 treated adopters predicts kWh growth $\hat{y}_i$ from baseline covariates, and we generate predictions for all 1,617 households. This estimate is **predictive, not causal**: it identifies which household profiles are associated with larger increases in billed electricity, but selection into adoption is endogenous and the forest conditions on this selection.

Joint classification: Splitting the sample at the median of each dimension yields a 2×2 matrix:

- **High Adopt, High Use** ("fuel switchers"): above-median on both margins.
- **High Adopt, Low Use** ("equipment replacers"): subsidy-responsive but below-median kWh growth.
- **Low Adopt, High Use**: below-median adoption response but above-median kWh growth.
- **Low Adopt, Low Use**: below-median on both dimensions.

Table H4 reports realized outcomes, adopter composition, and demographics for the four cells. Several patterns merit discussion.

The "High/Low Adopt" labels refer to predicted *marginal response* to a subsidy ($\hat{\tau}_i$), not to adoption level. This distinction matters: realized adoption rates do not follow the labels monotonically. Low Adopt, High Use households have a realized adoption rate of 60.4%, higher than the 45.9% for High Adopt, High Use, because they tend to have high baseline propensity (56% already own a stove) and would adopt at elevated rates regardless. High

Adopt households have low baseline propensity (18% stove ownership) but respond strongly to the subsidy on the margin.

The composition of adoption varies sharply across cells. Among fuel switchers, 37% purchased the complete bundle versus only 18% among equipment replacers, who are predominantly cookware-only adopters (61%), consistent with households that already own a stove adding cookware without changing cooking behavior. Fuel switchers also have the highest share of first-time electric cookers (81% vs. 51%), reinforcing that these households are genuinely transitioning rather than replacing equipment.

The Δ log(kWh) column validates the usage dimension: fuel switchers show +0.14 log points between months 0–2 and 12–14, while equipment replacers show −0.11, consistent with experimentation followed by reversion. Table H5 reports energy behavior and targeting variables for the same cells.

Table H4: Realized Outcomes and Demographics by Predicted Household Type

	High Adopt, High Use	High Adopt, Low Use	Low Adopt, High Use	Low Adopt, Low Use
Cell definition				
$\hat{\tau}_i$ (adoption)	Above med.	Above med.	Below med.	Below med.
$\hat{y}_i$ (usage)	Above med.	Below med.	Above med.	Below med.
Realized outcomes (subsidy arms)				
N	314	219	230	307
Adoption rate	0.459	0.571	0.604	0.541
Δ log(kWh)	+0.136	−0.105	+0.163	−0.072
Adopter composition (%, all adopters)				
Complete	37.3	17.7	22.9	21.9
Cookware only	38.0	60.8	45.8	57.2
Stove only	24.1	21.5	31.4	20.9
First-time elec. cooker	81.0	50.6	72.5	43.3
Household demographics				
HH size	3.8	4.1	4.2	5.3
Head age	49.8	50.0	64.3	66.5
Higher education (%)	9.1	30.2	7.0	28.4
Owns stove at BL (%)	17.7	43.0	22.3	56.4
Initial log(kWh)	4.83	5.42	4.83	5.55

Notes: Household types are defined by median splits on the causally estimated adoption treatment effect $\hat{\tau}_i$ (causal forest, 4,000 trees, honesty splitting) and predicted kWh growth $\hat{y}_i$ (regression forest trained on 574 treated adopters' billing data) across $N = 1{,}617$ households in subsidy and control arms. Realized outcomes are from subsidy-arm households ($N = 1{,}070$). Adopter composition and first-time rates are among all 656 adopters with matched Nepal Electricity Authority billing data. Demographics are baseline-survey cell means over all 1,617 households. Δ log(kWh) = mean log(kWh) in months 12–14 minus months 0–2. First-time = did not own an electric stove at baseline. Complete = stove + cookware.

Table H5: Energy and Targeting Variables by Predicted Household Type

	High Adopt, High Use	High Adopt, Low Use	Low Adopt, High Use	Low Adopt, Low Use
Energy behavior				
LPG consumption (kg/month)	11.6	10.6	11.8	12.8
Meals on LPG stove (of 12)	10.4	10.0	10.6	10.2
Cooking time (hrs/week)	12.2	15.2	11.7	15.0
Electricity perceptions				
Reliability concern (1–10)	6.90	7.34	6.55	7.09
Num. electric appliances	12.3	19.2	13.2	23.1

Notes: Household types are defined by median splits on the causally estimated adoption treatment effect $\hat{\tau}_i$ (causal forest) and predicted kWh growth $\hat{y}_i$ (regression forest) across $N = 1{,}617$ households in subsidy and control arms. All values are cell-level means from the baseline household survey. Reliability concern is a Likert scale (1 = not worried, 10 = very worried about electricity supply reliability). LPG consumption and cooking time are self-reported. Number of electric appliances includes all plug-in devices owned by the household.

3 Additional Results

Adoption heterogeneity: The mean adoption CATE is 0.378 (sd = 0.025), confirming a large average subsidy effect (Figure H3). A best linear projection (BLP) of the CATE onto covariates (Figure H4) identifies one significant predictor: households reporting unplanned outages as their main electricity problem have a 4.4 percentage point larger adoption response. Household size (−0.034), head age (−0.034), and reduced non-essential spending (−0.033) are suggestive negative predictors but not individually significant.

Electricity usage heterogeneity: The regression forest identifies a distinct set of predictive drivers (Figure H5). The number of electric appliances is the strongest predictor of kWh growth (normalized importance = 0.28), followed by cooking time (0.14), head age (0.11), and reliability beliefs (0.10). Prior stove ownership and education rank near the bottom despite being correlated with adoption, confirming that the two margins are driven by different household characteristics. This divergence in predictive drivers underlies the near-orthogonality reported in the main text.

Joint scatter: Figure H2 plots each household's adoption CATE against predicted kWh growth. The low correlation ($r = 0.17$) is visible in the near-circular cloud.

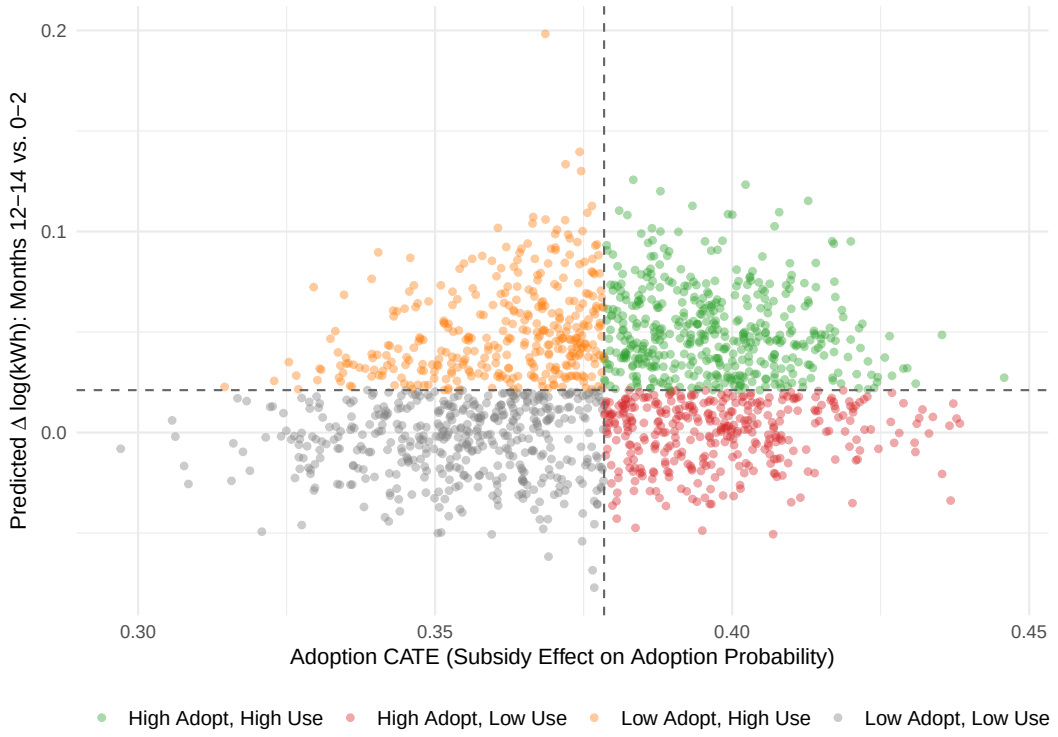


Figure H2: Joint Distribution of Predicted Adoption Response and Electricity Usage Growth

Notes: Each point represents one household (N = 1,617 in subsidy and control arms). Horizontal axis: household-level conditional average treatment effect of subsidy receipt on adoption, causally estimated by a causal forest (4,000 trees, honesty splitting). Vertical axis: predicted change in log(kWh) between months 0–2 and 12–14 post-intervention, from a regression forest trained on 574 treated adopters' Nepal Electricity Authority billing data. Dashed lines indicate median splits defining the four predicted household types. Correlation between the two dimensions: $r = 0.17$.

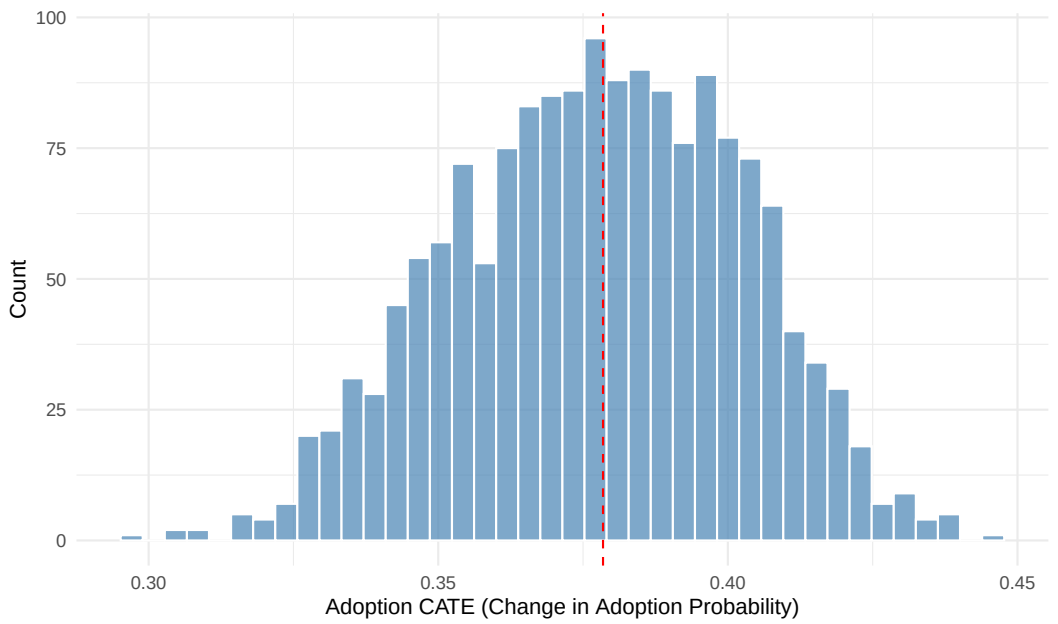


Figure H3: Distribution of Household-Level Adoption Treatment Effects

Notes: Histogram of household-level conditional average treatment effects of subsidy receipt on electric stove adoption ($\hat{\tau}_i$), estimated by a causal forest (4,000 trees, honesty splitting) on $N = 1{,}617$ households in subsidy and control arms. Treatment is an indicator for assignment to any subsidy arm. Adoption is defined as purchasing an electric induction stove by the endline survey. The dashed red line indicates the sample median. Mean $\hat{\tau} = 0.378$ (sd $= 0.025$).

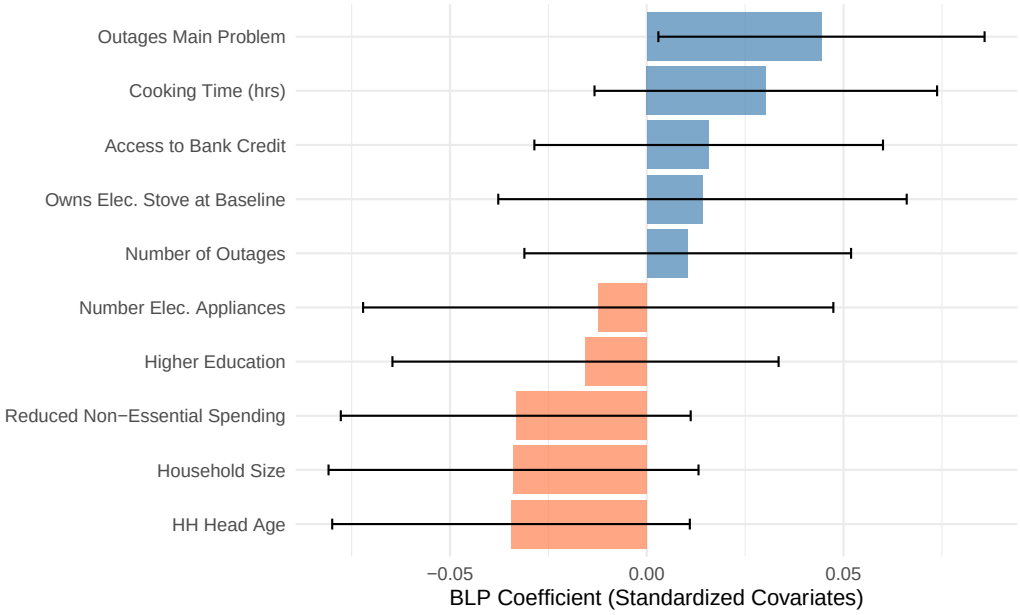


Figure H4: Best Linear Projection of Adoption Treatment Effects onto Baseline Covariates

Notes: Coefficients from a best linear projection of the household-level adoption treatment effect $\hat{\tau}_i$ onto 15 standardized baseline covariates (N = 1,617 households in subsidy and control arms). The projection identifies which observable characteristics are associated with larger or smaller adoption responses to subsidies. Whiskers show 95% confidence intervals (cluster- and heteroskedasticity-robust standard errors). The ten covariates with the largest absolute coefficients are shown.

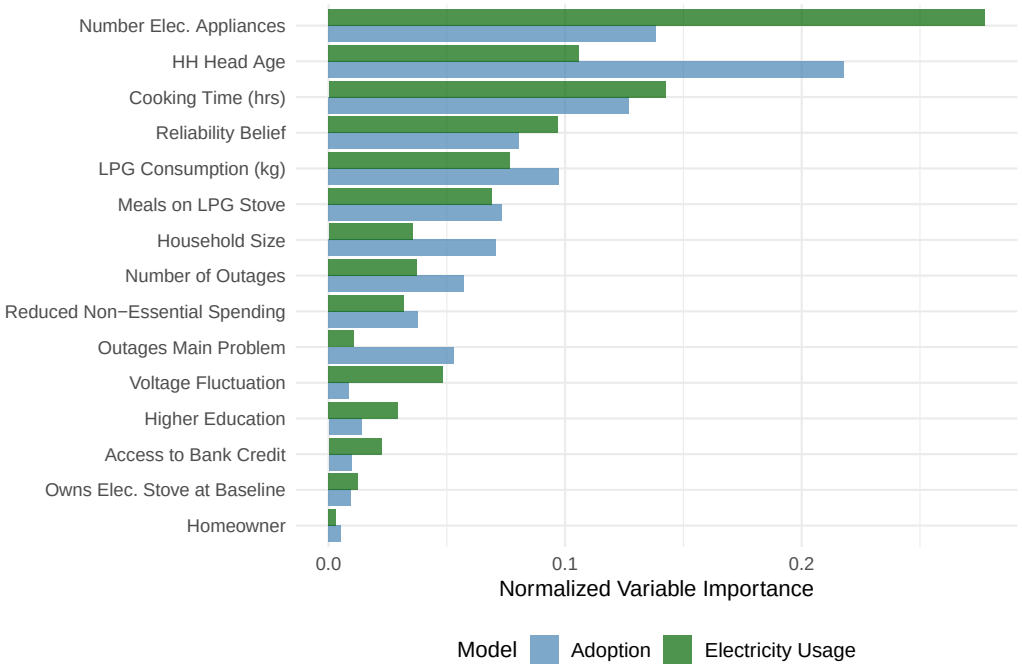


Figure H5: Variable Importance: Adoption Response versus Electricity Usage Prediction

Notes: Normalized variable importance from the causal forest (adoption treatment effect, $N = 1{,}617$ households) and regression forest (predicted electricity usage growth, trained on 574 treated adopters' billing data). Variable importance measures each covariate's contribution to the forest's splits, capturing nonlinear and interactive effects. Values are normalized so that the most important variable equals 1 within each model. All 15 baseline covariates are included in both models.