On the Back Burner: Experimental Evidence For Energy Transitions *

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Abstract

Economic development requires expanding energy consumption, but the global energy transition demands that this growth be clean. In many lower-income countries, households remain dependent on imported fossil fuels even where domestic renewable electricity is abundant, raising the question of what interventions can shift demand toward clean energy, and whether their effects persist. We study this through a scalable randomized controlled trial with 3,521 households in Kathmandu Valley, Nepal, where hydropower makes electrification feasible but LPG dominates cooking. Households were randomly assigned to subsidy vouchers at two levels, information treatments highlighting cost or health benefits, their interactions, and a control group. Subsidies had large effects, increasing electric stove adoption by 23 percentage points and cookware purchases by 41 percentage points; information alone had little impact, suggesting upfront cost is the binding constraint. Endline survey data show short-run substitution away from LPG toward electric cooking, indicating real behavioral change. Yet sustained increases in aggregate electricity consumption emerge only over time. Using 29 months of administrative billing records, we estimate dynamic treatment effects and find that combined subsidy-and-information arms increase billed usage by 7.4 percent, with effects appearing after roughly one year. These results suggest that while subsidies drive adoption, sustained use of behaviorally demanding energy technologies may require complementary information to support use.

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1 Introduction

Many technologies promise both private benefits and positive externalities. For instance, water and sanitation technologies reduce individuals' exposure to disease, as well as community transmission (Deutschmann et al., 2024; Geruso and Spears, 2018; Kremer et al., 2011). Agricultural trainings, fertilizers, and irrigation raise farm productivity, and more broadly, regional food security (Duflo and Pande, 2007; Duflo et al., 2008). Electric vehicles lower drivers' operating costs while also reducing global greenhouse gas emissions (Holland et al., 2016; Rapson and Muehlegger, 2023). Motivated by such dual gains, governments frequently promote technology adoption.[1]

Yet adoption beyond a critical threshold can create public costs from congestion, resource overuse, or fiscal strain. Rapid sewerage expansion may incur large social costs (Bancalari, 2024), 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 EV charging can overload grids (Bailey et al., 2024). The policy challenge is therefore not only to spur adoption, but to determine when further expansion remains socially desirable. This raises the question: how should governments promote technology adoption when welfare depends not only on household frictions but also on planner constraints?

We address this question in the context of energy transitions–central to global decarbonization efforts–which exemplify this tension between household and planner decision-making. These transitions generate large private and social gains from cleaner technologies, yet household adoption decisions, when scaled, can impose fiscal pressures, strain infrastructure, and shape environmental outcomes. We focus on an increasingly salient shift from LPG to electricity in household cooking, a transition from an often imported fossil fuel to a cleaner,

[1] Existing literature illustrates how reducing household frictions through interventions providing subsidies, information, and credit can induce adoption or use of such technologies (Bailey et al., 2025; Berry et al., 2020; Devoto et al., 2012; Duflo et al., 2011; Dupas et al., 2023; Guiteras et al., 2015; Lipscomb and Schechter, 2018; Muehlegger and Rapson, 2022).

domestically produced energy source. Governments must boost electricity demand without overloading fragile electric grids or fiscal budgets. At the same time, they must efficiently allocate incentives to households in the face of barriers to adopting and using new cooking technologies.[2] We develop a structural framework that embeds household behavior within planner constraints to recover key behavioral parameters and identify welfare-optimal policies, treating technology adoption as both a household choice and a planner's problem.

Guided by our model framework, we implement a randomized controlled trial (RCT) in Kathmandu Valley with 3,521 LPG-using households. Nepal, a lower-middle income country with a population of approximately 30 million people (National Statistics Office, 2025), provides a suitable setting for this question: with abundant clean hydropower, electricity is, in principle, cheaper and more secure than imported LPG. The government actively promotes electric cooking, given past LPG import supply shocks (Acharya and Adhikari, 2021). Yet, adoption remains puzzlingly low despite low electricity prices, and a sharp improvement in supply reliability (Acharya et al., 2024). 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. Households were randomly assigned to nine groups combining two subsidy levels (USD 7.5 or 22.5), two information treatments (cost or health), their interactions, and a control group. 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).[3]

Designed in partnership with the national electric utility, the interventions were implemented in a sample of the target population—urban LPG-using households. Subsidies were provided via vouchers redeemable at the country's largest retail chain, enabling realistic scale-up. In this way, the experiment meets the "scalability test" emphasized by List

[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., 2016).

[3]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)

(2022), embedding randomization in the population and delivery channels a planner would use. 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 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. This dynamic pattern indicates that adoption does not mechanically 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 into the structural model to evaluate counterfactual subsidy designs under alternative macro conditions such as varying grid reliability, fiscal costs, and LPG prices shaped by import volatility and pollution externalities, showing how optimal policy depends critically on the planner's fiscal and infrastructure environment. Because planners care about which households are most responsive, we systematically unpack heterogeneity in responses across households to inform optimal subsidy targeting. We estimate conditional average treatment effects using machine-learning methods, which allow us to predict which households benefit most from subsidies. A utility-targeting rule based on these predictions delivers the largest welfare gains, effectively prioritizing households whose traits predict the highest returns. Simpler rules—such as targeting heavy LPG users or households optimistic about electricity reliability—raise welfare gains over a "no-policy" baseline by 30–50 percent above random allocation, and in some cases nearly match full utility targeting.

First, our paper contributes to the literature on technology adoption and use in de-

veloping countries by providing evidence that the determinants of adoption can differ from the determinants of sustained use. Consistent with evidence from bednets, water treatment, and ACTs (Cohen and Dupas, 2010; Cohen et al., 2015; Dupas et al., 2023), we show that adoption of electric induction cookstoves is highly responsive to subsidies. In contrast, information alone does not increase adoption, and adding information to subsidies yields no additional take-up. This is consistent with a broader literature on health technologies (Dupas, 2011, 2014a; Dupas et al., 2024) that information alone does not overcome binding financial or structural constraints. Our results somewhat diverge from much of the preventive health literature on the intensive margin. While free or subsidized distribution has increased the use of certain technologies (Cohen and Dupas, 2010; Dupas, 2014b; Dupas et al., 2023), we find that subsidies alone do not generate sustained cookstove use. Instead, durable and gradually emerging consumption gains are concentrated in the combined high-subsidy plus information arms, suggesting that for complex, behaviorally demanding technologies like electric induction stoves, information plays a critical role not in overcoming liquidity constraints at purchase, but in facilitating learning, habit formation, and sustained substitution after acquisition. Our study therefore contributes new evidence that while subsidies remain central for adoption, sustained use of energy technologies may depend more heavily on complementary information and behavioral reinforcement.

Second, we contribute new evidence to the literature on residential end-use electrification in developing countries. Global strategies emphasize that electric cooking can lower CO_2 emissions (International Energy Agency, 2025), reduce indoor air pollution, and strengthen resilience to LPG import shocks (Gould et al., 2023; Guta et al., 2022). Yet despite expectations that LMICs offer "many of the most cost-effective opportunities for mitigation" (Glennerster and Jayachandran, 2023), causal evidence on end-use electrification in these settings remains scarce.[4] Renewable expansion in LMICs also faces supply-side barriers such as contract risk (Ryan, 2022), transmission limits (Gonzales et al., 2023), and infrastructure

[4]By contrast, evidence from high-income countries—especially on electric vehicles—is extensive (see, e.g., Bailey et al., 2025; Bushnell et al., 2022; Rapson and Muehlegger, 2023; Rapson and Bushnell, 2024).

lock-in (Wang, 2023). Our study connects household demand for clean end-use technologies to these system constraints by embedding experimentally estimated adoption behavior within a social planner's problem that accounts for grid reliability, fiscal costs, and import dependence. This structural approach contributes to a growing literature that uses RCT evidence within models to extrapolate experimental results (Burgess et al., 2023; Guiteras et al., 2025; Oliva et al., 2020), and connects to recent work on targeting and mechanism design for energy subsidies (e.g., Abubakari et al., 2024).

Finally, we contribute to a rich literature on the welfare gains from cleaner cooking. Existing evidence documents household willingness to shift from biomass to cleaner fuels (Bensch et al., 2015; Guta et al., 2022; Pattanayak et al., 2019) and highlights the benefits of moving from LPG to electricity (Gould et al., 2024, 2023). By focusing on a transition from a relatively modern but imported fuel (LPG) to a cleaner, domestically produced source (hydropower), we shed light on trade-offs central to clean energy transitions in both low- and high-income settings (Borenstein, 2023)—trade-offs that require not only understanding household frictions but also accounting for the strains that scaled adoption places on budgets, infrastructure, and administrative capacity (List, 2022; Muralidharan and Niehaus, 2017). Our findings therefore speak to broader questions of resilience and vulnerability to fossil-fuel import shocks (Cheng et al., 2025).

The paper proceeds as follows. Section 2 develops the structural model that formalizes household adoption, and the social planner problem. Section 3 discusses the local context in Nepal, while 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. Section 9 details the estimation procedure for the structural model, while Section 10 uses the estimated model to simulate policy counterfactuals and assess welfare implications. Section 11 concludes.

2 Model

We develop a tractable structural model to guide both our experimental design and our policy analysis. The model captures the frictions households face in adopting and using electric cooking technology: upfront liquidity constraints, misperceptions about relative operating costs, heterogeneity in preferences, and social spillovers. Importantly, the model also allows adoption to generate broader changes in electricity use over time through learning, experience, and complementary investments. In this setting, technology adoption is not merely a discrete purchase decision, but a gateway 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.

2.1 Household choice

Each household i in group g chooses between two cooking modes, LPG ($m = L$) or electricity ($m = E$), and an intensity of use T_{mg}. Households differ in their idiosyncratic preferences ε_i, which determine how attractive each mode is.[5]

Utility has three components: (i) consumption benefits net of perceived costs C_{mg}, (ii) any transfers (subsidies) received for adopting electricity S_{mg}, and (iii) an idiosyncratic taste shock ε_i:

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

Consumption utility C_{mg} depends on cooking time and the perceived cost P_{mg} (which includes both monetary prices and health costs):

$$C_{mg} = T_{mg}^{\eta} - P_{mg} T_{mg} \tag{1}$$

Perceived electricity costs may be influenced by information treatments. We model information as shifting perceived operating costs rather than actual tariffs. Let I_g^c and I_g^h denote cost and health information treatments. Perceived electricity cost is then given by:

$$\log P_{Eg} = \log P_{E0g} - \kappa_c I_g^c - \kappa_h I_g^h, \tag{2}$$

where P_{E0g} is baseline perceived cost and κ_c, κ_h capture how information shifts beliefs about operating costs or health damages.

We show extended working through of how to maximize the above function in the appendix. Specifically, Appendix Section A Equations (3)-(6) walk through how to obtain

[5] We define groups g to generate flexible mappings to characteristics that vary by group (such as treatment status, or household size).

optimal cooking time which comes out to be:

$$T^*_{mg} = \left(\frac{\eta}{P_{mg}}\right)^{1/(1-\eta)}.$$

Here η is the curvature parameter of cooking utility: higher η implies that households' demand for cooking time is less price sensitive, while lower η implies strong reductions in cooking time when costs rise. Estimating η thus tells us how households adjust intensity of use to changes in perceived price.

Transfers S_{mg} capture the benefits of subsidies for adopting electricity. LPG use is not subsidized, so $S_{Lg} = 1$. For electricity, we allow subsidies to shift utility in a concave way:

$$\log S_{Eg} = s^{\rho}_{Eg} + \gamma_P \, s_{Eg} P_{Eg} + \gamma_X \, s_{Eg} X_g + \gamma_A \, s_{Eg} A_{-i,g}.$$

The s^{ρ}_{Eg} term captures concavity in the value of subsidies, with $\hat{\rho} = 0.45$ estimated from the RCT. This nests common functional forms such as $\sqrt{s}$ ($\rho = 0.5$) or $\log(1+s)$ (as $\rho \to 0$). The interaction terms capture heterogeneity: γ_X allows households with certain characteristics to benefit more from subsidies (e.g. larger households or those with more compatible appliances), and γ_A captures social spillovers in adoption (BenYishay and Mobarak, 2019; Mobarak et al., 2012).

2.2 Adoption

Indirect utilities V_{mg} depend on prices, policy levers, and are scaled by idiosyncratic preference shocks ε_i drawn from a Fréchet distribution with shape parameter θ. This assumption, standard in the random utility literature, yields a closed-form multinomial logit adoption probability, allowing us to map relative utilities directly into market shares (Eaton and Kortum, 2002). Economically, θ controls the degree of heterogeneity: higher θ implies households are more homogeneous in preferences, so small changes in relative utility translate into large

swings in adoption, while lower θ implies greater dispersion and more inertia in switching. We adopt the Fréchet form for tractability, but the key economic content lies in this interpretation of θ, which can be estimated from the randomized variation in our experiment.

Appendix Section A equation (9) walks through how we leverage the fact that indirect utilities are scaled by a preference term drawn from a Fréchet distribution. It allows us to arrive at the following expression where the share of individuals in group g that adopt electricity is:

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

Substituting for V_{mg} generates a specification estimable with data:

$$\log \frac{\pi_{Eg}}{1-\pi_{Eg}} = -\frac{\eta\theta}{1-\eta} \log P_{Eg} + \theta\, s_{Eg}^{\rho} + \theta\gamma_P \left(s_{Eg} P_{Eg}\right) + \theta\gamma_X \left(s_{Eg} X_g\right) + \theta\gamma_A \left(s_{Eg} A_{-i,g}\right). \quad (3)$$

Equation (3) is our adoption equation. It makes clear that lower perceived electricity costs (P_{Eg}), higher subsidies (s_{Eg}), favorable group characteristics (X_g), or greater spillovers ($A_{-i,g}$) all raise adoption. In the empirical section we estimate η, θ, γ_X, and γ_A directly from randomized variation in our experiment.

2.3 Post-adoption electrification and billed electricity use

Adoption of electric cooking may generate broader changes in household electricity use over time. Households that adopt gain experience with electricity, increase confidence in reliability, and may purchase complementary appliances. We capture this channel with a long-run electrification factor $H_g \geq 1$, which scales total household electricity demand among adopters.

Let baseline non-cooking electricity demand be K_g^0. Total long-run billed electricity consumption for group g is given by

$$KWh_g = K_g^0 + \pi_{Eg} \cdot \alpha T_{Eg}^* + \pi_{Eg} \cdot (H_g - 1)K_g^0. \tag{4}$$

The first term reflects baseline electricity use. The second term captures electricity used for cooking among adopters. The third term captures broader electrification effects among adopters, such as increased appliance adoption or more intensive electricity use beyond cooking.

We allow the electrification factor to depend on policy:

$$H_g = 1 + \omega_s s_{Eg} + \omega_c I_{Eg}^c + \omega_h I_{Eg}^h + \omega_{sc} s_{Eg} I_{Eg}^c + \omega_{sh} s_{Eg} I_{Eg}^h. \tag{5}$$

This formulation allows information to play a limited role in adoption while affecting long-run electricity use through experience and complementary investment. In particular, interaction terms between subsidies and information allow combined treatment arms to generate larger sustained increases in billed consumption.

2.4 Social planner

The social planner chooses subsidy levels and information policies to maximize aggregate welfare. Higher electricity use is socially desirable because it reduces reliance on imported LPG and improves health outcomes. However, additional electricity demand is not costless when generation or distribution capacity is constrained. Serving incremental load may require costly imports, peaking generation, or network upgrades. The planner therefore weighs household welfare gains against the marginal cost of supplying electricity under capacity constraints and the fiscal cost of subsidies.

The planner chooses subsidy levels s_{Eg} and information treatments I_{Eg}^c, I_{Eg}^h to maximize:

$$\max_{s_{Eg}, I^c_{Eg}, I^h_{Eg}} \quad \sum_i U_{ig} - \delta \sum_{Eg} KWh_{Eg} - \lambda(1 - \pi_{Eg}) - (s_{Eg} + \psi s^2_{Eg}), \tag{6}$$

where:

- δ is the marginal social cost of supplying electricity under capacity constraints. It reflects generation costs, import costs, and reliability preserving expenditures required to serve additional load.
- λ is the social penalty from continued LPG reliance, capturing both health externalities and import dependence.
- ψ is the marginal cost of public funds.

Substituting the expressions for indirect utility and billed electricity use, the planner's objective can be written as:

$$\max_{s_{Eg}, I^c_{Eg}, I^h_{Eg}} \quad \underbrace{\bar{\eta} \left[\left(P_{Eg}^{\frac{-\eta}{1-\eta}} S_{Eg} \right)^{\theta} + 1 \right]^{1/\theta}}_{\text{(i) Household option value}} \tag{7}$$

$$- \underbrace{\delta \, KWh_{Eg}}_{\text{(ii) Capacity-constrained supply cost}} \tag{8}$$

$$- \underbrace{\lambda(1 - \pi_{Eg})\bar{\eta}}_{\text{(iii) LPG dependence}} \tag{9}$$

$$- \underbrace{(s_{Eg} + \psi s^2_{Eg})}_{\text{(iv) Subsidy cost}}. \tag{10}$$

(i) Household option value. This term captures the welfare gains households obtain from being able to choose between LPG and electricity. Adoption increases expected utility through lower perceived operating costs and subsidies.

(ii) Capacity-constrained supply cost. Total billed electricity consumption KWh_{Eg} depends on baseline electricity use, electric cooking among adopters, and broader electrification effects captured by H_{Eg}. The parameter δ reflects the marginal social cost of serving additional electricity demand when capacity is tight. Even when increased electricity use is desirable, it carries real supply costs that the planner must internalize.

(iii) LPG dependence. Households that do not adopt remain reliant on LPG. The parameter λ captures the social cost of continued exposure to indoor air pollution and macroeconomic risks associated with imported fuel dependence.

(iv) Subsidy cost. Subsidies impose fiscal costs. The linear term reflects the transfer itself, while the quadratic term captures distortionary costs of public finance or administrative inefficiencies as subsidy programs scale.

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 (3), which then discipline counterfactual policy simulations in Sections 9 and 10.

3 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).

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.

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 (≈

[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.

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.

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

[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).

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 by project staff, and the logo of Bhat Bhateni super store, which is the largest chain store in

[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.

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.

[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.

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.

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:

$$\begin{aligned} Y_i = \alpha &+ \beta_1 \text{HighSubsidy}_i + \beta_2 \text{LowSubsidy}_i + \beta_3 \text{CostInfo}_i + \beta_4 \text{HealthInfo}_i \\ &+ \beta_5 (\text{HighSubsidy}_i \& \text{CostInfo}_i) + \beta_6 (\text{HighSubsidy}_i \& \text{HealthInfo}_i) \\ &+ \beta_7 (\text{LowSubsidy}_i \& \text{CostInfo}_i) + \beta_8 (\text{LowSubsidy}_i \& \text{HealthInfo}_i) + \varepsilon_i \end{aligned} \tag{11}$$

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:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{k=-6, k\neq -1}^{17} \beta_k \times \mathbb{1}\{\text{Month}_t = k\} \times \mathbb{1}\{\text{Treatment}_i = T\} + \epsilon_{it} \tag{12}$$

where Y_{it} represents the log electricity consumption for household i in month t. As in the main specification, α_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:

$$Y_{it} = \alpha_i + \lambda_t + \sum_{T=1}^{8} \beta_T \left(Post_t \times \mathbb{1}\{\text{Treatment}_i = T\} \right) + \epsilon_{it} \tag{13}$$

where Y_{it} denotes the electricity consumption for household i at time t. The terms 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 9. 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 infor-

mation 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 Heterogeneity by Household Characteristics

Government interventions to promote adoption of efficient appliances such as electric stoves face significant challenges when households do not internalize the benefits of switching from traditional technologies. Barriers such as high upfront costs or misconceptions about electric stoves can vary across households, making universal policies inefficient. Understanding this heterogeneity in treatment response is essential for designing targeted interventions that maximize adoption while minimizing campaign costs.

To understand differences in adoption rates across treated households, we implement a Conditional Average Treatment Effect (CATE) analysis using causal forests (Wager and Athey, 2018). With this approach, we identify key household characteristics that predict higher adoption rates of induction stoves or induction compatible cookware.[15] We estimate the causal forest using households assigned to any treatment arm with a subsidy component as the treated group and households in the pure control group as the control group. For details in the variables we use to estimate the causal forest, see Table B6.

After we estimate individual treatment effects for each household, we use a best linear projection (BLP) to identify which observable characteristics are strongly associated with treatment effect variation. Figure 6 shows the distribution of individual treatment effects of the sample we use to estimate the causal forest. We standardize all covariates to compare their relative importance, as each BLP coefficient represents the expected change in treatment effects from a one standard deviation increase in that variable. Figure 7 shows the top 10 most important variables to explain heterogeneity in the treatment effect based on the standardize variables' coefficients.

Some of the demographic variables that are relevant to explain treatment heterogeneity

[15] We use the `grf` library in R and the `causal_forest()` function with the default settings.

are household size and household head age. Both of these characteristics are negatively associated with the treatment effect. In particular, bigger households could be reluctant to adopt electric stoves due to higher upfront costs or higher opportunity costs if the electricity is not reliable. Household head age could be negatively correlated with the treatment effect as older household heads may prefer more traditional cooking practices. Other highly ranked variables are related to beliefs. In particular, households that believe that the electricity cost has been increasing recently are the ones with the lowest treatment effect everything else constant. The other beliefs variables have contrary signs to what intuition may tell us. For example, the households that believe that the electricity cost has been decreasing have on average lower treatment effects.

These results provide some insights for optimizing government interventions, though several patterns may seem counterintuitive at first glance. The demographic findings suggest that larger and older households may be more difficult to reach, potentially due to financial constraints, which could require higher subsidies rather than exclusion from programs.

9 Estimation of Structural Parameters

We estimate the model parameters by jointly fitting the structural adoption equation to experimental variation in our randomized controlled trial. Recall from equation (3) that the adoption share for electricity in group g is given by

$$\pi_{Eg} = \frac{V_{Eg}^{\theta}}{V_{Eg}^{\theta} + V_{Lg}^{\theta}},$$

which can be expressed in log-odds form as

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

Equation (11) shows the reduced-form specification that identifies the causal effect of randomized treatments on adoption outcomes, with estimates reported in Table 4. These reduced-form estimates establish three key patterns: (i) subsidies had large effects on adoption, (ii) information alone had little effect, and (iii) interactions between subsidies and information generated responses similar in magnitude to the subsidies alone. These results provide the experimental variation we use to identify the parameters of the structural model.

Calibration strategy. We jointly discipline the structural adoption equation using two sources of variation. First, we use adoption rates across the randomized arms (control, low subsidy, high subsidy, information only, and their interactions). Second, we exploit the shape of the adoption–subsidy curve between the low and high subsidy levels, interpolated to obtain a continuous benchmark. The adoption equation implies that the log-odds of adoption are linear in s_{Eg}^{ρ}, $\log P_g$, and their interaction, with slope parameters θ, η, and γ_P.

To estimate these parameters, we proceed as follows. We normalize the baseline adoption in the control group, π_{Control}, which pins down the intercept β_0. We then perform a grid search over the concavity parameter ρ, choosing the value that minimizes the loss function combining squared deviations between observed and predicted adoption rates across RCT arms and along the subsidy curve. Given ρ, the responsiveness parameter θ is identified from the slope between the low- and high-subsidy groups. Because information treatments alone do not shift adoption, the adoption moments provide limited independent identification of perceived price parameters. We therefore discipline the curvature parameter η primarily using the administrative billed consumption response, while using adoption moments to identify how subsidies shift the extensive margin.

Parameter estimates. This procedure yields parameter estimates of $\rho \approx 0.45$, $\theta \approx 3.6$, $\eta \approx 0.19$, and $\gamma_P \approx -0.10$. These magnitudes suggest that adoption is highly responsive to

small subsidies but quickly displays diminishing returns, that perceived price changes alone do not induce large behavioral shifts, and that subsidies are less effective when electricity is perceived as costly.

9.1 Long-run billed electricity consumption

We next discipline the post-adoption electrification margin using administrative billing data from the Nepal Electricity Authority. The model allows adoption to generate longer-run increases in electricity use beyond cooking through experience and complementary investments, captured by the electrification factor H_g.

We match treatment-arm effects on log(kWh) in the long-run post period (12 to 18 months after intervention). Because subsidies strongly increase adoption while sustained billing increases are concentrated in the subsidy & information combination arms, these billing moments identify how information amplifies post-adoption electrification rather than shifting the extensive margin itself.

Estimating δ (Capacity-constrained supply cost) We calibrate δ to capture the marginal social cost of supplying an additional kWh of electricity when generation or distribution capacity is constrained. In Nepal, the Nepal Electricity Authority (NEA) often relies on costly imports during the dry winter season, with average import costs of about NPR 10.5 per kWh in FY2022/23 and peak costs as high as NPR 32 per kWh (Alternative Energy Promotion Centre , AEPC; ShareSansar News, 2024). Meanwhile, the value of lost load (VoLL) to households is estimated at around NPR 5–15 per kWh (Alberini et al., 2022). To balance these figures, we anchor the penalty at roughly NPR 15-30 per kWh, which reflects the social cost of additional demand at peak times when the grid is most constrained.

In practice for our counterfactual targeting exercise, we are using subsidies in NR, and therefore the scale of the household utility term in the social lanner function is on the scale of 100,000. To keep cost terms comparable and appropriately scaled, we rescale this per-kWh

penalty so that it enters the welfare calculation in the correct proportion relative to adoption gains and subsidy spending. With this normalization, the working value used in simulations is $\delta = 3000$, which preserves the interpretation of a penalty in the order of tens of NPR per kWh once expressed relative to household utility levels.

Estimating λ (LPG Dependence Penalty) The parameter λ reflects two disutilities of continued LPG use: (i) health costs from indoor air pollution, and (ii) risks from dependence on imported LPG. We model λ as a per-household penalty rather than per-cylinder, since the planner internalizes risks from continued dependence itself (e.g. import vulnerability, political capital, and household health exposure), rather than cylinder counts that may not directly translate into social cost.

On the health side, household air pollution caused nearly 25,000 premature deaths in Nepal in 2019, with an associated welfare burden of roughly NPR 40 billion annually (Malla et al., 2025). On a per-household basis, this amounts to about NPR 10–12,000 per year, or NPR 800–1000 per month.

On the import side, Nepal spent NPR 55.6 billion on LPG imports from India in FY2023/24 (about 3.5% of its import bill), making households vulnerable to geopolitical shocks such as the 2015–2016 blockade (Al Jazeera, 2015; Farsight Nepal, 2023).

To incorporate both health and energy security concerns, we target $\lambda \approx$ NPR 1000 per household per month (roughly one cylinder equivalent), decomposed into about NPR 700 for health impacts and NPR 300 for security risks. As with δ, the numerical value is rescaled in the simulation code to ensure comparability with household utilities and adoption benefits; the working parameter is set at $\lambda = 1000$, which preserves the correct order of magnitude once utilities are scaled.

Estimating ψ (Subsidy Cost) We calibrate the marginal cost of public funds ψ to account for the deadweight loss from raising additional revenue. Evidence from developing

countries suggests an MCF well above unity, with typical values in the range 1.2–1.3 (International Monetary Fund, 2015). For Nepal, where taxation is narrow and reliant on import duties, the marginal cost of public funds is plausibly high. We therefore set $\psi \approx 0.2$, implying each NPR 1 of subsidy requires NPR 1.2 of resources once distortionary costs are accounted for.

Because our budget constraint is expressed in absolute NPR terms (with a fixed outlay of NPR 2.288 million in the main simulations), ψ does not require further scaling: the parameter is applied directly to the subsidy bill in the planner's welfare function.

Model validation Figure 8 validates the calibration along two complementary dimensions. Panel 8b compares predicted adoption rates with those observed across experimental treatment arms. The model reproduces the large jump in adoption in the high-subsidy groups and the limited effect of the information-only treatment, while also capturing the intermediate adoption rates in the low-subsidy and interaction arms. Although no reduced-form specification can perfectly match all experimental variation, the alignment across arms demonstrates that the structural adoption equation embeds the right comparative statics.

Panel 8a shows predicted versus observed adoption along a continuous subsidy schedule. Here the model closely tracks the interpolated adoption curve, especially in the range between the low- and high-subsidy arms that is most informative for identifying the responsiveness parameter θ and concavity ρ. At very high subsidy levels the model predicts slightly higher adoption than the interpolated curve, which is expected given the functional form, but the overall fit is strong.

These two validation exercises show that the model replicates both the discrete shifts induced by the randomized treatments and the smooth adoption response to subsidy intensity. This provides confidence that the calibrated parameters capture the key behavioral margins, supporting the use of the model for counterfactual policy simulations where no experimental variation is directly observed.

10 Optimal policy simulations and targeting

We use the calibrated model to simulate the design of optimal subsidy and information policies under alternative planner-side constraints. The planner internalizes three forces: (i) household welfare gains from adoption and electrification, (ii) the marginal social cost of supplying additional electricity under capacity constraints, captured by δ, and (iii) the social cost of continued LPG dependence, captured by λ. Fiscal costs are governed by ψ.

10.1 Optimal subsidy and information policy

Figure 9 illustrates how the socially optimal electricity subsidy varies with the capacity-constrained supply cost δ and the LPG dependence penalty λ, holding ψ fixed. Darker shading corresponds to higher optimal subsidies.

When λ is large relative to δ, the planner places greater weight on reducing LPG reliance. In this region, higher subsidies are optimal because they increase adoption and amplify long-run electrification effects through H_g. As δ rises, the marginal cost of serving additional electricity demand increases, leading the planner to scale back subsidy levels.

Unlike a framework that treats increased electricity use as inherently problematic, this model recognizes that higher demand is socially desirable but not free. The optimal policy therefore balances the benefits of electrification against the real supply costs of serving incremental load.

Because long-run billed electricity effects are strongest in the subsidy $\times$ information arms, the planner may also optimally combine financial incentives with targeted information provision. In simulations where information amplifies post-adoption electrification (through the H_g margin), combined policies can dominate subsidy-only designs, particularly when the social value of reducing LPG dependence is high.

10.2 Targeting

The model also allows us to evaluate how targeting subsidies to specific households compares with randomized allocation. This builds directly on the heterogeneity analysis in Section 8. There we showed that treatment effects vary systematically with household characteristics such as household size, baseline LPG use, and beliefs about electricity reliability.

Universal policies may be inefficient if households differ in both their probability of adoption and their post-adoption electrification response. Targeting rules can therefore trade off administrative feasibility against welfare gains. Figure 10 reports welfare outcomes under alternative targeting rules, holding the total subsidy budget fixed at the RCT level. Simple rules such as prioritizing high LPG users or households with greater predicted electrification response outperform randomized allocation.

A utility-based targeting rule that prioritizes households with the highest predicted welfare gains delivers the largest improvements, raising welfare relative to the RCT design. These gains arise not only from higher adoption, but from directing subsidies toward households whose post-adoption electrification response is strongest. While fully utility-based targeting may be administratively demanding, the model highlights that even relatively simple targeting criteria can substantially increase welfare by aligning policy with heterogeneous behavioral responses.

To conclude, these counterfactual exercises illustrate how the structural model translates experimental estimates into policy-relevant prescriptions. By jointly considering adoption, long-run electricity use, and capacity-constrained supply costs, the framework provides a disciplined way to design electrification policy in settings where both demand expansion and system constraints matter.

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 subsidies substantially increase adoption of electric cooking technologies, while information treatments alone do not, indicating that upfront cost, not misperceptions, is the binding constraint. These effects exhibit rich heterogeneity: households respond differently depending on baseline ownership, and the form of adoption (stoves versus cookware). To our knowledge, this is among the first studies to document such detailed heterogeneity at the LPG–electricity margin, which is increasingly relevant for countries seeking to reduce dependence on imported gas.

Crucially, we go beyond adoption to trace long-run electricity usage using 29 months of confidential billing data from the Nepal Electricity Authority. While self-reported survey responses suggest substantial substitution from LPG toward electricity, the billing records reveal a more nuanced picture. Effects on metered consumption vary by adopter type and emerge gradually over time, with some treatment arms showing significant increases only in the longer run. These dynamics underscore that the welfare consequences of electrification cannot be inferred from short-run adoption patterns alone, and highlight the value of administrative data in evaluating energy transition policies.

A structural framework embeds these experimental estimates into a planner's problem

with fiscal, grid, and fuel-security constraints, allowing us to evaluate counterfactual targeting rules. Targeting subsidies toward the most responsive households amplifies welfare gains by up to 40–50 percent relative to random allocation. More broadly, combining randomized evidence with administrative consumption data and structural modeling offers a template for designing energy transition policies that are grounded in causal evidence, attentive to heterogeneity, and cognizant of system-level trade-offs.

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Figures and Tables

Figures

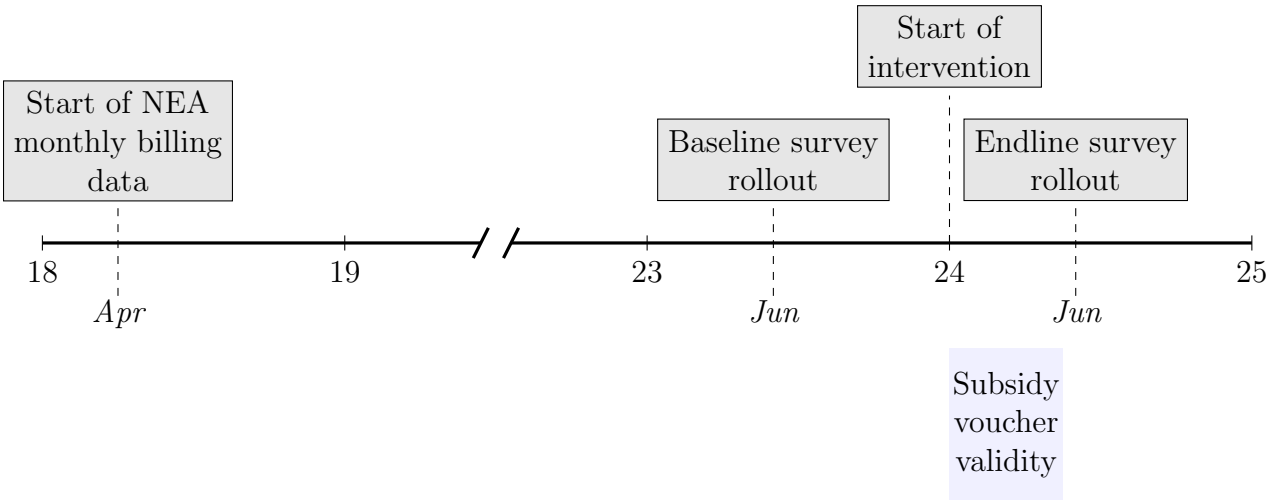
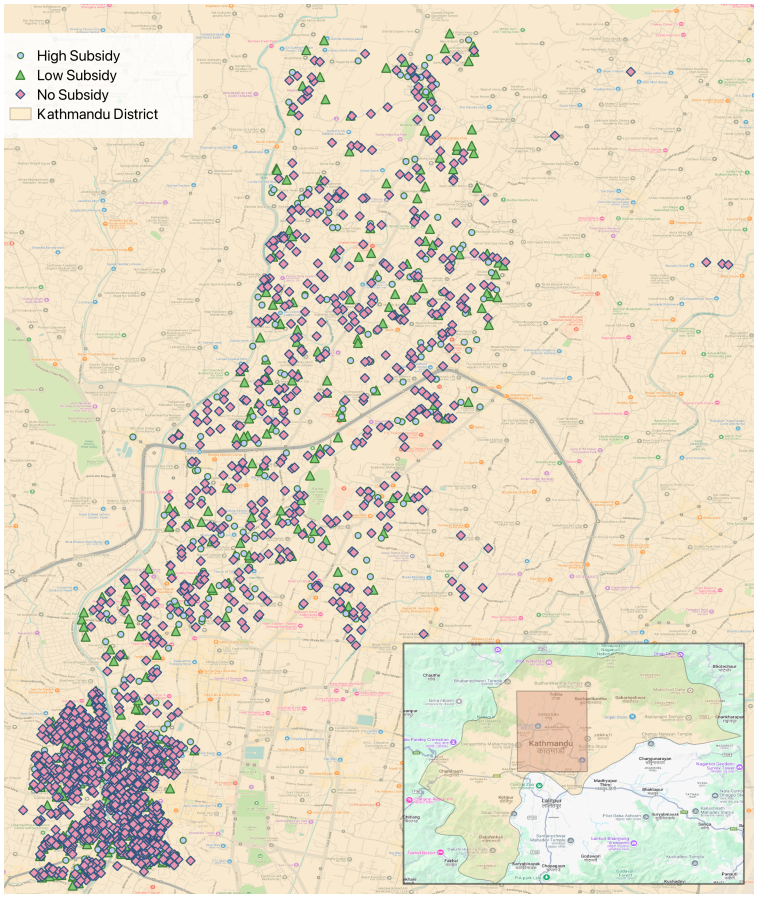


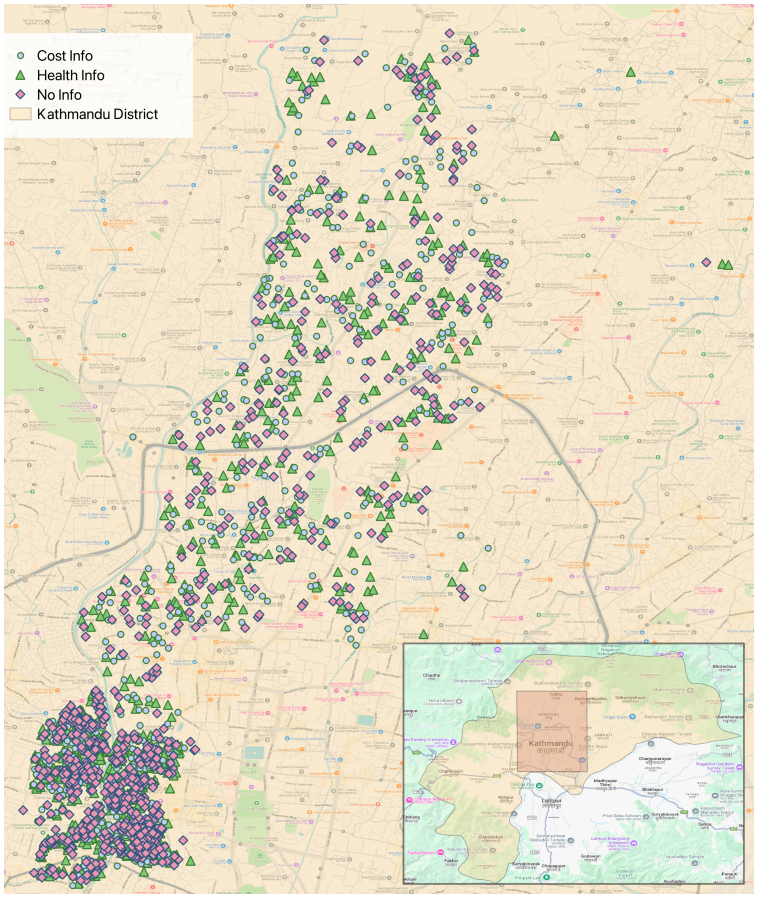
Figure 1: Timeline of surveys and key activities

Figure 2: Spatial spread of households by subsidy treatment group



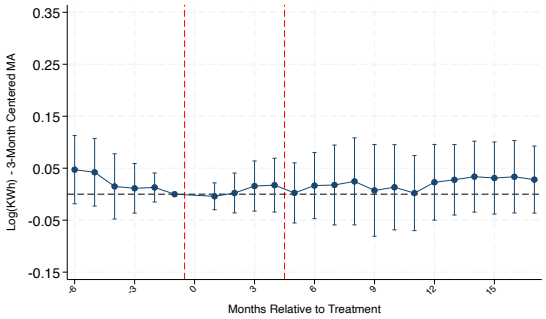
Source: Kathmandu district boundary is from 2015 and was obtained from Code for Nepal.

Figure 3: Spatial spread of households by information treatment group

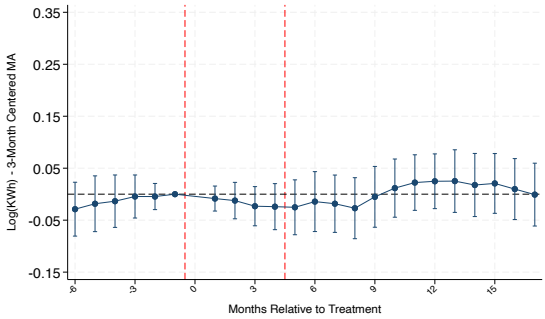


Source: Kathmandu district boundary is from 2015 and was obtained from Code for Nepal.

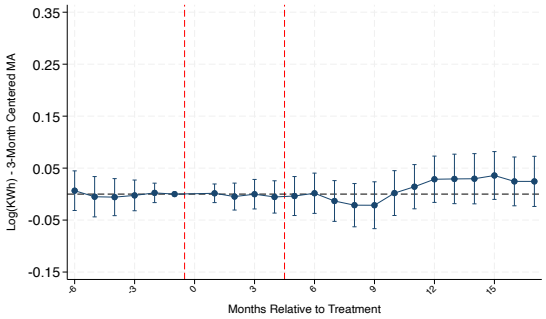
Figure 4: Event Study Estimates of Treatment Effects on Log Electricity Consumption



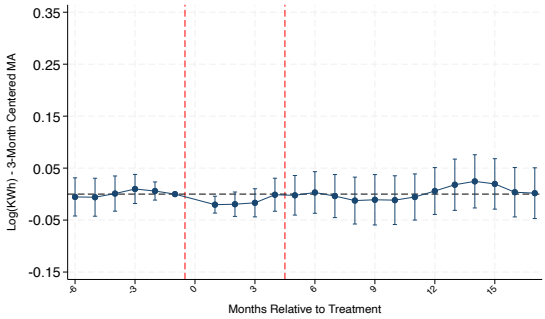
(a) High Subsidy Only



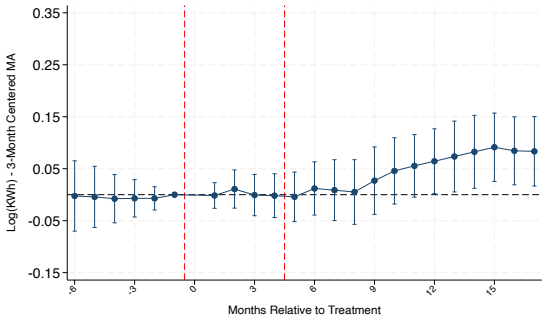
(b) Low Subsidy Only



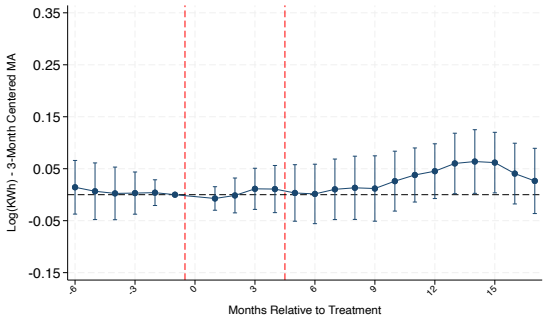
(c) Cost Information Only



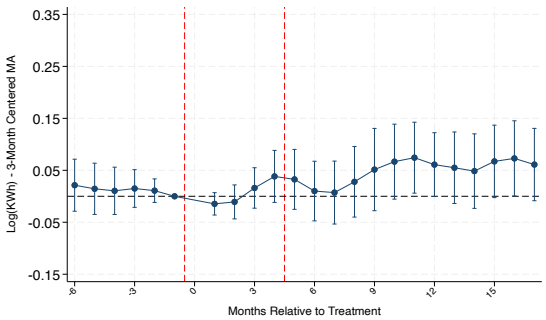
(d) Health Information Only



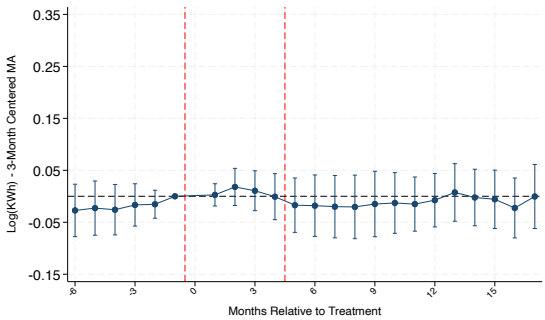
(e) Cost Information & High Subsidy



(f) Cost Information & Low Subsidy



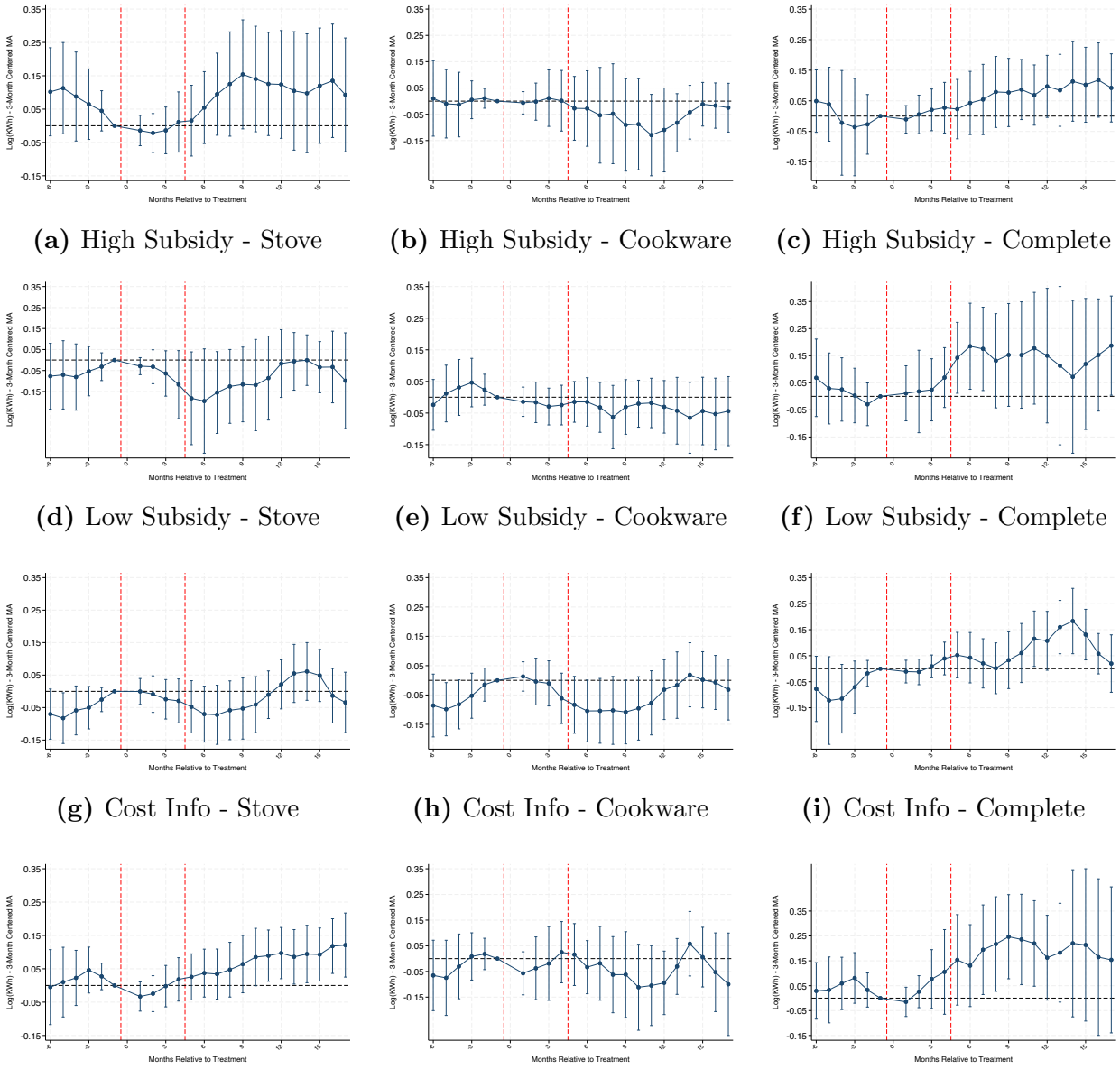
(g) Health Information & High Subsidy



(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 (12). 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

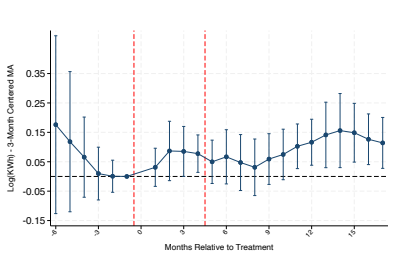
(d) Low Subsidy - Stove **(e)** Low Subsidy - Cookware **(f)** Low Subsidy - Complete

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

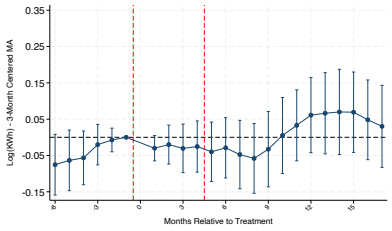
(j) Health Info - Stove **(k)** Health Info - Cookware **(l)** Health Info - Complete

Notes: This figure plots event study estimates of the effect of treatment on log electricity consumption (three-month centered moving average), based on Equation (12). 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.

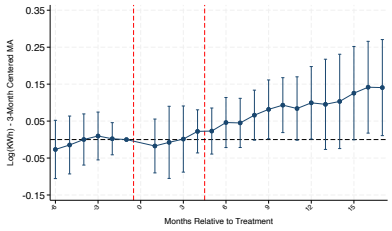
Figure 5: Event Study Estimates on Log Electricity Consumption by Adopter Type (continued...)



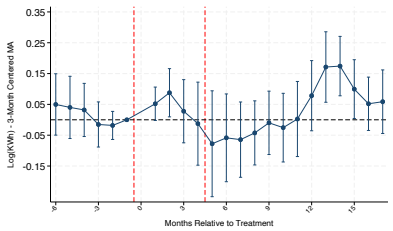
(m) High Sub. & Cost - Stove



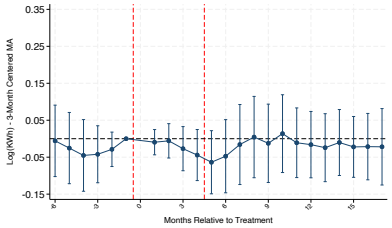
(n) High Sub. & Cost - Cookware



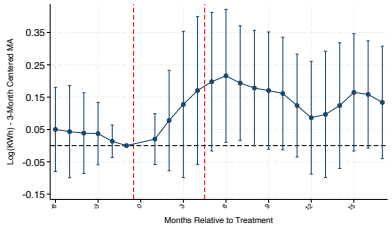
(o) High Sub. & Cost - Complete



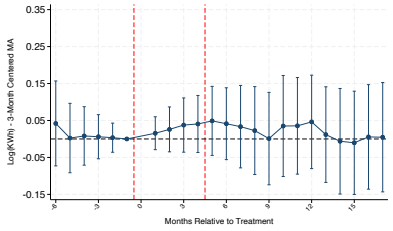
(p) Low Sub. & Cost - Stove



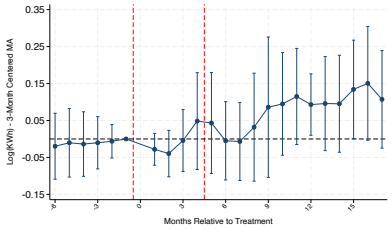
(q) Low Sub. & Cost - Cookware



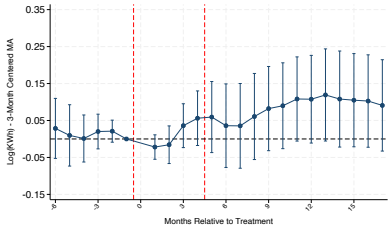
(r) Low Sub. & Cost - Complete



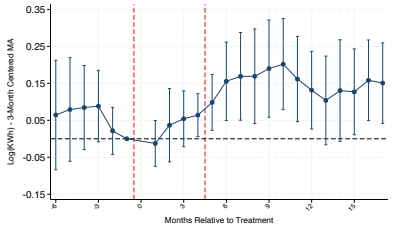
(s) High Sub. & Health - Stove



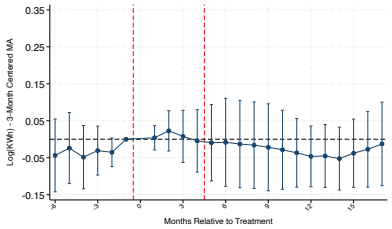
(t) High Sub. & Health - Cookware



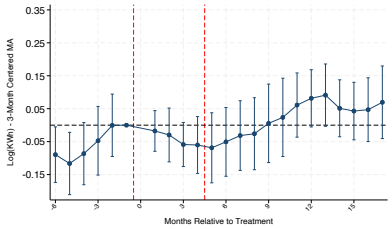
(u) High Sub. & Health - Complete



(v) Low Sub. & Health - Stove



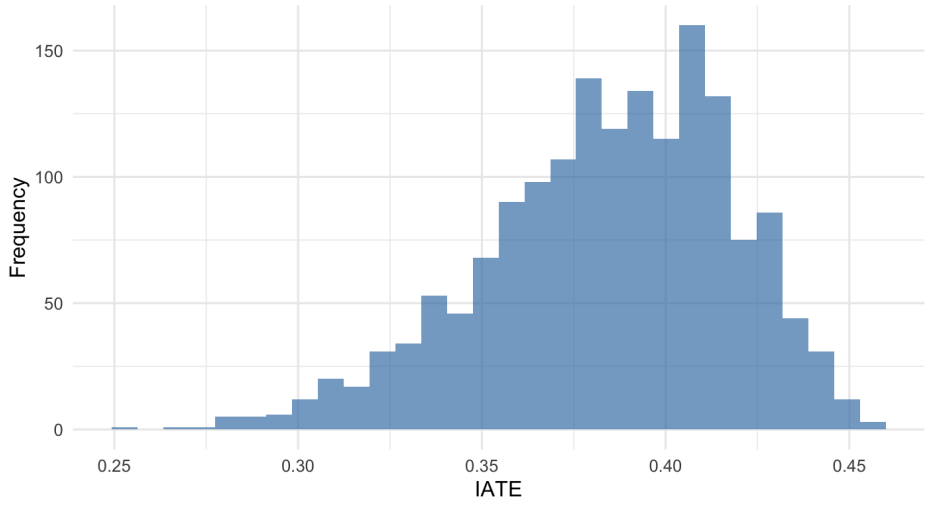
(w) Low Sub. & Health - Cookware



(x) Low Sub. & Health - Complete

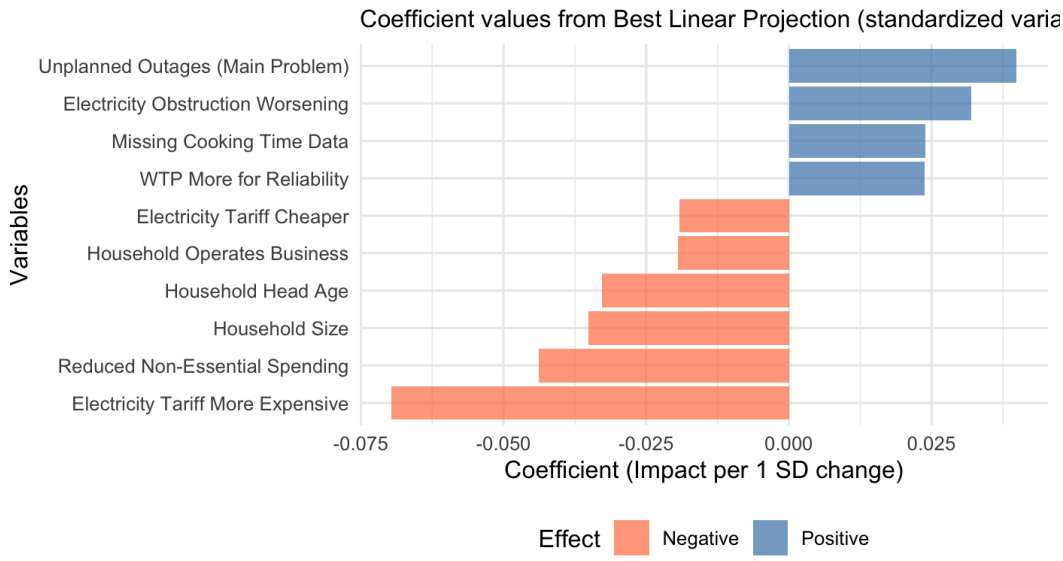
Notes: This figure plots event study estimates of the effect of treatment on log electricity consumption (three-month centered moving average), based on Equation (12). The columns display heterogeneity by adoption type relative to the control group: Column 1 includes treated households who adopted only 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: Distribution of Individual Average Treatment Effects (IATEs) from Causal Forest Estimation.



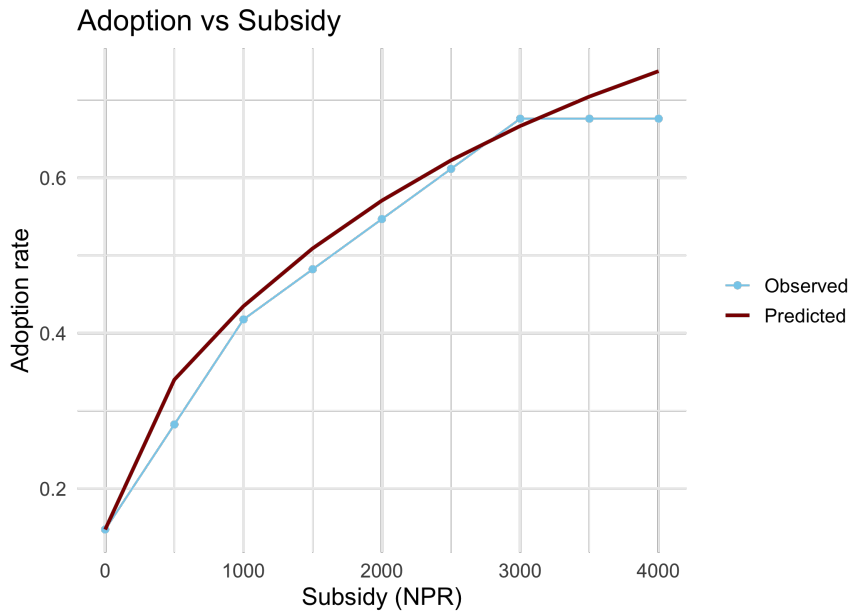
Notes: The histogram shows the distribution of individual average treatment effects (IATEs) estimated using causal forest for 1,645 households. The sample includes all households assigned to treatment arms with subsidy components (treated group) and households in the pure control group. Treatment effects represent the impact of subsidies on the probability of adopting induction stoves or induction-compatible cookware. The distribution ranges from approximately 0.25 to 0.45, indicating substantial heterogeneity in treatment response across households.

Figure 7: Top 10 most important variables for explaining treatment heterogeneity

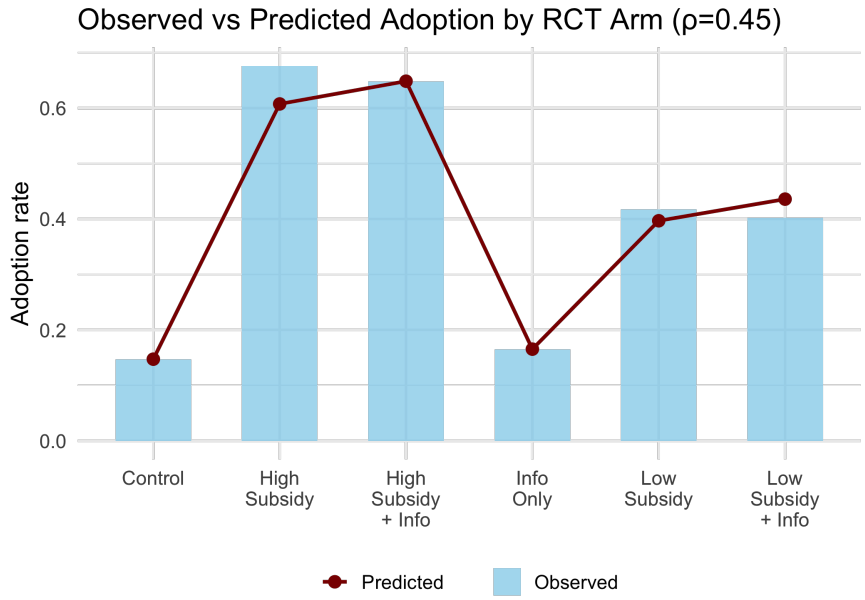


Notes: The figure displays the ten most important variables for explaining treatment effect heterogeneity based on best linear projection coefficients from standardized covariates. Positive coefficients (blue bars) indicate variables associated with higher treatment effects, while negative coefficients (coral bars) indicate variables associated with lower treatment effects. Each coefficient represents the expected change in treatment effects from a one standard deviation increase in the respective variable. Variables are ranked by absolute magnitude of their coefficients.

Figure 8: Validation of model calibration against observed adoption. Panel (a) compares predicted and observed adoption curves. Panel (b) compares adoption rates across RCT treatment arms.



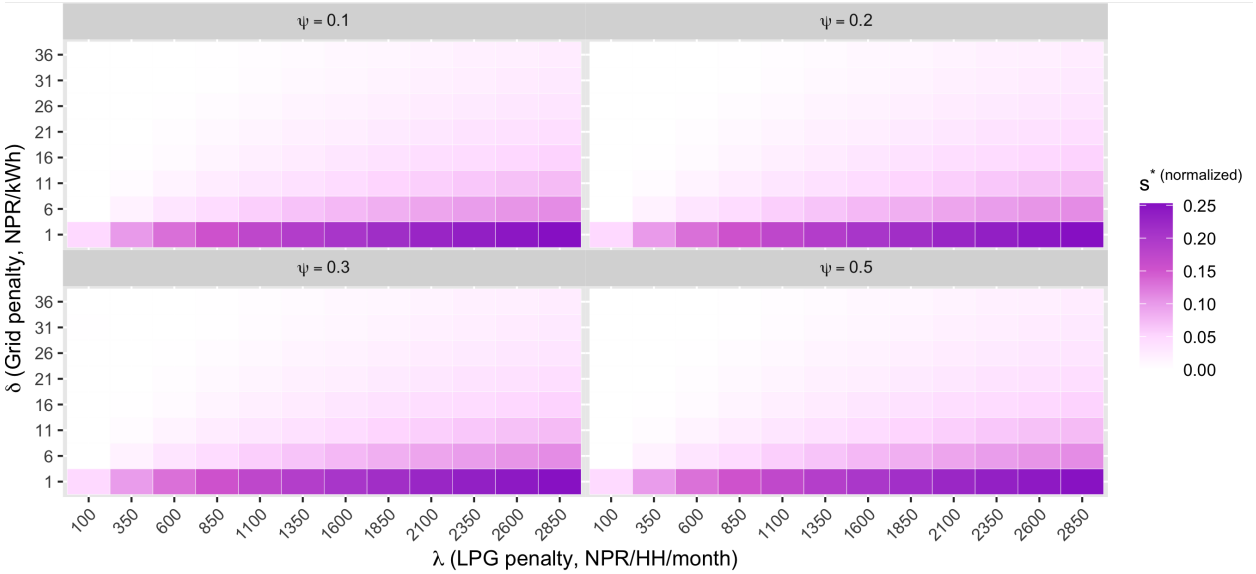
(a) Predicted vs. observed adoption curve by subsidy level.



(b) Predicted vs. observed adoption by RCT treatment arm.

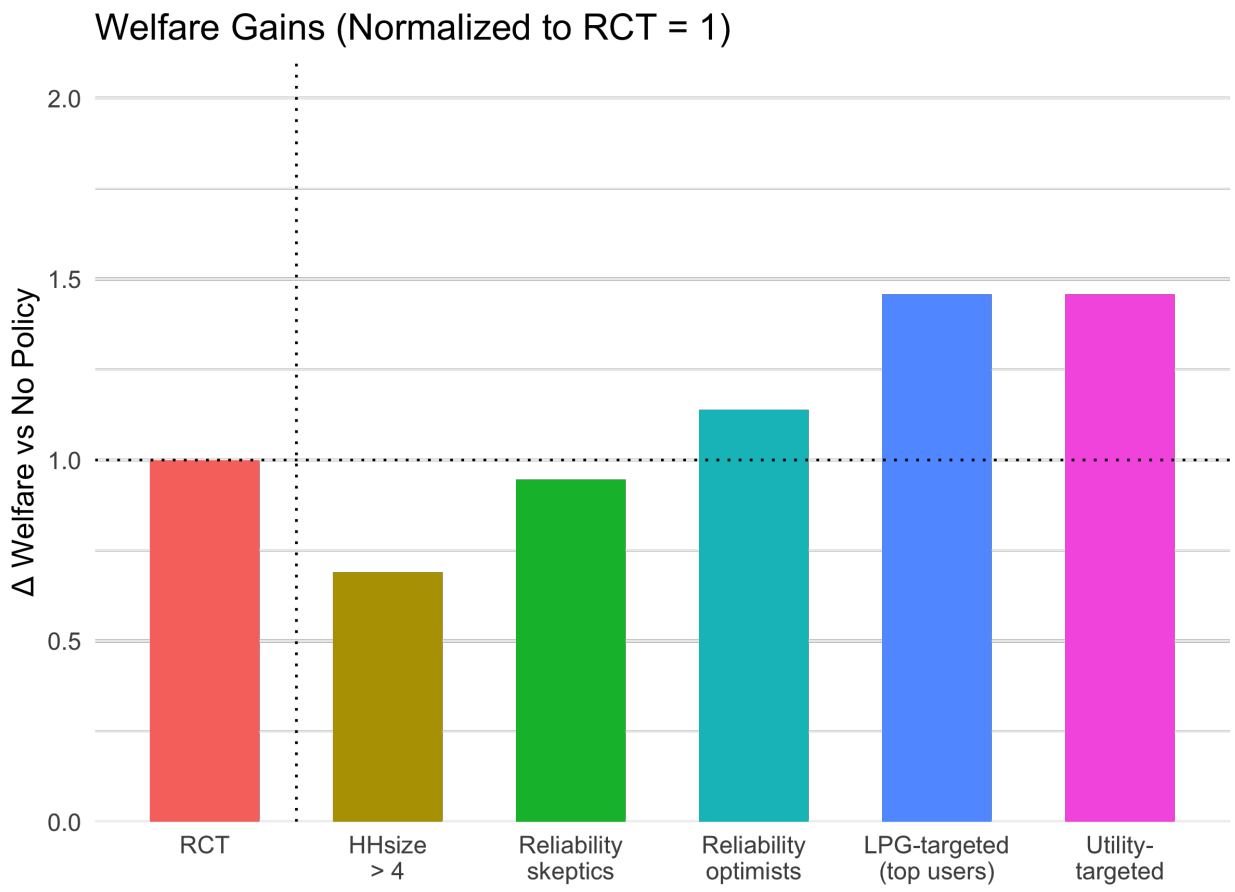
Notes: Figures validate the structural model calibration. Panel (a) shows that the model's predicted adoption curve (red line) tracks observed household adoption (blue points) across subsidy levels. Panel (b) compares predicted and observed adoption across randomized treatment arms in the RCT. The close alignment indicates that the model reproduces key experimental patterns, supporting its use for counterfactual policy simulations.

Figure 9: Optimal subsidies in response to macro indicators



Notes: The heatmaps plot the optimal subsidy level (s^*) as a function of two macro parameters: the grid penalty δ (higher values reflect higher costs of electricity production and provision, such as reliability constraints), and the LPG penalty λ (reflecting the social costs of LPG dependence, including import reliance and adverse health effects). The parameter ψ captures the deadweight loss from raising fiscal resources to fund subsidies. Darker shading indicates higher optimal subsidies. The figure shows how the socially optimal subsidy varies as these parameters change.

Figure 10: Welfare effects of targeting counterfactuals



Notes: Bars show relative welfare under alternative targeting strategies, normalized to the RCT welfare gains over baseline (no policy). Targeting rules include household size ($HHsize > 4$), reliability perceptions, LPG use, and utility-based targeting. Several strategies including targeting reliability optimists, high LPG users, or households ranked by expected utility, yield higher welfare than the RCT, holding the subsidy budget constant to the RCT level.

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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

A Additional Details on Structural Model

This appendix provides additional derivations and assumptions underlying the structural model presented in Section 2 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:

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

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:

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

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

A.3 Social Planner's Problem

The social planner chooses subsidy levels s_{Eg} and information treatments I^c_{Eg}, I^h_{Eg} 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:

$$\max_{s_{Eg}, I^c_{Eg}, I^h_{Eg}} \quad \sum_i U_{ig} - \delta KWh_{Eg} - \lambda(1 - \pi_{Eg}) - (s_{Eg} + \psi s^2_{Eg}), \tag{14}$$

where:

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

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

$$KWh_{Eg} = K^0_g + \pi_{Eg}\alpha T^*_{Eg} + \pi_{Eg}(H_g - 1)K^0_g, \tag{15}$$

where K^0_g 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:

$$\max_{s_{Eg}, I^c_{Eg}, I^h_{Eg}} \quad \underbrace{\bar{\eta}\left[\left(P_{Eg}^{\frac{-\eta}{1-\eta}} S_{Eg}\right)^{\theta} + 1\right]^{1/\theta}}_{\text{(i) Household option value}} \tag{16}$$

$$- \quad \underbrace{\delta\, KWh_{Eg}}_{\text{(ii) Capacity-constrained supply cost}} \tag{17}$$

$$- \quad \underbrace{\lambda(1-\pi_{Eg})\bar{\eta}}_{\text{(iii) LPG dependence}} \tag{18}$$

$$- \underbrace{\left(s_{Eg} + \psi s_{Eg}^2\right)}_{\text{(iv) Subsidy cost}}. \tag{19}$$

First-order condition with respect to s_{Eg}. Differentiating the planner's objective with respect to s_{Eg} gives:

$$\frac{\partial W}{\partial s_{Eg}} = \frac{\partial \pi_{Eg}}{\partial s_{Eg}}\left[\bar{\eta} P_{Eg}^{\frac{-\eta}{1-\eta}} - \delta\left(\alpha T^*_{Eg} + (H_g - 1)K_g^0\right) + \lambda\bar{\eta}\right] - (1 + 2\psi s_{Eg}). \tag{20}$$

This condition makes clear that the optimal subsidy balances three forces: (i) the welfare gain from increasing adoption, (ii) the marginal social cost of additional electricity consumption under capacity constraints, and (iii) 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

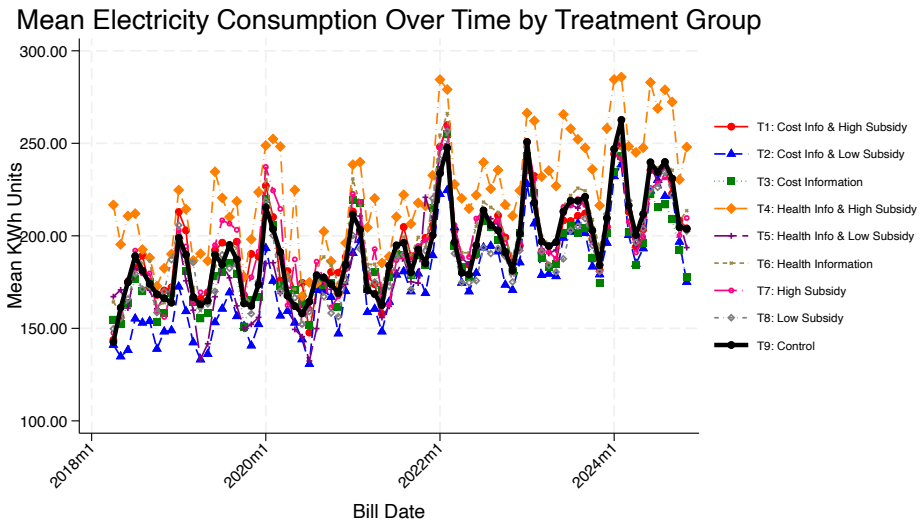


Table B6: Variables Used in Causal Forest Analysis

Variable	Description
Household Size	Number of household members
Household Head Age	Age of household head
Higher Education	indicator variable: 1 if household head has high education (bachelor or above)
Home Owner	indicator variable: 1 if household owns home, 0 if rents/other
Banking Online	indicator variable: 1 if household uses online banking services
Formal Loans Access	indicator variable: 1 if household has access to formal loans
Appliance Damage	1 if any electronic appliance/s damaged by voltage fluctuation in past 12 months
Unplanned Outages Problem	indicator variable: 1 if unplanned outages are most serious electricity problem
Voltage Fluctuation Problem	indicator variable: 1 if voltage fluctuation is most serious electricity problem
Reduced Non-Essential Spending	indicator variable: 1 if reduced expenditure on non-essential items
Daily Cooking Time	Time spent cooking daily (minutes)
Missing Cooking Time	indicator variable: 1 if cooking time data is missing
Willing to Switch to E-Stove	indicator variable: 1 if willing to switch to electric stove
Microwave Replaces LPG	indicator variable: 1 if uses microwave to replace LPG
Electricity Bill More Expensive	indicator variable: 1 if electricity bill became more expensive (last 12 months)
Electricity Bill Cheaper	indicator variable: 1 if electricity bill became cheaper (last 12 months)
Electricity Obstruction Better	indicator variable: 1 if electricity obstruction improved (last 12 months)
Electricity Obstruction Worse	indicator variable: 1 if electricity obstruction worsened (last 12 months)
Worry About Reliability	indicator variable: 1 if agrees electricity reliability is concerning
WTP More for Reliability	indicator variable: 1 if willing to pay more for reliable electricity
Electricity Burden on Family	indicator variable: 1 if agrees electricity costs burden family
Operates Business	indicator variable: 1 if household operates a business
LPG Consumption (kg)	Monthly LPG consumption in kilograms
Elec. Consumption (KWh)	Billed electricity at December 2023.
Electric Stove at Baseline	indicator variable: 1 if owned electric stove at baseline

Notes: All variables are used as covariates in the causal forest estimation to predict heterogeneous treatment effects. Indicator variables are coded as 1 for "yes" and 0 for "no." Missing values for continuous variables are replaced with 0 and flagged with separate missing indicator variables.

Table B7: 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 B8: 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
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

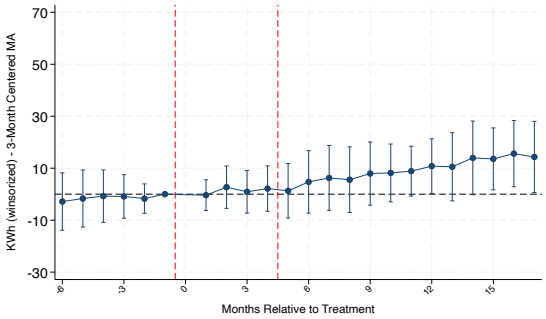
Notes: This table presents the DiD intensive margin analysis for the control group, examining the effects of treatment intensity on cooking behavior and appliance usage. The regressions measure outcomes related to time spent cooking, the use of electric and LPG stoves, LPG usage (in kilograms), and the 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 B9: Spillovers: Effects of transformer treatment intensity and household treatment status

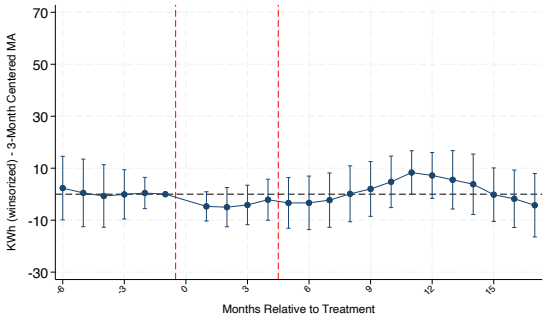
	(1) Adoption (v2)	(2) Bought Ind. Compatible Cookware (v2)	(3) Induction Stove (v2)
control_PropTG_mid	-0.0801	-0.0739	-0.0493
	(0.141)	(0.133)	(0.284)
control_PropTG_high	-0.105	-0.0633	-0.0472
	(0.051)	(0.191)	(0.297)
subsidy_high_PropTG_low	0.385***	0.340***	0.132
	(0.000)	(0.000)	(0.106)
subsidy_high_PropTG_mid	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.

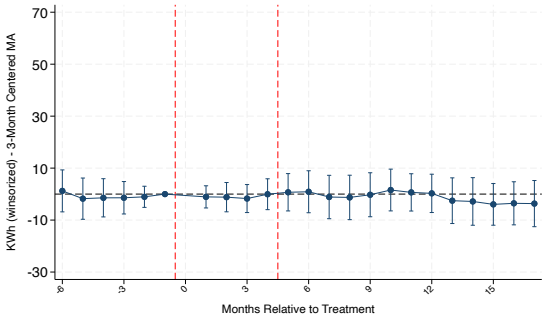
Figure B2: Event Study Estimates on Electricity Consumption



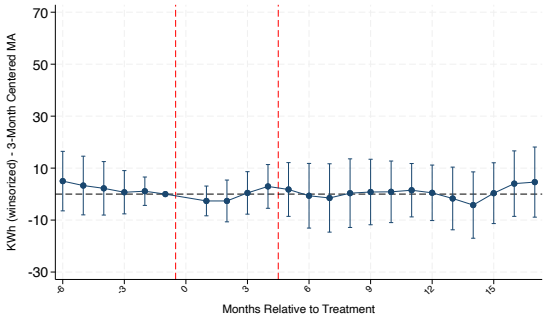
(a) Cost Information & High Subsidy



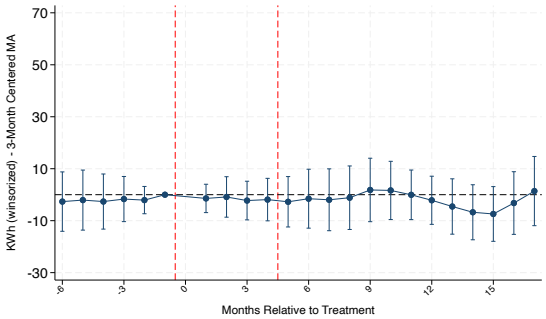
(b) Cost Information & Low Subsidy



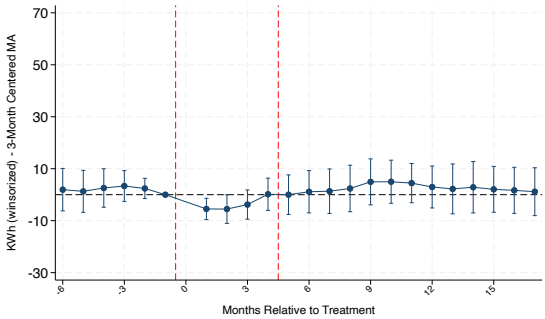
(c) Cost Information Only



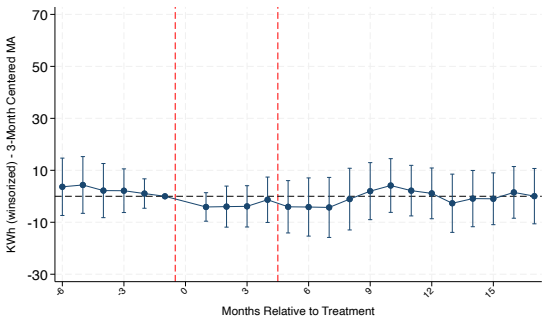
(d) Health Information & High Subsidy



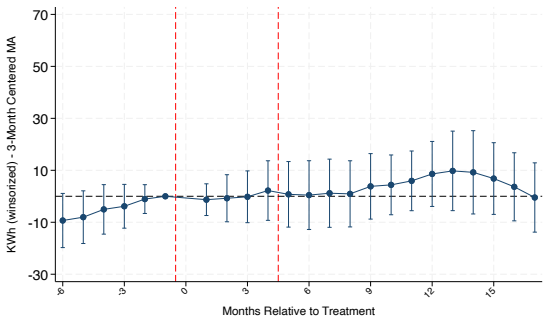
(e) Health Information & Low Subsidy



(f) Health Information Only



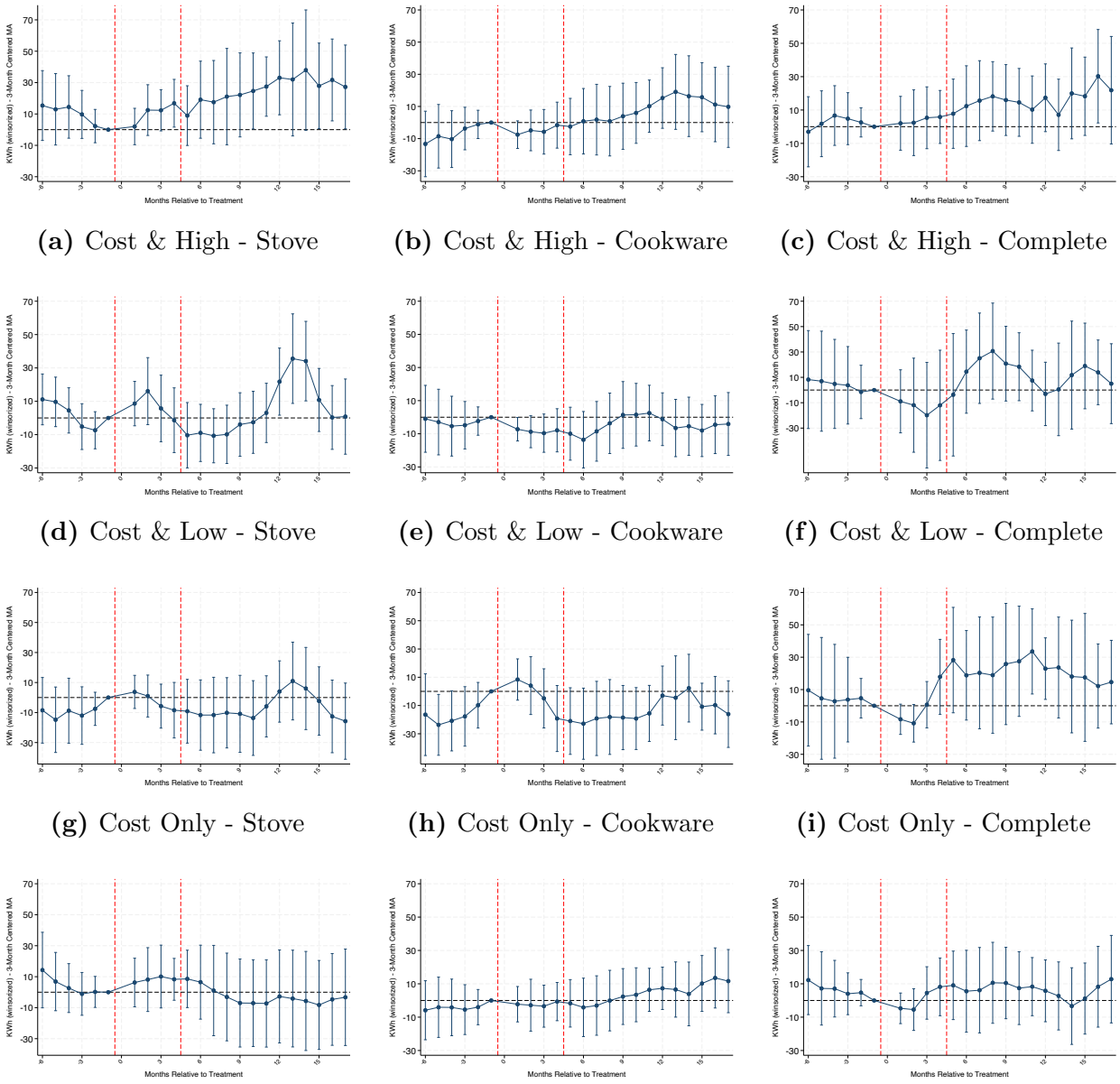
(g) High Subsidy Only



(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 (12). 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

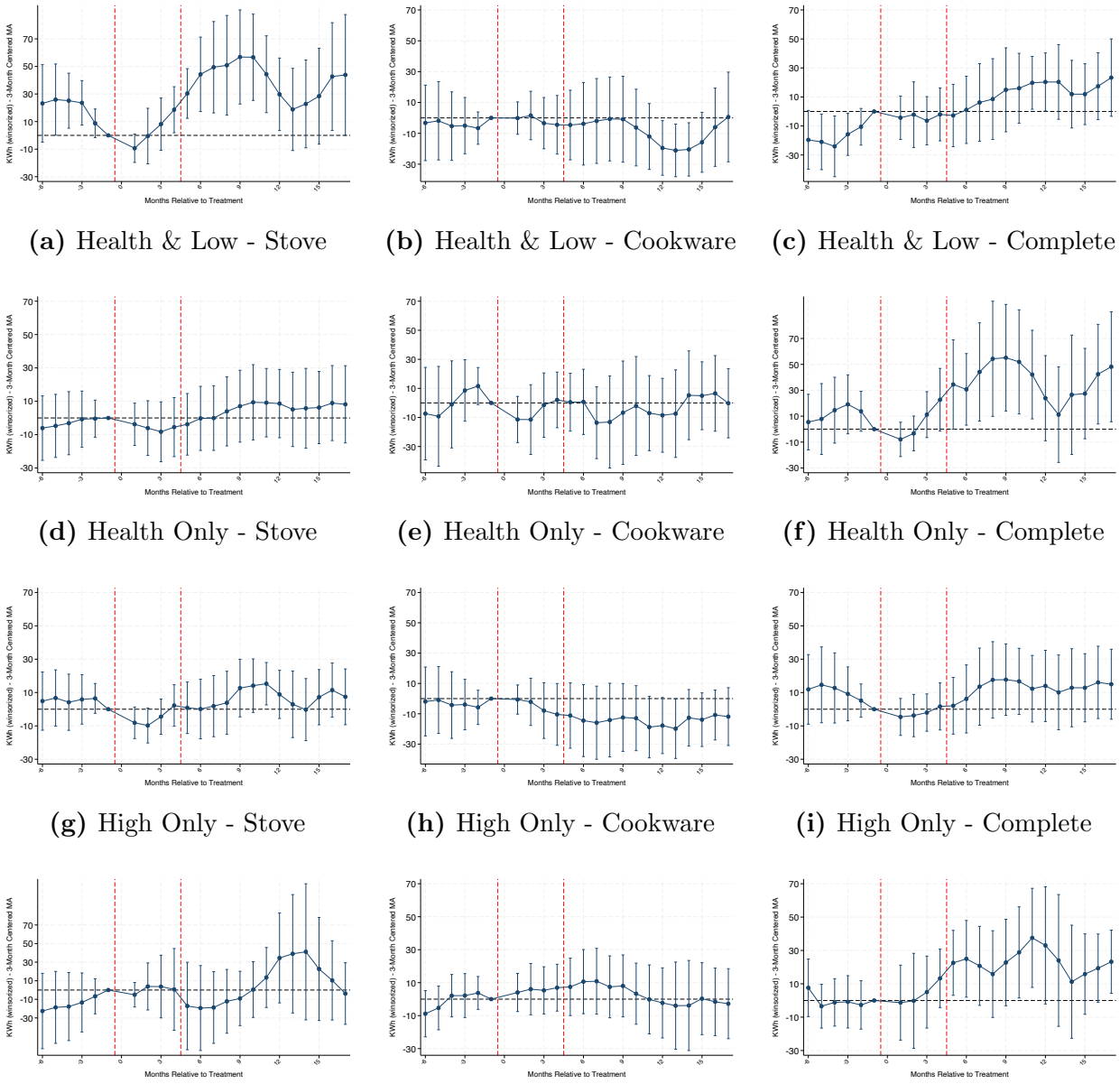
(d) Cost & Low - Stove **(e)** Cost & Low - Cookware **(f)** Cost & Low - Complete

(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 (12). 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

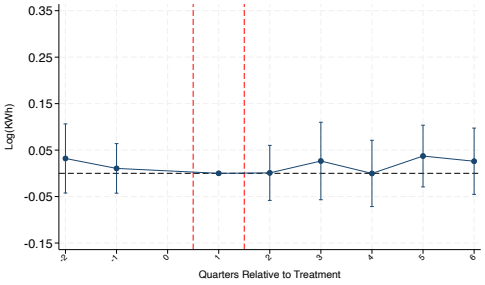
(d) Health Only - Stove **(e)** Health Only - Cookware **(f)** Health Only - Complete

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

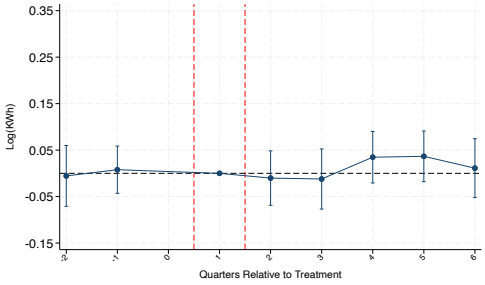
(j) Low Only - Stove **(k)** Low Only - Cookware **(l)** Low Only - Complete

Notes: This figures plots event study estimates of the effect of treatment on electricity consumption (three-month centered moving average), based on Equation (12). 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.

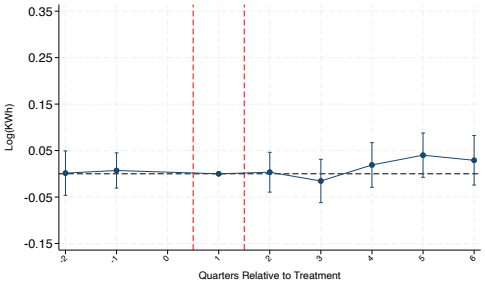
Figure B5: Quarterly Event Study Estimates of Treatment Effects on Log Electricity Consumption



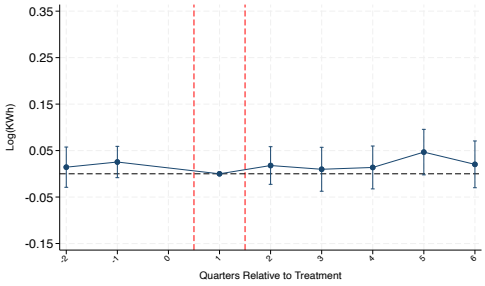
(a) High Subsidy Only



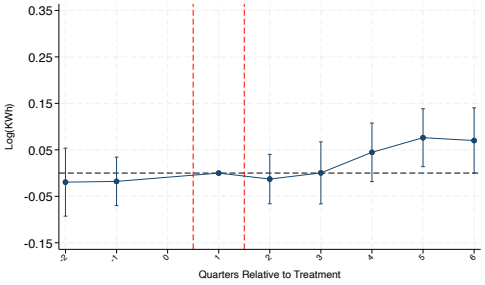
(b) Low Subsidy Only



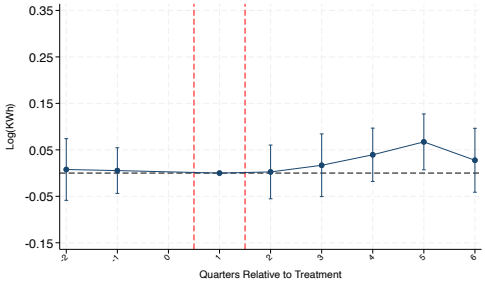
(c) Cost Information Only



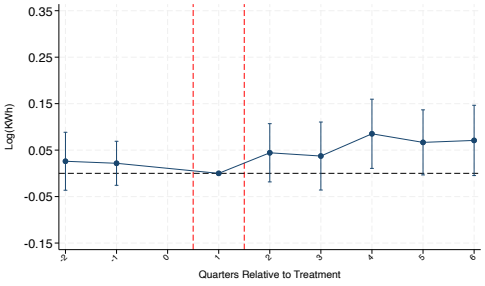
(d) Health Information Only



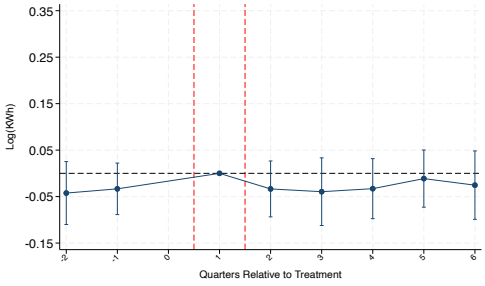
(e) Cost Info & High Subsidy



(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 (12). 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

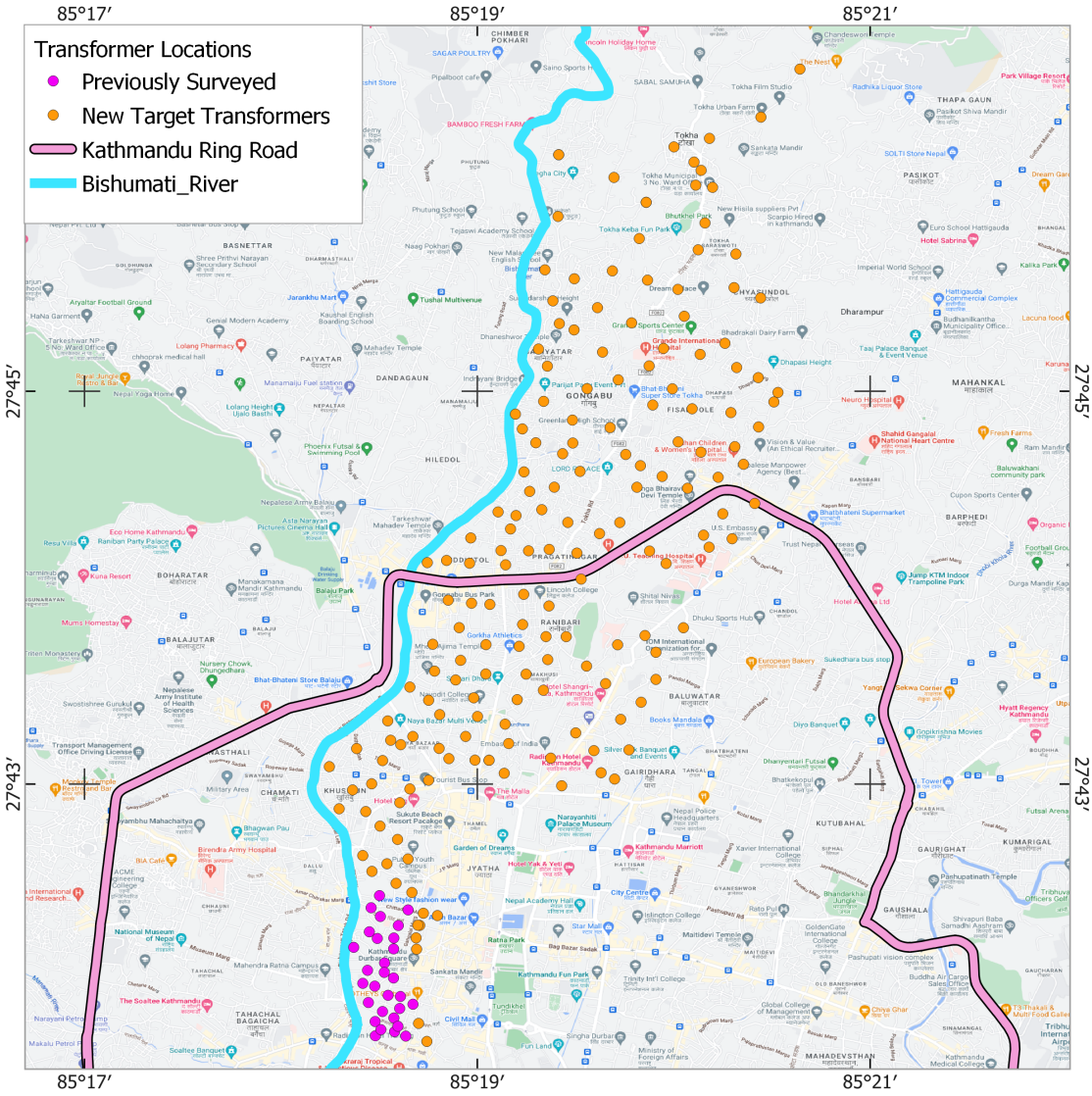


Figure C1: Map of Transformers Used in the Sampling Strategy

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

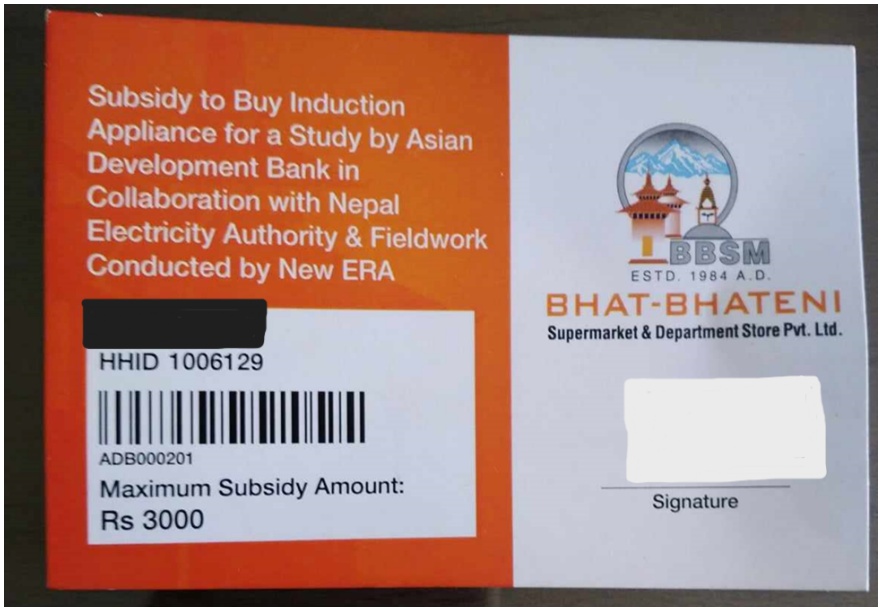


Figure D3: Example of Subsidy Card Provided

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.

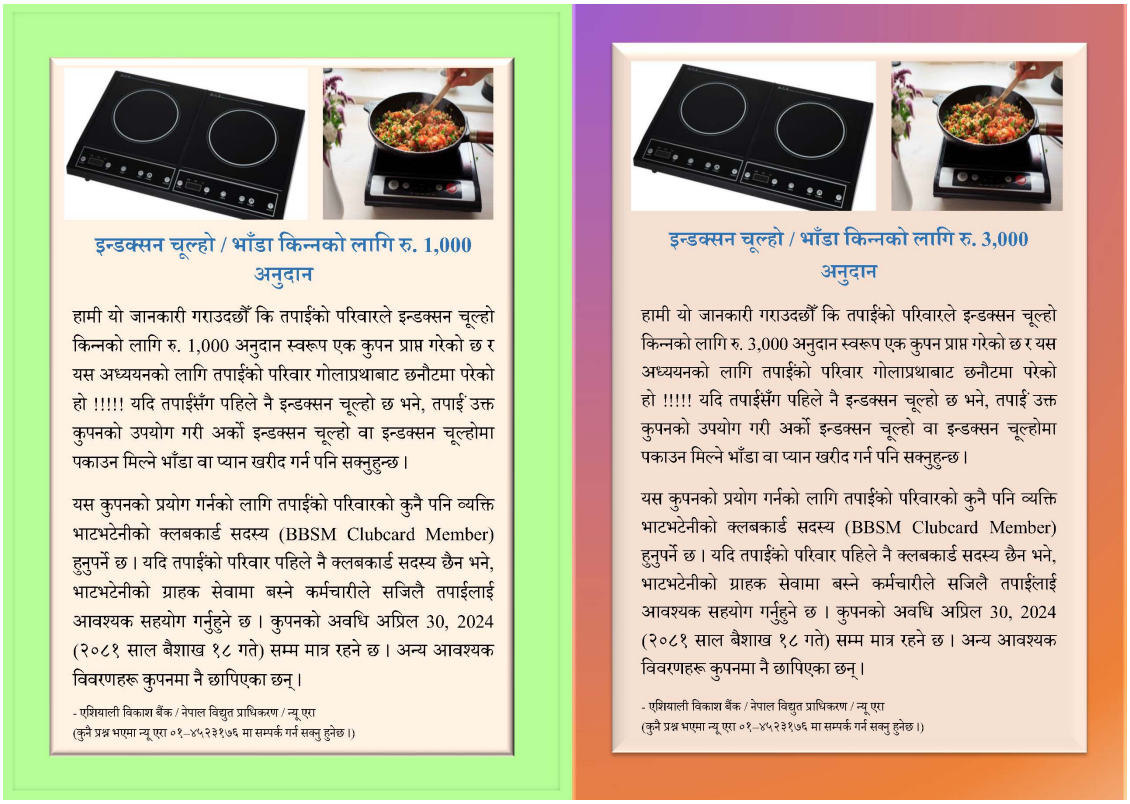


Figure D4: Messages Regarding Subsidies

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.

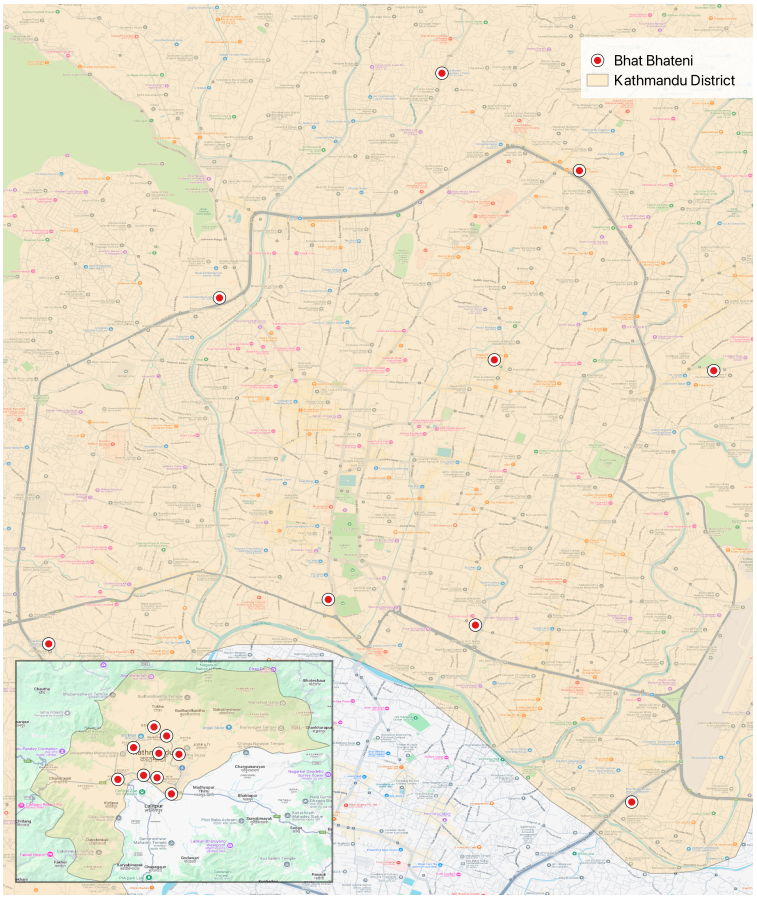


Figure D5: Locations of Bhat Bhateni stores in Kathmandu

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[16] and 3.6 MJ/kWh for electricity. According to Nepal Gas, a big cylinder contains 14.2 kg of LPG[17], which means a cylinder holds 724.2 MJ of heat energy in it. Using an efficiency of 90%[18] for Induction Heat stoves and a conservative estimate of 55%[19] 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

[16] 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.

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

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

[19] 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/.