On the Back Burner: Experimental Evidence For Energy Transitions *

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September 9, 2025

Abstract

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A central challenge in the global transition to cleaner energy is how governments can design policies that deliver large social benefits while facing trade-offs in national energy security, fiscal costs, and household adoption frictions. We study this challenge in urban Nepal, where cooking is still dominated by imported LPG, but abundant hydropower makes both large-scale electrification and improving the country's energy security feasible. We embed household adoption decisions within a generalizable structural model of a planner that balances fiscal, fuel supply, and security considerations, and causally estimate its key parameters using a randomized controlled trial conducted in the Kathmandu Valley. Subsidies had large effects, raising electric stove adoption by 23 percentage points and cookware purchases by 41 percentage points. In contrast, the two information treatments, which provided information that electric cooking is either cheaper or healthier than LPG, alone had little impact. Using rich survey and administrative electricity billing data, we find substitution away from LPG toward electricity, though with meaningful heterogeneity across households. Disciplined by these experimental estimates, the model evaluates counterfactual targeting rules and identifies the conditions under which governments can design optimal subsidies to generate welfare gains in broader energy transition contexts.

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

Keywords: Electrification, Energy transition, Technology adoption, Policy design, Development, Climate change, Energy security

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

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1 Introduction

Access to clean and reliable energy underpins economic development, health, and climate mitigation. Yet, even though some of the most cost-effective opportunities for climate mitigation lie in low- and middle-income countries Glennerster and Jayachandran (2023), households in many developing countries still cook with fossil fuels. With increasingly cleaner electricity generation in many countries, electric cooking offers substantial CO_2 emission reductions, while also addressing growing energy security concerns. In today's geopolitical climate, marked by wars, sanctions, tariffs, and volatile prices, countries face pressure to reduce dependence on imported fossil fuels (Reuters, 2025; The New York Times, 2025). Policies that encourage households to shift from imported LPG to domestic electricity can therefore deliver multiple benefits from reducing carbon emissions to stabilizing public finances. However, households face adoption frictions such as liquidity constraints, misperceptions about costs, and inertia in preferences, which limit their willingness to increase electricity use and reduce LPG. Additionally, energy is typically provided or regulated by the state, so fuel choice has implications for imports, generation, and fiscal spending, creating additional constraints for planners. Therefore, managing such a transition requires government policy that considers both individual choices as well as system-wide welfare.

Nepal provides a suitable setting to study these competing priorities. With abundant clean hydropower, electricity is, in principle, cheaper and more secure than imported LPG. The government is actively promoting electric cooking, given past LPG supply shocks (Acharya and Adhikari, 2021; Giri, 2015). Yet, adoption remains puzzlingly low despite favorable incentives, policy pushes, and a sharp improvement in supply reliability (Acharya et al., 2024; Spotlight Nepal, 2023). This gap motivates our central question: what frictions limit household adoption of a seemingly beneficial technology, and how should policymakers design optimal subsidies when the welfare gains depend as much on planner trade-offs as on household behavior?

We answer this question by demonstrating that to design optimal policies, it is essential to embed these household frictions within the planner's problem. We focus on a crucial energy transition: a shift from LPG to electricity. Governments want to expand clean energy use, but face difficult trade-offs: increasing electricity demand without overloading fragile electric grids, incentivizing adoption of e-technologies without ballooning fiscal costs, and managing the opportunity costs of scarce public resources while efficiently targeting incentives to the most responsive households. At the same time, when encouraging changes to households' cooking technologies, adoption frictions such as liquidity constraints (Berkouwer and Dean, 2022; Gertler et al., 2016), misperceptions about running costs (Mobarak et al., 2012), and heterogeneity in preferences (Hanna et al., 2016) are often present. We develop a structural framework that embeds household decisions within these planner-side constraints, allowing us to recover the behavioral parameters governing adoption, and evaluate what subsidy policies maximize aggregate welfare. In doing so, we treat technology adoption not only as a household choice, but as a planner's problem.

Guided by our model framework, we implement a large randomized controlled trial (RCT) in Kathmandu Valley with 3,521 LPG-using households. The 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 one of nine groups: (i) a high subsidy (NPR 3,000, about USD 22.5), (ii) a low subsidy (NPR 1,000, approximately 7.5 USD), (iii) cost information, (iv) health information, (v–vi) high subsidy with cost or health information, (vii–viii) low subsidy with cost or health information, or (ix) a pure control. The information treatments provided either (a) information on how cooking with electricity may be cheaper than cooking with LPG for most, or (b) information on the health benefits of induction cooking, highlighting reductions in indoor air pollution and associated risks. The cost information treatment is designed to address misperceptions about the relative cost of LPG versus electricity.[1] The subsidy

[1]By correcting misperceptions about operating costs, the cost information treatment should boost adoption, especially among price-sensitive households who may underestimate the savings from switching (Allcott and Taubinsky, 2015; Bensch and Peters,

treatments were deliberately designed to be readily implementable by a social planner, while substantially mitigating household liquidity constraints. To demonstrate an approach realistically scalable country-wide, the subsidies were provided via vouchers redeemable at the country's largest retail chain store.[2]

This 9-cell design allows us to separately identify the effects of subsidies and information, as well as their combined effects. Beyond causal impacts, the experimental variation provides estimates to recover the structural parameters needed for policy evaluation. In particular, the randomized subsidies serve as instruments for induction stove adoption, enabling us to measure how adoption causally affects outcomes, such as LPG use and electricity use. Moreover, by observing adoption rates at different subsidy levels, we infer households' valuation of the new technology, which feeds into the estimation of preference and misperception parameters in our model. Yet, in addition to the average response, a planner targeting subsidies also cares about what types of households are most responsive. We unpack this heterogeneity in a systematic manner, to help design an optimal subsidy structure.

The randomized experiment yields three main results. First, subsidies had large effects on adoption, while information alone did not. Households offered the high subsidy were 23 percentage points more likely to acquire an induction cookstove than those in the control group. Even a modest subsidy of NRP 1,000 raised adoption by 10 percentage points. By contrast, neither the cost- nor health-information interventions shifted adoption rates when not coupled with a subsidy: information raised knowledge but did not change behavior, suggesting that price was the binding constraint. To interpret these findings and connect them to policy design, we embed the experimental estimates into a structural model, which yields key behavioral parameters: a concave response to subsidies ($\rho \approx 0.45$), a modest perceived

2015). The health information treatment emphasizes indoor air pollution risks from LPG (Daouda et al., 2024; Lebel et al., 2022), appealing to non-monetary motives. Yet, because health benefits are typically delayed, we expect its effect to be weaker than cost information, as credit and budget constraints typically dominate adoption decisions (Dupas, 2011).

[2]The low and high subsidies cover meaningful proportions of electric cooking's upfront costs, an investment that requires households to purchase both an electric induction stove (30 - 45 USD for a one-burner stove and double that for a two-burner stove) and induction-appropriate cookware (E.g., a frying pan costs 10 USD and a wok or pressure cooker is approximately 22 USD).

price elasticity ($\eta \approx -0.19$), and a dampening interaction between subsidies and high perceived electricity prices ($\gamma_p \approx -0.10$). These magnitudes—comparable to but distinct from estimates in credit markets (Karlan and Zinman, 2010), health technologies (Ashraf et al., 2010), fertilizer adoption (Duflo et al., 2011), and energy demand in LMICs (Wolfram et al., 2012)—show that small subsidies generate large responses, but adoption is concave with diminishing marginal benefits at higher subsidy levels. They also confirm that price signals are weak and that information must be accompanied by subsidies.

Second, leveraging the randomized subsidies as instruments, and using surveys conducted before and after the experiment, we estimate how induction stove adoption affects household fuel consumption. Adopting an induction stove led to substitution toward electricity, with households cooking 27 percentage points more of their meals on induction, and reducing the share of meals cooked with LPG by 14 percentage points. We find consistent patterns with other outcomes as well: households that adopted reported a significant increase in electricity cooking time of close to an hour, while there was a 30 minute drop in cooking time with LPG. Therefore, induction stoves appear to have displaced a meaningful share of gas use rather than sitting idle, though most households continued to "fuel stack" (using LPG for some meals), a common pattern in fuel transitions (Guta et al., 2022; Masera et al., 2000; Shankar et al., 2020), and one that reflects the persistence of cooking preferences or the need for backup.[3]

Third, we study how adoption affects electricity demand and grid load. A common concern is that widespread electrification will strain fragile networks, but our results show a more nuanced picture. Using detailed billing records from the Nepal Electricity Authority, we find that adoption raises billed use by 3–10 kWh per month (2–5 percent of baseline) on average, but with striking heterogeneity. Some households—especially those already owning stoves and purchasing only compatible cookware—show modest increases or even declines, while others display larger gains. These patterns highlight the importance of household heterogene-

[3]Some households reported using LPG for certain dishes, while others cited electricity outages as concerns.

ity in shaping aggregate load and suggest both efficiency gains and possible outage-induced reductions as mechanisms. Importantly, self-reported time-use data show no evidence that households reduced use of other appliances; overall, reported electricity use rose.

Finally, we use the estimated model to study counterfactual subsidy design under alternative macro conditions—varying grid reliability, fiscal costs, and the costs of LPG cooking, such as import volatility and indoor air pollution. In an "efficiency case," where the grid absorbs added load, LPG costs and subsidy expenditures remain substantial. In an "outage case," where added load risks interruptions, optimal subsidies shrink as grid penalties rise. To capture heterogeneity, 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. These results show how combining causal experimental evidence, structural modeling, and heterogeneity-aware targeting can guide welfare-improving subsidy design.

This paper makes three main contributions. First, we combine household adoption incentives and planner-side constraints to guide the design of optimal policies for energy transitions. While much of the prior economics literature has focused on evaluating policies in isolation, our framework situates such interventions within a planner's multiple – and at times competing – concerns over climate mitigation and energy security. Crucially, the framework helps policymakers assess not only how to design interventions, but also whether they are desirable in the first place, moving beyond the question of whether a specific experimental setup generates adoption to simulating optimal policy design under varying grid capacity, fiscal limits, and LPG dependence. In doing so, we contribute to a growing literature that

embeds RCT evidence in structural models to interpret and extrapolate experimental results (Burgess et al., 2023; Guiteras et al., 2025; Oliva et al., 2020). We also contribute broadly to work on social protection (Hanna and Olken, eds, 2026), which can come in the form of energy subsidies as redistributive tools (Abubakari et al., 2024; Burlig and Sudarshan, Forthcoming) and instruments of the energy transition (McRae and Wolak, 2024).

Second, our framework is broadly generalizable. We estimate it in Nepal—a natural laboratory given hydropower abundance and LPG dependence—but the structural parameters and simulated trade-offs are relevant wherever governments aim to cut fossil fuel use, manage import volatility, or respond to supply shocks. Leveraging experimental variation, we causally identify key behavioral parameters and, by exploiting household-level heterogeneity, reveal who responds most to incentives—yielding externally valid insights, while flagging context-specific pitfalls. The literature finds that at least in the context of the adoption of energy-related technologies, while households often respond to subsidies (Meriggi et al., 2021), heterogeneity in preferences and characteristics may lead to inefficient outcomes (Muehlegger and Rapson, 2022). Our framework provides a disciplined way of addressing these past concerns, embedding causal response estimates and heterogeneity in a simple structural framework, and generating counterfactual policy targeting rules under different fiscal, grid, or import-dependence conditions. Further, by studying the shift from a relatively modern but imported fuel (LPG) to a cleaner, renewable domestic source (hydropower), we speak to a challenge faced not only in low- and middle-income countries but also in high-income countries (Borenstein, 2023). Our findings, therefore, extend beyond technology adoption to resilience and trade risks from fossil fuel dependence (Cheng et al., 2025).

Third, this paper adds to the literature on residential end-use electrification. Global strategies emphasize that electric cooking lowers CO_2 emissions (International Energy Agency, 2025), reduces indoor air pollution, and builds resilience to LPG import shocks (Gould et al., 2023; Guta et al., 2022). Yet even though LMICs are expected to provide "many of

the most cost-effective opportunities for mitigation" (Glennerster and Jayachandran, 2023) and electrification is a popular strategy for reducing CO_2 emissions, there is relatively little causal evidence on end-use electrification in LMICs.[4] Progress requires clean generation, yet even in LMICs with reliable power, grids face barriers such as contract risk (Ryan, 2022), transmission limits (Gonzales et al., 2023), and infrastructure lock-in (Wang, 2023). Given evidence of demand to shift from biomass to clean fuels (Abubakari et al., 2024; Bensch et al., 2015; Guta et al., 2022; Pattanayak et al., 2019) and the benefits of moving from LPG to electric cooking (Gould et al., 2024, 2023), this paper informs policy tradeoffs in clean energy transitions.

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: cost barriers, misperceptions about relative costs, heterogeneity in preferences, and potential spillovers. At the same time, it incorporates the constraints faced by a social planner who must weigh fiscal costs, grid reliability, and dependence on imported LPG. By combining these elements, the model formalizes the central problem we emphasize: technology adoption in this setting is not just a household choice but a planner's

[4]By contrast, HICs have extensive evidence, especially on electric vehicles (see, e.g., Bailey et al., 2025; Bushnell et al., 2022; Rapson and Muehlegger, 2023; Rapson and Bushnell, 2024).

problem, where welfare gains depend on both individual behavior and system-wide trade-offs.

The model generates clean empirically estimatable equations that allow us to directly model structural parameters to reduced-form coefficients. Although we calibrate the model to Nepal, the structure is intentionally simple and portable, to ease wider applicability. The household demand side can be estimated wherever (as-if) random variation in adoption incentives is available, while the planner's constraints, captured by three shadow values for fiscal resources, grid stress, and LPG dependence, can be reparameterized to reflect other country contexts. In this way, the framework provides a general tool for identifying the optimal design 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):

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

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

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 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 Kor-

tum, 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:

$$\log \frac{\pi_{Eg}}{1-\pi_{Eg}} = -\frac{\eta\theta}{1-\eta} \log P_{Eg} + \theta\, s_{Eg}^{\rho} + \theta\gamma_P \left(s_{Eg} P_{Eg}\right) + \theta\gamma_X \left(s_{Eg} X_g\right) + \theta\gamma_A \left(s_{Eg} A_{-i,g}\right). \quad (2)$$

Equation (2) 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 Social planner

A planner maximizes total household utility but faces real-world tradeoffs. Adoption raises electricity demand, which may strain the grid, and subsidies are fiscally costly. At the same time, reducing LPG dependence yields health and energy security benefits. The planner chooses to target price/health information and subsidies to various groups g, while maximizing aggregate household utility:

$$\max_{P_{Eg},\, s_g} \quad \sum_i U_{ig} - \delta\, \tilde{T}_E - \lambda\, \tilde{T}_L - (1+\psi)\tilde{s},$$

where δ is the marginal cost of grid stress, which reflects import costs or outage risks (Alberini et al., 2022); λ is the penalty from continued LPG use, capturing both health externalities (household air pollution, Lebel et al., 2022) and geopolitical import risk (Cheng et al., 2025; Farsight Nepal, 2023); ψ is the marginal cost of public funds, reflecting fiscal inefficiency (Dahlby, 2008; International Monetary Fund, 2015).

The objective is therefore not simply to maximize adoption, but to balance household welfare against these system-level costs and risks. These three "shadow values" extend the model's generalizability: by adjusting δ, λ, ψ, policymakers can re-calibrate the planner's tradeoffs for different country contexts (e.g. high import dependence, fragile grids, or efficient tax systems), making the framework portable beyond Nepal.

$$\max_{P_{Eg},s_g} \quad \underbrace{\bar{\eta}\left(\left(P_{Eg}^{\frac{-\eta}{1-\eta}} S_{Eg}\right)^{\theta} + 1\right)^{\frac{1}{\theta}}}_{\text{(i) Household option value}} - \underbrace{\delta\, \mathcal{G}\big(\pi_{Eg}, P_{Eg}, s_g, T^*_{Eg}\big)}_{\text{(ii) Grid cost}} \tag{3}$$

$$- \underbrace{\lambda(1-\pi_{Eg})\bar{\eta}}_{\text{(iii) LPG dependence}} - \underbrace{\big(s_g + \psi\, s_g^2\big)}_{\text{(iv) Subsidy cost}}$$

(i) Household option value. This term reflects the indirect utility households gain from being able to choose between LPG and electricity. The CES aggregator captures the fact that adoption gives households an outside option, with η governing demand elasticity and θ shaping how responsive adoption is to subsidies and information.

(ii) Grid cost.

Adoption raises electricity use. The expected grid load is

$$\pi_{Eg}\, \phi(P_{Eg}, s_g)\, T^*_{Eg},$$

the share of adopters (π_{Eg}) multiplied by their optimal cooking time (T^*_{Eg}) and a conversion or efficiency factor $\phi(\cdot)$. This load is valued at δ, the marginal cost of strain on the grid (e.g. higher generation costs or reliability risks). We consider two ways in which this load may evolve:

$$\mathcal{G}(\pi_{Eg}, P_{Eg}, s_g, T^*_{Eg}) = \begin{cases} \pi_{Eg}\, \phi(P_{Eg}, s_g)\, T^*_{Eg} & \text{(Efficiency case)} \\ \left(\pi_{Eg}\, T^*_{Eg}\right)^2 & \text{(Overload case)} \end{cases} \tag{4}$$

In the **efficiency case**, switching from LPG to induction stoves improves the efficiency of energy use. The factor $\phi(\cdot)$ captures this dampening effect: if induction stoves convert electricity to cooking services more efficiently than LPG, then the increase in load per adopter is smaller than one-for-one with adoption.

In the **overload case**, by contrast, electricity use rises more directly with adoption and grid stress increases convexly. Here the $\phi(\cdot)$ factor does not offset demand, and the grid cost term grows rapidly with the number of adopters, reflecting the possibility that concentrated increases in electric cooking push networks beyond capacity.

(iii) LPG dependence. Each non-adopter $(1 - \pi_{Eg})$ continues to rely on LPG. This carries a penalty λ, which captures both local health costs from indoor air pollution and macroeconomic risks of imported fuel dependence.

(iv) Subsidy cost. We model fiscal costs as having both a linear and a convex component: $s_g + \psi s_g^2$. The linear term captures the direct budgetary transfer to households, while the quadratic term captures the increasing marginal deadweight cost of public funds, administrative frictions, or political economy pressures as subsidies grow large. This formulation allows small subsidies to be relatively cheap, but penalizes very large subsidies more heavily.

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

3 Background

Nepal's energy landscape makes it a natural laboratory for studying cooking transitions. The 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). In response, the government reduced LPG subsidies, offered induction stove discounts, and expanded investments in hydropower, which now supplies nearly 99 percent of electricity with minimal carbon emissions (Bhandari and Subedi, 2023; IFC News, 2019; U.S. Agency for International Development, 2017). Expanded generation and new independent power producer contracts have also improved reliability (Ghising, 2022; Kathmandu Post, 2023; Open Data Nepal, 2022), making electricity increasingly viable for cooking (Timilsina and Steinbuks, 2021). Despite these favorable conditions, most urban households continue to rely primarily on LPG, reflecting persistent barriers such as upfront costs, price misperceptions, and cultural preferences (Daouda et al., 2024; Lebel et al., 2022; Saha et al., 2021).

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. In the sub-sections that follow we describe the sampling procedures employed, the experimental design, and the intervention details.

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

[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.

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, 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, a lower subsidy of 1,000 NPR, or no subsidy – that can be used to purchase electric cookstoves (or the pots/pans specific to electric induction stoves). 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

[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.

[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.

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 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

[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).

[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.

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 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.

[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 Data

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

5.1 Survey Data

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

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

From NEA, we have monthly data for the 3500 consumers in the 2023 survey starting in April 2018 and going through September 2024. These data can be matched to the utility billing data via the consumer id and serial number.

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.

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, first combining the two information treatments together as follows:

$$\begin{aligned} \mathrm{Y}_i = \alpha + \beta_1 \mathrm{HighSubsidy}_i + \beta_2 \mathrm{LowSubsidy}_i + \beta_3 \mathrm{Info}_i \\ + \beta_4(\mathrm{HighSubsidy}_i \times \mathrm{Info}_i) + \beta_5(\mathrm{LowSubsidy}_i \times \mathrm{Info}_i) + \epsilon_i \end{aligned} \tag{5}$$

The variable Y_i represents outcome variables of interest for household i, either at the extensive or intensive margins. Regarding the former, the variable may denote adoption of induction cookstoves or compatible cookware. On the intensive margin, it refers to usage of fuels – such as LPG or electricity, the proportion of meals cooked using each fuel, and other metrics related to fuel usage. $\mathrm{HighSubsidy}_i$ is an indicator variable equal to 1 if household i is randomly assigned to the high subsidy treatment group and 0 otherwise. Similarly, $\mathrm{LowSubsidy}_i$ is an indicator equal to 1 if household i is assigned to the low subsidy group and 0 otherwise. Info_i is an indicator variable equal to 1 if household i received any information treatment (either cost or health) and 0 otherwise. With these variables in the specification, the omitted group is comprised of the pure control households – those who were assigned to neither subsidies nor information treatments. The constant term is denoted by α, while β_1, β_2, and β_3 capture the effects of the high subsidy, low subsidy, and the combined information treatments, respectively.

The equation also includes two interaction terms to estimate the combined effect of treatments that overlap due to the cross randomization. The term $\mathrm{HighSubsidy}_i \times \mathrm{Info}_i$ represents the interaction of being in the high subsidy group and receiving any information treatment, while $\mathrm{LowSubsidy}_i \times \mathrm{Info}_i$ represents the interaction of being in both the low subsidy group and receiving any information treatment. As a result, β_4 and β_5 capture the

combined effects of high and low subsidies when interacted with the information treatment, respectively. Lastly, ϵ_i represents the error term for household i.

Additionally, we estimate an alternate specification in which the different information treatments – cost and health information – are estimated separated as follows:

$$\begin{aligned} \mathrm{Y}_i = \alpha &+ \beta_1 \mathrm{HighSubsidy}_i + \beta_2 \mathrm{LowSubsidy}_i + \beta_3 \mathrm{CostInfo}_i + \beta_4 \mathrm{HealthInfo}_i \\ &+ \beta_5(\mathrm{HighSubsidy}_i \times \mathrm{CostInfo}_i) + \beta_6(\mathrm{HighSubsidy}_i \times \mathrm{HealthInfo}_i) \\ &+ \beta_7(\mathrm{LowSubsidy}_i \times \mathrm{CostInfo}_i) + \beta_8(\mathrm{LowSubsidy}_i \times \mathrm{HealthInfo}_i) + \epsilon_i \end{aligned} \tag{6}$$

$\mathrm{HighSubsidy}_i$, $\mathrm{LowSubsidy}_i$, $\mathrm{CostInfo}_i$, and $\mathrm{HealthInfo}_i$ are indicator variables that take the value 1 if households were randomly assigned to those respective treatments, and 0 otherwise. The interaction terms depict households who received a combination of both a subsidy (high or low) and an information treatment (cost or health). The error term is denoted by ϵ_i.

6.2 Treatment on the Treated

Second, we estimate the effect of the intervention on those that received treatment using 2SLS. We examine the effect on appliance and fuel usage by instrumenting for the adoption of induction cookware or stoves using the subsidy treatment assignments as instruments. The subsidies were tied tightly to purchasing only an induction stove or induction compatible cookware, and could only have affected intensive margin consumption via the channel of adoption, satisfying the exclusion restriction. The second-stage regression, where adoption of induction cookware and induction stoves is instrumented using the subsidy treatment assignments, is specified as:

$$\mathrm{Y}_i = \alpha + \lambda \hat{\mathrm{Adoption}}_i + \gamma X_i + \epsilon_i \tag{7}$$

We instrument for adoption using only the assignment of households to either of the subsidy arms. In these specifications, Outcomes_i refers to appliance or fuel usage (e.g., electricity usage, LPG usage, cooking time). The variable $\hat{\text{Adoption}}_i$ is an indicator variable for whether a household adopted either an induction stove or induction-compatible cookware, instrumented by the treatment assignment. ϵ_i is the error term.

The first-stage regression for the adoption of induction cookware or induction stoves, instrumenting using the subsidy treatment arms is given by:

$$\text{Adoption}_i = \alpha + \beta_1 \text{HighSubsidy}_i + \beta_2 \text{LowSubsidy}_i + \epsilon_i \tag{8}$$

In this first-stage regression, Adoption_i is an indicator variable that is equal to 1 if the household adopted either an induction stove or induction-compatible cookware. HighSubsidy_i and LowSubsidy_i are indicator variables indicating whether a household received the high or low subsidy treatment, respectively. ϵ_i is the error term.

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%. Information treatments had negligible standalone effects, and their interaction 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 in the Nepal context.

Table B1 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 7 presents 2SLS estimates instrumenting adoption with subsidy treatment assignment. Adoption increased the share of meals cooked with induction stoves by 27 percentage points and raised the probability of using electricity for cooking by 43 percentage points. Consistent with this substitution, LPG consumption fell by 3 kilograms per month and the share of meals cooked with LPG declined by 15 percentage points. Cooking time also reallocated across fuels: electric cooking time rose by nearly 60 minutes per day, while LPG cooking time fell by about 30 minutes. The magnitudes are economically meaningful: they imply that households that adopted shifted a substantial portion of their daily cooking toward electricity, though LPG use was not eliminated. This is consistent with fuel-stacking patterns observed elsewhere.

Table 6 shows reduced-form estimates by treatment arm to understand the direct effect of treatments on various intensive margin variables. Both high and low subsidy groups increased their share of meals cooked with electricity by 7–9 percentage points, with daily electric cooking time rising by about 14–17 minutes. LPG consumption declined modestly

(0.7–0.8 kg per month), concentrated among subsidy recipients, while information treatments again show negligible effects. Taken together, these results indicate that subsidies translated into real changes in cooking behavior, though substitution was partial rather than complete.

7.2 Effects on billed electricity consumption

We examine household electricity billing records, which allow us to track actual consumption from detailed billing records shared with us from the Nepal Electricity Authority. Table 8 shows intent-to-treat estimates using a difference-in-differences design. Average effects are small but mask substantial heterogeneity. In the high-subsidy group, households show declines in electricity use in some specifications (–8 percent in log kWh, column 3), while the low-subsidy group shows modest increases (about 3 percent). Interactions with information treatments attenuate or reverse these patterns, producing positive and significant effects when cost or health information is layered onto subsidies.

To interpret magnitudes, Table 11 reports estimates in levels. High-subsidy households consumed 8–14 kWh less per month after treatment, while low-subsidy households consumed 7–17 kWh more, depending on specification. For context, average household monthly consumption in the sample was about 200 kWh, so these effects represent changes on the order of 4–8 percent. Importantly, the sign and size of the estimates vary by treatment arm, highlighting that aggregate adoption does not translate into uniform increases in demand. We investigate various reasons behind these mixed effects. We rule out adoption leading to substitution away from other electric appliances as Table 6 suggests increases in reported electricity for the high subsidy group (the group that sees the largest declines in billed consumption).

7.2.1 Heterogeneity by baseline ownership and adopter type

We explore heterogeneity in various sub-samples of our data in order to obtain suggestive evidence for the heterogeneity observed in the billed consumption results above. Part of this heterogeneity reflects baseline conditions. Table 8 shows that effects are concentrated among households that already owned an induction stove at baseline: for them, the high subsidy reduced billed electricity use significantly. One interpretation is that such households may have previously been using less efficient or smaller stoves and, upon receiving subsidies, shifted to more compatible cookware, thereby increasing efficiency and lowering measured electricity consumption. By contrast, households without a baseline stove show small and mostly positive effects.

Table 10 further decomposes treatment effects by adopter type. Complete adopters (who purchased both stove and cookware) and stove-only adopters show small or positive changes in electricity use. By contrast, households that primarily adopted cookware show negative impacts, with reductions in electricity consumption of 8 percent relative to controls. While we cannot causally identify the mechanism, the pattern is consistent with an efficiency story: cookware adopters may have previously used stoves inefficiently, and the subsidy enabled them to purchase compatible cookware that reduced wasted electricity. This explanation aligns with the model's framework, where adoption can raise welfare through efficiency improvements even if observed electricity consumption does not increase.

We take advantage of the flexibility afforded by our structural model to explore both explanations. The empirical results map onto the two versions of grid constraints in our structural model. In the efficiency case, subsidies increase welfare by facilitating adoption and improving the productivity of electricity use, consistent with the negative or muted effects on billed kWh among cookware adopters. In the outage case, higher adoption could, in principle, exacerbate grid stress. While it is unlikely that the sample size of our RCT was in any way responsible for grid outages, we cannot rule this out as a channel, particularly

at transformer or sub-station level (decentralized units of electricity supply that could, in principle, experience local level outages when overloaded.)

Our findings suggest that substitution toward electricity was meaningful but not uniform; in particular, high-subsidy adopters may not have driven large increases in consumption, mitigating potential overload. Instead, the more modest increases among low-subsidy households and heterogeneous effects across adopter types point to nuanced welfare consequences. This heterogeneity reinforces the importance of designing targeted policies that account for differences in baseline ownership and the form of adoption.

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 B9.

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

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

treatment effect variation. Figure 4 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 5 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 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 (2) 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 (6) shows the reduced-form specification that identifies the causal effect of randomized treatments on adoption outcomes, with estimates reported in Table 5. 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 heterogeneous responses. 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_g^{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. The perceived price elasticity η is identified from the effect of the information treatment, and the dampening parameter γ_P

from its interaction with subsidies.

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.

Estimating δ (Grid Penalty) We calibrate the grid penalty parameter δ to capture the marginal social cost of an additional kWh of electricity demand. 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

Model validation Figure 6 validates the calibration along two complementary dimensions. Panel 6b 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 6a 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 subsidies under different planner-side constraints. Figure 7 illustrates how the socially optimal subsidy s^* varies with

the grid penalty δ (which captures the costs of increased electricity demand) and the LPG penalty λ (which captures the social costs of continued LPG dependence). The parameter ψ reflects the deadweight loss of public funds. In both panels, color intensity reflects the level of the predicted optimal subsidy. Darker shading corresponds to higher subsidies, which arise because under the efficiency interpretation, the model predicts larger welfare gains from higher subsidy levels. By contrast, in the overload case darker shading is rare, since raising subsidies increases the risk of straining the grid.

Panel 7a presents the *efficiency case*, in which adoption dampens net load through efficiency gains. Here the planner sets relatively high subsidies, since the reduction in LPG dependence dominates the costs of increased electricity use. By contrast, Panel 7b shows the *overload case*, in which adoption risks straining the grid. In this setting, the optimal subsidy declines sharply as δ rises, reflecting the risk of outages that offset the welfare benefits of adoption.

Taken together, these results underscore the sensitivity of optimal subsidy design on conditions shaping the relative costs of LPG dependence, fiscal resources, and grid reliability. From a policy perspective, these results highlight that the efficiency case sets an aspirational benchmark: if the planner could be confident that subsidies primarily drive efficiency gains, relatively generous subsidies would be justified. By contrast, if grid overload is a plausible interpretation, more cautious subsidies may be optimal, even if this means forgoing some LPG-reduction benefits. The value of the model is precisely to make these tradeoffs transparent.

The model also allows us to evaluate how targeting subsidies to specific households compares with a randomized allocation. This builds directly on the heterogeneity analysis in Section 8. There we showed, using CATE estimates from a causal forest, that treatment effects vary systematically with household characteristics such as household size, baseline LPG use, and perceptions of electricity reliability. These results highlight that universal policies

may be inefficient, since households differ in the extent to which subsidies induce adoption. Targeting rules can therefore be thought of as tools for trading off feasibility against efficiency: simple rules based on observable household traits may be cheap to implement but capture only part of the welfare gains, while utility-based targeting provides a benchmark that is more ambitious but likely harder to operationalize.

Figure 8 reports the welfare implications of alternative targeting rules, holding the overall subsidy budget fixed at the RCT level. Several simple rules such as targeting larger households, high LPG users, or those more optimistic about electricity reliability (those that report high belief in the reliability of electricity in our post-experiment survey), achieve higher welfare gains than the gains from RCT design. (All gains are in comparison to a "no policy" counterfactual.

A utility-based targeting rule, which prioritizes households with the highest predicted welfare gains, delivers the largest improvements, raising welfare gains by roughly 40–50 percent relative to the gains from our RCT. These gains are especially pronounced in the efficiency case, but even in the overload case targeted subsidies outperform random allocation. Of course, implementing such a utility-based rule in practice may be administratively demanding, requiring detailed household data and predictive modeling capacity. While it provides a useful benchmark, policymakers may prefer simpler rules that capture a large share of the gains at lower cost.

The rich RCT data provide the variation needed to recover heterogeneous treatment effects, while the structural model translates these estimates into optimal policy prescriptions that account for planner-side tradeoffs. This combination shows that relatively simple targeting strategies can substantially increase welfare, while the general framework provides a portable tool for evaluating energy transition policies across diverse contexts.

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.

This paper brings together several complementary pieces of evidence to advance our understanding of household energy transitions, while staying cognizant of economy wide considerations. Using a large-scale randomized controlled trial, we provide causal estimates of how subsidies and information shape adoption of electric cooking. These estimates are notable not only for their magnitude, but also for the rich heterogeneity they reveal: households respond differently depending on baseline ownership, perceptions of costs, and the form of adoption (stoves versus cookware). To our knowledge, this is among the first studies to document such detailed heterogeneity in the LPG–electricity margin, which is increasingly relevant for countries seeking to reduce dependence on imported gas, and green their fuel consumption.

We also leverage confidential billing data from the Nepal Electricity Authority to connect adoption and usage decisions to actual electricity demand. This allows us to paint a more complete picture of the energy transition: while adoption leads to substantial substitution away from LPG, its implications for billed consumption are heterogeneous—sometimes positive, sometimes muted, and in some cases even negative (consistent with efficiency gains or overloaded-grid outages). These billing results underscore that policy impacts cannot be

inferred from adoption alone. Incorporating household behavior into system-level outcomes is critical for understanding the welfare consequences of electrification.

The structural framework ties these strands together. By embedding empirically estimated household frictions into a planner's problem that accounts for fiscal, grid, and fuel-security constraints, we illustrate how the same micro parameters can generate very different optimal subsidy policies depending on the macro environment. While the framework is generalizable, our results show that context-specific heterogeneity is not a second-order detail but a first-order determinant of welfare gains. In Nepal, targeting subsidies toward households predicted to be most responsive amplifies the effectiveness of policy by up to 40–50 percent, even under conservative assumptions about planner constraints.

Looking forward, this integrated approach—combining randomized evidence, administrative data, and structural modeling—can inform policy in a wide range of energy transitions. Extending the analysis to other countries, technologies, and time horizons is invaluable for building a comparative understanding of when electrification delivers both private and social returns. The broader lesson is that clean energy transitions cannot be managed through one-size-fits-all policies: they require grounding in causal evidence, attention to heterogeneity, and careful recognition of the planner's trade-offs. Our study provides a template for how such evidence can be generated and used to design more effective policy.

References

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

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

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

Al Jazeera, "Crisis on Nepal-India Border as Blockade Continues," Technical Report, Al Jazeera 2015. Published December 24, 2015. Photo essay on the blockade's impact on fuel and goods in Nepal.

Alberini, Anna, Evgenijs Steinbuks, and Govinda R. Timilsina, "How Valuable is the Reliability of Residential Electricity Supply in Low-Income Countries? Evidence from Nepal," *The Energy Journal*, 2022, *43* (4), 97–118.

Allcott, Hunt and Dmitry Taubinsky, "Behavior and Energy Policy," *Science*, 2015, *347* (6224), 208–210. Accessed: 2024-09-23.

Alternative Energy Promotion Centre (AEPC), "Complementing Hydropower with Utility-Scale Solar Electricity in Nepal," 2024.

Ashraf, Nava, James Berry, and Jesse Shapiro, "Can Higher Prices Stimulate Product Use? Evidence from a Field Experiment in Zambia," *American Economic Review*, 2010, *100* (5), 2383–2413. Finds that small user fees screen for users with higher valuation but sharply reduce take-up, highlighting credit/liquidity frictions and present bias in health technology adoption.

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

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

_ , Michael Grimm, and Jörg Peters, "Why do households forego high returns from technology adoption? Evidence from improved cooking stoves in Burkina Faso," *Journal of Economic Behavior & Organization*, 2015, *116*, 187–205.

BenYishay, Ariel and Ahmed Mushfiq Mobarak, "Social Learning and Incentives for Experimentation and Communication," *Review of Economic Studies*, 2019, *86* (3), 976–1009.

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

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

Borenstein, Severin, "Time to Dump the Gas Stove," September 2023.

Burgess, Robin, Michael Greenstone, Nicholas Ryan, and Anant Sudarshan, "Demand for Electricity on the Global Electrification Frontier," Technical Report 1445, University of Warwick, Department of Economics 2023.

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

Bushnell, James B, Erich Muehlegger, and David S Rapson, "Energy Prices and Electric Vehicle Adoption," *NBER WORKING PAPER SERIES*, 2022, *29842*.

Cheng, Jing, Dan Tong, Hongyan Zhao, Ruochong Xu, Yue Qin, Qiang Zhang, Karan Bhuwalka, Ken Caldeira, and Steven J. Davis, "Trade risks to energy security in net-zero emissions energy scenarios," *Nature Climate Change*, 2025, *15*, 505–513.

Dahlby, Bev, *The Marginal Cost of Public Funds: Theory and Applications*, MIT Press, 2008.

Daouda, Misbath, Annie Carforo, Heather Miller, Jennifer Ventrella, Yu Ann Tan, Michelle Feliciano, Jessica Tryner, Andrew Hallward-Driemeier, Steve Chillrud, Roisin Commane, Diana Hernández, Michael Johnson, and Darby Jack, "Out of Gas, In with Justice: Findings from a Gas-to-Induction Pilot in Low-Income Housing," *Energy Research & Social Science*, 2024, *116*, 103662. Accessed: 2024-09-23.

Duflo, Esther, Michael Kremer, and Jonathan Robinson, "Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya," *American Economic Review*, 2011, *101* (6), 2350–2390. Identifies present bias as a key friction: farmers delay adopting profitable fertilizer unless given small, timely nudges.

Dupas, Pascaline, "Health Behavior in Developing Countries," *Annual Review of Economics*, 2011, *3*, 425–449. Accessed: 2024-09-23.

Eaton, Jonathan and Samuel Kortum, "Technology, Geography, and Trade," *Econometrica*, 2002, *70* (5), 1741–1779.

Farsight Nepal, "LPG Price Keeps Soaring: How Feasible an Alternative is Electric Cooking?," 2023.

Gertler, Paul J., Orie Shelef, Catherine D. Wolfram, and Alan Fuchs, "The Demand for Energy-Using Assets among the World's Rising Middle Classes," *American Economic Review*, 2016, *106* (6), 1366–1401. Shows nonlinear relationship between income and energy-using asset acquisition, driven by credit constraints; rising middle class demand drives global energy trends.

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

Giri, Sanjeev, "Blockade, Energy Shortages Goad Country into Looking for Solutions," *The Kathmandu Post*, October 2015. Accessed: 2024-09-23.

Glennerster, Rachel and Seema Jayachandran, "Think Globally, Act Globally: Opportunities to Mitigate Greenhouse Gas Emissions in Low- and Middle-Income Countries," *Journal of Economic Perspectives*, August 2023, *37* (3), 111–135.

Gonzales, Luis E., Koichiro Ito, and Mar Reguant, "The Investment Effects of Market Integration: Evidence From Renewable Energy Expansion in Chile," *Econometrica*, 2023, *91* (5), 1659–1693.

Gould, Carlos F., Lissete Davila, M. Lorena Bejarano, Marshall Burke, Darby W. Jack, Samuel B. Schlesinger, José R. Mora, and Alfredo Valarezo, "Exposure

to Nitrogen Dioxide and Fine Particulate Matter When Cooking with Electricity Compared to Gas, a Randomized Crossover Study in Quito, Ecuador," *Environmental Health Perspectives*, January 2024, *132* (1), 017702.

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

Guiteras, Raymond P., James Levinsohn, and A. Mushfiq Mobarak, "Demand Estimation with Strategic Complementarities: Sanitation in Bangladesh," April 2025. Working paper.

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

Hanna, Rema and Benjamin A. Olken, eds, *The Handbook of Social Protection: Evidence and New Directions for Low- and Middle-Income Countries*, Cambridge, MA: MIT Press, 2026. 504 pp., 43 figures.

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

IFC News, "IFC, Partners Provide More than $450 Million to Support Major Hydro-Electric Plant in Nepal," 2019. Accessed: 2024-09-23.

International Energy Agency, "Clean and Efficient Cooking," Technical Report, International Energy Agency 2025. Energy Efficiency Policy Toolkit 2025.

International Monetary Fund, "Options for Low Income Countries' Effective and Efficient Use of Tax Incentives for Investment," Technical Report, International Monetary Fund 2015. Includes discussion of marginal cost of public funds in LICs.

Karlan, Dean and Jonathan Zinman, "Expanding Credit Access: Using Randomized Supply Decisions to Estimate the Impacts," *Review of Financial Studies*, 2010, *23* (1), 433–464. Estimates consumer credit elasticities; shows access to small loans significantly affects household consumption and welfare.

Kathmandu Post, "Behind the Mega Electricity Deal," *Kathmandu Post*, January 2023. Accessed: 2024-09-23.

Lebel, Eric D., Colin J. Finnegan, Zutao Ouyang, and Robert B. Jackson, "Methane and NOx emissions from natural gas stoves, cooktops, and ovens in residential homes," *Environmental Science & Technology*, 2022, *56* (4), 2529–2539. Accessed: 2024-09-23.

Malla, Sunil, Govinda R. Timilsina, and Martin P. Heger, "Economics of Household Cooking Using Electricity in Nepal," Policy Research Working Paper 11157, World Bank, Development Economics Research Group 2025.

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

McRae, Shaun and Frank A Wolak, "Electricity Pricing for the Energy Transition," *Working Paper*, 2024.

Meriggi, Niccolò F., Erwin Bulte, and Ahmed Mushfiq Mobarak, "Subsidies for technology adoption: Experimental evidence from rural Cameroon," *Journal of Development Economics*, 2021, *153*, 102710.

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

Muehlegger, Erich and David S. Rapson, "Subsidizing low- and middle-income adoption of electric vehicles: Quasi-experimental evidence from California," *Journal of Public Economics*, 2022, *216*, 104752.

Oliva, Paulina, B. Kelsey Jack, Samuel Bell, Elizabeth Mettetal, and Christopher Severen, "Technology Adoption under Uncertainty: Take-Up and Subsequent Investment in Zambia," *The Review of Economics and Statistics*, 2020, *102* (3), 617–632.

Open Data Nepal, "List of Currently Operating IPPs' Hydro Power Projects - Nepal Electricity Authority," 2022. Accessed: 2024-09-23.

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

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

_ **and James Bushnell**, "The Limits and Costs of Full Electrification," *Review of Environmental Economics and Policy*, January 2024, *18* (1), 26–44.

Reuters, "The energy transition is now a national security issue. Just ask India," *Reuters*, 2025. Column by Gavin Maguire.

Ryan, Nicholas, "Holding Up Green Energy: Counterparty Risk in the Indian Solar Power Market," *Working Paper*, 2022.

Saha, Avijit, Md. Abdur Razzak, and M. Rezwan Khan, "Electric Cooking Diary in Bangladesh: Energy Requirement, Cost of Cooking Fuel, Prospects, and Challenges," *Energies*, 2021, *14* (21).

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

ShareSansar News, "Nepal Grapples with Soaring Electricity Import Costs at Rs 16 Per Unit Amid Profitable NEA Performance," 2024.

Spotlight Nepal, "Nepal's Energy Transition: Gaps In The Pathway," *Spotlight Nepal*, 2023. Accessed: 2024-09-23.

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

The New York Times, "Europe Grapples With Energy Crisis, Three Years After Ukraine Invasion," *The New York Times*, 2025. By Stanley Reed and Liz Alderman.

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

U.S. Agency for International Development, "Nepal Factsheet: Nepal Hydropower Development Program," December 5 2017.

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

Wang, Zhenxuan, "Bridge or Barrier to Net Zero? Gas Infrastructure Expansion and the Cost of Electrification," *Working Paper*, 2023.

Wolfram, Catherine, Orie Shelef, and Paul Gertler, "How Will Energy Demand Develop in the Developing World?," *Journal of Economic Perspectives*, 2012, *26* (1), 119–138. Emphasizes rising energy demand as incomes grow in developing countries; highlights uncertainty about household-level elasticities and the role of credit constraints.

Figures and Tables

Figures

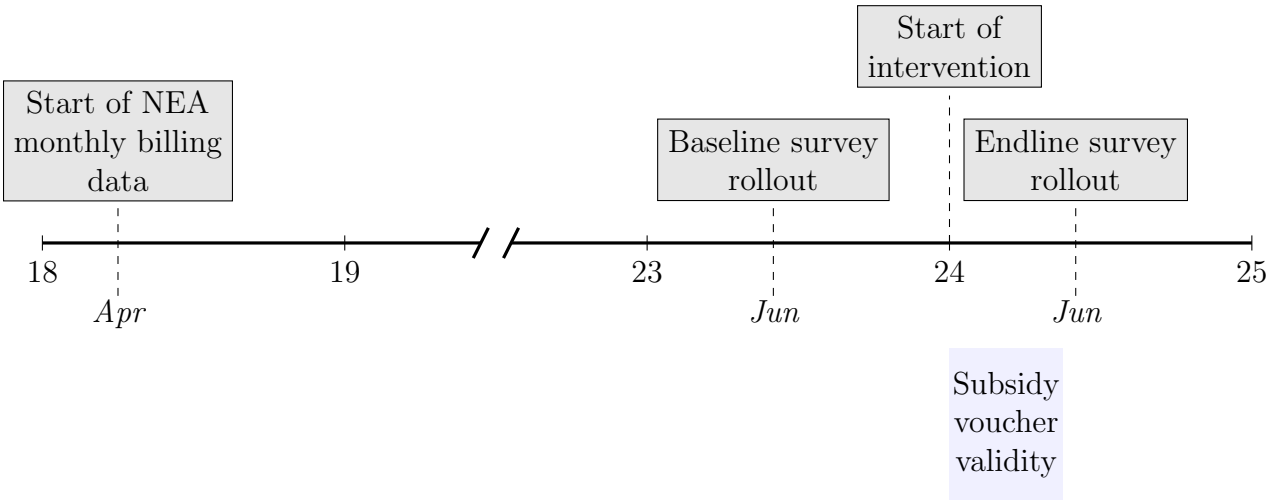
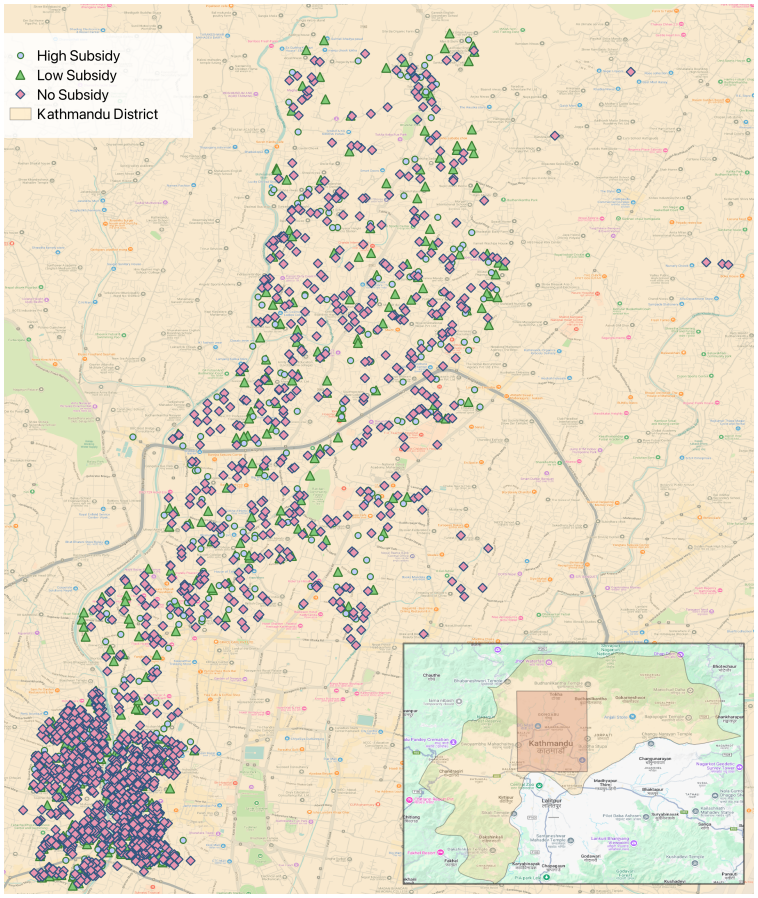


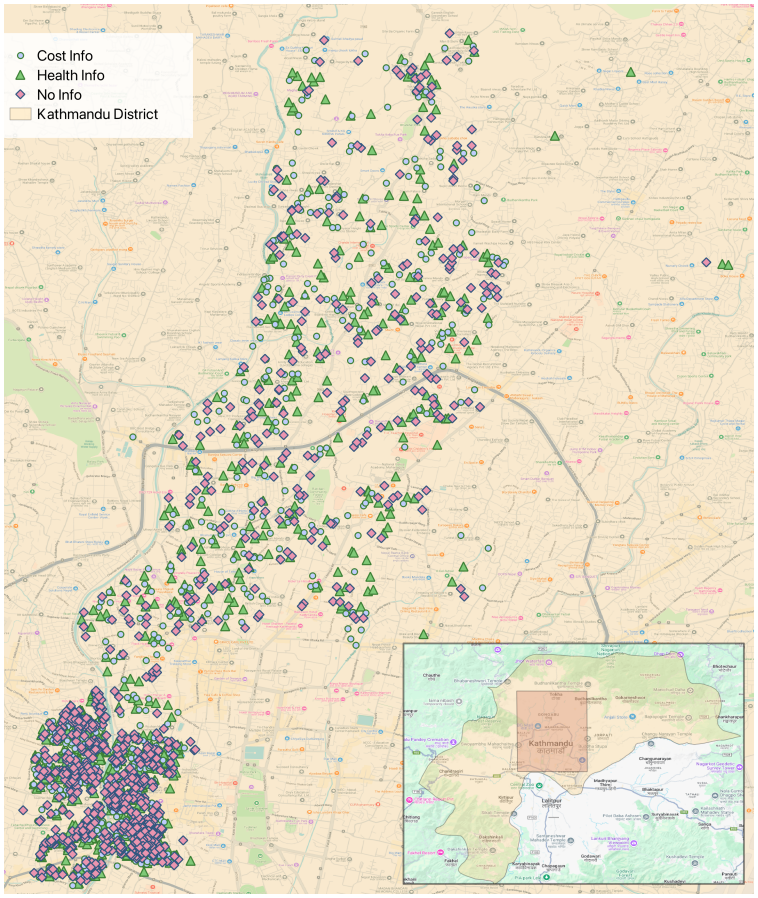
Figure 1: Timeline of surveys and key activities

Figure 2: Spatial spread of households by subsidy treatment group



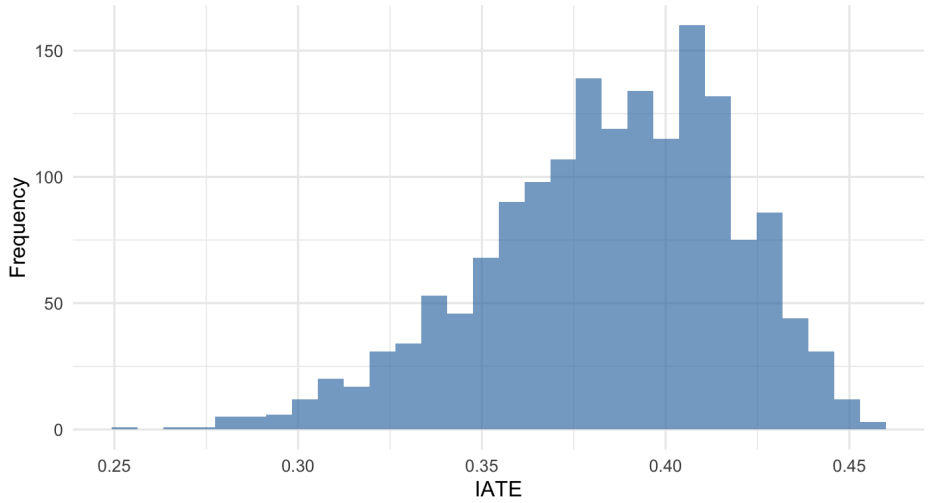
Source: Kathmandu district boundary is from 2015 and was obtained from Code for Nepal.

Figure 3: Spatial spread of households by information treatment group



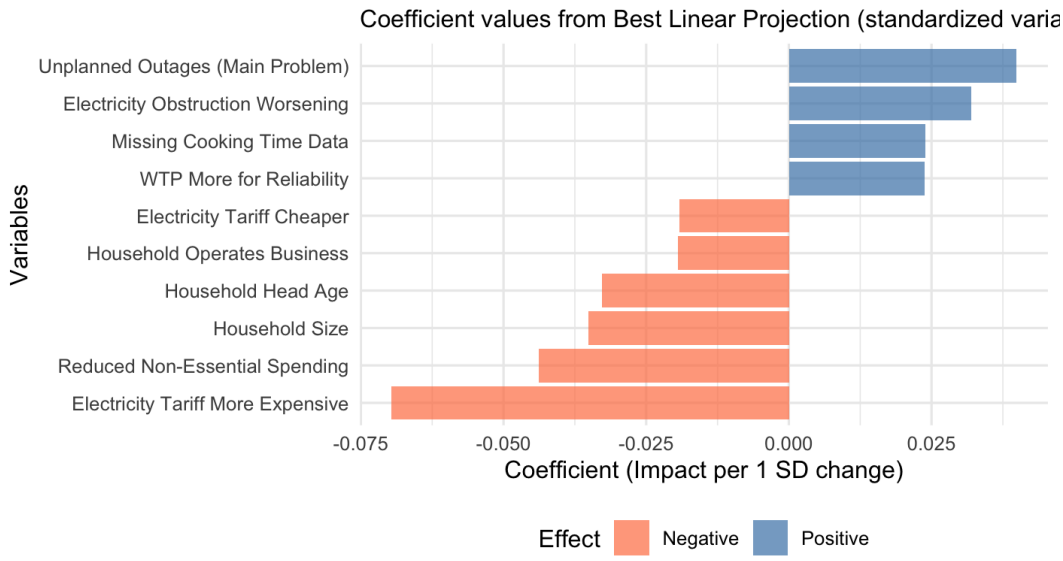
Source: Kathmandu district boundary is from 2015 and was obtained from Code for Nepal.

Figure 4: Distribution of Individual Average Treatment Effects (IATEs) from Causal Forest Estimation.



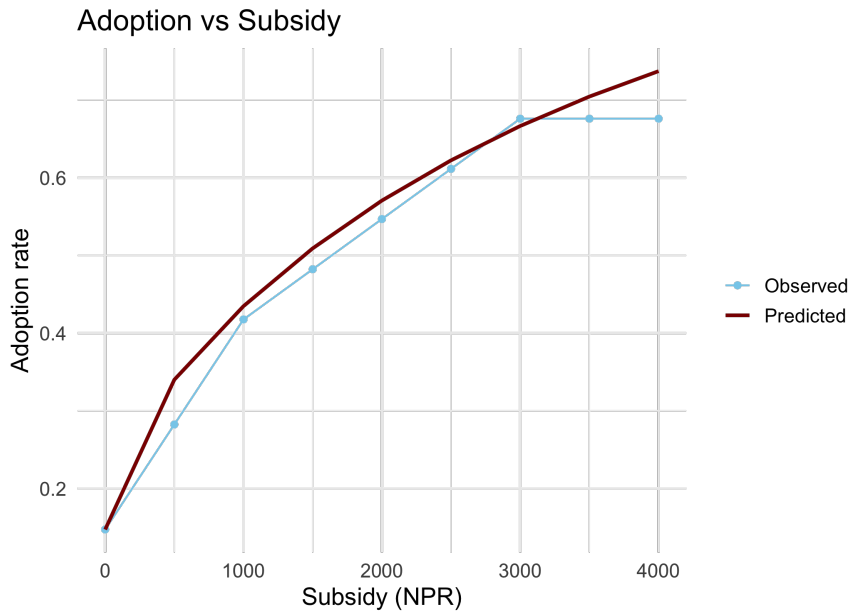
Notes: The histogram shows the distribution of individual average treatment effects (IATEs) estimated using causal forest for 1,645 households. The sample includes all households assigned to treatment arms with subsidy components (treated group) and households in the pure control group. Treatment effects 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 5: Top 10 most important variables for explaining treatment heterogeneity

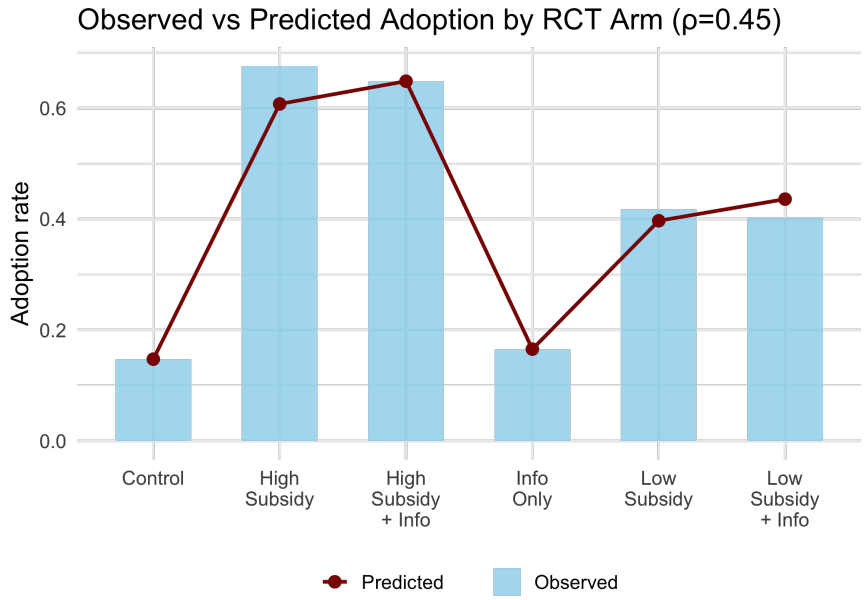


Notes: The figure displays the ten most important variables for explaining treatment effect heterogeneity based on best linear projection coefficients from standardized covariates. Positive coefficients (blue bars) indicate variables associated with higher treatment effects, while negative coefficients (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 6: 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.

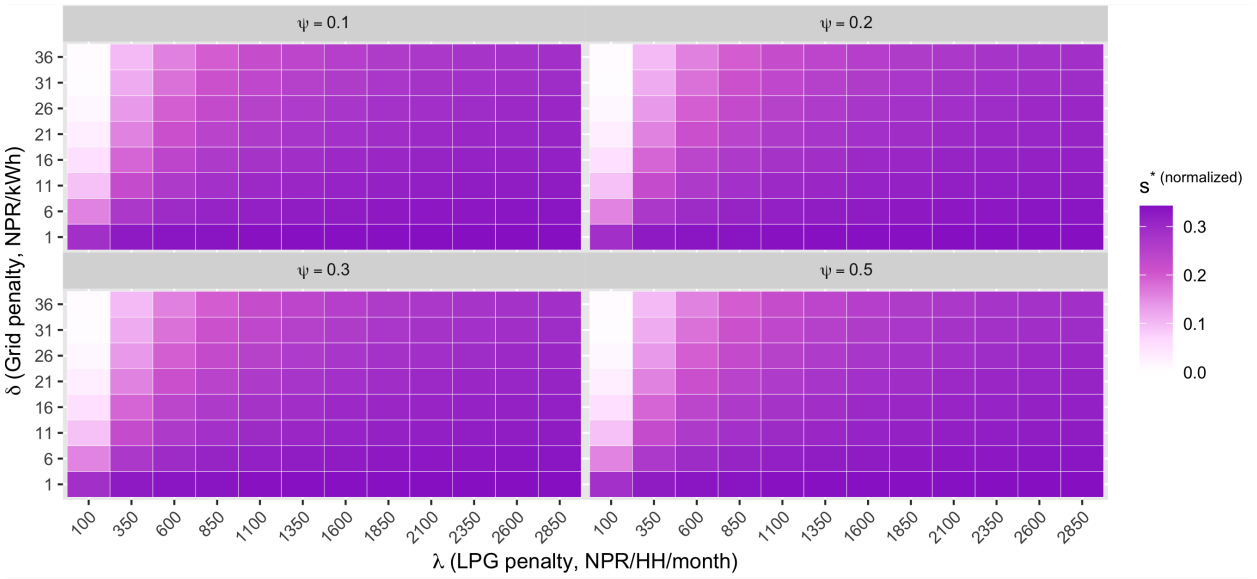


(b) Predicted vs. observed adoption by RCT treatment arm.

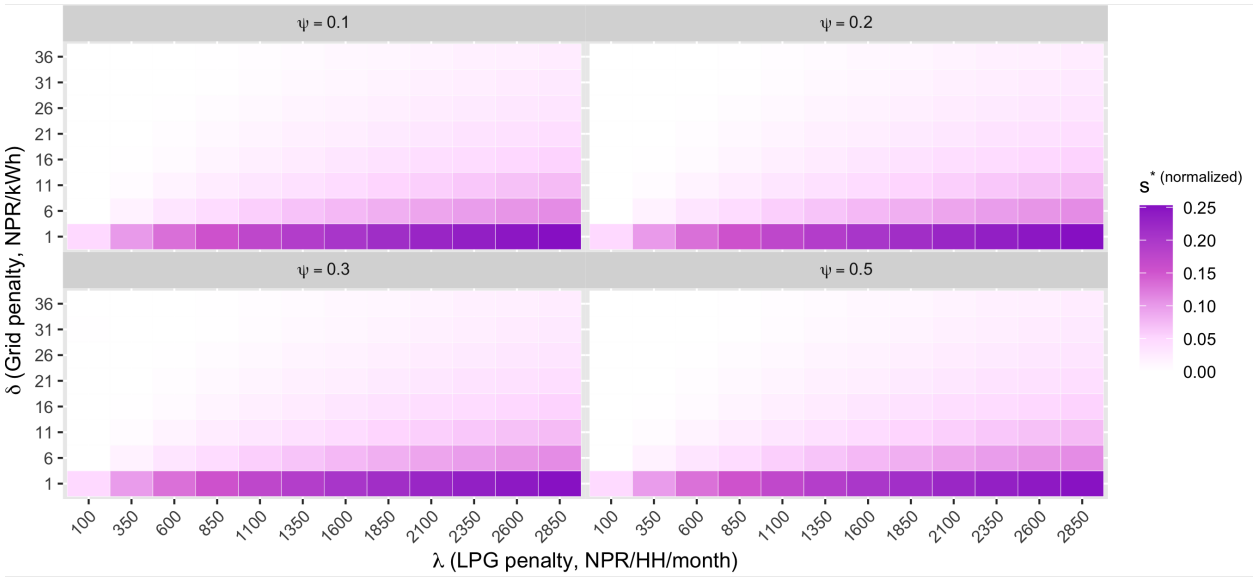
Notes: Figures validate the structural model calibration. Panel (a) shows that the model's predicted adoption curve (red line) tracks observed household adoption (blue points) across subsidy levels. Panel (b) compares predicted and observed adoption across randomized treatment arms in the RCT. The close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

Figure 7: Optimal subsidies in response to macro indicators under two mechanisms. Panel (a) shows the efficiency case. Panel (b) shows the outage case.

(a) Higher subsidies increase efficiency of usage, leading to higher welfare.

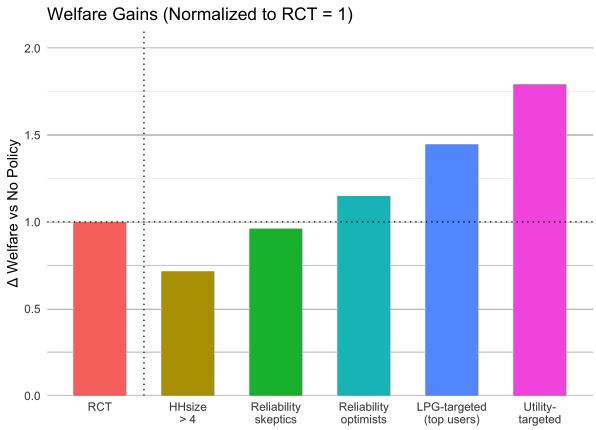


(b) Higher adoption generates reliability issues, causing outages and reducing effective consumption.

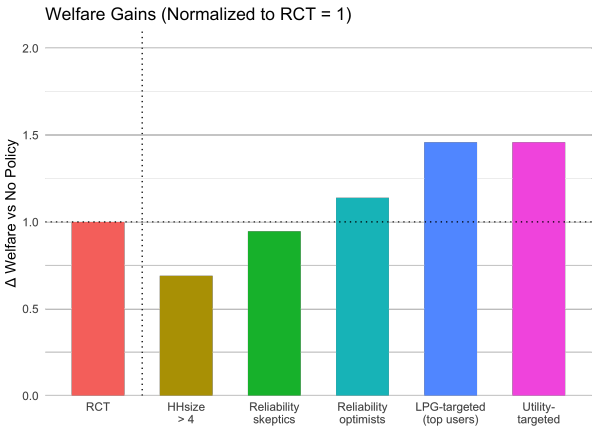


Notes: The heatmaps plot the optimal subsidy level (s^*) as a function of two macro parameters: the grid penalty δ (higher values reflect higher costs of electricity production and provision, such as reliability constraints), and the LPG penalty λ (reflecting the social costs of LPG dependence, including 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 8: Welfare effects of targeting counterfactuals under two mechanisms. Panel (a) shows the efficiency case. Panel (b) shows the outage case.



(a) Efficiency case: higher subsidies increase efficiency of usage and welfare.



(b) Outage case: higher adoption generates grid overload, leading to reduced effective consumption.

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. In the efficiency case, higher subsidies raise welfare by improving efficiency; in the outage case, greater adoption leads to grid overload and welfare losses. 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)	(0.0302)
Low Subsidy	0.270***	0.245***	0.0439
	(0.0356)	(0.0322)	(0.0300)
Only Information	0.0181	0.00146	0.0225
	(0.0217)	(0.0196)	(0.0183)
High Subsidy & Information	0.501***	0.403***	0.255***
	(0.0280)	(0.0253)	(0.0236)
Low Subsidy & Information	0.256***	0.268***	0.0509**
	(0.0282)	(0.0255)	(0.0238)
Constant	0.147***	0.0844***	0.0880***
	(0.0177)	(0.0160)	(0.0149)
Observations	2740	2740	2740

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

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 by Type of Intervention

	(1) Adoption	(2) Bought Ind. Compatible Cookware	(3) Induction Stove
Subsidy	0.398***	0.328***	0.136***
	(0.0286)	(0.0256)	(0.0241)
Subsidy & Information	0.380***	0.337***	0.154***
	(0.0239)	(0.0214)	(0.0201)
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 6: Treatment Effect on Cooking Behavior (OLS)

	(1) % of Meals with induction stove	(2) Elec. Time Cooking	(3) Use Elec. cooking	(4) LPG (KG)	(5) LPG Time Cooking	(6) % of Meals with LPG stove
High Subsidy	0.0694**	17.39***	0.119***	-0.840**	-7.340	-0.0461**
	(0.0292)	(5.037)	(0.0428)	(0.401)	(4.701)	(0.0210)
Low Subsidy	0.0853***	14.27***	0.115***	-0.715*	-9.978**	-0.0247
	(0.0290)	(5.005)	(0.0426)	(0.400)	(4.672)	(0.0209)
Only Information	0.0229	1.988	0.0461*	-0.375	-1.985	-0.0201
	(0.0177)	(3.051)	(0.0259)	(0.243)	(2.850)	(0.0127)
High Subsidy & Information	0.0938***	14.88***	0.122***	-0.219	-7.311**	-0.0529***
	(0.0228)	(3.941)	(0.0335)	(0.315)	(3.682)	(0.0165)
Low Subsidy & Information	0.0394*	8.882**	0.0964***	-0.804**	-6.940*	-0.0373**
	(0.0230)	(3.964)	(0.0337)	(0.316)	(3.710)	(0.0166)
Constant	0.159***	47.72***	0.445***	10.75***	120.0***	0.887***
	(0.0144)	(2.484)	(0.0211)	(0.198)	(2.320)	(0.0104)
Observations	2740	2740	2740	2730	2731	2740

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) time spent cooking in minutes on an average day using electric appliances, (3) binary indicator for using electric appliances to cook, (4) household consumption of LPG in the last month, (5) time spent cooking in minutes on an average day using a LPG stove, (6) percentage of meals cooked with a LPG stove. Significance: $***$ p $<$ 0.01, $**$ p $<$ 0.05, $*$ p $<$ 0.10.

Table 7: Treatment Effect on Cooking Behavior (2SLS)

	(1) % of Meals with induction stove	(2) Elec. Time Cooking	(3) Use Elec. cooking	(4) LPG (KG)	(5) LPG Time Cooking	(6) % of Meals with LPG stove
Adoption	0.275***	60.77***	0.436***	-2.965**	-30.07**	-0.146**
	(0.0785)	(13.80)	(0.113)	(1.273)	(14.04)	(0.0580)
Constant	0.0302	18.79**	0.239***	12.15***	134.0***	0.958***
	(0.0465)	(8.172)	(0.0667)	(0.753)	(8.309)	(0.0344)
F-statistic	32.03	32.03	32.03	31.85	32.24	32.03
Observations	918	918	918	915	917	918

Notes: The table presents estimates of the treatment effects on cooking behavior using 2SLS where an indicator for receiving a subsidy treatment without information serves as an instrument for adoption (i.e. adoption of either induction compatible cookware or induction stove). The estimation sample is households that received a low or high subsidy without information and the control group. The outcome variables are (1) percentage of meals cooked with an induction stove, (2) time spent cooking in minutes on an average day using electric appliances, (3) binary indicator for using electric appliances to cook, (4) household consumption of LPG in the last month, (5) time spent cooking in minutes on an average day using a LPG stove, (6) percentage of meals cooked with a LPG stove. Significance: $***$ p $<$ 0.01, $**$ p $<$ 0.05, $*$ p $<$ 0.10.

Table 8: Treatment effects on logged electricity consumption (ITT) - DID using monthly billing data with all treatments (separate information)

	(1) Log(KWh)	(2) Log(KWh)	(3) Log(KWh)
Post x High Subsidy	-0.0180	0.00799	-0.0703***
	(0.0128)	(0.0165)	(0.0197)
Post x Low Subsidy	0.0114	0.00169	0.0340*
	(0.0126)	(0.0170)	(0.0180)
Post x Cost Information	-0.00982	-0.0128	0.0000237
	(0.00894)	(0.0117)	(0.0134)
Post x Health Information	-0.0100	-0.000846	-0.0239*
	(0.00882)	(0.0115)	(0.0134)
Post x Cost Info & High Subsidy	0.0207*	0.00315	0.0544***
	(0.0124)	(0.0167)	(0.0179)
Post x Cost Info & Low Subsidy	-0.00642	0.00108	-0.0183
	(0.0129)	(0.0168)	(0.0195)
Post x Health Info & High Subsidy	0.0162	0.0234	-0.00743
	(0.0125)	(0.0158)	(0.0203)
Post x Health Info & Low Subsidy	0.00402	-0.0134	0.0383**
	(0.0124)	(0.0163)	(0.0185)
Constant	5.061***	4.916***	5.322***
	(0.00307)	(0.00396)	(0.00472)
Observations	36270	23346	12924
Month-Year FE	Yes	Yes	Yes
Years used as pre-period	2023	2023	2023
Owned estove at baseline	Full Sample	No	Yes
Household FE	Yes	Yes	Yes

Notes: The table shows estimates of a DiD where we use household and month-year fixed effects. The pre-treatment (2023) and post-treatment (2024) periods incorporate data from May to November. The dependent variable is winsorized log electricity consumption. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Placebo Tests: Pre-Treatment Electricity Consumption Trends (2022 vs 2023)

	(1) Log(KWh)	(2) Log(KWh)	(3) Log(KWh)
Placebo Post x High Subsidy	-0.0312	-0.0394	-0.0149
	(0.0295)	(0.0399)	(0.0378)
Placebo Post x Low Subsidy	0.0228	0.00410	0.0484
	(0.0249)	(0.0344)	(0.0342)
Placebo Post x Cost Information	-0.0240	-0.0188	-0.0334
	(0.0188)	(0.0256)	(0.0257)
Placebo Post x Health Information	-0.00949	-0.0248	0.0177
	(0.0186)	(0.0246)	(0.0268)
Placebo Post x Cost Info & High Subsidy	-0.0174	-0.0509	0.0287
	(0.0440)	(0.0617)	(0.0548)
Placebo Post x Cost Info & Low Subsidy	0.00638	0.0263	-0.0223
	(0.0393)	(0.0532)	(0.0554)
Placebo Post x Health Info & High Subsidy	0.0532	0.0690	0.0289
	(0.0380)	(0.0499)	(0.0554)
Placebo Post x Health Info & Low Subsidy	-0.0196	0.0213	-0.0851*
	(0.0387)	(0.0542)	(0.0498)
Constant	5.025***	4.878***	5.291***
	(0.00539)	(0.00716)	(0.00754)
Observations	37487	24124	13363
Month-Year FE	Yes	Yes	Yes
Years used as pre-period	2022	2022	2022
Owned estove at baseline	Full Sample	No	Yes
Household FE	Yes	Yes	Yes

just

Notes: This table presents placebo tests examining pre-treatment trends in electricity consumption. The placebo "post-treatment" period is defined as June 2023 onwards, while the placebo "pre-treatment" period covers June 2022 through December 2022. All periods precede the actual intervention which began in January 2024. Column (1) includes the full sample, Column (2) restricts to households without baseline electric stoves, and Column (3) includes only households with baseline electric stoves. The COVID period (March 2020 - February 2021) is excluded from all analyses. Standard errors are clustered at the household level. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Treatment Effects by Adopter Type on Electricity Consumption

	Log(KWh) by Adopter Type vs Controls				
	(1)	(2)	(3)	(4)	(5)
Post x High Subsidy	-0.0180	-0.0152	0.0206	-0.0808***	0.0515**
	(0.0128)	(0.0204)	(0.0259)	(0.0213)	(0.0261)
Post x Low Subsidy	0.0114	0.0362**	-0.0852***	-0.0253	0.151***
	(0.0126)	(0.0157)	(0.0329)	(0.0222)	(0.0471)
Post x Cost Information	-0.00982	-0.0148	0.00106	-0.0423	0.126***
	(0.00894)	(0.00936)	(0.0201)	(0.0292)	(0.0333)
Post x Health Information	-0.0100	-0.0206**	0.0504**	-0.0241	0.131***
	(0.00882)	(0.00918)	(0.0206)	(0.0276)	(0.0365)
Post x Cost Info & High Subsidy	0.0207*	0.0230	-0.0323	0.0125	0.0801***
	(0.0124)	(0.0185)	(0.0275)	(0.0208)	(0.0259)
Post x Cost Info & Low Subsidy	-0.00642	-0.0189	-0.0618	-0.0179	0.136***
	(0.0129)	(0.0157)	(0.0471)	(0.0238)	(0.0354)
Post x Health Info & High Subsidy	0.0162	-0.0238	0.000876	0.0592***	0.0335
	(0.0125)	(0.0203)	(0.0247)	(0.0228)	(0.0223)
Post x Health Info & Low Subsidy	0.00402	-0.0278*	0.108***	0.0226	0.0532
	(0.0124)	(0.0155)	(0.0380)	(0.0224)	(0.0332)
Constant	5.061***	5.037***	5.105***	5.096***	5.073***
	(0.00307)	(0.00304)	(0.00301)	(0.00321)	(0.00295)
Observations	36270	25662	10640	12286	9747
Month-Year FE	Yes	Yes	Yes	Yes	Yes
Years used as pre-period	2023	2023	2023	2023	2023
Adopter Type	Full Sample	Non-adopter	Only Stove	Only Cookware	Complete Adopter
Household FE	Yes	Yes	Yes	Yes	Yes

Notes: The table shows estimates of a DiD where we use household and month-year fixed effects. The pre-treatment (2023) and post-treatment (2024) periods incorporate data from May to November. The dependent variable is winsorized log electricity consumption. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Treatment effects on electricity consumption (ITT) - DID using monthly billing data

	(1) KWh	(2) KWh	(3) KWh
Post x High Subsidy	-4.563	0.646	-14.99***
	(3.385)	(4.322)	(5.370)
Post x Low Subsidy	7.189**	1.469	15.22***
	(3.337)	(4.465)	(4.906)
Post x Cost Information	-3.867	-2.915	-5.551
	(2.370)	(3.076)	(3.653)
Post x Health Information	-1.684	-2.796	0.281
	(2.338)	(3.012)	(3.649)
Post x Cost Info & High Subsidy	4.583	-3.143	15.89***
	(3.293)	(4.384)	(4.875)
Post x Cost Info & Low Subsidy	3.405	12.13***	-12.85**
	(3.413)	(4.401)	(5.313)
Post x Health Info & High Subsidy	0.136	3.157	-6.934
	(3.325)	(4.156)	(5.536)
Post x Health Info & Low Subsidy	0.0840	-7.073*	12.38**
	(3.289)	(4.282)	(5.036)
Constant	213.5***	196.6***	244.1***
	(0.813)	(1.040)	(1.287)
Observations	36270	23346	12924
Month-Year FE	Yes	Yes	Yes
Years used as pre-period	2023	2023	2023
Owned estove at baseline	Full Sample	No	Yes
Household FE	Yes	Yes	Yes

Notes: The table shows estimates of a DiD where we use household and month-year fixed effects. The pre-treatment (2023) and post-treatment (2024) periods incorporate data from May to November. The dependent variable is electricity consumption. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 planner maximizes household utility but faces costs from grid stress, continued LPG dependence, and subsidy expenditures. The objective is:

$$\max_{P_{Eg},\, s_g} \sum_i U_{ig} - \delta \tilde{T}_E - \lambda \tilde{T}_L - (1+\psi)\tilde{s}, \tag{14}$$

where δ is the marginal grid cost, λ is the penalty for LPG dependence, and ψ is the marginal cost of public funds.

Expanded formulation Substituting expressions for household utility and aggregate load, the planner's problem can be written as:

$$\max_{P_{Eg},\, s_g} \quad \underbrace{\bar{\eta}\left[\left(P_{Eg}^{\frac{-\eta}{1-\eta}} S_{Eg}\right)^{\theta} + 1\right]^{1/\theta}}_{\text{(i) Household option value}} \tag{15}$$

$$- \underbrace{\delta\, \mathcal{G}(\pi_{Eg}, P_{Eg}, s_g, T^*_{Eg})}_{\text{(ii) Grid cost}} \tag{16}$$

$$- \underbrace{\lambda(1-\pi_{Eg})\bar{\eta}}_{\text{(iii) LPG dependence}} \tag{17}$$

$$- \underbrace{(s_g + \psi s_g^2)}_{\text{(iv) Subsidy cost}}. \tag{18}$$

Grid cost cases We consider two cases for $\mathcal{G}$:

$$\mathcal{G}(\pi_{Eg}, P_{Eg}, s_g, T^*_{Eg}) = \begin{cases} \pi_{Eg}\, \phi(P_{Eg}, s_g)\, T^*_{Eg}, & \text{Efficiency case,} \\ (\pi_{Eg} T^*_{Eg})^2, & \text{Overload case.} \end{cases} \tag{19}$$

First-order condition with respect to s_g: Differentiating the planner's objective with respect to subsidies s_g gives:

$$\frac{\partial W}{\partial s_g} = \theta\rho s_g^{\rho-1}\pi_{Eg}(1-\pi_{Eg})\big(\bar{\eta} P_{Eg}^{\frac{-\eta}{1-\eta}}\big) - \delta\frac{\partial \tilde{T}_E}{\partial s_g} - (1+2\psi s_g). \tag{20}$$

This condition shows explicitly how grid costs (δ) and fiscal inefficiency (ψ) tilt the optimal subsidy downward relative to the unconstrained case.

ONLINE APPENDIX

B Additional Tables

Table B1: 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)	(0.0369)
Low Subsidy	0.241***	0.204***	0.0690	0.305***	0.286***	0.0220
	(0.0449)	(0.0383)	(0.0422)	(0.0586)	(0.0562)	(0.0335)
Only Information	0.0310	0.0201	0.0258	-0.00845	-0.0398	0.0232
	(0.0264)	(0.0225)	(0.0248)	(0.0379)	(0.0363)	(0.0216)
High Subsidy & Information	0.515***	0.402***	0.327***	0.474***	0.402***	0.124***
	(0.0340)	(0.0291)	(0.0321)	(0.0490)	(0.0469)	(0.0280)
Low Subsidy & Information	0.230***	0.248***	0.0656**	0.299***	0.297***	0.0299
	(0.0344)	(0.0294)	(0.0324)	(0.0489)	(0.0468)	(0.0279)
Constant	0.130***	0.0459**	0.116***	0.182***	0.160***	0.0321*
	(0.0213)	(0.0182)	(0.0201)	(0.0312)	(0.0299)	(0.0178)
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 B2: Treatment Effect on Cooking Behavior (2SLS)

	(1) % of Meals with induction stove	(2) Elec. Time Cooking	(3) Use Elec. cooking	(4) LPG (KG)	(5) LPG Time Cooking	(6) % of Meals with LPG stove
Panel A: with baseline elec. stove ownership as control						
Adoption	0.256***	59.22***	0.418***	-2.884**	-27.72**	-0.147**
	(0.0736)	(13.44)	(0.108)	(1.284)	(14.13)	(0.0575)
HH own elec. stove (baseline survey)	0.242***	29.93***	0.306***	-0.0230	-12.89	-0.0933**
	(0.0467)	(8.526)	(0.0682)	(0.814)	(8.967)	(0.0365)
Constant	-0.0430	9.322*	0.144***	12.12***	137.1***	0.991***
	(0.0301)	(5.491)	(0.0439)	(0.525)	(5.776)	(0.0235)
F-statistic	46.67	46.67	46.67	46.40	46.67	46.67
Observations	918	918	918	915	917	918
Panel B: without baseline elec. stove ownership as control						
Adoption	0.275***	60.77***	0.436***	-2.965**	-30.07**	-0.146**
	(0.0785)	(13.80)	(0.113)	(1.273)	(14.04)	(0.0580)
Constant	0.0302	18.79**	0.239***	12.15***	134.0***	0.958***
	(0.0465)	(8.172)	(0.0667)	(0.753)	(8.309)	(0.0344)
F-statistic	32.03	32.03	32.03	31.85	32.24	32.03
Observations	918	918	918	915	917	918

Notes: This table presents estimates of the treatment effects on cooking behavior variables using two-stage least squares (2SLS) where an indicator for receiving a subsidy serves as an instrument for adoption. The estimation sample are the households that received subsidies without information and the control group. Panel A includes baseline electric stove ownership as a control variable, while Panel B excludes this control. The dependent variables are: (1) percentage of meals cooked with an induction stove, (2) electricity time spent cooking in minutes, (3) binary indicator for using electric cooking, (4) LPG consumption in kilograms, (5) LPG time spent cooking in minutes, and (6) percentage of meals cooked with an LPG stove. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

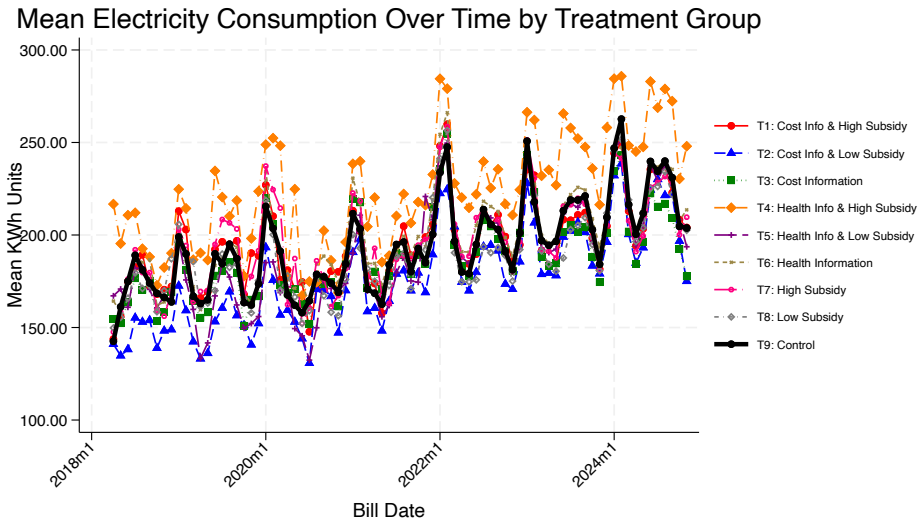


Table B3: Treatment effects on logged electricity consumption (ITT) - DID using monthly billing data

	(1) Log(KWh)	(2) Log(KWh)	(3) Log(KWh)
Post x High Subsidy	-0.0416***	-0.0207	-0.0835***
	(0.0129)	(0.0168)	(0.0197)
Post x Low Subsidy	0.0231*	0.00463	0.0556***
	(0.0128)	(0.0174)	(0.0180)
Post x Cost Information	-0.0234***	-0.0200*	-0.0258*
	(0.00906)	(0.0120)	(0.0134)
Post x Health Information	-0.0147*	-0.0101	-0.0212
	(0.00894)	(0.0117)	(0.0134)
Post x Cost Info & High Subsidy	-0.0109	-0.0396**	0.0371**
	(0.0126)	(0.0170)	(0.0178)
Post x Cost Info & Low Subsidy	-0.00339	0.0120	-0.0305
	(0.0130)	(0.0171)	(0.0195)
Post x Health Info & High Subsidy	0.0163	0.0192	0.00482
	(0.0127)	(0.0162)	(0.0203)
Post x Health Info & Low Subsidy	-0.000925	-0.00665	0.0118
	(0.0126)	(0.0166)	(0.0184)
Constant	5.041***	4.897***	5.301***
	(0.00226)	(0.00295)	(0.00341)
Observations	54795	35262	19533
Month-Year FE	Yes	Yes	Yes
Years used as pre-period	2022-2023	2022-2023	2022-2023
Owned estove at baseline	Full Sample	No	Yes
Household FE	Yes	Yes	Yes

Notes: The table shows estimates of a DiD where we use household and month-year fixed effects. The pre-treatment (2022 and 2023) and post-treatment (2024) periods incorporate data from May to November. The dependent variable is winsorized log electricity consumption. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Treatment effects on logged electricity consumption (ITT) - DID using monthly billing data from different post periods

	(1) Log(KWh)	(2) Log(KWh)	(3) Log(KWh)	(4) Log(KWh)
Post x High Subsidy	-0.0458***	-0.0520***	-0.0416***	-0.0494***
	(0.0118)	(0.0144)	(0.0129)	(0.0170)
Post x Low Subsidy	0.0123	0.0123	0.0231*	0.0308*
	(0.0117)	(0.0142)	(0.0128)	(0.0168)
Post x Cost Information	-0.0270***	-0.0320***	-0.0234***	-0.0296**
	(0.00828)	(0.0101)	(0.00906)	(0.0119)
Post x Health Information	-0.0230***	-0.0231**	-0.0147*	-0.00904
	(0.00817)	(0.00997)	(0.00894)	(0.0118)
Post x Cost Info & High Subsidy	-0.0331***	-0.0449***	-0.0109	-0.0148
	(0.0115)	(0.0140)	(0.0126)	(0.0166)
Post x Cost Info & Low Subsidy	-0.0103	-0.0196	-0.00339	-0.0138
	(0.0119)	(0.0145)	(0.0130)	(0.0172)
Post x Health Info & High Subsidy	0.00482	-0.0124	0.0163	-0.00671
	(0.0116)	(0.0142)	(0.0127)	(0.0167)
Post x Health Info & Low Subsidy	0.00156	-0.000207	-0.000925	-0.00494
	(0.0115)	(0.0141)	(0.0126)	(0.0166)
Constant	5.048***	5.062***	5.041***	5.062***
	(0.00209)	(0.00259)	(0.00226)	(0.00305)
Observations	79147	55904	54795	31552
Month-Year FE	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Start of post period	Feb 2024	Feb 2024	May 2024	May 2024
End of post period	Nov 2024	Aug 2024	Nov 2024	Aug 2024

Notes: This table presents regression results with the heterogeneous treatment impact of subsidy and information treatments on log electricity consumption. All models control for household fixed effects and month-year fixed effects. The first two columns start the post period in Feb 2024, the earliest point that households could have used vouchers to adopt stoves. The third and fourth columns start the post period in May 2024, after the latest point households could have used their vouchers. These columns do not include Jan-Apr in the pre-period (2022 and 2023). Columns 2 and 4 further drop months starting in Sept 2024 when major flooding affected the Kathmandu Valley. The dependent variable is winsorized log electricity consumption. Standard errors are clustered at the household level. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Reduced-form impact of adoption and treatment on log(KWh) by stove ownership (ITT)

	(1) Log(KWh)	(2) Log(KWh)	(3) Log(KWh)	(4) Log(KWh)	(5) Log(KWh)	(6) Log(KWh)	(7) Log(KWh)	(8) Log(KWh)
Post x Adoption (v2)	0.0101	0.0172**	0.0457***	0.0294***	0.0277***	0.0278***	0.0547***	0.0334***
	(0.00924)	(0.00715)	(0.0102)	(0.00759)	(0.0103)	(0.00794)	(0.0112)	(0.00840)
Post x High Subsidy					-0.0362*	-0.0494***	-0.103***	-0.102***
					(0.0195)	(0.0151)	(0.0233)	(0.0174)
Post x Low Subsidy					-0.0370*	-0.0192	-0.00435	0.0387**
					(0.0195)	(0.0151)	(0.0209)	(0.0156)
Post x Information					-0.0339***	-0.0275***	-0.0261*	-0.0217**
					(0.0114)	(0.00881)	(0.0133)	(0.00995)
Post x Information & High Subsidy					-0.0907***	-0.0491***	-0.0217	-0.0000829
					(0.0155)	(0.0120)	(0.0179)	(0.0134)
Post x Information & Low Subsidy					-0.000234	0.00170	-0.0281	-0.0298**
					(0.0150)	(0.0116)	(0.0176)	(0.0131)
Constant	4.904***	4.910***	5.256***	5.320***	4.908***	4.916***	5.259***	5.325***
	(0.00166)	(0.00167)	(0.00190)	(0.00188)	(0.00213)	(0.00258)	(0.00251)	(0.00297)
Observations	116564	61616	64688	34127	116564	61616	64688	34127
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years used as pre-period	All years	2022-2023	All years	2022-2023	All years	2022-2023	All years	2022-2023
Owned estove at baseline	No	No	Yes	Yes	No	No	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Notes: This table presents monthly difference-in-differences (DID) regression results estimating the impact of adoption on log electricity consumption, disaggregated by baseline stove ownership. Columns 1–4 show results for models without subsidy and interaction terms, while Columns 5–8 include subsidies and interaction terms. Columns 1, 3, 5, and 7 use all available pre-period years for comparison, whereas Columns 2, 4, 6, and 8 restrict the pre-period to 2022–2023. Models are further split by households that did not own an electric stove at baseline (Columns 1, 2, 5, and 6) and those that did (Columns 3, 4, 7, and 8). All models control for household fixed effects and month-year fixed effects. Standard errors are clustered at the household level. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: ITT: Effect of Treatments on Hours of Electricity Consumed (reported)

	(1) Hours Appliances	(2) Hours Appliances	(3) Hours Appliances
Post x High Subsidy	1.255	0.728	2.324
	(0.932)	(1.118)	(1.659)
Post x Low Subsidy	1.663*	2.318**	0.978
	(0.917)	(1.148)	(1.524)
Post x Cost Information	1.234*	1.588**	0.815
	(0.644)	(0.783)	(1.122)
Post x Health Information	1.379**	1.273	1.688
	(0.641)	(0.774)	(1.127)
Post x Cost Info & High Subsidy	1.534*	2.863**	-0.201
	(0.895)	(1.115)	(1.499)
Post x Cost Info & Low Subsidy	1.490	2.114*	0.475
	(0.945)	(1.146)	(1.647)
Post x Health Info & High Subsidy	1.772*	1.576	2.054
	(0.904)	(1.053)	(1.717)
Post x Health Info & Low Subsidy	0.498	1.018	-0.243
	(0.905)	(1.105)	(1.561)
Post	0.441	0.892*	-0.481
	(0.452)	(0.539)	(0.813)
Constant	39.32***	35.18***	46.80***
	(0.146)	(0.178)	(0.251)
Observations	5150	3315	1835
HH FE	Yes	Yes	Yes
Owned estove at baseline	Full Sample	No	Yes

Notes: This table presents ITT regression results estimating the effect of treatments on reported hours of electricity used. All models control for household fixed effects. Standard errors are clustered at the household level. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B7: Treatment Effects on Electric Cooking Usage by Adopter Type

	Electric Cooking Usage by Adopter Type				
	(1)	(2)	(3)	(4)	(5)
Cost Info & High Subsidy	0.109**	-0.0394	0.126	0.114*	0.421***
	(0.0422)	(0.0629)	(0.0964)	(0.0683)	(0.0659)
Cost Info & Low Subsidy	0.0780*	-0.0606	0.221	0.252***	0.430***
	(0.0436)	(0.0523)	(0.159)	(0.0735)	(0.0858)
Cost Information	0.0389	-0.0388	0.337***	0.305***	0.555***
	(0.0302)	(0.0317)	(0.0599)	(0.0849)	(0.0212)
Health Info & High Subsidy	0.135***	-0.124*	0.0976	0.242***	0.388***
	(0.0424)	(0.0660)	(0.0873)	(0.0705)	(0.0616)
Health Info & Low Subsidy	0.113***	-0.0301	0.483***	0.215***	0.388***
	(0.0420)	(0.0524)	(0.0724)	(0.0706)	(0.0909)
Health Information	0.0530*	-0.00923	0.305***	0.367***	0.421***
	(0.0299)	(0.0313)	(0.0640)	(0.0725)	(0.0908)
High Subsidy	0.119***	-0.0242	0.00930	0.186***	0.367***
	(0.0427)	(0.0689)	(0.0897)	(0.0676)	(0.0726)
Low Subsidy	0.115***	0.0208	0.239**	0.182**	0.555***
	(0.0425)	(0.0536)	(0.109)	(0.0712)	(0.0212)
Constant	0.445***	0.445***	0.445***	0.445***	0.445***
	(0.0211)	(0.0211)	(0.0212)	(0.0212)	(0.0212)
Observations	2740	1946	802	925	738
Type of Adopter	Full Sample	Non-adopters	Only Stove	Only Cookware	Complete Adopters

Notes: The table shows differential treatment effects on electric cooking usage (0 or 1) by analyzing different subsamples based on adopter type. Each subsample contains the control group and treated units that adopted different combinations of electric induction stoves and appropriate cookware. Non-adopters purchased neither item; Only Stove adopters purchased induction stoves but not appropriate cookware; Only Cookware adopters purchased appropriate cookware but not induction stoves; Complete Adopters purchased both induction stoves and appropriate cookware. Statistical significance: $***$ $p < 0.01$, $**$ $p < 0.05$, $*$ $p < 0.10$.

Table B8: Substitution Analysis: Other Electric Cooking Appliance Hours by Adopter Type

	Other Elec. Appliances Usage Hours by Adopter Type vs Controls				
	(1)	(2)	(3)	(4)	(5)
Post x High Subsidy	-0.0556	-0.0508	0.0104	-0.304	0.331
	(0.0915)	(0.139)	(0.200)	(0.190)	(0.214)
Post x Low Subsidy	0.163*	0.221**	0.228	0.0778	-0.131
	(0.0900)	(0.106)	(0.264)	(0.200)	(0.366)
Post x Cost Information	0.186***	0.181***	0.166	0.218	0.293
	(0.0632)	(0.0628)	(0.155)	(0.267)	(0.257)
Post x Health Information	0.115*	0.101	0.298*	-0.126	0.360
	(0.0629)	(0.0622)	(0.160)	(0.256)	(0.289)
Post x Cost Info & High Subsidy	0.143	0.0402	0.238	0.0559	0.465**
	(0.0879)	(0.124)	(0.215)	(0.182)	(0.208)
Post x Cost Info & Low Subsidy	0.134	0.0637	0.258	0.131	0.565*
	(0.0927)	(0.107)	(0.361)	(0.216)	(0.306)
Post x Health Info & High Subsidy	0.177**	0.166	0.366*	-0.0138	0.258
	(0.0887)	(0.138)	(0.194)	(0.199)	(0.174)
Post x Health Info & Low Subsidy	0.183**	0.0904	0.527*	0.216	0.346
	(0.0888)	(0.106)	(0.301)	(0.197)	(0.269)
Post	-0.258***	-0.258***	-0.258***	-0.258***	-0.258***
	(0.0444)	(0.0417)	(0.0469)	(0.0571)	(0.0477)
Constant	0.995***	0.961***	1.011***	1.143***	1.020***
	(0.0143)	(0.0159)	(0.0278)	(0.0317)	(0.0295)
Observations	5150	3653	1513	1743	1397
Adopter Type	Full Sample	Non-adopter	Only Stove	Only Cookware	Complete
Household FE	Yes	Yes	Yes	Yes	Yes

Notes:

Table B9: 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 B10: 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 B11: 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 B12: 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.

C Additional Maps

1 For Sampling Strategy Using Transformers

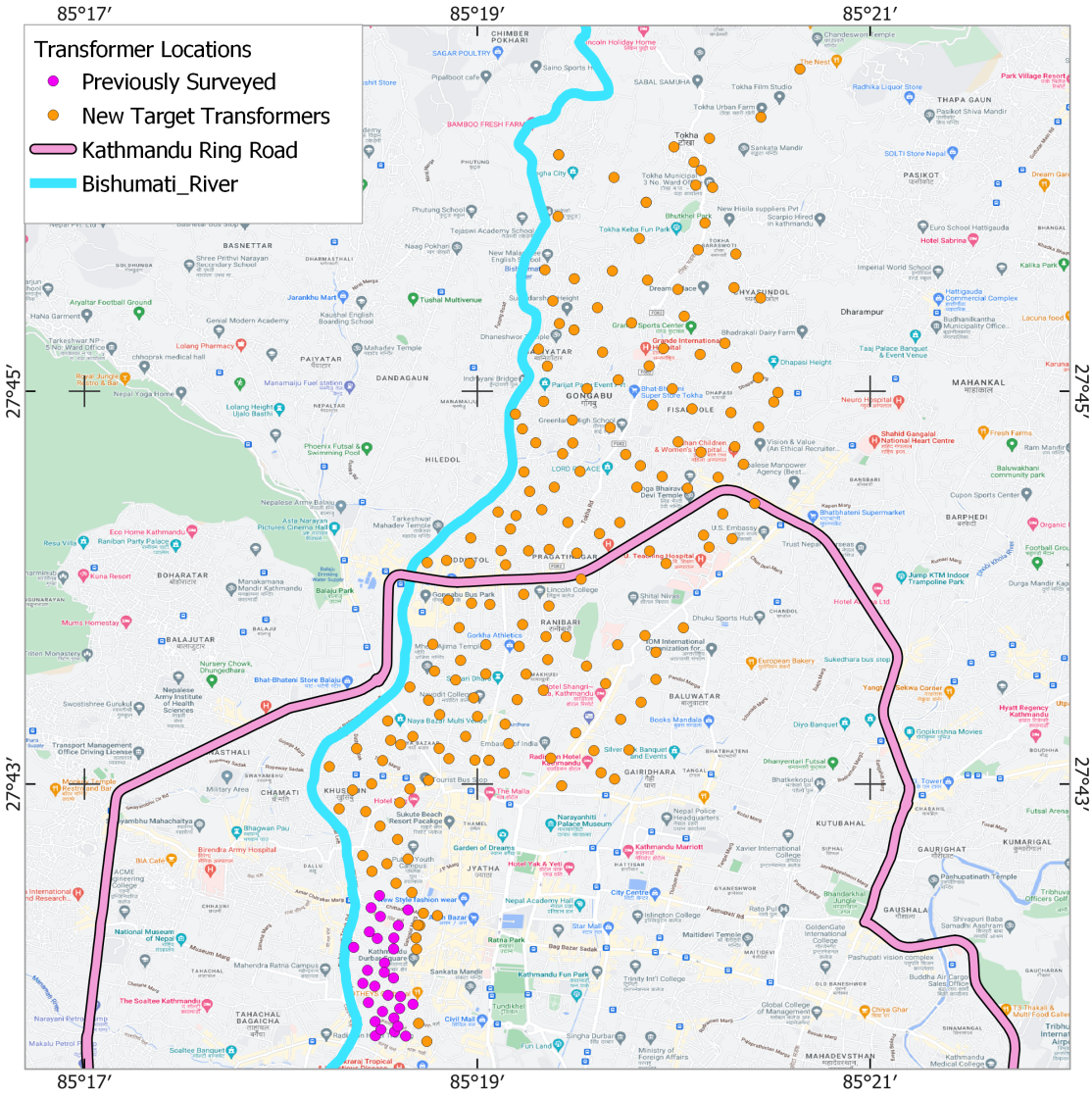


Figure C1: Map of Transformers Used in the Sampling Strategy

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

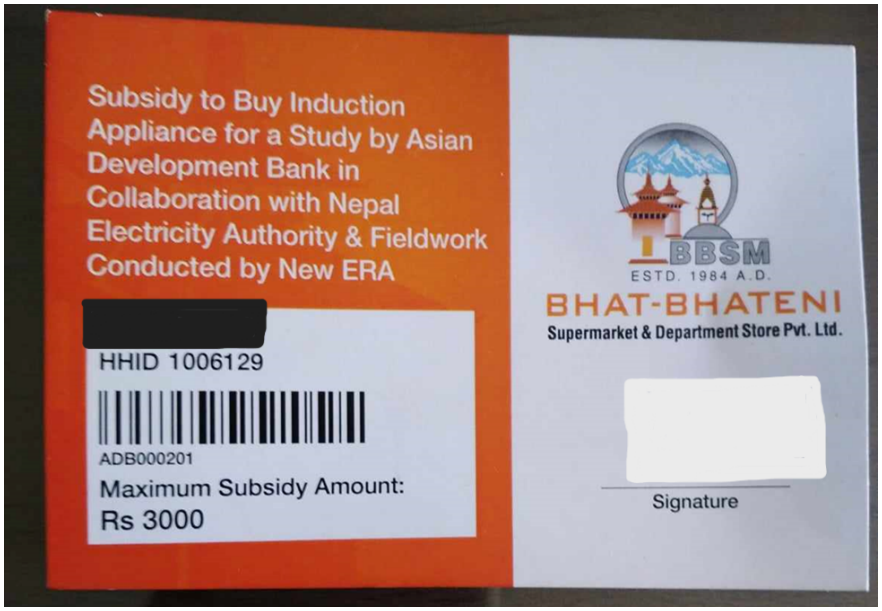


Figure D3: Example of Subsidy Card Provided

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.

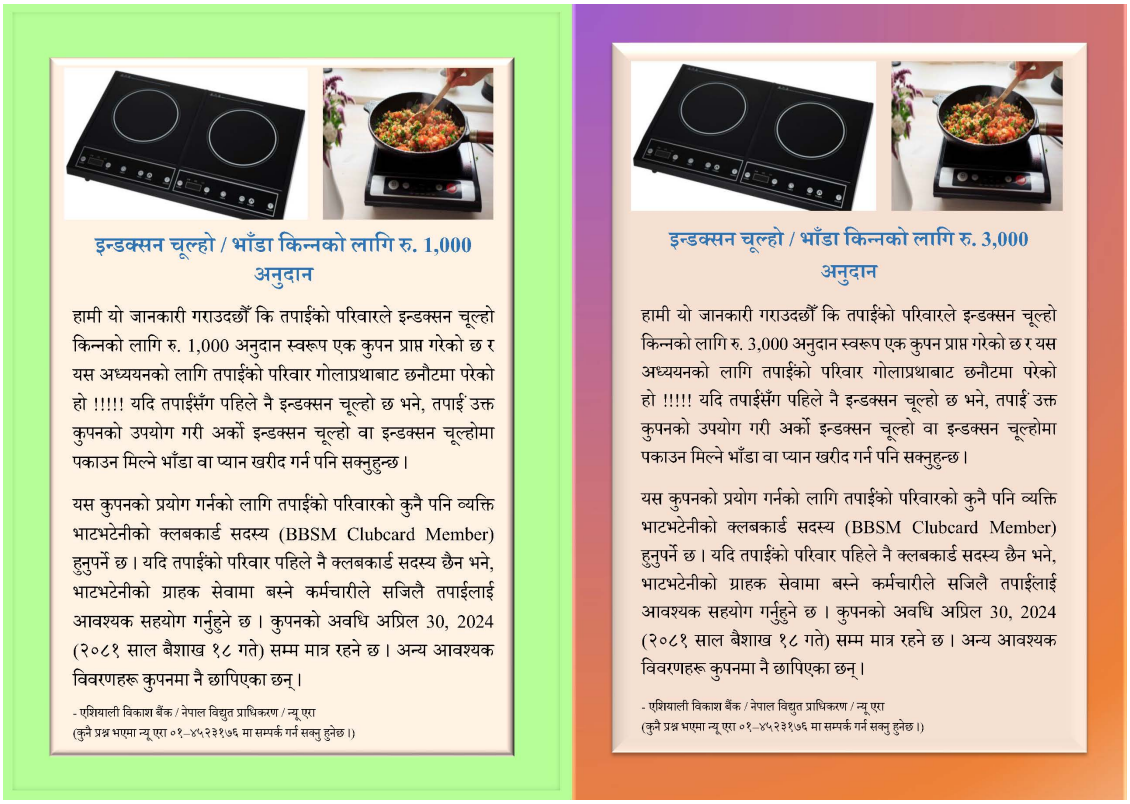


Figure D4: Messages Regarding Subsidies

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.

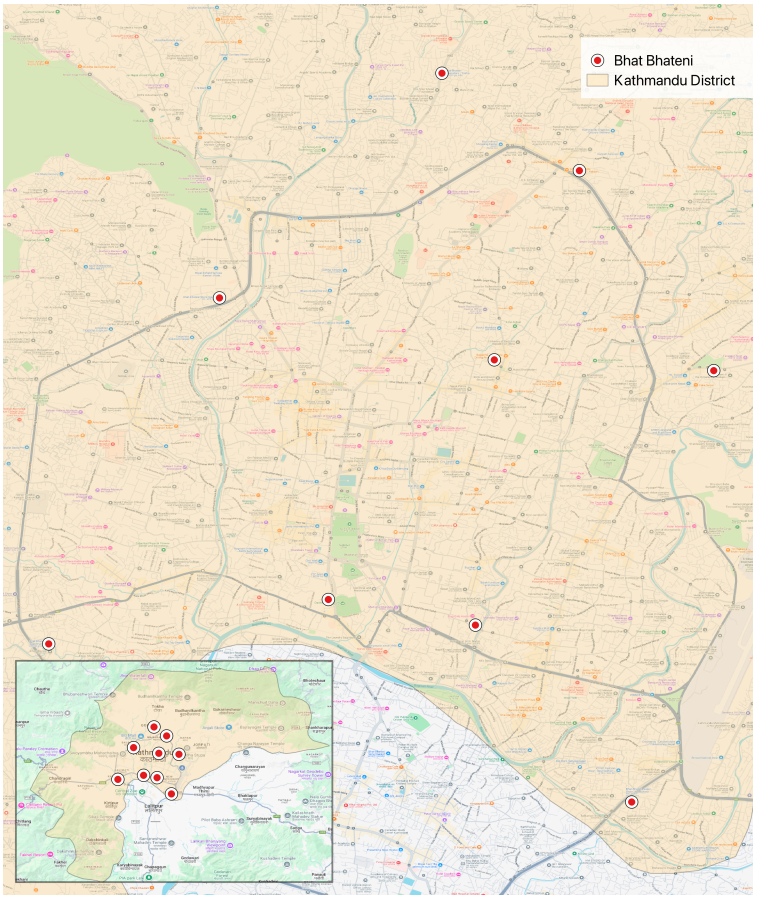


Figure D5: Locations of Bhat Bhateni stores in Kathmandu

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/.