

# Green subsidies with demand distortions

Susanna B. Berkouwer<sup>§</sup>

Joshua T. Dean<sup>†</sup>

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## Abstract

Standard Pigouvian theory predicts that externalities should be corrected at the margin. However, demand distortions such as credit constraints or behavioral biases create a wedge between marginal benefit and marginal cost. While these distortions can lower aggregate abatement, they can *increase* the efficiency of green subsidy spending. In theory, this happens through two channels: by shifting the marginal adopter toward higher private and social benefits, and by increasing demand elasticity. We test these predictions by cross-randomizing fixed cost subsidies, marginal cost subsidies, and loan access for an induction stove among 2,134 charcoal users in Kenya. Marginal cost subsidies that lower electricity costs by up to 75% have a precise zero effect on both adoption and usage. Fixed cost subsidies abate at just US\$13 per ton of CO<sub>2e</sub>, and demand distortions are responsible for making this cost low: reducing credit constraints raises abatement costs to US\$22 per tCO<sub>2e</sub>. These efficiency gains operate through the two hypothesized channels: demand distortions increase the marginal positive externality by 19% and lower the subsidy cost per marginal adoption by 30%. We estimate the model to generate counterfactual simulations and find that, without any distortions, abatement costs would increase more than tenfold, up to US\$137 per tCO<sub>2e</sub>. The social welfare gain would be US\$2.8 per subsidy dollar; in our context we estimate US\$20. Contexts with larger demand distortions, including many low- and middle-income economies, could generate some of the lowest-cost opportunities on the abatement cost curve.

**JEL:** O12, Q56

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<sup>§</sup>The Wharton School, University of Pennsylvania and NBER; [sberkou@wharton.upenn.edu](mailto:sberkou@wharton.upenn.edu). <sup>†</sup>The Booth School of Business, University of Chicago; [joshua.dean@chicagobooth.edu](mailto:joshua.dean@chicagobooth.edu). For generous financial support we thank the International Growth Center, the Weiss Fund for Research in Development Economics, the Penn Global Holman Africa Fund, the Mack Institute, the Wharton Behavioral Lab, and the University of Chicago Development Economics Research Fund. We thank numerous seminar participants for helpful comments. Busara (in particular Suleiman Amanela and Debra Opiyo) superbly implemented field activities. We thank Marta Westerstahl and Rosemary Zhang for excellent research assistance. This study has research approval in Kenya ([MIRERC 069/2025](#) and Nakuru County Unified Trade Permit No. 2025/H23H7831401) and the US (University of Pennsylvania IRB Protocol #855529). A [Pre-Analysis Plan](#) was filed with the AEA RCT Registry ([ID: 16832](#)). A disclosure statement is [available here](#).

# 1 Introduction

The foundational insight of Pigouvian economics is that externalities should be corrected at the margin: a first-best policy sets a tax or subsidy equal to the marginal external cost or benefit (Pigou, 1920). This logic underlies the design of many green subsidy programs worldwide: electric utilities and electric car manufacturers offer subsidized electricity tariffs for electric vehicle owners (PG&E, 2025; Volvo Cars, 2025), and utilities in Kenya and Uganda have introduced e-cooking tariffs to promote electric stoves (Kenya Ministry of Energy, 2024a; UEDCL, 2025). In theory, marginal cost subsidies offer key advantages over fixed cost subsidies of equivalent net present value. They can improve selection on the extensive margin by encouraging adoption among higher-usage agents, who stand to benefit more from lower operating costs, and induce treatment effects on the intensive margin by incentivizing greater usage of the clean technology conditional on adoption.

However, many markets face additional distortions like behavioral biases and financial market failures, which cannot be corrected through first best policy in the short run.<sup>1</sup> This creates a wedge between marginal benefit and marginal cost—or between observed demand and a hypothetical frictionless benchmark—at the market equilibrium (Atkin et al., 2025; Bergquist, Lashkari, and Verhoogen, 2026; Ghatak and Mookherjee, 2025; Indarte et al., 2026) and calls for second best policies (Lipsey and Lancaster, 1956).

Demand distortions can lower global abatement: for example, weak institutions in many low- and middle-income countries have exacerbated global capital misallocation, undermining the green transition as cleaner technologies often require more upfront capital (Acemoglu, Johnson, and Robinson, 2005; Nunn, 2007; Shapiro, 2025; Pande et al., 2025). Demand distortions can also dampen responsiveness to price signals, reducing the impact of marginal cost subsidies on both adoption and usage (Gillingham and Palmer, 2014). However, unlike this dampening effect on abatement and on marginal cost subsidies, this paper argues that demand distortions can *increase* the efficiency of *fixed cost* subsidies. We offer theory and evidence to demonstrate that distortions increase green subsidy efficacy not just relative to marginal cost subsidies, but in absolute terms.

This paper’s first contribution is to document in theory how two key channels can cause demand distortions to increase the welfare gains from green subsidies. The first channel is that distortions can push high-benefit agents below the purchase threshold. A fixed cost subsidy then reaches marginal adopters who generate larger consumer surplus. When private and social benefits are positively correlated, as when fuel savings reduce emissions and fuel expenditures, this also increases marginal environmental benefits. The second channel is that distortions can increase demand elasticity, increasing the percentage of additional adopters and reducing the share of expenditure on inframarginal buyers—a widespread concern for environmental subsidy programs (Sallee, 2025; Boomhower and Davis, 2014; Segerson et al., 2024; Gaarder et al., 2026).

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<sup>1</sup>Solving credit market frictions requires institutional intermediation between borrowers and lenders that overcome classic information asymmetries at the root of moral hazard and adverse selection problems (Bernanke, 2023). Weak institutions pervasive in low- and middle-income countries undermine this (Acemoglu, Johnson, and Robinson, 2005). Section 2 discusses this more.

Testing the theory requires a setting where we can (i) identify the private and social benefits of a green technology, (ii) experimentally vary both fixed and marginal cost subsidies, and (iii) experimentally manipulate demand distortions. We do so in the context of induction cookstoves among 2,134 charcoal-cooking households in Nakuru County, Kenya, where capital market distortions are severe: even with sophisticated credit technologies, paying in installments incurs 75% in interest over 6 months, corresponding to an annualized rate 215% above the central bank lending rate. We cross-randomize three treatments: fixed cost subsidies off the US\$82 price (of 10% or 75%), marginal cost subsidies that lower the electricity cost of operating the stove (by 0%, 25%, or 75%), and access to a loan. The marginal cost subsidy applies only to electricity consumed by the induction stove. Willingness-to-pay is elicited using an incentive-compatible Becker, DeGroot, and Marschak (1964) mechanism. Randomly assigned prices generate exogenous variation in adoption, allowing us to causally estimate private and social benefits. Temperature sensors measure charcoal stove usage continuously and electric stove usage is transmitted in real time.

The paper’s second main finding is that induction stoves generate large private and social benefits. Adoption decreases daily charcoal cooking by 31 minutes and reduces monthly charcoal expenditures by US\$10 (66%). After accounting for increased electricity spending of US\$2.3 per month, net monthly energy savings are US\$8.9 (36%), implying a 112% annual return on investment over the stove’s 1.9 year lifetime. Credit market failures heavily distort demand in this context: average willingness-to-pay is only 11% of the net present value of future discounted fuel savings, but when given access to an interest-free loan this increases to 19%. Assuming a 38% fraction of non-renewable biomass (Ghilardi and Bailis, 2024), we estimate that adoption abates 2.5 tCO<sub>2e</sub> per year across all energy sources. Modest reductions in LPG usage offset a small increase in electricity emissions.

Our third finding is that marginal cost subsidies have no impact. Despite providing detailed information and drawing attention to the reduction in cooking costs before eliciting willingness-to-pay, each US\$1 in electricity subsidy has a US\$0.01 impact on WTP (we can rule out more than US\$0.16). On the intensive margin, despite transferring subsidies weekly via Kenya Power’s standard token system, we estimate a demand elasticity of -0.04 and can rule out that a 1% price decrease increases electric stove usage by more than 0.13%. Both null results hold with and without access to a loan, suggesting the presence of additional demand distortions beyond credit constraints alone, such as inattention to marginal electricity costs or myopia.

Our fourth finding is that fixed cost subsidies increase adoption dramatically. Each US\$1 of subsidy spending generates US\$20 in aggregate welfare gains when valuing reductions in climate change damages at a social cost of carbon (SCC) of US\$230 per ton of CO<sub>2e</sub> avoided, including US\$2.8 in private welfare gains for adopters. In terms of abatement costs, the subsidies incur US\$13 in government expenditure per ton of CO<sub>2e</sub> avoided. This is significantly lower than most abatement technologies available today. The economic cost of abatement is *negative*: fuel savings exceed the stove’s production cost, so each ton of CO<sub>2e</sub> abated saves US\$24 in economic resources.

Combining these results yields the paper’s main, overarching finding: demand distortions in this context decrease abatement cost from US\$22 to US\$13 per ton of CO<sub>2e</sub> (a reduction of 41%)

and increase the welfare gain per US\$1 of government spending by 68%, from US\$12 to US\$20. Distortions operate through both channels identified in the theory. First, over the stove’s 1.9-year lifespan, marginal adopters with larger demand distortions generate 30% more in private fuel savings than those whose distortion was partly relaxed (from US\$154 to US\$200) and abate 19% more CO<sub>2e</sub> (from 4.2 tCO<sub>2e</sub> to 5 tCO<sub>2e</sub>). Second, credit constraints increase demand elasticity from -0.9 to -2.3, reducing inframarginal expenditure from 38% down to 6.5%. This reduces the subsidy expenditure per marginal sale by 30%, from US\$93 to US\$65, which results from a combination of a greater percentage point increase in marginal adopters and a reduction in the number of inframarginal adopters (who receive the subsidy transfer but generate no emissions reductions).

The experiment only partially relaxes distortions: loan access reduces the estimated demand distortion from 0.11 to 0.19, but willingness-to-pay remains well below discounted private benefits in both conditions. A natural question is then: how efficient would fixed cost subsidies be in a setting without distortions, where willingness-to-pay equals the private benefit (termed ‘frictionless’ demand in Indarte et al., 2026). To answer this, we estimate the theoretical model using two-step Generalized Method of Moments and simulate counterfactuals across a wider range of distortions. The model is identified using the randomized variation from the experiment. Fully eliminating distortions such that WTP equals the discounted stream of fuel savings would raise abatement costs to US\$137 per tCO<sub>2e</sub> (10 times the cost under the credit control condition) and decrease the MVPF down to US\$2.8. We use the model to show how this result depends on two key features: the correlation between private and social benefits, and the heterogeneity of distortions across agents. The positive correlation that characterizes fuel-saving green technologies is what makes distortions beneficial for subsidy efficacy in this class of problems: higher users save more money and generate larger externalities.

Annual carbon mitigation financing exceeds US\$1 trillion (Buchner, 2024). Efficient abatement requires allocating each marginal dollar towards the lowest cost abatement technology. Our results suggest that many of the lowest cost portions of the global abatement supply curve could be found in these contexts. For example, the U.S. has a sophisticated financial market for consumer goods, with around 60% of new cars sold with financing and an additional 20% leased (Experian, 2023). The mechanisms identified in this paper could partly explain why U.S. electric vehicle subsidies cost over US\$1,300 in government expenditure per tCO<sub>2e</sub> abated (Hahn et al., 2026)—more than 100 times more costly than the US\$13 per ton abatement cost in our setting. Even holding the underlying technology fixed, our results indicate that green subsidy expenditure could be significantly more effective in contexts with more constrained credit markets.

This paper contributes to several literatures. First, we contribute to a longstanding literature on optimal environmental policy instruments and second best environmental policies (Jacobsen et al., 2020; Knittel and Sandler, 2018; Holland et al., 2016) and optimal environmental policy in the presence of two or more market failures (Fowlie, Reguant, and Ryan, 2016), including those related to behavioral biases (Allcott and Taubinsky, 2015) and those motivating fixed cost subsidies (Carlton and Loury, 1980). We show that demand distortions such as behavioral biases and credit

constraints can *increase* the efficiency of some green subsidies.

Second, we contribute to a literature on selection and mechanism design for subsidy allocation (Einav, Finkelstein, and Cullen, 2010). In the absence of demand distortions, a negative correlation between private WTP and social benefits can generate adverse selection into abatement (Aspelund and Russo, 2026). A positive correlation can cause advantageous selection into abatement, but this can then cause adverse selection into subsidy programs (as in Ryan, 2018). Demand distortions can mitigate these effects in contexts with a positive correlation between private and social benefits. This positive correlation characterizes a broad class of abatement opportunities, including those required for broad scale electrification, a key component of the world’s decarbonization strategy and one of the largest and most fundamental overhauls of our economy that the world has ever embarked on. Electrification involves replacing technologies that directly combust fuel—such as gasoline vehicles, gas or charcoal stoves, gas water heaters, or gas furnaces—with electric substitutes for those same technologies: electric vehicles, induction stoves, electric water heaters, or heat pumps. These green technologies reduce fuel usage and thus lower both private energy expenditures and emissions.

Third, we contribute to a literature studying how demand distortions (or ‘wedges’) affect market outcomes (Atkin et al., 2025; Bergquist, Lashkari, and Verhoogen, 2026; Ghatak and Mookherjee, 2025). This includes a large literature in development economics on credit constraints and technology adoption (Banerjee and Duflo, 2014; Duflo, Kremer, and Robinson, 2008; Berkouwer and Dean, 2022; Fowlie and Meeks, 2021). This literature has documented that credit constraints depress adoption of privately beneficial technologies. We show that credit constraints also change the efficiency properties of subsidy instruments: not just whether people adopt, but how cost-effective it is to induce them to do so.

Fourth, we contribute to a large empirical literature that estimates extensive margin subsidy impacts (Houde and Aldy, 2017; Boomhower and Davis, 2014; Hahn et al., 2026; Borenstein and Davis, 2025) and intensive margin elasticities, largely in high-income countries.<sup>2</sup> The optimal policy is actively debated (Campbell, 2025), including in the context of marginal versus average cost misperception (Ito and Zhang, 2025; Ito, 2014; Kahn and Wolak, 2013). The precise null on marginal cost subsidies contributes to the literature on energy cost inattention from a very different context. We advance the policy debate around electricity tariffs designed to spur decarbonization. E-cooking and electric vehicle charging tariffs in East Africa are seeing similar debates to those happening across many other countries (Borenstein, 2025). Research has studied the impacts of innovative pricing schemes on electric vehicle charging, but our research design circumvents the technological constraint of subsidies inadvertently incentivizing the use of electricity for other purposes (Borenstein, 2025).

Finally, we contribute to a growing literature on electric cooking. Using experimental variation,

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<sup>2</sup>Inattention (as described in DellaVigna, 2009) to energy costs has been documented in the context of cars (Grigolon, Reynaert, and Verboven, 2018; Sallee, West, and Fan, 2016; Sallee, 2014; Allcott and Wozny, 2014; Busse, Knittel, and Zettelmeyer, 2013; Allcott, 2011; Gillingham, Houde, and Van Benthem, 2021; Kahn, 1986; Klier and Linn, 2010; Bushnell, Muehlegger, and Rapson, 2025), housing (Myers, 2019; Myers, 2020; Palmer and Walls, 2015; Myers, Puller, and West, 2022), and other household technologies (Hausman, 1979; Allcott and Taubinsky, 2015; De Groote and Verboven, 2019; Sejas-Portillo, Moro, and Stowasser, 2025; Gerster and Kramm, 2024).

Desbureaux et al. (2025) and Mahadevan et al. (2025) find that fixed cost subsidies increase adoption of electric cooking technologies in the DRC and in Nepal, respectively, which increases electricity usage and generates important social benefits. Gould et al. (2023) find that the nationwide transition from gas towards electric cooking reduced Ecuador’s CO<sub>2e</sub> emissions due to its predominantly hydroelectric powered grid. Other recent descriptive research and laboratory experiments have shed light on perceptions, usage patterns, energy efficiency, and potential for scale of both induction stoves and pressure cookers (Aemro, Moura, and Almeida, 2021; Leary et al., 2021; Saha, Razzak, and Khan, 2021; Clements et al., 2020; Alem, Hassen, and Köhlin, 2014; Banerjee et al., 2016; Rubinstein et al., 2022).

## 2 Background on green subsidies and demand distortions

While Pigouvian taxes are theoretically first-best (Pigou, 1920), carbon taxes are often politically intractable: in Canada, a residential carbon tax efficiently designed with lump sum transfers was recently repealed due to political pressures (Department of Finance Canada, 2025). Energy expenditures tend to be inelastic, such that low-income households spend a disproportionate share of their incomes on energy costs. Rising electricity prices in Kenya have seen significant political backlash (CNN, 2023), preventing meaningful political action on this front. Taxation may also be logistically infeasible: Kenya’s charcoal sector is largely informal and recent government intervention trying to ban or fine logging have seen very poor enforcement (Sola and Cerutti, 2021; Daghar, 2021). Technological requirements can also make accurately pricing the marginal externality cost prohibitive (Jacobsen et al., 2020).

Many environmental principals (including for example multilateral donors, environmental agencies, the UNFCCC, voluntary carbon offsets markets, philanthropists, and other investors) furthermore lack the legal authority to levy a tax. Instead, their focus is on subsidizing climate change mitigation. Doing so efficiently requires identifying technologies and contexts with the lowest marginal abatement costs, starting at the lowest end of the abatement supply curve and then moving up over time (Gillingham and Stock, 2018; Kolstad, 2011). Demand distortions may reduce the level of abatement but increase the return to abatement spending. Abatement spending might be more effective in contexts with more severe demand distortions, such as capital constraints.

Well-functioning credit markets require institutional intermediation between borrowers and lenders to overcome classic information asymmetries (Bernanke, 2023). However, institutional failures are pervasive in low- and middle-income countries (Acemoglu, Johnson, and Robinson, 2005), weakening credit markets. Particular institutional shortcomings include lack of a centralized credit bureau to intermediate borrower information; incomplete property rights undermining collateral usage; widespread informality (more than 1 billion people lack a bank or mobile money account); relational economics, which can make threats of punishment non-credible; a lack of deposit insurance to stimulate saving; and constrained legal systems impeding debt recovery. These exacerbate the classic information asymmetries, adverse selection, and moral hazard problems facing financial

markets.

As a result, credit market failures are pervasive in many low- and middle-income countries, creating pecuniary or non-pecuniary borrowing costs (such as high interest rates, short repayment periods, short grace periods, and appeals to social networks for repayment) that depress adoption of a wide range of technologies with large private benefits.<sup>3</sup> Agents may also face psychological borrowing frictions that serve to prevent costly default (Martínez-Marquina and Shi, 2024; Prelec and Loewenstein, 1998; Sussman and Shafir, 2011).

Demand distortions vary in the degree to which a policy maker can correct them directly. Plenty of demand distortions could be addressed directly through a first-best policy intervention: as an example, widespread undervaluation of potential energy savings could be corrected through an information campaign. In this case, the policy maker might consider the costs of targeting the distortion directly against the fixed cost subsidy to determine the optimal policy. This paper focuses specifically on distortions that cannot be targeted directly, such as credit market failures resulting from underlying institutional capacity constraints as described above. For example, these constraints can also hamper the availability of appropriate insurance instruments, exacerbating risk aversion and distorting demand. The model is largely agnostic as to the source of the demand distortion.

### 3 Theory

An agent consumes energy services (e.g., transportation or cooking) using an incumbent dirty technology (e.g., a gasoline vehicle or a charcoal cookstove). The agent may adopt a cleaner substitute (e.g., an electric vehicle or an electric cookstove) at a one-time cost  $p$  equal to the marginal cost of producing the technology, and then choose what fraction of their energy consumption to shift to the clean technology. This allows for ‘stacking’; households can fulfill their energy needs with multiple technologies. This framework builds on Allcott, Mullainathan, and Taubinsky (2012; 2014) and the theory of the second best developed in Lipsey and Lancaster (1956).

Agents are heterogeneous in their demand for energy services  $\theta_i$  and in a (dis)taste parameter  $\alpha_i$  for the clean technology, distributed  $g(\alpha)$  with an increasing hazard rate.<sup>4</sup> Each agent receives income  $Y$  and derives linear utility from a numéraire good. We assume that total demand for energy services is perfectly inelastic ( $\theta_i$  is fixed) and assume no intertemporal discounting. The dirty technology has per-unit fuel cost  $f_H$  and emits  $\phi_H$  per unit of energy service. The clean technology has per-unit fuel cost  $f_L < f_H$  and emits  $\phi_L < \phi_H$ . Define, respectively, the per-unit

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<sup>3</sup>Credit constraints have been shown to dampen technology adoption by firms (Banerjee and Duflo, 2014; Mel, McKenzie, and Woodruff, 2008; Fafchamps et al., 2014; Kremer et al., 2013; McKenzie and Woodruff, 2008; McKenzie and Woodruff, 2006; Banerjee and Duflo, 2005; Quinn and Woodruff, 2019) and households (Blattman, Fiala, and Martinez, 2014; Duflo, Kremer, and Robinson, 2008; Anagol and Udry, 2006), and in the adoption of green technology in particular (Adhvaryu, Kala, and Nyshadham, 2020; Berkouwer and Dean, 2022; Rom, Günther, and Pomeranz, 2023; Fowlie and Meeks, 2021).

<sup>4</sup>The economic content of this distributional assumption is that we don’t have too many “super users”, which ensures that the demand elasticity is monotonically increasing in price. This is satisfied for many common distributions including uniform, normal, and exponential. It is violated for heavy-tailed distributions like Pareto or log-normal.

cost saving and the per-unit externality reduction from using the clean technology:

$$\pi \equiv f_H - f_L > 0 \quad \phi \equiv \phi_H - \phi_L > 0$$

**Policy instruments** The principal has access to three instruments: (1) a fixed cost subsidy  $s_1$ , reducing the one-time adoption price to  $p - s_1$ ; (2) a marginal cost subsidy  $s_2$  on the clean fuel, reducing its per-unit cost to  $f_L - s_2$ ; (3) a marginal cost tax  $\tau$  on the dirty fuel, raising its per-unit cost to  $f_H + \tau$ . A tax  $\tau$  and a marginal subsidy  $s_2 = \tau$  differ in the direction of the fiscal transfer but have identical effects on the relative fuel price signal facing the agent:

$$\pi' = (f_H + \tau) - (f_L - s_2) = \pi + \tau + s_2$$

**The agent's problem** At  $t = 1$ , agent  $i$  decides whether to buy the clean technology at price  $p - s_1$ :  $d_{1i} \in \{0, 1\}$ . If they adopt, at  $t = 2$  they choose the share of energy services  $\theta_i$  to shift to the clean technology:  $d_{2i} \in [0, 1]$ . Each unit shifted to the clean technology saves  $\pi'$  in fuel costs but generates a non-pecuniary switching cost  $\mu'(d_{2i}\theta_i - \alpha_i)$  such as learning or habit change, where  $d_{2i}\theta_i - \alpha_i$  denotes the total quantity of clean energy services consumed in excess of their taste parameter,  $\alpha_i$ . Higher- $\alpha_i$  agents have less distaste for the clean technology. We assume  $\mu(0) = 0$ ,  $\mu'(0) = 0$ ,  $\mu'' < 0$ , and  $\lim_{x \rightarrow \infty} \mu'(x) = -\infty$ , so that  $\mu(x) \leq 0$  for all  $x \geq 0$ .<sup>5</sup> Total utility from usage conditional on adoption is:

$$f(d_{2i}, \pi', \theta_i, \alpha_i) = d_{2i}\theta_i\pi' + \mu(d_{2i}\theta_i - \alpha_i)$$

The agent chooses  $d_{2i}^*$  to maximize  $f(\cdot)$ , shifting clean-energy consumption until the marginal disutility equals the per-unit fuel saving:  $\mu'(d_{2i}^*\theta_i - \alpha_i) = -\pi'$ . The agent adopts iff their willingness-to-pay  $wtp_i \equiv f(d_{2i}^*, \pi', \theta_i, \alpha_i) > p - s_1$ . Market demand is given by  $Q(p) = \Pr(wtp_i > p)$ . It will be useful to define the constant  $a$  as capturing the common component of WTP shared by all agents, which consists of the fuel savings and switching costs evaluated at  $x^*$ , the unique solution to  $\mu'(x^*) = -\pi'$ :

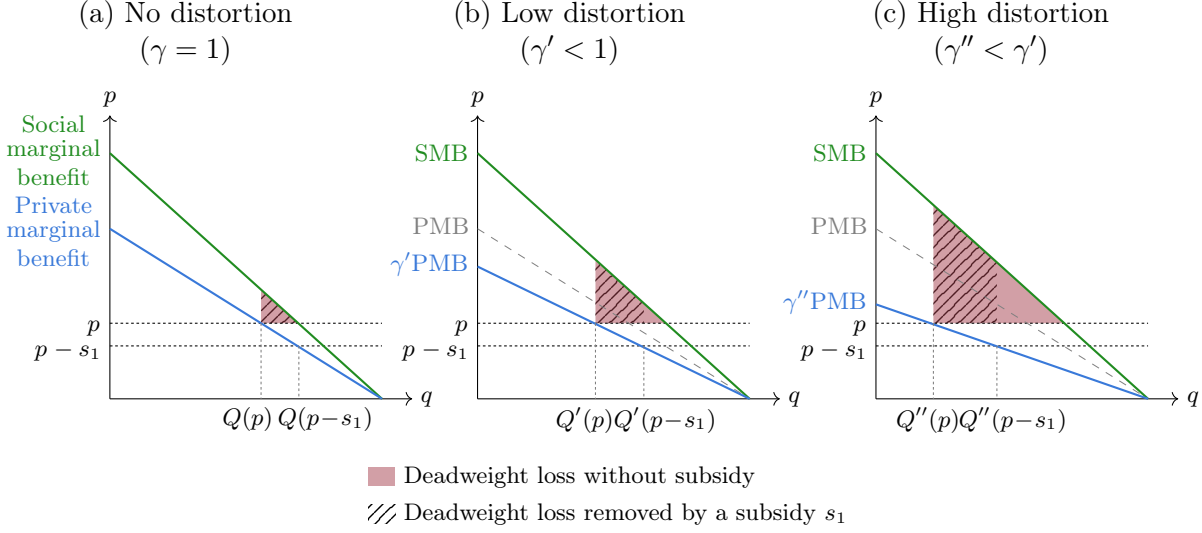
$$wtp_i = (x^* + \alpha_i)\pi' + \mu(x^*) = \underbrace{x^*\pi' + \mu(x^*)}_{\equiv a} + \alpha_i\pi' \quad (1)$$

Given that  $a$  and  $\pi'$  are common across all agents, heterogeneity in WTP depends only on  $\alpha_i$ . WTP and abatement both increase in  $\alpha_i$ : agents with a stronger taste for the clean technology use it more, abate more, and save more on fuel, and are willing to pay more. WTP does not depend on  $\theta_i$  because heavy users substitute proportionally up to the same bliss point.

**Lemma 1.** *Willingness-to-pay is increasing in  $\alpha_i$  and does not depend on  $\theta_i$ , and heterogeneity in usage and willingness-to-pay depend only on  $\alpha_i$ .* Proof in [Section IV.1](#)

<sup>5</sup>Allowing non-pecuniary impacts from adoption ( $\mu(0) \neq 0$ ) does not change the results meaningfully. We discuss this in [Section 3.2](#) below with formal proofs in [Section IV.4](#).

Figure 1: How demand distortions affect deadweight loss at equilibrium and with a subsidy



Notes: Distortions increase both the deadweight loss (DWL) at equilibrium and also increase the DWL that is removed through a subsidy.

**The social planner's problem** The planner chooses  $(s_1, s_2, \tau)$  to maximize total welfare, which includes the externality reduction plus the private value of adoption (fuel savings net of switching costs) minus the technology cost for all adopters. The social value of agent  $i$  adopting is given by:

$$SV(\alpha_i) \equiv \underbrace{(x^* + \alpha_i)\phi}_{\text{externality reduction}} + \underbrace{(x^* + \alpha_i)\pi + \mu(x^*)}_{\text{private value}} - \underbrace{p}_{\text{technology cost}}$$

The first-best policy taxes each fuel at its marginal external cost ( $\tau^* = \phi$ ), with no fixed cost subsidy. At this tax  $\pi' = \pi + \phi$ , so the agent's WTP internalizes the externality. The adoption rule  $wtp_i \geq p$  is therefore equivalent to  $SV_i \geq 0$ . This is the Pigouvian result (Pigou, 1920).

**Intertemporal distortions ( $\gamma$ ).** Intertemporal demand distortions reduce WTP by  $\gamma \in (0, 1]$  at the time of the purchase decision but do not affect usage conditional on adoption. Examples include credit constraints (where  $\gamma = \frac{1}{1+r}$  reflects an inflated borrowing rate), myopia, or present bias:

$$\widetilde{wtp}_i = \gamma wtp_i = \gamma[(x^* + \alpha_i)\pi' + \mu(x^*)]$$

Figure 1 shows how intertemporal distortions dampen adoption and increase DWL by pushing agents with positive private value below the adoption threshold.

**Marginal distortions ( $\delta$ ).** Marginal distortions reduce the perceived relative fuel price to  $\delta\pi'$  with  $\delta \in (0, 1]$ . This reduces usage  $\tilde{x}^* < x^*$  which in turn decreases savings and non-pecuniary costs, both of which decrease WTP. Examples include inattention to fuel costs or incorrect beliefs about

savings. Unlike intertemporal distortions, the agent discounts the savings portion of the technology but experiences and anticipates switching costs in full. Define  $\tilde{a}$  to be the distorted counterpart of  $a$  and define  $k = \tilde{a} - \delta a$ . WTP is then lowered by  $\delta$  and by the reduction in expected usage ( $k \leq 0$ ):

$$\widetilde{wtp}_i = \delta wtp_i + k \leq \delta wtp_i$$

**Lemma 2.** *Marginal distortions reduce WTP by at least as much as proportional scaling by  $\delta$ .*

Proof in [Section IV.1](#).

Both classes of distortion dampen the efficacy of instruments that operate through the relative fuel price. Marginal distortions further reduce their efficacy by also dampening their impact on usage.

**Lemma 3.** *Demand distortions reduce the efficacy of marginal cost instruments, but fixed cost subsidies bypass the relative fuel price channel.*

Proof in [Section IV.1](#).

### 3.1 Why distortions increase the efficacy of fixed cost subsidies

Demand distortions increase fixed cost subsidy efficiency through two channels. We present intuition and formal results for a social planner, a social principal, and an environmental principal.

**Channel 1: The marginal adopter generates larger private and social benefits** Since the distortion lowers adoption to below the efficient point, the subsidy helps reduce the deadweight loss (DWL). The solid red region in [Figure 1](#) represents the reduction in DWL that results from a fixed cost subsidy. This reduction is larger for larger demand distortions.

**Lemma 4.** *Demand distortions increase the marginal adopter's private benefit. If private and social benefits are positively correlated then this increases the marginal adopter's social benefit.*

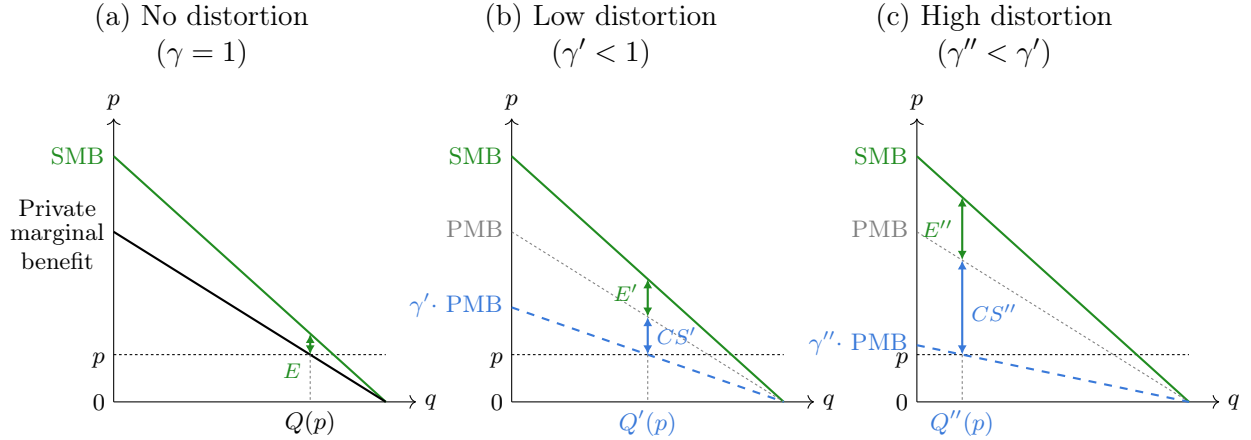
$$\frac{\partial \alpha}{\partial \gamma} < 0 \quad \frac{\partial \alpha}{\partial \delta} < 0$$

Proof in [Section IV.1](#).

Define the marginal adopter as  $\alpha : \gamma wtp_i(\alpha) = p - s_1$ . A decrease in  $\gamma$  increases  $\alpha$  and thus the  $wtp_i$  of the agent marginal to  $s_1$ . Since  $\alpha_i$  and  $wtp_i$  are positively correlated with  $\phi_i$  (since  $\phi_i = (\tilde{x}^* + \alpha_i)\phi$ ), this increases the positive externality generated by the marginal adopter. [Figure 2](#) offers graphical intuition for this increase in the marginal private and social benefit.

This mechanism operates whenever WTP and the externality reduction are positively correlated. This characterizes a broad class of green technology adoption problems where higher users generate larger private benefit and abate more emissions. Demand distortions that reduce WTP, such as intertemporal and marginal distortions, push high-value agents to just below the adoption threshold. Those agents generate the largest social benefits of all non-adopters: a fixed cost subsidy that incentivizes them into adopting thus generates more abatement than it would in a market without distortions. [Section 3.2](#) discusses the case of negatively correlated private and social benefits.

Figure 2: Effect of demand distortions on the marginal consumer surplus and externality benefit



Notes: At the market price  $p$ , larger demand distortions that decrease willingness-to-pay increase the marginal adopter's consumer surplus ( $CS < CS' < CS''$ , with  $CS = 0$  since anyone with  $CS > 0$  already adopts at equilibrium). If private and social benefits are positively correlated this also increases the marginal adopter's positive externality ( $E < E' < E''$ ). [Figure A1](#) shows the case of negatively correlated private and social benefits.

### Channel 2: Demand distortions increase demand elasticity

Demand distortions can increase demand elasticity, decreasing the inframarginal share of subsidy recipients and reducing the cost per marginal adopter. [Figure 3](#) illustrates this intuition graphically: the distortion shrinks the inframarginal region (dark) relative to the marginal region (light).

**Lemma 5.** *Both classes of demand distortions increase demand elasticity  $|\mathcal{E}|$ , decreasing the subsidy cost per marginal adoption.*

The distorted elasticity at price  $p$  equals the undistorted elasticity at the higher effective price  $p/\gamma$ . Since  $|\mathcal{E}|$  is increasing in price for most standard demand curves (with the exception of isoelastic demand, where it is constant), intertemporal distortions increase demand elasticity.<sup>6</sup>

$$\tilde{\mathcal{E}}(p) = \frac{p}{\tilde{Q}(p)} \tilde{Q}'(p) = \frac{p}{Q(p/\gamma)} \cdot \frac{Q'(p/\gamma)}{\gamma} = \mathcal{E}(p/\gamma)$$

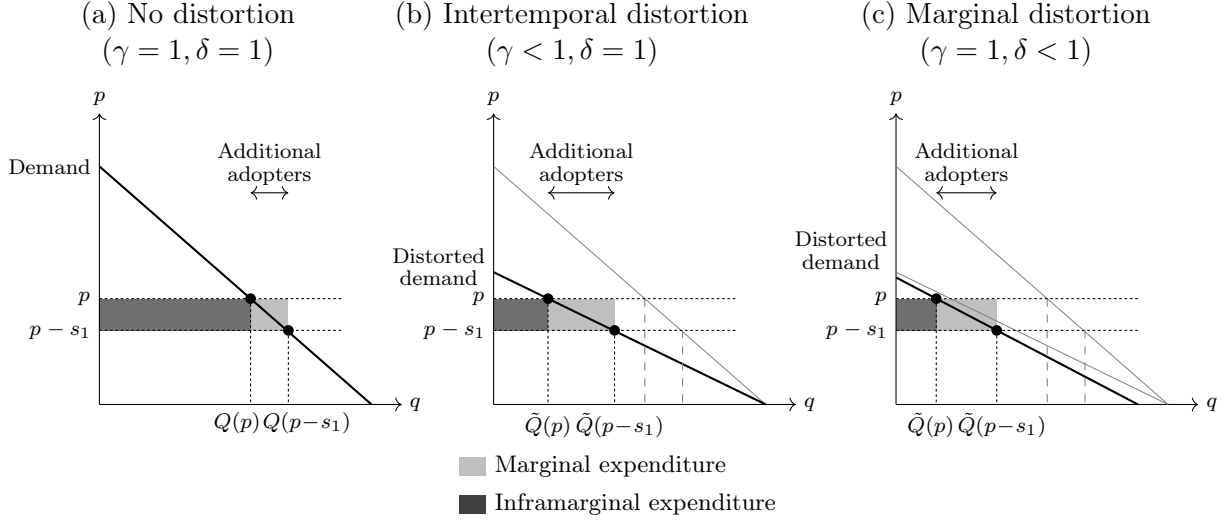
Defining the principal's cost  $C(s_1) = s_1 Q(p - s_1)$ , the marginal cost per adoption comprises the marginal agent's subsidy plus increased subsidies to inframarginal agents defined by the elasticity:

$$\frac{dC(s_1)}{dQ(p - s_1)} = \frac{\partial C(s_1)}{\partial s_1} \cdot \frac{\partial s_1}{\partial Q(p - s_1)} = s_1 - \frac{Q(p - s_1)}{Q'(p - s_1)} = s_1 + \frac{p - s_1}{|\mathcal{E}|}$$

Marginal distortions also increase demand elasticity (derivation in [Section IV.5](#)). This requires a stronger condition (our assumed increasing hazard rate) than the  $\gamma$  case (which only needed  $|\mathcal{E}|$  increasing in  $p$ ), but holds for a broad class of empirically relevant distributions of  $\alpha_j$ .

<sup>6</sup>A corner solution is possible here where  $Q(\gamma wtp < p) = 0$  such that there is no demand at the competitive price. Any subsidy  $s_1$  with  $Q(\gamma wtp < p - s_1) = 0$  would then trivially have no impact on adoption since elasticity is undefined at  $q = 0$ . A subsidy would then incentivize a larger increase in quantity in the undistorted case than in the distorted case. The model assumes an interior solution, which reflects the data as well as the fact that any corner solution is an artefact of the assumed linear demand curve and homogenous distortion.

Figure 3: Marginal and inframarginal subsidy expenditures with and without distortions



*Notes:* All panels show subsidy expenditures from reducing the price from  $p$  to  $p - s_1$ . Dark regions represent spending on inframarginal buyers; light regions represent spending on marginal buyers. Panel b: an intertemporal distortion ( $\gamma$ ) compresses the demand curve toward the origin by rotating around the quantity intercept, since at zero price all agents still adopt. Panel c: a marginal distortion ( $\delta$ ) both rotates and shifts the demand curve leftward. In both cases, the number of marginal adopters increases and spending on inframarginal adopters decreases.

### Aggregate impact of distortions on green subsidy efficacy

**Proposition 1.** *Demand distortions increase total abatement per dollar of fixed subsidy expenditure.*

Defining  $A$  as the objective (either the sum of private benefits and emissions reductions, or emissions reductions alone), distortions impact subsidy efficiency as follows:

$$\frac{\partial}{\partial \gamma} \left( \frac{\partial A}{\partial C} \right) = \frac{\frac{\partial^2 A}{\partial Q, \partial \gamma} \cdot \frac{\partial C}{\partial Q} - \frac{\partial A}{\partial Q} \cdot \frac{\partial^2 C}{\partial Q, \partial \gamma}}{\left( \frac{\partial C}{\partial Q} \right)^2}$$

Since a larger demand distortion ( $\gamma < 1$ ) reduces average subsidy cost (Lemma 5), a larger demand distortion increases average abatement (Lemma 4), and  $\frac{\partial C}{\partial Q}, \frac{\partial A}{\partial Q} > 0$ , distortions increase the abatement per dollar of subsidy expenditure. Figure 4 shows these results intuitively.

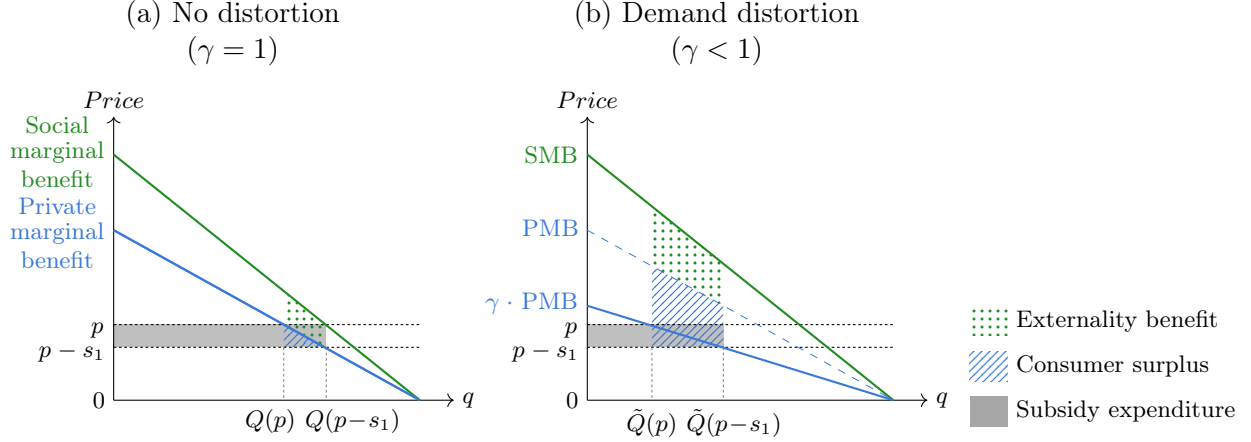
Under an increasing hazard rate, the marginal distortions case is symmetric.

**The social planner's problem** With distortions, agent  $i$ 's social value of adopting is given by:

$$SV(\alpha_i) \equiv \underbrace{(\tilde{x}^* + \alpha_i)\phi}_{\text{externality reduction}} + \underbrace{(\tilde{x}^* + \alpha_i)\pi + \mu(\tilde{x}^*)}_{\text{private value (true price, actual usage)}} - \underbrace{p}_{\text{technology cost}}$$

**Proposition 2.** *Intertemporal demand distortions ( $\gamma < 1$ ) increase the social planner's optimal fixed subsidy and marginal demand distortions ( $\delta < 1$ ) increase the optimal marginal tax:*

Figure 4: Aggregate effect of demand distortions on welfare gain from subsidy



*Notes:* The dotted green area represents the total positive externality generated, the striped blue area represents the consumer surplus generated, and the gray area represents the subsidy expenditure incurred when a subsidy lowers the price to  $p - s_1$ . Subsidy efficiency is the ratio of externality benefit plus consumer surplus to total subsidy expenditure. Demand distortions increase this ratio through the two channels identified above.

$$s_1^* = p(1 - \gamma) \quad \tau^* = \frac{\phi + \pi(1 - \delta)}{\delta} \quad \text{Proof in Section IV.1.}$$

The planner's optimal policy is to introduce a positive fixed cost subsidy and increase the marginal tax ( $s_1^*$  collapses to 0 when  $\gamma = 1$ ). The  $\delta$  distortion can be fully corrected by the optimal tax, which exceeds the Pigouvian benchmark:  $\tau^* > \phi$ , while the fixed cost subsidies compensate for  $\gamma$ .

**The social principal's problem** With only subsidies available, the principal chooses  $(s_1, s_2)$  to maximize social welfare subject to a fixed budget  $B$ :

$$(s_1^*, s_2^*) = \arg \max_{\alpha} \int_{\alpha}^{\infty} SV(\alpha_i) g(\alpha) d\alpha \quad \text{s.t.} \quad s_1 Q + s_2 U \leq B$$

where  $\alpha$  corresponds to the  $\alpha_i$  of the marginal adopter such that  $wtp_i(\alpha) = p - s_1$ ,  $Q \equiv 1 - G(\alpha)$  (number of adopters), and  $U \equiv \int_{\alpha}^{\infty} (\tilde{x}^* + \alpha_i) g(\alpha) d\alpha$  (total clean energy usage by adopters).  $Q$  and  $U$  depend on the instruments through  $\alpha$  (who adopts) and  $\tilde{x}^*$  (how much each adopter uses).

The FOC's for both subsidies include own subsidy spending (both marginal and inframarginal), as well as other-subsidy spending (since adoptions increase total usage and marginal savings induce adoptions). However, unlike  $s_1$ , the marginal cost subsidy  $s_2$  increases both usage and WTP by raising the effective fuel price  $\pi' = \pi + s_2$ . Combining the  $s_1$  FOC (LHS) and the  $s_2$  FOC (RHS) characterizes the optimal allocation between  $s_1$  and  $s_2$ , elucidating how benefits from the marginal

adopter ( $SV(\alpha)$ ) and demand elasticity ( $|\tilde{\mathcal{E}}(p - s_1)|$ ) affect relative subsidy efficacy:

$$\frac{\overbrace{SV(\alpha)}^{\text{social value per new adopter}}}{\underbrace{s_1 + s_2(\tilde{x}^* + \alpha)}_{\text{total subsidy to new adopters}} + \underbrace{\frac{p - s_1}{|\tilde{\mathcal{E}}(p - s_1)|}}_{\text{inframarginal cost}}} = \frac{\overbrace{[\pi + \phi + \mu'(\tilde{x}^*)] \frac{d\tilde{x}^*}{ds_2} Q}_{\text{social value of additional usage}} + \overbrace{SV(\alpha)g(\alpha) \left(-\frac{\partial \alpha}{\partial s_2}\right)}_{\text{social value of new adopters}}}{\underbrace{s_2 \frac{d\tilde{x}^*}{ds_2} Q}_{\text{cost of increased usage}} + \underbrace{[s_1 + s_2(\tilde{x}^* + \alpha)]g(\alpha) \left(-\frac{\partial \alpha}{\partial s_2}\right)}_{\text{total subsidy to new adopters}} + \underbrace{U}_{\text{inframarginal cost}}} \quad (2)$$

Proof in [Section IV.2](#).

To highlight mechanisms, write  $\bar{\alpha} \equiv E[\alpha_i | \alpha_i \geq \alpha]$  for the mean taste among adopters,  $U/Q = \tilde{x}^* + \bar{\alpha}$ , and define  $MSV \equiv \pi + \phi + \mu'(\tilde{x}^*)$  (the marginal social value of additional clean energy usage). Define  $\kappa \equiv (p - s_1)/|\tilde{\mathcal{E}}(p - s_1)|$  (the inframarginal cost per new adopter) and  $\Delta \equiv MSV \cdot (\tilde{x}^* + \alpha) - SV(\alpha) = \mu'(\tilde{x}^*)(\tilde{x}^* + \alpha) - \mu(\tilde{x}^*) + p$  (how much the value of an additional unit of usage by the marginal adopter differs from the total social value generated by their adoption):

$$\frac{MSV \cdot (s_1 + \kappa) + s_2 \cdot \Delta}{SV(\alpha)} = \frac{\overbrace{(\tilde{x}^* + \bar{\alpha}) - \gamma\delta(\tilde{x}^* + \alpha)}^{\text{extensive margin disadvantage of } s_2}}{\underbrace{\frac{d\tilde{x}^*}{ds_2}}_{\text{intensive margin advantage of } s_2}} \quad (3)$$

Proof in [Section IV.2](#).

When  $\gamma\delta < 1$ , each dollar of  $s_2$  raises the marginal adopter's WTP by only  $\gamma\delta(\tilde{x}^* + \alpha)$  rather than  $(\tilde{x}^* + \alpha)$ , widening  $s_2$ 's extensive margin disadvantage.

To understand how an intertemporal distortion  $\gamma$  affects the optimal fixed cost subsidy, set  $\delta = 1$ :

$$\frac{ds_1^*}{d\gamma} = \underbrace{-wtp(\alpha^*)}_{\text{direct effect}} - \underbrace{\gamma\pi' \cdot \frac{d\alpha^*}{d\gamma}}_{\text{re-optimization}} \quad (4)$$

Proof in [Section IV.2](#).

The first term is the direct effect, which is always negative: when  $\gamma$  rises (distortions weaken), agents value the technology more, so the principal can reduce  $s_1^*$  while holding the adoption threshold fixed. The second term captures the principal's re-optimization of the adoption threshold. The appendix shows that  $ds_1^*/d\gamma < 0$  for all demand elasticities under an increasing hazard rate.

**Proposition 3.** *Intertemporal distortions  $\gamma < 1$  increase the social principal's optimal fixed cost subsidy  $s_1^*$ .*

Proof in [Section IV.2](#).

**The environmental principal's problem** The environmental principal's only objective is to maximize total abatement  $A = \phi U$ . This yields equivalents of [Equation 2](#) and [Equation 3](#), with  $SV_i = (\tilde{x}^* + \alpha)\phi$ ,  $MSV = \phi$ ,  $SV(\alpha) = \phi u$ , and  $\Delta = 0$ .

Proof in [Section IV.3](#).

Since the budget constraint and  $ds_1^*/d\gamma$  decomposition are identical to the social principal’s, Proposition 3 extends to the environmental principal under IHR (Section IV.3).

### 3.2 Model discussion and possible extensions

**Non-pecuniary benefits** Allowing non-pecuniary benefits to clean technology adoption ( $\mu(0) = c$ ) does not change the results above meaningfully, because the mechanisms on which they depend do not involve the level of  $\mu(0)$ . Channel 1 persists because WTP and abatement both remain increasing in  $\alpha_i$ . Marginal distortions continue to reduce the WTP response to fuel price instruments ( $\partial \widetilde{wtp}_i / \partial \tau < \partial wtp_i / \partial \tau$ ). The envelope theorem and the inequality  $\tilde{x}^* < x^*$  both hold whenever  $\pi' > 0$ , regardless of  $\mu(0)$ . The social planner’s result remains unchanged because  $SV_i + p = \widetilde{wtp}_i$  is independent of  $\mu(0)$ . Equation 3 depends on the adoption and usage conditions and the Lagrangian, none of which involve  $\mu(0)$ . These results are derived more formally in Section IV.4.

**Negative correlation between private and social benefits** When WTP and abatement are negatively correlated, distortions push low-externality agents below the threshold, reversing the mechanism of channel 1 (for example as in Aspelund and Russo, 2026). For example, suppose the dirty fuel is cheaper than the clean fuel: then WTP is *decreasing* in  $\alpha_i$  (high-taste agents incur large fuel premiums) while abatement remains increasing in  $\alpha_i$  for interior agents. Agents who value adoption most generate the *least* abatement, while agents who would abate the most have the lowest WTP. In the EV example, status buyers who rarely drive might adopt first, but habitual commuters who would displace the most gasoline are loath to adopt. Channel 1 now works *against* fixed cost subsidies: a subsidy that brings excluded agents back into the adopter pool reaches marginal adopters who generate less abatement per dollar than they would absent the distortion (Figure A1). Channel 2 (increased demand elasticity) still operates, so which channel dominates is an empirical question. Section IV.4 discusses these mechanisms more formally and offers additional implications. The counterfactual estimation in Section 8 examines this in our context.

In undistorted markets, a positive correlation can generate advantageous selection into the market resulting in adverse selection into who remains marginal to the subsidy, lowering the benefit of subsidies (as in Chen, Ryan, and Xu, 2025). The presence of a demand distortion reverses this effect, with the positive correlation now increasing the marginal externality.

**Standards and bans** Standards and bans are common alternatives to the direct pricing of externalities (Fowlie, Reguant, and Ryan, 2020; Goulder and Parry, 2008), and can be more efficient than taxes when customers misperceive energy costs (Houde and Myers, 2025). Kenya has promoted the adoption of energy-efficient lighting through CFL distribution programs and standards (Kovacova, 2026; Wambui, 2010), and is now one of Africa’s largest LED markets (IMARC Group, 2025).

In the context of cooking such policies face political and enforcement hurdles. Much of Kenya’s charcoal-related deforestation is informal, and national logging bans have been largely ineffective due to enforcement gaps (Sola and Cerutti, 2021; Daghar, 2021). Traditional cookstoves are often

produced locally and thus suffer from similar enforcement constraints. Given widespread informality in the charcoal and stove sectors, bans or standards likely require inefficiently costly enforcement.

**Open questions** Future research could explore a range of model extensions. The model above could accommodate a budget neutral policy if environmental tax revenues must be earmarked for an accompanying environmental subsidy, leveraging the inelastic response to a marginal tax to fund a fixed cost subsidy. Heterogeneity in  $\gamma$  across agents could shift the optimal instrument mix towards marginal pricing as this increases targeting on the externality (the counterfactual estimation in [Section 8](#) assumes  $\gamma_i$  are distributed logit-normally). Solving explicitly for the optimal instrument mix  $s_1^*, s_2^*, \tau^*$  as a function of  $\gamma$  could offer a threshold at which the distortions get sufficiently large at which point marginal pricing alone is no longer optimal. Loss aversion could play a role if agents weight losses (taxes) more than gains (subsidies): extensions could explore the efficacy of carbon taxes under distortions and estimate how large this asymmetry would need to be to generate the marginal distortions observed in many papers studying marginal subsidies (including ours).

## 4 Study setting and experimental design

Low- and middle-income countries are home to billions of people who lack modern cooking technologies (World Bank, [2020](#)). Across Africa 73% of households (more than 1 billion people) use charcoal or firewood as their primary cooking fuel ([Table A7](#)). Given steady population growth across Africa, projections forecast approximately one billion people across Africa to still be cooking with biomass as their primary cooking fuel in 2050 (IEA, [2025](#)). At the same time, in the past two decades more than 2 billion people have gained access to electricity (World Bank, [2024](#)). The rapid rise of household electricity access combined with the persistent use of biomass fuel for cooking has generated widespread policy interest in ‘leapfrogging’ populations towards electric cookstoves. Per the Organization of the Petroleum Exporting Countries (OPEC) Fund for International Development, “most specialists agree that electric cooking from renewable energy sources remains the ideal solution over the longer term” (OPEC, [2024](#)).

### 4.1 Setting

East Africa is at the forefront of the global push towards electric cooking. 65% of Kenyan households use wood or charcoal as their primary cooking fuel ([Table A7](#)). The most common biomass stove in Kenya is a *jiko*, shown on the left in [Figure 5](#). As a back-of-the-envelope calculation, at baseline respondents use on average 3.1 kilograms of charcoal per day, the production and burning of which emits approximately 4.9 tCO<sub>2e</sub> per year ([Table 1](#) presents these and additional household statistics; [Section 4.6](#) discusses the conversion from kilograms of charcoal to tons of CO<sub>2e</sub> emitted). This is roughly the same as the annual emissions of residential gasoline vehicles: the average U.S. household drives a gasoline vehicle 11,500 miles per year at 22.2 miles per gallon of gasoline, emitting 8.9 kilograms of CO<sub>2</sub> per gallon or 4.6 tons of CO<sub>2</sub> per year (EPA, [2025](#)).

To mitigate the negative externalities associated with charcoal production and to stimulate revenue for the financially distressed electric utility, in 2023 Kenya’s national electricity distribution launched the "Pika na Power" (“cook with electricity”) program. It aims to increase uptake of electric cooking “to 5% (500,000 customers) in the short term and to 10% in the medium term” (Kenya Power, 2023). The Kenyan government’s “National Electric Cooking Strategy Action Plan” (Ministry of Energy, 2024b) announced several programs to incentivize electric cooking, including VAT waivers for new electric appliances, behavior change campaigns, expanded support for consumer financing, investments in grid capacity and reliability. This also included a lower ‘e-cooking’ electricity tariff for customers consuming between 31-100kWh per month designed to make electric cooking more attractive relative to LPG and biomass stoves. Electric cooking is a particularly effective climate mitigation strategy given the low average emissions of many African grids. In 2023, 45% of Kenya’s annual on-grid electricity generation was geothermal, 19% was hydroelectric, 17% was wind power, and 3% was solar power (Kenya Power, 2023).

Other East African countries are on similar paths. Uganda’s 2022 Nationally Determined Contribution (NDC) was for “electricity to reach 50% of cooking fuel share by 2025”, including “decreasing the share of biomass energy used for cooking from 88% at baseline to 40% in 2030” (Republic of Uganda, 2022). In 2021, Tanzania adopted a National Environmental Policy stating that “the government shall promote affordable, accessible and reliable alternative energy to charcoal and firewood so as to reduce wood-biomass energy dependency” (Republic of Tanzania, 2021).

## 4.2 The ECOA induction stove

We study the induction stove manufactured by ECOA (formerly Burn Manufacturing) shown on the right in Figure 5. Stoves are manufactured at their factory in Ruiru outside Nairobi, Kenya. Purchase of an induction stove also includes one pot, allowing the buyer to continue using their old pot on their old charcoal stove if they wish (‘stacking’), for example during a power outage or because some foods taste better when cooked on charcoal. The induction stove has a power rating of 200W–2000W depending on the desired functionality (from low simmer to high boil) and a voltage rating of 240–250VAC and 50–60Hz.

At the time of our study launch in August 2025, more than 50,000 induction stoves had been sold, primarily through women’s group and pilot programs implemented through their sales agent programs in Tanzania and Kenya. That said, as the stoves were not yet commercially available, our study population was generally not familiar with the product.

We estimate the expected lifetime of the stove by applying a Cox proportional hazard model to the 23,444 stoves that had been sold on or before December 31, 2024.<sup>7</sup> Using this method, the median ECOA induction stove has a lifespan of 1.9 years (Figure B2 shows the survival curve).

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<sup>7</sup>The time variable is the number of days between first usage and last usage. A breakage event is the last observed usage if that usage happened more than 3 months before the end of our dataset.

Figure 5: Charcoal stove and induction stove



*Notes:* On the left is a charcoal stove instrumented with a high-frequency temperature sensor. On the right is the induction stove we study with the two pots and the frying pan that are included in the purchase bundle.

**The marginal cost of using the stove** Domestic residential customers in Kenya face an increasing block tariff. At the start of our study, customers consuming on average less than 30 kWh per month paid US\$0.166 per kWh, customers consuming on average between 30–100 kWh per month paid US\$0.20 per kWh, and customers consuming on average more than 100 kWh per month paid US\$0.22 per kWh.<sup>8</sup> In our sample, 86% consume less than 30 kWh per month and 99% consume less than 100 kWh per month; since bands can change, to minimize error we use the lowest tariff band in our calculations.

**The fixed cost of buying the stove** At the time of the study, the stove with one pot was priced at US\$72 in Kenya, with additional pots available for purchase separately. During the study, we offer participants a bundle consisting of the stove plus three pots, which had a marginal cost of US\$82.

**Buying the stove on credit** Subject to a small number of eligibility criteria (such as presentation of a national identification card and registration of a next of kin), anyone who wanted to buy the stove in installments was eligible to do so. The company uses many of the sophisticated credit technologies that have been developed in recent years to help address widespread credit market failures. Customers can choose whether to pay using monthly, weekly or even daily deadlines depending on what would best facilitate their repayment. In the lead-up to each payment deadline, participants who have not yet paid receive SMS reminders. Delinquent accounts are manually checked and followed-up with by a dedicated agent team (BURN Manufacturing, 2023). If the customer does not make the required payment within seven days, the device is remotely turned off and only turned back on once the owner makes the payment (a ‘digital collateral’ practice that is standard in East Africa; see Gertler, Green, and Wolfram, 2024). If after 14 days the owner

<sup>8</sup>Kenya’s electricity tariff has a fixed component as well as a floating component that is pegged to international fuel prices and changes monthly. There were no changes in the fixed component over the study duration. The total price per kWh for customers consuming on average more than 100 kWh per month fluctuated between US\$0.2129 and US\$0.2219 over the eight month study duration.

has still not made the required payment, the agent visits the respondent in the field to either restructure the loan (if non-payment is due to unforeseen circumstances) or, if needed, to repossess the device. To cover the cost of these sophisticated procedures, buyers paying in installments must pay back 175% of the amount they borrowed. For those paying on a monthly plan, an initial down payment of US\$15 would be followed by six monthly payments of US\$19 each for a total price of US\$132. Respondents could repay their loans early if they wished, but this would not reduce the total payment amount. The payment structure corresponds to an effective annualized percentage rate (APR) of 224%, which is 215% above Kenya’s central bank rate of 9.75% during the experiment (Central Bank of Kenya, 2026).<sup>9</sup>

### 4.3 Implementation

Study enumerators recruited 2,511 people into the study residing in the urban and peri-urban areas around the cities of Naivasha, Gilgil, and Nakuru in Nakuru county in Kenya. Respondents were enrolled by enumerators walking around the study areas. To be eligible for study participation, participants had to spend at least half of their cooking fuel expenditures on charcoal for a standard Kenyan stove, shown on the left in [Figure 5](#). They also had to be at least 18 years of age, have a pre-paid Kenya Power electricity meter in their homes, have a household size of at least 3 individuals, have basic literacy skills, spend at least US\$4 per week on charcoal, and not currently own an electric or energy efficient charcoal stove.

Respondents were visited up to four times. During the baseline survey enumerators completed a short survey consisting of demographic and socioeconomic questions. 2,134 respondents completed the main survey, which was conducted around 50 days after the baseline visit (attrition of enrolled participants occurred prior to randomization or adoption decisions, attrition at this stage should not affect outcomes). During the main survey the enumerators implemented the random treatments, provided (randomized) information about the induction stove, and elicited willingness-to-pay (WTP). All respondents were given the opportunity to buy the induction stove shown in [Figure 5](#) at this time, which also included three pieces of induction cookware (two pots and one frying pan). An endline survey was conducted 40 days after the main survey visit.<sup>10</sup> Finally, enumerators visited respondents around 180 days after the initial sensor deployment to download temperature data. [Figure A2](#) presents a more detailed study timeline.

The sections below describe the randomized treatments and the data collection in more detail. [Table 1](#) presents summary statistics collected during the baseline survey for participants who also subsequently participated in the main study.

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<sup>9</sup>For comparison, in 2025 U.S. auto loans had an average interest rate of 6.8% for new vehicles and 11.5% for used vehicles (Experian, 2025).

<sup>10</sup>Attrition is balanced by random treatment assignment ([Table B4](#)). Stove adopters are 2.2 percentage points less likely to attrit ([Table B4](#)). 68% of attriters had moved outside the study area ([Table B5](#)).

Table 1: Summary statistics from respondent surveys at baseline

|                                                           | Mean  | SD    | 25 <sup>th</sup> | 50 <sup>th</sup> | 75 <sup>th</sup> | N    |
|-----------------------------------------------------------|-------|-------|------------------|------------------|------------------|------|
| Number of residents                                       | 5.0   | 1.7   | 4                | 5                | 6                | 2134 |
| Age                                                       | 35.8  | 10.1  | 28               | 35               | 42               | 2134 |
| Male (=1)                                                 | 0.1   | 0.3   | 0                | 0                | 0                | 2134 |
| Charcoal cooking time (minutes/day)                       | 186.0 | 71.1  | 140              | 180              | 220              | 2134 |
| Daily charcoal usage (KG per day)                         | 3.1   | 1.0   | 2                | 3                | 4                | 2134 |
| Number of charcoal stoves                                 | 1.1   | 0.3   | 1                | 1                | 1                | 2134 |
| Charcoal spending (USD/month)                             | 19.4  | 6.2   | 14               | 16               | 23               | 2134 |
| Annual emissions from charcoal usage (tCO <sub>2e</sub> ) | 4.9   | 1.5   | 3                | 4                | 6                | 2134 |
| Number of LPG stoves                                      | 0.6   | 0.6   | 0                | 1                | 1                | 2126 |
| LPG spending (USD/month)                                  | 9.1   | 12.0  | 8                | 8                | 9                | 1228 |
| Annual emissions from LPG usage (tCO <sub>2e</sub> )      | 0.3   | 0.4   | 0                | 0                | 0                | 1228 |
| Number of wood stoves                                     | 0.1   | 0.4   | 0                | 0                | 0                | 2134 |
| Wood spending (USD/month)                                 | 4.3   | 3.1   | 2                | 3                | 6                | 301  |
| Respondent income (USD/month)                             | 101.5 | 115.3 | 46               | 69               | 116              | 2127 |
| Household income (USD/month)                              | 246.9 | 204.8 | 116              | 196              | 300              | 1815 |
| Monthly rent paid by household (30d; USD)                 | 24.4  | 16.6  | 15               | 23               | 31               | 1797 |
| Max willing to pay if phone broke (USD)                   | 32.9  | 38.9  | 8                | 12               | 46               | 2134 |
| Hours of power outage (30d)                               | 13.9  | 27.5  | 1                | 4                | 12               | 2134 |
| Hours of voltage fluctuation (30d)                        | 2.0   | 10.9  | 0                | 0                | 1                | 2134 |

*Notes:* Mean, standard deviation, and 25<sup>th</sup>, 50<sup>th</sup>, 75<sup>th</sup> for key socio-economic variables collected during the baseline survey. 31% of participants who use wood report getting some (or all) of their monthly wood consumption for free; rather than noisily estimate emissions, we omit CO<sub>2e</sub> emissions from direct firewood burning from our calculations (if anything, this likely underestimates total CO<sub>2e</sub> abatement from electric stove adoption and understates aggregate subsidy efficiency).

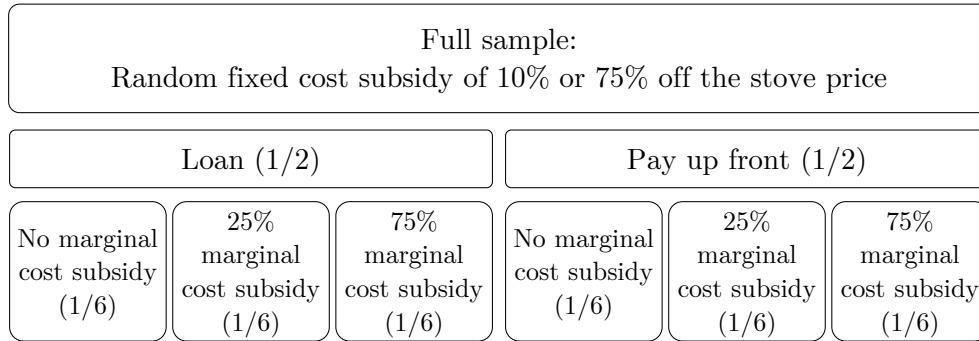
#### 4.4 Randomized treatments

Between the baseline and main surveys, each respondent is assigned to several randomized treatments, as shown in [Figure 6](#). All treatments are fully cross-randomized and stratified on each other. All treatment assignments are furthermore stratified by baseline LPG ownership, baseline electricity expenditure, and baseline charcoal expenditure. Treatment assignment is balanced on observable baseline characteristics ([Table B1](#)).

**Fixed cost subsidy** Participants were cross-randomized into different subsidy amounts for the fixed cost of buying the induction stove bundle (including the two pots and frying pan, shown in [Figure 5](#)), which had a marginal production cost of US\$82 at the time of the experiment. 49% of participants received a discount of 10% (for a price of US\$73) and 46% received a discount of 75% (for a price of US\$20).<sup>11</sup>

<sup>11</sup>The remainder of participants had discounts of 46% (0.2% of participants), 50% (2.5%), or 69% (1.8%). All prices had positive probability of being selected from the feasible range of US\$20 (since a down payment of \$12 was

Figure 6: Randomized treatments



*Notes:* Random assignment for the 2,134 study participants. To preserve incentive-compatibility, 4% of the sample received a different subsidy between 10% and 75%. [Section 4.4](#) discusses the randomized treatments in more detail.

**Marginal cost subsidy** Participants in the usage subsidy treatment groups receive a subsidy on the cost of the electricity that is used to operate the induction stove. During the main visit, prior to the WTP elicitation, respondents in the treatment groups are told that they would receive this subsidy, and the level they were assigned. They are informed that only electricity used by the electric stove is subsidized; they do not receive any subsidies on electricity used for other purposes. One-third of participants do not receive a marginal cost subsidy, one-third receive a subsidy of 25%, and one-third receive a subsidy of 75%. For a sense of magnitude, given ex post realized stove usage rates of on average 13 kWh per month at a tariff of US\$0.166, total marginal cost subsidy payouts over the six month subsidy period averaged US\$3.3 and US\$9.9 for respondents in the 25% and 75% subsidy groups, respectively.

All respondents have pre-paid electricity meters, which is the norm in Kenya and across many African utilities.<sup>12</sup> Consuming electricity runs down the meter: a customer must periodically ‘top up’ their meter to avoid it reaching zero (at which point electricity gets shut off).<sup>13</sup> They can do so by purchasing a unique 20-digit token code either at a kiosk or via the Kenya Power mobile application, and then manually entering this code on their meter. We implement electricity transfers through this same channel: the research team collects respondents’ account numbers to purchase electricity tokens on their behalf, and then sends customers the 20-digit token code via SMS, which they then enter manually into their meter. The code is unique to the meter and cannot be transferred, sold, or returned. We process electric stove usage data, calculate subsidy amounts, and send respondents token codes on a weekly basis. For comparison, the median respondent in our sample purchases electricity four times per month, or once every 7.5 days, suggesting our implementation matches respondents’ own purchasing habits.

On the one hand, the manual entry of tokens could add an additional hurdle that lowers the

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required by the stove firm) to US\$73 (for ethical reasons all study participants received a discount of at least 10%).

<sup>12</sup>87% of all Kenyan residential electricity customers have pre-paid meters, and 95% of all residential customers who were connected since 2015—which includes most low-income connected households—do.

<sup>13</sup>For 59% of our sample this had not happened in the past month. For 31% it had happened once or twice in the past month.

value of marginal cost subsidies. On the other hand, it could make the transfer more salient than an automatic bill rebate. Rather than trying to bound these opposing forces, we only note that the utility recently used this same method of token transfers to implement a subsidy pilot study.<sup>14</sup> Our implementation methodology thus reflects the realistic implementation of such a program by the electric utility and the empirical estimates can be interpreted as policy relevant.

**Payment structure** Participants in the ‘pay up front’ group had to pay the full (randomly assigned) price during the main visit. Participants in the ‘loan’ group had to pay a down payment of US\$12 during the main visit.<sup>15</sup> One half of participants were randomly assigned to pay up front and one half to pay with a loan.

For those paying with a loan, starting one month after the purchase date ( $t = 31$ ) the amount due would increase by the daily installment amount for the 90 subsequent days. Respondents could pay early but this would not reduce the total amount owed. If a respondent did not meet the amount due by a particular date, the stove would shut off until they make another daily payment, at which the new amount due stream is calibrated to the new payment date.

**Information treatment** All respondents receive an information sheet that shows what meals can be cooked with a charcoal stove and an information sheet that shows what meals can be cooked with an electric stove (Figure A3). Participants in the information treatment group receive two information sheets about the cost of the electricity used to cook various meals on an induction stove, as well as the cost of the charcoal used to cook those same meals on a charcoal stove. For participants in the usage subsidy groups, the information sheets show prices both with and without the subsidy amounts. 14% of participants are assigned to the information control group and 86% are assigned to the information treatment group.

## 4.5 Data collection

During the baseline visit and the endline visit, enumerators conducted a socio-economic survey aimed primarily at measuring fuel expenditures. The survey specifically asked about the ownership of cookstoves with different fuel types, including charcoal, wood, electricity, and liquefied petroleum gas (LPG) or liquid bioethanol fuel. During the main visit, they measured beliefs and WTP.

During the baseline visit, enumerators also installed charcoal stove monitors that continuously collected temperature data throughout the study period. The continuous collection of induction stove usage and loan repayment data began after the main visit. Figure A2 presents a more detailed timeline of data collection activities.

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<sup>14</sup>Kenya Power’s e-cooking tariff development study states that “Rebates are provided as electricity tokens sent via SMS to pre-paid customers” (Ministry of Energy, 2024a).

<sup>15</sup>On the first two days of surveying, September 23 and 24, a down payment of \$20 was used due to a miscommunication with the study partner. The exclusion of surveys collected on these days (which comprise 5% of the sample) does not meaningfully affect outcomes.

**Charcoal stove usage** During the baseline visit, enumerators install temperature sensors to monitor usage of households’ charcoal stoves. The sensors record a temperature measurement once every two minutes and store this on a local memory card that we download once per month. For households who owned two or more charcoal stoves at baseline, we installed monitoring devices on all stoves that were less than three years old (older stoves than this often caused the device to malfunction). The temperature sensors are drilled into the stove and securely fastened without damaging the functionality of the stove. [Figure 5](#) shows a charcoal stove instrumented with a temperature sensor. The installation occurs during the baseline visit such that we are able to estimate a within-individual treatment effect. Prior research has found minimal Hawthorne effects from electronic stove monitoring;<sup>16</sup> still, any Hawthorne effect resulting from the installation of stove sensors would be symmetric across treatment groups.

We develop a basic algorithm to convert the 2-minute temperature series to a 2-minute cooking dataset, which we then aggregate to the hourly level for the analyses ([Figure B1](#) shows several example household-days of data). Specifically, an observation is marked as ‘cooking’ if the temperature is above 40°C, or increased by more than 1°C since the previous observation for at least two observations in a row, but not if the stove is cooling rapidly for two observations in a row and has passed the midway point between the maximum and minimum temperatures.

**Willingness-to-pay** We measure Willingness-to-pay (WTP) using the Becker, DeGroot, and Marschak (1964) mechanism, building on the implementations developed in Berry, Fischer, and Guiteras (2020), Dean (2024), and Berkouwer and Dean (2022). Neither the respondent nor the enumerator know the respondent’s randomly assigned price. The enumerator conducts a binary search over the range of Ksh 1,500 to Ksh 18,000 (US\$12 to US\$139), first asking “*If the price of the ECOA is Ksh 9,792 [US\$76] would you want to buy it?*”, then proceeding to a higher or lower price based on the respondent’s answer, and repeating this process until arriving to the nearest Ksh 10 (US\$0.08). After arriving at a final WTP, the envelope is opened and the respondent buys the stove for the price in the envelope if and only if it is less than or equal to their WTP. Since the price is fixed ex ante, the mechanism is incentive compatible. Since upfront prices are randomly assigned, purchasing is random conditional on WTP within the support of random prices. Practice randomized BDM and take-it-or-leave-it (TIOLI) elicitation result in similar estimates.

Crucially, respondents with a WTP between the minimum and maximum of the support of random prices are the adopters for whom the instrumental variables (IV) approach estimates the local average treatment effect (LATE) of purchasing a stove. These same respondents are defined as marginal (or ‘additional’) adopters in the subsidy efficacy calculations, as they would buy the stove if and only if there was a subsidy. The fact that these groups are naturally equivalent allows us to conduct several relevant policy calculations.

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<sup>16</sup>For example, in a randomized trial of improved cookstoves in Rwanda, Thomas et al. (2016) randomly assigned respondents to have a monitor installed in either a visible or hidden part of the cookstove. The visible monitor increases usage by 6% in the first week but causes no difference in cooking behavior from week two onwards.

**Induction stove usage** The electric stoves record power usage in kilowatt-hours (kWh) on a 15-minute interval basis. This is transmitted to remote servers in real-time via a continuous wireless connection. This enables the seller to disconnect the stove in case of non-payment, and—crucially for our study—allows us to subsidize only electricity used for the induction stove. The household surveys also record self-reported measures of electricity spending, which we convert to usage using the marginal tariff relevant for most customers, which is US\$0.166 per kWh.

**Market price survey** We collect a panel dataset of charcoal prices by conducting market surveys over the course of the experiment across all three cities. This allows us to convert household charcoal expenditure data to kilograms of charcoal purchases.

#### 4.6 Converting energy usage to CO<sub>2</sub>e emissions

**Charcoal** We assume a fraction of non-renewable biomass (fNRB) of 38% reflecting the most recent Modeling Fuelwood Savings Scenarios (MoFuSS) estimates for Kenya (Ghilardi and Bailis, 2024; UNFCCC, 2023). Still, our conclusions and results are relatively stable even when assuming an fNRB of 10% or 100% (Section 9.1).

We use estimates of combustion emissions and non-combustion (production and processing) emissions of CO<sub>2</sub>, CH<sub>4</sub> and N<sub>2</sub>O from Floess et al. (2023). We convert this to total CO<sub>2</sub>-equivalent emissions assuming a 50-year time horizon. This results in an emissions factor of 161 tCO<sub>2</sub>e per terajoule, consisting of 36 tons of combustion CO<sub>2</sub>e and 124 tons of non-combustion CO<sub>2</sub>e (Gill-Wiehl, Kammen, and Haya, 2024; Whitman and Lehmann, 2011). With a calorific value of 0.027 terajoules per ton of charcoal, this yields an estimated 4.3 kilograms of CO<sub>2</sub>e per kilogram of charcoal.<sup>17</sup> Sample average household usage of 3.1 kilograms of charcoal per day thus emits 4.9 tCO<sub>2</sub>e per year.

**Electricity** Renewable sources of energy (primarily geothermal, hydropower, and wind) generate 85% of Kenya’s annual grid electricity (Kenya Power, 2023). While Kenya Power meets short-term demand increases with fossil fuels, almost all capacity expansions in recent years have been renewable. When considering the electrification of the cooking sector as a whole, Kenya’s average grid emissions are therefore a reasonably representative margin. To convert the remaining 15% of generation (primarily relatively dirty coal) to CO<sub>2</sub>e emissions we conservatively assume an emissions factor of 1 tCO<sub>2</sub>e per MWh of electricity, resulting in an average emissions intensity of 154 gCO<sub>2</sub>e per kWh. We also report outcomes if Kenya’s grid had the average emissions intensity of the U.S. grid, which is approximately 366 grams of CO<sub>2</sub>e per kWh (EIA, 2024).

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<sup>17</sup>Intuitively, the mass of oxygen is approximately 16 g/mol and the mass of carbon (which charcoal largely consists of) is approximately 12 g/mol. Each carbon atom combines with two oxygen atoms to generate CO<sub>2</sub> such that 12 grams of charcoal generates 44 grams of CO<sub>2</sub>, or 3.7 kilograms CO<sub>2</sub> per kilogram of charcoal. However, this does not factor in production, processing, and transportation; the purity of charcoal in East Africa (it does not consist exclusively of carbon); nor reforestation rates, and is thus a more naive approximation.

**Liquefied Petroleum Gas** We convert LPG expenditures to cylinders purchased using local prices, and convert cylinders to CO<sub>2e</sub> emissions using a conversion ratio of 4.6 kilograms of CO<sub>2e</sub> per kilogram of LPG refill.<sup>18</sup>

**Firewood** 17% of households report ever using firewood to cook. Because we do not track the quantity of wood collected nor firewood prices, we refrain from estimating the CO<sub>2e</sub> abatement resulting from a reduction in the use of firewood for cooking. As a result, the abatement and cost estimates are if anything conservative.

## 5 Private and social impacts of electric stoves

Of the 2,134 respondents who successfully completed the main visit, 626 (29%) bought the induction stove. Since stove purchasing itself was not randomly assigned, we use an instrumental variables (IV) approach to estimate the causal impacts of an induction stove purchase on private and social outcomes. Regressions use the randomly assigned subsidy, the randomly assigned loan access, and their interaction as instruments for adoption, which consistently yields an  $F$ -statistic above 40. 56% of respondents with a high subsidy and access to a loan bought the stove, whereas 1% of respondents with a low subsidy and paying up front bought the stove.<sup>19</sup>

### 5.1 Charcoal stove usage

We convert the temperature data collected by the Stove Use Monitors (SUMs) to an hourly panel dataset of cooking time by respondent, spanning from 45 minutes before and 90 days after the main visit. We then estimate how induction stove adoption affects this measure of cooking time.

Figure 7 estimates separate coefficients of the daily difference between adopters and non-adopters from 45 days before the main visit until 90 days after the main visit. Standard errors are clustered by respondent. Column 1 of panel a in Table 2 shows that daily time spent cooking using a charcoal stove, as measured by the Stove Use Monitors (SUMs), decreases by 31 minutes per day (Table A1 shows additional robustness checks). This corresponds to a 34% reduction in daily cooking time caused by adoption of the electric stove.

### 5.2 Energy expenditures

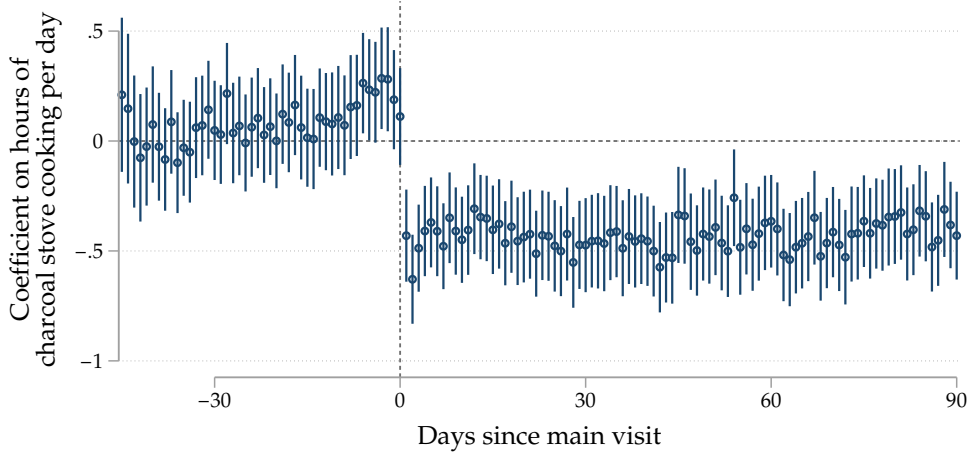
Table 2 presents estimates of the causal effect of stove adoption on energy expenditures. Self-reported monthly charcoal expenditures, shown in Column 2 of panel a, decrease by US\$10 (66%). Using the methodology described in Section 4.6, this reduction in charcoal usage corresponds to emissions abatement of 2.5 tCO<sub>2e</sub> per year.

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<sup>18</sup>One refill of a 6 kg canister of LPG in East Africa emits 27.8 kg CO<sub>2e</sub>, or 4.6 kg CO<sub>2e</sub> per kg LPG (USAID, 2021). This includes 3.0 kg CO<sub>2e</sub> during combustion, 1.2 kg CO<sub>2e</sub> during production, and 0.4 kg CO<sub>2e</sub> during transport and raw materials production. A typical 6 kg LPG canister in Kenya costs approximately Ksh 1,400.

<sup>19</sup>23% of respondents with a low subsidy and access to a loan bought the stove. 39% of respondents with a high subsidy but no access to a loan bought the stove.

Figure 7: Charcoal stove usage from Stove Use Monitors



*Notes:* Coefficients from a fixed effects regression using hourly data in which the outcome variable is the fraction of that hour the respondent was cooking (derived from the temperature data using the detection algorithm described in Section 4.5), multiplied by 24 for ease of interpretation. The regression includes date, event date, and hour of day fixed effects. Standard errors are clustered by respondent. Estimates from regressions with data collapsed to pre- and post-period differences in Table A1.

This estimate is an average measure across all buyers that are compliers in the instrumental variables approach. Thus, it factors in behaviors like ‘stacking’ (where households continue to use their old stoves) as well as households choosing not to use their stoves. Without those behaviors, the estimated CO<sub>2e</sub> reduction would likely have been higher.

Columns 5 and 6 show that self-reported monthly electricity expenditures increase by US\$2.3 (65%) per month.<sup>20</sup> This is very close to the value of the induction stoves’ average consumption of 13 kWh per month, which equates to US\$2.2 per month at the Kenya Power tariff of US\$0.166 per kWh. There are additional, smaller decreases in wood and LPG expenditure. Aggregate monthly energy expenditures decrease by US\$8.9 (36%). Assuming a 10% annual discount rate, this corresponds to US\$184 over the 1.9 year lifetime of the stove.

At the time of the study, the market price of the stove was US\$82. At this price, the savings generate an annual return on investment (ROI) of 112% after 1.9 years. When paying with the commercial installment plan described in Section 4.2, the total price was US\$132, with a 70% ROI.

However, while this ROI is positive and substantial, the commercial plan required six monthly payments of US\$19, more than twice the monthly savings that we estimate. The 224% equivalent APR of this loan exceeds the stove’s 112% rate of return. For most households, the monthly energy savings are thus not sufficient to cover the monthly repayment requirements, rendering adoption with credit prohibitively expensive despite the large savings. For comparison, the high and low subsidy pay plans offered in the experiment required three monthly payments of US\$3 and US\$21, respectively.

<sup>20</sup>To address the confounding effect of the electricity subsidies, Column 5 defines total electricity spending as self-reported electricity spending plus subsidy receipts. Column 6 estimates self-reported electricity spending among the subsidy control group.

Table 2: Impact of induction stove purchase (instrumental variables)

## (a) Energy usage

|                             | Hours per<br>day cooking<br>with charcoal | Monthly expenditures (USD) |                 |                 |                   |                   | Total              |
|-----------------------------|-------------------------------------------|----------------------------|-----------------|-----------------|-------------------|-------------------|--------------------|
|                             |                                           | Charcoal                   | LPG             | Wood            | Electricity       |                   |                    |
|                             | (1)                                       | (2)                        | (3)             | (4)             | (5)               | (6)               | (7)                |
| Bought induction stove (=1) | -0.52***<br>(0.16)                        | -10.01***<br>(0.82)        | -0.85<br>(0.56) | -0.33<br>(0.21) | 2.30***<br>(0.38) | 2.18***<br>(0.66) | -8.89***<br>(1.06) |
| Observations                | 5301720                                   | 2081                       | 2081            | 2081            | 2081              | 703               | 2081               |
| Control Mean                | 1.52                                      | 15.11                      | 5.52            | 0.74            | 3.51              | 0.33              | 24.89              |
| F-Stat                      |                                           | 241.34                     | 241.34          | 241.34          | 241.34            | 45.32             | 241.34             |

(b) Emissions (tons of CO<sub>2</sub>e per year)

|                             | Charcoal           | LPG             | Electricity       | Total              |
|-----------------------------|--------------------|-----------------|-------------------|--------------------|
|                             | (1)                | (2)             | (3)               | (4)                |
| Bought induction stove (=1) | -2.53***<br>(0.20) | -0.03<br>(0.02) | 0.02***<br>(0.00) | -2.53***<br>(0.20) |
| Observations                | 2081               | 2081            | 2081              | 2081               |
| Control Mean                | 3.77               | 0.17            | 0.04              | 3.99               |
| F-Stat                      | 122.03             | 122.03          | 122.03            | 122.03             |

*Notes:* Instrumental variables estimates use the randomized treatment price, the randomized credit condition, and their interaction as exogenous instruments. LPG is liquefied petroleum gas. Panel a shows the impact of induction stove purchasing on daily cooking and monthly energy expenditures. Column 1 uses hourly SUMS data (standard errors clustered by respondent and by date). Column 5 adds subsidies to electricity expenditure, Column 6 estimates among subsidy control group. Panel b shows the impact on emissions. [Section 4.6](#) describes the methodology for converting energy expenditures to emissions. ‘Control mean’ evaluated among non-adopters in the complier sample.

### 5.3 Emissions

We convert energy expenditures to CO<sub>2</sub>e emissions using the methodology described in [Section 4.6](#). Panel b of [Table 2](#) shows an annual emissions reduction of 2.5 tCO<sub>2</sub>e. This effectively entirely reflects the reduction in charcoal-related emissions, since the modest increase in electricity-related emissions is offset by a modest decrease in LPG-related emissions (we do not quantify fuelwood reductions).<sup>21</sup> While electricity expenditures constitute approximately 36% of total household energy expenditure among those who bought the stove, they constitute less than 3% of their baseline household emissions.<sup>22</sup> The increase in electricity usage thus generates a negligible increase in grid emissions of 0.02 tCO<sub>2</sub>e per year. For comparison, emissions from charcoal cooking average 4.9 tCO<sub>2</sub>e per year (250 times more) and from LPG cooking average 0.3 tCO<sub>2</sub>e per year (15 times more) ([Table 1](#)). Induction stoves are highly efficient in converting energy to heat.

The low emissions from induction stove cooking in this context also result in part from Kenya’s

<sup>21</sup>Due to uncertainty in its origin, we refrain from converting the reduction in firewood usage to CO<sub>2</sub>e emissions: the aggregate emissions reduction is thus a lower bound.

<sup>22</sup>These numbers exclude transportation-related emissions or other emissions generated outside the home.

grid being 85% renewable. However, even when assuming U.S. average grid emissions, the emissions increase from electricity usage would only increase to 0.05 tCO<sub>2e</sub> per year, still well below the decrease in charcoal-related emissions.<sup>23</sup>

## 5.4 Other impacts

Induction stove adoption generates a 12 percentage point decrease in the fraction of people who cook ugali, mukimo, or matoke (three starch staples) and an 11 percentage point increase in the fraction of people who cook rice (Table B2). Anecdotally, rice is easier to cook on an electric stove than other starches. We observe no other meaningful changes in which foods people cook nor the number of unique foods they cook.

We see meaningful reductions in self-reported cough and breathlessness among respondents and their children (Table B3). In a similar context, Berkouwer and Dean (2026a) found that similar health improvements—while potentially important for welfare—did not generate benefits in terms of long term clinical health or economic outcomes like hours worked. While respondents almost never use a charcoal stove exclusively for space heating, this is a co-benefit of charcoal cooking and could thus reduce the welfare gain from electric stove adoption (Berkouwer and Dean, 2022).

These outcomes are important and valuable from the perspective of poverty reduction and welfare improvement. However, they only affect the cost of subsidies per ton of CO<sub>2e</sub> abated by moving WTP and usage directly, which our measurements already incorporate. They matter for a social planner whose decisions incorporate welfare gains such as these, however even then they remain difficult to quantify. We therefore refrain from trying to quantify them. Berkouwer and Dean (2026c) presents additional detail on the drivers and impacts of electric stove adoption that relate to health, socioeconomic status, and the electrical grid.

## 6 Green subsidy efficacy

### 6.1 Fixed cost subsidies

We first evaluate the subsidy cost of incentivizing a marginal adoption by leveraging the demand curve elicited through the BDM exercise (panel a of Figure 10). At baseline, the high price is the competitive market price minus a small subsidy  $p - s_l$ . A larger subsidy lowers the price further to  $p - s_h$ , such that  $0 \leq s_l < s_h$ . Denote  $\rho_l$  and  $\rho_h$  to be the fraction of individuals who would buy the stove with the low or high subsidy, respectively. The subsidy cost required to incentivize one additional adoption can then be denoted as follows:

$$C_s = \frac{\text{Additional subsidy cost}}{\text{Additional adoptions}} = \frac{\rho_h s_h - \rho_l s_l}{\rho_h - \rho_l} \quad (5)$$

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<sup>23</sup>As discussed in Section 4.6, average U.S. grid emissions are 366 gCO<sub>2e</sub>/kWh as opposed to Kenya’s 154 gCO<sub>2e</sub>/kWh. As a back of the envelope calculation: if people consume around 0.5 kWh per day, or 183 kWh per year, then at 366 gCO<sub>2e</sub>/kWh this would constitute 67 kgCO<sub>2e</sub> or 0.07 tCO<sub>2e</sub>.

In the context of this study, 40% of respondents would buy the stove with the high subsidy whereas 2.6% of respondents would buy the stove with the low subsidy. Applying Equation 5, it costs the principal US\$65 in subsidy expenditures to incentivize one additional adoption.

The cost per ton of CO<sub>2</sub>e abated can then be calculated by combining this with the average abatement per additional adoption. Marginal buyers of induction stoves in our context abate 2.6 tCO<sub>2</sub>e per year, or 5 tCO<sub>2</sub>e over the 1.9 year lifetime of the stove when not also being given access to a loan (Table 5).<sup>24</sup> This causal estimate from the instrumental variables (IV) regression was identified off of the compliers, who have a willingness-to-pay (WTP) between  $p - s_h = \text{US\$}20$  and  $p - s_l = \text{US\$}73$  and thus correspond exactly to adopters who are marginal to an increase in the subsidy from  $s_l$  to  $s_h$ .

We evaluate four different costs per ton that might be relevant to different companies, policy-makers, or organizations depending on their goals: subsidy cost per ton of CO<sub>2</sub>e, economic cost per ton of CO<sub>2</sub>e, marginal value of public funds, and abatement per stove sold.

**Subsidy cost per ton of CO<sub>2</sub>e** Consider an environmental principal who wishes to maximize CO<sub>2</sub>e abatement while minimizing subsidy expenditure (referred to as the ‘government cost per ton’ in Hahn et al., 2026). This could be a budget-constrained government agency or a cost-minimizing company or organization that wishes to meet an abatement target.

Given the estimated abatement per additional adoption  $\hat{\phi}$ , the additional subsidy expenditure required to abate one additional ton of CO<sub>2</sub>e is then given by:

$$\text{Subsidy cost per tCO}_2\text{e} = \frac{\text{Subsidy cost per additional adoption}}{\text{Abatement in tCO}_2\text{e per adoption}} = \frac{C_s}{\hat{\phi}} \quad (6)$$

Given that each additional adoption abates 5 tCO<sub>2</sub>e, subsidies for induction stoves in this context abate greenhouse gas emissions at a cost of US\$13 per tCO<sub>2</sub>e. This is a relatively low abatement cost compared to other technologies, as we discuss further below.

**Marginal Value of Public Funds** We evaluate the efficacy of green subsidies from the perspective of a social principal using the Hendren and Sprung-Keyser (2020) Marginal Value of Public Funds (MVPF) approach. Since willingness-to-pay is distorted and thus cannot be taken as a measure of private benefit, we calculate this directly as the sum of fuel savings plus the direct cash transfer, which is valued at US\$1. The MVPF is then given by:

$$\begin{aligned} \text{MVPF} &= \text{Cash transfer benefit of marginal subsidy} + \frac{\text{Stove adoption benefit of marginal subsidy}}{\text{Marginal subsidy cost per stove adoption}} \\ &= 1 + \frac{\hat{b} + \phi - p}{C_s} \end{aligned} \quad (7)$$

Each marginal adoption costs the principal  $C_s$  in subsidy expenditure and generates net energy savings of US\$200, abates 5 tCO<sub>2</sub>e, and incurs US\$82 in stove cost. This yields an MVPF of US\$2.8

<sup>24</sup>Section 9.1 quantifies subsidy costs under alternative assumptions, such as a 1-year or 3-year average lifetime.

when excluding environmental benefits and an MVPF of either US\$12, US\$20, or US\$29 per US\$1 of spending when using a Social Cost of Carbon (SCC) of US\$120, US\$230, or US\$340, respectively.<sup>25</sup>

**Economic cost per ton of CO<sub>2</sub>e** A social planner values the economic cost of producing each stove  $p$  and fuel savings  $\hat{b} = \pi'\hat{\theta}\hat{d}_2$  but disregards inframarginal transfers. They instead consider the economic cost of abatement, as follows:

$$\text{Economic cost per tCO}_2e = \frac{\text{Economic cost per adoption}}{\text{Abatement in tCO}_2e \text{ per adoption}} = \frac{p - \hat{b}}{\phi} \quad (8)$$

Column 8 of [Table 5](#) (multiplied by 23 months to reflect the stove’s 1.9 year expected lifespan, discounted 10% per year) shows US\$200 in total energy savings. Since this exceeds the US\$82 marginal cost of the stove, the economic cost per ton is *negative*: each cookstove will *save* on average US\$118 in economic resources in this context. Abating one ton of CO<sub>2</sub>e thus *reduces* total economic costs by US\$24.

**Abatement per stove sold** Finally, we consider a principal who wishes to contract on the total number of stoves sold. Under the high subsidy, 6.5% of stoves that are sold are not additional and would have been sold even with the low subsidy. Thus, while adoption of an additional stove causes abatement of 2.6 tons of CO<sub>2</sub>e per year, only 94% of sales are additional to a subsidy. Any single stove sale therefore abates 2.5 tCO<sub>2</sub>e per year in expectation, or 4.6 tCO<sub>2</sub>e if we assume a 1.9 year stove lifetime. This would be the relevant number to use for example when the principal contracts carbon credit issuances on aggregate sales.

These abatement costs are significantly lower than many other green technologies. Panel a of [Table 3](#) summarizes the abatement cost estimated in this paper as well as in other papers evaluating energy efficient technologies in contexts where adopters likely face significant demand distortions. Panel b lists estimates of green household technologies receiving subsidies in the U.S. By and large, subsidies for green technologies in low- and middle-income contexts generate larger social benefits per subsidy dollar spent than similar subsidies for green household technologies in high-income contexts.

These differences are partly driven by technological differences. Each US\$82 stove abates on average 2.5 tCO<sub>2</sub>e per year: for comparison, a US\$40,000 electric vehicle abates between 0.1–1.5 tCO<sub>2</sub>e per year relative to the counterfactual (Muehlegger and Rapson, 2023). However, even conditioning on technology, the channels identified in this paper—differences in the marginal adopter and the demand elasticity—drive increases in subsidy efficiency. [Section 7](#) first disentangles how the two channels contribute to subsidy efficiency. [Section 8](#) then estimates the model presented in [Section 3](#) to disentangle how much demand distortions per se reduce abatement costs relative to estimate from contexts with fewer demand distortions.

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<sup>25</sup>These SCC numbers reflect Environmental Protection Agency estimates using a 2.5%, 2%, or 1.5% discount rate, respectively (EPA, 2023).

Table 3: Efficiency of selected green subsidies

| Technology subsidized                      | MVPF<br>(US\$)   | Subsidy spend<br>per tCO <sub>2e</sub> abated<br>(US\$) | Source                                         |
|--------------------------------------------|------------------|---------------------------------------------------------|------------------------------------------------|
| <i>(a) Low- and middle-income contexts</i> |                  |                                                         |                                                |
| Electric stoves                            | 20               | 13                                                      | <i>This paper</i>                              |
| Solar lanterns                             | 13               | 10                                                      | Rom, Günther, and Pomeranz (2023)              |
| Energy efficient motors                    | 5.1              | <sup>a</sup>                                            | Chaurey et al. (2025)                          |
| Improved charcoal stoves                   | 323 <sup>b</sup> | 6                                                       | Berkouwer and Dean (2026b), Hahn et al. (2026) |
| <i>(b) High-income contexts</i>            |                  |                                                         |                                                |
| Electric vehicles                          | 1.4              | 1,356                                                   | Hahn et al. (2026)                             |
| Electric vehicles                          | 1.3              | 1,202                                                   | Allcott et al. (2026)                          |
| Wind production credits                    | 5.9              | 46                                                      | Hahn et al. (2026)                             |
| Residential solar                          | 3.9              | 90                                                      | Hahn et al. (2026)                             |
| Appliance rebates                          | 1.2              | 474                                                     | Hahn et al. (2026)                             |
| Vehicle retirement                         | 1.0              | 876                                                     | Hahn et al. (2026)                             |
| Hybrid vehicles                            | 1.0              | 5,940                                                   | Hahn et al. (2026)                             |
| Weatherization                             | 1.0              | 779                                                     | Hahn et al. (2026)                             |

*Notes:* The Marginal Value of Public Funds (MVPF) is the total private and social value generated per US\$1 subsidy (Hendren and Sprung-Keyser, 2020). We assume a social cost of carbon (SCC) of US\$230; assuming the US\$193 from Hahn et al. (2026) would slightly lower our MVPF to US\$18. <sup>a</sup>Chaurey et al. (2025) estimate the impact of disseminating energy efficient motors for free to non-adopters. <sup>b</sup>The US\$323 MVPF estimated by Berkouwer and Dean (2026b) results from the low technology cost (US\$40), large emissions reductions (2.1 tCO<sub>2e</sub> per year), large financial savings (US\$78–114 per year), and a long stove lifetime (2.7 years).

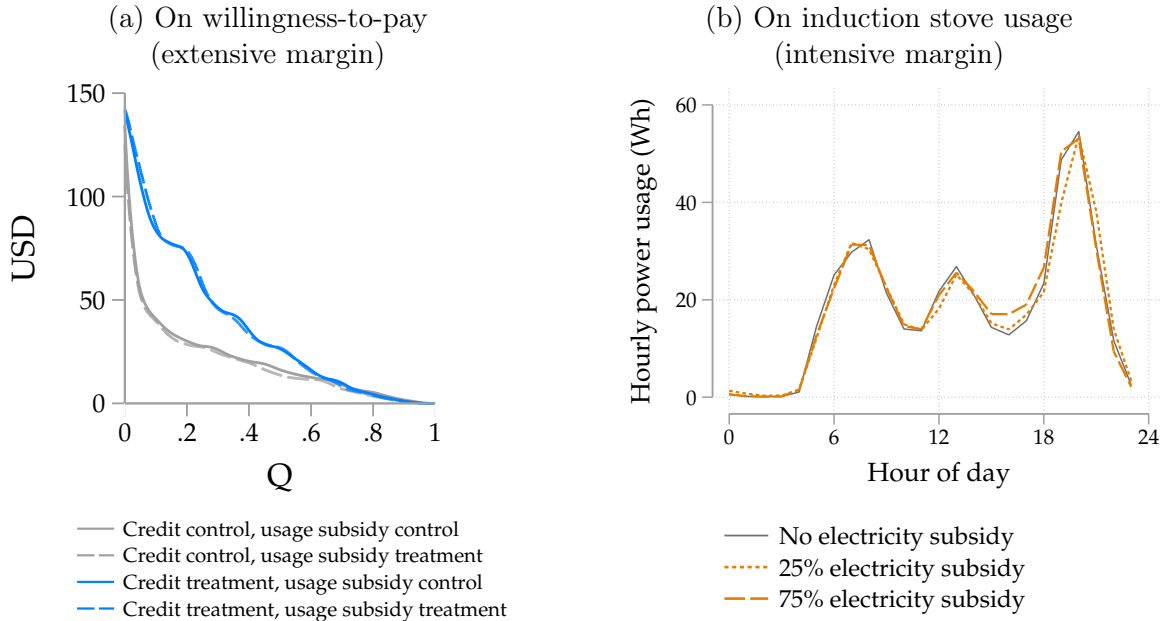
## 6.2 Marginal cost subsidies

The absolute efficacy of fixed cost subsidies does not inform their relative efficacy compared with marginal cost subsidies, which could offer two advantages over a fixed cost subsidy of equivalent net present value. First, marginal cost subsidies could encourage selection into adoption by higher users. Second, they could incentivize switching conditional on adoption. Both channels could increase average usage levels conditional on adoption, increasing the efficiency of marginal cost subsidies in terms of CO<sub>2e</sub> abated per dollar of subsidy expenditure relative to an equivalent fixed cost subsidy.

On the other hand, if respondents are myopic or imperfectly attentive to electricity expenditures, they might undervalue electricity subsidies that accrue in the future. This could undermine the efficacy of marginal cost subsidies. The relative efficacy of these two subsidy instruments is thus an empirical question.

We evaluate the impact of the randomly assigned electricity subsidies, which lowered the cost of cooking by 25% (one-third of the sample) or 75% (one-third of the sample). Since we announced

Figure 8: Impacts of marginal cost subsidies



*Notes:* Panel a shows the impact of access to credit and electricity subsidies on demand, with demand curves constructed using WTP values elicited through the Becker-DeGroot-Marschak mechanism (point estimates in [Table A2](#)). In panel b, electric stove usage in Watt-hours recorded by the induction stoves, separated by whether the respondent was in the electricity subsidy control group, the 25% electricity subsidy group, or the 75% electricity subsidy group (point estimates in [Table A4](#)). [Figure B3](#) presents demand curves that adjust for observed repayment rates.

the electricity subsidy prior to eliciting WTP, the announcement of the usage subsidy could have affected usage both through a direct effect as well as a selection channel. [Figure 8](#) therefore shows the impact of usage subsidies on both the extensive margin (purchasing the stove) and the intensive margin (using the stove). Panel a shows WTP by whether the respondent was given access to a loan and whether they received a marginal cost subsidies. The electricity subsidy has no statistically detectable effect on average WTP. We can rule out that each US\$1 in electricity subsidy has more than a US\$0.16 impact on WTP (Column 3 of [Table A4](#)). Pooled regressions and separate regressions by subsidy level all show no statistically significant impact on WTP ([Table A2](#)). The interaction term between credit and subsidies is positive, but this effect is not significant and very noisy: electricity subsidies may have a positive impact on WTP when respondent’s credit constraints are relaxed, or credit causes selection by people who are slightly more price elastic, but we are unable to cleanly evaluate whether this is the case in this context.

Panel b of [Figure 8](#) presents average hourly induction stoves usage by electricity subsidy treatment group. We estimate a demand elasticity of -0.04, and we can rule out that a 1% increase in price causes more than a 0.13% decrease in usage (Column 6 of [Table A4](#)). The point estimate for the 75% subsidy is larger than the point estimate for the 25% subsidy but less than 10% and not statistically different from zero.

Table 4: Impact of demand distortions on subsidy efficacy through the two channels

|                                                  | Less distorted<br>( $\gamma_1 = 0.19$ ) | More distorted<br>( $\gamma_0 = 0.11$ ) | Difference |
|--------------------------------------------------|-----------------------------------------|-----------------------------------------|------------|
| <i>Channel 1: Marginal adopter</i>               |                                         |                                         |            |
| Fuel savings per marginal adoption ( $\hat{b}$ ) | US\$154                                 | US\$200                                 | +30%       |
| Abatement per marginal adoption ( $\hat{\phi}$ ) | 4.2 tCO <sub>2e</sub>                   | 5 tCO <sub>2e</sub>                     | +19%       |
| <i>Channel 2: Subsidy cost</i>                   |                                         |                                         |            |
| Extensive margin elasticity to fixed subsidy     | $\mathcal{E} = -0.9$                    | $\mathcal{E} = -2.3$                    |            |
| Fraction of subsidy expenditures inframarginal   | 38%                                     | 6.5%                                    |            |
| Subsidy expenditure per marginal adoption        | US\$93                                  | US\$65                                  | -30%       |
| <i>Aggregate difference</i>                      |                                         |                                         |            |
| Welfare gain per \$1 spending (MVPF)             | US\$12                                  | US\$20                                  | +68%       |
| Subsidy spending per tCO <sub>2e</sub> abated    | US\$22                                  | US\$13                                  | -41%       |

*Notes:* How demand distortions affect subsidy efficacy. ‘Less distorted’ are respondents with access to a loan; ‘more distorted’ are respondents who pay the full price up front. Fuel savings and abatement per marginal adoption are totals over the stove’s 1.9-year lifespan. [Section 3.1](#) describes the theoretical underpinnings of channels 1 and 2. [Section 7.1](#) presents empirical estimates for channel 1. [Section 7.2](#) presents empirical estimates for channel 2.

## 7 Effect of demand distortions on subsidy efficacy

One of this paper’s central findings is that the relatively low abatement costs discussed above are caused at least in part by demand distortions. [Section 5](#) showed that the stove’s average discounted fuel savings are US\$184 after 1.9 years. Respondents paying up front have an average WTP of US\$20. Defining willingness to pay as the distortion times the private benefit ( $wtp = \gamma_c \cdot b$ ), this suggests a demand distortion of  $\gamma_0 = 0.11$ .

[Figure 8](#) shows the distributions of WTP by credit treatment status. Access to credit in this context increases WTP by 81% (Column 4 of [Table A2](#)). Respondents given access to a loan have an average WTP of US\$35 suggesting a demand distortion of  $\gamma_1 = 0.19$ . By the end of data tracking, which was between 152–209 days after stove sale across respondents, respondents who had bought the stove with a loan had paid on average 83% of the total payment amount ([Table A5](#) provides additional summary statistics). Accounting for observed repayment rates either increases or decreases the treatment effect in percentage terms depending on which outcome is used, but the effect is always large and statistically significant ([Table B6](#)).

Without access to a loan, WTP relative to the stream of monthly savings of US\$8.9 corresponds to an implicit discount factor of 0.544 per month, or 0.001 per year. Put differently, respondent decision-making reflects indifference between receiving US\$1 today or receiving US\$1,484 one year from today. When given access to a loan, the discount factor increases to 0.031, at which point US\$1 today is worth US\$32 in one year. The difference between these values illustrates the degree to which capital constraints distort decision-making in this context.

Table 5: Abatement among marginal adopters by credit condition

|                             | Charcoal          |                   |                         |                         | Electricity     |                 | Total            |                  |                         |                          |
|-----------------------------|-------------------|-------------------|-------------------------|-------------------------|-----------------|-----------------|------------------|------------------|-------------------------|--------------------------|
|                             | (1)<br>USD        | (2)<br>USD        | (3)<br>CO <sub>2e</sub> | (4)<br>CO <sub>2e</sub> | (5)<br>USD      | (6)<br>USD      | (7)<br>USD       | (8)<br>USD       | (9)<br>CO <sub>2e</sub> | (10)<br>CO <sub>2e</sub> |
| Credit (=1)                 | -1.0<br>(1.4)     | -1.0<br>(1.4)     | -0.2<br>(0.4)           | -0.2<br>(0.4)           | 0.1<br>(0.8)    | 0.1<br>(0.8)    | -0.7<br>(2.0)    | -0.7<br>(2.0)    | -0.2<br>(0.4)           | -0.2<br>(0.4)            |
| Bought induction stove (=1) | -10.5***<br>(0.6) |                   | -2.6***<br>(0.2)        |                         | 2.3***<br>(0.3) |                 | -9.7***<br>(0.9) |                  | -2.6***<br>(0.2)        |                          |
| Bought X No credit          |                   | -10.5***<br>(0.6) |                         | -2.6***<br>(0.2)        |                 | 2.3***<br>(0.3) |                  | -9.7***<br>(0.9) |                         | -2.6***<br>(0.2)         |
| Bought X Credit             | 1.6*<br>(0.9)     | -8.9***<br>(0.6)  | 0.4*<br>(0.2)           | -2.2***<br>(0.2)        | -0.2<br>(0.5)   | 2.2***<br>(0.3) | 2.2*<br>(1.2)    | -7.4***<br>(0.8) | 0.4*<br>(0.2)           | -2.2***<br>(0.2)         |
| Observations                | 754               | 754               | 754                     | 754                     | 754             | 754             | 754              | 754              | 754                     | 754                      |
| Control Mean                | 15.7              | 15.7              | 3.9                     | 3.9                     | 3.6             | 3.6             | 25.5             | 25.5             | 4.1                     | 4.1                      |

*Notes:* Instrumental variables regressions using the randomly assigned price as an instrument for adoption to estimate its impact on spending and emissions among marginal adopters (i.e.,  $WTP \in (20, 73)$  US\$). IV compliers correspond to marginal adopters. Odd columns test whether the marginal adopters' average externality differs by credit condition. Even columns estimate the positive externality by credit condition. Visit 3 surveys were only conducted with 754 of the 765 marginal adopters (98.6%).

How do these demand distortions affect subsidy efficacy? [Table 4](#) presents abatement cost and MVPF estimates for respondents whose demand was more distorted and less distorted. Among respondents given access to a loan to buy the induction stove, who face a lower demand distortion, fixed cost subsidies decrease emissions at a cost of US\$22 per tCO<sub>2e</sub>, which is 70% higher than the US\$13 per tCO<sub>2e</sub> abatement cost among those with a higher demand distortion. Similarly, the MVPF is 68% higher, at US\$20 when using an SCC of US\$230 per tCO<sub>2e</sub>.

Economic cost differences are exacerbated by the fact that estimated private energy savings are US\$154 for adopters with access to credit, which is 23% lower than average energy savings among the credit control group. In aggregate, CO<sub>2e</sub> abatement saves 34% more in economic resources among those with the largest distortions.

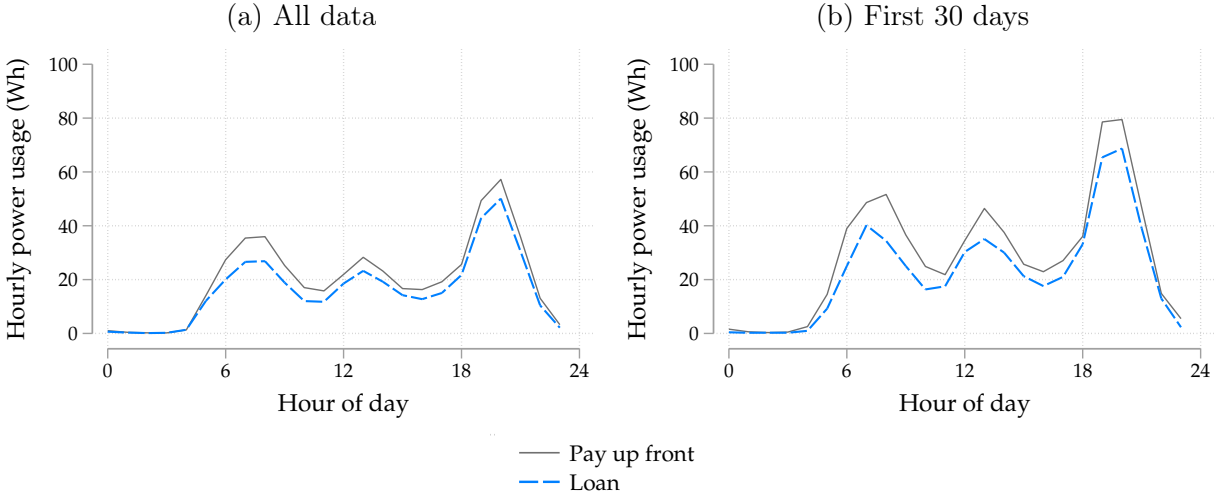
The following two sections quantify how the two channels hypothesized in theory contribute to this aggregate empirical result. [Section 7.1](#) quantifies in more detail how demand distortions affect the externality generated by the marginal adopter (channel 1). [Section 7.2](#) quantifies how they affect demand elasticity and subsidy efficacy (channel 2).

## 7.1 Channel 1: Fuel reduction of marginal adopters

We first test the impact of demand distortions on the average externality of the marginal adopter. Throughout, we define a marginal adopter as having a WTP between the low price and the high price, so that they would adopt the stove if and only if there was an increase in the subsidy:  $p - s_h < wtp < p - s_l$ . There are 387 marginal adopters in the credit control group and 378 marginal adopters in the credit treatment group for a total sample of 765 marginal adopters.

In the context of the model, when agents face larger demand distortions, agents who are marginal

Figure 9: Electric stove usage among marginal adopters by credit condition



Notes: Hourly usage in Watt-hours by randomized credit condition among marginal adopters, defined as having a  $p - s_h < wtp_i < p - s_l$ . Table A3 presents point estimates, which are significant with  $p < 0.05$ . The IV  $F$ -stat is 3,151 for all regressions.

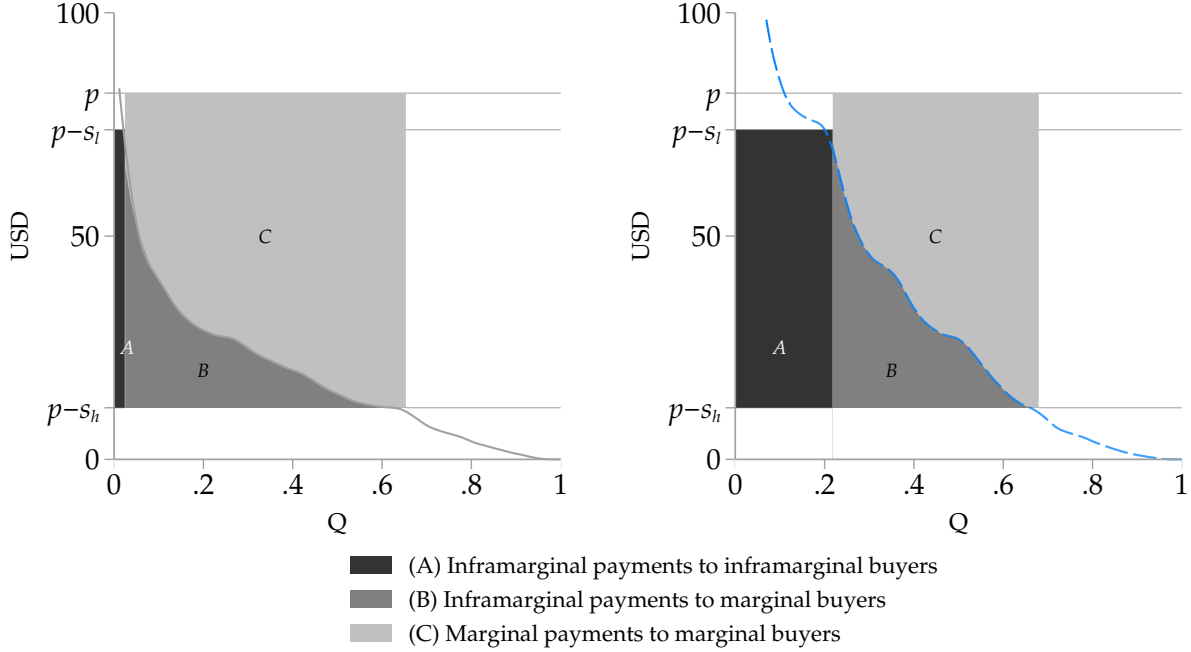
to a subsidy should unambiguously have higher average private benefits. Columns 7 and 8 of Table 5 offer a test of this. Marginal adopters with a larger demand distortion generate on average US\$200 in discounted private savings over the course of 1.9 years of ownership, whereas adopters whose demand distortion was reduced through access to credit generate US\$154, a statistically significant difference.

Since social and private benefits are positively correlated in this context, this translates into a similar difference in positive externalities. Columns 9 and 10 of Table 5 show that this is the case. Marginal adopters in the credit control group abate 5 tCO<sub>2e</sub> after 1.9 years whereas marginal adopters in the credit treatment group abate 4.2 tCO<sub>2e</sub>. In other words, the credit constraints in this context increase the abatement caused by marginal adopters by 19%.

Figure 9 plots induction stove usage over the course of the day among adopters who were marginal to the subsidy, by credit treatment group. Marginal adopters in the credit control group have an average usage of 599 Wh per day, which is 34% higher than marginal adopters in the credit treatment group, who have an average daily usage of 445 Wh per day (Table A3 shows the estimates corresponding to panel a).

This difference could reflect a treatment effect rather than selection. For example, having to pay back a loan leaves less money available for electricity expenditures. However, panel b shows that these effects begin within the first month, when adopters paying up front would have just faced a large direct liquidity shock from adoption. If anything, this would bias the estimates toward finding less usage among adopters paying up front. The difference in usage across the two groups is therefore likely to be a result purely of selection rather than a treatment effect. Either way, the interpretation of this wedge does not affect the subsidy efficacy calculations.

Figure 10: Marginal and inframarginal expenditures by credit condition  
(a) More distorted demand (b) Less distorted demand



*Notes:* Demand curves constructed using WTP values elicited through the BDM mechanism. Respondents having to pay up front have more distorted demand than respondents randomly given access to a loan. Demand distortions increase the proportion of marginal buyers and decrease the proportion of inframarginal buyers that result from an increase in the subsidy from  $s_l$  to  $s_h$ .

## 7.2 Channel 2: Subsidy expenditure per marginal adoption

The second channel through which demand distortions increase subsidy efficacy is by increasing demand elasticity, which both increases the number of agents who are marginal to the subsidy, and also reduces the number of inframarginal payments. Figure 10 presents intuition on how these effects operate in the context of the demand curves elicited through the BDM. Area  $A$  represents the first term in Equation 9 and  $B$  represents the second term. Area  $A$  as a fraction of areas  $A \cup B \cup C$  denotes the fraction of additional subsidy expenditures disbursed to inframarginal buyers. The width of area  $B \cup C$  represents the number of buyers that are marginal to a subsidy increase. Comparing panels a and b, demand distortions in this context both decrease payouts to inframarginal payments and increase the number of marginal buyers.

Intuitively, the cost increase resulting from a subsidy increase can consist of subsidy expenditures towards both inframarginal and marginal buyers. In other words, the numerator in Equation 5 can be disaggregated as follows:

$$\rho_h s_h - \rho_l s_l = \underbrace{\rho_l (s_h - s_l)}_{\text{Increased payouts to inframarginal buyers}} + \underbrace{s_h (\rho_h - \rho_l)}_{\text{Full payouts to marginal buyers}} \quad (9)$$

In terms of inframarginal adopters, 2.6% of people in the credit control group would buy the

Table 6: Extensive margin demand elasticities by credit treatment group

|              | Quantity (%)       |                    |                    | Log(Quantity)      |                    |                    |
|--------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
|              | (1)                | (2)                | (3)                | (4)                | (5)                | (6)                |
| Price (USD)  | -0.84***<br>(0.01) | -0.96***<br>(0.02) | -0.80***<br>(0.01) |                    |                    |                    |
| Log(Price)   |                    |                    |                    | -1.23***<br>(0.01) | -2.33***<br>(0.02) | -0.88***<br>(0.01) |
| Observations | 765                | 387                | 378                | 765                | 387                | 378                |
| Sample       |                    | C=0                | C=1                |                    | C=0                | C=1                |

*Notes:* We estimate elasticities over the policy relevant sample of compliers, i.e., anyone with willingness-to-pay between  $p - s_h$  and  $p - s_l$ . Column 1 show that a US\$1 increase in price causes a 0.8 percentage point decrease in the quantity demanded. Columns 2 and 3 show that this decrease is steeper for respondents in the control group than in the treatment group. The lower rate of inframarginal adoption exacerbates the difference in elasticities in Columns 5 and 6, as the small denominator among the credit control group causes a larger demand elasticity.

stove at the high price whereas 21% of people in the credit treatment group would. As a result, among the credit treatment group 38% of subsidy expenditures flow to inframarginal buyers whereas in the credit control group only 6.5% of expenditures do.

The subsidy also increases sales by 35 percentage points among respondents in the credit treatment group, but by 37 percentage points among the credit control group. The same subsidy thus has a slightly larger increase in adoption rates among more credit constrained subsidy recipients.

Taken together, the environmental principal incurs a total subsidy cost of US\$93 per additional sale among respondents with access to a loan, whereas respondents in the credit control group require additional subsidy spending of US\$65 per additional sale. In other words, relaxing demand distortions increases the subsidy cost of achieving one additional sale by 43%.

These impacts can be summarized by the change in the demand elasticity, which as a percentage term reflects both marginal adopters (in the numerator) and inframarginal adopters (in the denominator). Table 6 estimates the price-quantity coefficients. Column 5 shows a demand elasticity of -2.3 among participants required to pay the entire price up front and Column 6 shows -0.9 among people paying with a loan.

An alternative, policy relevant measure of demand elasticity would be to take  $s_l$  as the policy baseline and then to estimate the percentage quantity and price change from this starting point. This results in a demand elasticity among the loan group of  $-2.5$  and among the upfront payment group of  $-30.8$ .

Columns 2 and 3 indicate that the increased elasticity includes an increase in the numerator: there are more marginal adopters per US\$1 subsidy. Given that there are also fewer inframarginal adopters (the denominator in the elasticity calculation), Column 5 shows respondents with a larger demand distortion have an even larger demand elasticity.

## 8 Model estimation and counterfactuals

Even among respondents who are given access to a loan, willingness-to-pay of US\$35 is still well below the total discounted savings of US\$184 after 1.9 years. It is reasonable to think that our short intervention did not fully alleviate all demand distortions experienced by households in this context. In addition, given that average monthly savings were US\$8.9 and the loan had a four-month repayment period, someone with a binding savings constraint might only be able to pay US\$36 over the period of the loan. We therefore estimate the model and generate counterfactuals to quantify outcomes in alternative scenarios where the demand distortion is alleviated further.

The goal of the model is to guide an understanding of how two parameters of particular interest—the demand distortion and the private-social benefit correlation—affect subsidy efficacy. We are agnostic about what drives this heterogeneity. For example, in another context a clean technology might generate a reduction in pollution exposure that increases WTP even in the absence of any financial savings: this would still cause a positive correlation between private and social benefits, and the model’s insights would still apply. The model is parameterized with five parameters, which generate seven moments that fit the data well.

### 8.1 Set-up

We estimate the stylized model specified in [Section 3](#). We assume agents  $i$  are distributed Weibull by their private benefit from adopting:  $b_i \sim \text{Weibull}(\Omega_1, \Omega_2)$ . The Weibull’s shape parameter governs tail thickness, allowing the data to discipline how concentrated WTP is around its mean; for  $\Omega_1 \geq 1$  it satisfies the increasing hazard rate (IHR) condition required by [Lemma 5](#) (the estimate of  $\Omega_1 = 1.9$  satisfies this condition). The correlation between social benefit and private willingness-to-pay is controlled by  $\Omega_3$ , as follows:  $\phi_i = \hat{\phi} [\Omega_3 b_i + (1 - \Omega_3)\epsilon_i]$ , with  $\hat{\phi} = 4.8 \text{ tCO}_2e$  (from panel b, Column 4 of [Table 2](#) multiplied by the 1.9 year lifespan),  $\Omega_3 \in [0, 1]$ , and  $\epsilon_i$  an independent draw from the same Weibull distribution.

For each credit condition  $c \in 0, 1$  the mean demand distortion  $\gamma_c \equiv E[\gamma_i|c]$  is defined by  $w\bar{t}p_c = \gamma_c \hat{b}$ , with discounted private benefits after 1.9 years  $\hat{b} = \text{US\$184}$  (from panel a, Column 7 of [Table 2](#)) and observed mean willingness-to-pay  $w\bar{t}p_0 = \text{US\$20}$  and  $w\bar{t}p_1 = \text{US\$35}$  (from [Table A2](#)), giving  $\gamma_0 = 0.11$  and  $\gamma_1 = 0.19$  (from [Table 4](#)). We assume a heterogeneous demand distortion  $\gamma_i = \text{logistic}(\mu_c + \sigma_c \eta_i)$ ,  $\eta_i \sim N(0, 1)$ , with dispersion  $\sigma_c = \log(1 + \exp(\Omega_4 + \Omega_5 \gamma_c))$ , such that  $\Omega_4$  governs baseline dispersion and  $\Omega_5$  controls how dispersion varies with the mean wedge, allowing for heterogeneity in credit impacts to affect the dispersion of WTP.<sup>26</sup> The location parameter  $\mu_c$  is pinned down by  $E[\gamma_i|c] = \gamma_c$ . Individual willingness-to-pay is then given by  $wtp_i = \gamma_i \cdot b_i$ .

The distributions of  $wtp_i$  and  $\phi_i$  can be used to calculate demand elasticity  $\epsilon^D$  and the average

<sup>26</sup>The logit-normal distribution across different  $E[\gamma]$  reasonably approximates the LASSO-generated empirical distributions ([Figure B4](#)). As a robustness check, [Table B8](#) presents results when estimating the model with a heavy-tailed logit- $t$  distribution. The empirical moments have a worse fit but the counterfactual simulations yield similar results to panel b of [Table 7](#). Even though it also operates on the interval  $[0, 1]$ , we do not apply the Beta distribution because its behavior at the boundaries of  $[0, 1]$  is inconsistent with what we observe in our data.

externality of adopters who are marginal to the subsidy, which we define:

$$\bar{\phi} = \mathbb{E}[\phi_i | p - s_h < wtp_i < p - s_l]$$

Where  $p - s_h = \text{US\$20}$  and  $p - s_l = \text{US\$73}$  as in the experiment.

## 8.2 Model estimation

We use method of simulated moments to target seven empirical moments: extensive margin elasticity  $\epsilon_c^D$ , average marginal externality  $\bar{\phi}_c$ , and cost per marginal adoption—all of which vary by credit groups  $c = \{0, 1\}$ —as well as a common  $\rho = \text{corr}(b_i, \phi_i)$ . For each moment  $n$  we define the simulated moment error  $e_n(\boldsymbol{\Omega})$  as a normalized function of the empirical moment  $m_n(x)$  and the simulated moment  $\hat{m}_n(\tilde{x})$ :

$$e_n(\boldsymbol{\Omega}) = \frac{\hat{m}_n(\tilde{x}) - m_n(x)}{m_n(x)}$$

We estimate the model parameters  $\boldsymbol{\Omega} = \{\Omega_1, \Omega_2, \Omega_3, \Omega_4, \Omega_5\}$  using 2-step Generalized Method of Moments (2GMM) with optimal weighting matrix  $\mathbf{W}$ , defining the estimator:

$$\hat{\boldsymbol{\Omega}}_{2GMM} = \boldsymbol{\Omega} : \min_{\boldsymbol{\Omega}} e(\boldsymbol{\Omega})^T \mathbf{W} e(\boldsymbol{\Omega})$$

## 8.3 Estimation results

The estimated coefficients are  $\hat{\Omega}_1 = 1.9$ ,  $\hat{\Omega}_2 = 1$ ,  $\hat{\Omega}_3 = 0.6$ ,  $\hat{\Omega}_4 = -2.7$ , and  $\hat{\Omega}_5 = 27$ . Panel a of [Table 7](#) compares the moments simulated with the estimated parameters and the empirical moments calculated using the data.

Using the simulated moments to estimate abatement costs yields US\$13 per tCO<sub>2e</sub> and US\$23 per tCO<sub>2e</sub> for the credit control and treatment groups, respectively (shown in panel b). Although these are not targeted moments, these aggregate efficiency numbers match the empirically estimated abatement costs of US\$13 and US\$22, respectively.

## 8.4 Counterfactual simulations

We run counterfactuals by simulating  $b_i \sim \text{Weibull}(\hat{\Omega}_1, \hat{\Omega}_2)$  and  $\epsilon_i \sim \text{Weibull}(\hat{\Omega}_1, \hat{\Omega}_2)$ . The first set of counterfactuals varies only the  $\gamma$  values. The second set of counterfactuals varies  $\gamma$  and  $\Omega_3$  to understand how a negative or positive correlation can cause a demand wedge to generate adverse selection or beneficial selection, respectively. The third set of counterfactuals varies the heterogeneity of  $\gamma$  across agents.

**Counterfactual I: Demand distortion** Panel b of [Table 7](#) shows the results implied by the model for different assumptions of  $\gamma$ . The estimated average marginal externalities follow the intuition offered by [Figure A1](#): demand distortions that dampen demand increase the positive externality generated by the marginal adopter. The estimated extensive margin elasticities follow

Table 7: Simulated estimates from observed and counterfactual parameters

(a) Estimation

| Moment                                          | RCT: Pay up front<br>( $\gamma = 0.11$ ) |           |           | RCT: Pay with loan<br>( $\gamma = 0.19$ ) |           |           |
|-------------------------------------------------|------------------------------------------|-----------|-----------|-------------------------------------------|-----------|-----------|
|                                                 | Empirical                                | Simulated | Deviation | Empirical                                 | Simulated | Deviation |
| Correlation ( $\rho$ )                          | 0.8                                      | 0.8       | -1%       | 0.8                                       | 0.8       | -1%       |
| Marginal externality ( $\phi$ )                 | 5                                        | 5         | 2%        | 4.2                                       | 4.2       | 0%        |
| Extensive margin elasticity ( $\mathcal{E}_D$ ) | -2.3                                     | -2.4      | -2%       | -0.9                                      | -0.7      | 15%       |
| USD per marginal adoption                       | 65.4                                     | 64.6      | -1%       | 93.4                                      | 96.1      | 3%        |

(b) Counterfactual simulations: Varying the distortion  $\gamma$ 

|                                                 | (1)  | (2)  | (3)  | (4)  | (5)   | (6)   | (7)   |
|-------------------------------------------------|------|------|------|------|-------|-------|-------|
| Assumed demand distortion ( $\gamma$ )          | 0.05 | 0.11 | 0.19 | 0.25 | 0.5   | 0.75  | 1     |
| Marginal externality ( $\phi$ )                 | 7.3  | 5    | 4.2  | 4    | 3.3   | 2.9   | 2.5   |
| Extensive margin elasticity ( $\mathcal{E}_D$ ) | -9.4 | -2.4 | -0.7 | -0.5 | -0.2  | -0.2  | -0.1  |
| USD per marginal adoption                       | 61.6 | 64.6 | 96.1 | 122  | 222.5 | 292.6 | 347.8 |
| USD per tCO <sub>2</sub> e (observed)           |      | 13.2 | 22.3 |      |       |       |       |
| USD per tCO <sub>2</sub> e (simulated)          | 8.4  | 12.8 | 22.9 | 30.8 | 68.1  | 101.9 | 136.7 |
| MVPPF per US\$1 (observed)                      |      | 20.3 | 12.1 |      |       |       |       |
| MVPPF per US\$1 (simulated)                     | 34.5 | 22.4 | 12.8 | 9.7  | 4.8   | 3.5   | 2.8   |

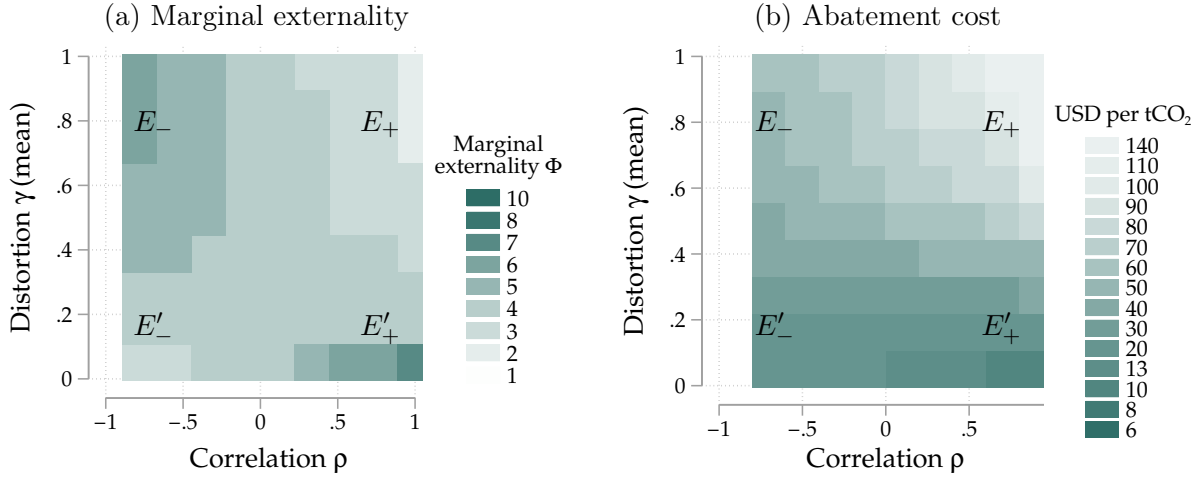
*Notes:* Panel a compares empirical moments and the simulated moments under the estimated model parameters. There are seven moments: a single correlation moment  $\rho$ , and one per treatment group for each of the other three moments. Panel b uses the model parameters to estimate key moments, as well as aggregate abatement cost, for counterfactual scenarios with higher or lower demand distortions, holding constant the correlation between private benefits and social benefits to match the empirical moment. [Table B7](#) also varies the correlation parameter  $\rho$ . [Table B8](#) shows that these results are not sensitive to the specific distributional assumption of  $\gamma_i$ .

the intuition offered by [Figure 3](#): a decrease in  $\gamma$  increases demand elasticity. Through these two channels, a demand distortion that dampens willingness-to-pay decreases the abatement cost in terms of US\$ per tCO<sub>2</sub>e. In the neoclassical case where private benefits equal willingness-to-pay—corresponding to no demand distortion—the abatement cost increases to US\$137 per tCO<sub>2</sub>e.

**Counterfactual II: The correlation between willingness-to-pay and social benefits** We extend the counterfactuals to include alternative correlations between willingness-to-pay and social benefits. [Figure 11](#) shows the results when varying not only the demand distortion parameter  $\gamma$  but also the correlation parameter  $\Omega_3$ . To help build intuition, we use labels  $E'_+$ ,  $E_+$ ,  $E'_-$ , and  $E_-$  to demarcate the approximate externalities labeled in panels a and b of [Figure A1](#).

In the neoclassical framework, where willingness-to-pay reflects private benefits and there is no distortion ( $\gamma = 1$ , such that  $wtp_i = b_i$ ), a positive correlation lowers the marginal externality and induces adverse selection, decreases the marginal positive externality ( $E_+ < E_-$ ). On the other hand,

Figure 11: Counterfactual estimates



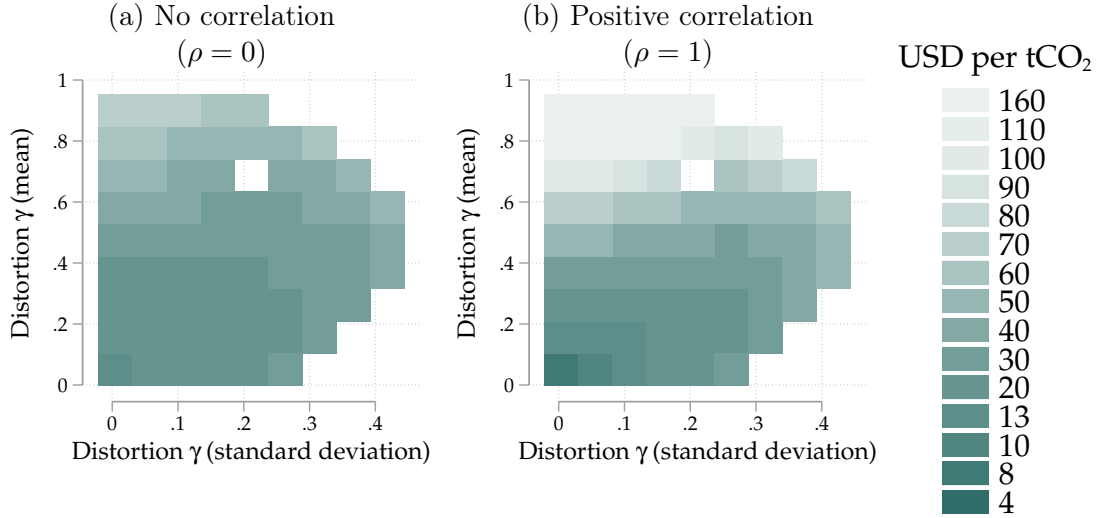
*Notes:* Both figures show how demand distortions as well as the correlation between willingness-to-pay and social benefits affect subsidy efficacy. Panel a shows the marginal externality. The labels  $E'_+$ ,  $E_+$ ,  $E'_-$ , and  $E_-$  correspond to the labels in panels a and b of Figure A1, which presents the theoretical underpinnings for channels 1 and 2. Panel b shows the combined effect of the marginal externality and the elasticity on abatement cost. The demand distortion decreases abatement costs everywhere in this context, regardless of correlation. Table B7 presents a subset of these estimates in the format of Table 7.

under a demand distortion that dampens willingness-to-pay by a factor  $\gamma < 1$ , a positive correlation means compliers generate larger positive externalities, inducing beneficial selection ( $E'_+ > E'_-$ ). The effect of a demand distortion thus hinges on the correlation between willingness-to-pay and social benefits: when this correlation is negative, a demand distortion decreases the average externality of compliers ( $E'_- < E_-$ ). It is only when it is positive that the distortion increases the average externality of compliers ( $E'_+ > E_+$ ).

Panel b shows how these dynamics subsequently affect the subsidy expenditure cost per ton of CO<sub>2</sub>e abated, factoring in the marginal externality shown in panel a as well as any changes in the demand elasticity caused by the demand distortion. Even when the correlation is negative and the demand distortion lowers the marginal externality, the demand distortion also simultaneously increases the extensive margin elasticity, regardless of the correlation between willingness-to-pay and social benefits. In this context, this effect outweighs the opposing effect on the average externality of compliers among negative correlation coefficients (such that even though  $E'_- < E_-$  in panel a, we have  $E'_- > E_-$  in panel b). As a result, the demand distortion unambiguously decreases abatement costs in this context, regardless of the correlation coefficient ( $E'_- < E_-$  and also  $E'_+ < E_+$ ).

**Counterfactual III: Heterogeneous demand distortions across agents** Finally, we explore how heterogeneity in the demand distortion affects subsidy efficacy. For simplicity we assume the  $\gamma_i$  are uncorrelated with any of the other parameters of interest (willingness-to-pay and social benefits). We conduct the same counterfactual exercises as above, holding fixed the correlation to be either perfectly negative, zero, or perfectly positive. We draw  $\gamma_i = \text{logistic}(\mu + \sigma\eta_i)$ ,  $\eta_i \sim N(0, 1)$ , varying  $\mu$  and  $\sigma$  to vary means and standard deviations of  $\gamma_i$  while ensuring  $\gamma_i \in [0, 1]$

Figure 12: Counterfactual estimates with heterogeneous demand distortions



*Notes:* This graph explores how different demand distortions and correlations affect abatement costs when demand distortions are allowed to be orthogonally heterogeneous across agents. Since we constrain  $\gamma \in [0, 1]$ , not all combinations of mean and standard deviation are feasible.

Figure 12 shows the results. When the standard deviation is 0, the graphs follow the patterns shown in Panel b of Figure 11: the mean distortion matters more when private and social benefits are positively correlated. Both panels show that this pattern weakens as the standard deviation increases.

## 9 Discussion

### 9.1 Results under alternative assumptions

The benchmark scenario evaluated in this paper assumes 1.9 years estimated stove durability and uses Kenya’s average grid emissions. Alternatively, assume that the stove’s lifespan is on average 1 year or 3 years. This changes the subsidy cost of abatement among respondents who were not also given access to a loan to US\$25 and US\$8, respectively (scenarios 1 and 2 of Table A6).

There is significant uncertainty around the fraction of non-renewable biomass (fNRB), which is the fraction of used biomass that is permanently removed (as opposed to forest that regrows naturally). Our primary estimates use the 38% rate that Ghilardi and Bailis (2024) estimate using their Modeling Fuelwood Savings Scenarios (MoFuSS) model, per the recommendations of Article 6.4 of the Paris Agreement. To measure the sensitivity of our results to this parameter, we also calculate costs under 10% and 100% rates. This changes the subsidy cost per ton of CO<sub>2</sub>e abated to US\$16 or US\$10, respectively (scenario 3 and 4 of Table A6). These differences are relatively minor because approximately half of charcoal-related emissions are incurred not during combustion but during production and processing, which are not affected by the assumed fNRB (Floess et al., 2023).

Finally, Kenya’s electricity generation mix is significantly cleaner than most other countries’, at 85% renewable and fewer than half the emissions per kWh than the U.S. grid. If Kenya’s grid emissions were equivalent to the U.S. grid, the abatement cost would remain essentially unchanged (scenario 5 of [Table A6](#)). The difference with the benchmark scenario is minor because cooking with charcoal is significantly dirtier than cooking with electricity, such that the reduction in charcoal cooking emissions is only very slightly offset by the increase in electricity cooking emissions (as discussed in [Section 5.3](#)).

## 9.2 Scale

Approximately 1.4 million Kenyan households use charcoal on a daily basis. Our results suggest that a price subsidy could incentivize adoption by 37% of households.<sup>27</sup> The induction stove usage data indicates that the 90<sup>th</sup> percentile of peak usage is on average 88 Wh per customer. Thus, scaling adoption in line with demand from our experiment would require an additional 45 MW in grid capacity. For context, Kenya’s current peak demand is 2,177 MW with an installed capacity of 3,243 MW (Kenya Power, 2024). While the intermittency of renewable resources means the grid generally does not generate at installed capacity, Kenya’s electric utility appears capable of meeting any demand increase associated with widespread electric stove adoption.

Approximately 54 million households across the world today use charcoal as their primary cooking fuel, including approximately 31 million households that live in Africa ([Table A7](#)). At annual abatement of 2.6 tCO<sub>2e</sub> per year and with 37% adoption at subsidized prices, a widespread cooking transition in Africa would abate approximately 30 million tons of CO<sub>2e</sub> per year.

In addition, more than 300 million households across the world still cook primarily with firewood. Households currently cooking primarily with firewood could generate additional abatement. And, the IEA (2025) estimates that the number of households cooking with wood or charcoal in Africa in 2050 will if anything be higher than the numbers today. A fruitful area of future research would be to better understand global cooking transition pathways given the heterogeneity of demand distortions across countries.

## 10 Conclusion

Demand distortions such as financial market frictions and behavioral biases are pervasive across many low- and middle-income countries, often operating by dampening willingness-to-pay (WTP) for profitable technologies. This paper shows that this has important implications for the efficiency of Pigouvian price instruments. In theory, fixed cost subsidies for green technologies generate a larger gain in consumer surplus as well as a larger positive externality when agents face demand

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<sup>27</sup>This assumes universal electricity access among charcoal users, which is not completely unreasonable. Charcoal is used primarily in urban and peri-urban areas with access to markets. Urban electricity access increased from 50% in 2000 to 98% in 2022 (World Bank, 2025). The rural access rate lags but now exceeds 66% and continues to increase rapidly in large part due to Kenya’s nationwide electrification programs.

distortions that dampen demand. This operates through two channels: increasing the WTP of the marginal adopter, and increasing demand elasticity.

We test this theory in a field experiment with more than 2,000 households in Nakuru County, Kenya, where we randomize marginal cost subsidies, fixed cost subsidies, and demand distortions for the purchase of an energy efficient technology: induction stoves. We first use the random variation in prices to estimate the causal impacts of stove adoption. We find that the stove abates 2.5 tCO<sub>2e</sub> per year and reduces (discounted) household energy expenditures by US\$184 over the 1.9 year lifetime of the stove. WTP among the control group is US\$20: access to a loan increases WTP to US\$35. Even factoring in continued use of charcoal stoves and imperfect additionality of the subsidies, green subsidies in this context offer a very low-cost abatement opportunity, at only US\$13 per ton of CO<sub>2e</sub> abated. This compares favorably to many other abatement technologies available today. Factoring in the private benefit to adopters, each dollar of subsidy generates US\$20 in total social welfare gain.

As predicted by the theory, demand distortions in this context contribute to these favorable numbers. When we relax demand distortions by randomly offering access to credit, the cost of abatement increases to US\$22 per ton of CO<sub>2e</sub> and the MVPF decreases to US\$12 per subsidy dollar. This operates through the two channels identified in the model: demand distortions increase the marginal adopter's positive externality by 19% and increase demand elasticity from -0.9 to -2.3.

The loan treatment increases WTP in this context but still does not close the adoption gap. To estimate abatement costs in the absence of any demand distortions, we estimate the model using 2-step Generalized Method of Moments (2GMM), using the random variation from the experiment to identify key parameters. Counterfactuals suggest that if WTP equaled the discounted stream of fuel savings the abatement cost would have increased more than tenfold, to US\$137 per tCO<sub>2e</sub>, and decreased the MVPF to US\$2.8 per subsidy dollar.

The mechanisms identified in this paper suggest that many of the most effective abatement opportunities may be found in contexts with larger demand distortions. As an example, the U.S. has relatively sophisticated financial markets for consumer durables, with the vast majority of new cars sold with financing. Our paper suggests that this could contribute to the high cost of abatement through electric vehicle subsidies, at more than US\$1,000 per ton.

More than US\$1 trillion is invested towards climate change mitigation each year, much of which targeted at rapid electrification combined with grid decarbonization. Maximizing the impact of these expenditures requires allocating this funding towards abatement opportunities at the lowest portion of the abatement cost curve. Given the results of this study, many of these opportunities may be found in low- and middle-income countries, where demand distortions are pervasive. Additional research is needed to identify specific mitigation opportunities.

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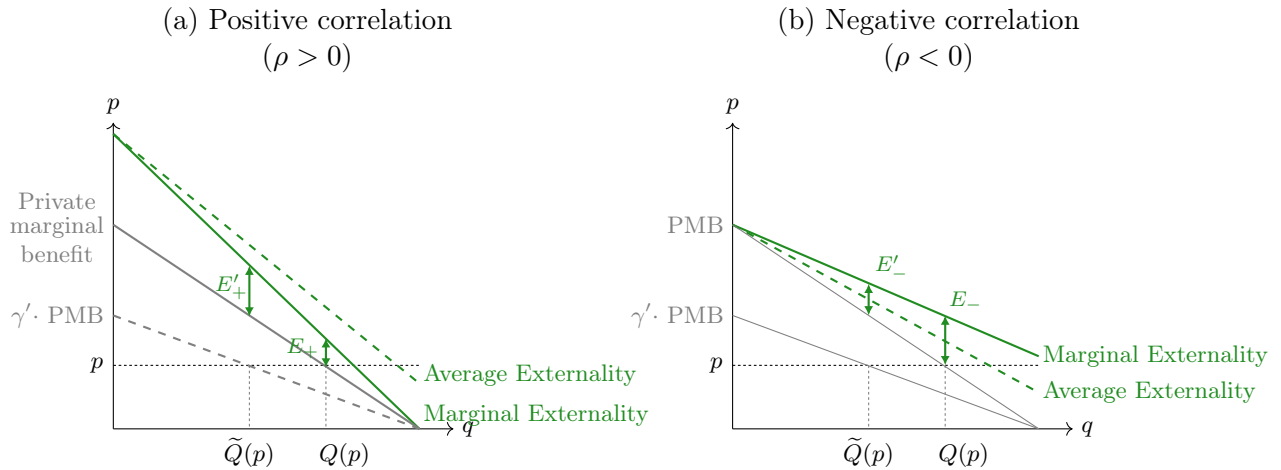
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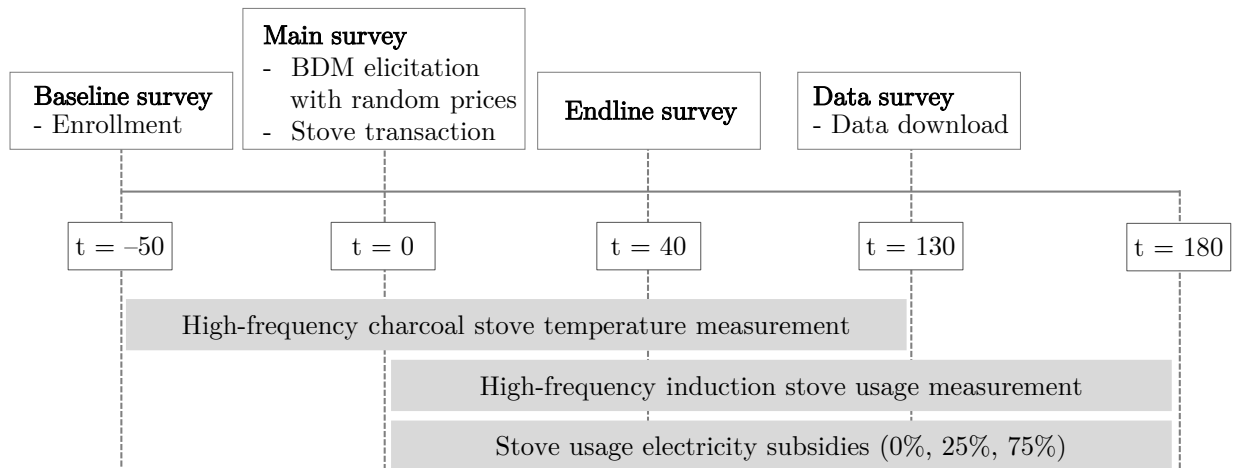
# I Additional figures

Figure A1: How the shape of the externality determines the role of selection



Notes: Demand distortions increase the marginal positive externality if willingness-to-pay and social benefits are positively correlated ( $E'_+ > E_+$ ) but decrease it when they are negatively correlated ( $E'_- < E_-$ ). A positive correlation generates advantageous selection that lowers the marginal externality of a subsidy in regular markets ( $E_+ < E_-$ ) but increases it when markets face distorted demand ( $E'_+ > E'_-$ ).

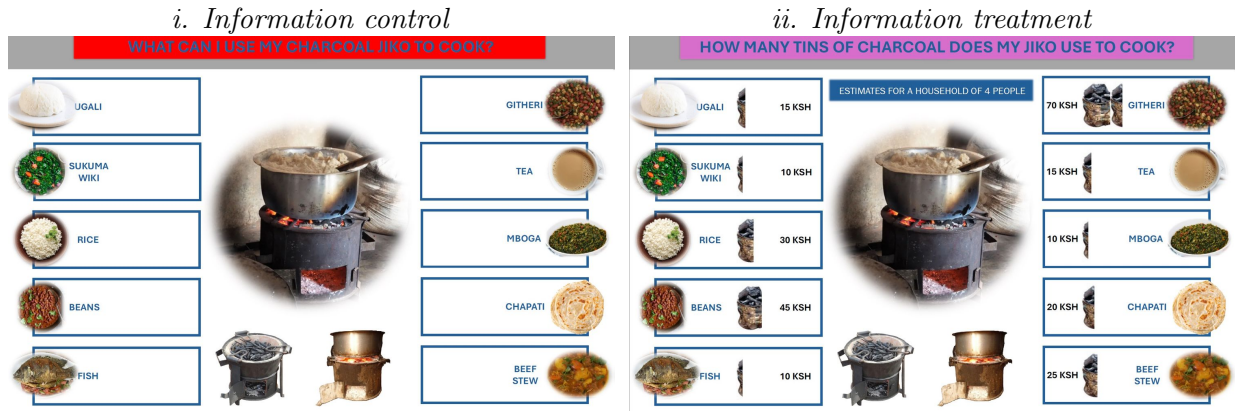
Figure A2: Experiment timeline



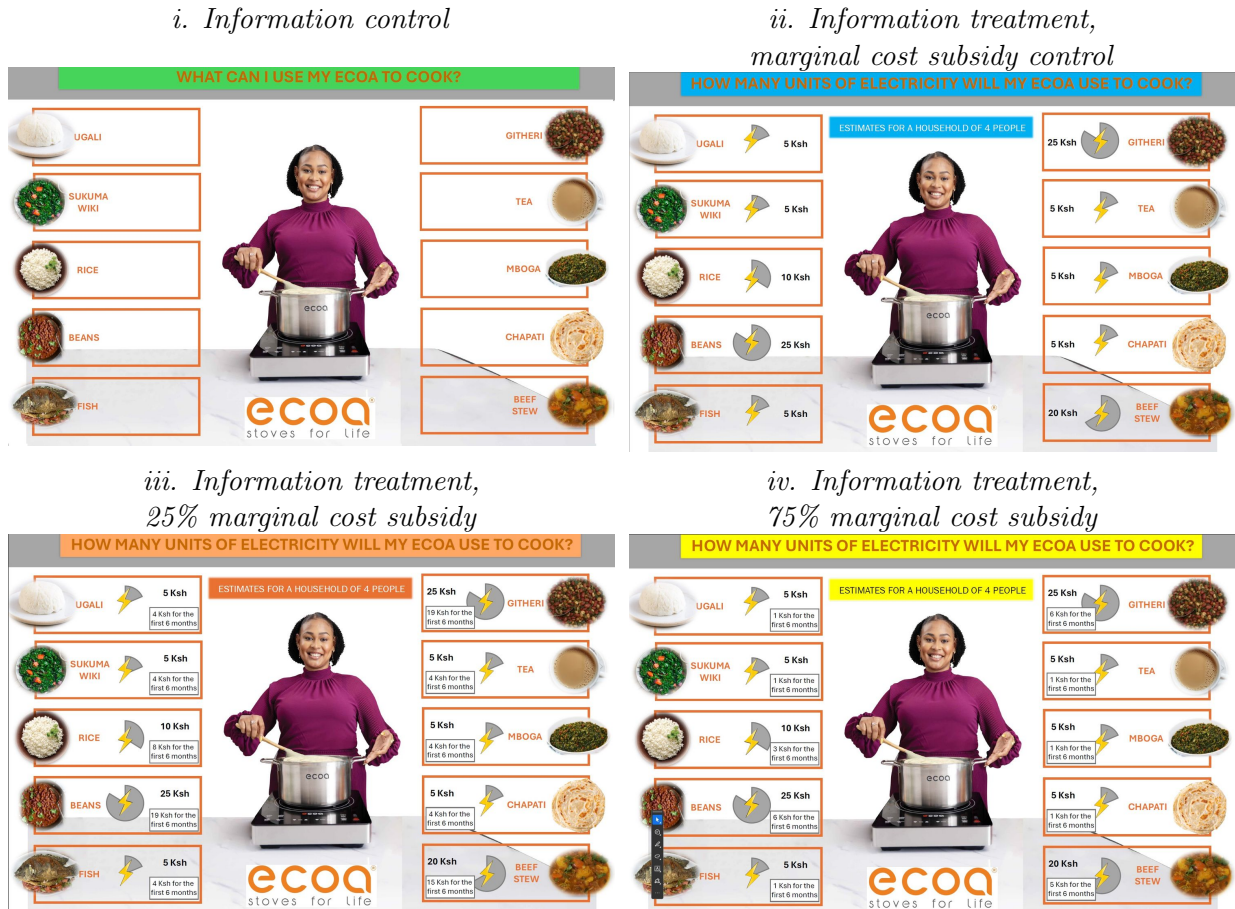
Notes: Timeline of study activities. The baseline survey was conducted on average 50 days before the main survey (10<sup>th</sup>, 90<sup>th</sup>: 40, 60 days), between August 12 and September 19, 2025. The main survey was conducted between 23 September and 19 November, 2025. The endline survey was conducted on average 40 days after the main survey ([25, 55]), between November 10 and December 12, 2025. The data download was conducted on average 130 days after the main survey ([110, 150]), between February 18 and March 6, 2026. High frequency induction stove usage monitoring and electricity subsidy transfers were completed remotely.

Figure A3: Randomized information sheets

(a) Charcoal sheet



(b) Electricity sheet



Notes: Each participant receives one charcoal sheet and one electricity sheet. 14% of participants are in the information control group and receive sheets with no cooking cost information (Figure *i* in both panels). 86% of participants are in the information treatment group and receive cost information; respondents in the marginal cost subsidy and information treatment groups saw cooking costs that incorporated the price reduction (Figure *ii* in panel a and Figure *ii*, *iii*, or *iv* in panel b).

## II Additional tables

Table A1: Effect of induction stove adoption on charcoal stove usage

|                        | Ordinary Least Squares |                    |                    |                    | Instrumental Variables |                    |                    |                    |
|------------------------|------------------------|--------------------|--------------------|--------------------|------------------------|--------------------|--------------------|--------------------|
|                        | (1)                    | (2)                | (3)                | (4)                | (5)                    | (6)                | (7)                | (8)                |
| Pre-period difference  | 0.09<br>(0.08)         |                    | 0.09<br>(0.08)     |                    | -0.15<br>(0.18)        |                    | -0.15<br>(0.18)    |                    |
| Post-period difference | -0.43***<br>(0.07)     |                    | -0.43***<br>(0.07) |                    | -0.52***<br>(0.16)     |                    | -0.52***<br>(0.16) |                    |
| Pre-post difference    |                        | -0.49***<br>(0.06) |                    | -0.49***<br>(0.06) |                        | -0.38***<br>(0.13) |                    | -0.38***<br>(0.13) |
| Observations           | 5301720                | 5301720            | 220905             | 220905             | 5301720                | 5301720            | 220905             | 220905             |
| Respondents            | 2010                   | 2010               | 2010               | 2010               | 2010                   | 2010               | 2010               | 2010               |
| Control Mean           | 1.72                   | 1.72               | 1.72               | 1.72               | 1.52                   | 1.52               | 1.52               | 1.52               |
| Level of data          | Hourly                 | Hourly             | Daily              | Daily              | Hourly                 | Hourly             | Daily              | Daily              |
| Respondent FE?         | No                     | Yes                | No                 | Yes                | No                     | Yes                | No                 | Yes                |

*Notes:* Odd columns estimate the treatment-control difference in the pre-period (a baseline balance test) and in the post-period (a treatment effect estimate). Even columns estimate the treatment-control differences in the post period relative to the treatment-control difference in the pre-period, where the latter is absorbed by respondent fixed effects. All regressions cluster standard errors by respondent. All regressions include date and days-since-main-visit fixed effects. Columns 1, 2, 5, and 6 also include hour-of-day fixed effects. Column (1) uses hourly charcoal stove usage data and most closely represents a weighted average of the pre-period and post-period treatment effects shown in [Figure 7](#). The ‘post-period’ coefficient in Column (5) is our preferred specification for the causal impact of stove adoption on daily cooking time.

Table A2: Effect of credit and marginal cost subsidy on willingness-to-pay

|                        | (1)              | (2)              | (3)              | (4)              | (5)              | (6)              | (7)              | (8)              |
|------------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| Credit treatment       | 14.1***<br>(2.1) | 14.2***<br>(2.1) | 14.7***<br>(1.9) | 15.8***<br>(2.0) | 14.1***<br>(2.1) | 14.2***<br>(2.1) | 14.7***<br>(1.9) | 15.8***<br>(2.0) |
| Subsidy                | -2.0<br>(1.3)    | -2.1<br>(1.3)    | -1.5<br>(1.2)    | -1.5<br>(1.3)    |                  |                  |                  |                  |
| Subsidy=25             |                  |                  |                  |                  | -2.2<br>(1.5)    | -2.3<br>(1.4)    | -0.8<br>(1.5)    | -0.4<br>(1.5)    |
| Subsidy=75             |                  |                  |                  |                  | -1.7<br>(1.5)    | -1.8<br>(1.4)    | -2.3<br>(1.4)    | -2.5*<br>(1.4)   |
| Credit X Subsidy (any) | 2.4<br>(2.6)     | 2.3<br>(2.5)     | 2.2<br>(2.4)     | 1.6<br>(2.4)     |                  |                  |                  |                  |
| Credit X 25% Subsidy   |                  |                  |                  |                  | 0.8<br>(3.0)     | 0.9<br>(2.9)     | 0.3<br>(2.8)     | -0.6<br>(2.9)    |
| Credit X 75% Subsidy   |                  |                  |                  |                  | 4.0<br>(2.9)     | 3.8<br>(2.9)     | 4.0<br>(2.7)     | 3.7<br>(2.7)     |
| Observations           | 2134             | 2134             | 2134             | 2134             | 2134             | 2134             | 2134             | 2134             |
| Control Mean           | 19.5             | 19.5             | 19.5             | 19.5             | 19.5             | 19.5             | 19.5             | 19.5             |
| SES controls           | None             | Some             | Many             | All              | None             | Some             | Many             | All              |

*Notes:* The effect of the credit treatment, the electricity subsidy treatment, and their interaction on willingness-to-pay. Columns 1, 2, 3, and 4 (as well as 5, 6, 7, and 8 respectively) vary only in using either no, some, many, or all socioeconomic controls.

Table A3: Impact of credit on daily induction stove usage

|              | All buyers         |                    | Marginal buyers   |                   |
|--------------|--------------------|--------------------|-------------------|-------------------|
|              | (1)<br>Daily       | (2)<br>Respondent  | (3)<br>Daily      | (4)<br>Respondent |
| Credit (=1)  | -95.6***<br>(27.4) | -97.4***<br>(30.0) | -83.0**<br>(33.8) | -86.8**<br>(39.8) |
| Observations | 109994             | 625                | 62875             | 358               |
| Respondents  | 625                |                    | 358               |                   |
| Control Mean | 415                | 415                | 404               | 403               |

*Notes:* Results from ordinary least squares regressions estimating how credit constraints affect the composition of marginal adopters. Standard errors in parentheses are clustered by respondent. Regressions include date fixed effects and control for randomization strata and other treatments. Columns 1 and 3 use daily data, with standard errors clustered by respondent. Columns 2 and 4 use respondent daily average.

Table A4: Extensive and intensive margin impacts of electricity subsidy

|                     | Willingness-to-pay |                 |                 | Daily induction stove usage |                  |                 |
|---------------------|--------------------|-----------------|-----------------|-----------------------------|------------------|-----------------|
|                     | (1)<br>USD         | (2)<br>USD      | (3)<br>USD      | (4)<br>Wh                   | (5)<br>Wh        | (6)<br>Log(Wh)  |
| Any subsidy         | -0.41<br>(1.22)    |                 |                 | 16.25<br>(27.16)            |                  |                 |
| =25                 |                    | -0.51<br>(1.44) |                 |                             | 9.18<br>(32.44)  |                 |
| =75                 |                    | -0.31<br>(1.39) |                 |                             | 23.93<br>(31.90) |                 |
| Subsidy value (USD) |                    |                 | -0.01<br>(0.08) |                             |                  |                 |
| Log(Marginal price) |                    |                 |                 |                             |                  | -0.04<br>(0.05) |
| Observations        | 2134               | 2134            | 2134            | 109994                      | 109994           | 42246           |
| Respondents         |                    |                 |                 | 625                         | 625              | 613             |
| Control mean        | 28                 | 28              | 28              | 360                         | 360              |                 |

*Notes:* Results from ordinary least squares regressions estimating how the electricity subsidy affects outcomes. Columns 1 and 4 pool the two subsidy levels of 25% and 75%; the remaining columns separate the levels. All columns control for randomization strata and other treatments. Columns 4-6 use data at the respondent-by-day level with date fixed effects and standard errors in parentheses clustered by respondent (results are qualitatively indistinguishable when averaging daily usage to the respondent level).

Table A5: Loan repayment statistics

|                                              | N   | Mean   | SD   | 25 <sup>th</sup> | 50 <sup>th</sup> | 75 <sup>th</sup> |
|----------------------------------------------|-----|--------|------|------------------|------------------|------------------|
| Payment ratio (Total paid/Price)             | 421 | 0.83   | 0.3  | 0.7              | 1.0              | 1.0              |
| ... (Price = 20)                             | 276 | 0.94   | 0.1  | 1.0              | 1.0              | 1.0              |
| ... (Price = 25)                             | 8   | 0.82   | 0.3  | 0.5              | 1.0              | 1.0              |
| ... (Price = 41)                             | 10  | 0.83   | 0.2  | 0.6              | 1.0              | 1.0              |
| ... (Price = 44)                             | 2   | 1.00   | 0.0  | 1.0              | 1.0              | 1.0              |
| ... (Price = 73)                             | 125 | 0.59   | 0.3  | 0.3              | 0.5              | 1.0              |
| Zero repayment (=1)                          | 421 | 0.00   | 0.0  | 0.0              | 0.0              | 0.0              |
| ... $\in$ (0, 0.25) (=1)                     | 421 | 0.06   | 0.2  | 0.0              | 0.0              | 0.0              |
| ... $\in$ [0.25, 0.50) (=1)                  | 421 | 0.10   | 0.3  | 0.0              | 0.0              | 0.0              |
| ... $\in$ [0.50, 0.75) (=1)                  | 421 | 0.13   | 0.3  | 0.0              | 0.0              | 0.0              |
| ... $\in$ [0.75, 1) (=1)                     | 421 | 0.10   | 0.3  | 0.0              | 0.0              | 0.0              |
| ... = 1 (=1)                                 | 421 | 0.61   | 0.5  | 0.0              | 1.0              | 1.0              |
| Repayment ratio (Principal repaid/Principal) | 421 | 0.76   | 0.4  | 0.4              | 1.0              | 1.0              |
| ... (Price = 20)                             | 276 | 0.87   | 0.3  | 1.0              | 1.0              | 1.0              |
| ... (Price = 25)                             | 8   | 0.66   | 0.5  | 0.1              | 1.0              | 1.0              |
| ... (Price = 41)                             | 10  | 0.67   | 0.4  | 0.2              | 1.0              | 1.0              |
| ... (Price = 44)                             | 2   | 1.00   | 0.0  | 1.0              | 1.0              | 1.0              |
| ... (Price = 73)                             | 125 | 0.51   | 0.4  | 0.2              | 0.4              | 1.0              |
| Zero loan repayment (=1)                     | 421 | 0.03   | 0.2  | 0.0              | 0.0              | 0.0              |
| ... $\in$ (0, 0.25) (=1)                     | 421 | 0.11   | 0.3  | 0.0              | 0.0              | 0.0              |
| ... $\in$ [0.25, 0.50) (=1)                  | 421 | 0.12   | 0.3  | 0.0              | 0.0              | 0.0              |
| ... $\in$ [0.50, 0.75) (=1)                  | 421 | 0.08   | 0.3  | 0.0              | 0.0              | 0.0              |
| ... $\in$ [0.75, 1) (=1)                     | 421 | 0.05   | 0.2  | 0.0              | 0.0              | 0.0              |
| ... = 1 (=1)                                 | 421 | 0.61   | 0.5  | 0.0              | 1.0              | 1.0              |
| Days On Track (0-158)                        | 421 | 100.48 | 53.0 | 44.0             | 109.0            | 156.0            |
| ... , Repayment Month 1 (0-29)               | 421 | 30.00  | 0.0  | 30.0             | 30.0             | 30.0             |
| ... , Repayment Month 2 (30-59)              | 421 | 19.83  | 12.3 | 7.0              | 28.0             | 30.0             |
| ... , Repayment Month 3 (60-89)              | 421 | 15.47  | 13.7 | 0.0              | 19.0             | 30.0             |
| ... , Repayment Month 4 (90-119)             | 421 | 13.09  | 13.6 | 0.0              | 6.0              | 30.0             |
| ... , Repayment Month 5 (120-149)            | 421 | 16.67  | 14.4 | 0.0              | 27.0             | 30.0             |
| ... , Repayment Month 6 (150-158)            | 421 | 5.42   | 4.4  | 0.0              | 9.0              | 9.0              |
| Days to Full Repayment                       | 257 | 86.09  | 42.1 | 68.0             | 94.0             | 117.0            |

*Notes:* Of the 626 respondents who bought the induction stove, 421 bought it using a loan. The difference between the price and the principal is the deposit amount, which was US\$12 and which was paid by all buyers. All amounts in USD.

Table A6: Alternative assumptions

| Assumption                                        | Cost per tCO <sub>2e</sub> |
|---------------------------------------------------|----------------------------|
| Benchmark                                         | US\$13                     |
| (1) One-year durability                           | US\$25                     |
| (2) Three-year durability                         | US\$8                      |
| (3) Fraction non-renewable biomass (fNRB) of 10%  | US\$16                     |
| (4) Fraction non-renewable biomass (fNRB) of 100% | US\$10                     |
| (5) US grid emissions intensity                   | US\$13                     |

*Notes:* Subsidy efficiency results under alternative assumptions. The benchmark is this paper’s main estimate. Scenarios (1) and (2) assume that the stove’s expected life span is one year or three years (the main estimate uses 1.9). Scenarios (3) and (4) assume that the fraction of the wood used for charcoal production that is non-renewable is either 10% or 100% (the main estimate assumes 38%). Scenario (5) assumes that Kenya’s average grid emissions were those of the U.S., at 366 grams of CO<sub>2e</sub> per kWh (the main estimate uses Kenya’s grid average of 154 grams of CO<sub>2e</sub> per kWh).

Table A7: Households using charcoal as their primary cooking fuel

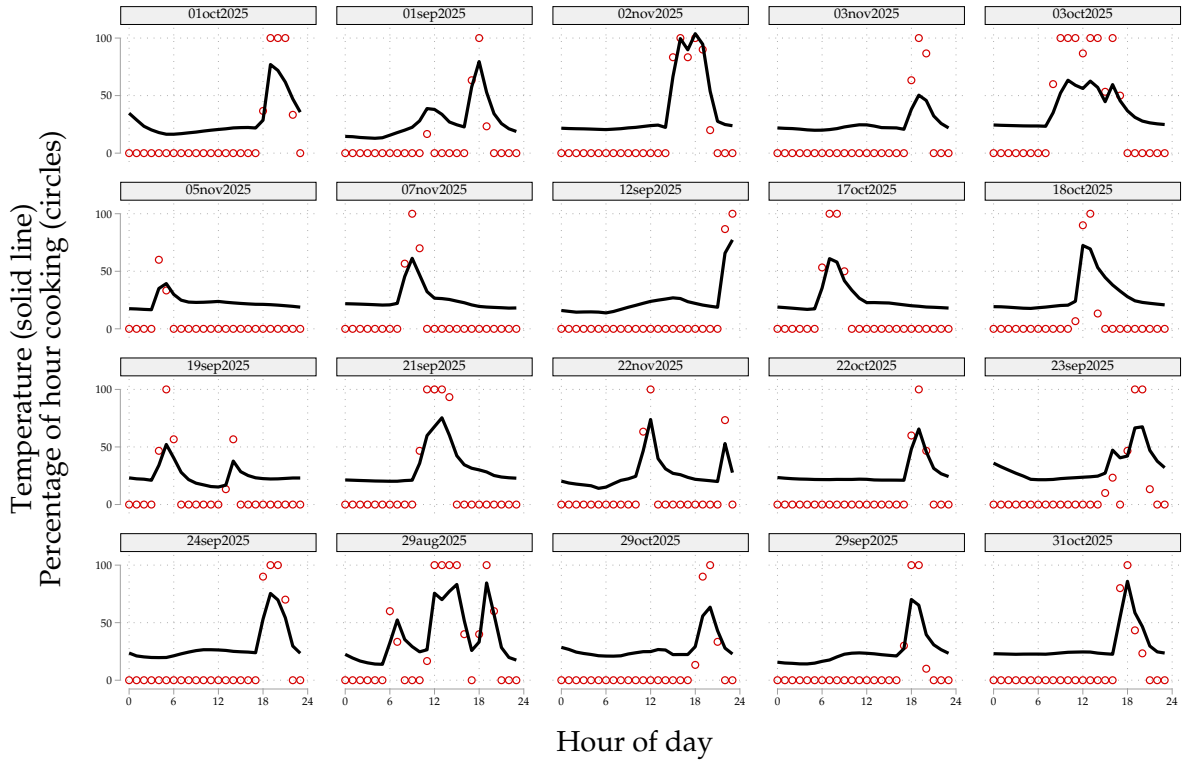
| Country                | Households (millions) | Charcoal (millions) | Wood (millions) | Source              |
|------------------------|-----------------------|---------------------|-----------------|---------------------|
| China                  | 522.7                 | 17.7                | 50.1            | CNSB (2020)         |
| Madagascar             | 6.9                   | 4.5                 | 2.2             | MNIS (2022a; 2022b) |
| Tanzania               | 13.8                  | 3.6                 | 7.7             | TNBS (2022)         |
| Nigeria                | 40.8                  | 3.2                 | 23.4            | NNBS (2024)         |
| Burkina Faso           | 18.3                  | 3.1                 | 4.4             | BFNISD (2021)       |
| Dem. Rep. of the Congo | 13.2                  | 3.1                 | 9.9             | DMPH (2021)         |
| Ghana                  | 8.4                   | 2.6                 | 3               | GSS (2022)          |
| Philippines            | 23                    | 2                   | 8.5             | PSA (2022)          |
| Bangladesh             | 41                    | 1.7                 | 28.2            | BBS (2023a; 2023b)  |
| Uganda                 | 7.2                   | 1.7                 | 5.1             | UBS (2020)          |
| Ethiopia               | 19.5                  | 1.6                 | 15.7            | EPHI (2019)         |
| Mozambique             | 6.2                   | 1.4                 | 4.3             | MNIS (2023)         |
| Kenya                  | 12                    | 1.4                 | 6.4             | KNBS (2022)         |
| Zambia                 | 2.8                   | 1.2                 | 1.4             | ZSA (2018)          |
| Myanmar                | 11.2                  | 1.1                 | 6.7             | MMPF (2017)         |
| Other                  |                       | 4.7                 | 128.7           |                     |
| Total                  |                       | 54.3                | 305.9           |                     |

*Notes:* Charcoal households are those that use charcoal as their primary cooking fuel. Numbers listed are from census data asking households which fuel they use as their primary cooking fuel. Only countries for which census data lists at least 1 million charcoal households are listed. Some countries may be missing.

On-line Appendix Begins Here

### III Online Appendix Figures and Tables

Figure B1: Temperature-to-cooking conversion algorithm examples



*Notes:* Comparison of raw temperature data in Celsius (black line) and the estimated cooking fraction (red dots), for 20 unique dates and unique respondents, randomly selected from the set with non-zero cooking events. [Section 4.5](#) describes the conversion algorithm.

Table B1: Balance on main treatment variables

|                                                                        | Sample<br>Mean     | Credit<br>Treatment | Low BDM<br>Price (<30) | Electricity<br>Treatment | N    |
|------------------------------------------------------------------------|--------------------|---------------------|------------------------|--------------------------|------|
|                                                                        | (1)                | (2)                 | (3)                    | (4)                      |      |
| Stratification variable: Charcoal spending<br>(USD/month)              | 19.43<br>[6.20]    | 0.23<br>(0.27)      | 0.02<br>(0.27)         | -0.04<br>(0.28)          | 2134 |
| Stratification variable: Use lpg/gas/ethanol for<br>cooking (=1)       | 0.58<br>[0.49]     | 0.00<br>(0.02)      | 0.00<br>(0.02)         | 0.00<br>(0.02)           | 2134 |
| Stratification variable: Electricity top-up<br>spending (USD, 5 weeks) | 4.68<br>[4.32]     | 0.39**<br>(0.19)    | -0.11<br>(0.19)        | -0.20<br>(0.20)          | 2134 |
| Household size                                                         | 4.95<br>[1.65]     | 0.01<br>(0.07)      | 0.08<br>(0.07)         | 0.03<br>(0.08)           | 2134 |
| Age                                                                    | 35.84<br>[10.15]   | 0.06<br>(0.44)      | -0.26<br>(0.44)        | -0.18<br>(0.47)          | 2134 |
| Male respondent                                                        | 0.10<br>[0.30]     | 0.00<br>(0.01)      | 0.02<br>(0.01)         | 0.01<br>(0.01)           | 2134 |
| Charcoal cooking time<br>(minutes/day)                                 | 186.00<br>[71.08]  | -2.02<br>(3.08)     | -3.09<br>(3.08)        | 3.00<br>(3.26)           | 2134 |
| LPG/ethanol spending (USD/month)                                       | 5.23<br>[10.16]    | 0.54<br>(0.44)      | -0.49<br>(0.44)        | -0.06<br>(0.47)          | 2128 |
| Respondent income (USD/month)                                          | 101.44<br>[115.35] | 2.33<br>(5.00)      | 1.09<br>(5.01)         | -2.86<br>(5.29)          | 2127 |
| Household income (USD/month)                                           | 246.99<br>[204.86] | 16.12*<br>(9.61)    | 16.38*<br>(9.62)       | -12.88<br>(10.18)        | 1815 |
| Blackout hours (last 30 days)                                          | 13.93<br>[27.49]   | 2.24*<br>(1.19)     | 0.50<br>(1.19)         | -0.44<br>(1.26)          | 2134 |
| Voltage fluctuation hours (last 30 days)                               | 2.04<br>[10.88]    | -0.70<br>(0.47)     | -0.44<br>(0.47)        | 0.20<br>(0.50)           | 2134 |
| Joint F-Test                                                           |                    | 0.09                | 0.09                   | 0.21                     |      |

*Notes:* Test for balance of baseline variables. We only include participants who completed the main survey because they are the only participants whom we assigned to a treatment group.

Table B2: Impact on food cooked

|                         | Control<br>Mean | Treatment<br>Effect | N    |
|-------------------------|-----------------|---------------------|------|
| Number of unique dishes | 4.42<br>[1.09]  | 0.06<br>(0.14)      | 2070 |
| Tea/Coffee/Milk         | 0.95<br>[0.22]  | 0.00<br>(0.03)      | 2070 |
| Ugali/Mukimo/Matoke     | 0.90<br>[0.30]  | -0.12***<br>(0.04)  | 2070 |
| Rice/lentils            | 0.55<br>[0.50]  | 0.11*<br>(0.06)     | 2070 |
| Leafy Greens            | 0.80<br>[0.40]  | -0.06<br>(0.05)     | 2070 |
| Beans/Corn              | 0.32<br>[0.47]  | 0.02<br>(0.06)      | 2070 |
| Potato                  | 0.30<br>[0.46]  | 0.03<br>(0.06)      | 2070 |
| Chapati/Pancakes        | 0.14<br>[0.35]  | 0.06<br>(0.04)      | 2070 |
| Fish                    | 0.14<br>[0.35]  | -0.02<br>(0.04)     | 2070 |
| Meat Stew               | 0.09<br>[0.29]  | 0.01<br>(0.04)      | 2070 |
| Eggs                    | 0.08<br>[0.28]  | 0.03<br>(0.04)      | 2070 |
| Porridge                | 0.11<br>[0.31]  | -0.04<br>(0.04)     | 2070 |

*Notes:* Impact on the number of unique dishes cooked in a day and which foods this consisted of.

Table B3: Impact on health outcomes

|                                 | Control<br>Mean | Treatment<br>Effect | N    |
|---------------------------------|-----------------|---------------------|------|
| Persistent cough (=1)           | 0.22<br>[0.41]  | -0.14***<br>(0.05)  | 2081 |
| Breathless at night (=1)        | 0.16<br>[0.37]  | -0.09**<br>(0.04)   | 2081 |
| Child: Persistent cough (=1)    | 0.40<br>[0.49]  | -0.14*<br>(0.08)    | 1324 |
| Child: Breathless at night (=1) | 0.15<br>[0.36]  | -0.09<br>(0.06)     | 1324 |

*Notes:* Impact on self-reported health outcomes for adults and children (among households with at least one child under the age of 5).

Table B4: Attrition by treatment assignment and adoption status

|                             | Control Mean | Attrited (Visit 3)   |
|-----------------------------|--------------|----------------------|
| Credit treatment (=1)       | 0.030        | -0.010<br>(0.007)    |
| BDM price < 30 USD          | 0.027        | -0.005<br>(0.007)    |
| Electricity treatment > 0   | 0.021        | 0.006<br>(0.007)     |
| Bought induction stove (=1) | 0.031        | -0.022***<br>(0.007) |
| Joint F-Test p-Value        |              | 0.00                 |
| Sample Mean                 |              | 0.02                 |

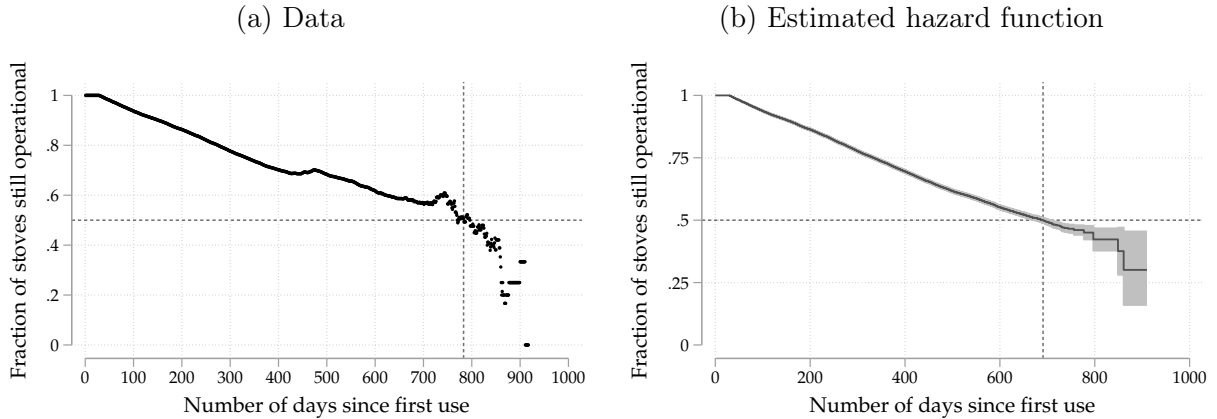
Notes: 2,134 respondents completed the main survey and 2,081 completed the endline survey. Predictors of attrition (defined as not completing an endline visit) among the sample of respondents who completed the main survey.

Table B5: Attrition: Participant availability

| Reason                              | Frequency |
|-------------------------------------|-----------|
| Completed survey                    | 2081      |
| Unavailable                         | 8         |
| Withdrew from study                 | 8         |
| Relocated outside survey team reach | 36        |
| Hospitalized                        | 1         |
| Total                               | 2134      |

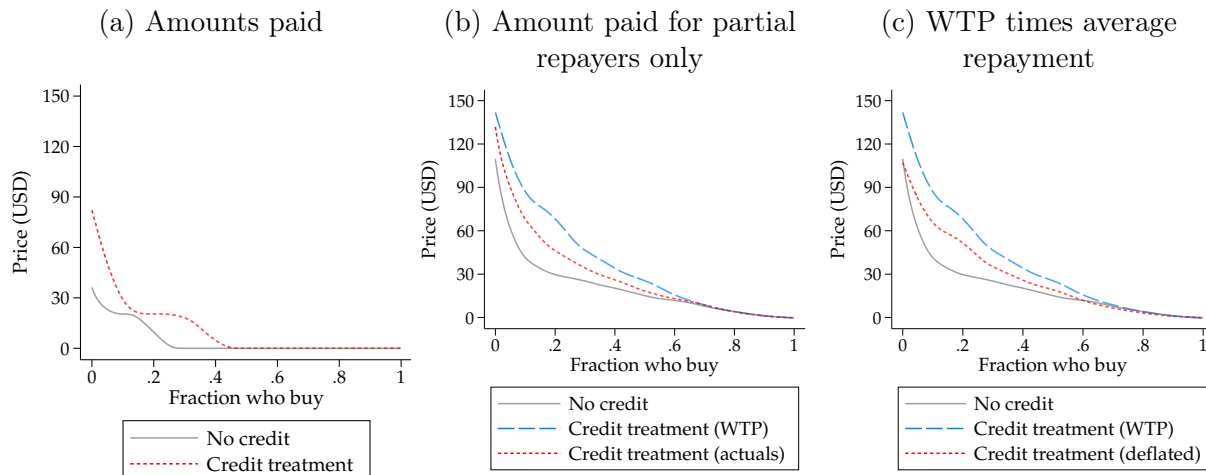
Notes: Completion of follow-up survey among the 2,134 respondents who completed the main survey. Participants were classified as relocated outside survey team reach if they had moved outside the survey area or outside Kenya either permanently or for at least 3 months and thus could not be contacted for follow-up.

Figure B2: Stove lifespan estimation



Notes: Stove breakage rates for the 23,444 stoves that had been sold on or before December 31, 2024. The time variable is the number of days between first usage and last usage. A breakage event is the last observed usage if that usage happened more than 3 months before the end of our dataset. We drop the 2% of stoves with less than 24 hours of usage as well as the 3% of stoves with usage between 1 and 29 days since faulty stoves identified within this period are replaced for free by the seller. Median lifespans are marked by the dotted lines. Panel a shows the empirical distribution of survival. Panel b shows the survival curve estimated using a Cox proportional hazard model, according to which the median induction stove sold by the seller has a lifespan of 1.9 years.

Figure B3: Willingness to pay adjusting for repayment rates



*Notes:* Demand curves that adjust for observed repayment rates. Panel a presents the actual amounts paid by the treatment group, counting non-adopters as zeros. Panel b replaces willingness to pay (WTP) with the actual amount paid only for buyers with credit who did not pay 100% of the loan. Panel c deflates WTP across the distribution by the average default rate. Columns 2, 3, and 4 of [Table B6](#) present regression estimates of the impact of the credit treatment using these three definitions, respectively.

Table B6: Robustness of Credit Treatment Effects to Default

|              | (1)                | (2)               | (3)               | (4)               |
|--------------|--------------------|-------------------|-------------------|-------------------|
|              | WTP                |                   |                   |                   |
| Credit       | 16.11***<br>(1.14) | 6.29***<br>(0.58) | 8.16***<br>(0.98) | 7.46***<br>(0.93) |
| Observations | 2134               | 2134              | 2134              | 2134              |
| Control Mean | 19.51              | 4.31              | 19.51             | 19.51             |

*Notes:* Robustness of the effect of the credit treatment on willingness to pay, adjusting for observed repayment rates. Column 1 replicates the main effect of credit on WTP. Column 2 uses the amount of money paid, counting those who did not adopt as zero. Column 3 replaces willingness to pay with the amount paid for those who paid less than 100%. Column 4 deflates WTP in the credit treatment by the average rate of default.

Table B7: Simulated estimates from observed and counterfactual parameters

|                            | Assumed<br>demand<br>distortion ( $\gamma$ ) | Assumed<br>correlation<br>( $\rho$ ) | Average marginal<br>externality ( $\phi$ ) | Extensive margin<br>elasticity ( $\mathcal{E}_D$ ) | US\$ per tCO <sub>2</sub> e |       |
|----------------------------|----------------------------------------------|--------------------------------------|--------------------------------------------|----------------------------------------------------|-----------------------------|-------|
| (1) <i>Counterfactual</i>  | .11                                          | -.7                                  | 3.3                                        | -2.4                                               | 64.4                        | 19.3  |
| (2) <i>Counterfactual</i>  | .11                                          | -.5                                  | 3.5                                        | -2.4                                               | 64.4                        | 18.4  |
| (3) <i>Counterfactual</i>  | .11                                          | -.2                                  | 3.8                                        | -2.4                                               | 64.4                        | 16.9  |
| (4) <i>Counterfactual</i>  | .11                                          | 0                                    | 4.1                                        | -2.4                                               | 64.4                        | 15.6  |
| (5) <i>Counterfactual</i>  | .11                                          | .2                                   | 4.5                                        | -2.4                                               | 64.4                        | 14.5  |
| (6) <i>Counterfactual</i>  | .11                                          | .6                                   | 4.8                                        | -2.4                                               | 64.4                        | 13.5  |
| (7) <i>Counterfactual</i>  | .11                                          | .7                                   | 4.9                                        | -2.4                                               | 64.4                        | 13    |
| (8) <i>Counterfactual</i>  | .11                                          | 1                                    | 5.8                                        | -2.4                                               | 64.4                        | 11.2  |
| (9) <i>Counterfactual</i>  | .19                                          | -.7                                  | 4                                          | -.8                                                | 95.5                        | 23.8  |
| (10) <i>Counterfactual</i> | .19                                          | -.5                                  | 4                                          | -.8                                                | 95.5                        | 23.7  |
| (11) <i>Counterfactual</i> | .19                                          | -.2                                  | 4.1                                        | -.8                                                | 95.5                        | 23.4  |
| (12) <i>Counterfactual</i> | .19                                          | 0                                    | 4.1                                        | -.8                                                | 95.5                        | 23.1  |
| (13) <i>Counterfactual</i> | .19                                          | .2                                   | 4.2                                        | -.8                                                | 95.5                        | 23    |
| (14) <i>Counterfactual</i> | .19                                          | .6                                   | 4.2                                        | -.8                                                | 95.5                        | 22.8  |
| (15) <i>Counterfactual</i> | .19                                          | .7                                   | 4.2                                        | -.8                                                | 95.5                        | 22.7  |
| (16) <i>Counterfactual</i> | .19                                          | 1                                    | 4.3                                        | -.8                                                | 95.5                        | 22.3  |
| (17) <i>Counterfactual</i> | .5                                           | -.7                                  | 5                                          | -.2                                                | 222.5                       | 44.4  |
| (18) <i>Counterfactual</i> | .5                                           | -.5                                  | 4.8                                        | -.2                                                | 222.5                       | 46    |
| (19) <i>Counterfactual</i> | .5                                           | -.2                                  | 4.5                                        | -.2                                                | 222.5                       | 49.5  |
| (20) <i>Counterfactual</i> | .5                                           | 0                                    | 4.1                                        | -.2                                                | 222.5                       | 53.7  |
| (21) <i>Counterfactual</i> | .5                                           | .2                                   | 3.8                                        | -.2                                                | 222.5                       | 58    |
| (22) <i>Counterfactual</i> | .5                                           | .6                                   | 3.5                                        | -.2                                                | 222.5                       | 63    |
| (23) <i>Counterfactual</i> | .5                                           | .7                                   | 3.4                                        | -.2                                                | 222.5                       | 65.9  |
| (24) <i>Counterfactual</i> | .5                                           | 1                                    | 2.6                                        | -.2                                                | 222.5                       | 85.4  |
| (25) <i>Counterfactual</i> | 1                                            | -.7                                  | 5.9                                        | -.1                                                | 347.8                       | 59.4  |
| (26) <i>Counterfactual</i> | 1                                            | -.5                                  | 5.5                                        | -.1                                                | 347.8                       | 63    |
| (27) <i>Counterfactual</i> | 1                                            | -.2                                  | 4.8                                        | -.1                                                | 347.8                       | 71.9  |
| (28) <i>Counterfactual</i> | 1                                            | 0                                    | 4.2                                        | -.1                                                | 347.8                       | 83.6  |
| (29) <i>Counterfactual</i> | 1                                            | .2                                   | 3.6                                        | -.1                                                | 347.8                       | 96.8  |
| (30) <i>Counterfactual</i> | 1                                            | .6                                   | 3                                          | -.1                                                | 347.8                       | 115   |
| (31) <i>Counterfactual</i> | 1                                            | .7                                   | 2.7                                        | -.1                                                | 347.8                       | 126.9 |
| (32) <i>Counterfactual</i> | 1                                            | 1                                    | 1.3                                        | -.1                                                | 347.8                       | 263.2 |

*Notes:* Additional counterfactual estimates using alternative values of demand distortion ( $\gamma$ ) and correlation between private and social benefits ( $\rho$ )

Table B8: Simulated estimates from observed and counterfactual parameters using alternate distributional assumption

(a) Estimation

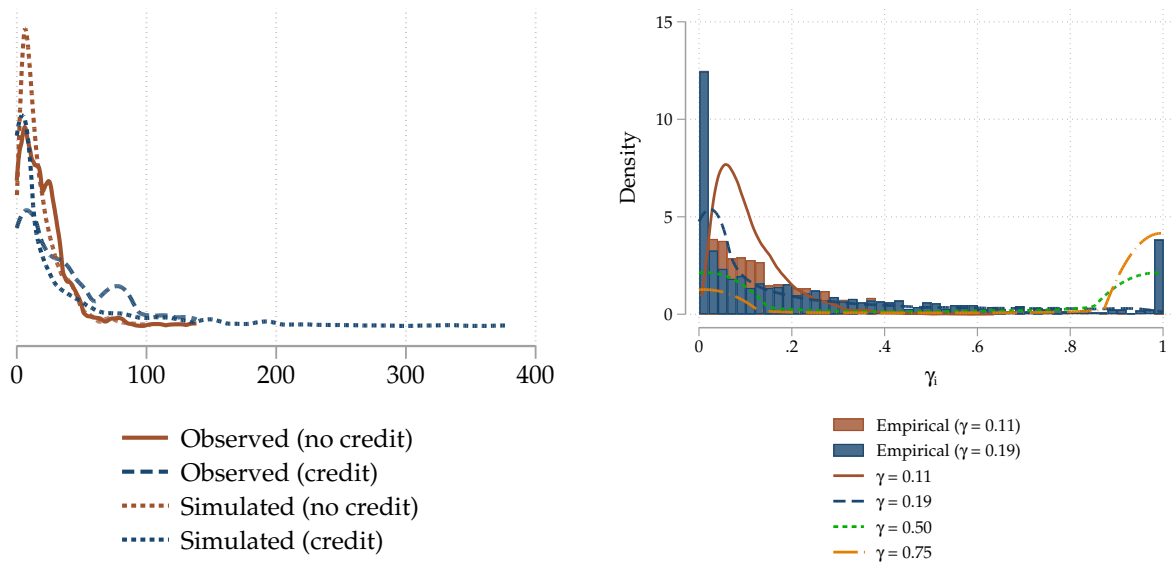
| Moment                                          | RCT: Pay up front<br>( $\gamma = 0.11$ ) |           |           | RCT: Pay with loan<br>( $\gamma = 0.19$ ) |           |           |
|-------------------------------------------------|------------------------------------------|-----------|-----------|-------------------------------------------|-----------|-----------|
|                                                 | Empirical                                | Simulated | Deviation | Empirical                                 | Simulated | Deviation |
| Correlation ( $\rho$ )                          | 0.8                                      | 0.8       | -1%       | 0.8                                       | 0.8       | -1%       |
| Marginal externality ( $\phi$ )                 | 5                                        | 5         | 2%        | 4.2                                       | 4.2       | 1%        |
| Extensive margin elasticity ( $\mathcal{E}_D$ ) | -2.3                                     | -2.5      | -8%       | -0.9                                      | -0.9      | -4%       |
| USD per marginal adoption                       | 65.4                                     | 64.1      | -2%       | 93.4                                      | 86.5      | -7%       |

(b) Counterfactual simulations: Varying the distortion  $\gamma$

|                                                 | (1)  | (2)  | (3)  | (4)   | (5)   | (6)   | (7)   |
|-------------------------------------------------|------|------|------|-------|-------|-------|-------|
| Assumed demand distortion ( $\gamma$ )          | 0.05 | 0.11 | 0.19 | 0.25  | 0.5   | 0.75  | 1     |
| Marginal externality ( $\phi$ )                 | 7    | 5.1  | 4.2  | 4     | 3.3   | 2.8   | 2.5   |
| Extensive margin elasticity ( $\mathcal{E}_D$ ) | -5.7 | -2.5 | -0.9 | -0.6  | -0.3  | -0.2  | -0.1  |
| USD per marginal adoption                       | 61.7 | 64.1 | 86.5 | 106.3 | 191.5 | 262.4 | 320.5 |
| USD per tCO <sub>2</sub> e (observed)           |      | 13.2 | 22.3 |       |       |       |       |
| USD per tCO <sub>2</sub> e (simulated)          | 8.8  | 12.7 | 20.4 | 26.8  | 58.5  | 92.6  | 129.4 |
| MVPF per US\$1 (observed)                       |      | 20.3 | 12.1 |       |       |       |       |
| MVPF per US\$1 (simulated)                      | 32.9 | 22.7 | 14.2 | 11    | 5.5   | 3.8   | 2.9   |

*Notes:* Robustness check of Table 7 with an alternative distributional assumption: estimating the model with a heavy-tailed logit- $t$  distribution such that  $\gamma_i = \text{logistic}(\mu_c + \sigma_c t_i)$ ,  $t_i \sim t(\nu = 5)$  rescaled to  $\text{Var}(t_i) = 1$  with  $\sigma_c = \log(1 + \exp(\Omega_4 + \Omega_5 \gamma_c))$ . Panel a shows that the fit is slightly worse than in Table 7. Panel b shows that the distributional assumption does not meaningfully affect the counterfactual simulations.

Figure B4: Empirical and simulated WTP and gamma distributions  
 (a) Willingness-to-pay (b) Demand distortion ( $\gamma_i$ )



Notes: Panel a: Simulated and observed distributions of WTP by credit treatment group. Panel b: The histograms show the empirical distributions of the  $\gamma_i$  after using LASSO to estimate heterogeneous treatment effects and then projecting resulting estimates onto respondent characteristics to predict their individual savings, and then dividing WTP by the result to estimate individual-level  $\gamma_i$ . The four lines show  $\gamma_i = \text{logistic}(\mu_c + \sigma_c \varepsilon_i)$ ,  $\varepsilon_i \sim N(0, 1)$ , with dispersion  $\sigma_c = \log(1 + \exp(\Omega_4 + \Omega_5, \gamma_c))$  for the estimated values of  $\Omega_4$  and  $\Omega_5$  across four different values of  $\gamma_c$ . Even though GMM estimates 5 parameters to match 7 moments simultaneously, the distributions appear to reasonably capture the estimated underlying distribution of  $\gamma_i$ .

## IV Additional derivations

### IV.1 Proofs: Model set-up

*Proof of Lemma 1.* Since  $\mu'' < 0$ ,  $\mu'$  is invertible. Recall that  $x^*$  is the unique solution to  $\mu'(x^*) = -\pi'$ . The FOC then implies  $d_{2i}^* \theta_i - \alpha_i = x^*$  for every agent: regardless of an agent's energy demand  $\theta_i$  or taste  $\alpha_i$ , the absolute quantity of clean energy consumed in excess of the agent's taste parameter is the same. Agents with higher  $\theta_i$  simply use a smaller fraction  $d_{2i}^*$  to reach the same level; agents with higher  $\alpha_i$  use more clean energy in total but face the same marginal trade-off.

Each agent's optimal fraction is determined by their preference parameters:  $d_{2i}^* = \frac{x^* + \alpha_i}{\theta_i}$ . Substituting  $d_{2i}^* \theta_i = x^* + \alpha_i$  into WTP:

$$wtp_i = (x^* + \alpha_i)\pi' + \mu(x^*) = \underbrace{x^* \pi' + \mu(x^*)}_{\equiv a} + \alpha_i \pi'$$

The constant  $a$  captures the common component of WTP shared by all agents — the fuel savings and switching costs evaluated at the common usage margin  $x^*$ . Or, put another way,  $x^*$  is the usage level for agents with  $\alpha_i = 0$  and  $a$  is the utility of adoption for such an agent. Utility then scales linearly in  $\alpha_i \pi'$ . Since heterogeneity in WTP depends only on  $\alpha_i$ , heterogeneity in the adoption decision is fully determined by  $\alpha_i$ .  $\square$

*Proof of Lemma 2.* From Equation 1,  $wtp_i = a + \alpha_i \pi'$  where  $a = x^* \pi' + \mu(x^*)$ . Under  $\delta$ , the agent perceives fuel price  $\delta \pi'$ , so define  $\tilde{x}^*$  as the unique solution to  $\mu'(\tilde{x}^*) = -\delta \pi'$ . Since  $\delta < 1$ , we have  $\mu'(\tilde{x}^*) = -\delta \pi' > -\pi' = \mu'(x^*)$ , and since  $\mu'$  is strictly decreasing ( $\mu'' < 0$ ), it follows that  $\tilde{x}^* < x^*$ : agents underuse the technology when they underperceive fuel savings. The same steps yield:

$$\widetilde{wtp}_i = (\tilde{x}^* + \alpha_i)(\delta \pi') + \mu(\tilde{x}^*) = \underbrace{\tilde{x}^* \delta \pi' + \mu(\tilde{x}^*)}_{\equiv \tilde{a}} + \alpha_i(\delta \pi')$$

Substituting  $\alpha_i = (wtp_i - a)/\pi'$ :

$$\widetilde{wtp}_i = \delta wtp_i + k \quad \text{where } k = \tilde{a} - \delta a$$

Expanding  $k$ :

$$\begin{aligned} k &= \tilde{a} - \delta a \\ &= [\tilde{x}^* \delta \pi' + \mu(\tilde{x}^*)] - \delta [x^* \pi' + \mu(x^*)] \\ &= \delta \pi'(\tilde{x}^* - x^*) + \mu(\tilde{x}^*) - \delta \mu(x^*) \end{aligned}$$

We now show that  $k \leq 0$ , meaning that marginal distortions reduce WTP by *at least* as much as proportional scaling by  $\delta$ . The strategy is to treat  $k$  as a function of  $\delta$  on  $[0, 1]$  and show it equals zero at both endpoints but is strictly convex in between, so it must be weakly negative throughout.

*Step 1.  $k(1) = 0$ : no distortion, no gap.* When  $\delta = 1$  there is no distortion,  $\widetilde{wtp}_i = wtp_i$  which implies  $k = 0$ .

*Step 2.  $k(0) = 0$ : complete distortion, both sides vanish.* When  $\delta = 0$  the agent perceives zero fuel savings and  $k$  reduces to  $\mu(\tilde{x}^*)$ . Intuitively, WTP shifts by the amount of disutility the agent will receive at their optimal level of usage given that there are no savings to be had. The FOC requires  $\mu'(\tilde{x}^*) = 0$ . Since  $\mu'(0) = 0$  by assumption, we have  $\tilde{x}^*(0) = 0$ . Because  $\mu(0) = 0$  we thus have  $k = 0$ .

*Step 3.  $k$  is strictly convex: the envelope theorem and diminishing returns.*

*First derivative.* Since  $k = \tilde{a}(\delta) - \delta a$ , where  $a$  does not depend on  $\delta$ :

$$\frac{dk}{d\delta} = \frac{d\tilde{a}}{d\delta} - a$$

To evaluate  $d\tilde{a}/d\delta$ , expand  $\tilde{a}(\delta) = \tilde{x}^*(\delta)\delta\pi' + \mu(\tilde{x}^*(\delta))$  by the chain rule:

$$\frac{d\tilde{a}}{d\delta} = \frac{d\tilde{x}^*}{d\delta} \delta \pi' + \tilde{x}^* \pi' + \mu'(\tilde{x}^*) \frac{d\tilde{x}^*}{d\delta}$$

Collecting the terms that involve  $d\tilde{x}^*/d\delta$ :

$$= \frac{d\tilde{x}^*}{d\delta} \underbrace{[\delta \pi' + \mu'(\tilde{x}^*)]}_{= 0 \text{ by the FOC}} + \tilde{x}^* \pi' = \tilde{x}^*(\delta) \pi'$$

The FOC zeroes out all terms involving re-optimization of usage, following the envelope theorem. Because the agent has already chosen  $\tilde{x}^*$  optimally, a small change in  $\delta$  affects the distorted value function  $\tilde{a}$  only through its direct effect on perceived savings, not through the induced change in behavior. Intuitively, the agent is already at a point where the marginal cost of switching equals the marginal benefit, so adjusting usage neither helps nor hurts to

first order. Substituting:

$$\frac{dk}{d\delta} = \tilde{x}^*(\delta)\pi' - a$$

*Second derivative.* As  $\delta$  increases,  $\tilde{x}^*$  rises—the agent shifts more consumption to clean energy. To find the rate, differentiate the FOC  $\mu'(\tilde{x}^*) = -\delta\pi'$  with respect to  $\delta$ :

$$\mu''(\tilde{x}^*)\frac{d\tilde{x}^*}{d\delta} = -\pi' \quad \implies \quad \frac{d\tilde{x}^*}{d\delta} = \frac{-\pi'}{\mu''(\tilde{x}^*)} > 0$$

(Positive because  $\mu'' < 0$ .) Therefore:

$$\frac{d^2k}{d\delta^2} = \frac{d\tilde{x}^*}{d\delta}\pi' = \frac{-(\pi')^2}{\mu''(\tilde{x}^*)} > 0$$

*Conclusion.* Since  $k$  is convex with  $k(0) = k(1) = 0$ , it follows that  $k(\delta) \leq 0$  for all  $\delta \in [0, 1]$ .<sup>28</sup> □

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<sup>28</sup>For any convex function  $f$  with  $f(0) = f(1) = 0$ :  $f(\delta) = f((1-\delta)0 + \delta 1) \leq (1-\delta)f(0) + \delta f(1) = 0$ .

*Proof of Lemma 3.* Under intertemporal distortions ( $\gamma$ ), the agent correctly perceives  $\pi'$  and optimizes usage accordingly, but discounts the resulting benefit by  $\gamma$  at the time of adoption. Since  $\widetilde{wtp}_i = \gamma wtp_i$ , carbon taxes and marginal cost subsidies are equally dampened:

$$\frac{\partial \widetilde{wtp}_i}{\partial \tau} = \gamma \frac{\partial wtp_i}{\partial \tau} = \gamma \frac{\partial wtp_i}{\partial s_2} = \frac{\partial \widetilde{wtp}_i}{\partial s_2}$$

Under marginal distortions ( $\delta$ ), the agent perceives only a fraction  $\delta$  of any change in  $\pi'$ . Since the envelope theorem implies that the distorted usage fraction  $\tilde{d}_{2i}^*$  does not adjust to first order, the effect on WTP operates entirely through the perceived price:

$$\frac{\partial \widetilde{wtp}_i}{\partial \tau} = \delta \tilde{d}_{2i}^* \theta_i < d_{2i}^* \theta_i = \frac{\partial wtp_i}{\partial \tau}$$

where the inequality holds because  $\delta < 1$  and because  $\tilde{d}_{2i}^* < d_{2i}^*$ .

**Result: Demand distortions reduce the efficacy of marginal cost instruments.** Whether the principal raises  $p_H$  (carbon tax), lowers  $p_L$  (marginal cost subsidy), or both, the agent's adoption response is dampened by  $\gamma$ ,  $\delta$ , or both. As distortions become severe, changes in the relative fuel price have vanishing effects on adoption.

**Result: Fixed cost subsidies bypass the relative fuel price channel.** A fixed cost subsidy  $s_1$  reduces the adoption threshold from  $p_{mc}$  to  $p_{mc} - s_1$ , which does not require the agent to respond to fuel price signals.  $\square$

*Proof of Lemma 4.* Differentiating the adoption condition  $\gamma wtp(\underline{\alpha}) = p_{mc} - s_1$  with respect to  $\gamma$ , holding instruments  $s_1$  and  $s_2$  fixed:

$$wtp(\underline{\alpha}) + \gamma \pi' \frac{\partial \underline{\alpha}}{\partial \gamma} = 0 \quad \implies \quad \frac{\partial \underline{\alpha}}{\partial \gamma} = -\frac{wtp(\underline{\alpha})}{\gamma \pi'} < 0$$

since  $wtp(\underline{\alpha}) > 0$  (the marginal adopter has positive willingness-to-pay) and  $\gamma, \pi' > 0$ .

For marginal distortions, the adoption condition (setting  $\gamma = 1$ ) is  $\widetilde{wtp}(\underline{\alpha}) = p_{mc} - s_1$ , where  $\widetilde{wtp}(\underline{\alpha}) = \tilde{a} + \underline{\alpha} \delta \pi'$ . Differentiating with respect to  $\delta$ , holding instruments fixed, and using  $d\tilde{a}/d\delta = \tilde{x}^* \pi'$  (envelope theorem, from the proof of Lemma 2):

$$\tilde{x}^* \pi' + \underline{\alpha} \pi' + \delta \pi' \frac{\partial \underline{\alpha}}{\partial \delta} = 0 \quad \implies \quad \frac{\partial \underline{\alpha}}{\partial \delta} = -\frac{\tilde{x}^* + \underline{\alpha}}{\delta} < 0$$

since  $\tilde{x}^* + \underline{\alpha} > 0$  (the marginal adopter has positive usage) and  $\delta > 0$ . □

*Proof of Proposition 2.* We first show the case with either an intertemporal distortion or a marginal distortion, and then derive the case with both.

**Intertemporal distortion** ( $\gamma < 1, \delta = 1$ ). Since  $\gamma$  does not affect usage (Section 1.4), the Pigouvian tax  $\tau^* = \phi$  still sets the socially efficient usage level. At this tax, the undistorted adoption rule would be  $wtp_i \geq p_{mc}$ , i.e.,  $SV_i \geq 0$ . But the distorted adoption rule is  $\gamma wtp_i \geq p_{mc} - s_1$ . At the socially optimal margin, the marginal adopter has  $SV = 0$ , i.e.,  $wtp = p_{mc}$ , so:

$$\gamma p_{mc} = p_{mc} - s_1 \quad \implies \quad s_1^* = p_{mc}(1 - \gamma)$$

**Marginal distortion** ( $\delta < 1, \gamma = 1$ ). Under  $\delta$ , both margins are distorted. To correct usage, the planner must set  $\pi'$  high enough that the perceived price  $\delta\pi'$  equals the socially efficient level:

$$\delta\pi' = \pi + \phi \quad \implies \quad \pi' = \frac{\pi + \phi}{\delta}$$

The optimal marginal tax is then given by:

$$\tau^* = \frac{\phi + \pi(1 - \delta)}{\delta}$$

This “super-Pigouvian” tax overshoots the externality to compensate for the agent’s underperception of fuel prices. At this tax, usage is first-best:  $\tilde{x}^* = x^{FB}$  where  $\mu'(x^{FB}) = -(\pi + \phi)$ . A key question is whether the planner also needs  $s_1 > 0$  to correct adoption.

The agent’s perceived WTP at this tax is:

$$\widetilde{wtp}_i = (\tilde{x}^* + \alpha_i)(\delta\pi') + \mu(\tilde{x}^*) = (x^{FB} + \alpha_i)(\pi + \phi) + \mu(x^{FB})$$

where the second equality substitutes  $\tilde{x}^* = x^{FB}$  and  $\delta\pi' = \pi + \phi$ . But this is exactly  $SV_i + p_{mc}$ . So the adoption rule  $\widetilde{wtp}_i \geq p_{mc} - s_1$  is equivalent to  $SV_i \geq -s_1$ , and the socially optimal margin ( $SV = 0$ ) obtains at  $s_1^* = 0$ .

The super-Pigouvian tax corrects *both* margins simultaneously, and no fixed cost subsidy is needed. The reason is that  $\delta$  operates purely through the fuel price channel: the agent underperceives the fuel price by factor  $\delta$ , and inflating the price by  $1/\delta$  perfectly undoes this at both the usage and adoption margins. In contrast,  $\gamma$  scales the *entire* future utility—including switching costs  $\mu$ —which no fuel-price instrument can reach.

**Both distortions** ( $\gamma < 1, \delta < 1$ ). At the super-Pigouvian tax ( $\delta\pi' = \pi + \phi$ ), the  $\delta$  distortion is corrected and the agent’s perceived WTP equals  $\gamma(SV_i + p_{mc})$ , by the same argument as above with an additional  $\gamma$  scaling:

$$\widetilde{wtp}_i = \gamma [(x^{FB} + \alpha_i)(\pi + \phi) + \mu(x^{FB})] = \gamma(SV_i + p_{mc})$$

The adoption rule  $\gamma(SV_i + p_{mc}) \geq p_{mc} - s_1$  at the optimal margin ( $SV = 0$ ) gives:

$$\gamma p_{mc} = p_{mc} - s_1 \quad \implies \quad s_1^* = p_{mc}(1 - \gamma)$$

The same expression as under  $\gamma$  alone. □

## IV.2 Proofs: Social principal

*Proof of Equation 2. First order condition (FOC) for  $s_1$ .* Since  $s_1$  does not affect usage  $\tilde{x}^*$ , it changes social welfare only through the adoption threshold  $\alpha$ .

*Marginal social welfare.* By the Leibniz rule, each marginal adopter contributes  $SV_i(\alpha) = (\tilde{x}^* + \alpha)(\pi + \phi) + \mu(\tilde{x}^*) - p_{mc}$  to social welfare:

$$\frac{\partial W}{\partial s_1} = [(\tilde{x}^* + \alpha)(\pi + \phi) + \mu(\tilde{x}^*) - p_{mc}] g(\alpha) \left( -\frac{\partial \alpha}{\partial s_1} \right)$$

*Marginal cost.* Recall  $C = s_1 Q + s_2 U$ . A dollar increase in  $s_1$  has three cost effects: (i) \$1 more to each existing adopter, (ii)  $s_1$  paid to new adopters, and (iii)  $s_2$  paid on new adopters' usage. By the product rule and Leibniz rule:

$$\begin{aligned} \frac{\partial C}{\partial s_1} &= \underbrace{Q}_{(i)} + \underbrace{s_1 g(\alpha) \left( -\frac{\partial \alpha}{\partial s_1} \right)}_{(ii)} + \underbrace{s_2 (\tilde{x}^* + \alpha) g(\alpha) \left( -\frac{\partial \alpha}{\partial s_1} \right)}_{(iii)} \\ &= Q + [s_1 + s_2 (\tilde{x}^* + \alpha)] g(\alpha) \left( -\frac{\partial \alpha}{\partial s_1} \right) \end{aligned}$$

*FOC.* Setting  $\partial W / \partial s_1 = \lambda \partial C / \partial s_1$  and dividing both sides by  $g(\alpha)(-\partial \alpha / \partial s_1)$ :

$$(\tilde{x}^* + \alpha)(\pi + \phi) + \mu(\tilde{x}^*) - p_{mc} = \lambda \left[ s_1 + s_2 (\tilde{x}^* + \alpha) + \frac{Q}{g(\alpha)(-\partial \alpha / \partial s_1)} \right]$$

Since  $g(\alpha)(-\partial \alpha / \partial s_1)$  is the slope of the demand curve at price  $p_{mc} - s_1$ , the ratio  $Q / [g(\alpha)(-\partial \alpha / \partial s_1)]$  equals  $(p_{mc} - s_1) / |\tilde{\mathcal{E}}(p_{mc} - s_1)|$ , giving the FOC for  $s_1$ :

$$\underbrace{(\tilde{x}^* + \alpha)(\pi + \phi) + \mu(\tilde{x}^*)}_{\substack{\text{fuel savings, abatement,} \\ \text{and switching costs from} \\ \text{one new adopter}}} - \underbrace{p}_{\substack{\text{technology cost} \\ \text{from one} \\ \text{new adopter}}} = \lambda \left[ \underbrace{s_1 + s_2 (\tilde{x}^* + \alpha)}_{\substack{\text{subsidy to new adopter}}} + \underbrace{\frac{p - s_1}{|\tilde{\mathcal{E}}(p - s_1)|}}_{\substack{\text{inframarginal cost}}} \right] \quad (10)$$

**First order condition (FOC) for  $s_2$ .** Since  $s_2$  affects both usage  $\tilde{x}^*$  (through  $\pi'$ ) and the adoption threshold  $\alpha$ , the social welfare derivative has an intensive and an extensive margin.

*Marginal social welfare.* Recall  $W = \int_{\alpha}^{\infty} [(\tilde{x}^* + \alpha_i)(\pi + \phi) + \mu(\tilde{x}^*) - p_{mc}] g(\alpha) d\alpha$ . By the Leibniz rule,  $s_2$  affects  $W$  through the integrand (via  $\tilde{x}^*$ ) and through the lower limit (via  $\alpha$ ):

$$\frac{\partial W}{\partial s_2} = \underbrace{[(\pi + \phi) + \mu'(\tilde{x}^*)] \frac{d\tilde{x}^*}{ds_2} Q}_{\text{intensive}} + \underbrace{[(\tilde{x}^* + \alpha)(\pi + \phi) + \mu(\tilde{x}^*) - p_{mc}] g(\alpha) \left( -\frac{\partial \alpha}{\partial s_2} \right)}_{\text{extensive}}$$

The intensive term captures the social value of each existing adopter shifting  $d\tilde{x}^*/ds_2$  more usage to clean energy: each additional unit saves  $\pi$  in fuel costs and  $\phi$  in emissions, but incurs marginal switching cost  $\mu'(\tilde{x}^*)$ . The extensive term is the social value of the marginal adopter,  $SV(\alpha)$ , times the number of new adopters.

*Marginal cost.* Applying the product rule to  $C = s_1Q + s_2U$ :

$$\frac{\partial C}{\partial s_2} = \underbrace{U}_{(i)} + \underbrace{s_2 \frac{d\tilde{x}^*}{ds_2} Q}_{(ii)} + \underbrace{[s_1 + s_2(\tilde{x}^* + \alpha)] g(\alpha)}_{(iii)} \left( -\frac{\partial \alpha}{\partial s_2} \right)$$

where (i) is \$1 more on all existing usage, (ii) is  $s_2$  on additional usage by existing adopters, and (iii) is the full subsidy package  $\sigma = s_1 + s_2(\tilde{x}^* + \alpha)$  to new adopters.

*FOC.* Setting  $\partial W/\partial s_2 = \lambda \partial C/\partial s_2$  gives the FOC for  $s_2$ :

$$\begin{aligned} & \underbrace{[(\pi + \phi) + \mu'(\tilde{x}^*)] \frac{d\tilde{x}^*}{ds_2} Q}_{\text{intensive: social value of additional usage}} + \underbrace{[(\tilde{x}^* + \alpha)(\pi + \phi) + \mu(\tilde{x}^*) - p] g(\alpha)}_{\text{extensive: social value of new adopters}} \left( -\frac{\partial \alpha}{\partial s_2} \right) \\ & = \lambda \left[ \underbrace{U}_{\text{cost of existing usage}} + \underbrace{s_2 \frac{d\tilde{x}^*}{ds_2} Q}_{\text{cost of additional usage}} + \underbrace{[s_1 + s_2(\tilde{x}^* + \alpha)] g(\alpha)}_{\text{subsidy package to new adopters}} \left( -\frac{\partial \alpha}{\partial s_2} \right) \right] \end{aligned} \quad (11)$$

□

*Proof of Equation 3. Step 1: Rewrite the  $s_1$  FOC in compact form.* Let  $\sigma \equiv s_1 + s_2(\tilde{x}^* + \underline{\alpha})$  and  $\kappa \equiv (p_{mc} - s_1)/|\tilde{\mathcal{E}}(p_{mc} - s_1)|$ . The  $s_1$  FOC is:

$$SV(\underline{\alpha}) = \lambda(\sigma + \kappa)$$

*Step 2: Rearrange the  $s_2$  FOC.* Group the intensive-margin terms (those with  $\frac{d\tilde{x}^*}{ds_2} Q$ ) separately from the extensive-margin terms (those with  $g(\underline{\alpha})(-\partial\underline{\alpha}/\partial s_2)$ ):

$$(MSV - \lambda s_2) \frac{d\tilde{x}^*}{ds_2} Q + [SV(\underline{\alpha}) - \lambda\sigma] g(\underline{\alpha}) \left( -\frac{\partial\underline{\alpha}}{\partial s_2} \right) = \lambda U$$

*Step 3: Substitute from the  $s_1$  FOC.* The extensive-margin bracket simplifies:  $SV(\underline{\alpha}) - \lambda\sigma = \lambda\kappa$ . Substituting:

$$(MSV - \lambda s_2) \frac{d\tilde{x}^*}{ds_2} Q + \lambda\kappa g(\underline{\alpha}) \left( -\frac{\partial\underline{\alpha}}{\partial s_2} \right) = \lambda U$$

*Step 4: Simplify the  $\kappa$  term using the derivative ratio.* Writing  $\kappa = Q/[g(\underline{\alpha})(-\partial\underline{\alpha}/\partial s_1)]$ , the  $g(\underline{\alpha})$  factors cancel:

$$\lambda\kappa g(\underline{\alpha}) \left( -\frac{\partial\underline{\alpha}}{\partial s_2} \right) = \lambda Q \cdot \frac{-\partial\underline{\alpha}/\partial s_2}{-\partial\underline{\alpha}/\partial s_1}$$

To evaluate this ratio, differentiate the adoption condition for the marginal adopter  $wtp(\underline{\alpha}) = \gamma[\tilde{a} + \underline{\alpha} \delta \pi'] = p_{mc} - s_1$  with respect to each instrument. With respect to  $s_1$  (noting  $\pi' = \pi + s_2$  does not depend on  $s_1$ , and neither does  $\tilde{a}$ ):

$$\gamma \delta \pi' \frac{\partial\underline{\alpha}}{\partial s_1} = -1 \quad \implies \quad -\frac{\partial\underline{\alpha}}{\partial s_1} = \frac{1}{\gamma \delta \pi'}$$

With respect to  $s_2$  (because the envelope theorem implies usage does not adjust to the first order and  $\tilde{a} = \tilde{x}^* \delta \pi' + \mu(\tilde{x}^*)$ , where  $s_2$  only enters through  $\pi'$ , we have that  $d\tilde{a}/ds_2 = \tilde{x}^* \delta$ ):

$$\gamma \left[ \tilde{x}^* \delta + \underline{\alpha} \delta + \delta \pi' \frac{\partial\underline{\alpha}}{\partial s_2} \right] = 0 \quad \implies \quad -\frac{\partial\underline{\alpha}}{\partial s_2} = \frac{\tilde{x}^* + \underline{\alpha}}{\pi'}$$

The  $\kappa$  term is therefore:

$$\lambda Q \cdot \frac{-\partial\underline{\alpha}/\partial s_2}{-\partial\underline{\alpha}/\partial s_1} = \lambda Q \cdot \frac{(\tilde{x}^* + \underline{\alpha})/\pi'}{1/(\gamma \delta \pi')} = \lambda Q \gamma \delta (\tilde{x}^* + \underline{\alpha})$$

Substituting:

$$(MSV - \lambda s_2) \frac{d\tilde{x}^*}{ds_2} Q + \lambda Q \gamma \delta (\tilde{x}^* + \underline{\alpha}) = \lambda U$$

*Step 5: Divide by  $Q$  and substitute  $U/Q = \tilde{x}^* + \bar{\alpha}$ .*

$$(MSV - \lambda s_2) \frac{d\tilde{x}^*}{ds_2} = \lambda [(\tilde{x}^* + \bar{\alpha}) - \gamma \delta (\tilde{x}^* + \underline{\alpha})]$$

*Step 6: Eliminate  $\lambda$ .* From the  $s_1$  FOC,  $\lambda = SV(\underline{\alpha})/(\sigma + \kappa)$ . Dividing both sides of Step 5 by  $\lambda$ :

$$\left[ \frac{MSV(\sigma + \kappa)}{SV(\underline{\alpha})} - s_2 \right] \frac{d\tilde{x}^*}{ds_2} = (\tilde{x}^* + \bar{\alpha}) - \gamma \delta (\tilde{x}^* + \underline{\alpha})$$

Step 7: Simplify the LHS. Since  $\sigma = s_1 + s_2(\tilde{x}^* + \underline{\alpha})$ :

$$\begin{aligned} \frac{MSV(\sigma + \kappa)}{SV(\underline{\alpha})} - s_2 &= \frac{MSV \cdot \sigma + MSV \cdot \kappa - s_2 \cdot SV(\underline{\alpha})}{SV(\underline{\alpha})} \\ &= \frac{MSV \cdot s_1 + s_2[MSV(\tilde{x}^* + \underline{\alpha}) - SV(\underline{\alpha})] + MSV \cdot \kappa}{SV(\underline{\alpha})} \\ &= \frac{MSV(s_1 + \kappa) + s_2 \cdot \Delta}{SV(\underline{\alpha})} \end{aligned}$$

where  $\Delta \equiv MSV(\tilde{x}^* + \underline{\alpha}) - SV(\underline{\alpha}) = \mu'(\tilde{x}^*)(\tilde{x}^* + \underline{\alpha}) - \mu(\tilde{x}^*) + p_{mc}$  collects the terms that distinguish the social principal from the environmental principal. Dividing by  $d\tilde{x}^*/ds_2$ :

$$\frac{MSV \cdot (s_1 + \kappa) + s_2 \cdot \Delta}{SV(\underline{\alpha})} = \frac{(\tilde{x}^* + \bar{\alpha}) - \gamma\delta(\tilde{x}^* + \underline{\alpha})}{\frac{d\tilde{x}^*}{ds_2}}$$

□

*Proof of Equation 4.* We set  $\delta = 1$  throughout to isolate  $\gamma$ , so that  $\tilde{x}^* = x^*$  and usage is undistorted. From the adoption condition  $s_1^* = p_{mc} - \gamma wtp(\underline{\alpha}^*)$ , where  $wtp(\underline{\alpha}^*) = a + \underline{\alpha}^* \pi'$  is the marginal adopter's undistorted WTP, differentiating with respect to  $\gamma$  and noting  $wtp'(\underline{\alpha}^*) = \pi'$ :

$$\frac{ds_1^*}{d\gamma} = \underbrace{-wtp(\underline{\alpha}^*)}_{\text{direct effect}} \underbrace{-\gamma \pi' \frac{d\underline{\alpha}^*}{d\gamma}}_{\text{re-optimization}}$$

The direct effect is unambiguously negative: when  $\gamma$  rises (distortions weaken), agents value the technology more, so the principal can reduce  $s_1^*$  while maintaining the same adoption threshold.

The sign of the re-optimization term depends on  $d\underline{\alpha}^*/d\gamma$ , how the principal's optimal adoption threshold responds to the distortion.<sup>29</sup> The proof of Proposition 3 solves for  $d\underline{\alpha}^*/d\gamma$  and substitutes back to sign  $ds_1^*/d\gamma < 0$ .

□

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<sup>29</sup>Note that earlier we showed greater distortions increase the adoption threshold, *for a given*  $s_1$  and  $s_2$ . This derivative asks a different question: how does the threshold change after allowing the principal to re-optimize  $s_1$  and  $s_2$ .

*Proof of Proposition 3.* From Equation 4,  $ds_1^*/d\gamma = -wtp(\underline{\alpha}^*) - \gamma\pi' \cdot d\underline{\alpha}^*/d\gamma$ , where the direct effect is unambiguously negative. We now solve for  $d\underline{\alpha}^*/d\gamma$  using the implicit function theorem and substitute back to sign  $ds_1^*/d\gamma$ . We set  $\delta = 1$  throughout to isolate  $\gamma$ , so that  $\tilde{x}^* = x^*$  and usage is undistorted.

*Step A: Express  $s_1$  and  $\kappa$  as functions of  $(\underline{\alpha}^*, \gamma)$ .* The adoption condition gives  $s_1^* = p_{mc} - \gamma wtp(\underline{\alpha}^*)$ . The inframarginal cost  $\kappa$  likewise depends only on  $\underline{\alpha}^*$  and  $\gamma$  once expressed in hazard rate form. From Section 3.1, the distorted elasticity satisfies  $\tilde{\mathcal{E}}(p_{mc} - s_1^*) = \mathcal{E}((p_{mc} - s_1^*)/\gamma)$ , evaluated at  $wtp(\underline{\alpha}^*)$ . Since  $wtp = a + \alpha\pi'$ , undistorted demand at price  $w$  is  $Q(w) = 1 - G(\frac{w-a}{\pi'})$ , so the undistorted elasticity at price  $w$  is:

$$|\mathcal{E}(w)| = \frac{w}{\pi'} \cdot h\left(\frac{w-a}{\pi'}\right)$$

where  $h(\cdot) \equiv g(\cdot)/(1 - G(\cdot))$  is the hazard rate of the  $\alpha$  distribution. Evaluating at  $w = wtp(\underline{\alpha}^*)$  and substituting into  $\kappa = (p_{mc} - s_1^*)/|\tilde{\mathcal{E}}|$ :

$$\kappa = \frac{\gamma\pi'}{h(\underline{\alpha}^*)}$$

*Step B: Construct the implicit function.* The social instrument mix equation (3) is:

$$\frac{MSV(s_1^* + \kappa) + s_2\Delta}{SV(\underline{\alpha})} = \frac{\bar{u} - \gamma u}{\eta}$$

where  $\underline{u} = x^* + \underline{\alpha}^*$ ,  $\bar{u} = x^* + \bar{\alpha}$ ,  $MSV = (\pi + \phi) + \mu'(x^*)$ ,  $\Delta = MSV \cdot \underline{u} - SV(\underline{\alpha})$ , and  $\eta = dx^*/ds_2$ . We treat  $s_2$  (and hence  $\pi' = \pi + s_2$ ,  $x^*$ ,  $\eta$ ) as a fixed parameter: if  $ds_1^*/d\gamma < 0$  holds for any fixed  $s_2$ , it holds at the equilibrium  $s_2$  in particular. With  $s_2$  held fixed,  $x^*$ ,  $\eta$ , and  $MSV$  are constants determined by  $\pi'$  alone — they depend on neither  $\underline{\alpha}^*$  nor  $\gamma$ . The terms  $\underline{u}$ ,  $\bar{u}$ ,  $SV(\underline{\alpha})$ , and  $\Delta$  depend on  $\underline{\alpha}^*$  but not on  $\gamma$  (since  $\gamma$  does not affect the distribution of  $\alpha$  or the usage level  $x^*$ ). The  $s_2\Delta$  term is likewise independent of  $\gamma$ . The only  $\gamma$ -dependent terms are  $s_1$  and  $\kappa$  (both explicitly, from Step A) and the  $\gamma u$  on the RHS. Since Step A expresses  $s_1$  and  $\kappa$  as functions of  $(\underline{\alpha}^*, \gamma)$ , the entire equation depends only on  $\underline{\alpha}^*$ ,  $\gamma$ , and  $s_2$ . Cross-multiplying and defining:

$$\Psi(\underline{\alpha}^*, \gamma) \equiv \eta MSV(s_1^* + \kappa) + \eta s_2\Delta - SV(\underline{\alpha})(\bar{u} - \gamma u) = 0$$

*Step C: Apply the implicit function theorem.* Totally differentiating  $\Psi(\underline{\alpha}^*(\gamma), \gamma) = 0$ :

$$\frac{d\underline{\alpha}^*}{d\gamma} = -\frac{\partial\Psi/\partial\gamma}{\partial\Psi/\partial\underline{\alpha}^*}$$

We compute the numerator  $\partial\Psi/\partial\gamma$  in Step D and the denominator  $\partial\Psi/\partial\underline{\alpha}^*$  in Step E, then substitute back into  $ds_1^*/d\gamma$  in Step F.

*Step D: Compute and simplify  $\partial\Psi/\partial\gamma$ .* From Step A,  $s_1^* + \kappa = p_{mc} + \gamma[-wtp + \pi'/h(\underline{\alpha}^*)]$ . Differentiating  $\Psi$  with respect to  $\gamma$  (holding  $\underline{\alpha}^*$  and  $s_2$  fixed):

$$\frac{\partial\Psi}{\partial\gamma} = \eta MSV \left[ -wtp + \frac{\pi'}{h(\underline{\alpha}^*)} \right] + SV(\underline{\alpha}) u$$

From Step A,  $\kappa = \gamma\pi'/h(\underline{\alpha}^*)$ , so  $\pi'/h(\underline{\alpha}^*) = \kappa/\gamma$ . And from the original definition  $\kappa = (p_{mc} - s_1^*)/|\tilde{\mathcal{E}}|$

with  $p_{mc} - s_1^* = \gamma wtp$ , we have  $\kappa/\gamma = wtp(\underline{\alpha}^*)/|\tilde{\mathcal{E}}|$ . Substituting into the bracket:

$$\frac{\partial \Psi}{\partial \gamma} = \underline{u} SV(\underline{\alpha}) - \eta MSV wtp(\underline{\alpha}^*) \cdot \frac{|\tilde{\mathcal{E}}| - 1}{|\tilde{\mathcal{E}}|} \quad (12)$$

*Step E: Compute  $\partial \Psi / \partial \underline{\alpha}^*$ .* Differentiating  $\Psi$  term by term:

The first term,  $\eta MSV(s_1^* + \kappa)$ , depends on  $\underline{\alpha}^*$  through  $wtp(\underline{\alpha}^*)$  and  $h(\underline{\alpha}^*)$ . Since  $s_1^* + \kappa = p_{mc} + \gamma[-wtp + \pi'/h(\underline{\alpha}^*)]$ , and  $\partial wtp / \partial \underline{\alpha}^* = \pi'$  and  $\partial[\pi'/h(\underline{\alpha}^*)] / \partial \underline{\alpha}^* = -\pi' h'(\underline{\alpha}^*) / h(\underline{\alpha}^*)^2$ , this contributes:

$$-\eta MSV \gamma \pi' \left[ 1 + \frac{h'(\underline{\alpha}^*)}{h(\underline{\alpha}^*)^2} \right]$$

The second term,  $\eta s_2 \Delta$ , depends on  $\underline{\alpha}^*$  through  $\Delta = MSV \cdot \underline{u} - SV(\underline{\alpha})$ . Since  $\partial \Delta / \partial \underline{\alpha}^* = MSV - (\pi + \phi) = \mu'(x^*)$ , this contributes  $\eta s_2 \mu'(x^*)$ .

The third term,  $-SV(\underline{\alpha}) \bar{u}$ , depends on  $\underline{\alpha}^*$  through both  $SV(\underline{\alpha})$  and  $\bar{u} = x^* + \bar{\alpha}$ . Since  $\partial SV / \partial \underline{\alpha}^* = \pi + \phi$  and  $\partial \bar{\alpha} / \partial \underline{\alpha}^* = h(\underline{\alpha}^*)(\bar{\alpha} - \underline{\alpha}^*)$ ,<sup>30</sup> the product rule gives:  $-(\pi + \phi) \bar{u} - SV(\underline{\alpha}) h(\underline{\alpha}^*)(\bar{\alpha} - \underline{\alpha}^*)$ .

The fourth term,  $\gamma SV(\underline{\alpha}) \underline{u}$ , contributes  $\gamma[(\pi + \phi) \underline{u} + SV(\underline{\alpha})]$  by the product rule.

Collecting:

$$\frac{\partial \Psi}{\partial \underline{\alpha}^*} = \underbrace{-\eta MSV \gamma \pi' \left[ 1 + \frac{h'(\underline{\alpha}^*)}{h(\underline{\alpha}^*)^2} \right]}_{\text{cost-side response}} + \eta s_2 \mu'(x^*) - (\pi + \phi) \bar{u} - SV(\underline{\alpha}) h(\underline{\alpha}^*)(\bar{\alpha} - \underline{\alpha}^*) + \gamma[(\pi + \phi) \underline{u} + SV(\underline{\alpha})] \quad (13)$$

*Step F: Substitute back and sign  $ds_1^*/d\gamma$ .* From the decomposition (Equation 4) and Steps C–E:

$$\frac{ds_1^*}{d\gamma} = -wtp(\underline{\alpha}^*) + \gamma \pi' \cdot \frac{\partial \Psi / \partial \gamma}{\partial \Psi / \partial \underline{\alpha}^*}$$

where  $\partial \Psi / \partial \gamma$  is given by (12) and  $\partial \Psi / \partial \underline{\alpha}^*$  by (13). Since  $\Psi = 0$  is the first-order condition and  $\underline{\alpha}^*$  is the only remaining choice variable (given  $s_2$ ), the second-order condition requires  $\partial \Psi / \partial \underline{\alpha}^* < 0$  at a welfare maximum.

To sign  $ds_1^*/d\gamma < 0$ , we rearrange it into an equivalent condition  $A > 0$ , decompose  $A$  into four terms, and sign each under IHR. From the decomposition (Equation 4) and Steps C–E:

$$\frac{ds_1^*}{d\gamma} = -wtp(\underline{\alpha}^*) + \gamma \pi' \cdot \frac{\partial \Psi / \partial \gamma}{\partial \Psi / \partial \underline{\alpha}^*}$$

Multiplying both sides by  $\partial \Psi / \partial \underline{\alpha}^* < 0$  (SOC) flips the inequality. So  $ds_1^*/d\gamma < 0$  is equivalent to:

$$A \equiv \gamma \pi' \cdot \frac{\partial \Psi}{\partial \gamma} - wtp(\underline{\alpha}^*) \cdot \frac{\partial \Psi}{\partial \underline{\alpha}^*} > 0 \quad (14)$$

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<sup>30</sup>The truncated mean derivative follows from Leibniz's rule:  $\partial \bar{\alpha} / \partial \underline{\alpha}^* = \partial \left[ \int_{\underline{\alpha}^*}^{\infty} \alpha dG(\alpha) / (1 - G(\underline{\alpha}^*)) \right] / \partial \underline{\alpha}^* = h(\underline{\alpha}^*)(\bar{\alpha} - \underline{\alpha}^*)$ .

Substituting  $\partial\Psi/\partial\gamma$  from (12) and  $\partial\Psi/\partial\alpha^*$  from (13):

$$A = \gamma\pi' \left[ \eta MSV \left( -wtp + \frac{\pi'}{h(\alpha^*)} \right) + SV(\alpha) \underline{u} \right] \\ - wtp \left[ -\eta MSV \gamma\pi' \left( 1 + \frac{h'(\alpha^*)}{h(\alpha^*)^2} \right) + \eta s_2 \mu'(x^*) \right. \\ \left. - (\pi + \phi)\bar{u} - SV(\alpha) h(\alpha^*)(\bar{\alpha} - \alpha^*) + \gamma((\pi + \phi)\underline{u} + SV(\alpha)) \right]$$

Regrouping (the  $-wtp$  and  $+wtp$  cancel in the  $\eta MSV \gamma\pi'$  terms):

$$A = \underbrace{\eta MSV \gamma\pi' \left( \frac{\pi'}{h(\alpha^*)} + \frac{wtp(\alpha^*) \cdot h'(\alpha^*)}{h(\alpha^*)^2} \right)}_{\text{Term I}} \quad (15)$$

$$+ \underbrace{SV(\alpha) [\gamma\pi' \underline{u} - \gamma wtp(\alpha^*) + wtp(\alpha^*) \cdot h(\alpha^*)(\bar{\alpha} - \alpha^*)]}_{\text{Term II}} \quad (16)$$

$$+ \underbrace{wtp(\alpha^*) \cdot (\pi + \phi) [\bar{u} - \gamma \underline{u}]}_{\text{Term III}} \quad (17)$$

$$+ \underbrace{(-wtp(\alpha^*) \cdot \eta s_2 \mu'(x^*))}_{\text{Term IV}} \quad (18)$$

*Signing.* We now show each term is non-negative. Note that  $wtp(\alpha^*) > 0$  at any interior optimum, since  $\gamma wtp = p_{mc} - s_1^* > 0$ .

*Term I*  $> 0$  under IHR.  $\eta > 0$ ,  $MSV = \phi - s_2 > 0$  (since  $s_2 < \phi$  at any interior optimum where the marginal subsidy does not exceed the externality),  $\gamma\pi' > 0$ . The first summand  $\pi'/h(\alpha^*) > 0$  always. Under IHR ( $h'(\alpha^*) \geq 0$ ), the second summand  $wtp \cdot h'(\alpha^*)/h(\alpha^*)^2 \geq 0$ .

*Term II*  $> 0$ .  $SV(\alpha) \geq 0$  at an interior optimum. Using  $wtp(\alpha^*) = \underline{u} \pi' + \mu(x^*)$ , the first two terms in the bracket simplify:  $\gamma\pi' \underline{u} - \gamma wtp = -\gamma \mu(x^*) \geq 0$  since  $\mu(x^*) \leq 0$  (from  $\mu(0) = 0$ ,  $\mu'(0) = 0$ ,  $\mu'' < 0$ ). The remaining term  $wtp \cdot h(\alpha^*)(\bar{\alpha} - \alpha^*) > 0$  since  $h(\alpha^*) > 0$  and  $\bar{\alpha} > \alpha^*$ . Both summands in the bracket are non-negative.

*Term III*  $> 0$ .  $\bar{u} - \gamma \underline{u} = (1 - \gamma)\underline{u} + (\bar{u} - \underline{u})$  with  $\underline{u} \geq 0$  and  $\bar{u} \geq \underline{u}$ .

*Term IV*  $\geq 0$ .  $\mu'(x^*) < 0$  (from  $\mu'(0) = 0$  and  $\mu'' < 0$ ), so  $-\mu'(x^*) > 0$ . When  $s_2 > 0$ , Term IV is strictly positive; when  $s_2 = 0$ , it vanishes.

Since  $A = \text{I} + \text{II} + \text{III} + \text{IV}$  with all terms non-negative and Terms I–III strictly positive,  $A > 0$ . Therefore  $ds_1^*/d\gamma < 0$  under IHR. □

### IV.3 Proofs: Environmental principal

*Proof.* The budget constraint, adoption condition, and cost structure are identical to the social principal's problem. The only difference is the objective: abatement  $\phi U$  rather than social welfare  $\int SV_i g(\alpha) d\alpha$ :

$$\max_{s_1, s_2} A(s_1, s_2) = \phi \int_{\underline{\alpha}}^{\infty} (\tilde{x}^* + \alpha_i) g(\alpha) d\alpha$$

where  $\phi$  is the per-unit externality reduction. This simplifies the FOCs because  $\phi$  factors out of both the intensive and extensive margins. The  $s_1$  FOC replaces  $SV(\underline{\alpha})$  on the LHS with  $(\tilde{x}^* + \underline{\alpha})\phi$ —abatement from the marginal adopter—while the cost side (RHS) is unchanged:

$$(\tilde{x}^* + \underline{\alpha})\phi = \lambda \left[ s_1 + s_2(\tilde{x}^* + \underline{\alpha}) + \frac{p_{mc} - s_1}{|\tilde{\mathcal{E}}(p_{mc} - s_1)|} \right] \quad (19)$$

The  $s_2$  FOC similarly replaces  $MSV$  with  $\phi$  in the intensive term and  $SV(\underline{\alpha})$  with  $(\tilde{x}^* + \underline{\alpha})\phi$  in the extensive term:

$$\phi \left[ \frac{d\tilde{x}^*}{ds_2} Q + (\tilde{x}^* + \underline{\alpha}) g(\underline{\alpha}) \left( -\frac{\partial \underline{\alpha}}{\partial s_2} \right) \right] = \lambda \left[ U + s_2 \frac{d\tilde{x}^*}{ds_2} Q + \sigma g(\underline{\alpha}) \left( -\frac{\partial \underline{\alpha}}{\partial s_2} \right) \right] \quad (20)$$

To take derivatives of  $A$  and  $C$ , we must first specify how  $\underline{\alpha}$  and  $\tilde{x}^*$  depend on the instruments.

*Adoption.* The marginal adopter  $\underline{\alpha}$  satisfies  $\widetilde{wtp}(\underline{\alpha}) = p_{mc} - s_1$ . From Section 1.4,  $\widetilde{wtp}_i = \gamma(\tilde{a} + \delta \alpha_i \pi')$ , where  $\tilde{a} = \tilde{x}^* \delta \pi' + \mu(\tilde{x}^*)$ . So the adoption condition is:

$$\gamma(\tilde{a} + \delta \underline{\alpha} \pi') = p_{mc} - s_1 \quad (21)$$

Note that  $s_1$  enters the RHS directly, while  $s_2$  enters through  $\pi' = \pi + s_2$  and  $\tilde{a}$  (which depends on  $\pi'$  through  $\tilde{x}^*$ ).

*Usage.* Clean energy usage per adopter is  $\tilde{x}^* + \alpha_i$ , where  $\tilde{x}^*$  is determined by the agent's perceived fuel price:

$$\mu'(\tilde{x}^*) = -\delta \pi' \quad (22)$$

Note that  $\tilde{x}^*$  depends on  $s_2$  (through  $\pi'$ ) but not on  $s_1$ .

**How the instruments affect adoption.** Both instruments lower the adoption threshold  $\underline{\alpha}$ , but through different channels:  $s_1$  reduces the upfront cost directly, while  $s_2$  raises the perceived fuel savings. Since the principal is choosing between the two, it is useful to compare their per-dollar effects on  $\underline{\alpha}$ . We derive each from the adoption condition (21).

*Effect of  $s_1$ .* Differentiating (21) with respect to  $s_1$  (only  $\underline{\alpha}$  depends on  $s_1$ ):

$$\gamma \delta \pi' \frac{\partial \underline{\alpha}}{\partial s_1} = -1 \quad \implies \quad \frac{\partial \underline{\alpha}}{\partial s_1} = \frac{-1}{\gamma \delta \pi'}$$

*Effect of  $s_2$ .* Differentiating (21) with respect to  $s_2$  ( $\tilde{a}$ ,  $\pi'$ , and  $\underline{\alpha}$  depend on  $s_2$ ):

$$\gamma \left( \frac{\partial \tilde{a}}{\partial s_2} + \delta \underline{\alpha} + \delta \pi' \frac{\partial \underline{\alpha}}{\partial s_2} \right) = 0$$

To evaluate  $\partial\tilde{a}/\partial s_2$ , expand  $\tilde{a} = \tilde{x}^*\delta\pi' + \mu(\tilde{x}^*)$  using the chain rule (noting  $\partial\pi'/\partial s_2 = 1$ ):

$$\frac{\partial\tilde{a}}{\partial s_2} = \frac{d\tilde{x}^*}{ds_2}\delta\pi' + \tilde{x}^*\delta + \mu'(\tilde{x}^*)\frac{d\tilde{x}^*}{ds_2} = \frac{d\tilde{x}^*}{ds_2} \underbrace{[\delta\pi' + \mu'(\tilde{x}^*)]}_{= 0 \text{ by (22)}} + \delta\tilde{x}^* = \delta\tilde{x}^*$$

This is the *envelope theorem*: the usage FOC zeroes out all terms involving the re-optimization of  $\tilde{x}^*$ , so the effect of  $s_2$  on the common utility level,  $\tilde{a}$ , operates only through the direct change in the perceived savings, which is  $\delta$  times the common usage level  $\tilde{x}^*$ .

Substituting back:

$$\gamma \left( \underbrace{\delta(\tilde{x}^* + \alpha)}_{\text{perceived increase in marginal adopter's savings}} + \underbrace{\delta\pi' \frac{\partial\alpha}{\partial s_2}}_{\text{offsetting threshold adjustment}} \right) = 0$$

Dividing by  $\gamma\delta$  and solving:

$$\frac{\partial\alpha}{\partial s_2} = -\frac{\tilde{x}^* + \alpha}{\pi'}$$

*Comparison.* Collecting both results:

$$\frac{\partial\alpha}{\partial s_1} = \frac{-1}{\gamma\delta\pi'} \quad \frac{\partial\alpha}{\partial s_2} = \frac{-(\tilde{x}^* + \alpha)}{\pi'} = \frac{\partial\alpha}{\partial s_1} \gamma\delta(\tilde{x}^* + \alpha)$$

A dollar of  $s_2$  moves the adoption threshold by  $\gamma\delta(\tilde{x}^* + \alpha)$  times as much as a dollar of  $s_1$ . The mechanism: a dollar of  $s_1$  reduces the upfront cost by \$1, while a dollar of  $s_2$  raises  $\pi'$  by \$1, which by the envelope theorem raises the marginal adopter's perceived WTP by  $\gamma\delta(\tilde{x}^* + \alpha)$ —proportional to their clean energy usage, scaled by the distortions. When  $\gamma\delta(\tilde{x}^* + \alpha) < 1$ , which is more likely under severe distortions (Section 1.5),  $s_1$  is more effective per dollar at moving the adoption threshold.

Equivalently, since  $\widetilde{wtp}_i = \gamma(\tilde{a} + \delta\alpha_i\pi')$  and  $\partial\tilde{a}/\partial s_2 = \delta\tilde{x}^*$  by the envelope theorem:

$$\frac{\partial\widetilde{wtp}_i}{\partial s_2} = \gamma\delta(\tilde{x}^* + \alpha_i)$$

For the marginal adopter,  $\partial\widetilde{wtp}_\alpha/\partial s_2 = \gamma\delta(\tilde{x}^* + \alpha)$ : the derivative ratio above is exactly the marginal adopter's WTP response to a dollar of  $s_2$ . This connects the dampening result of Section 1.5 to the instrument comparison: the dampened WTP derivative is what determines  $s_2$ 's ability to move the adoption threshold, and it reappears as the second term in the numerator of the instrument mix equation (3) below.

**How  $s_2$  affects usage.** Unlike  $s_1$ , the marginal cost subsidy also changes how much each adopter uses. A higher  $s_2$  raises the effective fuel price  $\pi'$ , making clean energy more attractive, so each adopter shifts more consumption toward the clean technology. Differentiating the usage condition (22) with respect to  $s_2$ :

$$\mu''(\tilde{x}^*)\frac{d\tilde{x}^*}{ds_2} = -\delta \quad \implies \quad \frac{d\tilde{x}^*}{ds_2} = \frac{-\delta}{\mu''(\tilde{x}^*)} > 0$$

This is positive (since  $\mu'' < 0$ ) and is the intensive margin that  $s_2$  has but  $s_1$  does not: each

existing adopter generates more abatement. Note, however, that the principal must pay  $s_2$  on every unit of this additional usage.

**FOC for  $s_1$ .** We begin with  $s_1$  because it is the simpler instrument: since it does not affect usage  $\tilde{x}^*$ , it changes both abatement and cost only through the adoption threshold  $\underline{\alpha}$ .

*Marginal abatement.* By the Leibniz rule, each marginal adopter uses  $(\tilde{x}^* + \underline{\alpha})$  units of clean energy, generating  $(\tilde{x}^* + \underline{\alpha})\phi$  in abatement:

$$\frac{\partial A}{\partial s_1} = \phi (\tilde{x}^* + \underline{\alpha}) g(\underline{\alpha}) \left( -\frac{\partial \underline{\alpha}}{\partial s_1} \right)$$

*Marginal cost.* Recall  $C = s_1 Q + s_2 U$ . A dollar increase in  $s_1$  has three cost effects: (i) \$1 more to each existing adopter, (ii)  $s_1$  paid to new adopters, and (iii)  $s_2$  paid on new adopters' usage. By the product rule and Leibniz rule:

$$\begin{aligned} \frac{\partial C}{\partial s_1} &= \underbrace{Q}_{(i)} + \underbrace{s_1 g(\underline{\alpha}) \left( -\frac{\partial \underline{\alpha}}{\partial s_1} \right)}_{(ii)} + \underbrace{s_2 (\tilde{x}^* + \underline{\alpha}) g(\underline{\alpha}) \left( -\frac{\partial \underline{\alpha}}{\partial s_1} \right)}_{(iii)} \\ &= Q + [s_1 + s_2 (\tilde{x}^* + \underline{\alpha})] g(\underline{\alpha}) \left( -\frac{\partial \underline{\alpha}}{\partial s_1} \right) \end{aligned}$$

*FOC.* Setting  $\partial A / \partial s_1 = \lambda \partial C / \partial s_1$ :

$$\phi (\tilde{x}^* + \underline{\alpha}) g(\underline{\alpha}) \left( -\frac{\partial \underline{\alpha}}{\partial s_1} \right) = \lambda \left[ Q + [s_1 + s_2 (\tilde{x}^* + \underline{\alpha})] g(\underline{\alpha}) \left( -\frac{\partial \underline{\alpha}}{\partial s_1} \right) \right]$$

For interpretability, divide both sides by  $g(\underline{\alpha})(-\partial \underline{\alpha} / \partial s_1)$ —the number of new adopters per dollar of  $s_1$ —to rescale to a per-marginal-adopter basis:

$$(\tilde{x}^* + \underline{\alpha})\phi = \lambda \left[ s_1 + s_2 (\tilde{x}^* + \underline{\alpha}) + \frac{Q}{g(\underline{\alpha})(-\partial \underline{\alpha} / \partial s_1)} \right] \quad (23)$$

Since  $g(\underline{\alpha})(-\partial \underline{\alpha} / \partial s_1)$  is the slope of the demand curve at price  $p_{mc} - s_1$ , this ratio equals  $(p_{mc} - s_1) / |\tilde{\mathcal{E}}(p_{mc} - s_1)|$

For later use, define the total subsidy to the marginal adopter:

$$\sigma \equiv s_1 + s_2 (\tilde{x}^* + \underline{\alpha})$$

and define the inframarginal cost per new adopter:

$$\kappa \equiv (p_{mc} - s_1) / |\tilde{\mathcal{E}}(p_{mc} - s_1)|$$

In this notation, (23) is simply  $(\tilde{x}^* + \underline{\alpha})\phi = \lambda(\sigma + \kappa)$ .

*Marginal abatement.* Since  $s_2$  affects both the integrand of  $A$  (through  $\tilde{x}^*$ ) and the lower limit (through  $\underline{\alpha}$ ):

$$\frac{\partial A}{\partial s_2} = \phi \left[ \underbrace{\frac{d\tilde{x}^*}{ds_2} Q}_{\substack{\text{intensive:} \\ \text{existing adopters} \\ \text{use more}}} + \underbrace{(\tilde{x}^* + \underline{\alpha}) g(\underline{\alpha}) \left( -\frac{\partial \underline{\alpha}}{\partial s_2} \right)}_{\substack{\text{extensive:} \\ \text{new adopters}}} \right]$$

The intensive term is the usage increase per adopter times the number of existing adopters. The extensive term parallels  $s_1$ :  $g(\underline{\alpha})(-\partial\underline{\alpha}/\partial s_2)$  new adopters enter, each generating  $(\tilde{x}^* + \underline{\alpha})\phi$  abatement.

*Marginal cost.* Applying the product rule to  $C = s_1Q + s_2U$ :

$$\frac{\partial C}{\partial s_2} = s_1 \frac{\partial Q}{\partial s_2} + U + s_2 \frac{\partial U}{\partial s_2}$$

By the Leibniz rule,  $\partial Q/\partial s_2 = g(\underline{\alpha})(-\partial\underline{\alpha}/\partial s_2)$ . For  $\partial U/\partial s_2$ , both the integrand  $(\tilde{x}^*)$  and the lower limit  $(\underline{\alpha})$  respond to  $s_2$ :

$$\frac{\partial U}{\partial s_2} = \frac{d\tilde{x}^*}{ds_2}Q + (\tilde{x}^* + \underline{\alpha})g(\underline{\alpha})\left(-\frac{\partial\underline{\alpha}}{\partial s_2}\right)$$

Substituting and regrouping into three cost effects paralleling  $s_1$ —(i) \$1 more on all existing usage, (ii)  $s_2$  on additional usage by existing adopters, (iii) full subsidy package to new adopters:

$$\frac{\partial C}{\partial s_2} = \underbrace{U}_{(i)} + \underbrace{s_2 \frac{d\tilde{x}^*}{ds_2}Q}_{(ii)} + \underbrace{[s_1 + s_2(\tilde{x}^* + \underline{\alpha})]g(\underline{\alpha})\left(-\frac{\partial\underline{\alpha}}{\partial s_2}\right)}_{(iii)}$$

*FOC.* Setting  $\partial A/\partial s_2 = \lambda \partial C/\partial s_2$  and substituting  $\sigma = s_1 + s_2(\tilde{x}^* + \underline{\alpha})$ :

$$\phi \left[ \frac{d\tilde{x}^*}{ds_2}Q + (\tilde{x}^* + \underline{\alpha})g(\underline{\alpha})\left(-\frac{\partial\underline{\alpha}}{\partial s_2}\right) \right] = \lambda \left[ U + s_2 \frac{d\tilde{x}^*}{ds_2}Q + \sigma g(\underline{\alpha})\left(-\frac{\partial\underline{\alpha}}{\partial s_2}\right) \right] \quad (24)$$

The parallel with (23) is instructive. The extensive margin terms—those involving  $g(\underline{\alpha})(-\partial\underline{\alpha}/\partial s_2)$ —have the same structure as in the  $s_1$  FOC: each new adopter generates  $(\tilde{x}^* + \underline{\alpha})\phi$  in abatement and costs the principal  $\sigma$ . The key differences are: (i) the inframarginal cost for  $s_1$  is  $Q$  (paying all existing adopters) while for  $s_2$  it is  $U$  (paying on all existing usage), and (ii)  $s_2$  has the intensive margin terms  $((d\tilde{x}^*/ds_2)Q$  on both sides) that  $s_1$  lacks entirely.

**Optimal instrument mix.** Eliminating  $\lambda$  between the two FOCs yields a single equation characterizing the optimal mix of  $s_1$  and  $s_2$ .

Recall from above that  $\sigma$  is the total subsidy to the marginal adopter and  $\kappa$  is the inframarginal cost per new adopter. The  $s_1$  FOC (23) is:

$$\phi(\tilde{x}^* + \underline{\alpha}) = \lambda(\sigma + \kappa)$$

*Rearranging the  $s_2$  FOC.* Expand both sides of (20) and group the intensive-margin terms (those with  $d\tilde{x}^*/ds_2 Q$ ) separately from the extensive-margin terms (those with  $g(\underline{\alpha})(-\partial\underline{\alpha}/\partial s_2)$ ):

$$(\phi - \lambda s_2) \frac{d\tilde{x}^*}{ds_2} Q + [\phi(\tilde{x}^* + \underline{\alpha}) - \lambda\sigma] g(\underline{\alpha})\left(-\frac{\partial\underline{\alpha}}{\partial s_2}\right) = \lambda U$$

*Substituting from the  $s_1$  FOC.* Both brackets can be replaced using the  $s_1$  FOC. The extensive-margin bracket is immediate: rearranging gives  $\phi(\tilde{x}^* + \underline{\alpha}) - \lambda\sigma = \lambda\kappa$ . For the intensive-margin bracket, divide the  $s_1$  FOC by  $(\tilde{x}^* + \underline{\alpha})$  and expand  $\sigma$ :

$$\phi = \frac{\lambda(\sigma + \kappa)}{\tilde{x}^* + \underline{\alpha}} = \lambda s_2 + \frac{\lambda(s_1 + \kappa)}{\tilde{x}^* + \underline{\alpha}}$$

so  $\phi - \lambda s_2 = \lambda(s_1 + \kappa)/(\tilde{x}^* + \alpha)$ . Making both substitutions and dividing by  $\lambda$ :

$$\frac{s_1 + \kappa}{\tilde{x}^* + \alpha} \frac{d\tilde{x}^*}{ds_2} Q + \kappa g(\alpha) \left( -\frac{\partial \alpha}{\partial s_2} \right) = U$$

*Simplifying.* Writing  $\kappa$  equivalently as  $Q/[g(\alpha)(-\partial\alpha/\partial s_1)]$ , the  $g(\alpha)$  factors in the second term cancel, leaving a ratio of derivatives:

$$\kappa g(\alpha) \left( -\frac{\partial \alpha}{\partial s_2} \right) = Q \frac{-\partial\alpha/\partial s_2}{-\partial\alpha/\partial s_1} = Q\gamma\delta(\tilde{x}^* + \alpha)$$

where the last equality uses the derivative ratio derived above. Substituting and dividing by  $Q$ :

$$\frac{s_1 + \kappa}{\tilde{x}^* + \alpha} \frac{d\tilde{x}^*}{ds_2} + \gamma\delta(\tilde{x}^* + \alpha) = \frac{U}{Q}$$

Writing  $\bar{\alpha} \equiv E[\alpha_i \mid \alpha_i \geq \alpha]$  for the mean taste among adopters,  $U/Q = \tilde{x}^* + \bar{\alpha}$ . Substituting, rearranging, and dividing by  $d\tilde{x}^*/ds_2$ :

$$\underbrace{\frac{s_1 + \kappa}{\tilde{x}^* + \alpha}}_{\substack{\text{cost of } s_1 \\ \text{per unit abated}}} = \frac{\overbrace{(\tilde{x}^* + \bar{\alpha}) - \gamma\delta(\tilde{x}^* + \alpha)}^{\text{extensive margin disadvantage of } s_2}}{\underbrace{\frac{d\tilde{x}^*}{ds_2}}_{\substack{\text{intensive margin} \\ \text{advantage of } s_2}}}$$

□

*Proof that Proposition 3 holds for the environmental principal.* The proof follows the same structure as the proof of Proposition 3 in Section IV.2 (Steps A–F). The environmental principal maximizes abatement  $\phi U$  rather than social welfare  $\int SV_i g(\alpha) d\alpha$ . Since abatement is linear in usage—every unit of clean energy generates the same externality reduction  $\phi$ —three objects from the social proof specialize:

- $MSV \rightarrow \phi$ : the marginal value of one unit of usage is the externality  $\phi$ , rather than the full social value  $(\pi + \phi) + \mu'(x^*)$  which includes private fuel savings and adjustment costs.
- $SV(\alpha) \rightarrow \phi \underline{u}$ : the value of the marginal adopter is their abatement  $\phi(\tilde{x}^* + \alpha)$ , not the full social surplus.
- $\Delta \rightarrow 0$ : the gap between marginal and total value vanishes because abatement is linear in usage (no nonlinear  $\mu$  terms creating a wedge).

The adoption condition and budget constraint are unchanged, so Steps A and C carry over identically.

*Step B specialization.* Substituting  $MSV = \phi$ ,  $SV(\alpha) = \phi \underline{u}$ , and  $\Delta = 0$  into  $\Psi$  from Step B:

$$\eta \phi (s_1^* + \kappa) + 0 - \phi \underline{u} (\bar{u} - \gamma \underline{u}) = 0$$

Dividing by  $\phi$ :

$$\eta (s_1^* + \kappa) - \underline{u} (\bar{u} - \gamma \underline{u}) = 0$$

*Step F specialization.* Substituting  $MSV = \phi$  and  $SV(\alpha) = \phi \underline{u}$  into Terms I–IV of the  $A > 0$  condition (14):

- *Term I* =  $\eta \phi \gamma \pi' (\pi' / h(\underline{\alpha}^*) + wtp \cdot h'(\underline{\alpha}^*) / h(\underline{\alpha}^*)^2) > 0$  under IHR.
- *Term II* =  $\phi \underline{u} [\gamma \pi' \underline{u} - \gamma wtp + wtp \cdot h(\underline{\alpha}^*) (\bar{\alpha} - \underline{\alpha}^*)] > 0$ , since  $\gamma \pi' \underline{u} - \gamma wtp = -\gamma \mu(x^*) \geq 0$  and  $wtp \cdot h(\underline{\alpha}^*) (\bar{\alpha} - \underline{\alpha}^*) > 0$ .
- *Term III* =  $wtp \cdot \phi [\bar{u} - \gamma \underline{u}] > 0$  (the  $(\pi + \phi)$  factor from the social case reduces to  $\phi$  since  $\partial[\phi \underline{u}] / \partial \underline{\alpha}^* = \phi$ ).
- *Term IV* =  $-wtp \cdot \eta s_2 \mu'(x^*) \geq 0$ , since  $\mu'(x^*) < 0$ .

All four terms are non-negative under IHR, so  $A > 0$  and  $ds_1^* / d\gamma < 0$ . □

#### IV.4 Non-pecuniary benefits from clean technology

The baseline model assumes  $\mu(0) = 0$ , making  $\mu$  a pure switching cost: an agent who uses the clean technology exactly at their taste level ( $d_{2i}\theta_i = \alpha_i$ ) receives no non-pecuniary benefit or cost. We now generalize to  $\mu(0) = c \geq 0$ , retaining  $\mu'(0) = 0$ ,  $\mu'' < 0$ , and  $\lim_{x \rightarrow \infty} \mu'(x) = -\infty$ . The parameter  $c$  captures non-pecuniary benefits of clean technology usage such as environmental preferences, social signaling, or intrinsic satisfaction. We assume  $\mu$  is defined on all of  $\mathbb{R}$  with  $\mu'' < 0$  everywhere, which ensures the FOC has a unique solution regardless of the sign of  $\pi'$ . Setting  $c = 0$  recovers the baseline.

This generalization has two consequences. First, when dirty fuel is more expensive ( $\pi' > 0$ ), the baseline results carry through with minor modifications to the level of WTP and the sign of  $k$ . Second, it enables a new case: adoption when clean fuel is more expensive ( $\pi' < 0$ ), driven entirely by non-pecuniary benefits. We treat each in turn.

**Dirty fuel more expensive ( $\pi' > 0$ ): generalized results.** The FOC  $\mu'(x^*) = -\pi'$  depends on  $\mu'$ , not on  $\mu(0)$ , so  $x^*$  is unchanged. The affine WTP structure is also unchanged:

$$wtp_i = a + \alpha_i \pi' \quad \text{where } a = x^* \pi' + \mu(x^*)$$

*Higher baseline WTP:*  $a \geq c \geq 0$ . The constant  $a$  is the value of the maximized objective:

$$a = \max_x [x\pi' + \mu(x)]$$

Evaluating at  $x = 0$  gives  $0\pi' + \mu(0) = c$ . Since  $x^*$  is the maximizer,  $a \geq c$ . Economically, even an agent with  $\alpha_i = 0$  now receives both the optimized fuel saving and the non-pecuniary benefit  $c$ , so their WTP is at least  $c$ .

*The  $k$  proof generalizes.* From Section 1.4,  $\widetilde{wtp}_i = \delta wtp_i + k$  with  $k(\delta) = \tilde{a}(\delta) - \delta a$ . We revisit the three-step proof from Section 1.4.

Step 1 ( $k(1) = 0$ ) is unchanged: when there is no distortion,  $\widetilde{wtp}_i = wtp_i$  and  $k = 0$ . Step 3 (strict convexity) is also unchanged:

$$\frac{d^2 k}{d\delta^2} = \frac{-(\pi')^2}{\mu''(\tilde{x}^*)} > 0$$

This expression depends on  $\mu''$  and  $\pi'$ , neither of which involves  $\mu(0)$ . The constant  $c$  enters  $k$  through  $\tilde{a} = \tilde{x}^* \delta \pi' + \mu(\tilde{x}^*)$ , but drops out upon double differentiation because  $c$  shifts  $\mu$  by a constant.

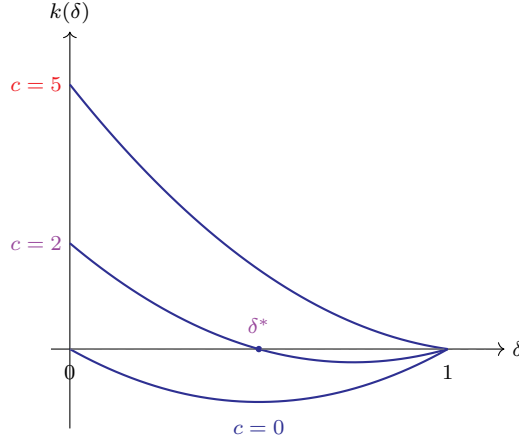
Step 2 changes. When  $\delta = 0$  the agent perceives zero fuel savings. The FOC  $\mu'(\tilde{x}^*) = -\delta \pi'$  becomes  $\mu'(\tilde{x}^*) = 0$ . Since  $\mu'(0) = 0$  by assumption, this gives  $\tilde{x}^* = 0$  when  $\delta = 0$ . Substituting into the definition  $\tilde{a} = \tilde{x}^* \delta \pi' + \mu(\tilde{x}^*)$ :

$$\tilde{a}(\delta=0) = 0 + \mu(0) = c$$

Since  $k(\delta) = \tilde{a}(\delta) - \delta a$ , we have  $k(0) = c - 0 = c$ .

In the baseline ( $c = 0$ ), the three steps gave  $k(0) = k(1) = 0$  with strict convexity, implying  $k \leq 0$  on  $[0, 1]$ . With  $c > 0$ ,  $k$  is strictly convex with  $k(0) = c > 0$  and  $k(1) = 0$ . The sign on the interior now depends on the slope at  $\delta = 1$ .

Figure B5:  $k(\delta)$  in the quadratic case  $\mu(x) = c - x^2$  for different values of  $c$



*Notes:* The function  $k(\delta) = (1 - \delta)[c - \delta(x^*)^2]$  for the quadratic case with  $(x^*)^2 = 4$ . Blue ( $c = 0$ ): baseline with  $k \leq 0$  everywhere. Purple ( $c = 2 < (x^*)^2$ ):  $k$  starts positive at  $c$ , crosses zero at  $\delta^* = c/(x^*)^2 = 0.5$ , and returns to zero at  $\delta = 1$ . Red ( $c = 5 > (x^*)^2$ ):  $k \geq 0$  on the entire interval. In all cases  $k$  is strictly convex and  $k(1) = 0$ .

*Sign of  $k$  when  $c > 0$ .* From Section 1.4,  $k'(\delta) = \tilde{x}^*(\delta)\pi' - a$ . Evaluating at  $\delta = 1$ :

$$k'(1) = x^*\pi' - a = x^*\pi' - [x^*\pi' + \mu(x^*)] = -\mu(x^*)$$

If  $\mu(x^*) \geq 0$ —the non-pecuniary benefit at optimal usage remains positive—then  $k'(1) \leq 0$ . Since  $k$  is strictly convex ( $k'' > 0$ ),  $k'$  is strictly increasing, so  $k'(1) \leq 0$  implies  $k'(\delta) < 0$  for all  $\delta \in [0, 1)$ . The function is therefore strictly decreasing on  $[0, 1)$  with  $k(1) = 0$ , giving  $k(\delta) \geq 0$  for all  $\delta \in (0, 1)$ . Marginal distortions reduce WTP by *less* than proportional scaling by  $\delta$ :  $\widehat{wtp}_i = \delta wtp_i + k > \delta wtp_i$ .

If  $\mu(x^*) < 0$ —switching costs dominate the non-pecuniary benefit at optimal usage—then  $k'(1) > 0$ , so  $k$  turns upward before reaching zero at  $\delta = 1$ . Since  $k$  is convex, starts at  $c > 0$ , and must dip low enough to return to zero while increasing, it must cross zero at some interior point. There exists a unique  $\delta^* \in (0, 1)$  where  $k(\delta^*) = 0$ : for severe distortions ( $\delta < \delta^*$ ),  $k > 0$  as the non-pecuniary benefit dominates; for mild distortions ( $\delta > \delta^*$ ),  $k < 0$  as in the baseline.

*Quadratic illustration.* Let  $\mu(x) = c - x^2$ , so  $\mu(0) = c$ ,  $\mu'(x) = -2x$ ,  $\mu'' = -2$ . Then  $x^* = \pi'/2$ , and the switching cost at optimal usage is  $\mu(x^*) = c - (x^*)^2$ . We can compute  $k$  in closed form:

$$k(\delta) = (1 - \delta)[c - \delta(x^*)^2]$$

This changes sign at  $\delta^* = c/(x^*)^2$ . When  $c \geq (x^*)^2$ —i.e., the non-pecuniary benefit exceeds the switching cost at optimal usage— $\delta^* \geq 1$  and  $k \geq 0$  on the entire interval. When  $c < (x^*)^2$ ,  $k$  changes sign at  $\delta^* = c/(x^*)^2 \in (0, 1)$ , matching the general analysis above. [Figure B5](#) illustrates the three cases.

*Interpretation.* Under severe marginal distortions ( $\delta$  near 0), the agent perceives nearly zero fuel savings, uses the technology minimally ( $\tilde{x}^* \approx 0$ ), and WTP reduces to approximately  $c$ : the non-pecuniary benefit alone. In the baseline ( $c = 0$ ), such an agent has near-zero WTP and drops out of the market. With  $c > 0$ , the non-pecuniary benefit provides a floor for WTP that marginal distortions cannot erode, because  $c$  does not operate through the fuel price channel. This is why  $k$  is positive under severe distortions: the floor  $c$  exceeds the proportionally scaled WTP  $\delta wtp_i$  when  $\delta$  is small.

*Unchanged results.* The following results carry through unchanged when  $\mu(0) = c$ , because the mechanisms on which they depend do not involve the level of  $\mu(0)$ .

- **Dampening** (Section 1.5): distortions reduce the WTP response to fuel price instruments ( $\partial wtp_i / \partial \tau < \partial wtp_i / \partial \tau$ ). Unchanged because: the envelope theorem and the inequality  $\tilde{x}^* < x^*$  both hold whenever  $\pi' > 0$ , regardless of  $\mu(0)$ .
- **Channel 2** (Section 1.6): WTP and abatement both increase in  $\alpha_i$ , so distortions exclude the highest-externality agents. Unchanged because: both are affine in  $\alpha_i$  with the same-sign coefficient when  $\pi' > 0$ .
- **Social planner** (Section 1.7): the super-Pigouvian tax corrects  $\delta$ ;  $s_1$  is needed only for  $\gamma$ . Unchanged because: the algebra showing  $SV_i + p = \widetilde{wtp}_i$  at the optimal tax is independent of  $\mu(0)$ .
- **Instrument-mix FOC** (Section 1.8): the structure of equation (3) is unchanged. It depends on the adoption and usage conditions and the Lagrangian, none of which involve  $\mu(0)$ .

Channel 1 under  $\delta$  (Section 1.6) may be affected when  $k > 0$ . Recall that the distorted elasticity under  $\delta$  is  $|\tilde{\mathcal{E}}(p)| = [p/(p-k)] \cdot |\mathcal{E}((p-k)/\delta)|$  (Section 1.6). When  $k < 0$ , the prefactor  $p/(p-k) < 1$  works against the evaluation-point effect. When  $k > 0$ , the prefactor  $p/(p-k) > 1$  and the two components reinforce each other: the demand curve shifts right, and both the evaluation point and the prefactor increase elasticity. The IHR condition remains sufficient, but is no longer necessary—the result holds more broadly when  $c$  is large.

**Clean fuel more expensive ( $\pi' < 0$ ): adoption from non-pecuniary benefits.** When  $c > 0$ , agents may adopt even when the clean technology has higher per-unit fuel costs: the non-pecuniary benefit outweighs the fuel premium. This case is relevant when the clean technology is a premium product—for example, an electric vehicle in a market where electricity is more expensive per kilometer than gasoline. The non-pecuniary benefit  $c$  captures the satisfaction of owning a clean vehicle (environmental preferences, social signaling, or intrinsic satisfaction), that the owner obtains at the level of usage  $\alpha_i$ . We use this EV example throughout to build intuition. Adoption requires  $c > p - s_1$ ; otherwise the non-pecuniary benefit does not cover the technology cost even for the agent with the highest WTP ( $\alpha_i = 0$ ).<sup>31</sup>

This case differs from the baseline in several important ways. Usage may be zero for some agents (corner solutions), WTP is decreasing rather than increasing in  $\alpha_i$ , adoption is determined by an upper threshold rather than a lower one, and both the dampening result and Channel 2 can reverse. We develop each in turn.

*Usage and the FOC.* The FOC  $\mu'(x^*) = -\pi'$  still determines  $x^*$ . Since  $\pi' < 0$ , we need  $\mu'(x^*) = -\pi' > 0$ . Because  $\mu'(0) = 0$  and  $\mu'' < 0$ , the function  $\mu'$  is strictly decreasing, so  $\mu'(x) > 0$  only for  $x < 0$ . Thus  $x^* < 0$ : agents use less clean energy than their taste alone would dictate, because the fuel premium discourages usage. In the EV example, the high cost of electricity relative to gasoline discourages driving the EV, even for agents who prefer it.

*Corner solutions.* Optimal clean energy usage for agent  $i$  is  $x^* + \alpha_i$ , which is positive only when  $\alpha_i > |x^*|$ . Agents with  $0 \leq \alpha_i \leq |x^*|$  would prefer negative usage, which is infeasible, so they set  $d_{2i} = 0$ : they adopt but do not use the technology at all. In the EV example, these are buyers who purchase the vehicle for the ownership satisfaction but leave it parked in the garage, driving their gasoline car instead. Their WTP comes entirely from the non-pecuniary benefit evaluated at zero usage:

$$wtp_i = 0\pi' + \mu(0 - \alpha_i) = \mu(-\alpha_i) \quad (\text{corner: } 0 \leq \alpha_i \leq |x^*|)$$

<sup>31</sup> $\alpha_i = 0$  has the highest WTP because they obtain the entire non-pecuniary benefit without having to use the device and in turn incur the difference in fuel costs.

For agents with  $\alpha_i > |x^*|$ , the interior solution gives:

$$wtp_i = (x^* + \alpha_i)\pi' + \mu(x^*) = a + \alpha_i\pi' \quad (\text{interior: } \alpha_i > |x^*|)$$

where  $a = x^*\pi' + \mu(x^*) \geq c$  by the same revealed-preference argument as before:  $a$  is the maximized value of  $x\pi' + \mu(x)$ , which is at least  $\mu(0) = c$ .

*WTP is continuous, differentiable, and decreasing.* WTP is defined by two different formulas on either side of  $\alpha_i = |x^*|$ : the concave  $\mu(-\alpha_i)$  for corner agents and the linear  $a + \alpha_i\pi'$  for interior agents. For the adoption threshold to be well-defined and the demand curve well-behaved, the two pieces must join smoothly. We verify that they agree at  $\alpha_i = |x^*|$  in both level and slope.

*Continuity.* At  $\alpha_i = |x^*|$ , the interior formula gives:

$$a + |x^*|\pi' = x^*\pi' + \mu(x^*) + (-x^*)\pi' = \mu(x^*)$$

using  $|x^*| = -x^*$ . The corner formula gives  $\mu(-|x^*|) = \mu(x^*)$ . Both agree.

*Differentiability.* The interior slope is  $\partial wtp_i / \partial \alpha_i = \pi' < 0$ . For the corner slope:

$$\frac{d}{d\alpha_i} \mu(-\alpha_i) = -\mu'(-\alpha_i)$$

At  $\alpha_i = |x^*|$ :  $-\mu'(-|x^*|) = -\mu'(x^*) = -(-\pi') = \pi'$ . Both slopes agree, confirming differentiability at the kink.

Since  $\mu'' < 0$  implies  $-\mu'(-\alpha_i)$  is strictly decreasing in  $\alpha_i$  (the corner WTP is concave), and the interior WTP is linear with negative slope  $\pi'$ , WTP achieves its unique maximum of  $\mu(0) = c$  at  $\alpha_i = 0$  and is strictly decreasing for  $\alpha_i > 0$ . The agent with  $\alpha_i = 0$  has the highest WTP because they receive the full non-pecuniary benefit  $c$  without incurring any fuel premium: their optimal usage is zero, so they pay no electricity costs. As  $\alpha_i$  increases, the agent needs heavier usage to realize their non-pecuniary benefit, which means paying more of the fuel premium, eroding WTP. In the EV example, the buyer who purchases the car for the status signal but rarely drives it has the highest WTP; the committed daily driver faces the largest electricity bills.

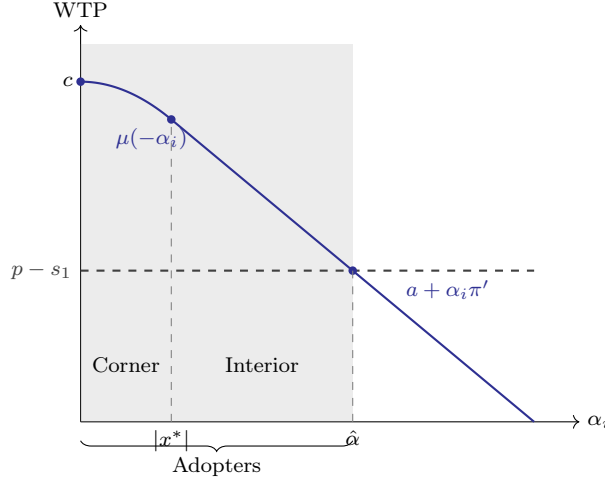
*Adoption reverses.* Since WTP is decreasing in  $\alpha_i$ , the adoption condition  $wtp_i > p - s_1$  defines an *upper* threshold  $\hat{\alpha}$ : agents with  $\alpha_i \leq \hat{\alpha}$  adopt. This reverses the baseline, where adoption required  $\alpha_i \geq \underline{\alpha}$ . Agents who must use the clean technology heavily to obtain the non-pecuniary benefit also incur large fuel premiums that erode willingness to pay. The agents who adopt are those with low to moderate usage requirements to obtain the benefit. In the EV example, it is the casual and status-motivated owners who adopt, not those who would need to be committed daily drivers to obtain the benefit—the opposite of the baseline.

**Figure B6** illustrates the WTP function. The concave portion ( $\alpha_i \leq |x^*|$ ) corresponds to corner agents whose WTP comes entirely from the non-pecuniary benefit  $\mu(-\alpha_i)$ . The linear portion ( $\alpha_i > |x^*|$ ) corresponds to interior agents with WTP  $a + \alpha_i\pi'$ . The two pieces join smoothly at  $\alpha_i = |x^*|$ , and the adoption threshold  $\hat{\alpha}$  is determined by the intersection with  $p - s_1$ .

**Demand distortions when  $\pi' < 0$ .** The qualitative effects of  $\gamma$  carry over from the baseline, but  $\delta$  introduces new features because the distortion now operates in the opposite direction: agents underperceive a cost rather than underperceiving a saving.

*Intertemporal distortions ( $\gamma$ ).* As in the baseline (Section 1.4),  $\widetilde{wtp}_i = \gamma wtp_i$ : the distortion scales WTP proportionally without affecting usage conditional on adoption. The key difference is the direction of selection. Since WTP is decreasing in  $\alpha_i$ , the adoption threshold  $\hat{\alpha}$  decreases under the distortion, and the agents excluded are the highest- $\alpha_i$  types at the margin. In the baseline

Figure B6: WTP as a function of  $\alpha_i$  when  $\pi' < 0$



( $\pi' > 0$ ),  $\gamma$  excluded the *lowest*- $\alpha_i$  adopters; here it excludes the highest. This reversal matters for Channel 2 (discussed below).

*Marginal distortions ( $\delta$ ): agents underperceive the fuel premium.* The agent perceives  $\delta\pi'$  instead of  $\pi'$ . Since  $\pi' < 0$ , the perceived fuel premium is  $|\delta\pi'| = \delta|\pi'|$ , which is smaller in magnitude than the true premium  $|\pi'|$ . Define  $\tilde{x}^*$  by  $\mu'(\tilde{x}^*) = -\delta\pi'$ . Since  $-\delta\pi' > 0$  but  $|\delta\pi'| < |\pi'|$ , we have  $\mu'(\tilde{x}^*) < \mu'(x^*)$ , and since  $\mu'$  is strictly decreasing,  $\tilde{x}^* > x^*$ :

$$x^* < \tilde{x}^* < 0$$

The distorted usage margin is closer to zero: under the distortion, agents perceive a smaller fuel premium and consequently use more clean energy than under full information. This is the opposite of the baseline ( $\pi' > 0$ ), where marginal distortions reduce usage.

This also affects corner solutions. Since  $|\tilde{x}^*| < |x^*|$ , the corner threshold shifts from  $|x^*|$  to  $|\tilde{x}^*|$ : agents with  $\alpha_i \in (|\tilde{x}^*|, |x^*|]$  who were at the corner under full information now have positive usage under the distortion. The reduced perceived penalty moves these agents from corner to interior solutions. In the baseline,  $\delta$  created no such effect because  $x^* > 0$  and all agents with  $\alpha_i \geq 0$  had interior solutions.

*Distorted WTP for interior agents.* For agents with interior solutions under both regimes ( $\alpha_i > |x^*|$ ), we can characterize the distorted WTP using the same steps as in Section 1.4. The distorted WTP is:

$$\widetilde{wtp}_i = (\tilde{x}^* + \alpha_i)(\delta\pi') + \mu(\tilde{x}^*) = \underbrace{\tilde{x}^* \delta\pi' + \mu(\tilde{x}^*)}_{\equiv \tilde{a}} + \alpha_i(\delta\pi')$$

Substituting  $\alpha_i = (wtp_i - a)/\pi'$  from the undistorted expression:

$$\widetilde{wtp}_i = \tilde{a} + \frac{wtp_i - a}{\pi'}(\delta\pi') = \delta wtp_i + (\tilde{a} - \delta a) = \delta wtp_i + k$$

The  $k$  analysis is identical to the generalized baseline:  $k(0) = c$ ,  $k(1) = 0$ ,  $k$  strictly convex, with the sign determined by whether  $\mu(x^*) \geq 0$ . The interpretation differs, however. In the baseline ( $\pi' > 0$ ), the distortion causes agents to underperceive a cost saving, reducing usage; here ( $\pi' < 0$ ), agents underperceive a cost premium, increasing usage relative to the undistorted case. When  $k > 0$ , the distorted WTP exceeds  $\delta wtp_i$ : the agent's WTP is higher under the distortion than proportional

scaling would suggest, because the non-pecuniary benefit  $c$  is unaffected by the distortion while the perceived fuel penalty is smaller.

*Distorted WTP for corner agents.* Agents who remain at the corner ( $\alpha_i \leq |\tilde{x}^*|$ ) set  $d_{2i} = 0$  regardless of the perceived fuel price, so their WTP is:

$$\widetilde{wtp}_i = \mu(-\alpha_i)$$

This is identical to the undistorted corner WTP: marginal distortions cannot affect agents who do not use the technology. The perceived fuel premium is irrelevant when usage is zero. This creates an asymmetry:  $\delta$  shifts the WTP of interior agents (through  $k$ ) but leaves corner agents untouched.

*Dampening can fail.* In the baseline ( $\pi' > 0$ ), marginal distortions unambiguously dampen the WTP response to fuel price instruments (Section 1.5). The envelope theorem gives  $\partial \widetilde{wtp}_i / \partial \tau = \delta(\tilde{x}^* + \alpha_i)$  and  $\partial wtp_i / \partial \tau = (x^* + \alpha_i)$ , and the inequality  $\delta(\tilde{x}^* + \alpha_i) < (x^* + \alpha_i)$  holds because both  $\delta < 1$  and  $\tilde{x}^* < x^*$  work in the same direction.

When  $\pi' < 0$ ,  $\tilde{x}^* > x^*$ , so the two forces oppose. The distorted usage base  $\tilde{x}^* + \alpha_i$  is *larger* than the undistorted base  $x^* + \alpha_i$ , because the agent underperceives the fuel premium and uses more. Whether the  $\delta$  scaling is enough to offset this depends on  $\alpha_i$ :

$$\delta(\tilde{x}^* + \alpha_i) \stackrel{?}{\lesseqgtr} x^* + \alpha_i$$

For large  $\alpha_i$ , the  $\alpha_i$  terms dominate both sides and  $\delta < 1$  ensures dampening. But for agents near the corner ( $\alpha_i$  slightly above  $|x^*|$ ),  $x^* + \alpha_i \approx 0$  while  $\tilde{x}^* + \alpha_i > 0$ , so  $\delta(\tilde{x}^* + \alpha_i)$  can exceed  $x^* + \alpha_i$ .

*Quadratic illustration.* With  $\mu(x) = c - x^2$ :  $x^* = \pi'/2 < 0$  and  $\tilde{x}^* = \delta\pi'/2$ . For an agent with  $\alpha_i = |x^*| + \epsilon$  (just above the undistorted corner), the usage bases are:

$$\begin{aligned} x^* + \alpha_i &= \epsilon \\ \tilde{x}^* + \alpha_i &= |x^*|(1 - \delta) + \epsilon \end{aligned}$$

where the second line uses  $\tilde{x}^* = -\delta|x^*|$  and  $\alpha_i = |x^*| + \epsilon$ . The dampening condition  $\delta(\tilde{x}^* + \alpha_i) < (x^* + \alpha_i)$  becomes:

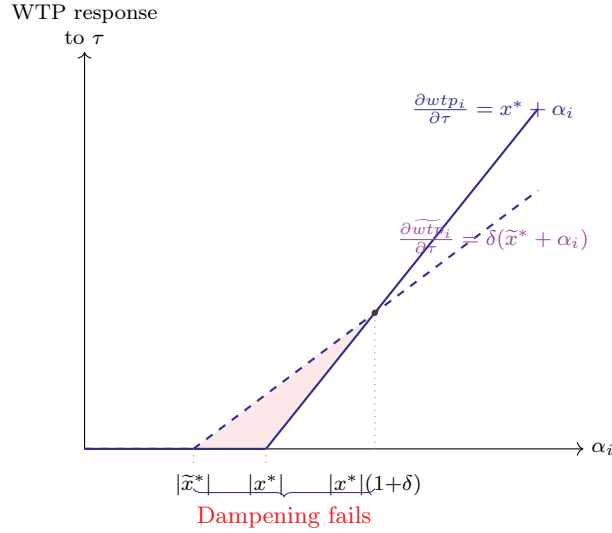
$$\delta[|x^*|(1 - \delta) + \epsilon] < \epsilon$$

Expanding and rearranging:  $\delta|x^*|(1 - \delta) < \epsilon(1 - \delta)$ , and dividing by  $(1 - \delta) > 0$ :  $\epsilon > \delta|x^*|$ . Dampening fails for agents within  $\delta|x^*|$  of the corner. The intuition is that near the corner, the undistorted agent barely uses the technology ( $x^* + \alpha_i \approx 0$ ), so a small increase in  $\tau$  has almost no effect on their WTP. The distorted agent, by contrast, has a non-trivial usage base ( $\tilde{x}^* + \alpha_i > 0$ ), so the same tax increase generates a meaningful WTP response—the distortion *amplifies* the instrument's effect. [Figure B7](#) illustrates: the distorted response starts earlier (at  $|\tilde{x}^*|$  instead of  $|x^*|$ ) and exceeds the undistorted response until  $\alpha_i$  is far enough from the corner that the  $\delta$  scaling dominates.

**Channel 2 reverses when  $\pi' < 0$ .** In the baseline ( $\pi' > 0$ ), both WTP and abatement are increasing in  $\alpha_i$  (Section 1.6): the agents who value the technology most are also the ones who abate the most, giving a correlation of +1. Distortions exclude these high-value, high-abatement agents from the adopter pool, so the marginal adopter under the distortion has higher  $\alpha_i$  and generates more abatement than the marginal adopter absent the distortion.

When  $\pi' < 0$ , WTP is *decreasing* in  $\alpha_i$  (high-taste agents incur large fuel premiums) while abatement  $(\tilde{x}^* + \alpha_i)\phi$  remains increasing in  $\alpha_i$  for interior agents. The correlation between WTP

Figure B7: Dampening failure near the corner when  $\pi' < 0$



*Notes:* The solid blue line shows the undistorted WTP response to a marginal fuel price instrument ( $\partial wtp_i / \partial \tau = x^* + \alpha_i$ ), which is zero for corner agents ( $\alpha_i \leq |x^*|$ ). The dashed purple line shows the distorted response ( $\partial \tilde{wtp}_i / \partial \tau = \delta(\tilde{x}^* + \alpha_i)$ ), which starts earlier at  $|\tilde{x}^*| < |x^*|$  because the distortion moves agents off the corner. For agents with  $\alpha_i < |x^*|(1 + \delta)$ , the distorted response exceeds the undistorted response: the distortion amplifies rather than dampens the instrument's effect. Illustrated for the quadratic case  $\mu(x) = c - x^2$  with  $\delta = 0.6$ .

and abatement is  $-1$ : the agents who value adoption most (low  $\alpha_i$ , who enjoy the non-pecuniary benefit without heavy usage) generate the *least* abatement, while the agents who abate the most (high  $\alpha_i$ , heavy users) have the lowest WTP. In the EV example, the status buyers who rarely drive adopt first, but the committed daily drivers who would displace the most gasoline are excluded.

Distortions reduce WTP, lowering the upper threshold  $\hat{\alpha}$  and excluding agents at the adoption margin. But these marginal agents—those with the highest  $\alpha_i$  among adopters—are precisely the ones who generate the most abatement. The new marginal adopter under the distortion has lower  $\alpha_i$  and generates less abatement. Channel 2 now works *against* fixed cost subsidies: a subsidy that brings excluded agents back into the adopter pool reaches marginal adopters who generate less abatement per dollar than they would absent the distortion. This is the mirror image of the baseline result. Figure B8 illustrates the contrast.

**Policy implications when  $\pi' < 0$ .** When  $\pi' < 0$ , fixed cost subsidies are not merely more efficient than marginal instruments—they are necessary. While  $\pi'$  remains non-positive, marginal subsidies generate no adoption incentive through the fuel price channel: the maximum WTP in the population is  $c = \mu(0)$  (achieved at  $\alpha_i = 0$ ), which does not depend on  $s_2$ . Adoption therefore requires  $c > p - s_1$ : the non-pecuniary benefit must exceed the net technology cost.

The case for  $s_1$  rests entirely on Channel 1 (demand elasticity under distortions reduces infra-marginal cost); Channel 2 works in the opposite direction, as the marginal adopter generates less abatement under distortions than without. Whether Channel 1 dominates depends on the distribution of  $\alpha_i$  and the severity of the distortions, but the qualitative conclusion is clear: the case for fixed cost subsidies is weaker than in the baseline on the Channel 2 margin.

*Regime-flipping.* A sufficiently large  $s_2$  can make  $\pi' = \pi + \tau + s_2 > 0$ , exiting the  $\pi' < 0$  regime entirely. At the transition: corner solutions vanish (as  $|\tilde{x}^*| \rightarrow 0$  when  $\pi' \rightarrow 0$ ), WTP switches from decreasing to increasing in  $\alpha_i$ , and the adoption threshold flips from the upper threshold  $\hat{\alpha}$  to the



## IV.5 Marginal distortions also increase demand elasticity

From Section 1.4,  $\widetilde{wtp}_i = \delta wtp_i + k$  with  $k \leq 0$ . Demand at price  $p$  is therefore:

$$\tilde{Q}(p) = \Pr(\delta wtp_i + k > p) = Q\left(\frac{p-k}{\delta}\right)$$

Differentiating by the chain rule:

$$\tilde{Q}'(p) = Q'\left(\frac{p-k}{\delta}\right) \frac{1}{\delta}$$

Which gives the elasticity as

$$\tilde{\mathcal{E}}(p) = p \frac{\tilde{Q}'(p)}{\tilde{Q}(p)} = \frac{p}{\delta} \frac{Q'\left(\frac{p-k}{\delta}\right)}{Q\left(\frac{p-k}{\delta}\right)} = \frac{p}{\delta} \frac{\mathcal{E}\left(\frac{p-k}{\delta}\right)}{\frac{p-k}{\delta}} = \frac{p}{p-k} \mathcal{E}\left(\frac{p-k}{\delta}\right)$$

Unlike the  $\gamma$  case, the two components of this expression work in opposite directions. The evaluation point  $(p-k)/\delta > p$  increases  $|\mathcal{E}|$  (the same force as under  $\gamma$ ), but the prefactor  $p/(p-k) \leq 1$  works against it. The prefactor arises from the level shift  $k$ : every agent's WTP falls by the same absolute amount, but this represents a larger *relative* reduction for low-WTP agents than for high-WTP agents, compressing the demand curve toward the origin.

Whether the net effect increases elasticity depends on the shape of the demand curve. The key condition turns out to be the *hazard rate* of the WTP distribution. Let  $f$  denote the density of WTP,  $F$  the CDF, and define the hazard rate:

$$h(p) \equiv \frac{f(p)}{1 - F(p)}$$

The hazard rate is the probability of an agent having WTP exactly equal to  $p$ , conditional on having WTP at least  $p$ . Since  $Q(p) = 1 - F(p)$ , the demand elasticity can be written:

$$|\mathcal{E}(p)| = \frac{pf(p)}{1 - F(p)} = ph(p)$$

Substituting  $|\mathcal{E}(z)| = zh(z)$  into the elasticity expression from above:

$$|\tilde{\mathcal{E}}(p)| = \frac{p}{p-k} \left| \mathcal{E}\left(\frac{p-k}{\delta}\right) \right| = \frac{p}{p-k} \left[ \frac{p-k}{\delta} h\left(\frac{p-k}{\delta}\right) \right] = \frac{p}{\delta} h\left(\frac{p-k}{\delta}\right)$$

Now using again the fact that  $|\mathcal{E}(p)| = ph(p)$ , we can write the condition:

$$\begin{aligned} |\tilde{\mathcal{E}}(p)| &> |\mathcal{E}(p)| \\ \frac{p}{\delta} h\left(\frac{p-k}{\delta}\right) &> ph(p) \\ h\left(\frac{p-k}{\delta}\right) &> \delta h(p) \end{aligned}$$

This holds whenever  $h$  is increasing in  $p$ : since  $(p-k)/\delta > p$ , the hazard rate on the left is evaluated at a higher price, and  $\delta < 1$  makes the right-hand side even smaller.

An increasing hazard rate means that the higher the price, the more “bunched” the remaining potential adopters are near the margin. When this holds, shifting demand leftward (via  $k < 0$ ) moves us into a region where the remaining buyers are even more concentrated near the cutoff, which more than offsets the  $p/(p - k)$  dampening.

This is a well-studied distributional property.<sup>32</sup>

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<sup>32</sup>Since  $wtp_i$  is affine in  $\alpha_i$  (Equation 1), the IHR condition is on the distribution of  $\alpha_i$ . Distributions of  $\alpha_i$  that satisfy IHR include: normal, uniform, logistic, Gumbel, and Weibull or Gamma with shape parameter  $\geq 1$ . Distributions that violate IHR include: Pareto (decreasing hazard rate; generates isoelastic demand), lognormal (hazard rate increases then decreases), log-logistic (decreasing or hump-shaped hazard rate), and Weibull or Gamma with shape parameter  $< 1$ . The common feature of the violating distributions is heavy tails: at high  $\alpha_i$ , a non-trivial mass of agents remains, so the hazard rate falls. See Bagnoli and Bergstrom (2005) for a comprehensive catalog.