A Welfare Analysis of Policies Impacting Climate Change[*]

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Abstract

What are the most effective ways to address climate change? This paper extends and applies the marginal value of public funds (MVPF) framework to help answer this question. We examine 96 US climate-related policy changes studied over the past 25 years. These policies span subsidies (wind, residential solar, electric and hybrid vehicles, vehicle retirement, appliance rebates, weatherization), nudges (marketing, energy conservation), and revenue raisers (fuel taxes, cap and trade). For each policy, we draw upon quasi-experimental or experimental evaluations of its causal effects and translate those estimates into an MVPF. We apply a consistent translation of these behavioral responses into measures of their associated externalities and valuations of those externalities. We also provide a new method for incorporating learning-by-doing spillovers. The analysis yields three main results: First, subsidies for investments that directly displace the dirty production of electricity, such as production tax credits for wind power and subsidies for residential solar panels, have higher MVPFs (generally exceeding 2) than all other subsidies in our sample (with MVPFs generally around 1). Second, nudges to reduce energy consumption have large MVPFs, with values above 5, when targeted to regions of the US with a dirty electric grid. By contrast, policies targeting areas with cleaner grids, such as California and the Northeast, have substantially smaller MVPFs (often below 1). Third, fuel taxes and cap-and-trade policies are highly efficient means of raising revenue (with MVPFs below 0.7). We contrast these conclusions with those derived from more traditional cost-per-ton metrics used in previous literature.

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1 Introduction

What are the most effective ways to address climate change? There is a robust and growing literature examining the causal effects of climate-related policy changes. These papers often assess the effectiveness of policies by measuring the cost per ton of carbon dioxide (CO_2) abated. Yet, comparisons of these costs per ton across studies face several challenges. First, the input assumptions in these calculations vary across papers. Second, there are at least three distinct (and often conflated) definitions of the cost per ton of CO_2 found in the literature: (1) resource costs expended per ton of CO_2 abated (Grubb et al. 1993, Enkvist et al. 2007, Mullainathan & Allcott 2010, Greenstone et al. 2022), (2) government expenditures per ton of CO_2 abated (Gillingham & Tsvetanov 2019, Knittel 2009), and (3) social costs per ton of CO_2 abated (Hughes & Podolefsky 2015, Fournel 2024). Third, even if researchers were to align on a single approach to measuring cost per ton, each of these metrics have inherent limitations when assessing the welfare effects of spending and revenue-raising policies. Resource cost per ton of CO_2 abstracts from the causal effects of policy changes, ignoring the cost and benefits of transfers to inframarginal individuals who do not change their behavior in response to those policy changes. Government expenditures per ton of CO_2 accounts for the cost of transfers to inframarginal individuals but ignores the benefit of those transfers to their recipients. Social cost per ton seeks to capture a comprehensive set of non-resource benefits but ignores the opportunity cost of transfers to inframarginal individuals.

It is with these concerns in mind that we extend and apply the marginal value of public funds (MVPF) framework to examine the welfare consequences of historical US spending and revenue raising policies addressing climate change. The MVPF approach quantifies the net benefits to individuals in society relative to the policy's net government cost. These benefits and costs incorporate behavioral responses to the policy and include inframarginal transfers, overcoming the primary limitations of the cost per ton approach.[1] As an added benefit, the MVPF facilitates policy comparisons both within and across policy categories, such as comparing climate policies to public investments in education or healthcare.

We apply our MVPF-based framework to a comprehensive set of climate policy interventions in the U.S. that affect greenhouse gas emissions and have been rigorously evaluated in the past 25 years using experimental or quasi-experimental methods. This yields a sample of 96 policy changes in three primary categories – subsidies, nudges and marketing, and revenue raisers. Within the category of subsidies, we examine policies targeting wind production, residential solar, electric and hybrid vehicle purchases, vehicle retirement, appliance rebates, and home weatherization. Within the category of nudges and marketing, we examine energy conservation policies such as home energy reports as well as marketing policies designed to encourage the

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[1] To the best of our knowledge, Berkouwer & Dean (2019) and Christensen, Francisco & Myers (2023) were the first to apply the MVPF framework in a climate setting. See also more recent work on peak energy usage incentives and water audits (Jacob et al. 2023, Akesson et al. 2023), and the work of Kotchen (2022) and Prest & Stock (2023) in using the MVPF framework as a lens to understand optimal environmental policy.

take-up of clean technologies. Within the category of revenue raisers, we examine gasoline taxes, taxes on other fuels such as jet fuel and diesel, and cap-and-trade policies. Lastly, we consider an illustrative set of international policies, including subsidies for energy-efficient cookstoves and deforestation-focused payments for ecosystem services.

Across all policies, we use a consistent method to translate a policy's causal effect on behavior into a valuation of that change in behavior. We proceed in two steps. First, we use a harmonized method to translate changes in behavior (e.g., changes in car purchases or electricity usage) into changes in emissions and other damaging outcomes (e.g., car accidents). For example, in the case of changes in electricity production or electricity usage, we use estimates from the EPA's AVERT model to measure associated changes in emissions resulting from compositional changes in the grid (EPA 2024*b*). In the case of changes to vehicle purchases (e.g., EVs versus internal combustion), we estimate the change in gallons of gasoline used relative to a counterfactual vehicle. We measure the total CO_2 emissions associated with the upstream production of gasoline and its combustion. We combine that with measures of local pollutants released such as particulate matter. Second, we apply a consistent dollar value for each externality measured. For the social cost of carbon (SCC), we draw from recent work by the US Environmental Protection Agency (EPA) (EPA 2023*c*) that places the social cost of carbon at \$193 in 2020 (and rising in the years to follow). We also explore the robustness of our results to alternate measures of the social cost of carbon, ranging from \$76 to \$337 in 2020. For local pollutants, we use estimates of the social cost of NH_3, HC, NO_X, $PM_{2.5}$ and SO_2 from the AP3 integrated assessment model, which monetizes health impacts from air pollution exposure using estimates on mortality and an associated value of a statistical life (VSL).

Our primary methodological contribution is the introduction of a new sufficient statistics approach to quantify the benefits of "learning-by-doing" effects, which can then be directly incorporated into the MVPF framework. There is a large literature that shows the prices of new technologies such as solar cells, wind turbines, and batteries have declined with cumulative global production (Way et al. 2022). These patterns often serve as a proposed justification for subsidizing particular low-carbon technologies: subsidizing specific technologies with relatively high abatement costs today may generate learning-by-doing spillovers that lower the future cost of these technologies and generate future environmental benefits (Romer 1986, van Benthem et al. 2008).

We show how these learning-by-doing effects can be incorporated directly into the MVPF framework. In particular, we show that when the marginal cost of production is an isoelastic function of cumulative production and when demand is an isoelastic function of price, the time path of production follows a second-order ordinary differential equation that can be solved to estimate the willingness-to-pay for the resulting learning-by-doing effects.

Learning by doing generates two types of benefits: first, reductions in the future cost of low-carbon technologies increase consumer welfare due to lower future prices, and second, these price reductions serve to increase future take-up and, consequently, reduce future emissions.[2] We apply our framework to study the potential implications of learning by doing for policies that increase the current production of solar cells, wind turbines, and batteries. While we focus here on learning-by-doing in the context of climate change, our framework can be used in other industrial policy settings where there may be learning-by-doing externalities.

1.1 Findings

We have three main findings. First, we find that subsidies for investments that directly displace the dirty production of electricity have higher MVPFs than all other subsidies in our sample. Policies providing production tax credits for wind power and subsidies for residential solar have MVPFs that generally exceed 2. In contrast, subsidies providing appliance rebates, home weatherization, vehicle retirement, or subsidies for hybrid vehicle purchases have MVPFs around 1. Electric vehicle subsidies have MVPFs around 1.5. The high MVPF values for wind production tax credits and residential solar subsidies are robust to a wide range of values of the social cost of carbon (e.g., \$76 or \$337). These conclusions are also robust to a wide range of additional assumptions regarding the construction of the MVPF. This includes the valuation of firm profits, the treatment of private energy savings, and the evaluation of non-marginal policy changes. The inclusion of learning-by-doing effects amplifies the MVPFs of these subsidies. In the case of wind, the MVPF rises from 3.85 to 5.87 with learning by doing. In the case of residential solar, the MVPF rises from a relatively low value of 1.45 to 3.86.[3]

Second, we find that behavioral nudges designed to reduce energy consumption can produce large welfare gains when administered in regions with relatively dirty electric grids (with MVPFs exceeding 5) but have lower MVPFs (below 1) in regions with cleaner grids.[4] This finding also suggests that the effectiveness of these nudges will decrease over time as more electricity comes from low- or zero-carbon sources.

Third, we find that implementing taxes on polluting goods can serve as an efficient means of raising revenue. In the context of revenue raisers, the MVPF measures the welfare burden imposed on individuals per dollar of revenue raised. This means that, all else equal, better revenue raisers have lower MVPFs. We analyze taxes on gasoline, diesel, and jet fuel, along with changes to the number of auctioned permits in cap-and-trade systems. We find that nearly all of these revenue-raising policies have MVPFs below 1, with most having MVPFs below 0.7.

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[2] Comparative statics of the model in Appendix B show that learning-by-doing externalities are generally decreasing over time, providing a theoretical rationale for subsidizing early adoption.

[3] While the MVPFs of subsidies for new technologies are higher than other climate-focused subsidies, they are not necessarily larger than non-environmental spending policies. For example, in previous work, Hendren & Sprung-Keyser (2020) found that policies providing direct investment in health and education for low-income children had MVPFs often in excess of 5.

[4] This echoes the conclusions in Borenstein & Bushnell (2022), who suggest the returns to reducing energy consumption are lowest in areas with clean grids. We find support for this conclusion in the context of energy conservation nudges, despite the fact that previous work has found treatment effects of nudges are larger in more environmentalist areas (Allcott 2015).

This means that taxes on polluting goods impose a welfare cost of only \$0.70 on society for every \$1 of revenue raised. This finding reflects the logic of Pigouvian taxation, quantifying the efficiency of raising rates when current tax rates fall below the associated environmental externalities.

While our primary focus is on US environmental policy, we also consider the welfare consequences of US spending abroad on policies that address climate change. We find such subsidies have the potential to produce high MVPFs, even when only considering the impact on US beneficiaries and US taxpayers. For example, we consider the case of subsidies for the take-up of efficient charcoal cookstoves in Kenya (Berkouwer & Dean 2022). Ignoring any benefits of these stoves to local residents and ignoring any non-US benefits of CO_2 reductions, the US-specific gains from reduced CO_2 emissions are 37 times larger than the net cost of the subsidy, generating a higher MVPF than any domestic subsidy in our sample. (When considering the full set of global benefits, the MVPF rises from 37 to 323). That said, there is substantial uncertainty associated with these international subsidy estimates. The estimated impacts of these policies often vary quite extensively, even within policy categories. As we discuss in Section 7, the magnitude of the US-specific MVPF depends heavily on the incidence of the social cost of carbon. In particular, it depends on the extent to which CO_2 damages have incidence on US residents and US government tax revenue.[5]

1.2 Relationship to Existing Literature

Our paper relates to an extensive literature in climate and environmental economics. It draws upon a large body of estimates examining the causal effects of individual policy changes and builds upon a body of work conducting comparative analyses of climate policies.

This kind of comparative analysis was popularized in work by McKinsey & Company (Enkvist et al. 2007), who calculated the resource cost per ton of CO_2 abated for a wide range of technologies. In recent years, alternative versions of this analysis have been performed by groups such as the International Energy Agency (IEA 2020) and the Environmental Defense Fund (Environmental Defense Fund 2021).

This line of work has been subject to criticism, both for the use of engineering estimates relied upon to construct these measures of resource costs per ton (Fowlie et al. 2018, Brandon et al. 2022) and for the focus on abatement cost of products rather than the abatement cost of policies (e.g., a solar panel rather than a subsidy for a solar panel) (Kesicki & Ekins 2012). In response, recent work has focused on the effects of specific policy changes when constructing estimates of cost per ton (see Gillingham & Stock (2018) for a broad compilation of such estimates).

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[5] Many models that agree on the level of the social cost of carbon still differ in the geographic incidence of those damages and the split between market and non-market damages (e.g., productivity declines versus mortality impacts.) The impact on US tax revenue is determined by the fraction of damages that reflects US-specific productivity changes, as the US Treasury has an equity stake in those changes.

While the recent focus on policies rather than products speaks to an important criticism of early abatement cost estimates, the definition of "cost per ton of CO_2" still varies within and across papers.[6] In order to compare across cost-per-ton definitions and assess the relative merits of the MVPF versus cost-per-ton metrics, we construct all three measures of cost per ton for each of the 96 policies in our sample. Our analysis in Section 8 reveals substantial variation in the cost per ton of each policy depending on the definition employed. For example, the cost per ton of appliance subsidies ranges from -\$2 to \$474 across the three measures. The resource cost per ton is -\$2 because the long-run energy savings are estimated to offset the higher upfront cost of the energy efficient appliance. By contrast, the government cost per ton is \$474 because subsidies lead to a large number of inframarginal transfers – money provided to individuals who would have purchased the energy-efficient appliances anyway.

Even if one were to consistently apply a single definition of cost per ton when comparing policies, the conclusions reached when using these metrics are not generally consistent with the primary findings from our MVPF analysis. We can see this when examining each definition of cost per ton in turn. From a resource cost perspective, appliance rebates have negative costs, -\$2, indicating they are far more cost-effective than vehicle retirement or hybrid vehicle subsidies, which have very high resource costs per ton at \$1,007 and \$577 respectively. When comparing their MVPFs, however, their values are essentially indistinguishable: 1.16 versus 1.05 and 1.01.[7] From a government cost perspective, the relative ordering of policies is broadly consistent with the ordering generated by the MVPF. However, we find high MVPFs even when the government cost per ton exceeds the SCC. In the case of electric vehicle (EV) subsidies, for example, at an SCC of \$193 per ton, we find an MVPF of 1.45 but a government cost per ton of \$1,356. This is driven by the omission of substantial benefits in the government cost-per-ton calculation, including inframarginal transfer benefits and consumer surplus from learning by doing. From a social cost perspective, we again find divergences from the MVPF ordering of policies. For example, a core finding of our work is that the MVPF of wind subsidies and residential solar subsidies exceed that of EV subsidies (5.87 and 3.86 versus 1.45). This is the exact opposite of the ordering we find when using the social cost per ton. EVs have the lowest social cost per ton (-\$415) followed by residential solar (-\$67) and wind PTCs (-\$32).

In short, each of the various cost-per-ton metrics do not easily capture the insights of the MVPF approach. In Section 8, we show that this is primarily because of their treatment (or omission) of key factors such as inframarginal benefits, inframarginal costs, and non-CO_2

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[6] For example, Table 2 of Gillingham & Stock (2018) compiles a set of cost-per-ton estimates from the existing literature. The best policy listed is a behavioral nudge for reducing energy where the net resource cost of the policy is reported. By contrast, residential solar panels appear to be one of the highest cost policies in their sample, but the reported cost per ton measures the government cost of the policy.

[7] Patterns of this sort emerge repeatedly when comparing individual policies. For example, we construct a resource cost per ton for energy-efficient refrigerators studied in Datta & Gulati (2014) and find a value of -\$512. We do the same for wind PTCs in Hitaj (2013) and find a resource cost per ton of -\$96. This relative ordering is consistent with previous estimates from McKinsey & Company (Enkvist et al. 2007). Despite this, we find the wind PTC has an MVPF that is much higher (4.63 versus 1.01).

benefits.[8]

Our approach also relates to a large literature on benefit cost analysis and its applications. A traditional approach would compare the benefits of a spending policy to the distortionary cost of raising revenue through a change in a linear income tax rate (Stiglitz & Dasgupta 1971, Atkinson & Stern 1974). The MVPF approach extends this approach by allowing researchers to choose from a menu of policies to close the budget constraint.[9] For example, if one treats individuals paying the gas tax and wind PTC beneficiaries as having similar social welfare weights, the comparison of an MVPF of 5.87 for wind PTCs to an MVPF of 0.67 for gas taxes suggests every $1 of government revenue raised from a gas tax and spent on wind PTCs generates $5.20 (=5.87-0.67) in net benefits to individuals in society.[10,11]

Finally, our paper also builds on a literature discussing the role of policy in areas where learning by doing is present (Bollinger & Gillingham 2019, Way et al. 2022, Bistline et al. 2023). Our approach relates most closely to work by van Benthem et al. (2008), who develop a dynamic model of learning by doing and use it to simulate the desirability of solar subsidies in California. Section 2.3 below shares many of the same features as their model. Our primary methodological contribution is to provide a sufficient statistics quantification of these learning-by-doing effects that can be directly incorporated into the MVPF framework. Moreover, we provide conditions under which one can obtain a closed-form solution to the model, providing a clear picture of how the results are determined by demand elasticities and the elasticity of marginal costs with respect to cumulative production.

1.3 Roadmap

The rest of this paper proceeds as follows. Section 2 discusses the MVPF framework and outlines how it can be used to examine the welfare effects of policies impacting climate change. Section 3 discusses our sample of policies and methods for harmonizing the measurement of externalities and the valuation of those externalities. Sections 4, 5, and 6 discuss our results

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[8] A modified version of the social cost per ton implemented by Fournel (2024) adjusts for the opportunity cost of inframarginal transfers using a "marginal cost of public funds" adjustment. This approach, however, yields measures that vary significantly even within the set of common assumptions about the efficiency of income tax policy. For example, we find a social cost per ton for EVs of -$259 when using a 10% adjustment and a positive $260 when using a 50% adjustment. In contrast, the MVPF does not require researchers analyzing particular environmental policies to take a stand on the efficiency of the income tax system.

[9] The MVPF is a form of benefit-cost ratio in which all benefits to individuals are incorporated in the numerator of the MVPF while all government costs are incorporated in the denominator. As shown in Section 2, the MVPF measures an implicit Lagrange multiplier on a government budget constraint when choosing policies to maximize social welfare.

[10] When policies affect different groups of beneficiaries, one can use the MVPF framework to transparently express concerns over equity. Given two policies, policy 1 and policy 2, a decision-maker prefers a budget neutral policy that spends more on policy 1 financed by raising revenue from policy 2 if and only if that decision-maker prefers giving $\$MVPF_1$ to policy 1 beneficiaries rather than $\$MVPF_2$ to policy 2 beneficiaries.

[11] In this literature, papers also measure welfare effects by constructing total surplus or net benefits. The MVPF approach is closely connected, but by measuring the per-dollar effect of spending, it facilitates comparisons across policies when the scale of such policies differ.

for subsidy policies, nudge and marketing policies, and revenue-raising policies, respectively.[12] Section 7 discusses our findings for a limited set of international subsidies. Section 8 contrasts the MVPF with cost per ton measures, explaining how our main conclusions would differ had we used those alternative welfare measures. Section 9 concludes.

2 Using the MVPF Approach for Policies Affecting Climate Change

We use the Marginal Value of Public Funds (MVPF) framework to examine the welfare impact of a range of policies affecting climate change. This section presents a formal modeling of the MVPF framework, tailored to the context of environmental policy. We begin by using the theory to illustrate how measures of willingness-to-pay and net cost to the government of policies feed into normative statements about the desirability of policy changes. After presenting the framework, we then consider an illustrative policy of a subsidy for a good that has a positive environmental externality. We show how we measure the willingness-to-pay and net cost.

Relative to existing literature, the key methodological contribution of this section is the derivation of a new sufficient statistics approach to incorporate learning-by-doing effects when examining the welfare consequences of subsidies. Section 2.3 below provides an overview of our approach, and Appendix A provides proofs within a generalized model that is rich enough to nest all of our policy applications.

2.1 Normative Framework

We consider a set of individuals indexed by i. This population contains all individuals globally, including both current and future generations. We consider a decision-maker for a particular country, which we refer to as the "government", that seeks to maximize a social welfare function,

$$W = \sum_i \psi_i u_i, \tag{1}$$

which is a weighted sum of individual utilities with Pareto weights ψ_i. Increasing individual i's utility by 1 "util" leads to a ψ_i increase in social welfare, W. We allow (but do not require) the government to place positive weight on individuals outside its jurisdiction. We do not specify particular weights in our analysis, but rather, we construct statistics that help a decision-maker apply their own weights when deciding whether to make a given policy change.

We wish to measure the welfare gain (or loss) from modifications to government policy using the causal effect of policy changes that have been rigorously evaluated using quasi-experimental

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[12] The Online Appendix provides a detailed description of the MVPF construction for each policy in our sample.

or experimental methods. These methods measure the causal effects of policy changes by clearly articulating an 'orthogonality' condition that isolates the causal effect of a policy change holding all else equal (e.g., the effect of a tax or subsidy on behavior). To capture this, let $p \in \mathbb{R}$ index a policy change where $p = 0$ corresponds to the status quo world. For example, $\tau_{gas}(p) = \tau_0 + p$ could correspond to a change in the tax rate on gasoline relative to the status quo, τ_0.

To first order, individual i is willing to pay $WTP_i = \frac{\frac{du_i}{dp}}{\lambda_i}$ for the policy change, where λ_i is the Lagrange multiplier on their budget constraint.[13] The total effect of the policy change on social welfare, W, can be expressed as $\sum_i \eta_i WTP_i$ where $\eta_i = \lambda_i \psi_i$ is the social marginal utility of income of individual i (providing individual i with \$1 at time $t = 0$ leads to an η_i increase in W).

Next we consider the impact of the policy on the government's budget. We can then write the welfare impact per dollar spent on the policy in a manner that separates the normative and positive aspects of the decision. Every dollar of net spending on the policy increases social welfare by

$$\frac{\frac{dW}{dp}}{\frac{dB}{dp}} = \bar{\eta} MVPF, \tag{2}$$

where

$$MVPF = \frac{\sum_i WTP_i}{dB/dp} \tag{3}$$

is the marginal value of public funds of the policy, which is the ratio of the sum of each individual's willingness-to-pay relative to the net cost to the government, and

$$\bar{\eta} = \frac{\sum_i WTP_i \eta_i}{\sum_i WTP_i} \tag{4}$$

is the incidence-weighted average social marginal utility of income of the policy beneficiaries, which depends on one's social preferences and the incidence of the policy.[14]

One of the key advantages of the MVPF is that constructing an MVPF does not require assumptions about how the budget constraint is closed for any given policy.[15] Instead, the MVPF framework can be used to construct budget-neutral policy experiments for the decision-maker by comparing any two MVPFs. Let us consider, for example, two policies, 1 and 2. The

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[13] Note that this measure represents the *net* benefits to individual i (i.e., monetized benefits minus the cost of the policy to them). We discount the WTP for each person back to the time of policy implementation.

[14] To see this, note that

$$\frac{\frac{dW}{dp}}{\frac{dB}{dp}}\Big|_{p=0} = \frac{\sum_i \eta_i WTP_i}{\frac{dB}{dp}} = \frac{\sum_i \eta_i WTP_i}{\sum_i WTP_i} \frac{\sum_i WTP_i}{\frac{dB}{dp}}$$

which equals $\bar{\eta} MVPF$.

[15] In contrast, the marginal excess burden (MEB) approach closes the budget constraint through individual-specific lump-sum transfers, thus requiring researchers to measure compensated as opposed to causal effects of a policy. The marginal cost of public funds (MCPF) approach envisions closing the budget constraint through changes in the linear income tax and incorporating the resulting deadweight loss from this tax change (e.g., Stiglitz & Dasgupta (1971), Atkinson & Stern (1974), Feldstein (1999)).

MVPF framework tells us that increased spending on policy 1 financed by raising revenue from 2 increases social welfare if and only if

$$\bar{\eta}^1 MVPF^1 > \bar{\eta}^2 MVPF^2 \tag{5}$$

where $MVPF^1 = \frac{\sum_i WTP_i^1}{dB/dp^1}$ is the marginal value of public funds of policy 1 (and similarly for 2). For example, if policy 1 has an MVPF of 1 and policy 2 has an MVPF of 2, then raising revenue from reductions in spending on policy 1 to finance increased spending on policy 2 will increase social welfare if and only if the government prefers \$2 going to policy 1 beneficiaries to \$1 going to policy 2 beneficiaries. While reasonable people may disagree about the relative value of giving benefits to policy 1 versus policy 2 beneficiaries, such disagreements do not lead to differences in the value of the MVPFs. Instead, the MVPF simply serves to characterize the trade-offs induced across policies. In cases when welfare weights are the same for policy 1 and policy 2 beneficiaries, the difference between $MVPF^1$ and $MVPF^2$ reveals the welfare gain to individuals in the economy per dollar spent on policy 1 using net revenue raised from policy 2.

While there is value in reporting a single MVPF estimate, it is important to note that policies may have multiple groups of distinct beneficiaries. Measuring the incidence of the policy on different groups helps to capture distributional concerns that may be of importance. In these cases, it can be helpful to decompose the MVPF and report the WTP as a sum across sub-groups with their own WTP and social welfare weights. We can write:

$$\bar{\eta} MVPF = \sum_g \bar{\eta}_g \frac{WTP_g}{dB/dp} \tag{6}$$

where $\eta_g = \frac{\sum_{i \in g} WTP_i \eta_i}{\sum_{i \in g} WTP_i}$ is the incidence-weighted average welfare weight of those in group g and $WTP_g = \sum_{i \in g} WTP_i$ is the willingness-to-pay for the policy by those in group g. Here, $MVPF = \frac{\sum_g WTP_g}{dB/dp}$. The task of the researcher is to estimate the WTP_g for these groups along with the net cost to the government, dB/dp. The policy maker must choose the weights they place on different members of society, η_g.

In the context of our analysis, we focus our efforts on a comprehensive and accurate characterization of the net cost to the government of the policy, $\frac{dG}{dp}$, and the willingness-to-pay for the various sub-groups impacted by each policy in our sample. In our empirical analysis below, we often discuss the orderings of policies using their aggregate MVPF, but we emphasize that different policies may have different distributional incidences that should be incorporated into an ultimate decision (i.e., decision-makers should apply their desired weights). The aim of our analysis is to provide as detailed a breakdown as possible to facilitate these decisions.

2.2 Measuring WTP and Net Cost

Given a policy change that has been evaluated using experimental or quasi-experimental methods, how do we measure the net cost to the government and the willingness-to-pay for each group of beneficiaries? We illustrate our approach with a simple example. Consider some good x with an environmental externality. For example, x may be an electric vehicle or a gallon of gasoline. Let V denote the monetized value of the environmental externality (or any externality) resulting from additional consumption of x. Let p denote the price of x paid by consumers and let τ denote the current subsidy (or tax) on good x such that producers receive $q = p + \tau$. Now, consider a policy change that alters the tax or subsidy on good x. For some infinitesimal increase in the subsidy $d\tau$, the willingness-to-pay for the policy change is given by

$$WTP = xd\tau + Vdx \tag{7}$$

Here, the first term is the monetary value of the subsidy (holding behavior fixed due to the envelope theorem), and the second term is the WTP from the change in the environmental externality.

Implicit in equation (7) are assumptions of perfect competition and full pass-through. We relax both of these assumptions in our implementation. In the presence of market power, the change in τ may not equal the change in price experienced by the consumer. Some of the price increase might be borne by the producer. Moreover, the change in consumption generated by the policy, dx, can generate a first-order benefit to firms. If consumers switch between goods with different levels of mark-ups, firms may have a willingness-to-pay for the consumption change due the differential mark-up they receive. We incorporate these effects in our empirical analysis but omit them from the notation here for simplicity.

The dx in equation (7) is the causal effect of the policy change. Upon first inspection, it might appear as though the value of dx can be calculated directly using "reduced form" evidence on the effect of the policy. A proper measure of dx, however, includes any "rebound" or broader general equilibrium effects that arise from the policy. These are not generally captured by most reduced-form empirical designs and can increase or decrease the welfare impact of the policy. For example, an EV subsidy may increase electricity demand. This can lead to slightly higher energy prices and, thus, lower energy consumption even by those not receiving the subsidy. This rebound effect on energy demand needs to be included in order to accurately measure the effect of the policy. In Appendix D, we show how we are able to incorporate these rebound effects using estimates of the market supply and demand curves and discuss how we apply this to account for the rebound created by upward-sloping local supply curves in the US electricity markets.

Turning next to the cost to the government, the cost of the subsidy has two terms:

$$Cost = xd\tau + \tau dx \tag{8}$$

where the first term is the cost to the government of the subsidy change holding behavior, and consequently x, fixed. The second term is the fiscal impact of the behavioral response to the policy, τdx. This is paid by the government but not valued by individuals due to the envelope theorem.

The ratio of WTP to government costs yields the MVPF for a change in τ:

$$MVPF = \frac{xd\tau + Vdx}{xd\tau + \tau dx} \tag{9}$$

$$= \frac{1 + \frac{V}{p}(-\epsilon)}{1 + \frac{\tau}{p}(-\epsilon)} \tag{10}$$

where $-\epsilon = \frac{dx}{-d\tau}\frac{p}{x} = \frac{dx}{dp}\frac{p}{x}$ is the percentage change in consumption of x in response to a 1% increase in consumer price (i.e., ϵ is the price elasticity of demand). Here, the environmental impact of the policy change is given by the elasticity, ϵ, times the environmental externality of the good relative to the price of the good, $\frac{V}{p}$. The fiscal externality is given by the elasticity, ϵ, times the tax rate relative to the price of the good $\frac{\tau}{p}$.[16] A natural benchmark is the case where $\tau = V$. In this case, the government fully internalizes the externality with a Pigouvian tax or subsidy, generating an MVPF of 1. When, as we often observe, the tax or subsidy diverges from its Pigouvian level, that moves the MVPF away from 1. For example, the MVPF on a subsidy can be very high if the per-dollar subsidy is well below the per-dollar externality benefit of the good. In this sense, the MVPF measures the extent to which status quo policy deviates from the optimal policy and quantifies the welfare gains of moving toward that optimum.

2.3 Learning by Doing

A common rationale for clean energy subsidies is that society can lower the future marginal cost of new technologies by subsidizing their demand today (Acemoglu et al. 2012, Bistline et al. 2023). Industries, particularly those characterized by rapidly changing technologies, may learn as the result of experience with production. These learning-by-doing gains mean that the cost of production falls with the total production of a good. Subsidies that encourage production today serve to bring down future costs by increasing total production. If the firms developing these new technologies do not internalize these future benefits, then subsidies can be welfare enhancing.

Existing evidence suggests that learning-by-doing effects may be present in the production of solar cells, wind turbines, and batteries. Appendix Figure 1 reproduces evidence from Way et al. (2022) showing the relationship between the marginal cost per kW for wind and solar (and per kWh of battery storage) plotted against cumulative production. Their analysis shows that

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[16] In the presence of firm markups (e.g., due to market power), there are additional terms in this expression. In the numerator, dx is multiplied by the firm markup net of taxes, and, in the denominator, dx is multiplied by the corporate tax revenue from firm profits.

a 1% increase in cumulative solar production is associated with a 0.319% reduction in price. For wind and EV batteries, the associated price reductions are 0.194% and 0.421%, respectively. If one believes that these patterns reflect causal learning-by-doing spillovers,[17] to what extent should that change their views about the welfare effects of subsidies for those goods?

The contribution of this section is to provide a new sufficient statistics result that incorporates learning-by-doing effects into the MVPF framework. Our approach relates to work by van Benthem et al. (2008), who develop a dynamic model of learning by doing, and Bistline et al. (2023), who incorporate learning by doing into their assessment of taxes and subsidies. We show that when the marginal cost of production is an isoelastic function of cumulative production and when demand is an isoelastic function of price, this leads to a second-order ordinary differential equation that can be solved to estimate society's willingness-to-pay for the learning-by-doing effects. Theorem 1 derives a closed-form expression for this willingness-to-pay. It includes both the benefits society gets from lower prices paid by consumers and the benefits society gets from reducing future emissions due to earlier future purchases of the good. Appendix B provides a formal derivation of these results along with a generalization to include imperfect competition and firm markups, time-varying externalities, and cases where the learning curve only applies to a subset of a product (e.g., batteries in EVs). Here, we present a simplified analysis that highlights the core insights of the framework.

We return to our example of a subsidy for a good, x. In order to think about learning by doing, we now bring the model into a continuous time environment, where time is indexed by $t \geq 0$. We imagine the subsidy of interest is a short-term subsidy enacted at time t^*. We wish to incorporate the welfare benefits accruing in future periods, $t > t^*$. Let $x(t)$ denote consumption of x at each time t and let $X(t) = \int_0^t x(s)ds + X(0)$ denote cumulative production through time t. Motivated by the historical evidence in Appendix Figure 1, suppose that the marginal cost of production at each point in time is an isoelastic function of cumulative demand,

$$c(X(t)) = \kappa X(t)^{\theta} \tag{11}$$

where $\theta < 0$ is the elasticity of marginal cost with respect to cumulative production. Suppose also that the choice of $x(t)$ at each point in time depends on the price with a constant price elasticity of demand, $\epsilon < 0$[18]

$$x(t) = ap(t)^{\epsilon} \tag{12}$$

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[17] The extent to which the curve represents learning spillovers has been debated (Nemet 2006, Nordhaus 2014*b*, Rubin et al. 2015). See Lafond et al. (2022) for an estimate of the causal impact of learning by doing on military production. In the context of this paper, we take these learning-by-doing effects as given and then show the robustness of our results to the omission of learning-by-doing effects. There is quasi-experimental work that has found evidence of potential spillovers in solar production (Banares-Sanchez et al. 2023) and in wind installations in California (Gillingham & Stock 2018). We supplement this in Appendix Table 1 with additional descriptive evidence on this point. We show that the learning curves continue to hold even after controlling for potentially confounding variables such as linear time trends and current production. This helps to rule out contemporaneous supply shocks or historical trends unrelated to learning.

[18] In practice, our value of ϵ will come from our existing estimates on the causal effect of a subsidy for x.

Finally, we assume that there is perfect static competition at all points in time and no future subsidies so that prices are set equal to marginal cost, $p(t) = c(X(t))$.

Learning by doing generates two types of externalities: a price externality and an environmental externality. The price externality arises because an increase in production of $x(t)$ today (e.g., at time $t = t^*$) will generate consumer surplus via a reduction in prices faced by future customers (at time $t > t^*$). Let $dp(t)$ denote this impact on prices at each time t. The envelope theorem implies that the WTP for the price decline at each time t is given by $-dp(t)x(t)$, where $x(t)$ is the planned consumption at time t. In other words, the welfare gain is given by the price reduction times the counterfactual path of consumption in the absence of the subsidy.[19] The environmental externality arises because the price reduction caused by the subsidy will increase future consumption of the good, $dx(t)$, and, consequently, generate a positive environmental externality. This externality is given by $V_t dx(t)$, where we now introduce a t subscript to allow the environmental externality to vary over time. For example, this allows the SCC to increase or the cleanliness of the electrical grid to improve over time. The key to measuring our two externality terms is that we need to know how much prices decline, $dp(t)$, and how much consumption increases, $dx(t)$, in response to an increase in consumption of x today (e.g., at time t^*). With those terms in hand, we can then integrate over all the future price benefits, $-dp(t)x(t)$, and environmental benefits, $V_t dx(t)$, over time $t > t^*$.

How can we use this setup to measure the future price and quantity impacts of a policy that increases demand today? Our analysis relies on two key insights. First, we know that the impact of a subsidy $x(t)$ at some time, t^*, will affect future prices proportional to the amount that it increases cumulative production. While this effect can be mathematically complicated, the use of an autonomous supply and demand system allows us to re-frame the problem: we can think of the subsidy as moving us forward in time by some amount, dt. That shift in time is proportional to the size of the subsidy and the magnitude of the demand response when the subsidy is operating at time t^*.

Moving forward in time lowers marginal costs at each point in time (and thus prices) by

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[19] We assume learning by doing provides knowledge externalities to the entire market. It could be that learning by doing occurs within firms and is fully internalized. In that latter case, a subsidy might have no learning-by-doing price benefits for consumers. Moreover, learning-by-doing externalities are different from economies of scale, which are about reducing the fixed costs of production. As Borenstein (2012) notes, this difference might have important implications for public policy. In our modeling, we provide an optimistic interpretation of current subsidies lowering future costs through learning-by-doing externalities. In particular, we assume no internal capture of learning-by-doing benefits and no economies of scale, although this assumption has been questioned in the solar and wind industries (Nemet 2006, Söderholm & Sundqvist 2007). Such concerns would dampen the magnitude of the true learning-by-doing benefits we estimate using our approach, but as we discuss below, this would not affect our core empirical lessons.

$dp(t)$, given by

$$\begin{align}
dp(t) &= c'(X(t))X'(t)dt \tag{13}\\
&= c'(X(t))x(t)dt \tag{14}\\
&= \kappa\theta X(t)^{\theta-1}x(t)dt \tag{15}
\end{align}$$

Also, moving forward in time leads to a change in consumption of the good given by $dx(t) = X'(t)dt$.

Our second insight is that our demand and cost equations imply that the future time path of $x(t)$ is the solution to a second-order autonomous ordinary differential equation. To see this, note that $\log(x(t)) = \log(a) + \epsilon\log(p(t))$ and $\log(c(t)) = \log(\kappa) + \theta\log(X(t))$. Totally differentiating yields

$$\begin{align}
d\log(x(t)) &= \epsilon d\log(p(t)) \tag{16}\\
&= \epsilon d\log(c(t)) \tag{17}\\
&= \epsilon\theta d\log(X(t)) \tag{18}\\
\tag{19}
\end{align}$$

Noting that $X'(t) = x(t)$ and the formula for the derivative of logs yields

$$\frac{X''(t)}{X'(t)} = \epsilon\theta\frac{X'(t)}{X(t)} \tag{20}$$

which is a second order autonomous ODE that we show has a closed-form solution. Combining these two insights leads to the core result in Theorem 1.

Theorem 1. *(Learning by Doing). Let the marginal cost be given by equation 11 and demand be given by equation 12. Suppose prices are set at marginal cost in all periods. Then, the MVPF of a subsidy at time t^* is given by*

$$MVPF = \frac{1 + \frac{V}{p}(-\epsilon) + DP + DE}{1 + \frac{\tau}{p}(-\epsilon)} \tag{21}$$

where the price externality, DP, is given by

$$DP = \theta\epsilon\left(t^*\right)^{-\theta\frac{(1+\epsilon)}{1-\epsilon\theta}}\int_{t^*}^{\infty} e^{-\rho(t-t^*)}t^{-1+\theta\frac{1+\epsilon}{1-\epsilon\theta}}dt \tag{22}$$

where

$$t^* = \frac{X_{init}}{x_{init}(1-\epsilon\theta)} \tag{23}$$

is the normalized ratio of cumulative to flow production at the time the subsidy is enacted, and *the environmental externality is given by*

$$DE = -\frac{\epsilon^2\theta}{(1-\epsilon\theta)c(X(t^*))} t^{*-\frac{\epsilon\theta}{1-\epsilon\theta}} \int_{t^*}^{\infty} e^{-\rho(t-t^*)} t^{\frac{2\epsilon\theta-1}{1-\epsilon\theta}} V_t dt \tag{24}$$

Proof: See Appendix B.

This theorem provides an MVPF formula that allows for the explicit incorporation of learning-by-doing externalities.[20] This differs from our static expression for the MVPF via the inclusion of dynamic externalities (DE) and dynamic price effects (DP). Calculating these dynamic terms requires four inputs: (1) the elasticity of demand with respect to price, ϵ, (2) the elasticity of marginal cost with respect to cumulative production, θ, (3) cumulative production at the time of the subsidy $X(t^*)$, and (4) product cost at the time the subsidy, $c(X(t^*))$. ϵ and $c(X(t^*))$ are generally necessary for the construction of the static MVPF, indicating that only two new terms, θ and $X(t^*)$, are needed to construct these learning-by-doing welfare estimates. We use estimates of historical sales numbers to construct $X(t^*)$ and use estimates from Way et al. (2022) of the relationship between cumulative production and price to construct our cost curve parameter θ. The price elasticities, ϵ, come directly from each paper in our sample.

In our analysis below, we incorporate these learning-by-doing effects into our estimates for the MVPFs of subsidies for wind, solar, and electric and hybrid vehicles (and the indirect effects of gasoline taxes on EVs).

3 Data and Sample

3.1 Sample

We analyze the welfare impact of 96 US spending and revenue-raising policies that affect greenhouse gas emissions and have been rigorously evaluated in the last 25 years using quasi-experimental or experimental methods. These policies span subsidies, revenue raisers, and nudges. We form our sample from the full set of articles in 18 major journals in economics from January 1999 through December 2023,[21] and supplement that with a "snowball" sam-

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[20] Appendix B provides the suitable generalization of the learning-by-doing analysis to the case when firms have markups over marginal cost.

[21] Our sample of journals includes (in alphabetic order) the *American Economic Journals* (*Applied, Economic Policy, Micro, and Macro*), the *American Economic Review*, the *American Journal of Agricultural Economics*, *Econometrica*, the *Economic Journal*, the *Journal of Agricultural Economics*, the *Journal of Association of Environmental* and *Resource Economists*, the *Journal of Environmental Economics and Management*, the *Journal of European Economic Association*, the *Journal of Political Economy*, the *Journal of Public Economics*, the *Quarterly Journal of Economics*, the *Review of Economic Studies*, the *Review of Economic Statistics*, and the *Review of Environmental Economics and Policy.* We also include any National Bureau of Economic Research Working Papers from the "Environment and Energy Economics" and "Public Economics" programs published since 2018.

ple of articles cited within these papers.[22] Within the category of subsidies, we analyze seven sub-categories: wind production tax credits, rooftop solar subsidies, electric vehicle subsidies, hybrid vehicle subsidies, vehicle buyback rebates, energy efficiency subsidies, and weatherization subsidies. Within the category of revenue raisers, we analyze four sub-categories: gasoline taxes, other fuel taxes (such as jet fuel and diesel taxes), other revenue raisers (including the California Alternative Rates for Energy), and cap-and-trade policies. We also supplement this sample with a selected set of international policies that have been evaluated in the past ten years.[23]

Table 1 presents a list of all of our policies. For each policy, we list the category, sub-category, year(s) of implementation, location of implementation, and the paper(s) estimating its causal effects. In certain cases, we observe some, but not all, of the relevant inputs necessary to construct an MVPF. In those instances, we provide an MVPF for the policy (under assumptions outlined in each policy's appendix) but only include it in our "extended" sample (denoted by "*" in Table 1). Extended sample policies are excluded from any category averages reported in the paper.

Publication Bias While we attempted to construct a comprehensive sample of the literature, we are subject to potential biases arising from the fact that statistically significant studies are more likely to be published. In Appendix F, we present evidence of modest publication bias in the environmental economics literature: We find that estimates are roughly two times more likely to be published if they cross a t-stat of around 2. In order to assess how this could impact our broad conclusions, we use the methods of Andrews & Kasy (2019) to correct for publication bias. We show this leaves our estimates largely unchanged and our conclusions unaffected.

In-Context versus Baseline MVPFs For each policy change in our sample, we form two conceptually distinct MVPF estimates. First, we construct a measure of the MVPF in the context (year and location) in which the policy change occurred. For example, if we have estimates from an EV subsidy program in California in 2014, we use measures of the CA electric grid in 2014 to quantify the externalities due to reductions in gasoline usage offset by increased electricity use. We use the CA gasoline tax rate in 2014 to quantify the lost state government revenue from reduced gas purchases. These "in-context" MVPFs measure the welfare impact of the policy as it was enacted.

Second, we construct an MVPF for each policy assuming it was implemented nationally in the US in 2020. We do so by assuming the original elasticity estimated in each paper would also determine the behavioral response to the federal policy in 2020. We then use those estimated elasticities along with 2020 measures of the tax rates and values of externalities to measure

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[22] We also form an "extended sample" of MVPF estimates for policies where we are unable to construct key components of the MVPF, and we exclude these policies from each category average measure discussed below.

[23] We also include several analyses of regulatory policies (CAFE standards and renewable portfolio standards) and show how to nest these into our framework. See Appendix G.

the environmental and fiscal externalities from the policy. This approach harmonizes welfare comparisons across policies holding the contextual environment fixed. We refer to this as our "baseline" MVPF.

In Section 4, we discuss how the harmonization of our estimates affects our results. Our high-level findings do not vary between our baseline and in-context MVPFs. That said, there are some cases where the distinction matters. For example, vehicle emissions were higher in previous decades, increasing the in-context MVPF for vehicle retirement policies implemented in the earliest years in our sample.

3.2 Valuing Environmental Externalities

We seek to apply a consistent and comprehensive method for valuing the range of externalities generated from each policy. We discuss these valuations briefly here and refer readers to Appendix C for a detailed discussion of our approach.

Greenhouse Gas Emissions CO_2 is a key greenhouse gas contributing to climate change. Our baseline estimates place a monetary cost on CO_2 emissions following the Environmental Protection Agency's 2023 guidance regarding the social cost of carbon at a 2% discount rate (EPA 2023*c*).[24] This model implies a social cost of carbon (SCC) of \$193 per ton for emissions in 2020 and is increasing over time.[25] We also show the robustness of our results to models with 2020 SCCs of \$76 and \$337.[26]

We use the time path of the SCC to measure the environmental externality from each policy. For example, a subsidy that leads to the installation of a wind turbine in 2020 will reduce emissions from 2020 through 2045. We use the year-specific SCC to value the associated externalities. For consistency, we apply the 2% discount rate to translate costs and benefits into 2020 present-value dollars.

In addition to CO_2, we also incorporate costs from other greenhouse gases where available, including methane (CH_4), nitrous oxide (N_2O), carbon monoxide (CO), and hydrocarbons (HC). For the baseline scenario corresponding to the \$193 SCC in 2020, the social costs of methane and nitrous oxide in 2020 are \$1,648 and \$54,139 in 2020, respectively (EPA 2023*c*). For carbon monoxide and hydrocarbons, we use global warming potential (GWP) factors from Masnadi et al. (2018) of 2.65 and 4.5 to convert these into CO_2 equivalent units, CO_2e, and then apply our baseline social cost of carbon.

There are three key things to note about our approach to quantifying the value of reducing

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[24] This is the typical discount rate used by environmental economists (Nesje et al. 2023).

[25] This SCC of \$193 in 2020 aligns closely with several other estimates from integrated assessment models (IAMs), such as the GIVE model in Rennert et al. (2022).

[26] The \$76 (calculated with a 2.5% discount rate) SCC comes from Interagency Working Group (2021) and represents the largest SCC estimate for 2020 presented in earlier guidelines. The \$337 (calculated with a 1.5% discount rate) represents the largest SCC for 2020 reported in the EPA's most recent guidelines (EPA 2023*c*).

greenhouse gas emissions. First, we require the SCC to be the sum of individuals' *private* willingnesses to pay for reduced CO_2 emissions. This is consistent with approach taken in typical Integrated Assessment Models (IAMs). RICE and DICE focus on GDP or GDP-equivalent damages, which correspond to private measures of damages. Other IAMs, such as the GIVE model, infer an SCC from VSL estimates and use private VSLs that are not adjusted with welfare weights. Again, these models generate an SCC that corresponds to a private willingness to pay. By contrast, some have proposed equity-weighted social costs of carbon that adjust for welfare weights when forming the SCC (Prest et al. 2024). While the MVPF framework allows for equity weights, such weights are most appropriately excluded from the MVPF and instead applied ex-post when making policy comparisons, as in equation (5).

Second, the SCC embeds within it a real discount rate (2% in our baseline case) that captures the real cost to society of moving resources across periods. The application of this discount rate normalizes the willingness to pay in units of 2020 dollars for all comparisons, even across future generations. This discount rate does not, however, make any claims about the decision-maker's preferences across time. If a decision-maker places greater (or lower) weight on future generations, they will simply place a higher (lower) social welfare weight on those future beneficiaries. In the context of equation (5), this represents a modification of $\bar{\eta}$ to reflect weights on future generations.

Third, our MVPF calculations rely on estimates of the incidence of the social cost of carbon. In particular, the MVPF approach separates the willingness to pay for a policy from its net cost to the government (the US government, in our case). Calculating these components, therefore, requires identifying the incidence of the SCC on the US government's budget. To account for this in our baseline specification, we assume an incidence that follows the US share of GDP in the global economy of 15%, which corresponds to the assumption made in many models such as DICE (Nordhaus 1993).[27] Within this 15%, we assume in our baseline specification that 50% of this valuation is the result of changes in productivity that have direct effects on tax revenue (e.g., due to changes in agricultural productivity).[28] We assume a tax rate of 25.54% as this is the 2020 tax-to-GDP ratio for the US (OECD 2021), which captures both corporate and individual (labor income) taxes. These numbers imply that 13% of the incidence from changes in carbon emissions falls directly on US residents while just under 2% falls on the US government as changes in tax revenue. As it turns out, accounting for this fiscal externality has no bearing on any of our results for domestic subsidies, nudges, or revenue raisers.[29] It

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[27] Other IAMs explicitly measure the distributional incidence of global damages. For example, Nordhaus (2014*a*, 2017) notes that the three models from the Interagency Working Group (Interagency Working Group 2021) on the social cost of carbon report US incidences of 10% for RICE2010 (Nordhaus 2010), 17% for FUND2013 (Anthoff & Tol 2010, 2013*b*,*a*), and 7% for PAGE2011 (Hope 2006, 2008).

[28] We note that many models that agree on the level of the social cost of carbon arrive at their headline number with different underlying components in their calculations. They differ in their split between market and non-market damages (i.e., impacts on productivity as measured via change in GDP versus valuations of mortality using a VSL.)

[29] The share of the incidence falling on the US Treasury is sufficiently small that modifications in our incidence assumptions do not impact our findings. Using alternate values for the geographic incidence of the SCC or the

does, however, significantly affect some conclusions regarding international policies where the US-specific fiscal externality can get quite large. In that section, we analyze the robustness of our conclusions to those incidence assumptions.

Local Pollutants While greenhouse gases yield global externalities, other pollutants primarily affect individuals residing near the source of emissions. These local pollutants generally produce negative effects via their impact on individual health. In order to value these externalities, we use the AP3 integrated assessment model (Tschofen et al. 2019), which measures the marginal health impacts of additional emission of NH_3, HC, NO_X, $PM_{2.5}$, and SO_2 in each county in the US.[30] We monetize those health impacts using a VSL of \$9.5 million (EPA 2010).[31]

From Causal Effects to Externalities For each policy in our analysis, we translate its causal effect (e.g., purchases of EVs in response to subsidies) into the externalities it generates (e.g., the various pollutants discussed above) using a consistent approach across all policies. For example, consider policies that alter electricity usage. Some of these policies, such as residential solar subsidies, might generate new sources of electricity. Other policies, such as rebates for energy-efficient appliances, might reduce existing electricity usage. In order to identify the change in emissions from changes in electricity generation, we use estimates from EPA's Avoided Emissions and Generation Tool (AVERT) (EPA 2024*b*). This provides year- and location-specific estimates of marginal emissions rates per kWh of electricity generated. We also consider a class of policies that affect vehicle usage and gasoline consumption. In those cases, we estimate the change in gallons of gasoline used relative to a counterfactual vehicle. We measure the total CO_2 associated both with the upstream production of gasoline and with its combustion. We draw upon estimates from National Emissions Inventory, the Inventory of U.S. Greenhouse Gas Emissions and Sinks, as well as the EIA's reported CO_2 emissions coefficients. We describe these estimates in detail in Appendix C.

Appendix Figure 2 presents the environmental damages from driving and using electricity over time. Panel A presents the dollar value of the local and global externalities generated per gallon of gasoline used by the average light-duty, gasoline-powered vehicle. It shows that average non-CO_2 emissions have declined over the last several decades, and there has been a shift in the share of total pollution externalities driven by CO_2 emissions.[32] Panel B reports

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split between market and non-market damages does not impact any of our primary findings.

[30] To measure the local pollution externality from increased electricity usage, we take county-level damages estimated in AP3 and weight by fuel consumed for electricity generation. To measure the local pollution externality from increased gasoline vehicle usage we weight by county-level total vehicle miles traveled.

[31] Unlike our estimates for the damages of global pollutants, we do not vary these marginal damages over time. This is because the damage function associated with marginal carbon emissions is time-varying, but the health impacts of local pollutants do not follow a clear time path.

[32] The graph also includes the impact of other vehicle externalities – congestion and accidents. For vehicle accidents, we use results from Jacobsen 2013*b*, who estimates that a 1% reduction in vehicle miles traveled leads to 263 fewer fatalities in the US. We again apply a VSL of \$9.5 million to yield a \$0.08 per-mile externality. For

average emissions from the electric grid over time. It shows a gradual reduction in emissions as more clean energy (and lower-carbon energy) has come online. This is supplemented by evidence in Appendix Figure 3, which shows the geographic variation across the US in emission externalities, as measured in 2020. The Northeast and California have the cleanest grids (lowest environmental externality per mWh) relative to the Midwest, which has the dirtiest electric grid. We discuss below how this leads to heterogeneity in the welfare impacts of policies that are targeted to different regions of the US.

4 Subsidies

The next four sections of the paper present our results for the MVPFs of subsidies, marketing and nudges, revenue raisers, and international policies. We begin with subsidies and a detailed description of the way in which we construct MVPF estimates for EV subsidies. We choose this example because it utilizes nearly all of the machinery we develop to construct environmental MVPFs. We then provide shorter descriptions for each of the remaining subsidy policies across each of our sub-categories. (See the Online Appendix for a detailed construction of each MVPF in our sample.) Finally, we compare MVPFs across sub-categories, identifying the types of policies that produce the highest MVPFs.

Subsidies for Electric Vehicles Over the past 15 years, many US states and the federal government have offered a range of subsidies to encourage the purchase of electric vehicles. We draw upon three papers measuring the response of EV purchases to federal or state subsidies, beginning with an analysis of the California Enhanced Fleet Modernization Program (EFMP) studied by Muehlegger & Rapson (2022). The EFMP subsidized EV purchases, varying the availability and the size of the subsidy based on each household's income and the zip code in which they resided. Muehlegger & Rapson (2022) use this variation to estimate that roughly 85 percent of the subsidy was passed through to consumers while 15% was captured by dealers via higher prices. They also estimate that a one percent decrease in the price of EVs led to a 2.1 percent increase in EV purchases.

We use these estimates to construct baseline and in-context MVPFs for the subsidy. We focus our discussion here on the baseline MVPF, which takes the estimated elasticity of -2.1 and considers the welfare effect of a national subsidy change implemented in 2020.[33]

Figure 1 presents the components of the WTP and net cost estimates used in the construction of the MVPF. All components are normalized by the mechanical cost of the subsidy change (i.e., the cost if individuals did not change their behavior). By construction, individuals are willing to pay \$1 per \$1 in mechanical subsidy cost. The pass-through rate on the subsidy

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congestion due to light-duty vehicles, we take an average of externality measures from Parry & Small (2005), Parry et al. (2014), and Couture et al. (2018) to yield an externality of \$0.03 per mile.

[33] Appendix Table 2 presents the results for the in-context MVPF.

means \$0.85 flows to those purchasing vehicles and \$0.15 flows to the owners of CA dealerships that sell EVs.

The next bars in Figure 1 report the environmental externalities associated with marginal EV purchases. We begin by estimating the change in externalities from reducing the usage of internal combustion engine (ICE) vehicles as individuals purchase EVs. We use estimates from Holland et al. (2016) to calculate the fuel economy of the counterfactual car that a marginal EV customer would have purchased. We find that EVs displace a cleaner-than-average new light-duty car.[34] We then combine this counterfactual fuel economy (41.2 MPG) with an estimate of the per-gallon externalities associated with gasoline. This includes both the global damages from CO_2 emitted as well as the local damages from NO_X, $PM_{2.5}$, HC, CO, SO_2, and NH_3. We measure these damages over an average 17-year lifespan of the vehicle (Greene & Leard 2023). We also use estimates from Zhao et al. (2023) to account for the fact that EV purchasers tend to drive their cars fewer miles than the average purchaser of a gas powered vehicle.[35] Taken together, the local and global pieces provide the lifetime environmental benefits from *not* driving the counterfactual gas-powered vehicle. This calculation leads to a WTP of \$0.17 from global pollutants and \$0.02 from local pollutants, for a total benefit of \$0.19 from the reduced gasoline consumption induced by the subsidy.

While the decrease in gasoline consumption yields environmental benefits, these effects are partially offset by the environmental damages from increased use of electricity. We incorporate the emissions from additional electricity usage over the lifespan of the EV using emissions estimates from the EPA's Avoided Emissions and Generation Tool, AVERT (EPA 2024*b*).[36] Combining the change in emissions with our valuations of those externalities, we find that the \$1 subsidy results in \$0.10 in global damages stemming from electricity usage and \$0.02 in local damages. This yields a total welfare cost of \$0.12. When combined with the damages avoided from gas-powered cars, society is willing to pay \$0.07 for the net global benefit and approximately \$0 for the net local benefit.

Some of the estimated increases in electricity usage from EVs could be offset through increases in the prices of electricity that drive down usage – i.e. a "rebound effect". To account for this, we use estimates of the demand and supply elasticity for electricity. Following the Department of Interior's approach in their MarketSim model, we use a demand elasticity of -0.19 and a supply elasticity of 0.78 (DOI 2021). Combining these estimates implies that roughly 20% of the electricity demand is offset by reduced demand due to higher electricity prices.[37]

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[34] Holland et al. (2016) estimate the counterfactual ICE vehicle purchased by EV buyers in 2013–2015. We take the percentage increase in MPG relative to the MPG of new cars in 2014 and apply that to the new car MPG figure in 2020. Below, we explore the robustness of our results to this particular MPG assumption and show it does not meaningfully impact our results.

[35] Zhao et al. (2023) show that the average EVs' vehicle miles traveled is roughly 61% of the average gas-powered car. This estimate is very similar to those in Davis (2019) and Burlig et al. (2021).

[36] We project future grid emissions using the mid-range 2023-2050 forecast from the Princeton REPEAT Project (Jenkins & Mayfield 2023) in combination with estimates from the AVERT model that translate combustion shares into externalities.

[37] We do not incorporate a rebound effect for gasoline because we assume that the gasoline price does not

This suggests that society is willing to pay an additional \$0.02 for the global benefits (and less than \$0.01 for the local benefits) created by the rebound effect. Summing the environmental benefits yields a total of \$0.09.[38]

In addition to environmental externalities from charging the EV, we also account for the fact that the upstream production of EVs is more carbon-intensive than the production of ICE vehicles. This is due to the nature of the battery production process. We incorporate estimates from Winjobi et al. (2022) that suggest that battery production releases 0.06 tons of CO_2 per kWh. This suggests the average EV imposes a global externality from battery production of \$838.34 per EV, leading to an externality of -\$0.03 per dollar of EV subsidy. This rounds to a total environmental externality of \$0.07 per dollar of EV subsidy.

In the case of EVs, there could also be learning-by-doing externalities in battery production. Way et al. (2022) estimate that a 1% increase in battery production leads to a reduction in battery costs of 0.42% ($\theta = -0.42$). Following the approach outlined in Section 2.3, we incorporate the impact of learning by doing into the MVPF of EV subsidies. Using the demand elasticity of $\epsilon = -2.1$ and discounting future benefits at a 2% discount rate, the increased future demand for EVs yields environmental benefits of \$0.04 per dollar of the mechanical subsidy (DE in Theorem 1). In addition to the environmental benefits, the effect of learning by doing on future prices creates a benefit of \$0.31 to future purchasers (DP in Theorem 1).[39] Taken together, the learning-by-doing effects increase the value of the subsidy by \$0.35 per dollar of EV subsidy.

It is worth noting that the inclusion of these \$0.35 in learning-by-doing benefits relies on the assumptions that i) the relationship between cumulative production and price is causal and ii) that these benefits are not internalized by firms through the patent system or other means. If the price declines were not causal and/or the effects are internalized by firms, the \$0.35 should not be included in the MVPF. Throughout, we present results with and without learning-by-doing effects so that readers can view the results for their preferred specification, based on their judgment of the learning by doing evidence.

The last benefit we consider is the impact of the policy change on the profits of gasoline and electricity producers. Our estimates suggest a marginal EV purchase in 2020 would reduce gasoline consumption by 2,857 gallons over the lifetime of the vehicle. We account for producer profits using an average markup per gallon of gas of \$0.61 per gallon, or 27% of the 2020 retail

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meaningfully change in response to the demand shock induced by EV purchases.

[38] Due to the envelope theorem, the change in electricity consumption from the rebound effect does not generate private welfare costs. Only the externalities that are not internalized matter for the total willingness to pay in the economy. In addition to the environmental externalities, the markup in the electricity market also generates a small additional externality on firm profits, which is incorporated into the firm profit numbers that we report.

[39] These learning by doing effects only apply to battery production, rather than than the production of the entire vehicle. Batteries made up only roughly 25% of the cost of EVs in 2020, muting the net impact of learning by doing on future EV prices. Appendix B discusses how we account for this dynamic in learning by doing. We also show that when only a fraction of the costs are subject to learning by doing, the value of these externalities falls more rapidly over time.

price. This lies above the economy-wide average markup of 8% (De Loecker et al. 2020), leading to a decline in overall producer profits as consumers shift away from gasoline consumption to other goods.[40] Applying a 21% effective corporate tax rate, we calculate post-tax lost producer profits are equal to \$0.04 per dollar of the subsidy.[41] By contrast, electricity suppliers benefit from increased electricity consumption. Electric utilities are a regulated industry with natural monopolies that sell electricity at a markup. We estimate this markup to be 12.9% in excess of the 8% economy-wide markup. While some of these profits flow directly to the government as 28% of utilities are publicly owned, private utilities also have a willingness to pay for their increase in after-tax profits. We estimate this WTP to be \$0.01 per \$1 of subsidy.

The numerator of the MVPF is the sum of these components. Figure 1 shows these yield a total WTP of \$1.38 in benefits per mechanical dollar of spending. The figure also illustrates the incidence of the subsidy: Roughly 95% of the benefits of EV subsidies flow to those buying and selling EVs, while 5% flow to current and future generations through reductions in environmental externalities.

Next, we calculate the denominator of the MVPF, which is net cost of the subsidy to the government. Each of these components is reported in Figure 1. We begin with the mechanical cost of the subsidy, which is \$1 by construction. We then consider the fiscal externality induced by pre-existing subsidies. When the subsidy causes an EV purchase, this generates an additional government cost equal to the pre-existing subsidy level. In 2020, federal credits for EVs had expired for most companies, such as Tesla, and so the average federal subsidy was just \$42.98. Meanwhile, the average state subsidy was \$604.27. The existence of these pre-existing subsidies means that the increase in EV purchases cost state governments \$0.02 and the federal government \$0.001 per each dollar of mechanical subsidy. (We obtain these numbers using equation 9 and multiplying the change in EV demand by the size of the pre-existing subsidy as a fraction of the total price of the vehicle).

In the next step, we consider the impact of the policy on tax revenue collected. The reduced gasoline consumption leads to a loss in gas tax revenue for the government of \$0.04 for every \$1 in subsidy. It also causes a reduction in corporate tax revenue of \$0.01 per dollar of subsidy.[42]

Finally, we incorporate a positive impact on the US government's budget due to reductions in climate damages. According to a wide class of IAMs, the SCC is driven by a combination of health and productivity effects. These productivity effects can have a direct effect on US government revenue. In our baseline specification, we assume that half of the SCC is due to productivity effects and that 15% falls on the US economy (proportional to its share of global

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[40] Appendix C.4.5 relates these gasoline producers' markups to the producer profit rates reported in (De Loecker et al. 2020).

[41] We obtain the corporate tax rate from Watson (2022). We also use that foregone tax rate estimate to adjust the net cost of the policy. This tax rate does not vary over time. In 2020, the pre-tax markup on gasoline was \$0.27 per dollar spent on gas, or \$0.21 per dollar spent on gas after adjusting for corporate taxes.

[42] While the policy increases utility profits, it also generate losses for gasoline producers. The sum of these two is a net decrease in government revenue.

GDP). Applying a 25.5% tax rate to these productivity gains yields a fiscal externality equal to \$0.003 for every \$1 in subsidies. These "climate fiscal externality" effects are quite small for all domestic policies in our sample, but we return to them in Section 7 when we analyze the MVPFs of international policies.

Adding these costs together, we estimate a net cost of \$1.07 for every \$1 in mechanical subsidy costs. When we take the ratio of the willingness-to-pay and the net cost, we arrive at a baseline MVPF of 1.30. The MVPF of 1.30 means that a \$1 increase in a 2020 subsidy for EVs would have led to \$1.30 in benefits for members of society.

This baseline MVPF considers the welfare impact of a marginal change in EV subsidies relative to their 2020 levels. We can also use the framework to assess larger (non-marginal) policy changes. In 2022, for example, federal credits were increased to \$7,500 as part of the 2022 Inflation Reduction Act. Appendix Figure 4 illustrates the MVPF of a non-marginal policy that increases the total subsidy level from \$647 to \$8,104 in 2020. The first dollar of the subsidy has an MVPF of 1.30. We can similarly construct the MVPF of each marginal dollar of subsidy expansion.[43] As the subsidy increases, the MVPFs fall slightly. This is because the fiscal externalities are increasing in the size of the pre-existing subsidy. The MVPF on the 7500th dollar is 1.02.[44] Integrating over all the marginal policy changes for subsidy levels between \$647 and \$8,104 yields an average (non-marginal) MVPF of 1.15. The non-marginal value of 1.15 looks relatively similar to our baseline first dollar MVPF estimate of 1.30, a pattern we see consistently in our evaluation of non-marginal subsidy changes.

In estimating the welfare effects of EV subsidies, we consider two other policy changes studied in the literature. Clinton & Steinberg (2019) study variation in subsidy generosity over states across time, finding an elasticity of demand with respect to price of -2.93. Li et al. (2017) use variation in the federal credit over time to measure EV demand, yielding a price elasticity of demand of -2.61. The estimated elasticities from these two papers lead to MVPFs of 1.56 and 1.47 in our baseline specification (with the larger MVPF driven by the stronger elasticity).

In order to draw lessons from these MVPF estimates, it is helpful to pool them together and form a category average. Following Hendren & Sprung-Keyser (2020), we imagine the government spends \$1 in initial program costs, splitting the programmatic expenditures evenly across the three EV policies. We construct an average WTP and average net cost across these policies and take the ratio to form a category average MVPF. This leads to an estimated baseline MVPF of 1.45 for EV subsidies.

The MVPF is not much above 1 because the cost of inframarginal transfers is large. Inducing a new EV purchase costs the government roughly \$30,000[45], much larger than the environmental

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[43] In this calculation, we assume the price elasticity of demand remains constant as the subsidy increases. We find similar results under alternative assumptions such as a constant semi-elasticity of demand.

[44] In principle, it is possible for the MVPF to increase with subsidy size. This occurs if V/p rises faster than the fiscal externality (e.g., τ/p). This is possible because p is inclusive of the subsidy.

[45] EV prices in 2020 were approximately \$54,000. The product of the price elasticity and pass-through rate from Muehlegger & Rapson (2022) is -1.78, implying a payment of approximately \$30,000 per induced purchase.

and learning-by-doing benefits of the subsidy.

One of the key advantages of our harmonized approach to measuring MVPFs is that we can explore the effect of varying input assumptions. For example, we can adjust our assumptions regarding the MPG of counterfactual ICE vehicles or the VMT of EVs. If we assume that EVs replace an average new car, rather than a more-efficient-than-average new car, the category average MVPF rises from 1.45 to 1.61. If we assume that the VMT of an EV is equal to that of an average car, rather than the lower VMT figures estimated in the literature, the MVPF rises from 1.49 to 1.62. The MVPF also rises from our baseline 1.45 to 1.53 if one assumes the EVs are charged using a grid as clean as California's. Switching to an SCC of \$76 and associated discount rate of 2.5% yields a baseline MVPF of 1.33. Increasing the SCC to \$337 with a discount rate of 1.5% yields a baseline MVPF of 1.57. As noted above, the learning-by-doing benefits play a key role in driving the MVPF estimates above 1. The MVPF falls to 0.96 if learning-by-doing effects are excluded. Ultimately, across our various alternative specifications, the MVPFs of EV subsidies fall in a range between 1 and 1.7.

Wind Subsidies We next examine the welfare consequences of production tax credits (PTCs) that encourage the production of wind energy. These subsidies pay producers a fixed payment per kilowatt hour of production of clean energy, typically for ten years after installation. We draw upon three papers estimating the elasticity of wind turbine investment with respect to these production tax credits in the US: Hitaj (2013), Metcalf (2010), and Shrimali et al. (2015). We also supplement these results with six elasticity estimates from papers studying the impact of variation in feed-in-tariff rates in Europe.[46]

We begin by using the results in Hitaj (2013), which uses local variation in wind production incentives between 1998 and 2007 to estimate impacts on wind installation. The estimates indicate that a one percent decrease in the cost of wind electricity generation leads to a 1.13 percent increase in wind turbine installations.

Figure 2 Panel A presents the components of WTP and net government cost using the elasticity from Hitaj (2013). Producers are willing to pay \$1 for a dollar's worth of mechanical subsidy. Next, we measure the environmental benefits of the PTC. We measure the environmental benefits of wind turbine installations using the EPA's AVERT model to measure the grid displacement from an additional unit of clean energy. We find that a \$1 mechanical subsidy leads to a large reduction in both global and local environmental externalities, valued at \$3.93 and \$0.52, respectively.[47] These benefits are larger than the per-dollar benefits for EVs despite a smaller price elasticity (the elasticity is -1.13 as opposed to -2.1 for EFMP above). This is

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Allcott et al. (2024) examine the MVPF of recent EV subsidies and find a very similar figure.

[46] We do not provide in-context estimates for non-US studies, but instead focus on the implications of their price elasticity estimates for the US 2020 MVPF of wind subsidies.

[47] In translating the PTC into a change in wind turbine prices, we discount the flow of benefits using a firm-specific measure of the cost of capital. This allows us to use firm-specific time preferences, a topic of substantial importance in current debates over the ITC versus the PTC.

because \$1 of induced spending on a wind turbine delivers significantly more than \$3 of global environmental benefits while \$1 of induced spending on an EV generates less than \$0.04 in global environmental benefits.

As with EVs, we incorporate potential rebound effects in the electricity markets. In contrast to EVs, the rebound effect leads to an increase in overall electricity use as opposed to a decline. Market supply and demand curves imply a 20% rebound effect due to lower prices, which means that environmental benefits are \$0.87 lower. We also account for life cycle greenhouse gas emissions (11 g of CO_2e per KWh) from activities such as turbine manufacturing and construction, which decrease environmental benefits by \$0.13 (Dolan & Heath 2012). Summing together, this implies a net initial environmental benefit of \$3.45.[48]

Next, we incorporate the potential benefits from learning-by-doing externalities. Way et al. (2022) estimate that a 1% increase in cumulative production leads to a reduction in wind turbine costs of 0.19% ($\theta = -0.19$). This leads to \$1 in future environmental benefits and \$0.46 in benefits from lower future prices of wind turbines. Combining together all our willingness to pay components produces a net WTP of \$5.90 per dollar of mechanical wind PTC.

In order to estimate net government costs, we begin with the \$1 mechanical cost of the policy and add the fiscal externality associated with the baseline PTC subsidy. In 2020 there was a PTC subsidy equal to 1.5 cents per kWh, which leads to a fiscal externality of \$0.35 per dollar in mechanical subsidy. Long-run climate benefits also generate a negative fiscal externality of \$0.08. Taken together we estimate a net cost of \$1.28. Dividing the WTP of \$5.90 by this net cost yields an MVPF of 4.63.

Figure 2 Panel B plots the MVPF estimates for wind subsidies and shows how they vary with the magnitude of the price elasticity. The other two studies we consider have elasticities of -1.3 (Metcalf 2010) and -1.75 (Shrimali et al. 2015), yielding MVPFs of 5.30 and 7.55, respectively.[49]

We draw upon three quasi-experimental estimates of the impact of PTCs in the US. In order to ensure that our results are not being driven by the small sample of available quasi-experimental estimates, we compare our results to studies of wind subsidies outside the US. In particular, we consider six elasticities estimated in Europe. These estimates primarily focus on the effects of "feed in tariff" policies that guarantee producers elevated prices for their clean energy generation. Figure 2 Panel B places the US-based MVPF estimates alongside six MVPF estimates that use elasticity estimates derived from variation in "feed in tariffs" in European contexts. These European subsidy elasticities range from -0.60 to -1.97 and yield MVPFs

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[48] We do not include any aesthetic costs associated with the installation of wind turbines. One could, in principle, estimate the associated individual WTP and incorporate that into the MVPF.

[49] We translate the elasticities to the 2020 baseline setting by assuming the elasticity of turbines installed with respect to price is constant over time. As turbine costs fall, a constant elasticity implies a rising semi-elasticity and larger environmental benefits per dollar of subsidy. If we adopt a more conservative assumption that the semi-elasticity is constant over time (despite prices falling more than half between the mid-2000s and 2020) we obtain a category average MVPF of 2.86. This continues to lie above all other subsidy categories in the sample except residential solar subsidies.

ranging from 1.50 to 9.15. The category average MVPF using only US policies is 5.87. If we were to include European subsidy estimates the value is very similar, rising slightly to 5.93.[50] These results using European elasticity estimates further reinforce the conclusion that subsidies for wind PTCs produce substantial returns per dollar of government expenditure.

Residential Solar Subsidies The US federal government and many US states have enacted large subsidies to encourage residential solar installation. We analyze estimates from five subsidies for residential solar that are studied in four papers (Pless & van Benthem 2019, Hughes & Podolefsky 2015, Gillingham & Tsvetanov 2019, Crago & Chernyakhovskiy 2017). We begin with Pless & van Benthem (2019) who use geographic variation in the California Solar Initiative to estimate the effect of the program. They find that a one percent reduction in the price of solar installations leads to a 1.14% increase in installations among residential homeowners. This elasticity of -1.14 is roughly at the mean of the solar elasticities in our sample.

Figure 3 Panel A presents the components of the WTP and net cost of the MVPF. Pless & van Benthem (2019) find that the subsidy has roughly 81% pass through, so that a \$1 mechanical subsidy leads to an \$0.81 benefit to consumers and a \$0.19 benefit to installers.

For environmental benefits, the \$1 mechanical subsidy leads to \$0.73 in global environmental benefits through the displacement of other sources of electricity production. This is the sum of \$1.03 in benefits via direct displacement of energy production minus \$0.20 from the rebound effect and \$0.10 from life cycle greenhouse gas emissions in the production of the solar panels. We also find \$0.11 in local environmental benefits, which is the sum of the direct (\$0.14) and rebound effects (-\$0.03). These environmental benefits are larger than the benefits from EVs, but they are smaller than the benefits for wind PTCs. The lower environmental benefits relative to wind PTCs is not primarily due to differences in the price elasticities but rather the fact that \$1 of private spending on residential solar panels delivers fewer environmental benefits than \$1 spent on utility-scale wind production. As we discuss below, this is driven by the difference between residential and utility scale, as opposed to wind versus solar.

While the initial environmental benefits from residential solar subsidies are smaller than those associated with the wind PTCs, the learning-by-doing benefits are larger. We find the solar subsidies induce \$1.08 in environmental benefits and \$0.86 in price benefits. These higher learning-by-doing effects are driven by the fact that: (i) the historical learning rate for solar,

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[50] There has been recent attention on regulatory costs for renewable energies such as wind power (Jarvis 2021, Davis et al. 2023, Huang & Kahn 2024). It is important to note that the existing causal estimates should already embed within them the regulatory costs in place at the time of estimation. We are not aware of any causal work in the US that quantifies the extent to which changing regulatory costs affect the LCOE of wind production. As noted above, however, if we assume that that the cost of wind generation is actually 50% higher than reported estimates, we find that our category average MVPF in the U.S. is still 4.51. Along similar lines, we can assume that increased permitting costs offset all the observed cost decline of wind turbines between 2014 and 2020. In that case, we would still get MVPF estimates for wind near 5. In fact, the superiority of wind subsidies relative to EVs and other energy efficiency subsidies continues to hold even if the LCOE were to double relative to current measures.

$\theta = -0.32$, is well above the historical learning rate for wind; and (ii) the demand elasticity for residential solar is higher in absolute value than for wind.

Lastly, we consider the impact of reductions in purchase of electricity on the profits of the utility companies. Subtracting this value, \$0.12, from the other components of willingness to pay, we arrive at a total value of \$3.67 per dollar of mechanical subsidy.

To estimate net government costs, we begin with the \$1 mechanical cost of the policy. Existing subsidies for solar were 26% in 2020. Multiplying the increase in solar purchases by this subsidy yields a fiscal externality of \$0.32 for every \$1 of mechanical subsidy.[51] We also estimate a reduction in tax revenue of \$0.06 from falling utility company profits and a climate fiscal externality of -\$0.03 from increased future tax revenue due to reduced climate change damages. Taken together, this means that \$1 of mechanical subsidy costs the government \$1.35. Comparing this value to the willingness to pay yields an MVPF of 2.71.

Figure 3 Panel B compares across our solar estimates and presents the MVPFs as a function of the price elasticity in each study. We present two curves to illustrate the MVPF with and without including the learning-by-doing effects. The MVPFs are quite large when learning-by-doing effects are present. We find MVPFs ranging from 1.63 to 5.06 for the elasticities in our main sample, with a category average of 3.86. By contrast, when learning-by-doing effects are excluded the MVPFs fall substantially, with MVPFs ranging from 1.17 to 1.69 and a category average of 1.45.

Even with learning by doing effects, residential solar subsidy MVPF estimates are substantially lower than our estimates for wind PTCs (3.86 versus 5.87). This difference may be driven by the distinction between utility-scale and residential energy production, rather than the distinction between wind and solar. With falling solar prices, the 2020 (levelized) cost of energy via utility-scale solar was roughly on par with the costs of utility-scale onshore wind. By contrast, the costs of residential solar remained more than two times higher than utility scale solar. While there are no quasi-experimental estimates of the impact of utility-scale solar, we can return to our wind PTC setting and imagine a similar subsidy for solar installations. Assuming the elasticity of solar installations is similar to historical wind PTC elasticities (-1.3), we can use the utility-scale solar costs per kWh to estimate an MVPF. Here, one motivation for assuming the -1.3 elasticity is similar for utility-scale wind and solar is that it captures a structural user cost elasticity that is plausibly constant across investment types. Under that assumptions, we find the MVPF of utility-scale solar subsidies would be 10.97, well above our estimates for the wind PTC. Given this, a natural conclusion from our analysis is that subsidies to utilities for either wind or solar have higher MVPFs than residential solar subsidies.

Hybrid Electric Vehicles (HEVs) We next consider subsidies for hybrid electric vehicles (HEVs). We use three estimates from two papers that evaluate the response of HEV purchases

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[51] If the preexisting subsidy were 0%, there would be no such fiscal externality. If the preexisting subsidy were the 30% rate implemented in the IRA, the fiscal externality would be \$0.40.

to state and federal HEV subsidies (Beresteanu & Li 2011, Gallagher & Muehlegger 2011).[52] We focus our discussion here on the Federal Income Tax Credit for Hybrid Vehicles evaluated in Beresteanu & Li (2011), whose findings imply a price elasticity of -1.98.

As in the case of EV subsidies, we measure the environmental externalities from HEV purchases by comparing HEVs to the counterfactual vehicles that subsidy recipients would have purchased in the absence of the subsidy. We draw upon estimates from Muehlegger & Rapson (2023), who show that the MPG of counterfactual vehicles is very close to the MPG of HEVs: the implied fuel-economy gap was just 1.9 MPG in 2020. As a result, we estimate that environmental damage reduction is less than \$0.01 per dollar of mechanical subsidy. The remaining components of the MVPF are also small, yielding an MVPF of 1.01. We find similar results across the other two HEV studies we analyze, leading to a category average MVPF of 1.01.[53] The small environmental benefits and MVPF values near 1 imply that HEV subsidies are primarily transfers to consumers already intending to purchase an HEV.

Vehicle Retirement Next, we consider subsidies encouraging the retirement of old vehicles. So-called "cash for clunkers" policies provide subsidies to those retiring old cars conditional on purchasing new cars that satisfy certain standards (e.g., fuel economy requirements). We consider three evaluations of such policies (Li et al. 2013, Hoekstra et al. 2017, Sandler 2012). We focus here on Li et al. (2013), who evaluate the federal cash for clunkers program in 2009. They find that the subsidy caused individuals to accelerate their purchase by several months and switch to a slightly more fuel-efficient vehicle.

By construction, a \$1 larger subsidy generates \$1 in benefits to those who were going to retire their vehicle anyway. We estimate that the re-timing of vehicle purchases and the increase in fuel efficiency of the new cars leads to a social willingness to pay of \$0.27 for global environmental benefits and \$0.02 for local environmental benefits. That calculation, however, holds driving behavior constant. So, next, we account for the fact that shifting to a more fuel efficient vehicle reduces the marginal cost of driving, potentially increasing total vehicle miles traveled. We use estimates from Small & Van Dender (2007) and show that this rebound effect reduces the net environmental benefits by \$0.02. On the cost side, the shift toward more fuel efficient vehicles generates a fiscal externality of \$0.06 from lost gas tax revenue and corporate tax revenue from gasoline producers. Combining these results yields an MVPF of 1.04.

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[52] We draw two estimates from (Gallagher & Muehlegger 2011) because they distinguish between upfront sales tax waivers and ex-post income tax credits.

[53] Here, the small MPG difference between the induced hybrid and the counterfactual vehicle means that the MVPF is not very responsive to changes in the elasticity. This is particularly relevant as our estimates from (Gallagher & Muehlegger 2011) have very large elasticities. They find an upfront subsidy has an elasticity of -6.92 and an ex-post tax credit has an elasticity of -0.43. These papers yield baseline MVPF estimates of 1.03 and 1.00, respectively. If we deviate from the counterfactual estimates in the literature and assume that HEVs displace an average new car sold in 2020, the MVPF estimates for HEVs still fall in a relatively limited range. Our category average assuming hybrids replace an average new car is 1.20. An elasticity of -1.98 yields 1.12 and our -6.92 elasticity from (Gallagher & Muehlegger 2011) still only yields an MVPF of 1.42.

The two other vehicle retirement policies in our sample have similar baseline MVPFs. We find MVPFs of 1.07 using the behavioral response to the 2009 cash for clunkers program estimated among consumers in Texas (Hoekstra et al. 2017) and 1.03 for the Bay Area Air Quality Management District's (BAAQMD) Vehicle Buy Back Program (Sandler 2012). Consequently, the category average MVPF for vehicle retirement is 1.05, with individual policies ranging from 1.03 to 1.07. The MVPF near 1 means that, like HEV subsidies, vehicle retirement subsidies are primarily transfers to people who would have retired their vehicle anyway.

While most of our analysis focuses on harmonized 2020 MVPF estimates, vehicle retirement is a unique case where the distinction between in-context and 2020 estimates has a meaningful impact on the results. In particular, the BAAQMD Vehicle Buy Back Program implemented in 1996 was designed to encourage the retirement of vehicles that were 26+ years old at the time. A 26-year-old vehicle in 1996 (one produced in 1970) produced far more emissions than a 26-year-old vehicle did in 2020. Using historical estimates of vehicle fleet emissions, we estimate that each \$1 in subsidy spending in 1996 produced \$2.85 in local environmental benefits and \$0.91 in global environmental benefits, leading to an in-context MVPF for BAAQMD of 2.38. Put simply, paying people to retire their 1970 Chevy had much higher returns in 1996 than paying people to retire their 1994 Toyota in 2020. Aside from this interesting case, the in-context and 2020 MVPF estimates are quite similar.

Weatherization We next consider weatherization assistance subsidies to improve home energy efficiency through better insulation, windows, lighting, and other energy-intensive aspects of the home. Our sample includes five different weatherization policies (Christensen, Francisco & Myers 2023, Fowlie et al. 2018, Hancevic & Sandoval 2022, Liang et al. 2018, Allcott & Greenstone 2024). We focus our discussion here on the Weatherization Assistance Program in Michigan studied by Fowlie et al. (2018). The program used an encouragement design to increase take-up of home weatherization and studied the impact of weatherization on home energy costs.

Measuring WTP of weatherization is more difficult than for price subsidies because the papers studying their effects generally focus on measuring the energy use impacts of the subsidies without measuring the fraction of inframarginal beneficiaries – those who would have weatherized anyway. Consequently, when constructing our measure of WTP, we explore the robustness of our estimates to variations in this fraction. By definition, this fraction must be between 0 and 100%. We make a baseline assumption that 50% of those receiving the weatherization benefits are inframarginal.

Those inframarginal individuals value the weatherization subsidy dollar-for-dollar while marginal individuals also have a valuation for the subsidy which must fall between 0 and \$1. When examining a discrete bundle of weatherization services, we do not know whether it was the first or last dollar of the policy that induced their response. If it was the first dollar, then they would value roughly the entirety of the transfer at its cost. If it were the last dollar, then they would have a near-zero valuation of the subsidy. Following the classic triangle approximation to measuring deadweight loss in Harberger (1964) (and the approach taken in Hendren & Sprung-Keyser (2020)), we assume that this latent value of the subsidy varies uniformly in the population (i.e., a linear demand curve). This suggests these marginal individuals value the subsidy at 50% of its value.[54] Putting together the valuations among marginal and non-marginal individuals, every $1 in initial spending on weatherization generates a benefit of $0.75 to those who take up the benefits.

In addition to the transfer benefits of weatherization our WTP also includes environmental benefits to society. The estimates of reduced energy consumption in Fowlie et al. (2018) imply a local environmental benefit of $0.01 and a global environmental benefit of $0.30. The reduction in electricity demand caused by the program also induces a rebound effect which we estimate to be -$0.05, so that the total environmental benefit is $0.27. Overall, our analysis suggests an MVPF of 0.92.

As noted above, this MVPF calculation requires taking stances on the fraction of beneficiaries that are marginal and the valuation of benefits among those marginal individuals. An attractive alternative approach is taken by Allcott & Greenstone (2024), who study a weatherization policy in Wisconsin. They combine experimental and observational variation to estimate a demand model that yields valuations of the weatherization program that imply an in-context MVPF of 0.93. Using our damage models to harmonize with our other estimates replicates the 0.93 in-context and produces an MVPF of 0.92 in the baseline 2020 specification.

Taking an average across all of the weatherization policies, we obtain a category average MVPF of 0.98.[55] These estimates assumes individuals are aware of the energy benefits of weatherization so they do not incorporate private energy savings as an additional benefit in the willingness to pay. The idea is that these individuals may value the energy savings, but the benefit of these savings are weighed against other considerations, such as the hassle cost of a construction project in their home. The logic of optimization tells us that the value of the policy to individuals is bounded by the size of the transfer, and it would be double counting to incorporate energy savings as a benefit on top of the transfer benefit of the program. It is, of course, possible that individuals were not aware of the cost savings they would receive from weatherization. If this were the case, then these benefits might reflect an "internality."[56] It would then be natural for the marginal individuals to value the energy savings as an additional benefit. Including the energy savings as an additional component of the benefits of the policy

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[54] We note that one could take alternative demand parameterizations to think about bounds on these magnitudes, as in Kang & Vasserman (2022).

[55] While most of these underlying estimates require assumptions about the fraction of recipients that are inframarginal, we find the estimate is robust to reasonable variations in this assumption. This is because the externality benefits are relatively similar to the transfer benefits of the policy. With an assumed marginal fraction of 0% the MVPF is 1 by construction and with an assumed marginal fraction of 100% the category average MVPF is 0.97.

[56] We note that Allcott & Greenstone (2024) find that only 68% of the projected energy savings are actually realized. As they explain, this may lead individuals to experience a welfare loss if their expenditures yield lower-than-expected benefits.

yields a category average MVPF of 1.37. Regardless of whether individuals were aware of the energy savings provided by weatherization, these subsidies do not generate large environmental benefits. They are instead best thought of primarily as a transfer to those weatherizing their homes.

Appliance Rebates We next consider subsidies designed to encourage the purchase of energy-efficient appliances, such as dishwashers, refrigerators, and stoves. We discuss here estimates from Houde & Aldy (2017), which studies energy efficiency rebates for clothes washers, dishwashers, and refrigerators as implemented in 2009. For subsidies for clothes washers, they estimate that roughly 90.5% of those receiving the subsidy are inframarginal – they would have purchased the energy-efficient product in the absence of the subsidy. These individuals value their subsidy dollar for dollar. For the remaining 9.5%, we once again invoke the Harberger approximation, assuming a linear demand curve so that 50% of the transfer is valued. Summing across marginal and inframarginal beneficiaries yields a total of \$0.95 in transfer benefits per dollar of subsidy. Turning to environmental benefits, the induced purchases of more efficient clothes washers generate a global environmental benefit of \$0.55 and a local benefit of \$0.08. This is partially offset by global and local rebound effects of -\$0.11 and -\$0.02, respectively. The reduction in electricity usage also leads to lost profits for utility companies of \$0.04 per dollar of subsidy. Combining these results leads to an MVPF of clothes washer subsidies of 1.41.[57] This MVPF is the highest of the three types of subsidies studied in Houde & Aldy (2017). We find MVPFs of 1.13 and 1.04 for dishwasher and refrigerator subsidies, respectively. When we combine these estimates with those of the five other appliance rebates estimates in our sample, we find a category average MVPF of 1.16. As is the case with many of the subsidies in our sample, the environmental benefits of appliance rebates are limited and these policies are primarily transfers to those who would have purchased these appliances anyway.

Other Subsidies Finally, we consider two other subsidy policies that do not neatly fit into our categorization above. The first is the CA electricity rebate, which provided consumers with a 20% discount on their electricity bill if they reduced consumption by 20% relative to their energy consumption the previous summer. Ito (2015) finds that many consumers who received the transfer would have lowered their consumption anyway in the absence of the transfer. Using those estimates, we value the transfer at \$0.88 per dollar of subsidy.[58] That said, the policy does lead to a large energy reduction, resulting in global environmental benefits of \$2.09 and local benefits of \$0.30 when evaluated in our 2020 baseline context. These effects are partially offset by global and local rebound effects of \$0.41 and \$0.06. The reduction in electricity usage

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[57] If we were to assume that marginal individuals were not ex-ante aware of the energy savings benefits of the policy, we would want to add those benefits into the willingness to pay. That would increase the MVPF to 1.97.

[58] The paper does not directly report the fraction of individuals in the control group who lowered their energy usage by 20%. It does, however, report that there was no meaningful reduction in energy usage in the coastal region where 88% of the payments were made. The MVPF estimates reported here are not sensitive to variation in this assumption because the paper reports the total energy reduction among all treated individuals.

leads to lost profits of \$0.13, so that the net WTP is \$2.67. Accounting for the program's cost, administrative costs, and lost revenue from utilities (\$0.07) leads to an MVPF of 2.57.[59] While this MVPF is quite large as compared to the others in our sample, we caution that a policy like this one might not be easily implementable because it conditions future prices on past behavior. If consumers knew that future prices would be reduced if they consume more energy today, they might increase their energy consumption today in order to qualify for greater discounts in the future. That anticipatory response would reduce the policy's effectiveness.

The second policy in this category is a US-based Payments for Ecosystem services policy studied by Aspelund & Russo (2024). The authors use a regression discontinuity design to estimate the effect of the policy on land conservation. They find that 79% of land receiving conservation payments would have been conserved in the absence of the policy. That yields a transfer value of \$0.89, when applying a Harberger approximation to the marginal recipients. Following the authors and using estimates from the USDA on the carbon abated by the program, we estimate global environmental benefits of \$0.92. The accompanying local benefits, including reduced nitrous oxide released from decreasing fertilizer use, are \$0.55. This yields an MVPF of 2.41.

Summary of MVPFs for Subsidies Figure 4 presents the baseline MVPF estimates for each of the subsidies in our sample. Following Hendren & Sprung-Keyser (2020), we also report "category average" MVPFs. These are constructed by considering \$1 in initial program costs and splitting those costs evenly over all the policies in a category. This means the category average MVPF equals the ratio of the average WTP and the average net cost of each policy in the category. The shaded blue regions report 95% confidence intervals for the category average MVPF derived from a parametric bootstrap of the underlying causal estimates from each policy.[60] The main lesson from this analysis is that subsidies for investments that directly displace the dirty production of electricity—namely, wind PTCs and residential solar subsidies—have the highest MVPFs. In particular, production tax credits for firms that produce wind energy have the highest MVPFs, generally exceeding 5. Subsidies to individuals who install residential solar panels also have high MVPFs exceeding 3. By contrast, EV subsidies have MVPFs around 1.45. All other subsidies tend to have smaller MVPFs, with values around 1 ± 0.2.

These results suggests the potential for meaningful welfare gains if climate spending is focused on policies that displace the production of dirty electricity. For example, every dollar of expanded spending on wind PTCs (with MVPFs above 5) financed by less spending on EV

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[59] Interestingly, the magnitude of this MVPF is heavily determined by the context in which it is analyzed. We report this MVPF using the national grid from 2020. If we re-analyze the policy using California's grid from 2005, the MVPF falls to 1.00. This is because producers' WTP rises in-context and because the CA grid in 2005 was cleaner than the national grid today.

[60] Appendix Table 3 provides measures of the confidence intervals for each policy in our sample. For a small number of policies, we are not able to obtain estimates of the underlying sampling uncertainty. We report the category average both for the full sample and the subset of policies for which we obtain sampling uncertainty estimates, and we broadly find similar results.

subsidies (with MVPFs around 1.5) would deliver \$3.50 in net benefits to society. Applying equation (5), this reallocation of spending would increase social welfare as long as social welfare weights on the beneficiaries of the EV subsidy (mostly EV buyers themselves) is no more than three times larger (5/1.5) than the social welfare weight on wind PTC beneficiaries (e.g., utility companies and future environmental beneficiaries).

This relative ordering of subsidies (i.e., the higher MVPFs for wind PTCs and residential solar) remains true under a wide range of specifications. For example, Figure 5 repeats our analysis from Figure 4 using a lower social cost of carbon of \$76 (with a 2.5% discount rate) and higher social cost of carbon of \$337 (with a 1.5% discount rate). The relative ordering of categories is similar, although a higher (lower) SCC accentuates (attenuates) the MVPF values for the policies that substantially reduce greenhouse gas emissions.[61]

We also consider a number of other sensitivity tests to explore robustness of our main conclusions. Appendix Table 6 shows the results when omitting any effects on firm profits. Appendix Table 7 shows the results when including measures of private energy savings in willingness to pay. Appendix Table 8 shows the results without learning-by-doing effects. In each of these cases, the relative ordering of policies remains largely unaffected. We note, however, that the MVPFs of EVs and residential solar are buoyed by learning-by-doing effects.[62] Without learning-by-doing, the values for EVs fall from 1.45 to 0.96, and the values for residential solar fall from 3.86 to 1.45. By contrast, even without learning by doing, subsidies for utility-scale wind produce relatively high MVPFs, with a category average of 3.85. Appendix Figure 5 shows, in blue bars, how the MVPF changes when only considering benefits to US residents and ignoring the benefits to the rest of the world. While the relative ordering again remains unchanged, the MVPF values decrease substantially. The wind and solar categories have MVPFs of 1.89 and 1.18 while other categories are often below 1. This is because only 13.1% of the global externality benefits are estimated to flow to US citizens and so the numerator of the MVPF falls in cases where the are meaningful global environmental benefits.

Our primary estimates report the MVPF for a marginal change in subsidies relative to 2020 subsidy levels. We also explore the robustness of our results to non-marginal changes in subsidy levels. For example, in the case of residential solar subsidies, our baseline analysis examines a marginal change relative to 26% subsidy in place in 2020. We can consider instead the policy change equal in magnitude to the change induced by Inflation Reduction Act (IRA), which prevented the expiration of residential solar subsidies and set the subsidy rate to 30%. If we examine the MVPF of a subsidy increase from 0% to 30%, we get an MVPF of 4.43, relatively close but slightly above our marginal category average of 3.86. We can repeat the same exercise for the wind PTC, examining the effect of increasing the PTC from 0 to 2.6 cents per kWh. That policy change results in an MVPF of 5.80 as compared to our baseline marginal MVPF estimate of 5.87. This once again contrasts with lower MVPFs for EV subsidies. A \$7500

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[61] Appendix Tables 4 and 5 report the estimates for all individual policies for the SCC of \$76 and \$337.

[62] Recall that it would be appropriate to omit these effects if one does not believe the empirical observed relationship between prices and historical quantities does not reflect spillover externalities.

EV subsidy has an average MVPF of 1.23, slightly lower than the MVPF of 1.45 for a $1 subsidy.[63] This analysis of non-marginal policy changes once again reinforces our conclusion about climate subsidies: those that directly displace the dirty production of electricity have the highest MVPFs.

5 Nudges and Marketing

We next consider policies that employ nudges or marketing strategies to lower carbon emissions by reducing residential energy consumption. Unlike subsidies, which provide direct financial incentives, these policies disseminate information or change choice architecture to encourage individuals to change energy usage or product purchases.

The Home Energy Report (HER) designed by Opower (now Oracle) is perhaps the most well-studied environmental nudge. The HER provides information on how to be more energy efficient in the home and often includes an element of social pressure (e.g., comparisons of a household's energy use with 100 similar neighbors). There have been over 200 rigorous RCTs showing the causal impact of such nudges on energy demand in the United States and around the world (Allcott 2011). Here, we show how to translate these estimates into the MVPF of these nudges using estimates from Allcott (2011) of the national average treatment effect of HERs aimed at reducing electricity use. We then consider the effects of nudges in different regions using 166 treatment effect estimates obtained from Opower.

We begin with the WTP for the Opower nudge. In our baseline specification, we assume people were close to indifferent about their change in energy usage, which implies that the value of the nudge to individuals is roughly zero. In particular, they do not place any additional valuation on private energy savings. They also don't have any value of shame or pride (independent on any change on demand) or value of information from the nudges. We acknowledge these sources of WTP may be important and so assess the robustness to including such estimates below (Allcott & Kessler 2019, Butera et al. 2022, List et al. 2023).[64]

HERs targeting electricity usage cause a reduction in consumption, which has an impact on environmental damages and utility company profits. Combining these treatment effects with the externality from electricity production in the US, we estimate that every $1 invested in these nudges leads to $3.87 in global environmental benefits and $0.44 in local environmental benefits. These benefits are partially offset by rebound effects of $0.76 and $0.09 due to the increased energy prices that result from reduced demand. We also estimate that utility companies experience a decrease in profits of $0.24 for each $1 spent on the Home Energy Report

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[63] This category average non-marginal MVPF is slightly higher than the 1.15 we discuss above that uses estimates from Muehlegger & Rapson (2022).

[64] For example, Allcott & Kessler (2019) suggest that individuals would be willing to pay on average about half (49%) of the energy savings that they experience from the nudge. As a conservative approach, Appendix Table 7 presents the results when we add in 100% of the energy savings, and shows that our conclusions remain broadly similar.

(HER) nudge.

On the government cost side, we assume the government pays for the electricity HER and thus include those administrative and logistical costs as a government cost.[65] Government revenue collected from utilities decreases by \$0.13, but the long-run climate fiscal externality saves the government \$0.06. Combining the willingness to pay and government costs, we obtain an MVPF of 3.01.

While this 3.01 estimate corresponds to an average electricity HER, it is important to note that the MVPF varies considerably across regions of the US due to the differences in the cleanliness of the electricity grid. Figure 6 illustrates the MVPF for HER nudges across five US regions where field experiments have been conducted and evaluated. The Mid-Atlantic, Northwest, and Midwest have high MVPFs with average values of 5.68, 5.50, and 3.76, respectively. By contrast, in California and New England, the MVPFs are 0.52 and 0.24, respectively.[66] In New England and California the grid is sufficiently clean such that the environmental benefits are smaller and are roughly offset by the loss of profits to the utility companies.[67,68] We also note the value of nudges depends heavily on the global externalities from the grid, but the regional patterns we observe are robust to those SCC variables. At an SCC of \$76 rather than \$193, the category average MVPF falls from 3.01 to 1.34. In that case, regions with dirty grids have MVPFs in the 1.92 to 2.76 range while regions cleaner grids have MVPFs near 0.

While we find large MVPFs for nudges to reduce electricity consumption, we find much smaller MVPFs for nudges to reduce natural gas consumption. On average HERs targeted at natural gas usage have an MVPF of 0.45. This lower MVPF is partially driven by the fact that nudges to reduce natural gas consumption have smaller treatment effects: the average natural gas nudge reduces consumption by 0.14% while the average electricity nudge reduces consumption by 0.26%. In addition, the environmental benefits are smaller than the associated benefits of reducing electricity consumption in areas with dirty grids.

In addition to examining nudges aimed at reducing overall energy consumption, we also evaluate the MVPF of nudges targeting energy usage reduction during peak load times. As the

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[65] This appears to be a reasonable approximation of what happens in practice, but it is also true that energy companies pay for nudges. This means that we measure the MVPF of the nudge *as if* the government were to enact the policy or pay utilities to enact the policy.

[66] It is possible that the effects of the nudge persist beyond the measured time periods in these studies. However, the MVPFs for CA and New England remain at 0.72 and 0.36 even if we assume that half of the treatment effects persist for two years after the nudge (Brandon et al. 2017, Allcott & Rogers 2014).

[67] Excluding the loss in firm profits, the MVPF for CA and New England increase to 2.02 and 0.96, respectively. They continue, however, to be substantially smaller than the MVPFs in the three regions with dirtier grids: 5.81 (Mid-Atlantic), 5.50 (Northwest), 3.86 (Midwest). We note that this dependence of the welfare effects on firm profits is similar to the argument in Buchanan (1969), who considers welfare with corrective taxes under competition and monopoly.

[68] Here, the Northwest is categorized as a dirty electric grid despite the substantial levels of hydroelectric power in the region. This is due to both (i) the high level of marginal emissions estimated in the AVERT model (as distinct from average emissions) and (ii) the nature of the regional aggregation used in the AVERT model of marginal emissions. The northwest region includes states with very high levels of grid emissions, such as Utah. Omitting the Northwest from our analysis does not change the broad trajectory of our findings regarding regional variation in nudge MVPFs.

grid increasingly relies on wind and solar power, reducing energy demand during periods when it is not sunny or windy becomes more valuable. The primary benefit of interventions focused on demand flexibility is not merely CO_2 reduction, but the ability to avoid costly blackouts or expensive marginal generation caused by the intermittency of renewable energy sources. An example of such nudges is the peak energy report, which informs consumers of their energy consumption during peak periods compared to their neighbors (Brandon et al. 2019). The field experiment showed the treatment led to a 4% reduction in energy use during peak hours. Constructing the MVPF requires placing a social value on this reduction in peak energy use. Here, we focus on the extent to which the marginal cost of peak production exceeds the price. We consider marginal costs ranging from ranging from $500/MWh$ to $1000/MWh$ and find associated MVPFs from 0.70 to 1.60.[69] If the demand reduction also decreased the frequency and/or duration of blackouts, these MVPF estimates could rise as high as 5.30.[70]

In addition to energy reports, we study marketing strategies and information treatments designed to encourage adoption of clean technologies and reduce electricity usage. For example, the Solarize program sought to increase residential solar installations by providing municipalities with a designated solar installer, group pricing, and an informational campaign led by volunteer ambassadors over the course of 20 weeks. Translating estimates of the impact of this program from Gillingham & Bollinger (2021), we estimate an MVPF of 1.81.[71]

By contrast, we find lower MVPFs when considering producer side marketing policies focused on weatherization. Christensen, Francisco & Myers 2023 study the provision of bonus incentives that provide payments to installers based on the energy savings that result from their installations. Encouraging installers to improve weatherization techniques modestly elevates the MVPF of existing weatherization subsidies. The MVPF rises from 0.98 without a bonus to 1.06-1.07 with a bonus, depending on the magnitude of the incentive. This policy has a relatively low MVPF not because the bonuses are ineffective per se but rather because the baseline weatherization subsidy results in small energy reductions relative to its baseline cost. This helps to explain the divergence with the larger MVPF for the Solarize program discussed above. Both policies encouraged take-up, but, in the context of residential solar, the induced take-up generates meaningful environmental benefits per dollar of government costs.

Summary of MVPFs for Nudges and Marketing We find that nudges to reduce electricity consumption can yield high MVPFs — on average exceeding 1.5 in our 2020 baseline

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[69] These values are consistent with peak electricity production costs in (CAISO 2021).

[70] For this calculation, we assume that the causal reduction in energy use from the treatment would be utilized by households that would otherwise experience a blackout in the counterfactual scenario. In order to estimate the value of avoiding a blackout, we use the value of lost load (VOLL) of $4,300 per MWh (Brown & Muehlenbachs 2024). We recognize that the VOLL may vary across different populations, times, and locations (Borenstein et al. 2023).

[71] Solarize uses a fairly unique peer marketing strategy in order to achieve its strong results. The generalizability of those findings depends heavily on the generalizability of the peer effects observed in the Solarize context.

specification. Crucially, we find that these MVPFs vary significantly across regions of the US. Regions characterized by a less clean energy grid have higher MVPFs. By contrast, in regions with cleaner grids such as California and New England, the MVPF values of HER nudges are below 1. This highlights the importance of the environmental context in space and time when evaluating the welfare impact of a nudge. We also find that nudges aimed at reducing natural gas consumption have lower MVPFs than those targeting electricity consumption due to the smaller treatment effects and lower environmental damages relative to electricity production. Finally, marketing strategies can also increase the MVPF, but only when targeting interventions that generate large environmental benefits.

6 Revenue Raisers

An alternative approach to address greenhouse gas (GHG) emissions is to tax the sources of those emissions. Such policies can reduce GHG emissions while also raising government revenue. For revenue-raising policies, the MVPF measures the welfare burden imposed on individuals per dollar of government revenue raised. This means that, all else equal, lower MVPFs correspond to better methods of raising revenue. For a point of reference, lump-sum taxes have an MVPF of 1 because they impose \$1 in welfare cost per each dollar of revenue raised. They are a transfer from individuals to the government. If a revenue-raising policy generates some form of societal benefit (e.g., from reducing CO_2), these can offset some of the burden and generate an MVPF below 1. In contrast, behavioral changes induced by taxes can lead to behavioral responses that reduce the revenue raised, which can increase the MVPF above 1. The key advantage of the MVPF framework is that we can use equation (5) to compare these taxes to other methods of raising revenue, such as reductions in spending on subsidies or increases in income taxes. Here, we estimate MVPFs for two types of revenue-raising policies: taxes and cap-and-trade policies. We also show how to place our MVPF estimates in the context of welfare estimates of regulation such as CAFE standards.

6.1 Taxes

A positive tax is just a negative subsidy. So, returning to equation 9 and replacing τ with $-\tau$ yields the MVPF for a change in a tax, τ , under perfect competition:

$$MVPF = \frac{1 - \epsilon\frac{V}{p}}{1 + \epsilon\frac{\tau}{p}} \tag{25}$$

where ϵ is once again the price elasticity of demand and V is the externality per unit of the good consumed. Taxes are often applied to goods (e.g., gasoline) that yield environmental harms, $V < 0$. In the case of taxes on polluting goods, the numerator of the MVPF reflects two countervailing forces. On the one hand, each dollar of tax imposes a \$1 of burden on the taxed individuals. On the other hand, the behavioral response to the tax changes consumption of the taxed good, x, generating environmental gains that partially offset the burden of the tax, $\epsilon \frac{V}{p}$. That change in consumption is also reflected in the denominator of the MVPF because changes in consumption impact tax revenue and diminish the net revenue raised from the tax, $\epsilon \frac{\tau}{p}$. In the case of a Pigouvian tax, where $\tau = -V$, the MVPF is 1. If the tax is below (above) the Pigouvian level, the MVPF of the tax will fall below (above) 1. While equation (25) provides a stylized example of the MVPF for a gasoline tax, we use an extended version below that includes externalities from imperfect competition and learning-by-doing effects (e.g., gas taxes induce the adoption of EVs, generating learning-by-doing).

We construct 12 MVPFs for gasoline taxes using estimates of the response of gasoline consumption to price and tax changes. These estimates imply price elasticities that range from -0.04 (Hughes et al. 2008) to -0.46 (Davis & Kilian 2011). We begin with an illustration of the construction of these MVPFs using the elasticity estimate from Small & Van Dender (2007) who find a price elasticity of -0.33. Figure 7 presents the components of WTP and net cost for this specification. We report these components for the gas tax using our baseline (2020) externalities and prices. Consistent with most existing literature, we assume that the gas tax is fully passed through to consumers. A \$1 increase in the gas tax leads to a WTP of consumers of \$1 to avoid the tax increase (Marion & Muehlegger 2011). We estimate that the reduced driving due to the tax leads to global benefits of \$0.27, local pollution benefits of \$0.03, and local benefits from reduced accidents and congestion of \$0.21.

Recent work suggests that gasoline prices can have a causal effect on EV adoption (Bushnell et al. 2022). Motivated by this, we use Slutsky symmetry to assess the potential impact of this substitution on our MVPF estimates. We translate the own-price elasticity of EV purchases of -2.1 (Muehlegger & Rapson 2022) into a cross-price elasticity between the price of gasoline and EV demand of 0.22.[72] These EV purchases generate \$0.0008 in combined global and local damages from electricity generation. They also generate learning-by-doing benefits of \$0.002 from reduced future EV prices and \$0.0002 from future environmental benefits.[73]

Lastly, we incorporate the profit impacts from reduced gasoline demand. We estimate this leads to a \$0.07 WTP by firms to avoid the tax. Gasoline producers have a positive WTP to avoid the tax, whereas utility companies benefit from the substitution toward EVs. On the cost side, the reduction in demand also leads to lost corporate and gas tax revenue of \$0.09.[74] The US government also raises \$0.01 in future revenue by abating greenhouse gases today. Combining our WTPs and cost implies an MVPF of 0.60. A dollar of government revenue

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[72] Under Slutksy symmetry, in combination with the assumption of no change in overall car demand (just shifting between EVs and ICE vehicles), the cross-price elasticity is given by the own-price elasticity multiplied by the ratio of the present discounted value of operating costs of a gasoline powered car relative to the price of an EV. See Appendix E.10 for our derivation.

[73] We also account for utilities' WTP for increased electricity usage by EVs as well as accompanying fiscal externalities associated with EV adoption. These effects are negligible.

[74] Consistent with the findings in West & Williams (2007) that gasoline is a relative complement to leisure rather than labor, we exclude any labor income related fiscal externality.

raised leads to a welfare cost of $0.60 on individuals.

Figure 8 presents the MVPF estimates for the full set of gasoline studies in our main sample. We find MVPFs ranging from 0.44 to 0.95, with a category average of 0.67.[75] We also construct MVPF estimates for taxes on diesel and jet fuel and find similarly low MVPFs with values around 0.8. A full description of those calculations can be found in Appendix E.11.[76] In each of these cases, the MVPF falls below 1 because the externalities avoided (environmental, congestion, or accidents) are larger than the fiscal externality induced by the policy.

On the whole, the results suggest fuel taxes raise revenue at a relatively low welfare cost. The MVPFs of these revenue raisers are well below the MVPF of changes to the income tax, which range from 1 to 2 depending on the income level of the taxed individuals (Hendren 2020, Hendren & Sprung-Keyser 2020). The MVPFs of fuel taxes are even below 1, the MVPF of a non-distortionary lump sum tax. Returning to equation (5), we can use the MVPFs to make statements about the welfare effects of budget neutral policy experiments. For example, we can directly compare an MVPF of .6 for gasoline taxes with an MVPF of 1.1 for income taxes on low-income earners. If society places equal weight on the individuals impacted by each policy, then every dollar of revenue shifted from income taxes to gasoline taxes generates 50 cents in additional welfare.[77] If, by contrast, a decision-maker would prefer the status quo, it implies they must place a higher welfare weight on drivers relative to an average low-income individual.

While the analysis here has focused on the impact of tax instruments, it is important to acknowledge that governments may also use regulatory policy to achieve the same ends. For example, Corporate Average Fuel Economy (CAFE) standards require automakers to meet certain mile per gallon standards for the fleet of vehicles they sell in the US. The MVPF approach is designed to examine the welfare consequences of government spending or tax policies where the primary tradeoff is between the government budget and individuals in the economy. In contrast, for regulatory policies such CAFE the primary tradeoff is between different groups of individuals (e.g., consumers paying higher prices versus other individuals benefiting from a cleaner environment). The incidence of on the government budget is non-existent or small. Therefore, an in-depth exploration of regulatory policies is beyond the scope of our analysis. That said, Appendix G shows that one can use the MVPF framework to compare the welfare consequences of regulations to typical tax and spend instruments. In particular, we ask whether the welfare consequences of a regulation can be replicated using a combination of taxes and transfers. Appendix Figure 6, for example, seeks to replicate the benefits offered by CAFE with a mix of gas taxes and income tax changes. We show that gasoline taxes combined with feasible

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[75] Even when omitting externality benefits that flow to residents outside the US, the MVPF still falls below 1 with a category average of 0.89.

[76] Diesel taxes have a higher MVPF than gas taxes because diesel demand is less elastic than gasoline demand. This increases the MVPF, despite the fact that diesel vehicles impose a larger per-gallon externality than gas-powered vehicles. The jet fuel tax has a higher MVPF than gas taxes due to fewer local externalities.

[77] Even ignoring environmental benefits and focusing solely on accidents and congestion, gas taxes have an MVPF of 0.95, which continues to be lower than the MVPFs identified for tax changes at any point across the income distribution (Hendren 2020).

income tax modifications can replicate CAFE's impact on the environment, producers, and consumers while also generating roughly \$1 in additional government revenue.[78] The key reason for the relative superiority of the tax instruments is that they generate reductions in driving, inducing additional benefits from reduced accidents and congestion. We conduct a similar exercise in Appendix G showing that wind subsidies combined with income tax modifications deliver welfare gains that are superior to Renewable Portfolio Standards (RPS) regulations.

6.2 Cap and Trade

Cap and trade systems are a common policy tool used to limit emissions. They impose quantity limits on emissions and let firms trade the rights to such emissions. We evaluate two cases where cap and trade has been used in the US: the Regional Greenhouse Gas Initiative (RGGI) in the Northeast and mid-Atlantic, and the California Cap-and-Trade Program. We also briefly discuss the European Emissions Trading System (ETS) to provide an additional point of comparison.

We can interpret changes in the number of permits in a cap and trade system in a manner similar to a change in the tax rate on polluting goods. The key distinction is that taxes change prices while cap and trade uses permits to directly change quantities. This means that there is a close analogy between the MVPF formula for changes in the number of permits in a cap and trade system and the MVPF formula for taxes on a polluting good, such as the gasoline tax outlined in equation (25).[79]

Formally, we construct the MVPF of cap and trade by considering a change in the number of permits sold at auction. Let q denote the number of permits issued. Assume that one fewer permit leads to $(1-L)$ reductions in emissions, where L is the "leakage" of emissions into areas not captured by the cap and trade program. Following equation (25), and multiplying through by qdp/dq, we can write the MVPF of changing the number of auctioned permits as

$$MVPF = \frac{-q\frac{dp}{dq} + V(1-L)}{-q\frac{dp}{dq} - p}. \tag{28}$$

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[78] Here, we focus on replicating the incidence across broad groups within society such as consumers or producers. We focus, for example, on offsetting producer losses with high income tax cuts, acknowledging that the beneficiaries of those tax cuts may not be the same firms that bore the burden of lost profits due to the CAFE standards.

[79] To see this, note that

$$\begin{aligned} MVPF &= \frac{-q\frac{dp}{dq} + V(1-L)}{-q\frac{dp}{dq} + p} && (26) \\ &= \frac{1 - \frac{dq}{dp}\frac{p}{q}V(1-L)}{1 - \frac{dq}{dp}\frac{p}{q}} && (27) \end{aligned}$$

which is equivalent to equation (25) noting that $\epsilon = (dq/dp)(p/q)$ and that the "tax" on permits applied in the denominator is 100% since they are owned by the government.

The first term is the firms' willingness to pay to avoid the increase in permit prices, which stem from the reduction in permit supply. This is offset by the environmental damages avoided, $V(1-L)$, due to a one-unit change in the number of permits auctioned. On the cost side, the government receives the mechanical revenue from the higher prices, $-qdp/dq > 0$, but also loses p in revenue from the forgone permit no longer auctioned.[80]

We begin with the in-context estimates of the effect of RGGI on greenhouse gas emissions using results from Chan & Morrow (2019). Between 2009 and 2016, there were 816.2 million permits auctioned (per short ton of CO_2), at an average clearing price of \$3.19 (in 2016 dollars). The authors estimate that RGGI reduced 22 million short tons of CO_2 during this period. This implies that a one unit reduction in the quantity of permits sold led to a $\$1.45 \times 10^{-7}$ dollar increase in the permit price, or $dp/dq = -1.45 \times 10^{-7}$. This suggests that if RGGI had auctioned one fewer permit between 2009 and 2016, it would have lost \$3.19 from the price of the permit but gained approximately $-dp/dq * q = 1.45 * 81.62 = \$118.48$ in additional revenue from higher permit prices.[81]

Higher prices impose a cost on firms purchasing permits, which totals to \$118.48. These higher prices will cause some firms to opt not to purchase permits and instead reduce their emissions. While the envelope theorem suggests these profit maximizing firms are indifferent between buying a permit and reducing emissions, the emissions reductions generate environmental externalities. The environmental benefit of releasing $1 - L = 0.49$ fewer short tons of CO_2 in 2016 is \$65.20. Adding the reduction in local pollutants SO_2 and NO_X yields an additional gain of \$117.21.[82] On net, these environmental benefits offset the cost to firms for a net positive willingness to pay of \$63.93. Raising revenue via a reduction in auctioned permits as part of RGGI led to a net win for individuals and taxpayers.[83]

While our in-context estimates suggest RGGI led to significant benefits to taxpayers and individuals in society, we caution that it is potentially difficult to extrapolate our in-context estimates to a 2020 policy reform. This is because one needs to know the marginal abatement cost curve in 2020 to understand how the number of permits would affect its price. One potential assumption is that it is stable over time – i.e., a 1 unit reduction in permits has the same marginal impact on price as it did in the sample context over which it was estimated in 2009-2016. This is arguably a more aggressive assumption than the constant price elasticity assumptions used in other MVPF calculations. That said, if we make such an assumption

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[80] p does not enter the numerator because we assume we assume that firms are optimizing: the marginal firm holding a permit has a marginal abatement cost equal to the permit price.

[81] We estimate a fiscal externality on the government budget to be \$1.27, which suggests a net government revenue of \$116.56 from issuing one fewer permit. Motivated by the evidence in Colmer et al. (2024) and Metcalf & Stock (2023), we assume that cap and trade induces no reduction in the productive capacity of firms, and so there is no additional corporate tax fiscal externality.

[82] Excluding local damages, society's WTP for pollution reductions is only \$65.20, implying an MVPF of 0.46.

[83] The positive net willingness to pay among individuals is the difference between the environmental benefits and the permit costs to firms. This corresponds to an increase in social welfare as long as one prefers \$1.54 flowing to the beneficiaries of an improved environment over \$1 in the hands of the firms paying the additional permit costs.

regarding the marginal abatement curve, we can analyze the policy in 2020 and find that reductions in cap and trade permits under RGGI produce net welfare gains for individuals alongside an increase in government revenue. Greater restrictions in auctioned permits would continue to increase government revenue ($123.01) while also delivering a net gain to individuals in society, as the WTP for environmental damages ($210.33) outweighs each dollar firms pay in permits ($127.78). It is, of course, not certain whether the marginal abatement cost curve has been constant over time. The primary channel through which RGGI affected emissions was by inducing a switch from coal to natural gas. It is less clear whether the same set of low cost substitution options continue to exist today after many coal plants have been retired. Consequently, it may be that dp/dq is larger in 2020 than in the early 2010's, leading to fewer environmental benefits per dollar of cost imposed on those buying permits.

In addition to our analysis of RGGI, we also consider the MVPF of permits in the California Cap-and-Trade Program using estimates from Hernandez-Cortes & Meng (2023). They estimate the impact of the introduction of the cap and trade system on small and medium sized manufacturing firms. A key challenge for our analysis is that existing data only track outcomes for a sub-sample of firms subject to the cap and trade system. These firms make up just 5% of GHG emissions subject to that system. As a conservative approach, we conduct our analysis assuming the other 95% of the market does not generate any reductions in emissions. In this case, it is straightforward to show that the MVPF would be around 0.95. In other words, a decrease in auctioned permits would raise $1 in revenue at a welfare cost of $0.95 on society. If we instead assumed that the other 95% of the regulated market had a similar response to the observed 5%, this generates a much larger environmental benefit. The associated benefits are sufficient to offset the costs imposed on firms paying higher permit costs. This would suggest that, like RGGI, the California Cap and Trade auctions raise revenue while also generating net welfare gains to society.

While our primary focus here is on US climate policy, we also consider the largest cap and trade system for CO_2 in the world – the European Union's Emissions Trading System (ETS). Colmer et al. (2024) find that the introduction of ETS led to permit prices that stabilized around $20 between 2005 and 2012 and ultimately generated a 15% reduction in emissions. (They find no evidence of leakage.) Assuming a linear response to prices, the price of $19.90 generating a 15% reduction in emissions suggests firms are willing to pay $131.32 ($q * dp/dq$) to avoid a one ton reduction in the number of allocated permits. Comparing this to a historical average SCC of $134.79 in this period, it suggests a net welfare gain of $3.47 ($134.79-$131.32). On the cost side, we find that selling one fewer permit leads to a net revenue gain of $114.06. Selling one fewer permit generates $114.06 in revenue and delivers $3.47 in net benefits to individuals.[84] This means that the evidence from ETS is consistent with the US evidence on cap and trade: Reductions in permits have the potential to raise revenue while also providing

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[84] We find a qualitatively similar conclusion when examining estimates on the impact of the ETS from Bayer & Aklin (2020). Fewer ETS permits lead to $134.68 in net benefits to society while also generating $14.41 in government revenue.

positive benefits to society.

Summary of Revenue-Raiser MVPFs The key lesson of this section is that taxes and other restrictions on pollution-emitting activities offer paths to raising revenues at low welfare costs. The MVPFs of these policies fall consistently below 1, suggesting they impose less than \$1 in burden for each dollar of revenue raised. This lies in contrast with other traditional revenue raisers, such as increases in income tax rates, which consistently have MVPFs above 1. Returning to equation (5), the results suggest a decision-maker setting tax policy would need to have high implicit social welfare weights on individuals engaged in pollution-emitting activities in order to justify status quo policies as optimal.[85] For cap and trade, the results show that there appear to be large quantities of emissions that can be reduced at relatively low cost - at least in settings where these markets have been established. The presence of this low hanging fruit means that small prices on carbon can lead to large reductions in emissions, generating a win for taxpayers and a net win for individuals affected by the policy. More broadly, our results suggest that the presence of these large environmental externalities creates opportunities for raising revenue at a low welfare cost relative to typical methods of raising revenue.

7 International Policies

Climate policies have international spillovers. The impacts of greenhouse gas emissions are felt worldwide, regardless of the source of the emissions. This means that many of the beneficiaries of US policies addressing climate change reside outside of the US, and that US residents are the beneficiaries of climate policies enacted in other countries.

In this section, we draw upon an illustrative set of climate-focused policies implemented in developing countries, largely by NGOs. We consider: to what extent is it beneficial to US residents to pay for policies implemented in other countries? For each policy, we imagine that the US government enacts the policy as a form of international aid. We consider 14 policies spanning five categories: cookstoves, deforestation payments for ecosystem services, payments to prevent rice field burning, wind subsidy offsets, and appliance and weatherization rebates.

We begin with subsidies for improved cookstoves in Kenya. Berkouwer & Dean (2022) find that small subsidies for these cookstoves help to overcome individual credit constraints and encourage the purchase of these appliances. When offered a \$30.37 subsidy (in 2020 dollars), 54.5% of individuals take up the cookstove. Nearly all of those beneficiaries are marginal, as only 0.6% would have taken up the cookstove in the absence of the policy. The paper also

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[85] Even ignoring environmental benefits and focusing solely on accidents and congestion, gas taxes have an MVPF of 0.95, which is 14 percent lower than the MVPF around 1.1 typically observed for income tax changes on low income individuals (Hendren 2020). This suggests an implicit welfare weight on drivers must be higher than the weight on the earnings of a typical low-income individual in order to rationalize current tax rates as optimal.

finds that each new cookstove reduces CO_2e by about 7 tons.[86] This translates into \$43.16 in global environmental benefits for each mechanical dollar of the subsidy. We combine those global externality benefits with the transfer benefits of the subsidy and the value of private energy savings. This yields a total willingness to pay of \$50.82 for each mechanical dollar of the subsidy.

Next, we consider the net cost of the policy. In our previous MVPF estimates, we considered the impact of climate damages on the US government's budget and noted such effects were minimal. Here, the impact of the policy on carbon emissions is sufficiently large such that the climate fiscal externality is quantitatively important. The precise value of that fiscal externality depends on the model underlying the social cost of carbon. In our baseline specification, we assume the US experiences 15% of the benefits of carbon abatement in proportion to its share of global GDP. Across SCC models these benefits are typically a mix of mortality reductions and productivity increases. We therefore assume 50% of the benefits are changes in productivity and therefore taxed by the US government at a rate of 25.5% (the US tax to GDP ratio in 2020). Taking these estimates as given, implies that the the US government recoups \$3.70 per ton of CO_2 and so for each mechanical dollar of subsidy, the net cost to the US government would be just \$0.157. When combined with the WTP for the policy, this yields an MVPF of 37 when only considering benefits to US residents and an MVPF of 323 when considering benefits to individuals globally.

A key factor in this calculation is the extent to which reductions in global warming have a positive impact on future US tax revenue (e.g., due. to higher future productivity). Models that report the same social cost of carbon can generate different MVPFs because they differ in the incidence on the US federal budget. For example, we could have assumed that the entirety of the SCC was driven by changes in market productivity. This approach is motivated by a literature estimating damages functions that relate carbon to GDP (Nath et al. 2024).[87] In this case, we find that the subsidy pays for itself. The net cost of policy is -\$11.31 for each dollar of mechanical subsidy (and the US-only MVPF is infinite). By contrast, other models suggest that the incidence of emissions damages on the US taxpayer could be quite small. For example, estimates from PAGE (Nordhaus 2017) suggest the US-incidence of carbon damages is just 7%. Similarly, estimates from the GIVE model (Rennert et al. 2022) suggest that changes in productivity are concentrated outside the US. If we drop the US-specific fiscal externality to zero, the US-only MVPF falls to 4.91 and the MVPF including global benefits falls to 49.97. This highlights the importance of articulating incidence when constructing measures of the social cost of carbon. While total damages estimates can be reported in GDP-equivalent terms, the distinction between the sources of damages can meaningfully impact the welfare

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[86] We note that these calculations assume that charcoal is derived entirely from non-renewable biomass. If we were to use a fraction non-rewewable biomass of 45% estimated by the United Nations (2023), the carbon reduction would be 1.67 tons.

[87] Some recent work has argued that carbon-driven GDP effects imply a SCC in excess of \$1,000 (Bilal & Känzig 2024), but this fiscal externality is still important for far more modest estimates of the SCC when greenhouse gas reductions are large.

consequences of a policy.

Figure 9 presents the MVPFs for the other international policies in our baseline sample.[88] MVPFs using only US benefits are shown in blue and those including global benefits is shown in orange. These estimates show the substantial variation in MVPF estimates both within and across program categories. For example, the evidence from Berkouwer & Dean (2022) differs from the findings in prior work on cookstove subsidies. Hanna et al. (2016) found that recipients simply did not use the cookstoves, which translates to an MVPF near zero. Similarly, we find large variation in the returns to policies designed to prevent deforestation. We find that payments to farmers in Sierra Leone to prevent deforestation yields an MVPF of 15.9 even when only considering benefits to US residents. This is one of the largest MVPFs in our sample. For deforestation prevention payments evaluated in Uganda, we find global MVPFs of 5.44 and a US-only MVPF of around 0.66. That said, not all deforestation programs appear to be as effective. We find a smaller MVPF for a program in Mexico evaluated in Izquierdo-Tort et al. (2024), with a global MVPF of 1.71 and a US-only MVPF of 0.1.

We also find large MVPFs for policies that use unique incentive contracts to discourage rice field burning. We find MVPFs between 10-15 when including global benefits and in the 1.3-1.8 range when only including US benefits. Additionally, we find potentially high returns to policies encouraging the adoption of wind turbines in India, with a global MVPF of 7.64 and a US-only MVPF of 0.9.[89] As is the case with our primary estimates, we find the lowest MVPFs for other policies that use rebates to encourage the purchase of other efficient appliances.

In sum, we find potentially high returns - even from a US-only perspective - from policies that invest in reducing greenhouse gas emissions in developing countries. Indeed, subsidies for cookstoves and deforestation subsidies in Sierra Leone have higher MVPFs than any domestic subsidy in our sample, even when only considering the benefits accruing to US residents. That said, we reiterate three notes of caution. First, our exact MVPF estimates depend on the incidence of the social costs of carbon and, in particular, whether the benefits accrue in the form of increased US productivity. Such productivity benefits have US tax revenue implications that meaningfully impact the net cost of the subsidies to the US government. Second, we find high variance in our international MVPFs estimates, even within policy categories. Even when spending within a promising category, high returns are certainly not guaranteed. Finally, our analysis assumes the US government could implement these policies with the same cost structure as the NGO conducting the evaluation. The US government may face different administrative

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[88] Table 2 discusses results for additional policies in our extended sample, which includes some policies which are not a natural fit when considering hypothetical US-based funding. This includes, for example, nudges for energy reduction in foreign countries.

[89] We draw upon estimates from Calel et al. (Forthcoming) examining the impact of a wind subsidy in India on greenhouse gas emissions. The authors argue that at least 52% of installations are inframarginal, suggesting that the carbon offsets are not fully offsetting carbon emissions. We take that implied inframarginal fraction as given, rather than a bound, and show that it results in an implied elasticity of -2.2 and an implied MVPF of 7.64. We note that the 52% inframarginal share is a lower bound so the ultimate MVPF could be lower if the leakage is higher.

costs when scaling these programs, meaningfully changing that MVPF. All of that said, the key lesson from our analysis mirrors the conclusions of Glennerster & Jayachandran (2023): International aid policies can be a valuable part of the toolkit for addressing climate change.

8 MVPF Versus Cost per Ton

The preceding analysis applies the MVPF framework to analyze the welfare consequences of US climate change policies. This represents a departure from the typical approach in the environmental economics literature, which constructs a measure of the cost per ton of CO_2 abated ("cost per ton"). And while existing work tends to refer to "cost per ton" as a singular object of interest, there are multiple conceptually distinct (and often conflated) definitions used in the literature. We that find three broad definitions serve to capture the conceptual distinctions in prior work. We refer to these measures as the (A) resource cost per ton of CO_2 abated, (B) government cost per ton of CO_2 abated, and (C) net social cost per ton of CO_2 abated.

In this section, we compare the MVPF with these cost per ton measures. We begin by discussing the conceptual differences between cost per ton measures and the MVPF. We then construct an estimate of each cost per ton measure for each of the policies in our sample. We highlight the ways in which these cost per ton measures fail to fully capture the lessons of the MVPF approach, often leading to different rankings across policies.

8.1 Definitions of Cost per Ton

Here, we outline the three common measures of the cost per ton of CO_2 abated and discuss their conceptual drawbacks relative to the MVPF.

Resource Cost per Ton The "resource cost per ton" approach has a long history in environmental economics (Grubb et al. 1993). It was popularized in influential work by McKinsey & Company (Enkvist et al. 2007), which ordered a wide range of abatement technologies using this measure.[90] The resource cost per ton evaluates the desirability of a product (or activity) by measuring the dollar value of the resources entailed in the production and use of the product, divided by the tons of carbon abated. For example, the resource cost of an EV is the difference in production cost for an EV versus a similar internal combustion engine (ICE) car minus the lifetime difference in gasoline costs versus electricity costs associated with operating the car. Similarly, the resource cost of an energy efficient appliance is the difference in cost of the appliance relative to its less efficient alternative minus the net energy savings from the more efficient appliance.

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[90] See also the discussion in Gillingham & Stock (2018).

There are two conceptual concerns associated with this measure. First, it focuses on a product or activity (e.g., the purchase of an EV) rather than a policy (e.g., a subsidy for an EV purchase). In practice, subsidies generate meaningful transfers to inframarginal beneficiaries – people who would obtain the subsidy without changing their behavior. With its focus on products rather than policies, the resource cost per ton approach ignores both the benefits and the costs of those inframarginal transfers. We suggest below that accounting for these transfers can substantially affect our welfare assessments. Policies with large quantities of inframarginal transfers may appear to be effective using a resource cost approach, but may be far less effective using other measures.

Second, when constructing the resource cost of an expenditure, this approach generally ignores any non-resource costs or benefits. For example, an individual's valuation of an EV may be influenced by the disutility from having to find charging stations or the utility from being able to go 0 to 60 in less than 3 seconds. These considerations are generally excluded when calculating the resource cost of an expenditure. This omission of non-CO_2 benefits is seen most starkly when considering revenue-raising policies. Applying the resource cost per ton approach to gasoline taxes suggests negative costs per ton. Society saves the resource costs of producing gasoline while also reducing emissions. The trouble here is that individuals derive utility from their resource expenditures and such benefits are generally ignored by the resource cost per ton.[91]

Government Cost per Ton The "government cost per ton" of carbon abated measures the reduction in tons of CO_2 emitted per dollar of net government outlay (Knittel 2009, Gillingham & Tsvetanov 2019).[92] Relative to the MVPF approach, this definition uses the denominator of the MVPF in its numerator (the net government cost of the policy), and compares this to the tons of carbon abated from the policy. The government cost per ton approach addresses one of the key criticisms of the resource cost per ton method, accounting for the cost of transfers to inframarginal beneficiaries. It does not, however, consider the benefits to those individuals. In other words, inframarginal transfers are treated as a cost but not a benefit. This omission can create concerns when comparing the government cost per ton to values of the social cost of carbon.[93] A comparison to the SCC often serves as a threshold by which to judge whether a policy is welfare enhancing. The omissions of inframarginal benefits, however, means that policies can have costs per ton that exceed the SCC while still delivering large welfare gains.[94]

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[91] Put another way, simply counting resource costs ignores crucial information revealed by individual purchase decisions.

[92] This measure is also sometimes referred to as the "program cost per ton" (Gillingham & Tsvetanov 2019, Davis et al. 2014).

[93] The government cost per ton of CO_2 also generally omits other non-resource benefits such as local pollutants avoided or congestion externalities.

[94] This particular criticism has been expressed in previous literature. For example, Davis (2023) provides a discussion of the cost effectiveness of heat pumps and notes "[i]t is tempting to compare the [cost per ton of CO2 estimates] to estimates in the literature for the social cost of carbon. For example, the U.S. government currently uses a social cost of carbon of $51 per ton (U.S. Interagency Working Group, 2021) and one recent

As with the resource cost per ton, the government cost per ton cannot be readily applied to revenue raising policies. Taxes typically have a negative government cost while abating carbon. A negative value of government cost per ton does not mean these taxes are a 'free lunch' when it comes to addressing climate change. Rather, taxes impose a welfare loss on the individuals who pay for the tax, and government cost per ton ignores those costs.

Social Cost per Ton A third measure found in the literature seeks to incorporate a comprehensive set of non-CO_2 costs and benefits into its calculation of cost per ton (Christensen, Francisco, Myers & Souza 2023, Hughes & Podolefsky 2015). We refer to this measure as the "social cost per ton," or SCPT. The numerator of this ratio is the net government cost minus all of the non-CO_2-related benefits of the policy. The denominator is equal to the tons of CO_2 abated.[95]

The SCPT approach is similar to the resource cost per ton approach. It is, therefore, subject to many of the same criticisms regarding its ability to reflect the causal effect of policy changes. The key difference, however, is that instead of measuring costs as resource outlays, the social cost per ton measures the change in social welfare (excluding CO_2 impacts on welfare) required to abate CO_2. This means it includes a wider range of costs and benefits omitted from the resource cost approach. For example, the social cost approach also allows vehicle driving to produce non-CO_2 damages such as accident, congestion, and local pollutant externalities.

Just like the MVPF, the SCPT approach often invokes assumptions of optimization to estimate non-CO_2 benefits.[96] For example, a \$1 subsidy for an energy efficient appliance is valued at \$1 for those who would have purchased it anyway, but not valued to first order by those induced to purchase due to the subsidy. In practice, this diverges from the resource cost per ton approach where there can be strictly positive (or negative) resource cost changes from the induced purchases (e.g., from their energy savings).

We can write out the formula for the SCPT using the subsidy example in Section 2.2. We delineate between the carbon externality and other externalities, $V = SCC * Tons + Other$, and write the SCPT as:

$$SCPT = \frac{(\tau - Other)\frac{\epsilon}{p}}{Tons\frac{\epsilon}{p}} = \frac{\tau - Other}{Tons} \tag{29}$$

Every induced purchase of the good imposes a social cost equal to the size of the subsidy, τ,

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study finds a preferred social cost of carbon of \$185 per ton (Rennert et al. 2022). However, this is not an apples-to-apples comparison. Subsidies are transfers, not economic costs, and many households value subsidies at close to \$1-for-\$1." A similar criticism can be found in Knittel (2009).

[95] If there are no non-resource costs or benefits associated with the policy change, the social cost per ton ratio equals the resource cost per ton.

[96] In invoking optimization, the SCPT approach shares a similarity to the "top down" approach discussed in Grubb et al. (1993). This top-down approach uses economic models with optimization to measure the marginal cost of abatement whereas the logic of SCPT invokes optimization to aid in the individual valuation of policy changes via the envelope theorem.

minus any non-CO_2 benefits, $Other$.[97] This highlights the primary drawback associated with the SCPT approach. Just like the resource cost per ton approach, the SCPT of the subsidy is independent of the magnitude of the behavioral response to the subsidy. In other words, if two policies both induce one more person to purchase a new good, the policies would have the same SCPT, regardless of how many inframarginal beneficiaries receive the transfer. This means that the assessment of welfare is independent of the causal effect of the policy on take-up.

It is worth noting that there is an alternate formulation of the SCPT used in work by Fournel (2024) that includes the opportunity costs of inframarginal transfers. While this approach is not in widespread use, it is worthy of discussion because it includes a social cost of inframarginal transfers. This approach assumes a given marginal cost of funds from a change in the income tax, ϕ, and adds it to the numerator to capture a distortionary cost of raising revenue. The resulting formula for the social cost per ton is given by:

$$SCPT_{\phi} = \frac{(\tau - Other)\frac{\epsilon}{p} + \phi(1 + \frac{\epsilon}{p}\tau)}{Tons\frac{\epsilon}{p}}. \tag{30}$$

In this case, the elasticity does not drop out of the expression and the social cost of the policy is determined, in part, by the marginal cost of raising revenue from an increase in income taxes, ϕ. As we discuss below, welfare comparisons using this approach are sensitive to the assumptions made regarding the nature of the income tax changes used to close the budget constraint (e.g., changes in taxes at the bottom vs. top of the income distribution). We focus our primary comparisons on the standard SCPT measure that does not incorporate any cost of raising revenue and report in Appendix Table 9 how the SCPT varies with different values of ϕ.

8.2 Results

Having highlighted the theoretical distinctions between the various cost per ton definitions, we now explore how those distinctions matter in practice. Table 3 reports all three measures of cost per ton for each policy sub-category alongside the associated MVPF (see Appendix Table 10 for each individual policy in our sample).[98] These results make clear that there is wide variation in reported "cost per ton" depending on the definition employed. For example, the cost per ton of appliance subsidies ranges from -\$2 to \$474 across the three measures. From a resource cost perspective, energy efficient appliances save enough energy to overcome the difference in upfront price as compared to counterfactual appliances. This leads to a net resource cost per ton of -\$2. The government cost per ton, however, is \$474, as many subsidies go to people who would have purchased those appliances even in the absence of the subsidy. The social cost per

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[97] Equivalently, the SCPT gives the level of the SCC such that benefits are equal to costs, or MVPF = 1.

[98] The estimates in Table 3 include learning-by-doing benefits; Appendix Table 11 shows the equivalent table if we exclude these effects.

ton is far lower than the government cost per ton at \$111 due to the addition of the non-CO_2 benefits and transfer benefits of the subsidy.

The wide variation in cost per ton across definitions within a policy category highlights the need to be consistent when constructing a measure of cost per ton. For example, Gillingham & Stock (2018) provide a ranking of policies according to their cost per ton of carbon abated. The lowest cost per ton policy in their list is the nudges studied in Mullainathan & Allcott (2010), who use a resource cost per ton measure — a measure that tends to be lower because it includes energy savings and omits inframarginal costs.[99] By contrast, solar subsidies are reported to have higher costs per ton, but some of these measure government cost per ton (e.g., (Gillingham & Tsvetanov 2019)). This approach generates a higher cost per ton relative to other measures because it includes inframarginal costs but not their benefits.

This comparison highlights the drawbacks of conflating different definitions of cost per ton when conducting welfare comparisons. That problem could potentially be solved, however, if researchers were to align on a single definition of cost per ton. It is therefore natural to ask: if one definition of cost per ton were used, would that measure capture the broad conclusions identified by the MVPF approach? In the section below, we show how the MVPF compares to each different cost per ton metric.

Resource Cost per Ton Our estimates of resource cost per ton lead to conclusions that diverge substantially from our conclusions using the MVPF approach. We can see this divergence in several ways. Consider, for example, a comparison between appliance rebate subsidies, vehicle retirement subsidies, and hybrid subsidies. Appliance rebates have negative resource costs (-\$2), far below the values for vehicle retirement and hybrid policies (\$987 and \$577). Despite that divergence, the policy categories have nearly indistinguishable MVPFs (1.16 versus 1.05 and 1.01).

We also see this pattern when examining individual policies, rather than policy categories. For example, rebates for energy efficient fridges as studied in Datta & Gulati (2014) have a resource cost per ton of -\$512. This is far below the resource costs for wind PTCs studied in Hitaj (2013), which have a value of -\$96.[100] This pattern of lower resource costs per ton for energy efficient appliances as opposed to wind turbines is consistent with previous resource cost calculations, such as the influential estimates constructed by McKinsey & Company. In contrast, the MVPF approach shows that spending \$1 on this efficient fridge subsidy delivers \$1.01 in benefits to individuals, far smaller than the \$4.63 in benefits per dollar spent on subsidies for wind turbines.

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[99] The paper describes its measure of costs as capturing the "long-run marginal cost of electricity minus the program cost to the utility."

[100] Here, the resource cost per ton estimates rely on inputs that are not required for the MVPF calculation. They include, for example, the relative price of the energy efficient versus counterfactual appliance.

Government Cost per Ton Our estimates of government cost per ton produce an ordering of policies that loosely aligns with our core MVPF findings: wind PTCs and residential solar have government costs per ton below that of any other subsidy or nudge category in our sample. That said, the omission of non-CO_2 benefits still produces a reordering relative to the MVPF across certain policy categories. For example, EVs have a government cost per ton of $1,356, substantially higher than the $474 cost for appliance rebates. The MVPF of EVs, however, is 1.45 as compared to the 1.16 for appliance rebates. This difference arises because government cost per ton does not include inframarginal benefits or the benefits from lower prices generated from learning-by-doing. As noted above, 95% of the benefits of EV subsidies flow to individuals who are buying or selling EVs. Those benefits are all omitted from the government cost per ton approach. This omission of benefits also influences the interpretation of the government cost per ton. At first glance, it might seem as though an EV subsidy with a government cost $1,356 per ton is not a worthwhile expenditure if the social cost of carbon is $193 per ton. The omission of transfer and non-CO_2 benefits, however, means that a comparison with the social cost of carbon does not provide a welfare-relevant benchmark.

Social Cost per Ton The final column of Table 3 reports the social cost per ton of each policy category. Across all of our policy categories, electric vehicles have the lowest SCPT at -$415. That is followed by residential solar at -$67 and wind PTCs at -$32. That ordering is the exact opposite of the ordering of our MVPFs, where the values are 1.45, 3.86 and 5.87 respectively.[101]

We see similar reversals when excluding learning-by-doing effects and comparing across policy categories. For example, hybrid vehicle subsidies have a SCPT of $43, half of the SCPT for residential solar at $83. This is true despite the fact that hybrid vehicle subsidies have an MVPF that is lower (1.00 versus 1.45).

A key source of divergence between SCPT and the MVPF is the fact that the canonical SCPT approach does not account for the opportunity cost of inframarginal transfers. As we noted above, a potential way to address this concern within the SCPT approach is to account for the marginal cost of funds (MCF) associated with inframarginal transfers. Appendix Table 9 reports the SCPT using three common values of the MCF: 10%, 30%, and 50%. The key takeaway here is that the cost per ton estimates are highly sensitive to one's views on the MCF. The SCPT for EV subsidies moves from -$415 with no MCF to -$259 with 10% a MCF and to $260 with a 50% MCF. The SCPT for appliance rebates changes from $111 without an MCF to $349 with a 50% MCF.

An advantage of the MVPF approach is that the MVPFs of our climate policies are determined by the causal effects of the policies being evaluated rather than assumptions about

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[101] An additional complication with the social cost per ton approach is that it is difficult to draw conclusions when comparing negative values. For a fixed quantity of CO_2 abated, high levels of non-carbon benefits reduce the value of the social cost per ton. By contrast, for a fixed quantity of non-carbon benefits, greater CO_2 abatement increases the social cost per ton.

the distortionary costs of additional policies used to close the budget constraint. Instead, one can conduct welfare analysis of budget neutral policy experiments by comparing MVPFs, as in equation (5). For example, if one believes there is a 30% MCF for income taxes and the policy is financed through an income tax, one can compare the MVPF of the policy to an MVPF of 1.3 for an income tax change. One can also think more broadly about other ways to raise revenue that do not change income tax policy. For example, if one treats individuals paying the gas tax and wind PTC beneficiaries as having similar social welfare weights, the comparison of the 5.87 for wind PTCs to the 0.67 for gas taxes suggests every $1 of government revenue raised from a gas tax and spent on wind PTCs generates $5.20 (=5.87-0.67) in benefits to individuals in society. Such a calculation avoids making any assumption about the MCF of changes in the income tax code.[102] When choosing between a wide menu of spending and revenue raising policies, MVPFs can be used to compare the welfare consequences of those various policy options.

9 Conclusion

What policies are most effective in addressing climate change? We conduct a comprehensive assessment of policies that have been rigorously evaluated using experimental and quasi-experimental methods. We draw three main lessons: First, subsidies for investments that directly displace the dirty production of electricity, such as production tax credits for wind power and subsidies for residential solar panels, have higher MVPFs (generally exceeding 3), than all other subsidies in our sample (with MVPFs generally around 1). Second, nudges to reduce energy consumption have large MVPFs, with values above 5, when targeted to regions of the US with a dirty electric grid. By contrast, nudges targeted toward areas with cleaner grids such as California and the Northeast have substantially smaller MVPFs (often below 1). Third, fuel taxes and cap-and-trade policies are highly efficient means of raising revenue (with MVPFs below 0.7) due to the presence of large environmental externalities. In addition to these lessons, we also note that some of the highest MVPFs in our sample are international subsidies. These policies can produce high returns, even when only considering benefits to US residents and the incidence on US taxpayers. We note that such policies appear to have highly variable returns and the incidence on climate damages on the US government remains uncertain. Nonetheless, the math suggests these types of policies have the potential to unlock large welfare gains to the residents of those countries, US residents, and US taxpayers.

Methodologically, our approach integrates learning-by-doing externalities directly into our welfare analysis, allowing us to quantify the potential size of those effects. This allows us to go beyond the typical qualitative treatment of learning-by-doing effects in welfare analysis. We

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[102] This is potentially useful in practice because a key conclusion of recent work in public economics is that the MCF varies depending on where in the income distribution revenue is raised (Kleven & Kreiner 2006, Hendren 2020).

find, for example, that the desirability of wind subsidies is modestly amplified by learning-by-doing effects, while the desirability of residential solar policies (and to some extent EV subsides) depends heavily on the potential for learning-by-doing spillovers. It is worth noting that our framework and new sufficient statistics result could also be applied to think about subsidies for relatively newer technologies such as carbon capture.

We use the MVPF approach to assess the desirability of policy changes and contrast our method with the more common cost per ton of CO_2 measures used in the literature. We argue that our key lessons would have been difficult to glean from an approach that relied on a cost per ton metric. This is not merely due to the fact that different papers tend to use different definitions of "cost" when reporting this metric. Even when using a harmonized measure – either resource, government, or social costs – these cost per ton approaches fall short of delivering the welfare conclusions provided by the MVPF framework. This is because these definitions fail to fully account for inframarginal benefits, the opportunity cost of inframarginal transfers, non-CO_2 benefits, or the relationship between products and policies.

We can also use the MVPF framework to examine whether historical environmental policy in the US has prioritized spending in areas with high returns. Here, we examine changes in policy focus over time by comparing the allocation of funds under the American Recovery and Reinvestment Act (ARRA) of 2009 with the allocation of funds under the Inflation Reduction Act (IRA) of 2022. The ARRA spent 3 times more on clean energy than on energy efficiency. By contrast, the IRA spent 9.4 times more on clean energy than energy efficiency. This represents a substantial relative reallocation, with far greater focus on spending in categories with higher MVPFs.[103] It is important to note, however, we also see a reallocation over time toward greater relative spending on EV subsidies, an area with comparatively lower returns. IRA funding on EVs exceeded its direct funding for clean energy while the ARRA spending on EVs was less than half its spending on clean energy.

We also believe the MVPF approach is valuable because it facilitates comparisons across policy domains. We can compare, for example, the MVPFs constructed herein to MVPFs for other major areas of spending and other common revenue raisers. The high MVPF values we find for spending on renewable energy generation exceeds the MVPFs found for many areas of spending on US adults documented in (Hendren & Sprung-Keyser 2020) and the Policy Impacts Library[104]. The values rival, but are slightly less than, the MVPFs for spending on health and education for low income children. By comparison, the MVPFs of climate-focused revenue raisers are far below the MVPFs of other common revenue raisers such as increasing tax rates or increasing tax enforcement (Boning et al. 2023). This suggests that climate policy

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[103] Details of this calculation can be found in Appendix J. We draw our estimates of ARRA spending from CEA (2016) and our estimates of the IRA from Della Vigna et al. (2023) and PWBM (2023). We show how these estimates vary using ex-ante versus ex-post budget scores. We also show how they vary with assumptions such as allocation of advanced manufacturing funds. Our basic conclusions regarding the relative allocation of clean energy and energy efficiency are not impacted by this allocation. 2022 projections regarding IRA budget expenditures on EVs were far below current estimates.

[104] www.policyimpacts.org/policy-impacts-library/

may be a particularly efficient means of raising revenue.

We believe that that the MVPF framework and the valuation methods used herein can serve as a useful tool for the analysis of climate policy. All of our code is available on GitHub. We hope this serves as an aid to researchers constructing their own MVPFs in future policy analysis.

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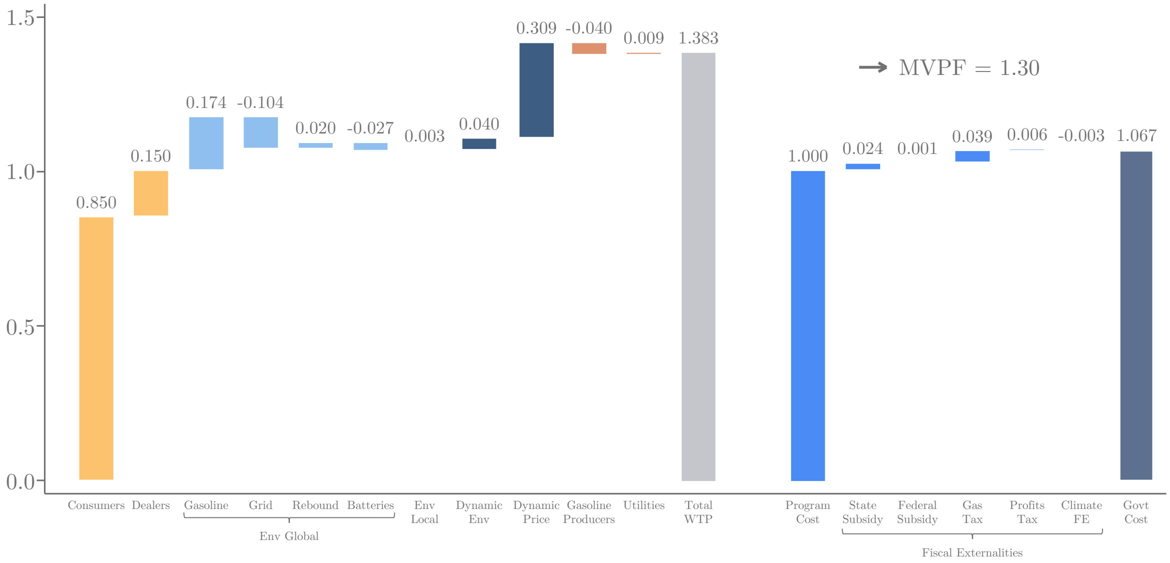
Ziegler, M. S. & Trancik, J. E. (2021), 'Re-examining rates of lithium-ion battery technology improvement and cost decline', *Energy amp; Environmental Science* **14**(4), 1635–1651.

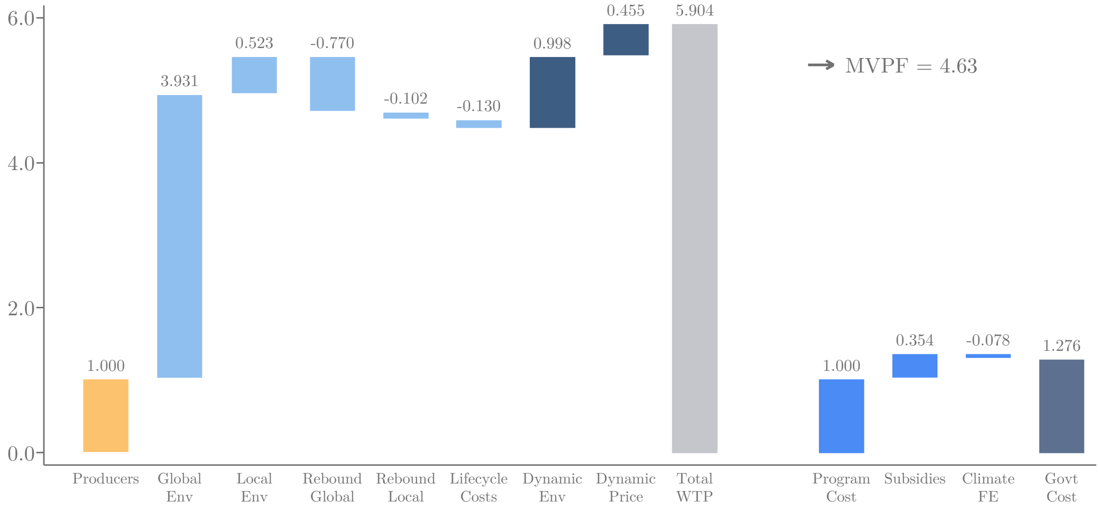
FIGURE 1: Electric Vehicle Subsidy
Baseline Estimates from Muehlegger and Rapson (2022)



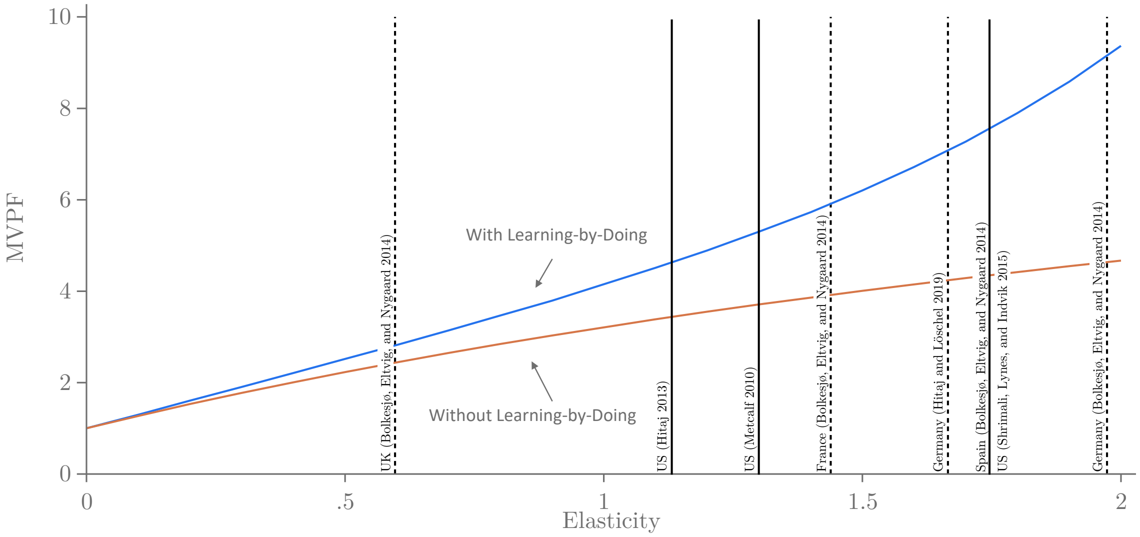
Notes: This figure presents the components of willingness to pay and net government cost for the EV subsidies in the California Enhanced Modernization Program (CEFMP) using the -2.1 price elasticity estimated in Muehlegger & Rapson (2022). We present estimates for our baseline specification that envisions a change to the federal 2020 subsidy. Each component is normalized relative to \$1 of mechanical cost of the policy change. The first two bars show how this transfer is passed through to consumers and car dealers. The next three bars report the environmental externalities, including the global (GHG) externalities, local (e.g. $PM_{2.5}$) externalities, and rebound effects from higher prices in the electricity market. The next two bars report learning-by-doing externalities from both future environmental benefits (DE) and lower prices (DP) using the approach in Theorem 1 and Appendix B. The last two columns report impacts on producer profits due to markups in the oil/gasoline and utility sectors. The Cost components start with the mechanical cost of the \$1 subsidy, then add the impact of the behavioral response on the cost of state and federal subsidies using national average subsidies in 2020, followed by the impact on changes in revenue from the gas tax and corporate profits taxes on oil/gasoline producers and utilities. Lastly, the climate FE term captures future tax revenue due to the impact of lower emissions today on future productivity. All numbers are calculated using our baseline path for the social cost of carbon (\$193 in 2020) and a 2% discount rate.

FIGURE 2: Utility-Scale Wind Subsidies & Production Tax Credits

A. Baseline Estimates from Hitaj (2013)



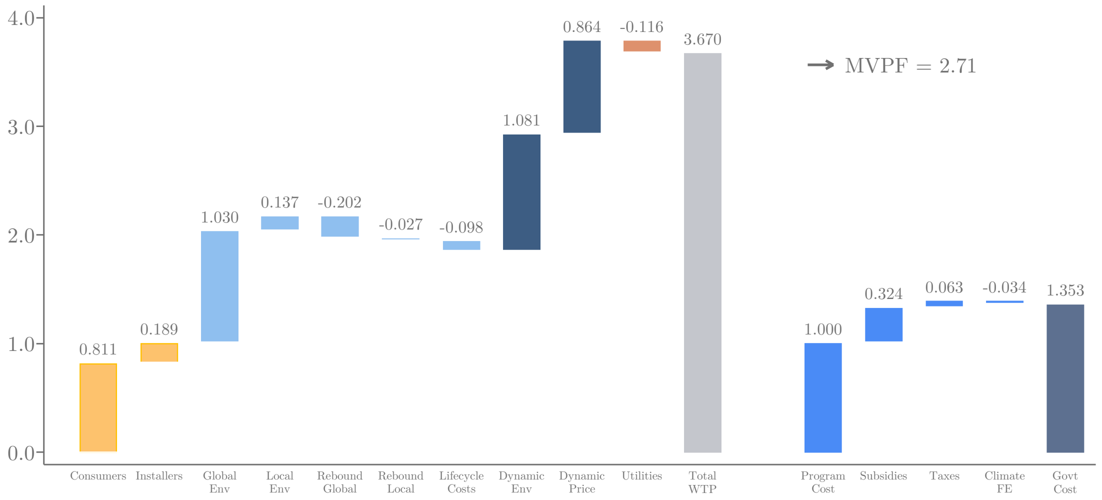
B. Baseline MVPFs by Price Elasticity



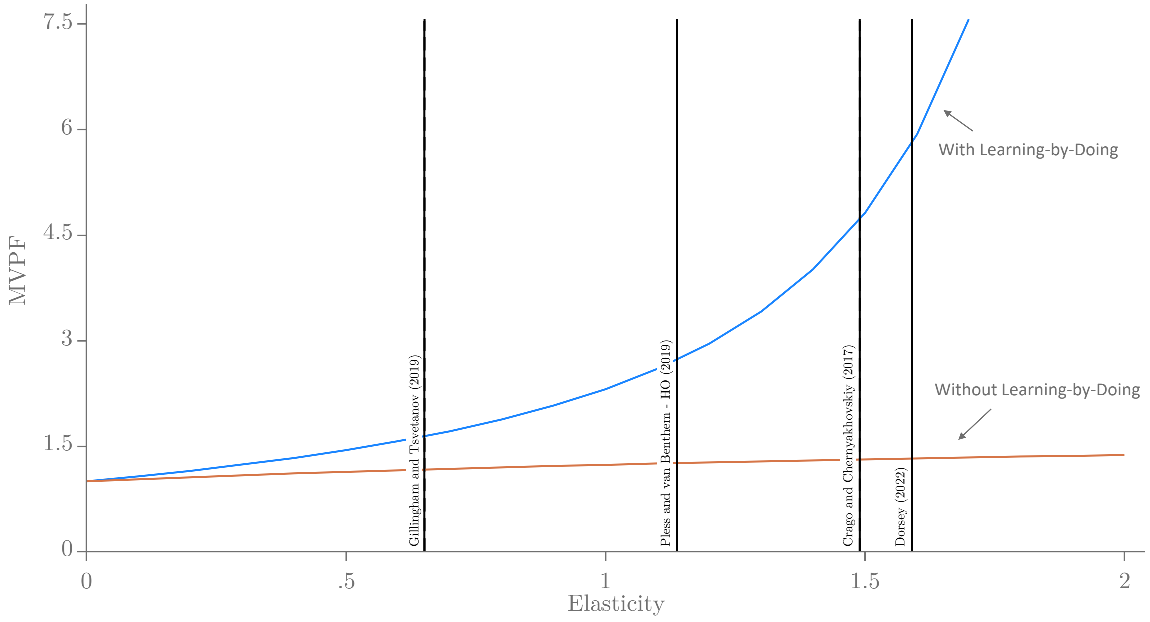
Notes: This figure illustrates the MVPF measurement for wind subsidies. Panel A shows the WTP and Cost components for the baseline specification for the wind production tax credit using a supply elasticity of 1.4 estimated in Hitaj (2013). The WTP components consist of the transfer (yellow), environmental externality (light blue), and learning by doing effects (dark blue). The subsidy cost is calculated using the wind PTC in 2020 of $0.015 per KWh. Panel B shows how the MVPF varies with the elasticity of wind turbine installation with respect to the price paid to suppliers for wind energy. We place solid vertical lines at the US estimates of the elasticities in our main sample and dotted vertical lines for international estimates in our extended sample. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

FIGURE 3: Residential Solar Subsidies

A. Baseline Estimates from Pless and Van Bentham (2019)

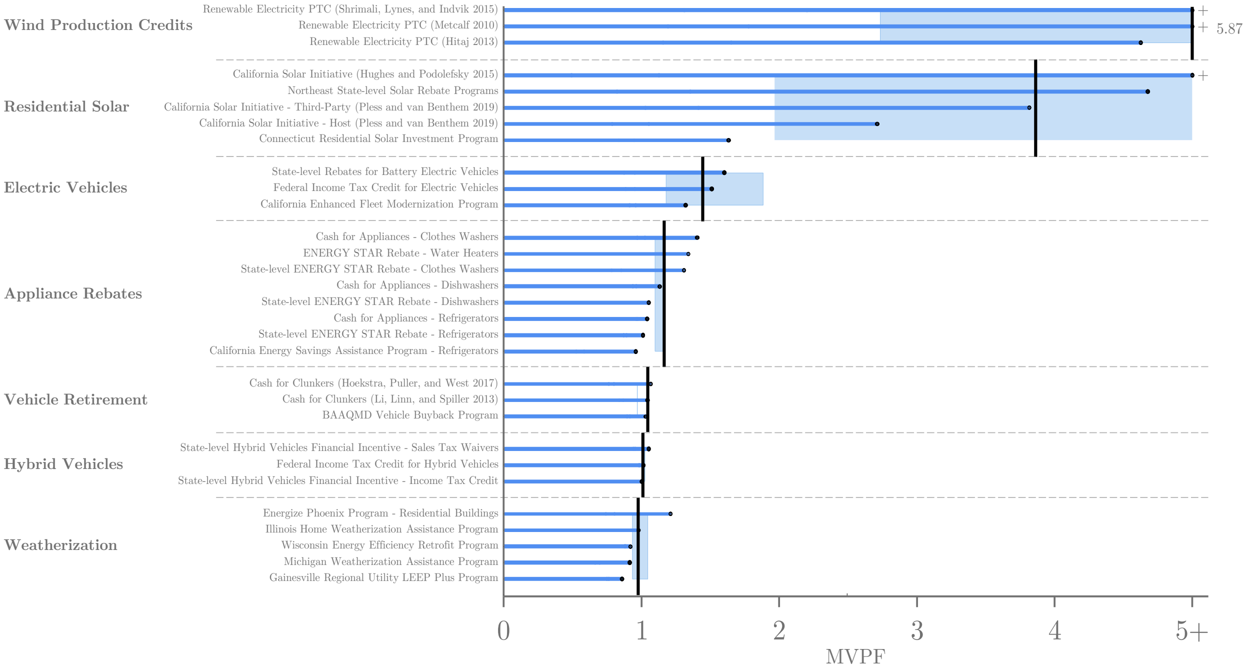


B. Baseline MVPFs by Price Elasticity



Notes: This figure illustrates the MVPF measurement for residential solar subsidies. Panel A shows the WTP and Cost components for our baseline specification for the California Solar Initiative using a demand elasticity of -1.14 estimated in Pless & van Benthem (2019). The WTP components consists of the transfer (yellow), environmental externality (light blue), learning by doing effects (dark blue), and utility profit loss (orange). The subsidy cost is calculated using the 26% investment tax credit for residential solar installations. Panel B shows how the MVPF varies with the elasticity of demand for residential solar panel capacity with respect to the price of residential solar panels. The MVPF with learning by doing is not shown above 7.5 for illustrative purposes. The solid lines represent the estimates of the elasticity in our sample. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

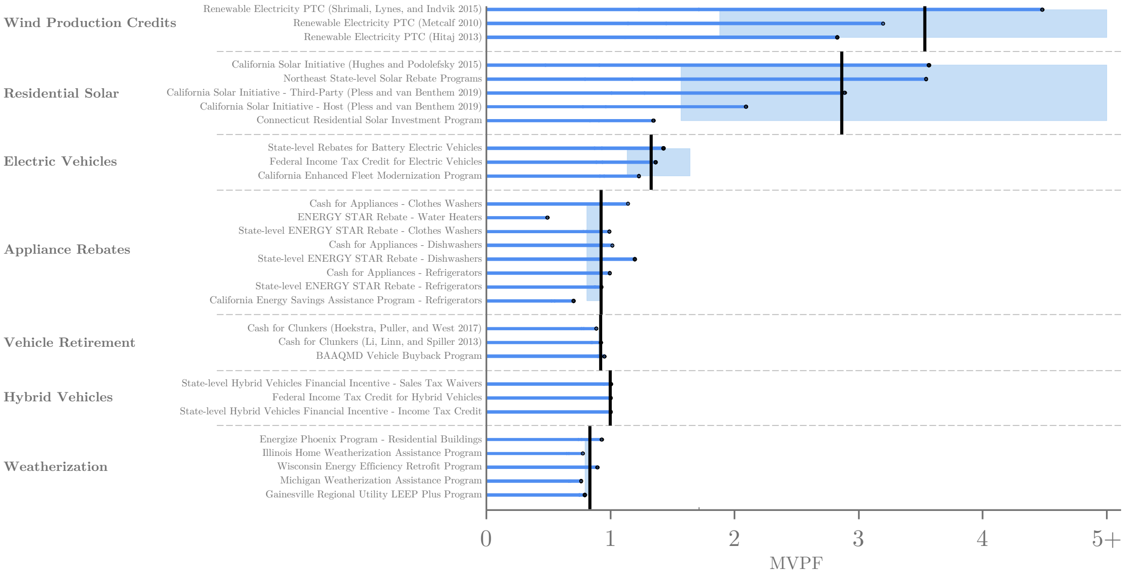
FIGURE 4: Baseline MVPFs for Subsidies



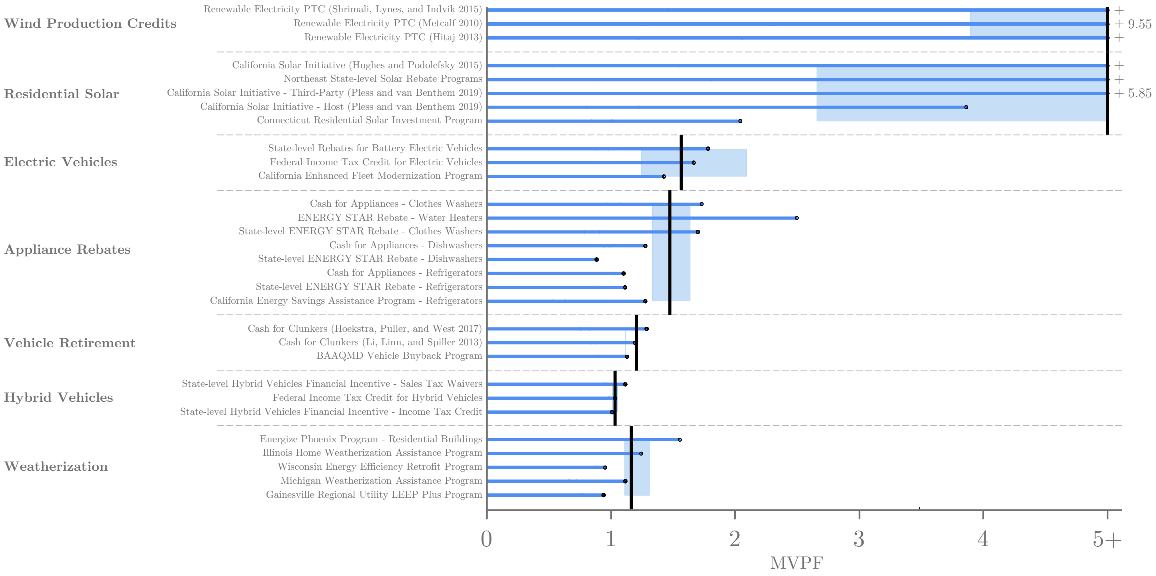
Notes: This figure shows the 2020 baseline MVPF estimates for all categorized subsidy policies in our main sample. We cap estimates at 5 with + signs indicating MVPFs above 5. The category average (shown by the black vertical lines) reports the MVPF associated with a conceptual experiment where $1 in initial program cost is split equally across each policy in the category, so that we take the average willingness to pay relative to the average net government cost within each category. The blue shading presents bootstrapped 95% confidence intervals for each category average MVPF, restricting to underlying estimates for which we have sampling uncertainty. See Appendix Table 3 for comparisons of the category averages on this subsample. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

FIGURE 5: Baseline MVPFs of Subsides using Alternative Social Costs of Carbon

A. $76 Social Cost of Carbon

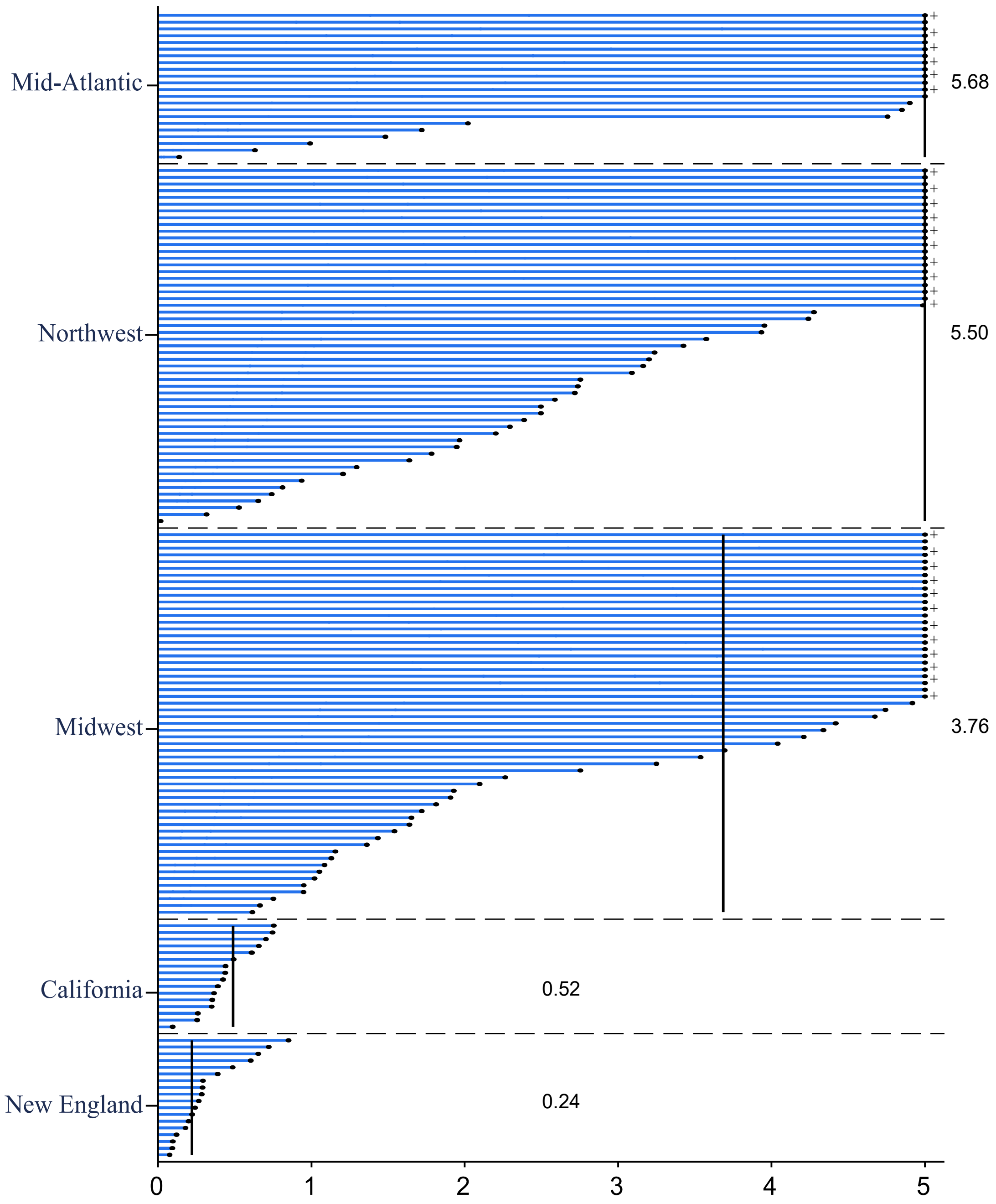


B. $337 Social Cost of Carbon



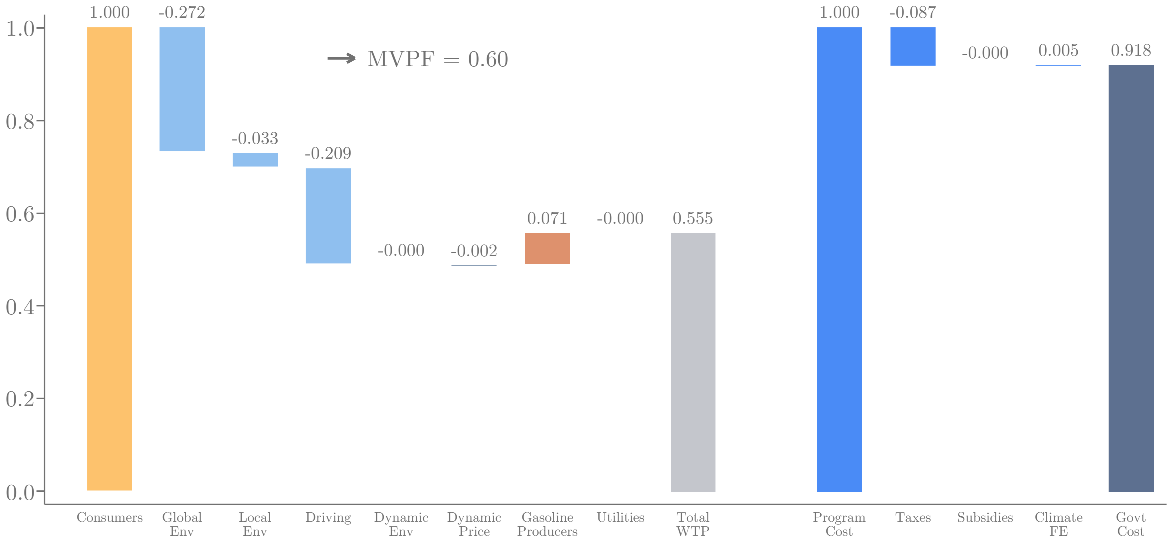
Notes: Panel A and B repeat Figure 4 using an alternative time path for the SCC corresponding to values of $76 and $337 in 2020 along with discount rates of 2.5% and 1.5%, respectively. Estimates are censored at 5.

FIGURE 6: Baseline MVPF of Home Energy Reports



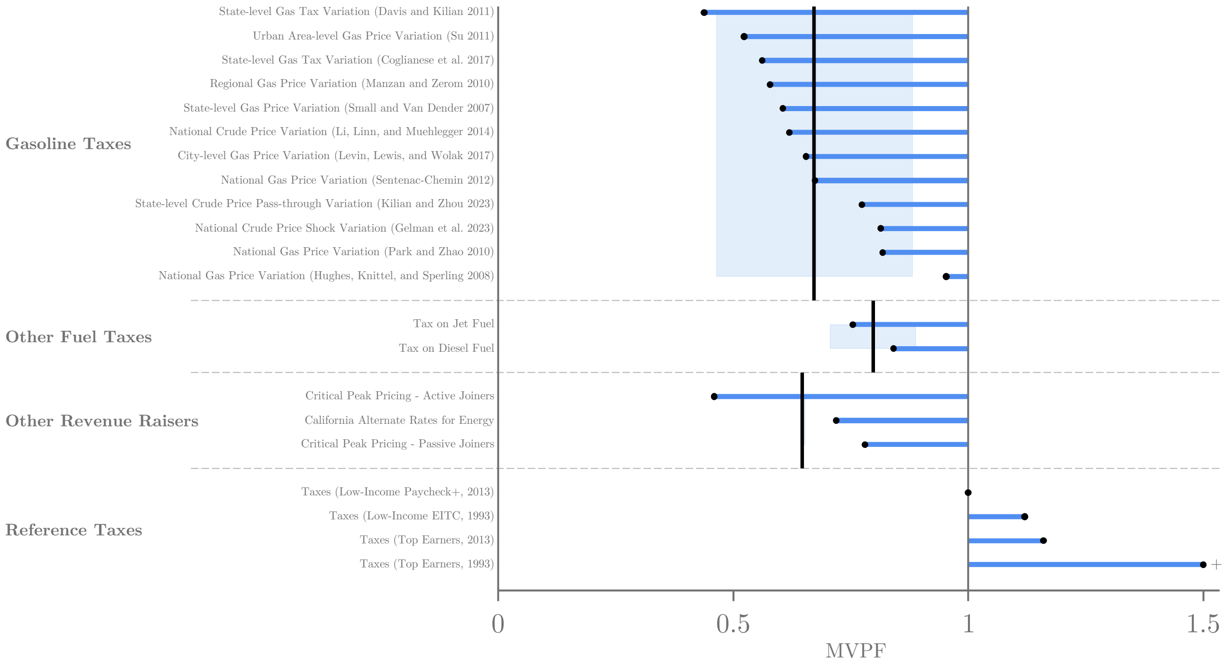
Notes: This figure illustrates the MVPF estimates for Opower Home Energy Reports split across the 5 AVERT model's electricity regions for which the experiments have been conducted. The benefits per dollar of government cost equal the environmental benefits minus the loss in utility profits. MVPFs above five are censored and the category averages are written to the right of each category. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

FIGURE 7: MVPF of a Gasoline Tax
Baseline Estimates from Small & Van Dender (2007)



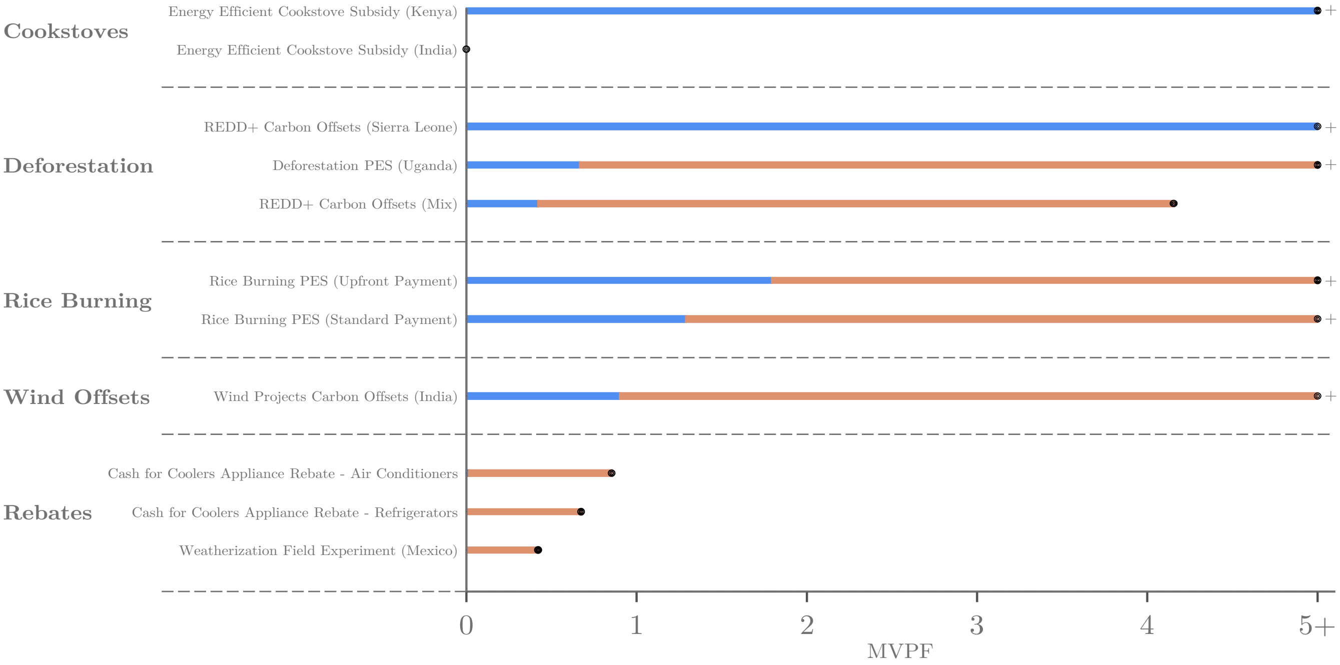
Notes: This figure presents the components of the baseline MVPF for the gasoline tax using a gasoline price elasticity of -0.334 from Small & Van Dender (2007). The WTP components include the transfer cost (yellow), global greenhouse gas benefits and local environmental externalities arising from accidents, congestion, and local pollutants (light blue), learning by doing benefits from increased EV purchases (bars not visible), and gasoline/electricity producer profits (orange). The tax cost arises from the impact of the response to the tax on gas tax revenue using the 2020 tax of $0.46 per gallon. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

FIGURE 8: Baseline MVPFs of Revenue Raisers



Notes: This figure illustrates the MVPF for revenue raisers in our sample. Note that the MVPF measures the welfare cost per dollar of revenue raised (or, equivalently, the welfare gain per dollar of net expenditures on tax cuts). We illustrate each MVPF relative to the MVPF of a non-distortionary lump sum tax of 1. The black lines are the category averages and the blue regions indicate the 95% confidence intervals computed via bootstrap. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

FIGURE 9: Baseline MVPFs of International Policies



Notes: This figure illustrates the 2020 baseline MVPF estimates for US spending on international policies. The denominator is net cost to the US government and the numerator is the sum of US and non-US WTP for the subsidy. We cap estimates at 5 with + signs indicating MVPFs above 5. The blue bars represent the MVPF only including US beneficiaries and the orange bars illustrate how the MVPF increases if one includes benefits to non-US residents. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

Table 1: All Policies in Our Sample

Panel A. Subsidies		**Short Label**	**Year**	**Geography**	**Source**
Wind Production Credits					
Renewable Electricity PTC (Shrimali, Lynes, and Indvik 2015)		PTC (Shrimali)	2011		Shrimali, Lynes, and Indvik (2015)
Renewable Electricity PTC (Metcalf 2010)		PTC (Metcalf)	2007		Metcalf (2010)
Renewable Electricity PTC (Hitaj 2013)		PTC (Hitaj)	2007		Hitaj (2013)
Feed-in Tariff - Germany (Bolkesjø, Eltvig, and Nygaard 2014)	*	FIT (Germany - BEN)		Germany	Bolkesjø, Eltvig, and Nygaard (2014)
Feed-in Tariff - Spain	*	FIT (Spain)		Spain	Bolkesjø, Eltvig, and Nygaard (2014)
Feed-in Tariff - Germany (Hitaj and Löschel 2019)	*	FIT (Germany - HL)		Germany	Hitaj and Löschel (2019)
Feed-in Tariff - France	*	FIT (France)		France	Bolkesjø, Eltvig, and Nygaard (2014)
Feed-in Tariff - United Kingdom	*	FIT (UK)		United Kingdom	Bolkesjø, Eltvig, and Nygaard (2014)
Feed-in Tariff - European Union	*	FIT (EU)		European Union	Nicolini and Tavoni (2017)
Residential Solar					
California Solar Initiative (Hughes and Podolefsky 2015)		CSI	2012	CA	Hughes and Podolefsky (2015)
Northeast State-level Solar Rebate Programs		NE Solar	2012	Multiple States	Crago and Chernyakhovskiy (2017)
California Solar Initiative - Third-Party (Pless and van Benthem 2019)		CSI (TPO)	2013	CA	Pless and van Benthem (2019)
California Solar Initiative - Host (Pless and van Benthem 2019)		CSI (HO)	2013	CA	Pless and van Benthem (2019)
Connecticut Residential Solar Investment Program		CT Solar	2014	CT	Gillingham and Tsvetanov (2019)
Solar Investment Tax Credit	*	ITC	2014		Dorsey (2022)
Electric Vehicles					
State-level Rebates for Battery Electric Vehicles		BEV (State - Rebate)	2011–2014	Multiple States	Clinton and Steinberg (2019)
Federal Income Tax Credit for Electric Vehicles		ITC (EV)	2011–2013		Li et al. (2017)
California Enhanced Fleet Modernization Program		EFMP	2015–2018	CA	Muehlegger and Rapson (2022)
State-level Income Tax Credits for Battery Electric Vehicles	*	BEV (State - ITC)	2011–2014	Multiple States	Clinton and Steinberg (2019)
Appliance Rebates					
Cash for Appliances - Clothes Washers		C4A (CW)	2010		Houde and Aldy (2017)
ENERGY STAR Rebate - Water Heaters		ES (WH)	2012		Allcott and Sweeney (2017)
State-level ENERGY STAR Rebate - Clothes Washers		ES (CW)	2006		Datta and Gulati (2014)
Cash for Appliances - Dishwashers		C4A (DW)	2010		Houde and Aldy (2017)
State-level ENERGY STAR Rebate - Dishwashers		ES (DW)	2006		Datta and Gulati (2014)
Cash for Appliances - Refrigerators		C4A (Fridge)	2010		Houde and Aldy (2017)
State-level ENERGY STAR Rebate - Refrigerators		ES (Fridge)	2006		Datta and Gulati (2014)
California Energy Savings Assistance Program - Refrigerators		CA ESA	2009	CA	Blonz (2023)
Vehicle Retirement					
Cash for Clunkers (Hoekstra, Puller, and West 2017)		C4C (TX)	2009		Hoekstra, Puller, and West (2017)
Cash for Clunkers (Li, Linn, and Spiller 2013)		C4C (US)	2009		Li, Linn, and Spiller (2013)
BAAQMD Vehicle Buyback Program		BAAQMD	2010	CA	Sandler (2012)
Hybrid Vehicles					
State-level Hybrid Vehicles Financial Incentive - Sales Tax Waivers		HY (S-STW)	2001–2006	Multiple States	Gallagher and Muehlegger (2011)
Federal Income Tax Credit for Hybrid Vehicles		HY (F-ITC)	2006	Multiple States	Beresteanu and Li (2011)
State-level Hybrid Vehicles Financial Incentive - Income Tax Credit		HY (S-ITC)	2000–2006	Multiple States	Gallagher and Muehlegger (2011)

Weatherization					
Energize Phoenix Program - Residential Buildings		EPP	2010	AZ	Liang et al. (2018)
Illinois Home Weatherization Assistance Program		IHWAP	2018	IL	Christensen, Francisco, and Myers (2023)
Wisconsin Energy Efficiency Retrofit Program		WI RF	2013	WI	Allcott and Greenstone (2024)
Michigan Weatherization Assistance Program		WAP	2011	MI	Fowlie, Greenstone, and Wolfram (2018)
Gainesville Regional Utility LEEP Plus Program		LEEP+	2012	FL	Hancevic and Sandoval (2022)
Other Subsidies					
California 20/20 Electricity Rebate Program		CA 20/20	2005	CA	Ito (2015)
USDA Conservation Reserve Program		CRP	2020		Aspelund and Russo (2024)
Panel B. Nudges and Marketing					
Home Energy Reports					
Home Energy Reports (17 RCTs)		HER (17 RCTs)	2009		Allcott (2011)
Opower Electricity Program Evaluations (166 RCTs)		Opower Elec. (166 RCTs)	2012		
Peak Energy Reports		PER	2014	CA	Brandon, List, and Metcalfe 2018
Opower Natural Gas Program Evaluations (52 RCTs)		Opower Nat. Gas (52 RCTs)	2012		
Other Nudges					
Energize CT Home Energy Solutions Program Energy Audit		Audit Nudge	2013		Gillingham and Tsvetanov (2018)
Solarize Connecticut		Solarize	2012	CT	Gillingham and Bollinger (2021)
ENERGY STAR Rebate - Water Heaters (w/ Sales Agent Incentive)		ES (WH) + Nudge	2012		Allcott and Sweeney (2017)
Illinois Home Weatherization Assistance Program (High Bonus)		IHWAP + Nudge (H)	2018	IL	Christensen, Francisco, and Myers (2023)
Illinois Home Weatherization Assistance Program (Low Bonus)		IHWAP + Nudge (L)	2018	IL	Christensen, Francisco, and Myers (2023)
Michigan Weatherization Assistance Program (Marketing)		WAP + Nudge	2011	MI	Fowlie, Greenstone, and Wolfram (2018)
Carbon Footprint Food Label Field Experiment	*	Food Labels	2020	United Kingdom	Lohmann et al. (2022)
Panel C. Revenue Raisers					
Gasoline Taxes					
State-level Gas Tax Variation (Davis and Kilian 2011)		Gas (DK)	2008		Davis and Kilian (2011)
Urban Area-level Gas Price Variation (Su 2011)		Gas (Su)	2001		Su (2011)
State-level Gas Tax Variation (Coglianese et al. 2017)		Gas (Coglianese)	2008		Coglianese et al. (2017)
Regional Gas Price Variation (Manzan and Zerom 2010)		Gas (Manzan)	1994		Manzan and Zerom (2010)
State-level Gas Price Variation (Small and Van Dender 2007)		Gas (Small)	2001		Small and Van Dender (2007)
National Crude Price Variation (Li, Linn, and Muehlegger 2014)		Gas (Li)	2008		Li, Linn, and Muehlegger (2014)
City-level Gas Price Variation (Levin, Lewis, and Wolak 2017)		Gas (Levin)	2009		Levin, Lewis, and Wolak (2017)
National Gas Price Variation (Sentenac-Chemin 2012)		Gas (Sentenac-Chemin)	2005		Sentenac-Chemin (2012)
State-level Crude Price Pass-through Variation (Kilian and Zhou 2023)		Gas (Kilian)	2022		Kilian and Zhou (2023)
National Crude Price Shock Variation (Gelman et al. 2023)		Gas (Gelman)	2016		Gelman et al. (2023)
National Gas Price Variation (Park and Zhao 2010)		Gas (Park)	2008		Park and Zhao (2010)
National Gas Price Variation (Hughes, Knittel, and Sperling 2008)		Gas (Hughes)	2006		Hughes, Knittel, and Sperling (2008)
Almost Ideal Demand System (West and Williams 2007)	*	Gas (West)	1998		West and Williams (2007)
Quadratic Almost Ideal Demand System (Tiezzi and Verde 2016)	*	Gas (Tiezzi)	2010		Tiezzi and Verde (2016)
Multimarket Simulation Model (Bento et al. 2009)	*	Gas (Bento)	2002		Bento et al. (2009)
National Gas Price Variation (Hughes, Knittel, and Sperling 2008)	*	Gas (Hughes - Ext)	1990		Hughes, Knittel, and Sperling (2008)
State-level Crude Price Pass-through Variation (Kilian and Zhou 2023)	*	Gas (Kilian - Ext)	2014		Kilian and Zhou (2023)
State-level Gas Price Variation (Small and Van Dender 2007)	*	Gas (Small - Ext)	2001		Small and Van Dender (2007)

Other Fuel Taxes					
Tax on Jet Fuel		Jet Fuel	2013		Fukui and Miyoshi (2017)
Tax on Diesel Fuel		Diesel	2006		Dahl (2012)
Tax on Heavy Fuel Oil	*	Heavy Fuel	2004		Mundaca, Strand, and Young (2021)
Windfall Profit Tax on Crude Oil	*	Crude (WPT)	1985		Rao (2018)
State-level Crude Oil Taxes	*	Crude (State)	2015		Brown, Maniloff, and Manning (2020)
Tax on E85 (Flex Fuel)	*	E85	2006		Anderson (2012)
Other Revenue Raisers					
Critical Peak Pricing - Active Joiners		CPP (AJ)	2020		Fowlie et al. (2021)
California Alternate Rates for Energy		CARE	2014	CA	Hahn and Metcalfe (2021)
Critical Peak Pricing - Passive Joiners		CPP (PJ)	2020		Fowlie et al. (2021)
Cap and Trade					
Regional Greenhouse Gas Initiative		RGGI	2008–2018	Multiple States	Chan and Morrow (2019)
California Cap-and-Trade Program		CA CT	2012–2017	CA	Hernandez-Cortes and Meng (2023)
EU Emissions Trading System (Bayer and Aklin)	*	ETS (BA)	2008–2016	European Union	Bayer and Aklin (2020)
EU Emissions Trading System (Colmer et al. 2024)	*	ETS (CMMW)	2005–2012	European Union	Colmer et al. (2024)
Panel D. International					
Cookstoves					
Energy Efficient Cookstove Subsidy (Kenya)		Cookstove (Kenya)	2019	Kenya	Berkouwer and Dean (2022)
Energy Efficient Cookstove Subsidy (India)		Cookstove (India)	2020	India	Hanna, Duflo, and Greenstone (2016)
Deforestation					
REDD+ Carbon Offsets (Sierra Leone)		REDD+ (SL)	2014	Sierra Leone	Malan et al. (2024)
Deforestation PES (Uganda)		Deforest (Uganda)	2012	Uganda	Jayachandran et al. (2017)
REDD+ Carbon Offsets (Mix)		REDD+	2020	Multiple Countries	West et al. (2023)
Deforestation PES (Mexico)	*	Deforest (Mexico)	2021	Mexico	Izquierdo-Tort, Jayachandran, and Saavedra (2024)
Rice Burning					
Rice Burning PES (Upfront Payment)		India PES (Upfront)	2020	India	Jack et al. (2023)
Rice Burning PES (Standard Payment)		India PES (Standard)	2020	India	Jack et al. (2023)
Wind Offset					
Wind Projects Carbon Offsets (India)		Offset (India)	2010	India	Calel et al. (2021)
International Rebates					
Cash for Coolers Appliance Rebate - Air Conditioners		Fridge (Mexico)	2009	Mexico	Davis, Fuchs, and Gertler (2014)
Cash for Coolers Appliance Rebate - Refrigerators		AC (Mexico)	2009	Mexico	Davis, Fuchs, and Gertler (2014)
Weatherization Field Experiment (Mexico)		WAP (Mexico)	2016	Mexico	Davis, Martinez, and Taboada (2020)
International Nudges					
Home Energy Reports - Qatar	*	Nudge (Qatar)	2018	Qatar	Al-Ubaydli et al. (2023)
Home Energy Reports - Germany	*	Nudge (Germany)	2014	Germany	Andor et al. (2020)
Panel E. Regulation					
CAFE Standards					
CAFE Standards (Leard and McConnell 2017)		CAFE (LM)			Leard and McConnell (2017)
CAFE (Anderson and Sallee 2011)		CAFE (AS)			Anderson and Sallee (2011)
CAFE (Jacobsen 2013)		CAFE (J)			Jacobsen (2013)
Renewable Portfolio Standards					
Renewable Portfolio Standards		RPS			Greenstone and Nath (2020)

Notes: This table lists each policy included in our sample. We provide the name of the policy, its short label name used in the subsequent tables, the year(s) the policy was implemented (corresponding to our "in-context" year(s)), the location where the policy was implemented, and the academic paper(s) used to construct the causal effect of the policy. We denote policies excluded from our primary sample by "*", which we refer to as our "extended sample."

Table 2: Baseline MVPF Components

	Willingness to Pay								Cost				
		Environmental Benefits			Learning by Doing					Fiscal Externalities			
Panel A. Subsidies	**Transfer**	**Global**	**Local**	**Rebound**	**Env.**	**Price**	**Profits**	**WTP**	**Program**	**Initial**	**Climate**	**Total**	**MVPF**
Wind Production Credits	**1.000**	**4.678**	**0.643**	**-1.074**	**1.900**	**0.645**		**7.793**	**1.000**	**0.435**	**-0.108**	**1.328**	**5.870**
PTC (Shrimali)	1.000	5.865	0.806	-1.346	3.277	0.920		10.522	1.000	0.546	-0.152	1.394	7.547
PTC (Metcalf)	1.000	4.368	0.601	-1.002	1.427	0.560		6.953	1.000	0.407	-0.094	1.312	5.298
PTC (Hitaj)	1.000	3.801	0.523	-0.872	0.998	0.455		5.904	1.000	0.354	-0.078	1.276	4.626
FIT (Germany - BEN) *	1.000	6.629	0.911	-1.521	4.841	1.170		13.030	1.000	0.617	-0.193	1.424	9.148
FIT (Spain) *	1.000	5.866	0.806	-1.346	3.277	0.920		10.522	1.000	0.546	-0.152	1.394	7.547
FIT (Germany - HL) *	1.000	5.596	0.769	-1.284	2.844	0.844		9.768	1.000	0.521	-0.140	1.381	7.072
FIT (France) *	1.000	4.837	0.665	-1.110	1.877	0.658		7.926	1.000	0.450	-0.110	1.340	5.913
FIT (UK) *	1.000	2.006	0.276	-0.460	0.223	0.199		3.243	1.000	0.187	-0.035	1.151	2.817
FIT (EU) *	1.000	0.546	0.075	-0.125	0.016	0.050		1.561	1.000	0.051	-0.009	1.042	1.498
Residential Solar	**1.106**	**1.718**	**0.252**	**-0.421**	**2.280**	**1.636**	**-0.214**	**6.356**	**1.000**	**0.714**	**-0.068**	**1.646**	**3.862**
CSI	1.000	4.299	0.631	-1.054	4.988	3.987	-0.535	13.316	1.000	1.787	-0.157	2.630	5.063
NE Solar	1.000	1.220	0.179	-0.299	3.132	1.610	-0.152	6.690	1.000	0.507	-0.076	1.431	4.676
CSI (TPO)	1.528	1.604	0.235	-0.393	1.982	1.371	-0.200	6.128	1.000	0.667	-0.061	1.606	3.815
CSI (HO)	1.000	0.932	0.137	-0.228	1.081	0.864	-0.116	3.670	1.000	0.387	-0.034	1.353	2.712
CT Solar	1.000	0.533	0.078	-0.131	0.216	0.346	-0.066	1.976	1.000	0.222	-0.012	1.209	1.634
ITC *	1.000	1.152	0.169	-0.282	3.825	1.944	-0.143	7.664	1.000	0.531	-0.088	1.443	5.312
Electric Vehicles	**1.000**	**0.057**	**0.000**	**0.032**	**0.073**	**0.452**	**-0.043**	**1.571**	**1.000**	**0.092**	**-0.004**	**1.087**	**1.445**
BEV (State - Rebate)	1.000	0.068	0.000	0.038	0.103	0.564	-0.051	1.722	1.000	0.108	-0.006	1.103	1.561
ITC (EV)	1.000	0.061	0.000	0.034	0.078	0.482	-0.046	1.609	1.000	0.097	-0.005	1.092	1.474
EFMP	1.000	0.042	0.000	0.023	0.040	0.309	-0.031	1.383	1.000	0.070	-0.003	1.067	1.296
BEV (State - ITC) *	1.000	-0.048	0.000	-0.027	0.000	0.000	0.036	0.961	1.000	-0.076	0.003	0.927	1.037
Appliance Rebates	**0.867**	**0.497**	**0.043**	**-0.089**			**-0.103**	**1.215**	**1.000**	**0.052**	**-0.009**	**1.044**	**1.164**
C4A (CW)	0.952	0.550	0.083	-0.124			-0.039	1.423	1.000	0.021	-0.009	1.012	1.405
ES (WH)	0.598	1.707	0.000	-0.201			-0.659	1.445	1.000	0.112	-0.033	1.078	1.340
ES (CW)	1.000	0.861	0.126	-0.193			-0.072	1.722	1.000	0.328	-0.014	1.315	1.310
C4A (DW)	0.929	0.243	0.037	-0.055			-0.017	1.138	1.000	0.009	-0.004	1.005	1.132
ES (DW)	1.000	-0.223	-0.033	0.050			0.019	0.813	1.000	-0.231	0.003	0.772	1.053
C4A (Fridge)	0.960	0.099	0.015	-0.022			-0.007	1.044	1.000	0.004	-0.002	1.002	1.042
ES (Fridge)	1.000	0.199	0.029	-0.045			-0.017	1.167	1.000	0.157	-0.003	1.154	1.011
CA ESA	0.500	0.541	0.083	-0.122			-0.034	0.968	1.000	0.018	-0.008	1.010	0.958
Vehicle Retirement	**0.910**	**0.280**	**0.102**	**-0.137**			**-0.049**	**1.106**	**1.000**	**0.060**	**-0.004**	**1.056**	**1.047**
C4C (TX)	1.000	0.410	0.030	-0.208			-0.074	1.157	1.000	0.091	-0.006	1.084	1.067
C4C (US)	1.000	0.271	0.020	-0.140			-0.049	1.102	1.000	0.060	-0.004	1.055	1.044
BAAQMD	0.730	0.161	0.255	-0.062			-0.025	1.059	1.000	0.031	-0.003	1.028	1.030

Hybrid Vehicles	**1.000**	**0.031**	**0.003**	**-0.026**	**0.000**	**0.014**	**-0.006**	**1.016**	**1.000**	**0.005**	**-0.001**	**1.004**	**1.012**
HY (S-STW)	1.000	0.070	0.007	-0.059	0.001	0.031	-0.014	1.036	1.000	0.010	-0.002	1.008	1.028
HY (F-ITC)	1.000	0.020	0.002	-0.017	0.000	0.009	-0.004	1.010	1.000	0.003	0.000	1.002	1.008
HY (S-ITC)	1.000	0.004	0.000	-0.004	0.000	0.002	-0.001	1.002	1.000	0.001	0.000	1.001	1.002
Weatherization	**0.774**	**0.297**	**0.029**	**-0.057**			**-0.054**	**0.989**	**1.000**	**0.017**	**-0.005**	**1.012**	**0.978**
EPP	0.750	0.593	0.083	-0.133			-0.057	1.237	1.000	0.031	-0.009	1.022	1.210
IHWAP	0.750	0.404	0.019	-0.064			-0.111	0.999	1.000	0.025	-0.007	1.019	0.980
WI RF	0.870	0.052	0.011	-0.012			-0.001	0.920	1.000	0.001	-0.001	1.000	0.920
WAP	0.750	0.297	0.013	-0.045			-0.088	0.927	1.000	0.018	-0.005	1.013	0.915
LEEP+	0.750	0.138	0.019	-0.031			-0.013	0.864	1.000	0.007	-0.002	1.005	0.859
Other Subsidies	**0.887**	**1.504**	**0.424**	**-0.234**			**-0.065**	**2.517**	**1.000**	**0.036**	**-0.025**	**1.010**	**2.492**
CA 20/20	0.882	2.090	0.297	-0.468			-0.131	2.671	1.000	0.071	-0.033	1.038	2.572
CRP	0.893	0.919	0.552	0.000			0.000	2.363	1.000	0.000	-0.018	0.982	2.407
Panel B. Nudges and Marketing													
Home Energy Reports													
HER (17 RCTs)	0.000	3.872	0.439	-0.844			-0.244	3.222	1.000	0.133	-0.061	1.072	3.006
Opower Elec. (166 RCTs)	0.000	3.246	0.368	-0.708			-0.205	2.701	1.000	0.111	-0.051	1.060	2.548
PER	0.000	0.230	0.064	0.000			0.695	0.989	1.000	-0.378	-0.004	0.618	1.600
Opower Nat. Gas (52 RCTs)	0.000	0.950	0.000	-0.112			-0.367	0.472	1.000	0.062	-0.016	1.046	0.451
Other Nudges	**0.507**	**4.799**	**0.613**	**-1.061**			**-0.659**	**4.199**	**1.000**	**2.243**	**-0.076**	**3.167**	**1.326**
Audit Nudge	0.000	8.678	1.333	-1.961			-0.542	7.507	1.000	2.683	-0.136	3.547	2.117
Solarize	1.145	15.001	2.200	-3.678			-1.844	12.824	1.000	6.320	-0.230	7.091	1.809
ES (WH) + Nudge	0.416	1.630	0.000	-0.192			-0.629	1.225	1.000	0.107	-0.032	1.075	1.140
IHWAP + Nudge (H)	0.739	0.517	0.019	-0.085			-0.105	1.085	1.000	0.023	-0.008	1.015	1.069
IHWAP + Nudge (L)	0.743	0.500	0.018	-0.082			-0.101	1.078	1.000	0.022	-0.008	1.014	1.062
WAP + Nudge	0.000	2.467	0.107	-0.371			-0.732	1.471	1.000	4.300	-0.041	5.259	0.280
Food Labels *	0.000	6.170	0.000	0.000			0.000	6.170	1.000	0.000	-0.120	0.880	7.015
Panel C. Revenue Raisers													
Gasoline Taxes	**1.000**	**-0.167**	**-0.149**		**0.000**	**-0.001**	**0.044**	**0.726**	**1.000**	**-0.054**	**0.003**	**0.950**	**0.765**
Gas (DK)	1.000	-0.274	-0.244		0.000	-0.001	0.071	0.553	1.000	-0.088	0.005	0.918	0.602
Gas (Su)	1.000	-0.236	-0.210		0.000	-0.001	0.062	0.614	1.000	-0.076	0.005	0.929	0.661
Gas (Coglianese)	1.000	-0.219	-0.195		0.000	-0.001	0.057	0.642	1.000	-0.070	0.004	0.934	0.687
Gas (Manzan)	1.000	-0.211	-0.188		0.000	-0.001	0.055	0.655	1.000	-0.068	0.004	0.936	0.699
Gas (Small)	1.000	-0.199	-0.177		0.000	-0.001	0.052	0.675	1.000	-0.064	0.004	0.940	0.718
Gas (Li)	1.000	-0.192	-0.171		0.000	-0.001	0.050	0.686	1.000	-0.062	0.004	0.942	0.728
Gas (Levin)	1.000	-0.175	-0.156		0.000	-0.001	0.046	0.713	1.000	-0.056	0.003	0.947	0.753
Gas (Sentenac-Chemin)	1.000	-0.166	-0.148		0.000	-0.001	0.044	0.727	1.000	-0.053	0.003	0.950	0.766
Gas (Kilian)	1.000	-0.117	-0.105		0.000	-0.001	0.031	0.807	1.000	-0.038	0.002	0.964	0.837
Gas (Gelman)	1.000	-0.097	-0.087		0.000	-0.001	0.025	0.840	1.000	-0.031	0.002	0.971	0.865
Gas (Park)	1.000	-0.095	-0.085		0.000	-0.001	0.025	0.843	1.000	-0.031	0.002	0.971	0.868
Gas (Hughes)	1.000	-0.025	-0.022		0.000	-0.001	0.006	0.958	1.000	-0.008	0.000	0.992	0.966

Gas (West) *	1.000	-0.272	-0.242		0.000	-0.001	0.071	0.555	1.000	-0.087	0.005	0.918	0.604
Gas (Tiezzi) *	1.000	-0.259	-0.230		0.000	-0.001	0.068	0.577	1.000	-0.083	0.005	0.922	0.626
Gas (Bento) *	1.000	-0.208	-0.185		0.000	-0.001	0.054	0.659	1.000	-0.067	0.004	0.937	0.704
Gas (Hughes - Ext) *	1.000	-0.199	-0.177		0.000	-0.001	0.052	0.674	1.000	-0.064	0.004	0.940	0.717
Gas (Kilian - Ext) *	1.000	-0.187	-0.166		0.000	-0.001	0.049	0.694	1.000	-0.060	0.004	0.944	0.736
Gas (Small - Ext) *	1.000	-0.039	-0.035		0.000	-0.001	0.010	0.934	1.000	-0.013	0.001	0.988	0.946
Other Fuel Taxes	**1.000**	**-0.185**	**-0.066**				**0.025**	**0.774**	**1.000**	**-0.033**	**0.004**	**0.970**	**0.798**
Jet Fuel	1.000	-0.310	-0.003				0.036	0.722	1.000	-0.048	0.006	0.958	0.754
Diesel	1.000	-0.059	-0.129				0.015	0.827	1.000	-0.019	0.001	0.982	0.842
Heavy Fuel *	1.000	-0.075	-0.001				0.007	0.931	1.000	-0.002	0.001	1.000	0.931
Crude (WPT) *	1.000	0.000	0.000				0.000	1.000	1.000	-0.002	0.000	0.998	1.002
Crude (State) *	1.000	-0.075	0.000				0.000	0.925	1.000	-0.364	0.001	0.637	1.451
E85 *	1.000	0.562	0.009				0.411	1.982	1.000	-0.361	0.011	0.650	3.051
Other Revenue Raisers	**0.979**	**-0.150**	**-0.014**	**0.012**			**-0.108**	**0.719**	**1.000**	**0.109**	**0.003**	**1.112**	**0.647**
CPP (AJ)	1.000	-0.107	-0.030	0.000			-0.323	0.540	1.000	0.176	0.002	1.178	0.459
CARE	0.936	-0.303	0.000	0.036			0.117	0.785	1.000	0.086	0.006	1.092	0.719
CPP (PJ)	1.000	-0.039	-0.011	0.000			-0.119	0.831	1.000	0.065	0.001	1.065	0.780
Cap and Trade													
RGGI	1.000	-0.657	-0.989					-0.646	1.000	-0.050	0.013	0.963	-0.671
CA CT	1.000	-0.061	-0.002					0.937	1.000	-0.006	0.001	0.996	0.941
ETS (BA) *	1.000	-9.192	0.000					-8.192	1.000	-0.900	0.180	0.280	-29.287
ETS (CMMW) *	1.000	-1.279	0.000					-0.279	1.000	-0.125	0.025	0.900	-0.310
Panel D. International													
Cookstoves													
Cookstove (Kenya)	7.656	43.161	0.000					50.817	1.000	0.000	-0.843	0.157	323.453
Cookstove (India)	0.545	-2.956	0.000					-2.410	1.000	0.000	0.058	1.058	-2.279
Deforestation													
REDD+ (SL)	0.000	35.840	0.000					35.840	1.000	0.000	-0.700	0.300	119.438
Deforest (Uganda)	0.421	4.538	0.000					4.959	1.000	0.000	-0.089	0.911	5.441
REDD+	0.965	2.951	0.000					3.916	1.000	0.000	-0.058	0.942	4.156
Deforest (Mexico) *	0.944	0.740	0.000					1.684	1.000	0.000	-0.014	0.986	1.709
Rice Burning													
India PES (Upfront)	0.972	10.642	0.000					11.614	1.000	0.000	-0.208	0.792	14.661
India PES (Standard)	0.915	8.128	0.000					9.043	1.000	0.000	-0.159	0.841	10.749
Wind Offset													
Offset (India)	1.000	9.355	0.000	-1.861				8.495	1.000	0.258	-0.146	1.112	7.641
International Rebates													
Fridge (Mexico)	0.750	0.125	0.000	-0.024				0.850	1.000	0.000	-0.002	0.998	0.852
AC (Mexico)	0.750	-0.094	0.000	0.018				0.675	1.000	0.000	0.001	1.001	0.674
WAP (Mexico)	0.500	-0.096	0.000	0.019				0.422	1.000	0.000	0.002	1.002	0.422

International Nudges													
Nudge (Qatar) *	0.000	7.201	0.000	-1.410				5.791	1.000	0.000	-0.113	0.887	6.529
Nudge (Germany) *	0.000	0.401	0.000	-0.079				0.323	1.000	0.000	-0.006	0.994	0.325

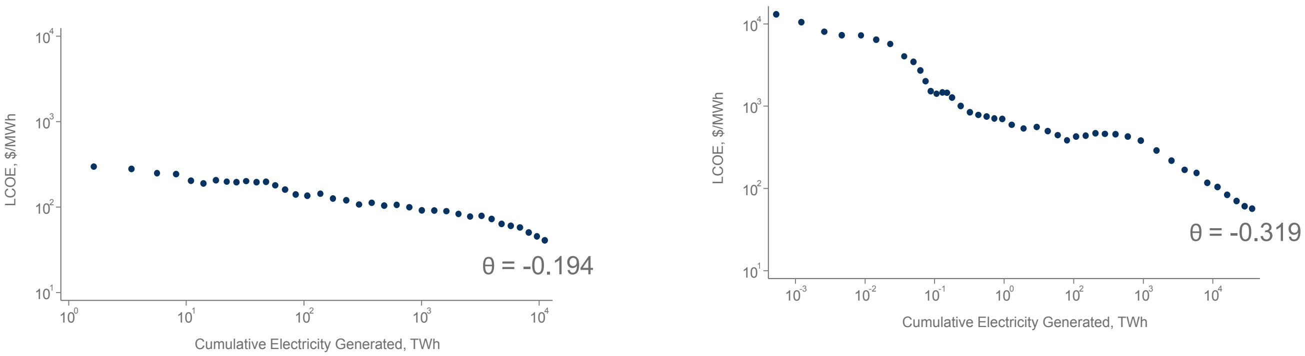
Notes: This table presents the WTP and cost components for each policy in our sample using the baseline specification. Each component is normalized per dollar of mechanical spending on the policy. The first column reports the size of the transfer. The next three columns report the environmental externality including local externalities, global greenhouse gas externalities, and rebound effects (both global and local). The next two columns report learning by doing components for both the environmental benefits and future price reductions. The next column reports impact on profits of oil/gas and utility sectors. The cost components report the mechanical cost, followed by the fiscal externalities (state and federal tax and subsidy impacts), and the climate fiscal externality from the impact of changes in climate on future GDP and thus future tax revenue. We report estimates for each policy in our sample along with category averages for each type of policy. We denote policies excluded from our primary sample by "*", and these policies are not included in our category average measures. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

Table 3: MVPF Versus Cost Per Ton

Panel A. With Learning by Doing	**MVPF**	**Cost Per Ton**		
		Resource	**Government**	**Social**
Subsidies				
Wind Production Credits	5.870	-103	46	-32
Residential Solar	3.862	-77	90	-67
Electric Vehicles	1.445	-458	1,356	-415
Appliance Rebates	1.164	-2	474	111
Vehicle Retirement	1.047	1,008	876	148
Hybrid Vehicles	1.012	577	5,892	-38
Weatherization	0.978	194	779	207
Nudges and Marketing				
Opower Elec. (166 RCTs)	2.548	-41	77	70
Revenue Raisers				
Gasoline Taxes	0.671	-104	-770	-64
Panel B. Without Learning by Doing				
Subsidies				
Wind Production Credits	3.851	-42	69	-8
Residential Solar	1.446	4	237	83
Electric Vehicles	0.961	963	2,422	283
Appliance Rebates	1.164	-2	474	111
Vehicle Retirement	1.047	1,008	876	148
Hybrid Vehicles	0.998	659	6,041	43
Weatherization	0.978	194	779	207
Nudges and Marketing				
Opower Elec. (166 RCTs)	2.548	-41	77	70
Revenue Raisers				
Gasoline Taxes	0.673	-104	-768	-62

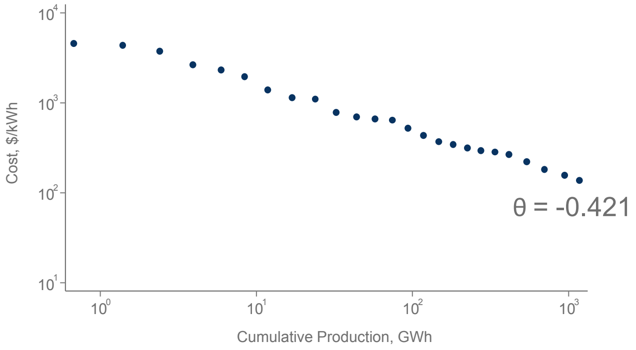
Notes: This table presents estimates of the MVPF and cost per ton measures using our three definitions: resource cost per ton, government cost per ton and social cost per ton. See text for precise definitions of each measure. We present estimates here for each policy category average; the Appendix provides estimates for each policy. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

Appendix Figure 1: Learning by Doing From Way et al. (2022)


A. Wind

B. Solar

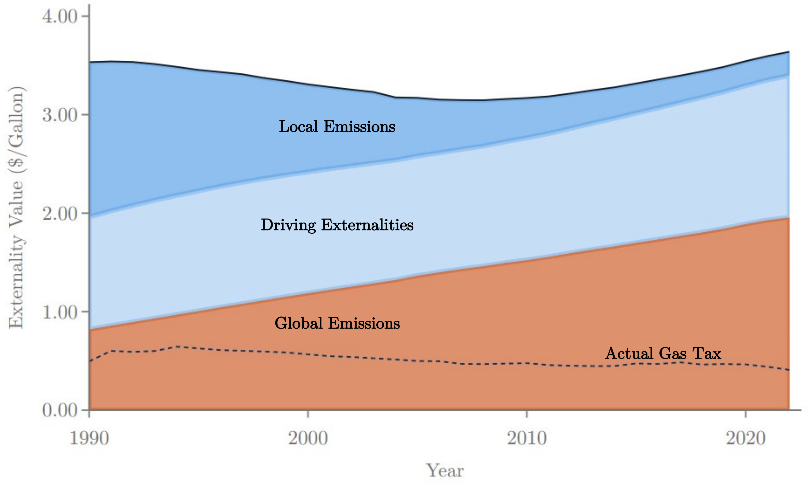
C. Electric Vehicle Batteries



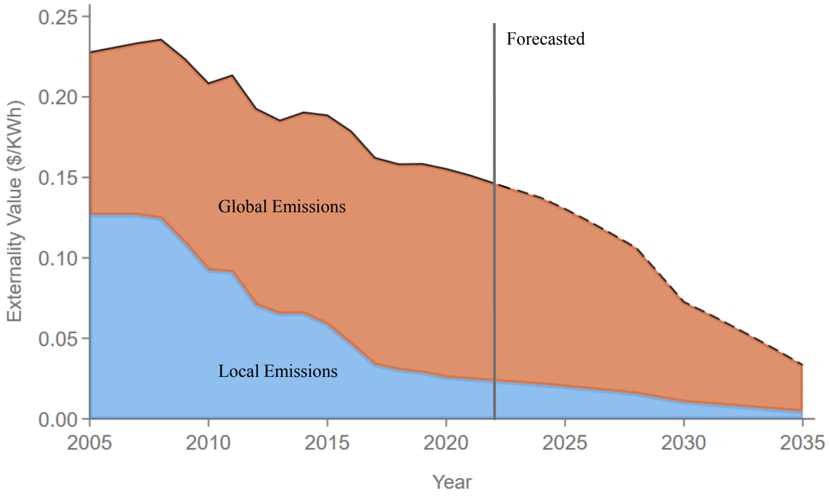
Notes: This figure reproduces estimates from Way et al. (2022) of the price of solar cells, wind energy, and battery storage as a function of cumulative global production. Panel A and B report the levelized cost per MWh of electricty (LCOE) from wind and solar, respectively. Panel C reports the electric vehicle battery cell cost per KWh. We report on each panel the value θ corresponding to the learning elasticity forecast from Way et al. (2022) in each setting, which we feed into our calculations of the benefits generated by learning by doing (DP and DE in Theorem 1).

Appendix Figure 2: Vehicle & Grid Externalities Over Time

A. Vehicle Externalities

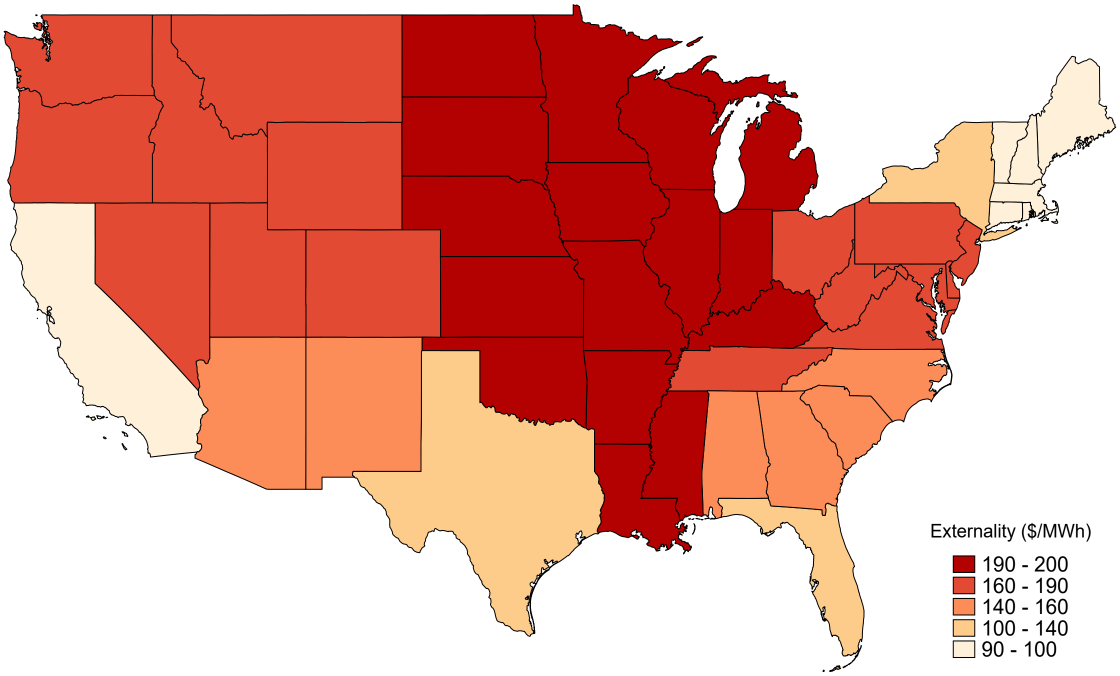


B. Electricity Grid Externalities



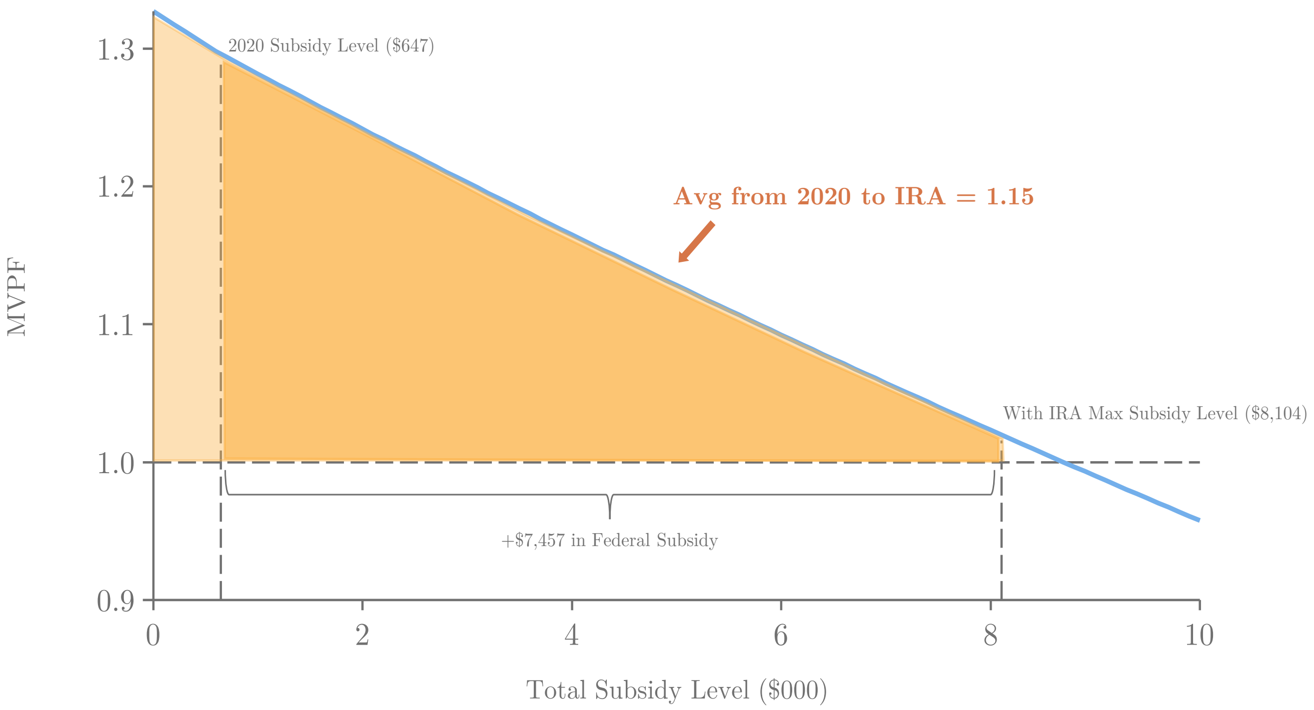
Notes: This figure illustrates the components of the vehicle and grid externalities over time. Panel A reports the dollar value of the vehicle externalities per gallon of gasoline. We split these into local emissions (e.g., NO_X), driving externalities (accidents and congestion), and global emissions $(e.g., CO_2)$. The top line represents the total dollar externality per gallon of gasoline. Panel B shows the change in the externality from 1 KWh of marginal emissions. The environmental externality prior to 2022 is calculated using the US average emissions factors from the EPA's AVERT model combined with our valuations of those pollutants discussed in Section 3. Values after 2022 use emissions information from (Jenkins & Mayfield 2023). All numbers are in 2020 dollars using a our baseline path of the social cost of carbon ($193 SCC in 2020) and a 2% discount rate.

Appendix Figure 3: Environmental Externality per MWh of Electricity Generation in 2020



Notes: This figure illustrates the dollar value of the environmental externality per MWh of electricity in 2020 using emissions rates from EPA's AVERT model separately for each AVERT model region in the US.

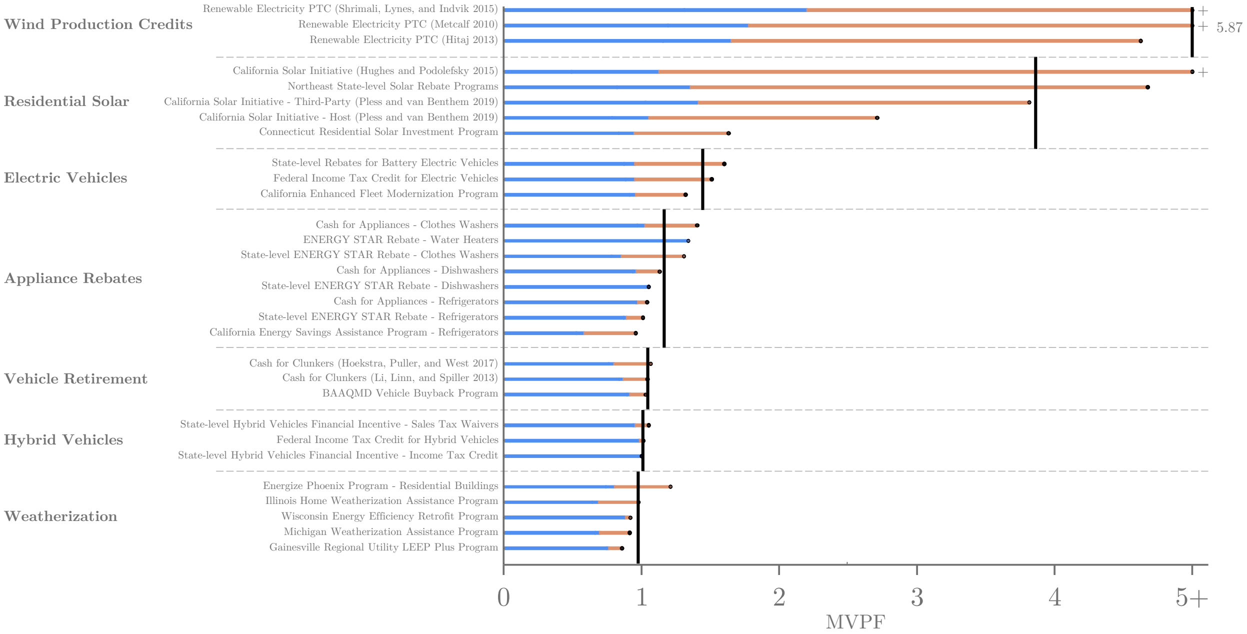
Appendix Figure 4: Electric Vehicles: Non-Marginal (Average) MVPF



Notes: This figure shows how the MVPF varies with the size of electric vehicle subsidies, holding the price elasticity of demand constant at -2.1 from Muehlegger & Rapson (2022). In 2020, the average subsidy value per vehicle, including state and federal subsidies, was $647.25, state subsidies were $604.27, and federal subsidies were $42.98. The IRA raised the federal subsidy amount to $7,500, yielding a combined total subsidy of $8,104.27. Taking an average of the MVPFs between the 2020 subsidy level ($647) and a post-IRA subsidy level ($8,104) yields a "non-marginal" MVPF of 1.15. On average, the additional $7.5K in spending induced by the IRA generated $1.15 in benefits to individuals in the economy per dollar of net government spending.

Appendix Figure 5: Baseline MVPFs

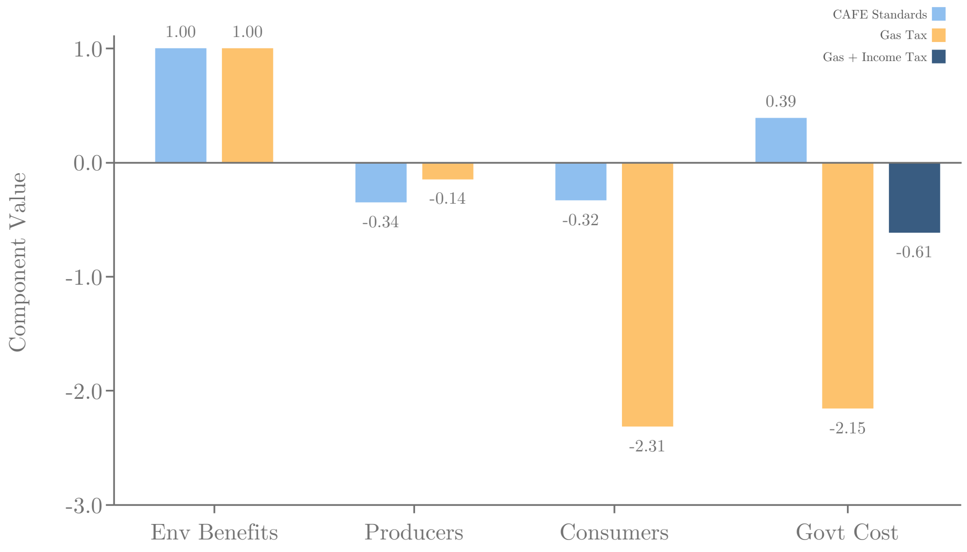
US and Rest of World Split



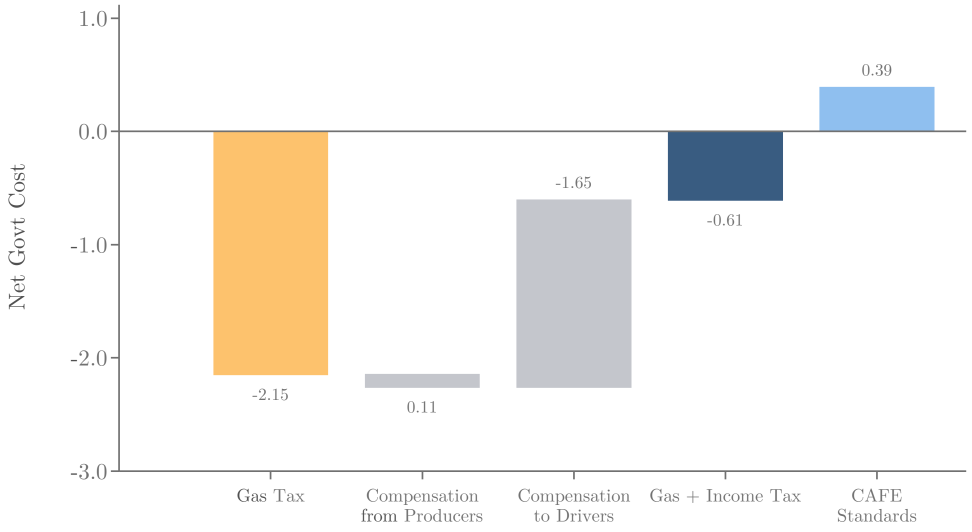
Notes: This figure repeats Figure 4 with blue bars showing the WTP for US beneficiaries and the orange bars show the non-US benefits. We cap estimates at 5 with + signs indicating MVPFs above 5. The category average (shown by the black vertical lines) represents the average WTP for a mechanical $1 transfer and is calculated by averaging the WTP and cost components for each category. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

Appendix Figure 6: CAFE vs. Gasoline + Income Tax

A. CAFE Comparison with Gasoline Tax (Leard & McConnell 2017)

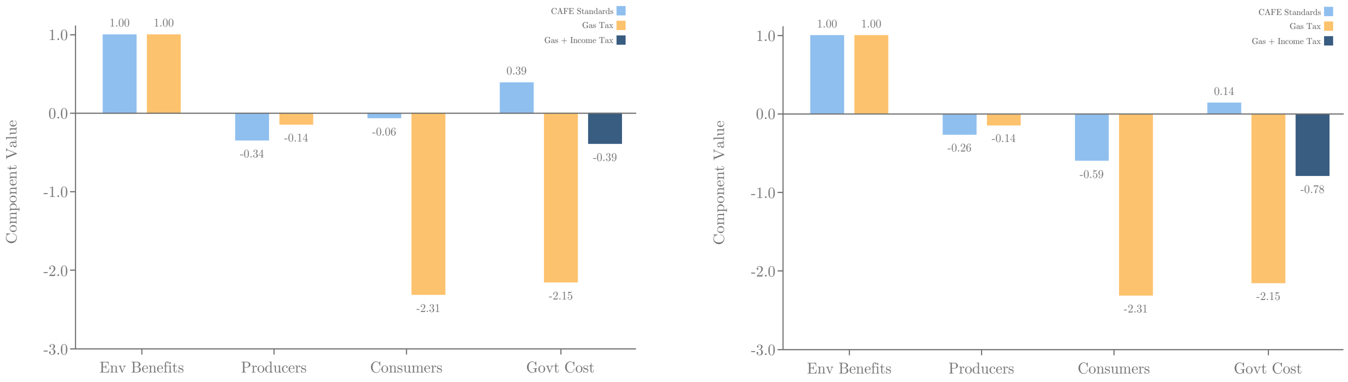


B. Net Government Revenue



Notes: This figure presents a comparison of the welfare impact of changes to the stringency of CAFE regulation to a gasoline tax, using our category average gasoline tax MVPF. Panel A presents the impact of CAFE and a gas tax, each normalized to deliver \$1 of environmental benefits using our baseline SCC of \$193. We present the WTP of producers, consumers and the government for CAFE (in blue) and the gas tax (in orange). In panel B, we consider the government revenue raised from the conceptual experiment of implementing the gas tax and using an income tax to compensate producers and consumers so that they obtain the same net WTP as CAFE. The first column shows the (negative) net cost of the gas tax. The second and third columns consider the cost of compensating producers and consumers (drivers). We use an MVPF for income taxes on producers of 1.8 and an MVPF for income taxes on consumers (drivers) of 1.2. The fourth column presents the net cost to the government of providing the gas and income tax combination that offers similar incidence to CAFE (which is replicated for comparison in the far right bar of Panel A). The fifth column provides the net cost to the government of CAFE.

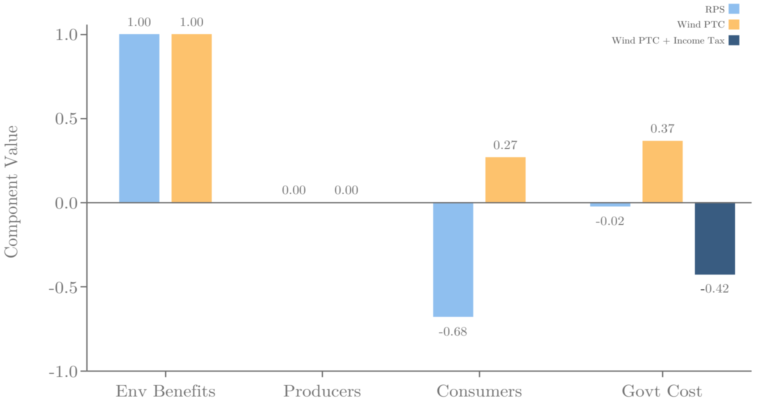
Appendix Figure 7: Additional Regulation Comparisons



A. CAFE Comparison with Gasoline Tax (Anderson & Sallee 2011)

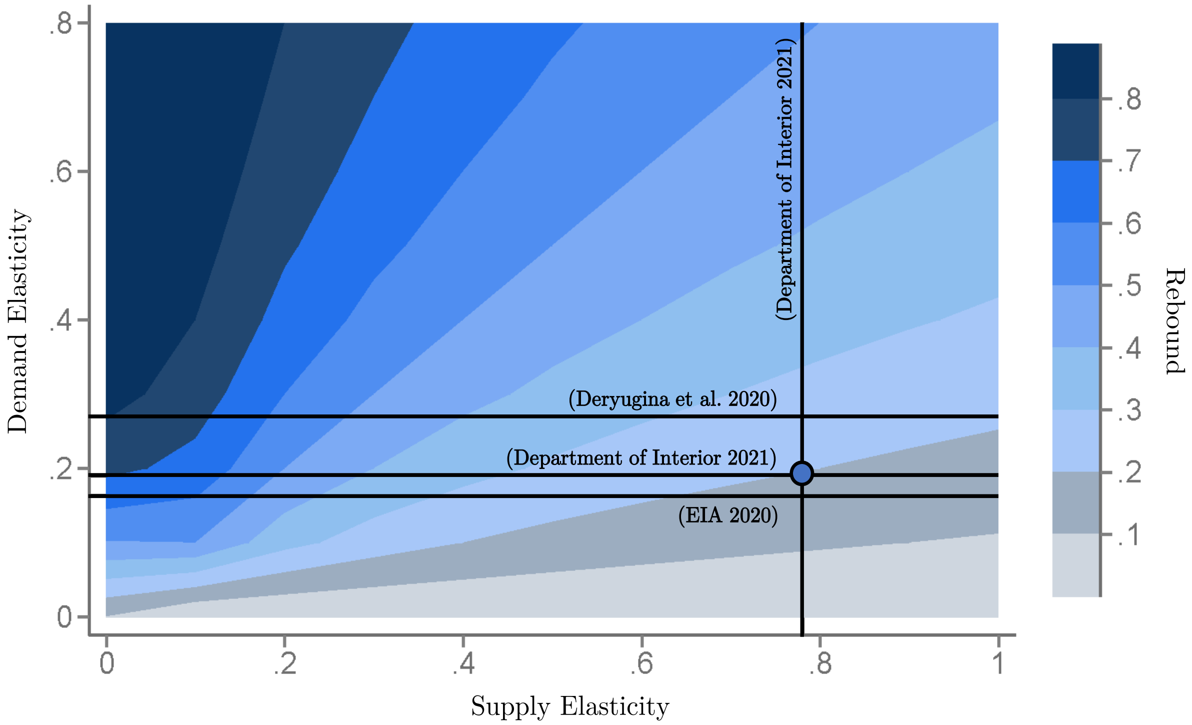
B. CAFE Comparison with Gasoline Tax (Jacobsen 2013a)

C. RPS Comparison with Wind PTC (Greenstone & Nath 2024)



Notes: This figure presents a comparison of the welfare impact of changes in regulation versus taxes. Panel A uses estimates of the impact of CAFE from (Anderson & Sallee 2011); Panel B uses estimates of the impact of CAFE from (Jacobsen 2013*a*); Panel C uses estimates of the impact of Renewable Portfolio Standards (RPS) from (Greenstone & Nath 2024). Panels A and B also present our baseline category average MVPF for gasoline taxes; Panel C presents the baseline category average MVPF for wind PTCs. For both gasoline taxes and wind PTCs, we exclude local benefits and learning by doing effects to align with the type of externalities estimated in the comparison papers studying regulation. The bars present the WTP of producers, consumers and the government for CAFE (in blue) and the gas tax (in orange), normalized to be per $1 of environmental benefits using our baseline $193 SCC model. The far right bar presents the net government cost from the conceptual experiment of replicating the distributional incidence of the regulation using the combination of gas taxes and income taxes (Panels A and B) and wind PTCs and income taxes (Panel C).

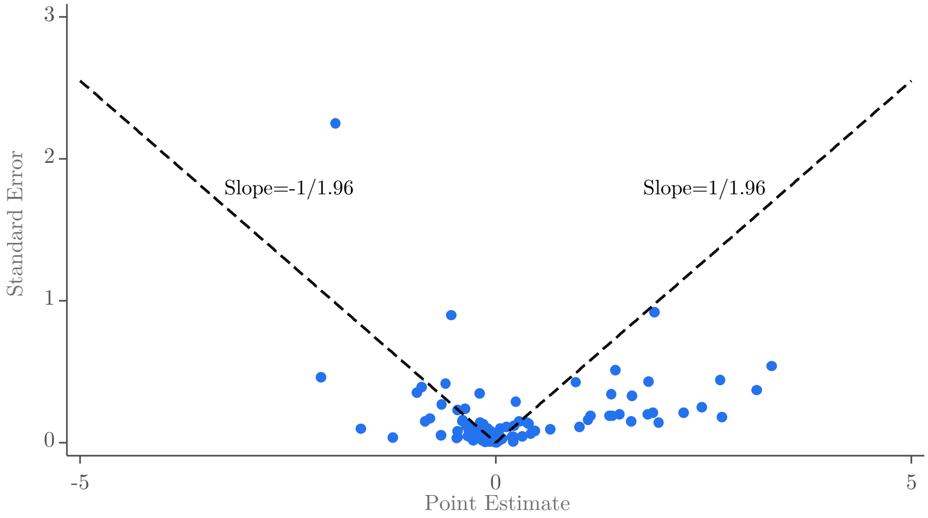
Appendix Figure 8: Electricity Rebound



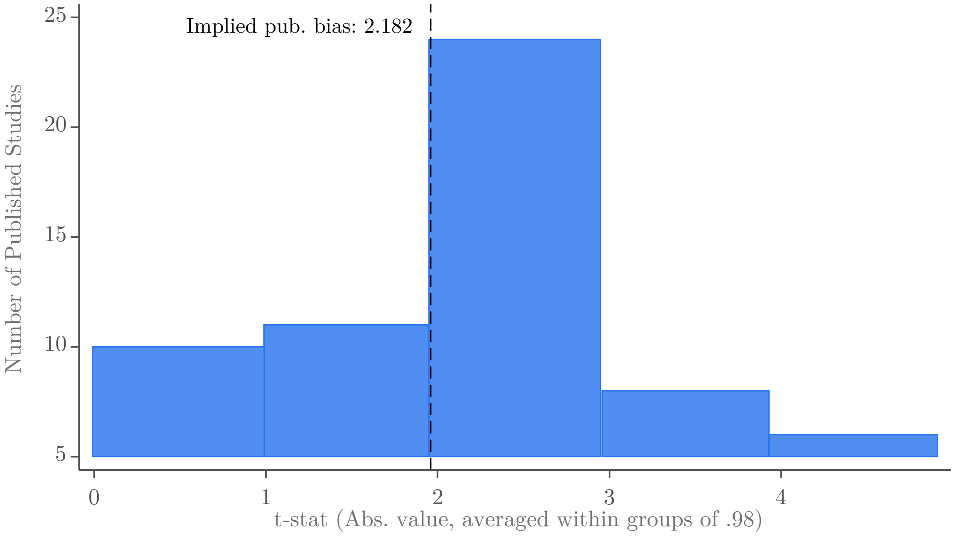
Notes: This figure shows how the electricity rebound effect varies as a function of the demand and supply elasticity. The y-axis represents the absolute value of the price elasticity of demand for electricity and the x-axis is the supply elasticity for electricity. Our baseline estimate of the demand elasticity (-0.19) and supply elasticity (0.78) corresponds to an electricity rebound rate of 19.6%. The baseline demand elasticity is a weighted average of the residential, commercial, and industrial price elasticities and the supply elasticity is a weighted average of the elasticities of each electricity generation source compiled by the Department of Interior for use in their 2021 MarketSim model.

Appendix Figure 9: Evidence of Publication Bias

A. Funnel Plot



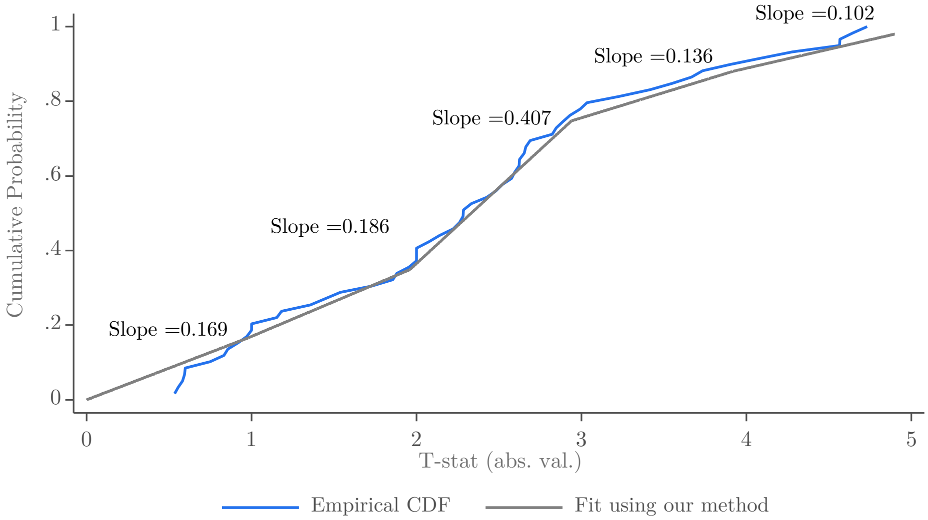
B. Histogram of t-statistics



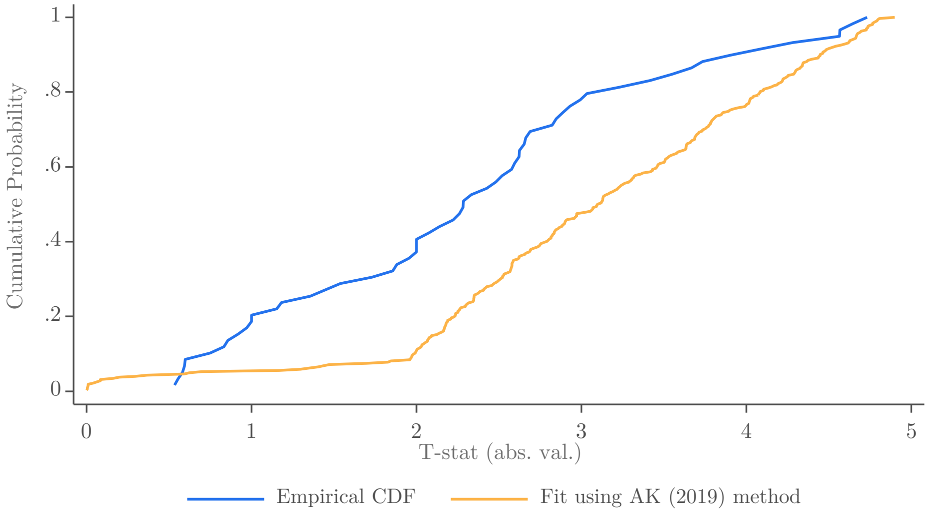
Notes: These figures present tests for publication bias in our baseline sample. Figure A shows a "funnel plot" of the standard errors in our sample against the point estimates in our sample. For ease of visualization, we restrict to point estimates between -5 and 5; this drops 5 estimates, all of which have t-statistics above 1.96. Panel B provides evidence in the form of a histogram of the t-statistics (in absolute value), with bins of width .98 to highlight the threshold around 1.96. We form our estimate of the implied publication bias as the ratio of the number of studies in the first bin above the threshold to that in the first bin below the threshold, which is 2.2. For ease of visualization, we drop t-statistics above 5, of which there are 44 in our sample.

Appendix Figure 10: Model Fits for Estimates of Publication Bias

A. Our Approach

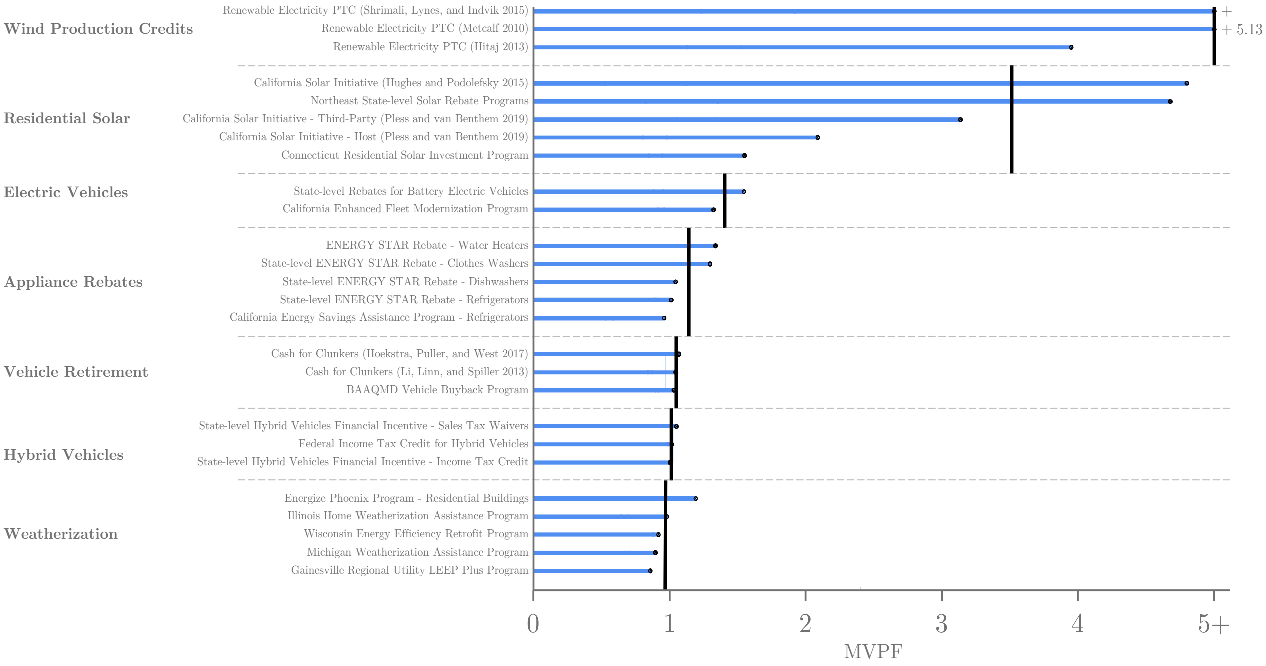


B. Andrews & Kasy (2019) Approach



Notes: These figures present the implied CDF from our estimates of publication bias and estimates using the method in Andrews & Kasy (2019), compared to the empirical CDF of the t-stats in our sample. In each panel, the blue line indicates the empirical CDF. In panel A, the gray line superimposes our estimate, a piecewise linear fit obtained by counting the number of observations in each bin of .98. In panel B, the orange line indicates the implied CDF using the estimates from Andrews & Kasy (2019). In particular, we apply their procedure, yielding estimates for the degree of publication bias, and the mean and standard deviation of the (assumed Gaussian) true distribution of t-stats. We then take 15 *times* the number of observations in our sample draws from a normal with that mean and standard deviation. For each draw, we further draw from a normal with mean at that draw's value and standard deviation of 1 (this reflect a hypothetical study's estimate of the true effect, where here effects are studentized so the variance is 1). This yields a vector of hypothetical estimates. We then keep $\frac{1}{p}$% of the observations that are below 1.96, where p is the estimated publication bias (probability of a significant study being published relative to an insignificant one). As noted in the text, the key conclusion is the superior fit of the method we implement in panel A.

Appendix Figure 11: MVPFs with Publication Bias–Corrected Estimates



Notes: This figure shows the 2020 baseline MVPF estimates for all subsidy policies in our main sample, using publication bias–corrected estimating following the procedure in Andrews & Kasy (2019). We cap estimates at 5 with + signs indicating MVPFs above 5. The category average (shown by the black vertical lines) show the MVPF associated with a conceptual experiment where \$1 in initial program cost is spent on each policy in the category. The category average MVPF is the constructed using the average WTP and cost components for each category. All numbers are calculated using our baseline path for the social cost of carbon (\$193 in 2020) and a 2% discount rate.

Appendix Table 1: Evidence of Learning By Doing, Using Data from Way et al. (2022)

	Wind			Solar			Batteries		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log Cum. Sales	-0.208	-0.131	0.096	-0.306	-0.853	-2.018	-0.498	-0.445	-0.461
	(0.007)	(0.054)	(0.084)	(0.024)	(0.237)	(0.287)	(0.008)	(0.077)	(0.073)
Log Marg. Sales		-0.083	0.070		0.558	0.478		-0.062	-0.215
		(0.059)	(0.069)		(0.241)	(0.163)		(0.090)	(0.120)
Year			-0.086			0.468			0.041
			(0.026)			(0.096)			(0.023)
Observations	36	36	36	22	22	22	23	23	23

Notes: This table uses data from Way et al. (2022) (displayed in Appendix Figure 1) to provide estimates of the relationship between cumulative production and prices for three technologies: wind, solar, and batteries. The first column regresses log prices on log cumulative global generation. The second column adds controls for yearly flow of sales. The third column further adds controls for a linear time trend. The next three columns repeat this exercise for solar cell production and prices. The last three columns repeat this for battery storage.

Appendix Table 2: In-Context MVPF Components

	Willingness to Pay								Cost				
		Environmental Benefits			Learning by Doing					Fiscal Externalities			
Panel A. Subsidies	**Transfer**	**Global**	**Local**	**Rebound**	**Env.**	**Price**	**Profits**	**WTP**	**Program**	**Initial**	**Climate**	**Total**	**MVPF**
Wind Production Credits	**1.000**	**2.378**	**0.971**	**-0.665**	**2.775**	**0.823**		**7.282**	**1.000**	**0.191**	**-0.088**	**1.103**	**6.601**
PTC (Shrimali)	1.000	2.359	0.714	-0.612	4.080	1.116		8.657	1.000	0.189	-0.112	1.077	8.040
PTC (Metcalf)	1.000	2.476	1.141	-0.717	2.517	0.751		7.168	1.000	0.200	-0.085	1.115	6.429
PTC (Hitaj)	1.000	2.298	1.059	-0.665	1.727	0.602		6.020	1.000	0.185	-0.068	1.118	5.386
FIT (Germany - BEN) *													
FIT (Spain) *													
FIT (Germany - HL) *													
FIT (France) *													
FIT (UK) *													
FIT (EU) *													
Residential Solar	**1.106**	**0.740**	**0.094**	**-0.180**	**2.459**	**2.191**	**-0.479**	**5.931**	**1.000**	**1.680**	**-0.052**	**2.627**	**2.257**
CSI	1.000	1.059	0.081	-0.247	2.315	5.001	-0.734	8.476	1.000	3.585	-0.058	4.527	1.872
NE Solar	1.000	0.700	0.232	-0.194	4.906	2.365	-0.157	8.852	1.000	1.226	-0.082	2.144	4.129
CSI (TPO)	1.528	1.053	0.077	-0.247	3.878	2.200	-0.795	7.694	1.000	1.436	-0.086	2.349	3.275
CSI (HO)	1.000	0.514	0.038	-0.121	1.036	1.011	-0.388	3.090	1.000	0.752	-0.027	1.725	1.791
CT Solar	1.000	0.372	0.043	-0.090	0.160	0.381	-0.321	1.545	1.000	1.400	-0.008	2.392	0.646
ITC *	1.000	1.096	0.253	-0.280	10.854	2.827	-0.113	15.638	1.000	0.614	-0.189	1.426	10.968
Electric Vehicles	**1.000**	**0.090**	**-0.016**	**0.041**	**0.139**	**0.340**	**-0.069**	**1.525**	**1.000**	**0.730**	**-0.006**	**1.723**	**0.885**
BEV (State - Rebate)	1.000	0.119	-0.024	0.052	0.138	0.403	-0.097	1.591	1.000	0.831	-0.007	1.824	0.873
ITC (EV)	1.000	0.068	-0.034	0.053	0.050	0.356	-0.110	1.383	1.000	0.641	-0.004	1.637	0.844
EFMP	1.000	0.083	0.010	0.017	0.229	0.261	0.000	1.600	1.000	0.717	-0.007	1.710	0.936
BEV (State - ITC) *	1.000	-0.039	0.043	-0.051	0.000	0.000	0.099	1.052	1.000	-0.611	0.002	0.391	2.689
Appliance Rebates	**0.867**	**0.488**	**0.166**	**-0.114**			**-0.134**	**1.273**	**1.000**	**0.064**	**-0.008**	**1.056**	**1.206**
C4A (CW)	0.953	0.462	0.232	-0.136			-0.034	1.477	1.000	0.018	-0.007	1.011	1.460
ES (WH)	0.598	1.429	0.000	-0.168			-0.760	1.099	1.000	0.129	-0.028	1.101	0.998
ES (CW)	1.000	1.458	0.935	-0.469			-0.108	2.816	1.000	0.348	-0.023	1.325	2.126
C4A (DW)	0.930	0.196	0.106	-0.059			-0.014	1.158	1.000	0.008	-0.003	1.005	1.153
ES (DW)	1.000	-0.255	-0.164	0.082			0.019	0.682	1.000	-0.232	0.004	0.772	0.883
C4A (Fridge)	0.960	0.086	0.040	-0.025			-0.006	1.055	1.000	0.003	-0.001	1.002	1.053
ES (Fridge)	1.000	0.228	0.146	-0.073			-0.017	1.284	1.000	0.157	-0.004	1.153	1.113
CA ESA	0.500	0.299	0.029	-0.064			-0.148	0.616	1.000	0.080	-0.005	1.076	0.572
Vehicle Retirement	**0.892**	**0.510**	**0.981**	**-0.235**			**-0.210**	**1.938**	**1.000**	**0.236**	**-0.009**	**1.228**	**1.579**
C4C (TX)	1.000	0.373	0.055	-0.199			-0.105	1.124	1.000	0.107	-0.006	1.101	1.021
C4C (US)	1.000	0.244	0.041	-0.133			-0.068	1.085	1.000	0.069	-0.004	1.065	1.018
BAAQMD	0.676	0.912	2.848	-0.373			-0.457	3.606	1.000	0.533	-0.016	1.517	2.377

Hybrid Vehicles	**1.000**	**0.024**	**0.005**	**-0.031**	**0.001**	**0.069**	**0.013**	**1.081**	**1.000**	**0.413**	**-0.001**	**1.413**	**0.765**
HY (S-STW)	1.000	0.052	0.012	-0.072	0.002	0.167	0.028	1.188	1.000	0.810	-0.002	1.809	0.657
HY (F-ITC)	1.000	0.017	0.002	-0.017	0.000	0.031	0.009	1.043	1.000	0.355	0.000	1.354	0.770
HY (S-ITC)	1.000	0.003	0.001	-0.005	0.000	0.009	0.002	1.011	1.000	0.075	0.000	1.075	0.940
Weatherization	**0.774**	**0.312**	**0.056**	**-0.063**			**-0.045**	**1.034**	**1.000**	**0.012**	**-0.005**	**1.007**	**1.027**
EPP	0.750	0.674	0.106	-0.153			-0.036	1.341	1.000	0.020	-0.011	1.009	1.329
IHWAP	0.750	0.398	0.048	-0.069			-0.073	1.053	1.000	0.012	-0.007	1.006	1.047
WI RF	0.870	0.046	0.030	0.000			-0.019	0.929	1.000	0.000	0.000	1.000	0.929
WAP	0.750	0.306	0.057	-0.058			-0.084	0.971	1.000	0.022	-0.005	1.017	0.955
LEEP+	0.750	0.139	0.039	-0.035			-0.014	0.878	1.000	0.008	-0.002	1.006	0.874
Other Subsidies	**0.887**	**0.991**	**0.316**	**-0.112**			**-0.266**	**1.817**	**1.000**	**0.144**	**-0.017**	**1.127**	**1.612**
CA 20/20	0.882	1.063	0.081	-0.224			-0.531	1.270	1.000	0.289	-0.017	1.272	0.999
CRP	0.893	0.919	0.552	0.000			0.000	2.363	1.000	0.000	-0.018	0.982	2.407
Panel B. Nudges and Marketing													
Home Energy Reports													
HER (17 RCTs)	0.000	3.165	3.116	-1.230			-0.258	4.793	1.000	0.140	-0.050	1.090	4.395
Opower Elec. (166 RCTs)	0.000	2.828	1.691	-0.885			-0.209	3.425	1.000	0.113	-0.044	1.069	3.205
PER	0.000	0.184	0.058	0.000			0.695	0.938	1.000	-0.378	-0.004	0.619	1.515
Opower Nat. Gas (52 RCTs)	0.000	0.796	0.000	-0.094			-0.423	0.279	1.000	0.072	-0.014	1.058	0.264
Other Nudges	**0.617**	**3.343**	**0.526**	**-0.753**			**-1.845**	**1.888**	**1.000**	**5.290**	**-0.053**	**6.237**	**0.303**
Audit Nudge	0.000	4.226	0.990	-1.022			-1.887	2.307	1.000	3.450	-0.066	4.384	0.526
Solarize	1.805	10.876	1.613	-2.672			-7.621	4.001	1.000	23.813	-0.166	24.647	0.162
ES (WH) + Nudge	0.416	1.365	0.000	-0.161			-0.726	0.895	1.000	0.123	-0.027	1.096	0.816
IHWAP + Nudge (H)	0.739	0.534	0.044	-0.094			-0.071	1.151	1.000	0.012	-0.009	1.003	1.147
IHWAP + Nudge (L)	0.743	0.515	0.042	-0.090			-0.069	1.140	1.000	0.012	-0.008	1.003	1.136
WAP + Nudge	0.000	2.539	0.470	-0.480			-0.693	1.836	1.000	4.328	-0.042	5.286	0.347
Food Labels *	0.000	6.170	0.000	0.000			0.000	6.170	1.000	0.000	-0.120	0.880	7.015
Panel C. Revenue Raisers													
Gasoline Taxes	**1.000**	**-0.131**	**-0.190**		**0.000**	**0.000**	**0.070**	**0.749**	**1.000**	**-0.070**	**0.003**	**0.933**	**0.803**
Gas (DK)	1.000	-0.166	-0.194		0.000	0.000	0.099	0.739	1.000	-0.080	0.003	0.923	0.801
Gas (Su)	1.000	-0.222	-0.380		0.000	0.000	0.122	0.519	1.000	-0.134	0.004	0.870	0.596
Gas (Coglianese)	1.000	-0.133	-0.155		0.000	0.000	0.079	0.792	1.000	-0.064	0.003	0.938	0.844
Gas (Manzan)	1.000	-0.179	-0.473		0.000	0.000	0.118	0.466	1.000	-0.153	0.004	0.851	0.548
Gas (Small)	1.000	-0.187	-0.320		0.000	0.000	0.102	0.595	1.000	-0.113	0.004	0.891	0.668
Gas (Li)	1.000	-0.116	-0.136		0.000	0.000	0.069	0.817	1.000	-0.056	0.002	0.946	0.864
Gas (Levin)	1.000	-0.149	-0.168		0.000	0.000	0.064	0.746	1.000	-0.065	0.003	0.938	0.796
Gas (Sentenac-Chemin)	1.000	-0.122	-0.164		0.000	0.000	0.067	0.781	1.000	-0.063	0.002	0.939	0.831
Gas (Kilian)	1.000	-0.104	-0.092		-0.001	-0.005	0.033	0.832	1.000	-0.032	0.002	0.970	0.858
Gas (Gelman)	1.000	-0.114	-0.109		0.000	-0.001	0.040	0.816	1.000	-0.043	0.002	0.960	0.850
Gas (Park)	1.000	-0.058	-0.068		0.000	0.000	0.035	0.909	1.000	-0.028	0.001	0.973	0.934
Gas (Hughes)	1.000	-0.017	-0.022		0.000	0.000	0.009	0.970	1.000	-0.009	0.000	0.992	0.978

Gas (West) *	1.000	-0.295	-0.606		0.000	0.000	0.170	0.270	1.000	-0.205	0.006	0.800	0.337
Gas (Tiezzi) *	1.000	-0.193	-0.211		0.000	0.000	0.092	0.687	1.000	-0.086	0.004	0.918	0.749
Gas (Bento) *	1.000	-0.216	-0.350		0.000	0.000	0.109	0.542	1.000	-0.124	0.004	0.881	0.616
Gas (Hughes - Ext) *	1.000	-0.141	-0.472		0.000	0.000	0.115	0.503	1.000	-0.117	0.003	0.886	0.567
Gas (Kilian - Ext) *	1.000	-0.136	-0.134		0.000	-0.001	0.072	0.801	1.000	-0.057	0.003	0.946	0.847
Gas (Small - Ext) *	1.000	-0.037	-0.064		0.000	0.000	0.020	0.919	1.000	-0.022	0.001	0.978	0.940
Other Fuel Taxes	**1.000**	**-0.061**	**-0.063**				**0.026**	**0.902**	**1.000**	**-0.020**	**0.001**	**0.981**	**0.920**
Jet Fuel	1.000	-0.090	-0.001				0.036	0.945	1.000	-0.024	0.002	0.978	0.967
Diesel	1.000	-0.032	-0.125				0.015	0.859	1.000	-0.016	0.001	0.984	0.872
Heavy Fuel *	1.000	-0.062	-0.001				0.008	0.944	1.000	-0.002	0.001	0.999	0.945
Crude (WPT) *	1.000	0.000	0.000				0.000	1.000	1.000	-0.020	0.000	0.980	1.020
Crude (State) *	1.000	-0.065	0.000				0.000	0.935	1.000	-0.374	0.001	0.628	1.489
E85 *	1.000	0.153	0.069				0.393	1.614	1.000	-0.294	0.003	0.709	2.276
Other Revenue Raisers	**0.979**	**-0.146**	**-0.014**	**0.011**			**-0.093**	**0.737**	**1.000**	**0.112**	**0.003**	**1.115**	**0.661**
CPP (AJ)	1.000	-0.107	-0.030	0.000			-0.323	0.540	1.000	0.176	0.002	1.178	0.459
CARE	0.936	-0.292	0.000	0.034			0.162	0.840	1.000	0.095	0.006	1.101	0.763
CPP (PJ)	1.000	-0.039	-0.011	0.000			-0.119	0.831	1.000	0.065	0.001	1.065	0.780
Cap and Trade													
RGGI	1.000	-0.550	-0.989					-0.540	1.000	-0.027	0.011	0.984	-0.549
CA CT	1.000	-0.055	-0.002					0.943	1.000	-0.005	0.001	0.997	0.946
ETS (BA) *	1.000	-8.053	0.000					-7.053	1.000	-0.402	0.157	0.755	-9.345
ETS (CMMW) *	1.000	-1.026	0.000					-0.026	1.000	-0.152	0.020	0.869	-0.030

Notes: This table presents the MVPF components as displayed in Table 2 but using our in-context specification for each policy. We do not construct in-context estimates for non-US policies. We denote policies excluded from our primary sample by "*", and these policies are not included in our category average measures. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020, but we align the time path of emissions with the SCC in the corresponding year for each policy's context) and a 2% discount rate.

Appendix Table 3: Baseline MVPF Components with Confidence Intervals

	MVPF, $193 SCC			**MVPF, $76 SCC**			**MVPF, $337 SCC**		
		95% CI			**95% CI**			**95% CI**	
Panel A. Subsidies	**Pt. Est**	**Lower**	**Upper**	**Pt. Est**	**Lower**	**Upper**	**Pt. Est**	**Lower**	**Upper**
Wind Production Credits	**5.870**			**3.533**			**9.548**		
(Sub)sample with SEs	**5.870**	**2.733**	**∞**	**3.533**	**1.878**	**28.468**	**9.548**	**3.894**	**∞**
PTC (Shrimali)	7.547	1.744	∞	4.479	1.353	127.072	12.889	2.213	∞
PTC (Metcalf)	5.298	2.649	9.275	3.196	1.796	5.491	8.429	3.722	16.676
PTC (Hitaj)	4.626	1.281	11.633	2.826	1.133	6.875	7.186	1.456	22.425
Residential Solar	**3.862**			**2.865**			**5.852**		
(Sub)sample with SEs	**3.282**	**1.966**	**33.888**	**2.543**	**1.567**	**21.953**	**5.006**	**2.657**	**∞**
CSI	5.063			3.565			7.956		
NE Solar	4.676	2.159	91.720	3.544	1.664	48.571	7.611	3.056	∞
CSI (TPO)	3.815			2.886			5.544		
CSI (HO)	2.712			2.092			3.861		
CT Solar	1.634	1.101	3.545	1.346	1.048	2.718	2.040	1.166	5.264
Electric Vehicles	**1.445**			**1.327**			**1.566**		
(Sub)sample with SEs	**1.431**	**1.884**	**1.178**	**1.316**	**1.641**	**1.135**	**1.548**	**2.093**	**1.242**
BEV (State - Rebate)	1.561	1.110	2.434	1.411	1.082	2.027	1.711	1.163	2.766
ITC (EV)	1.474			1.348			1.602		
EFMP	1.296	1.084	1.487	1.218	1.061	1.367	1.379	1.133	1.606
Appliance Rebates	**1.164**			**0.922**			**1.472**		
(Sub)sample with SEs	**1.148**	**1.099**	**1.173**	**0.849**	**0.809**	**0.923**	**1.531**	**1.333**	**1.637**
C4A (CW)	1.405			1.142			1.729		
ES (WH)	1.340	1.250	1.367	0.491	0.451	0.624	2.496	2.094	2.617
ES (CW)	1.310	1.134	1.440	0.990	0.987	0.996	1.700	1.302	1.999
C4A (DW)	1.132			1.015			1.276		
ES (DW)	1.053			1.194			0.884		
C4A (Fridge)	1.042	0.000	0.000	0.994	0.000	0.000	1.100	0.000	0.000
ES (Fridge)	1.011	1.000	1.020	0.928	0.871	1.001	1.113	0.999	1.202
CA ESA	0.958	0.930	0.990	0.701	0.689	0.715	1.276	1.227	1.329
Vehicle Retirement	**1.047**			**0.919**			**1.204**		
(Sub)sample with SEs	**1.047**	**0.968**	**1.002**	**0.919**	**0.903**	**0.935**	**1.204**	**1.117**	**1.132**
C4C (TX)	1.067	0.924	0.974	0.885	0.862	0.910	1.286	1.125	1.148

C4C (US)	1.044	0.955	1.003	0.922	0.900	0.946	1.192	1.099	1.119
BAAQMD	1.030	1.025	1.036	0.951	0.947	0.955	1.128	1.121	1.136
Hybrid Vehicles	**1.012**			**0.997**			**1.031**		
(Sub)sample with SEs	**1.012**	**1.006**	**1.025**	**0.997**	**0.995**	**0.999**	**1.031**	**1.012**	**1.054**
HY (S-STW)	1.028	1.010	1.058	0.993	0.989	0.998	1.070	1.022	1.127
HY (F-ITC)	1.008	1.008	1.010	0.998	0.998	0.998	1.020	1.018	1.021
HY (S-ITC)	1.002	0.998	1.006	1.000	0.999	1.000	1.004	0.996	1.013
Weatherization	**0.978**			**0.831**			**1.162**		
(Sub)sample with SEs	**0.992**	**0.933**	**1.047**	**0.815**	**0.793**	**0.837**	**1.214**	**1.108**	**1.310**
EPP	1.210	0.928	1.434	0.929	0.819	1.015	1.554	1.060	1.948
IHWAP	0.980	0.961	1.001	0.776	0.771	0.783	1.243	1.207	1.294
WI RF	0.920	0.000	0.000	0.894	0.000	0.000	0.951	0.000	0.000
WAP	0.915	0.817	1.045	0.762	0.734	0.812	1.115	0.907	1.364
LEEP+	0.859	0.801	0.918	0.792	0.770	0.815	0.940	0.839	1.042
Other Subsidies	**2.492**			**1.710**			**3.484**		
(Sub)sample with SEs	**2.492**	**2.130**	**2.858**	**1.710**	**1.551**	**1.869**	**3.484**	**2.863**	**4.143**
CA 20/20	2.572	1.902	3.262	1.606	1.323	1.896	3.805	2.632	5.026
CRP	2.407	2.152	2.660	1.821	1.674	1.968	3.148	2.754	3.541
Panel B. Nudges and Marketing									
Home Energy Reports									
HER (17 RCTs)	3.006	2.354	3.658	1.341	1.057	1.621	5.216	4.049	6.405
Opower Elec. (166 RCTs)	2.548			1.142			4.393		
PER	1.600	0.043	7.495	1.369	0.037	6.314	1.887	0.050	9.024
Opower Nat. Gas (52 RCTs)	0.451			-0.033			1.061		
Other Nudges	**1.326**			**0.599**			**2.233**		
(Sub)sample with SEs	**1.326**	**2.130**	**2.858**	**0.599**	**1.551**	**1.869**	**2.233**	**2.863**	**4.143**
Audit Nudge	2.117	1.638	2.337	0.939	0.730	1.034	3.628	2.790	4.016
Solarize	1.809	1.703	1.927	0.821	0.742	0.913	3.011	2.872	3.165
ES (WH) + Nudge	1.140	1.080	1.148	0.328	0.318	0.410	2.243	1.985	2.277
IHWAP + Nudge (H)	1.069	0.903	1.237	0.809	0.764	0.855	1.404	1.084	1.726
IHWAP + Nudge (L)	1.062	0.991	1.138	0.810	0.794	0.825	1.386	1.240	1.537
WAP + Nudge	0.280	0.103	0.508	0.038	-0.010	0.129	0.597	0.222	1.020
Panel C. Revenue Raisers									
Gasoline Taxes	**0.671**			**0.820**			**0.488**		
(Sub)sample with SEs	**0.671**	**0.465**	**0.880**	**0.820**	**0.705**	**0.933**	**0.488**	**0.166**	**0.814**
Gas (DK)	0.437	-0.208	0.997	0.691	0.333	0.997	0.124	-0.870	0.996
Gas (Su)	0.523	0.113	0.907	0.738	0.511	0.948	0.256	-0.378	0.855
Gas (Coglianese)	0.561	-0.079	1.113	0.759	0.405	1.060	0.315	-0.671	1.178
Gas (Manzan)	0.578	0.287	0.863	0.768	0.607	0.923	0.342	-0.109	0.786
Gas (Small)	0.605	0.498	0.717	0.783	0.723	0.844	0.384	0.218	0.559

Gas (Li)	0.619	0.420	0.821	0.791	0.681	0.901	0.406	0.097	0.720
Gas (Levin)	0.654	0.583	0.731	0.810	0.770	0.851	0.461	0.350	0.580
Gas (Sentenac-Chemin)	0.673	0.550	0.801	0.821	0.752	0.890	0.490	0.299	0.690
Gas (Kilian)	0.773	0.656	0.896	0.875	0.810	0.942	0.646	0.463	0.838
Gas (Gelman)	0.814	0.762	0.869	0.897	0.869	0.927	0.709	0.629	0.796
Gas (Park)	0.818	0.786	0.852	0.900	0.882	0.918	0.716	0.666	0.769
Gas (Hughes)	0.953	0.939	0.968	0.973	0.965	0.981	0.927	0.905	0.951
Other Fuel Taxes	**0.798**			**0.913**			**0.656**		
(Sub)sample with SEs	**0.754**	**0.706**	**0.888**	**0.950**	**0.893**	**0.932**	**0.511**	**0.474**	**0.834**
Jet Fuel	0.754	0.563	0.936	0.950	0.911	0.987	0.511	0.135	0.872
Diesel	0.842			0.878			0.797		
Other Revenue Raisers	**0.647**			**0.723**			**0.553**		
(Sub)sample with SEs	**0.647**	**0.645**	**0.652**	**0.723**	**0.690**	**0.756**	**0.553**	**0.509**	**0.606**
CPP (AJ)	0.459	0.393	0.529	0.514	0.455	0.577	0.391	0.317	0.469
CARE	0.719	0.562	0.914	0.870	0.822	0.929	0.534	0.244	0.895
CPP (PJ)	0.780	0.697	0.869	0.803	0.728	0.882	0.752	0.658	0.852
Cap and Trade									
RGGI	-0.671	-1.357	0.389	-0.261	-0.758	0.627	-1.168	-2.091	0.093
CA CT	0.941			0.979			0.895		

Notes: This table reports the MVPFs and their confidence intervals for specifications using our baseline ($193 in 2020) SCC, along with specifications using a $76 and $337 SCC. Confidence intervals are produced using a parametric bootstrap procedure from each causal estimate and its standard error. We restrict to the subset of our baseline sample for which we are able to ascertain the sampling uncertainty in the primary input(s) into the MVPF. We ascertain this sampling uncertainty either from reported t-stats or SEs from each relevant paper. Because we do not obtain sampling uncertainty estimates for every policy, the confidence interval for the category average corresponds to the confidence interval of the average over the policies in our sample (i.e. the conceptual experiment of spending $1/n in upfront expenditures on each of n policies for which we ascertain sampling uncertainty). We therefore report a separate row for each category that displays the category average components when restricting to this subsample.

Appendix Table 4: Baseline MVPF Components Using an SCC of $76 in 2020

	Willingness to Pay								Cost				
		Environmental Benefits			Learning by Doing					Fiscal Externalities			
Panel A. Subsidies	**Transfer**	**Global**	**Local**	**Rebound**	**Env.**	**Price**	**Profits**	**WTP**	**Program**	**Initial**	**Climate**	**Total**	**MVPF**
Wind Production Credits	**1.000**	**1.932**	**0.639**	**-0.516**	**1.261**	**0.573**		**4.888**	**1.000**	**0.437**	**-0.053**	**1.384**	**3.533**
PTC (Shrimali)	1.000	2.422	0.801	-0.647	2.199	0.809		6.583	1.000	0.547	-0.077	1.470	4.479
PTC (Metcalf)	1.000	1.804	0.597	-0.482	0.936	0.500		4.355	1.000	0.408	-0.045	1.363	3.196
PTC (Hitaj)	1.000	1.569	0.519	-0.419	0.649	0.409		3.727	1.000	0.355	-0.036	1.319	2.826
FIT (Germany - BEN) *	1.000	2.737	0.906	-0.731	3.282	1.019		8.213	1.000	0.619	-0.102	1.516	5.416
FIT (Spain) *	1.000	2.422	0.801	-0.647	2.199	0.809		6.584	1.000	0.547	-0.077	1.470	4.479
FIT (Germany - HL) *	1.000	2.310	0.764	-0.617	1.901	0.745		6.103	1.000	0.522	-0.070	1.452	4.204
FIT (France) *	1.000	1.997	0.661	-0.534	1.240	0.585		4.949	1.000	0.451	-0.053	1.398	3.541
FIT (UK) *	1.000	0.828	0.274	-0.221	0.141	0.181		2.203	1.000	0.187	-0.015	1.172	1.880
FIT (EU) *	1.000	0.225	0.075	-0.060	0.010	0.046		1.295	1.000	0.051	-0.004	1.047	1.237
Residential Solar	**1.106**	**0.697**	**0.244**	**-0.198**	**1.663**	**1.467**	**-0.203**	**4.777**	**1.000**	**0.708**	**-0.041**	**1.667**	**2.865**
CSI	1.000	1.746	0.612	-0.495	3.612	3.589	-0.508	9.556	1.000	1.772	-0.092	2.680	3.565
NE Solar	1.000	0.495	0.174	-0.140	2.351	1.411	-0.144	5.147	1.000	0.503	-0.050	1.452	3.544
CSI (TPO)	1.528	0.651	0.228	-0.185	1.419	1.241	-0.189	4.693	1.000	0.661	-0.035	1.626	2.886
CSI (HO)	1.000	0.378	0.133	-0.107	0.783	0.778	-0.110	2.855	1.000	0.384	-0.020	1.364	2.092
CT Solar	1.000	0.216	0.076	-0.061	0.147	0.318	-0.063	1.633	1.000	0.220	-0.006	1.214	1.346
ITC *	1.000	0.468	0.164	-0.133	2.889	1.687	-0.136	5.939	1.000	0.527	-0.060	1.467	4.049
Electric Vehicles	**1.000**	**0.020**	**0.000**	**0.015**	**0.028**	**0.423**	**-0.041**	**1.443**	**1.000**	**0.090**	**-0.002**	**1.088**	**1.327**
BEV (State - Rebate)	1.000	0.024	0.000	0.018	0.039	0.527	-0.050	1.557	1.000	0.106	-0.002	1.104	1.411
ITC (EV)	1.000	0.021	0.000	0.016	0.029	0.451	-0.044	1.473	1.000	0.095	-0.002	1.093	1.348
EFMP	1.000	0.014	0.000	0.011	0.015	0.290	-0.030	1.300	1.000	0.068	-0.001	1.067	1.218
BEV (State - ITC) *	1.000	-0.017	0.000	-0.013	0.000	0.000	0.035	1.006	1.000	-0.072	0.001	0.927	1.085
Appliance Rebates	**0.867**	**0.198**	**0.042**	**-0.040**			**-0.100**	**0.966**	**1.000**	**0.052**	**-0.003**	**1.048**	**0.922**
C4A (CW)	0.953	0.225	0.082	-0.060			-0.038	1.161	1.000	0.021	-0.004	1.017	1.142
ES (WH)	0.598	0.655	0.000	-0.077			-0.638	0.538	1.000	0.108	-0.013	1.095	0.491
ES (CW)	1.000	0.348	0.123	-0.092			-0.070	1.309	1.000	0.327	-0.005	1.322	0.990
C4A (DW)	0.930	0.100	0.036	-0.027			-0.016	1.023	1.000	0.009	-0.002	1.007	1.015
ES (DW)	1.000	-0.090	-0.032	0.024			0.018	0.920	1.000	-0.231	0.001	0.770	1.194
C4A (Fridge)	0.960	0.040	0.015	-0.011			-0.007	0.997	1.000	0.004	-0.001	1.003	0.994
ES (Fridge)	1.000	0.080	0.028	-0.021			-0.016	1.071	1.000	0.156	-0.001	1.155	0.928
CA ESA	0.500	0.223	0.082	-0.060			-0.034	0.712	1.000	0.018	-0.003	1.015	0.701
Vehicle Retirement	**0.910**	**0.110**	**0.100**	**-0.102**			**-0.048**	**0.971**	**1.000**	**0.059**	**-0.002**	**1.057**	**0.919**
C4C (TX)	1.000	0.158	0.029	-0.155			-0.071	0.960	1.000	0.088	-0.002	1.085	0.885
C4C (US)	1.000	0.105	0.019	-0.104			-0.047	0.973	1.000	0.057	-0.002	1.056	0.922
BAAQMD	0.730	0.068	0.253	-0.047			-0.025	0.979	1.000	0.031	-0.001	1.029	0.951

Hybrid Vehicles	**1.000**	**0.012**	**0.003**	**-0.021**	**0.000**	**0.013**	**-0.006**	**1.001**	**1.000**	**0.004**	**0.000**	**1.004**	**0.997**
HY (S-STW)	1.000	0.027	0.007	-0.047	0.000	0.030	-0.014	1.002	1.000	0.010	-0.001	1.009	0.993
HY (F-ITC)	1.000	0.008	0.002	-0.013	0.000	0.008	-0.004	1.001	1.000	0.003	0.000	1.003	0.998
HY (S-ITC)	1.000	0.002	0.000	-0.003	0.000	0.002	-0.001	1.000	1.000	0.001	0.000	1.001	1.000
Weatherization	**0.774**	**0.117**	**0.028**	**-0.026**			**-0.051**	**0.842**	**1.000**	**0.016**	**-0.002**	**1.014**	**0.831**
EPP	0.750	0.240	0.081	-0.063			-0.055	0.953	1.000	0.030	-0.004	1.026	0.929
IHWAP	0.750	0.154	0.019	-0.027			-0.103	0.793	1.000	0.024	-0.003	1.021	0.776
WI RF	0.870	0.021	0.011	-0.006			-0.001	0.895	1.000	0.001	0.000	1.000	0.894
WAP	0.750	0.115	0.013	-0.019			-0.084	0.774	1.000	0.018	-0.002	1.016	0.762
LEEP+	0.750	0.056	0.019	-0.015			-0.013	0.797	1.000	0.007	-0.001	1.006	0.792
Other Subsidies	**0.887**	**0.622**	**0.423**	**-0.115**			**-0.065**	**1.753**	**1.000**	**0.035**	**-0.010**	**1.025**	**1.710**
CA 20/20	0.882	0.880	0.295	-0.230			-0.130	1.697	1.000	0.071	-0.014	1.057	1.606
CRP	0.893	0.364	0.552	0.000			0.000	1.808	1.000	0.000	-0.007	0.993	1.821
Panel B. Nudges and Marketing													
Home Energy Reports													
HER (17 RCTs)	0.000	1.708	0.439	-0.421			-0.244	1.483	1.000	0.133	-0.027	1.106	1.341
Opower Elec. (166 RCTs)	0.000	1.432	0.368	-0.353			-0.205	1.243	1.000	0.111	-0.022	1.089	1.142
PER	0.000	0.091	0.064	0.000			0.695	0.850	1.000	-0.378	-0.002	0.621	1.369
Opower Nat. Gas (52 RCTs)	0.000	0.376	0.000	-0.044			-0.367	-0.035	1.000	0.062	-0.006	1.056	-0.033
Other Nudges	**0.507**	**1.942**	**0.599**	**-0.498**			**-0.632**	**1.918**	**1.000**	**2.232**	**-0.031**	**3.201**	**0.599**
Audit Nudge	0.000	3.582	1.319	-0.960			-0.537	3.403	1.000	2.680	-0.056	3.624	0.939
Solarize	1.145	6.091	2.135	-1.727			-1.749	5.894	1.000	6.269	-0.093	7.175	0.821
ES (WH) + Nudge	0.416	0.625	0.000	-0.074			-0.609	0.358	1.000	0.103	-0.012	1.091	0.328
IHWAP + Nudge (H)	0.739	0.203	0.019	-0.036			-0.100	0.824	1.000	0.022	-0.003	1.019	0.809
IHWAP + Nudge (L)	0.743	0.196	0.018	-0.034			-0.097	0.825	1.000	0.021	-0.003	1.018	0.810
WAP + Nudge	0.000	0.955	0.104	-0.157			-0.701	0.201	1.000	4.294	-0.016	5.278	0.038
Food Labels *	0.000	2.443	0.000	0.000			0.000	2.443	1.000	0.000	-0.048	0.952	2.566
Panel C. Revenue Raisers													
Gasoline Taxes	**1.000**	**-0.093**	**-0.204**		**0.000**	**-0.002**	**0.060**	**0.761**	**1.000**	**-0.074**	**0.002**	**0.928**	**0.820**
Gas (DK)	1.000	-0.153	-0.333		0.000	-0.002	0.098	0.610	1.000	-0.120	0.003	0.883	0.691
Gas (Su)	1.000	-0.132	-0.288		0.000	-0.002	0.084	0.663	1.000	-0.104	0.003	0.899	0.738
Gas (Coglianese)	1.000	-0.122	-0.267		0.000	-0.002	0.078	0.688	1.000	-0.096	0.002	0.906	0.759
Gas (Manzan)	1.000	-0.118	-0.257		0.000	-0.002	0.075	0.699	1.000	-0.093	0.002	0.910	0.768
Gas (Small)	1.000	-0.111	-0.242		0.000	-0.002	0.071	0.716	1.000	-0.087	0.002	0.915	0.783
Gas (Li)	1.000	-0.107	-0.234		0.000	-0.002	0.069	0.726	1.000	-0.084	0.002	0.918	0.791
Gas (Levin)	1.000	-0.098	-0.214		0.000	-0.002	0.063	0.749	1.000	-0.077	0.002	0.925	0.810
Gas (Sentenac-Chemin)	1.000	-0.093	-0.203		0.000	-0.002	0.060	0.762	1.000	-0.073	0.002	0.929	0.821
Gas (Kilian)	1.000	-0.066	-0.143		0.000	-0.002	0.042	0.831	1.000	-0.052	0.001	0.950	0.875
Gas (Gelman)	1.000	-0.054	-0.119		0.000	-0.002	0.035	0.860	1.000	-0.043	0.001	0.958	0.897
Gas (Park)	1.000	-0.053	-0.116		0.000	-0.002	0.034	0.863	1.000	-0.042	0.001	0.959	0.900
Gas (Hughes)	1.000	-0.014	-0.030		0.000	-0.002	0.009	0.963	1.000	-0.011	0.000	0.989	0.973

Gas (West) *	1.000	-0.152	-0.332		0.000	-0.002	0.097	0.612	1.000	-0.120	0.003	0.883	0.693
Gas (Tiezzi) *	1.000	-0.144	-0.315		0.000	-0.002	0.093	0.631	1.000	-0.114	0.003	0.889	0.710
Gas (Bento) *	1.000	-0.116	-0.254		0.000	-0.002	0.074	0.703	1.000	-0.091	0.002	0.911	0.772
Gas (Hughes - Ext) *	1.000	-0.111	-0.243		0.000	-0.002	0.071	0.716	1.000	-0.088	0.002	0.915	0.782
Gas (Kilian - Ext) *	1.000	-0.104	-0.227		0.000	-0.002	0.067	0.733	1.000	-0.082	0.002	0.920	0.797
Gas (Small - Ext) *	1.000	-0.022	-0.048		0.000	-0.002	0.014	0.942	1.000	-0.018	0.000	0.983	0.958
Other Fuel Taxes	**1.000**	**-0.075**	**-0.067**				**0.025**	**0.884**	**1.000**	**-0.033**	**0.001**	**0.968**	**0.913**
Jet Fuel	1.000	-0.126	-0.003				0.036	0.907	1.000	-0.048	0.002	0.955	0.950
Diesel	1.000	-0.024	-0.129				0.015	0.862	1.000	-0.019	0.000	0.982	0.878
Heavy Fuel *	1.000	-0.030	-0.001				0.007	0.976	1.000	-0.002	0.001	0.999	0.977
Crude (WPT) *	1.000	0.000	0.000				0.000	1.000	1.000	-0.002	0.000	0.998	1.002
Crude (State) *	1.000	-0.037	0.000				0.000	0.963	1.000	-0.364	0.001	0.637	1.512
E85 *	1.000	0.246	0.009				0.411	1.666	1.000	-0.361	0.005	0.643	2.590
Other Revenue Raisers	**0.979**	**-0.059**	**-0.014**	**0.005**			**-0.108**	**0.802**	**1.000**	**0.109**	**0.001**	**1.110**	**0.723**
CPP (AJ)	1.000	-0.042	-0.030	0.000			-0.323	0.605	1.000	0.176	0.001	1.176	0.514
CARE	0.936	-0.120	0.000	0.014			0.117	0.947	1.000	0.086	0.002	1.089	0.870
CPP (PJ)	1.000	-0.016	-0.011	0.000			-0.119	0.855	1.000	0.065	0.000	1.065	0.803
Cap and Trade													
RGGI	1.000	-0.260	-0.989					-0.249	1.000	-0.050	0.005	0.955	-0.261
CA CT	1.000	-0.024	-0.002					0.974	1.000	-0.006	0.000	0.995	0.979
ETS (BA) *	1.000	-3.640	0.000					-2.640	1.000	-0.900	0.071	0.171	-15.411
ETS (CMMW) *	1.000	-0.506	0.000					0.494	1.000	-0.125	0.010	0.885	0.558
Panel D. International													
Cookstoves													
Cookstove (Kenya)	7.637	17.018	0.000					24.656	1.000	0.000	-0.332	0.668	36.929
Cookstove (India)	0.545	-1.167	0.000					-0.622	1.000	0.000	0.023	1.023	-0.608
Deforestation													
REDD+ (SL)	0.000	14.191	0.000					14.191	1.000	0.000	-0.277	0.723	19.632
Deforest (Uganda)	0.421	3.862	0.000					4.283	1.000	0.000	-0.075	0.925	4.632
REDD+	0.965	1.169	0.000					2.134	1.000	0.000	-0.023	0.977	2.183
Deforest (Mexico) *	0.944	4.548	0.000					5.492	1.000	0.000	-0.089	0.911	6.028
Rice Burning													
India PES (Upfront)	0.972	4.214	0.000					5.186	1.000	0.000	-0.082	0.918	5.651
India PES (Standard)	0.915	3.218	0.000					4.134	1.000	0.000	-0.063	0.937	4.411
Wind Offset													
Offset (India)	1.000	3.694	0.000	-0.735				3.959	1.000	0.258	-0.058	1.200	3.298
International Rebates													
Fridge (Mexico)	0.750	0.049	0.000	-0.010				0.789	1.000	0.000	-0.001	0.999	0.790
AC (Mexico)	0.750	-0.037	0.000	0.007				0.720	1.000	0.000	0.001	1.001	0.720
WAP (Mexico)	0.500	-0.037	0.000	0.007				0.470	1.000	0.000	0.001	1.001	0.470

International Nudges													
Nudge (Qatar) *	0.000	2.851	0.000	-0.558				2.293	1.000	0.000	-0.045	0.955	2.400
Nudge (Germany) *	0.000	0.159	0.000	-0.031				0.128	1.000	0.000	-0.002	0.998	0.128

Notes: This table presents the MVPF components as displayed in Table 2 but using our baseline specification with a modified time path for the social cost of carbon that yields an SCC of $76 in 2020 and a real discount rate of 2.5% per year. We denote policies excluded from our primary sample by "*", and these policies are not included in our category average measures.

Appendix Table 5: Baseline MVPF Components Using an SCC of $337 in 2020

	Willingness to Pay								Cost				
		Environmental Benefits			Learning by Doing					Fiscal Externalities			
Panel A. Subsidies	**Transfer**	**Global**	**Local**	**Rebound**	**Env.**	**Price**	**Profits**	**WTP**	**Program**	**Initial**	**Climate**	**Total**	**MVPF**
Wind Production Credits	**1.000**	**7.852**	**0.648**	**-1.718**	**3.393**	**0.746**		**11.920**	**1.000**	**0.434**	**-0.186**	**1.248**	**9.548**
PTC (Shrimali)	1.000	9.844	0.812	-2.154	5.919	1.077		16.498	1.000	0.545	-0.265	1.280	12.889
PTC (Metcalf)	1.000	7.332	0.605	-1.604	2.514	0.642		10.488	1.000	0.406	-0.161	1.244	8.429
PTC (Hitaj)	1.000	6.380	0.526	-1.396	1.745	0.519		8.774	1.000	0.353	-0.132	1.221	7.186
FIT (Germany - BEN) *	1.000	11.126	0.918	-2.435	8.891	1.389		20.889	1.000	0.616	-0.341	1.275	16.385
FIT (Spain) *	1.000	9.845	0.812	-2.154	5.920	1.077		16.499	1.000	0.545	-0.265	1.280	12.890
FIT (Germany - HL) *	1.000	9.392	0.775	-2.055	5.111	0.984		15.206	1.000	0.520	-0.242	1.277	11.906
FIT (France) *	1.000	8.118	0.669	-1.776	3.330	0.759		12.099	1.000	0.449	-0.189	1.260	9.601
FIT (UK) *	1.000	3.367	0.278	-0.737	0.383	0.223		4.514	1.000	0.186	-0.060	1.127	4.006
FIT (EU) *	1.000	0.916	0.076	-0.201	0.027	0.055		1.873	1.000	0.051	-0.015	1.036	1.808
Residential Solar	**1.106**	**2.931**	**0.260**	**-0.690**	**4.108**	**1.868**	**-0.226**	**9.356**	**1.000**	**0.720**	**-0.122**	**1.599**	**5.852**
CSI	1.000	7.335	0.651	-1.727	8.862	4.533	-0.565	20.089	1.000	1.803	-0.278	2.525	7.956
NE Solar	1.000	2.081	0.185	-0.490	5.908	1.895	-0.160	10.419	1.000	0.512	-0.143	1.369	7.611
CSI (TPO)	1.528	2.738	0.243	-0.645	3.481	1.548	-0.211	8.681	1.000	0.673	-0.107	1.566	5.544
CSI (HO)	1.000	1.590	0.141	-0.374	1.921	0.983	-0.122	5.138	1.000	0.391	-0.060	1.331	3.861
CT Solar	1.000	0.910	0.081	-0.214	0.367	0.382	-0.070	2.454	1.000	0.224	-0.021	1.203	2.040
ITC *	1.000	1.965	0.174	-0.463	7.392	2.319	-0.151	12.236	1.000	0.535	-0.169	1.366	8.956
Electric Vehicles	**1.000**	**0.103**	**0.000**	**0.052**	**0.102**	**0.488**	**-0.044**	**1.701**	**1.000**	**0.094**	**-0.007**	**1.086**	**1.566**
BEV (State - Rebate)	1.000	0.124	0.000	0.063	0.142	0.610	-0.053	1.885	1.000	0.111	-0.009	1.102	1.711
ITC (EV)	1.000	0.110	0.000	0.056	0.108	0.521	-0.047	1.748	1.000	0.099	-0.008	1.091	1.602
EFMP	1.000	0.075	0.000	0.038	0.055	0.333	-0.032	1.470	1.000	0.071	-0.005	1.066	1.379
BEV (State - ITC) *	1.000	-0.087	0.000	-0.044	0.000	0.000	0.037	0.906	1.000	-0.075	0.005	0.927	0.978
Appliance Rebates	**0.867**	**0.873**	**0.043**	**-0.149**			**-0.106**	**1.528**	**1.000**	**0.053**	**-0.015**	**1.038**	**1.472**
C4A (CW)	0.953	0.945	0.084	-0.202			-0.040	1.741	1.000	0.021	-0.015	1.007	1.729
ES (WH)	0.598	3.079	0.000	-0.362			-0.681	2.634	1.000	0.115	-0.060	1.055	2.496
ES (CW)	1.000	1.482	0.129	-0.316			-0.074	2.221	1.000	0.330	-0.023	1.306	1.700
C4A (DW)	0.930	0.418	0.037	-0.089			-0.017	1.279	1.000	0.009	-0.007	1.003	1.276
ES (DW)	1.000	-0.383	-0.033	0.082			0.019	0.684	1.000	-0.232	0.006	0.774	0.884
C4A (Fridge)	0.960	0.170	0.015	-0.036			-0.007	1.102	1.000	0.004	-0.003	1.001	1.100
ES (Fridge)	1.000	0.342	0.030	-0.073			-0.017	1.282	1.000	0.157	-0.005	1.152	1.113
CA ESA	0.500	0.929	0.084	-0.199			-0.034	1.281	1.000	0.019	-0.015	1.004	1.276
Vehicle Retirement	**0.910**	**0.486**	**0.103**	**-0.178**			**-0.051**	**1.269**	**1.000**	**0.062**	**-0.008**	**1.055**	**1.204**
C4C (TX)	1.000	0.710	0.031	-0.271			-0.077	1.394	1.000	0.094	-0.011	1.083	1.286
C4C (US)	1.000	0.470	0.021	-0.184			-0.050	1.257	1.000	0.062	-0.007	1.055	1.192
BAAQMD	0.730	0.276	0.257	-0.080			-0.025	1.158	1.000	0.031	-0.005	1.026	1.128

Hybrid Vehicles	**1.000**	**0.055**	**0.003**	**-0.033**	**0.001**	**0.015**	**-0.007**	**1.035**	**1.000**	**0.005**	**-0.001**	**1.003**	**1.031**
HY (S-STW)	1.000	0.122	0.007	-0.073	0.003	0.034	-0.015	1.078	1.000	0.010	-0.003	1.007	1.070
HY (F-ITC)	1.000	0.035	0.002	-0.021	0.000	0.009	-0.004	1.022	1.000	0.003	-0.001	1.002	1.020
HY (S-ITC)	1.000	0.008	0.000	-0.005	0.000	0.002	-0.001	1.005	1.000	0.001	0.000	1.000	1.004
Weatherization	**0.774**	**0.521**	**0.030**	**-0.095**			**-0.057**	**1.172**	**1.000**	**0.017**	**-0.008**	**1.009**	**1.162**
EPP	0.750	1.021	0.086	-0.217			-0.060	1.580	1.000	0.033	-0.016	1.017	1.554
IHWAP	0.750	0.721	0.020	-0.110			-0.119	1.262	1.000	0.027	-0.012	1.015	1.243
WI RF	0.870	0.090	0.011	-0.020			-0.001	0.951	1.000	0.001	-0.001	0.999	0.951
WAP	0.750	0.533	0.013	-0.078			-0.092	1.126	1.000	0.019	-0.009	1.010	1.115
LEEP+	0.750	0.238	0.020	-0.051			-0.014	0.944	1.000	0.008	-0.004	1.004	0.940
Other Subsidies	**0.887**	**2.589**	**0.426**	**-0.379**			**-0.066**	**3.457**	**1.000**	**0.036**	**-0.044**	**0.992**	**3.484**
CA 20/20	0.882	3.573	0.300	-0.758			-0.132	3.864	1.000	0.072	-0.056	1.015	3.805
CRP	0.893	1.605	0.552	0.000			0.000	3.049	1.000	0.000	-0.031	0.969	3.148
Panel B. Nudges and Marketing													
Home Energy Reports													
HER (17 RCTs)	0.000	6.545	0.439	-1.368			-0.244	5.372	1.000	0.133	-0.103	1.030	5.216
Opower Elec. (166 RCTs)	0.000	5.487	0.368	-1.147			-0.205	4.504	1.000	0.111	-0.086	1.025	4.393
PER	0.000	0.401	0.064	0.000			0.695	1.160	1.000	-0.378	-0.008	0.615	1.887
Opower Nat. Gas (52 RCTs)	0.000	1.659	0.000	-0.195			-0.367	1.097	1.000	0.062	-0.029	1.034	1.061
Other Nudges	**0.507**	**8.277**	**0.628**	**-1.748**			**-0.688**	**6.976**	**1.000**	**2.255**	**-0.131**	**3.124**	**2.233**
Audit Nudge	0.000	14.907	1.348	-3.184			-0.548	12.523	1.000	2.686	-0.234	3.452	3.628
Solarize	1.145	25.595	2.270	-6.027			-1.948	21.035	1.000	6.377	-0.391	6.986	3.011
ES (WH) + Nudge	0.416	2.942	0.000	-0.346			-0.650	2.361	1.000	0.110	-0.057	1.053	2.243
IHWAP + Nudge (H)	0.739	0.914	0.020	-0.146			-0.109	1.417	1.000	0.024	-0.015	1.010	1.404
IHWAP + Nudge (L)	0.743	0.883	0.019	-0.141			-0.106	1.398	1.000	0.023	-0.014	1.009	1.386
WAP + Nudge	0.000	4.420	0.110	-0.644			-0.764	3.122	1.000	4.307	-0.074	5.233	0.597
Food Labels *	0.000	10.774	0.000	0.000			0.000	10.774	1.000	0.000	-0.210	0.790	13.645
Panel C. Revenue Raisers													
Gasoline Taxes	**1.000**	**-0.398**	**-0.204**		**0.000**	**-0.002**	**0.060**	**0.456**	**1.000**	**-0.074**	**0.008**	**0.934**	**0.488**
Gas (DK)	1.000	-0.652	-0.333		0.000	-0.002	0.098	0.111	1.000	-0.120	0.013	0.893	0.124
Gas (Su)	1.000	-0.562	-0.288		0.000	-0.002	0.084	0.232	1.000	-0.104	0.011	0.907	0.256
Gas (Coglianese)	1.000	-0.521	-0.267		0.000	-0.002	0.078	0.288	1.000	-0.096	0.010	0.914	0.315
Gas (Manzan)	1.000	-0.503	-0.257		0.000	-0.002	0.075	0.313	1.000	-0.093	0.010	0.917	0.342
Gas (Small)	1.000	-0.473	-0.242		0.000	-0.002	0.071	0.354	1.000	-0.087	0.009	0.922	0.384
Gas (Li)	1.000	-0.457	-0.234		0.000	-0.002	0.069	0.375	1.000	-0.084	0.009	0.925	0.406
Gas (Levin)	1.000	-0.417	-0.214		0.000	-0.002	0.063	0.429	1.000	-0.077	0.008	0.931	0.461
Gas (Sentenac-Chemin)	1.000	-0.396	-0.203		0.000	-0.002	0.060	0.458	1.000	-0.073	0.008	0.935	0.490
Gas (Kilian)	1.000	-0.280	-0.143		0.000	-0.002	0.042	0.617	1.000	-0.052	0.005	0.954	0.646
Gas (Gelman)	1.000	-0.232	-0.119		0.000	-0.002	0.035	0.682	1.000	-0.043	0.005	0.962	0.709
Gas (Park)	1.000	-0.227	-0.116		0.000	-0.002	0.034	0.689	1.000	-0.042	0.004	0.962	0.716
Gas (Hughes)	1.000	-0.058	-0.030		0.000	-0.002	0.009	0.918	1.000	-0.011	0.001	0.990	0.927

Gas (West) *	1.000	-0.649	-0.332		0.000	-0.002	0.097	0.115	1.000	-0.120	0.013	0.893	0.128
Gas (Tiezzi) *	1.000	-0.616	-0.315		0.000	-0.002	0.092	0.159	1.000	-0.114	0.012	0.898	0.177
Gas (Bento) *	1.000	-0.495	-0.253		0.000	-0.002	0.074	0.323	1.000	-0.091	0.010	0.918	0.352
Gas (Hughes - Ext) *	1.000	-0.474	-0.243		0.000	-0.002	0.071	0.352	1.000	-0.088	0.009	0.922	0.382
Gas (Kilian - Ext) *	1.000	-0.444	-0.227		0.000	-0.002	0.067	0.393	1.000	-0.082	0.009	0.927	0.424
Gas (Small - Ext) *	1.000	-0.093	-0.048		0.000	-0.002	0.014	0.870	1.000	-0.018	0.002	0.984	0.884
Other Fuel Taxes	**1.000**	**-0.321**	**-0.067**				**0.025**	**0.637**	**1.000**	**-0.033**	**0.006**	**0.973**	**0.655**
Jet Fuel	1.000	-0.540	-0.003				0.036	0.492	1.000	-0.048	0.011	0.963	0.511
Diesel	1.000	-0.102	-0.129				0.015	0.783	1.000	-0.019	0.002	0.983	0.797
Heavy Fuel *	1.000	-0.131	-0.001				0.007	0.875	1.000	-0.002	0.003	1.001	0.875
Crude (WPT) *	1.000	0.000	0.000				0.000	1.000	1.000	-0.002	0.000	0.998	1.002
Crude (State) *	1.000	-0.128	0.000				0.000	0.872	1.000	-0.364	0.002	0.638	1.367
E85 *	1.000	0.970	0.009				0.411	2.390	1.000	-0.361	0.019	0.658	3.635
Other Revenue Raisers	**0.979**	**-0.262**	**-0.014**	**0.021**			**-0.108**	**0.616**	**1.000**	**0.109**	**0.005**	**1.114**	**0.553**
CPP (AJ)	1.000	-0.187	-0.030	0.000			-0.323	0.461	1.000	0.176	0.004	1.179	0.391
CARE	0.936	-0.530	0.000	0.062			0.117	0.585	1.000	0.086	0.010	1.097	0.534
CPP (PJ)	1.000	-0.069	-0.011	0.000			-0.119	0.802	1.000	0.065	0.001	1.066	0.752
Cap and Trade													
RGGI	1.000	-1.147	-0.989					-1.136	1.000	-0.050	0.022	0.972	-1.168
CA CT	1.000	-0.107	-0.002					0.892	1.000	-0.006	0.002	0.997	0.895
ETS (BA) *	1.000	-16.051	0.000					-15.051	1.000	-0.900	0.313	0.414	-36.384
ETS (CMMW) *	1.000	-2.233	0.000					-1.233	1.000	-0.125	0.044	0.918	-1.342
Panel D. International													
Cookstoves													
Cookstove (Kenya)	7.675	75.221	0.000					82.895	1.000	0.000	-1.469	-0.469	∞
Cookstove (India)	0.545	-5.174	0.000					-4.629	1.000	0.000	0.101	1.101	-4.204
Deforestation													
REDD+ (SL)	0.000	62.581	0.000					62.581	1.000	0.000	-1.222	-0.222	∞
Deforest (Uganda)	0.421	5.564	0.000					5.985	1.000	0.000	-0.109	0.891	6.715
REDD+	0.965	5.154	0.000					6.119	1.000	0.000	-0.101	0.899	6.803
Deforest (Mexico) *	0.944	1.649	0.000					2.593	1.000	0.000	-0.032	0.968	2.679
Rice Burning													
India PES (Upfront)	0.972	18.582	0.000					19.555	1.000	0.000	-0.363	0.637	30.693
India PES (Standard)	0.915	14.192	0.000					15.107	1.000	0.000	-0.277	0.723	20.899
Wind Offset													
Offset (India)	1.000	16.384	0.000	-3.256				14.128	1.000	0.258	-0.256	1.002	14.104
International Rebates													
Fridge (Mexico)	0.750	0.220	0.000	-0.043				0.927	1.000	0.000	-0.003	0.997	0.930
AC (Mexico)	0.750	-0.166	0.000	0.032				0.617	1.000	0.000	0.003	1.003	0.615
WAP (Mexico)	0.500	-0.172	0.000	0.034				0.362	1.000	0.000	0.003	1.003	0.361

International Nudges													
Nudge (Qatar) *	0.000	12.574	0.000	-2.463				10.111	1.000	0.000	-0.197	0.803	12.599
Nudge (Germany) *	0.000	0.701	0.000	-0.137				0.564	1.000	0.000	-0.011	0.989	0.570

Notes: This table presents the MVPF components as displayed in Table 2 but using our baseline 2020 specification with a modified time path for the social cost of carbon that yields an SCC of $337 in 2020 and a real discount rate of 1.5% per year. We denote policies excluded from our primary sample by “*”, and these policies are not included in our category average measures.

Appendix Table 6: Baseline MVPF Components Excluding Profits

	Willingness to Pay								Cost				
		Environmental Benefits			Learning by Doing					Fiscal Externalities			
Panel A. Subsidies	**Transfer**	**Global**	**Local**	**Rebound**	**Env.**	**Price**	**Profits**	**WTP**	**Program**	**Initial**	**Climate**	**Total**	**MVPF**
Wind Production Credits	**1.000**	**4.678**	**0.643**	**-1.074**	**1.900**	**0.645**		**7.793**	**1.000**	**0.435**	**-0.108**	**1.328**	**5.870**
PTC (Shrimali)	1.000	5.865	0.806	-1.346	3.277	0.920		10.522	1.000	0.546	-0.152	1.394	7.547
PTC (Metcalf)	1.000	4.368	0.601	-1.002	1.427	0.560		6.953	1.000	0.407	-0.094	1.312	5.298
PTC (Hitaj)	1.000	3.801	0.523	-0.872	0.998	0.455		5.904	1.000	0.354	-0.078	1.276	4.626
FIT (Germany - BEN) *	1.000	6.629	0.911	-1.521	4.841	1.170		13.030	1.000	0.617	-0.193	1.424	9.148
FIT (Spain) *	1.000	5.866	0.806	-1.346	3.277	0.920		10.522	1.000	0.546	-0.152	1.394	7.547
FIT (Germany - HL) *	1.000	5.596	0.769	-1.284	2.844	0.844		9.768	1.000	0.521	-0.140	1.381	7.072
FIT (France) *	1.000	4.837	0.665	-1.110	1.877	0.658		7.926	1.000	0.450	-0.110	1.340	5.913
FIT (UK) *	1.000	2.006	0.276	-0.460	0.223	0.199		3.243	1.000	0.187	-0.035	1.151	2.817
FIT (EU) *	1.000	0.546	0.075	-0.125	0.016	0.050		1.561	1.000	0.051	-0.009	1.042	1.498
Residential Solar	**1.106**	**1.718**	**0.252**	**-0.421**	**2.280**	**1.636**		**6.570**	**1.000**	**0.598**	**-0.068**	**1.530**	**4.295**
CSI	1.000	4.299	0.631	-1.054	4.988	3.987		13.851	1.000	1.496	-0.157	2.339	5.921
NE Solar	1.000	1.220	0.179	-0.299	3.132	1.610		6.842	1.000	0.424	-0.076	1.348	5.075
CSI (TPO)	1.528	1.604	0.235	-0.393	1.982	1.371		6.328	1.000	0.558	-0.061	1.498	4.225
CSI (HO)	1.000	0.932	0.137	-0.228	1.081	0.864		3.786	1.000	0.324	-0.034	1.290	2.934
CT Solar	1.000	0.533	0.078	-0.131	0.216	0.346		2.042	1.000	0.185	-0.012	1.173	1.740
ITC *	1.000	1.152	0.169	-0.282	3.825	1.944		7.807	1.000	0.453	-0.088	1.365	5.720
Electric Vehicles	**1.000**	**0.057**	**0.000**	**0.032**	**0.073**	**0.452**		**1.614**	**1.000**	**0.077**	**-0.004**	**1.073**	**1.505**
BEV (State - Rebate)	1.000	0.068	0.000	0.038	0.103	0.564		1.773	1.000	0.091	-0.006	1.085	1.634
ITC (EV)	1.000	0.061	0.000	0.034	0.078	0.482		1.655	1.000	0.081	-0.005	1.076	1.538
EFMP	1.000	0.042	0.000	0.023	0.040	0.309		1.414	1.000	0.059	-0.003	1.056	1.339
BEV (State - ITC) *	1.000	-0.048	0.000	-0.027	0.000	0.000		0.925	1.000	-0.061	0.003	0.939	0.985
Appliance Rebates	**0.867**	**0.497**	**0.043**	**-0.089**				**1.318**	**1.000**	**0.027**	**-0.009**	**1.018**	**1.294**
C4A (CW)	0.953	0.550	0.083	-0.124				1.461	1.000	0.000	-0.009	0.991	1.474
ES (WH)	0.598	1.707	0.000	-0.201				2.104	1.000	0.000	-0.033	0.967	2.176
ES (CW)	1.000	0.861	0.126	-0.193				1.794	1.000	0.289	-0.014	1.276	1.406
C4A (DW)	0.930	0.243	0.037	-0.055				1.155	1.000	0.000	-0.004	0.996	1.159
ES (DW)	1.000	-0.223	-0.033	0.050				0.795	1.000	-0.221	0.003	0.782	1.016
C4A (Fridge)	0.960	0.099	0.015	-0.022				1.051	1.000	0.000	-0.002	0.998	1.053
ES (Fridge)	1.000	0.199	0.029	-0.045				1.183	1.000	0.148	-0.003	1.144	1.034
CA ESA	0.500	0.541	0.083	-0.122				1.002	1.000	0.000	-0.008	0.992	1.010
Vehicle Retirement	**0.910**	**0.280**	**0.102**	**-0.137**				**1.155**	**1.000**	**0.050**	**-0.004**	**1.045**	**1.105**
C4C (TX)	1.000	0.410	0.030	-0.208				1.231	1.000	0.071	-0.006	1.065	1.156
C4C (US)	1.000	0.271	0.020	-0.140				1.151	1.000	0.047	-0.004	1.042	1.104
BAAQMD	0.730	0.161	0.255	-0.062				1.084	1.000	0.031	-0.003	1.028	1.054

Hybrid Vehicles	**1.000**	**0.031**	**0.003**	**-0.026**	**0.000**	**0.014**	**1.023**	**1.000**	**0.006**	**-0.001**	**1.005**	**1.017**
HY (S-STW)	1.000	0.070	0.007	-0.059	0.001	0.031	1.051	1.000	0.014	-0.002	1.012	1.038
HY (F-ITC)	1.000	0.020	0.002	-0.017	0.000	0.009	1.014	1.000	0.004	0.000	1.003	1.011
HY (S-ITC)	1.000	0.004	0.000	-0.004	0.000	0.002	1.003	1.000	0.001	0.000	1.001	1.002
Weatherization	**0.774**	**0.297**	**0.029**	**-0.057**			**1.043**	**1.000**	**0.000**	**-0.005**	**0.995**	**1.048**
EPP	0.750	0.593	0.083	-0.133			1.294	1.000	0.000	-0.009	0.991	1.306
IHWAP	0.750	0.404	0.019	-0.064			1.109	1.000	0.000	-0.007	0.993	1.117
WI RF	0.870	0.052	0.011	-0.012			0.921	1.000	0.000	-0.001	0.999	0.921
WAP	0.750	0.297	0.013	-0.045			1.015	1.000	0.000	-0.005	0.995	1.021
LEEP+	0.750	0.138	0.019	-0.031			0.877	1.000	0.000	-0.002	0.998	0.879
Other Subsidies	**0.887**	**1.504**	**0.424**	**-0.234**			**2.582**	**1.000**	**0.000**	**-0.025**	**0.975**	**2.650**
CA 20/20	0.882	2.090	0.297	-0.468			2.802	1.000	0.000	-0.033	0.967	2.897
CRP	0.893	0.919	0.552	0.000			2.363	1.000	0.000	-0.018	0.982	2.407

Panel B. Nudges and Marketing

Home Energy Reports												
HER (17 RCTs)	0.000	3.872	0.439	-0.844			3.466	1.000	0.000	-0.061	0.939	3.691
Opower Elec. (166 RCTs)	0.000	3.246	0.368	-0.708			2.906	1.000	0.000	-0.051	0.949	3.062
PER												
Opower Nat. Gas (52 RCTs)	0.000	0.950	0.000	-0.112			0.838	1.000	0.000	-0.016	0.984	0.852
Other Nudges	**0.507**	**4.799**	**0.613**	**-1.061**			**4.857**	**1.000**	**1.979**	**-0.076**	**2.903**	**1.673**
Audit Nudge	0.000	8.678	1.333	-1.961			8.050	1.000	2.373	-0.136	3.237	2.487
Solarize	1.145	15.001	2.200	-3.678			14.669	1.000	5.306	-0.230	6.077	2.414
ES (WH) + Nudge	0.416	1.630	0.000	-0.192			1.854	1.000	0.000	-0.032	0.968	1.915
IHWAP + Nudge (H)	0.739	0.517	0.019	-0.085			1.190	1.000	0.023	-0.008	1.015	1.173
IHWAP + Nudge (L)	0.743	0.500	0.018	-0.082			1.179	1.000	0.022	-0.008	1.014	1.162
WAP + Nudge	0.000	2.467	0.107	-0.371			2.203	1.000	4.149	-0.041	5.107	0.431
Food Labels *	0.000	6.170	0.000	0.000			6.170	1.000	0.000	-0.120	0.880	7.015

Panel C. Revenue Raisers

Gasoline Taxes	**1.000**	**-0.229**	**-0.204**		**0.000**	**-0.002**	**0.565**	**1.000**	**-0.058**	**0.004**	**0.947**	**0.597**
Gas (DK)	1.000	-0.374	-0.333		0.000	-0.002	0.290	1.000	-0.094	0.007	0.913	0.318
Gas (Su)	1.000	-0.323	-0.288		0.000	-0.002	0.387	1.000	-0.081	0.006	0.925	0.419
Gas (Coglianese)	1.000	-0.299	-0.267		0.000	-0.002	0.432	1.000	-0.075	0.006	0.931	0.464
Gas (Manzan)	1.000	-0.289	-0.257		0.000	-0.002	0.452	1.000	-0.073	0.006	0.933	0.484
Gas (Small)	1.000	-0.272	-0.242		0.000	-0.002	0.484	1.000	-0.068	0.005	0.937	0.517
Gas (Li)	1.000	-0.263	-0.234		0.000	-0.002	0.501	1.000	-0.066	0.005	0.939	0.534
Gas (Levin)	1.000	-0.240	-0.214		0.000	-0.002	0.544	1.000	-0.060	0.005	0.944	0.576
Gas (Sentenac-Chemin)	1.000	-0.228	-0.203		0.000	-0.002	0.567	1.000	-0.057	0.004	0.947	0.599
Gas (Kilian)	1.000	-0.161	-0.143		0.000	-0.002	0.694	1.000	-0.041	0.003	0.963	0.721
Gas (Gelman)	1.000	-0.133	-0.119		0.000	-0.002	0.746	1.000	-0.034	0.003	0.969	0.770
Gas (Park)	1.000	-0.130	-0.116		0.000	-0.002	0.751	1.000	-0.033	0.003	0.970	0.775
Gas (Hughes)	1.000	-0.034	-0.030		0.000	-0.002	0.934	1.000	-0.009	0.001	0.992	0.941

Gas (West) *	1.000	-0.373	-0.332		0.000	-0.002	0.293	1.000	-0.094	0.007	0.914	0.321
Gas (Tiezzi) *	1.000	-0.354	-0.315		0.000	-0.002	0.329	1.000	-0.089	0.007	0.918	0.358
Gas (Bento) *	1.000	-0.285	-0.254		0.000	-0.002	0.460	1.000	-0.072	0.006	0.934	0.492
Gas (Hughes - Ext) *	1.000	-0.272	-0.243		0.000	-0.002	0.483	1.000	-0.069	0.005	0.937	0.515
Gas (Kilian - Ext) *	1.000	-0.255	-0.227		0.000	-0.002	0.515	1.000	-0.064	0.005	0.941	0.548
Gas (Small - Ext) *	1.000	-0.054	-0.048		0.000	-0.002	0.896	1.000	-0.014	0.001	0.987	0.907
Other Fuel Taxes	**1.000**	**-0.185**	**-0.067**				**0.749**	**1.000**	**-0.027**	**0.004**	**0.977**	**0.767**
Jet Fuel	1.000	-0.310	-0.003				0.687	1.000	-0.038	0.006	0.968	0.710
Diesel	1.000	-0.059	-0.129				0.812	1.000	-0.015	0.001	0.986	0.823
Heavy Fuel *	1.000	-0.075	-0.001				0.924	1.000	0.000	0.001	1.001	0.923
Crude (WPT) *	1.000	0.000	0.000				1.000	1.000	-0.002	0.000	0.998	1.002
Crude (State) *	1.000	-0.075	0.000				0.925	1.000	-0.364	0.001	0.637	1.451
E85 *	1.000	0.562	0.009				1.572	1.000	-0.252	0.011	0.759	2.071
Other Revenue Raisers	**0.979**	**-0.150**	**-0.014**	**0.012**			**0.827**	**1.000**	**0.021**	**0.003**	**1.024**	**0.808**
CPP (AJ)	1.000	-0.107	-0.030	0.000			0.864	1.000	0.000	0.002	1.002	0.862
CARE	0.936	-0.303	0.000	0.036			0.668	1.000	0.064	0.006	1.070	0.624
CPP (PJ)	1.000	-0.039	-0.011	0.000			0.950	1.000	0.000	0.001	1.001	0.949
Cap and Trade												
RGGI	1.000	-0.657	-0.989				-0.646	1.000	-0.050	0.013	0.963	-0.671
CA CT	1.000	-0.061	-0.002				0.937	1.000	-0.006	0.001	0.996	0.941
ETS (BA) *	1.000	-9.192	0.000				-8.192	1.000	-0.900	0.180	0.280	-29.287
ETS (CMMW) *	1.000	-1.279	0.000				-0.279	1.000	-0.125	0.025	0.900	-0.310

Notes: This table presents the baseline MVPF components as displayed in Table 2 but excludes firm profits from the MVPF components. We denote policies excluded from our primary sample by "*", and these policies are not included in our category average measures. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

Appendix Table 7: Baseline MVPF Components Including Energy Savings Additional Benefits

	Willingness to Pay									Cost				
		Environmental Benefits			Learning by Doing						Fiscal Externalities			
Panel A. Subsidies	**Transfer**	**Global**	**Local**	**Rebound**	**Env.**	**Price**	**Profits**	**Savings**	**WTP**	**Program**	**Initial**	**Climate**	**Total**	**MVPF**
Wind Production Credits	**1.000**	**4.678**	**0.643**	**-1.074**	**1.900**	**0.645**		**0.000**	**7.793**	**1.000**	**0.435**	**-0.108**	**1.328**	**5.870**
PTC (Shrimali)	1.000	5.865	0.806	-1.346	3.277	0.920		0.000	10.522	1.000	0.546	-0.152	1.394	7.547
PTC (Metcalf)	1.000	4.368	0.601	-1.002	1.427	0.560		0.000	6.953	1.000	0.407	-0.094	1.312	5.298
PTC (Hitaj)	1.000	3.801	0.523	-0.872	0.998	0.455		0.000	5.904	1.000	0.354	-0.078	1.276	4.626
FIT (Germany - BEN) *	1.000	6.629	0.911	-1.521	4.841	1.170		0.000	13.030	1.000	0.617	-0.193	1.424	9.148
FIT (Spain) *	1.000	5.866	0.806	-1.346	3.277	0.920		0.000	10.522	1.000	0.546	-0.152	1.394	7.547
FIT (Germany - HL) *	1.000	5.596	0.769	-1.284	2.844	0.844		0.000	9.768	1.000	0.521	-0.140	1.381	7.072
FIT (France) *	1.000	4.837	0.665	-1.110	1.877	0.658		0.000	7.926	1.000	0.450	-0.110	1.340	5.913
FIT (UK) *	1.000	2.006	0.276	-0.460	0.223	0.199		0.000	3.243	1.000	0.187	-0.035	1.151	2.817
FIT (EU) *	1.000	0.546	0.075	-0.125	0.016	0.050		0.000	1.561	1.000	0.051	-0.009	1.042	1.498
Residential Solar	**1.106**	**1.718**	**0.252**	**-0.421**	**2.280**	**1.636**	**-0.214**	**3.131**	**9.487**	**1.000**	**0.714**	**-0.068**	**1.646**	**5.764**
CSI	1.000	4.299	0.631	-1.054	4.988	3.987	-0.535	7.837	21.153	1.000	1.787	-0.157	2.630	8.043
NE Solar	1.000	1.220	0.179	-0.299	3.132	1.610	-0.152	2.224	8.914	1.000	0.507	-0.076	1.431	6.230
CSI (TPO)	1.528	1.604	0.235	-0.393	1.982	1.371	-0.200	2.925	9.053	1.000	0.667	-0.061	1.606	5.636
CSI (HO)	1.000	0.932	0.137	-0.228	1.081	0.864	-0.116	1.699	5.368	1.000	0.387	-0.034	1.353	3.967
CT Solar	1.000	0.533	0.078	-0.131	0.216	0.346	-0.066	0.972	2.948	1.000	0.222	-0.012	1.209	2.437
ITC *	1.000	1.152	0.169	-0.282	3.825	1.944	-0.143	2.099	9.763	1.000	0.531	-0.088	1.443	6.767
Electric Vehicles	**1.000**	**0.057**	**0.000**	**0.032**	**0.073**	**0.452**	**-0.043**	**0.078**	**1.649**	**1.000**	**0.092**	**-0.004**	**1.087**	**1.517**
BEV (State - Rebate)	1.000	0.068	0.000	0.038	0.103	0.564	-0.051	0.094	1.816	1.000	0.108	-0.006	1.103	1.646
ITC (EV)	1.000	0.061	0.000	0.034	0.078	0.482	-0.046	0.083	1.693	1.000	0.097	-0.005	1.092	1.550
EFMP	1.000	0.042	0.000	0.023	0.040	0.309	-0.031	0.057	1.440	1.000	0.070	-0.003	1.067	1.350
BEV (State - ITC) *	1.000	-0.048	0.000	-0.027	0.000	0.000	0.036	-0.066	0.895	1.000	-0.073	0.003	0.927	0.966
Appliance Rebates	**0.867**	**0.497**	**0.043**	**-0.089**			**-0.103**	**0.565**	**1.780**	**1.000**	**0.052**	**-0.009**	**1.044**	**1.705**
C4A (CW)	0.953	0.550	0.083	-0.124			-0.039	0.575	1.997	1.000	0.021	-0.009	1.012	1.973
ES (WH)	0.598	1.707	0.000	-0.201			-0.659	2.051	3.496	1.000	0.112	-0.033	1.078	3.242
ES (CW)	1.000	0.861	0.126	-0.193			-0.072	1.066	2.787	1.000	0.328	-0.014	1.315	2.120
C4A (DW)	0.930	0.243	0.037	-0.055			-0.017	0.246	1.385	1.000	0.009	-0.004	1.005	1.377
ES (DW)	1.000	-0.223	-0.033	0.050			0.019	-0.276	0.538	1.000	-0.231	0.003	0.772	0.696
C4A (Fridge)	0.960	0.099	0.015	-0.022			-0.007	0.106	1.151	1.000	0.004	-0.002	1.002	1.148
ES (Fridge)	1.000	0.199	0.029	-0.045			-0.017	0.246	1.413	1.000	0.157	-0.003	1.154	1.225
CA ESA	0.500	0.541	0.083	-0.122			-0.034	0.504	1.471	1.000	0.018	-0.008	1.010	1.457
Vehicle Retirement	**0.910**	**0.280**	**0.102**	**-0.137**			**-0.049**	**0.232**	**1.338**	**1.000**	**0.060**	**-0.004**	**1.056**	**1.267**
C4C (TX)	1.000	0.410	0.030	-0.208			-0.074	0.348	1.505	1.000	0.091	-0.006	1.084	1.388
C4C (US)	1.000	0.271	0.020	-0.140			-0.049	0.228	1.331	1.000	0.060	-0.004	1.055	1.261
BAAQMD	0.730	0.161	0.255	-0.062			-0.025	0.118	1.177	1.000	0.031	-0.003	1.028	1.145

Hybrid Vehicles	**1.000**	**0.031**	**0.003**	**-0.026**	**0.000**	**0.014**	**-0.006**	**0.030**	**1.047**	**1.000**	**0.005**	**-0.001**	**1.004**	**1.043**
HY (S-STW)	1.000	0.070	0.007	-0.059	0.001	0.031	-0.014	0.068	1.104	1.000	0.010	-0.002	1.008	1.095
HY (F-ITC)	1.000	0.020	0.002	-0.017	0.000	0.009	-0.004	0.019	1.029	1.000	0.003	0.000	1.002	1.027
HY (S-ITC)	1.000	0.004	0.000	-0.004	0.000	0.002	-0.001	0.004	1.006	1.000	0.001	0.000	1.001	1.006
Weatherization	**0.774**	**0.297**	**0.029**	**-0.057**			**-0.054**	**0.397**	**1.386**	**1.000**	**0.017**	**-0.005**	**1.012**	**1.370**
EPP	0.750	0.593	0.083	-0.133			-0.057	0.852	2.089	1.000	0.031	-0.009	1.022	2.044
IHWAP	0.750	0.404	0.019	-0.064			-0.111	0.555	1.554	1.000	0.025	-0.007	1.019	1.525
WI RF	0.870	0.052	0.011	-0.012			-0.001	0.000	0.920	1.000	0.001	-0.001	1.000	0.920
WAP	0.750	0.297	0.013	-0.045			-0.088	0.379	1.306	1.000	0.018	-0.005	1.013	1.289
LEEP+	0.750	0.138	0.019	-0.031			-0.013	0.199	1.062	1.000	0.007	-0.002	1.005	1.057
Other Subsidies	**0.887**	**1.504**	**0.424**	**-0.234**			**-0.065**	**0.969**	**3.486**	**1.000**	**0.036**	**-0.025**	**1.010**	**3.451**
CA 20/20	0.882	2.090	0.297	-0.468			-0.131	1.939	4.609	1.000	0.071	-0.033	1.038	4.440
CRP	0.893	0.919	0.552	0.000			0.000	0.000	2.363	1.000	0.000	-0.018	0.982	2.407
Panel B. Nudges and Marketing														
Home Energy Reports														
HER (17 RCTs)	0.000	3.872	0.439	-0.844			-0.244	3.622	6.844	1.000	0.133	-0.061	1.072	6.385
Opower Elec. (166 RCTs)	0.000	3.246	0.368	-0.708			-0.205	3.036	5.738	1.000	0.111	-0.051	1.060	5.411
PER	0.000	0.230	0.064	0.000			0.695	0.000	0.989	1.000	-0.378	-0.004	0.618	1.600
Opower Nat. Gas (52 RCTs)	0.000	0.950	0.000	-0.112			-0.367	1.142	1.613	1.000	0.062	-0.016	1.046	1.543
Other Nudges	**0.507**	**4.799**	**0.613**	**-1.061**			**-0.659**	**6.911**	**11.109**	**1.000**	**2.243**	**-0.076**	**3.167**	**3.508**
Audit Nudge	0.000	8.678	1.333	-1.961			-0.542	8.042	15.550	1.000	2.683	-0.136	3.547	4.384
Solarize	1.145	15.001	2.200	-3.678			-1.844	27.346	40.170	1.000	6.320	-0.230	7.091	5.665
ES (WH) + Nudge	0.416	1.630	0.000	-0.192			-0.629	1.959	3.184	1.000	0.107	-0.032	1.075	2.963
IHWAP + Nudge (H)	0.739	0.517	0.019	-0.085			-0.105	0.501	1.586	1.000	0.023	-0.008	1.015	1.563
IHWAP + Nudge (L)	0.743	0.500	0.018	-0.082			-0.101	0.474	1.552	1.000	0.022	-0.008	1.014	1.530
WAP + Nudge	0.000	2.467	0.107	-0.371			-0.732	3.142	4.614	1.000	4.300	-0.041	5.259	0.877
Food Labels *	0.000	6.170	0.000	0.000			0.000	0.000	6.170	1.000	0.000	-0.120	0.880	7.015

Notes: This table presents the MVPF components as displayed in Table 2 but using our baseline 2020 specification and includes energy savings as an additional component of WTP for vehicle replacement, appliance subsidies, weatherization, and nudges/marketing policies (displayed in Column 9). We denote policies excluded from our primary sample by “*”, and these policies are not included in our category average measures. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

Appendix Table 8: Baseline MVPF Components Excluding Learning by Doing

	Willingness to Pay								**Cost**				
		Environmental Benefits			**Learning by Doing**					**Fiscal Externalities**			
Panel A. Subsidies	**Transfer**	**Global**	**Local**	**Rebound**	**Env.**	**Price**	**Profits**	**WTP**	**Program**	**Initial**	**Climate**	**Total**	**MVPF**
Wind Production Credits	**1.000**	**4.678**	**0.643**	**-1.074**				**5.248**	**1.000**	**0.435**	**-0.073**	**1.363**	**3.851**
PTC (Shrimali)	1.000	5.865	0.806	-1.346				6.326	1.000	0.546	-0.091	1.455	4.349
PTC (Metcalf)	1.000	4.368	0.601	-1.002				4.966	1.000	0.407	-0.068	1.339	3.710
PTC (Hitaj)	1.000	3.801	0.523	-0.872				4.451	1.000	0.354	-0.059	1.295	3.438
FIT (Germany - BEN) *	1.000	6.629	0.911	-1.521				7.019	1.000	0.617	-0.103	1.514	4.637
FIT (Spain) *	1.000	5.866	0.806	-1.346				6.326	1.000	0.546	-0.091	1.455	4.349
FIT (Germany - HL) *	1.000	5.596	0.769	-1.284				6.081	1.000	0.521	-0.087	1.434	4.241
FIT (France) *	1.000	4.837	0.665	-1.110				5.391	1.000	0.450	-0.075	1.375	3.921
FIT (UK) *	1.000	2.006	0.276	-0.460				2.822	1.000	0.187	-0.031	1.156	2.442
FIT (EU) *	1.000	0.546	0.075	-0.125				1.496	1.000	0.051	-0.009	1.042	1.435
Residential Solar	**1.106**	**1.718**	**0.252**	**-0.421**			**-0.214**	**2.440**	**1.000**	**0.714**	**-0.026**	**1.688**	**1.446**
CSI	1.000	4.299	0.631	-1.054			-0.535	4.341	1.000	1.787	-0.066	2.721	1.595
NE Solar	1.000	1.220	0.179	-0.299			-0.152	1.948	1.000	0.507	-0.019	1.488	1.309
CSI (TPO)	1.528	1.604	0.235	-0.393			-0.200	2.775	1.000	0.667	-0.025	1.642	1.690
CSI (HO)	1.000	0.932	0.137	-0.228			-0.116	1.724	1.000	0.387	-0.014	1.373	1.256
CT Solar	1.000	0.533	0.078	-0.131			-0.066	1.414	1.000	0.222	-0.008	1.213	1.166
ITC *	1.000	1.152	0.169	-0.282			-0.143	1.895	1.000	0.531	-0.018	1.513	1.252
Electric Vehicles	**1.000**	**0.057**	**0.000**	**0.032**			**-0.043**	**1.046**	**1.000**	**0.092**	**-0.003**	**1.088**	**0.961**
BEV (State - Rebate)	1.000	0.068	0.000	0.038			-0.051	1.055	1.000	0.108	-0.004	1.105	0.955
ITC (EV)	1.000	0.061	0.000	0.034			-0.046	1.049	1.000	0.097	-0.003	1.093	0.960
EFMP	1.000	0.042	0.000	0.023			-0.031	1.034	1.000	0.070	-0.002	1.067	0.969
BEV (State - ITC) *	1.000	-0.048	0.000	-0.027			0.036	0.961	1.000	-0.073	0.003	0.927	1.037
Appliance Rebates	**0.867**	**0.497**	**0.043**	**-0.089**			**-0.103**	**1.215**	**1.000**	**0.052**	**-0.009**	**1.044**	**1.164**
C4A (CW)	0.953	0.550	0.083	-0.124			-0.039	1.423	1.000	0.021	-0.009	1.012	1.405
ES (WH)	0.598	1.707	0.000	-0.201			-0.659	1.445	1.000	0.112	-0.033	1.078	1.340
ES (CW)	1.000	0.861	0.126	-0.193			-0.072	1.722	1.000	0.328	-0.014	1.315	1.310
C4A (DW)	0.930	0.243	0.037	-0.055			-0.017	1.138	1.000	0.009	-0.004	1.005	1.132
ES (DW)	1.000	-0.223	-0.033	0.050			0.019	0.813	1.000	-0.231	0.003	0.772	1.053
C4A (Fridge)	0.960	0.099	0.015	-0.022			-0.007	1.044	1.000	0.004	-0.002	1.002	1.042
ES (Fridge)	1.000	0.199	0.029	-0.045			-0.017	1.167	1.000	0.157	-0.003	1.154	1.011
CA ESA	0.500	0.541	0.083	-0.122			-0.034	0.968	1.000	0.018	-0.008	1.010	0.958
Vehicle Retirement	**0.910**	**0.280**	**0.102**	**-0.137**			**-0.049**	**1.106**	**1.000**	**0.060**	**-0.004**	**1.056**	**1.047**
C4C (TX)	1.000	0.410	0.030	-0.208			-0.074	1.157	1.000	0.091	-0.006	1.084	1.067
C4C (US)	1.000	0.271	0.020	-0.140			-0.049	1.102	1.000	0.060	-0.004	1.055	1.044
BAAQMD	0.730	0.161	0.255	-0.062			-0.025	1.059	1.000	0.031	-0.003	1.028	1.030

Hybrid Vehicles	**1.000**	**0.031**	**0.003**	**-0.026**	**-0.006**	**1.002**	**1.000**	**0.005**	**-0.001**	**1.004**	**0.998**
HY (S-STW)	1.000	0.070	0.007	-0.059	-0.014	1.004	1.000	0.010	-0.002	1.008	0.996
HY (F-ITC)	1.000	0.020	0.002	-0.017	-0.004	1.001	1.000	0.003	0.000	1.002	0.999
HY (S-ITC)	1.000	0.004	0.000	-0.004	-0.001	1.000	1.000	0.001	0.000	1.001	1.000
Weatherization	**0.774**	**0.297**	**0.029**	**-0.057**	**-0.054**	**0.989**	**1.000**	**0.017**	**-0.005**	**1.012**	**0.978**
EPP	0.750	0.593	0.083	-0.133	-0.057	1.237	1.000	0.031	-0.009	1.022	1.210
IHWAP	0.750	0.404	0.019	-0.064	-0.111	0.999	1.000	0.025	-0.007	1.019	0.980
WI RF	0.870	0.052	0.011	-0.012	-0.001	0.920	1.000	0.001	-0.001	1.000	0.920
WAP	0.750	0.297	0.013	-0.045	-0.088	0.927	1.000	0.018	-0.005	1.013	0.915
LEEP+	0.750	0.138	0.019	-0.031	-0.013	0.864	1.000	0.007	-0.002	1.005	0.859
Other Subsidies	**0.887**	**1.504**	**0.424**	**-0.234**	**-0.065**	**2.517**	**1.000**	**0.036**	**-0.025**	**1.010**	**2.492**
CA 20/20	0.882	2.090	0.297	-0.468	-0.131	2.671	1.000	0.071	-0.033	1.038	2.572
CRP	0.893	0.919	0.552	0.000	0.000	2.363	1.000	0.000	-0.018	0.982	2.407
Panel B. Nudges and Marketing											
Home Energy Reports											
HER (17 RCTs)	0.000	3.872	0.439	-0.844	-0.244	3.222	1.000	0.133	-0.061	1.072	3.006
Opower Elec. (166 RCTs)	0.000	3.246	0.368	-0.708	-0.205	2.701	1.000	0.111	-0.051	1.060	2.548
PER	0.000	0.230	0.064	0.000	0.695	0.989	1.000	-0.378	-0.004	0.618	1.600
Opower Nat. Gas (52 RCTs)	0.000	0.950	0.000	-0.112	-0.367	0.472	1.000	0.062	-0.016	1.046	0.451
Other Nudges	**0.507**	**4.799**	**0.613**	**-1.061**	**-0.659**	**4.199**	**1.000**	**2.243**	**-0.076**	**3.167**	**1.326**
Audit Nudge	0.000	8.678	1.333	-1.961	-0.542	7.507	1.000	2.683	-0.136	3.547	2.117
Solarize	1.145	15.001	2.200	-3.678	-1.844	12.824	1.000	6.320	-0.230	7.091	1.809
ES (WH) + Nudge	0.416	1.630	0.000	-0.192	-0.629	1.225	1.000	0.107	-0.032	1.075	1.140
IHWAP + Nudge (H)	0.739	0.517	0.019	-0.085	-0.105	1.085	1.000	0.023	-0.008	1.015	1.069
IHWAP + Nudge (L)	0.743	0.500	0.018	-0.082	-0.101	1.078	1.000	0.022	-0.008	1.014	1.062
WAP + Nudge	0.000	2.467	0.107	-0.371	-0.732	1.471	1.000	4.300	-0.041	5.259	0.280
Food Labels *	0.000	6.170	0.000	0.000	0.000	6.170	1.000	0.000	-0.120	0.880	7.015
Panel C. Revenue Raisers											
Gasoline Taxes	**1.000**	**-0.229**	**-0.204**		**0.060**	**0.627**	**1.000**	**-0.073**	**0.004**	**0.931**	**0.673**
Gas (DK)	1.000	-0.375	-0.333		0.098	0.390	1.000	-0.120	0.007	0.887	0.439
Gas (Su)	1.000	-0.324	-0.288		0.084	0.473	1.000	-0.104	0.006	0.903	0.524
Gas (Coglianese)	1.000	-0.300	-0.267		0.078	0.512	1.000	-0.096	0.006	0.910	0.562
Gas (Manzan)	1.000	-0.289	-0.257		0.076	0.529	1.000	-0.093	0.006	0.913	0.579
Gas (Small)	1.000	-0.272	-0.242		0.071	0.557	1.000	-0.087	0.005	0.918	0.606
Gas (Li)	1.000	-0.263	-0.234		0.069	0.571	1.000	-0.084	0.005	0.921	0.620
Gas (Levin)	1.000	-0.241	-0.214		0.063	0.609	1.000	-0.077	0.005	0.928	0.656
Gas (Sentenac-Chemin)	1.000	-0.228	-0.203		0.060	0.628	1.000	-0.073	0.004	0.931	0.675
Gas (Kilian)	1.000	-0.161	-0.143		0.042	0.737	1.000	-0.052	0.003	0.951	0.775
Gas (Gelman)	1.000	-0.134	-0.119		0.035	0.782	1.000	-0.043	0.003	0.960	0.815
Gas (Park)	1.000	-0.131	-0.116		0.034	0.787	1.000	-0.042	0.003	0.961	0.819
Gas (Hughes)	1.000	-0.034	-0.030		0.009	0.944	1.000	-0.011	0.001	0.990	0.954

Gas (West) *	1.000	-0.373	-0.332				0.097	0.392	1.000	-0.119	0.007	0.888	0.442
Gas (Tiezzi) *	1.000	-0.355	-0.315				0.093	0.423	1.000	-0.114	0.007	0.893	0.473
Gas (Bento) *	1.000	-0.285	-0.254				0.074	0.536	1.000	-0.091	0.006	0.914	0.586
Gas (Hughes - Ext) *	1.000	-0.273	-0.243				0.071	0.555	1.000	-0.087	0.005	0.918	0.605
Gas (Kilian - Ext) *	1.000	-0.256	-0.227				0.067	0.583	1.000	-0.082	0.005	0.923	0.632
Gas (Small - Ext) *	1.000	-0.054	-0.048				0.014	0.911	1.000	-0.017	0.001	0.984	0.927
Other Fuel Taxes	**1.000**	**-0.185**	**-0.067**				**0.025**	**0.774**	**1.000**	**-0.033**	**0.004**	**0.970**	**0.798**
Jet Fuel	1.000	-0.310	-0.003				0.036	0.722	1.000	-0.048	0.006	0.958	0.754
Diesel	1.000	-0.059	-0.129				0.015	0.827	1.000	-0.019	0.001	0.982	0.842
Heavy Fuel *	1.000	-0.075	-0.001				0.007	0.931	1.000	-0.002	0.001	1.000	0.931
Crude (WPT) *	1.000	0.000	0.000				0.000	1.000	1.000	-0.002	0.000	0.998	1.002
Crude (State) *	1.000	-0.075	0.000				0.000	0.925	1.000	-0.364	0.001	0.637	1.451
E85 *	1.000	0.562	0.009				0.411	1.982	1.000	-0.361	0.011	0.650	3.051
Other Revenue Raisers	**0.979**	**-0.150**	**-0.014**	**0.012**			**-0.108**	**0.719**	**1.000**	**0.109**	**0.003**	**1.112**	**0.647**
CPP (AJ)	1.000	-0.107	-0.030	0.000			-0.323	0.540	1.000	0.176	0.002	1.178	0.459
CARE	0.936	-0.303	0.000	0.036			0.117	0.785	1.000	0.086	0.006	1.092	0.719
CPP (PJ)	1.000	-0.039	-0.011	0.000			-0.119	0.831	1.000	0.065	0.001	1.065	0.780
Cap and Trade													
RGGI	1.000	-0.657	-0.989					-0.646	1.000	-0.050	0.013	0.963	-0.671
CA CT	1.000	-0.061	-0.002					0.937	1.000	-0.006	0.001	0.996	0.941
ETS (BA) *	1.000	-9.192	0.000					-8.192	1.000	-0.900	0.180	0.280	-29.287
ETS (CMMW) *	1.000	-1.279	0.000					-0.279	1.000	-0.125	0.025	0.900	-0.310

Notes: This table presents the baseline MVPF components as displayed in Table 2 but excludes learning by doing effects from the MVPF components. We denote policies excluded from our primary sample by "*", and these policies are not included in our category average measures. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

Appendix Table 9: MVPF Versus Social Cost Per Ton with MCF Adjustment

Panel A. With Learning by Doing	**MVPF**	**Net Social Cost Per Ton** **0% DWL**	**10% DWL**	**30% DWL**	**50% DWL**
Subsidies					
Wind Production Credits	5.870	-32	-24	-15	-6
Residential Solar	3.862	-67	-48	-31	-14
Electric Vehicles	1.445	-415	-259	1	260
Appliance Rebates	1.164	111	159	254	349
Vehicle Retirement	1.047	148	235	411	586
Hybrid Vehicles	1.012	-38	555	1,749	2,942
Weatherization	0.978	207	285	441	596
Nudges and Marketing					
Opower Elec. (166 RCTs)	2.548	70	78	93	109
Revenue Raisers					
Gasoline Taxes	0.671	-64	-140	-294	-448

Notes: This Table presents estimates of the net social cost per ton using different adjustments for the marginal cost of funds of raising revenue (a.k.a. the deadweight loss (DWL) of taxation). As noted in the text, the net social cost is augmented with an additional ϕ multiplied by the net government cost of the policy. The table shows the results for $\phi = 10\%$, 30% and 50%, along with a comparison to the net social cost per ton for $\phi = 0$ and the MVPF.

Appendix Table 10: MVPF Versus Cost Per Ton Measures for All Policies

		Cost Per Ton		
Panel A. Subsidies	**MVPF**	**Resource**	**Government**	**Social**
Wind Production Credits	**5.870**	**-103**	**46**	**-32**
PTC (Shrimali)	7.547	-113	34	-28
PTC (Metcalf)	5.298	-100	51	-28
PTC (Hitaj)	4.626	-96	61	-28
Residential Solar	**3.862**	**-77**	**90**	**-67**
CSI	5.063	-77	62	-53
NE Solar	4.676	-111	69	-54
CSI (TPO)	3.815	-70	98	-75
CSI (HO)	2.712	-77	147	-53
CT Solar	1.634	-52	370	-40
Electric Vehicles	**1.445**	**-458**	**1,356**	**-415**
BEV (State - Rebate)	1.561	-527	1,069	-383
ITC (EV)	1.474	-467	1,279	-391
EFMP	1.296	-379	2,056	-398
Appliance Rebates	**1.164**	**-2**	**474**	**111**
C4A (CW)	1.405	4	433	14
ES (WH)	1.340	209	136	143
ES (CW)	1.310	170	359	78
C4A (DW)	1.132	69	972	61
ES (DW)	1.053	507	-816	233
C4A (Fridge)	1.042	-298	2,385	89
ES (Fridge)	1.011	-512	1,365	174
CA ESA	0.958	-162	440	208
Vehicle Retirement	**1.047**	**1,008**	**876**	**148**
C4C (TX)	1.067	-1	620	148
C4C (US)	1.044	14	922	148
BAAQMD	1.030	3,010	1,426	147
Hybrid Vehicles	**1.012**	**577**	**5,892**	**-38**
HY (S-STW)	1.028	576	2,646	-41
HY (F-ITC)	1.008	577	9,371	-40
HY (S-ITC)	1.002	577	43,443	-40
Weatherization	**0.978**	**194**	**779**	**207**
EPP	1.210	111	405	104
IHWAP	0.980	101	561	200
WI RF	0.920	39	4,559	555
WAP	0.915	197	752	253
LEEP+	0.859	523	1,709	430

Panel B. Nudges and Marketing

Home Energy Reports				
HER (17 RCTs)	3.006	-51	65	59
Opower Elec. (166 RCTs)	2.548	-41	77	70
PER	1.600	-194	509	-116
Opower Nat. Gas (52 RCTs)	0.451	132	236	319

Panel C. Revenue Raisers

Gasoline Taxes	**0.671**	**-104**	**-770**	**-64**
Gas (DK)	0.437	-104	-449	-63
Gas (Su)	0.523	-104	-529	-63
Gas (Coglianese)	0.561	-104	-575	-63
Gas (Manzan)	0.578	-104	-598	-63
Gas (Small)	0.605	-104	-640	-63
Gas (Li)	0.619	-104	-664	-63
Gas (Levin)	0.654	-104	-732	-63
Gas (Sentenac-Chemin)	0.673	-104	-775	-64
Gas (Kilian)	0.773	-104	-1,120	-64
Gas (Gelman)	0.814	-104	-1,366	-65
Gas (Park)	0.818	-104	-1,397	-65
Gas (Hughes)	0.953	-104	-5,581	-73
Other Fuel Taxes	**0.798**	**-70**	**-995**	**-12**
Jet Fuel	0.754	-42	-585	45
Diesel	0.841	-99	-3,160	-313
Other Revenue Raisers	**0.647**	**-701**	**-1,525**	**-350**
CPP (AJ)	0.459	-1,018	-2,086	-940
CARE	0.719	-67	-772	-28
CPP (PJ)	0.780	-1,018	-5,131	-940

Notes: This table presents estimates of the MVPF and cost per ton measures using our baseline specification (including learning by doing effects). We denote policies excluded from our primary sample by "*", and these policies are not included in our category average measures. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

Appendix Table 11: MVPF Versus Cost Per Ton, Excluding Learning By Doing

		Cost Per Ton		
Panel A. Subsidies	**MVPF**	**Resource**	**Government**	**Social**
Wind Production Credits	**3.851**	**-42**	**69**	**-8**
PTC (Shrimali)	4.349	-42	59	-8
PTC (Metcalf)	3.710	-42	73	-8
PTC (Hitaj)	3.438	-42	81	-8
Residential Solar	**1.446**	**4**	**237**	**83**
CSI	1.595	4	153	98
NE Solar	1.309	4	295	98
CSI (TPO)	1.690	4	247	19
CSI (HO)	1.256	4	356	98
CT Solar	1.166	4	550	98
Electric Vehicles	**0.961**	**963**	**2,422**	**283**
BEV (State - Rebate)	0.955	963	2,049	281
ITC (EV)	0.960	963	2,276	281
EFMP	0.969	963	3,250	292
Appliance Rebates	**1.164**	**-2**	**474**	**111**
C4A (CW)	1.405	4	433	14
ES (WH)	1.340	209	136	143
ES (CW)	1.310	170	359	78
C4A (DW)	1.132	69	972	61
ES (DW)	1.053	507	-816	233
C4A (Fridge)	1.042	-298	2,385	89
ES (Fridge)	1.011	-512	1,365	174
CA ESA	0.958	-162	440	208
Vehicle Retirement	**1.047**	**1,008**	**876**	**148**
C4C (TX)	1.067	-1	620	148
C4C (US)	1.044	14	922	148
BAAQMD	1.030	3,010	1,426	147
Hybrid Vehicles	**0.998**	**659**	**6,041**	**43**
HY (S-STW)	0.996	659	2,729	43
HY (F-ITC)	0.999	659	9,455	43
HY (S-ITC)	1.000	659	43,526	43
Weatherization	**0.978**	**194**	**779**	**207**
EPP	1.210	111	405	104
IHWAP	0.980	101	561	200
WI RF	0.920	39	4,559	555
WAP	0.915	197	752	253
LEEP+	0.859	523	1,709	430

Panel B. Nudges and Marketing

Home Energy Reports				
HER (17 RCTs)	3.006	-51	65	59
Opower Elec. (166 RCTs)	2.548	-41	77	70
PER	1.600	-194	509	-116
Opower Nat. Gas (52 RCTs)	0.451	132	236	319

Panel C. Revenue Raisers

Gasoline Taxes	**0.673**	**-104**	**-768**	**-62**
Gas (DK)	0.439	-104	-448	-62
Gas (Su)	0.524	-104	-528	-62
Gas (Coglianese)	0.562	-104	-574	-62
Gas (Manzan)	0.579	-104	-597	-62
Gas (Small)	0.606	-104	-638	-62
Gas (Li)	0.620	-104	-662	-62
Gas (Levin)	0.656	-104	-730	-62
Gas (Sentenac-Chemin)	0.675	-104	-772	-62
Gas (Kilian)	0.775	-104	-1,116	-62
Gas (Gelman)	0.815	-104	-1,359	-62
Gas (Park)	0.819	-104	-1,390	-62
Gas (Hughes)	0.954	-104	-5,471	-62
Other Fuel Taxes	**0.798**	**-70**	**-995**	**-12**
Jet Fuel	0.754	-42	-585	45
Diesel	0.841	-99	-3,160	-313
Other Revenue Raisers	**0.647**	**-701**	**-1,525**	**-350**
CPP (AJ)	0.459	-1,018	-2,086	-940
CARE	0.719	-67	-772	-28
CPP (PJ)	0.780	-1,018	-5,131	-940

Notes: This table presents estimates of the MVPF and cost per ton measures using our baseline specification but excluding learning by doing externalities. We denote policies excluded from our primary sample by "*", and these policies are not included in our category average measures. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

Appendix Table 12: Average Light-duty, Gasoline-powered Vehicle Externalities

	Externality Value (\$/Gallon)		
Externality	**Upstream**	**On-Road**	**Total**
Pollution Externalities			
Ammonia (NH_3)	0.000		0.000
Carbon Dioxide (CO_2)	0.218	1.612	1.830
Carbon Monoxide (CO)	0.000	0.052	0.052
Hydrocarbons (HC)	0.004	0.036	0.040
Methane (CH_4)	0.025	0.001	0.026
Nitrous Oxide (N_2O)	0.001	0.012	0.013
Oxides of Nitrogen (NO_X)	0.003	0.071	0.074
Particulate Matter ($PM_{2.5}$)	0.005	0.084	0.089
Sulfur Dioxide (SO_2)	0.007	0.003	0.010
	0.264	1.871	2.135
Driving Externalities			
Accidents		0.992	0.992
Congestion		0.412	0.412
		1.404	1.404
Total Vehicle Externality	0.264	3.274	3.538

Notes: This table reports estimates of the per-gallon externalities from pollution and driving externalities separately for each component. On-road $PM_{2.5}$ emissions include $PM_{2.5}$ from vehicle exhaust (\$0.066) and from tires and brakes (\$0.018). HC and CO include global and local damages. Accidents, congestion, and $PM_{2.5}$ from tires and brakes have been scaled by our preferred estimate of the share of the price elasticity of gasoline that arises from changes in VMT (0.52) (Small & Van Dender 2007). We do not observe on-road NH_3. All values are expressed in 2020 dollars. This table applies only when considering a change in gasoline usage by the average vehicle in the fleet in 2020.