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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 environmental 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 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) due to the presence of large environmental externalities. 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 environmental policy changes. These papers often assess the effectiveness of those policies by measuring its cost per ton of carbon dioxide (CO_2) abated. Yet, input assumptions in these calculations vary across papers, making comparisons across policies difficult. Moreover, 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 2019a, Knittel 2009), and (3) social costs per ton of CO_2 abated (Hughes & Podolefsky 2015, Fournel 2024). Even if one were to choose a consistent approach to measuring cost per ton, each of these measures has its own limitations when it comes to drawing conclusions about 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. 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 cost of transfers to inframarginal individuals who do not change their behavior in response to policy changes.

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 policies addressing climate change. The MVPF approach quantifies the net benefits of a policy to each group of people relative to the policy's net government cost. This approach captures the behavioral response to the policy and includes both the costs and benefits from inframarginal transfers. In addition to overcoming the shortcomings of the cost per ton measures above, an added benefit of the MVPF is the ability to transparently express concerns over equity without requiring the researcher to embed normative assumptions of welfare weights into the estimates. [1] Another advantage is that the framework allows for comparisons of climate policies with other policy areas, such as education or healthcare.[2]

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

[1] Given 2 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. Aside from adjustments for equity concerns, higher MVPFs are good sources of spending, and lower MVPFs are good sources of revenue.

[2] 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.

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 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 estimates by the US Environmental Protection Agency (EPA) (EPA 2023*a*). They place 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.[3] 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.[4]

Our primary methodological contribution is the introduction of a new sufficient statistics approach for incorporating "learning-by-doing" effects 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

[3] The $76 figure comes from the Interagency Working Group (2021) estimates with a 2.5% discount rate. The $337 figure comes from the EPA's recent estimates applying a 1.5% discount rate.

[4] Damages in the AP3 model are calculated using a statistical life of $9.5 million. For these local damages, we allow the social cost per metric ton to vary based on the location of the emissive activity. This is because the damage of a metric ton of pollution varies with local density, amongst other factors. In the case of electricity-induced damages, we take county-level damages estimated in AP3 and weight by fuel consumed for electricity generation in that county. For vehicle damages, we take county-level damages and weight by total VMT in that county.

spillovers that lower the future cost of these technologies and generate future environmental benefits (Romer 1986, 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.[5] 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.

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, while policies providing appliance rebates, home weatherization, or subsidies for electric and hybrid vehicle purchases have MVPFs that are generally around 1.[6] 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 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.[7]

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 comparatively low MVPFs (below 1) in regions with cleaner grids. This finding also suggests that the effectiveness of these nudges will fall over time as more electricity

[5]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.

[6]As we discuss below, the MVPF of electric vehicle subsidies is 1.45. This is slightly above the non-wind, non-solar categories we analyze.

[7]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.

comes from low- or zero-carbon sources.[8]

Third, we find that implementing taxes on polluting goods can serve as an efficient means of raising revenue. Here, we analyze taxes on gasoline and other fuels such as diesel and jet fuel. We also analyze cap-and-trade policies that auction emission permits. We estimate that current tax rates fall below the Pigouvian rates determined by the associated environmental externalities. As a result, nearly all of these revenue-raising policies have MVPFs below 1, with most having MVPFs below 0.7. In the case of revenue raisers, lower MVPFs are, all else equal, a better method of raising revenue. A value of 0.7 means the policy imposes a welfare cost of $0.70 per dollar of revenue raised. In contrast, the MVPFs of other revenue raisers, such as increases in income taxes, are generally above 1. For example, Hendren & Sprung-Keyser (2020) report MVPFs of 0.9–1.1 for the earned income tax credit (EITC) expansions and 1.2–2 for recent changes to the top marginal income tax rate. The lower MVPFs for environmental taxes relative to income taxes are consistent with classic theories of taxation suggesting that taxing goods with negative externalities enables raising revenue at a relatively low welfare cost.[9]

While our primary focus is on US environmental policy, we also consider the welfare consequences of US spending internationally 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 policies often vary quite extensively, even within policy categories. And, 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, the MVPF depends on the extent to which CO_2 damages have incidence on US residents and US government tax revenue.[10]

[8] We also note that nudges to reduce energy consumption in periods of peak demand can have high MVPFs if they serve to prevent outages. Nudges of this sort could become more useful as a greater share of electricity is drawn from renewable energy sources, which are intermittent by nature.

[9] It is important to note that the Federal gas tax has not increased since 1993. One way to rationalize this is with a very high implicit welfare weights on drivers. But, even excluding environmental benefits, the MVPF falls below the MVPF typically observed for tax changes on low-income individuals. This suggests these implicit welfare weights on drivers must be higher than the typical low-income earner.

[10] 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.

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 tended to focus 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).

While the recent focus on policies rather than products addresses an important criticism of early abatement cost estimates, the definition of "cost per ton of CO_2" still varies within and across papers.[11] We show in Section 8 that, even after harmonizing the inputs used in these measures, there is a wide variation in 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 are estimated to save people money in the long run. The private energy savings are large enough to overcome any difference in the upfront price between the energy-efficient appliance and its alternative. This leads to a net resource cost per ton of -\$2. While the appliances might save energy, subsidies for those appliances lead to a large number of inframarginal transfers – substantial subsidies are provided to individuals who would have purchased the energy-efficient appliances anyway. This leads to a government cost per ton of \$474.

Even if one were to consistently apply a single definition of cost per ton, we show that 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

[11] 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.

their MVPFs, however, their values are essentially indistinguishable: 1.16 versus 1.05 and 1.01.[12] 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 subsidies, for example, at an SCC of $193 per ton, we find an MVPF of 1.45 but a government cost per ton of $1356. This is driven by the omission of substantial benefits in the government cost-per-ton calculation, including inframarginal transfer benefits and and consumer surplus from learning by doing. From a social cost perspective, we once again find divergences from the MVPF ordering of policies. For example, we find that electric vehicles have a far lower cost per ton (-$415) than either residential solar (-$67) or wind subsidies (-$32). This is the exact opposite of the ordering we find for the values of the MVPF (1.45 versus 3.86 and 5.87).[13] In short, each of the various cost-per-ton metrics diverges from one another and diverges from the MVPF approach. They do not easily capture the insights of the MVPF approach because of their treatment (or omission) of key factors such as inframarginal benefits, inframarginal costs, and non-CO_2 benefits. We discuss these comparisons in detail in Section 8. Our paper also builds on a literature discussing the role of policy in areas where learning by doing is present (Acemoglu et al. 2012, Bollinger & Gillingham 2019, Way et al. 2022, Bistline et al. 2023). Our approach relates most closely to work by 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 for subsidy policies, nudge and marketing policies, and revenue-raising policies, respectively.

[12]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).

[13]A modified version of the social cost per ton includes a "marginal cost of public funds" adjustment to account for this opportunity cost. This, however, yields measures that vary significantly even within the set of common assumptions about the efficiency of 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. The MVPF does not require researchers analyzing particular environmental policies to take a stand on the efficiency of the income tax system.

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 costs 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 costs. Along the way, we show how this approach allows us to highlight the distributional impacts of policies across beneficiaries, both locally and globally, in current generations and future ones.

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 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.[14] 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.[15]

One of the key advantages of the MVPF is that it can be constructed without making specific assumptions about how the budget constraint is closed for any given policy.[16] Instead,

[14] Note that this measure represents the *net* benefits to individual i (*i.e.,* monetized benefits minus the cost of the policy to them). Formally, the WTP for each person is present discounted value measured at the time of policy implementation.

[15] 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 $\bar{\eta} MVPF$.

[16] This avoids the need to impose ad-hoc assumptions such as the existence of individual-specific lump-sum transfers or changes to a linear income tax rate. In contrast to the MVPF approach, 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

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 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.

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, particularly when WTP is positive for some beneficiaries and negative for others. 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.

incorporating the resulting deadweight loss from this tax change (e.g., Stiglitz & Dasgupta (1971), Atkinson & Stern (1974), Feldstein (1999)).

2.2 Measuring WTP and Net Costs

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) is an assumption of perfect competition. 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 an additional externality on 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 $\frac{\tau}{p}$[17] 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.

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 a 1% increase in cumulative solar production is associated with a 0.319% reduction in price. For

[17] 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.

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,[18] 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 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, $\epsilon < 0$[19]

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

Finally, we assume that there is perfect static competition at all points in time and no future

[18] 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 some 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.

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

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.[20] 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 $dp(t)$, given by

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

[20] 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.

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

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

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 2nd 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

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

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.[21] 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 of the historical relationship between cumulative production and price to construct our cost curve parameter θ. The ϵ's 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 of papers from 18 major journals in economics,[22] and supplement that with a "snowball" sample of articles cited within these papers. 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

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

[22] 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.

evaluated in the past ten years.[23]

Table 1 presents a list of all of our policies. For each policy, we list the category, subcategory, 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 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.

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

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*a*).[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 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.[27] 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*a*). 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 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 IAM models. 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

[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*a*).

[27]For in-context estimates, we use estimates of the SCC in years prior to 2020 by fitting a linear regression to SCC estimates for 2020–2050 and extrapolating back to previous years. (We note this extrapolation does not affect our baseline specification).

weights when forming the SCC.[28] 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 costs 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).[29] 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).[30] We assume a tax rate of 25.54% as this is the 2020 tax-to-GDP ratio for the US (OECD 2021). This means 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.[31] It 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

[28] For example, see the estimate used by the University of California Santa Cruz that applies welfare weights to the GIVE and FUND regional estimates.

[29] 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).

[30] 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.)

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

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.[32] We monetize those health impacts using a value of a statistical life of \$9.5 million (EPA 2010).[33]

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. Others, 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 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.[34] Panel B reports 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.

[32] County-level variation in these damages per ton of emissions is determined by factors such as population density and the age profile of residents.

[33] 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.

[34] 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 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.

4 Subsidies

The next four sections of the paper present our results for the MVPF 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. 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.[35]

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 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.[36] We then combine this counterfactual fuel economy (41.2 MPG) with an estimate

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

[36] 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

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.[37] 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 EVs purchasers tend to drive their cars fewer miles than the average purchases of a gas powered vehicle.[38] 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 \$0.003 from local pollutants, for a total benefit of \$0.17 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*).[39] 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 close to \$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 – i.e. a "rebound effect". To account for this, we use estimates of the demand and supply elasticity estimates 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) (Appendix D discusses how we calculate these elasticities). Combining these estimates implies that roughly 20% of the electricity demand is offset by reduced demand due to higher electricity prices.[40] 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 \$0.07

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

show it does not meaningfully impact our results.

[37] Full details on our approach can be found in Appendix C.

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

[39] 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.

[40] We do not incorporate a rebound effect for gasoline because we assume that the gasoline price does not meaningfully change in response to the demand shock induced by EV purchases.

\$838.34 per EV, leading to an externality of -\$0.03 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) estimates that a 1% increase in battery production leads to a reduction in battery costs of 0.42% ($\theta = -0.42$). However, batteries only made up roughly 25% of the cost of EVs in 2020, muting the net impact of learning by doing on future EV prices.[41] Using the demand elasticity of $\epsilon = -2.1$ and discounting future benefits at a 2% discount rate, the increased future demand for EVs resulting from learning by doing yields environmental benefits of \$0.03 per dollar of the mechanical cost of the subsidy (DE in Theorem 1). In addition to environmental benefits, the lower future prices induced by learning-by-doing creates a benefit of \$0.31 to future purchasers (DP in Theorem 1). Taken together, the learning-by-doing effects increase the value of the subsidy by \$0.34 per dollar of EV subsidy. The fact that the price impacts dominate the environmental benefits from learning by doing is perhaps not surprising because this is also true for the static benefits: the mechanical value of the price reduction from the subsidy is larger than the static environmental benefits it generates (\$0.07 per dollar of subsidy).

The inclusion of the \$0.34 in learning by doing benefits requires that the relationship between cumulative production and price is causal and 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 \$0.34 should not be included in the MVPF. Throughout, we present both cases so that readers can assess the potential welfare impact of learning-by-doing and adopt their preferred specification given their view of the 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 price.[42] 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.[43] Applying a 21% effective corporate tax rate, we calculate post-tax lost producer profits are equal to \$0.04 per dollar of the subsidy.[44] By contrast, electricity suppliers benefit from increased electricity consumption. Electric utilities are a regulated industry with

[41] Appendix B discusses how we account for this dynamic in learning by doing. There are many components of the vehicle (such as seats and tires) that are probably not subject to learning by doing. For a fixed reduction in battery prices and a given elasticity of demand with respect to price, a smaller battery share of total costs yields a smaller effect on future purchases. As a result, we find that this leads to the learning-by-doing effects of EV subsidies falling rapidly over time. Intuitively, as the battery costs decline, there is a limit to the extent to which lower battery prices can lower future EV costs.

[42] Appendix E.10 describes how we calculate gasoline producers' markups.

[43] Appendix E.10 describes how we calculate gasoline producers' markups and how they relate to the producer profit rates in (De Loecker et al. 2020).

[44] 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.

natural monopolies that sell electricity at a markup. We estimate this markup to be 12.9% in excess of the 8% economy-wide markup. Some of these profits flow directly to government revenue, as 28% of utilities are publicly owned. Private utilities have a willingness to pay for their increase in after-tax profits, which we estimate to be around $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 these benefits flow to those buying and selling EVs, while 5% of the benefits 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. The mechanical cost of the subsidy 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, so that the average federal subsidy was $42.98. Meanwhile, the average state subsidy was $604.27.[45] The existence of these subsidies means that the increase in EV purchases cost state governments $0.02 and the federal government $0.001 (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).

The next step is to 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.[46] Finally, we incorporate a positive impact on the US government's budget due to reductions in climate damages as measured in the IAM models underlying our estimate of the SCC. The associated productivity gains generate a fiscal externality equal to $0.003 for every $1 in subsidies.

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 these net costs, 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.

The 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 policy changes. In 2022, for example, federal credits were increased to $7,500 as part of the 2022 Inflation Reduction Act. If federal subsidies were $7,500 in 2020, this would increase the fiscal externality per dollar of subsidy to 0.37 and thus lower the MVPF to 1.02.[47] Put differently, the first dollar

[45] We discuss below how the MVPF differs if one assumes there is a pre-existing $7,500 credit, such as the one implemented as part of the Inflation Reduction Act (IRA).

[46] In practice, utilities make profits, some of which flow to the government while gasoline producers generate losses. The effect on profits for utilities is larger than the effect on gasoline producers.

[47] While the fiscal externality increases as the subsidy increases, the environmental benefit also increases as

of a subsidy relative to 2020 levels has an MVPF of 1.30, but the 7,500$^{\text{th}}$ dollar of the subsidy has an MVPF of 1.02. For a non-marginal policy that increases the subsidy level from \$0 to \$7,500, the average MVPF is 1.21.

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 (in addition to a role of charging stations). Importantly, Li et al. (2017) include the feedback effect of the EV subsidy on the existence of charging stations, which further increases demand. This generates 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.

Varying Assumptions 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. While new EVs can result in thousands of dollars of externality damages avoided, inducing a new EV purchase costs the government roughly \$30,000.[48] Consequently, the environmental benefits for each new EV remain below the mechanical transfers

V/p, increases, but in this case the environmental benefits increase at a slower rate than the fiscal externality, leading the last dollar of the subsidy to have a lower MVPF than the first dollar of the subsidy

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

needed to induce the new EV purchase. This means, that across wide range of specifications, the MVPFs fall below 2.

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.[49]

We begin by using the results in Hitaj (2013), who uses local variation in wind production incentives between 1998 and 2007 to estimate impacts on wind installation. Their estimates indicate that a one percent decrease in the price of the production[50] 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.[51] These benefits are larger than the per-dollar benefits for EVs not because of higher behavioral responses (the elasticity is -1.13 as opposed to -2.1 for EFMP above) but rather because \$1 of induced spending on a wind turbine delivers significantly more global environmental benefits from reduced CO_2 emissions (\$3.48) as compared to \$1 of induced spending on an EV (\$0.08) after including rebound effects

As with EVs, we incorporate potential rebound effects in the electricity markets. In contrast to EVs,expanded production of clean energy now means some of this expanded supply leads to increased overall energy use as opposed to a displacement of dirty energy production. Market supply and demand curves imply a 20% rebound effect from 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 decreases environmental benefits by \$0.13 (Dolan & Heath 2012). Summing together, this implies a net initial environmental benefit of \$3.45.[52]

[49]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.

[50]This is the discounted LCOE net of the subsidy.

[51]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.

[52]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.

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 all our willingness to pay components together, this 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. 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 withthe 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.[53] Stronger investment responses to prices yields higher MVPFs primarily because it generates larger environmental benefits per dollar of mechanical subsidy.

To our knowledge, there are only three quasi-experimental estimates of the impact of PTCs in the US. In order to ensure that our results are not being driven by a small sample, 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 elasticities range from -0.60 to -1.97 and yield MVPFs ranging from 1.50 to 9.15. The category average MVPF using only US policies is 5.87. This rises to 5.93 if we were to include European subsidy estimates.[54]

The conclusion that the MVPF for wind PTCs is higher than other subsidies is robust

[53]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. 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, which continues to lie above all other subsidy categories in the sample except residential solar subsidies.

[54]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.

to a range of other concerns such as excluding learning by doing benefits (which lowers the MVPF to 3.85), concerns about unobserved regulatory costs[55], or mis-measurement of the LCOE. Our baseline results take as given DOE estimates of a $0.033 LCOE from on-shore wind turbines in 2020. One concern with this statistic is that it is constructed from successfully completed projects, potentially omitting upfront costs incurred from projects that are delayed or not completed due to regulatory or cost barriers. Yet, even if we assume the cost of wind generation is actually twice as high as what is measured by DOE, the MVPF would be 3.81, still larger than any other category studied in our sample. In this sense, the finding that wind PTCs exceeds 3 (and is thus higher MVPFs than other subsidies in our sample) is robust to a wide range of alternative assumptions.

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*a*, Crago & Chernyakhovskiy 2017). We begin with Pless & van Benthem (2019) who use geographic variation in the California Solar Initiative program 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 a $0.81 benefit to consumers and $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 smaller than the benefits for wind PTCs. The lower environmental benefits relative to wind PTCs is not due to different 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.

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

[55] There has been recent attention on regulatory costs for renewable energies such as wind power (Jarvis 2021, Davis et al. 2023, Huang & Kahn 2024). As an additional robustness analysis, we can assume that increased permitting costs offset all the observed cost decline of wind turbines between 2014 and 2020. This yields an MVPF near 5.

learning-by-doing effects are driven by the fact that: (i) the historical learning rate for solar, $\theta = -0.32$, 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.[56] 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 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. Under those assumptions, we find the MVPF of utility-scale solar subsidies would be 10.97, well above our estimates for the wind PTC. In this sense, the most natural conclusion from this analysis is that subsidies to utilities for clean energy production (wind or solar) have higher MVPFs than subsidies to residential consumers.

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

[56] 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).[57] 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 effects from HEV purchases by comparing the HEVs to the counterfactual vehicles that subsidy recipients would have purchase 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 similarly 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.[58] The MVPF near 1 and small environmental benefits means that HEV subsidies are primarily transfers to consumers already intending to purchasing an HEV.

Vehicle Retirement Subsidies aimed at retiring old vehicles have been tried periodically over the past several decades. 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 on Li et al. (2013), who evaluate the federal cash for clunkers program in 2009. They find that the subsidy causes individuals to accelerate their purchase by several months and switch to a slightly more fuel-efficient vehicle.

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 this purchase and the change in fuel efficiency of the new car leads to a social willingness to pay of \$0.27 for global and \$0.02 for local environmental benefits, holding vehicle miles traveled (VMT) constant. However, some of these benefits are offset by the fact that those with more fuel efficient cars drive more due to the lower marginal cost of driving. 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.

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

[58] 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 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 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 HEVs, vehicle retirement subsidies are primarily subsidies to people who would have retired their vehicle anyway.

While most of our analysis focuses on the harmonized 2020 MVPF, vehicle retirement is a unique case where this 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 1970 vehicle produced far more emissions in 1996 than did a 26-year-old (1994) vehicle 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. Paying people to retire their 1965 Chevy had much higher returns in 1996 than paying people to retire their 1991 Toyota in 2020. Aside from this interesting case, the in-context and 2020 MVPF estimates are quite similar.

Weatherization We next consider weatherization 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 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 its impact on home energy costs.

Measuring the WTP of weatherization is more difficult than for price subsidies for two reasons. First, weatherization policies offer a discrete set of services to households. As a result, we cannot invoke the envelope theorem and need to consider potential benefits accruing to marginal households. For those who are induced to weatherize their homes from the subsidy, 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.[59] A second difficulty

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

with measuring the benefits of weatherization policy is that papers studying their effects do not generally estimate the fraction of weatherization users who are inframarginal, and so we explore the robustness of our MVPF result to variations in this fraction. As our baseline, we assume that 50% of those receiving the weatherization benefits are inframarginal. This means that every $1 in government cost of weatherization generates a benefit of $0.75 to those who take up the benefits.

Weatherization also generates 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.

A potential limitation of our MVPF calculation is that we need to make an assumption about 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 a measure of the consumer surplus from the weatherization program. They find valuations very similar to our estimates, yielding an MVPF of 0.93 in-context for 2013 in Wisconsin. Harmonizing this to our 2020 national specification suggests an MVPF of 0.92.

Taking an average across all of the weatherization policies, we obtain a category average MVPF of 0.98.[60] These estimates assumes individuals are aware of the energy benefits of weatherization so that we do not include private energy savings in the willingness to pay. The logic is that these individuals may value the energy savings, but other considerations, such as the hassle cost of a construction project in their home, offset the monetary savings. 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."[61] It would then be natural for the marginal individuals to value the energy savings at cost. Including the energy savings as an additional component of the benefits of the policy yields a category average MVPF of 1.37. Either way, weatherization does not generate large environmental benefits and is instead best thought of 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. For appliance subsidies, we

[60]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.

[61]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.

consider 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 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 assume a linear demand curve so that 50% of the transfer is valued. Summing, this yields a total of \$0.95 in benefits per dollar of subsidy. Turning to environmental benefits, the induced purchases of more efficient clothes washers generates 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.[62] 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. So, while there are some environmental benefits generated by these subsidies, they are primarily transfers to those who would have purchased these appliances anyway.

Other Subsidies In addition to appliance subsidies, 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.[63] But, the policy does lead to a large energy reduction that results 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 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.[64] While this is one of the larger MVPFs 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 their future prices would be reduced if they consume more energy today, they might increase their energy consumption today to qualify for greater

[62]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.

[63]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.

[64]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.

discounts in the future, which would reduce the policy's effectiveness.

The second policy 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.[65]

Summary of MVPFs for Subsidies Figure 4 presents the baseline MVPF estimates for each of the subsidies in our sample. The shaded blue regions report 95% confidence intervals derived from a parametric bootstrap of the underlying estimates from each policy.[66] 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. Production tax credits for firms that produce wind energy have the highest MVPFs, generally exceeding 5. Subsidies for individuals who install residential solar panels also have high MVPFs exceeding 3. By contrast, all other subsidies tend to have smaller MVPFs, with values around 1 ± 0.2. Within this set, EVs have the highest MVPFs at around 1.42.

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).[67] Appendix Figure 4 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. The value of the various MVPFs decrease because the numerator (willingness to pay) decreases by the estimated benefits to the rest of the world, but the denominator (net cost to the government) remains the same for each MVPF. Only 13.1% of the global externality benefits are estimated to flow to US citizens. The MVPFs of the wind PTCs and solar policies remain above all other categories (with averages of 1.89 and 1.18 as compared to the other values often below 1).

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, we examine a marginal change relative to 26% subsidy in place in 2020. We can consider instead the policy change induced by

[65] This calculation assumes that the carbon sequestration benefits of the program last forever, despite the fact that the PES contract lasts 10 years.

[66] 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.

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

the 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 that 0-30% rate increase, we get an MVPF of 4.43, relatively close to 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.

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.[68] It is worth noting, however, that the MVPFs of EVs and residential solar are buoyed by learning-by-doing effects.[69] 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.

5 Nudges and Marketing

We now consdier policies that employ nudges or marketing strategies to lower carbon emissions by reducing residential energy consumption. Unlike direct subsidies, these policies disseminate information or change the choice architecture to encourage individuals to change energy usage or product purchases without direct financial incentives.

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.

To measure the MVPF, one first needs to estimate how much HER recipients value the reports. In our baseline specification, we assume people were close to indifferent about their energy choice at the outset, which implies that the value of the nudge to individuals is roughly zero.[70] While we find large MVPFs for nudges to reduce electricity consumption, we find much

[68] Appliance rebates and weatherization MVPFs rise slightly, but the policies are not particularly effective at increasing energy savings.

[69] 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.

[70] While not formalized in a paper to our knowledge, this view has been espoused by Kevin Murphy in seminar

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 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, which is challenging. One path is to use the extent to which the marginal cost of peak production exceeds the price, which suggests marginal costs ranging from $500/MWh$ to $1000/MWh$. These imply MVPFs ranging from 0.70 to 1.60.[77] If the demand reduction also decreased the frequency and/or duration of blackouts, these MVPF estimates could rise as high

conversations. In particular, we do not place any additional valuation on private energy savings. We also do not include any value of shame or pride (independent on any change on demand) or value of information from the nudges, although we acknowledge these may be important and assess the robustness to including such estimates below (Allcott & Kessler 2019, Butera et al. 2022, List et al. 2023).[71]

HERs targeting electricity usage cause a reduction in consumption, which can affect 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 (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.[72] 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. On average, nudges can deliver significant welfare gains even if they do not benefit those who are actually nudged.

While the 3.01 corresponds to an average electricity HER, 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.[73] By contrast, in California and New England, the MVPFs are 0.52 and 0.24, respectively.[74] 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.[75,76] We also note that the value of nudges depend heavily on the global externalities from the grid. At an SCC of $76 rather than $193, the category average MVPF falls from 3.01 to 1.34. But, even at a lower SCC, the relative ordering across regions remains the same. Dirty grids have MVPFs in the 1.92 to 2.76 range while cleaner grids have MVPFs around -0.18.

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

as 5.30.[78]

In addition to energy reports, there is also a set of marketing strategies seeking to foster the adoption of clean technologies within homes. 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. This suggests marketing and information policies about energy efficient technologies can have high returns.[79]

We also study nudges aimed at the producer side of weatherization policies. 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. In contrast, the Solarize program encouraged the take-up of residential solar, which has large 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 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.

[78] 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 2023). We recognize that the VOLL may vary across different populations, times, and locations (Borenstein et al. 2023).

[79] 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.

6 Revenue Raisers

An alternative approach to address greenhouse gas 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 approach measures the welfare cost imposed on individuals per dollar of revenue raised from the policy. All else equal, lower MVPFs correspond to better methods of raising revenue. Revenue raisers can yield a lower MVPF when they have some societal benefits (e.g., from reducing CO_2) in addition to raising revenue. 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 a negative subsidy. Replacing τ with $-\tau$ in equation 9 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 $-\epsilon$ continues to be 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 so that $V < 0$. People are willing to pay \$1 per dollar of tax increase, but this is partially offset by the environmental gains induced by the behavioral response to the tax. This behavioral response also diminishes the net revenue raised from the tax by $\epsilon \frac{\tau}{p}$. A Pigouvian tax would set, $\tau = -V$, and yield an MVPF of 1. More generally, if the tax is below the Pigouvian level, the MVPF of the tax will generally fall below 1: increasing the tax raises revenue at a lower cost than a lump-sum tax that has an MVPF of 1. More generally, the MVPF framework enables us to compare the welfare cost of raising revenue through taxes like gasoline taxes to other methods such as income taxes. While equation (25) provides a stylized example of the MVPF for a gasoline tax, we use an extended version below to include externalities from imperfect competition and learning-by-doing effects (e.g., from gas taxes inducing the adoption of EVs).

We construct 12 MVPFs for gasoline taxes using estimates of the response of gasoline consumption to prices and taxes. These estimates imply price elasticities that range from -0.04 (Hughes et al. 2008) to -0.46 (Davis & Kilian 2011). To illustrate the construction of the MVPF, we consider the analysis of Small & Van Dender (2007) who find a price elasticity of -0.33. Figure 7 presents the components of WTP and costs components of this specification. We present 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 $0.272, 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.[80] 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.[81]

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 utilities 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.[82] 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 raised leads to a welfare cost of $0.60 on individuals.

Figure 8 presents the MVPF estimates for the range of gasoline studies in our main sample for our baseline specifications that envision a change in the gas tax in 2020. We find MVPFs ranging from 0.44 to 0.95, with a category average of 0.67. The relatively low welfare cost of raising revenue from gasoline taxes remains true even if one only includes US externalities—rising to an average MVPF of 0.89.

On net, the results suggest fuel taxes[83] raise revenue at a relatively low welfare cost. The MVPFs these revenue raisers fall below the MVPF of a non-distortionary lump sum tax (MVPF of 1) and well below the MVPF of changes to the income tax (which generally range between 1 and 2 and average around 1.2).

In addition to comparing gasoline taxes to income taxes, we can also compare gasoline taxes to regulations that seek to improve the gas mileage of vehicles on the road. For example,

[80] 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.

[81] 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.

[82] 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.

[83] We also construct MVPFs for taxes on diesel and jet fuel using externality measures discussed in Appendix E.11. We find MVPFs around 0.80 for diesel and jet fuel taxes. 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.

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. Regulatory policies such as CAFE are beyond the primary scope of our analysis, which focuses on tax and spending policies. From a theoretical perspective, regulatory policy changes often have small (or even zero) impacts on the government budget. and account for distributional incidence. In particular, Appendix Figure 5 illustrates whether we can feasibly replicate the benefits offered by CAFE through taxes and transfers instead of regulation. We show that gasoline taxes combined with feasible income tax modifications can not only replicate CAFE's impact on the environment, producers, and consumers but also generate roughly \$1 in additional government revenue.[84] In this sense, gasoline taxes are more efficient than CAFE regulation.[85]

6.2 Cap and Trade

Cap and trade is another policy tool often used to limit emissions. It imposes quantity limits on emissions and lets firms trade the rights to such emissions. We evaluate two uses of cap and trade in the US to limit greenhouse gas emissions: the Regional Greenhouse Gas Initiative (RGGI), which limits emissions from power plants in the Northeast, and the California Cap-and-Trade Program. We also briefly discuss the European Emissions Trading System (ETS) to provide an additional point of comparison.

There is a close analogy between the MVPF formula for cap and trade and the MVPF formula for a change in a tax on a polluting good, such as a gasoline tax in equation (25).[86] The key distinction is that for the gasoline tax we are concerned with the impact of a change in prices on the quantity of gasoline consumed. By contrast, the MVPF for cap and trade depends on the impact of a change in quantity of permits on the price of those permits.

We consider the MVPF of a change in the number of permits to sell at auction. Let q denote the number of permits issued. Assume that one fewer permit leads to $(1 - L)$ actual 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

[84] Part of the reason for the superiority of taxes is that they generate additional benefits from reduced driving such as reductions in accidents and congestion.

[85] We also show in Appendix G that wind subsidies combined with income tax modifications deliver welfare gains that are superior to Renewable Portfolio Standards (RPS) regulations.

[86] To see this, note that

$$MVPF = \frac{-q\frac{dp}{dq} + V(1-L)}{-q\frac{dp}{dq} + p} \tag{26}$$

$$= \frac{1 - \frac{dq}{dp}\frac{p}{q}V(1-L)}{1 - \frac{dq}{dp}\frac{p}{q}} \tag{27}$$

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.

write the MVPF of changing the number of auctioned permits as

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

where the first term is the firms' willingness to pay to avoid the higher permit prices because of reduced supply. This is offset by the environmental damages, $V(1-L)$, generated by a one-unit change in the number of permits. On the cost side, the government receives the mechanical revenue from the higher prices, $-qdp/dq > 0$, but also loses revenue from fewer permits being auctioned, p. Note that this p does not enter the numerator because we assume that firms are optimizing: the marginal firm holding a permit has a marginal abatement cost equal to the permit price.

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 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 means 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. [87]

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 profit maximization and the envelope theorem suggests these firms are indifferent between buying a permit and reducing emissions, the emissions reductions generates environmental externalities. The environmental benefit of releasing $1 - L = 0.49$ fewer short tons of CO_2 in 2016 is \$65.20.[88] Adding the reduction in local pollutants SO_2 and NO_X yields an additional gain of \$117.21.[89] 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.[90]

[87] Relative to the formula in equation (28), we note that we need to place some of the environmental gains into the denominator of the MVPF to account for the incidence of climate change on the US government budget. Using the average social cost of carbon between 2009 and 2016 (weighted by permits auctioned), we estimate this 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.

[88] Results in Chan & Morrow (2019) are presented in short rather than metric tons. We account for this when evaluating RGGI by adjusting our externality calculations.

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

[90] The positive net willingness to pay among individuals is the difference between the environmental benefits and the permit costs to firms. This corresponds to a higher social welfare gain as long as one prefers \$1.54 in the hands of those benefiting from an improved environment over \$1 in the hands of the firms paying the additional permit costs.

While our in-context estimates suggest RGGI led to significant benefits to taxpayers and individuals in society, it is potentially difficult to extrapolate our in-context estimates to a 2020 policy reform. In order to do so, one must assume that the marginal abatement cost curve 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.[91] If we make such an assumption, we continue to find a 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 not certain, however, 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. Hernandez-Cortes & Meng (2023) note that it is reasonable to assume that these firms and utilities were more responsive to permit pricing than the non-observed units. 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 imposed 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 that is 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 cosider the largest cap and trade systems for CO_2 in the world – namely 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 ($q * dp/dq$)

[91]When moving between our in-context and current estimates, we adjust the change in permit price for inflation, but otherwise the marginal abatement cost curve is unchanged.

to avoid a 1 ton reduction in the number of allocated permits. Comparing this to a historical average SCC of \$134.79 in 2012, 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 \$134.79 in environmental benefits.[92] In sum, the evidence from ETS is consistent with the US evidence on cap and trade: Reductions in permits have the potential raise revenue while also providing positive benefits to society.

Summary of Revenue-Raiser MVPFs The key lesson of this section is that raising revenue from restrictions and taxes on pollution-emitting activities offers paths to raising revenues at MVPFs well below 1. These MVPFs are meaningful lower than the MVPFs of other revenue raisers. For example, Hendren & Sprung-Keyser (2020) find MVPFs for the income tax ranging from 0.9–1.1 at the bottom of the income distribution to 2 at the top of the income distribution. Taxes on fuels impose a meaningfully lower welfare cost per dollar of revenue raised.[93] The key lesson from cap and trade is that, in the cases where these markets have been established, there appear to be large quantities of emissions that can be reduced at relatively low cost. The presence of these 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 these policies are efficient methods of addressing climate change and 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

[92] We find similar conclusion when examining estimates on the impact of the ETS from Bayer & Aklin (2020). In particular, we find that fewer ETS permits leads to \$134.68 in net benefits to society while also generating \$14.41 in government revenue.

[93] We note, however, that this gap may be the result of different implicit welfare weights across types of beneficiaries. The Federal gas tax has not increased since 1993. This is true despite the fact that if one were to ignore all the environmental effects of gasoline and only consider the effect of gas taxes on accidents and congestion, our estimates suggest an MVPF of 0.95 associated with the gas tax. This is 14% lower than the MVPF around 1.1 typically observed for tax changes on low income individuals (Hendren & Sprung-Keyser 2020). This suggests an implicit welfare weight on drivers that is higher than the weight on the earnings of a typical low-income individual.

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. This means the policy costs $16.55 per each subsidy offered (16.55 = 30.37*0.545). The paper also finds that each new cookstove reduces CO_2e by about 7 tons, or 3.7 tons of carbon per subsidy offered.[94] This translates into $44.00in global environmental benefits for each mechanical dollar of the subsidy.

The incidence of the $44.00 in environmental benefits depends on the model underlying the social cost of carbon. In our baseline specification, we assume the US experiences 15% of these benefits ($6.60) in proportion to its share of global GDP. These benefits are generally a combination of reductions in mortality and increases in productivity, with different models yielding different estimates. We 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). This implies that the US government recoups $13.95 of the initial $16.55 cost of the subsidy, for a net cost of just $2.60. This $2.60 in spending delivers $5.76 in benefits to US residents for a US-specific MVPF of 37. Adding in benefits to the rest of the world pushes the MVPF to 323.

A key force driving the MVPF is the extent to which reductions in global warming have positive impact on future US tax revenue (e.g. due. to higher future productivity). Even models that have the same social damage from carbon can generate different MVPFs because they have different incidence on the US federal budget. For example, we could assume instead that the 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).[95] In this case, we find that the subsidy nearly 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 nearly 50% of global damages are driven by changes in agricultural productivity, but those damages are heavily concentrated outside the US. If we drop the US-specific fiscal externality

[94]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.

[95]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 potentially large.

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 impact of the welfare consequences of policy.

While we find high MVPFs for these improved cookstoves studied in Berkouwer & Dean (2022), we note that many other studies of cookstoves found minimal effects (e.g. Hanna et al. (2016)). In many cases, recipients did not use the cookstoves. Such subsidies have MVPFs near zero.

Figure 9 presents the MVPFs for the other international policies in our baseline sample.[96] MVPF using only US benefits are shown in blue; including global benefits is shown in orange. We find a very high MVPF for payments to farmers in Sierra Leone to prevent deforestation. Even from a US-only perspective, the MVPF is 15.9, one of the largest MVPFs in our sample. For deforestation prevention payments evaluated in Uganda evaluation 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 payments 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.[97] As is the case with our primary estimates, we find the lowest MVPFs for other policies using 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 some of the highest MVPFs in our sample even when only considering the benefits accruing to US residents. Our exact MVPF estimates depend on the incidence of the social costs of carbon and, in particular, whether the benefit accrue in the form of increased US productivity. Such benefits have US tax revenue implications, meaningfully reducing the net cost to the US government of the subsidies. However, we caution that we also find high variance across studies even within categories (suggesting such returns are not guaranteed). Moreover, one should exert some degree of caution in our assumption that the US government could implement these policies

[96]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.

[97]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.

with the same cost structure as the NGO conducting the evaluation. The key lesson from our analysis, however, 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

In our analysis thus far we have used the MVPF framework to analyze the welfare consequences of US climate change policy. This represents a deviation from the typical approach to welfare analysis in the environmental economics literature, which calculates a cost per ton of CO_2 abated. There are, in fact, several measures of cost per ton that are used (sometimes interchangeably) in existing work. Not all existing cost per ton estimates fall neatly into categories, but we that find three broad definitions serve to capture the conceptual distinctions in prior work: (A) resource costs per ton of CO_2 abated, (B) government costs per ton of CO_2 abated, and (C) net social cost per ton of CO_2 abated. In this section, we compare the various cost per ton measures with the MVPF approach.[98] We construct these measures for each policy in our sample. We highlight the ways in which these cost per ton measures diverge from the MVPF and reach alternate conclusions regarding the rankings of a wide range of policies.[99]

8.1 Definitions of Cost per Ton

We begin by providing a definition of three common measures of the cost per ton of CO_2 abated. We also discuss briefly their conceptual drawbacks relative to the MVPF. In the next subsection, we construct each of these measures for each of our policies and compare between them.

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.[100] 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 the product,

[98] While we focus here on the distinction between the MVPF and cost per ton metrics, Appendix H discusses how the MVPF approach compares to traditional benefit-cost analysis, including measures of net social benefits and typical benefit-cost ratios. We discuss how the MVPF is a type of benefit-cost ratio where the ratio is well-defined based on the incidence of the policy: the numerator is beneficiaries' WTP and the denominator is government cost. This contrasts with typical benefit-cost ratios, which are subject to the criticism that ratios are arbitrary because it is not always clear what constitutes a benefit versus a cost. We briefly discuss these metrics and explain the advantage of our focus on the MVPF.

[99] Our discussion here relates to a broader literature discussing the pros and cons of cost-benefit versus cost-effectiveness analysis. See Weinstein & Stason (1977) for an early discussion of cost effectiveness in the context of health outcomes. For an early comparison of cost-effectiveness analysis with benefit-cost analysis, see Lave (1981).

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

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. 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.

In many cases, such resource costs are constructed using engineering estimates, leading to a robust debate about the quality of these estimates (Fowlie et al. 2018). Setting aside the accuracy of existing resource cost estimates, there are two key conceptual concerns associated with this measure.

First, this approach focuses on a product or activity (e.g., the purchase of an EV) rather than a policy (e.g., the subsidy of an EV purchase). In practice, most government spending policies lead to a meaningful transfer 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.[101] We suggest below that accounting for these transfers can substantially impact 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, this approach generally omits other non-resource benefits of a policy. For example, when considering purchasing an EV, individuals may have disutility from having to find charging stations or have utility from being able to go 0 to 60 in less than 3 seconds. Energy efficient appliances might have other benefits or costs that are not solely captured by their energy savings.

Government Cost per Ton The second cost per-ton measure commonly found in the literature is the "government cost per ton" of carbon abated (Gillingham & Stock 2018).[102] This approach measures the reduction in tons of CO_2 emitted per each dollar of net government outlay. Relative to the MVPF, it 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.

This approach addresses one of the key criticisms of the resource cost method, accounting for the cost of transfers to inframarginal beneficiaries, (i.e., the cost of giving subsidies to individuals who did not change their behavior in response to the policy). It does not, however, consider the benefits to those inframarginal individuals. In other words, dollar-for-dollar transfers are treated as a cost but not a benefit.

[101] Sometimes researchers will adjust for the "deadweight cost of taxation" when constructing cost per ton measures. This approach does not typically appear in resource cost calculations. We discuss this as part of the net social cost per ton approach.

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

Relatedly, the government cost per ton of CO_2 continues to omit other non-resource benefits such as local pollutants avoided or congestion externalities. This omission can create concerns when comparing the government cost per ton to values of the social cost of carbon. A comparison to the SCC often serves as a threshold by which to judge whether a policy is welfare enhancing. The omission of non-CO2 benefits may generate bias in this comparison.[103]

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. Formally, 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 abated tons of CO_2.[104]

The social cost 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. Additionally, the individual benefits of an EV purchase may include the thrill of going 0 to 60 in under 3 seconds. Similarly, while the resource cost of LED lightbulbs might be negative, the social cost approach allows individuals to have a preference for the softer light provided by incandescent bulbs.

It is of course quite difficult to measure all the relevant reasons individuals might benefit from a product. Perhaps because of this difficulty, the social cost per ton approach often invokes assumptions of optimization to help measure individuals' willingnesses to pay. Let us consider, for example, a subsidy that induces some people to purchase an energy-efficient appliance that reduces energy usage. It may be that individuals are optimizing when making their private choices about energy-efficient products.[105] If they are aware of the energy savings of such an appliance, then their valuation can be no larger than the size of the subsidy. By

[103] This criticism is not novel. 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 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).

[104] 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.

[105] 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.

contrast, if those individuals were not aware of the energy saving benefits of the appliance, the net social cost per ton approach would seek to incorporate private energy savings as a benefit to consumers.[106] Similarly, this logic of optimization applies to utilities deciding whether to invest in clean energy. Their valuation is bound by the size of the subsidy they received. Those induced to purchase in response to the subsidy must be approximately indifferent to it.[107]

In relying on a comprehensive measure of benefits and cost and considering the role of optimization, the social cost per ton has a close relationship to the MVPF. In order to see this, let us return to the example of a subsidy for a good that reduces carbon emissions. The MVPF can be written as

$$MVPF = \frac{1 + \frac{\epsilon}{p}(SCC * Tons + Other)}{1 + \frac{\epsilon}{p}\tau} \tag{29}$$

where $V = SCC * Tons + Other$ is the externality from the subsidized good. This is comprised of the carbon externality, $SCC * Tons$, which is the product of the change in carbon emissions per unit of product purchased, $Tons$, and the social cost of carbon, SCC, and the sum of the monetary value of all other externalities per unit of product purchased, $Other$. In our context, this includes non-CO2 environmental externalities, such as local pollution, changes in road congestion or accidents, firm markups, and dynamic learning-by-doing benefits.

A subset of these elements can also be used to form the social cost per ton. The numerator of the social cost per ton ratio is given by the difference between the government costs, $1 + \frac{\epsilon}{p}\tau$, and the WTP excluding the CO2 benefits, $1 + \frac{\epsilon}{p}Other$. The tons of carbon abated by the policy is equal to $\frac{\epsilon}{p}Tons$, where ϵ/p is the induced increase in purchases of the product per dollar of subsidy and Tons is the tons of carbon abated per unit of the product purchased. In formulating the social cost per ton, the ϵ cancels out yielding the following expression:

$$SCPT = \frac{(\tau - Other)\frac{\epsilon}{p}}{Tons\frac{\epsilon}{p}} = \frac{\tau - Other}{Tons} \tag{30}$$

The social cost per ton of a small change in the subsidy is equal to the magnitude of the economic cost for each good purchased, which is the distortion caused by the subsidy t, minus the value of any other externalities generated with an additional unit of consumption, relative to the tons of carbon abated by the good per additional unit of consumption.

This formulation highlights the the primary drawback of the canonical social cost approach: the ratio is independent of the causal effect of that subsidy on the purchase of the subsidized good. In other words, if two policies both induce one more person to purchase an new good,

[106] We note that MVPF analysis also requires distinguishing between these types of cases. Our broad conclusions do not depend on specific assumptions regarding individual optimization. We show in Appendix Table 7 how our MVPF results vary with the inclusion of energy savings in the willingness to pay.

[107] When a policy focuses on profit-maximizing firms and there are no non-CO_2 environmental externalities, the resource cost and social cost approach are, in principle, pursuing the same measure of cost. The envelope theorem would suggest that the net resource cost gain to the marginal firm is zero. So while the resource cost would attempt to measure all these costs and benefits, the social cost approach would invoke optimization and assume the net resource cost gain for the marginal adopters is zero.

the policies would have the same social cost per ton, 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 social cost per ton approach used in work by Fournel (2024) and others which includes the opportunity costs of inframarginal transfers. This approach assumes a given marginal cost of funds, ϕ, and adds it to the numerator to capture the distortionary cost of raising revenue. The resulting formula for the social cost per ton is given by:

$$SCPT_{\phi} = \frac{(\tau - Other)\frac{\epsilon}{p} + \phi(1 + \frac{\epsilon}{p}\tau)}{Tons\frac{\epsilon}{p}}. \tag{31}$$

Now 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 a linear income tax, ϕ. We focus our primary comparisons on the standard SCPT measure that does not incorporate DWL calculations. Appendix Table 9 shows how the SCPT varies with different values of ϕ.

8.2 Results

Table 3 compares the MVPF with each of the three cost per ton estimates. It reports the values for each policy sub-categories (and Appendix Table 10 contains the value for each individual policy in our sample).[108] These results make clear that there is often 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 are estimated to save people money in the long run — enough to overcome any difference in the upfront price. This leads to a net resource cost per ton of -$2. While the appliances might save energy, subsidies for those appliances lead to a large quantity of inframarginal transfers – transfers that are paid to people who would have purchased those appliances even in the absence of the subsidy. As a result, the cost to the government of abating a ton of carbon through these subsidies is $474. The social cost per ton is far lower than the government cost, at only $111 per ton. This is because the government cost approach i) ignores that inframarginal transfers are valued by the recipients, and ii) omits non-CO_2 benefits of the policy (e.g., local pollutants, relative disutility of the appliance).[109]

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

[109] Our baseline approach to measuring social costs follows the MVPF approach and invokes the envelope theorem to argue that marginal purchasers are indifferent to the policy change, which means any energy cost savings they obtain is offset by any private disutility of the product. It is straightforward to modify this assumption and suppose individuals are not accurately informed about energy savings so that they have a positive benefit from these savings. While this generates an additional benefit (and thus reduces social cost), its overall effects are muted by the fact that the behavioral response is relatively small for this policy. Appendix

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.[110] By contrast, solar subsidies are reported to have higher costs per ton, but these measures tend to use government cost per ton (Davis et al. 2014, Gillingham & Stock 2018, Gillingham & Tsvetanov 2019*a*). This approach generates a higher cost per ton relative to other measures because it includes inframarginal costs but not their benefits.

Even if one were to agree on which metric to use, it is natural to ask whether our broad conclusions would have been identified using a consistent measure of cost per ton. In the section below, we show how the MVPF approach is necessary to reach our welfare conclusions.

Resource Cost per Ton Our estimates of resource cost per ton lead to conclusions that would 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 can see this pattern repeatedly when examining the resource cost per ton associated with individual policies in our sample. For example, we find that 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.[111] This general pattern is consistent with previous resource cost calculations, such as those constructed by McKinsey & Company. Despite this, the two policies differ substantially in their MVPFs, 1.01 versus 4.63.

Finally, it is worth noting that the resource cost per ton does not provide an clear way to interpret the welfare consequences of revenue raising policies. In the context of the MVPF, lower values imply revenue being raised at lower welfare cost. They allow us to compare current tax rates to an optimal level. In the case of a tax on resources, the natural definition of the resource cost per ton is an engineering estimate of the carbon intensity of the resource, which does not provide clear guidance on the welfare impact of taxing those resources.

Table 7 provides the estimates of the MVPF when including energy savings as an additional WTP component.

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

[111]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. As we note below, for negative values of cost per ton, welfare benefits are not monotonic in the cost effectiveness ratio. In that case, an increase in tons abated increases the cost per ton.

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 and solar have government costs 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, which is substantially higher than the $474 figure for appliance rebates. The MVPF of EVs, however, is 1.45 as compared to the 1.16 for appliance rebates. This difference is driven by the lack of inframarginal benefits and the failure to incorporate learning-by-doing price effects in the government cost per ton measure.

That same critique 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 might not be a worthwhile expenditure if the social cost of carbon is $193 per ton. As noted, however, this high cost per ton is driven by the omission of non-CO_2 benefits. The value of government cost per ton cannot easily be compared to the SCC.

A related, but perhaps more subtle, point is that the government cost per ton cannot be used to compare the effectiveness of taxes versus subsidies. Taxes typically have a negative government cost of abatement (i.e., net government revenues go up and therefore net costs go down for each ton abated). In the case of gas taxes, for example, we estimates a government cost per ton of -$768. This does not necessarily mean these policies are a 'free lunch' when it comes to addressing climate change. Rather, these taxes impose a welfare cost on individuals in society when raising that revenue. In considering overall welfare, that cost should be accounted for when deciding whether or not the taxes are desirable.

Social Cost per Ton The social cost per ton addresses some of the concerns with other cost per ton measures by accounting for non-CO_2 benefits. The canonical implementation does not, however, factor in the opportunity cost of funds associated with inframarginal transfers. Once again, this leads to different policy rankings than those generated by the MVPF.

For example, across all of our policy categories, electric vehicles have the lowest social cost per ton 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.[112]

We once again see these patterns with or without the inclusion of learning-by-doing effects in our estimates of the total quantity of carbon abated. In the absence of learning-by-doing effects we find, for example, that hybrid vehicle subsidies have a social cost per ton of $43, half the level of residential solar at $83. This is true despite the fact that hybrid vehicle subsidies

[112]Interestingly, for negative values, the social cost per ton approach is not monotonic in welfare. For a a fixed quantity of carbon 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, an increase in the tons of carbon abated increases the value of the social cost per ton (because it reduces the absolute value of the ratio.

have an MVPF that is lower far lower (1.00 versus 1.45).

As we noted above, a potential way to address the presence of inframarginal beneficiaries in the social cost per ton approach is to account for the marginal cost of funds associated with inframarginal transfers. Appendix Table 9 reports the net social cost per ton statistic for the 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 deadweight loss of taxation. The value for appliance rebates changes from \$111 without a MCF adjustment to \$349 with a 50% adjustment. We find an even more dramatic movement in the case of EV subsidies. The values changes from -\$415 with no MCF to -\$259 with 10% MCF and \$260 with a 50% MCF. The net social cost per ton approach with a MCF adjustment is in spirit quite similar to the MVPF comparison: using a 30% MCF adjustment and asking whether net social costs exceed the SCC is similar to the MVPF approach of assuming an SCC and asking whether the MVPF exceeds 1.3. The MVPF, however, is able to accomplish the comparison across policies without needing to bring in additional assumptions about the welfare impacts of policies, such as tax policies, in other domains. It also enables researchers to decide how they wish to close the budget constraint. 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, regardless of one's view about the efficiency of the income tax system.

Summary We find that the definition of costs leads to a large impact on the measure of cost per ton of a given policy. But, even if one were to harmonize the cost per ton metric employed, each of these measures have limitations that would make it difficult to arrive at the core lessons we draw when using the MVPF framework.

9 Conclusion

What policies are most effective in addressing climate change? We conduct a comprehensive assessment of policies that have 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 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 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 an 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 economic 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. We see that 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.[113] It is important to note, however, we also see a reallocation over time toward greater relative spending on EVs subsidies, an area with comparative 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.

[113]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.

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 (Hendren & Sprung-Keyser 2020). The values rival, but are not quite as high, as 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 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. We hope this serves as an aid to researchers constructing their own MVPFs in future policy analysis.

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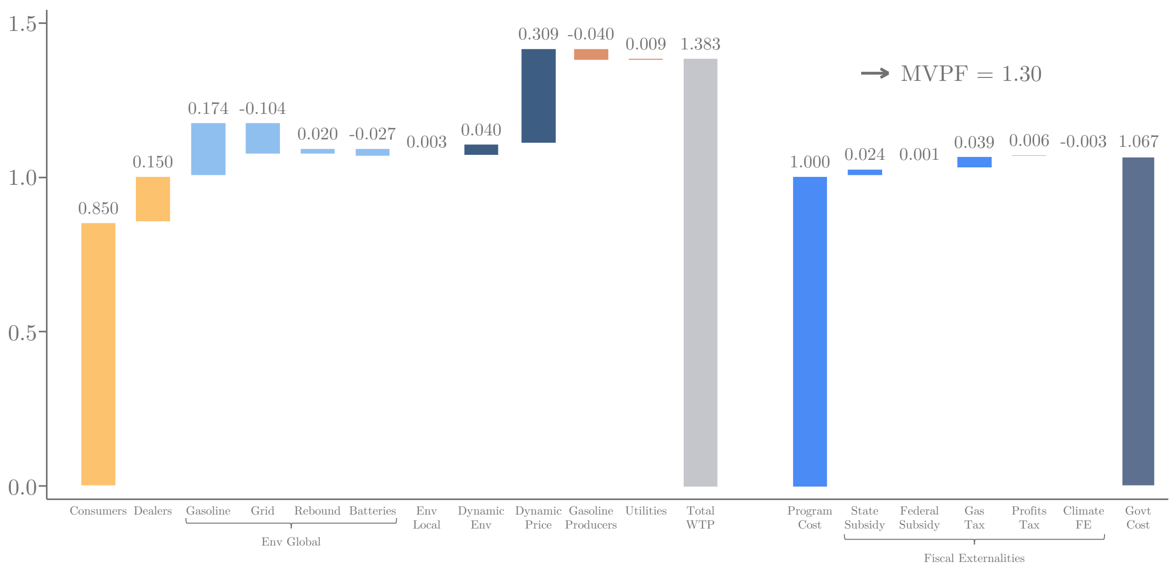
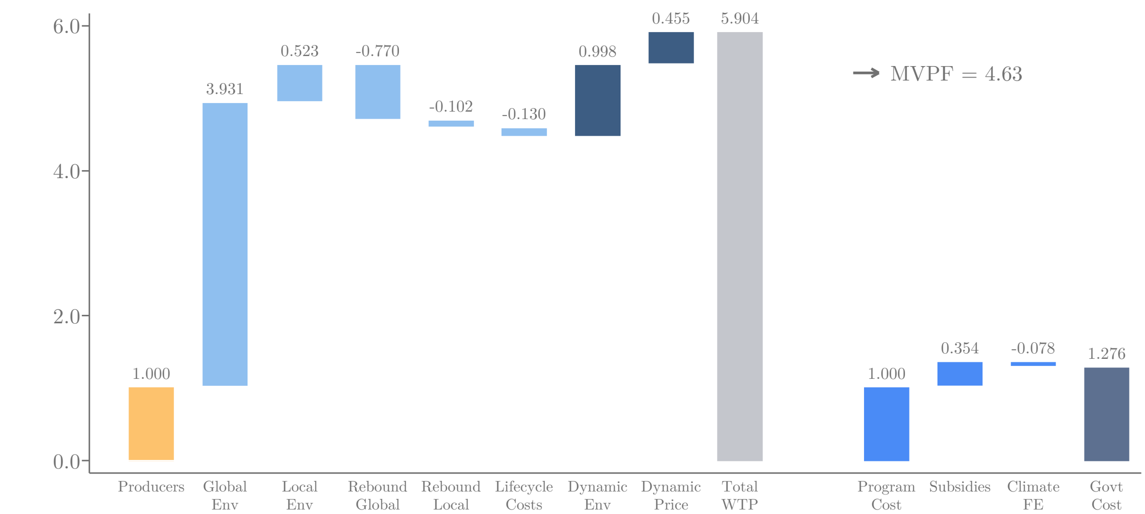
FIGURE 1: Electric Vehicle Subsidy
Baseline Estimates from Muehlegger and Rapson (2022)



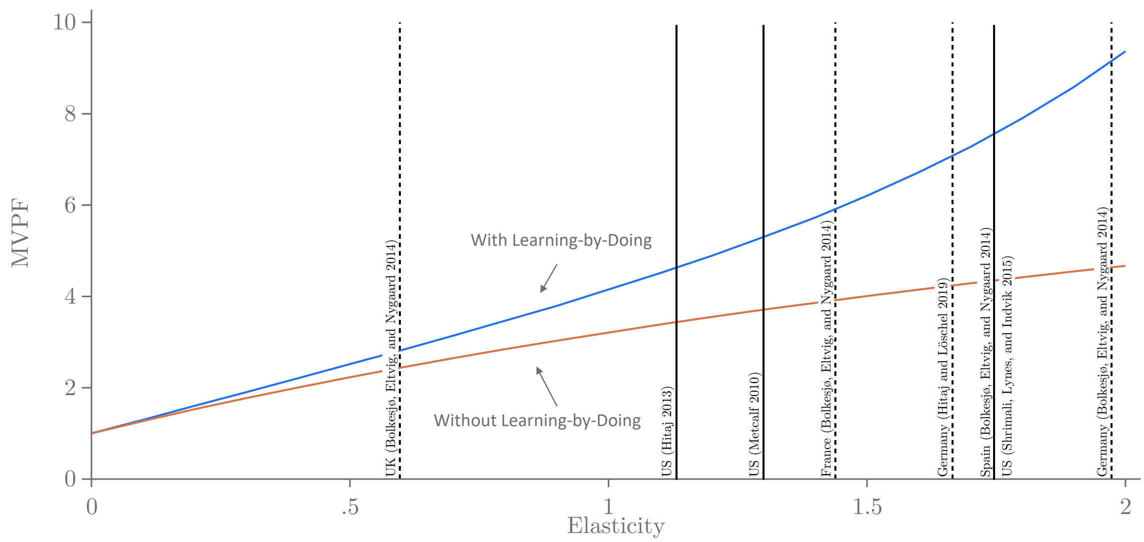
Notes: This figure presents the components of willingness to pay and net government cost for the EV subsidies in the California Enhanced Modernization Program (CEFMP) using the -2.1 price elasticity estimated in Muehlegger & Rapson (2022). We present estimates for our baseline specification that envisions 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 and lower prices 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 GDP. 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)

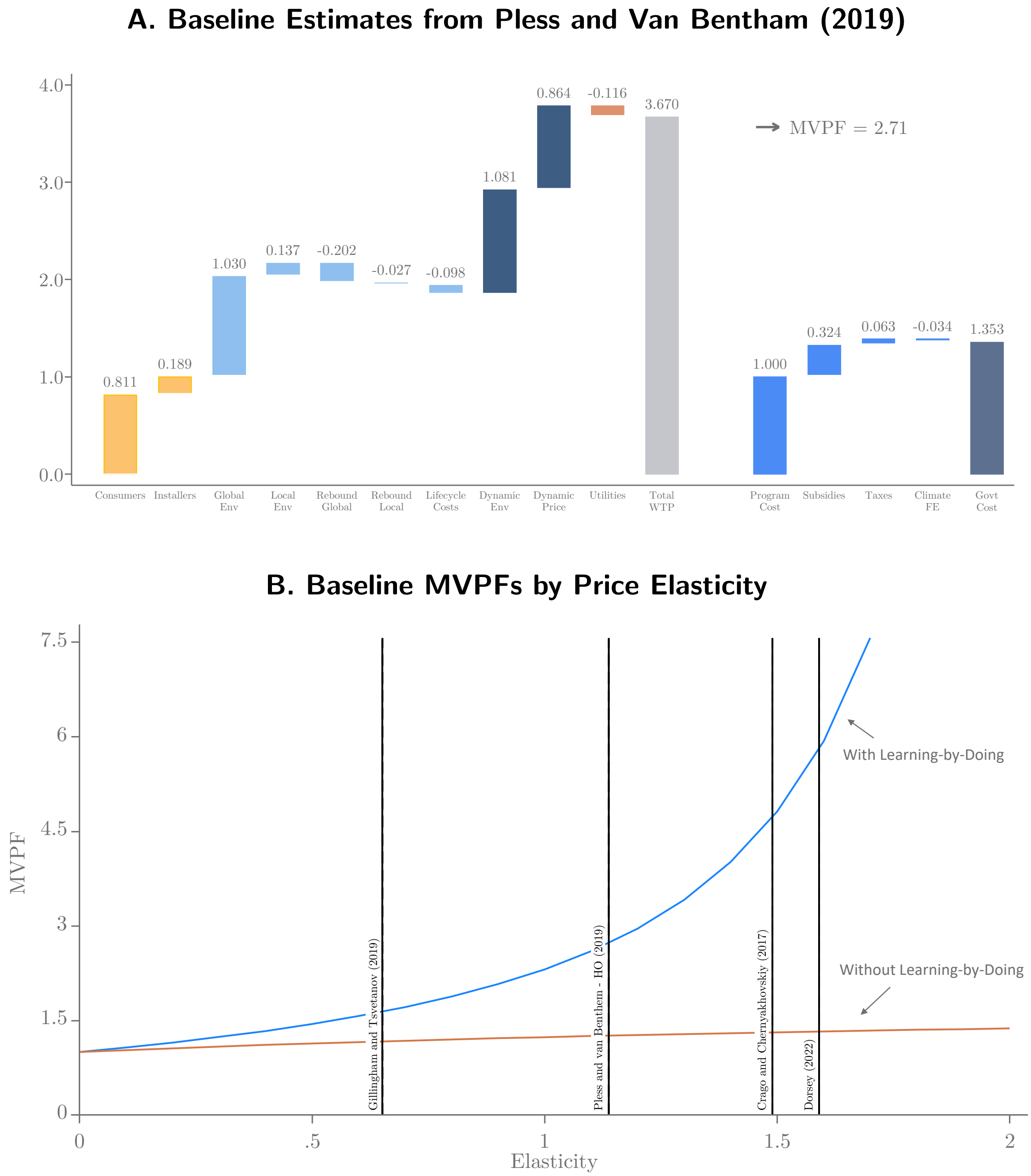


B. Baseline MVPFs by Price Elasticity



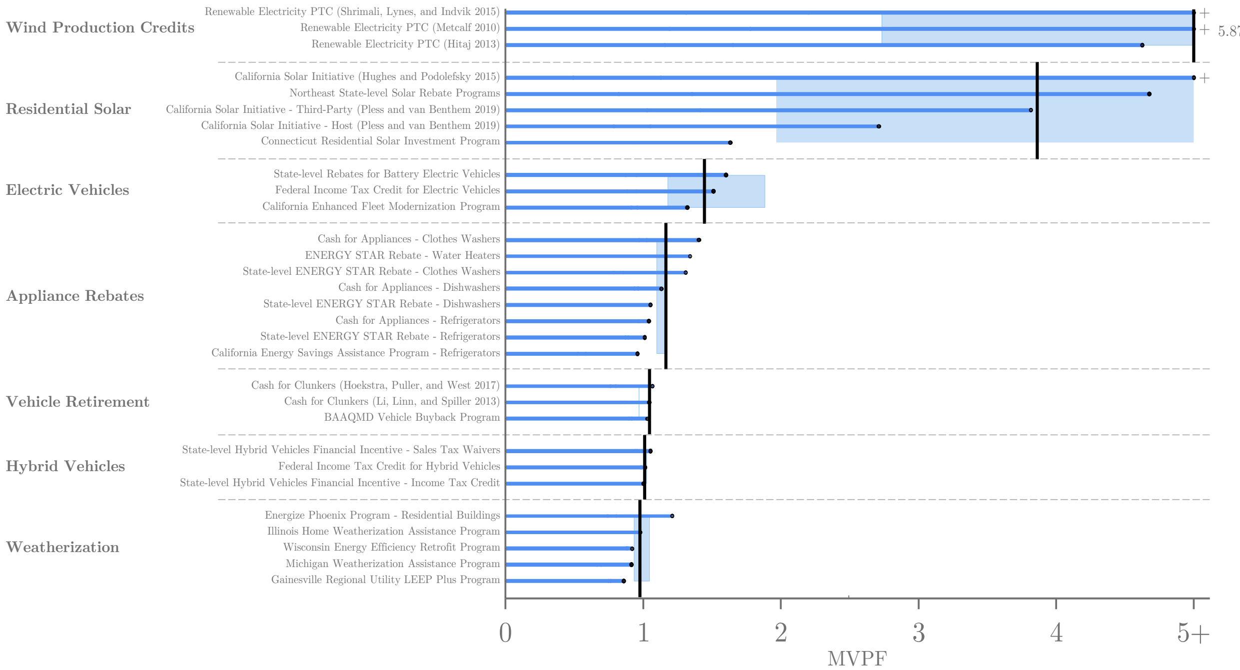
Notes: This figure illustrates the MVPF measurement for wind subsidies. Panel A shows the WTP and Cost components for the baseline specification for the wind production tax credit using a supply elasticity of 1.4 estimated in Hitaj (2013). The WTP components consist of the transfer (yellow), environmental 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. The MVPF with learning by doing effects is capped above 10. 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



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 capped above 7.5. 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.

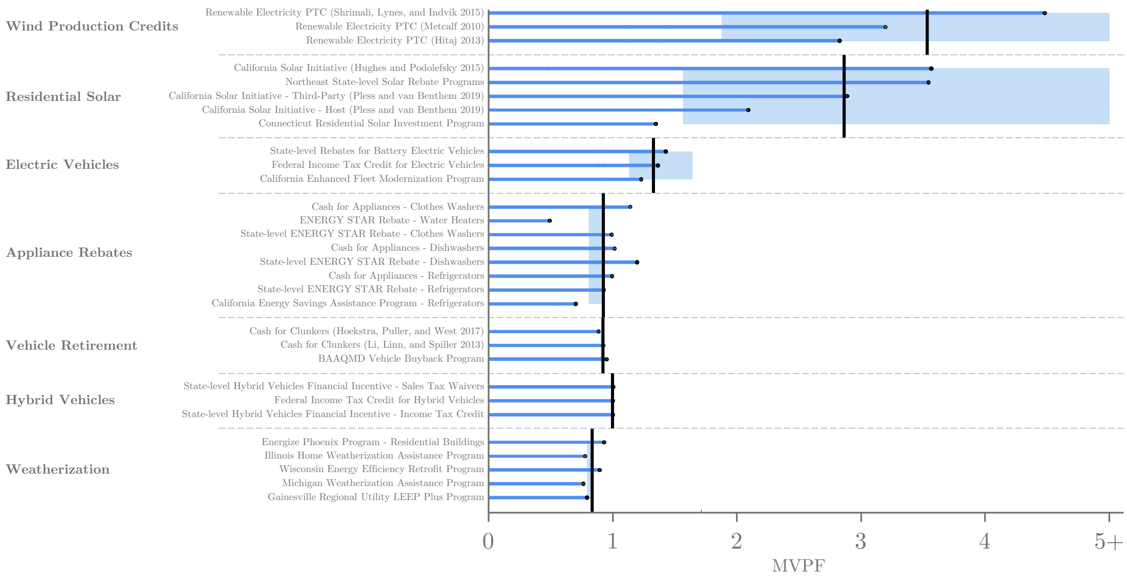
FIGURE 4: Baseline MVPFs for Subsidies



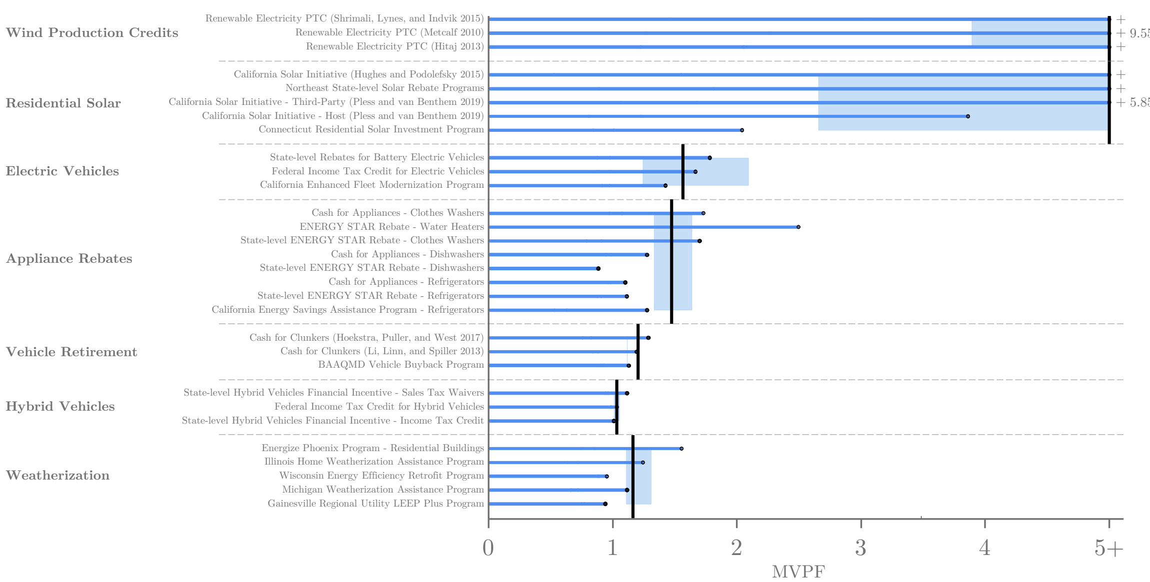
Notes: This figure shows the 2020 baseline MVPF estimates for all categorized subsidy policies in our main sample. We cap estimates at 5 with + signs indicating MVPFs above 5. The category average (shown by the black vertical lines) reports the MVPF associated with a conceptual experiment where \$1 in 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 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

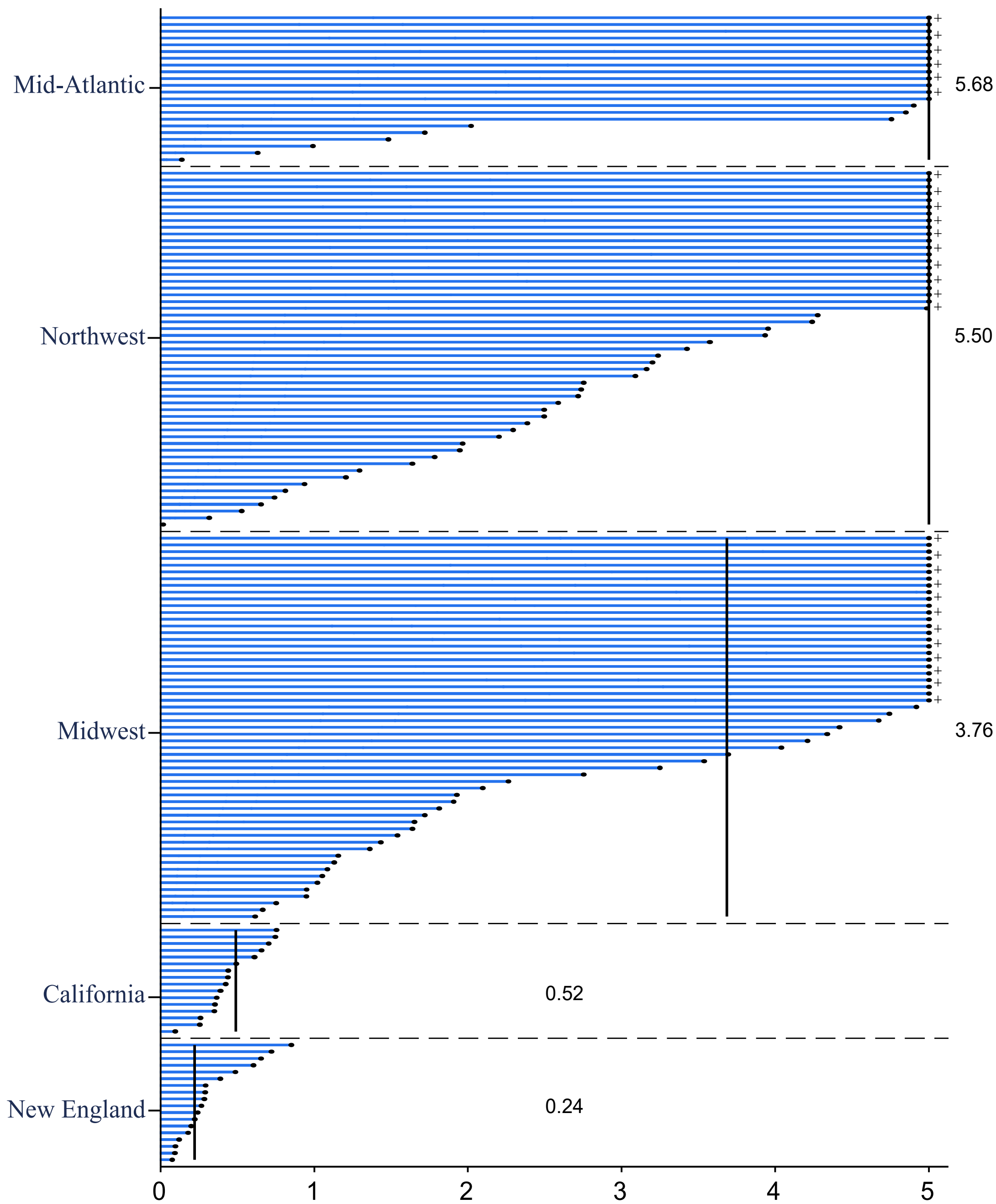


B. $337 Social Cost of Carbon



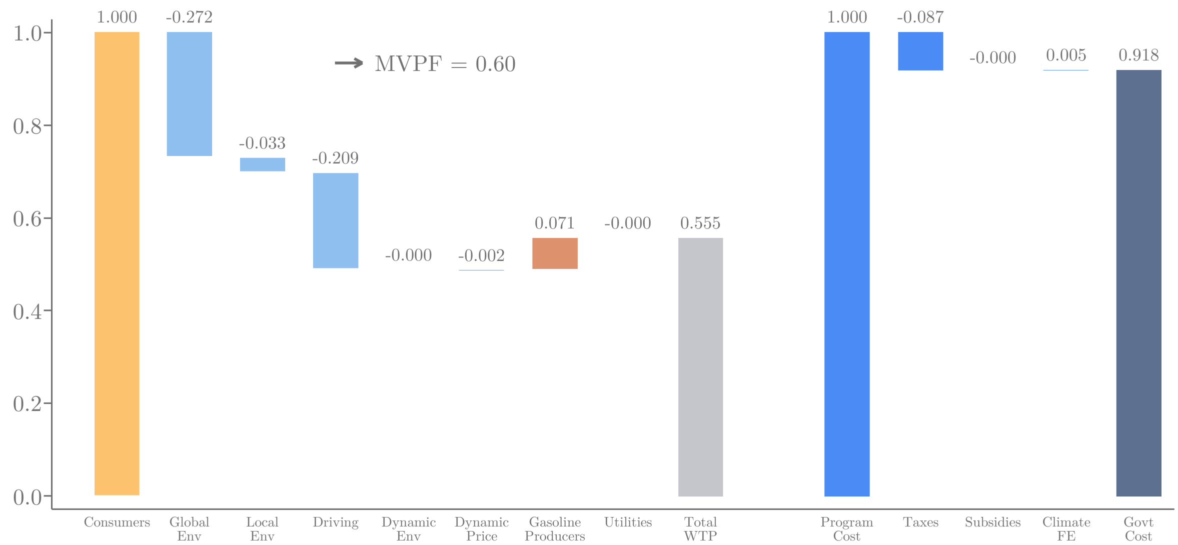
Notes: Panel A and B repeat Figure 4 using an alternative time path for the SCC corresponding to values of $76 and $337 in 2020 along with discount rates of 2.5% and 1.5%, respectively. Estimates are censored at 5.

FIGURE 6: Baseline MVPF of Home Energy Reports



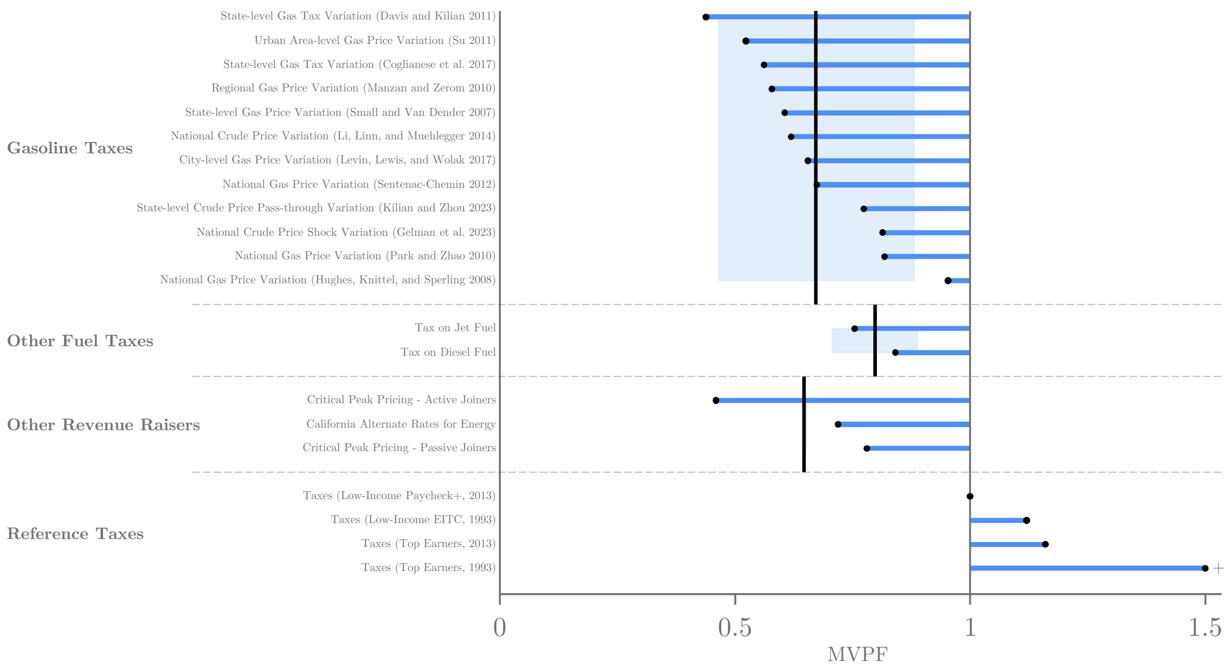
Notes: This figure illustrates the MVPF estimates for Opower Home Energy Reports split across the 5 AVERT model's electricity regions for which the experiments have been conducted. The benefits per dollar of government cost equal the environmental benefits minus the loss in utility profits. MVPFs above 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)



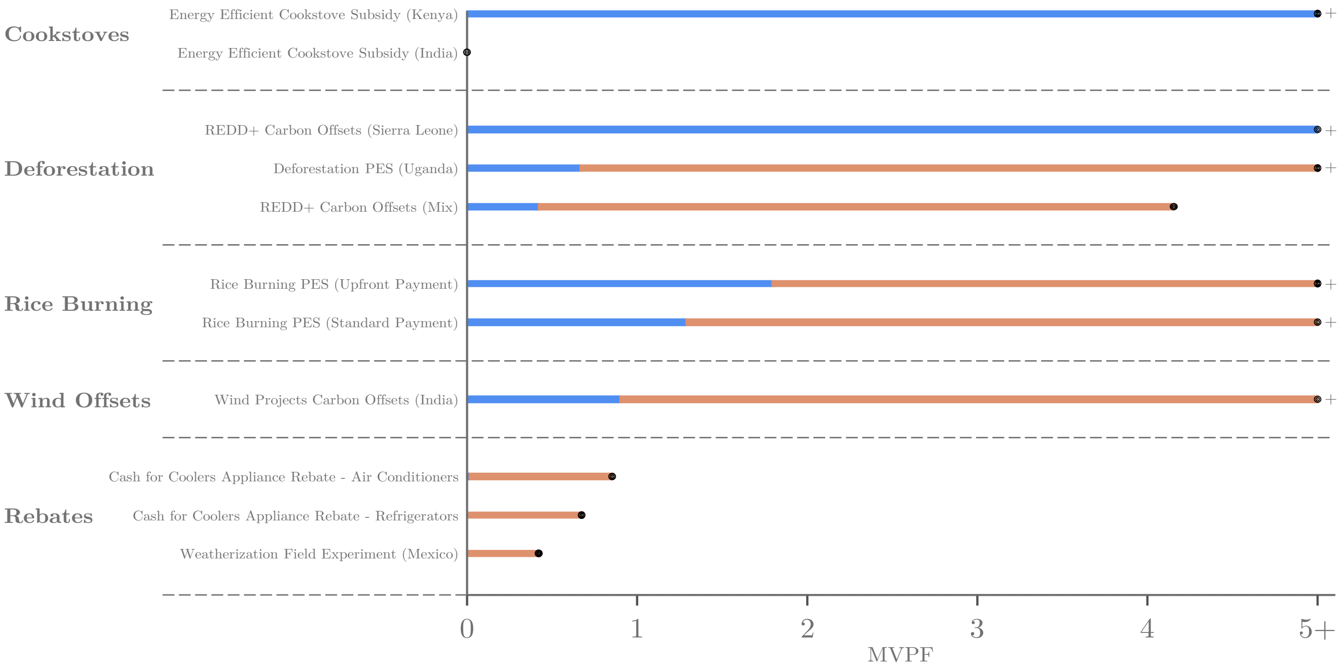
Notes: This figure presents the components of the baseline MVPF for the gasoline tax using a gasoline price elasticity of -0.334 from Small & Van Dender (2007). The WTP components include the transfer cost (yellow), global greenhouse gas benefits and local environmental externalities arising from accidents, 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 measuring the welfare cost per dollar of revenue raised. 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 international policies. We cap estimates at 5 with + signs indicating MVPFs above 5. The blue bars represent the WTP for US beneficiaries and the orange bars represent non-US benefits. 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	-0.073	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**	**0.000**	**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**	**-0.229**	**-0.204**		**0.000**	**-0.002**	**0.060**	**0.625**	**1.000**	**-0.074**	**0.004**	**0.931**	**0.671**
Gas (DK)	1.000	-0.374	-0.333		0.000	-0.002	0.098	0.388	1.000	-0.120	0.007	0.887	0.437
Gas (Su)	1.000	-0.323	-0.288		0.000	-0.002	0.084	0.472	1.000	-0.104	0.006	0.903	0.523
Gas (Coglianese)	1.000	-0.299	-0.267		0.000	-0.002	0.078	0.510	1.000	-0.096	0.006	0.910	0.561
Gas (Manzan)	1.000	-0.289	-0.257		0.000	-0.002	0.075	0.527	1.000	-0.093	0.006	0.913	0.578
Gas (Small)	1.000	-0.272	-0.242		0.000	-0.002	0.071	0.555	1.000	-0.087	0.005	0.918	0.605
Gas (Li)	1.000	-0.263	-0.234		0.000	-0.002	0.069	0.570	1.000	-0.084	0.005	0.921	0.619
Gas (Levin)	1.000	-0.240	-0.214		0.000	-0.002	0.063	0.607	1.000	-0.077	0.005	0.928	0.654
Gas (Sentenac-Chemin)	1.000	-0.228	-0.203		0.000	-0.002	0.060	0.627	1.000	-0.073	0.004	0.931	0.673
Gas (Kilian)	1.000	-0.161	-0.143		0.000	-0.002	0.042	0.736	1.000	-0.052	0.003	0.951	0.773
Gas (Gelman)	1.000	-0.133	-0.119		0.000	-0.002	0.035	0.781	1.000	-0.043	0.003	0.960	0.814
Gas (Park)	1.000	-0.130	-0.116		0.000	-0.002	0.034	0.786	1.000	-0.042	0.003	0.961	0.818
Gas (Hughes)	1.000	-0.034	-0.030		0.000	-0.002	0.009	0.943	1.000	-0.011	0.001	0.990	0.953
Gas (West) *	1.000	-0.373	-0.332		0.000	-0.002	0.097	0.391	1.000	-0.120	0.007	0.888	0.440
Gas (Tiezzi) *	1.000	-0.354	-0.315		0.000	-0.002	0.093	0.421	1.000	-0.114	0.007	0.893	0.472
Gas (Bento) *	1.000	-0.285	-0.254		0.000	-0.002	0.074	0.534	1.000	-0.091	0.006	0.914	0.584
Gas (Hughes - Ext) *	1.000	-0.272	-0.243		0.000	-0.002	0.071	0.554	1.000	-0.088	0.005	0.918	0.604
Gas (Kilian - Ext) *	1.000	-0.255	-0.227		0.000	-0.002	0.067	0.582	1.000	-0.082	0.005	0.923	0.630
Gas (Small - Ext) *	1.000	-0.054	-0.048		0.000	-0.002	0.014	0.910	1.000	-0.018	0.001	0.984	0.925

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	-0.130				0.015	0.826	1.000	-0.019	0.001	0.982	0.841
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

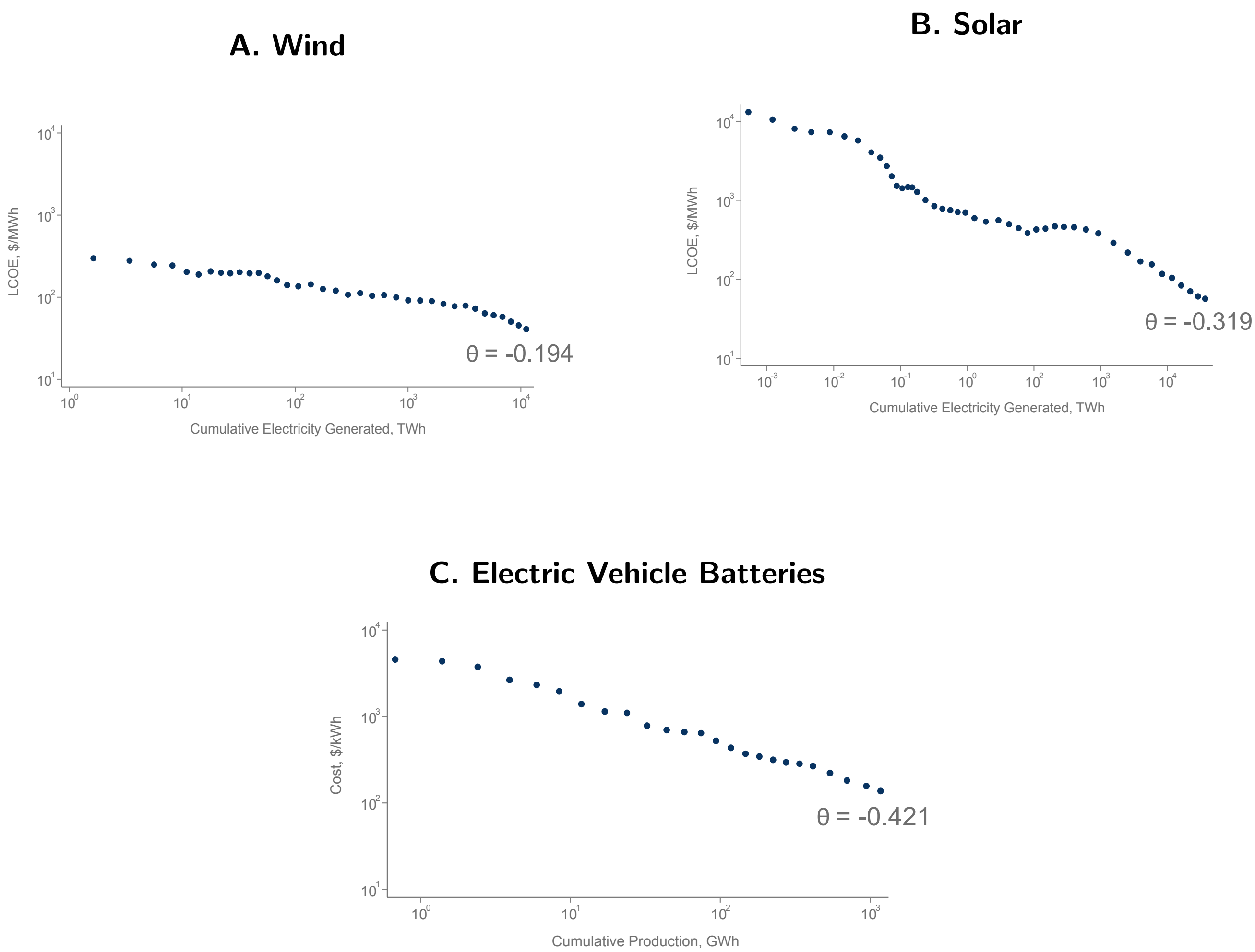
Notes: This table presents the WTP and cost components for each policy in our sample using the baseline specification. Each component is normalized per dollar of mechanical spending on the policy. The first column reports the size of the transfer. The next three columns report the environmental externality 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	Cost Per Ton Government	Cost Per Ton 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	987	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	987	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

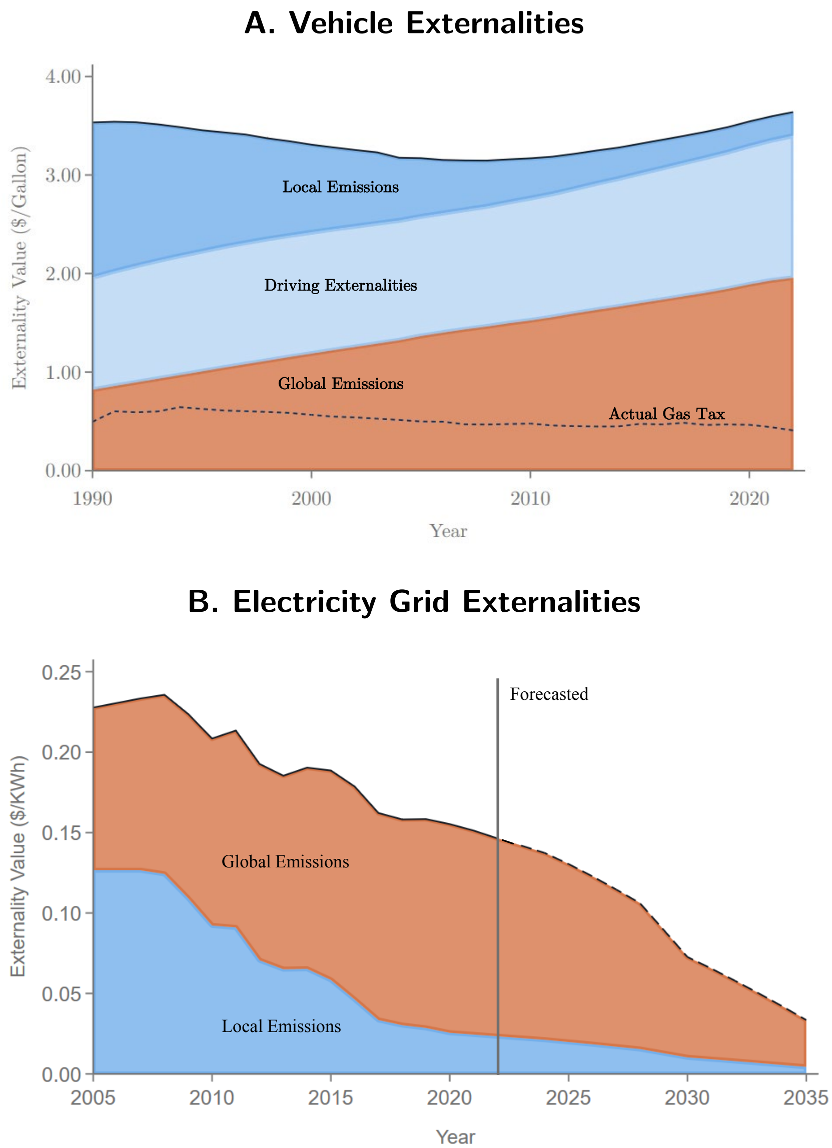
Notes: This table presents estimates of the MVPF and cost per ton measures using our three definitions: resource cost per ton, government cost per ton social cost per ton. See text for precise definitions of each measure. We present estimates here for each policy category average; the Appendix provides 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)



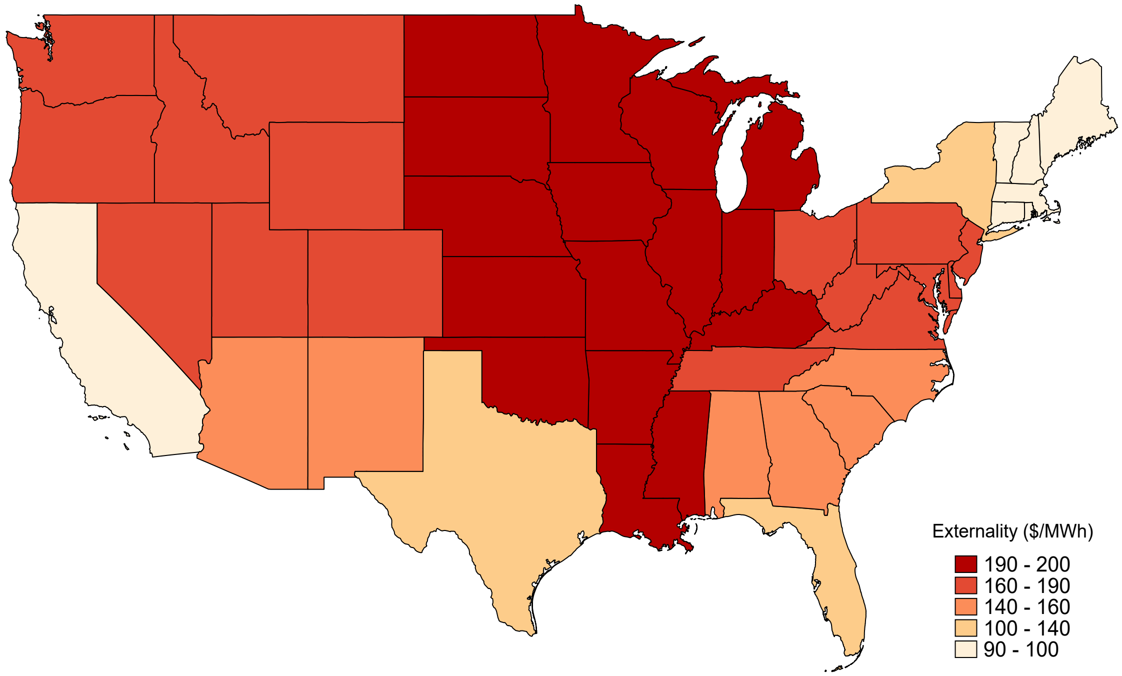
Notes: This figure reproduces estimates of the price of solar cells, wind energy, and battery storage from Way et al. (2022). Panel A and B report the levelized cost per MWh of electricty (LCOE) from wind and solar, respectively. Panel C reports the electric vehicle battery cell cost per KWh. We report 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 learning by doing model.

Appendix Figure 2: Vehicle & Grid Externalities Over Time



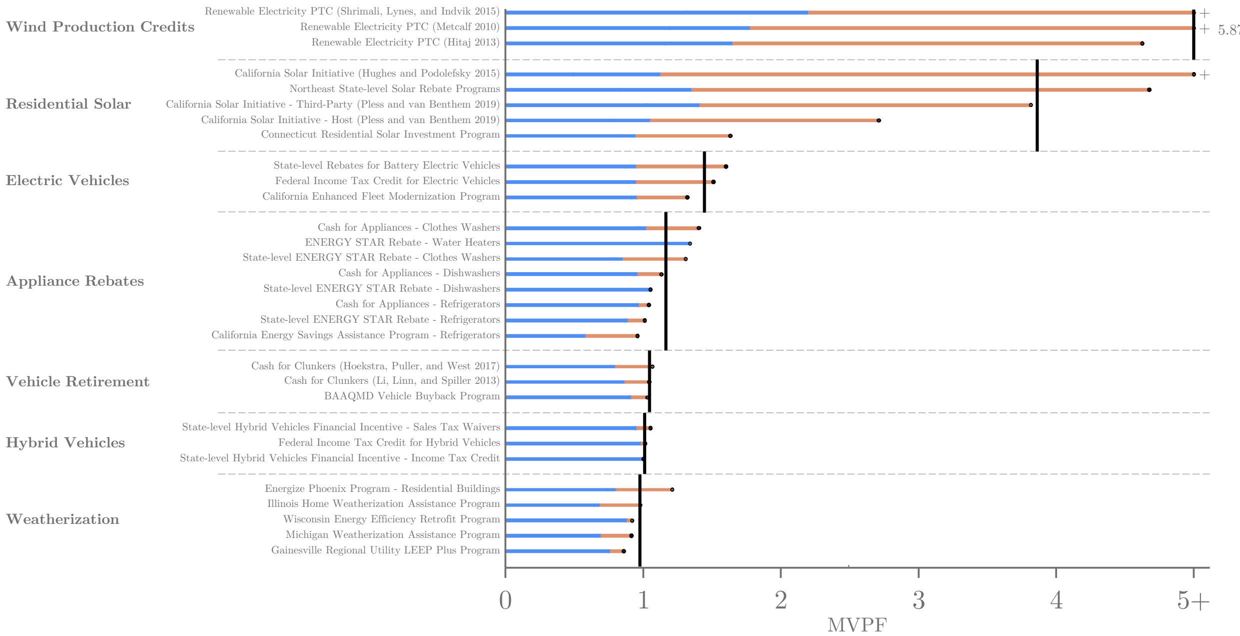
Notes: This figure illustrates the components of the vehicle and grid externalities over time. Panel A reports the dollar value of the vehicle externalities per gallon of gasoline. We split these into local emissions (e.g., NO_X), driving externalities (accidents and congestion), and global emissions ($e.g., CO_2$). 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.

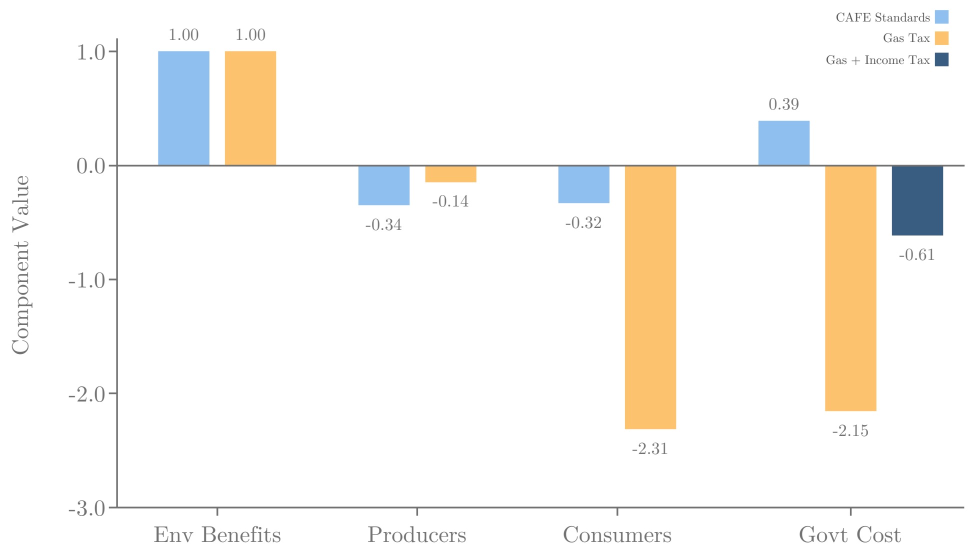
Appendix Figure 4: Baseline MVPFs
US and Rest of World Split



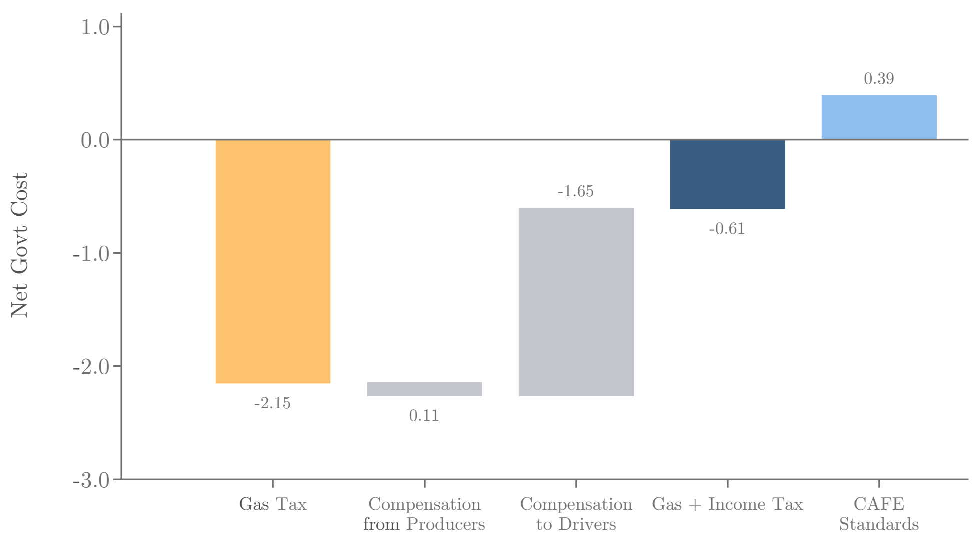
Notes: This figure repeats Figure 4 with blue bars showing the WTP for US beneficiaries and the orange bars show the non-US benefits. We cap estimates at 5 with + signs indicating MVPFs above 5. The category average (shown by the black vertical lines) represents the average WTP for a mechanical $1 transfer 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 5: CAFE vs. Gasoline + Income Tax

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



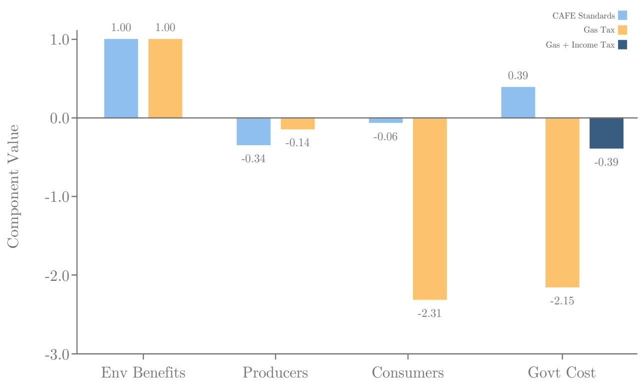
B. Net Government Revenue



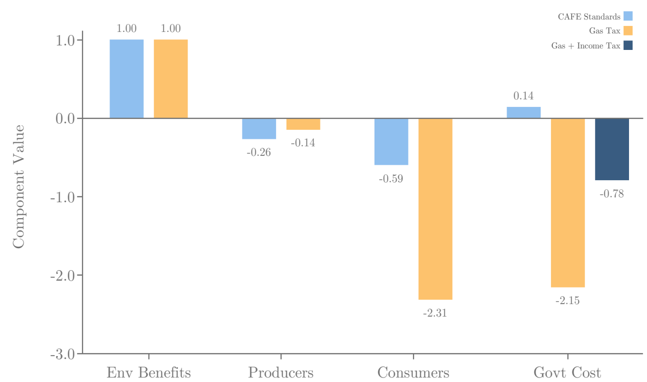
Notes: This figure presents a comparison of the welfare impact of changes to the stringency of CAFE regulation to a gasoline tax, using our category average gasoline tax MVPF. Panel A presents the impact of CAFE and a gas tax, each normalized to deliver \$1 of environmental benefits using our baseline 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 6: Additional Regulation Comparisons

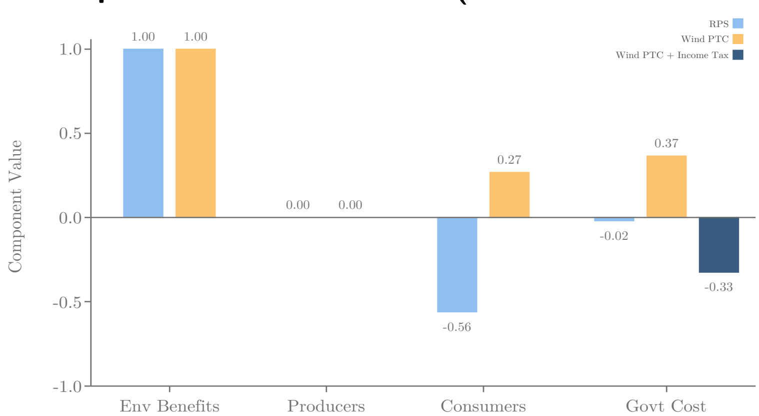
A. CAFE Comparison with Gasoline Tax (Anderson & Sallee 2011)



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

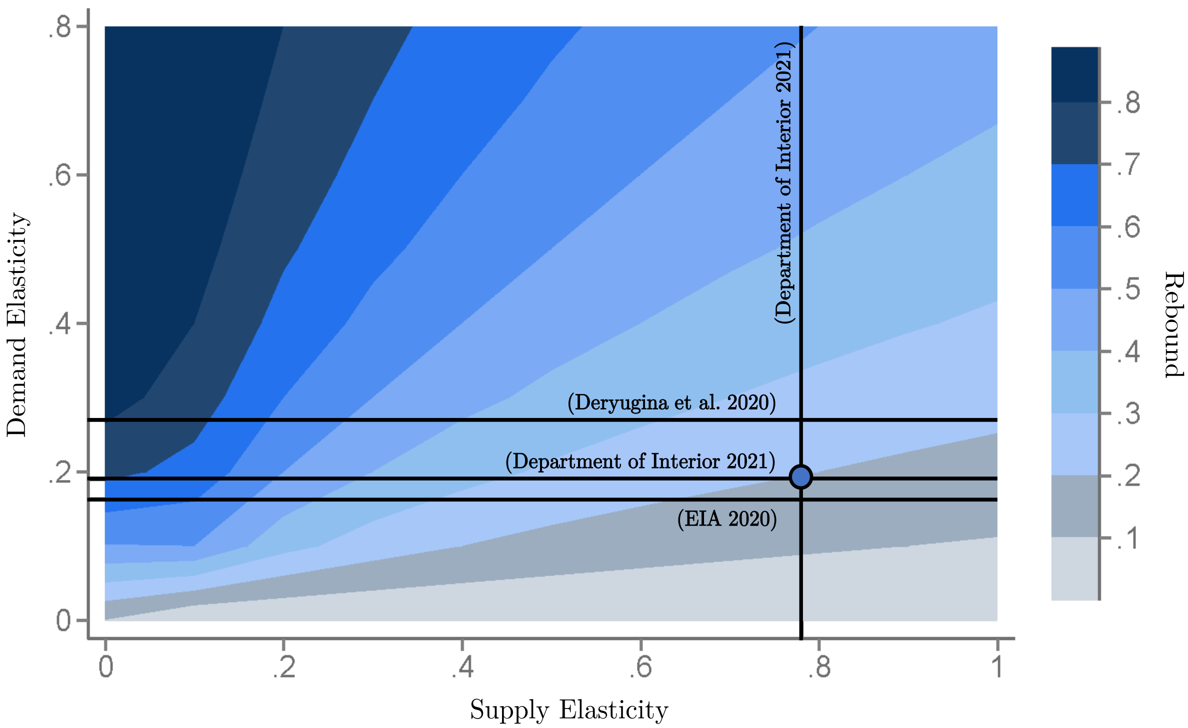


C. RPS Comparison with Wind PTC (Greenstone & Nath 2020)



Notes: This figure presents a comparison of the welfare impact of changes 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 2020). 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).

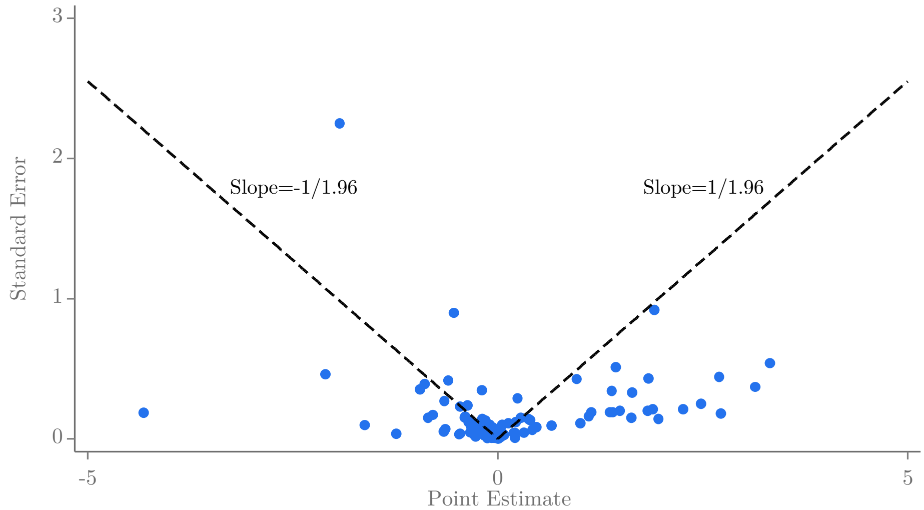
Appendix Figure 7: Electricity Rebound



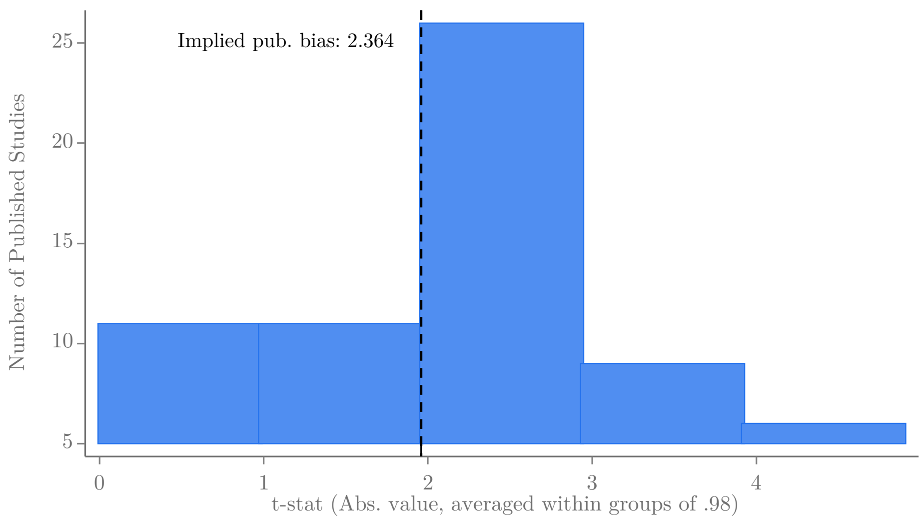
Notes: This figure shows the electricity rebound as a function of the demand and supply elasticity. The y-axis represents the absolute value of the price elasticity of demand for electricity and the x-axis is the supply elasticity for electricity. Our baseline estimate of the demand elasticity (-0.19) 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 8: Evidence of Publication Bias

A. Funnel Plot

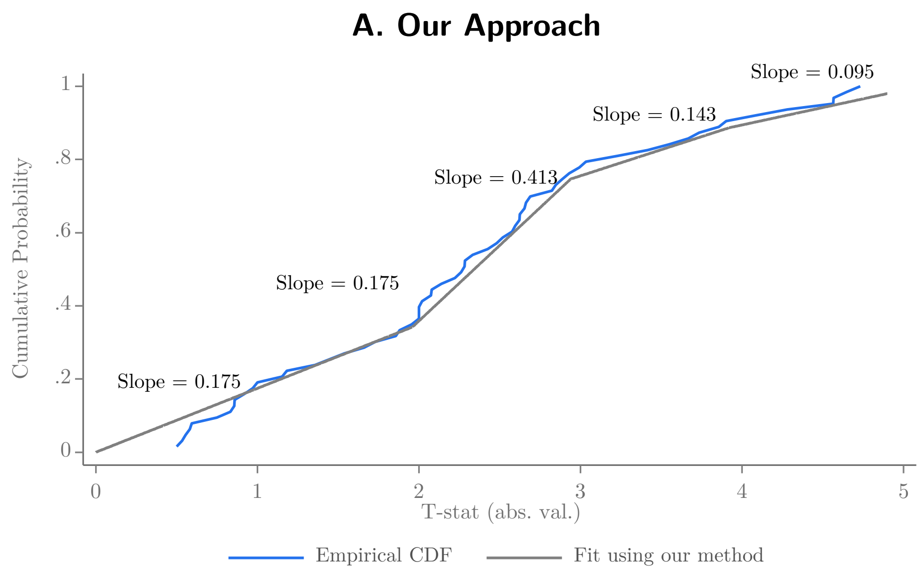


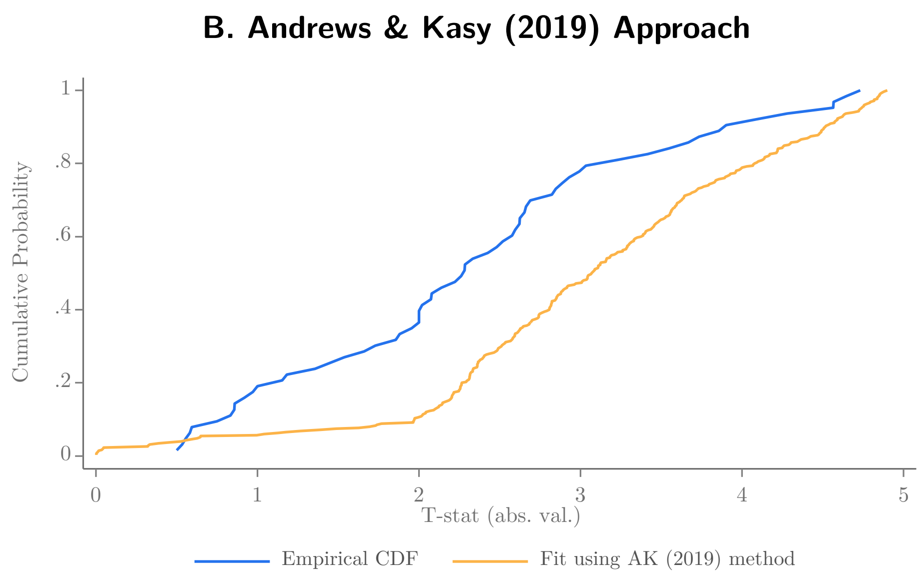
B. Histogram of t-statistics



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. 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.

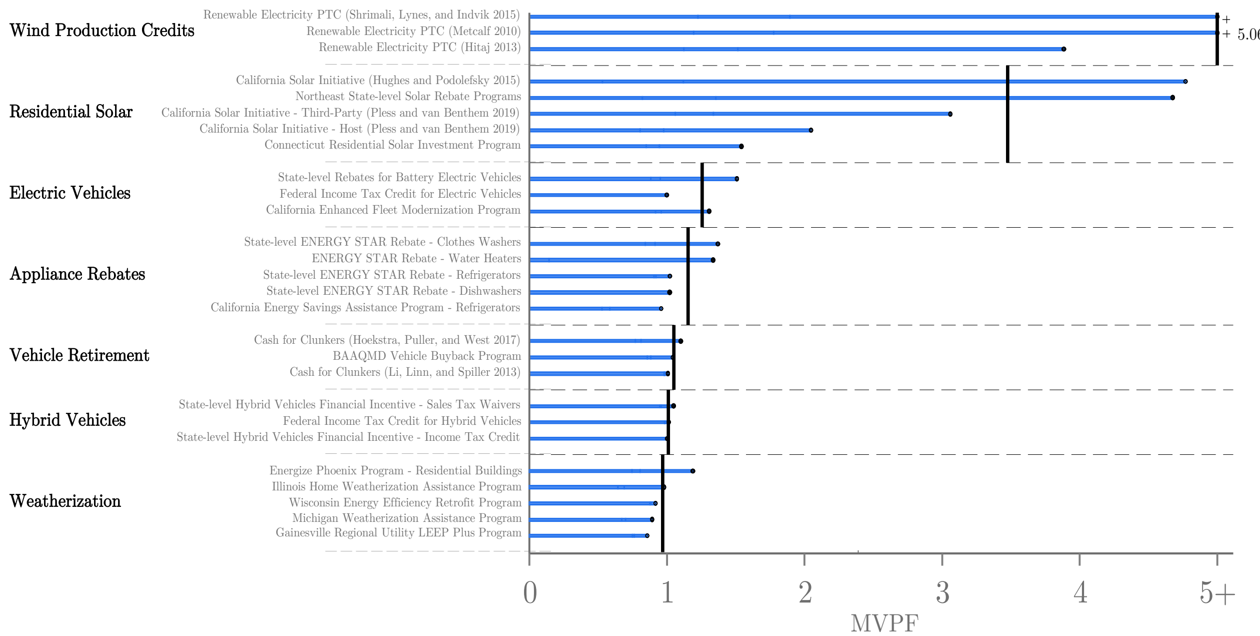
Appendix Figure 9: Model Fits for Estimates of Publication Bias





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).

Appendix Figure 10: 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). The benefits per dollar of net government cost are decomposed into US benefits and non-U.S. benefits where the latter is computed as 85% of the global greenhouse gas benefits. 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
Log Marg. Sales		-0.083	0.070		0.558	0.478		-0.062	-0.215
Year			-0.086			0.468			0.041
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 cumulative global generation on prices. The second column adds controls for yearly 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**	**1.035**	**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			-0.083	0.971	1.000	0.022	-0.005	1.017	0.956
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			-0.692	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				0.016	0.859	1.000	-0.016	0.001	0.984	0.873
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 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	0.988	1.200	1.194	0.955	1.734	0.884	0.566	1.027
C4A (Fridge)	1.042			0.994			1.100		
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			0.894			0.951		
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**			**0.655**		
(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	0.841								
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 for a \$193, \$76, and \$337 social cost of carbon. It includes the parametric bootstrap confidence intervals for each policy in 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	-0.130				0.015	0.861	1.000	-0.019	0.000	0.982	0.877
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	-0.130				0.015	0.782	1.000	-0.019	0.002	0.983	0.796
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	-0.130					0.811	1.000	-0.015	0.001	0.986	0.822
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	-0.130				0.015	0.826	1.000	-0.019	0.001	0.982	0.841
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

		Net Social Cost Per Ton			
Panel A. With Learning by Doing	**MVPF**	**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. 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

Panel A. Subsidies	MVPF	Cost Per Ton: Resource	Cost Per Ton: Government	Cost Per Ton: 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**	**987**	**876**	**148**
C4C (TX)	1.067	-1	620	148
C4C (US)	1.044	14	922	148
BAAQMD	1.030	2,948	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	-105	-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**	**987**	**876**	**148**
C4C (TX)	1.067	-1	620	148
C4C (US)	1.044	14	922	148
BAAQMD	1.030	2,948	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	Externality Value ($/Gallon) Upstream	On-Road	Total
Pollution Externalities			
Ammonia (NH_3)	0.000		0.000
Carbon Dioxide (CO_2)	0.218	1.612	1.830
Carbon Monoxide (CO)	0.000	0.052	0.052
Hydrocarbons (HC)	0.004	0.036	0.040
Methane (CH_4)	0.025	0.001	0.026
Nitrous Oxide (N_2O)	0.001	0.012	0.013
Oxides of Nitrogen (NO_X)	0.003	0.071	0.074
Particulate Matter ($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). All values are expressed in 2020 dollars.