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 the policy under consideration by providing a measure of the cost per ton of carbon dioxide (CO_2) abated. Yet, input assumptions in these calculations vary across papers, making comparisons between them quite difficult. Moreover, there are at least three distinct definitions of the dollar per ton of CO_2 found in the literature: (1) resource costs expended per ton of CO_2 abated (Grubb et al. 1993, Enkvist et al. 2007, Mullainathan & Allcott 2010, Greenstone et al. 2022), (2) government expenditures per ton of CO_2 abated (Gillingham & Tsvetanov 2019, Knittel 2009), and (3) social costs per ton of CO_2 abated (Hughes & Podolefsky 2015, Fournel 2024).

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 costs per ton of CO_2 abstracts from the causal effects of policy changes, ignoring the cost 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 costs per ton seeks to capture a comprehensive set of non-resource benefits, but the canonical formulation ignores the cost of transfers to inframarginal individuals who do not change their behavior in response to policy changes.[1] This means that, just like the resource cost measure, social cost per ton is often entirely independent of the extent to which people take up the policy.

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.[2] Another advantage is that the framework allows for comparisons of climate policies with other policy areas, such as education or healthcare.[3]

[1]As we discuss in Section 8 below, some formulations of the net social cost per ton approach impose a marginal cost of funds that captures the cost of raising tax revenue necessary to fund the policy (Fournel 2024). We show how, within a given policy, variation in this assumption leads to substantial changes in the estimated cost per ton. For example, electric vehicle (EV) subsidies range from -\$313 with a 10% MCF to +\$316 with a 50% MCF.

[2]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 raising revenue.

[3]To the best of our knowledge, Berkouwer & Dean (2019) and Christensen, Francisco & Myers (2023) were

We apply our MVPF-based framework to a comprehensive set of climate policy interventions in the U.S. that affect greenhouse gas emissions and have been rigorously evaluated in the past 25 years using experimental or quasi-experimental methods. This yields a sample of 96 policy changes in three primary categories – subsidies, nudges and marketing, and revenue raisers. Within the category of subsidies, we examine policies targeting wind production, residential social, 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*).[4] 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.[5,6] 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.[7] 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

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.

[4]We supplement this with a harmonized treatment of rebound effects using estimates of energy demand and supply curves. Our core results do not depend on adjustments for these effects.

[5]If a policy change affects vehicle miles traveled, we also incorporate estimates of the impact on accidents (Jacobsen 2013*b*) and congestion (Parry & Small 2005, Parry et al. 2014, Couture et al. 2018), as well as road damage for policies affecting heavy-duty vehicles (FHWA 1997).

[6]In our analysis we distinguish between emissions with global damages and those with local damages. Greenhouse gas emissions with global damages include CO_2, carbon monoxide (CO), hydrocarbons (HC), methane (CH_4), and nitrous oxide (N_2O). Our air pollution emissions with local damages include particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), ammonia (NH_3), HC, CO, and oxides of nitrogen (NO_X). We account for local and global damages from HC and CO.

[7]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.

using estimates on mortality and an associated value of a statistical life.[8]

For each set of causal estimates, we construct two distinct MVPF estimates, which we refer to as the "in-context and "baseline" estimates. The "in-context" estimates construct the MVPF using the time and place in which the policy change was enacted. For example, if an electric vehicle (EV) subsidy policy was implemented in California in 2014, we use estimates of the 2014 California grid and state-specific subsidies and taxes. The "baseline" estimates construct the MVPF of the policy *as if* it were implemented nationally in 2020, assuming that the elasticities estimated in-context also apply nationally in 2020. We use the "baseline" specification to present our primary results because it allows us to harmonize estimates across time and place. That said, we also explore how our results vary between these two specifications. For example, our discussion of energy conservation nudges in Section 5 highlights how the geographic variation in the grid produces large regional variation in the welfare consequences of those policies.

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 spillovers that lower the future cost of these technologies and generate future environmental benefits (Benthem et al. 2008, Acemoglu et al. 2012).

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.[9] 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.

[8]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.

[9]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.

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.[10] 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).[11] 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.[12,13]

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 comes from low- or zero-carbon sources.[14]

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

[10] As we discuss below, the MVPF of electric vehicle subsidies is 1.42. This is slightly above the non-wind, non-solar categories we analyze.

[11] 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.

[12] In the case of electric vehicles, the MVPF rises from 0.96 to 1.42.

[13] 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.

[14] 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.

goods with negative externalities enables raising revenue at a relatively low welfare cost.[15]

While our primary focus is on US environmental policy, we also consider the welfare consequences of international climate expenditures. We find that international 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. (When considering the full set of global benefits, the MVPF rises 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.[16]

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

[15]It is important to note that the Federal gas tax has not increased since 1993. This indicates the presence of very high implicit welfare weights on drivers. 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. This suggests an implicit welfare weight on drivers that is higher than the typical low-income earner.

[16]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 (ex: 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.

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.[17] 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 $470 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 $470.

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 their MVPFs, however, their values are essentially indistinguishable: 1.18 versus 1.05 and 1.01.[18] 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 1.42 but a government cost per ton of $1685. This is driven by the omissions 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 (-$518) 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 (5.87 versus 3.86 and 1.42).[19] In short, each of the various cost-

[17]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 that calculates the net resource cost of the policy including energy savings to individuals. 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.

[18]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 Blonz (2023) 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 1.03).

[19]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

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. 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

-\$313 when using a 10% adjustment and a positive \$316 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.

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 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. For simplicity, we refer to this decision maker as the "government".

The government 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. It is more natural to discuss welfare weights in dollars, not utils. To change this measurement into dollars, let λ_i denote the Lagrange multiplier on individual i's budget constraint.[20] Then, let $\eta_i = \lambda_i \psi_i$ denote 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. We allow (but do not require) the government to place positive weight on individuals outside its jurisdiction. We also note that at no point do we specify particular weights, but rather we construct statistics that help a decision-maker apply their own weights when deciding whether to prefer a given policy.

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

[20] To do this formally, we need to identify the period for evaluating each individual's budget constraint: giving an individual \$1 today differs in value from \$1 in the future. This introduces an important subtlety about the rate at which we discount over time. We assume the government can move money across time at an interest rate ρ, which we use to normalize all dollars to present-day dollars (e.g., 2020 USD in our implementation). Social preferences, of course, do not need to align with this discounting. We allow the government to place arbitrary weights on future versus current generations. Any deviation in discounting from ρ is captured by a higher (or lower) welfare weight on future generations.

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, the impact of the policy change on social welfare is a weighted sum of individuals' willingness to pay for the policy change, $WTP_i = \frac{\frac{dU_i}{dp}}{\lambda_i}$.[21]

The weighted sum is given by

$$\frac{dW}{dp}_{p=0} = \sum_i \eta_i WTP_i \tag{2}$$

with weights determined by each individual's social marginal utility of income, η_i.[22]

Next, we consider the impact of the policy on the government's budget. Let B denote the present discounted value of the government budget evaluated at $t = 0$ so that dB/dp is the net impact of the policy change on the government budget.[23] 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 problem:

$$\frac{\frac{dW}{dp}}{\frac{dB}{dp}} = \bar{\eta} MVPF, \tag{3}$$

where

$$MVPF = \frac{\sum_i WTP_i}{dB/dp} \tag{4}$$

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

$$\bar{\eta} = \frac{\sum_i WTP_i \eta_i}{\sum_i WTP_i} \tag{5}$$

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.[24]

One of the key advantages of the MVPF is that it can be constructed without making

[21]Note that this measure represents the *net* benefits to individual i (*i.e.,* monetized benefits minus the cost of the policy to them).

[22]Formally, the WTP for each person is measured with respect to the budget constraint at time $t = 0$, discounting at rate ρ.

[23]Regulatory policy changes do not fit naturally into this formulation because the government budget implications are potentially small. For these cases, it is well-known that researchers can measure everyone's WTP and ask whether $\sum_i \eta_i WTP_i > 0$ given the decision-maker's welfare weights, η_i. We discuss how to compare regulatory policies to tax/transfer/subsidy policies in Section 6.2. For example, we show how one can use the MVPF estimates for gas taxes and income taxes to assess the relative desirability of CAFE regulation versus gas taxes.

[24]To see this, note that

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

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

specific assumptions about how the budget constraint is closed for any given policy.[25] Instead, the MVPF framework can be used to construct budget-neutral policy experiments for the decision-maker by comparing any two MVPFs. Let us consider, for example, two policies 1 and 2. The MVPF framework tells us that increased spending on policy 1 financed by raising revenue from 2 increases social welfare if and only if

$$\bar{\eta}^1 MVPF^1 > \bar{\eta}^2 MVPF^2 \tag{6}$$

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. Summarizing that incidence using a single welfare weight, $\bar{\eta}$, may obfuscate 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:

$$\bar{\eta} MVPF = \sum_g \bar{\eta}_g \frac{WTP_g}{dB/dp} \tag{7}$$

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.

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

In our empirical analysis below, we will often discuss orderings of policies using their aggregate MVPF, but we emphasize that different policies may have different distributional incidence that should be incorporated into an ultimate decision (i.e., decision makers should apply their desired weights). The aim of our analysis is to provide as detailed a breakdown as possible to facilitate these decisions.

2.2 Measuring WTP and Net 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

$$WTP = xd\tau + Vdx \tag{8}$$

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.

The dx reflects the causal effect 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. The proper value for dx, however, includes any "rebound" or broader general equilibrium effects that arise from the policy. Appendix D shows how we incorporate these effects using estimates of the market supply and demand curves.[26]

It is worth noting here that this setup is very flexible regarding the nature of V. V may be greater than zero if good x reduces negative externalities (e.g., x is a wind turbine that reduces greenhouse gas emissions). V may be less than zero if good x produces negative externalities (e.g., x is a gallon of gasoline). V can be a sum of multiple externalities (e.g., CO_2 emissions and road congestion). V can also have an incidence across multiple groups of

[26] For example, let us consider the case of policies that subsidize the purchase of electric vehicles (EVs). Studies of these policies typically compare a treatment group of individuals eligible for the subsidy with a control group of ineligible individuals (e.g., Muehlegger & Rapson (2022)). The reported treatment effect is the difference in EV purchases across groups. Estimating the full causal effect of the policy change requires incorporating any rebound effect from the increase in EV purchases. In particular, EV purchases may increase electricity demand, causing electric prices to rise and reducing electricity consumption in both the treatment and control group. As a result, simple comparisons of treatment and control groups may not be sufficient to measure the full causal effect of the policy on electricity consumption, dx. In the context of our estimation to follow, we incorporate these rebound effects using estimates of the market supply and demand curves for electricity.

beneficiaries. The material that follows will separate V into global versus local externalities such that $V = V_{global} + V_{local}$. Here, V_{global} is composed of greenhouse emissions such as CO_2 and methane (CH_4), which produce global damages. V_{local} is composed of local pollutants, such as $PM_{2.5}$, and local non-emissions externalities, such as traffic congestion. Our discussion below highlights the relative contributions of V_{local} and V_{global} in our empirical analysis.

The cost to the government of the subsidy has two terms:

$$Cost = xd\tau + \tau dx \tag{9}$$

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.

If we assume perfect competition in the market for x (so that there are no producer profits, an assumption we relax below), and we assume V captures all the externalities due to a change in the quantity of good x, then the MVPF is given by:

$$MVPF = \frac{xd\tau + Vdx}{xd\tau + \tau dx} \tag{10}$$

$$= \frac{1 + \frac{V}{p}(-\epsilon)}{1 + \frac{\tau}{p}(-\epsilon)} \tag{11}$$

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 $\frac{\tau}{p}$. 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. 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). The logic is as follows: 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 learning-by-doing effects may be present in several key industries: solar, wind, and battery storage. Appendix Figure 1 presents 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 an 0.319% reduction in price. For wind and EV batteries the associated price reductions are 0.194% and 0.421% respectively.

If one believes that these patterns reflect causal learning-by-doing spillovers,[27] 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 allows for the incorporation of these 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 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 $t > 0$. 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 iso-elastic function of cumulative demand,

$$c(X(t)) = \kappa X(t)^{\theta} \tag{12}$$

[27]The extent to which the curve represents learning spillovers has been debated (Nemet 2006, Rubin et al. 2015). 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.

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, $\epsilon < 0$[28]

$$x(t) = ap(t)^{\epsilon} \tag{13}$$

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

As noted above, learning by doing will generate two types of externalities: a price externality and an environmental externality. First, a subsidy that increases production of $x(t)$ today (e.g., at time $t = t^*$) will generate consumer surplus via 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.[29] Second, 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

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

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

$dp(t)$, given by

$$dp(t) = c'(X(t))X'(t)dt \tag{14}$$
$$= c'(X(t))x(t)dt \tag{15}$$
$$= \kappa\theta X(t)^{\theta-1}x(t)dt \tag{16}$$

And, 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

$$d\log(x(t)) = \epsilon d\log(p(t)) \tag{17}$$
$$= \epsilon d\log(c(t)) \tag{18}$$
$$= \epsilon\theta d\log(X(t)) \tag{19}$$
$$\tag{20}$$

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

$$\frac{X''(t)}{X'(t)} = \epsilon\theta\frac{X'(t)}{X(t)} \tag{21}$$

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 12 and demand be given by equation 13. Suppose prices are set at marginal cost in all periods. Then the MVPF of a subsidy at time t^* is given by*

$$MVPF = \frac{1 + \frac{V}{p}(-\epsilon) + DP + DE}{1 + \frac{\tau}{p}(-\epsilon)} \tag{22}$$

where the price externality, DP, is given by

$$DP = \theta\epsilon\,(t^*)^{-\theta\frac{(1+\epsilon)}{1-\epsilon\theta}} \int_{t^*}^{\infty} e^{-\rho(t-t^*)}t^{-1+\theta\frac{1+\epsilon}{1-\epsilon\theta}}dt \tag{23}$$

where

$$t^* = \frac{X_{init}}{x_{init}(1-\epsilon\theta)} \tag{24}$$

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

$$DE = -\frac{\epsilon^2\theta}{(1-\epsilon\theta)c(X(t^*))} t^{*-\frac{\epsilon\theta}{1-\epsilon\theta}} \int_{t^*}^{\infty} e^{-\rho(t-t^*)} t^{\frac{2\epsilon\theta-1}{1-\epsilon\theta}} V_t dt \tag{25}$$

Proof: See Appendix.

This theorem provides an MVPF formula that allows for the explicit incorporation of learning-by-doing externalities.[30] 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.

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). We show, among other findings, that they can meaningfully increase the return to spending on residential solar, but have a more muted effect on wind production tax credits.[31]

Imperfect competition Thus far, we have assumed that the market for x is perfectly competitive. In our applications, it is important to consider the role of imperfect competition in the market for x. Imperfect competition introduces two modifications to the components of the MVPF. First, some of the incidence of a tax (or subsidy) change can accrue to producers instead of being passed on to consumers. While imperfect pass-through to consumers does not affect the total WTP for the transfer[32], it changes the incidence of that willingness-to-pay across consumers and producers.

Second, a change in consumption of the good can impact firm profits, which introduces an additional term into the MVPF. For example, let c denote a constant marginal cost to firms of producing a unit of x . Then, the increase in profits from a change in x is given by $(q-c)dx$. Of that total, $(1-\tau_c)\%$ accrues to firm owners and $\tau_c\%$ accrues to the government (where τ_c is

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

[31]Learning-by-doing externalities do change the relative ordering of EV subsidies relative to the high return policies in the sample. That said, the MVPF of EV subsidies changes from 0.96 without learning by doing to 1.42 with learning by doing.

[32]For any change in the subsidy $d\tau$, let dp and dq denote the change in consumer and producer prices. Market clearing implies $d\tau = dp - dq$ so that consumers WTP, $-xdp$, plus producer WTP, xdq, equals $xd\tau$.

the tax rate on firm profits). Dividing the MVPF through by $xd\tau$, we arrive at an additional term of $(1-\tau_c)\frac{q-c}{p}(-\epsilon)$ that is added to the numerator of equation (22) and $\tau_c\frac{q-c}{p}(-\epsilon)$ that is added to the denominator in equation (22).[33] Here, we can see that when the producer price equals marginal cost, $q = c$, the MVPF reduces to the competitive case in equation 10.[34] In the analysis to follow, we report our results with and without effects on firm profits and discuss their impact on our conclusions.[35]

3 Data and Sample

3.1 Sample

We analyze the welfare impact of 96 US climate-related policies that 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 by drawing upon papers from 18 major journals in economics,[36] and supplement that with a "snowball" sample of articles cited within these papers. We restrict our analysis to studies that use rigorous methods to estimate the causal effect of the policy of interest on the taxed or subsidized behavior (for example, the impact of a gas tax on gas consumption, or the impact of an EV subsidy on EV consumption). 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

[33]If we were to extend the analysis above to multiple goods, it would be clear that the appropriate additional term to add to the MVPF corresponds to the difference in the markup for good x relative to other goods in the economy so that we get the net willingness to pay by firms for the change in the consumption basket of consumers. Therefore, in our empirical analysis we focus on capturing markups for sectors (such as regulated utilities) that might have larger markups than the average markup in the economy.

[34]The incorporation of market power into the MVPF framework allows us to incorporate the insight from previous literature that subsidizing goods with negative externalities could potentially be welfare enhancing in markets with imperfect competition (Buchanan 1969). In order to see this, suppose the after-tax markup on good x is equal to the environmental externality, $V/p = (1-\tau_c)(q-c)/p$. Then, $MVPF = 1$ regardless of the magnitude of the elasticity. Indeed, if markups exceed the environmental externality, this will lead to an MVPF that exceeds 1. It is, however, important to distinguish between the incidence on firm owners and those harmed from the environmental externalities. A policy with an MVPF above 1 may not be welfare enhancing if the beneficiaries have a low social marginal utility of income. In our empirical analysis that follows, we are careful to delineate the incidence of willingness-to-pay across groups of beneficiaries.

[35]As we discuss in Section 4, incorporating markups does not affect our main conclusions but has a meaningful effect on the MVPFs of certain policies such as energy conservation nudges in markets with large producer markups.

[36]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.

category of revenue raisers, we analyze four sub-categories: gasoline taxes, other fuel taxes (such as jet fuel and diesel taxes), other revenue raisers (including the California Alternative Rates for Energy), and cap-and-trade policies. We also supplement this sample with a selected set of international policies that have been evaluated in the past ten years.[37]

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

Publication Bias While we attempted to construct a comprehensive sample of the literature, we are of course 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 this 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 in which the policy change occurred. In particular, we do so using the year and location in which it 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. This approach provides us a measure of the welfare impact of the policy as it was enacted. We refer to this as our "in-context" MVPF estimate.

Second, we construct an MVPF for each policy, assuming that it was implemented nationally in 2020. We accomplish this by assuming the original elasticity estimated in-context 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 enables us to harmonize welfare comparisons across policies holding the contextual environment fixed. We refer to this as our "baseline" MVPF estimate.

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

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 individual cases where the failure to harmonize estimates impacts our assessment of certain policies. For example, vehicle emissions were substantially higher in previous decades, increasing the in-context MVPF for vehicle retirement policies implemented in the earliest years covered in our sample.

3.2 Valuing Environmental Externalities

We seek to use a comprehensive and consistent method to value environmental externalities over time. We discuss these valuations briefly here and refer readers to Appendix C for a detailed discussion of our approach. We begin by discussing the valuation of global greenhouse gas emissions and then discuss local pollutants and other externalities.

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 recent guidance regarding the social cost of carbon at a 2% discount rate (EPA 2023*a*). This model implies a social cost of carbon of $193 per ton for emissions in 2020.[38] In constructing present-day measures of costs and willingness to pay, we apply the 2% discount rate[39] In cases where our in-context estimates seek to measure externalities before 2020, we fit a linear regression to SCC estimates for 2020–2050 and then extrapolate back to previous years. (We note this extrapolation does not affect our baseline specification).

Our 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). In the discussion below, we show how our results change under alternate measures of the social cost of carbon, including values of $76 and $337.[40]

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 methane and nitrous oxide, we take measures of social cost from the EPA's recent guidance.[41] For carbon monoxide and hydrocarbons, we use global warming potential (GWP) factors to convert these into CO_2 equivalent units, CO_2e, and then apply our baseline social

[38] The EPAs SCC rises over time and we use the time path of these valuations to measure the social cost of emissions changes 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 those year-specific social costs of carbon to value the associated externalities.

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

[40] 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*).

[41] The EPA reports the time paths of the social costs of methane and nitrous oxide. For the baseline scenario corresponding to the $193 SCC, the social costs of methane and nitrous oxide in 2020 are $1,648 and $54,139, respectively.

cost of carbon.[42]

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. Models such as RICE or DICE consider GDP or GDP-equivalent damages. Other IAMs, such as the GIVE model, infer an SCC from VSL estimates but use private VSLs that are not adjusted for welfare weights. By contrast, some have proposed equity-weighted social costs of carbon that adjust for welfare weights when forming the SCC.[43] 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 (6).

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 into 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. In the context of the MVPF framework, 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 (6), 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 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).[44] 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).[45] 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

[42] We use a GWP of 2.65 for CO and 4.5 for HC. See Masnadi et al. (2018).

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

[44] Other IAMs explicitly measure the distributional incidence of global damages. For example, Nordhaus (2014, 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).

[45] 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.)

no bearing on any of our results for subsidies, nudges, or revenue-raisers.[46] 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 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.[47] We monetize those health impacts using EPA's preferred value of a statistical life of $9.5 million (EPA 2010).[48]

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 common approach across all policies. For example, consider the case of policies that alter electricity usage. Some of these policies, such as residential solar subsidies, might generate new sources of electricity while 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 describe these estimates in detail in Appendix C.) We also consider a class of policies that affect vehicle usage. In those cases, we estimate the change in gallons of gasoline used relative to a counterfactual vehicle. We measure the total CO_2 associated both with the upstream production of gasoline and with its combustion. We draw upon estimates from National Emissions Inventory, the Inventory of U.S. Greenhouse Gas Emissions and Sinks, as well as the EIA's reported CO_2 emissions coefficients. We combine that with per-mile measures of local pollutants released, such as particulate matter (Jacobsen et al. 2023, Argonne National Laboratory 2013).

Appendix Figure 2 presents the environmental damages from driving and using electricity over time. Panel A presents the dollar value of the externality generated per gallon of gasoline used by the average light-duty, gasoline-powered vehicle. As noted, this includes both the emissions generated while producing a gallon of gasoline and the emissions from burning the

[46] 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 do not impact any of our primary findings.

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

[48] 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 marginal carbon emissions are time-varying but the health impacts of local pollutants do not follow a clear time path.

fuel. The graph distinguishes between the production of local and global pollutants. 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.[49] 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.

4 Subsidies

The next four sections of the paper present our results, focusing in turn on the welfare consequences of: 1) subsidies, 2) marketing and nudges, 3) revenue raisers, and 4) international policies. We begin with the first of those categories: subsidy. Here, we start with 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 sub-categories of subsidy policies: production tax credits for wind, subsidies for home rooftop solar installations, hybrid vehicles, vehicle retirement, appliance rebates, and home weatherization. After discussing each sub-category of subsidies, we then compare the MVPFs across sub-categories, identifying the types of policies that produce the highest returns.

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. In our analysis we draw upon three papers measuring the response of EV purchases to federal or state subsidies. We begin with an analysis of the California Enhanced Fleet Modernization Program (EFMP) studied by Muehlegger & Rapson (2022). The EFMP provided subsidies for 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 (with 15% captured by dealers via higher prices) and that a one percent decrease in the price of EVs led to a 2.1 percent increase in EV purchases.

Using these estimates, we form both our baseline and in-context MVPFs. We focus our

[49] 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.

discussion in the main text on the baseline MVPF, which takes the estimated elasticity of -2.1 and considers the welfare effect of a national policy change implemented in 2020. Appendix E.3 presents the analogous discussion of the in-context MVPF, examining a marginal change in the subsidy in CA between 2015 and 2018, the period in which the causal effect was estimated.[50]

Figure 1 presents the components of our 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 the cars 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.[51] We then combine this counterfactual fuel economy (41.2 MPG) with an estimate of the per-gallon externalities associated with gasoline. This includes both the global damages from CO_2 emitted as well as the local damages from NO_X, $PM_{2.5}$, HC, CO, SO_2, and NH_3.[52] We measure these damages over the lifetime of the vehicle, using estimates from Zhao et al. (2023) to account for an EV-specific measure of vehicle miles traveled (VMT.)[53] Taken together, the local and global pieces provide the lifetime environmental benefits from *not* driving the counterfactual gas-powered vehicle. This leads to a WTP of $0.17 from global pollutants and $0.02 from local pollutants. This sums to a total benefit of $0.19 from the reduced gasoline consumption induced by the subsidy.

While the decrease in gasoline consumption leads to environmental benefits, the additional

[50] Appendix Table 2 presents the in-context MVPF components.

[51] 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. In the Appendix, we explore the robustness of our results to this particular MPG assumption and show it does not meaningfully impact our results.

[52] As we explain in Appendix C, we use EIA figures for the CO_2 associated with gasoline combustion EIA (2023*b*). We adjust those figures to account for the small share of ethanol in gasoline. We also add upstream emissions from gasoline production based on estimates from the National Emissions Inventory and the Inventory of U.S. Greenhouse Gas Emissions and Sinks. We use estimates from Jacobsen et al. (2023) to get per-mile emissions from hydrocarbon and carbon monoxide, which have a global externality component to their damages. Finally, we use estimates from Argonne National Laboratory (2013) to get the CH_4 emissions and N_2O emissions associated with gasoline combustion. When it comes to the local damages, we once again use estimates from Jacobsen et al. (2023) to get the per-mile emissions for NO_X, HC, and CO. We get estimates of per-mile exhaust $PM_{2.5}$ from Argonne National Laboratory (2013).

[53] 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). We assume the average EV and the average counterfactual car both have 17-year lifetimes (Greene & Leard 2023). Since we assume the same VMT between gas-powered vehicles and EVs, we do not need to account for damages from accidents, congestion, or $PM_{2.5}$ from tires and brakes, which arise per mile traveled. Appendix C describes this approach in further detail.

use of electricity leads to partially offsetting environmental damages. As described in detail in Appendix C, we incorporate the emissions from additional electricity usage drawing estimates from the EPA's Avoided Emissions and Generation Tool, AVERT (EPA 2024*b*).[54] For our baseline specification, we use a national average externality in each year the new EV is in operation. For the in-context specification, we use location- and time-specific grid estimates (e.g., cars purchased in California in 2015-2018). 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 global benefit and approximately $0 for the local benefit.

Some of these increases in electricity usage from EVs may be offset through a rebound effect: increases in electricity demand can increase prices, leading to lower electricity consumption. In order to account for this, we use estimates of the demand and supply elasticities of 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).[55] Combining these estimates implies that roughly 20% of the electricity demand is offset by reduced demand due to higher electricity prices.[56] This suggests that roughly $0.02 of the environmental harms from increased electricity consumption are offset by the rebound effect. In particular, due to this rebound effect, society is willing to pay an additional $0.02 for global benefits and $0 for local benefits per each $1 in mechanical subsidy.

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

We now turn to the effects of learning-by-doing externalities, which potentially arise in the context of EVs due to the production of batteries. We use estimates of the recent slope of the

[54] In the years after 2023, we use grid projections rather than direct emissions estimates from the AVERT model. In particular, we use the Princeton REPEAT Project's mid-range forecast from 2023-2050 to estimate the average combustion share of the grid (Jenkins & Mayfield 2023). We then use estimates from the AVERT model to map this combustion share of the grid to the environmental externality per kWh. We compute these estimates at both the state and national level. For projections beyond 2050, we repeat the same process but assume the combustion share remains constant.

[55] We construct the demand elasticity using a weighted average of the demand elasticities for residential (0.29), commercial (0.13) and industrial electricity demand (0.13) from Serletis et al. (2010) and Jones (2014). We construct the supply elasticity using an average of the supply elasticities of each generation source weighted by each source's share of the US electric grid in 2020. We use the EPA's National Energy Modeling System estimate of 0.27 for coal (EIA 2020*a*). For natural gas, nuclear, hydroelectric, wind, and solar, we use elasticity estimates from the Annual Energy Outlook of 1.50, 0.53, 0.05, 0.65, and 2.03, respectively (EIA 2023*a*).

[56] We do not incorporate a rebound effect for gasoline. This is because we treat gasoline as a global market where the price does not meaningfully change in response to the demand shock induced by EV purchases. This differs from the local electricity market.

learning-by-doing curve for batteries of $\theta = -0.42$ from Way et al. (2022). This indicates that a 1% increase in battery production leads to a reduction in battery costs of 0.42%. Crucially, while this is the trajectory of battery costs, batteries only made up roughly 25% of the cost of EVs in 2020. We account for this fact when measuring the effect of EV subsidies on future EV prices.[57] We then use a demand elasticity of $\epsilon = -2.1$ and a future discount rate of 2% to estimate the effect on future EV demand. This yields an environmental benefit from increased future consumption of EVs that is $0.03 per dollar of mechanical cost of the subsidy.[58]

We also estimate that learning-by-doing lowers the price of EVs for future purchasers. This generates a willingness of $0.31. This component is the dominate factor is driving the MVPF of EV subsidies above 1, driven by the steep learning curve and strong demand elasticity. Taken together, the learning-by-doing effects increase the value of the subsidy by $0.34 per dollar of EV subsidy. In these estimates we take as given the relationship between total production and price, and we assume it reflects a causal relationship. In particular, we assume it reflects spillovers across firms that are not internalized through the patent system or other means. This cross-sectional relationship may, of course, not all be the result of learning-by-doing effects. For example, it could be that the general advancement of technology drives down costs over time in a manner not dependent on quantity. This means that our MVPFs here represent a potential upper bound on the MVPF estimates for EVs. Throughout, we consider the robustness of our results to the elimination of learning-by-doing effects.

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.[59] This lies above the economy-wide average markup of 8% (De Loecker et al. 2020), leading to a relative profit loss by producers due to the shift away from gasoline towards other goods.[60] Applying a 21% effective corporate tax rate, we calculate post-tax lost producer

[57]There are many components of the vehicle (such as seats and tires) that are 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 the learning-by-doing effects of EV subsidies to fall rapidly over time. Intuitively, as the battery costs decline, there is a limit in the extent to which lower battery prices can lower future EV costs. We show in Appendix B how we account for this dynamic in learning by doing.

[58]As we discuss in Appendix C, these damage estimates account for forecasted changes in the cleanliness of the electric grid over time (i.e. cleaner electric grids in the future) as well as projected improvements in the fuel economy of counterfactual new light-duty cars.

[59]We calculate the markup on a gallon of gasoline by summing the profits at each step in the gasoline supply chain. First, we estimate crude oil producer profits by subtracting the landed cost of crude oil (EIA 2024*d*) from the US refiner crude oil acquisition cost (EIA 2024*b*). We divide by the average US refinery yield (EIA 2024*g*) to convert from barrels of crude oil to gallons of petroleum product. Next, we calculate refiner profits using the average cost of refining a barrel of crude (Favennec 2022) and the share of the gasoline price that comes from refiner costs and profits (EIA 2024*a*). We determine retailer profits by subtracting the average retail gasoline price (EIA 2024*c*) from the price retailers pay for a gallon of gasoline (EIA 2022), assuming no long-run costs to retailers.

[60]Here, for ease of explanation, we use the term markup to refer to the producer profit rate. In De Loecker et al. (2020), this term is referred to as the average profit rate while markup is used to refer to the levels of

profits are equal to \$0.04 per dollar of the subsidy.[61] By contrast, electricity suppliers benefit from increased electricity consumption. Electric utilities are a regulated industry with natural monopolies that sell electricity at a markup. We estimate this to be 12.9% on top of the 8% economy-wide markup.[62,63] We find that the subsidy generates an increase in electricity company profits of \$0.01 per \$1 of subsidy.

Having constructed all the components of our willingness-to-pay, we can now measure the total WTP for the policy. We estimate that a marginal increase in EV subsidies leads to \$1.37 in benefits per mechanical dollar in spending.

Next, we calculate the net cost of the subsidy to the government. Each of these components is reported in Figure 1. We begin with the mechanical cost of the subsidy, which is \$1 by construction. Next, we consider the fiscal externality induced by pre-existing subsidies. When the subsidy causes a EV purchase, this generates an additional government cost equal to pre-existing subsidy level. In 2020, federal credits for EVs had expired for most companies, such as Tesla. The average federal subsidy was therefore just \$42.98, while the average state subsidy was \$604.27.[64] The existence of these subsidies means that the increase in EV purchases cost the federal government an additional \$0.001 for every \$1 in subsidy. (The source of this estimate can be seen in equation 10 above. We get \$0.001 by multiplying the elasticity by the size of the pre-existing subsidy as a fraction of the total price of the vehicle.) The state subsidies leads to an additional cost of \$0.02.

Next, we consider the impact of the policy on tax revenue collected. The reduced gasoline consumption leads to a loss in gas tax revenue for the government of \$0.04 for every \$1 in subsidy.[65] It also causes a reduction in corporate tax revenue of \$0.01 per dollar of subsidy.[66] Finally, we incorporate a positive impact on the US government's budget due to reductions in climate damages. The associated productivity gains generate a fiscal externality equal to

prices relative to marginal costs (excluding capital expenditures, fixed costs and overhead costs).

[61]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.

[62]Appendix C explains our approach in further detail. We start by using the EIA's levelized cost of electricity (LCOE) (EIA 2015). We construct total cost per mWh at the state and national level by taking an average of the LCOEs weighted by the share of the grid made up of each generation source. We also add transmission and distribution costs from the EIA to the LCOE (EIA 2023*a*). The EIA does not report the state specific LCOE for each generation source. It only reports the minimum, average, and maximum. We create 50 discrete equally spaced buckets from the minimum to maximum LCOE for each generation source and assign states into each bucket using the BLS's power generation industry wage index. We then compare these costs to the retail price of electricity by year and state from the BLS (BLS 2024).

[63]As in the gasoline market case, we split this markup into two components: after-tax profits and government revenue. In our baseline specification, we assume that 28% of utilities are publicly owned, that the the effective corporate tax rate on private utilities is 10% (drawing from (DOT 2016)) and 100% on public utilities.

[64]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).

[65]Total gas taxes in the US were \$0.46 per gallon. This is due to the a federal gas tax of \$0.18 per gallon and a state gas tax of \$0.28 per gallon.

[66]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.

$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 1.28. The MVPF of 1.28 means that a $1 increase in a 2020 subsidy for EVs would have led to $1.28 in benefits for members of society.

Our 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 think about larger policy changes. Indeed, in 2022, federal credits were increased to $7,500 as part of the 2022 Inflation Reduction Act. If federal subsidies were $7,500 in 2020, this would increase the fiscal externality per dollar of subsidy to 0.37 and thus lower the MVPF to 1.01.[67] Put differently, the first dollar of a subsidy relative to 2020 levels has an MVPF of 1.28, but the 7,500$^{\text{th}}$ dollar of the subsidy has an MVPF of 1.01. For a non-marginal policy that increases the subsidy level from $0 to $7,500, the average MVPF is 1.13.

In estimating the welfare effects of EV subsidies, we consider two other estimates from 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 (s.e. 1.01). 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 an ultimate price elasticity of demand of -2.61. The estimated elasticities from these two papers lead to MVPFs of 1.53 and 1.45 in our baseline specification (with the larger MVPF driven by the larger 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 our category average MVPF. This leads to an estimated baseline MVPF of 1.42 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 1.42 to 1.49. 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

[67]The fiscal externality induced by the preexisting subsidy is the dominant force driving down the MVPF relative to our baseline estimate, as it increases τ/p in equation 10. We note that the assumption of a common elasticity with respect to consumer prices also produces a counter-veiling force. As the subsidy rises, and the net of subsidy price falls, so that the externality per dollar, V/p, increases.

literature, the MVPF rises from 1.49 to 1.63. The MVPF also rises from our baseline 1.42 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 1.34. Increasing the SCC to $337 with a discount rate of 1.5% yields a baseline MVPF of 1.60. 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, the transfer cost per new vehicle is tens of thousands of dollars.[68] Consequently, the environmental benefits per each new EV remains below the mechanical transfers needed to induce the new EV purchase.[69]

Wind Subsidies Next we examine the welfare consequences of production tax credits (PTCs) that encourage the production of wind energy. These subsidies pay the producer of renewable energy a fixed payment per kilowatt hour of production of clean energy, typically for 10 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.[70]

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[71] leads to a 1.13 percent increase in wind turbine installations. This elasticity of -1.13 is smaller in magnitude than the other two papers we study (Metcalf 2010, Shrimali et al. 2015). Figure 2 Panel A presents the components of WTP and net government cost using the elasticity from Hitaj (2013). The envelope theorem implies that the producers are willing to pay $1 for a dollar's worth of mechanical subsidy. Next, we measure the environmental benefits of the PTC. We use estimates from the EPA's AVERT model to measure the grid displacement from an additional unit of clean energy and calculate the damages associated with those emissions. 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.[72] These benefits are larger than the per-dollar benefits for EVs

[68]EV prices in 2020 were approximately $54,000. As noted above, Muehlegger & Rapson (2022) estimates a pass-through scaled elasticity with respect to prices of -1.78. This means every induced EV purchase requires roughly $30,000 of government payments to inframarginal beneficiaries.

[69]In order to generate an MVPF that rises well above 2, the elasticity would need to far exceed the values currently reported in the literature. This could occur, for example, if there were a non-linearity in elasticities around the point where EV prices rivaled ICE prices. It could also occur if the presence of alternative infrastructure such as charging stations impacted people's relative preferences for EV versus gas vehicles.

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

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

[72]In translating the PTC into a change in wind turbine prices, we discount the flow of benefits using a firm-

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 (\$3.36) as compared to \$1 of induced spending on an EV (\$0.02).

As with EVs, we incorporate potential rebound effects in the electricity markets. In contrast to EVs, the rebound effect for expanded production of clean energy now means some of this expanded supply leads to increased overall energy use. This 20% rebound effect suggests that environmental benefits are \$0.87 lower due to the induced demand increase from lower energy prices. 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.[73]

Next, we incorporate the potential benefits from learning-by-doing externalities. Here, we use estimates of the recent slope of the learning-by-doing curve for wind production of $\theta = -0.19$ from Way et al. (2022), indicating that a 1% reduction in wind turbine costs of 0.19%.

This leads to an additional environmental gain of \$1 and reductions in future prices of turbines that are valued at \$0.46. Combining all our willingness to pay components together, this produces a net WTP of \$5.90 per dollar of mechanical wind PTC.

On the cost side, 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 a fiscal externality of \$0.35 per dollar in mechanical subsidy. Long-run climate benefits also generate a negative fiscal externality of \$0.08. Taken together we estimate a net cost of \$1.28, and when combined with the WTP, an MVPF of 4.63.

Figure 2 Panel B plots each of our MVPF estimates for wind subsidies. It shows how the MVPFs vary as a function of the price elasticity. Our other primary estimates have elasticities of 1.3 (Metcalf 2010) and 1.75 (Shrimali et al. 2015), and MVPFs of 5.30 and 7.55, respectively.[74] This rise in MVPF is driven primarily by increased environmental benefits as elasticities rise. For example, Table 2 shows the breakdown for our MVPF estimate from Shrimali et al. (2015) with an elasticity of 1.75. For every \$1 in mechanical benefits, we find \$5.33 of upfront environmental benefits. The larger elasticity also increases the learning-by-doing environmental benefits, which rise to \$3.28. (The future price effects from learning by doing are more muted

specific measure of the cost of capital. This allows us to firm-specific time preferences, a topic of substantial importance in current debates over the ITC versus the PTC.

[73]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.

[74]Here, we have translated our in-context estimates to our 2020 baseline estimates by assuming the elasticity of turbines installed with respect to price is constant over time. As turbine costs fall, a constant elasticity corresponds to a rising semi-elasticity. The impact of a \$1 subsidy rises as the sticker price of a turbine falls. Alternatively, we could assume that the semi-elasticity is constant even as prices fell more than half between the mid-2000s and 2020. In that case, the category average MVPF is still 2.86. That is above all the other subsidy categories in our sample except for residential solar subsidies.

in relative terms with a WTP of \$0.92, up from \$0.46 in the case of Hitaj (2013).)[75]

The evidence here suggests that wind subsidies may be highly welfare enhancing. In order to ensure that our results are not being driven by a small sample of elasticity estimates found in the US context, 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 these estimates side by side with our US estimates. They paint a very similar picture. The elasticities range from 0.60 to 1.97 and MVPFs range from 1.50 to 9.15. Our category average MVPF using only US policies is 5.87. If we were to include European subsidy estimates, the average would be 5.93.[76]

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 separate academic papers (Pless & van Benthem 2019, Hughes & Podolefsky 2015, Gillingham & Tsvetanov 2019, Crago & Chernyakhovskiy 2017). We begin our discussion here with results from 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 1.14% increase in installations among residential homeowners. This elasticity 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 our MVPF estimate. 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.

Turning to environmental benefits, we find that 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

[75]We also explore the robustness of our wind estimates alternate category-specific assumptions. In particular, our existing calculations take as given DOE estimates for the average LCOE of installed on-shore wind turbines in 2020. This figure was \$0.033 per kWh. We explore the robustness of our calculations to alternate estimates of the LCOE. If we assume the true LCOE is 50% larger, the category average MVPF falls just slightly to 4.51. If we assume the true LCOE is actually 100% larger, the MVPF is 3.81, still larger than any other category studied in our sample.

[76]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.

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). While these estimates lie well above our estimates for EV subsidies, they fall below our estimates for wind PTCs. This is primarily because \$1 of spending on residential solar panels delivers fewer environmental benefits than \$1 spent on utility-scale wind production.[77]

While the initial environmental benefits from residential solar subsidies are smaller than those associated with the wind PTCs, the learning-by-doing benefits are larger: we find the solar subsidies induce \$1.08 in environmental benefits and \$0.86 in price benefits. These higher learning-by-doing effects are driven by the fact that i) the historical learning rate for solar, $\theta = -0.32$, is well above the historical learning rate for wind and ii) the elasticity for residential solar is higher than for wind. (As shown in Theorem 1, learning-by-doing benefits are driven by the product of the elasticity and the learning rate).

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.

Turning to government costs, we begin with the \$1 mechanical cost of the policy. Existing subsidies for solar were 26% in 2020, which means that the increase in solar purchases generates a fiscal externality of \$0.32 for every \$1 of mechanical subsidy.[78] 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 ultimately costs the government \$1.35. Comparing this value to the willingness to pay yields an MVPF of 2.71.

Figure 3 Panel B compares across our solar estimates and presents the MVPFs as a function of the price elasticity. 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 eliminated the MVPFs fall substantially. We find MVPFs that range from 1.17 to 1.70.[79]

Even when learning by doing effects are incorporated, the solar subsidy MVPF estimates are substantially lower than our estimates for wind PTCs. The category average of 3.86 falls below the wind estimate of 5.87. It is important to note, however, that 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.

[77]As we discuss below, this gap may be driven by the contrast between utility-scale and residential installations, rather than solar versus wind as a means of renewable energy production.

[78]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.

[79]For our category average we get an MVPF of 1.45 when learning-by-doing effects are omitted.

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.

Hybrid Electric Vehicles (HEVs) Next we consider subsidies for hybrid electric vehicles (HEVs). We use three estimates from two papers that evaluate the response of HEV purchases to state and federal HEV subsidies (Beresteanu & Li 2011, Gallagher & Muehlegger 2011).[80] We focus our discussion here on the Federal Income Tax Credit for Hybrid Vehicles evaluated in Beresteanu & Li (2011), whose findings imply an elasticity of -1.98.

Just 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.[81] As a result, we estimate that environmental damage reduction is less than \$0.01 per dollar of mechanical spending. (This figure is \$0.02 in the absence of a rebound effect but falls below \$0.01 when we account for the increase in VMT that stems from a decline in per-mile driving costs after purchasing a more fuel-efficient vehicle.) The remaining components of the MVPF are similarly small, with negligible effects on producers and learning by doing. This results in 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.[82]

Vehicle Retirement Next, we consider subsidies encouraging the retirement of old vehicles. So-called "cash for clunkers" policies provide subsidies to those retiring old cars conditional on purchasing new cars that satisfy certain standards (e.g., fuel economy requirements). We consider three evaluations of such policies in our sample (Li et al. 2013, Hoekstra et al. 2017, Sandler 2012). These papers generally find that cash-for-clunkers policies do not generate new purchases. Rather, purchases are shifted forward in time. In some cases, those taking up

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

[81] The fuel-economy gap is just 1.9 MPG in 2020.

[82] 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 1.08. An elasticity of -1.98 yields 1.05 and our -6.92 elasticity from (Gallagher & Muehlegger 2011) still only yields an MVPF of 1.17.

the subsidy choose a more fuel efficient vehicle when they make their next purchase. Table 2 presents the MVPF estimates for these studies, which range from 1.01 to 1.10.

We focus here on Li et al. (2013), who evaluate changes in the US automotive market following the federal cash for clunkers program in 2009. They find that individuals using the subsidy, switch to a slightly more fuel efficient vehicle.[83] By construction, beneficiaries are willing to pay $1 for each $1 in mechanical cost of the policy. The slight improvement in vehicle MPG and resulting reduction in gasoline usage leads to a social willingness to pay of $0.03 for global pollutants and $0.005 for local pollutants, holding VMT constant. We then use estimates from Small & Van Dender (2007), who estimate that individuals drive more after purchasing a more fuel efficient car. We estimate that this rebound effect reduces the net environmental benefits by $0.02.[84] On the cost side, the shift toward more fuel efficient vehicles generates a fiscal externality of $0.01 from lost gas tax revenue and corporate tax revenue from gasoline producers. Combining these results yields an MVPF of 1.01.

The two other vehicle retirement policies have similar baseline MVPFs. We find MVPFs of 1.10 using the behavioral response to the 2009 cash for clunkers program estimated among consumers in Texas (Hoekstra et al. 2017) and 1.04 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, a lower value than the MVPF EV subsidies (1.42) but higher value than the HEV subsidies (1.01).

As noted above, vehicle retirement is an important case where the harmonization of externality estimates has a meaningful impact on the results. The in-context effects of the BAAQMD Vehicle Buy Back Program are well above the baseline estimates. This is because the original policy was implemented in 1996 and was designed to encourage the retirement of vehicles that were 25 years old at the time. 25-year-old vehicles produced far more emissions in 1996 than 25-year-old vehicles do today. Using historical fleet figures, we estimate that each $1 in subsidy spending in 1996 produced $4.57 in local environmental benefits and $0.96 in global environmental benefits. The in-context MVPF for BAAQMD is 4.33. While the global benefits are also larger than the effects today due to considerable improvements in fuel economy, the key distinction here is that cars manufactured in the 1970s (25 years before 1996) produced substantially more local pollutants than cars manufactured a few decades later.

Weatherization Next, we consider subsidies to home energy efficiency through weatherization efforts that improve insulation, windows, lighting, and other energy-intensive aspects of one's home. Our sample includes five different weatherization policies (Christensen, Francisco & Myers 2023, Fowlie et al. 2018, Hancevic & Sandoval 2022, Liang et al. 2018, Allcott &

[83]We apply this estimate to the 2020 context by allowing the average new vehicle MPG to vary over time, and then applying a constant percentage improvement (1%) in MPG measured from Li et al. (2013). This results in an MPG increase of 0.24 (as compared to the 0.21 value in 2009.)

[84]When incorporating the rebound effect, we include damages from accidents, congestion, and $PM_{2.5}$ from tires and brakes, as these vary on a per-mile basis.

Greenstone 2024).

Table 2 presents the components of WTP and cost for the Weatherization Assistance Program, which was studied by Fowlie et al. (2018) in a subset of Michigan households. As implemented, the program used an encouragement design to increase take-up of home weatherization and studied the impact of weatherization on home energy costs.

By construction, the subsidy provides \$1 in mechanical benefits for any inframarginal individual who would have taken up the weatherization in the absence of the subsidy. In contrast to other policies where we can consider marginal changes in prices, the weatherization policies we consider are often offers of discrete services to households. As a result, we need to consider potential benefits accruing to marginal households. For those who are induced to get weatherization products and services 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 the DWL in Harberger (1964) (and the approach taken in Hendren & Sprung-Keyser (2020)), a natural assumption is 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.[85]

The paper does not provide an estimate of the fraction of weatherization users who are inframarginal, and so we explore the robustness of our MVPF result to this assumption. As our baseline, we assume that 50% of those receiving the weatherization benefits are inframarginal.[86] This yields a total transfer benefit of \$0.75 when summing across marginal and inframarginal individuals.

In addition to the monetary benefits of \$0.75 per dollar of mechanical spending, we estimate a local environmental benefit of \$0.01 and a global environmental benefit of \$0.30 for our 2020 baseline MVPF.[87] The reduction in electricity demand caused by the program also induces a rebound effect. Using our local electricity supply and demand curves, we estimate a rebound effect of -\$0.05, so that the total environmental benefit is \$0.27. Overall, our analysis suggests an MVPF of 0.92.[88]

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

[86] We show that, in the case of weatherization policies, the MVPF is not particularly sensitive to this assumption.

[87] We note that some of these weatherization policies affect the use of natural gas. We quantify those externalities using yearly data on the emissions factors for natural gas reported by EPA (2024*c*). The EPA reports emissions factors at the national level for CO_2, CH_4, and N_2O. For natural gas markups, we use the city gate prices for the total cost per MMBtu and retail prices from the EIA. After subtracting the economy-wide markups, we estimate a natural gas markup of approximately 43% in the U.S. in 2021. We use the 2021 natural gas markup instead of the 2020 markup for our baseline estimates. The markup in 2020 was an outlier due to factors such as COVID-19.

[88] As expected, these values vary depending on the cleanliness of the grid. If we consider a weatherization policy targeted to grids with the cleanliness of California compared to the Midwest, we get category average MVPF estimates of 0.88 and 0.95 respectively.

As noted above, this MVPF calculation requires taking a stance on the fraction of beneficiaries that are marginal and the valuation of benefits among those marginal individuals. An attractive alternative approach is one taken by Allcott & Greenstone (2024), who study a weatherization policy in Wisconsin. They use a combination of experimental variation and observational variation in benefits from weatherization to estimate a demand model that yields a measure of the consumer surplus from the weatherization program. They find an MVPF of 0.93 in-context for 2013 in Wisconsin. We harmonize this to our 2020 national specification using ratios of 2013 Wisconsin to 2020 national externalities, though these adjustments have minimal effects. We also incorporate our rebound effect in the energy market (the reduction in usage leads to lower prices that increase consumption by others). This lowers the MVPF ever so slightly from 0.93 to 0.92 in our baseline specification.

Taking an average across all of the weatherization policies in our sample, we obtain a category average MVPF of 0.98.[89] These estimates do not incorporate private energy savings into individual willingness to pay. It assumes that individuals are aware of the private energy savings offered by weatherization. Consequently, it means, on the margin, individuals who are induced to take up the weatherization subsidy are indifferent between doing so and not doing so. 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."[90] 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.

Appliance Rebates Next, we consider subsidies designed to encourage the purchase of energy-efficient appliances, such as dishwashers, refrigerators, and stoves. For appliance subsidies, we 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 beneficiaries are inframarginal. Those individuals would have purchased the energy-efficient product in the absence of the subsidy. We value their subsidy dollar for dollar. For the remaining 9.5%, we apply the same approximation as above and value these transfers at 50%. This yields a total of \$0.95 per dollar of subsidy. In our baseline specification, we estimate a global environmental benefit of \$0.55 and a local

[89] 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 relative 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.

[90] 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.

benefit of $0.08 associated with reductions in electricity usage. We find that this is offset by global and local rebound effects of -$0.11 and -$0.02. 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 1.41.[91] 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 1.18.

Other Subsidies In addition to appliance subsidies, we also consider two other subsidy policies that do not neatly fit into our categorization above. The first of these policies 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. Estimates from Ito (2015) indicates that most 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.[92] The policy leads 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. We also estimate 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.[93] We note, however, that a policy like this one might not be easily implementable because it conditions future prices on past behavior. If consumers knew this was going to happen, they might increase their energy consumption today in order to qualify for greater discounts in the future, which would reduce the policy's effectiveness.

The second of these policies 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 (and applying our baseline $193 SCC), we estimate global environmental benefits of $0.92. The accompanying local benefits, including reduced nitrous oxide released from decreasing fertilizer use, are $0.55.

[91] 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.

[92] 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.

[93] 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 meaningfully cleaner than the national grid today.

This yields an MVPF of 2.41.[94]

Summary of MVPFs for Subsidies Figure 4 presents the MVPF estimates for each of the subsidies in our sample, focusing on the baseline specification.[95] 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.[96] Production tax credits to firms to produce wind have the highest MVPFs, generally exceeding 5. Subsidies to individuals to 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).[97] 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 MVPF of the wind and solar PTCs remain above all other categories (with averages of 1.88 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 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 4.41, 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 5.76 as compared to our baseline

[94] This calculation assumes that the carbon sequestration benefits of the program are released in perpetuity, despite the fact that the PES contract lasts 10 years. We also discuss this assumption in the Appendix in the context of our international PES calculations.

[95] The shaded blue regions report 95% confidence intervals derived from a parametric bootstrap of the underlying estimates from each policy. 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.

[96] Appendix G shows how one can compare the welfare gains from subsidies for adopting clean energy to regulation that forces utility companies to source their electricity from clean sources. Using existing estimates of the welfare impacts of Renewable Portfolio Standards regulation from Greenstone & Nath (2020), we show that such subsidies are more efficient.

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

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.[98] It is worth noting, however, that the MVPFs of EVs and residential solar are buoyed by learning-by-doing effects.[99] Without learning-by-doing, the values for EVs fall from 1.42 to 0.96. For residential solar, the value falls from 3.86 to 1.45, close to the rest of our consumer subsidies. 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

Now, we turn to policies that employ nudges or marketing strategies to lower carbon emissions or facilitate increased adoption of clean technologies. Unlike direct subsidies for the technologies, these policies seek to disseminate information or encourage individuals to adopt a new technology at its current cost.

Formally, nudges are defined as interventions that change the choice architecture of a policy but do not change the direct financial incentives associated with that choice (Thaler & Sunstein 2009). The most well-documented version of environmentally focused nudges is the Home Energy Report (HER) designed by Opower (now Oracle). The HER provides information on how to be more energy efficient in the home and often uses 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 present an example of the MVPF calculation using national average treatment effects from home energy report estimates from Allcott (2011). Appendix Figure 5 displays the willingness-to-pay (WTP) and cost components.

One reason a nudge might change a person's behavior is because they were close to indifferent about the choice to begin with. In this spirit, we model the willingness-to-pay for a nudge to be zero for those who are directly nudged. Consistent with our prior approach, this means we do not place any additional valuation on private energy savings. It also means we 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

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

[99] 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.

to including such estimates below (Allcott & Kessler 2019, Butera et al. 2022).[100]

Next, we incorporate externality benefits in much the same manner as our subsidy calculations. These nudges cause a reduction in electricity usage, reducing the damages associated with that electricity generation. We estimate that every \$1 invested in these nudges leads to \$3.87 in global environmental benefits and \$0.44 in local environmental benefits. The analysis also reveals a local rebound effect of \$0.09 and a global rebound effect of \$0.76 due to reduced demand impacting energy prices. Utility profits decrease by \$0.24 for each \$1 spent on the Home Energy Report (HER) nudge.

On the cost side, we assume the government pays for the nudge and thus include those administrative and logistical costs as a government cost.[101] Revenue collected from utilities decreases by \$0.13, but the long-run climate fiscal externality saves the government \$0.06. Combining the willingness to pay and government costs, we obtain an MVPF of 3.01.

While the results in Appendix Figure 5 consider a nudge implemented across the entire US, it turns out that the MVPF of the nudges varies considerably across regions. 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.[102] By contrast, in California and New England, the MVPFs are below 1, sitting at 0.52 and 0.24, respectively.[103] This pattern is largely driven by the differences in the grid composition across regions. 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.[104,105] We also note that the value of these estimates is heavily dependent on the value of the SCC. As a category, nudge MVPFs are not influenced

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

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

[102]These MVPFs are even larger if we include persistence effects identified by Brandon et al. (2017).

[103]As noted above, our baseline approach assumes individuals do not receive benefits from the nudge themselves. However, we can use the results from Allcott & Kessler (2019) who suggest that individuals would be willing to pay on average about half (49%) of the energy savings that they experience from the nudge. With this assumption, the relative ordering of MVPFs across regions remains similar, but the MVPFs rise in CA and New England to 2.13 and 1.23.

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

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

by components such as the inframarginal transfers or learning-by-doing effects. As a result, these MVPFs are driven heavily by 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. Even at that 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 -.18.

While we find large MVPFs for nudges to reduce electricity consumption, we find much smaller MVPFs for nudges to reduce natural gas consumption. On average HERs targeted at natural gas usage have an MVPF of 0.45. This lower MVPF is partially driven by the fact that nudges to reduce natural gas consumption have smaller treatment effects: the average natural gas nudge reduces consumption by 0.12% while the average electricity nudge reduces consumption by 0.24%. 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. Assigning value to this peak demand reduction is challenging. If we assume, for example, that the reduction eliminates the need for expensive energy variation with marginal costs from $500/MWh$ to $1000/MWh$, the MVPFs could range from 0.70 to 1.60.[106] If the demand reduction also decreased the frequency and/or duration of blackouts, these MVPF estimates could rise as high as 5.30.[107]

Next, we study the impact of marketing strategies aimed at fostering the adoption of clean technologies within homes. This includes nudges that promote low carbon solutions such as the Solarize initiative. Gillingham & Bollinger (2021) examine the peer effects of the Solarize program in Connecticut, which was designed to encourage the adoption of residential solar. Under the program, municipalities receive a designated solar installer, group pricing, and an informational campaign led by volunteer ambassadors over the course of 20 weeks. We estimate an MVPF of 5.36 for this Solarize program, which is slightly above the largest MVPF of the residential solar subsidies evaluated above. It is worth noting that this program uses a fairly

[106] These values are consistent with peak costs in (CAISO 2021).

[107] 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).

unique 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.

Akin to our study of weatherization subsidies, 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. This contrasts with other information policies, such as the Solarize program discussed above, which encourage the take-up of technologies with 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 (and to an extent lower markups) 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. Analogously, marketing strategies can also increase the MVPF, but only when targeting interventions that generate large environmental benefits. We note that the effectiveness of policies that reduce electricity consumption will likely diminish as the grid becomes cleaner, unless those nudges yield other benefits such as increased reliability of the energy grid.

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. When these revenue raisers have some societal benefit (e.g., from reducing CO_2), this lowers the welfare cost of raising the revenue. Here, we consider two types of revenue-raising policies: taxes and cap-and-trade policies. Along the way, we also show how to place our MVPF estimates in the context of existing estimates of the welfare impacts of regulation such as CAFE standards.

6.1 Taxes

In order to gain intuition about the MVPF of a tax, we can return to the simple version of the MVPF in equation 10. We now imagine the good x delivers a negative externality $V < 0$. The MVPF for a marginal increase in taxes tax on a good, x, is obtained by switching $d\tau$ with $-d\tau$ in the MVPF expression and noting that the effect of x on government revenue is now of opposite sign as well. This yields an MVPF expression when τ is a tax that is given by:

$$MVPF = \frac{1 + (-\epsilon)\frac{V}{p}}{1 - (-\epsilon)\frac{\tau}{p}} \tag{26}$$

where ϵ is the price elasticity of demand and now $V < 0$ is the externality imposed per unit of x consumed. A natural interpretation of the numerator of the MVPF is that people are WTP \$1 to avoid the \$1 mechanical cost of the tax. The change in behavior induced by the higher prices also reduces an environmental externality and lowers the ultimate welfare cost by $-\epsilon(V/p)$. If the tax is set to the Pigouvian level, i.e., it perfectly offsets the externality, $\tau = -V$ and the $MVPF = 1$. More generally, if the tax is below the Pigouvian level, the MVPF of the tax will generally fall below 1. In that case, the tax is a relatively efficient method of raising revenue when compared to a lump sum tax with an MVPF of 1. As we show below, 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 the equation above provides a stylized example of the MVPF for a gas tax, we use an extended version of equation (26) in our implementation. This also includes terms for imperfect competition and learning-by-doing effects that emerge when gas taxes induce the adoption of EVs.

6.1.1 Gasoline Taxes

Our main sample of gasoline taxes contains 12 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). Here, we present an example MVPF using an elasticity estimate from Small & Van Dender (2007) who find an 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 per \$1 of mechanical tax revenue.[108]

Recent work by Bushnell et al. (2022) estimates that gasoline prices have a causal effect on

[108]In per-gallon terms, the externality generated by the average, light-duty vehicle is \$3.54 per gallon, with \$1.65 coming from local damages.

EV adoption. 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 of 0.40.[109] These EV purchases generate \$0.0008 in combined global and local damages from electricity generation. They also generate learning-by-doing effects that we quantify as \$0.002 for reduced future EV prices and \$0.0002 in future environmental benefits.[110]

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.[111] 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: Every \$1 of government revenue raised leads to a welfare cost of \$0.60 on individuals.

The relatively low welfare cost of raising revenue from gasoline taxes remains true even if one only includes US externalities—rising to an MVPF of 0.86. This is because we estimate damages from local pollutants (namely, HC, $PM_{2.5}$, and NO_X) to be \$0.03 per dollar of mechanical tax revenue in 2020 and damages from accidents and congestion to be \$0.21 per dollar of mechanical tax revenue. Summing local damages and the share of global damages that flow to future US citizens (\$0.04), these exceed the sum of the gas and corporate tax (\$0.09) and producer losses on gasoline (\$0.07) in 2020, leading to an MVPF below 1.

Figure 8 presents the MVPF estimates for the range of gasoline studies in our 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 0.66. Incorporating only US environmental benefits leads these MVPFs to rise to 0.88. Appendix Table 4 shows how these estimates change if we use a lower social cost of carbon of \$76, which leads to an MVPF of 0.81 on average.

6.1.2 Other Fuel Taxes

Using the same method as for gas taxes, we also construct MVPFs for taxes on diesel and jet fuel. We estimate the environmental externality for each taxed fuel. (See Appendix C for more details and for a discussion of how these externalities compare to one another.) We find MVPFs around 0.80 for diesel and jet fuel taxes. The diesel tax has a higher MVPF than gas taxes because diesel demand is less elastic than gasoline demand. This increases the MVPF, despite

[109] 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.

[110] 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.

[111] 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.

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 the lack of driving externalities.[112] One caveat to our analyses is that we do not incorporate fiscal externalities that could arise from the impact of diesel taxes on aggregate economic activity – such effects could raise the MVPF relative to our reported estimates. In our extended sample, we also consider a tax on bunker fuel used by international cargo ships, a tax on E85 (or "flex fuel", a blend of ethanol and gasoline), and taxes on crude oil production.

On net, the results suggest fuel taxes are relatively efficient methods of raising revenue compared with other common methods of raising revenue such as changes to income taxes.

6.2 Comparison with Regulation: CAFE

Our primary focus in this paper is on the application of the MVPF approach to study the welfare consequences of policies which have an initial statutory impact the government budget: subsidies, taxes and nudges. The MVPF approach is particularly well-suited to analyze policies of this sort because the key tradeoff is between the government budget and individuals in the economy. A substantial portion of environmental policy-making, however, uses regulation rather than taxes or subsidies. Regulatory policy changes often have small (or even zero) impacts on the government budget. Here, the key tradeoffs are across multiple groups of potential beneficiaries. Some individuals are made better off and some are made worse off.

In this section we provide a brief explanation of how MVPF estimates can be used to think about the welfare consequences of regulatory changes. Full details of our approach can be found in Appendix G. The key idea is ask whether taxes and/or subsidies can deliver the same benefits to individuals as delivered by regulation at a lower net cost to the government. In other words, can use a combination of taxes and subsidies to match the distributional incidence of the regulation in a way that generates a relative budget surplus. This question differs from the conceptual experiment in equation (6). Rather, it follows more closely to the ideas of using compensating transfers to neutralize distributional incidence as outlined in the seminal work of Kaldor (1939) and Hicks (1940). The key contribution of the MVPF framework is that the compensating transfers are conducted using actual policy instruments (and their associated MVPFs) as opposed to individual-specific lump-sum transfers.

We illustrate our approach by analyzing Corporate Average Fuel Economy (CAFE) Stan-

[112] In our baseline MVPF for a tax on jet fuel, we include the carbon and sulfur emissions from burning a gallon of jet fuel, as well as upstream emissions from producing a gallon of petroleum product. Including local damages released by the aviation sector (as estimated in the National Emissions Inventory) raises the per-gallon externality from \$2.20 to \$2.37, although this value includes emissions from sources (e.g., ground support equipment at airports) whose responsiveness to a jet fuel tax we do not observe. We exclude these local emissions from our baseline calculation. We do not include any externalities that are analogous to congestion and accidents (which are included for gasoline taxes), but we note the MVPF of a tax on jet fuel could be lower if one were able to quantify these types of externalities. See Schlenker & Walker (2015) for a broader discussion of this topic.

dards. CAFE standards have have been an important method for regulating vehicle emissions in the US. These standards require automakers selling light-duty vehicles for a given model year in the US to meet a specified fleet-wide average fuel economy rating (typically stated in terms of miles per gallon).

In order to understand the welfare consequences of CAFE standards, we begin by measuring the incidence of the policy on each of group of individuals it impacts. Appendix Figure 6, Panel A illustrates this breakdown. We use estimates from Leard & McConnell (2017) on the traded price of CAFE credits to estimate the cost imposed on consumers. CAFE standards increase vehicle prices, which imposes a burden on consumers.[113] We use estimates on the change in gasoline purchases to measure the costs imposed on producers. We combine that with a measure of the change in the environmental externality induced by the higher fuel efficiency standards. Here, we normalize our estimates so that they are measured relative to each $1 of environmental benefits. We estimate that each dollar in environmental benefits leads to a cost on producers of $0.34 and a cost on consumers of $0.32. Additionally, more stringent CAFE regulation has an incidence on the government's budget. The lost gas tax revenue generates a cost to the government of $0.39.

A common method of analysis in the existing literature would sum these benefits to show that more stringent CAFE regulation that creates $1 of environmental benefits delivers an unweighted sum of benefits of roughly 0 (-$0.05).[114] In principle, while it is possible to evaluate CAFE and other regulations in isolation, it may be more informative to ask how these regulations compare to alternative policy tools. Here, we analyze whether the environmental benefits offered by CAFE standards can be achieved more efficiently through the tax code. More specifically, we ask whether a combination of gasoline taxes and income taxes that do more to increase social welfare than CAFE standards.

More specifically, we seek to find a combination of taxes that generate generate at least (a) $1 of environmental benefits, (b) -$0.34 in producer benefits, and (c) -$0.32 in consumer benefits at a cost to the government that is less than $0.39. If this were the case, we would replicate the distributional incidence of CAFE standards at a lower cost to the government. (Any excess revenue could then be redistributed to make all groups better off.)[115]

Appendix Figure 6, Panel A presents our results. First, we consider the impact of the gas tax alone: every $1 of environmental benefits provided by the gas tax generates a cost to producers of $0.14 and a cost to consumers of $2.25. The tax also generates $2.09 in government revenue. Relative to CAFE, the tax leaves the government and producers better off but consumers worse off. Next, we combine the gas tax with a tax on producers of $0.20

[113]In the Appendix we repeat this exercise using alternate measures of the impact of CAFE from Anderson & Sallee (2011) and Jacobsen (2013*a*).

[114]One could also apply welfare weights as in equation (2).

[115]This test of "efficiency" dates back to the classic definition of Kaldor (1939) and Hicks (1940) with the modification that we use actual tax and transfer policies instead of lump-sum redistribution to neutralize distributional incidence. See also Coate (1999) and Hendren (2020)

to make them indifferent between the tax changes and the CAFE standards. We assume the MVPF of taxes on producers is 1.8, consistent with estimates of the MVPF of taxes on top earners from Hendren & Sprung-Keyser (2020).[116] This suggests imposing a \$0.19 cost on producers raises \$0.11 (=0.19/1.8) in revenue for the government, which we show in the second column of Appendix Figure 6, Panel B. Next, we provide consumers \$1.94 in benefits to compensate for the difference between their losses under CAFE versus the gas tax. The MVPF of raising revenue from the average consumer is around 1.2 (Hendren 2020). This means that costs the government \$1.62 (\$1.94/1.2), as shown in the third column of Appendix Figure 6, Panel B. Putting this all together, the net cost to the government of the gas taxes plus income taxes that replicate CAFE is $-\$0.59$ ($= -2.09 - .11 + 1.62$). In other words, replicating the distributional incidence of CAFE using taxes generates a \$0.59 surplus, whereas CAFE itself creates a \$0.38 deficit. This means that it is \$0.97 cheaper to the government to generate the \$1 of environmental benefits through taxes instead of CAFE.

Appendix Figure 7 presents similar conclusions using other estimates of the impact of CAFE regulation from Anderson & Sallee (2011) (Panel A) and Jacobsen (2013*a*) (Panel B).[117] While each of these papers suggests that CAFE standards would increase net social benefits at an SCC of \$193, we find that in each case the gas tax would be more efficient than CAFE at providing these environmental gains. This is perhaps not surprising as gas taxes generate additional benefits from reduced driving such as reductions in accidents and congestion.[118] In short, this approach provides a means of comparing the efficiency of regulatory policy changes to policy's primarily impacting the government budget. It also provide additional evidence that gasoline taxes are a relatively efficient method of raising revenue.

6.3 Cap and Trade

Cap and trade policies are another policy tool often used to limit emissions. These impose quantity limits on emissions and let firms trade the rights to such emissions. There have been evaluations of two notable 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.

A key question for a cap-and-trade policy is how many permits to issue. In this section, we show how to use the MVPF framework to think about the welfare impact of changes in the number of permits issued. We focus here on variation in permits issued at auction, but one

[116] Crucially, this approach assumes that the incidence of CAFE standards on producers and consumers can be matched via the tax code. While this may be true for broad groups of individuals, it may be difficult to make the incidence on the specific individuals who bear the burden of the gas tax (e.g., high mileage drivers)

[117] Appendix G also presents a comparison of Wind PTCs to Renewable Portfolio Standard (RPS) regulation that requires utility companies to source a certain fraction of their energy from clean sources. See Appendix Figure 7, Panel C.

[118] CAFE standards also impose implicit taxes on fleet characteristics beyond purely a tax on gasoline emissions, as studied in Ito & Sallee (2018). These potentially also reduce the value of CAFE relative to taxes.

could conduct a similar analysis to study changes in the number of grandfathered permits.

Let q denote the quantity of auctioned permits for a particular emission. When one fewer permit is auctioned, we assume this leads to a $(1-L)\%$ reduction in emissions, where L is the "leakage" of emissions into other areas. For example, let us consider the case of RGGI. If selling one fewer CO_2 permit leads to 0.25 tons more CO_2 produced in states not in the RGGI system, then $L = 0.25$. Let V denote the value of the environmental externality per unit of emissions ($V < 0$), so that the net environmental benefit from one fewer permit is $(1-L)(-V)$. Let $p(q)$ denote the auction price when q permits are issued, so that $-dp/dq > 0$ denotes the impact of fewer permits on the auction price. The MVPF of changing the number of permits is given by

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

where the first term is the firms' willingness to pay to avoid the higher permit prices. 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.[119]

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 (26).[120] 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.

Let $\eta = -(dp/dq)q/p$ denote the elasticity of the equilibrium permit price with respect to a change quantity. One interpretation of η is that it is the elasticity of the marginal cost of abating carbon in the economy. This is because, in equilibrium, we expect the marginal abatement cost to be equal to the permit price.[121] Using this definition, we can re-write the

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

[120] To see this, note that

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

$$= \frac{1 - \frac{dq}{dp}\frac{p}{q}V(1-L)}{1 - \frac{dq}{dp}\frac{p}{q}} \tag{29}$$

which is equivalent to equation (26) 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.

[121] We can also interpret η as the inverse of the elasticity of demand for permits with respect to the auction price. Letting $\epsilon = (dq/dp)p/q = 1/\eta$, it's straightforward to see that the MVPF can be written as

$$MVPF = \frac{1 + \epsilon\frac{V(1-L)}{p}}{1-\epsilon}, \tag{30}$$

which is identical to (10) with the modification that $\tau = p$ because the government collects all permit revenue.

MVPF as

$$MVPF = \frac{\eta + \frac{V(1-L)}{p}}{\eta - 1}. \tag{31}$$

In the context of our results, we discuss permits as potential revenue-raisers because this aligns with the empirical tendency we will observe. This formulation highlights, however, that it is not clear, a priori, whether auctioning fewer permits, dq, increases or decreases government revenue. It depends on whether η is above or below 1.

Appendix Figure 8 illustrates this idea by plotting the MVPF of a change in cap and trade permits as a function of the elasticity, η. When $\eta < 1$ (Region 1 in Appendix Figure 8), reducing the number of permits imposes a net cost on the government because the lost mechanical revenue to the government is not sufficiently offset by the increase in the permit price. When the marginal abatement curve is flat, $\eta = 0$, the cost of the policy is given by the cost of a permit no longer auctioned, as there is no change in equilibrium prices. The environmental gain of the policy is given by the gain from removing a permit, $-V(1-L)$. For higher values of $\eta \in (0,1)$, the reduction in permits causes an increase in permit prices. This causes the government to recoup some of the foregone revenue from the unauctioned permit. In this region, the MVPF is increasing in values of η as long as the externality exceeds the permit price, $-V(1-L) > p$. Indeed, the MVPF approaches ∞ as $\eta \to 1$. If $\eta = 1$, then the net revenue impact of changing permits is zero. The increase in prices fully offsets the forgone revenue from the auctioned permit. In this case, reducing permits increases welfare if and only if $-V(1-L)/p > 1$.

When $\eta > 1$, the denominator of the MVPF is positive and the policy is a revenue raiser for the government. Restricting permits leads to price increases that more than offset the mechanical revenue lost from the permit sales. Interestingly, the sign of the numerator still varies with values of η above 1. In particular, when $\eta \in (1, -V(1-L)/p)$ (Region 2 in Appendix Figure 8), the numerator is negative. This implies that the environmental gains from reducing permits exceed the cost imposed on firms. Hence, for these intermediate values of the elasticity of the marginal abatement curve, restricting the number of permits at auction leads to both more revenue for the government and a net welfare gain to individuals in society. When $\eta > -V(1-L)/p$ (Region 3 in Appendix Figure 8), the environmental gains no longer exceed the losses to permit holders. The policy now raises revenue for the government, but also imposes a net cost on society (as measured by the sum of WTP). Here, the policy raises revenue relatively efficiently, with MVPF values below 1, as long as $-V(1-L)/p > 1$. As $\eta \to \infty$, the MVPF converges to 1. In that case, the change in equilibrium permit prices dominates any environmental effects and the policy is effectively a transfer from permit holders to the government.

In sum, when the abatement elasticity is below 1 (i.e., where there is "low hanging fruit" for abating carbon), restricting permits may impose a cost on the government, but it will generate an MVPF that exceeds $V(1-L)/p$. When the abatement cost elasticity exceeds 1, restricting permits will generate revenue for the government. When $1 < \eta < V(1-L)/p$, the MVPF is below 0 – reducing permits increases government revenue and also generates a positive total willingness to pay. (Any environmental gains outweigh the costs imposed on permit holders.) When $\eta > 1$ and $\eta > V(1-L)/p$, the MVPF will be below 1. A reduction in permits raises revenue, but imposes costs on firms that are only partially offset by the environmental gains.

We estimate the MVPF for two cap and trade policies in the US: RGGI and the California Cap-and-Trade Program. We begin with the in-context estimates of the effect of RGGI on greenhouse gas emissions using results from Chan & Morrow (2019) covering 2008–2018. Between 2008 and 2018, there were 972.6 million permits auctioned (per short ton of CO_2), at an average clearing price of \$3.43 (in 2018 dollars). The authors estimate that RGGI reduced 22 million short tons of CO_2 implies that a one unit reduction in the quantity of permits sold led to a $\$1.56 \times 10^{-7}$ dollar increase in the permit price, or $dp/dq = -1.56 \times 10^{-7}$. This means that if RGGI had auctioned one fewer permit between 2008 and 2018, it would have lost \$3.43 from the price of the permit but gained approximately $-dp/dq * q = 1.56 * 97.26 = \$151.77$ in additional revenue from higher permit prices. In the context of equation (27) above, this corresponds to a value of $1 < \eta < V(1-L)/p$.[122] Relative to the formula in equation (27), 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 2008 and 2018 (weighted by permits auctioned), we estimate this to be \$1.35, which suggests a net government revenue of \$149.69 from issuing one fewer permit.[123]

Higher prices impose a cost on firms purchasing permits, which totals to \$151.77.[124] The environmental benefit of releasing $1 - L = 0.49$ fewer short tons of CO_2 in 2018 is \$68.94.[125] Adding the reduction in local pollutants SO_2 and NO_X yields an additional gain of \$122.63.[126] On net, these environmental benefits offset the cost to firms for a net positive willingness to pay of \$39.80. With an MVPF of -0.27, RGGI falls in Region 2 of Appendix Figure 8. Raising revenue via a reduction in auctioned permits as part of RGGI led to a net win for individuals and taxpayers.[127]

While our in-context estimates suggest RGGI led to significant benefits to taxpayers and individuals in society, we caution that there is some potential difficulty in extrapolating our

[122] Here, $\eta = 44.22$ and $V(1-L)/p = 55.82$

[123] 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.

[124] Marginal firms that no longer obtain permits are indifferent to doing so by the envelope theorem.

[125] All estimates in the paper report in short rather than metric tons. We account for this when evaluating RGGI by adjusting our externality calculations.

[126] Excluding local damages, society's WTP for abated pollution is only \$68.94, implying an MVPF of 0.55.

[127] We note while the policy produces a net positive willingness to pay, there is still a cost to firms and so the policy does not simply result in a Pareto improvement. We can use our estimates to show that, in order for this policy to *not* improve social welfare, one would have to prefer \$1 in the hands of firms to more than \$1.26 in the hands of benefiting from an improved environment.

in-context estimates to a 2020 policy reform. The MVPF is heavily determined by the shape of the marginal abatement cost curve. In order to construct our 2020 baseline estimates, we need to assume that the marginal abatement cost curve is stable over time – i.e., here we assume 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 2008-2018.[128] If we make such an assumption, we continue to find a negative MVPF. Greater restrictions in auctioned permits would continue to bring in additional government revenue ($151.69) 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 ($156.45). These results imply an MVPF of -0.36. 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.

Having laid out these consideration in the context of RGGI, we next 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 difficulty of our analysis is that existing data only tracks 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 the cap and trade 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.[129] In other words, the policy falls into Region 3 of Appendix Figure 8. A decrease in auctioned permits would raises revenue but imposes a net cost 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. It suggests that permit reductions would raise revenue while also generating a net gain to individuals in society (i.e., Region 2 of Appendix Figure 8), with an MVPF of -0.15.

While our primary focus here is on US climate policy, it is worth noting that one of the largest cap and trade systems for CO_2 in the world is the European Union's Emissions Trading System (ETS). In our extended sample, we include estimates from the ETS. These estimates suggest large welfare gains, akin to our findings in the US. For example, 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

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

[129]The MVPF remains around 0.95 when excluding benefits from local pollution.

leakage.) Taking a price of \$19.90 and the 15% reduction in emissions, the evidence suggests that firms are willing to pay \$131.32 ($q * dp/dq$) to avoid a 1 ton reduction in the number of allocated permits. Comparing this to a historical average SCC of \$137.43 in 2012 (adjusted for future US government revenue), it suggests a net welfare gain of \$3.47 (\$131.32 minus global environmental benefits of \$134.79). On the cost side, reducing the number of permits issued would lose \$19.90 at the existing price, but would generate \$131.32 in revenue due to higher permit prices. This results in a a net revenue gain of \$114.06. In this sense, the estimates in Colmer et al. (2024) imply that reducing carbon emissions through ETS generates \$114.06 in revenue per reduced permit and \$134.79 in environmental benefits. As with RGGI, it appears permit reductions under ETS raise revenue without imposing a net cost to individuals in society.

We find similar conclusion when examining estimates on the impact of the ETS from Bayer & Aklin (2020). That work suggest that the \$7.69 price of carbon in ETS reduced 1.2 billion tons of carbon between 2008 and 2016. Their estimates suggest that each additional reduction in auction permit increases permit prices by $\$6.30 \times 10^{-9}$ per permit, or by \$19.09 when summing across all permits. The fiscal externality from reduced climate change damages generates an additional \$3.00 in net revenue for the government. When it comes to WTP, the increase in prices impose \$19.09 in burden on firms. This is more than offset by the environmental benefits of \$153.78 per reduced permit.[130] This leads to \$134.68 in net benefits to society while also generating \$14.41 in government revenue. 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 at large.

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 significantly lower than the MVPFs of other revenue raisers. For example, Hendren & Sprung-Keyser (2020) and Hendren (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. 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. The key lesson from cap and trade is that, in many of 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

[130]The benefits could be even larger if the decrease in local pollutants are incorporated into the welfare calculation (see Basaglia et al. (2024)).

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 carbon 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. While this impacts the US-specific gains from the policies above, it also means that the US has a stake in policies that are implemented elsewhere.

In this section, we draw upon an illustrative set of climate-focused policies implemented in developing countries, largely by NGOs. We consider eleven policies spanning five categories: cookstoves, deforestation payments for ecosystem services, payments to prevent rice field burning, wind subsidy offsets, and appliance and weatherization rebates. For each policy, we imagine that the US enacts the policy as a form of international aid. US-specific costs are in the denominator of the MVPF. We then construct two baseline MVPFs: one that includes only US benefits in the numerator and another that includes all US and non-US benefits in the numerator.

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 energy-saving appliances. The policy generates large monetary gains to individuals through reductions in future charcoal purchases. In addition, the reduction in charcoal usage generates a substantial reduction in CO_2e. The paper finds that each new cookstove reduces CO_2e by $\sim$7 tons. The paper estimates that, when offered a \$30 subsidy (2019 dollars), 54.5% of individuals take up the cookstove.[131] 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 \$16.35 per each subsidy offered (16.35 = 30*.545) and removes 3.7 tons of carbon per each subsidy offered.[132] At an average inflation-adjusted SCC of \$190.62, this translates into \$43.16 in global benefits for each mechanical dollar of the subsidy.

We can use these estimates to construct two measures of the MVPF – one with benefits to all individuals and one with US-only benefits. When examining benefits to all individuals, we combine those global externality benefits with the transfer benefits of the subsidy and the value of private energy savings. This yields a total willingness to pay of \$50.82 for each mechanical

[131] For consistency, we use 2019 dollars when discussing the MVPF for subsidies for improved cookstoves in Kenya.

[132] 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.

dollar of the subsidy. In measuring costs we need to account for the climate FE term, the incidence of the social cost of carbon on the US government. We explore this term in greater detail in a moment, but we begin with our baseline assumption that 1.9% of the social cost of carbon is borne by the US government. In that case, the fiscal externality is nearly $0.84 for each dollar spent on the subsidy. This yields an MVPF of 323 when considering benefits to all individuals.

Next, we construct an MVPF when only considering effects on US-beneficiaries. In this calculation we omit any private energy savings to cookstoves recipients and only consider the fraction of the SCC borne by US residents (our baseline assumption allocates the SCC in accordance with the US share of GDP, 15%). Here, we find an MVPF of 37. This means that the US-benefits of this international policy exceeds the global benefits of many of our US-based policies.

As we discussed in Section 3.2, a key question for our calculations is: how much of this $193 SCC reflects benefits to the US government? Identifying that component of the incidence is necessary to estimate the net cost of the policy from the perspective of the US government (and to allocate benefits to US residents.)

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 (ex: productivity declines versus mortality impacts.) Our baseline approach assumes 15% of the SCC falls on US residents, in proportion with the US share of GDP. Of the 15% incidence, we assumed 50% of this reflected changes in productivity (that is taxed by the US government) and taxed at a rate of 25.5%.

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).[133] In this case, we find that the subsidy nearly pays for itself. The net cost of policy is just over $0.08 for each dollar of mechanical subsidy (and the US-only MVPF is 32.41.) 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 to zero, the US-benefit MVPF falls to 3.60 (and the MVPF including global benefits is 28.15).

This analysis demonstrates 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 have a large impact of the welfare consequences of policy. This is particularly when assessing the welfare consequences of

[133]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.

the policy from the perspective of a given government actor.

It is also important to note that, prior to the work of Berkouwer & Dean (2022) examining 'improved' cookstoves, most studies of cookstoves found minimal effects. In many cases, recipients did not use or like the cookstoves. As a result, many other evaluations of cookstove subsidies would not have high MVPFs. For example, we find an MVPF near zero (and even negative[134]) for cookstove subsidies analyzed in Hanna et al. (2016). This comparison foreshadows the broad finding of high potential returns but large variation even within policy categories.

Figure 9 presents the MVPFs for the other international policies in our baseline sample.[135] We present the MVPF using only US benefits in blue, and we show in orange the additional benefits if one were to include all global benefits. 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 Davis et al. (2014), with a global MVPF of 0.95 and a negative US-only MVPF.

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.[136] 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. 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 with the same cost structure as the NGO conducting the evaluation. The key lesson from our analysis, however, mirrors the conclusions

[134]We note that a negative MVPF here means that *not* spending money on the cookstoves would be an improvement both to the government and individuals, which is analogous to the cap and trade examples where restricting permits raises revenue while also delivering benefits to individuals.

[135]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.

[136]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 is an underestimate so that the ultimate MVPF could be lower if the leakage is higher.

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 Marginal Value of Public Funds 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.[137] 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.[138]

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.[139] 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,

[137] 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.

[138] 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).

[139] 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.[140] 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).[141] 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.

[140] 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.

[141] This is also sometimes referred to as the "program cost per ton" (Gillingham & Tsvetanov 2019, 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 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.[142]

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.[143]

The social cost approach is similar to the resource cost per ton approach. It is, therefore, subject to many of the same criticism 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 of an energy-efficient appliance and leads to a reduction in energy usage. It may be that individuals are optimizing when making their private choices about energy-efficient products.[144] 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

[142] 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).

[143] 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.

[144] 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.[145] 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.[146]

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

$$MVPF = \frac{1 + \frac{\epsilon}{p}(SCC * Tons + Other)}{1 + \frac{\epsilon}{p}\tau} \tag{32}$$

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:

$$SCPT = \frac{(\tau - Other)\frac{\epsilon}{p}}{Tons\frac{\epsilon}{p}} = \frac{\tau - Other}{Tons} \tag{33}$$

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,

[145] 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.

[146] 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:

$$SCPT_{\phi} = \frac{(\tau - Other)\frac{\epsilon}{p} + \phi(1 + \frac{\epsilon}{p}\tau)}{Tons\frac{\epsilon}{p}}. \tag{34}$$

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 we display the SCPT for several alternative 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).[147] 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 \$470 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 \$470. The social cost per ton is far lower than the government cost, at only \$107 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).[148]

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

[148]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.[149] 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). 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 ($1,007 and $577). Despite that divergence, the policy categories have nearly indistinguishable MVPFs (1.18 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 Blonz (2023) 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.[150] This general pattern is consistent with previous resource cost calculations, such as those constructed by McKinsey & Company. Despite this, the two policy differ substantially in their MVPFs, 4.63 versus 1.03.

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.

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

[150]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 $1,685, which is substantially higher than the $470 figure for appliance rebates. The MVPF of EVs, however, is 1.42 as compared to the 1.18 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 $1,685 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 -$750. 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 -$518. 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 1.42, 3.86 and 5.87 respectively.[151]

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

[151]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 \$107 without a MCF adjustment to \$342 with a 50% adjustment. We find an even more dramatic movement in the case of EV subsidies. The values changes from -\$518 with no MCF to -\$313 with 10% MCF and \$316 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 0.66 for gas taxes suggests every \$1 of government revenue raised from a gas tax and spent on wind PTCs generates \$5.21 (=5.87-0.66) in benefits to individuals in society, regardless of one's view about the efficiency of the income tax system.

Summary In 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.[152] 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.

[152]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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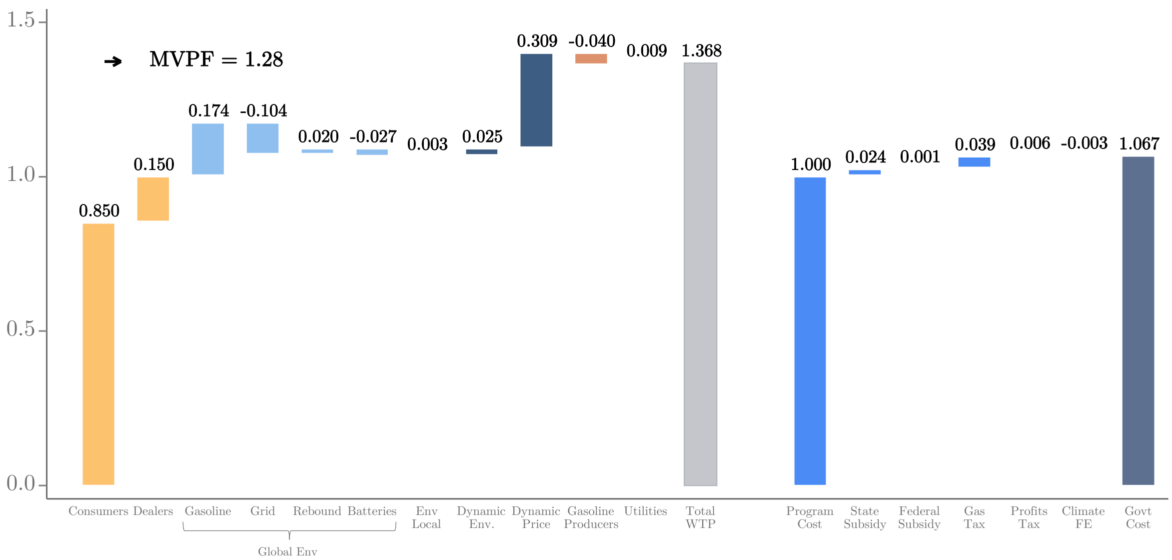
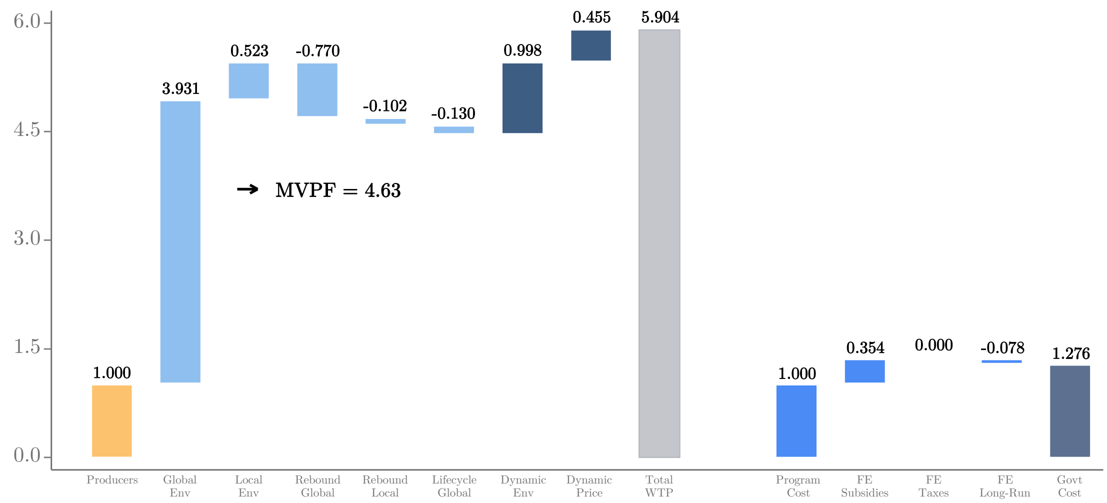
FIGURE 1: Electric Vehicle Subsidy
Baseline Estimates from Muehlegger and Rapson (2022)



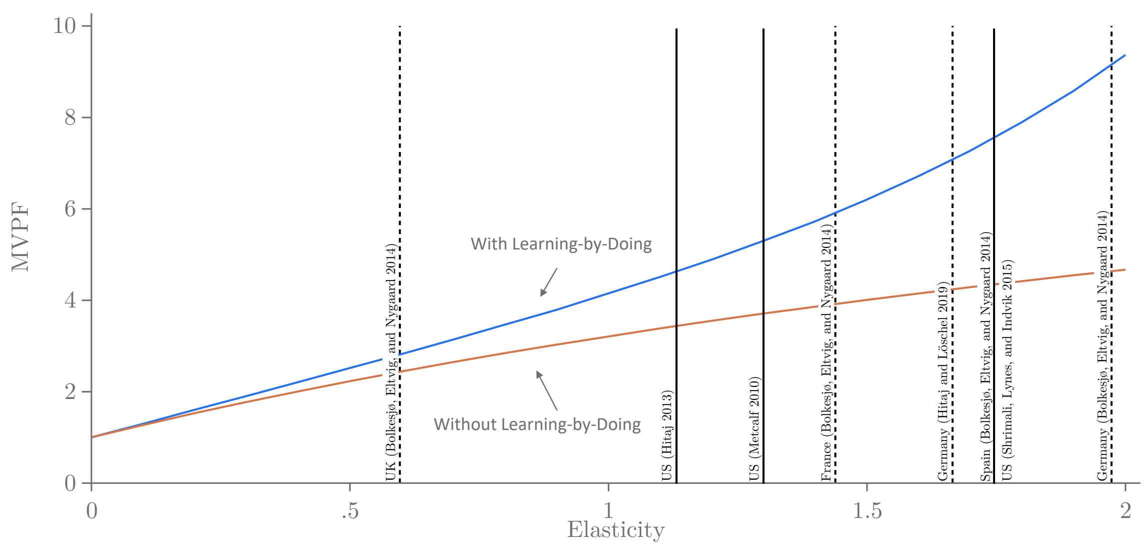
Notes: This figure presents the components of willingness to pay and net government cost for the EV subsidies in the California Enhanced Modernization Program (CEFMP) using the -2.1 price elasticity estimated in Muehlegger & Rapson (2022). We present estimates for our baseline specification that envisions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



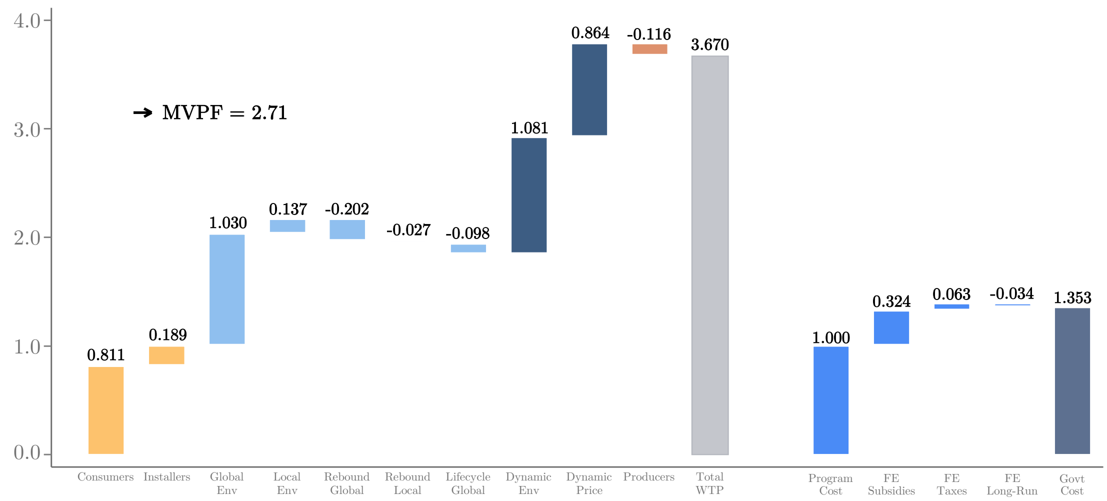
B. Baseline MVPFs by Price Elasticity



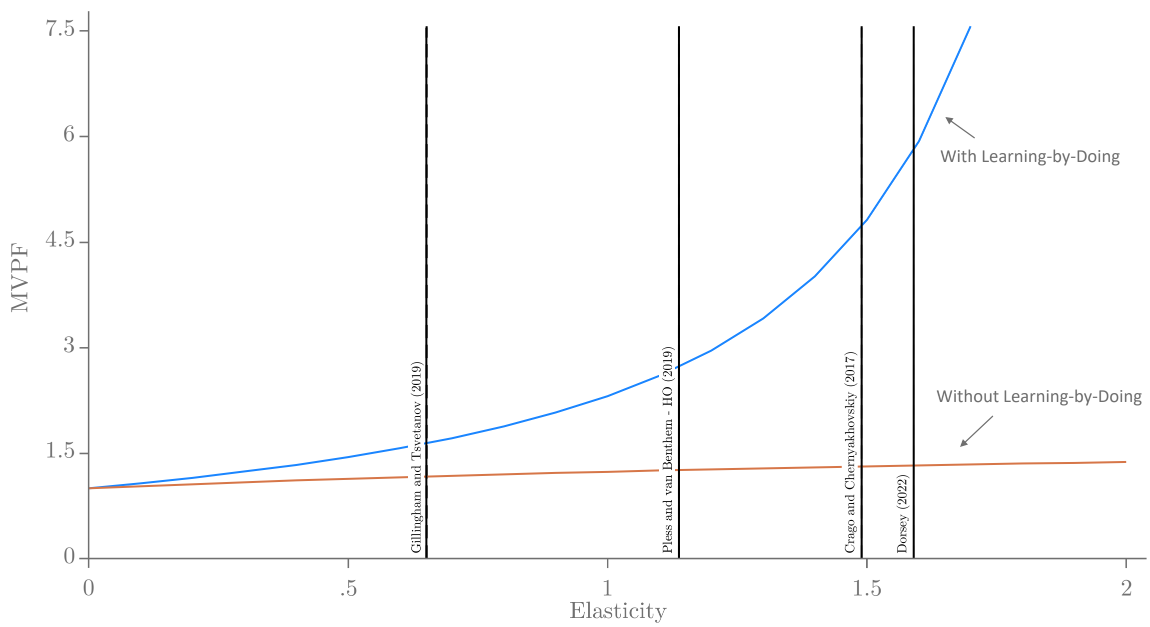
Notes: This figure illustrates the MVPF measurement for wind subsidies. Panel A shows the WTP and Cost components for the baseline specification for the wind production tax credit using a supply elasticity of 1.4 estimated in Hitaj (2013). The WTP components consist of the transfer (yellow), environmental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

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

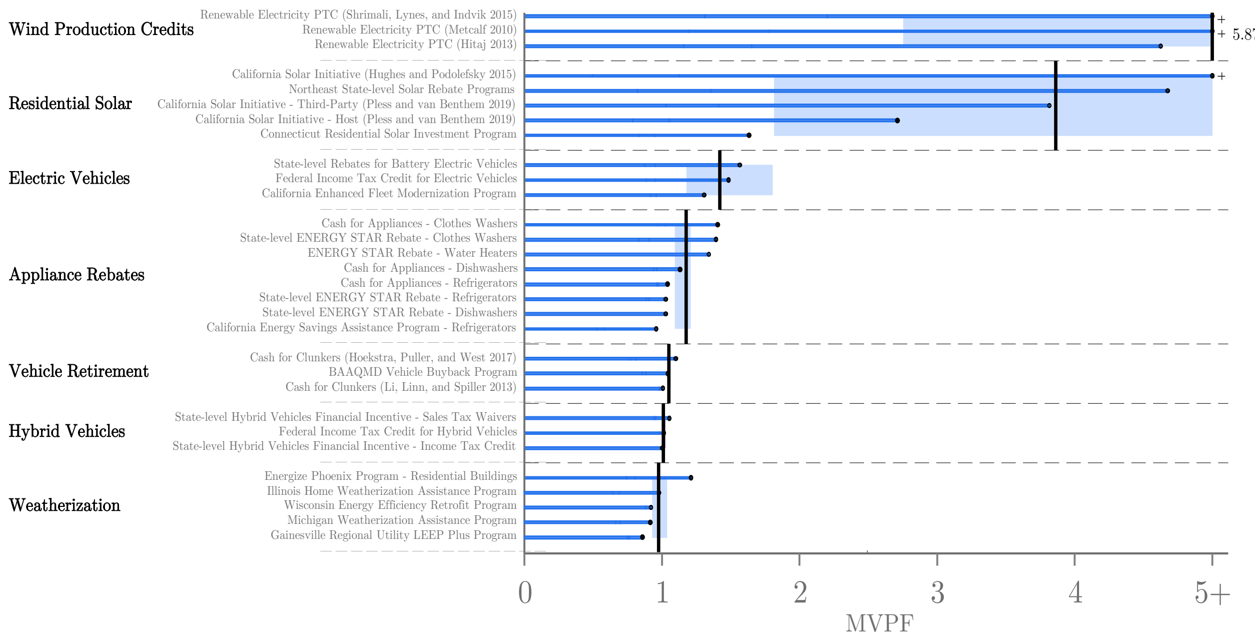


B. Baseline MVPFs by Price Elasticity



Notes: This figure illustrates the MVPF measurement for residential solar subsidies. Panel A shows the WTP and Cost components for our baseline specification for the California Solar Initiative using a demand elasticity of -1.14 estimated in Pless & van Benthem (2019). The WTP components consists of the transfer (yellow), environmental externality (light blue), learning by doing effects (dark blue), and utility profit loss (orange). The subsidy cost is calculated using the 26% investment tax credit for residential solar installations. Panel B shows how the MVPF varies with the elasticity of demand for residential solar panel capacity with respect to the price of residential solar panels. The MVPF with learning by doing is 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.

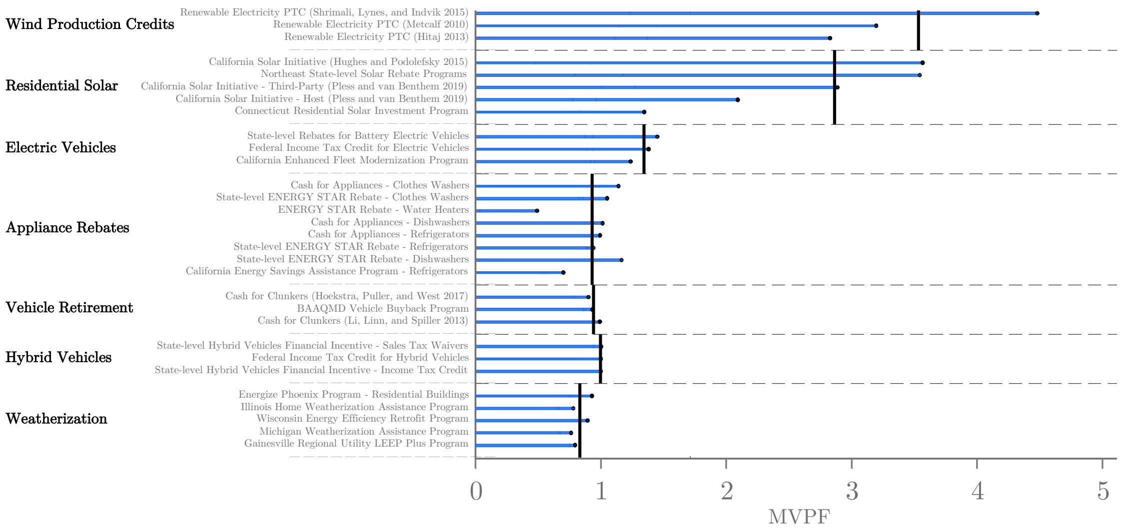
FIGURE 4: Baseline MVPFs for Subsidies



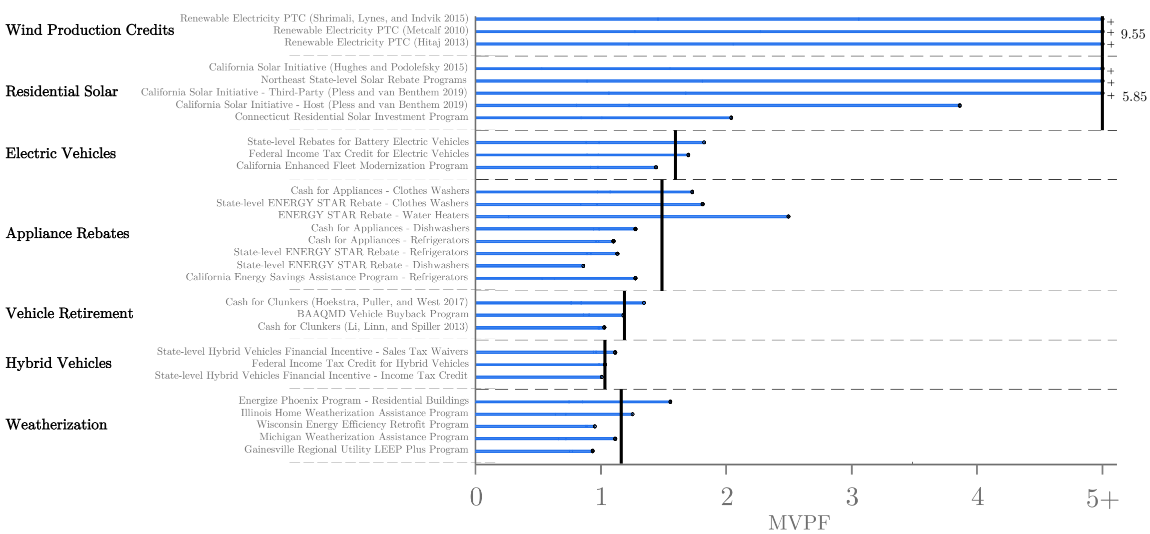
Notes: This figure shows the 2020 baseline MVPF estimates for all categorized subsidy policies in our main sample. We cap estimates at 5 with + signs indicating MVPFs above 5. The category average (shown by the black vertical lines) reports the MVPF associated with a conceptual experiment where $1 in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

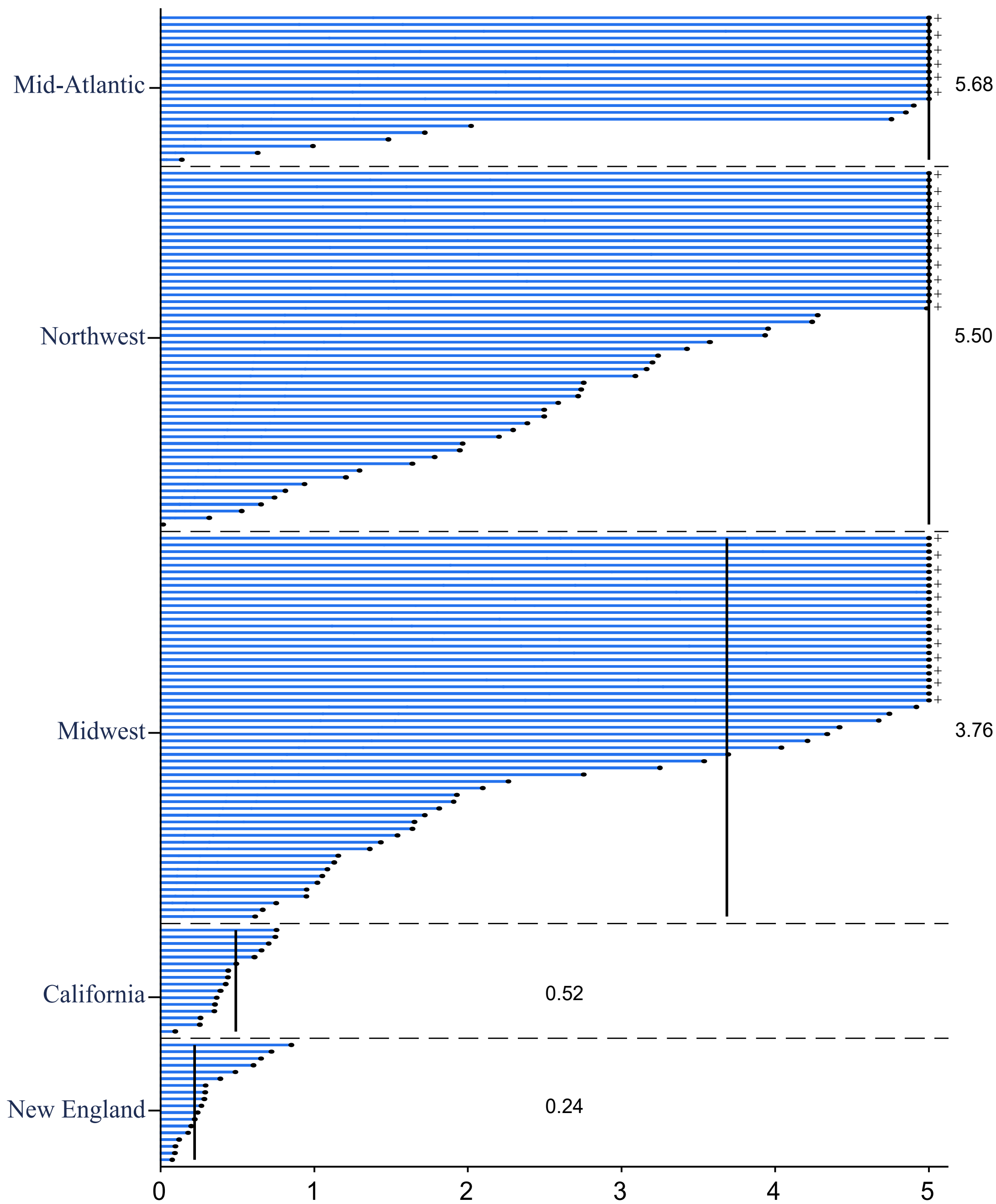


B. $337 Social Cost of Carbon



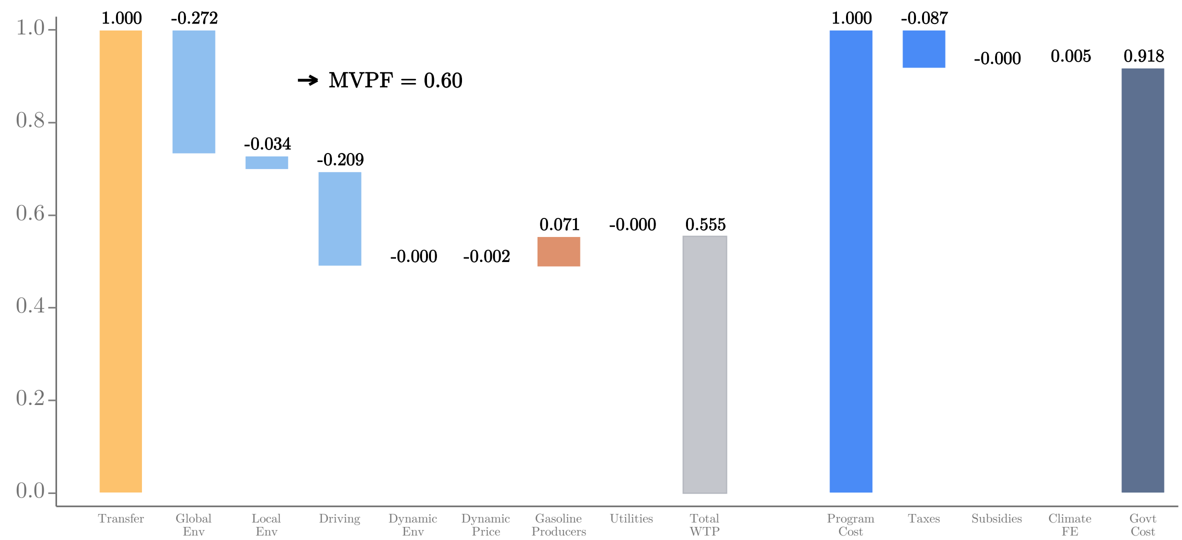
Notes: Panel A and B repeat Figure 4 using an alternative time path for the SCC corresponding to values of $76 and $337 in 2020 along with discount rates of 2.5% and 1.5%, respectively. Estimates are censored at 5.

FIGURE 6: Baseline MVPF of Home Energy Reports



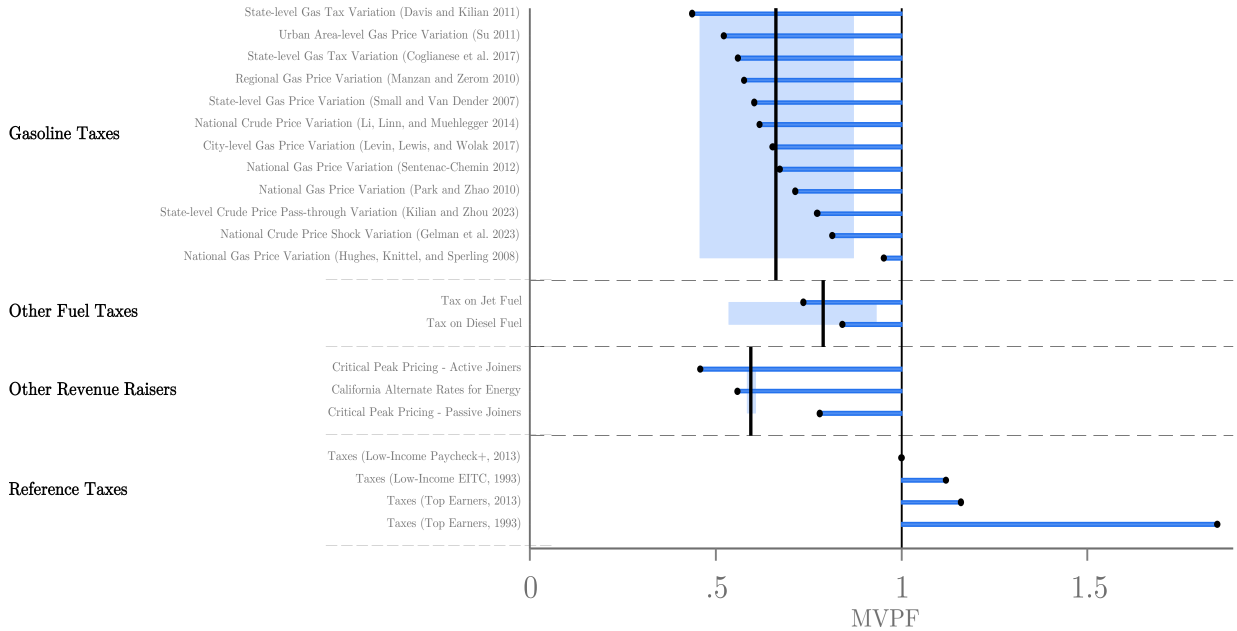
Notes: This figure illustrates the MVPF estimates for Opower Home Energy Reports split across the 5 AVERT model's electricity regions for which the experiments have been conducted. The benefits per dollar of government cost equal the environmental benefits minus the loss in utility profits. MVPFs above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



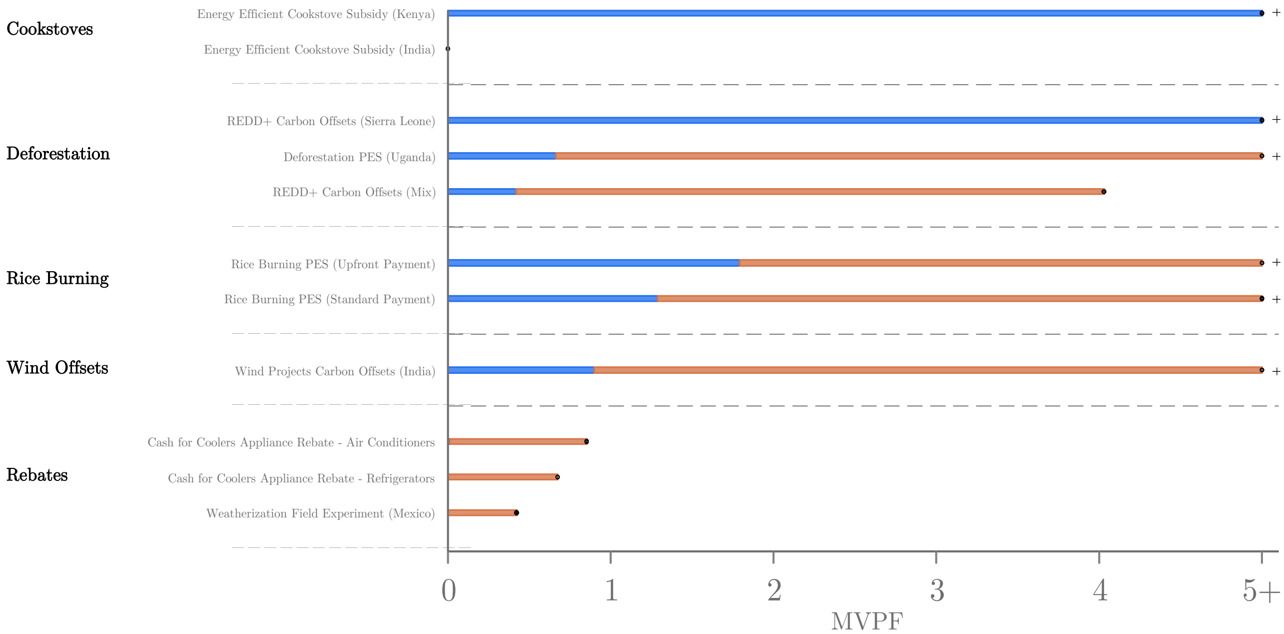
Notes: This figure presents the components of the baseline MVPF for the gasoline tax using a gasoline price elasticity of -0.334 from Small & Van Dender (2007). The WTP components include the transfer cost (yellow), global greenhouse gas benefits and local environmental externalities arising from accidents, 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)
State-level ENERGY STAR Rebate - Clothes Washers	ES (CW)	2006		Datta and Gulati (2014)
ENERGY STAR Rebate - Water Heaters	ES (WH)	2012		Allcott and Sweeney (2017)
Cash for Appliances - Dishwashers	C4A (DW)	2010		Houde and Aldy (2017)
Cash for Appliances - Refrigerators	C4A (Fridge)	2010		Houde and Aldy (2017)
State-level ENERGY STAR Rebate - Refrigerators	ES (Fridge)	2006		Datta and Gulati (2014)
State-level ENERGY STAR Rebate - Dishwashers	ES (DW)	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)
BAAQMD Vehicle Buyback Program	BAAQMD	2010	CA	Sandler (2012)
Cash for Clunkers (Li, Linn, and Spiller 2013)	C4C (US)	2009		Li, Linn, and Spiller (2013)
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				
Solarize Connecticut	Solarize	2012	CT	Gillingham and Bollinger (2021)
Energize CT Home Energy Solutions Program Energy Audit	Audit Nudge	2013		Gillingham and Tsvetanov (2018)
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)
National Gas Price Variation (Park and Zhao 2010)	Gas (Park)	2008		Park and Zhao (2010)
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 (Hughes, Knittel, and Sperling 2008)	Gas (Hughes)	2006		Hughes, Knittel, and Sperling (2008)
State-level Gas Price Variation (Small and Van Dender 2007)	* Gas (Small - Ext)	2001		Small and Van Dender (2007)
State-level Crude Price Pass-through Variation (Kilian and Zhou 2023)	* Gas (Kilian - Ext)	2014		Kilian and Zhou (2023)
National Gas Price Variation (Hughes, Knittel, and Sperling 2008)	* Gas (Hughes - Ext)	1990		Hughes, Knittel, and Sperling (2008)
Multimarket Simulation Model (Bento et al. 2009)	* Gas (Bento)	2002		Bento et al. (2009)
Quadratic Almost Ideal Demand System (Tiezzi and Verde 2016)	* Gas (Tiezzi)	2010		Tiezzi and Verde (2016)
Almost Ideal Demand System (West and Williams 2007)	* Gas (West)	1998		West and Williams (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 (Colmer et al. 2024)	* ETS (CMMW)	2005–2012	European Union	Colmer et al. (2024)
EU Emissions Trading System (Bayer and Aklin)	* ETS (BA)	2008–2016	European Union	Bayer and Aklin (2020)
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**	**0.046**	**0.452**	**-0.043**	**1.544**	**1.000**	**0.092**	**-0.004**	**1.088**	**1.420**
BEV (State - Rebate)	1.000	0.069	0.000	0.038	0.064	0.564	-0.051	1.684	1.000	0.108	-0.005	1.104	1.525
ITC (EV)	1.000	0.061	0.000	0.034	0.049	0.482	-0.046	1.580	1.000	0.097	-0.004	1.093	1.447
EFMP	1.000	0.042	0.000	0.023	0.025	0.309	-0.031	1.368	1.000	0.070	-0.003	1.067	1.282
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**	**0.043**	**-0.009**	**1.034**	**1.175**
C4A (CW)	0.952	0.550	0.083	-0.124			-0.039	1.423	1.000	0.021	-0.009	1.012	1.405
ES (CW)	1.000	0.861	0.126	-0.193			-0.072	1.722	1.000	0.250	-0.014	1.237	1.392
ES (WH)	0.598	1.707	0.000	-0.201			-0.659	1.445	1.000	0.112	-0.033	1.078	1.340
C4A (DW)	0.929	0.243	0.037	-0.055			-0.017	1.138	1.000	0.009	-0.004	1.005	1.132
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	0.139	-0.003	1.135	1.027
ES (DW)	1.000	-0.223	-0.033	0.050			0.019	0.813	1.000	-0.211	0.003	0.792	1.027
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	**0.892**	**0.225**	**0.108**	**-0.081**			**-0.042**	**1.102**	**1.000**	**0.052**	**-0.004**	**1.048**	**1.051**
C4C (TX)	1.000	0.449	0.061	-0.225			-0.082	1.203	1.000	0.101	-0.007	1.093	1.100
BAAQMD	0.676	0.192	0.259	0.000			-0.038	1.088	1.000	0.047	-0.004	1.043	1.043
C4C (US)	1.000	0.034	0.005	-0.018			-0.006	1.015	1.000	0.007	-0.001	1.007	1.008
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	**0.576**	**4.928**	**0.631**	**-1.092**			**-0.678**	**4.365**	**1.000**	**1.490**	**-0.078**	**2.412**	**1.809**
Solarize	1.560	15.745	2.309	-3.860			-1.936	13.818	1.000	1.817	-0.241	2.576	5.364
Audit Nudge	0.000	8.678	1.333	-1.961			-0.542	7.507	1.000	2.668	-0.136	3.532	2.126
ES (WH) + Nudge	0.416	1.599	0.000	-0.188			-0.629	1.197	1.000	0.107	-0.031	1.075	1.113
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	2.533	0.108	-0.379			-0.756	1.506	1.000	4.305	-0.042	5.262	0.286
Food Labels *	0.000	1.920	0.000	0.000			0.000	1.920	1.000	0.000	-0.037	0.963	1.994
Panel C. Revenue Raisers													
Gasoline Taxes	**1.000**	**-0.235**	**-0.210**		**0.000**	**-0.002**	**0.061**	**0.615**	**1.000**	**-0.075**	**0.005**	**0.929**	**0.662**
Gas (DK)	1.000	-0.374	-0.334		0.000	-0.002	0.098	0.387	1.000	-0.120	0.007	0.887	0.436
Gas (Su)	1.000	-0.323	-0.288		0.000	-0.002	0.084	0.471	1.000	-0.104	0.006	0.903	0.522
Gas (Coglianese)	1.000	-0.299	-0.267		0.000	-0.002	0.078	0.509	1.000	-0.096	0.006	0.910	0.560
Gas (Manzan)	1.000	-0.289	-0.258		0.000	-0.002	0.075	0.527	1.000	-0.093	0.006	0.913	0.577
Gas (Small)	1.000	-0.272	-0.243		0.000	-0.002	0.071	0.555	1.000	-0.087	0.005	0.918	0.604
Gas (Li)	1.000	-0.263	-0.235		0.000	-0.002	0.069	0.569	1.000	-0.084	0.005	0.921	0.618
Gas (Levin)	1.000	-0.240	-0.214		0.000	-0.002	0.063	0.606	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	0.626	1.000	-0.073	0.004	0.931	0.673
Gas (Park)	1.000	-0.201	-0.179		0.000	-0.002	0.053	0.670	1.000	-0.065	0.004	0.939	0.714
Gas (Kilian)	1.000	-0.161	-0.144		0.000	-0.002	0.042	0.735	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	0.813
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	-0.333		0.000	-0.002	0.097	0.390	1.000	-0.120	0.007	0.888	0.439
Gas (Tiezzi) *	1.000	-0.354	-0.316		0.000	-0.002	0.093	0.420	1.000	-0.114	0.007	0.893	0.471
Gas (Bento) *	1.000	-0.285	-0.254		0.000	-0.002	0.074	0.533	1.000	-0.091	0.006	0.914	0.583
Gas (Hughes - Ext) *	1.000	-0.272	-0.243		0.000	-0.002	0.071	0.553	1.000	-0.088	0.005	0.918	0.603
Gas (Kilian - Ext) *	1.000	-0.255	-0.228		0.000	-0.002	0.067	0.581	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**	**-0.073**				**0.025**	**0.768**	**1.000**	**-0.031**	**0.004**	**0.973**	**0.789**
Jet Fuel	1.000	-0.310	-0.016				0.036	0.710	1.000	-0.043	0.006	0.964	0.736
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	-0.083	-0.001				0.000	0.916	1.000	0.000	0.002	1.002	0.915
Crude (WPT) *	1.000	-0.009	0.000				0.000	0.991	1.000	-0.030	0.000	0.970	1.021
Crude (State) *	1.000	-0.075	0.000				0.000	0.925	1.000	-0.315	0.001	0.686	1.347
E85 *	1.000	0.547	-0.702				0.282	1.127	1.000	-0.327	-0.011	0.662	1.702
Other Revenue Raisers	**0.901**	**-0.125**	**-0.014**	**0.015**			**-0.121**	**0.657**	**1.000**	**0.104**	**0.002**	**1.106**	**0.594**
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	0.704	-0.228	0.000	0.045			0.080	0.601	1.000	0.071	0.004	1.076	0.558
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	-0.536	-0.808					-0.344	1.000	-0.041	0.010	0.970	-0.355
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)	0.544	-2.956	0.000					-2.412	1.000	0.000	0.058	1.058	-2.280
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+	0.846	2.951	0.000					3.797	1.000	0.000	-0.058	0.942	4.030
Deforest (Mexico) *	0.970	-0.016	0.000					0.954	1.000	0.000	0.000	1.000	0.954
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

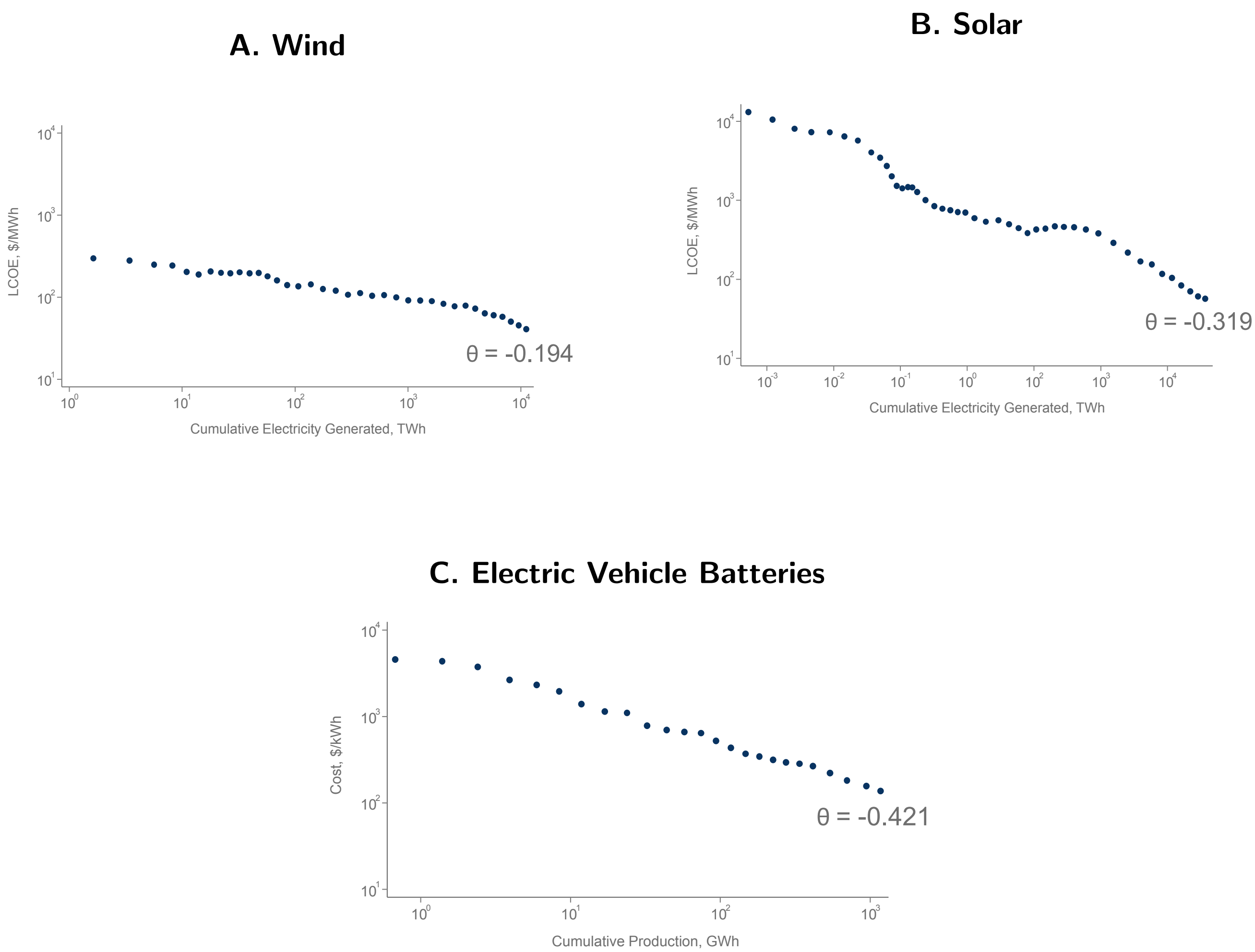
Notes: This table presents the WTP and cost components for each policy in our sample using the baseline specification. Each component is normalized per dollar of mechanical spending on the policy. The first column reports the size of the transfer. The next three columns report the environmental externality 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	1.420	-458	1,685	-518
Appliance Rebates	1.175	-2	470	107
Vehicle Retirement	1.051	1,007	882	76
Hybrid Vehicles	1.012	577	5,892	-39
Weatherization	0.978	194	779	207
Nudges and Marketing				
Opower Elec. (166 RCTs)	2.548	-41	77	70
Revenue Raisers				
Gasoline Taxes	0.662	-104	-750	-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	962	2,422	283
Appliance Rebates	1.175	-2	470	107
Vehicle Retirement	1.051	1,007	882	76
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	0.663	-104	-748	-62

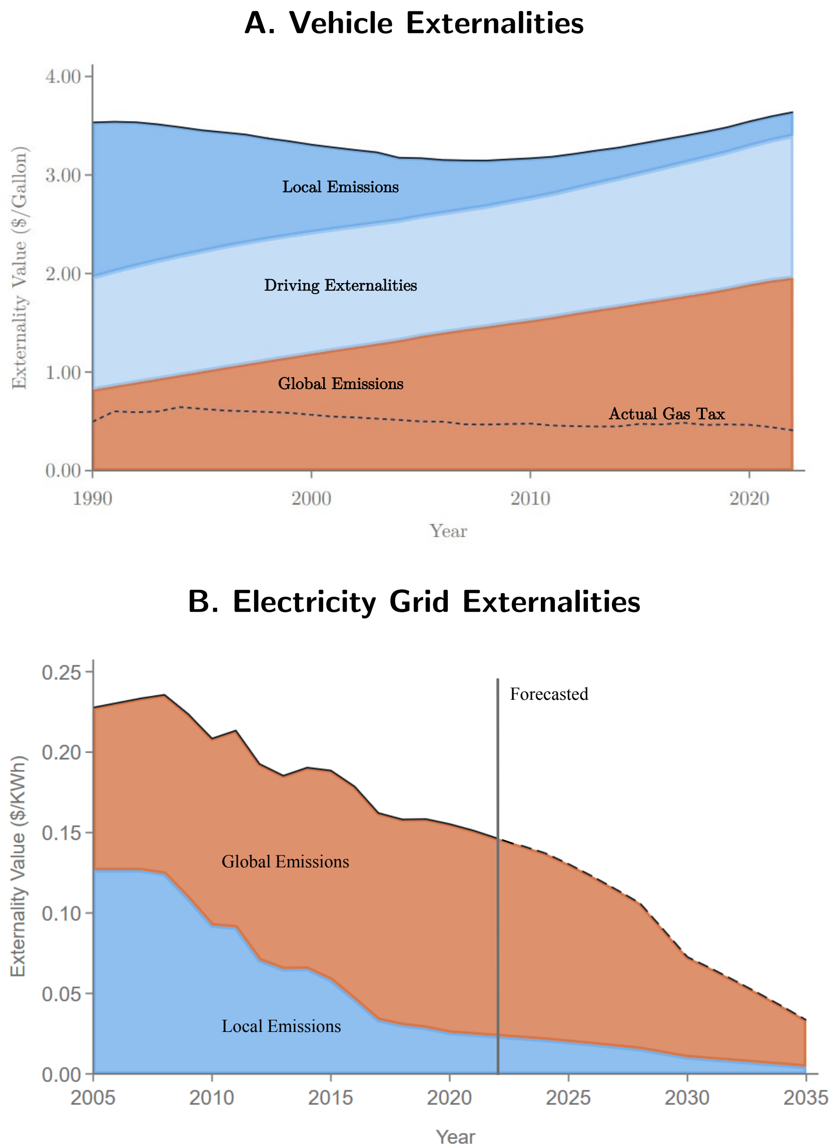
Notes: This table presents estimates of the MVPF and cost per ton measures using our three definitions: resource cost per ton, government cost per ton social cost per ton. See text for precise definitions of each measure. We present estimates here for each policy category average; the Appendix provides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



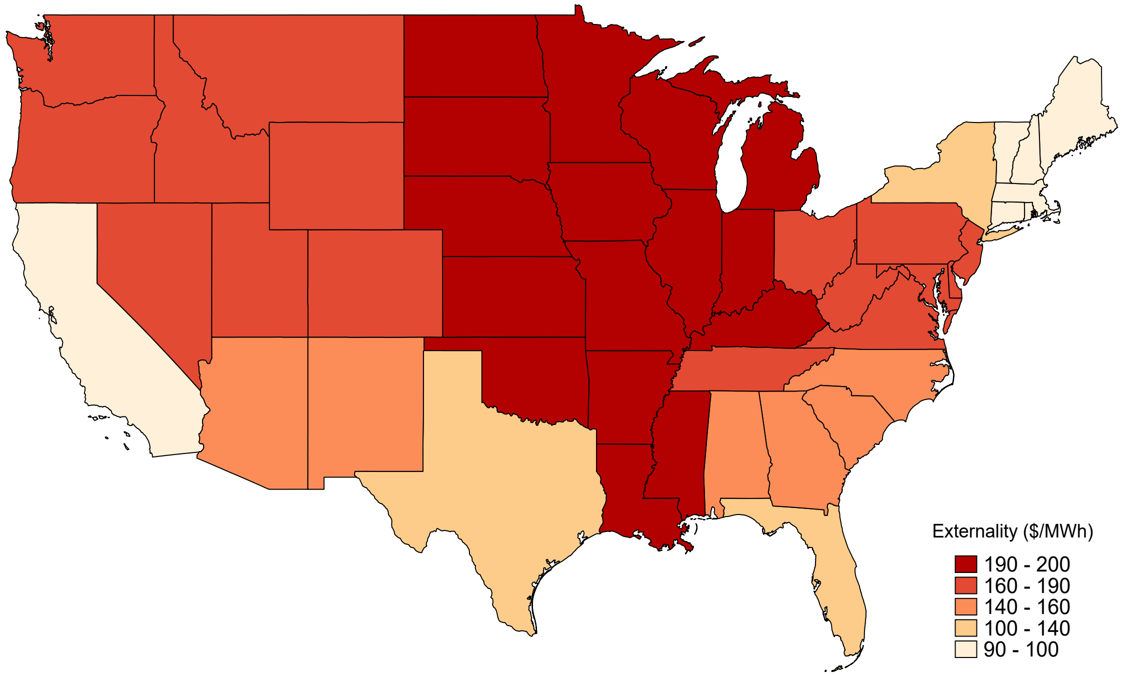
Notes: This figure reproduces estimates of the price of solar cells, wind energy, and battery storage from Way et al. (2022). Panel A and B report the levelized cost per MWh of electricty (LCOE) from wind and solar, respectively. Panel C reports the electric vehicle battery cell cost per KWh. We report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



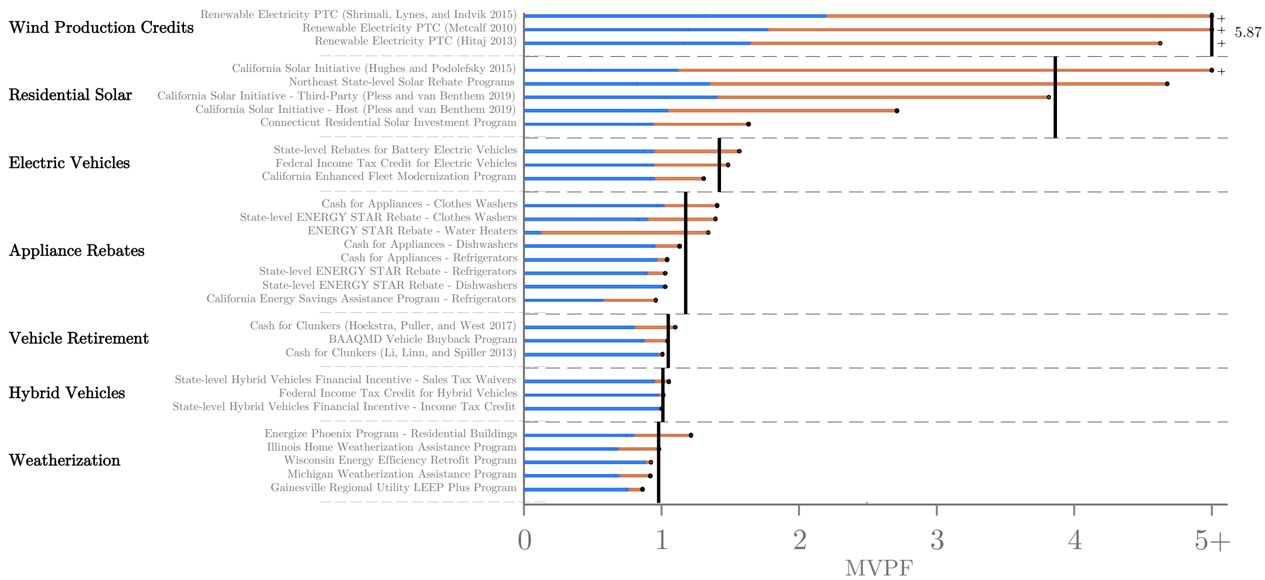
Notes: This figure illustrates the components of the vehicle and grid externalities over time. Panel A reports the dollar value of the vehicle externalities per gallon of gasoline. We split these into local emissions (e.g., NO_X), driving externalities (accidents and congestion), and global emissions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



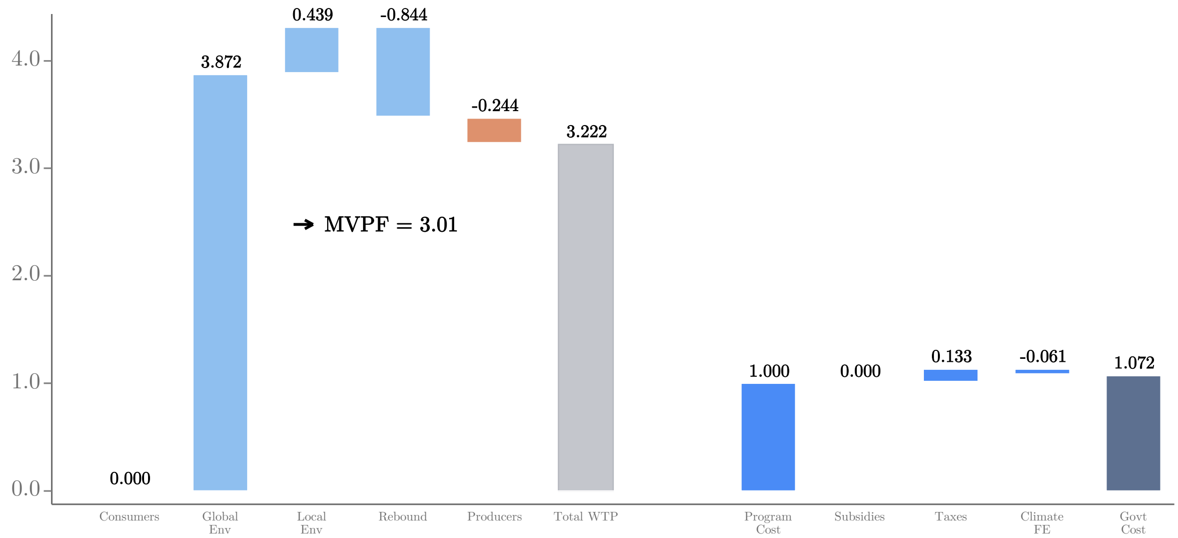
Notes: This figure illustrates the dollar value of the environmental externality per MWh of electricity in 2020 using emissions rates from EPA's AVERT model separately for each AVERT model region in the US.

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.

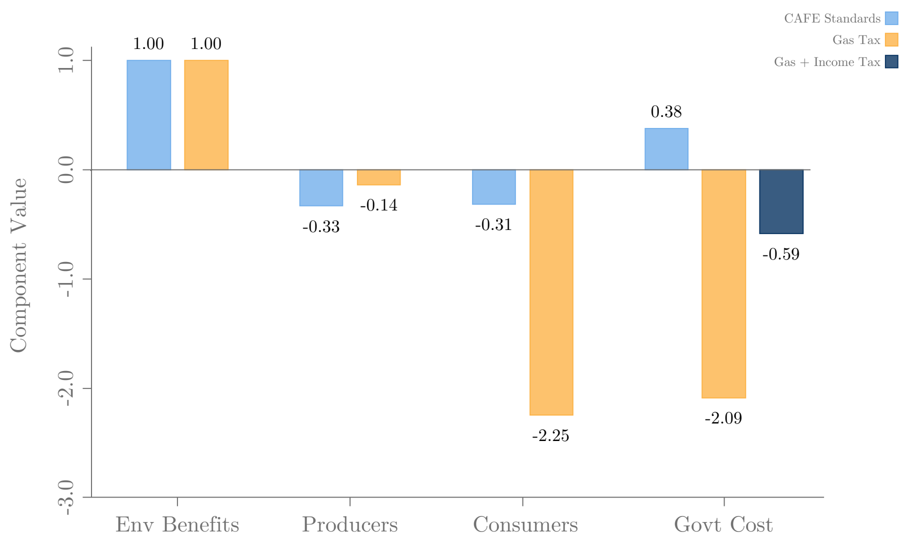
Appendix Figure 5: Home Energy Reports
Baseline Estimates from Alcott (2011)



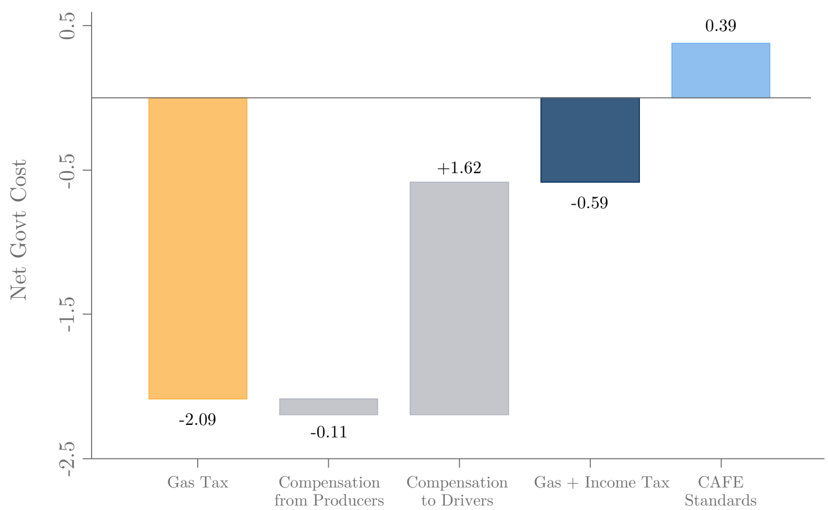
Notes: This figure presents the components of the MVPF for the home energy report using estimates from Allcott (2011). The WTP components include the environmental benefits (light blue) and electricity profits (orange). We assume nudges have no direct WTP to recipients. All numbers are calculated using our baseline path for the social cost of carbon ($193 in 2020) and a 2% discount rate.

Appendix Figure 6: CAFE vs. Gasoline + Income Tax

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



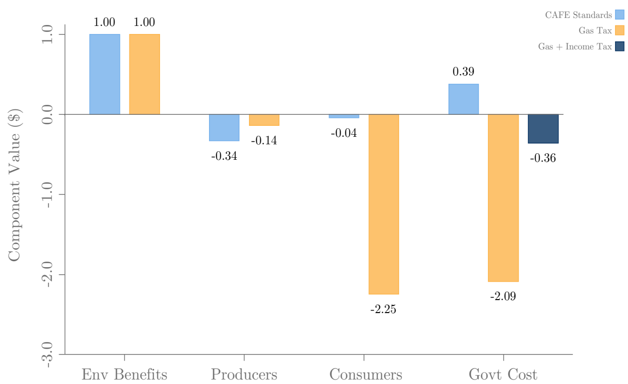
B. Net Government Revenue



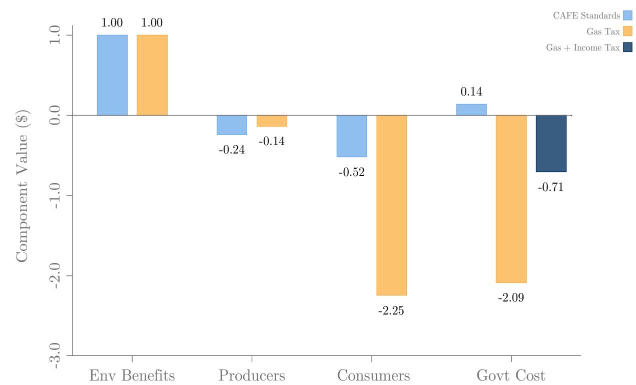
Notes: This figure presents a comparison of the welfare impact of changes to the stringency of CAFE regulation to a gasoline tax, using our category average gasoline tax MVPF. Panel A presents the impact of CAFE and a gas tax, each normalized to deliver \$1 of environmental benefits using our baseline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

Appendix Figure 7: Additional Regulation Comparisons

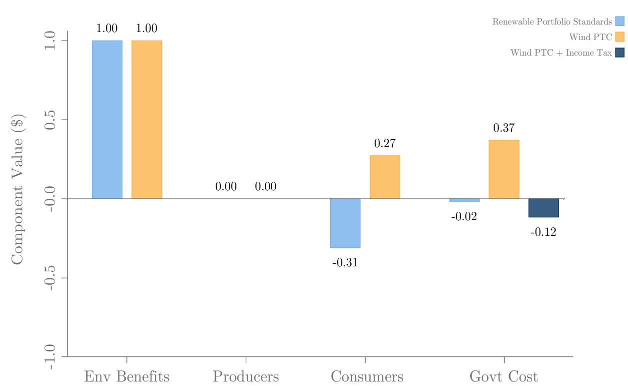
A. CAFE Comparison with Gasoline Tax (Anderson & Sallee 2011)



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

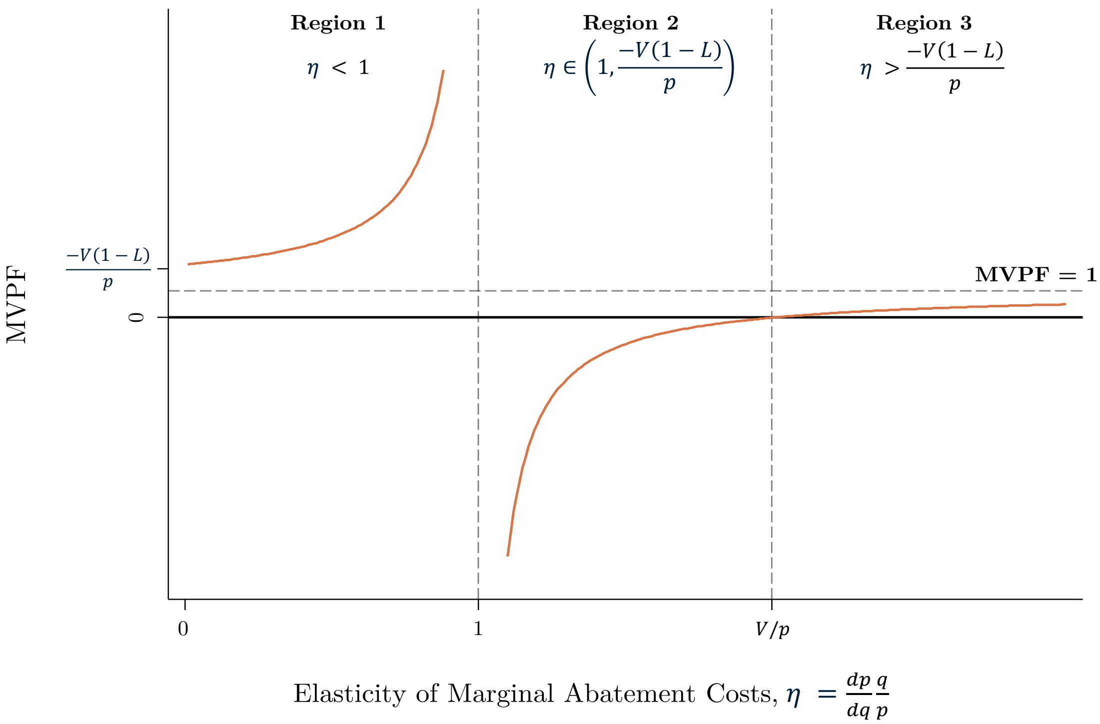


C. RPS Comparison with Wind PTC (Greenstone & Nath 2020)



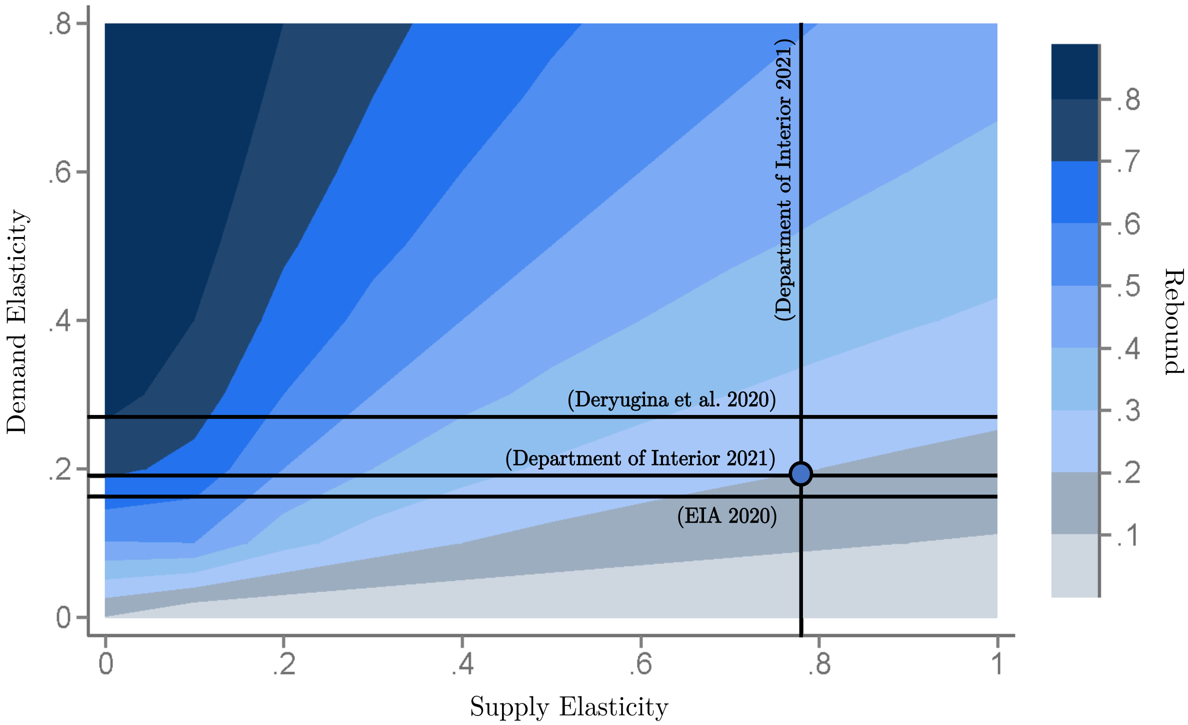
Notes: This figure presents a comparison of the welfare impact of changes regulation versus taxes. Panel A uses estimates of the impact of CAFE from (Anderson & Sallee 2011); Panel B uses estimates of the impact of CAFE from (Jacobsen 2013*a*); Panel C uses estimates of the impact of Renewable Portfolio 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 8: Cap and Trade



Notes: This figure illustrates the MVPF as a function of the elasticity, η of the permit price with respect to the quantity of permits offered (which one would expect to equal the elasticity of the marginal abatement cost). We split the graph into three regions. In Region 1, selling fewer permits costs the government money because the permit price does not rise fast enough to offset the mechanical loss from selling fewer permits. The MVPF starts from a value of $-V(1-L)/p$ when $\eta = 0$ and increases towards ∞ as $\eta \to 1$. In Region 2, restricting the number of permits auctioned raises government revenue and generates a net gain to individuals, as the environmental gain exceeds the loss to permit holders from higher prices (this is denoted by a negative MVPF as the net cost is negative while the gains to individuals are positive, although we note the ordering of policies with negative MVPFs is not directly informative). In Region 3, the slope of the marginal abatement curve is steep so that restricting permits leads to significantly higher prices. When $\eta > -V(1-L)/p$, the costs to the permit holders exceed the environmental gains. As long as the permit price falls below the externality net of leakage, $p < -V(1-L)$, restricting the number of permits auctioned raises \$1 revenue at a cost to individuals that is below \$1.

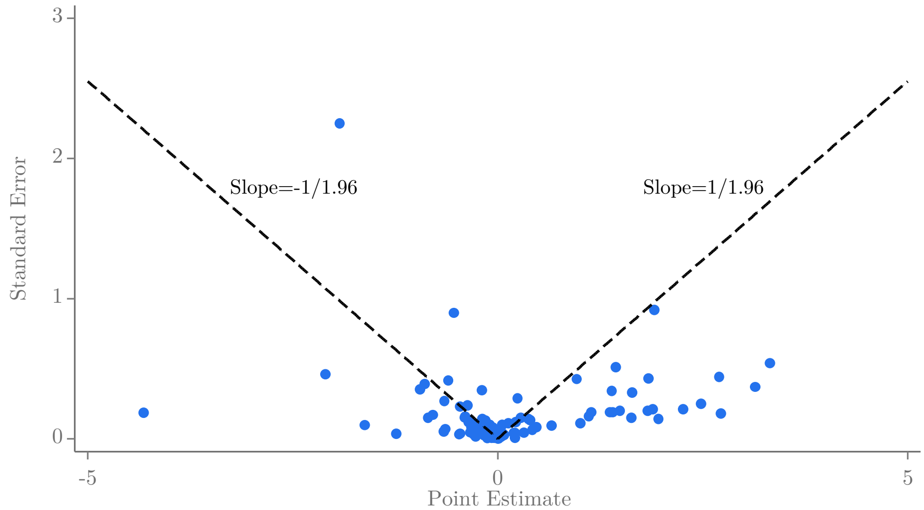
Appendix Figure 9: Electricity Rebound



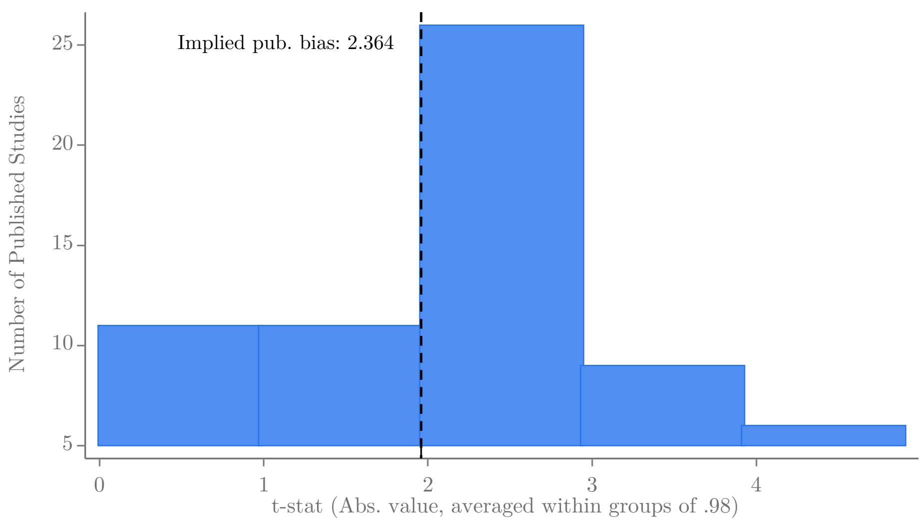
Notes: This figure shows the electricity rebound as a function of the demand and supply elasticity. The y-axis represents the absolute value of the price elasticity of demand for electricity and the x-axis is the supply elasticity for electricity. Our baseline estimate of the demand elasticity (-0.19) 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 10: Evidence of Publication Bias

A. Funnel Plot



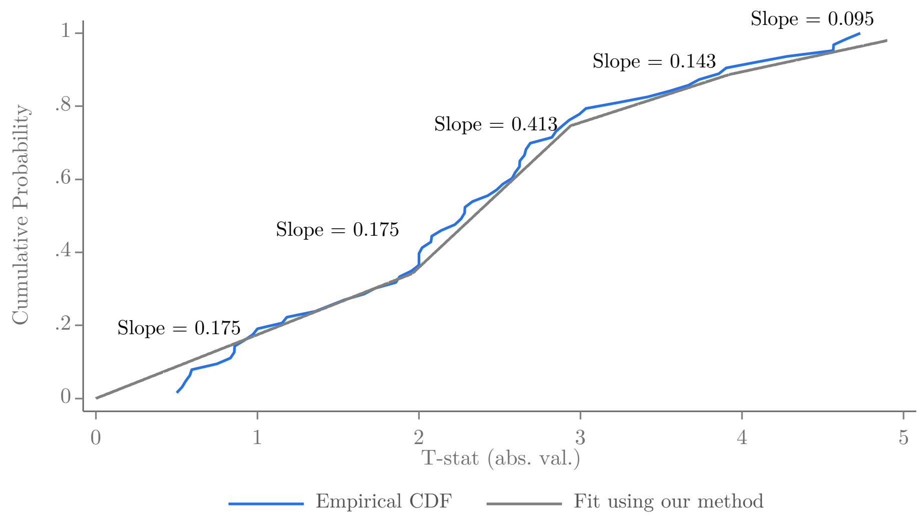
B. Histogram of t-statistics



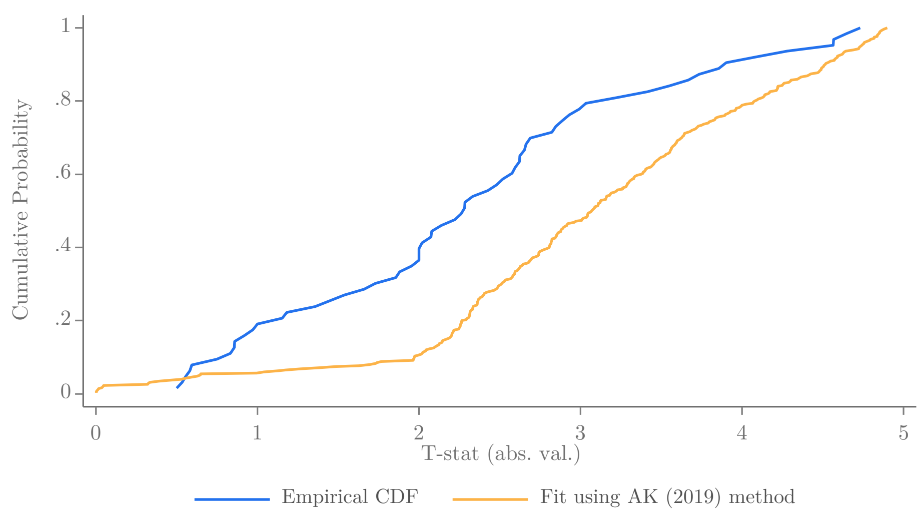
Notes: These figures present tests for publication bias in our baseline sample. Figure A shows a "funnel plot" of the standard errors in our sample against the point estimates in our sample. For ease of visualization, we restrict to point estimates between -5 and 5; this drops 5 estimates, all of which 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 11: Model Fits for Estimates of Publication Bias

A. Our Approach

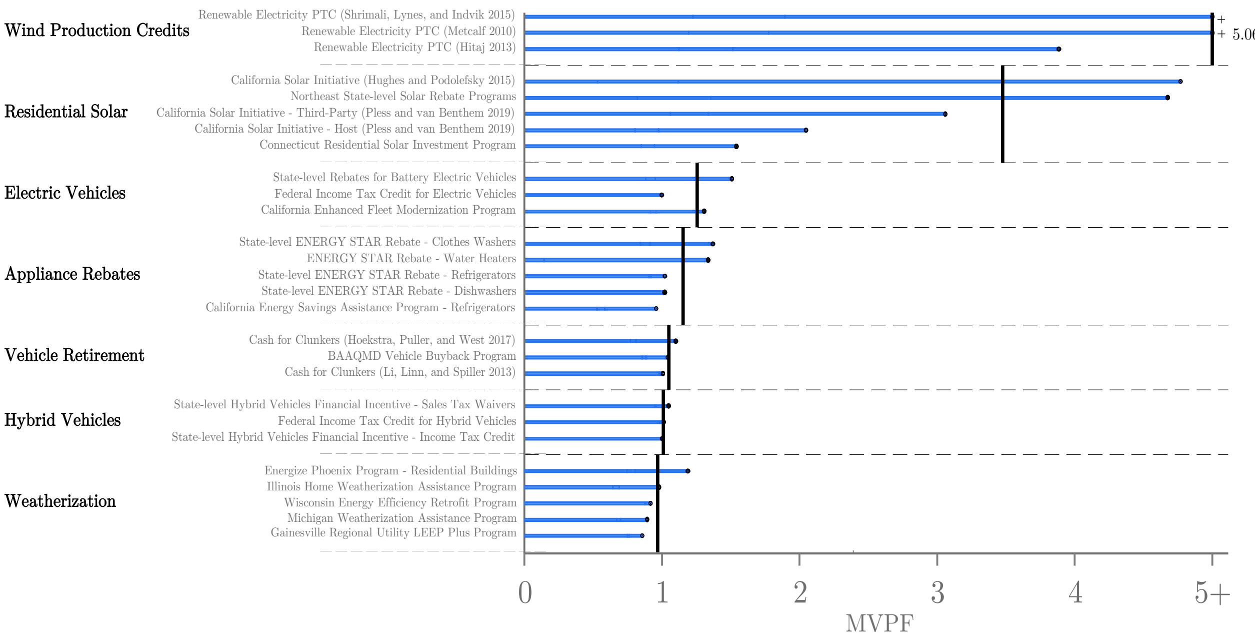


B. Andrews & Kasy (2019) Approach



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

Appendix Figure 12: 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	-0.321	-0.661	-0.455	-0.490	-0.383	-0.375
	(0.007)	(0.054)	(0.083)	(0.011)	(0.088)	(0.094)	(0.008)	(0.067)	(0.068)
Log Marg. Sales		-0.083	0.070		0.346	0.459		-0.129	-0.220
		(0.059)	(0.069)		(0.089)	(0.083)		(0.081)	(0.132)
Year			-0.086			-0.105			0.020
			(0.026)			(0.028)			(0.023)
Observations	36	36	36	44	44	44	24	24	24

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**	**0.823**	**0.122**	**-0.203**	**2.775**	**2.191**	**-0.498**	**6.316**	**1.000**	**1.654**	**-0.058**	**2.597**	**2.432**
CSI	1.000	1.059	0.081	-0.247	2.225	5.001	-0.734	8.385	1.000	3.330	-0.056	4.274	1.962
NE Solar	1.000	1.116	0.370	-0.310	7.015	2.365	-0.250	11.307	1.000	1.548	-0.120	2.429	4.655
CSI (TPO)	1.528	1.053	0.077	-0.247	3.485	2.200	-0.795	7.301	1.000	1.340	-0.079	2.261	3.229
CSI (HO)	1.000	0.514	0.038	-0.121	0.995	1.011	-0.388	3.049	1.000	0.699	-0.026	1.673	1.822
CT Solar	1.000	0.372	0.043	-0.090	0.153	0.381	-0.321	1.538	1.000	1.355	-0.008	2.347	0.655
ITC *	1.000	1.096	0.253	-0.280	10.408	2.827	-0.113	15.191	1.000	0.541	-0.181	1.359	11.178
Electric Vehicles	**1.000**	**0.090**	**-0.016**	**0.041**	**-0.031**	**0.340**	**-0.072**	**1.352**	**1.000**	**0.728**	**-0.003**	**1.725**	**0.784**
BEV (State - Rebate)	1.000	0.119	-0.023	0.052	-0.233	0.403	-0.097	1.221	1.000	0.831	0.000	1.831	0.667
ITC (EV)	1.000	0.068	-0.034	0.053	0.035	0.356	-0.113	1.365	1.000	0.642	-0.004	1.638	0.833
EFMP	1.000	0.083	0.010	0.017	0.105	0.261	-0.006	1.471	1.000	0.711	-0.005	1.706	0.862
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	2.688
Appliance Rebates	**0.867**	**0.488**	**0.166**	**-0.114**			**-0.134**	**1.273**	**1.000**	**0.050**	**-0.008**	**1.041**	**1.223**
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 (CW)	1.000	1.458	0.935	-0.469			-0.108	2.816	1.000	0.231	-0.023	1.208	2.332
ES (WH)	0.598	1.429	0.000	-0.168			-0.760	1.099	1.000	0.129	-0.028	1.101	0.998
C4A (DW)	0.930	0.196	0.106	-0.059			-0.014	1.158	1.000	0.008	-0.003	1.005	1.153
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	0.138	-0.004	1.135	1.131
ES (DW)	1.000	-0.255	-0.164	0.082			0.019	0.682	1.000	-0.211	0.004	0.793	0.860
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**	**0.471**	**1.568**	**-0.084**			**-0.151**	**2.697**	**1.000**	**0.169**	**-0.009**	**1.161**	**2.324**
C4C (TX)	1.000	0.424	0.129	-0.233			-0.122	1.199	1.000	0.124	-0.007	1.117	1.073
BAAQMD	0.676	0.957	4.566	0.000			-0.321	5.878	1.000	0.375	-0.019	1.356	4.334
C4C (US)	1.000	0.033	0.010	-0.019			-0.009	1.014	1.000	0.009	0.000	1.009	1.006
Hybrid Vehicles	**1.000**	**0.024**	**0.005**	**-0.031**	**0.001**	**0.069**	**0.013**	**1.081**	**1.000**	**0.413**	**-0.001**	**1.413**	**0.765**
HY (S-STW)	1.000	0.052	0.012	-0.072	0.002	0.167	0.028	1.188	1.000	0.810	-0.002	1.809	0.657

HY (F-ITC)	1.000	0.017	0.002	-0.017	0.000	0.031	0.009	1.043	1.000	0.355	0.000	1.354	0.770
HY (S-ITC)	1.000	0.003	0.001	-0.005	0.000	0.009	0.002	1.011	1.000	0.075	0.000	1.075	0.940
Weatherization	**0.774**	**0.312**	**0.056**	**-0.063**			**-0.045**	**1.034**	**1.000**	**0.012**	**-0.005**	**1.007**	**1.027**
EPP	0.750	0.674	0.106	-0.153			-0.036	1.341	1.000	0.020	-0.011	1.009	1.329
IHWAP	0.750	0.398	0.048	-0.069			-0.073	1.053	1.000	0.012	-0.007	1.006	1.047
WI RF	0.870	0.046	0.030	0.000			-0.019	0.929	1.000	0.000	0.000	1.000	0.929
WAP	0.750	0.306	0.057	-0.058			-0.084	0.971	1.000	0.022	-0.005	1.017	0.955
LEEP+	0.750	0.139	0.039	-0.035			-0.014	0.878	1.000	0.008	-0.002	1.006	0.874
Other Subsidies	**0.887**	**0.991**	**0.316**	**-0.112**			**-0.266**	**1.817**	**1.000**	**0.144**	**-0.017**	**1.127**	**1.612**
CA 20/20	0.882	1.063	0.081	-0.224			-0.531	1.270	1.000	0.289	-0.017	1.272	0.999
CRP	0.893	0.919	0.552	0.000			0.000	2.363	1.000	0.000	-0.018	0.982	2.407
Panel B. Nudges and Marketing													
Home Energy Reports													
HER (17 RCTs)	0.000	3.165	3.116	-1.230			-0.258	4.793	1.000	0.140	-0.050	1.090	4.395
Opower Elec. (166 RCTs)	0.000	2.828	1.691	-0.885			-0.209	3.425	1.000	0.113	-0.044	1.069	3.205
PER	0.000	0.184	0.058	0.000			0.695	0.938	1.000	-0.378	-0.004	0.619	1.515
Opower Nat. Gas (52 RCTs)	0.000	0.796	0.000	-0.094			-0.423	0.279	1.000	0.072	-0.014	1.058	0.264
Other Nudges	**0.724**	**3.438**	**0.540**	**-0.776**			**-1.911**	**2.015**	**1.000**	**4.022**	**-0.055**	**4.968**	**0.406**
Solarize	2.449	11.415	1.693	-2.804			-7.999	4.754	1.000	16.257	-0.175	17.082	0.278
Audit Nudge	0.000	4.226	0.990	-1.022			-1.887	2.307	1.000	3.398	-0.066	4.332	0.533
ES (WH) + Nudge	0.416	1.339	0.000	-0.157			-0.726	0.871	1.000	0.123	-0.026	1.097	0.794
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	2.597	0.473	-0.488			-0.713	1.869	1.000	4.332	-0.043	5.289	0.353
Food Labels *	0.000	1.920	0.000	0.000			0.000	1.920	1.000	0.000	-0.037	0.963	1.994
Panel C. Revenue Raisers													
Gasoline Taxes	**1.000**	**-0.133**	**-0.194**		**0.000**	**0.000**	**0.071**	**0.744**	**1.000**	**-0.071**	**0.003**	**0.931**	**0.799**
Gas (DK)	1.000	-0.166	-0.195		0.000	0.000	0.099	0.738	1.000	-0.080	0.003	0.923	0.800
Gas (Su)	1.000	-0.222	-0.381		0.000	0.000	0.122	0.518	1.000	-0.134	0.004	0.870	0.596
Gas (Coglianese)	1.000	-0.133	-0.156		0.000	0.000	0.079	0.791	1.000	-0.064	0.003	0.938	0.843
Gas (Manzan)	1.000	-0.179	-0.474		0.000	0.000	0.118	0.465	1.000	-0.153	0.004	0.851	0.547
Gas (Small)	1.000	-0.187	-0.321		0.000	0.000	0.102	0.595	1.000	-0.113	0.004	0.891	0.668
Gas (Li)	1.000	-0.116	-0.137		0.000	0.000	0.069	0.816	1.000	-0.056	0.002	0.946	0.863
Gas (Levin)	1.000	-0.149	-0.169		0.000	0.000	0.064	0.745	1.000	-0.065	0.003	0.938	0.795
Gas (Sentenac-Chemin)	1.000	-0.122	-0.165		0.000	0.000	0.067	0.780	1.000	-0.063	0.002	0.939	0.831
Gas (Park)	1.000	-0.089	-0.104		0.000	0.000	0.053	0.860	1.000	-0.043	0.002	0.959	0.897
Gas (Kilian)	1.000	-0.104	-0.092		0.000	-0.004	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	0.815	1.000	-0.043	0.002	0.960	0.849
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	-0.607		0.000	0.000	0.170	0.269	1.000	-0.205	0.006	0.800	0.336
Gas (Tiezzi) *	1.000	-0.193	-0.213		0.000	0.000	0.092	0.686	1.000	-0.086	0.004	0.918	0.747
Gas (Bento) *	1.000	-0.216	-0.351		0.000	0.000	0.109	0.542	1.000	-0.124	0.004	0.881	0.615
Gas (Hughes - Ext) *	1.000	-0.141	-0.473		0.000	0.000	0.115	0.502	1.000	-0.117	0.003	0.886	0.567
Gas (Kilian - Ext) *	1.000	-0.136	-0.135		0.000	-0.001	0.072	0.800	1.000	-0.057	0.003	0.946	0.846
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**	**-0.095**	**-0.067**				**0.026**	**0.864**	**1.000**	**-0.027**	**0.002**	**0.975**	**0.886**
Jet Fuel	1.000	-0.157	-0.010				0.036	0.869	1.000	-0.037	0.003	0.966	0.900
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	-0.069	-0.001				0.000	0.930	1.000	0.000	0.001	1.001	0.928
Crude (WPT) *	1.000	-0.002	0.000				0.000	0.998	1.000	-0.047	0.000	0.953	1.047
Crude (State) *	1.000	-0.065	0.000				0.000	0.935	1.000	-0.315	0.001	0.686	1.362
E85 *	1.000	0.130	-0.303				0.277	1.104	1.000	-0.263	-0.003	0.734	1.504
Other Revenue Raisers	**0.895**	**-0.120**	**-0.014**	**0.014**			**-0.111**	**0.664**	**1.000**	**0.105**	**0.002**	**1.108**	**0.600**
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	0.685	-0.213	0.000	0.042			0.108	0.621	1.000	0.076	0.004	1.080	0.575
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	-0.454	-0.808					-0.262	1.000	-0.023	0.009	0.986	-0.266
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

	Willingness to Pay								Cost				MVPF		
		Environmental Benefits			Learning by Doing					Fiscal Externalities				95% CI	
Panel A. Subsidies	Transfer	Global	Local	Rebound	Env.	Price	Profits	WTP	Program	Initial	Climate	Total	Pt. Est	Lower	Upper
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**		
(Sub)sample with SEs	**1.000**	**4.678**	**0.643**	**-1.074**	**1.900**	**0.645**		**7.793**	**1.000**	**0.435**	**-0.108**	**1.328**	**5.870**	**2.757**	∞
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	1.716	∞
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	2.596	9.232
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	1.321	19.706
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**		
(Sub)sample with SEs	**1.000**	**0.876**	**0.129**	**-0.215**	**1.674**	**0.978**	**-0.109**	**4.333**	**1.000**	**0.364**	**-0.044**	**1.320**	**3.282**	**1.815**	**13.950**
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	1.957	26.398
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	1.094	2.969
Electric Vehicles	**1.000**	**0.057**	**0.000**	**0.032**	**0.046**	**0.452**	**-0.043**	**1.544**	**1.000**	**0.092**	**-0.004**	**1.088**	**1.420**		
(Sub)sample with SEs	**1.000**	**0.055**	**0.000**	**0.031**	**0.045**	**0.436**	**-0.041**	**1.526**	**1.000**	**0.089**	**-0.004**	**1.085**	**1.406**	**1.180**	**1.804**
BEV (State - Rebate)	1.000	0.069	0.000	0.038	0.064	0.564	-0.051	1.684	1.000	0.108	-0.005	1.104	1.525	1.118	2.285
ITC (EV)	1.000	0.061	0.000	0.034	0.049	0.482	-0.046	1.580	1.000	0.097	-0.004	1.093	1.447		
EFMP	1.000	0.042	0.000	0.023	0.025	0.309	-0.031	1.368	1.000	0.070	-0.003	1.067	1.282	1.093	1.459
Appliance Rebates	**0.867**	**0.497**	**0.043**	**-0.089**			**-0.103**	**1.215**	**1.000**	**0.043**	**-0.009**	**1.034**	**1.175**		
(Sub)sample with SEs	**0.820**	**0.617**	**0.041**	**-0.102**			**-0.153**	**1.223**	**1.000**	**0.062**	**-0.011**	**1.051**	**1.164**	**1.095**	**1.208**
C4A (CW)	0.952	0.550	0.083	-0.124			-0.039	1.423	1.000	0.021	-0.009	1.012	1.405		
ES (CW)	1.000	0.861	0.126	-0.193			-0.072	1.722	1.000	0.250	-0.014	1.237	1.392	1.164	1.573
ES (WH)	0.598	1.707	0.000	-0.201			-0.659	1.445	1.000	0.112	-0.033	1.078	1.340	1.250	1.367
C4A (DW)	0.929	0.243	0.037	-0.055			-0.017	1.138	1.000	0.009	-0.004	1.005	1.132		
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	0.139	-0.003	1.135	1.027	1.000	1.049
ES (DW)	1.000	-0.223	-0.033	0.050			0.019	0.813	1.000	-0.211	0.003	0.792	1.027	0.994	1.093
CA ESA	0.500	0.541	0.083	-0.122			-0.034	0.968	1.000	0.018	-0.008	1.010	0.958	0.930	0.990
Vehicle Retirement	**0.892**	**0.225**	**0.108**	**-0.081**			**-0.042**	**1.102**	**1.000**	**0.052**	**-0.004**	**1.048**	**1.051**		
(Sub)sample with SEs	**0.892**	**0.225**	**0.108**	**-0.081**			**-0.042**	**1.102**	**1.000**	**0.052**	**-0.004**	**1.048**	**1.051**	**1.042**	**1.061**
C4C (TX)	1.000	0.449	0.061	-0.225			-0.082	1.203	1.000	0.101	-0.007	1.093	1.100	1.076	1.123
BAAQMD	0.676	0.192	0.259	0.000			-0.038	1.088	1.000	0.047	-0.004	1.043	1.043	1.036	1.050
C4C (US)	1.000	0.034	0.005	-0.018			-0.006	1.015	1.000	0.007	-0.001	1.007	1.008	1.005	1.011

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**		
(Sub)sample with SEs	**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**	**1.005**	**1.021**
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	1.009	1.050
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	1.007	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	0.998	1.005
Weatherization	**0.774**	**0.297**	**0.029**	**-0.057**			**-0.054**	**0.989**	**1.000**	**0.017**	**-0.005**	**1.012**	**0.978**		
(Sub)sample with SEs	**0.750**	**0.358**	**0.034**	**-0.068**			**-0.067**	**1.007**	**1.000**	**0.021**	**-0.006**	**1.015**	**0.992**	**0.932**	**1.037**
EPP	0.750	0.593	0.083	-0.133			-0.057	1.237	1.000	0.031	-0.009	1.022	1.210	0.928	1.434
IHWAP	0.750	0.404	0.019	-0.064			-0.111	0.999	1.000	0.025	-0.007	1.019	0.980	0.961	1.001
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	0.817	1.045
LEEP+	0.750	0.138	0.019	-0.031			-0.013	0.864	1.000	0.007	-0.002	1.005	0.859	0.801	0.918
Other Subsidies	**0.887**	**1.504**	**0.424**	**-0.234**			**-0.065**	**2.517**	**1.000**	**0.036**	**-0.025**	**1.010**	**2.492**		
(Sub)sample with SEs	**0.887**	**1.504**	**0.424**	**-0.234**			**-0.065**	**2.517**	**1.000**	**0.036**	**-0.025**	**1.010**	**2.492**	**2.130**	**2.858**
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	1.902	3.262
CRP	0.893	0.919	0.552	0.000			0.000	2.363	1.000	0.000	-0.018	0.982	2.407	2.152	2.660
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	2.354	3.658
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	0.043	7.495
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	**0.576**	**4.928**	**0.631**	**-1.092**			**-0.678**	**4.365**	**1.000**	**1.490**	**-0.078**	**2.412**	**1.809**		
(Sub)sample with SEs	**0.576**	**4.928**	**0.631**	**-1.092**			**-0.678**	**4.365**	**1.000**	**1.490**	**-0.078**	**2.412**	**1.809**	**1.731**	**1.959**
Solarize	1.560	15.745	2.309	-3.860			-1.936	13.818	1.000	1.817	-0.241	2.576	5.364	5.173	5.554
Audit Nudge	0.000	8.678	1.333	-1.961			-0.542	7.507	1.000	2.668	-0.136	3.532	2.126	1.643	2.348
ES (WH) + Nudge	0.416	1.599	0.000	-0.188			-0.629	1.197	1.000	0.107	-0.031	1.075	1.113	1.058	1.120
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	0.980	1.152
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	0.991	1.138
WAP + Nudge	0.000	2.533	0.108	-0.379			-0.756	1.506	1.000	4.305	-0.042	5.262	0.286	0.106	0.517
Panel C. Revenue Raisers															
Gasoline Taxes	**1.000**	**-0.235**	**-0.210**		**0.000**	**-0.002**	**0.061**	**0.615**	**1.000**	**-0.075**	**0.005**	**0.929**	**0.662**		
(Sub)sample with SEs	**1.000**	**-0.238**	**-0.212**		**0.000**	**-0.002**	**0.062**	**0.610**	**1.000**	**-0.076**	**0.005**	**0.928**	**0.657**	**0.456**	**0.869**
Gas (DK)	1.000	-0.374	-0.334		0.000	-0.002	0.098	0.387	1.000	-0.120	0.007	0.887	0.436	-0.209	0.998
Gas (Su)	1.000	-0.323	-0.288		0.000	-0.002	0.084	0.471	1.000	-0.104	0.006	0.903	0.522	0.112	0.908
Gas (Coglianese)	1.000	-0.299	-0.267		0.000	-0.002	0.078	0.509	1.000	-0.096	0.006	0.910	0.560	-0.079	1.114
Gas (Manzan)	1.000	-0.289	-0.258		0.000	-0.002	0.075	0.527	1.000	-0.093	0.006	0.913	0.577	0.287	0.864
Gas (Small)	1.000	-0.272	-0.243		0.000	-0.002	0.071	0.555	1.000	-0.087	0.005	0.918	0.604	0.498	0.718
Gas (Li)	1.000	-0.263	-0.235		0.000	-0.002	0.069	0.569	1.000	-0.084	0.005	0.921	0.618	0.420	0.822
Gas (Levin)	1.000	-0.240	-0.214		0.000	-0.002	0.063	0.606	1.000	-0.077	0.005	0.928	0.654	0.584	0.732
Gas (Sentenac-Chemin)	1.000	-0.228	-0.203		0.000	-0.002	0.060	0.626	1.000	-0.073	0.004	0.931	0.673	0.551	0.802
Gas (Park)	1.000	-0.201	-0.179		0.000	-0.002	0.053	0.670	1.000	-0.065	0.004	0.939	0.714	0.715	0.715
Gas (Kilian)	1.000	-0.161	-0.144		0.000	-0.002	0.042	0.735	1.000	-0.052	0.003	0.951	0.773	0.657	0.897
Gas (Gelman)	1.000	-0.133	-0.119		0.000	-0.002	0.035	0.781	1.000	-0.043	0.003	0.960	0.813	0.763	0.870
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	0.936	0.974

Other Fuel Taxes	**1.000**	**-0.185**	**-0.073**				**0.025**	**0.768**	**1.000**	**-0.031**	**0.004**	**0.973**	**0.789**		
(Sub)sample with SEs	**1.000**	**-0.310**	**-0.016**				**0.036**	**0.710**	**1.000**	**-0.043**	**0.006**	**0.964**	**0.736**	**0.534**	**0.931**
Jet Fuel	1.000	-0.310	-0.016				0.036	0.710	1.000	-0.043	0.006	0.964	0.736	0.534	0.931
Diesel	1.000	-0.059	-0.130				0.015	0.826	1.000	-0.019	0.001	0.982	0.841		
Other Revenue Raisers	**0.901**	**-0.125**	**-0.014**	**0.015**			**-0.121**	**0.657**	**1.000**	**0.104**	**0.002**	**1.106**	**0.594**		
(Sub)sample with SEs	**0.901**	**-0.125**	**-0.014**	**0.015**			**-0.121**	**0.657**	**1.000**	**0.104**	**0.002**	**1.106**	**0.594**	**0.584**	**0.608**
CPP (AJ)	1.000	-0.107	-0.030	0.000			-0.323	0.540	1.000	0.176	0.002	1.178	0.459	0.393	0.529
CARE	0.704	-0.228	0.000	0.045			0.080	0.601	1.000	0.071	0.004	1.076	0.558	0.450	0.690
CPP (PJ)	1.000	-0.039	-0.011	0.000			-0.119	0.831	1.000	0.065	0.001	1.065	0.780	0.697	0.869
Cap and Trade															
RGGI	1.000	-0.536	-0.808					-0.344	1.000	-0.041	0.010	0.970	-0.355	-0.906	0.503
CA CT	1.000	-0.061	-0.002					0.937	1.000	-0.006	0.001	0.996	0.941		

Notes: This table repeats the information in Table 2 but 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**	**0.045**	**0.423**	**-0.041**	**1.461**	**1.000**	**0.090**	**-0.002**	**1.088**	**1.343**
BEV (State - Rebate)	1.000	0.024	0.000	0.018	0.063	0.527	-0.050	1.582	1.000	0.106	-0.002	1.104	1.434
ITC (EV)	1.000	0.021	0.000	0.016	0.048	0.451	-0.044	1.492	1.000	0.095	-0.002	1.092	1.365
EFMP	1.000	0.014	0.000	0.011	0.024	0.290	-0.030	1.309	1.000	0.068	-0.001	1.067	1.227
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**	**0.042**	**-0.003**	**1.039**	**0.930**
C4A (CW)	0.952	0.225	0.082	-0.060			-0.038	1.161	1.000	0.021	-0.004	1.017	1.142
ES (CW)	1.000	0.348	0.123	-0.092			-0.070	1.309	1.000	0.252	-0.005	1.246	1.051
ES (WH)	0.598	0.655	0.000	-0.077			-0.638	0.538	1.000	0.108	-0.013	1.095	0.491
C4A (DW)	0.929	0.100	0.036	-0.027			-0.016	1.023	1.000	0.009	-0.002	1.007	1.015
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	0.139	-0.001	1.138	0.942
ES (DW)	1.000	-0.090	-0.032	0.024			0.018	0.920	1.000	-0.212	0.001	0.790	1.165
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	**0.892**	**0.089**	**0.107**	**-0.060**			**-0.041**	**0.987**	**1.000**	**0.050**	**-0.002**	**1.049**	**0.941**
C4C (TX)	1.000	0.174	0.058	-0.167			-0.079	0.986	1.000	0.097	-0.003	1.094	0.902
BAAQMD	0.676	0.080	0.257	0.000			-0.038	0.975	1.000	0.047	-0.002	1.045	0.933
C4C (US)	1.000	0.013	0.004	-0.013			-0.006	0.999	1.000	0.007	0.000	1.007	0.992
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**	**0.119**	**0.028**	**-0.026**			**-0.051**	**0.844**	**1.000**	**0.016**	**-0.002**	**1.014**	**0.832**
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	0.160	0.019	-0.028			-0.103	0.797	1.000	0.024	-0.003	1.021	0.781
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	0.058	0.019	-0.015			-0.013	0.799	1.000	0.007	-0.001	1.006	0.793
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	**0.576**	**1.994**	**0.617**	**-0.512**			**-0.651**	**2.024**	**1.000**	**1.479**	**-0.032**	**2.447**	**0.827**
Solarize	1.560	6.393	2.241	-1.813			-1.836	6.545	1.000	1.763	-0.098	2.665	2.456
Audit Nudge	0.000	3.582	1.319	-0.960			-0.537	3.403	1.000	2.665	-0.056	3.609	0.943
ES (WH) + Nudge	0.416	0.610	0.000	-0.072			-0.609	0.345	1.000	0.103	-0.012	1.091	0.316
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	0.980	0.105	-0.160			-0.724	0.201	1.000	4.298	-0.016	5.282	0.038
Food Labels *	0.000	0.760	0.000	0.000			0.000	0.760	1.000	0.000	-0.015	0.985	0.772
Panel C. Revenue Raisers													
Gasoline Taxes	**1.000**	**-0.096**	**-0.210**		**0.000**	**-0.002**	**0.061**	**0.754**	**1.000**	**-0.075**	**0.002**	**0.926**	**0.814**
Gas (DK)	1.000	-0.153	-0.334		0.000	-0.002	0.098	0.609	1.000	-0.120	0.003	0.883	0.690
Gas (Su)	1.000	-0.132	-0.288		0.000	-0.002	0.084	0.662	1.000	-0.104	0.003	0.899	0.737
Gas (Coglianese)	1.000	-0.122	-0.267		0.000	-0.002	0.078	0.687	1.000	-0.096	0.002	0.906	0.758
Gas (Manzan)	1.000	-0.118	-0.258		0.000	-0.002	0.075	0.698	1.000	-0.093	0.002	0.910	0.767
Gas (Small)	1.000	-0.111	-0.243		0.000	-0.002	0.071	0.716	1.000	-0.087	0.002	0.915	0.782
Gas (Li)	1.000	-0.107	-0.235		0.000	-0.002	0.069	0.725	1.000	-0.084	0.002	0.918	0.790
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	0.761	1.000	-0.073	0.002	0.929	0.820
Gas (Park)	1.000	-0.082	-0.179		0.000	-0.002	0.053	0.789	1.000	-0.065	0.002	0.937	0.842
Gas (Kilian)	1.000	-0.066	-0.144		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 (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	-0.333		0.000	-0.002	0.097	0.611	1.000	-0.120	0.003	0.883	0.692
Gas (Tiezzi) *	1.000	-0.144	-0.316		0.000	-0.002	0.093	0.630	1.000	-0.114	0.003	0.889	0.709
Gas (Bento) *	1.000	-0.116	-0.254		0.000	-0.002	0.074	0.702	1.000	-0.091	0.002	0.911	0.771
Gas (Hughes - Ext) *	1.000	-0.111	-0.243		0.000	-0.002	0.071	0.715	1.000	-0.088	0.002	0.915	0.782
Gas (Kilian - Ext) *	1.000	-0.104	-0.228		0.000	-0.002	0.067	0.733	1.000	-0.082	0.002	0.920	0.796
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**	**-0.073**				**0.025**	**0.877**	**1.000**	**-0.031**	**0.001**	**0.971**	**0.904**
Jet Fuel	1.000	-0.126	-0.016				0.036	0.894	1.000	-0.043	0.002	0.960	0.931
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	-0.034	-0.001				0.000	0.966	1.000	0.000	0.001	1.001	0.965
Crude (WPT) *	1.000	-0.004	0.000				0.000	0.996	1.000	-0.030	0.000	0.970	1.026
Crude (State) *	1.000	-0.037	0.000				0.000	0.963	1.000	-0.315	0.001	0.686	1.404
E85 *	1.000	0.237	-0.702				0.282	0.817	1.000	-0.327	-0.005	0.668	1.223
Other Revenue Raisers	**0.901**	**-0.049**	**-0.014**	**0.006**			**-0.121**	**0.724**	**1.000**	**0.104**	**0.001**	**1.105**	**0.655**
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	0.704	-0.090	0.000	0.018			0.080	0.712	1.000	0.071	0.002	1.073	0.663
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	-0.212	-0.808					-0.020	1.000	-0.041	0.004	0.963	-0.021
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)	0.544	-1.167	0.000					-0.623	1.000	0.000	0.023	1.023	-0.609
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+	0.846	1.169	0.000					2.015	1.000	0.000	-0.023	0.977	2.062
Deforest (Mexico) *	0.970	-0.074	0.000					0.897	1.000	0.000	0.001	1.001	0.895
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**	**0.132**	**0.488**	**-0.044**	**1.732**	**1.000**	**0.094**	**-0.008**	**1.086**	**1.595**
BEV (State - Rebate)	1.000	0.124	0.000	0.063	0.185	0.610	-0.053	1.929	1.000	0.111	-0.010	1.101	1.752
ITC (EV)	1.000	0.110	0.000	0.056	0.140	0.521	-0.047	1.780	1.000	0.099	-0.008	1.091	1.632
EFMP	1.000	0.075	0.000	0.038	0.071	0.333	-0.032	1.486	1.000	0.071	-0.005	1.066	1.394
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**	**0.043**	**-0.015**	**1.028**	**1.486**
C4A (CW)	0.952	0.945	0.084	-0.202			-0.040	1.741	1.000	0.021	-0.015	1.007	1.729
ES (CW)	1.000	1.482	0.129	-0.316			-0.074	2.221	1.000	0.249	-0.023	1.226	1.812
ES (WH)	0.598	3.079	0.000	-0.362			-0.681	2.634	1.000	0.115	-0.060	1.055	2.496
C4A (DW)	0.929	0.418	0.037	-0.089			-0.017	1.279	1.000	0.009	-0.007	1.003	1.276
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	0.138	-0.005	1.133	1.132
ES (DW)	1.000	-0.383	-0.033	0.082			0.019	0.684	1.000	-0.211	0.006	0.795	0.860
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	**0.892**	**0.391**	**0.110**	**-0.106**			**-0.043**	**1.243**	**1.000**	**0.053**	**-0.007**	**1.047**	**1.188**
C4C (TX)	1.000	0.784	0.064	-0.294			-0.085	1.468	1.000	0.104	-0.012	1.092	1.344
BAAQMD	0.676	0.330	0.261	0.000			-0.039	1.228	1.000	0.048	-0.006	1.041	1.179
C4C (US)	1.000	0.060	0.005	-0.024			-0.006	1.034	1.000	0.008	-0.001	1.007	1.027
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**	**0.522**	**0.030**	**-0.095**			**-0.057**	**1.173**	**1.000**	**0.017**	**-0.008**	**1.009**	**1.163**
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	0.733	0.020	-0.112			-0.119	1.272	1.000	0.027	-0.012	1.015	1.253
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	0.231	0.019	-0.049			-0.013	0.938	1.000	0.007	-0.004	1.004	0.935
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	**0.576**	**8.501**	**0.647**	**-1.799**			**-0.708**	**7.217**	**1.000**	**1.503**	**-0.134**	**2.368**	**3.047**
Solarize	1.560	26.864	2.382	-6.325			-2.044	22.436	1.000	1.876	-0.410	2.466	9.098
Audit Nudge	0.000	14.907	1.348	-3.184			-0.548	12.523	1.000	2.671	-0.234	3.437	3.644
ES (WH) + Nudge	0.416	2.898	0.000	-0.341			-0.650	2.323	1.000	0.110	-0.057	1.054	2.205
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	4.541	0.111	-0.659			-0.790	3.203	1.000	4.312	-0.076	5.235	0.612
Food Labels *	0.000	3.352	0.000	0.000			0.000	3.352	1.000	0.000	-0.065	0.935	3.587
Panel C. Revenue Raisers													
Gasoline Taxes	**1.000**	**-0.408**	**-0.210**		**0.000**	**-0.002**	**0.061**	**0.441**	**1.000**	**-0.075**	**0.008**	**0.933**	**0.473**
Gas (DK)	1.000	-0.652	-0.334		0.000	-0.002	0.098	0.110	1.000	-0.120	0.013	0.893	0.123
Gas (Su)	1.000	-0.562	-0.288		0.000	-0.002	0.084	0.231	1.000	-0.104	0.011	0.907	0.255
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	-0.258		0.000	-0.002	0.075	0.313	1.000	-0.093	0.010	0.917	0.341
Gas (Small)	1.000	-0.473	-0.243		0.000	-0.002	0.071	0.353	1.000	-0.087	0.009	0.922	0.383
Gas (Li)	1.000	-0.457	-0.235		0.000	-0.002	0.069	0.375	1.000	-0.084	0.009	0.925	0.405
Gas (Levin)	1.000	-0.417	-0.214		0.000	-0.002	0.063	0.429	1.000	-0.077	0.008	0.931	0.460
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 (Park)	1.000	-0.349	-0.179		0.000	-0.002	0.052	0.521	1.000	-0.065	0.007	0.942	0.553
Gas (Kilian)	1.000	-0.280	-0.144		0.000	-0.002	0.042	0.616	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 (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	-0.333		0.000	-0.002	0.097	0.114	1.000	-0.120	0.013	0.893	0.127
Gas (Tiezzi) *	1.000	-0.616	-0.316		0.000	-0.002	0.092	0.158	1.000	-0.114	0.012	0.898	0.176
Gas (Bento) *	1.000	-0.495	-0.254		0.000	-0.002	0.074	0.322	1.000	-0.091	0.010	0.918	0.351
Gas (Hughes - Ext) *	1.000	-0.474	-0.243		0.000	-0.002	0.071	0.351	1.000	-0.088	0.009	0.922	0.381
Gas (Kilian - Ext) *	1.000	-0.444	-0.228		0.000	-0.002	0.067	0.392	1.000	-0.082	0.009	0.927	0.423
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**	**-0.073**				**0.025**	**0.631**	**1.000**	**-0.031**	**0.006**	**0.976**	**0.647**
Jet Fuel	1.000	-0.540	-0.016				0.036	0.480	1.000	-0.043	0.011	0.968	0.495
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	-0.145	-0.001				0.000	0.854	1.000	0.000	0.003	1.003	0.852
Crude (WPT) *	1.000	-0.015	0.000				0.000	0.985	1.000	-0.030	0.000	0.970	1.015
Crude (State) *	1.000	-0.128	0.000				0.000	0.872	1.000	-0.315	0.002	0.687	1.269
E85 *	1.000	0.947	-0.702				0.282	1.527	1.000	-0.327	-0.018	0.654	2.333
Other Revenue Raisers	**0.901**	**-0.218**	**-0.014**	**0.026**			**-0.121**	**0.575**	**1.000**	**0.104**	**0.004**	**1.108**	**0.519**
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	0.704	-0.399	0.000	0.078			0.080	0.464	1.000	0.071	0.008	1.079	0.430
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	-0.937	-0.808					-0.745	1.000	-0.041	0.018	0.977	-0.762
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)	0.544	-5.174	0.000					-4.630	1.000	0.000	0.101	1.101	-4.205
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+	0.846	5.154	0.000					6.000	1.000	0.000	-0.101	0.899	6.671
Deforest (Mexico) *	0.970	-0.032	0.000					0.938	1.000	0.000	0.001	1.001	0.938
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**	**0.046**	**0.452**		**1.587**	**1.000**	**0.077**	**-0.004**	**1.073**	**1.479**
BEV (State - Rebate)	1.000	0.069	0.000	0.038	0.064	0.564		1.735	1.000	0.091	-0.005	1.086	1.597
ITC (EV)	1.000	0.061	0.000	0.034	0.049	0.482		1.626	1.000	0.081	-0.004	1.077	1.510
EFMP	1.000	0.042	0.000	0.023	0.025	0.309		1.399	1.000	0.059	-0.003	1.056	1.325
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)	0.952	0.550	0.083	-0.124				1.461	1.000	0.000	-0.009	0.991	1.474
ES (CW)	1.000	0.861	0.126	-0.193				1.794	1.000	0.289	-0.014	1.276	1.406
ES (WH)	0.598	1.707	0.000	-0.201				2.104	1.000	0.000	-0.033	0.967	2.176
C4A (DW)	0.929	0.243	0.037	-0.055				1.155	1.000	0.000	-0.004	0.996	1.159
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
ES (DW)	1.000	-0.223	-0.033	0.050				0.795	1.000	-0.221	0.003	0.782	1.016
CA ESA	0.500	0.541	0.083	-0.122				1.002	1.000	0.000	-0.008	0.992	1.010
Vehicle Retirement	**0.892**	**0.225**	**0.108**	**-0.081**				**1.144**	**1.000**	**0.044**	**-0.004**	**1.040**	**1.100**
C4C (TX)	1.000	0.449	0.061	-0.225				1.285	1.000	0.079	-0.007	1.072	1.199
BAAQMD	0.676	0.192	0.259	0.000				1.126	1.000	0.047	-0.004	1.043	1.080
C4C (US)	1.000	0.034	0.005	-0.018				1.021	1.000	0.006	-0.001	1.005	1.015
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	**0.576**	**4.928**	**0.631**	**-1.092**			**5.043**	**1.000**	**1.220**	**-0.078**	**2.142**	**2.354**
Solarize	1.560	15.745	2.309	-3.860			15.754	1.000	0.753	-0.241	1.512	10.420
Audit Nudge	0.000	8.678	1.333	-1.961			8.050	1.000	2.373	-0.136	3.237	2.487
ES (WH) + Nudge	0.416	1.599	0.000	-0.188			1.826	1.000	0.000	-0.031	0.969	1.885
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	2.533	0.108	-0.379			2.262	1.000	4.149	-0.042	5.106	0.443
Food Labels *	0.000	1.920	0.000	0.000			1.920	1.000	0.000	-0.037	0.963	1.994
Panel C. Revenue Raisers												
Gasoline Taxes	**1.000**	**-0.235**	**-0.210**		**0.000**	**-0.002**	**0.554**	**1.000**	**-0.059**	**0.005**	**0.945**	**0.586**
Gas (DK)	1.000	-0.374	-0.334		0.000	-0.002	0.289	1.000	-0.094	0.007	0.913	0.317
Gas (Su)	1.000	-0.323	-0.288		0.000	-0.002	0.386	1.000	-0.081	0.006	0.925	0.418
Gas (Coglianese)	1.000	-0.299	-0.267		0.000	-0.002	0.431	1.000	-0.075	0.006	0.931	0.463
Gas (Manzan)	1.000	-0.289	-0.258		0.000	-0.002	0.451	1.000	-0.073	0.006	0.933	0.484
Gas (Small)	1.000	-0.272	-0.243		0.000	-0.002	0.484	1.000	-0.068	0.005	0.937	0.516
Gas (Li)	1.000	-0.263	-0.235		0.000	-0.002	0.501	1.000	-0.066	0.005	0.939	0.533
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 (Park)	1.000	-0.201	-0.179		0.000	-0.002	0.618	1.000	-0.051	0.004	0.953	0.648
Gas (Kilian)	1.000	-0.161	-0.144		0.000	-0.002	0.693	1.000	-0.041	0.003	0.963	0.720
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 (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	-0.333		0.000	-0.002	0.293	1.000	-0.094	0.007	0.914	0.320
Gas (Tiezzi) *	1.000	-0.354	-0.316		0.000	-0.002	0.328	1.000	-0.089	0.007	0.918	0.357
Gas (Bento) *	1.000	-0.285	-0.254		0.000	-0.002	0.459	1.000	-0.072	0.006	0.934	0.491
Gas (Hughes - Ext) *	1.000	-0.272	-0.243		0.000	-0.002	0.482	1.000	-0.069	0.005	0.937	0.515
Gas (Kilian - Ext) *	1.000	-0.255	-0.228		0.000	-0.002	0.514	1.000	-0.064	0.005	0.941	0.547
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**	**-0.073**					**0.743**	**1.000**	**-0.024**	**0.004**	**0.980**	**0.758**
Jet Fuel	1.000	-0.310	-0.016					0.674	1.000	-0.033	0.006	0.973	0.693
Diesel	1.000	-0.059	-0.130					0.811	1.000	-0.015	0.001	0.986	0.822
Heavy Fuel *	1.000	-0.083	-0.001					0.916	1.000	0.000	0.002	1.002	0.915
Crude (WPT) *	1.000	-0.009	0.000					0.991	1.000	-0.030	0.000	0.970	1.021
Crude (State) *	1.000	-0.075	0.000					0.925	1.000	-0.315	0.001	0.686	1.347
E85 *	1.000	0.547	-0.702					0.845	1.000	-0.252	-0.011	0.737	1.147
Other Revenue Raisers	**0.901**	**-0.125**	**-0.014**	**0.015**				**0.778**	**1.000**	**0.018**	**0.002**	**1.021**	**0.762**
CPP (AJ)	1.000	-0.107	-0.030	0.000				0.864	1.000	0.000	0.002	1.002	0.862
CARE	0.704	-0.228	0.000	0.045				0.520	1.000	0.054	0.004	1.059	0.491
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	-0.536	-0.808					-0.344	1.000	-0.041	0.010	0.970	-0.355
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**	**0.046**	**0.452**	**-0.043**	**0.078**	**1.622**	**1.000**	**0.092**	**-0.004**	**1.088**	**1.491**
BEV (State - Rebate)	1.000	0.069	0.000	0.038	0.064	0.564	-0.051	0.094	1.777	1.000	0.108	-0.005	1.104	1.610
ITC (EV)	1.000	0.061	0.000	0.034	0.049	0.482	-0.046	0.083	1.664	1.000	0.097	-0.004	1.093	1.523
EFMP	1.000	0.042	0.000	0.023	0.025	0.309	-0.031	0.057	1.425	1.000	0.070	-0.003	1.067	1.336
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**	**0.043**	**-0.009**	**1.034**	**1.721**
C4A (CW)	0.952	0.550	0.083	-0.124			-0.039	0.575	1.997	1.000	0.021	-0.009	1.012	1.973
ES (CW)	1.000	0.861	0.126	-0.193			-0.072	1.066	2.787	1.000	0.250	-0.014	1.237	2.254
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
C4A (DW)	0.929	0.243	0.037	-0.055			-0.017	0.246	1.385	1.000	0.009	-0.004	1.005	1.377
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	0.139	-0.003	1.135	1.244
ES (DW)	1.000	-0.223	-0.033	0.050			0.019	-0.276	0.538	1.000	-0.211	0.003	0.792	0.679
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	**0.892**	**0.225**	**0.108**	**-0.081**			**-0.042**	**0.198**	**1.300**	**1.000**	**0.052**	**-0.004**	**1.048**	**1.241**
C4C (TX)	1.000	0.449	0.061	-0.225			-0.082	0.385	1.588	1.000	0.101	-0.007	1.093	1.452
BAAQMD	0.676	0.192	0.259	0.000			-0.038	0.181	1.269	1.000	0.047	-0.004	1.043	1.216
C4C (US)	1.000	0.034	0.005	-0.018			-0.006	0.029	1.043	1.000	0.007	-0.001	1.007	1.036
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	**0.576**	**4.928**	**0.631**	**-1.092**			**-0.678**	**7.150**	**11.515**	**1.000**	**1.490**	**-0.078**	**2.412**	**4.773**
Solarize	1.560	15.745	2.309	-3.860			-1.936	28.701	42.519	1.000	1.817	-0.241	2.576	16.504
Audit Nudge	0.000	8.678	1.333	-1.961			-0.542	8.042	15.550	1.000	2.668	-0.136	3.532	4.403
ES (WH) + Nudge	0.416	1.599	0.000	-0.188			-0.629	1.959	3.156	1.000	0.107	-0.031	1.075	2.935
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	2.533	0.108	-0.379			-0.756	3.224	4.730	1.000	4.305	-0.042	5.262	0.899
Food Labels *	0.000	1.920	0.000	0.000			0.000	0.000	1.920	1.000	0.000	-0.037	0.963	1.994

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	0.069	0.000	0.038			-0.051	1.056	1.000	0.108	-0.004	1.105	0.956
ITC (EV)	1.000	0.061	0.000	0.034			-0.046	1.050	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**	**0.043**	**-0.009**	**1.034**	**1.175**
C4A (CW)	0.952	0.550	0.083	-0.124			-0.039	1.423	1.000	0.021	-0.009	1.012	1.405
ES (CW)	1.000	0.861	0.126	-0.193			-0.072	1.722	1.000	0.250	-0.014	1.237	1.392
ES (WH)	0.598	1.707	0.000	-0.201			-0.659	1.445	1.000	0.112	-0.033	1.078	1.340
C4A (DW)	0.929	0.243	0.037	-0.055			-0.017	1.138	1.000	0.009	-0.004	1.005	1.132
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	0.139	-0.003	1.135	1.027
ES (DW)	1.000	-0.223	-0.033	0.050			0.019	0.813	1.000	-0.211	0.003	0.792	1.027
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	**0.892**	**0.225**	**0.108**	**-0.081**			**-0.042**	**1.102**	**1.000**	**0.052**	**-0.004**	**1.048**	**1.051**
C4C (TX)	1.000	0.449	0.061	-0.225			-0.082	1.203	1.000	0.101	-0.007	1.093	1.100
BAAQMD	0.676	0.192	0.259	0.000			-0.038	1.088	1.000	0.047	-0.004	1.043	1.043
C4C (US)	1.000	0.034	0.005	-0.018			-0.006	1.015	1.000	0.007	-0.001	1.007	1.008
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	**0.576**	**4.928**	**0.631**	**-1.092**			**-0.678**	**4.365**	**1.000**	**1.490**	**-0.078**	**2.412**	**1.809**
Solarize	1.560	15.745	2.309	-3.860			-1.936	13.818	1.000	1.817	-0.241	2.576	5.364
Audit Nudge	0.000	8.678	1.333	-1.961			-0.542	7.507	1.000	2.668	-0.136	3.532	2.126
ES (WH) + Nudge	0.416	1.599	0.000	-0.188			-0.629	1.197	1.000	0.107	-0.031	1.075	1.113
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	2.533	0.108	-0.379			-0.756	1.506	1.000	4.305	-0.042	5.262	0.286
Food Labels *	0.000	1.920	0.000	0.000			0.000	1.920	1.000	0.000	-0.037	0.963	1.994
Panel C. Revenue Raisers													
Gasoline Taxes	**1.000**	**-0.235**	**-0.210**				**0.061**	**0.616**	**1.000**	**-0.075**	**0.005**	**0.929**	**0.663**
Gas (DK)	1.000	-0.375	-0.334				0.098	0.388	1.000	-0.120	0.007	0.887	0.438
Gas (Su)	1.000	-0.324	-0.289				0.084	0.472	1.000	-0.104	0.006	0.903	0.523
Gas (Coglianese)	1.000	-0.300	-0.267				0.078	0.511	1.000	-0.096	0.006	0.910	0.561
Gas (Manzan)	1.000	-0.289	-0.258				0.076	0.528	1.000	-0.093	0.006	0.913	0.578
Gas (Small)	1.000	-0.272	-0.243				0.071	0.556	1.000	-0.087	0.005	0.918	0.606
Gas (Li)	1.000	-0.263	-0.235				0.069	0.571	1.000	-0.084	0.005	0.921	0.620
Gas (Levin)	1.000	-0.241	-0.214				0.063	0.608	1.000	-0.077	0.005	0.928	0.655
Gas (Sentenac-Chemin)	1.000	-0.228	-0.203				0.060	0.628	1.000	-0.073	0.004	0.931	0.674
Gas (Park)	1.000	-0.201	-0.180				0.053	0.672	1.000	-0.064	0.004	0.939	0.715
Gas (Kilian)	1.000	-0.161	-0.144				0.042	0.737	1.000	-0.052	0.003	0.951	0.774
Gas (Gelman)	1.000	-0.134	-0.119				0.035	0.782	1.000	-0.043	0.003	0.960	0.815
Gas (Hughes)	1.000	-0.034	-0.031				0.009	0.944	1.000	-0.011	0.001	0.990	0.954
Gas (West) *	1.000	-0.373	-0.333				0.097	0.391	1.000	-0.119	0.007	0.888	0.441
Gas (Tiezzi) *	1.000	-0.355	-0.316				0.093	0.422	1.000	-0.114	0.007	0.893	0.472
Gas (Bento) *	1.000	-0.285	-0.254				0.074	0.535	1.000	-0.091	0.006	0.914	0.585
Gas (Hughes - Ext) *	1.000	-0.273	-0.243				0.071	0.555	1.000	-0.087	0.005	0.918	0.604
Gas (Kilian - Ext) *	1.000	-0.256	-0.228				0.067	0.583	1.000	-0.082	0.005	0.923	0.631
Gas (Small - Ext) *	1.000	-0.054	-0.048				0.014	0.911	1.000	-0.017	0.001	0.984	0.926

Other Fuel Taxes	**1.000**	**-0.185**	**-0.073**				**0.025**	**0.768**	**1.000**	**-0.031**	**0.004**	**0.973**	**0.789**
Jet Fuel	1.000	-0.310	-0.016				0.036	0.710	1.000	-0.043	0.006	0.964	0.736
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	-0.083	-0.001				0.000	0.916	1.000	0.000	0.002	1.002	0.915
Crude (WPT) *	1.000	-0.009	0.000				0.000	0.991	1.000	-0.030	0.000	0.970	1.021
Crude (State) *	1.000	-0.075	0.000				0.000	0.925	1.000	-0.315	0.001	0.686	1.347
E85 *	1.000	0.547	-0.702				0.282	1.127	1.000	-0.327	-0.011	0.662	1.702
Other Revenue Raisers	**0.901**	**-0.125**	**-0.014**	**0.015**			**-0.121**	**0.657**	**1.000**	**0.104**	**0.002**	**1.106**	**0.594**
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	0.704	-0.228	0.000	0.045			0.080	0.601	1.000	0.071	0.004	1.076	0.558
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	-0.536	-0.808					-0.344	1.000	-0.041	0.010	0.970	-0.355
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	1.420	-518	-313	2	316
Appliance Rebates	1.175	107	154	248	342
Vehicle Retirement	1.051	76	164	340	517
Hybrid Vehicles	1.012	-39	555	1,748	2,941
Weatherization	0.978	207	285	441	596
Nudges and Marketing					
Opower Elec. (166 RCTs)	2.548	70	78	93	109
Revenue Raisers					
Gasoline Taxes	0.662	-64	-139	-289	-439

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

		Cost Per Ton		
Panel A. Subsidies	**MVPF**	**Resource**	**Government**	**Social**
Wind Production Credits	**5.870**	**-103**	**46**	**-32**
PTC (Shrimali)	7.547	-113	34	-28
PTC (Metcalf)	5.298	-100	51	-28
PTC (Hitaj)	4.626	-96	61	-28
Residential Solar	**3.862**	**-77**	**90**	**-67**
CSI	5.063	-77	62	-53
NE Solar	4.676	-111	69	-54
CSI (TPO)	3.815	-70	98	-75
CSI (HO)	2.712	-77	147	-53
CT Solar	1.634	-52	370	-40
Electric Vehicles	**1.420**	**-458**	**1,685**	**-518**
BEV (State - Rebate)	1.525	-527	1,358	-471
ITC (EV)	1.447	-467	1,587	-472
EFMP	1.282	-379	2,451	-465
Appliance Rebates	**1.175**	**-2**	**470**	**107**
C4A (CW)	1.405	4	433	14
ES (CW)	1.392	170	338	57
ES (WH)	1.340	209	136	143
C4A (DW)	1.132	69	972	61
C4A (Fridge)	1.042	-298	2,385	89
ES (Fridge)	1.027	-512	1,344	152
ES (DW)	1.027	507	-837	212
CA ESA	0.958	-162	440	208
Vehicle Retirement	**1.051**	**1,007**	**882**	**76**
C4C (TX)	1.100	-10	461	48
BAAQMD	1.043	2,931	1,030	145
C4C (US)	1.008	99	5,529	46
Hybrid Vehicles	**1.012**	**577**	**5,892**	**-39**
HY (S-STW)	1.028	576	2,646	-42
HY (F-ITC)	1.008	577	9,371	-41
HY (S-ITC)	1.002	577	43,439	-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	**0.662**	**-104**	**-750**	**-64**
Gas (DK)	0.436	-104	-449	-63
Gas (Su)	0.522	-104	-529	-64
Gas (Coglianese)	0.560	-104	-575	-64
Gas (Manzan)	0.577	-104	-598	-64
Gas (Small)	0.604	-104	-640	-64
Gas (Li)	0.618	-104	-664	-64
Gas (Levin)	0.654	-104	-732	-64
Gas (Sentenac-Chemin)	0.673	-104	-774	-64
Gas (Park)	0.714	-104	-886	-64
Gas (Kilian)	0.773	-104	-1,120	-65
Gas (Gelman)	0.813	-104	-1,366	-65
Gas (Hughes)	0.953	-105	-5,581	-74
Other Fuel Taxes	**0.789**	**-72**	**-998**	**-21**
Jet Fuel	0.736	-46	-588	34
Diesel	0.841	-99	-3,160	-313
Other Revenue Raisers	**0.594**	**-701**	**-1,905**	**-584**
CPP (AJ)	0.459	-1,018	-2,086	-940
CARE	0.558	-67	-1,109	-301
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**	**962**	**2,422**	**283**
BEV (State - Rebate)	0.956	962	2,048	280
ITC (EV)	0.960	962	2,275	280
EFMP	0.969	962	3,249	291
Appliance Rebates	**1.175**	**-2**	**470**	**107**
C4A (CW)	1.405	4	433	14
ES (CW)	1.392	170	338	57
ES (WH)	1.340	209	136	143
C4A (DW)	1.132	69	972	61
C4A (Fridge)	1.042	-298	2,385	89
ES (Fridge)	1.027	-512	1,344	152
ES (DW)	1.027	507	-837	212
CA ESA	0.958	-162	440	208
Vehicle Retirement	**1.051**	**1,007**	**882**	**76**
C4C (TX)	1.100	-10	461	48
BAAQMD	1.043	2,931	1,030	145
C4C (US)	1.008	99	5,529	46
Hybrid Vehicles	**0.998**	**659**	**6,041**	**43**
HY (S-STW)	0.996	659	2,729	43
HY (F-ITC)	0.999	659	9,454	43
HY (S-ITC)	1.000	659	43,522	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	**0.663**	**-104**	**-748**	**-62**
Gas (DK)	0.438	-104	-448	-62
Gas (Su)	0.523	-104	-528	-62
Gas (Coglianese)	0.561	-104	-574	-62
Gas (Manzan)	0.578	-104	-597	-62
Gas (Small)	0.606	-104	-638	-62
Gas (Li)	0.620	-104	-662	-62
Gas (Levin)	0.655	-104	-730	-62
Gas (Sentenac-Chemin)	0.674	-104	-772	-62
Gas (Park)	0.715	-104	-883	-62
Gas (Kilian)	0.774	-104	-1,116	-62
Gas (Gelman)	0.815	-104	-1,359	-62
Gas (Hughes)	0.954	-104	-5,471	-62
Other Fuel Taxes	**0.789**	**-72**	**-998**	**-21**
Jet Fuel	0.736	-46	-588	34
Diesel	0.841	-99	-3,160	-313
Other Revenue Raisers	**0.594**	**-701**	**-1,905**	**-584**
CPP (AJ)	0.459	-1,018	-2,086	-940
CARE	0.558	-67	-1,109	-301
CPP (PJ)	0.780	-1,018	-5,131	-940

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

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

	Externality Value ($/Gallon)		
Externality	**Upstream**	**On-Road**	**Total**
Pollution Externalities			
Ammonia (NH_3)	0.000		0.000
Carbon Dioxide (CO_2)	0.218	1.612	1.831
Carbon Monoxide (CO)	0.000	0.052	0.052
Hydrocarbons (HC)	0.004	0.036	0.040
Methane (CH_4)	0.025	0.001	0.026
Nitrous Oxide (N_2O)	0.001	0.012	0.013
Oxides of Nitrogen (NO_X)	0.003	0.076	0.079
Particulate Matter ($PM_{2.5}$)	0.005	0.084	0.089
Sulfur Dioxide (SO_2)	0.007	0.003	0.010
	0.264	1.876	2.140
Driving Externalities			
Accidents		0.992	0.992
Congestion		0.412	0.412
		1.404	1.404
Total Vehicle Externality	0.264	3.279	3.544

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.