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Environmental and Technology Policy Options in the Electricity Sector: Interactions and Outcomes

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Abstract

Myriad policy measures aim to reduce greenhouse gas emissions from the electricity sector, promote generation from renewable sources, and encourage energy conservation. To what extent do innovation and energy efficiency (EE) market failures justify additional interventions when a carbon price is in place? We extend the model of Fischer and Newell (2008) with advanced and conventional renewable energy technologies and short and long-run EE investments. We incorporate both knowledge spillovers and imperfections in the demand for energy efficiency. We conclude that some technology policies, particularly correcting R&D market failures, can be useful complements to emissions pricing, but ambitious renewable targets or subsidies seem unlikely to enhance welfare when placed alongside sufficient emissions pricing. The desirability of stringent EE policies is highly sensitive to the degree of undervaluation of EE by consumers, which also has implications for policies that tend to lower electricity prices. Even with multiple market failures, emissions pricing remains the single most cost-effective option for reducing emissions.

JEL-Code: Q420, Q520, Q550, Q580.

Keywords: climate change, cap-and-trade, renewable energy, portfolio standards, subsidies, spillovers, energy efficiency, electricity.

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Introduction

Over the last decade, concerns about global warming, local air quality, and energy security have led to a plethora of actual and proposed initiatives at the federal and state levels, particularly in the power sector. These measures aim to reduce emissions, promote electricity generation from renewable sources, and encourage energy conservation. Examples of policies include:

- Portfolio standards and market share mandates, such as those requiring production shares for renewable or "clean" energy sources.
- Subsidies and tax relief for renewable sources like wind power, solar, geothermal, and biomass generation.
- Policies to price greenhouse gas (GHG) emissions through cap and trade or a carbon tax, and related proposals to shift more of the tax burden onto energy or pollution.
- Performance standards, such as maximum emission rates per KWh of electricity and energy efficiency standards for household appliances.

However, little attention has been paid to whether these myriad policy efforts work together or at cross purposes. Research on policy instrument choice in the context of multiple interacting policies and market failures has been identified as an important area of further investigation (Goulder and Parry 2008). In other words, it is important to recognize that the whole of our energy policy mix is going to be quite distinct from the sum of its parts—and possibly less than that sum (Fischer and Preonas 2010).

For many of these policies, the primary motivation is addressing an emissions externality, such as the damages from air pollution or the risks of climate change. If that were the only market inefficiency, then only one policy instrument would be needed: an appropriate emissions price or other mechanism to "internalize the environmental externality." Indeed, if a binding emissions cap is in place, supplemental policies for renewable energy and energy efficiency (EE) lead to no incremental emissions reductions, but rather drive down the emissions price, which tends to benefit the dirtiest energy sources (Boehringer and Rosendahl 2010a). By distorting the market allocation of abatement, the supplemental policies actually increase overall compliance costs—*unless* there are other market failures.

Perhaps the "kitchen sink" approach we observe of combining many modest policies represents an attempt to compensate for a policy failure—political constraints against imposing a sufficiently robust emissions price. However, two additional kinds of market failures are often cited as rationales for technology-related incentives. One is imperfections in the market demand for energy efficiency. These imperfections may arise due to the lack of credible information, landlord-tenant arrangements, or myopic behavior, but they generally present themselves as an undervaluation of energy efficiency in the purchase of energy using appliances or homes (Gillingham et al. 2009). A second is spillovers from knowledge accumulated through research and development (R&D) or learning-by-doing (LBD). Because firms are unable to appropriate the full benefits arising from their innovations, they do not have sufficient incentive to develop and deploy new technologies (Jaffe et al. 2005). The presence of such policy and/or market failures will affect the relative desirability of different policy combinations.

Fischer and Newell (2008, henceforth FN) assessed different policies for reducing carbon dioxide emissions and promoting innovation and diffusion of renewable energy, with an application to the U.S. electricity sector. The stylized model represents two stages, one in which investments in R&D and LBD are made, and a second stage in which the resulting innovations are applied. The article revealed that, due to knowledge spillovers, optimal policy involves a portfolio of different instruments targeting not only emissions, but also learning and R&D. Despite those spillovers, however, the most cost-effective single policy for reducing emissions is an emissions price, followed by (in descending order of cost-effectiveness) an emissions performance standard, fossil power tax, renewables share requirement, renewables subsidy, and lastly an R&D subsidy.

In this paper, we extend and update the FN analysis in several important ways. First, we distinguish between conventional renewable energy sources (like wind or biomass) and advanced technologies (like solar), which have different costs and learning or innovation potential. In this way we can better assess the performance of overlapping policies in terms of the kinds of technological change they induce. Second, by allowing for potential long-run growth in nuclear energy, we can also evaluate nuclear power as a zero-carbon alternative alongside renewable generation.

Third, we incorporate a richer representation of electricity demand over time, including short and long-run investments in energy efficiency improvements. As a result, we can incorporate demand-side policies for improving energy or fuel efficiency. We also allow for imperfections in the demand for energy efficiency, as well as in the market for innovation. We analyze how these different imperfections affect optimal policy combinations and also the relative cost-effectiveness of single or otherwise suboptimal policies. Finally, we update the entire parameterization based on more recent data, particularly for renewable energy supplies.

The electricity sector is an appropriate subject for this analysis, being the most affected sector by proposed policies for climate mitigation. Electricity generation accounted for roughly 40 percent of CO_2 emissions in the United States in 2010 (EPA 2012). Moreover, the potential emissions reductions from this sector are much larger than its share of total emissions. One analysis of an economy-wide policy for climate mitigation concluded that well over 80 percent of cost-effective emissions abatement would stem from the electric power sector (EIA 2011a).

In our framework, a carbon price is a powerful and necessary tool, but on its own it is not fully efficient. To bring the incentives of the individual actors in line with that of society, the optimal policy portfolio requires additional tools, including: subsidies for early-stage LBD to correct for learning spillovers for each technology; an R&D subsidy equal to the R&D spillover rate for each technology; and subsidies to EE investments to offset the unvalued share of EE benefits, both in the short and long term. While conceptually valid, the empirical magnitude of such additional incentives is an important focus of this paper.

An important point to note is that we allow the market failures to vary by technology: conventional versus advanced supply technologies, and short versus long-term EE investments. When these market failures vary by technology, a “technology neutral” policy will not in principle be optimal. Thus, we can represent some of the tensions between wanting to avoid “picking winners” and wanting to target specific technologies.

We then compare a variety of plausible combinations of policy instruments to evaluate how they interact, what these interactions imply for both emissions reductions and overall welfare costs, and how these effects depend on market failures other than environmental externalities. We apply the model numerically to get an empirical sense of the relative magnitude of different policy levels and effects.

We find that while some technology policies can be useful complements to emissions pricing, ambitious renewable portfolio standards or production subsidies seem unlikely to enhance welfare when imposed alongside a sufficiently stringent carbon price. Correcting R&D market failures has a larger potential for reducing the costs of achieving significant emissions reductions. The desirability of stringent energy efficiency policies is highly sensitive to the assumed degree of undervaluation, which also has implications for the cost-effectiveness of policies (like renewable energy subsidies) that tend to lower electricity prices. Even with multiple market failures, emissions pricing remains the single most cost-effective option for meeting emissions reduction goals.

Model

The model is stylized to be as simple as possible while still being able to address the key features of multiple interacting market failures. (Parameter definitions are summarized in the Appendix.) The supply side of the model is based on FN. It includes two energy supply subsectors, one characterized by mature technologies using nonrenewable fuel sources and the other characterized by innovating technologies using renewable energy sources. Both subsectors are assumed to be perfectly competitive and supplying an identical product, kWh of electricity.[1] Nonrenewable production includes sources with different emissions intensities: a CO_2-intensive technology reliant on coal, lower-emitting technologies using natural gas, and nonemitting nuclear energy that serves primarily as baseload. To the extent that renewable energy is made more competitive, it displaces the marginal mix of nonrenewable generation.

The model has two stages: a first stage made up of n_1 years, representing the time it takes for innovation and longer-term energy efficiency (EE) improvements to occur, and a second stage of n_2 years, roughly representing the lifetime of the new technologies and investments. Electricity generation, consumption, short-term EE improvements, and emissions occur in both stages, while investment in long-term energy efficiency and in knowledge takes place during the first stage. Through technological change, knowledge investments made during the first period lower the cost of renewables generation in the second period, while long-term EE investments lower energy consumption rates. An important assumption is that both consumers and firms take not only current prices as given, but also take prices in the second stage as given, having perfect foresight about those prices.

For simplicity, we assume that no discounting occurs within the first stage; this assures that behavior within that stage remains identical. However, let δ represent the discount factor between stages. It is possible to allow for discounting within the second, longer stage by altering n_2 to reflect such discounting; in that case n_2 can be thought of as "effective" years.

Nonrenewable Sectors

We distinguish the nonrenewable sectors as mature sources of power generation that are assumed will not experience significant technological change relative to renewable sources.

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[1] Although large portions of the electricity sector remain regulated, policy-induced changes to marginal production costs are likely to be passed along to consumers, and in a longer horizon, a transition to more deregulated markets is also likely to make markets relatively competitive in the future.

These sources include coal (x), natural gas turbines (ng), and nuclear (nu).[2] Of course it is not strictly true that nonrenewable technologies will experience no further technological advance, and we do allow for some modest autonomous cost changes over time along the lines commonly forecast. Strictly speaking, the assumption is therefore the absence of an *endogenous* technology response among these sources.[3]

Most opportunities for CO_2 abatement in electricity generation arise from fuel switching; generation efficiency improvements tend to explain little of the predicted reductions in climate policy models (see, e.g., [10]). Hence, we assume that these emissions factors μ^i are fixed, where $\mu^x > \mu^{ng} > \mu^{nu} = 0$. Carbon capture and sequestration (CCS) technologies are also excluded; their use would only be triggered by a sufficiently large carbon price, which is outside the range of policies we consider in this paper. Let q_t^i be output from source i. Consequently, total emissions in year t equal $E_t = \mu^x q_t^x + \mu^{ng} q_t^{ng}$.

Each technology has an upward-sloping supply curve. In other words, marginal production costs for source i, $C'_{it}(q_t^i)$, are assumed to be increasing in output ($C_{it}''(q_t^i) > 0$). In our numerical model, we will assume these supply curves are linear in the neighborhood of the price changes considered.

Let P_t be the consumer price of electricity. Let τ_t be the price of emissions at time t, as might be implemented with an emissions tax or through a cap-and-trade system. Let ϕ_t^i represent the net tax on generation from source i, which may be explicit or implicit, as with the portfolio standard. Profits for the representative firm of nonrenewable source i are revenues net of production costs and taxes paid:

$$\pi^i = n_1\left((P_1 - \phi_1^i)q_1^i - C_{i1}(q_1^i) - \tau_1\mu^i q_1^i\right) + \delta n_2\left((P_2 - \phi_2^i)q_2^i - C_{i2}(q_2^i) - \tau_2\mu^i q_2^i\right).$$

The firm maximizes profits with respect to output from each fuel source, yielding the following first-order conditions:

[2] We are ignoring oil generation here; although the quantities are relatively small, oil generation is included explicitly in the numerical model below.

[3] Incorporation of an endogenous technology response in nonrenewables would complicate the analysis without adding substantial additional insights. An exception is room for advancement in lowering costs of cleaner generation technologies for fossil fuels, like carbon capture and storage. Our qualitative results should carry over to policies targeting other low-carbon technologies, although the quantitative results would depend on the cost, technology, and emission parameters particular to those other technologies.

$$\frac{\partial \pi^i}{\partial q_t^i} = 0: \quad P_t = C'_{it}(q_t^i) + \phi_t^i + \tau_t \mu^i .$$

Thus, each source of generation is used until its marginal costs—inclusive of their respective emissions costs—are equalized with each other and the price received. Totally differentiating, we see that

$$dq_t^i = \frac{dP_t - d\phi_t^i - d\tau_t \mu^i}{C_{it}''} . \tag{1}$$

This equation reveals that renewable energy policies crowd out each nonrenewable source in direct proportion to the changes in the net price received and in inverse proportion to the slopes of their competing supply curves. Note that an emissions price is the only policy to differentiate among emitting sources, so higher emissions prices lead to a larger reduction in more emissions-intensive sources, like coal, than policies that treat the nonrenewable sources alike.

Renewable Energy Sector

We characterize the renewable energy sector as not only being clean (nonemitting), but also as being a less mature industry that is still experiencing significant technological change. Within this sector, we make a distinction between two kinds of renewable energy technologies: a conventional technology (*w*), such as wind or biomass, and an advanced technology (*s*), like solar. We do include hydropower (*h20*) in the baseline, but assume it provides baseload capacity that does not change over time, in quantity or in cost. The focus here is on the newer renewable sources.

To represent technological change, the costs of generation for renewable sources depend on a stock of knowledge that can be increased through R&D or LBD. We assume that for $j=\{w,s\}$, these generation costs, $G_t(K_t^j, q_t^j)$, are increasing and convex in output, and declining and convex its own knowledge stock, K_t^j, so that $G_q > 0$, $G_{qq} > 0$, $G_K < 0$, and $G_{KK} > 0$, where lettered subscripts denote derivatives with respect to the subscripted variable. Furthermore, since marginal costs are declining in knowledge and the cross-partials are symmetric, $G_{qK} = G_{Kq} < 0$.

The knowledge stock $K^j(H_t^j, Q_t^j)$ is a function of cumulative knowledge from R&D, *H*, and of cumulative experience through LBD, Q_t, where $K_H \geq 0$ and $K_Q \geq 0$, and $K_{QH} = K_{HQ}$. Cumulative R&D-based knowledge increases in proportion to annual R&D knowledge generated in each stage, h_t, so $H_2 = H_1 + n_1 h_1$. Cumulative experience increases with total output during the first stage, so $Q_2 = Q_1 + n_1 q_1$. Research expenditures, $R^j(h_t^j)$, are increasing and convex in the amount of new R&D knowledge generated in any one year, with $R_h(h) > 0$ for $h > 0$, $R_h(0) = 0$, and $R_{hh} > 0$. The strictly positive marginal costs imply that real resources—specialized scarce inputs, employees, and equipment—must be expended to gain any new knowledge.[4] A subtle issue is whether research and experience are substitutes, in which case $K_{HQ} \le 0$, or complements, making $K_{HQ} > 0$.

Two price-based policies are directly targeted at renewable energy: a renewable energy production subsidy (s), and a renewables technology R&D subsidy in which the government offsets a share (σ) of research expenditures.

In our two-stage model, profits for the representative nonemitting firm are

$$\pi^j = n_1\left((P_1 + s_1^j)q_1^j - G_1^j(K_1^j, q_1^j) - (1-\sigma)R\left(h_1^j\right)\right) + \delta n_2\left((P_2 + s_2^j)q_2^j - G_2^j(K_2^j, q_2^j)\right) \tag{2}$$

where $K_2^j = K^j(H_2^j, Q_2^j)$.

Let ρ be a factor reflecting the degree of appropriability of returns from knowledge investments.[5] For example, $\rho = 1$ would reflect an extreme with perfect appropriability and no knowledge spillovers, while $\rho = 0$ reflects the opposite extreme of no private appropriability of knowledge investments. Similarly, $1-\rho$ reflects the degree of knowledge spillovers.[6]

The resulting first-order conditions are (dropping the superscripts for now):

$$R_h(h_1) = -\delta \frac{\rho}{(1-\sigma)} n_2 G_K(K_2, q_2) K_H(H_2, Q_2); \tag{3}$$

$$G_q(K_1, q_1) = P_1 + s_1 - \delta\rho n_2 G_K(K_2, q_2) K_Q(H_2, Q_2); \tag{4}$$

$$G_q(K_2, q_2) = P_2 + s_2. \tag{5}$$

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4 As a partial equilibrium model, we do not explicitly explore issues of crowding out in the general economy, but those opportunity costs may be reflected in the R&D cost function.

5 We model general knowledge as being appropriable, with no distinction according to the source of that knowledge, R&D or learning. While an empirical basis is lacking for such a distinction, one might expect that some forms of learning are less easily appropriated by other firms. We discuss the implication of relaxing this assumption in the context of the numerical simulations.

6 This representation of aggregate appropriation as a share of the total benefits of innovation was formally derived in FN. We assume that all knowledge is ultimately adopted, either by imitation or by licensing. Therefore, the spillover factor does not enter directly into the aggregate profit function, which reflects operating profits. Licensing revenues also do not appear because they represent transfers among firms. However, the spillover factor does enter into the first-order conditions for R&D and learning, since it determines the share of future profit changes that can be appropriated by the representative innovator. These issues are further elaborated in the Appendix of FN.

An important difference between the renewable and nonrenewable sectors is the response across time to policies. The nonrenewable sector behavior depends only on current period prices and policies, while renewable sector responses are linked over time through innovation incentives. In the first stage, the firm invests in research until the discounted appropriated returns from additional R&D—lower production costs in the second stage—equal investment costs on the margin (equation (3)). By influencing future costs, policies in the second stage thus influence current private innovation decisions. Similarly, in equation (4), each renewable energy source produces until the marginal cost of production equals the value it receives from additional output, including the market price, any production subsidy, and the appropriable contribution of such output to future cost reduction through learning-by-doing (note that the last term in equation (4) is positive overall). Second-stage output does not generate a learning benefit, so there is no related term in equation (5); at that point, given the costs inherited from the knowledge investments in the first period, renewable energy providers simply equate the marginal costs with the net price received. Thus, for the same price effects, the renewable energy production decisions respond differently in the two periods.

Note that if appropriation rates are imperfect ($\rho < 1$), from a societal perspective, firms have insufficient incentive to engage in extra production for the purpose of learning by doing. Similarly, if the R&D subsidy does not fully reflect the spillover values ($\sigma < 1 - \rho$), firms have insufficient incentive to invest in R&D. Thus, a knowledge externality accompanies the emissions externality, and both can be affected by policies that target one or the other.

Consumer Demand and Energy Efficiency Investments

Demand for electricity is derived from consumers' own optimization problem. Consumers experience utility $u_t(v_t)$ from energy services v_t, and they are indifferent to the generation source, be it renewable or fossil-fueled energy.[7] The quantity of energy consumed is $\psi_t v_t$, where ψ_t is the energy consumption rate per unit of energy services. The cost of energy services thus depends on both the consumer electricity price and the energy consumption rate.

The energy consumption rate (or energy intensity) is a function of reductions that can be made in both the short- and long-run by investments in EE improvements. This formulation allows us to separately consider rebound effects, factors affecting EE decisionmaking, and

[7] Note that *u* is money-metric utility to simplify the optimization problem.

behavioral responses to price changes. Specifically, we assume that in the first stage, $\psi_1 = \psi_1^0 e^{-(\theta_1^S+\theta^L)}$, where ψ_1^0 is the baseline consumption rate, and θ_1^S and θ^L are the percentage reductions in energy intensity from short and long-run investments, respectively. In the second stage, we assume that $\psi_2 = \psi_2^0 e^{-(\theta_2^S+\theta^L)}$, where ψ_2^0 reflects the second period consumption rate in the baseline, and θ_2^S results from additional investments in short-run EE improvements in the second stage. We allow baseline EE to differ, to allow for autonomous changes in EE (e.g., $\psi_2^0 = \psi_1^0 e^{-\bar{\theta}}$, where $\bar{\theta}$ represents any exogenous innovation in EE).

Costs of short-run reductions $Z_{S,t}(\theta_t^S)$ occur in both periods, while costs of long-run reduction $Z_L(\theta_t^L)$ are incurred in the first period. One might think of short-lived electronics, light bulbs, and similar equipment in the first category, while changes to buildings, infrastructure, durable equipment, and other long-lived determinants of energy demand fall in the latter. However, given the longer duration of the second stage, those "short-run" improvements may reflect a blend of both shorter and longer-run opportunities over this horizon.

We also allow for market imperfections in the demand for EE reductions. The representative agent may face incomplete information, may be myopic, or may otherwise perceive that it would not fully benefit from EE investments. Let β_t^S be the perceived short-run EE valuation rate within period *t*, β_1^L the valuation rate for EE benefits of long-run EE investments in the 1st period and β_2^L the valuation rate for those benefits that accrue in the 2nd period. "Undervaluation", or $\beta_t^i < 1$, indicates a market failure; for whatever reason, the consumer does not expect to receive the full benefits. Since information and other policies might influence these valuation rates in different stages, we retain a time period distinction between the two stages. As with the valuation rate for renewable energy innovation, these EE valuation rates reveal themselves in the first-order conditions but do not appear directly in the aggregate net utility function.

Let b_{St} be the percentage subsidy for investments in short-run EE improvements made in period *t*; let b_L be the subsidy for investments in long-run EE improvements, which are by assumption made only in period 1. Aggregate net consumer utility in the first stage of our two-stage model is then

$$\begin{aligned} U = & n_1\left(u(v_1) - P_1 v_1 \psi_1^0 e^{-(\theta_1^S+\theta^L)} - (1-b_{S1})Z_{S,1}(\theta_1^S) - (1-b_L)Z_L(\theta^L)\right) \\ & + \delta n_2\left(u(v_2) - P_2 v_2 \psi_2^0 e^{-(\theta_2^S+\theta^L)} - (1-b_{S2})Z_{S,2}(\theta_2^S)\right) \end{aligned} \tag{6}$$

The representative consumer maximizes net utility by choosing a level of energy services and rates of EE improvements in each stage (i.e., $v_1, v_2, \theta_1^S, \theta_2^S, \theta_1^L$).

In period *t*, given any energy consumption rate per unit of service (which is determined simultaneously), the representative consumer maximizes utility with respect to *v*, resulting in the first-order condition

$$u_t'(v_t) = P_t\psi_t \tag{7}$$

Let $D_t(P_t, \psi_t)$ be the derived consumer demand for electricity, a function of the price and an energy consumption rate. Because $D = \psi v$, we can rewrite the energy demand function as $D_t = \psi_t u'^{-1}\left(P_t\psi_t\right)$. We assume functional forms for utility that lead to a constant-elasticity demand function (derived in the Appendix):

$$D_t = N_t \psi_t^{1-\varepsilon} P_t^{-\varepsilon} \tag{8}$$

where $\varepsilon < 1$ represents a very-short-run elasticity of demand, and *N* is an exogenous demand growth factor. With this functional form, we find that energy expenditures, given efficiency levels, are $P_t D_t = N_t \psi_t^{1-\varepsilon} P_t^{1-\varepsilon}$, and $\partial\{P_t D_t\} / \partial P_t = (1-\varepsilon) D_t > 0$; i.e., price increases raise total expenditures.

Differentiating consumer utility with respect to short-run EE improvements, and simplifying the expression for energy payments, we obtain the following first-order conditions in each stage:

$$(1-b_{S2}) Z_{S,2}{}'(\theta_2^S) = \beta_2^S P_2 D_2 \tag{9}$$

$$(1-b_{S1}) Z_{S,1}{}'(\theta_1^S) = \beta_1^S P_1 D_1 \tag{10}$$

In other words, consumers balance the marginal net cost of improving EE with the perceived energy costs of that period.

The choice of long-run EE improvements depends on both current and future energy spending, as well as the respective EE benefit valuation rates:

$$(1-b_L) Z_L{}'(\theta^L) = \beta_1^L P_1 D_1 + \frac{n_2}{n_1} \beta_2^L \delta P_2 D_2 \tag{11}$$

Thus, policies that raise energy prices and thereby energy expenditures lead to increased investment in energy efficiency.

In equilibrium, total consumption must equal total electricity production, the sum of nonrenewable and renewable energy generation:

$$D_t = \sum_i q_t^i \,. \tag{12}$$

Change in consumer surplus is calculated as the change in net utility.

Economic Surplus

Policies also have implications for government revenues, which we denote as *V*. We assume that any changes in government revenues are compensated by (or returned in) lump-sum transfers. The amount of these transfers equals the tax revenues net of the cost of the subsidies:

$$\begin{aligned}\Delta V = {} & n_1\left(\sum_i \phi_1^i q_1^i + \tau_1 \sum_i \mu^i q_1^i - s_1^w q_1^w - s_1^s q_1^s - \sigma R(h_1) - b_{S1} Z_{S,1}(\theta_1^S) - b_L Z_L(\theta^L)\right) \\ & + \delta n_2\left(\sum_i \phi_2^i q_1^i + \tau_2 \sum_i \mu^i q_2^i - s_2^w q_2^w - s_2^s q_2^s - b_{S2} Z_{S,2}(\theta_2^S)\right)\end{aligned} \tag{13}$$

Environmental damages are a function of the annual emissions and the length of each stage; however, we will hold cumulative emissions constant across the policy scenarios, so a change in damages will not be a factor in the welfare comparisons. The change in *economic surplus* (excluding environmental benefits) due to a policy is then the sum of the changes in consumer and producer surplus and revenue transfers from the subsidy or tax:

$$\Delta W = \Delta U + \Delta \Pi + \Delta V \,, \tag{14}$$

where $\Delta \Pi = \sum_i \pi^i$.

Since consumer payments to firms and tax and subsidy payments are transfers, we can simplify the representation of economic surplus to be

$$\begin{aligned}W = {} & n_1\left(u(v_1) - Z_{S,1}(\theta_1^S) - Z_L(\theta^L) - \sum_{i=x,ng,nu} C_{i1}(q_1^i) - \sum_{j=w,s}\left(G^j(K_1^j, q_1^j) - R\left(h_1^j\right)\right)\right) \\ & + \delta n_2\left(u(v_2) - Z_{S,2}(\theta_2^S) - \sum_{i=x,ng,nu} C_{i2}(q_2^i) - \sum_{j=w,s}\left(G^j(K_2^j, q_2^j)\right)\right)\end{aligned} \tag{15}$$

Of course, economic surplus is unlikely to be the only metric for evaluating policy. Other indicators may be consumer surplus, renewable energy market share, and so on. General equilibrium factors—like interactions with tax distortions, leakage, or other market failures—can also be important for determining welfare impacts.[8] Political economy constraints may also be important for determining policy goals. To the extent that these unmodeled issues are present, this partial equilibrium presentation of economic surplus within the sector will not reflect the full social impacts; still, it represents a useful baseline metric.

Policies

Policy interventions cause the entire system to re-equilibrate. In all cases, the consumer price of electricity is an endogenous variable that signals the value to producers (and consumers), and policies can create a wedge between the consumer price and the price received by a particular kind of producer. As seen in the preceding equations, the slope of the supply curve determines the sensitivity of the quantity produced with a given technology to changes in the net price. Importantly, the effect of individual policies and combinations thereof on the consumer price—not only in magnitude but in some cases in direction—can depend on the slopes of these curves in relation to one another. For example, using a static model, Fischer (2009) explains how renewable portfolio standards may decrease or increase consumer electricity prices, depending on these factors. Lecuyer (2013) shows that when the electricity sector is already regulated with a cap-and-trade system, feed-in-tariffs necessarily lower consumer prices. The current model adds more complexity through the dynamic effects of induced technological change.

FN distinguishes between fixed-price policies and endogenous price policies. Fixed-price policies set a particular tax or subsidy rate, such as an emissions tax, a nonrenewable energy tax, or subsidies for renewable sources. Endogenous price policies are market mechanisms that rely on tradable allowances—such as emissions cap and trade, renewable portfolio standards, or low carbon fuel standards—and allow the market to set the price that reflects the cost of complying with the regulation. Imposing new policies on sectors that are already regulated under these latter schemes will only affect the market price of allowances—the new policies will not affect the

[8] Allowing for distortionary taxes in the model is likely to widen the efficiency gap between revenue-raising policies (e.g., emissions taxes) and revenue-using policies (e.g., renewable subsidies). For a comprehensive survey of the tax interaction literature, see Goulder [16].

regulatory outcome (i.e., emissions or renewable energy level), which is already set by the cap or standard.

In other words, with a binding emissions trading scheme, zero incremental emissions reduction will be realized from a supplementary renewables quota system; rather, the additional shift toward renewables will cause the emission allowance price to fall. Böhringer and Rosendahl (2010a) point out that the lower permit prices can favor the dirtiest fossil fuel technologies; while overall fossil fuel production falls as a result of the combined regulations (which lower the prices received by these producers), the dirtiest producers may actually *increase* output to keep total CO_2 emissions at the binding emissions cap.

Fischer and Preonas (2010) extend this analysis with a unified model of policy interactions. They further show that policies that impose market share mandates, by definition link renewable generation to fossil energy generation. Additional policies that raise the cost of fossil energy therefore not only lower generation from fossil sources, they also reduce renewable generation by relaxing the portfolio constraint. (See also Amundsen and Mortensen 2001). Moreover, under a portfolio standard, additional policies that support renewable energy (like production subsidies) also may induce fossil sources to expand alongside them to maintain the mandated market shares, resulting in higher emissions. These are a few examples of the unintended consequences of combining policies with tradable quota mechanisms.

If the emissions pricing system is otherwise efficient—that is, in the absence of other market failures—then supplementary policies for renewable energy are unnecessary and actually raise total compliance costs, even though emissions prices are lower. Fischer and Preonas (2010) review several articles making this argument. If an emissions cap (or sufficient carbon tax) is politically infeasible, then clean energy policies may be deemed a second-best alternative for reducing emissions. However, under an aggregate emissions constraint, they lose this effect, so the rationale for supplemental support for clean technologies must be to address other market failures. In this paper, we address two important market failures frequently raised regarding clean technologies: knowledge spillovers, and undervaluation of the benefits of EE investments.

Optimal policies

In the presence of multiple market failures, a carbon price is a powerful and necessary tool, but on its own full efficiency is not achieved. Additional tools are necessary to bring the first-order conditions of the individual actors in line with that of the social optimum. The optimal policy portfolio would include multiple instruments:

1. A carbon price to address the environmental externality, rising according to the discount factor ($\tau_1 = \delta\tau_2$).

2. Subsidies for early-stage LBD in the first stage to correct for learning spillovers for each technology ($s_1^j = -\delta(1-\rho)n_2 G_K^j(K_2^j, q_2^j)K_Q^j(H_2^j, Q_2^j)$).

3. An R&D subsidy equal to the R&D spillover rate ($\sigma = 1-\rho$).

4. Subsidies to EE investments to offset the unvalued share of EE benefits, both in the short and long term: $b_{St} = 1-\beta_t^S, b_L = 1-\beta^L$.

An important point to note is that we allow the market failures to vary by technology: mature versus advanced supply technologies, and short versus long-term EE investments. If these market failures do vary, a "technology neutral" policy will not be efficient.

Formally, the welfare implications of additional policy-induced changes can be derived by totally differentiating the social welfare function and using the decentralized first-order conditions that must hold in equilibrium, as well as the fact that total changes in consumption equal total production changes. We derive these expressions in the Appendix. Taking a carbon price alone as a starting point (with $\tau_1 = \delta\tau_2$), we consider the effects of a policy variation that includes an additional intervention, *X*, where $X \in \{s_t, b_{jt}, \sigma, \phi_{jt}\}$ is some combination of the tax and subsidy options. We look at deviations in which total emissions are held constant with the policy variation (i.e., by the carbon price adjusting in response to other policy changes). As a result, we can express the potential benefits and costs of additional intervention:

$$
\begin{aligned}
&\frac{dW}{dX} = \\
&\left.\begin{aligned}
&n_1 P_1 D_1 \left(\frac{(1-\beta_1^S)-b_{S1}}{(1-b_{S1})} \frac{d\theta_1^S}{dX} + \frac{(1-\beta_1^L)-b_L}{(1-b_L)} \frac{d\theta^L}{dX} \right) \\
&+\delta n_2 P_2 D_2 \left(\frac{(1-\beta_2^L)-b_L}{(1-b_L)} \frac{d\theta^L}{dX} + \frac{(1-\beta_2^S)-b_{S2}}{(1-b_{S2})} \frac{d\theta_2^S}{dX} \right)
\end{aligned}\right\} \text{Value of EE changes} \\
&\left. +n_1 \left(\sum_{j=w,s} -\delta n_2 G_K^j(K_2^j, q_2^j)(1-\rho) K_{Q_2} - s_1^j \right) \frac{dq_1^j}{dX} \right\} \text{Value of LBD changes} \qquad (16) \\
&\left. +\delta n_1 n_2 \sum_{j=w,s} -G_K^j(K_2^j, q_2^j) K_{H_2} \left(\frac{(1-\rho)-\sigma}{(1-\sigma)} \right) \frac{dh_1^j}{dX} \right\} \text{Value of R\&D changes} \\
&\left. +n_1 \sum_{i=x,ng,nu} \phi_1^i \frac{dq_1^i}{dX} + \delta n_2 \sum_{i=x,ng,nu} \phi_2^i \frac{dq_2^i}{dX} - \delta n_2 \sum_{j=w,s} s_2^j \frac{dq_2^j}{dX} \right\} \text{Other cost changes}
\end{aligned}
$$

The first four lines represent the marginal benefits versus the policy expenditures for a change in energy efficiency, production, and knowledge ($d\theta_t^i, dq_t^j, dh_1^j$). For a positive change in the variable, the net marginal benefits are positive to the extent that the corresponding market failures are insufficiently internalized. For example, an intervention that increases EE investment raises welfare on the margin to the extent that the EE subsidy is smaller than the undervaluation rate. Similarly, an intervention that increases first-stage renewable energy production raises welfare if the subsidy is less than the spillover benefits.

The last line represents the costs: additional fossil taxes that reduce fossil generation lower surplus (since the climate externality is internalized by the emissions price), as do additional renewable subsidies that increase renewable generation in the second period (when there is no learning externality).

Note that if we substitute in the optimal policies listed above, we have $dW = 0$, and economic surplus cannot be increased with additional policy deviations. However, if the additional market failures are not fully corrected by the relevant subsidies, increases in energy efficiency, LBD, or R&D that result from intervention X have additional value on the margin. On the other hand, if a subsidy overcorrects for an externality, a further increase in that variable generates a welfare loss. These components of Equation (16) form the essence of the intuition underpinning our numerical results.

Numerical Application

Functional Forms

Electricity Generation and Knowledge

The functional forms for generation and knowledge follow those of FN unless otherwise noted. All production cost functions are quadratic in output, yielding linear electricity supply curves for each fuel source. For nonrenewable sources of electricity generation, the costs all take the form $C_{it}(q_t^i) = c_{0t}^i + c_{1t}^i \cdot (q_t^i - q_{0t}^i) + c_{2t}^i \cdot (q_t^i - q_{0t}^i)^2 / 2$, where q_{0t}^i is the baseline (no policy) output in stage *t* for source *i*. Furthermore, from the first-order conditions for the baseline, the marginal cost of generation is $c_{1t}^i = P_{t,base}$. Total baseline cost, c_{0t}^i, does not affect nonrenewable energy decisions; we assume in effect zero profits in the baseline ($c_{0t}^i = P_{t,base} q_{t,base}$), to focus only on the changes in profits induced by policy.

For renewables generation (j={w,s}), the cost function is inversely related to the knowledge stock: $G_{jt}\left(K_t^j, q_t^j\right) = \left(g_{0t}^j + g_{1t}^j \cdot (q_t^j - q_{t,base}^j) + g_{2t}^j \cdot (q_t^j - q_{t,base}^j)^2 / 2\right)\left(K_{t,base}^j / K_t^j\right)$, so that technological change lowers both the intercept and slope of the renewables supply curve. Since total baseline costs indicate the potential scope for cost reductions, we err on the high side (an optimistic assumption for optimal renewable generation subsidies) and normalize $g_{0,t}^j$ so that baseline profits for renewable generation are zero. This parameter will be varied later in sensitivity analysis.

The knowledge stock assumes a commonly used functional form expressing a constant elasticity relationship with respect to both the stock of experience and the stock of R&D: $K_t\left(Q_t, H_t\right) = \left(\frac{Q_t}{Q_1}\right)^{k_1}\left(\frac{H_t}{H_1}\right)^{k_2}$, implying that $K_1 = 1$. First period R&D knowledge stock is normalized to $H_1 = 1$. From the first-order conditions, with these functional forms, the baseline marginal cost is $g_{1,t}^j = P_{1,base} + k_1 \delta \rho n_2 g_{0,2}^j / Q_{2,base}^j$.

R&D investment is also modeled as a constant elasticity function: $R\left(h_1\right) = \gamma_0 h_1^{\gamma_1}$, with increasing marginal costs assuming $\gamma_1 > 1$.

Energy Efficiency

Details of our energy efficiency parameterization are in the Appendix. We assume a utility function that leads to constant elasticity of demand: $D_t = N_t \psi_t^{1-\varepsilon} P_t^{-\varepsilon}$, where $0 < \varepsilon < 1$. The elasticity ε can be interpreted as a very short run elasticity, as might be reflected in the rebound effect (i.e., the rebound effect reflects the change in energy services, such as lumens, with respect to the change in the cost of those services). The full short-run elasticity of demand for electricity will also include short-run responses in the energy intensity of those services.

We assume linear marginal cost of EE improvements around the baseline, so for each type of improvement *j*, costs are a quadratic function $Z_j(\theta_t^j) = z_1{}^j \theta_t^j + z_2{}^j \cdot (\theta_t^j)^2 / 2$, with marginal costs $Z_j{}'(\theta_t^j) = z_1{}^j + z_2{}^j \cdot (\theta_t^j)$ and slope $Z_j{}''(\theta_t^j) = z_2^j$.

In the baseline $\theta_2^S = 0$, so from the first-order condition, we get $z_1^S = \beta_t^S P_t^0 D_t^0$ and $z_1^L = \beta_1^L P_1^0 q_1^0 + \frac{n_2}{n_1} \beta_2^L \delta P_2^0 q_2^0$. In other words, the intercepts of the marginal cost functions are determined in part by our assumptions regarding the perceived valuation factor for each type of EE improvement.

To calibrate the slopes of the marginal costs of EE improvements, we derive the implicit short, medium and long-run elasticities of electricity demand. To do so, we solve for energy efficiency investments from the first-order conditions, evaluated with no additional policy measures (i.e., in the absence of subsidies). Next, we totally differentiate the demand function (since changes in energy efficiency depend on quantities as well as prices in each period), evaluated at the baseline. Solving for the equilibrium quantity changes due to a price change, this gives us a system of four equations (own and cross-price elasticities for each period). Setting these expressions equal to our target elasticities, we solve for our calibrated values of $z_2^{S_1}, z_2^{S_2}, z_2^L$ and the relationship that must hold between β_1^L and β_2^L. See the Appendix for more detail.

Parameterization

We have closely followed FN in parameterizing this model. Certain parameters have been updated and disaggregated, especially those based on EIA NEMS model projections or relating to generation from natural gas, renewables, and nuclear. Additions to the demand side of the model have introduced several new parameters relating to the demand elasticity and energy efficiency investments.

The slope parameters for each generation source (c_{it}, g_{it2}) are calibrated to the EIA Annual Energy Outlook (AEO) 2013. By comparing net prices and generation levels in the AEO side cases “No GHG Concern” and “GHG Policy Economy-wide,” we derived these implicit supply parameters for each source in each time period. Baseline generation levels (q_{it}^0) and emissions intensities (μ^i) are likewise calibrated to NEMS model projections, namely the AEO 2013 Reference case. As in the above model, we classify non-hydro renewables into two categories: solar (*s*) and wind/other more mature renewables (*w*) (includes wind, biomass, municipal solid waste, and geothermal) (IEA 2010a, 134). We also set our baseline electricity price at 9.3 cent/kWh based on AEO 2013, with all monetary values adjusted to 2011 dollars. The remaining renewables cost parameters (g_{it1}) are solved for in the baseline scenario. Nuclear generation in the first stage is fixed at baseline levels, reflecting the long lead time in bringing new nuclear facilities online. For simplicity, we also fix oil and hydro generation in both periods.

To parameterize separate knowledge functions for wind/other and solar, we consider both their respective knowledge stocks and the relative impacts of research or learning-by-doing to reduce costs going forward. It is very difficult to estimate cumulative public and private R&D expenditures. However, cumulative historic U.S. federal research spending on solar technologies appears close to combined spending on other renewable technologies (Schilling and Esmundo 2009). Hence, we normalize the first-period R&D knowledge stock for both wind/other and solar, so that $H_1^w = H_1^s = 1$. We set $Q_1^w = 2.2 \times 10^{12}$ and $Q_1^s = 9.5 \times 10^{10}$ so that annual wind and solar generation represent, respectively, about 11 percent and 33 percent contributions to their stock of experience. These estimates are consistent with the current contribution of wind/other and solar to cumulative U.S. generation of each technology (EIA 2010).[9]

Distinguishing k_1^j and k_2^j by renewable technology allows us to consider their relative responses to learning-by-doing and R&D knowledge. Several studies[10] have compared learning rates for established renewables (wind) and developing technologies (solar), but they typically do not separate knowledge into learning and research components.[11] We use technological learning assumptions from both EIA (2013b) and IEA (2009; 2010b) to estimate $k_1^w = 0.10$ and $k_1^s = 0.30$.[12] In other words, a doubling of cumulative production leads to a 7 percent cost reduction for wind/other and a 19 percent cost reduction for solar. Using these values, we calibrated k_2^j

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[9] Using EIA(2010) and EIA (2013a), we calculate that cumulative historic/projected generation (thru 2014) of the mature renewable technologies in our "wind" category (i.e., wind, biomass, geothermal, and municipal solid waste) is approximately 9 times greater than AEO's projected 2015 generation for those technologies. Likewise, cumulative solar generation (i.e., photovoltaics and solar thermal) is approximately 3 times greater than 2015 projected solar generation.

[10] See Lindman and Söderholm (2012) for a meta-analysis, and also Jamasb (2007).

[11] One exception is Kobos et al. (2006), which empirically derives two-factor learning curves for wind and solar. However, their results across several scenarios are inconclusive on whether R&D or learning-by-doing has a stronger effect on either technology.

[12] For wind, EIA (2013b, 104) assumes $k_1^w = 0.01$, while IEA (2009, 17) assumes $k_1^w = 0.10$. For solar, EIA (2013b, 104) assumes $0.15 < k_1^s < 0.32$, while IEA (2010b, 18) assumes $k_1^s = 0.29$.

such that total baseline renewables cost reduction was in line with EIA NEMS projected total technological improvement, giving us $k_2^w = 0.15$ and $k_2^s = 0.20$ (EIA 2013, 104). As in FN, we specify the R&D investment functions by setting $\gamma_1^w = \gamma_1^s = 1.2$.[13] We assume that annual baseline R&D expenditures represent about 2.5 percent of wind/other and 3.0 percent of solar revenues,[14] and solve for each γ_0^j in the baseline scenario. We also retain FN's assumed knowledge appropriability rate for both wind/other and solar of $\rho = 0.5$ in the central scenarios.[15]

An extensive empirical literature has estimated the price elasticity of electricity demand. We assume a very short-run demand elasticity of $\varepsilon = 0.10$, based on several studies of the rebound effect in household electricity consumption.[16] Other demand elasticities for electricity are based on this estimate, with η_{11}=0.2, η_{22}=0.4, and η_{21}=0.05, representing roughly short term, long term, and cross period demand elasticities. For a permanent 10 percent change in the electricity price (i.e., across both periods), the implicit elasticity of demand in the 1st stage is 0.30.

We set exogenous demand growth at 13 percent, based on AEO 2011 projected electricity generation, annualized across each stage; these demand scalars include exogenous trends in energy efficiency. We assume a first stage length of n_1 = 5 years, starting in 2015, and a second stage length of 21 years, matching AEO projections out to 2040. Because we discount the second stage back to the present at a rate of 7 percent, this implies a discount factor $\delta = 0.71$ and a second stage with the effective length of n_2 = 11.6.

Table 1 shows the parameters associated with electricity generation cost functions and energy efficiency investment functions (derived using the equations in the Appendix). Table 2 lists the other parameters that do not vary over time, including CO_2 emissions intensity, R&D investment, knowledge appropriation rates, and target demand elasticities. As the model does not

[13] For example, Jaffe (1986) finds an elasticity of patents with respect to R&D of over 0.8 in his preferred specification; Bottazzi and Peri (2003) cite a relationship of similar magnitude. Our model uses the inverse of this elasticity for the comparable knowledge production to R&D elasticity (1/0.8=1.2).

[14] The average R&D intensity of U.S. industry lies in this range (NSF 2006). Limited information is available on current private U.S. renewables R&D spending.

[15] This estimate comes from economy-wide studies such as Griliches (1992) and Jones and Williams (1998); emerging work from Dechelpretre et al. (2013) indicates that spillovers may be higher for clean technologies.

[16] See Kamerschen and Porter (2004), U.S. EPA (2005), and Sorrel et al. (2009).

permit an analytical solution, we numerically solve the nonlinear system of equations using Newton's method.

Table 1. Supply and Demand Parameters by Stage[17]

	Stage 1	*Stage 2*
Slope of coal electricity supply ($c_{2\,x,t}$) ($/kWh^2)	1.5×10^{-15}	1.0×10^{-14}
Slope of natural gas electricity supply ($c_{2\,ng,t}$) ($/kWh^2)	4.0×10^{-14}	1.1×10^{-13}
Slope of nuclear electricity supply, stage 2 (c_{nu2}) ($/kWh^2)	—	2.1×10^{-13}
Slope of wind/other electricity supply (g_{2wt}) ($/kWh^2)	2.1×10^{-13}	1.0×10^{-13}
Slope of solar electricity supply (g_{2st}) ($/kWh^2)	1.7×10^{-12}	4.6×10^{-13}
Intercept of short-run energy efficiency investment cost supply (z_{St1}) ($)	3.6×10^{11}	4.2×10^{11}
Slope of short-run energy efficiency investment cost supply (z_{St2}) ($/%)	7.7×10^{12}	1.2×10^{12}
Intercept of long-run energy efficiency investment cost supply (z_{L1}) ($)	1.1×10^{12}	—
Slope of long-run energy efficiency investment cost supply (z_{L2}) ($/%)	3.4×10^{12}	—
Exogenous demand growth	–	13%

[17] The six parameters related to energy efficiency are derived given an assumption about the appropriation rate; these assume a base case where beta = 0.9.

Table 2. Other Baseline Parameters

	Base value
CO_2 intensity of coal electricity (μ^x) (tons CO_2/kWh)	9.8×10^{-4}
CO_2 intensity of oil electricity (μ^{oil}) (tons CO_2/kWh)	8.8×10^{-4}
CO_2 intensity of natural gas electricity (μ^{ng}) (tons CO_2/kWh)	4.0×10^{-4}
Learning parameter for wind/other (k_1^w)	0.10
R&D parameter for wind/other (k_2^w)	0.15
Learning parameter for solar (k_1^s)	0.30
R&D parameter for solar (k_2^s)	0.20
Wind/other R&D cost parameter (γ_0^w)	2.9×10^{10}
Wind/other R&D cost parameter (γ_1^w)	1.2
Solar R&D cost parameter (γ_0^s)	6.3×10^9
Solar R&D cost parameter (γ_1^s)	1.2
Degree of knowledge appropriability (ρ)	0.5
Very short-run demand elasticity (ε)	0.10
Short-run demand elasticity (η_{11})	0.20
Long-run demand elasticity (η_{22})	0.40
Cross-period demand elasticity (η_{12})	0.05

Results

Baseline

The baseline results are reported in Table 3 and represent the no-policy scenario. Of note is the relatively small share of non-hydro renewable energy in the baseline (7 percent in the first stage and 9 percent in the second), nearly all in the form of mature non-hydro renewables, such as wind, biomass, and geothermal. Solar remains a fraction of a percent of generation. Significant renewable energy cost reductions occur in the baseline, with wind/other costs falling 7 percent and solar costs falling 29 percent.

An important point is that market behavior in the model is independent of the assumptions about the perceived energy efficiency benefit valuation rates (β_{jt}). Essentially, the model is calibrated to observations or projections of market outcomes, being agnostic about the underlying drivers in demand for energy efficiency. These parameters, however, are important for calculating the welfare costs of policy interventions.

Table 3. Baseline Results with No Policy

	Stage 1		*Stage 2*	
Price of electricity (P_t) (¢/kWh)	9.3		9.8	
Electricity demand (D_t) (kWh/yr)	4.26×10^{12}		4.78×10^{12}	
Coal generation (q_t^x) (kWh/yr, % of generation)	1.59×10^{12},	37.3%	1.76×10^{12},	36.8%
Oil generation (q_t^{oil}) (kWh/yr, % of generation)	1.82×10^{10},	0.4%	1.78×10^{10},	0.4%
Natural gas generation (q_t^{ng}) (kWh/yr, % of generation)	1.19×10^{12},	27.9%	1.38×10^{12},	28.9%
Nuclear generation (q_t^{nu}) (kWh/yr, % of generation)	8.56×10^{11},	20.1%	8.95×10^{11},	18.7%
Hydro generation (q_t^{h2o}) (kWh/yr, % of generation)	3.09×10^{11},	7.3%	3.15×10^{11},	6.6%
Wind/other generation (q_t^w) (kWh/yr, % of generation)[18]	2.64×10^{11},	6.2%	3.58×10^{11},	7.5%
Solar generation (q_t^s) (kWh/yr, % of generation)	3.53×10^{10},	0.8%	5.37×10^{10},	1.1%
CO_2 emissions (E_t) (billion metric tons CO_2/year)	2.05		2.30	
Rate of wind/other cost reduction (%)	7%		—	
Rate of solar cost reduction (%)	29%		—	

Emissions Price and Optimal Policy Combinations

In all subsequent comparisons, we require each policy (or combination thereof) to meet the same cumulative emissions target, which is 40 percent below baseline emissions. Although this target is more stringent than most pledges for economy-wide emissions reduction over the time horizon, for this single-sector model, it reflects the disproportionate opportunities for emissions reductions in electricity generation. The policy scenario results will be reported in relation to the baseline values; welfare consequences will be reported relative to the benchmark policy of an emissions price without supplementary policies.

Table 4 compares the effects of an emissions price program to optimal policy combinations, depending on the EE benefit valuation rates. Again, under the emissions price alone, market behavior is independent of these valuation rates, but the welfare costs of the policy are smaller in the presence of an EE market failure. The additional investments in EE induced by higher electricity prices confer additional benefits when these improvements are undervalued.

The cumulative emissions target implies that the emissions price will rise over time, from \$14 per ton CO_2 in stage 1 to \$35 in stage 2 in the single-policy case. With only innovation market failures (i.e., no EE undervaluation), the optimal policy combination still involves similar emissions prices in the two stages (\$12 and \$30, respectively). To internalize the innovation

[18] This includes all non-solar, non-hydro renewable generation.

spillovers, these prices would be combined with a substantial 50 percent R&D subsidy. The optimal first-stage subsidy for learning is a modest 0.7 cents/kWh for wind/other, but a more substantial 4.9 cents/kWh for solar. Altogether, the optimal combination of policies lowers costs 16 percent relative to the cap alone, again assuming no EE market imperfections.

Table 4. Emissions Price Alone versus Optimal Policy Combinations

Policy	**Emissions price alone**		**Optimal policy combination**	
	No EE failures $\beta = 1$	10% EE undervaluation $\beta = 0.9$	No EE failures $\beta = 1$	10% EE undervaluation $\beta = 0.9$
Emissions reduction target	40%		40%	40%
Emissions price, stage 1 (τ_1) (\$/ton CO_2)	13.67		11.64	9.89
Emissions price, stage 2 (τ_2) (\$/ton CO_2)	34.73		29.58	25.12
Learning subsidy (wind/other) 1 (¢/kWh)			0.70	0.64
Learning subsidy (solar) 1 (¢/kWh)			4.93	4.54
R&D subsidy (wind/other)			50%	50%
R&D subsidy (solar)			50%	50%
EE subsidy, stage 1 (b_{S1}, b_{L1})			0%	10%
EE subsidy, stage 2 (b_{S2}, b_{L1})			0%	10%
Electricity price, stage 1 (% change from baseline)	13.6%		11.5%	9.6%
Electricity price, stage 2 (% change from baseline)	23.8%		18.7%	14.5%
% Non-hydro renewables, stage 1	9.8%		10.9%	10.6%
% Non-hydro renewables, stage 2	19.8%		22.1%	20.5%
% EE improvement, stage 1[19]	3.9%		3.2%	5.3%
% EE improvement, stage 2	8.1%		6.5%	10.0%
Δ Welfare (billion \$, annualized)	-10.12	-6.99	-8.50	-5.27
%W improvement (from emissions price alone)	–		16%	25%

In the presence of market failures in demand for EE improvements—we model a 10 percent undervaluation—the optimal policy mix changes more substantially. The inclusion of EE subsidies induces more demand-side conservation, allowing for lower emissions prices (over 25 percent lower than with an emissions price alone) to achieve the same emissions target. The optimal subsidies for learning among renewable energy sources also fall. Relative to an emissions price alone, the optimal combination of policies lowers costs by 25 percent.

[19] This is the percent reduction in the energy consumption rate, relative to the baseline.

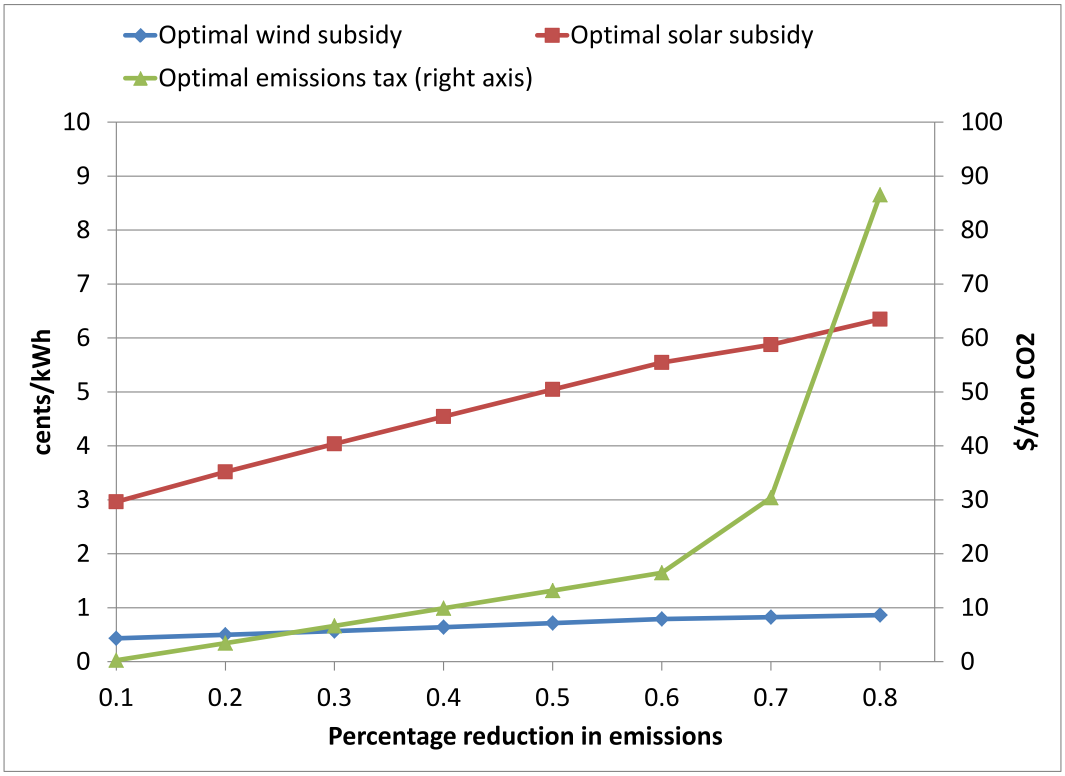
Sensitivity of Optimal Policies to Assumptions

A striking result from these results is that the optimal renewable energy subsidies are relatively low, especially for the non-solar technologies that represent the majority of renewables generation. It would appear that the 2.3 cent/kWh Federal Renewable Electricity Production Tax Credit (PTC) may be overly generous for wind/other energy, at least in combination with the other policies. Feed-in tariffs among many European countries far exceed these levels of support. The comparison with current U.S. policy is more difficult for solar, which is supported at the federal level by a 30 percent investment tax credit, although the per-kWh equivalent value of current U.S. solar incentives appears to be well-above the optimal levels identified here in combination with emissions and R&D policies. How sensitive are these results to our model assumptions?

Let us call the previously described parameterization the "reference" scenario. Note that as we vary certain parameters, we continue to calibrate the model to replicate the same baseline prices and generation quantities. We next consider the influence of different assumptions on the levels of the optimal subsidies for learning, as well as on the distribution of the optimal technology policy portfolio. That is, what should be the relative scale of public spending on learning and R&D, as compared to each other and to total private revenues?

Stringency of emissions target. First, we consider a wider range of targets for emissions reductions. Indeed, much of the motivation for ambitious alternative energy policies in EU countries is in preparation for a transition to a dramatically lower-carbon energy system. In our model, we find that a more stringent target does increase the optimal renewable subsidies; at an 80 percent reduction goal renewable subsidies are more than double those of the 20 percent target, but those levels are still less than 1 cent/kWh for non-solar renewables. Meanwhile, the optimal emissions price increases by an order of magnitude, indicating that it becomes relatively more important as a policy instrument (Figure 1).

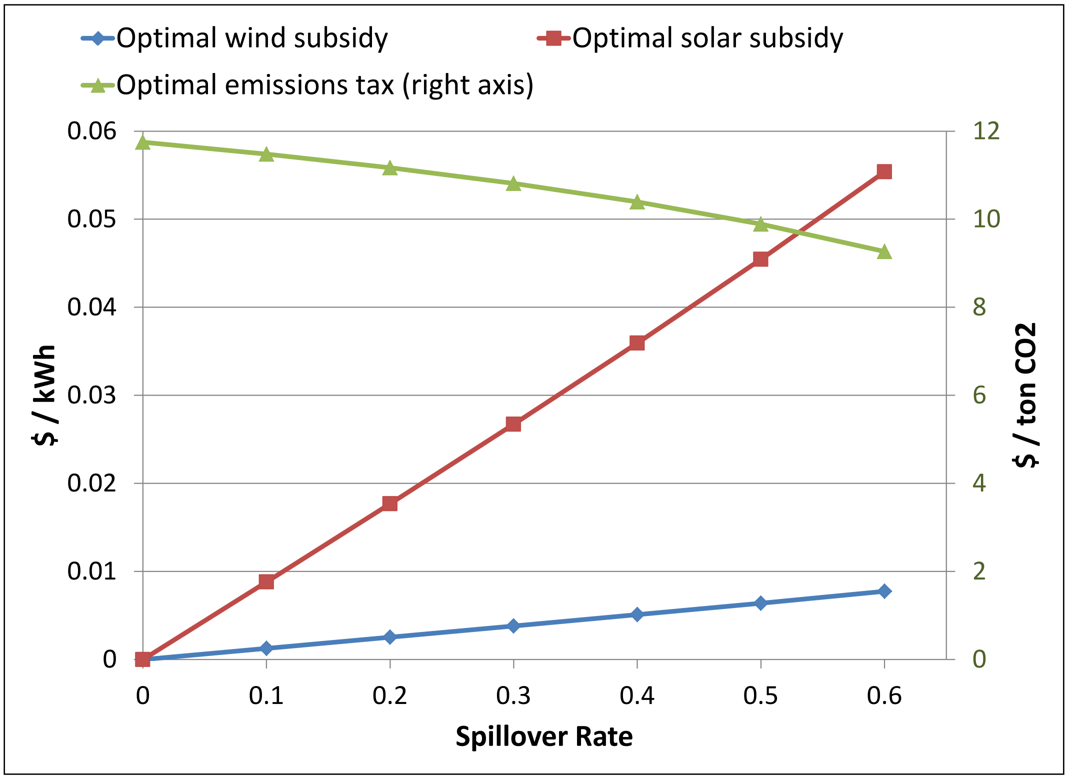
Figure 1. Sensitivity of Optimal First-Stage Policies to Emissions Target $(\beta = .9)$



Degree of knowledge spillovers. Next, we consider the role of our market failure parameters. As modeled, the optimal R&D subsidy increases one-for-one with the spillover rate. In Figure 2, we see that the optimal renewable subsidy (for learning) also rises proportionally with the spillover rate, with a steeper relationship for solar energy than for wind/other. Still, extrapolating to even higher spillover rates,[20] the optimal subsidy for solar energy remains under 10 cents/kWh. As larger knowledge market failures are internalized, driving larger increases renewable energy provision, the emissions price needed to meet the target falls (shown on the right axis).

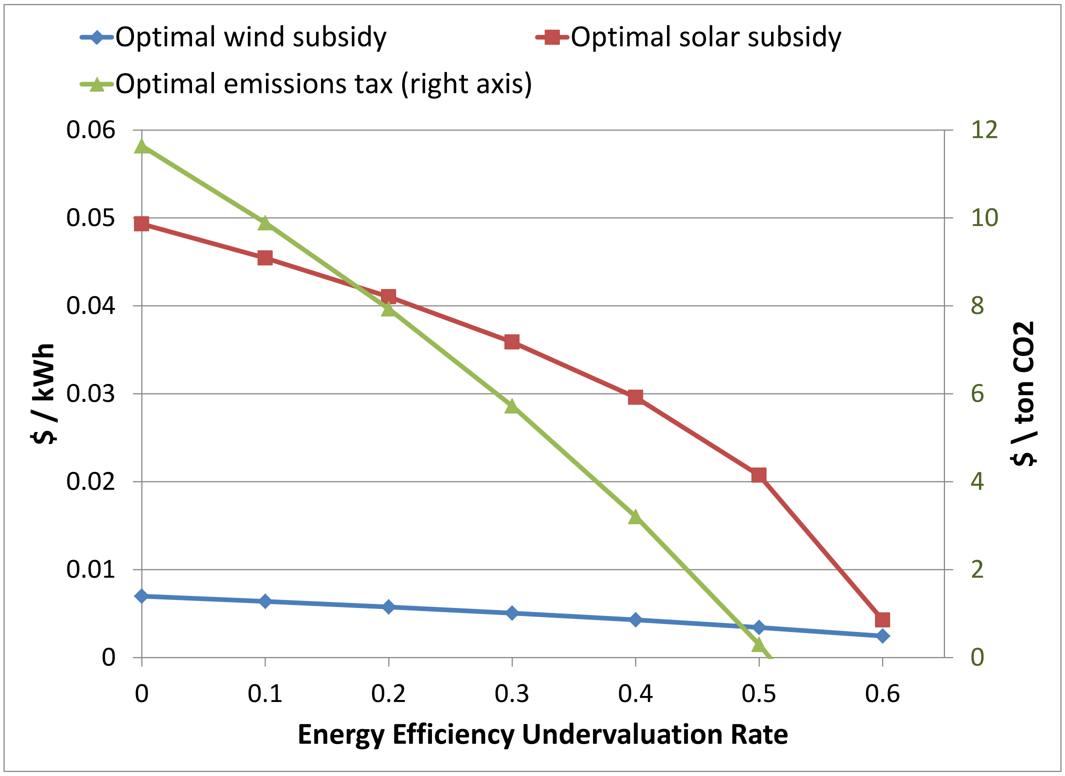
[20] Baseline R&D behavior becomes unreasonable at very high spillover rates, so we limit the range of exploration.

Figure 2. Sensitivity of Optimal First-Stage Policies to Knowledge Spillovers



Degree of EE undervaluation. Energy efficiency demand failures have the opposite effect on learning subsidies. As energy efficiency subsidies increase to combat greater undervaluation, less renewable energy is needed. As a consequence, both learning subsidies and the emissions price fall, and rather steeply at larger values of undervaluation (Figure 3). Of course, these are optimal combinations, and it may be more difficult in practice to counteract demand-side market failures. Nonetheless, in the case of uninternalized energy efficiency failures, optimal learning subsidies also fall. By driving down electricity prices, renewable subsidies exacerbate the pre-existing EE market failure. Thus, in either situation, greater concern about energy demand-side failures tends to undermine the case for more generous subsidies for learning through renewable energy subsidies.

Figure 3. Sensitivity of Optimal Policies to Energy Efficiency Undervaluation



Specification of knowledge accumulation. Other important assumptions regard the knowledge parameters and the opportunities for cost reductions. In our reference scenario, even with identical spillover rates for R&D and LBD, at least 80 percent of the welfare benefits of internalizing knowledge externalities come from the R&D subsidy. The reason lies in the assumed relative cost of achieving additional generation cost reductions through R&D versus LBD. For LBD, that cost is rising with the first-stage production cost curve, which is quite steep, particularly relative to the R&D investment cost curve. Although our parameters are drawn from available data, empirical evidence, and modeling practice, the true values for these specific sectors are far from certain. Thus, we construct several additional scenarios to test their relevance. Among other things, we will compute the ratio of total spending on LBD and R&D subsidies, relative to total revenues in the wind/other and solar sectors. In all scenarios, we assume there is no undervaluation of energy efficiency, to focus on the knowledge market failures.

The first two alternate scenarios are variations on the potential for cost reductions. First, we assume that the period for knowledge application is much longer, and extend the second stage to 100 years, before discounting ("Long stage 2"). With discounting, the effective length of the second stage increases by a third, and the benefits to knowledge spending increase accordingly, though in somewhat greater proportion for wind/other than for solar, due to the larger market share for wind/other.

Second, we recognize that we may have overestimated the total cost reduction potential of second-stage generation because we assumed it applied to total generation including previously installed capacity. In reality, innovation may not bring down the supply costs for capacity already installed in the first stage, but rather only for capacity added in the second stage. If we suppose instead that total second-stage costs equal the area under the supply curve for capacity built after the first stage ("Lowers incremental capacity costs"), we find that optimal learning subsidies fall roughly 20 percent for wind/other and 5 percent for solar.[21]

The next set of variations regard the knowledge production and cost functions. The third alternative scenario ("LBD more important") uses specifications that increase the spillovers from learning to 80 percent (while holding R&D spillovers at 50 percent), increase the cost reductions from learning ($k_1^w = 0.3, k_1^s = 0.4$), and increase the slope of R&D investment costs ($\gamma_1 = 2$). In this case, the LBD subsidy contributes roughly three quarters of the welfare gains from internalizing the knowledge externality, compared to less than 20 percent in the baseline scenario.[22] In this case, the optimal learning subsidy reaches 3 cents/kWh for wind/other and nearly 9 cents/kWh for solar. Meanwhile, of total public spending on renewable energy subsidies, the portion going to deployment as opposed to R&D rises from 35 percent in the reference scenario to 87 percent for wind/other, and from 65 percent to 91 percent for solar.

However, our reference parameters may have been more likely to err on the side of overestimating the contribution of learning to cost reductions, as few studies have attempted to separate the effects of deployment from R&D. The fourth ("Low LBD") scenario assumes learning is less productive ($k_1^w = 0.01, k_1^s = 0.1$), making R&D relatively more important (though not increasing k_2^w, k_2^s). This swings the optimal R&D share of total public spending to 95 percent for wind/other and just over 50 percent for solar.

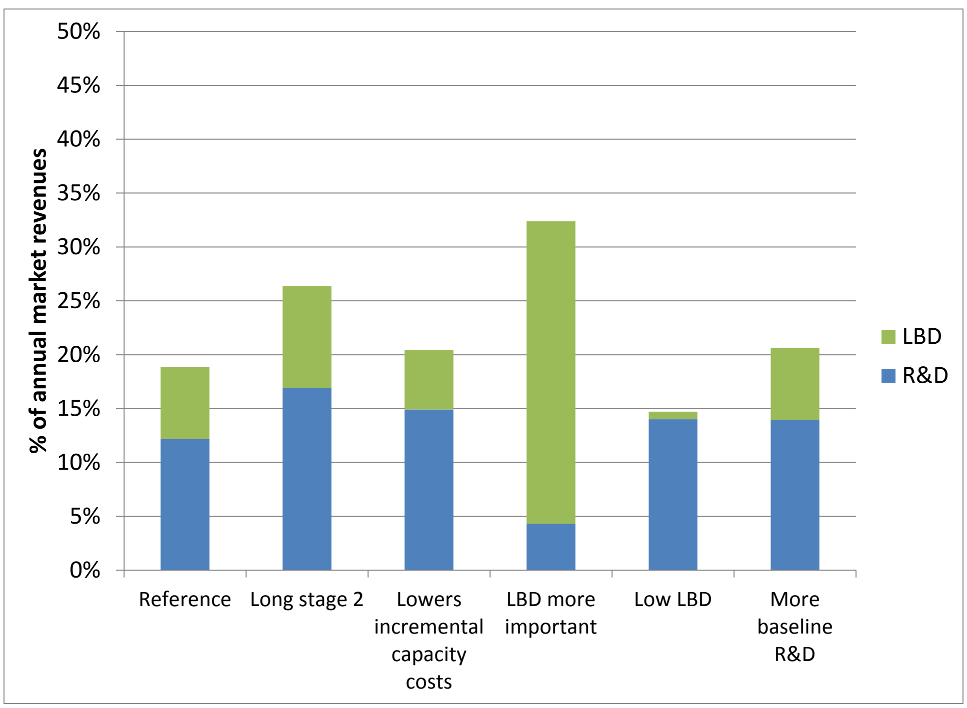
[21] The effects on the optimal subsidies are much smaller than the changes in second period costs (75% and 50% lower for wind and solar, respectively), because the innovation parameters must be recalibrated to explain the projected R&D and learning in the no-policy baseline.

[22] Note that equilibrium cost reductions in the baseline are fixed by our calibration.

Finally, lacking reasonable data on private R&D spending for renewable energy, we consider a scenario with significantly higher baseline investment, particularly for solar ("More baseline R&D"). Specifically, we assume baseline R&D expenditures are 5 percent for Wind/Other (double the reference case) and 15 percent for solar (five times the reference case).[23] The cost parameters adjust to make this spending justified in the baseline, maintaining the same degree of cost reductions. The result is more public spending on R&D in the optimum, but far less than in proportion to the baseline increase (15 percent more for wind/other and 25 percent more for solar), and only a slight complementary enhancement to LBD.

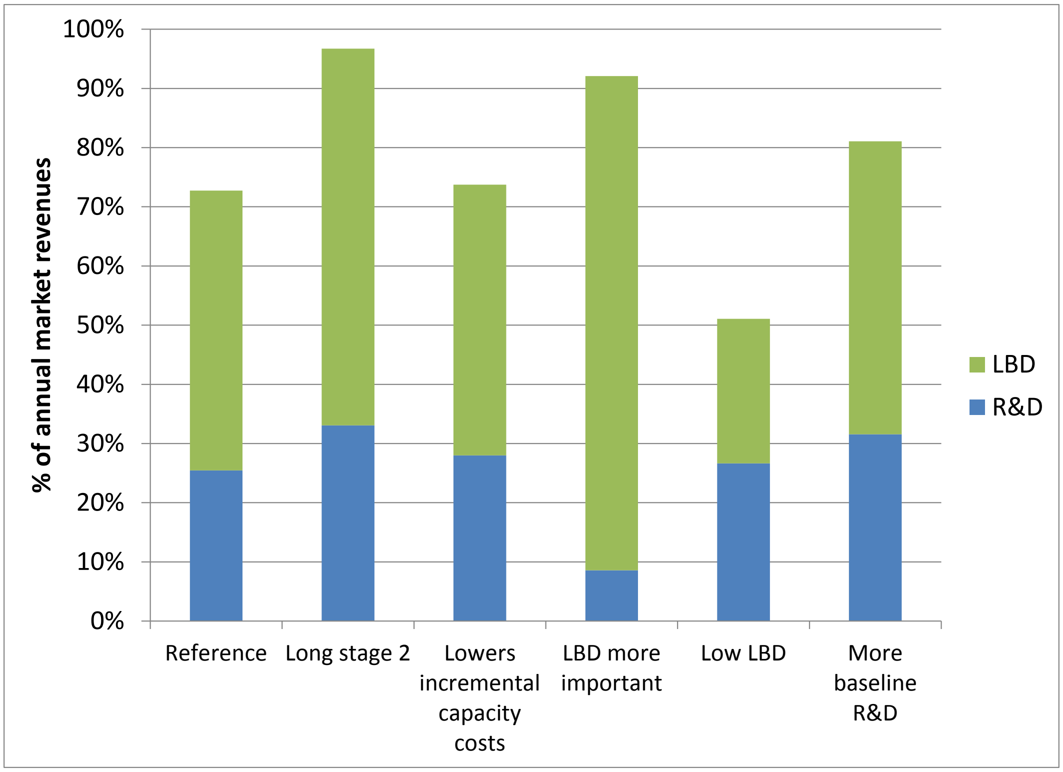
Figures Figure 4 and Figure 5 compare the results of these alternative sets of assumptions on the optimal supplementary technology policy portfolio. They depict total public spending on LBD and R&D subsidies, measured as a share of the total market revenues from wind/other and solar generation, respectively.

Figure 4. Optimal Public Spending on LBD and R&D as a Share of Total Revenues from Generation for Wind/Other



[23] This percentage represents the top end of R&D expenditure shares across industries (Newell 2010).

Figure 5. Optimal Public Spending on LBD and R&D as a Share of Total Revenues from Generation for Solar



In sum, even with rather extreme parameters for the productivity of LBD, it is difficult to drive optimal subsidies up to the 10 cent/kWh mark, even for solar. Optimal overall public spending toward technological innovation seems in the range of 15 – 30 percent of market generation revenues for wind/other and 50 – 100 percent for solar. Meanwhile, in almost all scenarios, the ratio of deployment spending to R&D spending does not exceed one for wind/other. The exception is the extreme case of "LBD more important," when that ratio goes to 6.5. In our reference scenario, solar energy is assumed to be more sensitive both to R&D, but even more so to learning. Thus we find that, except with "Low LBD", the ratio of public spending on solar deployment to R&D exceeds one, but not by much; even in the "LBD more important" scenario it just reaches 10-to-1. By contrast, estimates of public spending programs, including tax breaks and implied subsidies through other policies, indicate a much greater financial support for deployment. Indeed recent calculations for six EU countries indicate a ratio of deployment to R&D spending of more than 150-to-1 (Zachmann et al. 2014).

Single Policies

Bearing in mind these optimal policy combinations helps for understanding the effects of single policies and non-optimal combinations. Similar to FN, we first consider the relative cost effectiveness of single policies for meeting the same 40 percent cumulative emissions reductions target. In each case, policy stringency is adjusted over time to minimize the present value of costs.

With the fixed-price policies, a single instrument is applied, without differentiating among the covered generation sources. For example, the fossil tax, ϕ_t, is imposed equally upon all fossil-fuel sources. The renewable subsidy (production tax credit) uses a fixed subsidy path for non-hydro renewables that does not distinguish between wind/other and solar. The EE subsidy is applied as a percentage of investment costs, although it does distinguish between short- and long-run investments.

We also consider three revenue-neutral policies with self-adjusting prices. The emissions performance standard sets an intensity target; in essence, it combines a CO_2 emissions price with a rebate to all generation in proportion to the standard, such that above-average emitters pay a net fee and below-average ones gain a net subsidy. Specifically, $-\phi_t^i = s_t^i = s_t$, and $\sum_i s_t q_t^i = \sum_i \tau_t \mu^i q_t^i$. The renewable portfolio standard funds a common subsidy to the innovating, non-hydro renewables with a fee on all generation, such that $\sum_{i=w,s} s_t q_t^i = \sum_i \phi_t q_t^i$.[24] The clean energy standard (CES) is a hybrid of the preceding two policies and is based on recent proposals. Although it nominally sets a target of a certain percentage of energy from clean sources, in essence it offers full credits to renewable sources, 50 percent credit to natural gas generation, and 10 percent credit to generation from existing nuclear and hydropower facilities. Credits are in

[24] Equivalently, the net subsidy to renewables is funded by an implicit fee on other sources $\sum_{i=w,s} \hat{s}_t q_t^i = \sum_{i\neq w,s} \phi_t q_t^i$, where $\hat{s}_t = s_t - \phi_t$. Since hydropower production is fixed as a baseload technology, the definition of the RPS is less important for determining generation outcomes, although it can have distributional effects.

effect funded through a revenue-neutral fee on all generation.[25] Table 5 reports the policy targets for each strategy.

Table 5. Single Policies to Achieve 40% Cumulative Emissions Reduction Target

	Emissions Price (\$/ton CO_2)	Emissions Performance Standard (ton CO_2/GWh)	Fossil Fuel Tax (¢/kWh)	Clean Energy Standard (%)	Renewable Portfolio Standard (%)	Renewable Production Tax Credit (¢/kWh)	EE Subsidy (%)[26]
Stage 1	13.67	409	1.45	53.8	11.2	3.10	33% short run 63% long run
Stage 2	34.73	285	3.67	69.3	31.1	7.87	33%

Figure 6 presents the relative welfare costs of each single policy option for achieving the reduction target, compared to the costs under an emissions pricing policy (and for different degrees of EE undervaluation). For example, when no EE market failure is present, using an emissions performance standard or a fossil fuel tax increases welfare costs by less than 1 percent, relative to an emissions price.[27] CES and RPS policies result in 11 percent and 65 percent higher costs, respectively. On the other hand, relying solely on a renewable production (or EE) subsidy costs 3 (8) times as much as the emissions price alone. The latter policies are especially costly because they do not encourage fuel switching among conventional energy sources or conservation through higher electricity prices.

The relative costs change when EE improvements are undervalued by consumers. In particular, the discrepancy is larger between policies that raise electricity prices (and thereby

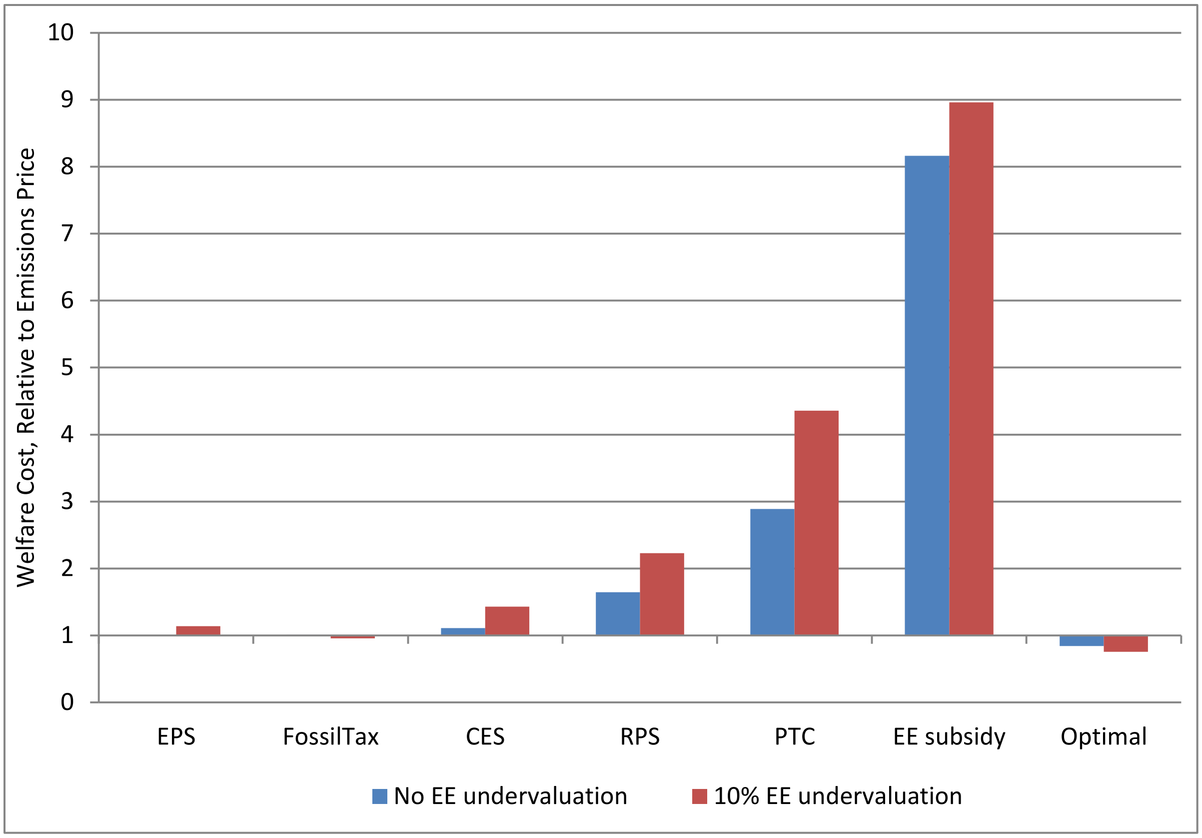
[25] We model the RPS as rewarding the full subsidy value to both wind and solar categories (i.e., all non-hydro renewables), and the sum of generation from these sources as a share of total generation (within a given period) must meet the RPS percentage requirement. The Clean Energy Standard operates the same way, except that each kWh of natural gas generation receives only 0.5 credits, hydro receives 0.1 credits/kWh, existing nuclear receives 0.1 credits/kWh, and new nuclear generaiton receives 1 credit/kWh. Table 5 reports the "nominal" CES percentage requirement, i.e. the sum of all renewable, hydro, nuclear, and 0.5*natural gas generation as a share of total generation.

[26] This is the percentage of energy efficient investments that are fully subsidized.

[27] If not for the presence of the R&D knowledge appropriability market failure, both the emissiosn performance standard and the fossil fuel tax would have strictly higher costs than the emissions price.

induce more of the underprovided EE improvements), and those that rely more on subsidies or renewable energy. Interestingly, the fossil fuel tax becomes more cost effective than either the emissions performance standard or the emissions price, meaning the EE interactions are more important than differentiating among fossil energy sources. Under the optimal policy, the gains from reducing EE underinvestment result in a 25 percent reduction in welfare costs, relative to an emission price alone.

Figure 6. Welfare Costs of Single Policies, Relative to Emissions Pricing (=1)



Notably, even with significant spillovers from technological change in renewable energy or undervaluation in energy efficiency, policies that focus solely on those problems are still much less cost-effective than emissions pricing.

Suboptimal Policy Combinations

Next, we consider the effects of policy combinations with stringent targets for renewable energy and energy efficiency, as inspired by the European Union’s 20/20/20 Directive. In each case, we have an emissions pricing program that ensures meeting the 40 percent cumulative reduction target—effectively, an emissions cap. The EU targets call for a 20 percent reduction in greenhouse gas (GHG) emissions by 2020 compared with 1990 levels, a 20 percent improvement in energy efficiency by 2020, and a 20 percent share of renewables in final energy consumption by 2020. Since these targets reflect economy-wide goals, we adjust our electricity sector targets to reflect the disproportionate share of reductions anticipated therein, and to ensure all targets remain binding. Specifically, as before, we assume a GHG target of a 40 percent reduction from our baseline.[28] We model the 20 percent renewables target as a binding RPS for non-hydro renewables in *both* stages, while we approximate the energy efficiency standard as a binding 10 percent reduction in energy intensity in *both* stages, reflecting ambitions for near-term deployment as a technology driver.

Importantly, the 20 percent renewables target is close to the welfare maximizing renewable share for the second stage. Likewise, the 10 percent energy efficiency target is close to the welfare maximizing level when undervaluation is in the range of 10 percent in the second stage. However, the near-term deployment targets are more aggressive than is optimal. In a scenario with 50 percent knowledge spillovers and 10 percent EE undervaluation (i.e., $\rho = 0.5$ and $\beta_x = .9$) there is some justification for complementary technology and energy efficiency policies. However, these market failures do not justify the 40/20/10 combination, which the model calculates as being almost twice as costly as the emissions price alone.

We note that some other variations can improve the cost effectiveness of the 40/20/10 policies. For example, adding an optimal R&D policy cuts costs by over 10 percent. Offering extra credits for solar, which more closely mimics the optimal production subsidy profile, lowers costs somewhat but not substantially.

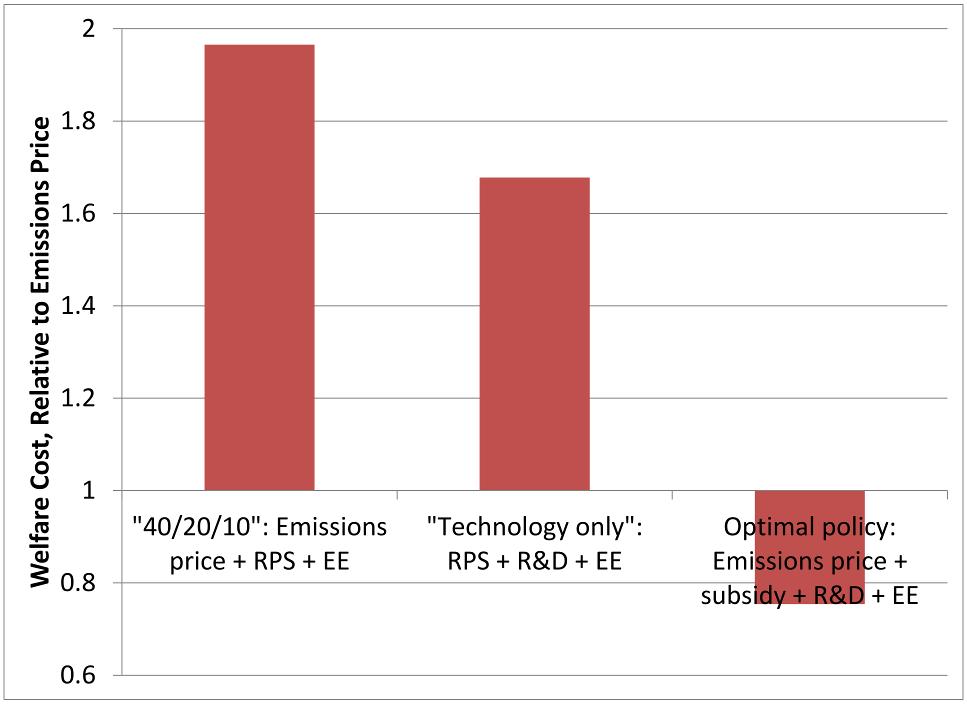
Recognizing issues in the political feasibility of carbon pricing, we also consider the consequences of a "technology-only" policy. This stylized policy combines the 10 percent EE target, a 50 percent R&D subsidy, and an increasing RPS sufficient to achieve the 20 percent reduction in emissions (roughly 11 percent non-hydro renewable share in the first stage and 26 percent in the second).

As shown in Figure 7, the 40/20/10 policy is the most expensive of these combinations, followed by the technology-only policy. Notably, having a better distributed technology policy mix—that is, internalizing the R&D market failure and setting an RPS that is less ambitious in

[28] This target ensures that emissions are equal across scenarios, allowing for consistent cost analysis..

the near term—has a stronger effect on reducing costs than losing the emissions price component of the 40/20/10 policies has in increasing them. Still, the technology-only policy is 68 percent more costly than the emissions price alone, and more than twice as costly as the optimal combination. (See Figure 7).

Figure 7. Welfare Costs of Combination Policies, Relative to Emissions Pricing (=1) (10% EE Undervaluation)

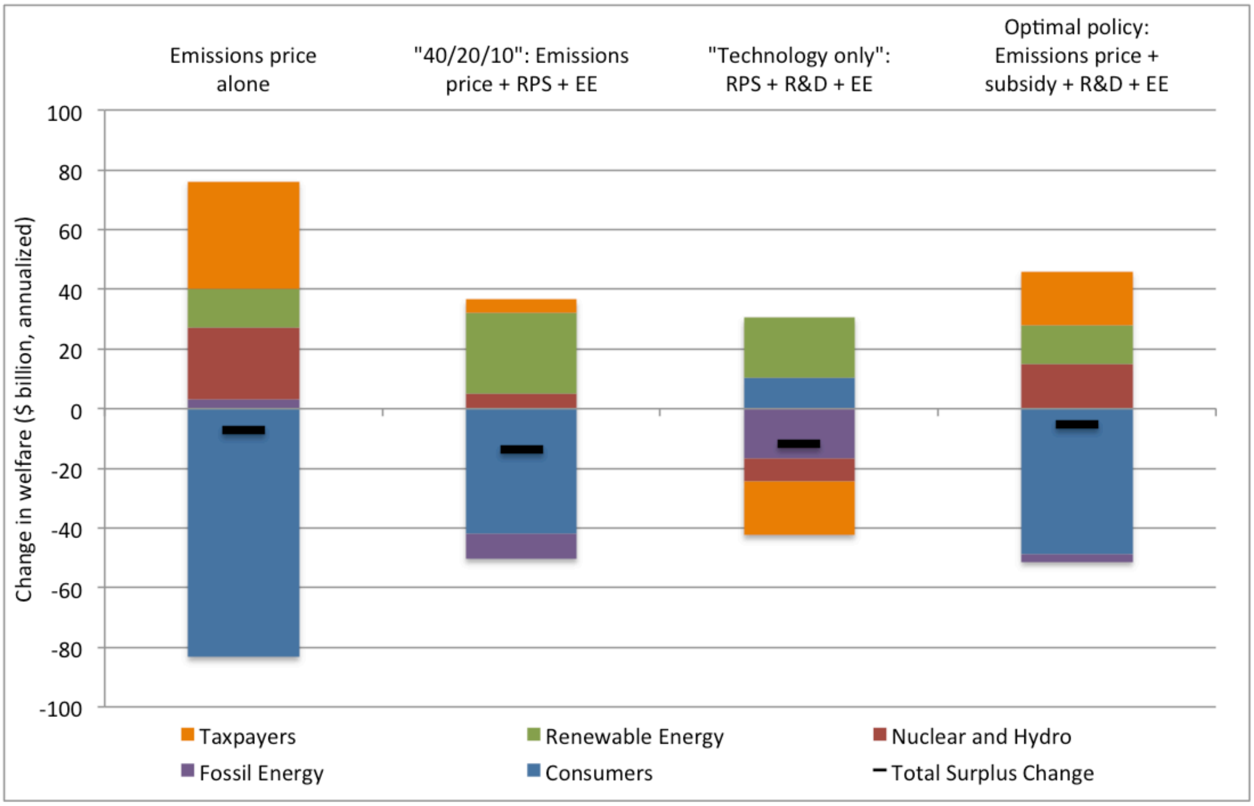


Distributional Consequences

Of course, cost-effectiveness is not the sole metric of interest to policymakers when choosing a climate strategy, which may help explain the great interest in policy combinations. Policymakers are concerned about the impacts on specific stakeholder groups, including ratepayers, taxpayers, and owners of different generation technologies.

Figure 8 presents the changes in welfare metrics for five categories of stakeholders, as well as the total change in surplus. We use the category “taxpayers” to represent the potential flow of revenues to or from the government, recognizing that additional policies can determine who is allocated emissions revenues and how subsidies are paid for.[29]

Figure 8. Distributional Consequences of Policy Combinations



We see that, although the emissions price policy alone has low overall costs, it has the largest distributional impacts, particularly for electricity consumers (who bear much of the cost), taxpayers (or more generally those who will enjoy the significant revenues), and the clean baseload generators (i.e. nuclear and hydro, who enjoy higher electricity prices). An optimal policy combination would have similar distributional impacts, but of smaller magnitude. Note, however, that to the extent that electricity consumers and taxpayers are the same individuals, the distributional impacts will not be as severe at the individual level. Alternatively, generous

[29] We model an emissions price by calibrating a carbon tax to achieve a 40% reduction from baseline emissions. Hence, "taxpayers" revenues could equivalently represent carbon tax revenues or auction revenues under a cap-and-trade system.

allocations of emissions revenues to fossil energy producers can allow them to enjoy higher profits under a cap.

The 40/20/10 policy changes the magnitudes, but not the direction, of welfare changes for the different stakeholders. It reduces the consumer burden substantially, as well as the taxpayer and baseload provider benefits. Renewable energy producers reap larger gains, while fossil-fuel generators lose more profits than with emissions pricing alone.

The technology-only policy has very different distributional consequences: consumers reap benefits from the energy efficiency and renewable energy subsidies, for which taxpayers foot the bill, and renewable energy providers reap higher profits, while nonrenewable producers bear more of the costs. The competitiveness of energy- and electricity-intensive manufacturing is also of notable concern in the policymaking process. We do not distinguish between residential, commercial, and industrial consumers of electricity here, but the direction and intensity of impacts on industrial consumers will follow those of our consumers more generally, although industries are often insulated to some degree from electricity rate increases by long-term contracts and differentiated tariff structures. Energy-intensive manufacturers with direct emissions of CO_2, which are outside of our model here, are affected by emission allowance price changes. When overlapping policies lower allowance prices, these sectors can benefit from lower costs of their emissions liabilities; of course, the value of any allowances they are allocated freely is likewise reduced.

Conclusion

We conclude that some technology policies can be useful complements to a program of emissions pricing for reducing greenhouse gases when additional market failures are present—namely knowledge spillovers and consumer undervaluation of energy efficiency improvements. However, the economic justification of promoting incremental innovation is likely to be much more modest than would support the suite of renewable energy policies being proposed.

In particular, even assuming high rates of knowledge spillovers from learning-by-doing, ambitious renewable portfolio standards seem unlikely to be welfare enhancing alongside an emissions price. Given that "getting the prices right" on emissions raises electricity prices and improves the competitiveness of renewable energy, large additional subsidies for renewables are unnecessary in that case. This result holds particularly true for conventional technologies like wind and biomass; however, even for technologies such as solar energy, with larger potential for cost reductions, the optimal subsidies in support of learning-by-doing may be quite modest. In our model, correcting R&D market failures, on the other hand, has a larger potential for reducing the costs of achieving significant emissions reductions.

The desirability of stringent energy efficiency policies, however, is very sensitive to the degree of EE undervaluation. Even the desirability of renewable energy policy measures is sensitive to demand-side market failures. The stronger influence of demand-side responses is a consequence of sheer size: demand represents the entire electricity market, while renewable energy is only a small portion, so a percentage change in demand has a much larger effect on emissions than a percentage change in renewables. Given the importance of these demand-side assumptions, and the lack of consensus within the literature on undervaluation, further empirical investigation of energy efficiency investment behavior will be of great benefit to policy analysis.

Our assumptions on the nature of knowledge accumulation and appropriation do play an important role, but they do not change the order of magnitude of the results. We therefore find that ambitious policies to subsidize the expansion of renewable generation are unlikely to be welfare enhancing alongside emissions pricing, unless other goals and benefits are in play. For example, we have not assigned value to energy supply diversification. Nor do we incorporate other costs and benefits that are relevant for electricity markets, like infrastructure requirements, intermittency of renewable sources, barriers to entry, economies of scale, imperfect competition, or damages from other pollutants that may not be internalized. A final point is the role of political constraints on emissions pricing; an important effect of the renewable energy policies is to redistribute the costs of an emissions cap, possibly in such a way as to make the policy more politically feasible (for example, by shifting compliance costs away from energy intensive industries and toward consumers).

With these caveats in mind, it is still telling that even with more refined representations of electricity generation options and market failures, emissions pricing still remains the single most cost-effective option for meeting emissions reduction goals. Technology policies are very poor substitutes, and when they overreach, they can be poor complements too.

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Appendix

Table 6. Variable Definitions

Variable	*Definition*
δ	discount factor between stages
n_t	Length of stage *t*
q_t^i	Annual generation output in stage *t* of source *i*
x	Coal-fired generation
oil	Oil-fired generation
ng	Natural gas-fired generation
nu	Nuclear generation
w	Convential renewable generation (including wind, biomass, geothermal, MSW)
s	Solar generation
h20	Hydro generation
μ^i	CO_2 intensity of source *i*
E_t	Total emissions in stage *t*
$C_{it}(q_t^i)$	Cost function for generation in stage *t* of source *i* ($i = \{x,ng,nu\}$)
P_t	Consumer price of electricity in stage *t*
τ_t	Price of emissions in stage *t*
φ_t^i	Net tax on generation in stage *t* of source *i* ($i = \{x,ng,nu\}$)
π^i	Profits from source *i*
$G_t^j(K_t^j, q_t^j)$	Cost of renewable energy generation in stage *t* of source *j* ($j=\{w,s\}$)
$K_t^j(H_t^j, Q_t^j)$	Knowledge stock in stage *t* of renewable source *j*
H_t^j	R&D knowledge stock in stage *t* of renewable source *j*
Q_t^j	Cumulative learning-by-doing in stage *t* of renewable source *j*
h_1^j	Annual R&D knowledge generation in stage 1 for renewable source *j*
$R^j(h_1^j)$	Annual R&D expenditures in stage 1 for renewable source *j*
s_1^j	Subsidy for renewable energy generaiton in stage *t* for source *j*
σ^j	R&D subsidy rate for renewable source *j*
ρ	Appropriation rate of returns from knowledge investments
v_t	Energy services in stage *t*
$u_t(v_t)$	Utility from energy services in stage *t*
U	Aggregate consumer net utility
ψ_t	Energy consumption rate in stage *t*
θ_t^S	Percentage reductions in energy intensity from short-run investments in stage *t*
θ_1^L	Percentage reductions in energy intensity from long-run investments in stage 1
$\bar{\theta}$	Exogenous innovation in energy intensity reductions
$Z_{j,t}(\theta_t^j)$	Cost of EE investments of type *j* in stage *t* ($j=\{S,L\}$)

b_{St}	Subsidy to short-term EE investments in stage *t*
b_L	Subsidy to long-term EE investments in stage 1
β_t^j	Perceived benefit valuation rate of EE investment type *j* in stage *t*
$D_t(P_t,\psi_t)$	Consumer demand for electricity in stage *t*
N_t	Exogenous demand growth factor
ε	Very short-run elasticity of electricity demand (rebound)
V	Government revenue
W	Economic surplus
r_t	Ratio of enewable to nonrenewable energy in an RPS
c_{it}	Slope of marginal cost curve in stage *t* for nonrenewable source *i*
g_{jt2}	Slope of marginal cost curve in stage *t* for renewable source *j*
g_{j11}	Intercept (above P_1^0) of marginal cost curve in stage 1 for renewable source *j*
k_1^j	Learning knowledge parameter for renewable source *j*
k_2^j	R&D knowledge parameter for renewable source *j*
γ_0^j	R&D investment cost parameter for renewable source *j*
γ_1^j	R&D investment cost parameter for renewable source *j*
z_1^j	Intercept of marginal costs of EE improvement, for type *j* ($j=\{S_1,S_2,L_1\}$)
z_2^j	Slope of marginal costs of EE improvement, for type *j* ($j=\{S_1,S_2,L_1\}$)

Derivation of Welfare Impacts of Policy Portfolio Change

The welfare implications of additional policy-induced changes can be derived by totally differentiating the social welfare function:

$$dW =$$

$$n_1\left(u'(v_1)dv_1 - Z_{S,1}{}'(\theta_1^S)d\theta_1^S - Z_L{}'(\theta^L)d\theta^L - \sum_{i=x,ng,nu} C_i{}'(q_1^i)dq_1^i - \sum_{j=w,s}\left(G^j{}_q(K_1^j,q_1^j)dq_1^j + R_h(h_1^j)dh_1^j\right)\right)$$

$$+\delta n_2\left(u'(v_2)dv_2 - Z_{S,2}{}'(\theta_2^S)d\theta_2^S - \sum_{i=x,ng,nu} C_i{}'(q_2^i)dq_2^i - \sum_{j=w,s}\left(G^j{}_q(K_2^j,q_2^j)dq_2^j + G^j{}_K(K_2^j,q_2^j)dK_2^j\right)\right)$$

Next, in a series of steps, we use the decentralized first-order conditions (Equations (1), (4)–(3), and (9)–(11)) to substitute for the expressions of marginal costs and marginal utility that must hold in equilibrium. Then, we use the fact that total changes in consumption equal total production changes:

$$\sum_{i=x,ng,nu,w,s} dq_t^i = dD_t = d\psi_t v_t + \psi_t dv_t = -\underbrace{\psi_t^0 e^{-(\theta_1^S+\theta^L)}}_{\psi_t} v_1\left(d\theta_1^S + d\theta^L\right) + \psi_t dv_1$$

With these substitutions and much rearranging, we find the change in economic surplus can be expressed as

$$
\begin{aligned}
dW &= n_1 P_1 D_1 \left(\frac{(1-\beta_1^S) - b_{S1}}{(1-b_{S1})} d\theta_1^S + \frac{(1-\beta_1^L) - b_L}{(1-b_L)} d\theta^L \right) \\
&+ \delta n_2 P_2 D_2 \left(\frac{(1-\beta_2^L) - b_L}{(1-b_L)} d\theta^L + \frac{(1-\beta_2^S) - b_{S2}}{(1-b_{S2})} d\theta_2^S \right) \\
&+ n_1 \sum_{i=x,ng,nu} (\phi_1^i + \tau_1 \mu^i) dq_1^i + \delta n_2 \sum_{i=x,ng,nu} (\phi_2^i + \tau_2 \mu^i) dq_2^i \\
&- n_1 \sum_{j=w,s} \left(s_1 + \delta n_2 G^j{}_K (K_2^j, q_2^j)(1-\rho) K_Q(H_2, Q_2) \right) dq_1^j \\
&- \delta n_2 \sum_{j=w,s} \left(s_2 dq_2^j + n_1 G^j{}_K (K_2^j, q_2^j) \left(\frac{(1-\rho) - \sigma}{(1-\sigma)} K_H(H_2, Q_2) dh_1^j \right) \right)
\end{aligned}
\tag{17}
$$

In other words, additional energy efficiency improvements are welfare enhancing if the subsidy is less than the degree of undervaluation. Similarly, increases in renewable generation improve welfare if the production subsidy is less than the spillovers from LBD. Additional R&D enhances surplus if the R&D subsidy does not exceed the R&D spillover rate.

Consider a carbon price alone as a starting point, with $\tau_1 = \delta \tau_2$. Next, consider a policy variation that includes an additional intervention, *X*, where $X \in \{s_t, b_{jt}, \sigma, \phi_{jt}\}$ is some combination of the tax and subsidy options. We look at deviations in which total emissions are held constant with the policy variation (i.e., by the carbon price adjusting in response to other policy changes), such that $n_1 \sum_{i=x,ng} \mu^i dq_1^i + n_2 \sum_{i=x,ng} \mu^i dq_2^i = 0$. Together, these restrictions imply that the change in discounted emissions values is also zero. Rearranging again, we get (16).

Derivation of Energy Demand Parameters

To derive energy demand, we assume that the utility consumers derive from energy services is $u(v_t) = -\mathrm{A}_t v_t^{-\alpha}$, where A is a scalar that also allows for exogenous demand growth and $\alpha > 0$. In period *t*, the quantity of energy demanded is $q_t = \psi_t v_t$, and we can equivalently write the consumer first-order condition for energy services as

$$
\alpha \mathrm{A}_t \left(\frac{D_t}{\psi_t} \right)^{-\alpha} / D_t = P_t
$$

To be consistent with the notation used in FN, let us rewrite this expression in terms of the price elasticity of demand:

$$
D_t = \psi_t^{\frac{\alpha}{1+\alpha}} \left(\frac{P_t}{\alpha \mathrm{A}_t} \right)^{\frac{-1}{1+\alpha}} = N_t \psi_t^{1-\varepsilon} P_t^{-\varepsilon} \tag{18}
$$

where $\alpha = (1-\varepsilon)/\varepsilon$ and $N_t = \mathrm{A}_t^{\varepsilon}(\varepsilon/(1-\varepsilon))^{-\varepsilon}$, and $0 < \varepsilon < 1$.

The elasticity ε can be interpreted as a very short run elasticity, as might be reflected in the rebound effect. Full short-run demand elasticity will include short-run responses in energy intensity. We derive these at the end.

We assume linear marginal costs of EE improvements around the baseline, so for each type of improvement *j*, costs are a quadratic function $Z_j(\theta_t^j) = z_1{}^j\theta_t^j + z_2{}^j \cdot (\theta_t^j)^2/2$, with marginal costs $Z_j{}'(\theta_t^j) = z_1{}^j + z_2{}^j \cdot (\theta_t^j)$ and slope $Z_j{}''(\theta_t^j) = z_2^j$.

In the baseline $\theta_2^S = 0$, so from the first-order condition, we get $z_1^S = \beta_t^S P_t^0 D_t^0$ and $z_1^L = \beta_1^L P_1^0 q_1^0 + \dfrac{n_2}{n_1}\beta_2^L \delta P_2^0 q_2^0$. In other words, the intercepts of the marginal cost functions are determined in part by our assumptions regarding the perceived valuation factor for each type of EE improvement.

Substituting these functional forms into the first-order conditions, we can derive the EE improvements:

$$\theta_2^S = \frac{\beta_2^S}{z_2{}^{S_2}}\left(\frac{P_2 D_2}{(1-b_{S_2})} - P_2^0 D_2^0\right) \tag{19}$$

$$\theta_1^S = \frac{\beta_1^S}{z_2{}^{S_1}}\left(\frac{P_1 D_1}{(1-b_{S_1})} - P_1^0 D_1^0\right) \tag{20}$$

$$\theta_1^L = \frac{\beta_1^L}{z_2{}^L}\left(\frac{P_1 D_1}{(1-b_L)} - P_1^0 D_1^0\right) + \frac{n_2}{n_1}\frac{\beta_2^L}{z_2{}^L}\delta\left(\frac{P_2 D_2}{(1-b_L)} - P_2^0 D_2^0\right) \tag{21}$$

The slopes of the marginal costs of EE improvements are thus important parameters, and we calibrate them by deriving the implicit short, medium and long-run elasticities of electricity demand.

First, the elasticity of demand with respect to the energy intensity of services reflects the rebound effect, resulting from the very-short-run price elasticity ε:

$$\frac{\partial D_t}{\partial \psi_t} = (1-\varepsilon)N_t \psi_t{}^{-\varepsilon} P_t^{-\varepsilon}; \quad \frac{\partial D_t / D_t}{\partial \psi_t / \psi_t} = (1-\varepsilon)$$

The rebound effect recognizes that *v* will also change in response to lower costs of energy services, mitigating some of the energy savings. If *v* were unchanged, we would have an elasticity of one.

The price elasticity of demand can be derived from the demand function:

$$\frac{dD_t}{dP_t} = -\varepsilon N_t \psi_t^{1-\varepsilon} P_t^{-\varepsilon-1} + (1-\varepsilon) N_t \psi_t^{-\varepsilon} P_t^{-\varepsilon} \left(\frac{\partial \psi_t}{\partial P_t} + \frac{\partial \psi_t}{\partial D_t}\frac{dD_t}{dP_t} + \frac{\partial \psi_t}{\partial D_s}\frac{dD_s}{dP_t} \right)$$

$$\Rightarrow \quad \frac{dD_t / D_t}{dP_t / P_t} = \frac{-\varepsilon + (1-\varepsilon)\left(\frac{\partial \psi_t}{\partial P_t}\frac{P_t}{\psi_t} + \frac{\partial \psi_t}{\partial D_s}\frac{D_s}{\psi_t}\frac{dD_s}{dP_t}\frac{P_t}{D_s} \right)}{\left(1-(1-\varepsilon)\frac{\partial \psi_t / \psi_t}{\partial D_t / D_t} \right)}$$

Thus, the elasticity is a combination of the very short-run demand elasticity (absent changes in energy intensity) and the longer run demand changes resulting from changes in energy intensity.

We also need to derive the "cross-price" elasticity of demand in one period with respect to the price in the other period. There is no direct effect on demand, but rather an indirect effect from changes in EE. Specifically, an increase in the other period's price increases long-run EE investments; however, some of these improvements will tend to be offset by fewer short-run investments.

$$\frac{dD_t}{dP_s} = (1-\varepsilon)\frac{D_t}{\psi_t}\left(\frac{\partial \psi_t}{\partial P_s} + \frac{\partial \psi_t}{\partial D_t}\frac{dD_t}{dP_s} + \frac{\partial \psi_t}{\partial D_s}\frac{dD_s}{dP_s} \right)$$

$$\Rightarrow \quad \frac{dD_t / D_t}{dP_s / P_s} = \frac{(1-\varepsilon)\left(\frac{\partial \psi_t}{\partial P_s}\frac{P_s}{\psi_t} + \frac{\partial \psi_t}{\partial D_s}\frac{D_s}{\psi_t}\frac{dD_s}{dP_s}\frac{P_s}{D_s} \right)}{\left(1-(1-\varepsilon)\frac{\partial \psi_t}{\partial D_t}\frac{D_t}{\psi_t} \right)}$$

Next, we derive the price elasticities of energy intensity:

$$\frac{\partial \psi_t}{\partial P_s} = -\psi_t \left(\frac{\partial \theta_t^S}{\partial P_s} + \frac{\partial \theta^L}{\partial P_s} \right) \quad \Rightarrow \quad \frac{\partial \psi_t / \psi_t}{\partial P_s / P_s} = -P_s \left(\frac{\partial \theta_t^S}{\partial P_s} + \frac{\partial \theta^L}{\partial P_s} \right)$$

$$\frac{\partial \psi_t}{\partial D_s} = -\psi_t \left(\frac{\partial \theta_t^S}{\partial D_s} + \frac{\partial \theta^L}{\partial D_s} \right) \quad \Rightarrow \quad \frac{\partial \psi_t / \psi_t}{\partial D_s / D_s} = -D_s \left(\frac{\partial \theta_t^S}{\partial D_s} + \frac{\partial \theta^L}{\partial D_s} \right)$$

From the simplified baseline first-order conditions (with no subsidies), we obtain the following partial derivatives:

$$\frac{\partial\theta_2^S}{\partial P_1}P_1=\frac{\partial\theta_2^S}{\partial D_1}D_1=0;\quad \frac{\partial\theta_2^S}{\partial P_2}P_2=\frac{\partial\theta_2^S}{\partial D_2}D_2=\frac{\beta_2^S}{z_2^{S_2}}P_2D_2;$$

$$\frac{\partial\theta_1^S}{\partial P_1}P_1=\frac{\beta_1^S}{z_2^{S_1}}D_1=\frac{\partial\theta_1^S}{\partial q_1}P_1D_1;\quad \frac{\partial\theta_1^S}{\partial P_2}P_2=\frac{\partial\theta_1^S}{\partial D_2}D_2=0;$$

$$\frac{\partial\theta_1^L}{\partial P_1}P_1=\frac{\partial\theta_1^L}{\partial D_1}D_1=\frac{\beta_1^L}{z_2{}^L}P_1D_1;\quad \frac{\partial\theta_1^L}{\partial P_2}P_2=\frac{\partial\theta_1^L}{\partial D_2}D_2=\frac{n_2}{n_1}\frac{\beta_2^L}{z_2{}^L}\delta P_2D_2;$$

Which gives us

$$\frac{\partial\psi_1/\psi_1}{\partial P_1/P_1}=\frac{\partial\psi_1/\psi_1}{\partial D_1/D_1}=-\left(\frac{\beta_1^S}{z_2^{S_1}}+\frac{\beta_1^L}{z_2{}^L}\right)P_1D_1;$$

$$\frac{\partial\psi_2/\psi_2}{\partial P_1/P_1}=\frac{\partial\psi_2/\psi_2}{\partial D_1/D_1}=-\frac{\beta_1^L}{z_2{}^L}P_1D_1;$$

$$\frac{\partial\psi_1/\psi_1}{\partial P_2/P_2}=\frac{\partial\psi_1/\psi_1}{\partial D_2/D_2}=-\delta\frac{n_2}{n_1}\frac{\beta_2^L}{z_2{}^L}P_2D_2;$$

$$\frac{\partial\psi_2/\psi_2}{\partial P_2/P_2}=\frac{\partial\psi_2/\psi_2}{\partial D_2/D_2}=-\left(\frac{\beta_2^S}{z_2^{S_2}}+\delta\frac{n_2}{n_1}\frac{\beta_2^L}{z_2{}^L}\right)P_2D_2;$$

Let $\eta_{ts}\equiv-\dfrac{dD_t/D_t}{dP_s/P_s}$ be the (absolute value of) the price elasticity of demand. Thus, the own- and cross-price elasticities are

$$\eta_{11}=\frac{\varepsilon+(1-\varepsilon)\left(\left(\frac{\beta_1^S}{z_2^{S_1}}+\frac{\beta_1^L}{z_2{}^L}\right)P_1D_1-\delta\frac{n_2}{n_1}\frac{\beta_2^L}{z_2{}^L}P_2D_2\eta_{21}\right)}{\left(1+(1-\varepsilon)\left(\frac{\beta_1^S}{z_2^{S_1}}+\frac{\beta_1^L}{z_2{}^L}\right)P_1D_1\right)}$$

$$\eta_{22}=\frac{\varepsilon+(1-\varepsilon)\left(\left(\frac{\beta_2^S}{z_2^{S_2}}+\frac{n_2}{n_1}\frac{\beta_2^L}{z_2{}^L}\delta\right)P_2D_2-\frac{\beta_1^L}{z_2{}^L}P_1D_1\eta_{12}\right)}{\left(1+(1-\varepsilon)\left(\frac{\beta_2^S}{z_2^{S_2}}+\frac{n_2}{n_1}\frac{\beta_2^L}{z_2{}^L}\delta\right)P_2D_2\right)}$$

$$\eta_{12} = \frac{(1-\varepsilon)\frac{n_2}{n_1}\frac{\beta_2^L}{z_2{}^L}\delta PD_2\left(1-\eta_{22}\right)}{\left(1+(1-\varepsilon)\left(\frac{\beta_1^S}{z_2{}^{S_1}}+\frac{\beta_1^L}{z_2{}^L}\right)P_1D_1\right)}$$

$$\eta_{21} = \frac{(1-\varepsilon)\frac{\beta_1^L}{z_2{}^L}P_1D_1\left(1-\eta_{11}\right)}{\left(1+(1-\varepsilon)\left(\frac{\beta_2^S}{z_2{}^{S_2}}+\frac{n_2}{n_1}\frac{\beta_2^L}{z_2{}^L}\delta\right)P_2D_2\right)}$$

From these four equations (for $\eta_{11},\eta_{12},\eta_{22},\eta_{21}$ to equal our target elasticities), we solve for our calibrated values of $z_2^{S_1}, z_2^{S_2}, z_2^L$ and the relationship that must hold between β_1^L and β_2^L:

$$\beta_1^L = \delta\frac{n_2P_2D_2\eta_{21}}{n_1P_1D_1\eta_{12}}\beta_2^L$$

and

$$z_2^{S_1} = \beta_1^S P_1^0 D_1^0 \frac{(1-\varepsilon)((1-\eta_{11})(1-\eta_{22})-\eta_{12}\eta_{21})}{\eta_{11}(1-\eta_{22})-(1-\eta_{12})\eta_{21}-\varepsilon(1-\eta_{21}-\eta_{22})}$$

$$z_2^{S_2} = \beta_2^S P_2^0 D_2^0 \frac{(1-\varepsilon)((1-\eta_{11})(1-\eta_{22})-\eta_{12}\eta_{21})}{\eta_{22}(1-\eta_{11})-(1-\eta_{21})\eta_{12}-\varepsilon(1-\eta_{11}-\eta_{12})}$$

$$z_2^L = \delta\frac{n_2}{n_1}\beta_2^L P_2^0 D_2^0 \frac{(1-\eta_{11})(1-\eta_{22})-\eta_{12}\eta_{21}}{\eta_{12}}$$