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. Do these measures work together or at cross purposes? A critical issue is the extent to which innovation and energy efficiency market failures justify additional interventions when a carbon price is in place. To assess the performance of overlapping policies, we extend the two-stage model of Fischer and Newell (2008) to include advanced and conventional renewable energy technologies and both short and long-run investments in energy efficiency improvements. We incorporate both knowledge spillovers and imperfections in the demand for energy efficiency. We conclude that some technology policies can be useful complements to emissions pricing, but ambitious renewable portfolio standards or production subsidies seem unlikely to enhance welfare. 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 degree of undervaluation, which also has implications for the cost-effectiveness of policies (like renewable energy subsidies) that keep electricity prices low. Even with multiple market failures, emissions pricing remains the single most cost-effective option for meeting emissions reduction goals. In sum, technology policies are very poor substitutes, and when they overreach, they can be poor complements too.

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Version: January 9, 2013

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 required 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 some 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 most 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

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problem, then only one policy instrument would be needed: an appropriate emissions price or other mechanism to "internalize the environmental externality." Indeed, once 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 model 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, 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.

Third, we expand our representation of the nonrenewable generating sectors, in order to better evaluate proposals like a Federal clean energy standard (CES). This requires differentiating between natural gas turbines and combined cycle generation, as well as recognizing greater long-run potential for nuclear energy. 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% of CO_2 emissions in the United States in 2010 (EPA 2012). However, the potential emissions reductions from this sector are much larger than its share of total emissions. Analysis of an economy-wide policy for climate mitigation concluded that well over 80% 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. The optimal policy portfolio would include additional tools to bring the incentives of the individual actors in line with that of society:

1. A carbon price to address the environmental externality;
2. Subsidies for early-stage LBD to correct for learning spillovers for each technology;
3. No additional taxes on fossil energy sources or subsidies to mature (second-period) renewable generation;
4. An R&D subsidy equal to the R&D spillover rate for each technology; and
5. Subsidies to EE investments to offset the unvalued share of EE benefits, both in the short and long term.

An important point to note is that we do 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, a “technology neutral” policy will not be optimal. Thus, we can represent some of the tensions between needing to target specific technologies and wanting to avoid “picking winners.”

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 in order 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, but ambitious renewable portfolio standards or production subsidies seem unlikely to enhance welfare. 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 degree of undervaluation, which also has implications for the cost-effectiveness of policies (like renewable energy subsidies) that keep electricity prices low. 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 to 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] Fossil-fueled 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 fossil-fueled generation.

The model has two stages: a first stage made up of n_1 years, representing the time it takes for innovation and certain kinds of 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

[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.

place in the first stage. Through technological change, knowledge investments 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 will not experience significant technological change relative to renewable sources.[2] These sources include coal (*x*), natural gas turbines (*ng*), natural gas combined cycle (*cc*), and nuclear (*nu*). 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 $\mu^x > \mu^{ng} > \mu^{cc} > \mu^{nu} = 0$. 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 $E_t = \mu^x q_t^x + \mu^{ng} q_t^{ng} + \mu^{cc} q_t^{cc}$.

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.

[2] While it is of course not strictly true that fossil-fueled technologies will experience no further technological advance, incorporation of a positive, but slower relative rate of advance in fossil fuels 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.

Let P_t be the retail 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:

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

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 relatively mature technology (*w*), such as wind or biomass, and an advanced technology (*s*), like solar. We do include hydropower in the baseline (*h20*), but assume it provides baseload capacity that does not change over time, in quantity or in cost. The focus here is on the new renewable sources.

Unlike the nonrenewable sources, the costs of generation for renewable sources depend on a stock of knowledge that can be increased through research and development (R&D) or learning-by-doing (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.[3] A subtle issue is whether research and experience are substitutes, in which case $K_{HQ} \leq 0$, 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.[4] 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. This

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[3] 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.

[4] 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.

representation of aggregate appropriation as a share of the total benefits 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.

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

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

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

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

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.[5] 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 retail 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 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, lightbulbs, 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 in the 1st period of long-

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

run EE investments 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 $D_t = \psi_t u'^{-1}(P_t \psi_t)$. 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* 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

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

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.[6] 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 retail price of electricity is an endogenous variable that signals the value to producers (and consumers), and policies can create a wedge between the retail 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 policies and combinations on the retail price—not only in magnitude

[6] 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].

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 retail electricity prices, depending on these factors. 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 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, so that the cap is maintained (e.g., Morris 2009; Pethig and Wittlich 2009). Böhringer and Rosendahl (2010a, 2010b) 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 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, additional policies that support renewable energy (like production subsidies) also 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 if 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 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. No additional taxes on fossil energy sources or subsidies to mature (second-period) renewable generation.
4. An R&D subsidy equal to the R&D spillover rate ($\sigma = 1-\rho$).
5. 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 do 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:

$$dW =$$

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

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

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:

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

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

$$\begin{aligned} dW &= n_1 P_1 D_1\left(\frac{(1-\beta_1^S)-b_{S1}}{(1-b_{S1})}d\theta_1^S + \frac{(1-\beta_1^L)-b_L}{(1-b_L)}d\theta^L\right) \\ &+\delta n_2 P_2 D_2\left(\frac{(1-\beta_2^L)-b_L}{(1-b_L)}d\theta^L + \frac{(1-\beta_2^S)-b_{S2}}{(1-b_{S2})}d\theta_2^S\right) \\ &+n_1 \sum_{\substack{i=x,ng,\\ cc,nu}} (\phi_1^i + \tau_1\mu^i)dq_1^i + \delta n_2 \sum_{\substack{i=x,ng,\\ cc,nu}} (\phi_2^i + \tau_2\mu^i)dq_2^i \\ &-n_1 \sum_{j=w,s}\left(s_1 + \delta n_2 G^j{}_K(K_2^j,q_2^j)(1-\rho)K_Q(H_2,Q_2)\right)dq_1^j \\ &-\delta n_2 \sum_{j=w,s}\left(s_2 dq_2^j + n_1 G^j{}_K(K_2^j,q_2^j)\left(\frac{(1-\rho)-\sigma}{(1-\sigma)}K_H(H_2,Q_2)dh_1^j\right)\right) \end{aligned} \tag{16}$$

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, we can look at deviations in which total emissions are held constant with the policy variation, $n_1 \sum_{i=x,ng,cc} \mu^i dq_1^i + n_2 \sum_{i=x,ng,cc} \mu^i dq_2^i = 0$. Together, these restrictions imply that the change in discounted emissions values is also zero. Rearranging again, we see the potential benefits and costs of additional intervention:

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

The last line represents the costs: additional fossil taxes that reduce fossil generation lower surplus, as do additional renewable subsidies that increase renewable generation.

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.

Suppose instead we impose a portfolio standard policy that pins down the ratio r between renewable and non-renewable generation, so

$$r_t = \frac{\sum_{j=w,s} (q_t^j + dq_t^j)}{\sum_{i=x,ng,cc,nu} (q_t^i + dq_t^i)},$$

which is implemented through a renewable credit system such that $\phi_t^i = r_t s_t^j$. Assuming the additional standard is binding, renewable energy must increase disproportionately to meet it, meaning $\sum_{i=x,ng,cc,nu} r_t s_t dq_t^i - \sum_{j=w,s} s_t dq_t^j < 0$. Although the policy is revenue neutral overall, on the margin it imposes a cost. Whether it increases welfare depends on the extent to which it helps internalize the non-environmental market failures. It will generate positive knowledge spillovers, but the energy efficiency effects depend on whether the portfolio standard raises or lowers the electricity price. This intuition will be useful in interpreting our numerical results.

Numerical application

Functional forms

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 incremental marginal cost is $c_{1t}^i = P_{t,base}$, while total baseline cost, c_{0t}^i, is calculated as the area under the marginal cost curve, evaluated at the baseline values.

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.

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 $g_{1jt} = P_{1,base} + k_1 \delta \rho n_2 g_{0,2}^j / Q_{2,base}^j$.

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 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 exercise 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) 2011. 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 2011 reference case.[7] We obtained disaggregated natural gas projections from EIA, in order to separate conventional and combined-cycle generation and emissions. We also set our baseline electricity price at 8.8 cent/kWh based on AEO 2011, with all monetary values adjusted to 2009 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 conventional natural gas generation (i.e. boilers and turbines) and hydro generation in both periods.

To parameterize separate knowledge functions for wind 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 and solar, so that $H_1^w = H_1^s = 1$. We set $Q_1^w = 2.5\times10^{12}$ and $Q_1^s = 7.4\times10^{10}$ so that annual wind and solar generation represent, respectively, about 10% and 5% contributions to their stock of experience. These estimates are consistent with the current contribution of wind and solar to cumulative U.S. generation of each technology (EIA 2010).

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[8] have compared learning rates for established renewables (wind) and developing technologies (solar), but they typically do not separate knowledge into learning and research components.[9] We use technological learning assumptions from both EIA (2011b) and IEA (2009; 2010b) to estimate $k_1^w = 0.10$ and $k_1^s = 0.30$.[10] Using these values, we calibrated k_2^j 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 2011b, 98). As in FN, we specify the R&D investment functions by setting

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[7] Baseline generation levels assign existing biomass, municipal solid waste, and geothermal to the "wind" category, as all of these renewables technologies are more mature than solar photovoltaics (IEA 2010a, 134).

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

[9] 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.

[10] For wind, EIA (2011b, 98) assumes $k_1^w = 0.01$, while IEA (2009, 17) assumes $k_1^w = 0.10$. For solar, EIA (2011b, 98) assumes $k_1^s = [0.15, 0.32]$, while IEA (2010b, 18) assumes $k_1^s = 0.29$.

$\gamma_1^w = \gamma_1^s = 1.2$. We assume that annual baseline R&D expenditures represent about 2.4% of wind and 2.7% of solar revenues and solve for each γ_0^j in the baseline scenario. We also retain FN's assumed knowledge appropriability rate for both wind and solar of $\rho = 0.5$ in the central scenarios.

An extensive empirical literature has been estimating 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.[11] Other demand elasticities for electricity were based on this estimate, doubling as we moved into the longer term. The assumed values of the energy demand elasticities are 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% change in the electricity price (i.e., across both periods), the implicit elasticity of demand in the 1st stage is –0.29.

We set exogenous demand growth to 11% (i.e., $N_2 / N_1 = 1.38/1.25 = 1.11$) 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 16 years, matching AEO projections out to 2035. Because we discount the second stage back to the present at a rate of 7%, this implies a discount factor $\delta = 0.71$ and a second stage with the effective length of n_2 = 10.1.

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

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

Table 1 – Supply and Demand Parameters by Stage

	Stage 1	Stage 2
Slope of coal electricity supply ($c_{2\,x,t}$) ($/kWh^2)	1.3×10^{-14}	1.3×10^{-14}
Slope of NGCC electricity supply ($c_{2\,cc,t}$) ($/kWh^2)	3.5×10^{-14}	2.4×10^{-14}
Slope of nuclear electricity supply, stage 2 (c_{nu2}) ($/kWh^2)	–	6.5×10^{-13}
Slope of wind electricity supply (g_{2wt}) ($/kWh^2)	1.4×10^{-13}	1.4×10^{-13}
Slope of solar electricity supply (g_{2st}) ($/kWh^2)	9.7×10^{-12}	6.7×10^{-12}
Intercept of short-run energy efficiency investment cost supply (z_{St1}) ($)	3.8×10^{11}	4.3×10^{11}
Slope of short-run energy efficiency investment cost supply (z_{St2}) ($/%)	8.6×10^{13}	1.1×10^{12}
Intercept of long-run energy efficiency investment cost supply (z_{L1}) ($)	1.0×10^{12}	–
Slope of long-run energy efficiency investment cost supply (z_{L2}) ($/%)	3.6×10^{12}	–
Exogenous demand growth	–	11%

Table 2 – Other Baseline Parameters

	Base value
CO_2 intensity of coal electricity (μ^x) (tons CO_2/kWh)	9.7×10^{-4}
CO_2 intensity of conventional natural gas electricity (μ^{ng}) (tons CO_2/kWh)	7.0×10^{-4}
CO_2 intensity of NGCC electricity (μ^{cc}) (tons CO_2/kWh)	4.0×10^{-4}
Learning parameter for wind ($k_1{}^w$)	0.10
R&D parameter for wind ($k_2{}^w$)	0.15
Learning parameter for solar ($k_1{}^s$)	0.30
R&D parameter for solar ($k_2{}^s$)	0.20
Wind R&D cost parameter ($\gamma_0{}^w$)	1.3×10^{10}
Wind R&D cost parameter ($\gamma_1{}^w$)	1.2
Solar R&D cost parameter ($\gamma_0{}^s$)	2.6×10^{8}
Solar R&D cost parameter ($\gamma_1{}^w$)	1.2
Degree of knowledge appropriability (ρ^w, ρ^s)	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 renewable energy in the baseline (6% in the first stage and 8% in the second), nearly all in the form of mature non-hydro renewables, such as wind, biomass, and geothermal (denoted “wind” for simplicity). Solar remains a fraction of a percent of generation. Significant renewable energy cost reductions are expected in the baseline, with wind costs falling 9% and solar costs falling 30%.

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)	8.8	9.0
Electricity demand (D_t) (kWh/yr)	4.33×10^{12}	4.81×10^{12}
Coal generation (q_t^x) (kWh/yr)	1.83×10^{12}	2.09×10^{12}
Natural gas generation from boilers and turbines (q_t^{ng}) (kWh/yr)[12]	3.34×10^{11}	3.87×10^{11}
Combined cycle natural gas generation (q_t^{cc}) (kWh/yr)	7.15×10^{11}	7.53×10^{11}
Nuclear generation (q_t^{nu}) (kWh/yr)	8.53×10^{11}	8.77×10^{11}
Wind generation (q_t^w) (kWh/yr)[13]	2.57×10^{11}	3.52×10^{11}
Solar generation (q_t^s) (kWh/yr)	1.66×10^{10}	1.89×10^{10}
Hydro generation (q_t^{h20}) (kWh/yr)	3.19×10^{11}	3.26×10^{11}
Wind share of generation (%)	5.95	7.32
Solar share of generation (%)	0.38	0.39
CO_2 emissions (E_t) (billion metric tons CO_2/year)	2.29	2.59
Rate of wind cost reduction (%)	9%	–
Rate of solar cost reduction (%)	30%	–

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 20% below baseline emissions. The policy scenario results will be reported in relation to these baseline values; welfare consequences will be reported relative to the benchmark policy of an emissions price without supplementary policies.

[12] We include oil generation in this category.

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

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 optimal emissions price will rise over time, from \$11 per ton CO_2 in stage 1 to \$24 in stage 2. With only innovation market failures (i.e., no EE undervaluation), the optimal policy combination still involves similar emissions prices in the two stages (\$10 and \$23, respectively). To internalize the innovation spillovers, these prices would be combined with a substantial 50% R&D subsidy, but a very modest subsidy to learning in the first stage: 0.3 cents/kWh for wind and 0.6 cents/kWh for solar. Altogether, the optimal combination of policies lowers costs 12% relative to the cap alone, again assuming no EE market imperfections.

In the presence of market failures in demand for EE improvements—we model a 10% undervaluation—the optimal policy mix changes more substantially. The inclusion of EE subsidies induces more demand-side conservation, allowing for lower emissions prices (nearly 30% 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 a third.

Table 4: Emissions Price Alone versus Optimal Policy Combinations

Policy	**Emissions price**		**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	20%		20%	20%
Emissions price, 1 (t1) ($/ton CO_2)	11.2		10.3	8.0
Emissions price, 2 (t2) ($/ton CO_2)	24.8		22.8	17.8
Learning subsidy (wind) 1 (¢/kWh)			.33	0.30
Learning subsidy (solar) 1 (¢/kWh)			0.63	0.57
R&D subsidy (wind)			50%	50%
R&D subsidy (solar)			50%	50%
EE subsidy 1 (b_{S1}, b_{L1})			0%	10%
EE subsidy 2 (b_{S2}, b_{L1})			0%	10%
Price 1 (% change from baseline)	8.3%		7.4%	4.9%
Price 2 (% change from baseline)	16.7%		14.8%	9.9%
% Renewables 1	8.0%		8.4%	8.0%
% Renewables 2	11.6%		12.8%	12.0%
% EE red 1	2.3%		2.1%	3.9%
% EE red 2	5.7%		5.1%	8.3%
Δ Welfare	-4.37	-2.47	-3.84	-1.57
Δ W (relative to emissions price alone)	—		-12%	-36%

Understanding the optimal policy combinations builds intuition for understanding the effects of single policies and non-optimal combinations.

Single policies

Similar to FN, we first consider the relative cost effectiveness of single policies for meeting the same 20% 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 that does not distinguish between wind or 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 tax on CO_2 with a rebate to all generation in proportion to the standard, such that above-average emitters pay a net tax 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 non-baseload renewables with a tax on all generation, such that $\sum_{i=w,s} s_t\, q_t^i = \sum_i \phi_t q_t^i$.[14] The clean energy standard is a sort of 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% credit to natural gas-CC generation, and 10% credit to generation from existing nuclear and hydropower facilities. Credits are funded through a revenue-neutral tax on all generation.

Table 5 reports the policy targets for each strategy.

Table 5: Single Policies to Achieve 20% 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 (%)
Stage1	11.2	485	1.40	46.8	11.2	4.08	30% short run 48% long run
Stage2	24.8	430	3.10	52.4	21.6	9.05	30%

[14] Equivalently, the net subsidy to renewables is funded by an implicit tax on other sources $\sum_{i=w,s} \hat{s}_t\, q_t^i = \sum_{i \neq w,s} \phi_t q_t^i$, where $\hat{s}_t = s_t - \phi_t$.

Figure 1: Welfare Effects of Single Policies, Relative to Emissions Pricing (=1)

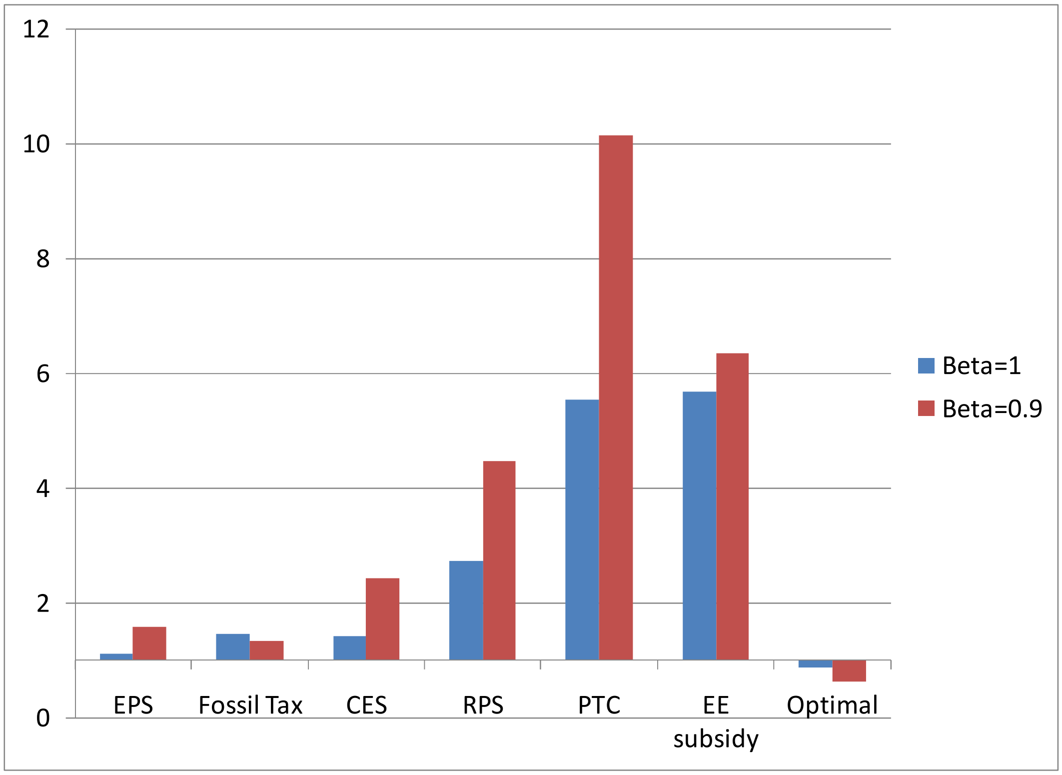

Figure 1 presents the relative welfare effects of each single policy option for achieving the reduction target, compared to the costs under an emissions pricing policy. For example, when no EE market failure is present, using an emissions performance standard costs 11% more than the emissions price, and the fossil fuel tax and CES policies have similar effects (less than 50% higher costs). On the other hand, relying solely on an RPS entails costs 2.7 times as high, and a renewable production subsidy or an EE subsidy costs 5 times as much as 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 effects change when EE improvements are undervalued by consumers. In particular, the discrepancy is larger between policies that raise electricity prices (and thereby 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 the emissions performance standard, meaning the EE interactions are more important than differentiating among fossil energy sources.

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

Combination policy scenarios

Next, we consider a variety of common policy combinations. In each case, we have an emissions pricing program that ensures meeting the 20% cumulative reduction target.

First, we consider the effects of an RPS. This policy implicitly subsidizes renewable energy production with a revenue-neutral tax on nonrenewable energy production. Recall that the optimal policy mix called for a small subsidy to production in the first stage, with the solar subsidy being about twice that of wind. Without the accompanying R&D subsidy to counter R&D spillovers, there may be additional benefits to knowledge accumulation through learning as a substitute. On the other hand, without the cost reductions from additional R&D, one expects less reliance on renewable energy (given a cap), which can reduce the expected benefits from learning.

In the reference scenario, renewable energy is 8.0% of generation in the first stage and 11.6% in the second. We calculate the RPS in each period that most improves welfare in conjunction with a cap, first assuming no undervaluation of energy efficiency. Those standards are 8.4% in the first stage and 12.1% in the second. The corresponding subsidies are 0.27 cents/kWh in the first stage, lower than the optimal subsidies, and 0.31 cents/kWh in the second, which is obviously higher than the optimal second-stage subsidy of zero. These differences arise due to the effects of the implicit tax that pays for the subsidies and the uninternalized R&D spillovers. These policies are very modest and together reduce the welfare costs of the cap by only 1.5%. Notably, any more aggressive renewable energy policies lower welfare.

The ability of an RPS to improve cost effectiveness is also influenced by the EE market failures. With 10% undervaluation, no RPS in the first stage can improve welfare, and the best second-stage RPS is barely binding. The reason is that the RPS—at these modest stringencies—actually lowers electricity prices, exacerbating the underprovision of EE improvements.

Similarly, we calculate EE standards that improve welfare in combination with a cap. In the reference scenario, EE improves by 2.3% in the first stage and 5.7% in the second. With no undervaluation, no EE standard improves welfare—not only because there is no demand-side market failure to internalize, but also because it exacerbates the knowledge market failure: reducing demand and the electricity price also reduces renewable energy knowledge investments, which are underprovided due to the spillovers. With 10% undervaluation, these second-best EE standards are close to the optimal EE improvements (3.7% and 8.3% in stage 1 and 2, compared to 3.9% and 8.3% in the optimal combination). However, the required subsidies are lower, due to the absence of the renewable energy technology policies, which would otherwise keep electricity prices lower. These EE policies lower the cost of the cap by 17% (whereas the optimal policy combination lowers costs 26%).

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. Its targets call for a 20 percent reduction in greenhouse gas (GHG) emissions by 2020 compared with 1990 levels, a 20 percent cut in energy consumption through improved energy efficiency by 2020 and a 20 percent increase in the use of renewable energy by 2020. We model these targets as binding in the second stage. Importantly, these targets far exceed the welfare maximizing levels we just calculated. Indeed, they are so stringent that the cap becomes nonbinding.[15]

Let us take as the main reference case $\rho = 0.5$ and $\beta_x = .9$, so there is some justification for complementary technology and energy efficiency policies. However, these market failures do not justify the 20/20/20 combination, which the model calculates as being 5.6 times as costly as the cap alone.

We then explore the sensitivity of the costs of these combination policies to our knowledge and EE market failures. Figure 1 holds knowledge spillovers as fixed at 0.5 and shows the effects of increasing the rate of undervaluation of energy efficiency. The cost effectiveness of the cap increases monotonically and even turns into a welfare gain by a 25% undervaluation, but the 20/20/20 policy cost effectiveness is even more sensitive to this parameter. We also compare to a policy without the RPS, of combining the cap with a 20% EE improvement standard by the second stage. For undervaluation rates exceeding a quarter, this policy generates higher welfare than the cap alone. (We do not explore larger values of undervaluation, since the model finds it hard to explain baseline behavior at higher values).

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[15] Our model predicts that the 20/20/20 policies reduce emissions by nearly 30%. We note that the welfare calculations include only the economic consequences in terms of consumer and producer surplus and government revenues, and do not include a valuation of these additional environmental benefits.

Figure 2: Sensitivity of Cost of Cap-and-Trade versus 20/20/20 Targets to EE Undervaluation $(\rho = 0.5)$

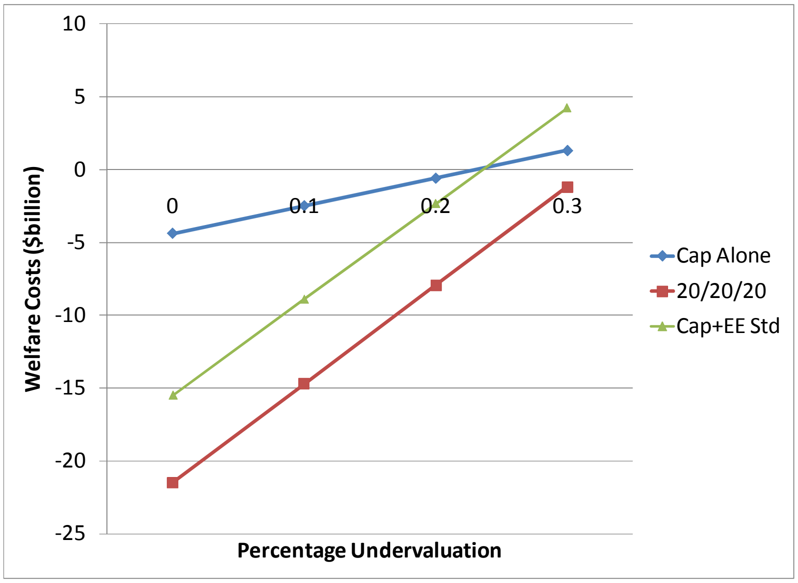
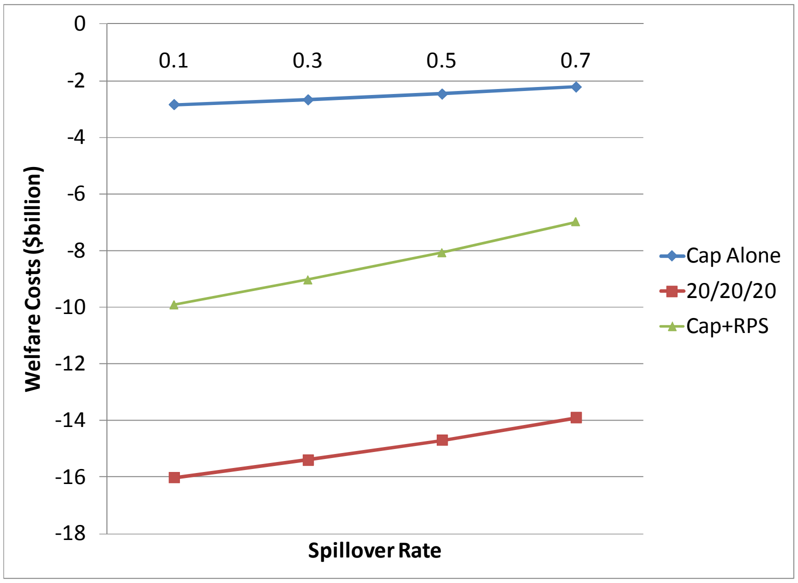


Figure 3 compares the welfare effects of these policies as we vary the rate of knowledge spillovers $(1-\rho)$. The costs of both the cap and the 20/20/20 policies decrease as the knowledge market failure increases, but less dramatically than with the energy efficiency undervaluation. In part, neither the RPS policy nor the EE standard directly target the main knowledge market failure, which is the R&D spillovers. When we exclude the EE standard and add only the 20% RPS by the second stage, we find that the costs are lower than the 20/20/20 policy and more sensitive to the spillover rate, but they still remain more than three times the cost of the cap alone.

Figure 3: Sensitivity of Cost of Cap-and-Trade versus 20/20/20 Targets to Knowledge Spillovers $(\beta = 0.9)$



We note that some other variations can improve the cost effectiveness of the 20/20/20 policies, but not to the point where costs are lower than the cap alone. For example, adding an optimal R&D policy cuts costs roughly in half. Offering double credits for solar, which more closely mimics the optimal production subsidy profile, lowers costs somewhat but not substantially.

Finally, we consider a wider range of targets for emissions reductions. Indeed, much of the motivation for aggressive 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 they are more than double those of the 20 percent target, but those levels are still small relative to policy ambitions. Meanwhile, the optimal emissions price increases by an order of magnitude, indicating that it becomes relatively more important as a policy instrument.

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, these justifiable policies are likely to be much more modest than 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. 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. Even for "next generation" technologies like solar energy, with larger potential for cost reductions, the optimal subsidies in support of learning-by-doing seem minor. In our model, correcting R&D market failures, on the other hand, has a much larger potential for reducing the costs of achieving significant emissions reductions.

Although we have not presented additional sensitivity analysis with respect to our assumptions regarding the nature of knowledge accumulation and appropriation, such an exercise was conducted in FN, without change to the basic results. We therefore find that ambitious renewable portfolio standards are unlikely to be welfare enhancing, unless other goals and benefits are in play, such as energy security or other benefits of energy supply diversification.

The desirability of stringent energy efficiency policies, on the other hand, is very sensitive to the degree of 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 this demand parameter, 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.

Finally, it is 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
ng	Conventional natural gas-fired generation (boilers and turbines)
cc	Combined cycle 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* ($i = \{x,ng,cc,nu\}$)
P_t	Retail 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* ($i = \{x,ng,cc,nu\}$)
π^i	Profits from source *i*
$G_{jt}(K_t^j, q_t^j)$	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^j	Appropriation rate of returns from knowledge investments for source *j*
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 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 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.

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 intensity elasticity of demand 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:

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

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

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

Which gives us

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

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

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

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

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

$$\eta_{11} = \frac{\varepsilon + (1-\varepsilon)\left(\left(\frac{\beta_1^S}{z_2^{S_1}} + \frac{\beta_1^L}{z_2^{\ L}} \right) P_1 D_1 - \delta \frac{n_2}{n_1} \frac{\beta_2^L}{z_2^{\ L}} P_2 D_2 \eta_{21} \right)}{\left(1 + (1-\varepsilon)\left(\frac{\beta_1^S}{z_2^{S_1}} + \frac{\beta_1^L}{z_2^{\ L}} \right) P_1 D_1 \right)}$$

$$\eta_{22} = \frac{\varepsilon + (1-\varepsilon)\left(\left(\frac{\beta_2^S}{z_2^{S_2}} + \frac{n_2}{n_1} \frac{\beta_2^L}{z_2^{\ L}} \delta \right) P_2 D_2 - \frac{\beta_1^L}{z_2^{\ L}} P_1 D_1 \eta_{12} \right)}{\left(1 + (1-\varepsilon)\left(\frac{\beta_2^S}{z_2^{S_2}} + \frac{n_2}{n_1} \frac{\beta_2^L}{z_2^{\ L}} \delta \right) P_2 D_2 \right)}$$

$$\eta_{12} = \frac{(1-\varepsilon) \frac{n_2}{n_1} \frac{\beta_2^L}{z_2^{\ L}} \delta P D_2 \left(1 - \eta_{22}\right)}{\left(1 + (1-\varepsilon)\left(\frac{\beta_1^S}{z_2^{S_1}} + \frac{\beta_1^L}{z_2^{\ L}} \right) P_1 D_1 \right)}$$

$$\eta_{21} = \frac{(1-\varepsilon) \frac{\beta_1^L}{z_2^{\ L}} P_1 D_1 \left(1 - \eta_{11}\right)}{\left(1 + (1-\varepsilon)\left(\frac{\beta_2^S}{z_2^{S_2}} + \frac{n_2}{n_1} \frac{\beta_2^L}{z_2^{\ L}} \delta \right) P_2 D_2 \right)}$$

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:

$$\beta_1^L = \delta \frac{n_2 P_2 D_2 \eta_{21}}{n_1 P_1 D_1 \eta_{12}} \beta_2^L$$

and

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

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

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