Environmental and Technology Policy Options in the Electricity Sector: Are We Deploying Too Many?

Carolyn Fischer, Louis Preonas, Richard G. Newell

Abstract: Myriad policy measures aim to reduce greenhouse gas emissions from the electricity sector, promote generation from renewable sources, and encourage energy efficiency (EE). Prior literature has argued that overlapping policies reduce the efficiency of emissions markets, absent other market failures. We extend the model of Fischer and Newell to incorporate knowledge spillovers for both advanced and conventional renewable energy technologies, as well as imperfections in demand for EE investments. EE undervaluation can justify interventions and raises the importance of fully pricing the social costs of electricity, making policies (like renewable subsidies) that lower electricity prices less desirable. Innovation market failures justify some technology policies, particularly correcting R&D incentives, but aggressive deployment policies seem unlikely to enhance welfare when placed alongside sufficient emissions pricing. Even with multiple market failures, emissions pricing remains the most cost-effective option for reducing emissions. However, technology-oriented policies can involve less redistribution of surplus.

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OVER THE PAST DECADE, concerns about global warming, local air quality, and energy security have led to a plethora of actual and proposed initiatives aiming to reduce emissions from the power sector, promote electricity generation from renewable sources, and encourage energy conservation. Examples 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 and solar,

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geothermal, and biomass generation; policies to price greenhouse gas (GHG) emissions through cap and trade or a carbon tax; and performance standards, such as maximum emission rates per kilowatt-hour (kWh) of electricity and energy efficiency standards for household appliances.

Those policies frequently coexist within the same jurisdiction, yet little attention has been paid to whether they work together or at cross purposes. Policy instrument choice in the context of multiple interacting policies and market failures has been identified as an important area for further investigation (Goulder and Parry 2008), and we should recognize that the whole of our energy policy mix is going to be distinct from the sum of its parts—and possibly less than that sum (Fischer and Preonas 2010).

Many of these policies aim to address an emissions externality, such as the damages from air pollution or the risks of climate change. If that were the only market inefficiency, then one policy instrument would be sufficient: 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; rather, they drive down the emissions price, which tends to benefit the dirtiest energy sources (Böhringer and Rosendahl 2010). By distorting the market allocation of abatement, supplemental policies actually increase overall compliance costs—unless there are other market failures.

Perhaps the "kitchen sink" approach 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 from the lack of credible information (Newell and Siikamäki 2014), landlord-tenant arrangements (Myers 2015), or myopic behavior (Allcott and Taubinsky 2015), but they generally present themselves as an undervaluation of energy efficiency in the purchase of energy-using appliances or homes (see the review by Gillingham, Newell, and Palmer 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 lack sufficient incentive to develop and deploy

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new technologies (Jaffe, Newell, and Stavins 2005). The presence of such policy and/or market failures will affect the relative desirability of different policy combinations.

Fischer and Newell (2008) assessed different policies for reducing carbon dioxide emissions and promoting innovation and diffusion of renewable energy, with an application to the US 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 because of knowledge spillovers, the optimal policy involves a portfolio of different instruments targeting not only emissions but also R&D and LBD. 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 last an R&D subsidy.

In this paper, we extend the Fischer and Newell framework in several important ways to enable a richer analysis of interacting market failures in the power sector. First, we expand Fischer and Newell's representation of electricity demand to include short- and long-run energy efficiency investments. We allow consumers to undervalue the returns to investing in energy efficiency, permitting an analysis of demand-side energy policies in the presence of energy efficiency market failures. Second, we refine the representation of clean energy options, distinguishing between conventional renewable energy sources (like wind and biomass) and advanced technologies (like solar) to capture differences in their costs and innovation potential. This refinement causes market failures to vary between conventional versus advanced renewable technologies, allowing us to represent some of the tensions between wanting to avoid picking winners and wanting to target specific technologies. We also allow for potential long-run growth in nuclear energy, treating it as a viable zero-carbon alternative alongside renewable generation. This paper's novel contribution is to analyze the joint effect of two market failures—knowledge spillovers in renewable technology innovation and undervaluation of energy efficiency investments—on the optimal policy combinations for reducing emissions and also on the relative cost-effectiveness of single or otherwise suboptimal policies.

The electricity sector is an appropriate subject for this analysis, being the sector most affected by proposed policies for climate mitigation.[1] Electricity generation accounted for roughly 40% of carbon dioxide (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% of cost-effective emissions abatement would stem from the electric power sector (EIA 2011).

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 the

1. See Anderson, Fischer, and Egorenkov (2016) for an analysis of overlapping policies and market failures in the transportation sector.

societal trade-offs, 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 supplemental policies are conceptually valid, the empirical magnitude of such additional incentives is an important focus of this paper.

We first compare common single and combined policy instruments to evaluate their cost-effectiveness in achieving target emissions reductions in the presence of market failures other than environmental externalities. The degree of EE undervaluation in particular has important implications for the relative cost-effectiveness of policies (especially those focused on renewables), since lower electricity prices exacerbate demand-side market failures. In fact, with sufficient unaddressed EE undervaluation, an emissions price might actually be less cost-effective at achieving emissions reductions than other policies that lead to higher electricity prices.

We then evaluate optimal and suboptimal, "technology-oriented" policy combinations. We find that although some technology policies can be useful complements to emissions pricing, it is difficult to generate scenarios calling for large subsidies to LBD in renewables. Overreliance on renewable portfolio standards or renewable energy deployment subsidies can raise costs relative to a carbon price alone. Our model results indicate that, as complementary policies, correcting R&D market failures has a larger potential for reducing the costs of achieving significant emissions reductions than correcting LBD spillovers of a similar scale. Correcting the undervaluation of energy efficiency has an even greater effect on those costs because a demand-side market failure affects the entire electricity market, whereas renewable generation is only a small share of supply. While technology-oriented policies are less cost-effective, they do entail less redistribution of surplus than emissions pricing, which may factor in the political feasibility of climate policy.

1. MODEL DESCRIPTION

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 app. A; apps. A, B available online.) The supply side of the model is based on Fischer and Newell. 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 to supply an identical product, kWh of electricity.[2] Nonrenewable pro-

2. 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.

duction 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 EE improvements to occur, and a second stage of n_2 years, roughly representing the lifetime of the new technologies and investments. Discounting between stages is represented by the factor δ. Electricity generation, consumption, short-term EE improvements, and emissions occur in both stages, but investment in long-term energy efficiency and in knowledge takes place during just the first stage. Both consumers and firms take as given not only current prices but also prices in the second stage, having perfect foresight about those prices. However, perfect foresight does not mean that all decisions are efficient.

Through technological change, knowledge investments made during the first period lower the cost of renewable generation in the second period. But not all the benefits of innovation—through either LBD or R&D—may be appropriable by the representative innovator. The appropriation factor (ρ) influences the incentives for knowledge investments; when appropriation is incomplete ($\rho < 1$), there are spillovers from the creation of knowledge.

We model similar market failures on the demand side. Whereas Fischer and Newell represented electricity demand with a static constant elasticity function, we now allow demand to respond also to short- and long-run energy price changes through energy efficiency investments. Consumers experience utility from energy services, and they are indifferent to the generation source, be it renewable or fossil-fueled energy. The cost of energy services depends on both the consumer electricity price and the energy consumption rate (or energy intensity). The latter is a function of reductions that can be made in both the short term and the long run by investments in EE improvements. This formulation allows us to separately consider rebound effects, factors affecting EE decision making, and behavioral responses to price changes.

Investments can be made in both short-run EE improvements in each period and in long-run reductions that span both periods. 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, taking the form of an undervaluation of the stream of benefits of EE at the time investments are made. The representative agent may have incomplete information, be myopic, or otherwise perceive that it would not fully benefit from EE investments. The valuation rate β is incorporated in similar fashion to the appropriation rate for renewable energy innovation, as developed in Fischer and Newell and described in appendix A. As a result, policies that raise energy prices and thereby energy expenditures lead to increased investment in energy efficiency and, to the extent there is undervaluation ($\beta < 1$), a positive benefit on the margin.

As in Fischer and Newell, we assume that any changes to government revenues are returned (or raised) in lump-sum fashion. By holding cumulative emissions constant across policy scenarios, we can make welfare comparisons without formally quantifying environmental benefits.[3] Hence, our welfare measure is the change in economic surplus (W), which comprises changes to consumer surplus (calculated as the change in net utility), producer surplus, and government revenue.[4]

In the presence of multiple market failures, a carbon price is a powerful and necessary tool, but if it is deployed 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 the social optimum. The optimal policy portfolio would include multiple instruments:

- a carbon price (τ) to reflect the shadow value of CO_2 reductions, rising according to the discount factor ($\tau_1 = \delta\tau_2$);
- subsidies (s) for early-stage LBD in the first stage to correct for learning spillovers for each technology;
- an R&D subsidy (σ) equal to the R&D spillover rate ($\sigma = 1 - \rho$); and
- subsidies to EE investments (b) to offset the unvalued share of EE benefits, in both the short and the long term ($b = 1 - \beta$).

An important point to note is that if market failures vary by technology, a technology-neutral policy will not be efficient. In fact, even with identical spillover rates (in the sense of $\sigma = 1 - \rho$), the marginal benefits of learning vary according to the production costs and knowledge production specific to each technology. Thus, the optimal policy portfolio would offer differentiated production subsidies to conventional and advanced renewable generation. Optimal EE investment subsidies would likewise be calibrated separately for short- and long-run investment undervaluation rates if those differ. Additional policies like taxes on nonrenewable energy sources (ϕ) may be used in second-best settings, in-

3. This assumes that decay in the global stock of CO_2 is negligible over our model horizon, making the timing of CO_2 emissions irrelevant.

4. General equilibrium factors—like interactions with tax distortions, emissions leakage, economy-wide R&D interventions, or other market failures—can also be important for determining welfare effects but are outside the scope of this paper. 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).

cluding the implementation of renewable energy targets that pay for the subsidies with implicit taxes on ineligible sources.[5]

2. NUMERICAL APPLICATION

2.1. Supply Curves and Knowledge Functions

The functional forms for generation and knowledge closely follow those of Fischer and Newell. As in Fischer and Newell, we distinguish between nonrenewable and renewable sectors. Nonrenewable sources include coal (x), natural gas turbines (ng), and nuclear (nu).[6] 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. Hence, we assume that these emissions factors μ^i are fixed, where $\mu^x > \mu^{ng} > \mu^{nu} = 0$. Carbon capture and sequestration technologies are also excluded; their use would be triggered only by carbon price levels that are outside the range of policies we consider in this paper. Output from source i at time t is given by q_t^i.

All production cost functions are quadratic in output, yielding linear electricity supply curves for each fuel source, calibrated around the baseline quantities.[7] These functional forms are intended to represent the quantity-price relationship of electricity supplies over a medium to long run, when capacities have time to adjust, as opposed to representing short-run dispatch issues.

The cost functions of new renewable energy technologies are distinguished by endogenous technical change. That is, they decline over time as a function of cumulative output ("experience"), Q_t^j, and cumulative R&D, H_t^j, for each renewable technology j at time t. With two stages of length n_t, we have $Q_2^j = Q_1^j + n_1 q_1^j$ and $H_2^j = H_1^j + n_1 h_1^j$, where h_1^j is annual research in stage 1 for technology j; no research occurs in stage 2.

An important addition to the Fischer and Newell model is the expansion of the renewable sector from a single, uniform technology to separate "conventional" (w) (i.e., wind, biomass, municipal solid waste, and geothermal) and "advanced" (s) (i.e., solar) technologies (IEA 2010a, 134). The latter have both higher costs and higher potential for technological innovation than conventional renewables.

Our assumptions do not preclude the possibility that nonrenewable technologies experience technological advances. Consistent with long-run forecasts, which incorporate recent and expected advances, such as the boom in hydraulic fracturing, we allow

5. For a deeper exploration of second-best policy responses in this model context, see Fischer, Huebler, and Schenker (2016).

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

7. As with any linearized models, the results will be more reliable for interventions that lead to modest deviations from the baseline values.

for some modest autonomous cost changes to fossil fuel generation over time. Strictly speaking, our assumption rules out any endogenous technological response among nonrenewable sources, beyond current forecasts.[8]

For renewables, technical change is incorporated, as in Fischer and Newell, by scaling production costs by the inverse of accumulated knowledge stocks, K_t^j, for each technology. This knowledge stock function assumes the common form of a constant-elasticity relationship with respect to both cumulative experience and cumulative R&D, relative to those inherited in the first stage: $K_t^j(Q_t^j, H_t^j) = (Q_t^j/Q_1^j)^{k_1^j}(H_t^j/H_1^j)^{k_2^j}$, so $K_1^j = 1$. With this functional form, the inverse has the desirable properties of being decreasing and convex (with $k_i^j \in (0, 1)$) and empirically supported by studies of the relationship between LBD and production costs and the relationship between productivity and R&D (see, e.g., Klaassen et al. 2005). Adding to cumulative R&D involves investments with increasing marginal costs; we follow Fischer and Newell in using a constant-elasticity functional form, now differentiated by renewable technology: $R^j(h_1^j) = \gamma_0^j(h_1^j)^{\gamma_1}$, $\gamma_1 > 1$.

To parameterize separate knowledge functions for wind/other and solar, we consider both their respective knowledge stocks and the relative ability 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, historical cumulative US 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 $Q_1^2 = 9.5 \times 10^{10}$ kWh, so that annual wind and solar generation represent, respectively, about 11% and 33% contributions to accumulated experience. These estimates are consistent with the current contribution of wind/other and solar to cumulative US generation of each technology (EIA 2013a).[9]

Distinguishing k_1^j and k_2^j by renewable technology allows us to consider their relative responses to LBD and R&D knowledge. Several studies have compared learning

8. 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 emissions parameters particular to those other technologies.

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

rates for established renewables (wind) and developing technologies (solar),[10] but they typically do not separate knowledge into learning and research components.[11] We use technological learning assumptions from both the Energy Information Administration (EIA 2013b) and the International Energy Agency (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% cost reduction for wind/other and a 19% cost reduction for solar. Using these values, we calibrated k_2^j such that total baseline renewables cost reduction was in line with total technological improvement as projected by EIA's National Energy Modeling System (NEMS), giving us $k_2^w = 0.15$ and $k_2^s = 0.20$ (EIA 2013b, 104). As in Fischer and Newell, 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% of wind/other revenues and 3.0% of solar revenues,[14] and we solve for each γ_0^j in the baseline scenario. We also retain Fischer and Newell's assumed knowledge appropriability rate for both wind/other and solar of $\rho = 0.5$ in the reference parameterization.[15]

2.2. Demand Functions and Parameterization

Let $D_t(P_t, \psi_t)$ be the derived consumer demand for electricity, a function of the price and an energy consumption rate, ψ_t.[16] We assume functional forms for utility that lead to a constant-elasticity demand function (derived in app. A): $D_t = N_t \psi_t^{1-\varepsilon} P_t^{-\varepsilon}$,

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

11. One exception is Kobos, Erickson, and Drennena (2006), who empirically derive two-factor learning curves for wind and solar. However, their results across several scenarios are inconclusive on whether R&D or LBD has a stronger effect on either technology.

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

13. For example, Jaffe (1986) finds an elasticity of patents with respect to R&D of more than 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 US industry lies in this range (NSF 2006). Limited information is available on current private US spending on renewables R&D.

15. This estimate comes from economy-wide studies such as Griliches (1992) and Jones and Williams (1998); emerging work from Dechezleprêtre et al. (2013) indicates that spillovers may be higher for clean technologies. Note that a constant appropriability rate across technologies will yield different degrees of knowledge spillovers because new R&D knowledge is relatively more valuable in the less mature solar industry.

16. For simplicity, we assume that in the absence of policy interventions, equilibrium consumer and producer electricity prices would be equal. In reality, retail prices have markups over wholesale prices to reflect transmission and distribution costs. To the extent that these discrepancies are roughly constant per unit, they do not affect our analysis and are essentially absorbed into the calibration.

where N is an exogenous demand growth factor and $\varepsilon \in (0, 1)$ represents a very short-run elasticity of demand, as might be reflected in the rebound effect (i.e., the change in energy services, like lumens, in response 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 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 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 conditions (see app. A), we get $z_1^S = \beta P_t^0 D_t^0$ and $z_1^L = \beta P_1^0 D_1^0 + \beta\delta P_2^0 D_2^0 n_2/n_1$. 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.

2.3. Calibration

Our baseline scenario is a no-policy scenario. We calibrate baseline parameters for each generation source to EIA's reference case model projects, published in the *Annual energy outlook* (AEO) of 2013. For each technology i, baseline generation levels (q_{0t}^i) and emissions intensities (μ^i) are likewise calibrated to NEMS model projections, namely, the AEO 2013 reference case. We set exogenous demand growth at 13%, based on AEO's projected electricity generation (EIA 2013a), annualized across each stage; these demand scalars include exogenous trends in energy efficiency. Importantly, all our baseline parameters incorporate the numerous existing federal, state, and local laws and regulations that are included in EIA's reference case, which assumes that current policies affecting the energy sector are largely unchanged throughout the projection period. Hence, our numerical results can be interpreted as representing the effect of incremental policies on top of this EIA baseline.[17]

We assume a first-stage length of $n_1 = 5$ years, starting in 2015, and a second-stage length of $n_2 = 21$ years, matching AEO projections to 2040. For simplicity, we assume that no discounting occurs within the first stage; this ensures that behavior within that stage remains identical. For the second stage, which is both longer and occurs in the future, we apply the discount factor δ. This factor includes both discount-

17. With our stylized model, we are unable to model interactions with these other policies. This caveat may be especially important to the extent that other overlapping policies involve tradable credit mechanisms (Fischer and Preonas 2010).

ing between the stages and discounting within the second stage. We discount the years within the second stage back to its beginning, and then discount that value back to the present, essentially calculating an average discount factor for the second stage (i.e., $\delta = (1 + r)^{-n_1}((1 - (1 + r)^{-n_2})(1 + r)/r)/n_2)$. At a rate of $r = 7\%$, this implies a discount factor $\delta = 0.39$, so activities in the second stage have an effective weight of $\delta n_2 = 8.3$. Table A1 (tables A1–A3 available online) lists the parameters that do not vary over time, including CO_2 emissions intensities, R&D investment parameters, knowledge appropriation rates, and target demand elasticities.

We set our baseline electricity price at 9.3 cents/kWh based on the AEO 2013 national average across end-use sectors, with all monetary values adjusted to 2011 dollars. This price equals the marginal cost of supply for all generation sources in the baseline. To derive the implicit slope of each generation technology's supply curve, for each time period, we compare net prices and generation levels in the AEO side cases "No GHG Concern" and "GHG Policy Economy-wide." 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. Table A2 lists these supply parameters. Our calibration gives coal by far the flattest supply curve, indicating that policies that crowd out fossil fuels will disproportionately crowd out this dirtiest source.

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.[18] Other demand elasticities for electricity are based on this estimate, with $\eta_{11} = 0.2$, $\eta_{22} = 0.4$, and $\eta_{21} = 0.5$ representing roughly short-term, long-term, and cross-period demand elasticities, respectively.

To calibrate the slopes of the marginal costs of energy efficiency improvements, we solve for EE 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. (See the app. A for the analytical derivations.) Solving for the equilibrium quantity changes due to a price change, this gives us a system of four equations (own-price elasticities for each period and the cross-price elasticities across periods). 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 between η_{12} and η_{21}, given β. Table A2 lists the parameters of the energy efficiency cost curves. For a permanent 10% change in the electricity price (i.e., across both periods), the implicit elasticity of demand in the first stage is 0.30.

18. See Kamerschen and Porter (2004), Sorrell, Dimitropoulos, and Sommerville (2009), and Gillingham, Rapson, and Wagner (2016).

An important point is that market behavior in the model is independent of the assumptions about the perceived energy efficiency benefit valuation rate (β). 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 costs of policy interventions in terms of lost economic surplus.

We solve this nonlinear system of equations using Matlab, and table 1 reports results for our baseline no-policy scenario. Of note is the relatively small share of nonhydro renewable energy in the baseline (7% in the first stage and 9% in the second), nearly all in the form of conventional nonhydro renewables, such as wind, biomass, and geothermal. Solar remains a fraction of 1% of generation. Significant renewable energy cost reductions occur in the baseline, with wind/other costs falling 7% and solar costs falling 29%. Table A2 also reveals that renewable supply curves become flatter in the second stage.

3. RESULTS

3.1. Single Policies and Stylized Combinations

Similar to Fischer and Newell, we first consider the relative cost-effectiveness of given policy strategies for meeting the same cumulative emissions target, 40% below baseline emissions. Although this target is more stringent than most pledges for economy-wide emissions reductions over the time horizon, for this single-sector model, it reflects the disproportionate opportunities for emissions reductions in electricity generation. In

Table 1. Baseline Results with No Policy

	Stage 1		Stage 2	
	Billion kWh/yr	% of gen.	Billion kWh/yr	% of gen.
Price of electricity (P_t^0) (¢/kWh)	9.3		9.8	
Electricity demand (D_t^0) (billion kWh/yr)	4,256		4,784	
Generation by source (billion kWh/yr | % of gen.):				
Coal (q_{0t}^{x})	1,587	37.3	1,760	36.8
Oil (q_{0t}^{oil})	18	.4	18	.4
Natural gas (q_{0t}^{ng})	1,187	27.9	1,384	28.9
Nuclear (q_{0t}^{nu})	856	20.1	895	18.7
Hydro (q_{0t}^{h2o})	309	7.3	315	6.6
Wind/other (q_{0t}^{w})[a]	264	6.2	358	7.5
Solar (q_{0t}^{s})	35	.8	54	1.1
CO_2 emissions (E_t) (billion metric tons/year)	2.05		2.30	
Rate of wind/other cost reduction (%)			7	
Rate of solar cost reduction (%)			29	

[a] This includes all nonsolar, nonhydro renewable generation.

each case, policy stringency is adjusted over time to minimize the present value of costs. Given the wide range of results in the empirical literature on energy efficiency valuation and the multiplicity of potential rationales for undervaluation (Gillingham et al. 2009), we hesitate to assign a single baseline value for β. We compare a situation with perfect valuation (no myopia, analogous to Fischer and Newell assumptions) with one having a 10% undervaluation. This amount is fairly conservative, but sufficient for demonstrating our results. Our reference parameterization will assume $\rho = 0.5$ and $\beta = 0.9$.

We consider four single-price policies in which a single tax or subsidy is applied. The first is emissions pricing, which differentiates among energy sources. The fossil tax, by contrast, is imposed equally on all fossil fuel sources. The renewable subsidy uses a fixed subsidy path for nonhydro renewables that does not distinguish between wind/other and solar. These taxes and subsidies follow a path that is increasing over time according to the discount factor. The EE subsidy is applied as a percentage of investment costs. These policies, along with the R&D subsidy, form the building blocks for common policy combinations.

We also consider two revenue-neutral policies with self-adjusting prices. The emissions performance standard (EPS) sets an intensity target, such that above-average emitters pay a net fee and below-average ones gain a net subsidy; in essence, the EPS combines a CO_2 emissions price with a rebate to all generation in proportion to the standard.[19] The renewable portfolio standard (RPS) funds a common subsidy to the innovating, nonhydro renewables with a fee on all generation.[20]

Finally, we add two combination approaches that emphasize technology support over emissions pricing. In the first combination, "overlapping standards," we model a 20% RPS for nonhydro renewables that is binding in both stages, and an energy efficiency standard of a binding 10% reduction in energy intensity in both stages, reflecting ambitions for near-term deployment as a technology driver.[21] A complementary emissions pricing program ensures meeting the 40% cumulative reduction target. The second combination eschews emissions pricing completely for a "technology-only" policy. This stylized policy combines the 10% EE target, a 50% R&D subsidy, and an increasing RPS sufficient to achieve the 40% reduction in emissions.

19. Specifically, $-\phi_t^i = s_t^i = s_t$, and $\Sigma_i s_t q_t^i - \Sigma_i \tau_t \mu^i q_t^i$.

20. Specifically, $\Sigma_{i=w,s} s_t q_t^i - \Sigma_i \phi_t q_t^i$. We model the RPS as rewarding the full subsidy value to both wind and solar categories (i.e., all nonhydro 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. Since hydropower production is fixed, the definition of the RPS is less important for determining generation outcomes, although it can have distributional effects.

21. This combination is loosely inspired by the European Union approach since the 20/20/20 targets; since those are economy-wide and we consider only the electricity sector, we have adjusted our targets accordingly. The emissions goal is more stringent, because disproportionate reductions are expected from electricity, while the EE goal is less stringent, reflecting higher costs than in other sectors.

Table 2 and figure 1 present results for the single policies, roughly in their order of cost-effectiveness with perfect valuation (as in Fischer and Newell), followed by the combination policies. Table 2 reports the policy targets for each strategy. These targets are invariant to the degree of EE undervaluation, but the economic costs associated with them are not, as we will see subsequently. We see that the initial \$13.67 carbon tax is actually quite close to the current permit price in California's cap-and-trade system[22] and toward the lower end of the range of US government estimates of the social cost of carbon.[23] Given our emissions factors for coal and natural gas, this is equivalent to a 1.34 cents/kWh tax on coal generation and a 0.55 cents/kWh tax on gas generation. Note that the undifferentiated fossil tax is higher, at 1.45 cents/kWh: by not targeting each fuel in proportion to its emission factor, a fossil tax is less effective at reducing total emissions. The required renewable subsidy at 3.1 cents/kWh in the first stage is more than twice as large as the fossil tax, since fossil fuels and consumption are not penalized. The stage 1 emissions performance standard corresponds to a 13% reduction in the 2015 US average emissions rate of 470 tons CO_2/GWh. These policy targets reflect modest predicted costs of abating emissions in the electricity sector; with coal having the flattest medium-run supply curve of all the sources in the calibrations (see table A2), its output is disproportionately displaced by price changes, resulting in large emissions reductions.

Next, we consider policies that were not evaluated in Fischer and Newell. Meeting the target with just energy efficiency improvements requires a scaling up of the investment subsidy to 53%. With overlapping standards, the required emissions price is 60% lower than with emissions pricing alone. With the technology-only policy, the supplementary policies lower the RPS needed to achieve the target by 6% in the first stage and 17% in the second stage.

Figure 1 presents the relative costs (in terms of lost economic surplus) of each single policy option for achieving the reduction target as a ratio 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 policy costs by less than 1%, relative to an emissions price.[24] In contrast, the RPS policy results in 65% higher costs, and relying solely on a renew-

22. In March 2016, California permits traded at \$12.69 to \$12.98 per ton CO_2.

23. Based on the updated July 2015 estimates, the Environmental Protection Agency's lowest estimate of the social cost of carbon, using 5% discounting, is \$11 for 2015 in 2007 dollars, which equals \$12 in 2011 dollars. EPA's social cost of carbon rises in real terms by 2% per year, reflecting dynamics in the estimated damages, so together with the 5% social discount rate, the effective discount rate is similar to our 7% assumption. To put the policy costs into context, with emissions reductions of 23 billion tons CO_2, the social benefit of those reductions at \$12 per ton would be \$281 billion.

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

Table 2. Policies to Achieve 40% Cumulative Emissions Reduction Target

	Stage 1	Stage 2
Emissions pricing (\$/ton CO_2)	13.67	34.73
Emissions performance standard (EPS) (ton CO_2/GWh)	409	285
Fossil tax (¢/kWh)	1.45	3.67
Renewable portfolio standard (RPS) (%)	11.2	31.1
Renewable subsidy (¢/kWh)	3.10	7.87
EE subsidy (%):		
Short-run	53	53
Long-run	53	0
Overlapping standards:		
Emissions price (\$/ton CO_2)	5.40	13.71
RPS (%)	20	20
EE improvement (%)	10	10
Technology only:		
RPS (%)	10.5	25.7
R&D subsidy (%)	50	50
EE improvement (%)	10	10

Note. EE = energy efficiency.

able production (or EE) subsidy costs three (five) 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.[25] Overlapping standards have costs similar to the RPS, and the technology-only strategy is slightly more cost-effective.

We observe important changes in the relative costs when EE improvements are undervalued by consumers. The policies interact with preexisting distortions, meaning in this case that increases in energy efficiency have additional social value on the margin, and decreases have additional welfare costs, because EE improvements are already underprovided.[26] 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, which tend to lower electricity prices. The two combination strategies incorporate both of these policies and thus seem somewhat less sensitive to undervaluation. We elaborate further on their efficiency and distributional effects later in section 3.3.

In absolute terms, the economic costs of the EE subsidy are indeed lower with EE undervaluation than without, since it in part corrects a market failure. However, as a

25. In fact, despite the implicit tax on generation, an RPS can even lower electricity prices (Fischer 2009).

26. See also Fischer et al. (2016) for more theoretical background.

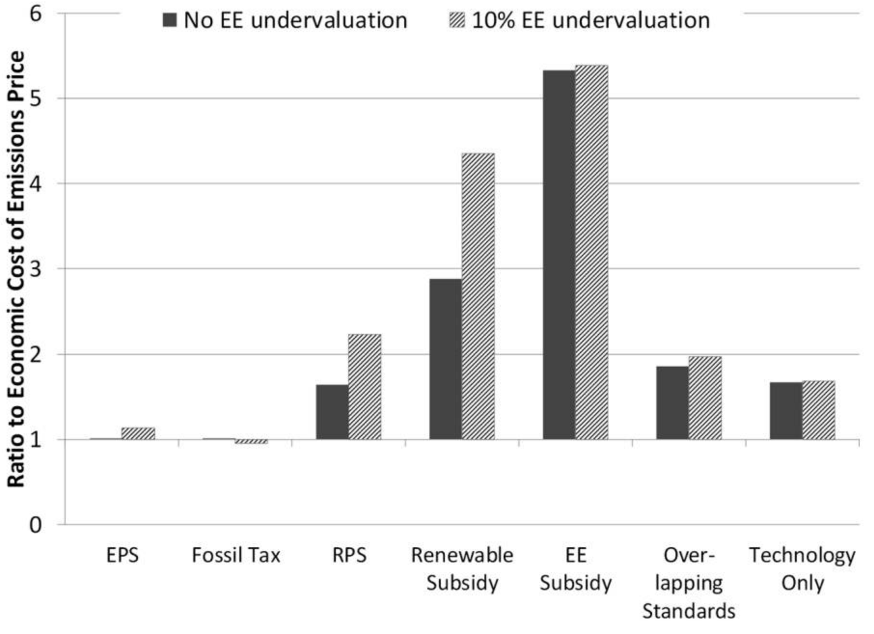

Figure 1. Economic costs of policies, relative to emissions pricing ($\rho = 0.5$). EE = energy efficiency; EPS = emissions performance standard; RPS = renewable portfolio standard.

single policy it performs worse in relative terms to the carbon tax; EE undervaluation also lowers the costs of using the carbon tax, since the ensuing higher electricity prices also induce additional energy efficiency.

Interestingly, the fossil fuel tax becomes relatively 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, which we discuss next in detail, the gains from addressing EE underinvestment result in a 25% reduction in the costs of the policy portfolio, relative to an emissions price alone. 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 alone.

3.2. Emissions Pricing and Optimal Policy Combination

Table 3 compares the effects of an emissions pricing program, implemented without complementary policies, with the optimal policy combination, depending on the EE benefit valuation rates. The policy scenario results are reported in relation to the baseline values; the economic consequences are reported relative to the benchmark policy of an emissions price without supplementary policies. As previously mentioned, with

Table 3. Emissions Pricing versus Optimal Policy Combination

	Policy			
	Emissions Pricing		Optimal Policy Combination	
	No EE Failures $\beta = 1$	10% EE Undervaluation $\beta = .9$	No EE Failures $\beta = 1$	10% EE Undervaluation $\beta = .9$
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 (s_1^w) (¢/kWh)			.70	.64
Learning subsidy, solar (s_1^s) (¢/kWh)			4.93	4.54
LBD subsidies as share of generation revenues, wind/other (s_1^w/P_1) (%)			7	6
LBD subsidies as share of generation revenues, solar (s_1^s/P_1) (%)			47	44
R&D subsidy rate (σ) (%)			50	50
R&D subsidies as share of generation revenues, wind/other ($R^w/(P_1 q_1^w)$) (%)			12	11
R&D subsidies as share of generation revenues, solar ($R^s/(P_1 q_1^s)$) (%)			25	23
EE subsidy (b) (%)			0	10
Electricity price (% change from baseline):				
Stage 1 (%)	13.6		11.5	9.6
Stage 2 (%)	23.8		18.7	14.5
% nonhydro renewables, stage 1	9.8		10.9	10.6
% nonhydro renewables, stage 2	19.8		22.1	20.5
% EE improvement, stage 1[a]	3.9		3.2	5.3
% EE improvement, stage 2	8.1		6.5	10.0
Δ surplus (billion $, annualized)	−10.12	−6.99	−8.50	−5.27
% improvement compared with emissions pricing from complementary policies	. . .		16	25

Note. EE = energy efficiency; LBD = learning by doing.

[a] This is the percentage reduction in the energy consumption rate, relative to the baseline.

only emissions pricing, market behavior is independent of these valuation rates, but the policy costs 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 spillovers, these prices would be combined with a substantial 50% R&D subsidy. The optimal first-stage subsidy for learning is 0.7 cents/kWh for wind/other, and a more substantial 4.9 cents/kWh for solar. This difference highlights the importance of targeting technologies with stronger learning potential and phasing down support over time as technologies mature and become more competitive. Altogether, the optimal combination of policies lowers costs 16% relative to the cap alone, again assuming no EE market imperfections.

In the presence of market failures in demand for EE improvements, the optimal policy mix changes more substantially. With a 10% undervaluation, the inclusion of EE subsidies induces more demand-side conservation, allowing for lower emissions prices (more than 25% lower than with just emissions pricing) to achieve the same emissions target. The optimal subsidies for learning among renewable energy sources also fall. Relative to emissions pricing alone, the optimal combination of policies lowers costs by 25%. Unsurprisingly, the benefits of optimal supplementary policies are increasing with the size of the market failures (i.e., $1 - \rho$ and $1 - \beta$); however, the benefits are less sensitive to the stringency of the cap, since the emissions price is the appropriate mechanism for addressing the emissions externality.

A striking result is that the optimal renewable energy subsidies for addressing learning spillovers are quite modest, especially for the nonsolar technologies that represent the majority of renewable generation. At only 0.7 cents/kWh, the optimal wind subsidy appears to be much less than the recently extended US federal production tax credit of 2.3 cents/kWh,[27] as well as the subsidies implied by many European feed-in tariffs, for which the median country in 2012 and 2013 gave 5 euro cents/kWh support for onshore wind (CEER 2015).[28] On the other hand, given that our model predicts that

27. These federal incentives, having been scheduled to expire, were not included in the EIA scenarios used for our parameterization.

28. In 2013, subsidies for new onshore wind ranged from 1.1 to 8.4 euro cents/kWh; in Germany they were 6.6 euro cents/kWh (CEER 2015). Of course, generous subsidies likely helped wind develop into a mature technology. Our model would suggest reducing these subsidy rates over time as knowledge stocks grow, technology matures, and knowledge spillover externalities decline. In fact, the production tax credit for wind is scheduled to decline 20% per year in real terms starting in 2017.

a 3.1 cents/kWh renewable production subsidy is sufficient to reach the emissions target, the optimal learning subsidy for wind is nearly one-quarter of the single-policy level. For solar photovoltaic, median feed-in tariffs in Europe have been 26 euro cents/kWh (CEER 2015); in the United States, the primary means of support at the federal level is a 30% investment tax credit, contributing to average levelized tax credits of 17.4 cents/kWh for plants entering service in 2018 (EIA 2016, table A1a).[29] Thus, current solar incentives also appear to be well above the optimal levels identified here in combination with emissions and R&D policies.

One can ask how sensitive these results are to our model assumptions. In the optimal policy mix, subsidy rates for energy efficiency and R&D investments are straightforwardly linked to the rates of undervaluation (or underappropriation). The optimal subsidy for LBD, however, is a more complex function representing the value of future cost reductions attributed to an additional kWh of generation, which depends inherently on the state of the market. Therefore, we explore the sensitivity of LBD subsidies to underlying assumptions and policies and report these results in depth in appendix B.

Overall, we find it difficult to generate large optimal learning subsidies. Wind/other subsidies in particular remain in the range of 1 cent/kWh or less. Solar, being a less mature technology, has more room for learning and is more sensitive to assumptions, but optimal subsidies do not exceed 10 cents/kWh. For example, learning subsidies are proportional to the spillover rate, and optimal solar subsidies increase roughly 1 cent/kWh for every 10 percentage point increase in the spillover rate. Other changes in the specification of the knowledge accumulation function have similar effects. By contrast, optimal learning subsidies are decreasing with the degree of EE undervaluation; in that case, the optimal response is to increase energy efficiency subsidies, meaning fewer reductions are needed via renewable energy.

We consider a wider range of targets for emissions reductions as well; for example, at an 80% reduction goal, renewable subsidies are more than double those of the 20% target, but those levels are still less than 1 cent/kWh for nonsolar renewables. The optimal emissions price, on the other hand, increases by an order of magnitude, indicating that it becomes relatively more important as a policy instrument.

We can also compare the relative contribution of our innovation policy instruments. Table 3 reports the total spending on LBD and R&D subsidies, relative to to-

29. This table indicates similar levelized tax credits for wind, since investors can choose between the investment and production tax credits. Another point of comparison is renewable energy credit (REC) trading prices in states with RPS policies. The US Department of Energy reports traded REC prices for 13 states; in recent years these prices ranged from 1 to 6 cents/kWh (in cases where the RPS policy has been binding). For states in the PJM Interconnection (http://www.pjm.com/about-pjm.aspx) market with separate solar RPS requirements, solar RECs have recently sold for as low as 6 cents/kWh and as high as 50 cents/kWh.

tal revenues in the wind/other and solar sectors. We see that optimal expenditures ratios are smaller for wind/other and more focused on R&D than on learning (roughly 2 to 1), whereas for solar the opposite is true (optimal expenditures on LBD are twice those of R&D for solar, and both are a more substantial share of first-period generation values).

With our reference parameterization (where $\rho = 0.5$, $\beta = 0.9$), even though spillover rates are identical for R&D and LBD, at least 80% 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. In appendix B, we construct several additional scenarios to test their relevance. The results indicate that even with rather extreme parameters favoring LBD, it is difficult to drive optimal subsidies up to the 10 cents/kWh mark, even for solar. Optimal overall public spending toward technological innovation seems to be in the range of 15%–30% of market generation revenues for wind/other and 50%–100% for solar. Meanwhile, in almost all scenarios, the ratio of deployment spending for LBD to R&D spending does not exceed 1 for wind/other. The ratio of public spending on solar deployment to R&D exceeds 1, but not by much, in nearly all scenarios. Assuming parameters that make LBD much more important for knowledge generation, this ratio just reaches 10 to 1. By contrast, estimates of public spending programs, including tax breaks and implied subsidies through other policies, indicate 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, Serwaah-Panin, and Peruzzi 2014).

3.3. Suboptimal Policy Combinations: Efficiency and Distributional Effects

In practice, climate and energy policy portfolios at all levels of government rely more heavily on technology support than on emissions pricing. In this section, we explore the effects of our stylized (suboptimal) policy combinations. Although a greater emphasis on targets for renewable energy and energy efficiency may have efficiency costs, it can mitigate and even reverse the redistribution of economic surplus that is associated with emissions pricing.

First, to better understand the efficiency effects of the suboptimal combinations, it is useful to compare the policy targets (table 2) with the optimal combinations (table 3). With overlapping standards the 20% RPS for nonhydro renewables is close to the cost-effective renewable share for the second stage. Likewise, the 10% EE target is close to the cost-effective level when undervaluation is in the range of 10% in the second stage. However, the near-term deployment targets are more aggressive than is optimal. With our reference parameterization, some complementary technology and energy efficiency policies are justified, but not to the extent of the overlapping standards combination, which the model calculates as being almost twice as costly as emissions pricing alone.[30]

The technology-only policy's 10% EE target is similar to the cost-effective level with 10% undervaluation, and its 50% R&D subsidy equals the optimal rate with our reference appropriation rate. However, instead of an emissions price to achieve the remaining reductions for the emissions target, this combination has an increasing RPS (roughly 11% nonhydro renewable share in the first stage and 26% in the second) that is more ambitious than would be needed with emissions pricing.

In terms of economic surplus, the technology-only policy is less costly than the overlapping standards policy. Notably, having a more balanced technology policy mix—that is, internalizing the R&D market failure and setting an RPS that is less ambitious in the near term—has a stronger effect on reducing costs than losing the emissions price component has on increasing them. Still, the technology-only policy is 68% costlier than emissions pricing and more than twice as costly as the optimal combination.

Of course, cost-effectiveness is not the sole metric of interest to policy makers when choosing a climate strategy, which may help explain the great interest in policy combinations. Policy makers are concerned about effects on specific stakeholder groups, including ratepayers, taxpayers, and owners of different generation technologies. Figure 2 presents the changes in welfare metrics for five categories of stakeholders, as well as the total change in surplus, for our base case. We use the category "taxpayers" to represent the potential flow of revenues to or from the government, recognizing that additional policies can determine to whom emissions revenues are allocated and how subsidies are financed.[31]

Although emissions pricing on its own has low overall costs, it has by far the largest redistributional effects, particularly for electricity consumers (who bear much of the cost), taxpayers (or, more generally, those who will receive the significant revenues), and the clean baseload generators (i.e., nuclear and hydro, which benefit from higher electricity prices). Under emissions pricing, the costs to coal-fired generators are largely offset by gains to natural gas-fired generators. An optimal policy combination (not pictured), which also relies predominately on emissions pricing, would have similar distributional effects, just of a somewhat smaller magnitude.

30. We note that some other variations can improve the cost-effectiveness of the overlapping standards. For example, adding an optimal R&D policy cuts costs by more than 10%. Offering extra credits for solar, which more closely mimics the optimal production subsidy profile, lowers costs somewhat but not substantially.

31. 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.

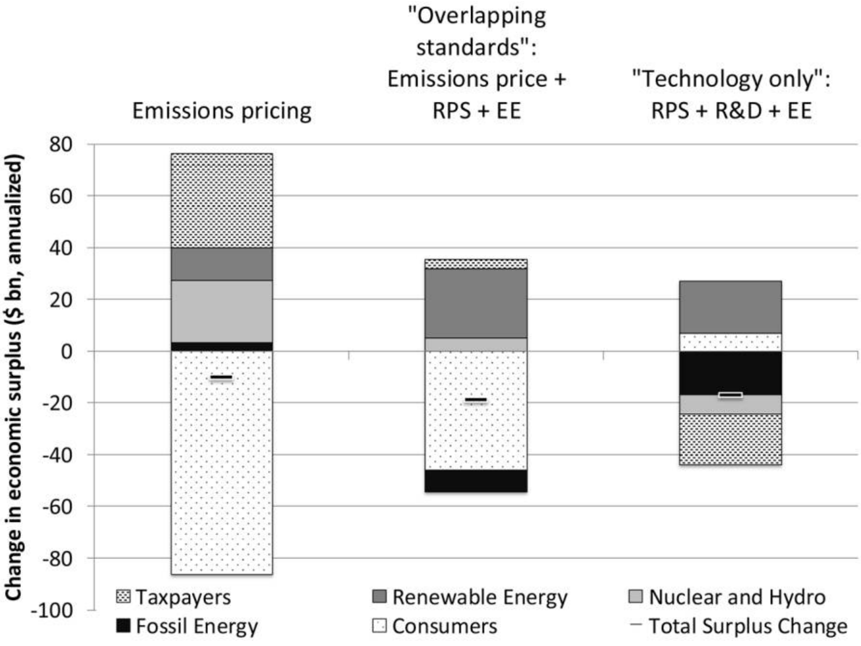

Figure 2. Distributional consequences of policy combinations ($\beta = 0.9$, $\rho = 0.5$). RPS = renewable portfolio standard; EE = energy efficiency.

The overlapping standards policy—which largely uses the optimal policy instruments, but with a greater emphasis on the supplementary policies—changes the magnitudes, but not the direction, of surplus 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. By contrast, 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—particularly the gas-fired generators—bear more of the costs.

Note that to the extent that electricity consumers and taxpayers are the same individuals, the distributional effects will not be as severe at the individual level. Alternatively, generous allocations of emissions revenues to fossil energy producers can allow them to enjoy higher profits under a cap.

The competitiveness of energy- and electricity-intensive manufacturing is also of notable concern in the policy-making process. We do not distinguish among residential, commercial, and industrial consumers of electricity here, but the direction and intensity of effects on industrial consumers will follow those of our consumers more generally.[32] Energy-intensive manufacturers with direct emissions of CO_2, which are outside our model here, are affected by emissions 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.

4. 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. However, overcompensating for these distortions can easily prove more costly than simply relying on emissions pricing—that is, the cure can be worse than the disease.

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 assuming high rates of knowledge spillovers from learning by doing. This result holds particularly true for more mature clean 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 has a larger potential for reducing the costs of achieving significant emissions reductions than internalizing learning spillovers. This stands in stark contrast to the current distribution of spending on renewable energy R&D versus deployment, which heavily favors the latter.

Accounting for energy efficiency undervaluation has important effects on the optimal policy portfolio and the relative costs of other strategies, even more so than accounting for knowledge spillovers. The stronger influence of demand-side responses is a consequence of sheer size: demand represents the entire electricity market, whereas 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. Even the desirability of renewable energy policy measures is sensitive to demand-side market failures. 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

32. Of course, long-term contracts and differentiated tariff structures often insulate industries from short-run electricity price increases, but over the time horizon we consider, many cost changes should pass through. An exception is when the policies themselves exempt certain consumers; for example, in Germany, industrial consumers are exempt from the electricity surcharge used to fund feed-in tariffs.

goals and benefits are in play. For example, we have not assigned a 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. R&D markets may also entail broader costs and benefits if renewable R&D competes for resources with other sectors (e.g., Goulder and Schneider 1999) or offers spillover benefits to other sectors (e.g., Dechezleprêtre, Martin, and Mohnen 2013). Perhaps the most important benefit we ignored could be from international spillovers and the reduction of carbon emissions in countries that do not price carbon, if domestic policies succeed in bringing down global renewable energy costs (see Fischer 2016, 2017).

A final point is the role that policy constraints may play. If political acceptability places limits on emissions pricing, renewable energy policies may enable more stringent targets by redistributing the costs of an emissions cap—for example, by shifting compliance costs away from energy consumers and toward taxpayers, or away from coal and toward natural gas and baseload generators. Although our model predicts simple optimal responses to R&D and energy efficiency undervaluation, in practice we still have a poor understanding of the complex roots of these market failures and how to deploy policies that target them effectively.

With those caveats in mind, it is still telling that even with more refined representations of electricity generation options and market failures, strategies that raise the costs of fossil energy remain the most cost-effective options 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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