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Supply Curves for Conserved Electricity

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RESOURCES FOR THE FUTURE

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Abstract

In this paper, we introduce a new top-down approach to modeling the effects of publicly financed energy-efficiency programs on electricity consumption and carbon dioxide emissions. The approach draws on a partial-adjustment econometric model of electricity demand and represents the results of a reverse auction for electricity savings from different levels of public investment. The model is calibrated to recent estimates of the cost-effectiveness of rate payer–funded efficiency programs at reducing electricity consumption. The results suggest that supply curves for conserved electricity are upward sloping, convex, and dependent on policy design and electricity prices. Under the scenarios modeled, electricity savings of between 1 and 3 percent are achievable at a marginal cost of $50 per megawatt hour (MWh) and a corresponding average cost of $25–$35/MWh.

Key Words: energy efficiency, climate change

JEL Classification Numbers: Q41, Q48, Q58

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Introduction

Growing concerns about the effects of global warming among scientists, citizens, and policymakers have prompted federal proposals as well as some state and regional policies to restrict emissions of greenhouse gases from sources within the United States. Economists have pushed for a carbon-pricing policy as the most efficient approach to controlling greenhouse gas emissions, and indeed it has been incorporated in many proposals. Most have combined carbon pricing with other measures designed to accelerate adoption of renewable energy sources or reduce overall energy use by improving end-use energy efficiency. The failure of the U.S. Congress to adopt a policy to explicitly limit greenhouse gas emissions—and subsequent statements by President Obama that energy policy is now likely to be implemented in smaller chunks—suggest that policies to promote renewables and energy efficiency are likely to become the core of a more piecemeal federal climate and energy policy. This paper explores the potential of energy-efficiency policies to reduce demand for electricity and the associated costs of achieving such reductions.

Most of the existing studies that assess potential electricity savings from energy-efficiency investments use a bottom-up approach based on the capital costs and energy-efficiency levels of alternative technologies.[1] Typically, this approach generates efficiency supply curves that suggest substantial electricity savings from efficiency gains for negative cost. The market and behavioral failures that may explain these negative-cost savings include asymmetric information, principal-agent problems, lack of access to capital, or consumers' failure to make optimal choices (Gillingham et al. 2009). Alternatively, the models may fail to capture either the differences in the quality of electricity services delivered by alternative technologies and corresponding consumer preferences or the time and other costs of changing to more energy-efficient equipment. These bottom-up models require data—including costs,

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[1] These studies are mostly in the gray literature and are surveyed in the next section.

efficiency measures, and electricity services delivered—that are also problematic because the set of products that use electricity is vast and the future of such products is hard to predict. Overall this literature may offer useful insights into which end uses and specific technologies are likely to be a source of untapped energy savings, but its poor treatment of market and behavioral factors leaves something to be desired.

In this paper, we introduce a new top-down approach to modeling the effects of publicly financed energy-efficiency and conservation programs. This approach draws on a partial-adjustment econometric model of electricity demand by customer class, region, and season that captures the long- and short-run effects of changes in retail electricity prices and other exogenous variables on electricity demand. Paul et al. (2009b) developed this model, which is based on one originally set forth by Houthakker and Taylor (1970). We integrate these estimated demand functions into Resources for the Future's Haiku electricity market model along with an algorithm for estimating the reductions in electricity demand that can be induced using financial incentives backed by public funds. We use the model to examine how different levels of investment in energy-efficiency programs affect electricity sales, electricity price, and other features of electricity markets.

A key result is the identification of supply curves for conserved electricity. The model generates a suite of supply curves under different assumptions about efficiency policy performance and design as well as other policies that affect electricity prices. The supply curves are upward sloping, convex, and higher in the presence of higher electricity prices, such as from a price on carbon emissions. Over the range of sensitivity cases analyzed, electricity savings of between 1 and 3 percent are achievable at a marginal cost of $50 per megawatt hour (MWh), which corresponds to an average cost of $25–$35/MWh depending on the sensitivity case.

Literature Review

Understanding and modeling the role that energy-efficiency investments and policies could play in electricity markets requires a representation of the relationship between potential energy savings from efficiency investments and their cost. The literature on estimating demand-side efficiency potential is burgeoning and currently populated primarily with bottom-up approaches that characterize electricity end-use technologies by their operational and cost parameters. They tend to assume that consumers will derive equivalent electricity services from any one of a set of technologies that satisfy each type of end use, then choose the technology for each end-use that minimizes a discounted stream of capital and operating costs. Comparing this set of technologies in terms of levelized costs, accounting for capital and energy costs, with the corresponding levelized costs for a baseline set of technologies yields an energy-efficiency supply curve.

This bottom-up approach typically does not fully account for important factors that could affect technology adoption, such as consumer attitudes about risk associated with adopting a different type of equipment, as well as differences in equipment performance or quality of energy service delivered between more- and less-efficient equipment types. These studies also tend to make assumptions about equipment and appliance use that may not be based on observational studies of real consumer behavior with respect to energy efficiency. Sathaye and Murtishaw (2004) and Gillingham et al. (2009) illustrate some of the market failures and consumer behaviors that are often ignored when analyzing efficiency potential from a bottom-up perspective. A bottom-up, structural model of equipment choice and electricity demand that includes economic, engineering, and behavioral interactions is the ideal for evaluating efficiency potential; however, the data required for these types of models are vast and the characterization of consumer behavior that underpins these models is not well developed.

Several recent studies have included bottom-up assessments of electric energy-efficiency potential at the regional or sectoral level (Itron, Inc. 2006; ACEEE 2008a, 2008b; Brown et al. 2010) or nationally (EPRI 2009; McKinsey & Company 2009; National Academies 2009). These studies estimate potential electricity savings that range from 8 percent to 40 percent;[2] many estimate savings potential of roughly 30 percent. Most include a significant quantity of energy-efficiency measures identified as having a negative cost of implementation. Studies of this sort use data and projections of energy consumption by end use and equipment type to determine how much energy would be saved by replacing existing equipment and displacing new investments with more energy-efficient models.

These assessments typically identify three categories of energy-savings potential: technical, economic, and achievable. Technical potential is the amount of energy savings that could be achieved if the most energy-efficient technologies available were utilized. Economic potential incorporates only those options where the presumed energy savings over the lifetime of the equipment pay for the additional capital cost of adopting more efficient equipment. Achievable potential further limits the savings to those resulting from measures that households

[2] The scenarios that yield this range of savings vary widely across the studies. In some cases, the savings correspond to technical potential (discussed in the next paragraph) and in others they correspond to a particular set of technology-efficiency upgrades that are presumed to be economical and easy to implement.

and businesses could conceivably adopt in a given time frame. None of these measures, however, fully consider the market barriers and consumer behavior discussed above.

Nadel et al. (2004) examine a number of bottom-up studies that estimate these three measures of efficiency potential. They calculate median technical, economic, and achievable potentials for electricity savings of 33 percent, 21.5 percent, and 24 percent, respectively.[3] Similarly, Chandler and Brown (2009) review a number of previous studies on energy efficiency in the southern United States, and they find electricity-savings potential in that region of roughly 20 percent, 10 percent, and 12 percent, respectively, for the same three categories of savings potential.

These bottom-up assessments of efficiency potential have been used to inform state energy-efficiency goals and identify which types of efficiency projects are likely to be most cost-effective. They also have been used as inputs to the construction of energy-efficiency supply curves to show the cost of electricity savings. Gellings et al. (2006), for example, estimate the electric energy-savings potential of more than 20 end uses in 2010, as well as the levelized cost of each efficiency investment. They then use these data to trace a supply curve, beginning with the least-cost measures, such as residential appliance removal, and extending to the highest-cost measures. This energy-efficiency supply curve shows that nearly 50 terawatt hours (TWh) of electricity can be avoided in 2010 at a cost of $50/MWh, with the curve extending approximately linearly to a point where about 200 TWh can be avoided at $200/MWh.

Bottom-up assessments of energy-efficiency potential also have been used to construct abatement cost curves for reductions of greenhouse gas emissions. These studies not only estimate the potential of a set of end-use technologies, but they also estimate the avoided emissions associated with avoided energy use. For example, McKinsey & Company (2007) develops an economy-wide abatement cost curve for the United States in 2030, including many segments of end-use electricity efficiency. This curve, however, presents many abatement opportunities at a negative marginal cost. Thus, market barriers, consumer behaviors, and/or rebound effects[4] must exist that this abatement cost curve is not capturing. Similarly, Sweeney and Weyant (2008) develop a greenhouse gas abatement cost curve for California, and this curve

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[3] Note that these median numbers are across different studies and the gaps between technical, economic, and achievable potential differ across studies, so these estimates rank differently from the way they would if they were from a single study.

[4] McKinsey & Company (2007, 2009) assumes constant demand for energy services.

also includes negative-cost abatement opportunities that are not representative of behaviors observed in the market.

Model Description

The Haiku electricity market model simulates the electricity sector in the contiguous U.S. states through the year 2035. It is deterministic and highly parameterized, and it calculates information similar to that of the Electricity Market Module of the National Energy Modeling System, which the Energy Information Administration uses, as well as the Integrated Planning Model developed by ICF Consulting and used by the U.S. Environmental Protection Agency. Because this paper focuses on electricity demand, the model description herein focuses on the demand side of the model.[5]

Before we turn to the Haiku electricity demand system and the demand conservation incentive (DCI), a few features of the model require explanation. Haiku subdivides the contiguous states into 21 separate modeling regions and the hours of each year into 3 seasons with 4 time blocks each. Electricity demand is modeled separately for 3 customer classes—residential, commercial, and industrial—and the model finds electricity-market equilibrium between total consumption and production in each of the 21 regions and 12 time blocks per year. Note that the full-blown model, including the supply side, is used in the analysis, but this paper focuses on the demand side.

Electricity Demand by Partial Adjustment

The Haiku demand system is based on a functional form known as partial adjustment, originally set forth by Houthakker and Taylor (1970). Under partial adjustment, consumption in any period depends on prices and other demand covariates in that period as well as consumption in prior periods. This characterization of demand captures the effects of capital immobility on consumers' responsiveness to market signals. The ideal model of electricity demand is derived from a system in which a consumer's utility function depends on electricity services, which are produced by two inputs: electricity and capital. Capital is characterized by its cost and energy efficiency, and a budget-constrained consumer trades off capital efficiency for electricity, depending on the relative prices of the two goods[6]. Unfortunately, this ideal model cannot be

[5] For a complete description of the model see Paul et al. (2009a).

[6] This is the model put forth by Dubin and McFadden (1984), who estimate the model for water and space heating.

implemented economy wide because a dearth of energy-efficiency data for the full range of the energy-using capital stock makes it impossible to estimate econometrically.

The partial-adjustment demand model implemented in Haiku is illustrated in Equations 1 through 4[7]. In these equations, the subscript t denotes time in one-month increments; Q^L is the quantity of electricity consumption (MWh) that would occur if capital were perfectly mobile (L stands for long-run); P is the price of electricity ($/MWh); ε_L is the long-run price elasticity of demand; X is a matrix of the covariates of electricity demand (income, temperature, daylight hours, and natural gas price); β is a vector of the coefficients on the demand covariates; Q is the realized quantity of electricity consumption (MWh); θ_1 and θ_{12} are the adjustment coefficients over 1 and 12 months, respectively; and ε is the short-run price elasticity of demand.

$$Q_t^L = P_t^{\varepsilon_L} X_t^{\beta} \tag{1}$$

$$\frac{Q_t^{\,2}}{Q_{t-1}Q_{t-12}} = \left(\frac{Q_t^L}{Q_{t-1}}\right)^{\theta_1}\left(\frac{Q_t^L}{Q_{t-12}}\right)^{\theta_{12}} \tag{2}$$

$$Q_t = P_t^{\varepsilon}\left(X_t^{\beta(\theta_1+\theta_{12})}Q_{t-1}^{1-\theta_1}Q_{t-12}^{1-\theta_{12}}\right)^{1/2} \tag{3}$$

$$\varepsilon = \frac{\theta_1+\theta_{12}}{2}\varepsilon_L \tag{4}$$

Equation 1 defines the level of electricity consumption, Q^L, that would occur if capital goods were perfectly mobile. Such mobility would allow consumers to simultaneously optimize over both electricity consumption and capital efficiency in every period. Capital goods are not perfectly mobile, however, so a stock of capital goods that are not necessarily of optimal energy efficiency will be employed in every time period and depend on the stocks employed in prior time periods. A consumer who optimizes electricity consumption conditional on partially immobile capital will consume Q units of electricity, and the relationship between Q and Q^L is defined by prior levels of Q and the estimated parameters θ_1 and θ_{12}, as shown in Equation 2. The two equations can be combined by substituting for Q^L to derive Equation 3, where ε is as defined in Equation 4. Equation 3 is estimated and implemented in Haiku.

[7] See Paul et al. (2009b) for a detailed description of the estimation procedure and results.

A simple example of price and quantity trajectories may be useful to build intuition about how this partial-adjustment system is a proxy for consumption outcomes that account for the energy efficiency of the capital stock. Consider two alternative electricity price trajectories over two periods in which prices are equivalent in period two but greater in period one in one trajectory than in the other. High prices in period one will yield a relatively low level of consumption in that period and also induce a relatively efficient capital stock as consumers trade-off relatively expensive electricity for more energy-efficient capital. Because the stock will partially carry over to the following period, high prices (and corresponding energy efficiency) in the first period will lead to less consumption in the second period than would result from low prices in the first period, even for identical period-two prices. This is exactly the outcome that results from Equation 3 because the estimated values of θ_1 and θ_{12} are between zero and one, and the short-run price elasticity, ε, is negative.

Table 1. Short- and Long-Run Price Elasticity of Electricity Demand

	Residential		Commercial		Industrial		*Average*	
	Short-run	Long-run	Short-run	Long-run	Short-run	Long-run	Short-run	Long-run
Regional results in annual average								
New England	-0.17	-0.51	-0.13	-0.37	-0.08	-0.20	*-0.13*	*-0.37*
Middle Atlantic	-0.05	-0.14	-0.01	-0.02	-0.20	-0.48	*-0.07*	*-0.19*
East North Central	-0.12	-0.36	-0.17	-0.70	-0.09	-0.22	*-0.12*	*-0.35*
West North Central	-0.21	-0.61	-0.14	-0.34	-0.11	-0.25	*-0.16*	*-0.39*
South Atlantic	-0.08	-0.27	-0.04	-0.09	-0.16	-0.44	*-0.08*	*-0.24*
East South Central	-0.32	-1.16	-0.22	-0.54	-0.19	-0.61	*-0.24*	*-0.75*
West South Central	-0.11	-0.33	-0.08	-0.22	-0.11	-0.28	*-0.10*	*-0.28*
Mountain	-0.19	-0.49	-0.14	-0.34	-0.18	-0.42	*-0.17*	*-0.42*
Pacific	-0.13	-0.37	-0.17	-0.45	-0.31	-0.82	*-0.20*	*-0.53*
National average	**-0.13**	**-0.40**	**-0.11**	**-0.29**	**-0.16**	**-0.40**	***-0.13***	***-0.36***
Seasonal results in national average								
Summer	-0.15	-0.52	-0.12	-0.34	-0.14	-0.36	*-0.14*	*-0.40*
Winter	-0.11	-0.32	-0.08	-0.22	-0.19	-0.48	*-0.13*	*-0.34*
Spring/Fall	-0.12	-0.35	-0.10	-0.27	-0.15	-0.39	*-0.12*	*-0.33*
Annual average	**-0.13**	**-0.40**	**-0.11**	**-0.29**	**-0.16**	**-0.40**	***-0.13***	***-0.36***

The demand function's parameter values used in this paper are those derived by Paul et al. (2009b), and the estimated elasticity values shown in Table 1 are critical to the demand conservation incentive that will be described next. Haiku disaggregates electricity demand into 3 customer classes—residential, commercial, and industrial—and 21 geographic Haiku market regions (HMRs). These regions do not strictly follow state borders, but the demand model is estimated for the nine census divisions, which do follow state borders. We assign state-level elasticity values according to their census division, and we solve the Haiku demand system for each overlapping pair of states/HMRs. The state/HMR-level electricity prices are downscaled from the HMR prices, and the calculated state/HMR-level consumption levels are aggregated back to the HMR level and passed to the rest of the model. The demand system operates on a monthly basis, but the parameter estimates vary seasonally, not monthly. Haiku disaggregates seasonal demand into four time blocks within each season that correspond to four vertical slices of the load duration curves. The allocation of seasonal demand to time blocks is based on a constant elasticity of substitution model of utility-optimizing consumers that is benchmarked to time block prices that are constant within a season. Since this analysis assumes no time-of-day pricing, the time-block allocation of seasonal demand never varies from the benchmark allocation.

Demand Conservation Incentive

The DCI mechanism in Haiku represents a behavioral, top-down approach to simulate electricity consumption reductions from public investments in end-use energy-efficiency improvements. The model finds an equilibrium price for a subsidy to avoided MWh of electricity consumption that exhausts an exogenously specified level of total funding and clears the market. Improvements in the technical efficiency of capital goods are not distinguishable from behavioral adjustments that reduce electricity consumption, but the model captures both. The behavior of consumers in response to the publicly funded program is captured by calibrating the model to observed cost and performance metrics of recent rate payer–funded electricity-efficiency programs. These metrics are derived from the work of Arimura et al. (2009). The calibration parameter enters the model as the fraction of economical consumption reductions that are inaccessible due to the inability of the program administrator either to reach or compel consumers to take up the subsidy and reduce their consumption. The model also accounts for the costs of program administration, which is assumed to be 40 percent of total program costs in the standard DCI case.[8]

This behavioral, top-down representation of efficiency improvement lacks the technological richness that is inherent in bottom-up, structural models of energy efficiency but also circumvents some problems that plague such models. A structural model that characterizes electricity end-use technologies by their operational and cost parameters is ideal when data on

[8] The authors construct this assumption and consider an alternative assumption of 20 percent in the Adm20 scenario described below.

the technologies are abundant and the interactions between the technologies and those who adopt them can be parameterized well. Unfortunately, the variety of end-use technologies for electricity consumption is vast, the technologies that will emerge in the coming decades are hard to anticipate, and a realistic characterization of consumer behavior with respect to electricity end-use technology is elusive because consumers often fail to make technology choices that accord with the economic theory that underpins such models.

One manifestation of these difficulties is the array of energy-efficiency supply curves generated by bottom-up models that suggest vast electricity-savings potential at negative cost. Such supply curves are presumably accurate in a limited engineering sense but fail to capture other factors that influence consumer adoption of energy-efficient technology. Many sound reasons explain the discrepancy between these supply curves and observed behavior that go beyond the data limitations and behavior characterization issues previously mentioned. They include principal-agent problems, access to capital, program free-ridership, and rebound effects.

The top-down model presented in this paper circumvents these issues and should yield reasonable conclusions, accounting for real-world consumer behavior, about the potential for end-use efficiency gains from publicly funded programs in the electricity sector. This is valuable for a variety of reasons but is attained at the expense of technological and end-use detail. Therefore, it is not prescriptive for program administration.

The equilibrium condition that defines the DCI subsidy price for a given amount of program funding is presented in Equation 5.

$$\frac{F_t(1-A)}{D_t} = K\sum_{rci} Q_{t,rci}\left[1-\left(1+\frac{D_t}{P_{t,rci}}\right)^{\varepsilon}\right] \forall\ t \tag{5}$$

Each element in the summation on the right-hand side of the equation defines the quantity of reduced electricity consumption that will occur in region r by customer class c in time block i of year t from the offer of a subsidy to avoided consumption of D_t in \$/MWh, payable on units of consumption avoided in year t. This equation is derived from the demand function (Equation 3) by $Q(P_{t,rci})$ - $Q(P_{t,rci}+ D_t)$ and the assumption that the DCI program administrator cannot price discriminate across consumers or end uses. Electricity prices, $P_{t,rci}$ in \$/MWh, vary by customer class and region and could, in general, vary by time block and season. In this analysis, however, we assume they never vary by time block within a season and vary across seasons only in the regions that price electricity in a market. $Q_{t,rci}$ is the level of electricity consumption in MWh that would have occurred in the absence of a subsidy, $Q(P_{t,rci})$. ε is the short-run price elasticity of demand, and K is the efficiency calibrator, which is unitless and will be described below. The right-hand side of the equation, including the summation and calibrator, is the total quantity of consumption reductions delivered by consumers. The left-hand side of the equation is the total quantity of reductions purchased by the program administrator, where F_t is the level of program funding, in \$, and A is the fraction of program costs that go to administration, which is assumed to be 40 percent in the standard DCI scenario. Equation 5 in its entirety is the equilibrium condition for the DCI program, and a unique value of D_t solves the equation because the left-hand side is strictly decreasing in D_t and the right-hand side is strictly increasing in D_t. Haiku finds this value.

Arimura et al. (2009) find that during the period 1995–2006, the average utility would have realized 1.1 percent electricity savings at an average cost of $30/MWh (2007 dollar year) for a efficiency program funding level of $8 per customer (2007 dollar year). To determine the efficiency calibrator, K, Haiku is solved for a DCI program funded at this level from 2010 through 2020, or about $1.25 billion in 2010, rising to about $1.4 billion in 2020 (2008 dollar year, the dollar year in the Haiku model). Arimura et al. (2009) also find that the demand effects of an efficiency program persist for six years, so the period 2016–2020 is the only time in the model in which a full set of lagged electricity savings are realized. Haiku finds average cost of electricity savings over this period by the quotient of total costs, including program administration, and total electricity savings, including lagged savings. Since Haiku is solving for a different time period than that evaluated by Arimura et al. (2009), it is impossible to simultaneously calibrate the model to both average cost and percent electricity savings if the electricity consumption intensity per customer is not identical in the two periods. We therefore calibrate the model to the quotient of average cost and percent electricity savings, or $0.15/GWh^2 (2008 dollar year), on average over the 2016–2020 time period. This yields a calibration value, K, of 0.035 at an average cost of electricity savings of $30.3/MWh (2007 dollar year), within 1 percent of the cost found by Arimura et al. (2009). This value for K suggests that the ability of a program administrator to identify and capture the most economical consumption reductions is very limited.

One aspect of the gains from program funding is the persistence and decay of electricity savings. This dynamic exists because an efficiency program would bring online long-lived capital goods and cause behavioral changes that may persist and abate in later years. Haiku captures these dynamics in the partial-adjustment demand system because, referring back to Equation 3, the estimated values for θ_1 and θ_{12} are between zero and one. As a result, any program-induced electricity savings realized in any period t have a demand-reducing effect in all subsequent periods that asymptotically decays over time. Another aspect is that the marginal amount of savings obtained by increasing the total amount of funding for efficiency investment will decline as funding increases. This follows from the convexity of the electricity demand curves in prices, which also implies that the DCI price for a particular level of efficiency spending will increase as electricity price increases. Another driver of declining marginal reductions is the assumption that the program administrator cannot price discriminate, which yields increasing payments to inframarginal consumption reductions under increased funding.[9]

Scenarios Description

This paper examines the cost of conserved electricity and associated climate benefits of a DCI program that would bring about energy-efficiency improvements in end-use electricity consumption. We model five levels of DCI funding to trace out supply curves for conserved electricity under four different assumptions about DCI program implementation and for a scenario in which carbon dioxide (CO_2) emissions are regulated under a cap-and-trade policy. This section describes the scenarios, all of which are evaluated relative to a baseline scenario. All scenarios simulate the time frame 2010–2035. We henceforth use the parenthetical acronyms in the headings to save space.

Baseline Scenario (BL)

We calibrate the BL scenario to yield electricity price and demand levels by region and customer class that match the levels reported in the *Annual Energy Outlook 2010* (U.S. EIA 2010). The BL incorporates several existing environmental policies, including the sulfur dioxide cap-and-trade program under Title IV of the Clean Air Act Amendments of 1990, the Clean Air Interstate Rule restrictions on emissions of sulfur dioxide in the eastern part of the country as well as the annual and ozone season restrictions on nitrogen oxide emissions, the cap on CO_2 emissions in the northeastern Regional Greenhouse Gas Initiative states, and the state-level mercury maximum achievable control technology programs. The BL scenario also includes a representation of the federal tax credits for renewables included in the American Recovery and Reinvestment Act, all of the state-level tax credits for renewables, and the existing state-level renewable portfolio standards (RPSs).

[9] A relaxation of this assumption will be considered in the PD scenarios described below.

Efficiency Scenarios

Each DCI policy scenario is modeled at five annual funding levels—$250 million, $1 billion, $2 billion, $5 billion, and $10 billion—for the years 2012–2025, with funding then linearly decreasing to zero in 2030. This timing corresponds to that of the allowance allocation schedule in H.R. 2454 (U.S. Congress 2009) and allows for an observation of the electricity savings that occur after DCI program termination but before the end of the modeling horizon in 2035. In addition to the BL, we examine the following scenarios:

Standard DCI (DCI): The standard DCI program is exactly as described in the previous section.

Twenty Percent Administrative Costs (Adm20): Adm20 is identical to the standard DCI scenario, except that administrative costs are reduced from 40 percent to 20 percent of total program funding. This scenario provides a sensitivity on this exogenously specified parameter.

Double Reductions (2Red): 2Red is identical to the standard DCI scenario except that it is calibrated based on the assumption that twice as much electricity savings are available at the average cost and funding level of the standard DCI calibration. Double reductions amount to 2.2 percent of total consumption. This outcome could be due to many factors; for example, consumer receptiveness to energy-efficiency inducements could improved, or Arimura et al. (2009) may have underestimated the ability of efficiency programs to reduce electricity use. Administrative costs under 2Red remain at the 40 percent level.

Price Discrimination (PD): Although we did not endogenously solve any scenarios in Haiku with DCI price discrimination, we used a post-processing procedure to calculate the outcomes if the program administrator could perfectly price discriminate across consumers and end uses when subsidizing avoided electricity consumption. Assuming price discrimination, the model can calculate the marginal cost of contemporaneous efficiency reductions relative to another solved scenario as the value of the efficiency subsidy in the other scenario adjusted to include administrative costs, or $D_t/(1\text{-}A)$ in the notation of Equation 5. This value is then multiplied by the ratio of contemporaneous reductions to lifetime reductions from the other scenario in order to approximate the marginal cost of lifetime efficiency reductions. We applied this procedure to the DCI and 2Red scenarios to create two new scenarios denoted DCI_PD and 2Red_PD.

DCI and Cap-and-Trade Program (CTP): The CTP policy includes not only the standard DCI, but also an economy-wide cap-and-trade program on CO_2 emissions. This policy is based on H.R. 2454, which was passed by the House of Representatives on June 26, 2009. The emissions targets would reduce U.S. emissions of CO_2 from major sources by 17 percent in 2020 and 80 percent in 2050 compared to 2005 levels. We modeled the CTP policy to include unlimited allowance banking and the same restrictions on offsets use that the bill specifies: up to 2 billion tons of offsets annually, with no more than 1.5 billion from foreign sources. The scenario modeled here differs from H.R. 2454 in the treatment of allowance allocation by modeling an allowance auction with no revenue recycling to the electricity sector.

Results

Electricity Consumption, Prices, and CO_2 Emissions

Our modeling effort evaluates the extent to which a DCI policy achieves its fundamental purpose to reduce electricity consumption by providing a subsidy to avoided electricity use. The left-hand panel of Figure 1 shows national electricity consumption over time for the BL scenario and all five funding levels under the standard DCI scenario. In all scenarios, electricity consumption begins at the same level in 2010 but then diverges as DCI funding starts in 2012. From 2012 to 2030, electricity consumption is, as expected, highest in the BL scenario, followed by the DCI funding scenario at $250 million annually, and continuing to decreasing levels of consumption as DCI funding increases. The lowest level of electricity consumption occurs with DCI funding of $10 billion annually. By 2035, five years after DCI funding concludes, the consumption effects dissipate and consumption levels in all scenarios are approximately equal. Note that exogenous growth in electricity use due to population growth and an increasing demand for electricity services more than offsets electricity reductions from the DCI program.[10] As a result, consumption grows in all scenarios, even at the highest level of efficiency funding.

The right-hand panel of Figure 1 presents a detailed look at consumption levels in 2025, a year when the DCI program is still fully funded and the lagged effects of previous efficiency gains are fully manifest. The figure shows the convexity of electricity savings in DCI funding—i.e., each additional dollar of DCI funding generates fewer reductions in electricity use than the previous dollar. For example, the first $250 million of funding generates electricity reductions of 0.6 percent, but the last $5 billion reduces electricity use by only an additional 0.3 percent. The

[10] This result is not fundamental to the Haiku model because electricity demand growth is benchmarked in the model to the consumption levels reported for the reference case scenario in the *Annual Energy Outlook 2010* (U.S. EIA 2010).

highest funding level reduces electricity consumption by 1.8 percent, which is considerably less than the roughly 30 percent found in other studies.[11]

Figure 1. National Electricity Consumption (TWh) under the Standard Demand Conservation Incentive

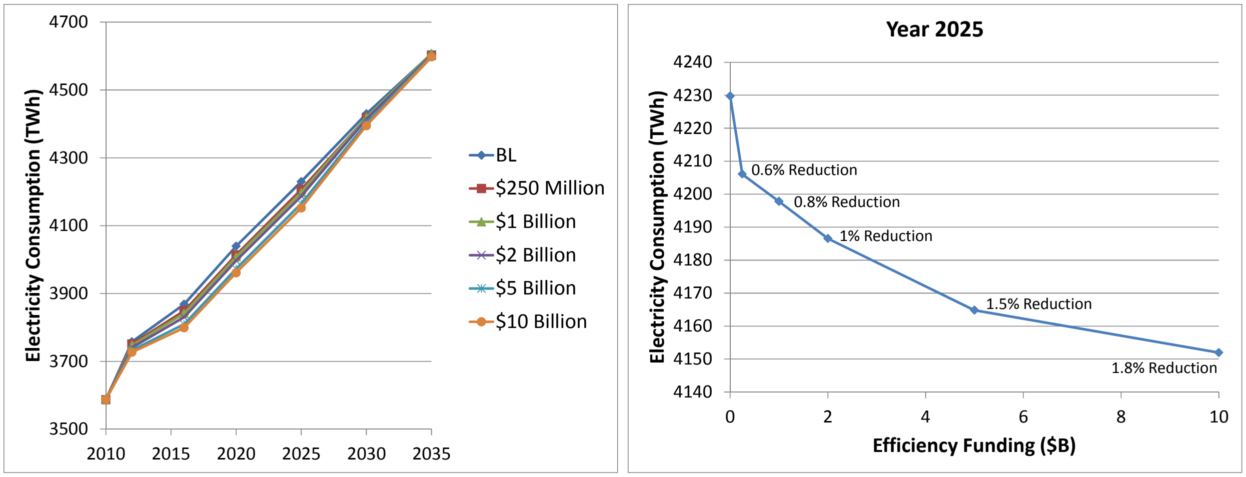
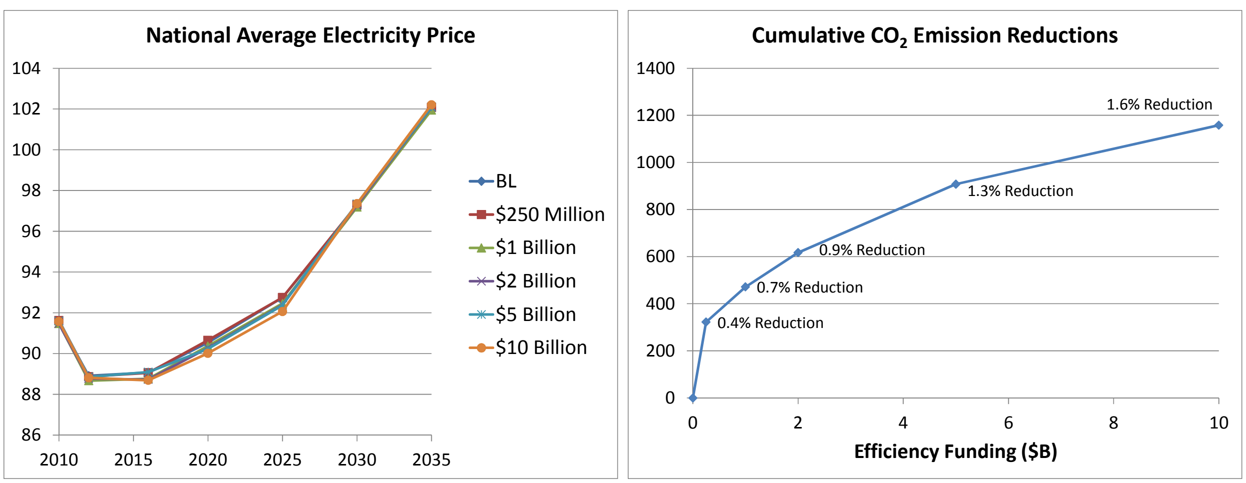


Figure 2. Electricity Prices ($/MWh) and CO_2 Emissions Reductions (M tons) under the Standard Demand Conservation Incentive



The direct effect of efficiency funding is a reduction in electricity consumption, but several other outcomes follow from this effect. One is reduced electricity prices. The left-hand

[11] This comparison is imprecise because the electricity savings being compared do not necessarily come for equivalent costs. For example, McKinsey & Company (2009) finds that at least 26 percent electricity savings could be achieved at negative cost, and National Academies (2009) finds that 30 percent energy savings could be achieved at negative cost.

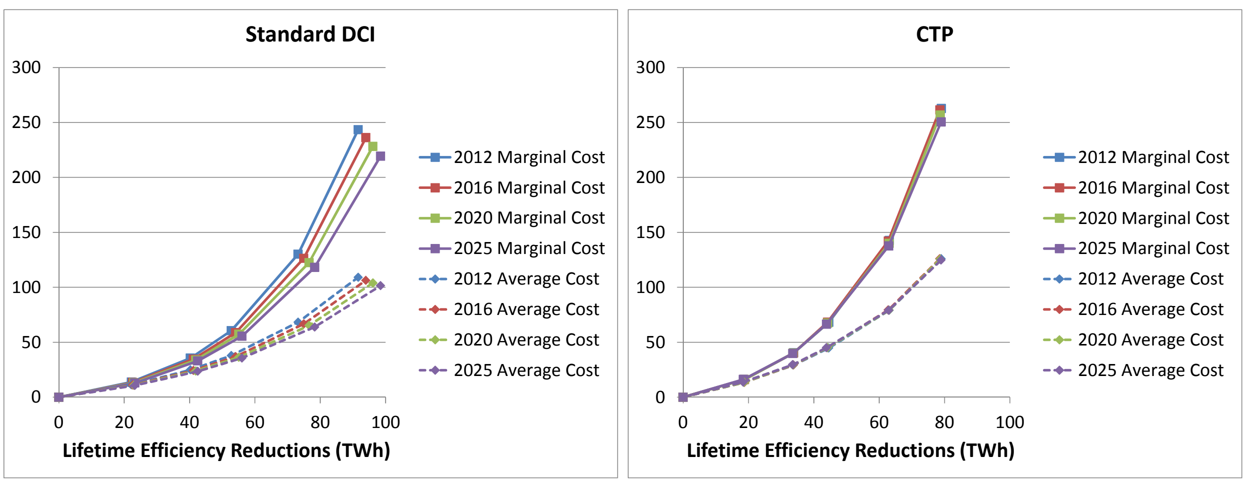
panel of Figure 2 shows the national average retail electricity price over time for the BL scenario and all five funding levels under the standard DCI. Beginning in 2012, when the DCI programs start, electricity prices are lower for the DCI scenarios than for the BL, with the lowest prices occurring under the highest level of DCI funding because electricity demand falls in DCI funding. This result is not surprising, but the small magnitude of the effects is notable. The greatest price effect occurs in 2025 under the $10 billion scenario and amounts to only a 0.7 percent reduction from BL. By 2030, when the DCI programs end, electricity prices return to approximately equal across the scenarios. In 2035, prices are highest in the $10 billion scenario, though by only a tiny margin. This ordering occurs because fewer investments are made in generation capacity in early years as electricity demand falls under higher levels of efficiency funding. By 2035 the demand effects of that funding have largely dissipated, so generation capacity must expand more under higher DCI funding levels. This capacity expansion necessitates higher prices in 2035 under higher funding levels.

Another result of reduced electricity consumption is a reduction in CO_2 emissions. The right-hand panel of Figure 2 shows the cumulative CO_2 emissions reductions at the different levels of DCI funding, relative to BL; these cumulative reductions are for the entire modeled time horizon of 2010 to 2035. The figure is concave—i.e., the first expenditures on DCI reduce CO_2 emissions by more than any additional expenditures. This follows directly from the shape of the right-hand panel of Figure 1 on electricity consumption. Comparing these two panels shows that consumption is reduced by a slightly larger fraction than emissions are reduced. For example, $10 billion of DCI funding yields electricity savings of 1.8 percent and an emissions reduction of 1.6 percent. This is an indication that the marginal electricity generation displaced by avoided consumption is slightly less carbon intensive than the fleet average.

Supply Curves for Conserved Electricity

The results of the DCI simulations for the five different funding levels can be used to trace out supply curves for conserved electricity. The left-hand panel of Figure 3 shows the average and marginal costs associated with the lifetime electricity savings from investments made under the standard DCI scenarios. Lifetime reductions refer to the cumulative stream of reductions harvested over time, including those in the initial year in which the subsidy is paid as well as the reductions that persist into the future and decay over time. Each point on each curve corresponds to one of the five program funding levels, where the upper-right point on each curve represents the $10 billion scenario. The average cost curves show the ratio of total DCI cost to total lifetime savings. We calculate the marginal cost curve by incrementing the DCI subsidy price by $1 and then finding the incremental cost divided by the incremental lifetime savings. The figure shows that average and marginal costs are increasing and convex in the level of lifetime savings, so marginal costs are necessarily greater than average costs. Both types of costs decline over time as a result of two countervailing factors. First, as population and demand for electricity services grow, so, too, will opportunities for efficiency improvements to conserve electricity at any cost level, making demand reductions cheaper over time. On the other hand, efficiency investments are made beginning with the cheapest opportunities, leaving fewer low-cost reductions in later years and thus increasing the cost of demand reductions over time. Although it is unknown a priori what will be the net effect of these factors, the observed outcome is that the growth of electricity demand outstrips the uptake of the cheapest reductions. An alternative example is shown in the right-hand panel of Figure 3, which contains similar cost curves but for the CTP scenarios. In these scenarios, the CO_2 allowance price causes a significant increase in electricity prices, which dampens the growth in electricity demand observed in the standard DCI scenarios.[12] In this case, the two countervailing effects roughly cancel, and the cost curves remain approximately constant over time.

Figure 3. Costs ($/MWh) for Conserved Electricity

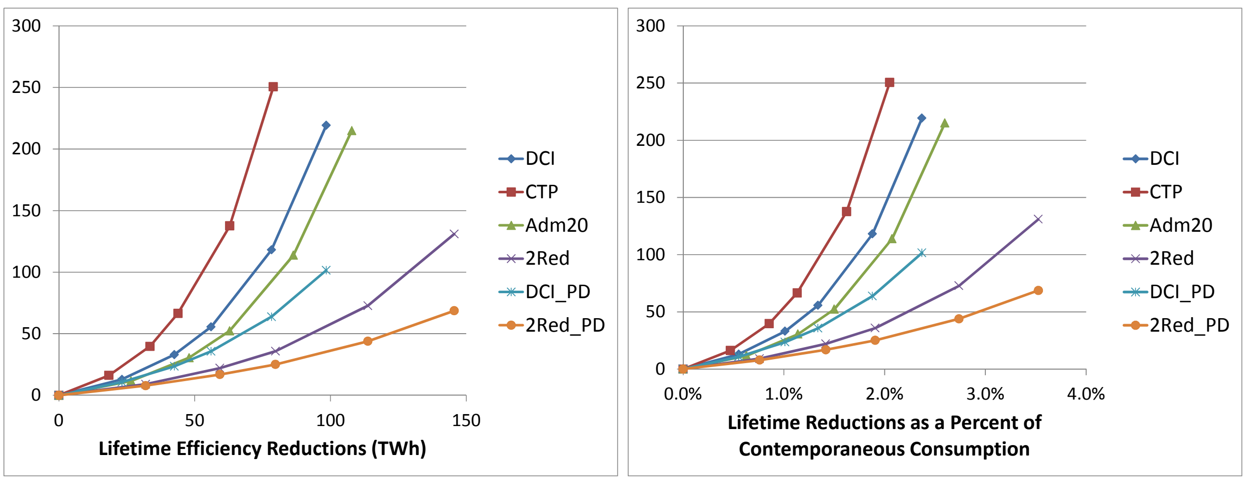


The cost curves displayed in the left-hand panel of Figure 3 are for the standard formulation of the DCI, which includes 40 percent administrative costs, calibration of electricity

12 National average electricity prices are approximately $8–$13/MWh (or 9–14 percent) higher in the CTP scenarios than in the BL scenarios for the years 2012–2025, which causes national electricity consumption to be roughly 2–7 percent lower.

savings and costs to those of Arimura et al. (2009), no carbon policy, and no price discrimination in the DCI market. The left-hand panel of Figure 4 presents the marginal cost curves when each of these assumptions is varied, shown for the year 2025. The highest marginal cost curve is for the CTP scenario, which includes a cap-and-trade policy for CO_2 emissions that substantially drives up electricity prices,[13] in part due to the assumption that allowance revenues are not recycled. The marginal costs of conserved electricity in this scenario are higher than in scenarios without climate policy because the electricity price efects of the policy will lead consumers to reduce their electricity consumption and improve the energy efficiency of their capital stock, even in the absence of an efficiency program. These endogenous demand-side changes take up the lowest cost efficiency–improvement opportunities and lead to higher costs for further improvements.

Figure 4. Marginal Costs ($/MWh) for Conserved Electricity in 2025



The other sensitivity cases all reduce the marginal costs of conserved electricity. Reducing the administrative cost burden from 40 percent to 20 percent (Adm20 scenario) leads to the smallest reduction in costs. The marginal cost of reductions for the Adm20 scenario amounts to 75 percent of the costs in the DCI scenario because the marginal cost ratio is equivalent to the ratio of the proportions of total funding received by consumers. In this case, 60 percent divided by 80 percent equals 75 percent. Changing the calibration of the DCI model to

[13] National average electricity prices in 2025 are $13/MWh (or 14 percent) higher in the CTP scenario with no DCI funding than in the BL scenario. All other funding levels under CTP have smaller price increases, and prices in all scenarios other than CTP vary from BL by less than 2 percent.

yield twice the percentage of savings at the original level of expenditures (2Red scenario) has a larger effect on marginal costs. Because of the convexity of the demand curve, the 2Red assumption implies marginal costs that are less than half the cost under the DCI scenario, and the difference grows with higher DCI funding levels. The PD scenarios allow the program administrator to price discriminate in the DCI market such that each consumption reduction is paid exactly its cost, not the cost of the marginal consumption reduction. This substantially lowers marginal costs for both the standard DCI and the 2Red scenarios because buying an additional consumption reduction does not raise the payments to inframarginal reductions and thus the amount that can be acquired for an additional amount of spending is larger. Because of demand convexity, greater marginal cost impacts of price discrimination are observed at higher funding levels.

The applicability of these supply curves to policy analysis can extend beyond the specific policies we modeled. One approach that several states are using to encourage energy efficiency is to establish an energy-efficiency resource standard requiring that a minimum share of the electricity sold to customers be supplied by energy efficiency. In some state policies and federal policy proposals that include an RPS, a certain amount of electricity savings from energy-efficiency programs can be used to satisfy the RPS requirement. The effectiveness of an RPS policy in encouraging renewables partly depends on how much of the requirement is likely to be satisfied with energy efficiency. In turn, this will depend on any explicit limits set on contributions from energy efficiency, the level of the alternative compliance payment, and the costs of saving electricity. The right-hand panel of Figure 4 shows the marginal cost curves for 2025 but with the horizontal axis relabeled in terms of lifetime energy savings divided by current-year consumption. These percentage units make the curves analogous to an RPS policy that requires a percentage demand be satisfied by renewable generation or efficiency gains. Although they look very similar to those in the left-hand panel of the figure, the curves are shifted slightly relative to one another because consumption levels vary across the scenarios. This figure indicates that if renewable generation under an RPS is valued at $50/MWh, the percentage of electricity savings that would be deliverable through conserved electricity would range from 1 percent to 3 percent across these scenarios. This percentage is less than the maximum amount of efficiency savings allowed under most federal RPS proposals that include a role for energy efficiency. This observation also should be interpreted cautiously because the supply curves are not the result of a combined policy and thus may be excluding important equilibrium effects.

Conclusion

As the U.S. federal government shifts its focus on CO_2 cap-and-trade policies to a more piecemeal approach to climate change legislation, the role of energy-efficiency policies will become more prominent. As a result, policymakers will need better estimates of the amount of emissions reductions these policies are likely to produce. The range of policies being debated include energy-efficiency standards for appliances, building codes, financing mechanisms for building retrofits, tax subsidies, information programs, and energy-efficiency resources standards, among others. This paper focuses on a policy that offers a payment to electricity consumers for avoided consumption. Under the policy, consumers basically make offers to reduce consumption (relative to a known baseline) for a payment per MWh reduced. This reverse-auction mechanism is used to determine the amount and costs of energy savings at levels of aggregate expenditures ranging from $250 million to $10 billion per year.

This top-down approach to evaluating energy savings and associated costs stands in contrast to the typical bottom-up method used to assess energy-efficiency potential and associated CO_2 emissions reductions. Bottom-up approaches tend to be rich in technological detail but generally fail to capture aspects of consumer behavior that have important implications for how much energy can be saved at what cost. The DCI model presented in this paper uses econometrically estimated electricity demand functions that capture these behavioral responses to changes in electricity price, including rewards or payments for non-consumption.

The efficiency scenarios that we model have very small effects on electricity consumption, electricity price, and CO_2 emissions. Under our standard DCI scenario, electricity demand is 0.8 percent lower and cumulative CO_2 emissions from the electricity sector are 0.7 percent lower when $1 billion is spent on energy efficiency each year, compared to a baseline scenario. When efficiency expenditures are $10 billion annually, electricity demand falls by 1.8 percent and cumulative CO_2 emissions are 1.6 percent lower than in the baseline. The declining marginal benefits of efficiency funding correspond to the convexity of the supply curves for conserved electricity. The difference between electricity savings and emissions reductions indicates that the average kWh saved by efficiency investments is slightly less carbon intensive than the average kWh produced by the electricity sector.

The costs of energy-efficiency policies in reducing electricity demand are higher in the presence of higher electricity prices, such as they would be under a CO_2 cap-and-trade program that fails to recycle allowance revenue. Higher electricity prices lead consumers to reduce their electricity consumption, in part through the purchase of more energy-efficient capital. This leaves any publicly funded efficiency program to harvest only more costly efficiency gains. The position and shape of the supply curves for conserved electricity depend on demand elasticity estimates, calibration to real-world efficiency program costs, and assumptions about program structure. Allowing for price discrimination across customers or end uses will lower the marginal cost of conserved electricity.

Many recent energy policy proposals allow savings from energy-efficiency programs to satisfy a certain portion of an RPS. While a full analysis of this type of integrated policy is beyond the scope of this paper, the supply curves produced in this analysis suggest that if renewable energy certificates were priced at $50/MWh, roughly 1 to 3 percent of the total RPS percentage could be obtained from energy-efficiency gains.

Many unresolved questions remain for future work. The effectiveness of the DCI mechanism modeled here in reducing electricity demand depends heavily on the price elasticity of demand values assumed. More exploration into how the effectiveness of this policy varies with elasticity values would be elucidating. In addition, we modeled the price discrimination feature in a post-processing sense and not as a part of the integrated model solution. Integrated analysis of this policy would be important to confirm that these results hold in equilibrium and would allow the harvesting of additional savings because the current post-processing approach results in only part of the efficiency funding being used. To make this feature most relevant for policy analysis, full integration of the RPS with a quantity-based version of the DCI (instead of one driven by aggregate funding levels) would reveal how such an integrated policy might work as well as how different design elements of the combined policy would affect the mix of renewables and conserved electricity that such a policy is likely to yield.

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