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# Modeling Energy Efficiency as a Supply Resource

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**Review**
This working paper has not undergone a formal review process. It is intended to stimulate discussion and inform debate on emerging issues.

## SUMMARY

Energy efficiency may be an inexpensive way to meet future demand and reduce greenhouse gas emissions, yet little work has been attempted to estimate annual energy efficiency supply functions for electricity planning. The main advantage of using a supply function is that energy efficiency adoption can change as demand changes. Models such as Duke University's Dynamic Integrated Economy/Energy/Emissions Model (DIEM) have had to rely on simplistic or fixed estimates of future energy efficiency from the literature rather than on estimates from energy efficiency supply curves.

This paper attempts to develop a realistic energy efficiency supply curve and to improve on the current energy efficiency modeling. It suggests an alternative approach based on saved-energy cost data from program administrators and explains the methodologies employed to create the supply curve. It illustrates this approach with results from DIEM for various electricity demand scenarios.

The analysis suggests that an additional 5%–9% of energy efficiency is deployed for every 10% increase in the cost of electricity. Therefore, DIEM "invested" in energy efficiency up to an inelastic point on the energy efficiency supply curve. By contrast, the U.S. Environmental Protection Agency's energy efficiency approach assumes that realized energy efficiency is fixed and has no elasticity, regardless of changes to marginal costs or constraints that affect emissions or economics.

## INTRODUCTION

Energy efficiency (EE) is an important element for electricity planning because it may be an inexpensive way to meet future demand or reduce emissions (Eto et al. 2000; Friedrich et al. 2009). The more costly electricity is, the more important energy efficiency becomes. In the context of electricity planning, energy efficiency involves service delivery with reduced electricity. Evaluating energy efficiency as a supply-side option in energy models for electricity planning is tricky because that option behaves differently than other options and comes in small increments. EE programs can be aggregated into a supply option by creating a supply function. Incorporating an EE supply function into electricity models would allow comparisons of investments in energy efficiency with investments in power plants.

The main advantage of using a supply function is that EE adoption can change as demand changes. An EE supply function is the relationship between marginal cost of increasing amounts of energy efficiency, a simple linear example of which is illustrated by the green line in Figure 1b. The typical approach to energy efficiency is shown in Figure 1a.

**Figure 1. Fixed EE supply and EE supply curve with shifting demand curves**

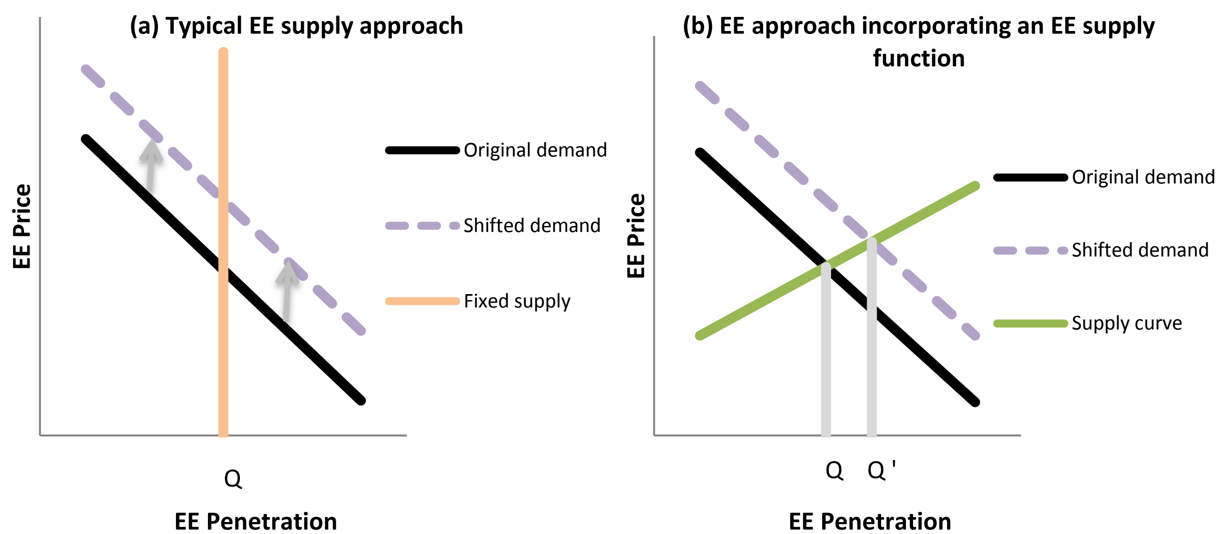


Figure 1b highlights how shifting the demand curve affects EE adoption. The black line represents original demand, whereas the purple dotted line represents demand under alternative conditions. Under these different conditions, more energy efficiency is cost effective, Q', compared to orginal conditions, where Q is the amount of cost effective energy efficiency.

As far as the authors know, no study has broadly estimated *annual* national, sectoral, or regional supply functions for electric energy efficiency. At the utility scale, some utilites such as the Tennessee Valley Authority have started modeling EE program performance at an hourly level (TVA 2015). Different studies use the phrase *EE potential* to mean different things, so this paper distinguishes meanings. Efficiency studies most often look at *cumulative* achievable EE potential (EPRI 2014), though some consider annual potential as the cumulative potential divided by look-ahead years (Neubauer 2014). Frequently, EE cost and supply estimates are made separately, making it difficult to consider energy efficiency with any level of complexity within an energy model. For this reason, models such as Duke University's Dynamic Integrated Economy/Energy/Emissions Model (DIEM) have used simplistic or exogenously derived fixed estimates for future energy efficiency from the literature, rather than from EE supply curves.[1]

To help fill these gaps in the literature, this paper attempts to develop realistic EE supply curves and to improve on the current EE modeling within the DIEM framework and also more broadly. To assess the possibility of constructing or estimating a more realistic EE supply function on the basis of available data, the method described herein defines a supply curve on historically achieved energy efficiency *and* achieved costs from Lawrence Berkeley National Lab's (LBNL) Demand-Side Management Program Impact Database. In contrast, the Environmental Protection Agency's (EPA) EE penetration is constructed from a combination of "achieved," annual incremental state energy efficiency, state targets, and literature estimates of future potentials (U.S. EPA 2015b).

This paper summarizes EE potential and cost data and projections in the literature. It then suggests an alternative approach to EE modeling based on data about the cost of saved energy from program administrators as well as explains the methodologies employed to create the supply curve. The supply curve maximum (asymptote) is derived from *technical potential* values from the literature. Next, it uses preliminary results from the new curve in DIEM for various electricity demand scenarios *as an illustration*. The paper concludes with a discussion of research needs.

## REVIEW OF CURRENT APPROACHES AND DATA AVAILABILITY

By nature, electricity models are simplified versions of enormously complicated systems that explore how different fuels and power plants can meet expected demand and capacity needs. Most new capacity options can be built at set future prices with similar generation features. In contrast, energy efficiency is usually characterized as a reduction in demand before supply options are optimized for meeting dispatch and capacity requirements.

### *EPA's Current Approach*

The EPA estimated future energy efficiency on a state-by-state basis for its Clean Power Plan (CPP) Regulatory Impact Analysis (U.S. EPA 2015b). For EE potential, the agency identified 56 studies with estimates published between 2009 and 2014. These studies and other metrics, including currently achieved state-by-state energy efficiency, EE resource standard (EERS) targets, and other non-ratepayer-funded EE opportunities such as building codes and appliance standards were all analyzed to determine a maximum savings level of 1.0% of sales per year. For costs, which were estimated *separately*, the EPA used cost estimates of saved electricity from bottom-up, top-down, and econometric analyses.[2]

To match costs with savings, the EPA used a three-tier approach, setting program costs at two times the highest estimate as its highest cost potential. The declining cost steps were not typical in the literature, but the EPA referred to two studies—Synapse (2008) and Plunkett et al. (2012)—that align with this

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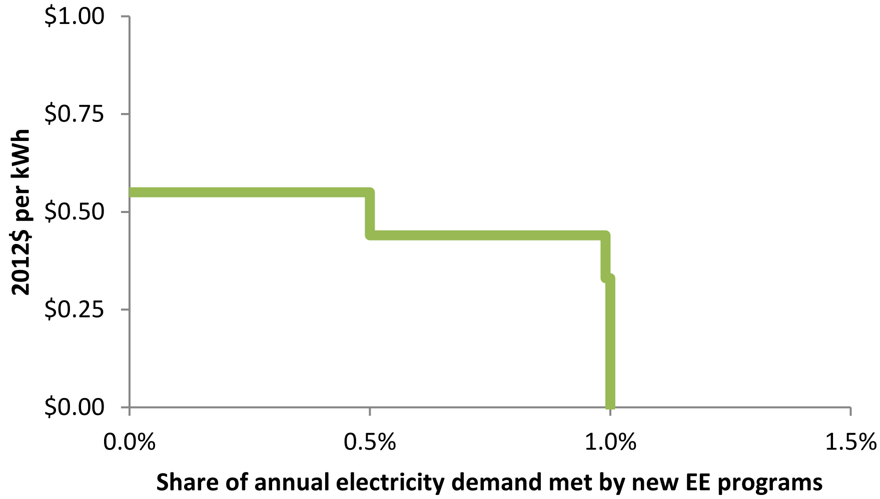
[1] The Dynamic Integrated Economy/Energy/Emissions Model was developed at Duke University's Nicholas Institute for Environmental Policy Solutions. Its Electricity component is described in Ross (2014b).

[2] The EPA found evidence for costs between $177–$275/MWh. These first-year EE program costs represent the investment for a certain amount of energy efficiency (avoided generation) measured as MWh avoided in the first year, X. In subsequent years (X+1, X+ 2, and so on), year X's efficiency is still applied, at no cost, but at a discounted amount. First-year program costs are similar to capital costs to build electricity capacity except that capacity is built in MW rather than MWh.

approach (U.S. EPA 2015b).[3] Figure 2 shows the EE supply shape that the EPA used to describe state-by-state EE potential for its Clean Power Plan (CPP) Regulatory Impact Analysis (RIA). These steps are characterized as a shape rather than a curve because costs are dependent on penetration rather than the other way around. The EPA uses the shape to count costs from exogenously determined fixed EE shares, whereas a supply curve compares costs to determine how much EE penetration if any is cost-effective.

**Figure 2. EPA's energy efficiency supply shape from Clean Power Plan RIA using first-year costs and savings**




Many power sector models have incorporated the EPA's approach for energy efficiency into their models for their own CPP modeling (Beasley et al. 2017).[4] One limitation of this approach is that the EE projections do not change from scenario to scenario. As previous DIEM-based analyses have shown, the EPA's approach will result in maximum EE consumption in the baseline scenario (1%), thus the EPA's approach is similar to that depicted in Figure 1a.

From a modeling perspective, developing an EE supply curve would be an improvement over using the supply shape by incorporating cost characteristics along with a wider range of available energy efficiency. Models using an EE supply curve would treat energy efficiency like other capacity expansion decisions, deploying energy efficiency when it is economic to do so on the basis of underlying conditions. The reason that many models use the EPA's CPP EE expectation or state EE targets for predictive purposes is that alternative approaches are limited. Not a lot of data are available to underpin future estimates, many potential studies do not include any cost estimates, and EE potential estimates are not readily comparable. Additionally, potential estimates are not without controversy. Economists suspect hidden costs when technologists identify significant availability of economic energy efficiency (Jaccard 2010).

[3] Synapse (2008) identified a trend of reducing costs as utility EE programs increased in scope. Plunkett et al. (2012) suggests that, when combined, two opposing forces in economic theory—diminishing returns and economies of scale—will reduce first-year costs at modest levels and then increase first-year costs for high levels of energy efficiency

[4] In general, EE modeling usually involves exogenous assumptions about energy efficiency, unless models reflect detailed equipment improvements, in which case energy efficiency may be endogenous. The EPA RIA assumptions for EE cost, supply, or both have been used in modeling by EPRI, the Bipartisan Policy Center, the Framework for Analysis of Climate-Energy-Technology Systems, Resources for the Future, the Midwest ISO, the Nicholas Institute for Environmental Policy Solutions, and the EPA.

### *State of the Literature*

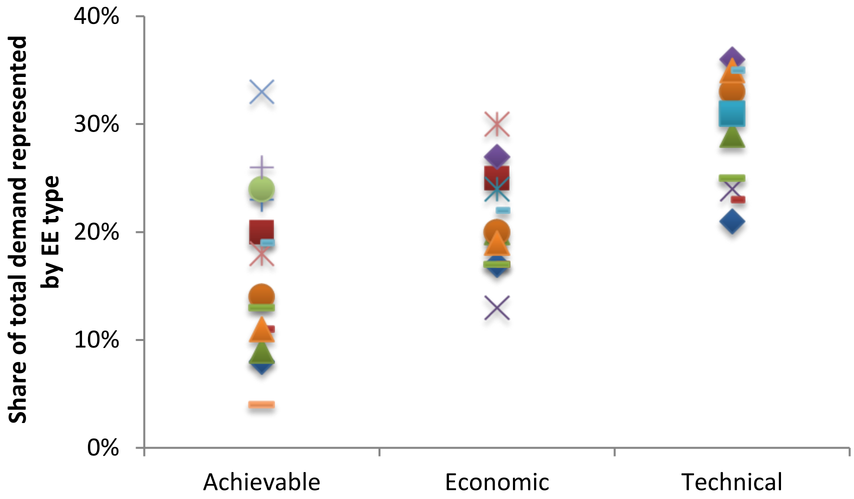
The energy efficiency (EE) literature generally defines three types of EE potential: *technical*, *economic*, and *achievable* (Neubauer 2014). *Technical* EE potential is calculated as the total EE savings available at complete implementation of all currently available EE measures. *Economic* EE potential is a subset of *technical* EE potential determined to be economically efficient to implement on the basis of a cost-effectiveness test. *Achievable* potential is a subset of *economic* EE potential that excludes economic options that are not undertaken for one reason or another. In other words, *achievable* refers to EE savings that can be realized after accounting for social, geographic, financial, and other non-economic-based realities.

State, utility, and regional EE potential studies are regularly done to inform utility and other energy planning. Most publicly available studies are for states or regions and focus on the quantity of energy efficiency that can be achieved through utility-administered programs, both to assess planning for IRPs and to assess utility program targets and design. The data availability literature reviewed for this study (see Appendix A) revealed that differences in data sources and estimation approaches are significant. There are national-level studies and some meta-analyses that could serve as the basis for defining supply curves that are relatively flexible and generalized. Most estimates of future EE potential are not national, consider different regions of the country, and use different methodologies.

A number of meta-analyses attempt to aggregate EE potential studies. For example, Sreedharan (2013) attempts to normalize many studies that have different approaches and geographies, and it estimates that annual achievable energy efficiency of ~0.3% to 1% is reasonable. However, this study does note national studies' wide range of economic potentials in 2020—from 10% to 25% (Sreedharan 2013). Similarly, the American Council for an Energy-Efficient Economy (ACEEE) performed a meta-analysis of 11 studies and calculated average cumulative economic and achievable electric potential at 20% and 24%, respectively (Nadel et al. 2004).[5] A subsequent ACEEE (2008) meta-analysis of 21 state, regional, and national studies estimated annual technical, economic, and achievable potentials at 2.3%, 1.8%, and 1.5%, respectively (Eldridge et al. 2008). A more recent ACEEE review looked at 45 EE potential studies since 2009, and these studies suggest that annual average achievable electric potential is 1.3%, similar to annual averages from the earlier ACEEE meta-analyses. However, individual potential studies' annual EE estimates ranged widely from 0.3% to 2.9% (Neubauer 2014). The ACEEE studies offer averages but no strong basis for establishing them, and they do not address the inherent uncertainty of those averages. Figure 3 shows the challenge of combining estimates from different sources by illustrating the range of potentials that were collected at the same time (Eldridge et al. 2008).

[5] Normally the *achievable* potential would be lower than *economic* potential. However, most of the reviewed studies did not estimate all types of potentials, so the averages are calculated from different studies and different geographies.

**Figure 3. Range of energy efficiency cumulative potentials from meta-analysis of 18 studies**




*Notes:* EE potential studies generally forecast EE potentials for a given year, perhaps 10 or 15 years in the future, rather than an annual EE potential. Different symbols represent EE potential values from original sources used in the meta-analysis study.
*Source:* Eldridge et al. (2008).

The three studies that have national EE supply estimates offer insight into the nuances in EE costs and potentials. *United States Energy Efficiency Potential through* 2035 (EPRI 2014) estimates EE potential for 2035 in a bottom-up national analysis. EPRI estimates cumulative achievable energy efficiency potential in 2035 at 11%–14% of total demand. It calculated the levelized cost of energy for EE achievable potential measures on an end-use basis.

McKinsey's *Unlocking Energy Efficiency in the U.S. Economy* (Granade et al. 2009) took a different approach to estimating national EE potential. The study's EE focus is on Net Present Value-positive potential, similar to what is generally called the economic potential, estimated at 23% relative to business as usual for total energy consumption in 2020.[6] One of the unique aspects of this analysis is that it does not attempt to estimate achievable EE potential; instead it explicitly suggests that overcoming EE barriers would lead to energy savings twice the cost of upfront EE measures. McKinsey does not publish the data underlying the multi-year efficiency supply-curve that combines attractive investments for natural gas and electric efficiency. Those data might help refine an annual electric EE supply function.

Lawrence Berkeley National Laboratory published a top-down national EE potential study called *The Future of Utility Customer-Funded Energy Efficiency Programs in the United States: Projected Spending and Savings to 2025* (LBNL 2013). It first identified a likely range of EE spending and then the corresponding annual incremental EE saving for the years 2015, 2020, and 2025. LBNL's top-down approach to evaluating EE potential as it correlates to likely investments in utility programs is unique; most studies assess the percentage of energy efficiency that is economic and behaviorally likely. LBNL expects that a high level of utility EE investment would result in a 1% first-year (FY) electricity savings (reduction) in 2020, whereas a low level would lead to about half as much savings.

[6] McKinsey's *business-as-usual* is defined as the Department of Energy's Reference case from *Annual Energy Outlook 2008*.

Using the existing literature to estimate future EE potentials, costs, or both together is problematic. Because the state, utility, and regional studies are too dissimilar (with regard to years, considered measures, geographical conditions, and economic measures) to aggregate, this analysis focused on national studies and meta-analyses. However, across geographies and methodologies, even these studies did not lend themselves to normalizing individual measures. The literature has an unsubstantial basis for future EE costs, because studies often apply different economic filters to technical potential and provide insufficient information to assess how individual measures were deemed cost-effective.

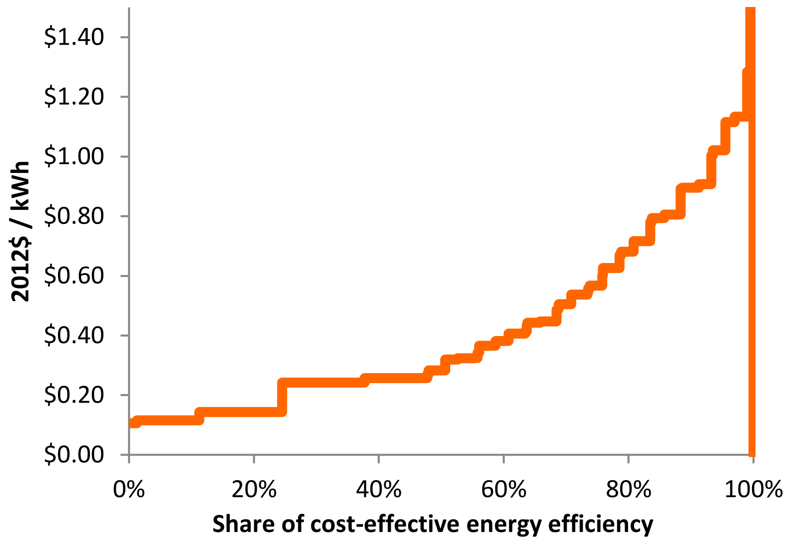
## HISTORICAL DATA AS THE BASIS FOR ENERGY EFFICIENCY CURVE

This analysis initially attempted to merge the three aforementioned national potential estimates into EE supply curves, but costs in these three studies were not sufficiently comparable or conformable. Therefore, the analysis relied on historical data from LBNL's DSM Program Impacts (PI) Database (Billingsley et al. 2014). These data are the most granular published source of EE costs, achieved potential, and persistence. The EE cost data are particularly rich and granular because they differentiate among EE subsectors and individual programs.

Figure 4 shows the EE supply curve derived from the LBNL database, which had collected EE program data from more than 2,000 program years as of 2014 and which allows for the matching of costs to EE achieved potential (quantities).[7] This curve defines the fraction of the annual energy efficiency that is cost-effective at different dispatchable costs, but it does not define the EE potential. The LBNL database provides information relating the amount of energy efficiency achievable at a given cost but it does not relate energy efficiency to total demand. An energy model would be comparing each incremental investment in EE savings with the cost of all the other ways to generate comparable amounts of electricity, accounting for current invesments' impact on future years. To use an oversimplified example, a model calculates how much to spend on EE programs each year by comparing the incremental per kWh cost with other low-cost alternatives, such as building a new natural gas combined cycle plant. If in some year the next best investment has a first-year cost equivalent of more than $1.30 per kWh, all of the energy efficiency programs would be chosen for investment. If the lowest-cost way to meet incremental generation was equivalent to ~ $0.28, only about 50% of the available energy efficiency programs—represented by the lower portion of the curve in Figure 4—would be chosen.

[7] LBNL defines "program year" as a unique year of data from a unique utility, meaning that two years of data from each of two utility programs count as four program years of data.

**Figure 4. Energy efficiency supply curve**

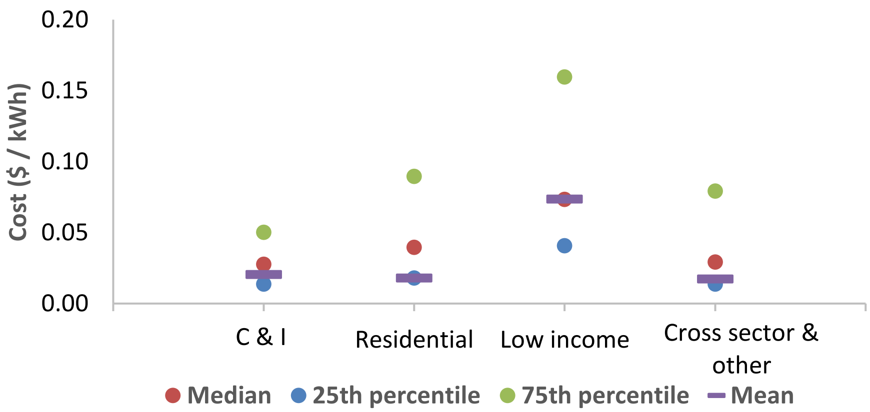



*Note*: The full amount of energy efficiency, the 100% value, is called *annual technically available potential*. Each year the supply curve can be evaluated independent of previous years' EE investment.

### *Extracting Energy Efficiency Costs*

The costs associated with a given level of EE savings can be measured in levelized, cumulative, or FY costs. For the curve presented here, 12 EE costs were obtained from Figure 5: the levelized cost of saved energy (CSE) for the median as well as the high and low interquartile costs for each of the four EE defined sectors. Additionally, the "high cost" for each type of energy efficiency was estimated at twice the high-end interquartile (75th percentile) cost.[8]

**Figure 5. National levelized cost of saved energy, by sector**




*Source*: Billingsley et al. (2014).

[8] Historically, according to the LBNL database, the amount of achieved EE program savings heavily skews to the lower-cost programs, begging the question of whether higher-cost programs have less efficiency potential or whether they are less likely to be implemented. Perhaps both answers are correct, but intuitively the second option appears more likely than the first. Without a strong basis for identifying how much of total efficiency potential should be attributed to low-, medium-, or high-cost programs, this paper's proposed supply curve offers amounts in a low, medium, and high range. It then linearly offers potential at regular price intervals between the previously identified price points (25%, median, and 75th percentile).

Most of the data from the PI database are presented in LBNL reports as the levelized cost of saved energy, a metric that accounts for the longevity of EE measures and for discount rates. For modeling purposes, it is useful to characterize EE costs as up-front rather than levelized and as FY savings rather than cumulative EE savings. Therefore, this analysis translated costs from Figure 5 into appropriate terms. The ratio between levelized cost and annual cost is defined as the capital recovery factor or CRF (Hoffman et al. 2015). The appropriate CRF can be calculated for the EE sectors per Billingsley et al. (2014), as seen in Table 1.

**Table 1. Program administrator CSE for electricity efficiency programs, 2009–2011, by sector**

| | Levelized CSE | First-Year CSE |
|---|---|---|
| Commercial and Industrial | $ 0.021 | $ 0.188 |
| Residential | $ 0.018 | $ 0.116 |
| Low Income | $ 0.070 | $ 0.569 |
| Cross Sectoral/Other | $ 0.017 | $ 0.120 |
| **National CSE** | **$ 0.021** | **$ 0.162** |

*Note*: Values are in 2012$/kWh. Levelized CSE uses a 6% discount rate.
*Source*: Billingsley et al. (2014).

### *Matching Costs and Energy Efficiency Potential*

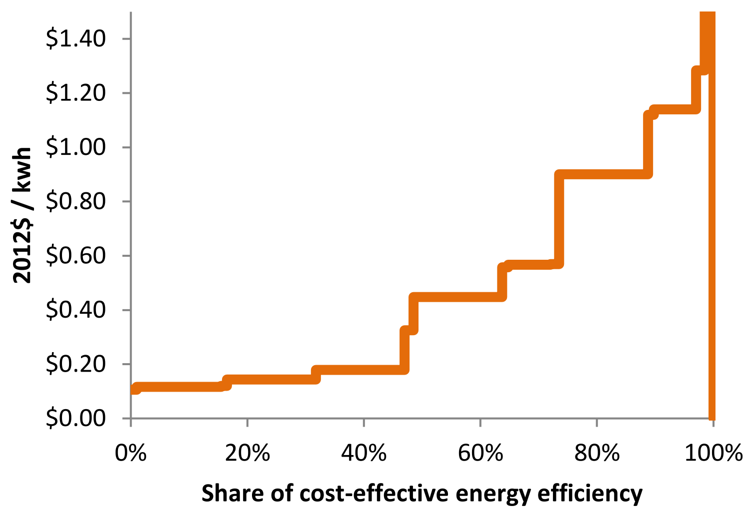
The first steps to derive a supply curve from the PI database are reflected in Table 2. The four types of energy efficiency are divided into four unequally sized partitions on the basis of their relative share in the database: 53% commercial and industrial, 40% residential, 2% low income, and 5% other (Billingsley et al. 2014). The four partitions for each type of EE were subsequently matched with four costs identified for each EE type. The first three costs are translated from the levelized values in Figure 5 to FY costs, assuming that the highest cost is two times that of the third quartile.

**Table 2. Initial matching of energy efficiency cost to potential**

| | Quartile | Share of Potential | Cost for each Quarter Potential |
|---|---|---|---|
| **Commercial and Industrial** | 1 | 13.25% | $0.14 |
| | 2 | 13.25% | $0.24 |
| | 3 | 13.25% | $0.45 |
| | 4 | 13.25% | $0.90 |
| **Residential** | 1 | 10.00% | $0.12 |
| | 2 | 10.00% | $0.26 |
| | 3 | 10.00% | $0.57 |
| | 4 | 10.00% | $1.13 |
| **Low Income** | 1 | 0.50% | $0.33 |
| | 2 | 0.50% | $0.60 |
| | 3 | 0.50% | $1.28 |
| | 4 | 0.50% | $2.57 |
| **Cross Sectoral or Other** | 1 | 1.25% | $0.11 |
| | 2 | 1.25% | $0.20 |
| | 3 | 1.25% | $0.56 |
| | 4 | 1.25% | $1.12 |

Data in Table 2 were rearranged by increasing cost to produce the 16-step curve in Figure 6. To increase granularity (i.e., the number of supply curve steps), each step in the middle of the curve was interpolated into 5 smaller steps creating a 44-step curve (Figure 4).[9]

**Figure 6. Energy efficiency supply curve with 16 steps**



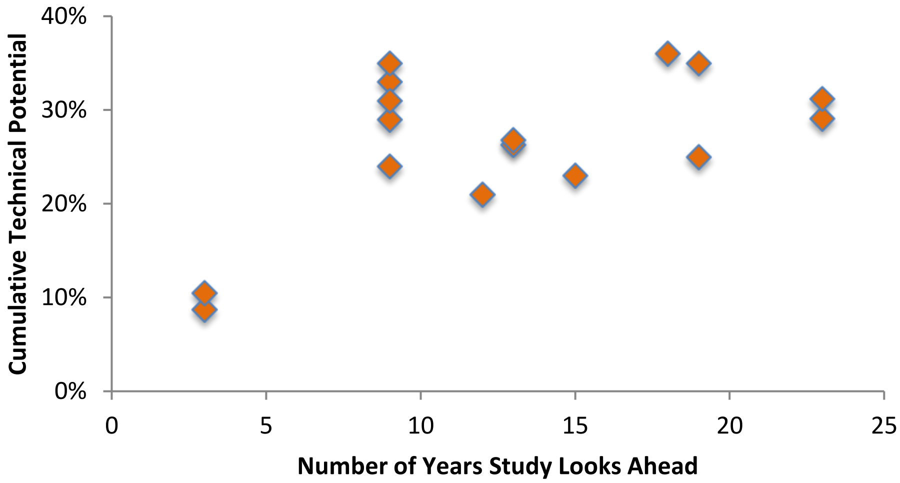

### *Estimating an Annual Potential*

The last critically important assumption required to complete the supply curve is defining how much energy efficiency could maximally be dispatched annually (i.e., the width of the curve in Figure 4). For modeling purposes, a subset of *technical* potential with an appropriate behavioral exclusion is of most interest, similar to "*achievable* potential" but without application of an economic filter. This paper uses the term "technically achievable potential." Economic models determine what is economic under varying future circumstances, so applying an exogenous economic filter to define "*economic* potential" would be limiting. Indeed, the LBNL PI database, which includes achieved energy efficiency, almost certainly contains some programs that are not cost-effective.

To estimate an annual energy efficiency (i.e., the supply curve's vertical asymptote in figures 4 and 6) that aligns with the steps from the LBNL PI database, this analysis started with *technical* potentials from the literature. Because most studies estimate *cumulative technical* potential rather than *annual technical* potential, a number of assumptions must be made to determine an appropriate estimate for *annual technical* potential. Cumulative technical potential as a function of number of years looking ahead is shown in Figure 7.

[9] Steps that start above 25 cents and below 60 cents per kWh were interpolated. This range includes more than half of the potential and is in the most important variable cost range.

**Figure 7. Cumulative technical potentials from 12 studies by number of years within forecast**



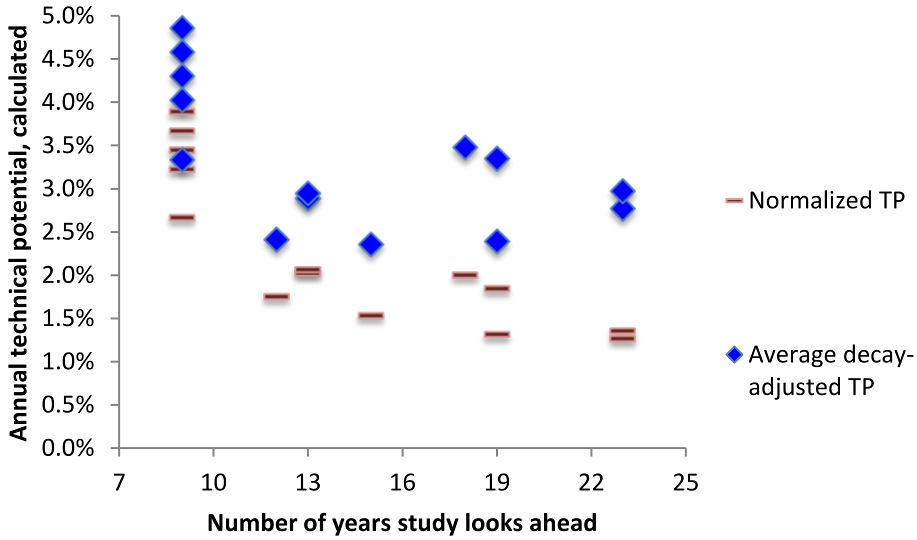

*Source: EPRI (2009), EPRI (2014), and Eldridge et al. (2008).*

This dataset is made from 10 state or regional studies (Eldridge et al. 2008) that were published before or by 2008 and two more recent sets of national estimates (EPRI 2009 and EPRI 2014). The studies complied by Eldridge et al. (2008), estimate an *annual technical* potential by dividing the *cumulative technical* potential by the study time period. However, Eldridge et al.'s estimate of annual technical potential does not account for EE savings exhausted in the years between the study year and the year for the cumulative technical potential estimate. To schedule how each year's EE savings diminishes over time, the EPA uses a weighted average EE measure persistence of 10.2 years, taken from an unpublished 2015 LBNL technical memo (EPA 2015b).

Because every EE program measure has a different time to exhaustion, a cumulative exhaustion rate becomes a complicated calculation. This analysis uses a simplified EE savings persistence approach, whereby annual energy efficiency diminishes by 5% per year. Accounting for persistence is fundamental to properly calculating annual savings from cumulative EE savings. In particular, ignoring persistence can lead to significant underestimation of the underlying annual savings. For example, after 10 years any program EE savings would be reduced by 50%, and for an EE study with a 20-year horizon, the cumulative EE in year 20 captures only half of the originally installed energy efficiency, because the other half of the measures would have diminished over time.

Figure 8 compares two sets of estimates for *annual technical potential*. The forecasted *cumulative technical* potentials (i.e., the values from Figure 7) divided by the number of years that Eldridge et al. (2008) reported are called *normalized technical potentials*. *Decay-adjusted annual technical potential*, likely a better estimate, has higher values than the normalized figures.

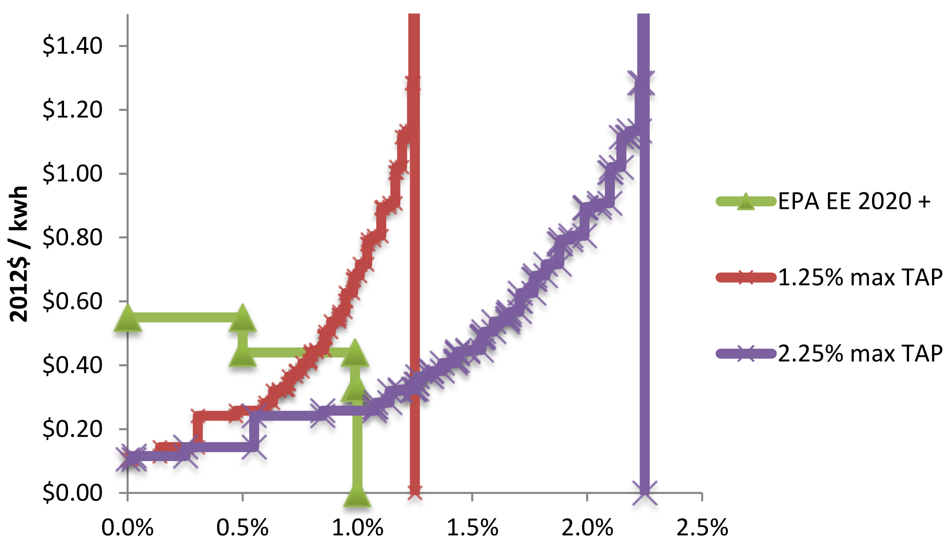
**Figure 8. Two ways of calculating technically achievable potentials**




*Note*: Dashes = Normalized technical potentials. Diamonds = decay-adjusted annual technical potentials.
*Source:* Calculated from EPRI (2009), EPRI (2014), and Eldridge et al. (2008).

The *decay-adjusted annual technical potentials* from Figure 8 range from 2.5% to 4.5% per year. Translating this annual technical range to an annual *technically achievable* value involves significant uncertainty. To address this uncertainty, half the value of these potentials were chosen as the technically achievable potentials for the modeling illustration presented below. When applied to the curve shown in Figure 4, potentials of 1.25% and 2.25% lead to the supply curves shown in Figure 9. The EPA supply shape from Figure 2 is shown for comparison.

**Figure 9. Supply curves with annual technically achievable potentials of 1.25% and 2.25%, compared with EPA's supply shape**



## MODELING IN DIEM

To illustrate the performance of the Nicholas Institute for Environmental Policy Solutions' supply curve, this analysis used the Dynamic Integrated Economy/Energy/Emissions Model (DIEM), which includes a detailed electricity dispatch model of U.S. wholesale electricity markets (Ross et al. 2016).[10] The model represents intermediate- to long-run decisions of the electricity industry regarding generation, transmission, capacity planning, and dispatch of units. To estimate policy impacts, the model minimizes the present value of generation costs (capital, fixed operating and maintenance or O&M, variable O&M, and fuel costs) subject to meeting electricity demands, reserve margins, and any policy constraints. Plants in the model are dispatched on a cost basis to meet demand within each of 40 markets or regions through 2060. Similarly, DIEM can select EE measures if they are a cost-effective alternative to generating the same amount of electricity within the industry. For this illustrative analysis, DIEM-Electricity was run as a stand-alone model, implying that electricity demands are fixed at their future forecast levels, aside from the EE considerations of interest.

Two futures were used for the EE comparison in DIEM. The Baseline Scenario uses the standard assumptions in DIEM regarding electricity demand, natural gas prices, and other factors (largely based on *Annual Energy Outlook 2015*). The National CPP Scenario uses one of the mass-based trading options outlined in the CPP Final Rule (U.S. EPA 2015a). The model has multiple endogenous options to meet carbon dioxide emissions targets, including EE programs. This scenario was chosen to examine how and if a scenario with increased generation costs would lead to different amounts of energy efficiency. Three treatments of energy efficiency were used as illustrative cases: the EPA standard approach was compared with two supply curves. The EPA approach determines the amount of energy efficiency and then the associated cost. For the supply curve sensitivities, the EE costs and quantities were input into DIEM through the two *decay-adjusted annual technical potential* curves shown in Figure 9. FY costs of EE measures were compared with other supply-side options' costs (capital, fixed, fuel/variable) already defined in the model to determine how much energy efficiency is cost-effective to initiate in any given year. To DIEM, adding energy efficiency is most similar to adding renewables, because there are no ongoing fuel expenses.

The "Modest EE" curve (the red curve in Figure 9) is assumed to have a potential electricity demand reduction of 1.25% per year from the previous year's baseline demand. That curve lead to cost-effective demand reductions of approximately 1.0% per year, a percent roughly aligned with EPA estimates (2015b). The "Higher EE" curve (the purple curve in Figure 9) is assumed to reach its potential at 2.25% per year, a result that aligns with the low end of the decay-adjusted technical potential value from Figure 8.

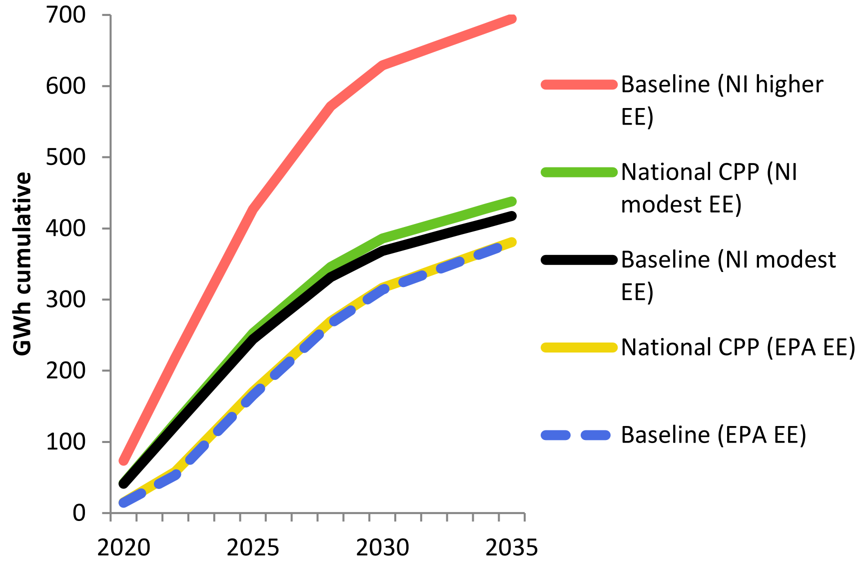
## INTERPRETATION OF MODELING RESULTS

The amount of energy efficiency resulting from five scenarios, between the years 2020 and 2035, is shown in Figure 10. Energy efficiency is reported as a demand growth reduction in GWh. In Figure 10, the red line represents the only scenario that uses the Higher EE annual potential assumption. The Modest EE curve, which was calibrated to select an amount of energy efficiency similar to that in the EPA's approach (1% per year), is used in the green and black scenarios. The yellow and blue scenarios represent those using the EPA's fixed EE approach. The early-year difference between the EPA's scenarios and the Nicholas Institute's scenarios reflects the EPA's ramp up to 1% energy efficiency per year; by contrast, the Nicholas Institute supply curve's efficiency potential is the same for every year. All five scenarios

[10] See Ross (2014a,b) for documentation of the previous version of DIEM.

show similarly decreasing slopes in 2029, representing the fact that the model reduces the effectiveness of EE measures taken in earlier years, that is, EE measures do not persist indefinitely.

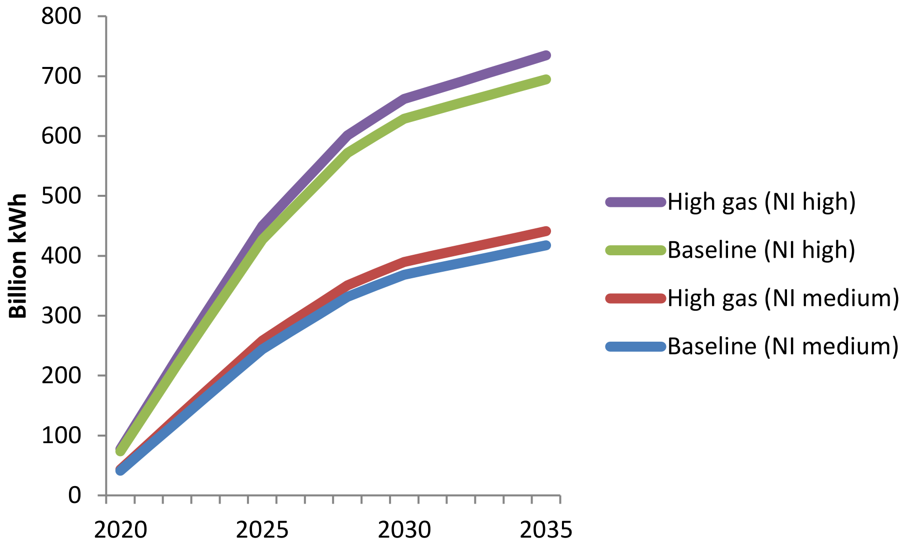
**Figure 10. Comparison of e projections from supply curves**




This figure helps highlight a couple of important points about modeling the different approaches to energy efficiency. The first is that the EPA's EE forecast is practically identical for its baseline and national CPP scenarios (blue and yellow curves). Second, the annual similarities between EE supply curves and the EPA's shape lead to cumulative differences, mostly due to the ramp-up effect and handling of the persistence of the EE measures. Third, as evidenced by comparing the Nicholas Institute's baseline curve (red curve) with the other curves, the variable most significantly related to how much energy efficiency will offset future demand is the annual EE potential assumption. Fourth, the CPP scenario, which leads to slightly higher system costs than the baseline scenario, does result in a small increase (3%–5%) in energy efficiency (green versus black) when the supply curve is used. Although this marginal increase points to a rather modest increase, it does behave as expected, because overall generation costs and electricity prices have only increased slightly in the CPP scenario.

One sensitivity analysis using DIEM compared EE supply curve results in a relatively high natural gas price future (see Figure 11) for both the modest and higher EE baselines. The supply curves in higher gas price scenarios consistently lead to 6% more energy efficiency. This result highlights the value of using EE supply curves rather than static EE projections. More important than the forecasted absolute value of energy efficiency is the fact that EE supply curves allow the model to capture incremental changes to the EE forecast, as it does for other fuels.

**Figure 11. Higher natural gas price sensitivities reveal increased energy efficiency**




## CONCLUSIONS AND RESEARCH NEEDS

The EE supply curve analysis above shows an approach to deriving a data-based EE supply function to be used in modeling, such as modeling with DIEM. The slope at the region of interest of the supply curve indicates an additional 5%–9% of energy efficiency for every 10% increase in willingness to pay for energy efficiency. In other words, all else equal, in the modeled scenario, in equilibrium, most of the EE supply curve has a point elasticity of 0.5–0.9. Therefore, DIEM "invested in energy efficiency" up to an inelastic point on the EE supply curve. Whereas, when using the EPA's EE approach, realized energy efficiency is the same regardless of changes to marginal costs or constraints that affect emissions or economics. There are many areas beyond the scope of this work in which the supply-curve approach described here could be further refined.

In this analysis, annual technical potential is the most important unknown—and perhaps the most important area for further study. Existing potential studies and EE data do not lend themselves to clear conclusions about short- or long-term annual potential. Additional historical data and research to determine year-over-year and long-term changes to annual potential would advance EE planning in addition to EE modeling.

Should additional data become available, the shape of the EE curve in any given future point in time as well as over time should be re-evaluated. Technological advancements may lead to low- or high-cost energy efficiency becoming relatively less expensive, and policy and other economic factors may lead to an EE supply function that is different from the one estimated in this analysis.

Another uncertainty related to how energy efficiency changes over time not examined here is energy efficiency as a percentage of demand growth. Future research should look at the question of how EE potential should change if demand growth increases or decreases from one scenario to another. Because this analysis was a static analysis, it did not attempt to answer this question.

Additionally, this analysis focused on national EE supply without sectoral differentiation. Differentiation by sector and possibly by region would also be valuable dimensions for improved granularity. Lastly, the likely future persistence of cumulative EE measures has not been well studied, but better estimates could affect the cost part of the supply curve.

The data-based supply curve developed in this analysis could be a reasonable starting point for improved modeling of energy efficiency as a supply-side resource. Scenario analysis with an eye toward comparing capacity expansion options will only benefit from having the option to invest in more or less energy efficiency. Scenarios with large price shocks or constraints related to emissions will benefit from modeling efforts that endogenously incorporate energy efficiency.

## DEFINITIONS

**Asymptote**—The theoretical ceiling for the EE supply curve, above 1.25% and 2.25%, were the two asymptotes for the modeled examples. This value is the source of significant uncertainty.

**Technical potential**—Technical EE potential is the total EE savings available with complete implementation of all available EE measures.

**Economic potential**—Economic EE potential is a subset of the *technical* EE potential that is determined to be economically efficient on the basis of a cost-effectiveness test.

**Achievable potential**—Achievable EE potential is the subset of *economic* EE potential that excludes cost-effetive EE projects that may not be undertaken due to social, geographic, or other realities.

**Annual potential and cumulative potential**—These two types of potential highlight the importance of time and the continuance of EE savings beyond one year. One challenge is to annualize the EE potential for modeling purposes, because the EE potentials identified in the literature are almost always presented as cumulative totals for a future year. For the curve developed in this study, the investment in some amount of energy efficiency relative to demand for any one year is the EE potential of interest, and it is called *annual EE potential*. However, most EE potential studies and literature consider EE potential to be the cumulative EE savings from many years' worth of EE investments realized in one particular future year relative to that future year's annual demand. In other words, if there is 1% annual EE potential available every year, cumulative EE potential would be descrbed as 5% for 5 years hence, but also as 10% for 10 years hence (on a *normalized* basis).

**Decay-adjusted potential**—Decay-adjusted potential is the annualized EE potential reflecting translation of cumulative potential into an annualized value assuming that EE savings are reduced over time. Eventually, after some number of years, the persistence of any particular EE measure leads to no energy savings.

**Normalized potential**—Normalized potential is the annualized EE potential reflecting translation of cumulative potential into an annualized value assuming no EE savings decay (i.e., assuming as much energy savings after five years as in the first year).

**Technically achievable potential**—Technically achievable potential is the potential that could be captured regardless of cost-effectiveness. This EE potential is a good input for economic models, which perform their own economic filtering. This term is defined in this study by applying the *achievable* filter directly to *technical EE potential* rather than relating various EE potentials one to another as in the EE literature.

**EE potential supply over time**—For the initial supply curve, the time dimension does not play a large role. Annual potential, as in most studies, is based on turnover potential rather than on retrofit potential, so one year's decisions do not affect the next year's. Over longer periods of time, EE potential may be increasing or decreasing and getting more or less expensive for a variety of reasons (new technologies, changes in baseline technologies, program learning, and so on).

**Highest-cost EE quartile by sector**—The highest price point for each of LBNL's database categories (commercial and industrial, residential, low income, and other) was estimated to be twice the cost of the 75th percentile cost. This analysis assumed that very few of the most expensive technical potential measures show up in the LBNL PI database (these opportunities are available on a continuum) and that EE measures can be found at any price point. Therefore, the fact that a number of programs exist with realized costs above the 75th percentile costs, even if they were carried out on a small scale, points to the idea that more expensive measures not undertaken likely exist near the theoretical cost maximum. The basis for doubling instead of tripling or increasing by 50% is limited, but it appears reasonable until there are more data to consider. Part of that basis is that the 75th percentile cost (as seen in Figure 5) is generally twice the cost of the median cost by category.

## REVIEWED LITERATURE

| Title | Organization | Cost Information |
|---|---|---|
| The Technical, Economic, and Achievable Potential for Energy Efficiency in the United States: A Meta-Analysis | ACEEE | |
| Quantifying the Savings of an Industry Energy Efficiency Program | Energy Efficiency | x |
| Unlocking Energy Efficiency in the US Economy | McKinsey (2009) | x |
| Energy Efficiency in Appalachia: How Much More Is Available, at What Cost, and by When? | SEEA | x |
| Modeling Detailed Energy-Efficiency Technologies and Technology Policies within a CGE Framework | The Energy Journal | |
| A Preliminary Look at Electric Efficiency Potential | Elsevier | x |
| Recent Estimates of Energy Efficiency Potential in the USA | Energy Efficiency | |
| Cracking the TEAPOT: Technical, Economic, and Achievable Energy Efficiency Potential Studies | ACEEE | |
| Georgia Power: 2013 IRP and Technical Appendix, Volume 2 | Georgia Power | |
| US Energy Efficiency: 5 Million Data Points (State by State) | EnergySavvy | |
| The Potential of Energy Efficiency: An Overview | The Brigde | x |
| Energy Efficiency Potential in Existing Commercial Buildings: Review of Selected Recent Studies | US DOE | |
| Energy Efficiency as a Low-Cost Resource for Achieving Carbon Emissions Reductions | US EPA | x |
| Database for Energy Efficiency Resources (DEER) | CPUC | x |
| Assessment of Achievable Potential from Energy Efficiency and Demand Response Programs in the US (2010-2030) | EPRI (2009) | x |
| US EE Potential through 2035 | EPRI (2014) | |
| Paradigms of Energy Efficiency's Cost and Their Policy Implications: déjà vu All Over Again | NAS, Jaccard (2010) | |
| EE Cost Curves: Empirical Insights for Energy-climate Modeling | NAS, Sathaye and Phadke (2011) | |
| Insights from Modeling the Proposed CPP | Bipartisan Policy Center | x |
| The future of Utility Customer-Funded EE Programs in the US: Projected Spending and Savings to 2025 | LBNL (2013) | x |
| Expanding the Energy Efficiency Pie: Serving More Customers, Saving More Energy through High Program Participation | ACEEE | |
| Cost-Availability Curves for Hierarchical implementation of Resider energy-Efficiency Measures | Energy Efficiency | x |
| 2013 California Energy Efficiency Potential and Goals Study | CPUC | |
| Assessment of Electricity Savings in the U.S. Achievable through New Appliance/Equipment Efficiency Standards and Building Efficiency Codes (2010 - 2025) | IEE | |
| The Potential for Energy Efficiency in the State of Iowa | Oak Ridge | |
| Energy Efficiency Potential Study for the State of New Mexico | Global Energy Partners | x |
| Increasing Energy Efficiency in New Hampshire | Vermont Energy | x |

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The Nicholas Institute for Environmental Policy Solutions at Duke University is a nonpartisan institute founded in 2005 to help decision makers in government, the private sector, and the nonprofit community address critical environmental challenges. The Nicholas Institute responds to the demand for high-quality and timely data and acts as an "honest broker" in policy debates by convening and fostering open, ongoing dialogue between stakeholders on all sides of the issues and providing policy-relevant analysis based on academic research. The Nicholas Institute's leadership and staff leverage the broad expertise of Duke University as well as public and private partners worldwide. Since its inception, the Nicholas Institute has earned a distinguished reputation for its innovative approach to developing multilateral, nonpartisan, and economically viable solutions to pressing environmental challenges.

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