Exploring Strategies for Implementing a Performance based State Efficiency Program: State Energy Consumption Metrics – Residential Sector Analyses

Authors: Colin Sheppard, Margaret Harper, Charles Chamberlin, and Arne Jacobson
Schatz Energy Research Center, Humboldt State University

Project Managers: Yerina Mugica, Dale Bryk
Center for Market Innovation, Natural Resources Defense Council

September 27, 2010

Executive Summary – Exploring Strategies for Implementing a Performance based State Efficiency Program: State Energy Consumption Metrics

Authors: Colin Sheppard, Margaret Harper, Charles Chamberlin, and Arne Jacobson
Schatz Energy Research Center, Humboldt State University

Project Managers: Yerina Mugica, Dale Bryk
Center for Market Innovation, Natural Resources Defense Council

Energy efficiency is the most cost effective means for reducing global warming pollution. According to McKinsey & Company, the energy bill savings from efficiency investments could roughly offset the cost of other measures needed to meet the necessary carbon reduction targets. And many of these investments already make sense economically: McKinsey estimates that a $50 billion per year investment could result in $1.2 trillion in energy bill savings by 2020 while reducing end-use energy consumption by about 23 percent of projected demand. In addition to saving Americans money on their utility bills, investments in energy efficiency would put downward pressure on electricity, natural gas, and carbon allowance prices (when a carbon cap has been established), while creating 600,000 to 900,000 new jobs. Establishing a reliable measurement for energy efficiency performance and rewarding success in improving performance will help America reach its full energy saving potential.

Across the country, the private sector has failed to take advantage of many available opportunities to increase efficiency, often due to market barriers and a lack of information about efficiency performance. With heightened awareness about the economic benefits of energy efficiency and increased focus on combating global warming, Congress and the states are starting to put in place the policies needed to overcome the regulatory and market barriers to increase efficiency. The American Recovery and Reinvestment Act (ARRA) provides significant support for energy efficiency efforts across the United States. And states and utilities are increasingly looking for ways to improve end-use energy efficiency. These measures have the potential to dramatically improve the efficiency of the U.S. economy, but currently there is no effort to track in a consistent manner how effectively states, utilities and others are using efficiency funding. Tracking efficiency gains at a broader level will provide the transparency and accountability needed to ensure that energy efficiency funding and programs achieve their full potential.

One approach to reliably measuring energy efficiency performance at the state level is to implement a Performance based State Efficiency Program (PSEP). PSEP addresses the question of whether energy intensity is improving or declining in the residential sector (and separately in the commercial sector.) In other words, are we making progress towards reducing overall energy consumption? Under this approach, states would be able to track the energy efficiency performance of residential and commercial buildings within their state compared to previous years. With this metric, States can easily see whether they are improving relative to their own baseline. State performance would be tracked using aggregate, state-level metrics.

In this report, we present and discuss a methodology for an aggregate, state-level metric of energy consumption intensity (ECI) in the residential sector and provide proof-of-concept simulations for each of the 50 U.S. states. The methodology provides a tool for identifying changes in state energy consumption intensity (i.e. energy consumption per capita) after adjusting for changes due to year-to-year variations in weather. This research confirms that it is possible to track trends in state energy consumption intensity, even with the imperfect data sets that are currently available. However, to increase the integrity of the results, improvements in the data collection process are necessary. With these improvements, the

approach could be further strengthened into a powerful tool for evaluating states' progress in reducing energy consumption.

Methodological Approach

The approach that we recommend for tracking ECI begins with aggregate energy consumption data for the residential sector in each state over a period of 10 years.[1] These data are adjusted according to state population, yielding annual per capita residential energy consumption intensity (MBtu/capita/year). The data are also corrected for an unrealistic assumption made by the EIA that primary energy associated with electricity consumption should be estimated using a national averaged fossil fueled heat rate. Our analysis estimates a state specific heat rate based on the composition of electricity production which assumes no conversion losses from renewable electricity, hydropower, and nuclear power.

While there are many causes for variation in energy consumption intensity, weather is most clearly beyond the influence of policy makers. Therefore, adjusting for this factor is an important step in the evaluation of consumption trends that result from policy changes. We perform a fixed effect multiple linear regression to determine the response of ECI to heating and cooling degree days (HDD and CDD), both strong indicators of the impact of climate on building energy consumption. The regression includes dummy coefficients to model the fixed differences in ECI from state to state as well as differences from year to year across all states. The estimated weather coefficients are used to adjust ECI in a given year to a normal weather year based on the state's 30 year average HDD and CDD values.

The result is an adjusted residential sector ECI trend (aECI) for each state that includes corrections for changes in residential heating and cooling energy use due to annual variations in state weather. In order to evaluate a state's performance in reducing aECI, we estimate the slope of a linear trend line through the five years preceding a given test year. States with a downward (negative) slope, which indicates a decrease in aECI, are considered to have achieved progress, while those with a flat or increasing slope are not. In order to decrease the occurrence of false positives, that is, to prevent rewarding states that actually made no improvement in aECI, we add the condition that the slope estimate for a given test period be negative with 80% confidence.

Simulation of Performance Evaluation

In Figure E1, we present the result of applying this analysis for the three states that demonstrated the most five-year decreases in aECI and three of the states that demonstrated no such decrease. The trends have been normalized to the aECI value in 1985 for each state. The top performing states clearly have more impressive trends than poorer performing states. However, it is important to note that the relatively short, five-year time horizon for estimating the slope can result in a situation like Nevada's. Nevada achieved progress according to our metric in a number of years, but periods of abrupt increase in aECI offset the gains made during periods of progress. This highlights the tension between the need for a metric that responds quickly to changes in a state's aECI trend (e.g., evaluation of progress over five year periods) versus rewarding steady, long-term progress (e.g., evaluation of progress over seven or ten-year periods).

[1] The energy data are from the Energy Information Agency of the U.S. Department of Energy's State Energy Data System (SEDS). Population data are from census and annual intercensal estimates from the U.S. Department of Commerce, Bureau of the Census.

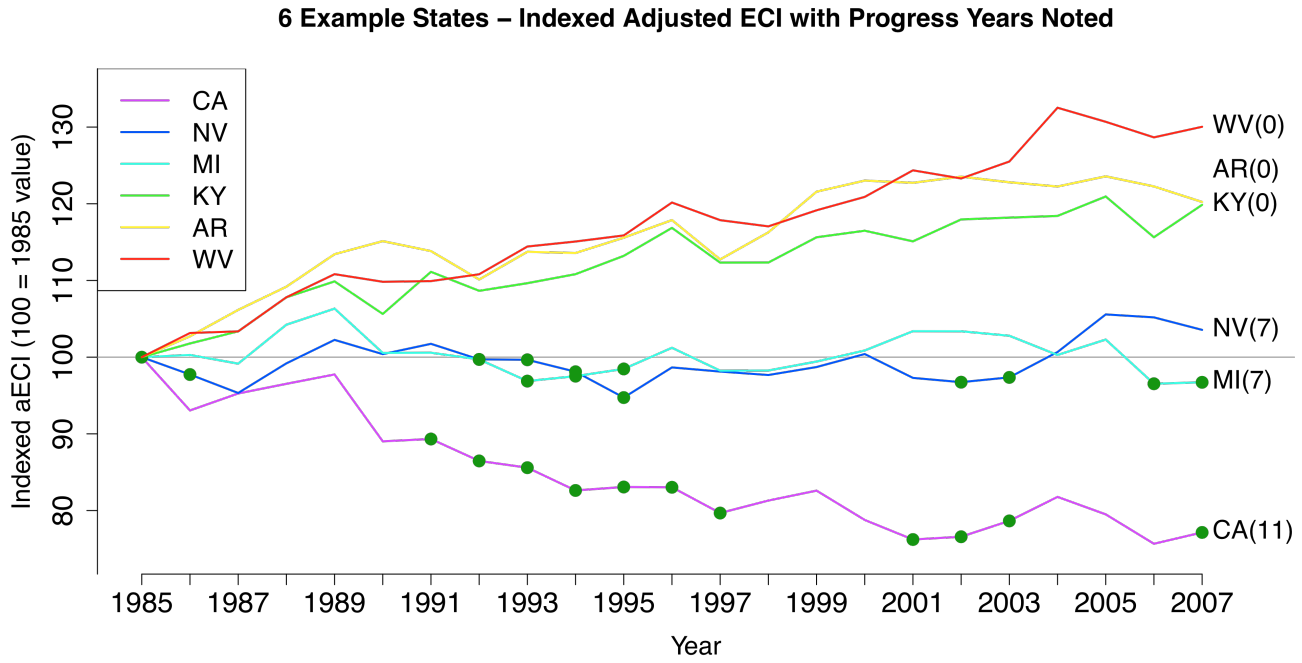

Figure E1: Indexed aECI trends for 6 states with progress years marked with green circles. Three of the states that achieved progress the most number of years were CA, MI, and NV (WA also achieved progress 7 times). Three of the states that achieve no progress were WV, AR, and KY (LA also did not achieve any progress). The trends have been normalized to the aECI value in 1985 for each state; five-year slope estimates and 80% confidence intervals were used to evaluate performance.

Key Considerations and Conclusions

The simulations that we have conducted indicate that it is possible to track trends in residential ECI by state. While ECI trends can be tracked, it is not possible to isolate changes in ECI that are due to policy choices from changes due to other factors with 100% reliability. While we were not able to explain all of the year-to-year variability in the ECI with this approach, including additional policy independent variables (e.g. disposable income, percent employment, GDP by state, etc.) did not dramatically improve the results.

Ground Truth Analysis as a Complement to the Metric

We have conducted a series of analyses we call "ground truth" reports to better understand the relationship between performance as measured by the PSEP metric and the history of residential sector energy consumption and residential efficiency policies in specific states. This ground truth work has proven extremely valuable on two accounts. Based on taking a detailed look at certain states, we have discovered important considerations that were originally missing from our methodology. We have subsequently addressed these considerations in this updated report. For example, analysis of Washington's consumption trends led us to realize that the SEDS data make an unrealistic assumption that all electricity consumption is treated as if produced by fossil fuel power plants. We have therefore estimated state specific heat rates and applied these for each state instead of the national average rates.

Secondly, the ground truth analysis of some states has led to important conclusions about what may be missing in current policies and programs or where lie opportunities for improvement. For example, Vermont has a long history of aggressive energy efficiency policies, however, they have largely been

focused on reducing electricity consumption. Growth in fuel oil consumption, the dominant form of energy in Vermont, has offset those electric efficiency policy achievements.

Ultimately, a combination of an aggregate level metric along with detailed ground truth analysis can yield conclusions and insights of more value than what either approach might accomplish on its own. The metric tracks overall progress and the ground truth analysis leads to strategies for improving performance.

Recommendations for Data Improvements

Almost all of the data used in the analyses in this report are from the EIA State Energy Data System (SEDS). The data for SEDS are self-reported by utilities and electric power generating plants, and the sectoral classifications (i.e., residential, commercial, etc.) are based on the supplier classification and may vary by supplier, by state, and by year. In order to successfully implement PSEP, improved data collection and reporting is required. While our analysis in this report focuses on the residential sector, these recommendations also apply to the commercial sector. The following improvements would increase the reliability of PSEP or other performance-based metrics:

1. Standardize and Disaggregate SEDS Classification System: For ideal implementation of the proposed program, the classification system associated with SEDS should be standardized across all states and suppliers.

2. Quarterly Energy Consumption and HDD/CDD Data: If quarterly, not just annual, energy consumption data were available on an annual basis, the statistical power of the proposed analysis would be increased substantially.

3. Implement System to Improve Reliability of Data reported through SEDS: assessing and improving the reliability of the self reported data from utilities and electric power generating plants is important to improving the reliability and integrity of the data.

4. Population Weight HDD and CDD using Current Year Populations: Currently, HDD and CDD values are weighted by the decennial census population data, this should be changed to use annual population estimates.

5. Publish Population Weighted HDD and CDD for the states of Alaska and Hawaii: Currently, the National Climatic Data Center (NCDC) do not make estimates of annual HDD and CDD available for these states. While stand-in estimates can be made based on available data, the NCDC should include these states in their product to ensure that a consistent methodology is used.

6. Publish Consumption-Based Grid Mix Data: Estimating the mix of generation types on the electricity grid would ideally be based on consumption (e.g. what fraction of energy consumed originated from each source). SEDS data does not have enough detail about electricity sales to accomplish this.

7. Establish Clear Leadership and Coordination across Agencies: At present the data required for this analysis are collected by a wide range of agencies, including the EIA, NCDC, and Census Bureau. All of the contributing agencies should explicitly be made responsible for providing their portion of the data on a timely basis and should be funded appropriately so they can do so.

8. Improve Timeliness of Data Reporting: For the state energy consumption tracking system to be effective and have its desired influence, the interval between the end of the reporting period and the release of the tracking results should be as brief as practical (e.g., 6-12 months).

A final point of discussion is the relationship between state policies to encourage energy efficiency and the time line for detection of this progress under a performance based system. In order to encourage states to develop and sustain effective efficiency programs, it may be important to have a responsive program that identifies progress relatively quickly (e.g., within 3-5 years). However, in the case of some policy measures, there is a moderately long lag time between enactment of the policy and delivery of measurable energy savings. For example, building code changes that would lead to more energy efficient building design and construction would only reduce energy consumption as the building stock is gradually replaced with new construction following the new code. Because of the time lags involved, the proposed ECI tracking method may not initially provide a strong motivation to states to enact such energy reduction strategies despite the large energy savings that can be achieved in the long term.

While this is a limitation of the proposed metric, the use of a performance metric in combination with policy-oriented metrics along the lines of the American Council for an Energy-Efficient Economy (ACEEE) Energy Efficiency Scorecard (Eldridge, 2008) can address this issue by immediately recognizing states that enact forward thinking policies. This combined approach would provide the benefits of a performance based system (i.e., states are evaluated based on measurable progress) while also recognizing states immediately for enacting policies aimed at improving energy efficiency.

As initially implemented, the proposed program would not be perfect, but it would provide a reasonable framework for tracking state level trends in aECI. With improvements in data collection and reliability, and in conjunction with bottom-up efficiency evaluation methods, the approach can provide a powerful tool for evaluating states' progress. The agency made responsible for tracking state energy consumption should, of course, be directed to periodically review the methodology and propose revisions.

Exploring Strategies for Implementing a Performance based State Efficiency Program: State Energy Consumption Metrics – Residential Sector Analyses

Authors: Colin Sheppard, Charles Chamberlin, and Arne Jacobson
Schatz Energy Research Center, Humboldt State University

Project Managers: Yerina Mugica, Dale Bryk
Center for Market Innovation, Natural Resources Defense Council

Introduction

Energy efficiency is the most cost effective means for reducing global warming pollution. According to McKinsey & Company, the energy bill savings from efficiency investments could roughly offset the cost of other measures needed to meet the necessary carbon reduction targets. And many of these investments already make sense economically: McKinsey estimates that a $50 billion per year investment could result in $1.2 trillion in energy bill savings by 2020 while reducing end-use energy consumption by about 23 percent of projected demand. In addition to saving Americans money on their utility bills, investments in energy efficiency would put downward pressure on electricity, natural gas, and carbon allowance prices (when a carbon cap has been established), while creating 600,000 to 900,000 new jobs. Establishing a reliable measurement for energy efficiency performance and rewarding success in improving performance will help America reach its full energy saving potential.

Across the country, the private sector has failed to take advantage of many available opportunities to increase efficiency, often due to market barriers and a lack of information about efficiency performance. With heightened awareness about the economic benefits of energy efficiency and increased focus on combating global warming, Congress and the states are starting to put in place the policies needed to overcome the regulatory and market barriers to increase efficiency. The American Recovery and Reinvestment Act (ARRA) provides significant support for energy efficiency efforts across the United States. And states and utilities are increasingly looking for ways to improve end-use energy efficiency. These measures have the potential to dramatically improve the efficiency of the U.S. economy, but currently there is no effort to track in a consistent manner how effectively states, utilities and other recipients of federal dollars are using those funds. Tracking efficiency gains at a broader level will provide the transparency and accountability needed to ensure that energy efficiency funding and programs achieve their full potential.

One approach to reliably measuring energy efficiency performance at the state level is to implement a Performance based State Efficiency Program (PSEP). PSEP addresses the question of whether energy intensity is improving or declining in the residential sector (and separately in the commercial sector.) In other words, are we making progress towards reducing overall energy consumption? Under this approach, states would be able to track the energy efficiency performance of residential and commercial buildings within their state compared to previous years. With this metric, States could easily see whether they are improving relative to their own baseline. State performance would be tracked using aggregate, state-level metrics.

A measure for tracking changes in energy consumption per capita would boost energy efficiency in two important ways. First, it would provide states and local distribution companies (LDCs) with a top-down, holistic way of measuring whether or not their policies, programs, and initiatives are reducing energy use in their states and service territories. This level of accountability and transparency would help them focus on the approaches to energy efficiency that are most effective. While it is still important for policy makers

to review "bottom up" data such as energy savings delivered from individual programs, this information does not show whether overall energy use is going up or down. For example, efficiency program administrators could dramatically reduce consumption in new homes and commercial refrigerators while ignoring growing energy demand from consumer electronics or home heating. In addition, it is difficult to ensure apple-to-apples comparisons among states with different program designs and different measurement and verification protocols. Simply establishing a credible, uniform assessment of the energy intensity of the residential and commercial sectors can drive friendly competition among states and result in improved efficiency results.

Second, in the context of a climate and energy policy, policymakers can use a performance-based measure to reward states for achieving aggregate-level energy efficiency improvements in the residential and commercial sectors. Such an approach would award incentives to states that lower per-capita end-use energy consumption relative to their own baseline—not a national average—giving all states an opportunity to compete for incentives on equal footing. This would encourage states to use the value of monetary rewards and ratepayer funds (small charges added to utility bills to support particular programs) in ways that maximize consumer benefits and put downward pressure on energy prices, reducing the overall cost of energy and carbon abatement for everyone.

Residential Sector Analysis

In this report, we present and discuss a methodology for an aggregate, state-level metric of energy consumption intensity (ECI) in the residential sector and provide proof-of-concept simulations for each of the 50 U.S. states. The methodology provides a tool for identifying changes in state energy consumption intensity (i.e. energy consumption per capita) after adjusting for changes due to year-to-year variations in weather. This research confirms that it is possible to track trends in state energy consumption intensity, even with the imperfect data sets that are currently available. However, to increase the integrity of the results, improvements in the data collection process are necessary. See the discussion on pages 33-34 for a summary of recommendations for refining state-level energy data collection efforts. With these improvements, the approach could be further strengthened into a powerful tool for evaluating states' progress in reducing energy consumption.

Other Sectors

In addition to the residential sector analysis presented here, we have explored possibilities to apply the metric to the commercial sector. While successful application of the method to the commercial sector presents additional challenges, early results indicate that with improved data quality the method can be extended to the commercial sector. Because the industrial sector can more reliably be analyzed using traditional bottom-up approaches or through direct survey, we do not believe this approach is appropriate for the industrial sectors. Hence, we do not explore the application of this metric to the industrial sector.

In the next section, we establish the objectives for our analysis. Then we describe the methodological approach and present the results of our analysis for the residential sector, with an emphasis on trends for two example states. We then proceed to summarize the findings of eight independent ground truth analyses. These ground truth reports investigate residential consumption trends and energy efficiency policies for specific states in light of their performance as measured by our metric. We close with a discussion of key conclusions and the data requirements for successful implementation of the program. In Appendices A through E, we provide a more detailed description of several components of the analysis presented in this report, along with several variations on the method. Finally, residential sector results for all 50 U.S. states along with supplementary plots useful for analyzing consumption trends can be found in Appendices F through K.

Key Objectives
We use the following objectives to inform the design choices of our methodology.

Measure and reward "all in" energy consumption reductions
The metric should reflect all sources of energy and end-uses. This criterion is intended to ensure that efficiency gains in one type of consumption (e.g. heating fuel) are not simply offset by increases in consumption in another type (e.g. electricity).

Compare "apples" to "apples" across states
With the wide range of efficiency program designs and different measurement and verification protocols used by states, efficiency agencies and utilities, it is difficult to ensure apples-to-apples comparisons among states using existing metrics. One objective of this metric is that it provides an effective method of comparing progress in reducing energy consumption per unit of measure over time that is consistent across all 50 states.

Identify an approach that works for both leading states and "opportunity" states
States that have a track record as leaders in energy efficiency have the infrastructure and experience to continue to improve their efficiency performance. At the same time, "opportunity" states – those that have historically taken limited or no action to advance efficiency – have significant "low-hanging fruit" in terms of low-cost (and "negative-cost") ways to improve their efficiency performance. A metric should therefore be capable of identifying future progress regardless of what historical efficiency gains have been achieved.

Create a "race to the top" not just set a minimum floor
Our objective is to promote competition among states; we seek to rank the states by the degree of progress as measured by the metric. By measuring continuous progress, we can inspire states to continue to make progress in order to stay on top of the performance metric.

Investigate the potential for distribution of monetary incentives
One aim of this analysis is to explore the potential for basing the distribution of monetary incentives at least in part on actual energy efficiency achievements. This metric could be used as a basis to distribute incentives to states that achieve a certain level of efficiency performance.

Correct for dependent factors but leave policy tools intact
Certain factors such as weather directly impact energy consumption but are clearly beyond the control of policies and programs designed to promote energy efficiency. The metric should correct for these factors. However, some factors also serve as a policy tool to achieve efficiency gains. Corrections for such factors would effectively negate the impact of those efficiency gains. For example, corrections for the price of energy would remove energy taxation as a policy tool that can make a measurable impact on state performance. For this reason, we avoided these types of corrections.

Maintain simplicity / transparency
In order to build broad confidence and trust in a performance metric, it should be transparent and intelligible to policy makers and efficiency program managers and should be applied equally and consistently across all states.

Reflect actual energy consumption
Our objective is to measure progress in reducing actual energy consumption per unit of measure (e.g. per capita in the residential sector.) Therefore, the metric should consider primary energy rather than site-based or delivered energy. Primary energy is preferable here because it includes both the energy consumed by the end users and the energy lost during generation and transmission. The distinction between primary and site energy is important when considering electrical energy consumption, since a significant fraction of the energy in the fuel consumed in generating and delivering electricity is lost to waste heat (conversion and transmission losses). If site energy consumption were used rather than primary energy, then "improvements" could be obtained by shifting fuels, e.g. by switching from natural gas based space heating to electrical resistance heating, which would actually increase primary energy consumption.

Methodological Approach

The approach that we recommend for tracking ECI begins with aggregate energy consumption data for the residential sector in each state over a period of 10 years.[2] These data are adjusted according to state population, yielding annual per capita residential energy consumption intensity (MBtu/capita/year)[3]. We then adjust for primary energy and heat rates, grid mix and weather variations. We also considered adjusting for demographic differences, energy prices and economic factors, but ultimately we decided not to adjust for these factors. We describe each of these decisions and methodologies in greater detail below.

Primary Energy and Heat Rates
Our calculations of ECI are based on total *primary* energy consumption rather than the *delivered* or *site-based* energy consumption.[4] Currently, the EIA estimates primary energy from electricity by applying a national averaged fossil fuel heat rate to all site electricity consumption. This choice results in an exaggeration of primary energy from electricity in states with substantial capacities of hydropower, renewable, and/or nuclear generation. This exaggeration can in some cases be very large, on the order of 200%.

For certain technologies, such as hydropower, wind power, geothermal, and solar power, the argument against the introduction of such an exaggeration is straightforward. These technologies simply do not consume fuel in the production of electricity; it therefore makes no sense to inflate our metric of energy consumption from these sources as if they were burning coal or natural gas. These technologies do have losses associated with their operation in the form of parasitic loads and may have higher transmission and distribution losses due to reduced proximity to load centers. While these losses have not been accounted

[2] The energy data are from the Energy Information Agency of the U.S. Department of Energy's State Energy Data System (SEDS). Population data are from census and annual intercensal estimates from the U.S. Department of Commerce, Bureau of the Census.
[3] Past studies have proposed energy intensity indices for residential energy consumption based on MBtu/capita/year, MBtu/ft^2/year, MBtu/household/year, MBtu/building/year, MBtu/gross state product, and others (Energy Information Administration, 1995). We recommend tracking MBtu/capita/year for residential energy consumption since population is the most important factor determining residential energy consumption. Moreover, this metric avoids confusion between actual reductions in energy consumption and reductions due to increases in average home area, persons per household, persons per building, or gross state product.
[4] The U.S. Department of Energy's State Energy Data System (SEDS), the main data source for our analysis, provides information about primary energy consumption in each sector. Primary (a.k.a. Total Energy) consumption values in the SEDS data set are estimated from existing reports from energy suppliers that give consumption, sales, or distribution of energy at the State level by account type, e.g. residential. Coal, natural gas, and petroleum are measured in physical units and are converted to energy units based on supplier reported energy content for each fuel. For electricity generated from nuclear power, hydroelectric, wood, waste, geothermal, wind, photovoltaic, and solar thermal energy sources, energy output in the form of electricity produced from these energy sources is used instead. All of these primary energy sources, including those used to generate electricity and transmission losses are totaled to give primary energy consumption.

for in this report, we recommend that they be factored into the estimate of the primary energy necessary to provide electricity from these sources.

For fuel consuming thermal power generation (e.g. nuclear and biomass), the argument is more qualitative. Nuclear electricity generation consumes fuel, but due to the highly specialized nature of that process the fuel cannot be readily consumed for other uses in the same way that coal or natural gas are used throughout most of the economy. These facts undermine the logic of inflating electricity produced by fission with a heat rate in the same manner as is done with fossil fuel fired power plants.

Finally, biomass power involves the consumption of a renewable resource, and therefore is similar to power production from wind or solar. So primary electricity from biomass should not be inflated as if it were a fossil fuel provided that the resource is managed in a sustainable manner.

The following sections describe how the energy consumption data from SEDS are adjusted in our analysis to account for the electricity grid mix in each state and how a similar process might be used to adjust for changes in demographic factors such as age.

Structural adjustments

Grid mix

In order to adjust the primary energy associated with electricity consumption for each state, we first estimate each state's heat rate. This process involves calculating a weighted average heat rate for each state based on electricity production fuel source data as reported by SEDS. The state-specific heat rate is then used to adjust the residential ECI for each state (the estimation process is described in detail in Appendix C along with an explanation of the SEDS methodology for calculating heat rates). The electricity fuel source data are reported by the EIA based on the location of the producing unit, not on the location of the consumer. This can result in erroneous grid mix estimates as data are not available to accurately account for imports and exports. We use these imperfect estimates in the following analysis. However, we include in our recommendations that the SEDS data be collected and reported in such a way that consumption based grid mix estimates can be determined.

Because the grid mix in each state changes from year to year, the heat rate estimate also changes. However, we seek to separate the impact on consumption of energy efficiency measures from changes in grid mix or conversion efficiency. To address this issue, we use a constant state specific heat rate for any given evaluation period. For example, if our metric is concerned with ECI trends in California for the period 2004-2008, then we use the average heat rate over the same period to make the adjustment to primary energy associated with electricity consumption.

The grid mix estimated for each state and the corresponding heat rates are presented in Appendix K.

Demography

The following analysis does not adjust for age distribution. However, certain demographic shifts, for example an increase in the population's average age, can increase per capita residential energy use. This effect is outside the influence of energy policy makers, and it may therefore be reasonable to correct the ECI trend to account for changes in age distribution within a state.

In Appendix E, we investigate the impact of age distribution on ECI and discuss how the SEDS data could be adjusted. Our analysis indicates that the effect of age distribution on energy consumption intensity is small in most states and that the demographic age shifts are similar from state to state

following a trend that is consistent with an aging baby boom generation. The effect is strongest in Vermont, where the increase in the average age in the population is larger than in any other state. These shifts in the age distribution of Vermont's population could account for an 8% increase in the state's ECI from 1990-2007.

Adjustments for annual variability

There are many causes of year-to-year variation in a state's residential energy consumption, including weather, energy price changes, and economic factors, as well as measures actively taken to reduce residential energy consumption. In order to distinguish between changes in ECI due to factors that can be influenced by energy policy and those that cannot, our method considers how ECI depends on those factors beyond the control of state government. We contemplated modeling ECI based on three different categories of factors. After careful consideration, we chose one of these: weather (represented by degree days). In the section below, we outline all of the factors that we considered and explain our ultimate choice to adjust ECI values based on degree days, but not for changes in disposable income and energy prices.

Weather

Since space heating and space cooling consume over 40% of residential primary energy consumption (Belzer, 2006), weather is a major cause of year-to-year variation in consumption. Both Energy Information Administration (1995) and Bernstein et al. (2003) use heating degree days (HDD) and cooling degree days (CDD) to adjust residential energy for weather variation. Although the amount of energy required to cool air depends strongly on the water content of the air, we did not account for the effect of relative humidity because no substitute for cooling degree days that adjusts for relative humidity is currently available.

As normally computed, both HDD and CDD are based on the difference between the daily average temperature and 65°F. On an annual basis HDD and CDD are the simple sum of the daily values. At the state level, HDD and CDD are computed as population weighted averages of the annual HDD and CDD values for each of the climatic divisions of a state.

Energy Prices

It is well known that consumers often respond to price signals by using less energy when prices are high and more when they are low. It is unsurprising, therefore, that Bernstein et al. (2003) observed a significant correlation between residential energy consumption per capita and the logarithm of electricity and natural gas prices.[5]

While this may suggest that the predicted ECI values should be adjusted for year-to-year variations in electricity, natural gas, and other associated prices, we do not make this adjustment because it might negate state efforts to reduce residential energy consumption by means of tiered billing that involves higher rates for higher levels of consumption. Although changes in prices due to other 'non-policy' related factors (e.g., speculation in the market, interruptions in supply, actual resource constraints, etc.)

[5] Bernstein et al (2003) used state level price data obtained from the EIA "State Energy Price and Expenditure Report" that they corrected using a gross domestic product (GDP) deflator factor, so that the real residential electricity or natural gas price was equal to the reported residential electricity or natural gas price divided by GDP deflator. The GDP deflator was obtained from the Bureau of Economic Analysis, Regional Accounts Data Web site (http://www.bea.doc.gov/bea/regional/data.htm).

would also cause variation in energy consumption, it is difficult to separate these price effects from policy induced price changes. With all of this in mind, the question of whether adjustments should be made for variations in residential energy consumption per capita due either to the regulatory or to market changes in prices is an important one. Because of this, we decided against making such adjustments, since policy driven price variation provides a natural and powerful tool to produce reductions in residential energy intensity. In Appendix A.2, we discuss additional difficulties in adjusting ECI for economic and price factors (e.g. in some ten year periods, the relationship between ECI and price is not statistically significant).

Economic Factors

Bernstein et al. (2003) observed strong sensitivity in residential energy consumption per capita to various demographic and economic factors such as the logarithms of average household size, real disposable income per capita, and employment per capita.[6]

State employment and disposable income are not factors that states can easily manipulate to reduce energy consumption. As such, they are reasonable candidates for factors with which to adjust year-to-year energy consumption. However, we question whether increases in consumption that are due to increases in disposable income should be excluded from a state's performance indicator.
Why reward some states for a temporary economic boom if they are actually increasing their per capita energy consumption? Moreover, a decrease in energy consumption that accompanies an economic downturn may be unintentional, but it still represents a decrease, however temporary. States that do not have an effective set of energy efficiency programs or policies in place would not be well positioned to sustain reductions, so any "unearned" recognition would be short lived. Further, as we note below in the discussion of our proposed methods (see Appendix A, Table A.2), adding adjustments for disposable income provided only modest improvements in explaining the year-to-year variation in state ECI. For these reasons, we ultimately chose not to adjust for disposable income or any other economic factor. See Appendix A.2 for further discussion.

Adjustment Methodology

We base our methodology on that used by Bernstein et al. (2003). Their approach is to use a multiple linear regression to estimate how energy intensity for each sector depends on several confounding factors, including weather (heating and cooling degree days), price of energy (such as retail price of electricity or natural gas), and economic indicators relevant to each sector (such as percent employment or disposable income per capita). The regression considers all states simultaneously and the coefficients estimated for each factor are the same for all states. These coefficients are then used to predict energy consumption for each state based on the climate, price of energy, and economic factors in a given year. Evaluation of a state's performance is based on whether the observed energy consumption is greater or less than the predicted consumption.

We used this approach to estimate the sensitivity of state energy consumption intensity (ECI) to the weather in each year. As noted previously we did not use their approach of adjusting for energy price or economic indicators. We then adjusted the observed state ECI for weather for each year of interest and estimated the time trend (i.e., the slope) of the adjusted ECI values. The estimated slope is used to

[6] Bernstein et al. (2003) obtained the state employment and disposable income data from the Bureau of Economic Analysis (BEA) and the state population and number of persons per household data from the Census Bureau. The real disposable income was equal to the disposable income divided by the GDP deflator.

evaluate and rank the states according to their performance. The following describes our methodology in greater detail:

- Choose a test period for the analysis (e.g., 1985-2008) and length *n* for the base period used in the regression to estimate the sensitivity to weather (e.g., 10 years). Choose length *m,* how often the regression coefficients will be updated (we chose to update every year). And finally, choose length *p*, the test interval used to estimate the slope of the adjusted ECI (we chose 5 years).
- For each year in the test period, estimate an ECI time series for the states using the state-specific heat rate averaged over the *p* years preceding (and including) the test year.
- Perform fixed-effect multiple linear regression on the *n* years of the revised ECI preceding the test year, including heating degree days (HDD) and cooling degree days (CDD) as the independent variables, along with a unique intercept for each state and for each year, move ahead *m* years in preparation for the next test year.
- Adjust the revised ECI for each of the p years used to estimate the slope using the coefficients for HDD and CDD estimated in the regression, the observed values of HDD and CDD, and the 30 year average HDD and CDD for each state.
- Estimate the slope of the adjusted ECI by performing a simple linear regression on the p years in the test period, including the year as the independent variable and the adjusted ECI as the dependent variable.
- Determine the upper limit of a one-sided 80% confidence interval for the slope. If the upper limit is negative, then the adjusted ECI is decreasing at a statistically significant rate and improvement has been detected.
- Rank states according to their performance based on the steepness of their p year slope: the more negative the slope the better the performance.

This method includes a fixed effect term for both state and year while estimating the response of ECI to HDD and CDD. These fixed effect terms control for inherent differences between states (such as overall climate) as well as variation that occurs across all states (such as the influence of Federal policies).

Using 1985-2007 as a test period, we analyzed ECI trends for the 50 United States. Figure 1 presents example trends for California and South Carolina for 1980-2007 (see Appendix F for plots of all 50 states). The solid lines in the figure show the actual measured ECI values, while the dashed lines show the weather adjusted values. The dashed lines, in other words, show the ECI values that one would expect for the state given weather conditions for that year and the historic relationship between ECI and weather as determined from base period data. The vertical red lines indicate adjustments associated with heating energy requirements, while the vertical blue lines indicate adjustments associated with cooling.

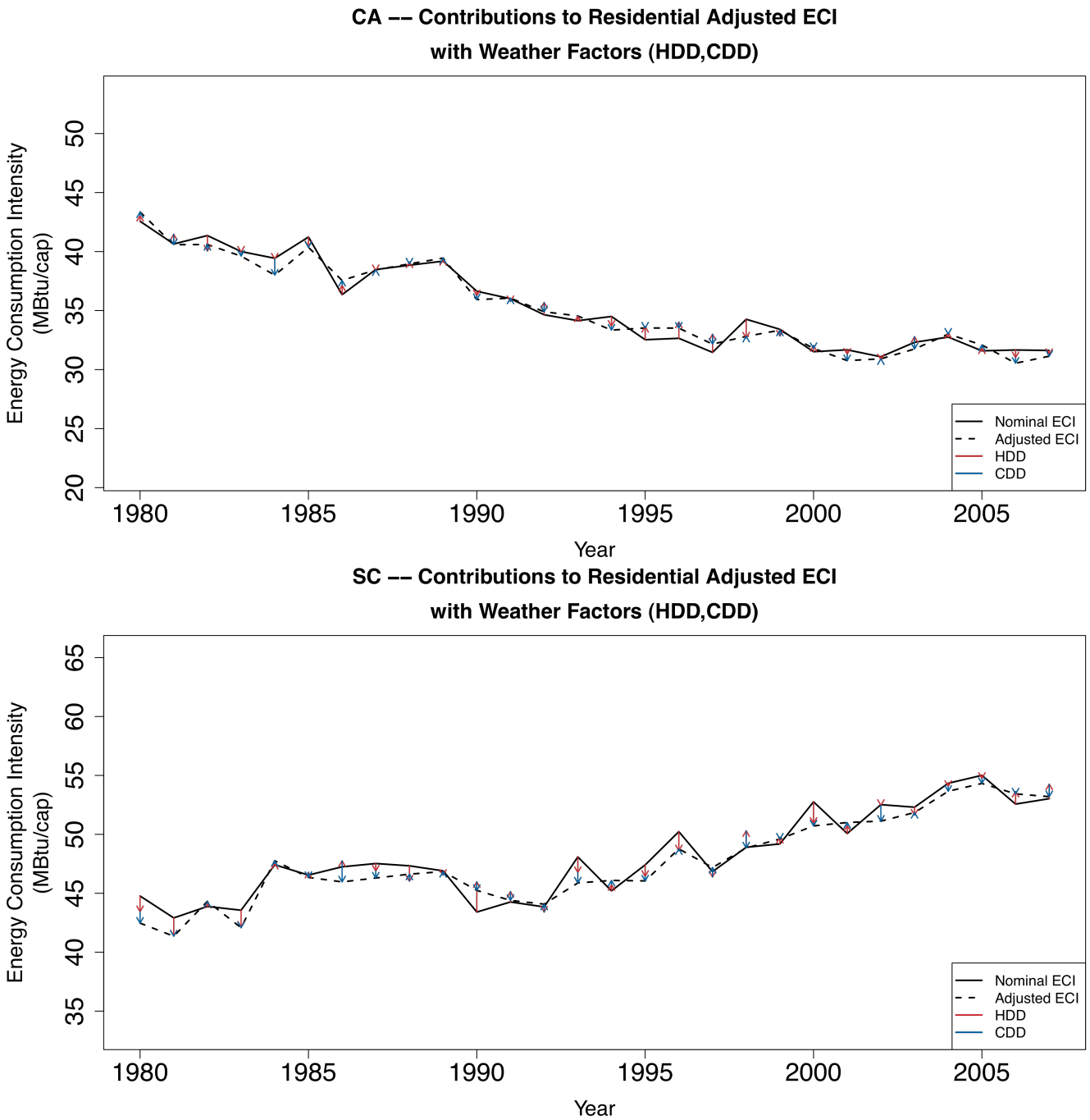

Figure 1: Actual and Adjusted Energy Consumption Intensity Trends from 1980 to 2007 for California (top) and South Carolina (bottom). The weather adjustments include heating and cooling degree day components (HDD and CDD).

Evaluating Progress

The ECI performance rankings for the states could be generated annually using the slope of the linear regression trend line for aECI for the previous five years. States with a downward (negative) slope, which indicates a decrease in aECI, would be considered to have achieved progress, while those with a flat or increasing slope would not. In order to decrease the occurrence of false positives, that is, to prevent detecting progress in states that actually made no improvement in aECI, we add the condition that the

slope estimate for a given test period be negative with 80% confidence. The issue of statistical significance is related to an evaluation of whether a state really has made progress in reducing its aECI. To evaluate this, we calculated single-tailed 80% confidence intervals for each of the aECI five-year regression line slopes for each state.

Figure 2 illustrates how the slope of the regression line measures the performance of California in three example years, 1985, 1997, and 2005. The colored (green and blue) regression lines indicate years when the five-year slope was negative, while grey lines are for periods where the slope was positive. The green and blue colors distinguish between periods when a statistical test indicates that the slope is or is not negative at the 80% confidence level.

We carried out the analysis presented in Figure 2 for the whole test period, 1985-2007, for all 50 U.S. states. Results of this analysis for California and South Carolina are presented in Figure 3 (see Appendix G for all 50 plots.) The upper graph for each state indicates years when the state does and does not achieve progress (green dots indicate that the state did achieve progress, while blue and grey dots indicate that they did not). The lower portion of Figure 3 shows the confidence intervals for the example states (see Appendices A and B for a more detailed discussion of the confidence intervals). This analysis indicates that we can be 80% certain that chance alone cannot explain why a state's five-year slopes of aECI were negative during the years marked with green circles. California's aECI five-year slopes were negative at the 80% confidence level for 11 of the 23 years from 1985-2007, while South Carolina's slopes were negative at the 80% confidence level for one of the years.

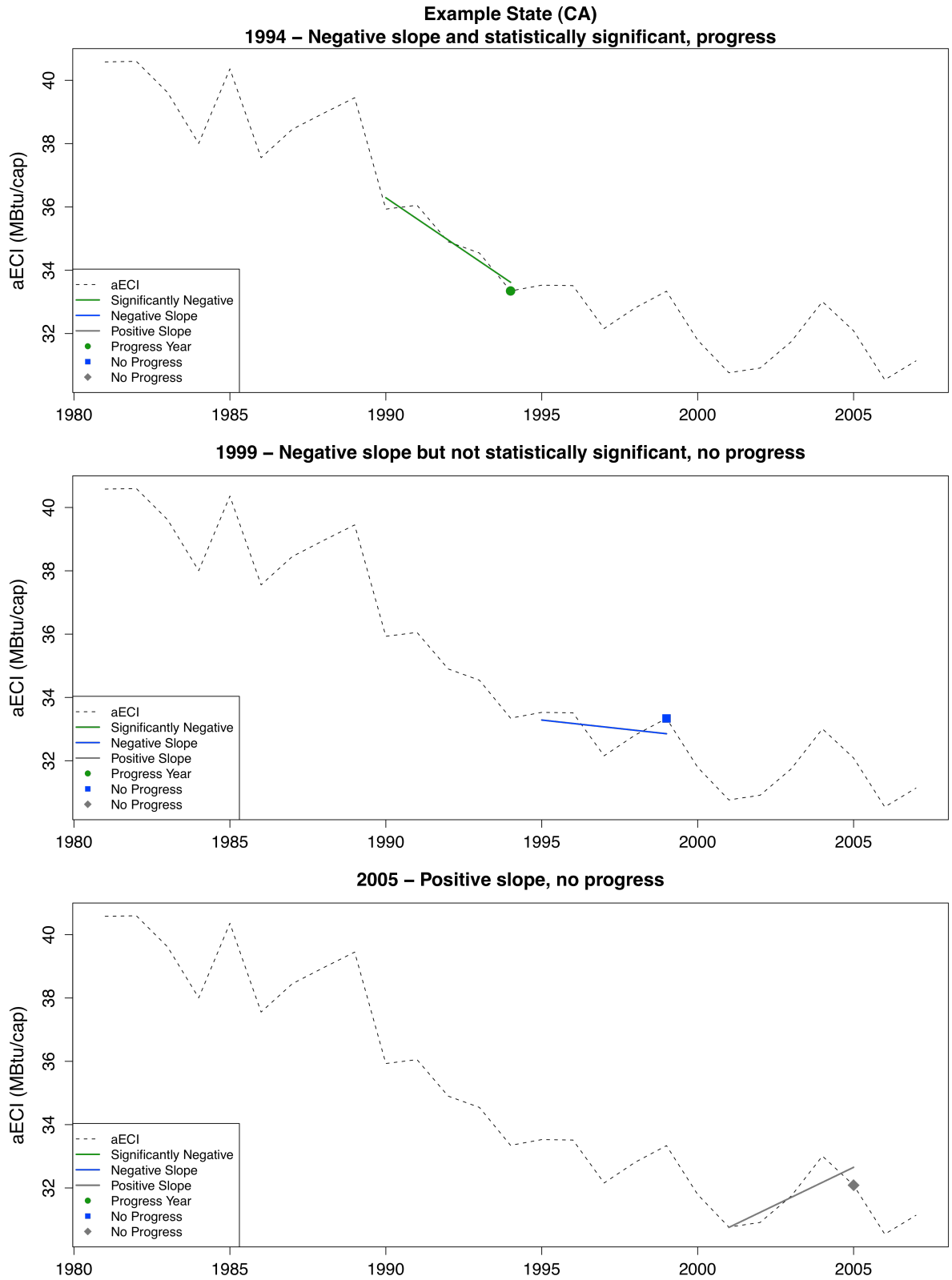

Figure 2. Adjusted ECI for California with Examples of Five-Year Linear Regression Trend Lines and Associated Metric for 1991, 1998, and 2005. The final year of the regression is when the metric is assigned. The green line indicates a negative slope at the 80% significance level, while the blue line indicates a negative slope that does not achieve this level of statistical significance. The grey line indicates a positive regression line slope. Note, for illustration purposes, the data used to produce these plots differ slightly from the data used to generate the final results in the rest of this report, see Appendix A.4 for further explanation.

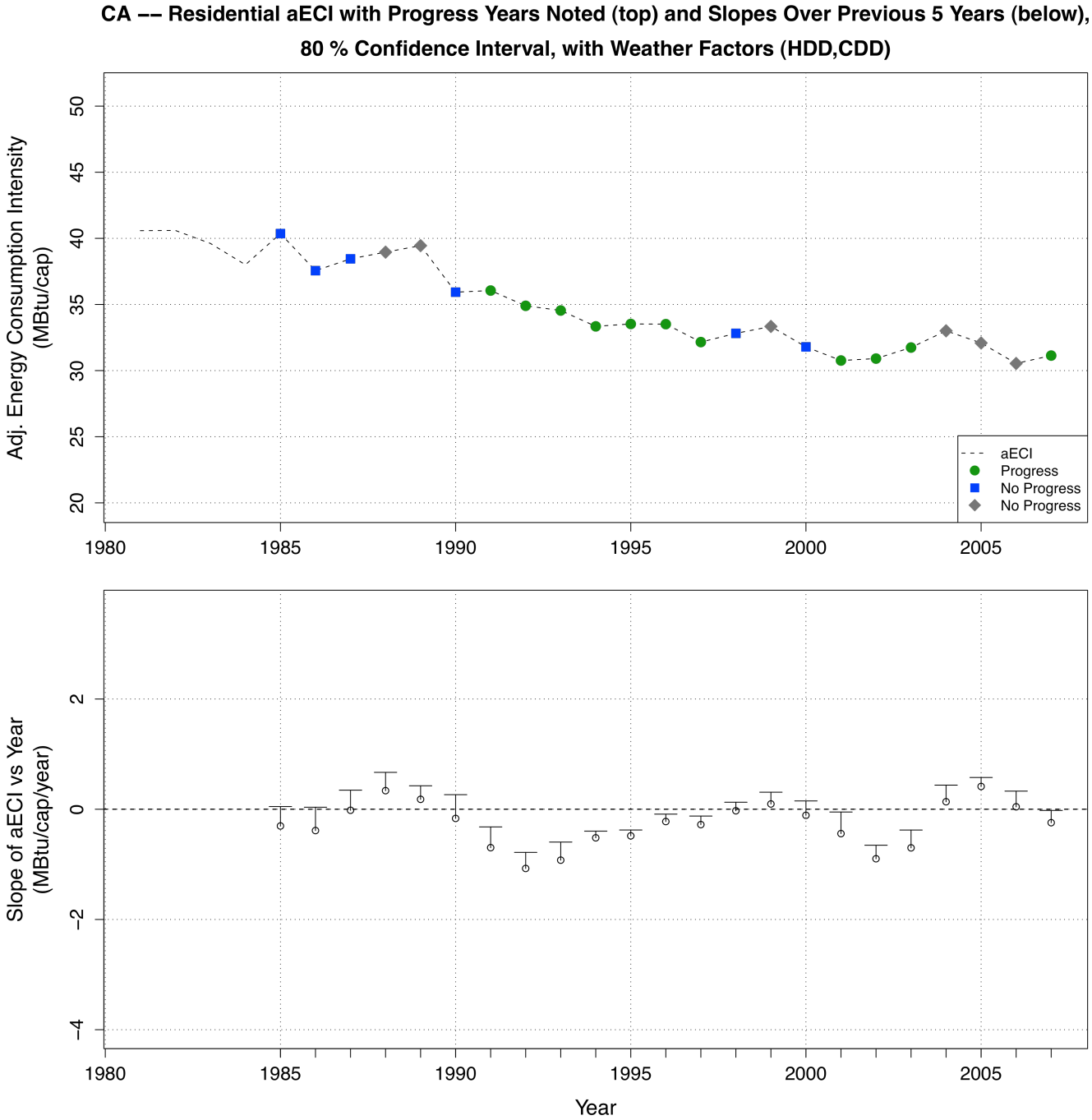

Figure 3a: Slope of the adjusted ECI five-year trend line with single-tailed 80% confidence intervals from 1985-2007 for (a) California and (b) South Carolina. The confidence interval tests the null hypothesis that there is no difference between the five-year linear regression line slope and zero (i.e., the test confirms if the slope is negative at the 80% confidence level). Note, for simplicity, only one aECI datum is plotted per year in the upper plot. However, each slope metric is based on five unique aECI data points specific to the grid mix over that interval (only one of which is represented here). See Appendix A.4 for elaboration. **(Continued on next page.)**

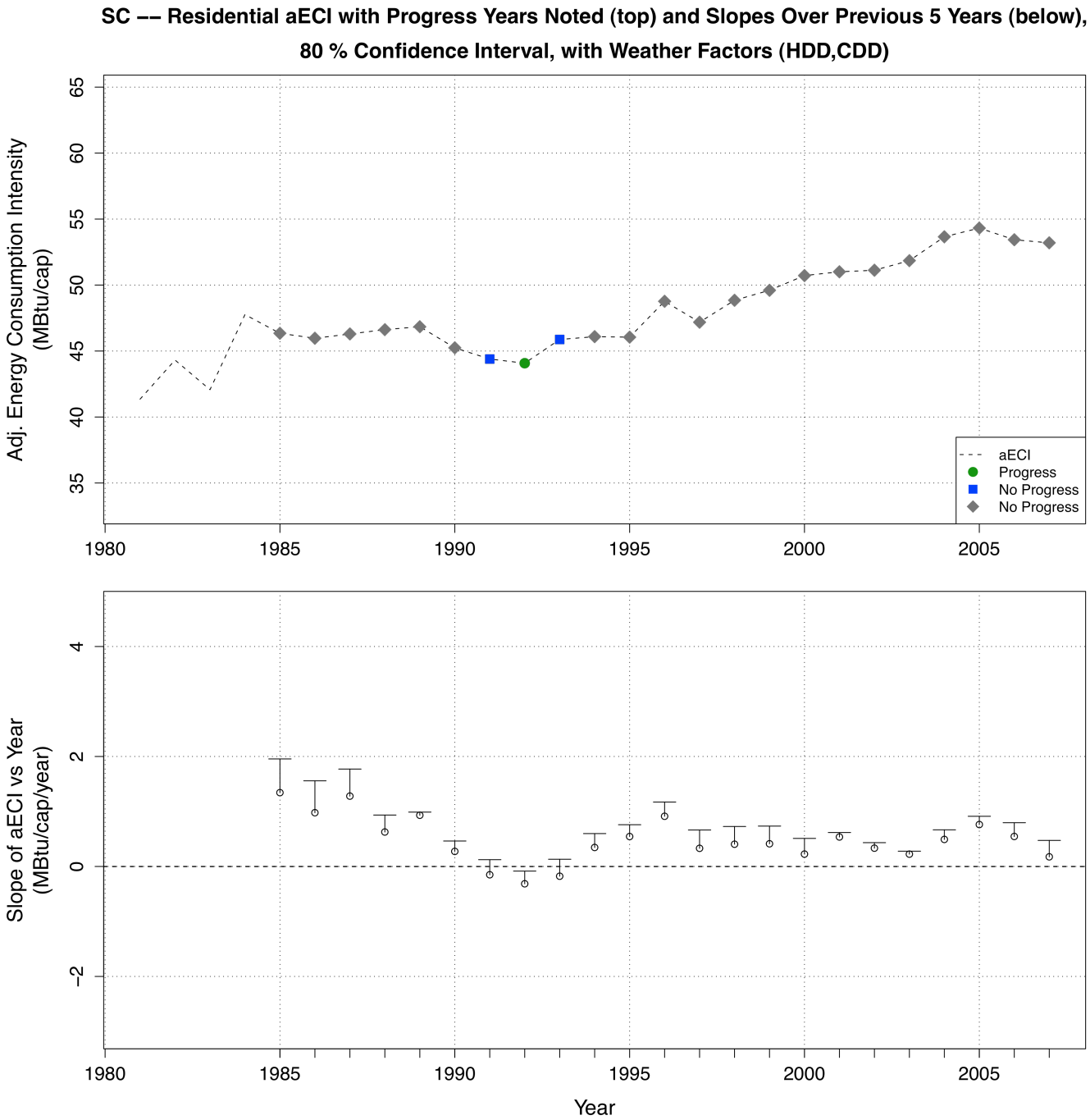

Figure 3b: Slope of the adjusted ECI five-year trend line with single-tailed 80% confidence intervals from 1985-2007 for (a) California and (b) South Carolina. The confidence interval tests the null hypothesis that there is no difference between the five-year linear regression line slope and zero (i.e., the test confirms if the slope is negative at the 80% confidence level). Note, for simplicity, only one aECI datum is plotted per year in the upper plot. However, each slope metric is based on five unique aECI data points specific to the grid mix over that interval (only one of which is represented here). See Appendix A.4 for elaboration.

Results

See Table 1 for residential sector simulation results for all 50 U.S. states for the period from 1985-2007. The table shows state rankings with respect to the steepness of the five-year linear regression aECI slope. Negative values (i.e., those that indicate progress) that achieve statistical significance at the 80% level are highlighted in yellow, while those that do not are highlighted in grey. Positive values (i.e., those where the slope was positive) are not highlighted. A heat map in Figure 4 and a histogram in Figure 5 provide a graphical summary of the number of years each state achieved progress according to our metric. The top performing states in this regard are California, Washington, Michigan, and Nevada. These results are illustrative; they should be interpreted with some caution as the evaluation method was actually not in place during these years (i.e., the states were not – in fact – responding to a performance metric or performance-based incentives) and there was no auditing system to ensure the accuracy of the SEDS data.

To compare states to each other it is useful to plot an indexed aECI trend for multiple states on the same plot. In Figure 6, we present three states that achieved the most progress years in our simulation and three of the states that achieved the fewest. The trends have been normalized to the aECI value in 1985 for each state. The top performing states clearly have more impressive trends than poorer performing states. However, it is important to note that the relatively short, five-year time horizon for estimating the slope can result in a situation like Nevada's. Nevada achieved progress according to our metric in a number of years, but periods of abrupt increase in aECI offset the gains made during periods of progress. This highlights the tension between the need for a metric that responds quickly to changes in a state's aECI trend (e.g., evaluation of progress over five year periods) versus rewarding steady, long-term progress (e.g., evaluation of progress over seven or ten-year periods). In Appendix A, we discuss this issue in further detail and present results from a simulation using ten-year periods for estimating the slope of aECI.

Table 1a: State residential sector rankings from 1985-1996 with respect to slope of aECI over the test year and previous four years (5-year period total). Units of the slope coefficient are MBtu/(cap*year^2).[7]

	1985		1986		1987		1988		1989		1990		1991		1992		1993		1994		1995		1996	
1	IA	-1.5	IA	-2.3	UT	-2.5	UT	-2.9	UT	-2.7	UT	-1.5	ME	-0.8	ME	-1.6	SD	-1.9	SD	-1.7	VT	-1.1	CT	-1.3
2	CT	-1.2	OK	-1.4	IA	-2.4	VT	-2.1	VT	-0.5	WI	-0.4	NJ	-0.8	DE	-1.1	NH	-1.4	OK	-0.9	CT	-0.9	MA	-1.3
3	WA	-1.0	CO	-1.2	WY	-1.7	AK	-1.5	AK	-0.3	ME	-0.3	NH	-0.7	CA	-1.1	NJ	-1.1	NH	-0.8	WI	-0.9	VT	-0.7
4	CO	-0.7	WY	-1.1	VT	-1.7	IA	-1.2	AZ	-0.2	ID	-0.2	CA	-0.7	NJ	-0.9	CA	-0.9	WI	-0.8	NM	-0.8	NV	-0.3
5	ND	-0.6	NV	-0.9	CO	-1.5	MT	-0.8	NM	0.0	IA	-0.2	NY	-0.7	VA	-0.9	MI	-0.9	MT	-0.8	NV	-0.8	CA	-0.2
6	HI	-0.6	KS	-0.7	OK	-1.3	IL	-0.5	WI	0.0	CA	-0.2	NC	-0.6	NH	-0.8	IL	-0.9	IL	-0.8	IL	-0.8	RI	-0.2
7	IN	-0.6	WA	-0.5	MT	-0.8	CO	-0.4	MT	0.1	WA	-0.2	DE	-0.6	SD	-0.8	MT	-0.8	NM	-0.8	MT	-0.7	AZ	-0.1
8	NV	-0.5	IN	-0.5	NE	-0.7	AZ	-0.3	IA	0.1	OR	-0.1	VA	-0.5	NY	-0.7	ME	-0.7	VT	-0.7	ND	-0.7	AK	-0.1
9	ID	-0.5	HI	-0.5	IL	-0.6	WY	-0.2	WY	0.1	NE	0.0	RI	-0.4	NC	-0.6	WI	-0.7	ND	-0.6	CO	-0.7	NM	0.0
10	WV	-0.4	NE	-0.5	KS	-0.6	OK	-0.2	CA	0.2	NY	0.0	MD	-0.2	NV	-0.6	TX	-0.7	NY	-0.6	AZ	-0.5	NY	0.0
11	CA	-0.3	AR	-0.4	ID	-0.3	NE	-0.2	CO	0.3	VA	0.1	WA	-0.2	MI	-0.5	NY	-0.6	ME	-0.6	CA	-0.5	HI	0.1
12	MN	-0.3	CA	-0.4	WA	-0.2	NV	-0.1	NV	0.3	NC	0.1	OR	-0.2	MD	-0.5	NV	-0.6	TX	-0.6	SD	-0.4	WI	0.1
13	MI	-0.2	MT	-0.2	MO	-0.2	NM	-0.1	ID	0.4	WY	0.2	SC	-0.2	WA	-0.5	TN	-0.6	WY	-0.5	MA	-0.4	OR	0.2
14	ME	-0.1	MN	-0.1	AK	-0.1	WI	-0.1	NE	0.5	NJ	0.2	GA	-0.1	WI	-0.4	VA	-0.6	CA	-0.5	WY	-0.3	IL	0.2
15	OK	-0.1	MI	0.0	AR	-0.1	KS	0.0	RI	0.5	MN	0.3	OH	-0.1	PA	-0.4	OH	-0.5	MI	-0.5	UT	-0.3	WA	0.2
16	SD	-0.1	IL	0.0	AZ	-0.1	TN	0.0	KS	0.5	SC	0.3	WI	0.0	OH	-0.4	PA	-0.5	AZ	-0.5	NY	-0.3	PA	0.3
17	NJ	0.0	MO	0.1	NV	-0.1	PA	0.0	OR	0.6	RI	0.3	MI	0.1	SC	-0.3	MN	-0.5	CO	-0.4	MI	-0.3	MT	0.3
18	OH	0.0	WV	0.1	CA	0.0	ID	0.1	WA	0.6	AZ	0.3	PA	0.1	GA	-0.3	DE	-0.4	OH	-0.3	OH	-0.3	ID	0.3
19	NE	0.2	TN	0.3	MI	0.0	OR	0.1	HI	0.7	NV	0.4	AL	0.2	OR	-0.3	AZ	-0.4	NV	-0.3	TN	-0.3	CO	0.3
20	PA	0.2	ID	0.4	NM	0.0	WA	0.2	ME	0.8	OH	0.4	NV	0.2	MT	-0.3	FL	-0.3	MN	-0.3	TX	-0.3	NJ	0.4
21	NY	0.2	AK	0.4	HI	0.1	MO	0.3	NY	0.9	KS	0.4	SD	0.2	IN	-0.2	NE	-0.3	KS	-0.3	NE	-0.3	MI	0.4
22	IL	0.2	CT	0.4	PA	0.3	CA	0.3	ND	0.9	MD	0.4	MN	0.3	NE	-0.2	AL	-0.3	CT	-0.3	KS	-0.2	UT	0.5
23	LA	0.2	AZ	0.5	OR	0.3	AR	0.4	MD	0.9	GA	0.5	MA	0.3	KS	-0.2	OK	-0.2	UT	-0.2	IN	-0.2	TX	0.5
24	AR	0.2	AL	0.5	IN	0.3	MD	0.4	OK	0.9	CO	0.5	CT	0.4	IA	-0.2	IN	-0.2	IA	-0.1	NH	-0.1	OH	0.6
25	OR	0.2	PA	0.5	MN	0.5	LA	0.5	MN	0.9	MI	0.5	IN	0.4	WY	-0.1	SC	-0.2	IN	-0.1	IA	-0.1	NH	0.7
26	KS	0.2	MS	0.5	TN	0.5	MN	0.5	SC	0.9	MO	0.5	NE	0.4	TX	-0.1	NC	-0.2	PA	-0.1	MN	-0.1	NE	0.7
27	MT	0.3	OR	0.5	WI	0.6	DE	0.5	PA	0.9	SD	0.5	IA	0.5	RI	-0.1	WY	-0.2	NE	0.0	NJ	0.0	FL	0.8
28	UT	0.4	LA	0.5	MS	0.8	HI	0.5	VA	1.0	ND	0.6	ID	0.5	OK	0.0	UT	-0.1	FL	0.1	PA	0.0	MN	0.8
29	MO	0.4	NM	0.6	ND	0.9	MI	0.6	MO	1.0	MT	0.6	KS	0.5	AZ	0.0	WA	-0.1	ID	0.1	ID	0.0	GA	0.8
30	AL	0.8	NJ	0.6	KY	1.0	MS	0.6	NJ	1.0	PA	0.6	UT	0.5	MN	0.0	CT	-0.1	MA	0.2	RI	0.1	VA	0.9
31	WI	0.8	NY	0.7	MD	1.0	SC	0.6	LA	1.1	NM	0.6	FL	0.6	AL	0.0	KS	-0.1	NJ	0.2	WA	0.1	IN	0.9
32	MS	0.9	KY	0.8	WV	1.0	TX	0.7	MS	1.1	NH	0.7	AZ	0.7	IL	0.1	NM	-0.1	TN	0.2	OR	0.1	SC	0.9
33	KY	0.9	OH	0.8	LA	1.0	FL	0.8	MI	1.1	IN	0.8	TX	0.7	UT	0.2	IA	0.0	MO	0.2	MO	0.2	ND	0.9
34	AZ	0.9	TX	0.9	NJ	1.0	NC	0.8	SD	1.1	KY	0.8	LA	0.7	MO	0.2	OR	0.0	VA	0.2	HI	0.2	IA	1.0
35	NM	0.9	ND	0.9	NY	1.1	SD	0.9	NC	1.2	AL	0.9	WY	0.7	FL	0.2	MS	0.0	AK	0.2	FL	0.4	MD	1.0
36	FL	1.0	SD	0.9	AL	1.1	AL	0.9	FL	1.2	HI	0.9	HI	0.7	CT	0.3	CO	0.0	MS	0.2	KY	0.4	TN	1.1
37	TN	1.0	MD	0.9	RI	1.2	IN	0.9	DE	1.3	DE	1.0	TN	0.7	MA	0.3	MD	0.0	LA	0.2	MS	0.5	SD	1.1
38	TX	1.0	SC	1.0	SD	1.3	NJ	0.9	TN	1.3	FL	1.0	MS	0.8	AR	0.3	MA	0.1	AR	0.3	MD	0.5	NC	1.1
39	MA	1.1	WI	1.1	SC	1.3	KY	0.9	IL	1.3	IL	1.0	NM	0.8	TN	0.4	GA	0.1	AL	0.3	VA	0.5	LA	1.1
40	GA	1.2	GA	1.2	FL	1.3	VA	1.0	MA	1.3	MA	1.0	IL	0.9	MS	0.4	ND	0.2	HI	0.3	OK	0.5	MS	1.1
41	MD	1.2	MA	1.4	MA	1.3	GA	1.0	NH	1.3	LA	1.1	MO	0.9	LA	0.5	AR	0.2	MD	0.3	SC	0.5	AR	1.2
42	NH	1.2	VT	1.4	TX	1.3	NY	1.0	GA	1.4	MS	1.1	KY	1.0	NM	0.5	MO	0.2	WA	0.3	AL	0.6	WY	1.2
43	SC	1.3	UT	1.4	GA	1.5	MA	1.0	TX	1.5	TN	1.2	AR	1.0	KY	0.5	ID	0.3	SC	0.3	GA	0.7	KS	1.2
44	WY	1.5	FL	1.4	OH	1.6	ND	1.0	AL	1.5	AR	1.3	MT	1.1	CO	0.5	LA	0.3	NC	0.4	AK	0.7	DE	1.3
45	NC	1.7	NC	1.7	CT	1.7	WV	1.1	AR	1.5	AK	1.3	CO	1.1	ID	0.5	KY	0.3	OR	0.4	NC	0.7	AL	1.3
46	VA	1.8	NH	1.8	NC	1.7	RI	1.1	IN	1.7	CT	1.4	WV	1.2	WV	0.6	HI	0.4	GA	0.4	AR	0.7	MO	1.4
47	AK	2.0	VA	1.9	VA	1.8	NH	1.2	OH	1.7	WV	1.4	AK	1.5	HI	0.8	RI	0.5	RI	0.5	LA	0.7	WV	1.4
48	VT	2.6	RI	2.2	NH	2.1	OH	1.4	KY	1.8	TX	1.4	ND	1.6	ND	0.9	VT	0.5	KY	0.5	DE	0.8	KY	1.4
49	RI	2.7	ME	2.7	DE	2.2	CT	2.1	WV	1.8	VT	2.0	OK	1.9	AK	1.6	WV	0.7	DE	0.6	WV	1.1	OK	1.6
50	DE	5.0	DE	3.4	ME	3.9	ME	3.3	CT	2.4	OK	2.8	VT	1.9	VT	1.6	AK	0.9	WV	0.9	ME	1.7	ME	3.3

[7] Cells shaded in yellow indicate years for the respective states in which the 80% single-tailed confidence interval for the slope estimate does not include zero, in other words, there is an 80% chance that these values are actually negative and not merely noise. Cells shaded in grey have a negative slope, but the confidence interval is large enough that it includes zero. Unshaded cells have positive slopes.

Table 1b: State residential sector rankings from 1997-2007 with respect to slope of aECI over the test year and previous four years (5-year period total). Units of the slope coefficient are MBtu/(cap*year^2).[8]

	1997		1998		1999		2000		2001		2002		2003		2004		2005		2006		2007		# Incentives	
1	MA	-1.7	AK	-1.4	AK	-1.1	AK	-1.0	CA	-0.4	ME	-2.5	ID	-0.9	NY	-0.5	WA	-0.9	MA	-1.2	ME	-1.9	CA	11
2	CT	-0.9	MA	-1.2	IL	-0.6	IL	-0.9	IL	-0.4	NH	-1.2	CA	-0.7	ID	-0.4	MA	-0.7	TX	-1.1	NH	-1.2	WA	7
3	VT	-0.7	CT	-0.6	RI	-0.4	RI	-0.6	SD	-0.3	CA	-0.9	NV	-0.5	MS	-0.4	TX	-0.6	WA	-0.7	CT	-1.2	NV	7
4	AK	-0.5	NJ	-0.4	WY	-0.4	NJ	-0.4	ME	-0.2	NV	-0.3	UT	-0.5	TX	-0.4	NE	-0.6	MI	-0.6	DE	-1.2	MI	7
5	CA	-0.3	RI	-0.3	PA	-0.3	TN	-0.3	NH	-0.2	HI	-0.3	VT	-0.2	UT	-0.2	MS	-0.5	OR	-0.5	MA	-1.1	VT	6
6	RI	-0.2	PA	-0.3	MD	-0.2	MD	-0.3	MT	-0.2	KS	-0.1	NM	-0.2	MA	-0.2	OR	-0.3	PA	-0.3	RI	-1.0	UT	6
7	OR	-0.2	WY	-0.3	GA	-0.1	SD	-0.3	HI	-0.1	UT	-0.1	HI	-0.1	NV	-0.2	NY	0.0	DE	-0.3	TX	-1.0	TX	6
8	PA	-0.1	IL	-0.3	VT	-0.1	NH	-0.2	UT	0.0	ID	-0.1	NH	-0.1	WA	-0.2	MI	0.1	MS	-0.2	OR	-0.9	NY	6
9	NV	-0.1	OR	-0.2	MA	0.0	WY	-0.2	MD	0.1	AZ	0.1	WA	-0.1	NE	0.0	AK	0.2	IL	-0.2	MI	-0.7	NH	6
10	AZ	0.0	DE	0.0	OH	0.0	ME	-0.2	IA	0.1	MD	0.1	NY	-0.1	AR	0.1	MO	0.2	WI	-0.2	PA	-0.7	ME	6
11	WI	0.1	CA	0.0	MI	0.0	OH	-0.2	NV	0.1	VT	0.1	AZ	0.0	AL	0.1	UT	0.2	NJ	-0.1	WA	-0.7	MA	6
12	AR	0.1	AR	0.0	OR	0.0	MO	-0.2	NJ	0.1	SD	0.2	OR	0.0	HI	0.1	AR	0.3	IN	-0.1	MD	-0.6	IL	6
13	GA	0.2	MD	0.0	NJ	0.0	CA	-0.1	OH	0.2	OR	0.2	IA	0.1	CA	0.1	HI	0.3	NE	-0.1	AK	-0.4	CT	6
14	NJ	0.2	TN	0.0	CT	0.1	DE	-0.1	RI	0.2	NJ	0.3	KS	0.1	OK	0.1	AL	0.4	OH	0.0	KS	-0.4	WI	5
15	KS	0.2	MI	0.1	NC	0.1	MT	-0.1	WA	0.3	WA	0.3	AR	0.2	CO	0.2	OK	0.4	LA	0.0	NJ	-0.3	NJ	5
16	WA	0.2	WA	0.1	DE	0.1	MI	-0.1	OR	0.4	IA	0.3	SC	0.2	NM	0.2	LA	0.4	RI	0.0	WI	-0.3	MT	5
17	IL	0.3	CO	0.1	CA	0.1	IN	0.0	MN	0.4	MT	0.3	ME	0.2	LA	0.2	CA	0.4	CA	0.0	CA	-0.2	CO	5
18	HI	0.3	OH	0.2	KY	0.2	NE	0.0	VA	0.4	NY	0.3	IL	0.3	MI	0.2	TN	0.4	SD	0.1	NC	-0.2	AK	5
19	DE	0.3	KY	0.2	FL	0.2	VT	0.0	IN	0.5	IL	0.3	AL	0.4	IL	0.2	IL	0.4	KY	0.1	MN	-0.2	SD	4
20	MD	0.3	ID	0.3	VA	0.2	NC	0.0	AK	0.5	SC	0.3	MD	0.4	GA	0.2	WI	0.5	KS	0.1	FL	-0.2	RI	4
21	SC	0.3	VT	0.3	WA	0.2	PA	0.1	SC	0.5	RI	0.4	TN	0.4	OR	0.2	SD	0.5	MD	0.1	SD	-0.2	OR	4
22	NH	0.3	NV	0.3	MT	0.2	WA	0.1	KS	0.6	NC	0.4	WI	0.5	TN	0.2	NJ	0.5	FL	0.2	GA	-0.2	OH	4
23	CO	0.3	MN	0.3	AR	0.2	OR	0.2	WY	0.6	VA	0.4	NC	0.5	AZ	0.3	PA	0.5	NC	0.2	NY	-0.1	IA	4
24	NY	0.4	IN	0.4	MN	0.3	MN	0.2	LA	0.6	NM	0.5	LA	0.5	IA	0.3	VT	0.5	CT	0.2	IL	0.0	DE	4
25	WY	0.4	MT	0.4	SD	0.4	OK	0.2	WI	0.6	MN	0.5	KY	0.5	KS	0.4	CO	0.5	NY	0.2	NE	0.0	WY	3
26	OH	0.5	WI	0.4	NH	0.4	KY	0.2	NC	0.6	OH	0.6	OH	0.5	VT	0.5	FL	0.6	CO	0.2	AR	0.0	VA	3
27	OK	0.5	AL	0.4	MO	0.4	SC	0.2	AZ	0.6	WI	0.6	MS	0.5	MO	0.5	NM	0.6	GA	0.2	OH	0.1	PA	3
28	MI	0.5	SC	0.4	SC	0.4	VA	0.2	ID	0.7	LA	0.6	IN	0.6	OH	0.5	NC	0.6	AR	0.3	VA	0.1	NE	3
29	VA	0.5	VA	0.4	OK	0.4	IA	0.3	DE	0.7	IN	0.6	VA	0.6	SC	0.5	KS	0.7	TN	0.3	VT	0.2	KS	3
30	TX	0.5	AZ	0.4	IN	0.5	WV	0.3	KY	0.7	TN	0.7	GA	0.6	NC	0.5	ID	0.7	MN	0.4	SC	0.2	HI	3
31	FL	0.5	GA	0.4	TX	0.5	WI	0.3	TN	0.7	GA	0.7	SD	0.6	WI	0.5	GA	0.7	IA	0.4	IN	0.2	AZ	3
32	IN	0.5	NC	0.5	WV	0.5	FL	0.4	TX	0.8	FL	0.7	NE	0.7	KY	0.6	IA	0.8	UT	0.4	OK	0.2	OK	2
33	NC	0.5	FL	0.5	CO	0.5	KS	0.4	OK	0.8	AR	0.8	AK	0.7	SD	0.6	SC	0.8	MO	0.4	CO	0.2	NM	2
34	TN	0.6	IA	0.5	AL	0.5	HI	0.4	MI	0.8	OK	0.8	NJ	0.7	FL	0.7	MN	0.8	OK	0.4	LA	0.2	NC	2
35	ID	0.6	WV	0.5	TN	0.5	NV	0.4	NE	0.9	KY	0.8	MA	0.7	MD	0.8	IN	0.8	AL	0.4	MS	0.3	MS	2
36	AL	0.7	MS	0.6	NE	0.5	UT	0.5	GA	0.9	NE	0.9	MT	0.8	IN	0.8	AZ	0.8	HI	0.5	IA	0.3	MD	2
37	MS	0.7	HI	0.6	NV	0.6	TX	0.5	PA	0.9	AL	1.0	MO	0.8	NJ	0.8	OH	0.9	SC	0.5	UT	0.3	ID	2
38	MN	0.7	UT	0.6	ID	0.6	CT	0.5	FL	0.9	TX	1.0	TX	0.8	MN	0.8	RI	0.9	VA	0.6	KY	0.3	FL	2
39	NM	0.8	KS	0.6	LA	0.6	GA	0.6	VT	1.0	PA	1.0	MI	0.8	PA	0.8	NV	0.9	NH	0.8	MO	0.4	TN	1
40	MO	0.8	NE	0.6	HI	0.6	AL	0.7	MO	1.0	WY	1.1	MN	0.8	VA	0.8	KY	1.0	WY	0.9	TN	0.5	SC	1
41	NE	0.8	TX	0.6	UT	0.7	AR	0.7	NY	1.1	MO	1.1	RI	0.9	RI	1.0	MD	1.1	NM	0.9	AL	0.5	ND	1
42	KY	0.8	MO	0.7	IA	0.7	MA	0.7	AR	1.1	MI	1.1	OK	0.9	MT	1.2	DE	1.3	AK	0.9	HI	0.6	MO	1
43	MT	0.8	SD	0.7	KS	0.7	CO	0.8	NM	1.1	CT	1.1	CO	0.9	WY	1.3	CT	1.3	AZ	0.9	NM	0.6	MN	1
44	LA	0.8	NH	0.7	WI	0.7	AZ	0.9	WV	1.2	CO	1.1	FL	1.0	ND	1.4	NH	1.4	ID	1.2	ID	0.7	IN	1
45	IA	0.8	NY	0.8	MS	0.7	LA	0.9	CT	1.2	AK	1.1	PA	1.0	NH	1.5	VA	1.4	VT	1.2	WV	0.7	GA	1
46	UT	0.8	OK	0.8	NY	0.8	MS	0.9	AL	1.3	DE	1.2	CT	1.0	DE	1.6	ND	1.5	WV	1.3	AZ	0.8	AL	1
47	WV	0.9	LA	0.8	AZ	0.9	NY	1.0	CO	1.4	WV	1.3	WV	1.1	CT	1.6	WV	1.6	ND	1.3	MT	0.9	WV	0
48	SD	1.1	NM	1.3	ME	0.9	NM	1.0	MA	1.5	MS	1.4	WY	1.3	WV	1.7	WY	1.6	NV	1.4	NV	1.1	LA	0
49	ND	2.0	ND	1.5	NM	1.5	ND	1.2	ND	1.6	MA	1.4	DE	1.5	AK	1.9	MT	1.7	MT	2.0	ND	1.2	KY	0
50	ME	2.3	ME	2.5	ND	1.6	ID	1.3	MS	1.8	ND	2.2	ND	1.6	ME	3.4	ME	3.6	ME	2.3	WY	1.3	AR	0

[8] Cells shaded in yellow indicate years for the respective states in which the 80% single-tailed confidence interval for the slope estimate does not include zero, in other words, there is an 80% chance that these values are actually negative and not merely noise. Cells shaded in grey have a negative slope, but the confidence interval is large enough that it includes zero. Unshaded cells have positive slopes.

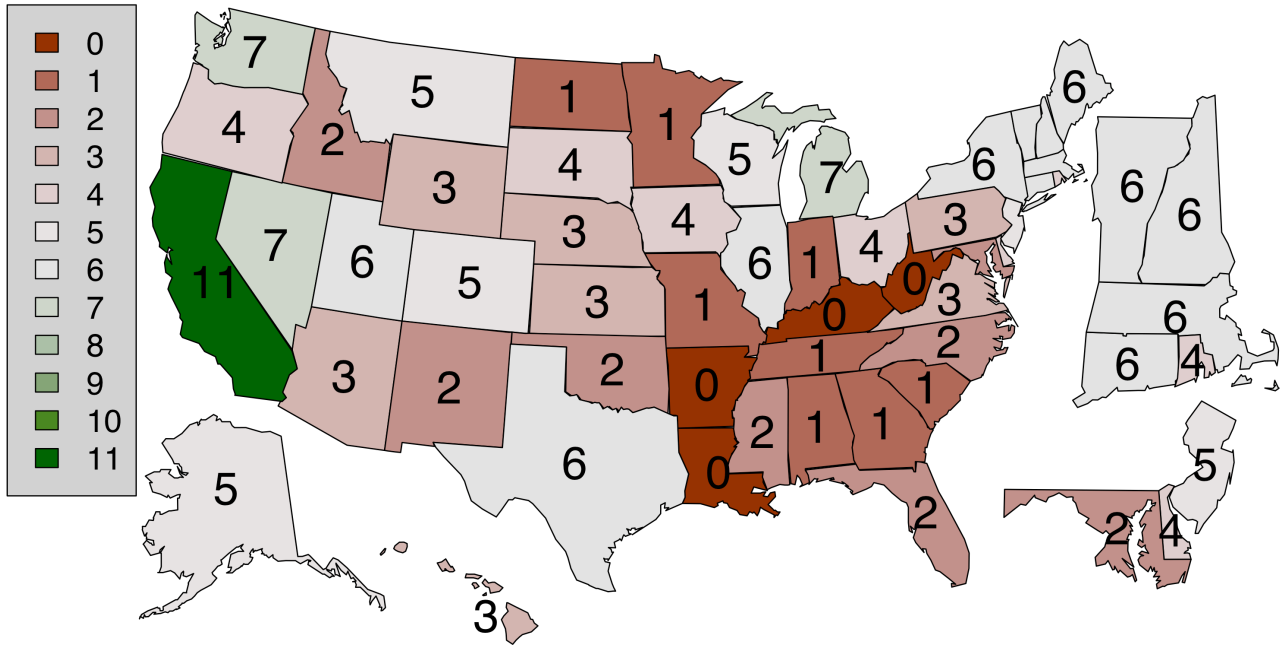

Figure 4: Number of progress years achieved over the simulation period from 1985-2007 using five-year slope estimates and 80% confidence intervals.

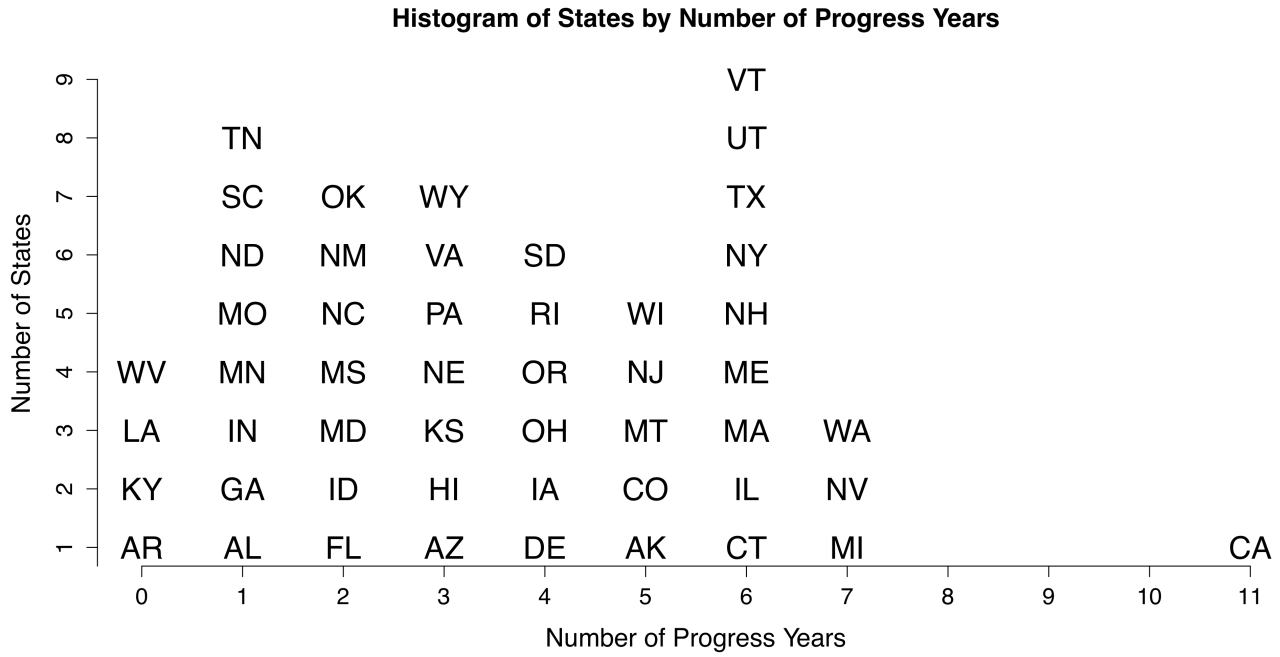

Figure 5: Histogram of 50 states showing the number of years each state achieved progress in the period from 1985-2007 using five-year slope estimates and 80% confidence intervals.

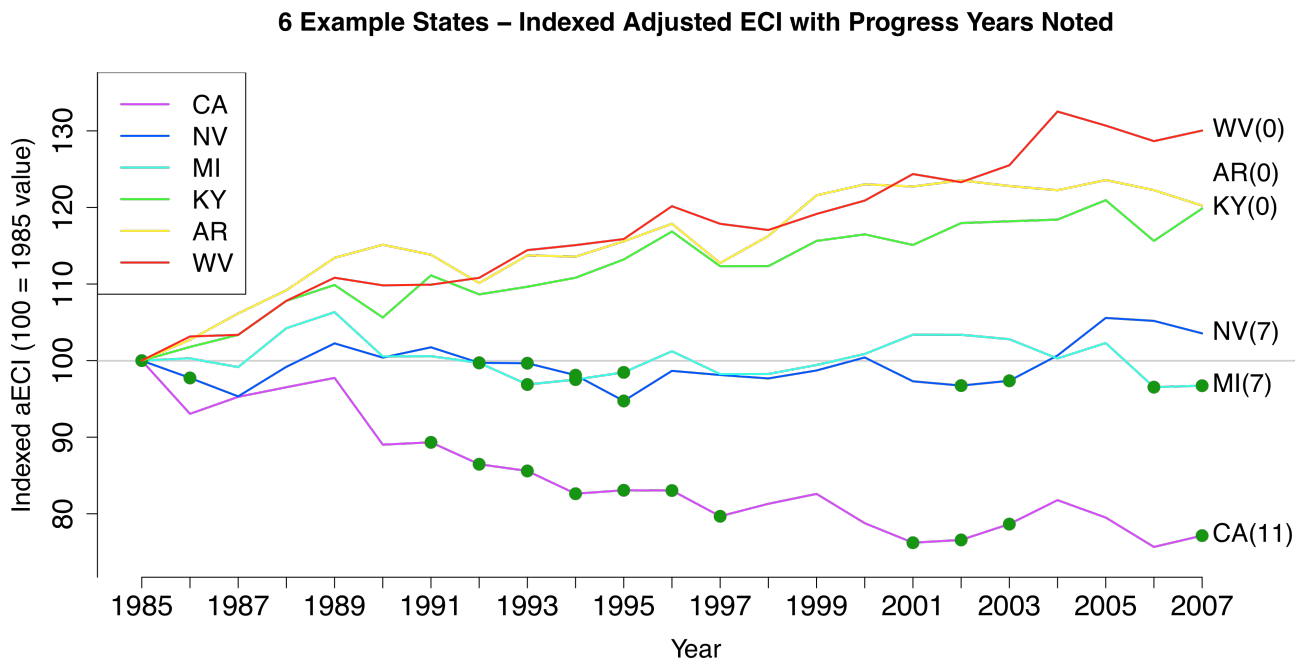

Figure 6: Indexed aECI trends for 6 states with progress years marked with green circles. Three of the states that achieved the most progress years in the simulation were CA, MI, and NV (WA also achieved progress 7 times). Three of the states that achieved no progress were WV, AR, and KY (LA also did not achieve any progress). The trends have been normalized to the aECI value in 1985 for each state; five-year slope estimates and 80% confidence intervals were used to evaluate performance.

Ground Truth Analysis

We have conducted a series of analyses we call "ground truth" reports to better understand the relationship between performance as measured by the PSEP metric and the history of residential sector energy consumption and residential efficiency policies in specific states. This ground truth work has proven extremely valuable on two accounts. Based on taking a detailed look at certain states, we have discovered important considerations that were originally missing from our methodology. We have subsequently addressed these considerations in this updated report. For example, analysis of Washington's consumption trends led us to realize that the SEDS data make an unrealistic assumption that all electricity consumption is treated as if produced by fossil fuel power plants.

Secondly, the ground truth analysis of some states has led to important conclusions about what may be missing in current policies and programs or where lie opportunities for improvement. For example, Vermont has a long history of aggressive energy efficiency policies, however, they have largely been focused on reducing electricity consumption. Growth in fuel oil consumption, the dominant form of energy in Vermont, has offset those electric efficiency policy achievements.

Ultimately, a combination of an aggregate level metric along with detailed ground truth analysis can yield conclusions and insights of more value than what either approach might accomplish on its own. The metric tracks overall progress and the ground truth analysis leads to strategies for improving performance. The following sections summarize our work on each state. The full ground truth reports can be found on the Schatz Energy Research Center website[9].

Washington - Investigating the effect of the heat rate applied to hydroelectric power

Our analysis of Washington State revealed the importance of properly estimating primary energy associated with electricity production. Using a previous version of the PSEP metric, over the period from 1985-2007, Washington achieved 13 progress years, the most of any state (Figure 7 left). Despite Washington's history of effective energy policies, this unparalleled performance in the historical simulation merited investigation.

A distinguishing feature of Washington State's total energy use is the high proportion of hydroelectricity in its electricity generation profile. The previous PSEP metric used data directly from the State Energy Data System (SEDS) which, when calculating the primary energy associated with electricity generation, applies an average fossil-fuel heat rate to renewable electricity generation. Use of this high heat rate makes hydroelectric power generation appear to be extremely energy intensive, and unrealistically exaggerates the impact of changes in electricity consumption on the state's total energy consumption. Additionally, SEDS applies a national average heat rate to all states, regardless of their state generation profile. As described in this report (pp 10-11 and Appendix C), the PSEP metric has been revised to use state-specific heat rates for the calculation of primary energy associated with residential electricity consumption. Further, the revised metric does not apply a heat rate to renewable energy sources, such as hydroelectric power. Repeating the historical simulation using revised state-specific heat rates substantially changed the performance of many of the states, including Washington (Figure 7 right). With the revised heat rates, WA achieved progress in 7 years over the period from 1985 – 2007.

[9] http://www.schatzlab.org/projects/psep

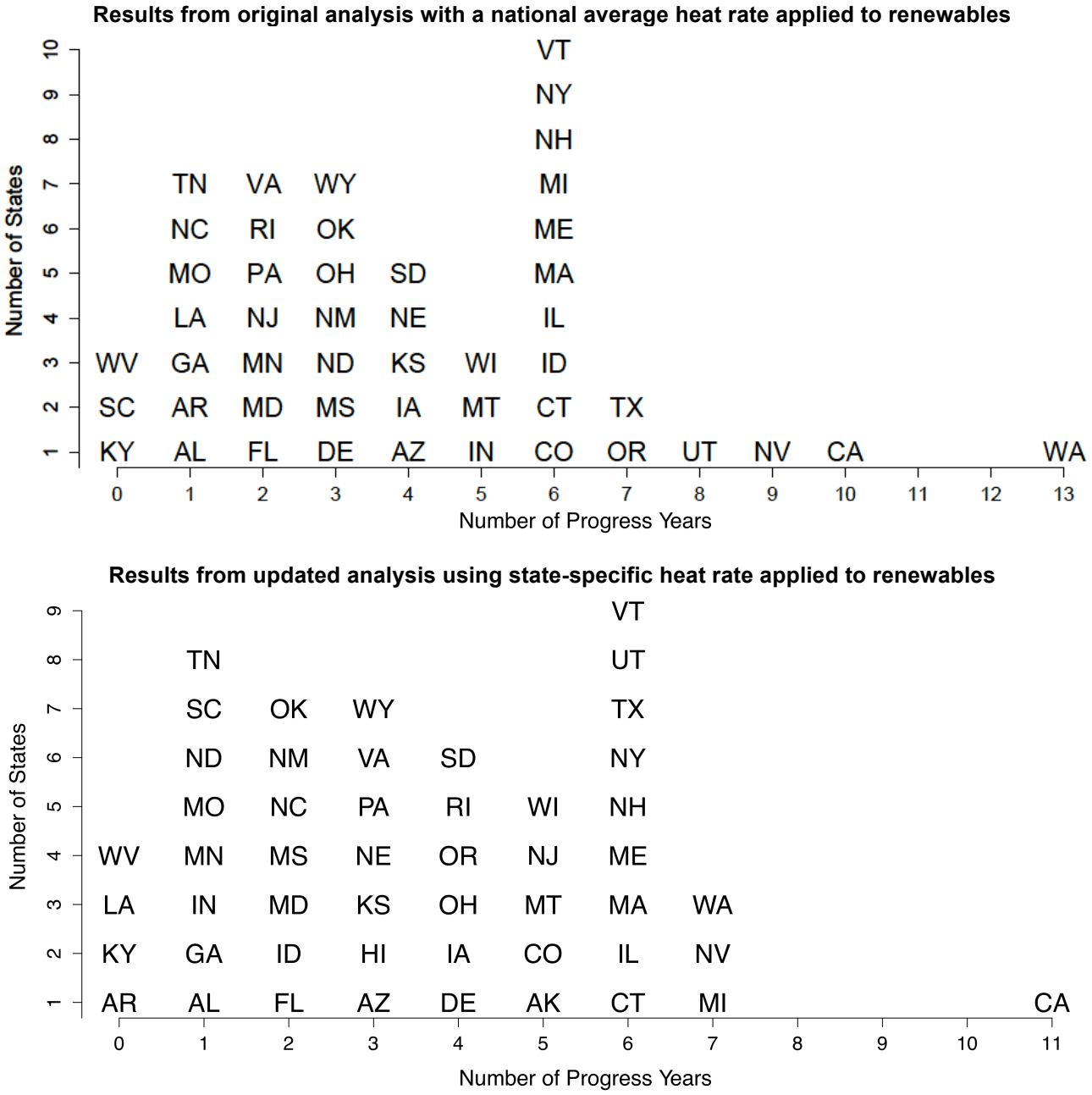

Figure 7: Histograms of States by Number of Progress Years. The top histogram displays the distribution of the states using the original analysis with a national average heat rate applied to renewables. The bottom histogram displays the distribution of the states using state-specific heat rates calculated assuming no additional primary energy is consumed in the production of electricity from renewable sources. Note the change in scale of both the x and y axes.

Vermont - Understanding Lack of Progress in Reducing per Capita Energy Consumption despite Aggressive Energy Efficiency Initiatives

For Vermont we investigated the counter-intuitive relationship between Vermont's aggressive energy efficiency efforts and the state's recent performance in the PSEP metric. Vermont has a long record of implementation of energy conservation policies dating back to the early 1970s. Key programs include a statewide building energy code, a low-income weatherization program, appliance standards, seasonal

electricity pricing, and aggressive utility DSM programs. These earlier efforts were followed in 2000 by the creation of Efficiency Vermont, a statewide organization dedicated to energy efficiency. Over the past seven years, Vermont has spent more money per capita on energy efficiency than any other state in the nation.

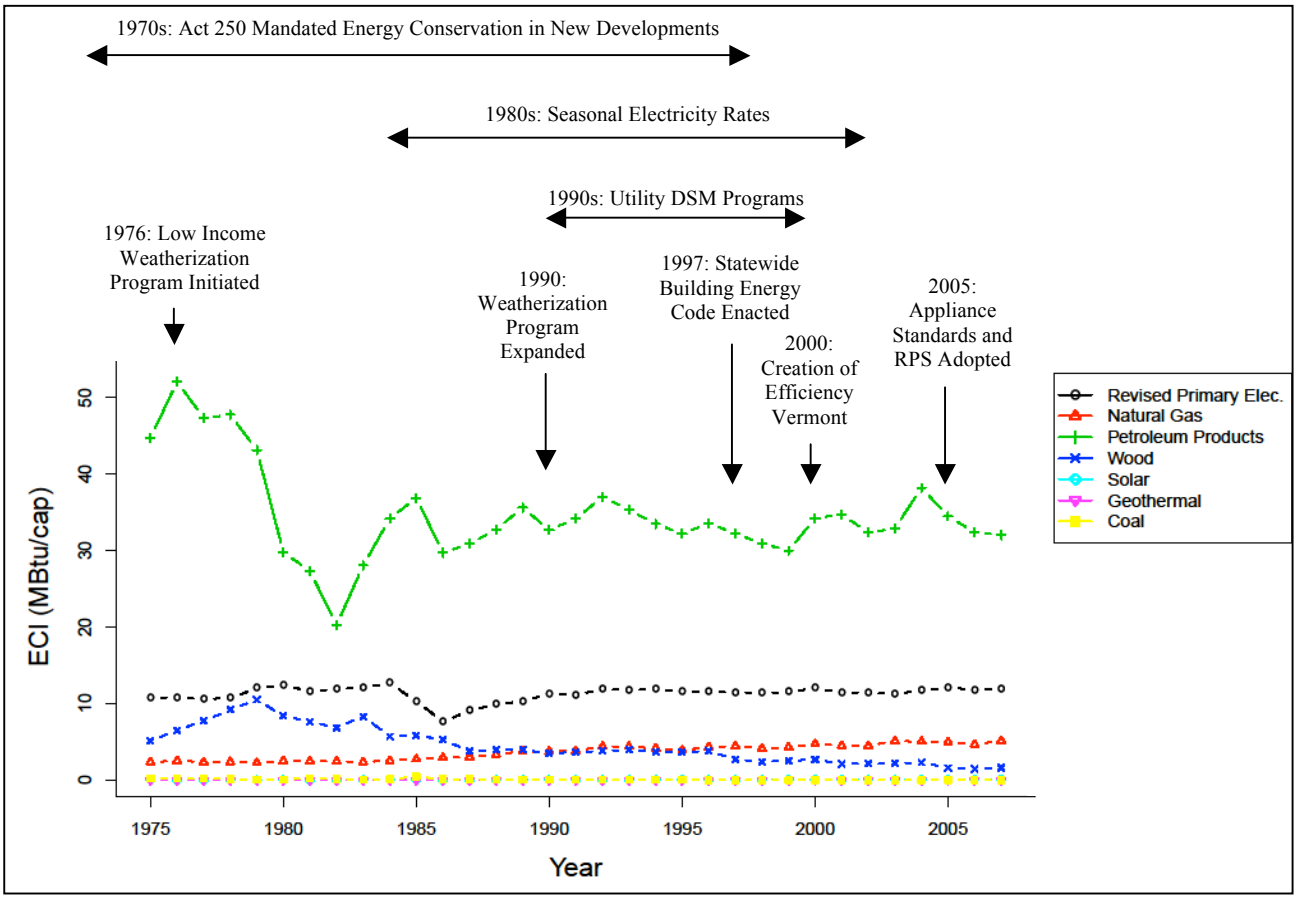

Figure 7: Implementation dates of Vermont's energy efficiency policies overlaying the state's per capita energy consumption distributed by fuel type

Despite these proactive efforts, Vermont's per capita energy use has remained relatively constant since the mid-1980s and the PSEP metric only recognized six years as progress years. The findings of our analysis indicate that the estimated electricity savings associated with Vermont's energy efficiency efforts have been offset by consumption increases related to demographic shifts within the state as well as increased electric appliance use. They also show that Vermont's efficiency programs have done little in recent years to address fuel oil consumption, which represents the largest component of residential sector energy consumption in the state.

Missouri – Investigating lack of performance

Over the period from 1985-2007, Missouri would not have performed well, with one progress year detected according to the PSEP methodology (Figure 5). The driving force behind the steady increase in energy consumption intensity in Missouri is an increase in electricity consumption. Because there is a corresponding reduction in natural gas consumption, it seems likely that consumers are switching from

natural gas to electric for heating services. The ground truth analysis examines available data to assess this hypothesis.

The observed growth in Missouri's per capita electricity consumption can be accounted for by shifts in the use of electricity for heating and the penetration of air conditioning within the state. The observed decline in natural gas consumption cannot easily be reconciled with the available data. This could in part be due to the lack of geographic resolution of the RECS data set, or the impact of other appliances and factors not scrutinized in the analysis.

Nevada – Is high performance related to a high rate of new housing starts?

Nevada achieved progress according to our metric in a number of years. Overall, their trend has remained relatively flat between 1985 and 2007. Such a flat trend is an achievement in comparison with the rest of the country. A natural hypothesis to explain this performance is the high rate of housing growth in Nevada combined with building codes and new materials that result in higher levels of efficiency. However, the data do not support this hypothesis. In addition, the evidence do not support the hypothesis that any of the following may be responsible for Nevada's trend: the impact of energy prices, the economy, changes in heating technologies, air conditioning penetration, and changes in the Nevada grid mix. Further analysis is needed to explain Nevada's strong performance by the PSEP metric.

North Dakota

North Dakota would not have performed well according to the PSEP metric, with only one progress year detected. This poor performance is not unexpected, as North Dakota has historically had very few residential energy efficiency programs and ranked at the bottom of the 2009 ACEEE energy efficiency scorecard. In part due to a lack of interest in energy efficiency, North Dakota has one of the highest rates of increase in their aECI, mostly driven by a steady increase in per capita electricity consumption (Figure 8).

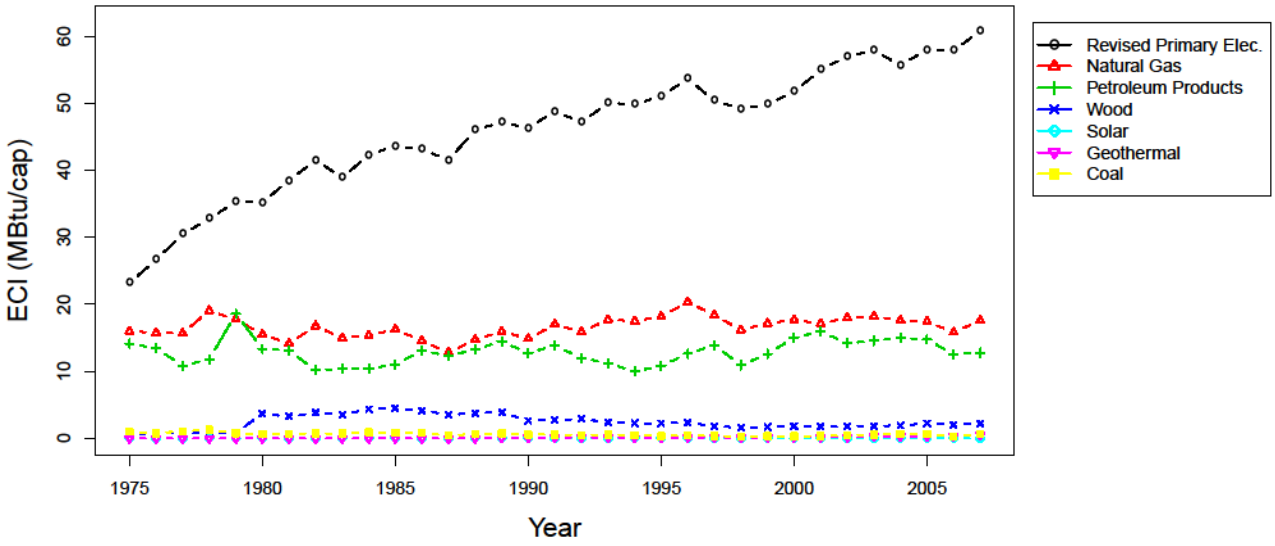

Figure 8: Residential ECI in North Dakota by fuel type from 1975-2007.

The observed rapid growth in North Dakota's residential electricity consumption is likely due to a combination of factors. Most prominently, the extremely low cost of electricity has made energy

efficiency efforts in the state a low priority and often uneconomical. Additionally, demographic shifts toward an older and more urban population with smaller household size could potentially increase consumption. Though it is unclear to what extent the use of electric heating equipment has increased in the state, due to the state's high number of heating degree days, a small percentage change in the number of heaters can affect a large change in the residential energy consumption. The increased use of air conditioners could also potentially contribute to the electricity consumption; however, due to the low number of cooling degree days, a small increase in air conditioning units would not have a substantial effect on the total electricity consumption.

Though North Dakota has historically performed poorly according to the PSEP metric, the state has considerable opportunity for improvement. Starting in 2008 and 2009, both the state and the utilities have become interested in energy efficiency programs, and have both made policy recommendations and enacted appliance rebate programs. Perhaps these and expanded energy efficiency efforts will enable North Dakota to significantly reduce their per capita energy consumption in the coming years.

New York

New York's record of energy efficiency policies is not reflected by strong progress according to the PSEP metric. The state had 6 progress years in the 23-year study. Residential consumption of electricity, natural gas and fuel oil were all analyzed to determine potential effects of efficiency efforts and factors that may influence residential consumption.

The increasing residential electricity consumption may be explained in part by a demographic shift in New York's population, as well as increasing appliance use, which could offset a significant portion of the savings from the state's electricity efficiency efforts. A decreasing trend in the price of electricity may also be encouraging growth in consumption. Increased penetration of air conditioners and the state's decreasing heat rate have not had a strong effect on residential electricity consumption. Further, electricity consumption does not seem to be strongly correlated with weather. The decreasing trend in fuel oil consumption may be due to switching of home heating fuels, increasing petroleum prices and the efforts of weatherization programs. Fluctuations in the use of natural gas seem to be highly correlated with weather, and increased demand due to fuel switching may be currently offset by the state's energy efficiency efforts.

Additionally, though New York started addressing energy efficiency in the mid-1970s, during a period of restructuring of New York's electric power industry between 1994 and the start of the New York Energy $mart^{SM} program in 1998, funding for both the state's and utilities' energy efficiency efforts was dramatically reduced. This reduction in funding and energy efficiency programs coincides with a period of increase in New York's per capita energy consumption as shown in Figure 9.

All of the prior analysis is based on historical energy data and savings estimates from 1985 until 2007. In 2008, New York adopted an energy efficiency portfolio standard, significantly expanding their energy efficiency programs and providing funding for the investor-owned utilities to manage additional programs. Further funding was allocated in 2009 to create programs specifically targeting natural gas use. Perhaps this increased funding for targeted programs will enable New York to reduce their future per capita energy consumption.

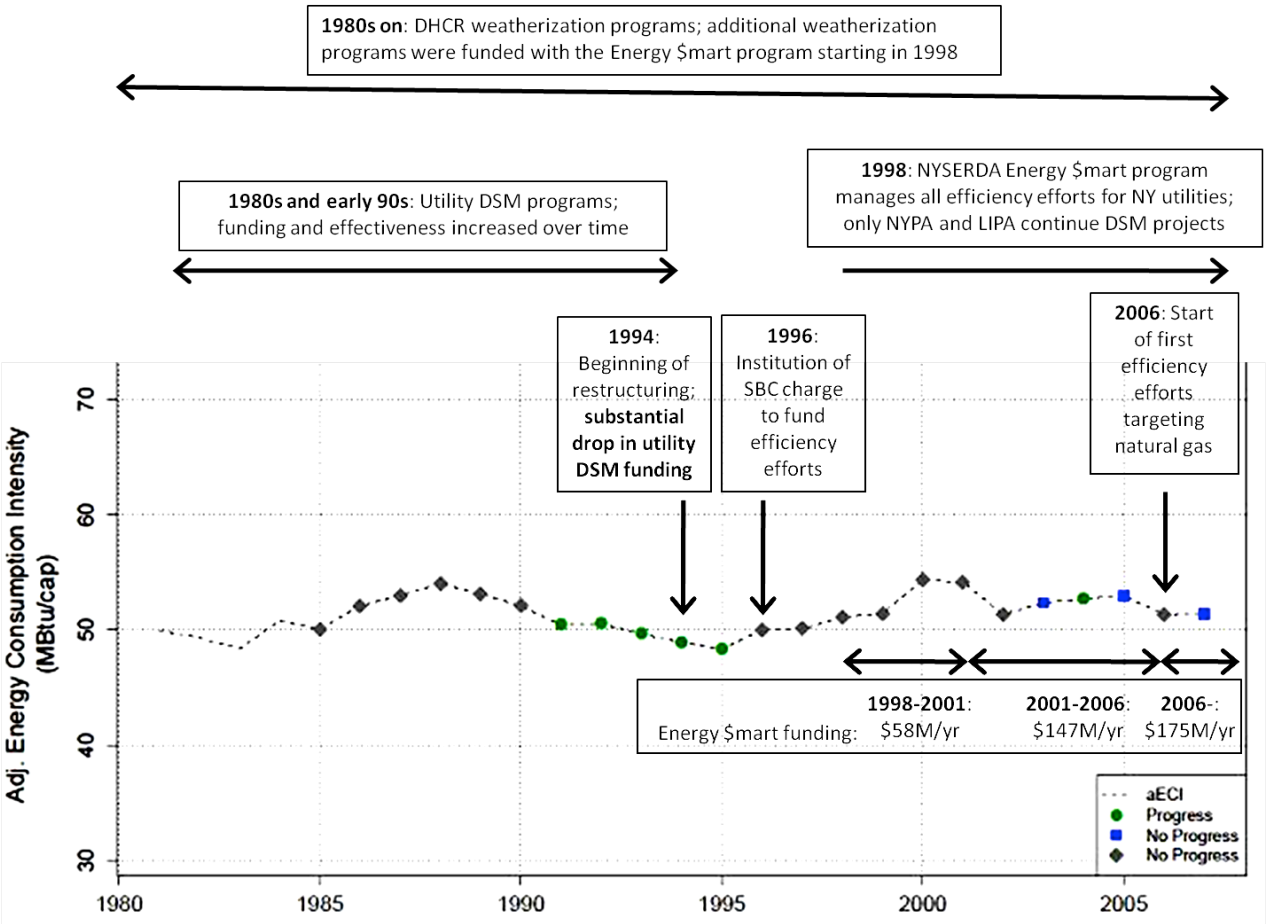

Figure 9. Timeline of New York's energy efficiency efforts overlaid on the adjusted ECI for New York from 1985-2007. Years without progress are indicated with gray diamonds, years with progress that are not statistically significant are indicated with blue squares, and years with statistically significant progress are indicated with green circles.

California

California performed very well according to the PSEP metric, as the state's aECI has consistently declined over the period of 1985-2007, decreasing by nearly 10 MBtu per person over the 23-year period. This consistent decline resulted in 11 progress years, more progress years detected by the PSEP metric than any other state. California's exemplary history of energy efficiency policies offers one explanation for the state's consistent reduction in per capita energy use and strong performance in the PSEP metric. Starting in the mid-1970s, California began implementing energy efficiency measures including the development of the California Energy Commission, the adoption of statewide building and appliance codes, investment in energy efficiency research and development, and the use of innovative policies such as "decoupling" utility company profits from their direct sales to encourage utilities to promote energy efficiency as part of their portfolio.

California's downward trend in residential energy consumption can be attributed to a consistent decrease in the consumption of natural gas while consumption of electricity remained relatively stable (Figure 10). Many studies have analyzed California's per capita residential electricity consumption, as it has barely changed in 30 years while the national average consumption has increased dramatically. Less attention has been paid to the state's consistent decrease in natural gas consumption, though this constant decline

has resulted in the state's reduction of total per capita residential energy use. In both cases, California's active energy efficiency measures have greatly affected the consumption trends; however, other factors have also had a strong influence, including the price of residential energy, California's mild climate, and the state's greater than average household size (see Sudarshan 2008 for a detailed investigation into these impacts).

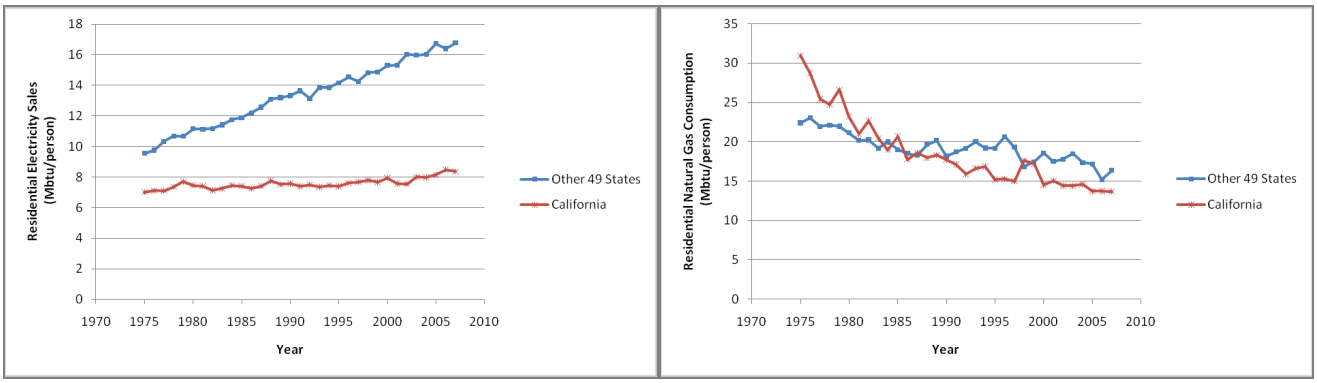

Figure 10: California's residential electricity and natural gas sales versus those of the other 49 states. Note the electricity sales do not include the primary energy necessary to produce the electricity.

Texas - What accounts for the recent decline in consumption?

Historically, Texas has not addressed energy consumption as actively as most of the other high performing states, such as California, Washington and many of the northeastern states, yet the PSEP metric indicates that Texas made progress in six years between 1985 and 2007 (Figure 5). In the late 1990s and early 2000s, Texas began to enact policies both to restructure the energy market and to encourage energy efficiency. In 1999, the Texas legislature passed Senate Bill 7, which both established an Energy Efficiency Resource Standard for the state's utilities and deregulated the energy market[10,11,12]. In 2001, Texas implemented its first statewide building energy code. The ground truth report examined the effect of these recent energy efficiency policies in an attempt to explain the recent decline in Texas' residential energy consumption. Additionally, the effect of factors such as energy prices, changes in the state's grid mix and disposable income were investigated. Some of the policies and factors we examined could account for a portion of the recent decline in the aECI, but their contribution was small (less than 5% with 95% of the decline remaining unexplained).

Additional Considerations

Implications of uncertainty

The values in Table 1 indicate that if an 80% confidence limit is used, in some years as many as 16 states would not achieve progress despite having negative slopes. These findings may appear to support the concerns expressed by Horowitz (2008), who argues that energy metrics like the ECI involve too much

[10] ACEEE, "Success with Energy Efficiency Resource Standards," American Council for and Energy Efficient Economy, 2009. http://aceee.org/energy/state/EERS_statesuccess0109.pdf

[11] Zarnikau, Jay and Doug Whitworth, "Has electric utility restructuring led to lower electricity prices for residential consumers in Texas?," *Energy Policy*, 34 (2006) 2191-2200.

[12] Summit Blue Consulting, LLC and Quantec, LLC. "Independent Audit of Texas Energy Efficiency Programs in 2003 and 2004," Final report for the Public Utility Comission of Texas, 2006.

uncertainty to be used for reliably evaluating progress. While caution is warranted, we nonetheless note three reasons to proceed with the development and use of a performance based metric similar to the one described here. First, although uncertainty is a concern, the levels are not so great that they preclude the possibility of identifying - with reasonable levels of statistical significance - states that have successfully achieved ECI reductions. Second, access to improved data (e.g., SEDS data collected on a quarterly rather than an annual basis) should result in narrower confidence intervals and, consequently, fewer false negative outcomes (i.e., situations where a state may have made progress, but the data are too uncertain to confirm that it has). Third, Horowitz's argument that energy metrics are too uncertain is made in relation to a situation with much higher stakes. He states that "…it would be risky to use … (performance based energy intensity metrics) … as the basis of a worldwide evaluation system for monitoring international climate change agreements" (Horowitz, 2008, p. 200). We heartily agree on this point. At the same time, we consider programs aimed at encouraging energy efficiency measures at the state level to be a somewhat lower-stakes circumstance, and we believe that the approach described here can provide significant value.

Metric Responsiveness and Accuracy

The proposed program seeks to encourage states to progressively reduce per capita energy consumption relative to prior performance regardless of whether the state has historically been a leader in energy efficiency or whether it has not previously taken advantage of its efficiency potential. To this end, we need a metric that allows states that have an historically increasing trend in per capita energy consumption to be in a position to compete for prominence on a relatively short time scale. These states would do this by establishing a downward aECI trend relative to their own record. Likewise, the intent of the proposed program is to ensure that states, which have a long history of improvement, are considered successful for continuing to make progress.

The aECI approach described here does a reasonable job of achieving these goals, albeit imperfectly due in large part to limitations in currently available data. For example, since 1985, South Carolina would have achieved progress for one year when its aECI declined despite the overall increase over the time period. The relatively rapid response of the metric is encouraging, as it indicates that states that begin to achieve progress would be noted in a timely fashion. Moreover, if South Carolina had been able to maintain the downward trend, it would have been in a position to continue to receive accolades for its progress. Likewise, the results presented in Figures 2 and 3 indicate that California would have achieved progress for 11 of the 22 years from 1985-2007. Consistent with its long term record of successful energy efficiency programs, this record is the best of all states for the same time period.

At the same time, a comparison of South Carolina and California's respective records raises some questions about tracking progress with the aECI metric. For example, it is possible that the brief periods of aECI decline in South Carolina's record may not have been – in practice – due to state or utility level policy initiatives. As noted above, if federal policy makers are concerned that states might occasionally be rewarded in years that they did not achieve progress, which may or may not have been the case for South Carolina, they could impose a stricter confidence interval requirement (e.g., 90%). See Appendix A.3 for further discussion on this point.

One potential disadvantage of tightening the confidence level is that this would increase the chance that a state would not be recognized for achieving progress in a period when it did, in fact, reduce its aECI. This can be illustrated by using California as an example. Using this metric, California would not have achieved progress for multi-year periods during the 80's, 90's, and 00's. For some of these years, California's five-year trend line slope was less than zero and appeared to be a part of a longer term trend,

but this cannot be verified at the 80% confidence level with currently available data. This may raise some concern that California did not receive recognition for periods when it did, in fact, make progress.

Fortunately, with improved data collection these apparent imperfections in the aECI method can be reduced. The key to achieving these improvements is to collect quarterly data through the annual SEDS reporting process. This would allow analysts to impose stricter confidence interval requirements without excluding too many states that did actually make progress. Collecting SEDS data on a quarterly basis reduce the number of situations where states received recognition of progress that they did not deserve and situations where states did not receive acknowledgement of progress that they did deserve (i.e., in statistical terms, Type I and Type II errors, respectively). See Appendix B for further discussion.

Data Improvements

Almost all of the data used in the analyses in this report are from the EIA State Energy Data System (SEDS). The data for SEDS are self-reported by utilities and electric power generating plants, and the sectoral classifications (i.e., residential, commercial, etc.) are based on the supplier classification and may vary by supplier, by state, and by year. These data, while valuable, would benefit from an auditing system that verifies their accuracy and reliability. For residential energy consumption data, the primary check appears to be the quadrennial Residential Energy Consumption Surveys (RECS), which provide a national and regional estimate based on end user data. Unfortunately, the SEDS estimates and the RECS estimates are not directly comparable so the RECS results provide a limited base for verification of the SEDS data.

In order to successfully implement the proposed PSEP, improved data collection and reporting is required. While our analysis in this report focuses on the residential sector, these recommendations also apply to the commercial sector. The following improvements would increase the reliability of PSEP or other performance-based metrics:

1. Standardize and Disaggregate SEDS Classification System: The sectoral classification system for the SEDS varies from state to state and even supplier to supplier. The resulting inconsistencies are most problematic for the commercial sector data, but may also affect the residential sector. For ideal implementation of the proposed program, the classification system associated with SEDS should be standardized across all states and suppliers. In addition, in the case of the commercial sectors, disaggregating the sectors into more homogeneous sub-sectors might improve the precision of the predictions by focusing on a group of energy consumers that share similar patterns and modes of energy consumption. For example, the commercial sector might be split into sub-sectors such as offices, retail space, and other subsets, each of which would have its own characteristic types of construction and uses of energy.

2. Quarterly Energy Consumption and HDD/CDD Data: If quarterly, not just annual, energy consumption data were available, the statistical power of the proposed analysis would be increased substantially. With quarterly data, the incidence of Type I and Type II statistical errors could be reduced considerably (see discussion on pp. 31-33 as well as Appendix B). Quarterly heating and cooling degree data (HDD & CDD) would also be needed to carry out the analysis. It is not necessary to increase the frequency of reporting. It would be sufficient to simply include quarterly data in the annual reports.

3. Implement System to Improve Reliability of Data reported through SEDS: Implementing a system to assess and improve the reliability of the self reported data from utilities and electric power generating plants to SEDS would improve the reliability and integrity of the data and provide a firmer basis for estimating the adjustment coefficients for degree days and disposable income. The EIA or one of the DOE national laboratories could perform this task if they were given the resources and personnel to do so.

4. Population Weight HDD and CDD using Current Year Populations: The HDD and CDD values we are using in this report are weighted by the decennial census population data, so that all of the HDD values for the 1990s, for example, use the 1990 census population data. Using annual population estimates would remove a systematic error from the population weighted HDD and CDD values. The National Climatic Data Center (NCDC) prepares the current estimates and would be able to implement this change using population figures provided by the Census Bureau.

5. Publish Population Weighted HDD and CDD for the states of Alaska and Hawaii: Currently, the NCDC do not make estimates of annual HDD and CDD available for Alaska and Hawaii. The authors adopted a stand-in methodology to estimate these values from degree day data available by weather station (Appendix D). But it would be necessary for these data to be compiled by NCDC in order to ensure that a consistent methodology is used.

6. Publish Consumption-Based Grid Mix Data: Estimating the mix of generation types on the electricity grid would ideally be based on consumption (e.g. what fraction of energy consumed originated from each source). SEDS data does not have enough detail about electricity sales to accomplish this.

7. Establish Clear Leadership and Coordination across Agencies: At present the data required for this analysis are collected by a range of agencies, including the EIA, NCDC, and Census Bureau. Whichever agency or agencies are made responsible for tracking state energy consumption, all of the contributing agencies should explicitly be made responsible for providing their portion of the data on a timely basis and should be funded so they can do so. In the absence of such coordination and funding, a delay in reporting by one agency could hamper efforts to implement the proposed program.

8. Improve Timeliness of Data Reporting: Currently, years elapse between the end of a year and the availability of the SEDS data for that year. For example, the SEDS data for 2005 were released on February 29, 2008 while the 2006 data were released on November 28, 2008. Timeliness has improved somewhat in recent years, the release data for 2008 data is June 30, 2010. For the state energy consumption tracking system to be effective and have its desired influence, the interval between the end of the reporting period and the release of the tracking results should be as brief as practical (e.g., 6-12 months).

Timeline for Implementation

A final point of discussion is related to the relationship between state policies to encourage energy efficiency and the time line for detection of this progress under a performance based system. In order to encourage states to develop and sustain effective efficiency programs, it may be important to have a responsive program that identifies progress relatively quickly (e.g., within 3-5 years). However, in the

case of some policy measures, there is a moderately long lag time between enactment of the policy and delivery of measurable energy savings. For example, building code changes that would mandate more energy efficiency building design and construction would only reduce energy consumption as the building stock is gradually replaced with new construction following the new code. Because of the time lags involved, the proposed ECI tracking method may not initially provide a strong motivation to states to enact such energy reduction strategies despite the large energy savings that can be achieve in the long term.

While this is a limitation of the proposed metric, the use of a performance metric in combination with policy-oriented metrics along the lines of the ACEEE Energy Efficiency Scorecard (see Eldridge, 2008) can address this issue by recognizing states that quickly enact forward thinking policies. This combined approach would provide the benefits of a performance based system (i.e., states are evaluated based on measurable progress) while also recognizing states immediately for enacting policies aimed at improving energy efficiency.

As initially implemented, the proposed program would not be perfect, but it would provide a reasonable framework for tracking state level trends in aECI. With improvements in data collection and reliability, and in conjunction with bottom-up efficiency evaluation methods, the approach can provide a powerful tool for evaluating states' progress. The agency made responsible for tracking state energy consumption should, of course, be directed to periodically review the methodology and propose revisions.

Conclusions

The simulations that we have conducted indicate that it is possible to track trends in residential ECI by state. However, it is not possible to isolate changes in ECI that are due to policy choices from changes due to other factors with 100% reliability. In our analysis, we estimated the sensitivity of residential and commercial state ECI to variations in weather (represented by Heating and Cooling Degree Days) specific to each state. While we were not able to explain all of the year-to-year variability in the ECI with this approach, including additional policy independent variables (e.g. disposable income, percent employment, GDP by state, etc.) did not dramatically improve the results (Appendix A). Moreover, even when we did include parameters that could be linked to state energy policy choices (e.g. energy prices, housing unit size), substantial year-to-year variability in the ECI remained. Other factors that may be responsible for the remaining variation include historical events limited to individual states such as the real and imaginary shortages during the 2000-2001 California energy crisis, national energy policy initiatives, and the variable quality of the energy consumption data, as well as – of course – the state level policy changes such as changes in building codes or appliance efficiency standards that the method is designed to capture. While no statistical approach can separate policy related changes in energy consumption from other factors with 100% reliability, they can nonetheless provide a very useful approach for tracking states' progress over time.

Acknowledgments
The authors and project managers wish to thank the following leading professionals for providing information and insights that contributed to this study:

Riley Allen and Richard Cowart, Regulatory Assistance Project
Stephanie J. Battles, Director, Consumption Division, Energy Information Administration
David Belzer, Pacific Northwest National Labs
Mark Bernstein, Managing Director, Energy Institute at University of Southern California
Adam Bickford, Sreedhar Upendram, John Noller, and Brenda Wilbers, Missouri Department of Natural Resources
Joe Bryson, Environmental Protection Agency
Steve Capanna, Sr. Associate, Research and Policy, ASE-Alliance to Save Energy
Nick Fugate, California Energy Comission
Teresa Gross, Public Utilities Commission Texas
Bruce Hagen, North Dakota Department of Commerce
Kathleen Hogan and staff, U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy
Chris Kavalec, California Energy Comission
Dave Lamont, Vermont Department of Public Service
Joe Loper, Senior Vice President, Policy and Research, ASE-Alliance to Save Energy
Sierra Martinez, NRDC
Joelle Michaels, CBECS Manager, Energy Information Administration
Phil Mosenthal, Optimal Energy
Derek Murrow, Director, Policy Analysis, Environment Northeast
Steven Nadel, Executive Director, ACEEE - American Council for an Energy Efficient Economy
Arthur Rosenfeld, California Energy Commission
Joseph Roop, Pacific Northwest National Labs
Jim Sweeney, Precourt Institute for Energy Efficiency, Stanford University
Phil Tseng, Statistical Methods -- Economic Analysis, Energy Information Administration
Lowell Ungar, Director of Policy, ASE-Alliance to Save Energy
Steve Wade, residential and commercial energy modeler, Energy Information Administration
Tom Whitehurst, National Climate Data Center
Lisa Wood, Edison Electric Institute
Zachary Weis, North Dakota Department of Commerce

In addition, we thank Rick Duke and Jacqueline Wong for valuable contributions to this effort during their tenure at the Natural Resources Defense Council. Likewise, we thank Michael Winkler of the Schatz Energy Research Center for his participation in the early stages of the analysis. We also thank Sheryl Carter and Dennis Aigner for valuable comments on an earlier draft. All errors and omissions are, of course, our own.

References

Belzer DB, and KA Cort. (2004), Statistical Analysis of Historical State-Level Residential Energy Consumption Trends, In Proceedings, 2004 ACEEE Summer Study on Energy Efficiency in Buildings, August 22-August 27, 2004 in Pacific Grove, California, vol. Panel 1, pp. 25-38. American Council for an Energy-Efficient Economy, Washington, DC.

Belzer, David B. (2006), Energy End-Use Flow Maps for the Buildings Sector, Pacific Northwest National Laboratory, Richland, Washington, prepared for the U.S. Department of Energy under Contract

DE-AC06-76RL01830, PNNL-16263, September 2006.

Belzer, David B. (2007) "Estimates of U.S. Commercial Building Electricity Intensity Trends: Issues Related to End-Use and Supply Surveys." Prepared for the U.S. Department of Energy by Pacific Northwest National Laboratory. September 2007.

Bernstein, Mark; Fonkych, Kateryna; Loeb, Sam; and Loughran, David (2003), State-Level Changes in Energy Intensity and Their National Implications, Science and Technology Policy Institute, Prepared for the U.S. Department of Energy by RAND.

Eldridge, Maggie, Max Neubauer, Dan York, Shruti Vaidyanathan, Anna Chittum, and Steven Nadel (2008) "The 2008 State Energy Efficiency Scorecard," ACEEE Report Number E086, American Council for an Energy-Efficient Economy.

Energy Information Administration (1995), Measuring Energy Efficiency in the United States' Economy: A Beginning, Energy Consumption Series, U.S. Department of Energy, DOE/EIA-0555(95)/2, October 1995.

Energy Information Agency. (2005) "State Energy Data System 2005: Consumption Introduction to the Technical Notes." Downloaded July 2008: http://www.eia.doe.gov/emeu/states/_seds_tech_notes.html

Horowitz, Marvin J. (2008), "The trouble with energy efficiency indexes: la aritmetic non e opinione", Energy Efficiency, 1 (3):199–210, August 2008.

Sudarshan, Anant and James Sweeney. (2008) "Deconstructing the 'Rosenfeld Curve'." Working paper, downloaded February 2009: http://piee.stanford.edu/cgi-bin/htm/Modeling/research/Deconstructing_the_Rosenfeld_Curve.php.

Appendix A - Details of the Methodology and Variations on the Primary Analysis

In this Appendix, we present detailed results associated with the statistical model used in the main body of this report. The information is presented with a focus on the analysis of aECI trends in the residential sector. We also provide information about several alternative analyses that we explored in the context of the study.

We begin the appendix with a summary of the regression coefficients for a representative version of the residential sector analysis (Section A.1; Table A.1). This is followed by a presentation of standard error and R^2 values for several different linear models that we considered for residential sector ECI in the context of the study (Table A.2), a discussion about the behavior of key regression coefficients (Figure A.1), and an investigation of the impact of including time-fixed effects in the model (Figures A.2 and A.3). We also include a discussion of the potential inclusion of disposable income and energy prices as independent variables (Section A.2; Figures A.4, A.5, and A.6). We present a comparison between the use of 80% and 90% confidence intervals on the 5-year slopes of aECI for the state of California (Section A.3 and Figure A.7). In Section A.4 (Figure A.8), we discuss a subtlety associated with summary plots in this report that could be a source of confusion for readers. Finally, we present the results of using a 10-year slope of aECI as the metric in (Section A.5, Figures A.9 and A.10, Table A.3).

A.1 Results of Regression for Residential Sector ECI

For the residential sector, the multiple linear regression included 50 dependent variables: HDD, CDD, and a unique intercept for each of the 50 states (insufficient degree day data were available for Alaska and Hawaii). Table A.1 presents an example of the resulting parameter estimates and their associated significance for the residential sector using data from 1991-2000. The first two parameters listed in Table A.1 are the response of ECI to heating degree days (HDD) and cooling degree days (CDD), while the remaining 50 are state specific regression intercept values.

Based upon the parameters estimated by the regression, the prediction equation for ECI would be the following:

$$ECI_{t,s} = \alpha_s + \alpha_t + \beta_{HDD}(HDD_{t,s}) + \beta_{CDD}(CDD_{t,s}) + \varepsilon_{t,s}$$

where $ECI_{t,s}$ is the energy consumption intensity in year *t* and state *s*, α_s is the fixed effect term for state *s*, α_t is the fixed effect term for year *t*, β_{HDD} and β_{CDD} are the estimated responses of ECI to HDD and CDD respectively, $HDD_{t,s}$ and $CDD_{t,s}$ are the observed degree days in year *t* and state *s*, and $\varepsilon_{t,s}$ is the residual associated with year *t* and state *s*.

The equation used to adjust ECI to average weather conditions is a slight modification of the above prediction equation:

$$aECI_{t,s} = ECI_{t,s} + \beta_{HDD}(HDD_{norm,s} - HDD_{t,s}) + \beta_{CDD}(CDD_{norm,s} - CDD_{t,s})$$

where $HDD_{norm,s}$ and $CDD_{norm,s}$ are the 30-year average annual heating and cooling degree day values respectively for state *s*.

Table A.1: Estimates of regression coefficients for Residential ECI from 1997-2006.

	Estimate	Units	Std. Error	t value	Pr(>|t|)	
HDD	0.0053	Mbtu/(DD*cap*yr)	0.00034	15.5	<2e-16	***
CDD	0.0048	Mbtu/(DD*cap*yr)	0.00071	6.7	0.00	***
SAK	15.4	Mbtu/(cap*yr)	3.8	4.1	0.00	***
SAL	41.4	Mbtu/(cap*yr)	1.9	21.2	<2e-16	***
SAR	33.5	Mbtu/(cap*yr)	2.0	16.5	<2e-16	***
SAZ	20.4	Mbtu/(cap*yr)	2.5	8.0	0.00	***
SCA	11.9	Mbtu/(cap*yr)	1.4	8.7	<2e-16	***
SCO	22.4	Mbtu/(cap*yr)	2.6	8.6	<2e-16	***
SCT	25.4	Mbtu/(cap*yr)	2.3	11.2	<2e-16	***
SDE	44.1	Mbtu/(cap*yr)	2.0	22.0	<2e-16	***
SFL	37.1	Mbtu/(cap*yr)	2.6	14.2	<2e-16	***
SGA	38.1	Mbtu/(cap*yr)	1.8	20.8	<2e-16	***
SHI	0.2	Mbtu/(cap*yr)	3.2	0.1	0.94	
SIA	27.1	Mbtu/(cap*yr)	2.6	10.5	<2e-16	***
SID	3.9	Mbtu/(cap*yr)	2.5	1.6	0.11	
SIL	24.7	Mbtu/(cap*yr)	2.4	10.3	<2e-16	***
SIN	43.9	Mbtu/(cap*yr)	2.3	19.2	<2e-16	***
SKS	36.3	Mbtu/(cap*yr)	2.3	16.0	<2e-16	***
SKY	47.9	Mbtu/(cap*yr)	2.0	23.9	<2e-16	***
SLA	41.5	Mbtu/(cap*yr)	2.2	18.6	<2e-16	***
SMA	25.7	Mbtu/(cap*yr)	2.3	11.0	<2e-16	***
SMD	28.4	Mbtu/(cap*yr)	2.0	14.1	<2e-16	***
SME	21.8	Mbtu/(cap*yr)	2.8	7.8	0.00	***
SMI	30.1	Mbtu/(cap*yr)	2.5	12.0	<2e-16	***
SMN	18.3	Mbtu/(cap*yr)	3.0	6.1	0.00	***
SMO	43.4	Mbtu/(cap*yr)	2.2	19.6	<2e-16	***
SMS	40.3	Mbtu/(cap*yr)	2.0	20.0	<2e-16	***
SMT	20.7	Mbtu/(cap*yr)	2.8	7.3	0.00	***
SNC	33.4	Mbtu/(cap*yr)	1.8	18.3	<2e-16	***
SND	34.8	Mbtu/(cap*yr)	3.3	10.7	<2e-16	***
SNE	31.0	Mbtu/(cap*yr)	2.5	12.4	<2e-16	***
SNH	14.0	Mbtu/(cap*yr)	2.7	5.2	0.00	***
SNJ	21.3	Mbtu/(cap*yr)	2.1	10.0	<2e-16	***
SNM	21.8	Mbtu/(cap*yr)	2.0	11.0	<2e-16	***
SNV	31.8	Mbtu/(cap*yr)	2.3	14.0	<2e-16	***
SNY	15.3	Mbtu/(cap*yr)	2.3	6.7	0.00	***
SOH	39.0	Mbtu/(cap*yr)	2.3	17.2	<2e-16	***
SOK	48.5	Mbtu/(cap*yr)	2.1	22.6	<2e-16	***
SOR	14.7	Mbtu/(cap*yr)	1.9	7.7	0.00	***
SPA	27.5	Mbtu/(cap*yr)	2.2	12.3	<2e-16	***
SRI	31.3	Mbtu/(cap*yr)	2.2	14.4	<2e-16	***
SSC	27.1	Mbtu/(cap*yr)	1.9	14.5	<2e-16	***
SSD	16.3	Mbtu/(cap*yr)	2.8	5.8	0.00	***
STN	36.6	Mbtu/(cap*yr)	1.9	18.9	<2e-16	***
STX	37.2	Mbtu/(cap*yr)	2.3	16.1	<2e-16	***
SUT	19.2	Mbtu/(cap*yr)	2.4	7.9	0.00	***
SVA	29.8	Mbtu/(cap*yr)	1.9	15.4	<2e-16	***
SVT	7.3	Mbtu/(cap*yr)	2.9	2.6	0.01	*
SWA	12.3	Mbtu/(cap*yr)	2.0	6.2	0.00	***
SWI	23.2	Mbtu/(cap*yr)	2.7	8.6	<2e-16	***
SWV	48.2	Mbtu/(cap*yr)	2.1	23.0	<2e-16	***
SWY	30.6	Mbtu/(cap*yr)	2.9	10.6	<2e-16	***
T1998	0.6	Mbtu/(cap*yr)	0.4	1.5	0.14	
T1999	1.4	Mbtu/(cap*yr)	0.4	3.8	0.00	***
T2000	1.9	Mbtu/(cap*yr)	0.3	5.4	0.00	***
T2001	2.3	Mbtu/(cap*yr)	0.4	6.4	0.00	***
T2002	2.4	Mbtu/(cap*yr)	0.4	6.4	0.00	***
T2003	3.1	Mbtu/(cap*yr)	0.4	8.9	<2e-16	***
T2004	4.2	Mbtu/(cap*yr)	0.4	11.8	<2e-16	***
T2005	4.5	Mbtu/(cap*yr)	0.4	11.9	<2e-16	***
T2006	3.4	Mbtu/(cap*yr)	0.4	8.4	0.00	***

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The R-squared and adjusted R-squared statistics were also calculated for the above base period to demonstrate the reduction in unexplained variance in ECI for several different regression scenarios. See Table A.2. These scenarios include a regression in which only state-fixed variables are used, as well as scenarios where HDD, CDD, DD (the sum of HDD and CDD), disposable income, and energy prices are included in the regression in a variety of combinations. The primary linear model used in the residential sector report is number six (highlighted yellow), which includes the state intercepts, heating degree days, and cooling degree days as model parameters. This model has one of the lowest standard error values (1.58 Mbtu/cap·yr) and a corresponding high R^2 value compared to the alternative models except for the three that also include disposable income and/or prices. The improvements gained by including these other factors were small. See pp. 12-13 in the main body of the report for a discussion of our decision not to use disposable income or price as a predictor in the model.

Table A.2: Standard Error, R-squared, and Adjusted R-squared statistics for several linear models of Residential ECI from 1997-2006.

#	Included Dependent Variables	St. Error (Mbtu/(cap•yr))	R^2	Adj R^2
1	State Fixed Terms Only	2.58	0.95	0.94
2	Time Fixed Terms Only	10.95	0.02	0.00
3	All Fixed Effect Terms ("Fixed Effects" below)	1.93	0.97	0.97
4	Fixed Effects + HDD	1.66	0.98	0.97
5	Fixed Effects + CDD	1.91	0.97	0.97
6	Fixed Effects + HDD + CDD	1.58	0.98	0.98
7	Fixed Effects + DD	1.58	0.98	0.98
8	Fixed Effects + Disp. Inc.	1.90	0.97	0.97
9	Fixed Effects + Price Nat. Gas + Price Elec.	1.90	0.97	0.97
10	Fixed Effects + Disp. Inc. + Price Nat. Gas + Price Elec.	1.87	0.97	0.97
11	Fixed Effects + Disp. Inc. + HDD + CDD	1.54	0.98	0.98
12	Fixed Effects + Price Nat. Gas + Price Elec. + HDD + CDD	1.55	0.98	0.98
13	Fixed Effects + Disp. Inc. + Price Nat. Gas + Price Elec. + HDD + CDD	1.51	0.98	0.98
14	State Fixed Terms + HDD + CDD	2.11	0.97	0.97

Our analysis involved recalculating the regression coefficients for each new test year. That is, a base period from 1975-1984 was used to adjust ECI in 1985, then a new regression over the years 1976-1985 was used to adjust ECI in 1986, and so on. To examine how the regression coefficients change over time, we generated a plot for each coefficient along with its 95% confidence interval over the period from 1984-2006. Figure A.1 shows how HDD and CDD change over the period (see Appendix H for plots of all coefficients including the state intercepts).

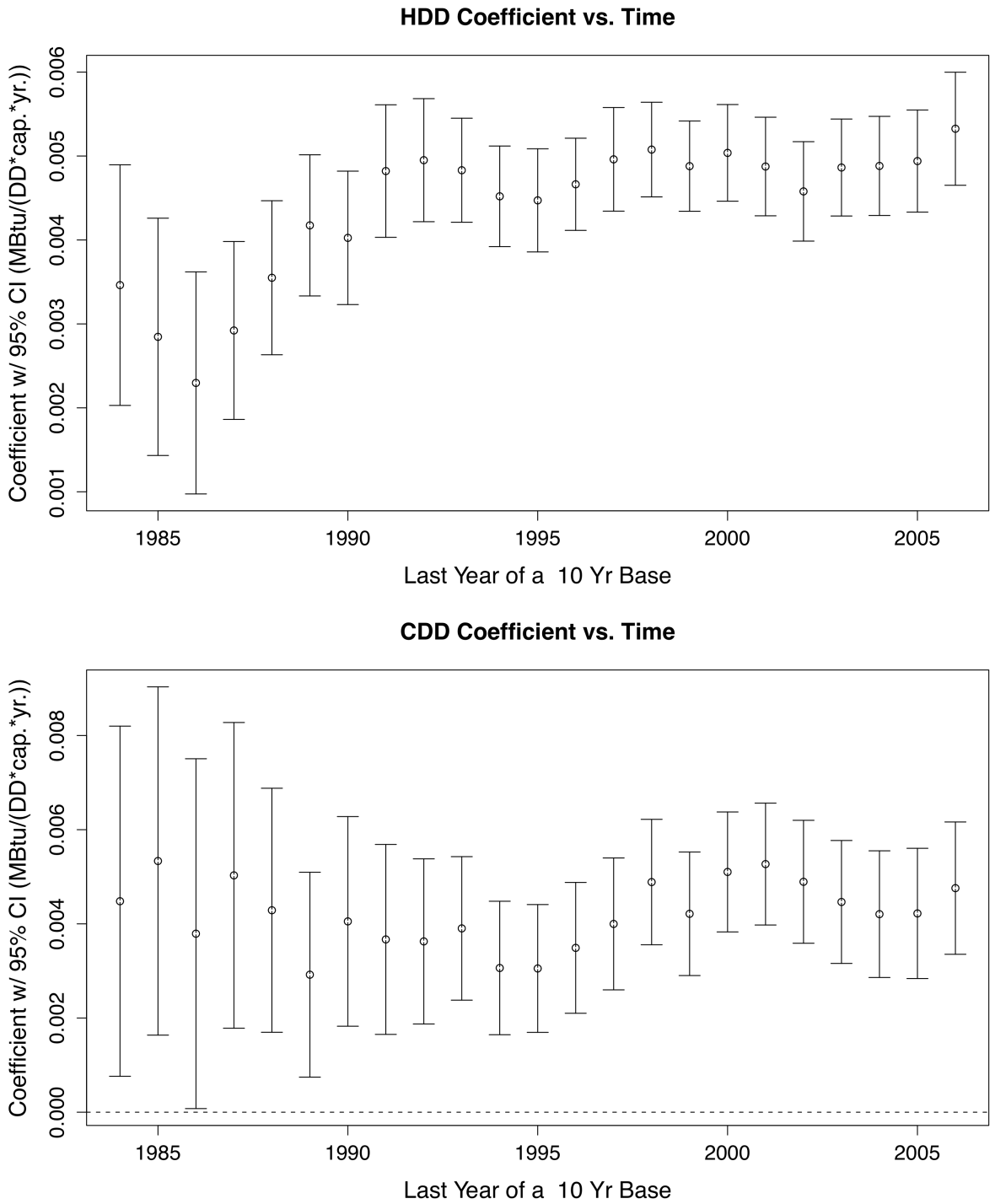

Figure A.1: Regression coefficients with 95% confidence intervals as estimated for each 10-year base period used in our analysis. Note that the vertical axis does not include the origin and so may distort the apparent variation in the coefficient values.

Finally, we investigate the impact that the time-fixed effect terms might have on the value of the HDD and CDD coefficients by producing the same plots of the HDD and CDD coefficient over time when model 14 (see Table A.2 above) is used (Figure A.2). By comparing Figures A.1 and A.2, it is apparent that the fixed effect terms do impact the value of the coefficients. This is a reasonable result as the terms are designed to explain year-to-year variations in energy consumption across all states, which may include national scale climatic events. However, the total result on the ECI adjustment process is relatively minor (Figure A.3). North Dakota has the highest variance of all 50 states in its annual HDD value and a relatively high variance in its CDD value, it therefore represents a worst case scenario for error introduced by biased HDD/CDD coefficients. The differences in adjusted ECI as produced from coefficients determined with model 6 versus model 14 are visible but minor. The largest differences occur in the early to mid 1980's and the differences become almost imperceptible past the turn of the century. This stability makes a strong argument that the inclusion of time fixed effects does not swallow variability that should be associated with climate, however its impact should be revisited if this methodology were applied to future data sets to ensure this remains the case.

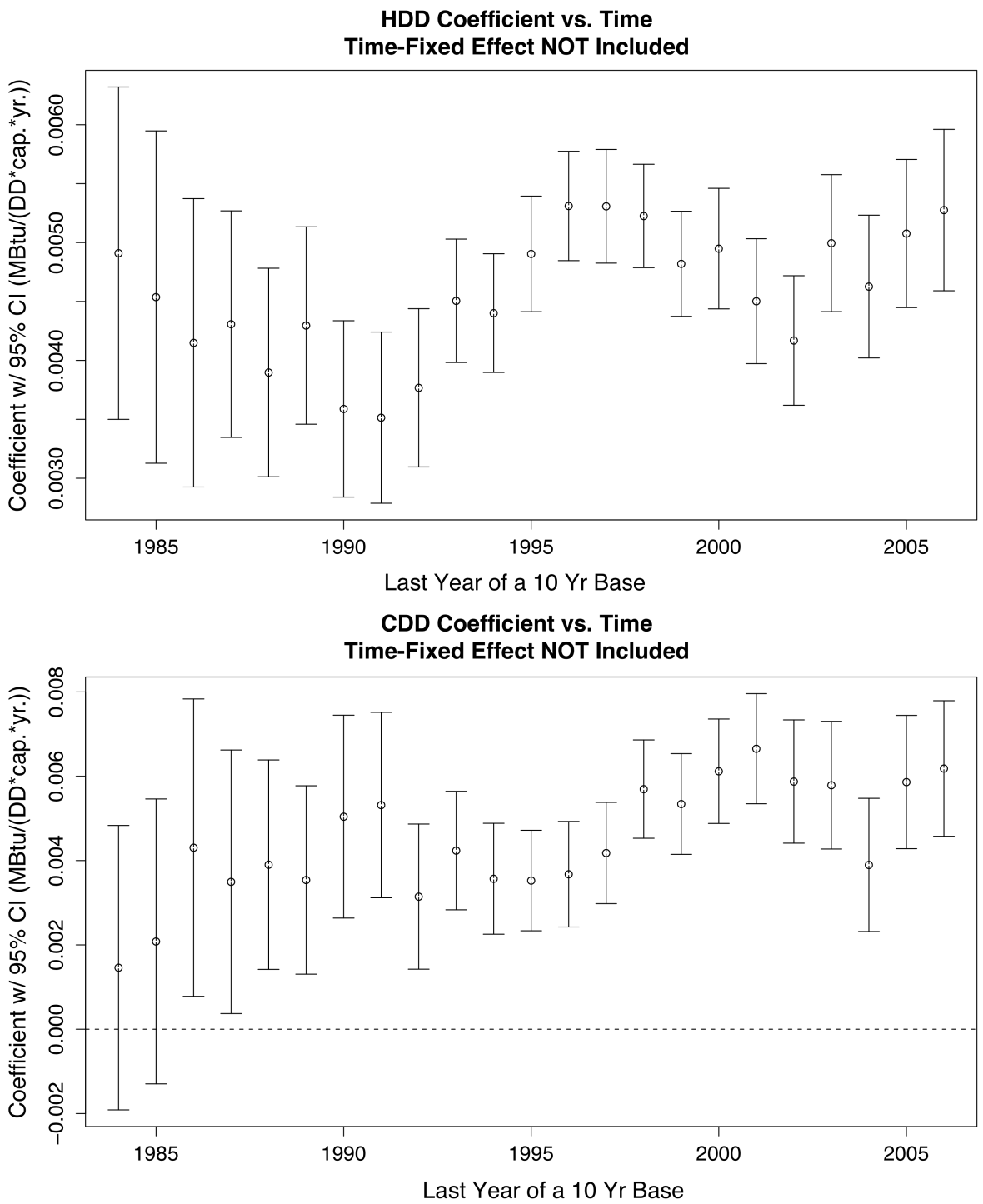

Figure A.2: Regression coefficients with 95% confidence intervals as estimated for each 10-year base period when time-fixed effects are not included in the regression. Note that the vertical axis does not include the origin and so may distort the apparent variation in the coefficient values.

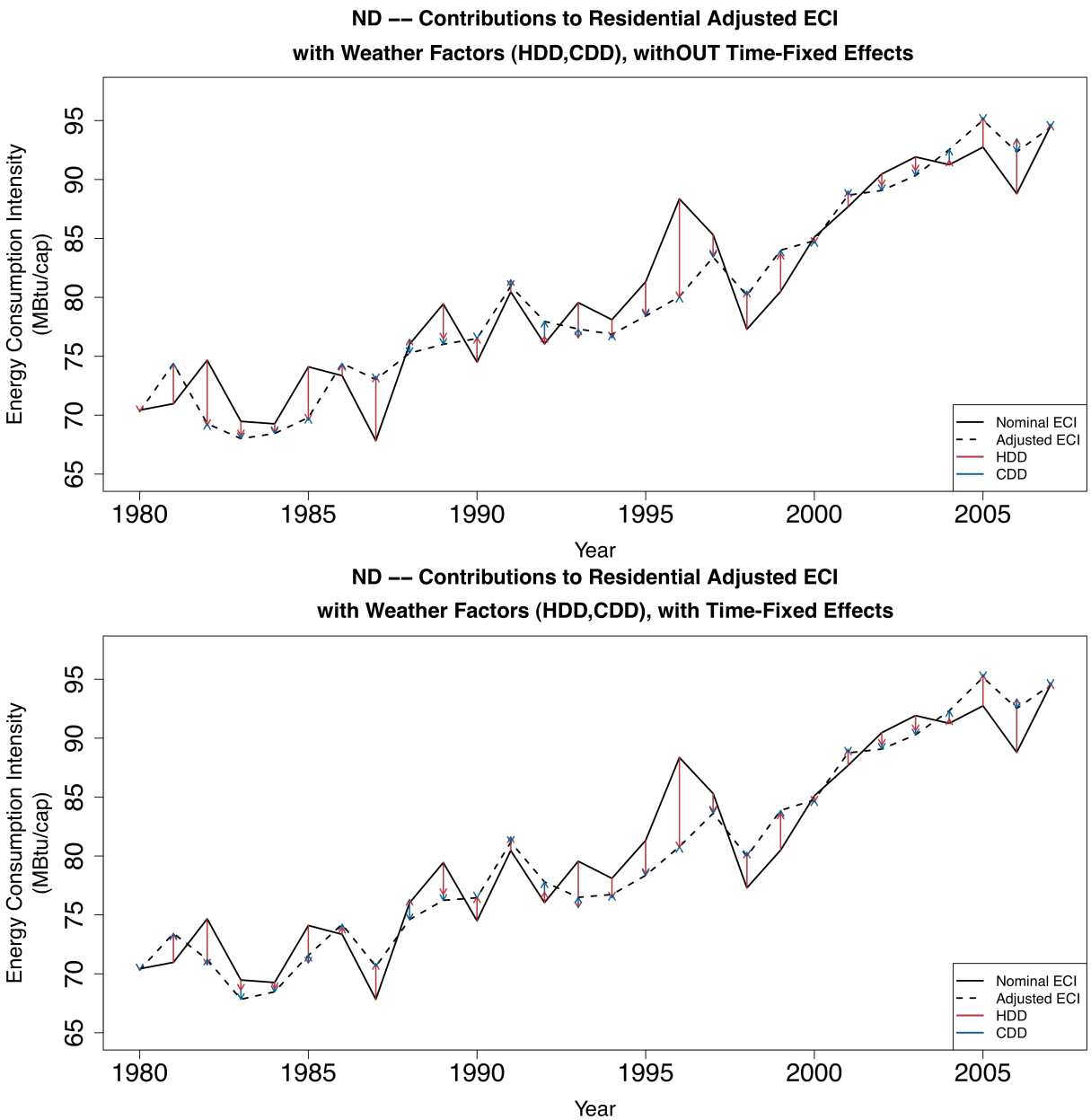

Figure A.3: Nominal and Adjusted ECI based on coefficients for HDD and CDD estimated in a linear model with (top) and without (bottom) time-fixed effect included.

A.2 Inclusion of Disposable Income and Price as Additional Dependent Variables

As noted above, we investigated the effect of including disposable income as well as the price of natural gas and electricity in the analysis. The values of the respective coefficients over time and their respective 95% confidence intervals are plotted in Figures A.4 through A.6. These coefficients were estimated using linear models 11 and 12 respectively from Table A.2.

In addition to the justifications presented on pp. 12-13 for excluding economic and price factors in our adjustment to ECI, there are technical complications associated with using these factors in the proposed methodology. For some of the base periods, the resulting coefficients associated

with disposable income and prices have counter intuitive values. Between 1999 and 2003, the response of ECI to disposable income is negative, as disposable income increases energy consumption per capita decreases. These potentially spurious results suggest that the real relationship between ECI and this economic factor may be confounded by other factors not included in the regressions. Alternatively, conventional wisdom about the response of energy consumption to economic activity may be incorrect over certain periods of recent history.

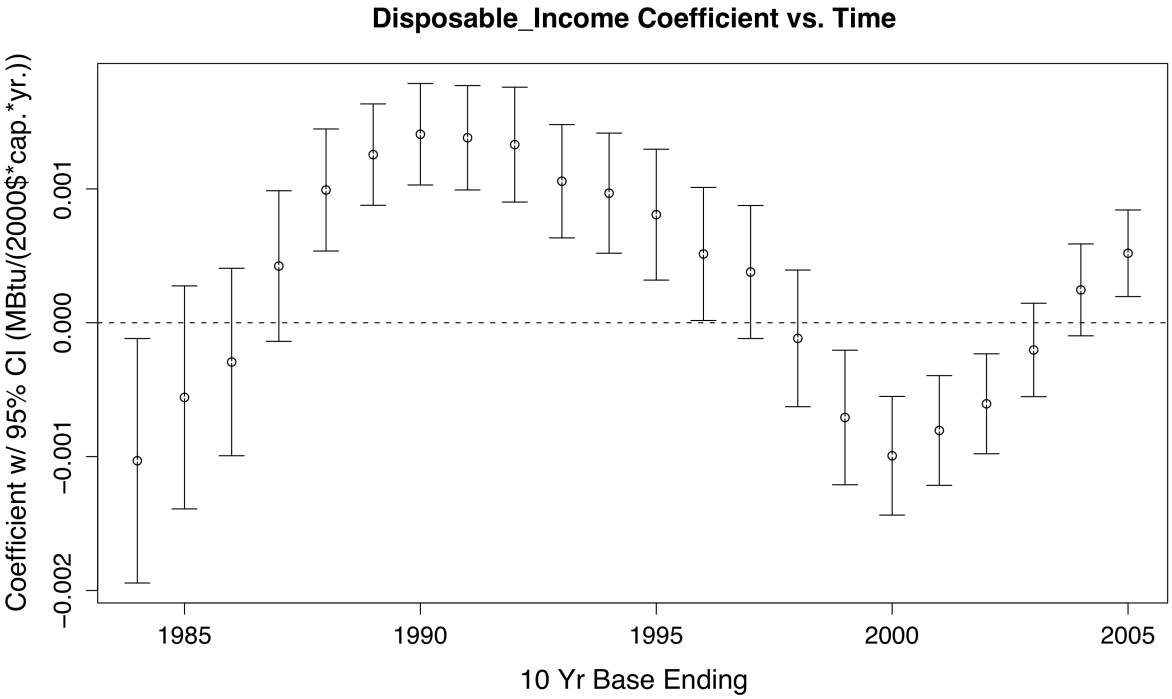

Figure A.4: Disposable Income related regression coefficients with 95% confidence intervals as estimated for each 10-year base period. Linear model 11 from Table A.2 was use to produce these coefficients.

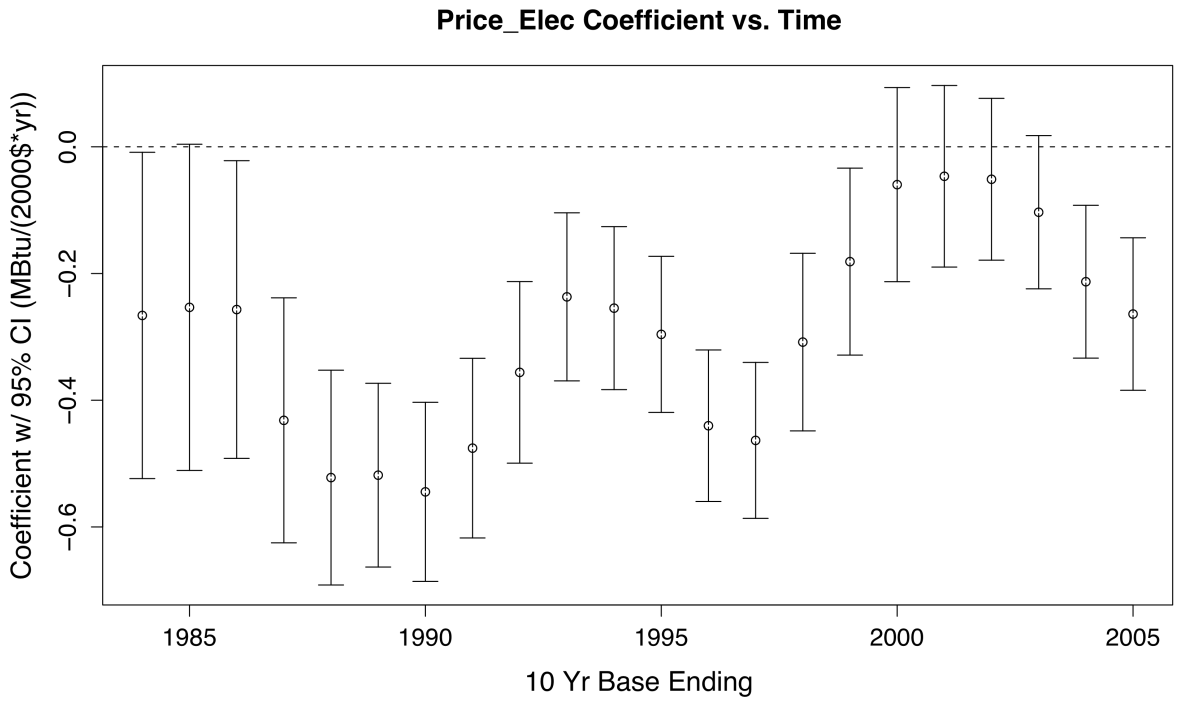

Figure A.5: Price of electricity related regression coefficients with 95% confidence intervals as estimated for each 10-year base period. Linear model 12 from Table A.2 was use to produce these coefficients.

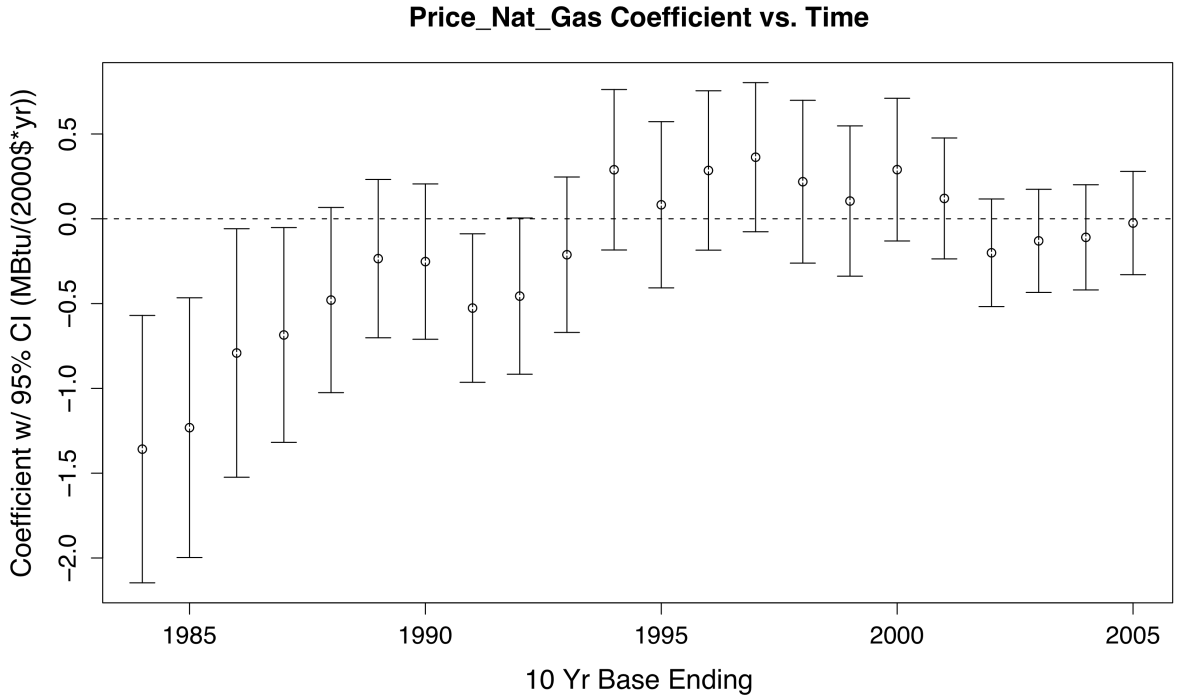

Figure A.6: Price of natural gas related regression coefficients with 95% confidence intervals as estimated for each 10-year base period. Linear model 12 from Table A.2 was use to produce these coefficients.

A.3 Choice of Confidence Level

The methodology presented in this report makes a distinction between a negative 5-year slope of aECI for a state and a *statistically significant* negative slope. The hypothesis test used for this distinction defines a probability, or level of confidence, that a state's negative slope is not just due to random chance. The decision of what probability to use is a matter of policy and risk assessment and a full analysis of the probability of false positive and false negative evaluations is presented in Appendix B. For comparison purposes, the plots in Figure A.7 illustrate the impact of choosing 80% versus 90% confidence intervals on the slope terms for the state of California. The difference is not extreme, but it is enough to toggle the status of some marginal slope values, 1991 for example, between statistically significant and non-significant results.

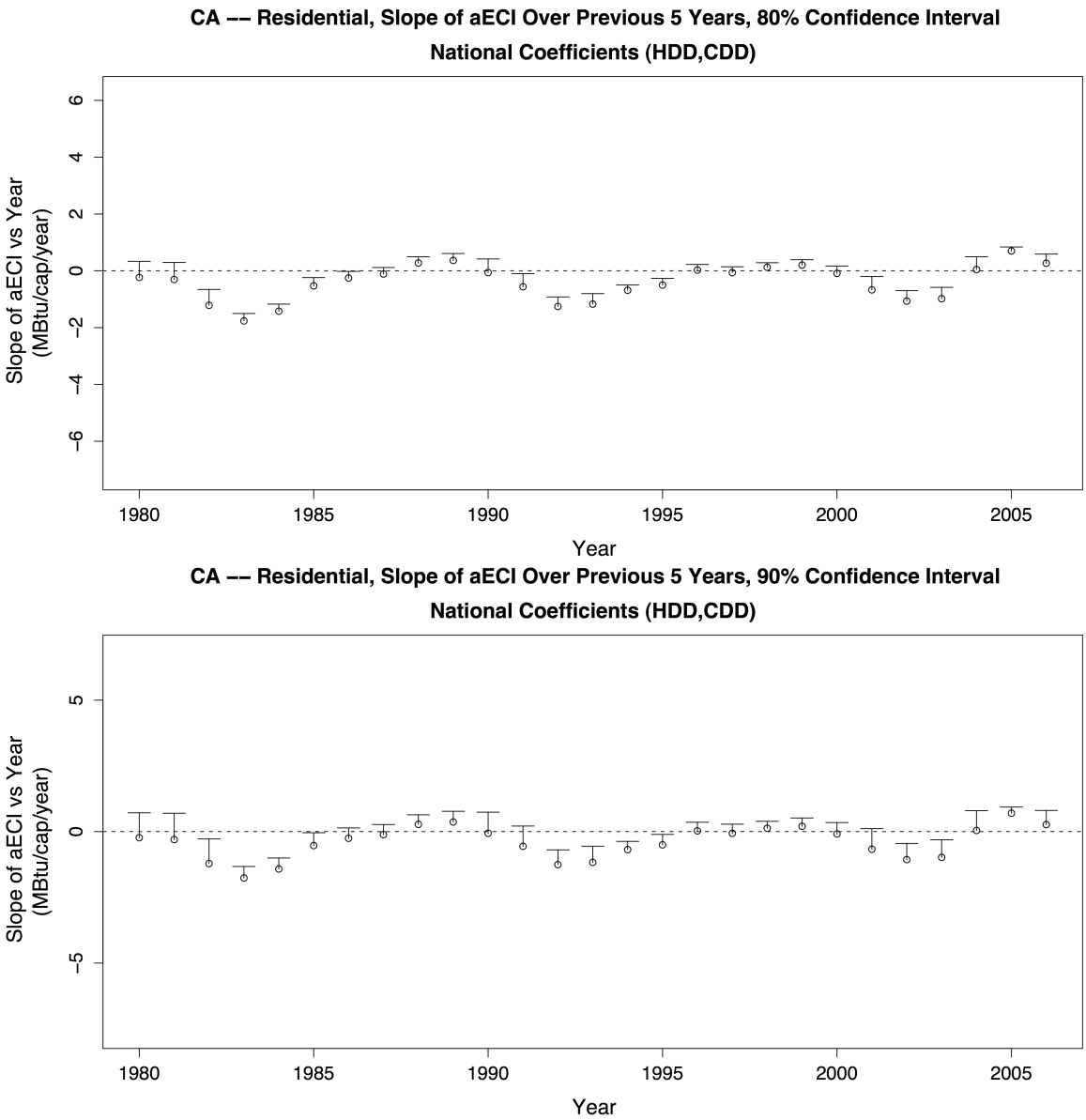

Figure A.7: Five-year slope of aECI versus time for California from 1980-2006 using 80% and 90% one-tailed confidence intervals.

A.4 Explanation of Summary Plots and the Moving Average Heat Rate Methodology

In Figures 2, 3 and Appendix G we present plots for specific states showing their aECI trend over the simulation period as well as the 5-year slope estimate associated with each test year. A close look at these results may confuse the reader because the slope term may not actually match the slope of the 5 years up to and including the test year. For example, the plot of Arizona (Figure A.8.1) has a blue square for the year 2003, signifying a negative 5-year slope of aECI. However, upon visual inspection of that 5-year period, it is obvious that the slope through those points is actually positive.

This discrepancy is due to the fact that we chose to present our results in a simplified form in order to communicate the important concepts about the metric and the methodology. A technically accurate (but more difficult to interpret) version of that plot for AZ is presented in Figure A.8.2. Each five-year period used to estimate a slope is composed of five distinct aECI values. The reason for this is due to the heat rate adjustment made to the raw ECI data from SEDS. As shown in Figure A.8.3, the heat rate is increasing in Arizona from 2002-2007. This increase in heat rate would contribute to a corresponding increase in adjusted ECI over the same period. To avoid rewarding changes in grid mix that lead to lower heat rates (and vice versa), we fix the heat rate in each state for the 5-year period used to generate the ultimate slope estimate. By fixing the heat rate, the changes in raw or adjusted ECI over that period cannot be attributed to changes in the state grid mix. The trend aECI in Arizona for the 1999-2003 test period (indicated by black circles and a black line in Figure A.8.2) is very slightly negative, reflecting the use of a fixed heat rate for that period. For each subsequent 5-year period, a new set of raw and adjusted ECI values are used based upon the state specific average heat rate from the corresponding period.

While more accurate, Figure A.8.2 is much more difficult to interpret due to the large amount of overlapping data. Therefore, we present our results in simplified form in this report and include this explanation of the apparent discrepancies therein.

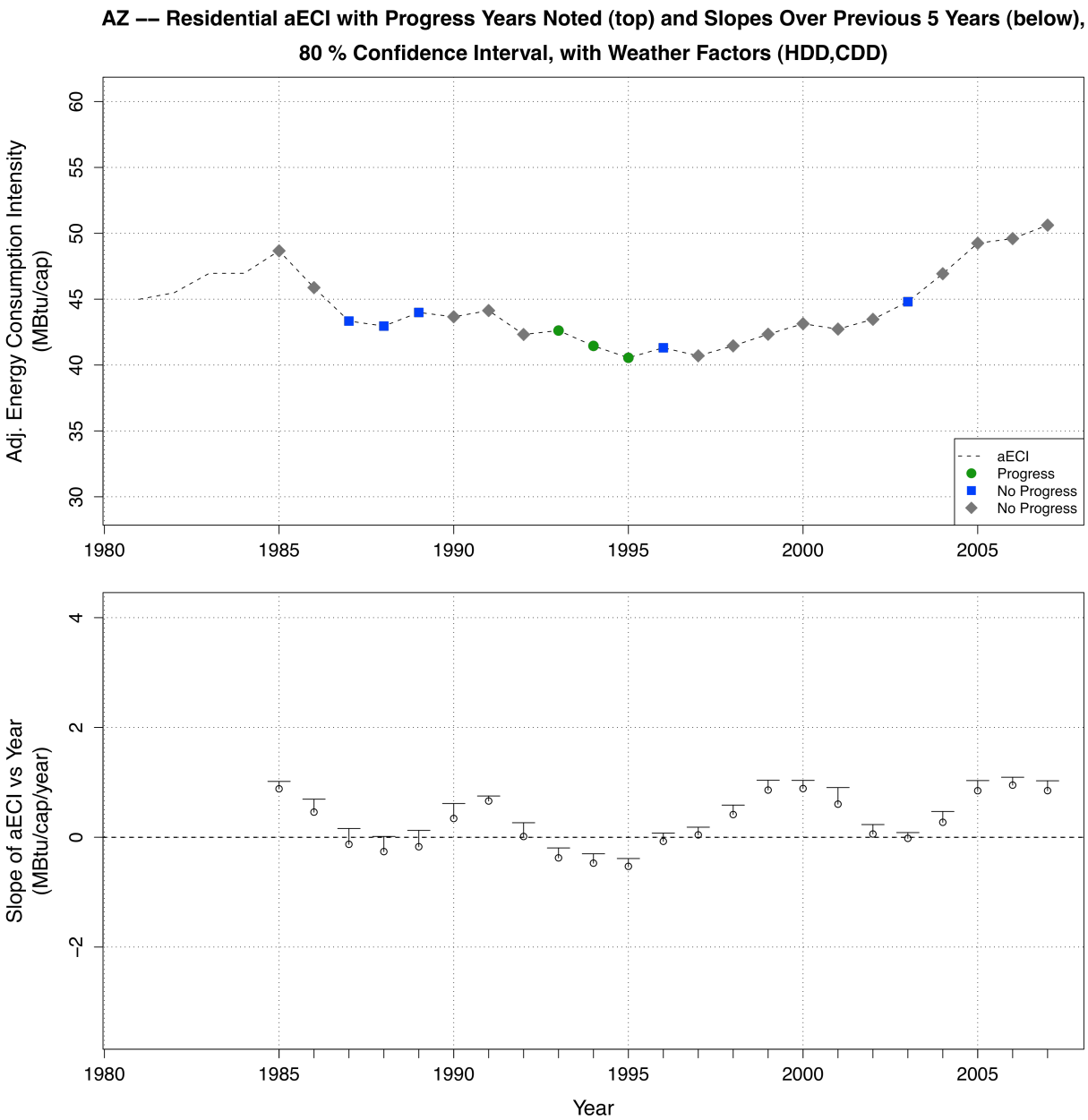

Figure A.8.1: Slope of the adjusted ECI five-year trend line with single-tailed 80% confidence intervals from 1985-2007 for Arizona. Note that a negative slope term is estimated for the test year of 2003 despite the appearance that aECI is actually increasing over that interval. (Continued on next page.)

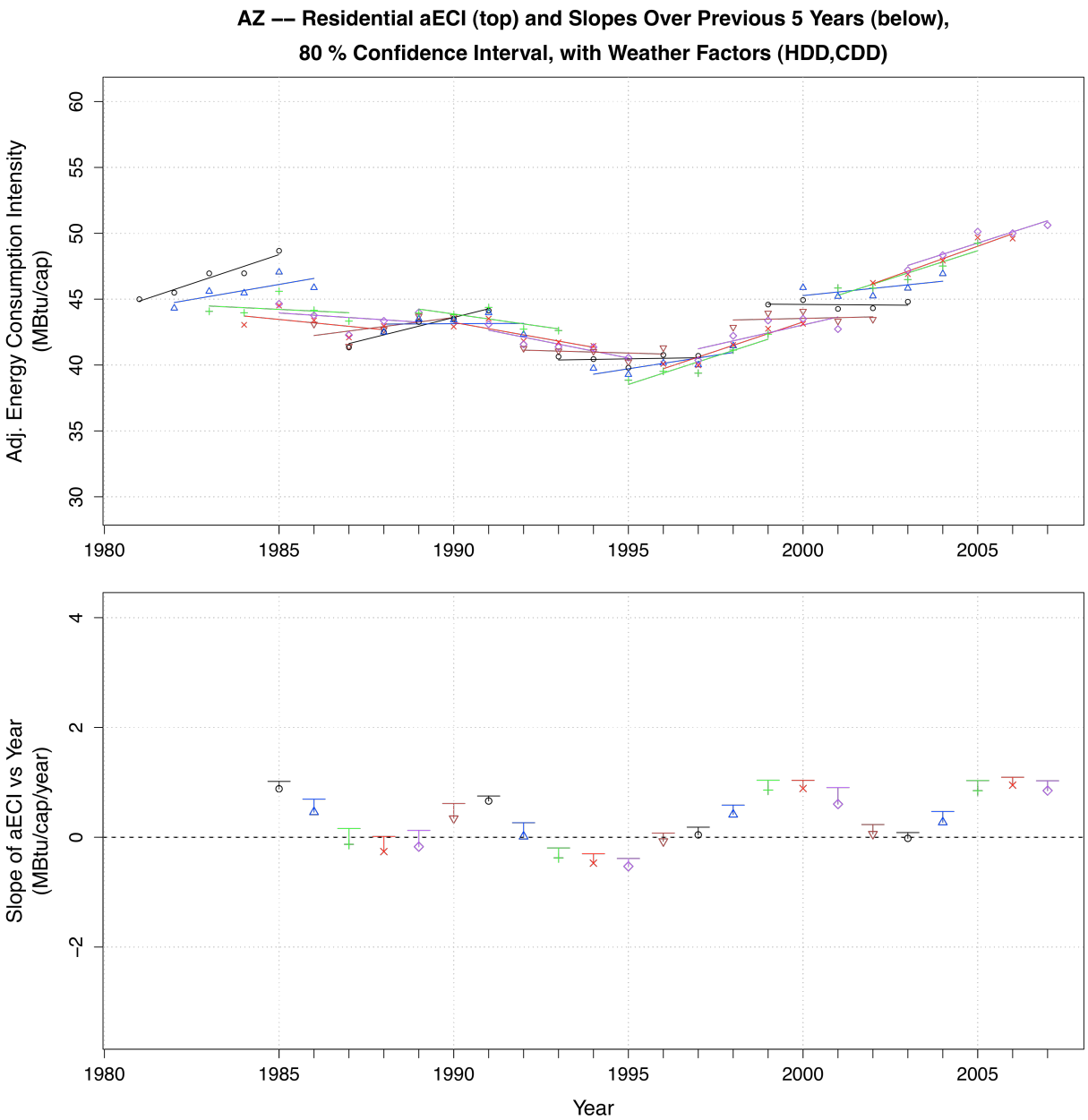

Figure A.8.2: Slope of the adjusted ECI five-year trend line with single-tailed 80% confidence intervals from 1985-2007 for Arizona. The aECI plot (top) distinguishes between the values of aECI used for each 5-year slope estimate. The distinct aECI values are due to the heat rate adjustment made to the raw ECI data from SEDS. To avoid rewarding changes in grid mix that lead to lower heat rates, we fix the heat rate in each state for the 5-year period used to generate the ultimate slope estimate.

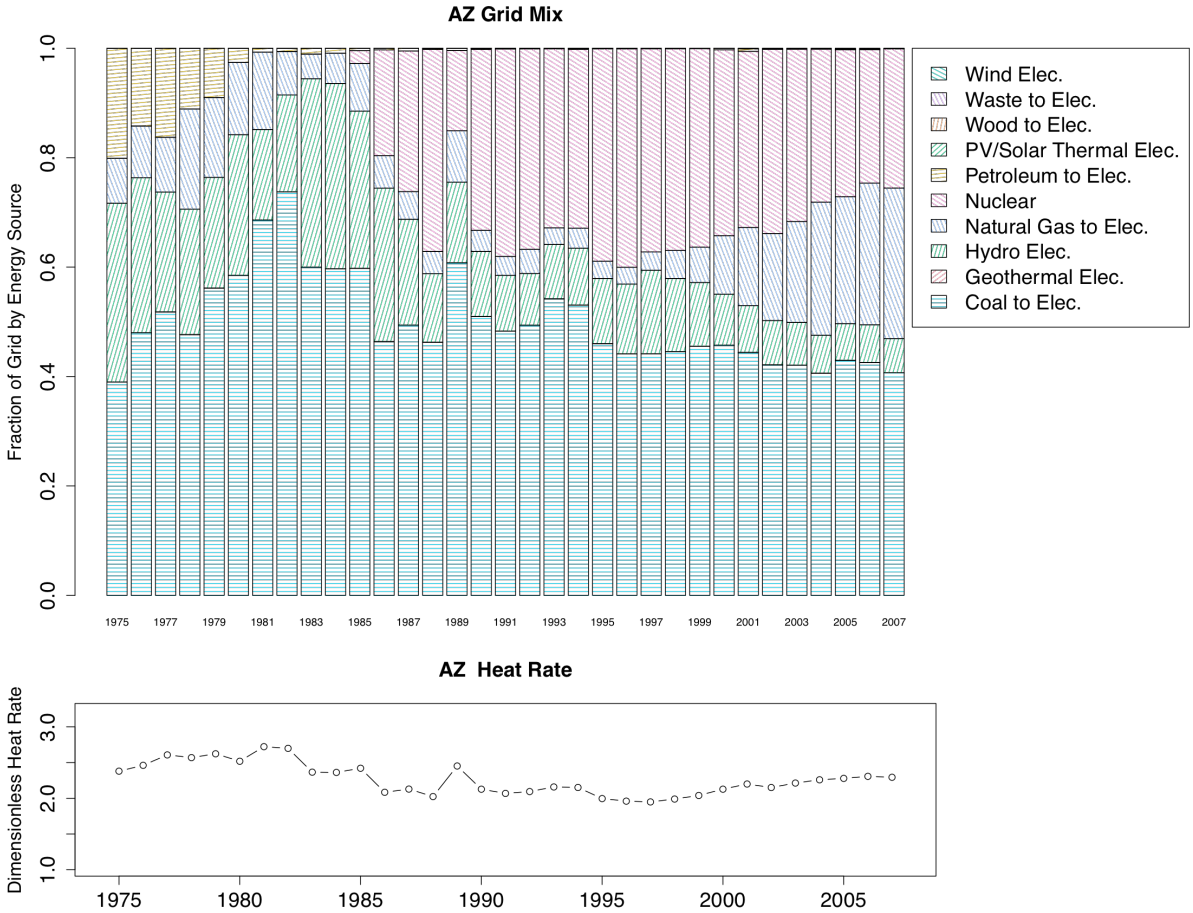

Figure A.8.3: Production based grid mix and associated heat rate from 1975-2007 for Arizona.

A.5 Simulation using 10-year Periods for Slope Estimates

As discussed in the main report, there is a tension between using shorter periods for estimating the slope of aECI over time because they respond more quickly to changes in state policy and the benefit a longer time period provides in consistently noting states that make consistent progress over time. When a longer period of 10 years is used to estimate the slopes, California achieves progress in every year from 1990-2007. See Figure A.9 for plot of indexed aECI (i.e. normalized to 1990 values for each state) for the three top performing states and three of the 23 states that showed no progress. The other top performing states, Illinois, Wisconsin, and Utah also achieve additional progress years compared to using 5-year periods.

The overall distribution of progress years using 10-year slope estimates is presented as a histogram in Figure A.10. While some states achieve progress much more often using this metric, there are many states that no longer achieve progress throughout the entire period compared to a 5-year slope. This is supported by Table A.3, which shows state residential sector rankings from 1990-2007 with respect to slope of aECI over a ten-year period. Using a longer time period is less sensitive to noise and random variation, but it has the drawback of increasing the time lag between effective state policies and the achievement of progress by the metric.

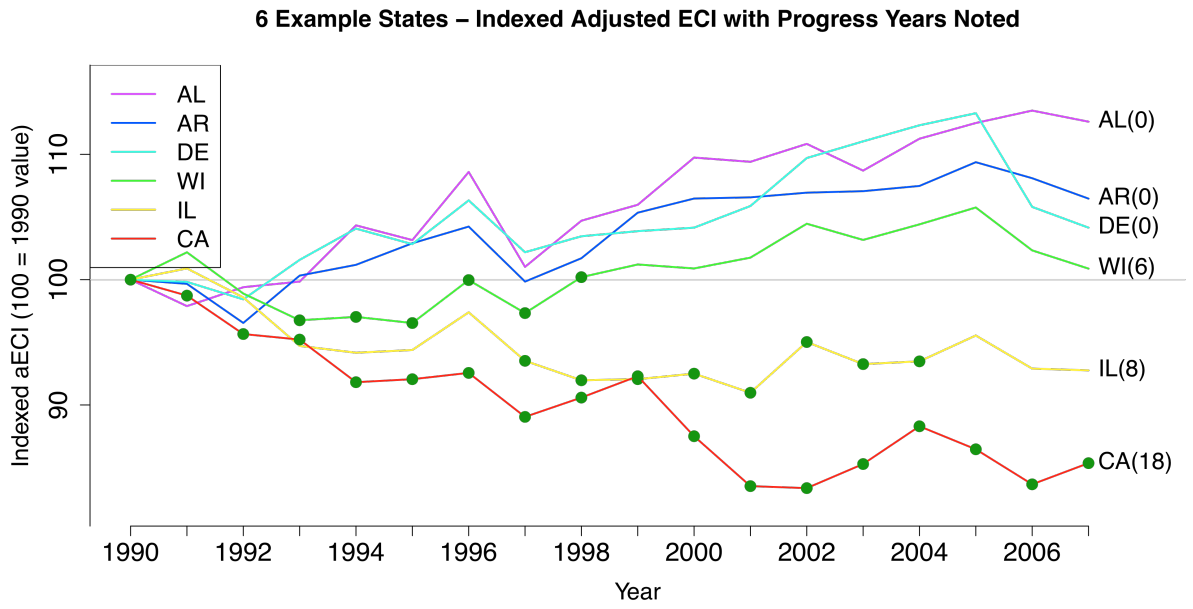

Figure A.9: Indexed aECI trends for 6 states with progress years marked with green circles. Three of the states that achieved the most progress in the simulation were CA, IL, and WI (UT also achieved progress in six years). Three of the states that never achieved progress were AL, AR, and DE (there were 23 other states with no progress achieved). The trends have been normalized to the aECI value in 1990 for each state; 10-year slope estimates and 80% confidence intervals were used to evaluate performance.

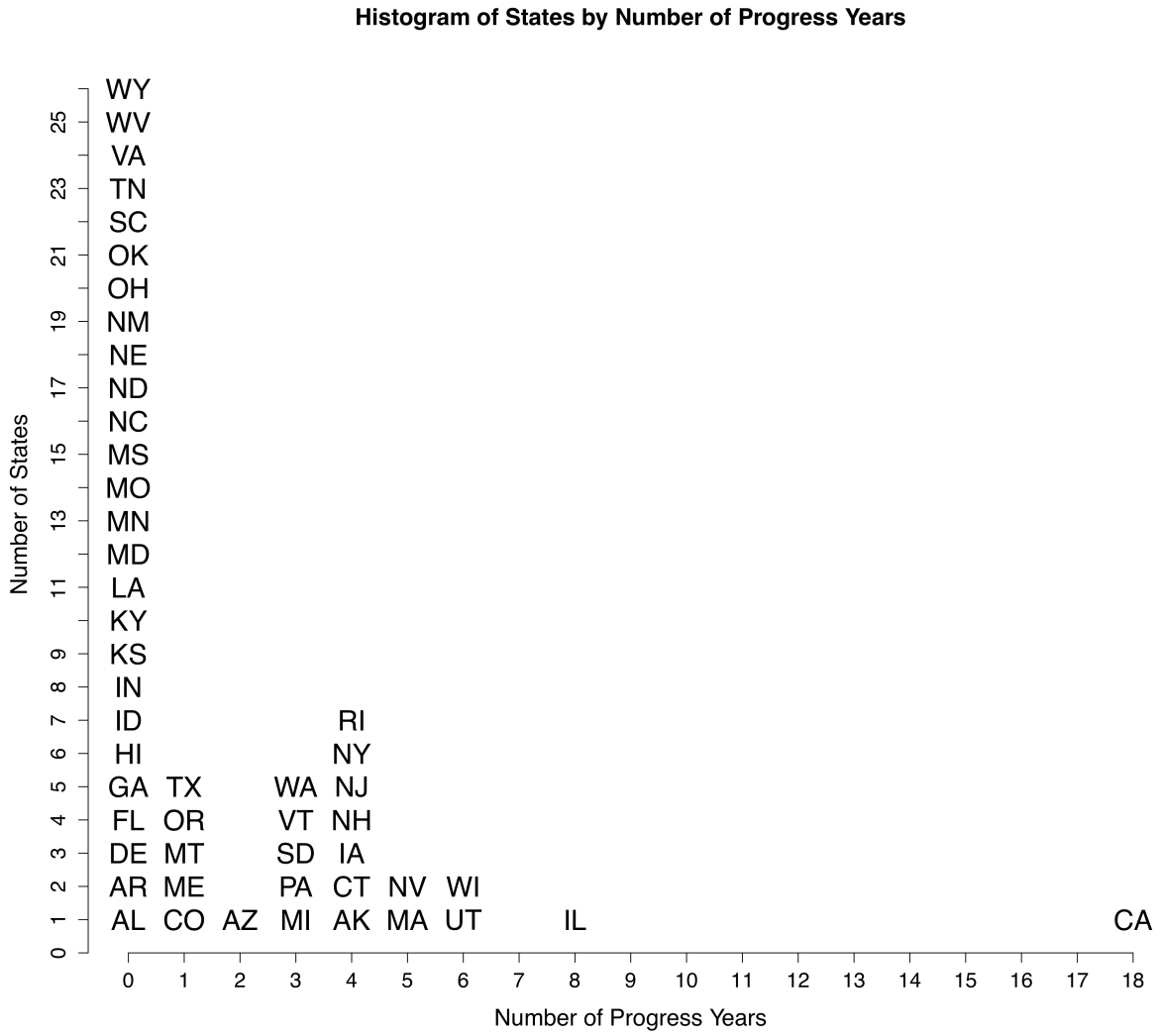

Figure A.10: Histogram of 50 states showing the number of years each state achieved progress in the period from 1990-2007 using 10-year slope estimates and 80% confidence intervals.

Table A.3: State residential sector rankings from 1990-2007 with respect to slope of aECI over the test year and previous four years (10 year period total). Units of the slope coefficient are MBtu/(cap*year2).[13]

	1990		1991		1992		1993		1994		1995		1996		1997		1998		1999		2000		2001		2002		2003		2004		2005		2006		2007		# Incentives	
1	UT	-1.1	UT	-0.8	UT	-1.2	UT	-0.9	UT	-0.8	SD	-0.6	CA	-0.6	CA	-0.6	CT	-0.7	MA	-0.7	AK	-0.6	IL	-0.4	AK	-0.3	CA	-0.3	CA	-0.2	CA	-0.2	WA	-0.2	WA	-0.3	CA	18
2	IA	-1.0	IA	-0.8	IA	-0.5	CA	-0.3	CA	-0.5	CA	-0.6	SD	-0.4	CT	-0.5	MA	-0.7	CT	-0.6	MA	-0.4	AK	-0.4	CA	-0.3	IL	-0.2	IL	-0.2	WA	-0.1	CA	-0.2	CA	-0.2	IL	8
3	CO	-0.4	CA	-0.2	CA	-0.3	WI	-0.3	WI	-0.4	WI	-0.5	NH	-0.4	MA	-0.4	IL	-0.5	VT	-0.5	IL	-0.4	MA	-0.3	IL	-0.2	AK	-0.1	WA	0.1	IL	-0.1	OR	0.0	TX	-0.2	WI	6
4	WA	-0.2	NV	-0.1	WY	-0.1	IA	-0.3	ME	-0.3	UT	-0.4	WI	-0.4	WI	-0.4	CA	-0.5	IL	-0.4	VT	-0.4	CA	-0.2	RI	-0.1	NH	0.0	UT	0.1	UT	0.0	UT	0.0	OR	-0.2	UT	6
5	CA	-0.2	WY	-0.1	WA	0.0	NJ	-0.1	NH	-0.3	NY	-0.4	NY	-0.4	NV	-0.4	NV	-0.3	AK	-0.3	CT	-0.3	RI	-0.2	NH	0.0	RI	0.0	NV	0.1	OR	0.1	TX	0.0	MA	-0.2	NV	5
6	NV	-0.1	CO	-0.1	NV	0.1	NV	0.0	SD	-0.2	NH	-0.3	NV	-0.3	NH	-0.3	SD	-0.3	CA	-0.2	CA	-0.2	CT	-0.2	MD	0.0	VT	0.0	OR	0.2	SD	0.1	IL	0.1	NH	-0.1	MA	5
7	NE	0.1	WA	0.0	AZ	0.1	NY	0.0	NY	-0.2	NJ	-0.3	NJ	-0.3	IL	-0.3	WI	-0.3	PA	-0.2	RI	-0.2	VT	-0.1	NJ	0.0	NJ	0.1	HI	0.2	HI	0.2	NY	0.2	NY	0.0	RI	4
8	MT	0.1	NE	0.1	CO	0.1	MT	0.0	NV	-0.1	NV	-0.3	CT	-0.1	NY	-0.3	PA	-0.2	RI	-0.1	NJ	0.0	NJ	0.0	MA	0.0	MD	0.1	NH	0.2	NH	0.2	MA	0.2	KS	0.1	NY	4
9	ID	0.1	MT	0.1	MT	0.1	NH	0.0	NJ	-0.1	MI	-0.1	MI	-0.1	NJ	-0.3	VT	-0.2	WI	-0.1	MT	0.0	OR	0.1	OR	0.1	NV	0.1	SD	0.2	NV	0.2	HI	0.2	UT	0.1	NJ	4
10	KS	0.2	KS	0.2	NE	0.1	AZ	0.0	MT	-0.1	MT	-0.1	MA	-0.1	SD	-0.2	NJ	-0.2	SD	-0.1	WY	0.0	NV	0.1	NV	0.1	OR	0.1	AK	0.2	NJ	0.2	SD	0.2	MI	0.1	NH	4
11	HI	0.2	AZ	0.2	WI	0.1	NE	0.0	AZ	-0.1	AZ	-0.1	MT	-0.1	MI	-0.2	MI	-0.2	MT	-0.1	WI	0.0	PA	0.1	VT	0.1	WA	0.1	MD	0.2	TX	0.2	NE	0.2	IL	0.1	IA	4
12	WY	0.2	OR	0.3	KS	0.2	DE	0.1	MI	-0.1	OH	-0.1	AZ	-0.1	AZ	-0.2	MT	-0.2	NV	-0.1	PA	0.0	OH	0.1	CT	0.1	HI	0.2	ID	0.2	MD	0.3	NJ	0.2	WI	0.1	CT	4
13	OR	0.3	WI	0.3	OR	0.2	WY	0.1	VA	0.0	VA	-0.1	OH	0.0	PA	-0.1	NH	-0.2	NJ	-0.1	NV	0.1	MD	0.2	MT	0.1	TN	0.3	OH	0.3	ID	0.3	NH	0.3	VT	0.2	AK	4
14	MI	0.3	MI	0.3	NJ	0.2	VA	0.1	IA	0.0	ME	-0.1	WA	0.0	MT	-0.1	AK	-0.1	MI	0.0	OR	0.1	NH	0.2	WA	0.2	UT	0.3	IA	0.3	TN	0.3	MI	0.3	NE	0.2	WA	3
15	AZ	0.3	ID	0.3	NY	0.3	PA	0.1	NM	0.1	NE	0.0	IL	0.0	OH	-0.1	OH	-0.1	WY	0.0	MI	0.1	WY	0.2	PA	0.2	SD	0.3	RI	0.3	KS	0.3	ID	0.3	HI	0.2	VT	3
16	IL	0.3	PA	0.4	VT	0.3	WA	0.1	WA	0.1	WA	0.0	PA	0.0	VT	-0.1	AZ	-0.1	OH	0.0	OH	0.1	MT	0.2	OH	0.2	ID	0.3	KS	0.3	IA	0.3	MD	0.3	RI	0.2	SD	3
17	WI	0.4	HI	0.4	PA	0.3	MI	0.1	WY	0.1	IL	0.0	OR	0.0	OR	0.0	NY	-0.1	AZ	0.0	WA	0.1	HI	0.2	SD	0.3	OH	0.3	VT	0.3	NE	0.3	KS	0.3	MD	0.2	PA	3
18	NM	0.4	NJ	0.4	NM	0.3	NC	0.1	NE	0.1	IA	0.0	MN	0.1	RI	0.0	OR	0.0	NH	0.1	NH	0.2	WA	0.2	HI	0.3	MA	0.3	NJ	0.3	NY	0.3	IA	0.3	MS	0.3	MI	3
19	PA	0.4	NM	0.4	MI	0.3	SD	0.1	OR	0.1	PA	0.0	TX	0.1	TX	0.0	CO	0.0	CO	0.1	SD	0.2	WI	0.2	UT	0.3	MT	0.3	MI	0.4	VT	0.3	NV	0.4	NJ	0.3	AZ	2
20	MN	0.4	NY	0.4	ID	0.3	MD	0.1	PA	0.1	MN	0.0	VA	0.1	WY	0.0	WY	0.0	NY	0.1	AZ	0.2	MI	0.3	WY	0.3	SC	0.3	NC	0.4	OH	0.4	RI	0.4	NC	0.3	TX	1
21	VT	0.4	IL	0.4	MD	0.4	OR	0.1	MN	0.2	NM	0.0	NE	0.1	WA	0.0	TX	0.0	TX	0.1	CO	0.3	SD	0.3	KS	0.3	IA	0.3	SC	0.4	NC	0.4	OH	0.4	SD	0.3	OR	1
22	OK	0.4	MN	0.4	IL	0.4	IL	0.2	KS	0.2	OR	0.0	NM	0.1	CO	0.1	RI	0.0	OR	0.1	MN	0.3	IN	0.4	SC	0.4	NC	0.4	AR	0.4	MI	0.4	WI	0.4	AR	0.3	MT	1
23	IN	0.4	OK	0.5	NH	0.5	KS	0.2	NC	0.2	WY	0.0	UT	0.1	NM	0.1	WA	0.1	MN	0.2	NE	0.3	TN	0.4	VA	0.4	PA	0.4	TN	0.4	RI	0.4	NC	0.4	ID	0.3	ME	1
24	NJ	0.4	AK	0.5	SC	0.5	SC	0.2	OH	0.2	NC	0.1	RI	0.1	VA	0.1	IN	0.1	MD	0.2	IN	0.3	AZ	0.4	NC	0.4	KS	0.4	TX	0.4	MA	0.4	LA	0.4	IA	0.3	CO	1
25	MO	0.5	IN	0.5	VA	0.5	NM	0.2	IL	0.2	KS	0.1	WY	0.2	MN	0.1	NM	0.1	TN	0.2	MD	0.3	MN	0.4	IN	0.4	VA	0.4	NE	0.4	SC	0.4	IN	0.4	ME	0.3	WY	0
26	NY	0.6	MO	0.6	MO	0.5	MN	0.2	DE	0.2	CT	0.1	IA	0.2	IN	0.1	MN	0.1	WA	0.2	TN	0.3	UT	0.4	AZ	0.4	MN	0.4	NY	0.5	LA	0.4	AR	0.5	LA	0.3	WV	0
27	AK	0.6	MD	0.6	OK	0.5	CO	0.2	CO	0.2	ID	0.2	DE	0.2	KS	0.1	TN	0.2	OK	0.2	HI	0.3	DE	0.4	ID	0.4	ME	0.4	KY	0.5	AR	0.5	SC	0.5	GA	0.4	VA	0
28	ND	0.6	VT	0.6	NC	0.5	TN	0.3	RI	0.2	SC	0.2	IN	0.2	DE	0.1	UT	0.2	IN	0.3	TX	0.4	GA	0.4	GA	0.4	AR	0.4	IN	0.5	WI	0.5	TN	0.5	PA	0.4	TN	0
29	AR	0.6	SC	0.6	MN	0.5	VT	0.3	SC	0.2	MD	0.2	KS	0.2	NE	0.1	VA	0.2	NE	0.3	KS	0.4	VA	0.4	IA	0.4	WI	0.4	MT	0.5	OK	0.5	MS	0.5	SC	0.4	SC	0
30	LA	0.7	TN	0.7	RI	0.6	ME	0.3	MD	0.3	TX	0.2	NC	0.2	MD	0.2	KS	0.2	GA	0.3	UT	0.4	IA	0.5	MN	0.4	MI	0.4	OK	0.5	IN	0.5	PA	0.5	TN	0.4	OK	0
31	TN	0.8	AR	0.7	HI	0.6	RI	0.3	ID	0.3	MA	0.2	CO	0.3	TN	0.2	NE	0.2	VA	0.3	DE	0.4	KS	0.5	MI	0.4	IN	0.5	WI	0.5	GA	0.5	GA	0.5	OH	0.4	OH	0
32	MD	0.8	VA	0.8	SD	0.6	ID	0.4	TX	0.4	RI	0.2	MD	0.3	IA	0.2	MD	0.2	NM	0.3	IA	0.4	SC	0.5	WI	0.4	AZ	0.5	MN	0.5	MS	0.5	VT	0.5	NV	0.4	NM	0
33	WV	0.8	AL	0.8	AK	0.6	TX	0.5	GA	0.4	IN	0.2	SC	0.3	UT	0.2	DE	0.3	KS	0.4	FL	0.5	NC	0.5	AR	0.4	WY	0.5	AZ	0.5	AK	0.5	MN	0.6	OK	0.4	NE	0
34	OH	0.9	NC	0.8	IN	0.6	OH	0.5	IN	0.4	CO	0.2	ID	0.3	NC	0.2	FL	0.3	FL	0.4	MO	0.5	FL	0.5	TN	0.5	GA	0.5	GA	0.5	AL	0.5	AZ	0.6	MN	0.4	ND	0
35	MS	0.9	RI	0.8	AR	0.7	GA	0.5	VT	0.5	GA	0.3	GA	0.4	SC	0.3	ID	0.3	UT	0.4	NY	0.5	TX	0.5	DE	0.5	KY	0.5	MA	0.5	AZ	0.5	NM	0.6	AL	0.4	NC	0
36	SD	0.9	LA	0.8	TN	0.7	AL	0.5	FL	0.5	TN	0.3	VT	0.4	FL	0.3	SC	0.3	AR	0.4	SC	0.5	ID	0.5	ME	0.5	CT	0.5	VA	0.5	MO	0.5	KY	0.6	FL	0.4	MS	0
37	SC	0.9	MS	0.8	GA	0.7	IN	0.5	ND	0.5	DE	0.3	FL	0.4	GA	0.3	IA	0.3	HI	0.4	VA	0.5	KY	0.5	KY	0.5	NE	0.5	MO	0.5	MN	0.6	MO	0.6	IN	0.5	MO	0
38	CT	0.9	GA	0.8	DE	0.7	MO	0.5	MO	0.6	ND	0.3	TN	0.4	ID	0.3	GA	0.3	IA	0.4	KY	0.5	AR	0.5	FL	0.6	NY	0.5	LA	0.6	PA	0.6	OK	0.6	DE	0.5	MN	0
39	AL	1.0	SD	0.8	AL	0.8	AK	0.5	AL	0.6	AL	0.4	HI	0.4	OK	0.4	AR	0.4	DE	0.4	AR	0.5	CO	0.5	OK	0.6	DE	0.6	WY	0.6	KY	0.6	VA	0.6	NM	0.5	MD	0
40	KY	1.0	OH	0.9	MA	0.8	FL	0.6	MA	0.6	FL	0.4	ME	0.4	HI	0.4	HI	0.4	ID	0.4	NC	0.5	NE	0.6	NY	0.6	MO	0.6	ME	0.6	VA	0.6	FL	0.6	AZ	0.5	LA	0
41	TX	1.1	MA	0.9	OH	0.8	MS	0.6	HI	0.6	MO	0.4	ND	0.5	AL	0.4	NC	0.4	SC	0.4	GA	0.5	NY	0.6	NE	0.6	AL	0.6	PA	0.6	FL	0.6	AL	0.7	MO	0.5	KY	0
42	GA	1.1	WV	0.9	MS	0.9	LA	0.6	TN	0.6	HI	0.5	AL	0.5	AR	0.5	OK	0.4	NC	0.5	ID	0.6	OK	0.7	TX	0.6	FL	0.6	FL	0.6	MT	0.6	AK	0.7	KY	0.6	KS	0
43	FL	1.1	NH	1.0	LA	0.9	OK	0.6	AK	0.7	MS	0.5	MO	0.6	MS	0.5	AL	0.4	MO	0.5	NM	0.6	LA	0.7	MO	0.6	OK	0.6	AL	0.6	NM	0.6	CO	0.7	CT	0.6	IN	0
44	NH	1.1	FL	1.0	FL	0.9	HI	0.7	MS	0.7	LA	0.6	MS	0.6	AK	0.5	MS	0.5	MS	0.5	OK	0.7	MO	0.7	CO	0.7	TX	0.6	CO	0.7	CO	0.8	DE	0.8	VA	0.6	ID	0
45	NC	1.1	KY	1.1	TX	0.9	MA	0.7	CT	0.7	VT	0.7	LA	0.7	MO	0.5	KY	0.5	AL	0.6	AL	0.8	AL	0.8	LA	0.7	LA	0.7	NM	0.7	WY	0.8	MT	0.8	CO	0.6	HI	0
46	MA	1.1	TX	1.1	ME	0.9	AR	0.7	LA	0.7	OK	0.7	AR	0.7	ME	0.6	MO	0.5	KY	0.6	MS	0.8	NM	0.8	AL	0.8	WV	0.8	MS	0.7	ME	0.8	ME	0.9	AK	0.7	GA	0
47	VA	1.2	CT	1.1	KY	1.1	KY	0.8	OK	0.8	AR	0.7	OK	0.7	KY	0.6	ND	0.6	LA	0.6	WV	0.8	WV	0.9	WV	0.8	CO	0.8	DE	0.8	DE	0.9	CT	0.9	MT	1.1	FL	0
48	ME	1.2	ND	1.1	WV	1.2	ND	0.9	AR	0.8	KY	0.7	AK	0.7	ND	0.6	LA	0.6	ND	0.7	LA	0.9	MS	0.9	NM	0.9	NM	0.8	CT	1.0	CT	1.0	WY	1.1	WV	1.2	DE	0
49	RI	1.2	ME	1.3	ND	1.2	CT	1.1	KY	0.8	AK	1.0	KY	0.8	LA	0.6	WV	0.8	WV	0.8	ND	0.9	ME	1.2	MS	1.0	MS	0.8	WV	1.1	WV	1.1	WV	1.2	WY	1.2	AR	0
50	DE	2.1	DE	1.5	CT	1.4	WV	1.1	WV	1.1	WV	1.0	WV	1.1	WV	0.9	ME	1.3	ME	1.5	ME	1.4	ND	1.4	ND	1.6	ND	1.6	ND	1.6	ND	1.6	ND	1.4	ND	1.5	AL	0

[13] Yellow shadings indicate years in which the slope is negative with 80% confidence using a single-tailed confidence interval. Cells shaded in grey have a negative slope, but the confidence interval includes zero. Unshaded cells have positive slopes.

Appendix B - Sample Size Selection and Limits on Detecting Improvements in aECI

1) Problem Statement: We wish to test for possible reduction in aECI by estimating the slope (i.e., the rate of change) of the aECI values for the n most recent years. This test can be posed as a conventional hypothesis test on the population mean slope. The null hypothesis is that there has been no improvement so the slope is zero or positive:

$$H_o: \mu_b = \mu_{Ho} \geq 0$$

where μ_b = population mean slope for the aECI values
μ_{Ho} = population mean slope according to the null hypothesis

The alternative hypothesis is that there has been improvement so the slope is negative:

$$H_a: \mu_b = \mu_{Ha} < 0$$

where μ_{Ha} = population mean slope according to the alternative hypothesis

Although we are using a single-sided hypothesis test instead of using a confidence interval, the resulting decisions about detecting or not detecting improvement would be equivalent.

2) Test Method: We can test the null hypothesis to determine if it is plausible by comparing the estimated slope to the null hypothesis relative to the estimated standard error of the slope:

$$t\{\alpha,(n-2)\} = \frac{\mu_{Ho} - \hat{b}}{s_{\hat{b}}}$$

where $t\{\alpha,(n-2)\}$ = Student's t value for the α significance level and n-2 degrees of freedom.
α = significance level = risk of Type I error (false positive)
df = degrees of freedom = n -2
$\hat{b}$ = estimated slope of the n aECI values
$s_{\hat{b}}$ = standard error of the estimated slope

If we limit the risk of Type I error (α) to 20%, then we can solve for the critical value of the slope that serves as the threshold for detection of statistically significant improvements in aECI:

$$\hat{b}^* = \mu_{Ho} - t\{\alpha,(n-2)\} \cdot s_{\hat{b}}$$

where $\hat{b}^*$ = critical value of the slope
= detection threshold

$$s_{\hat{b}} = s_e \cdot \frac{1}{\sqrt{n-1} \cdot s_x}$$

s_e = standard deviation of regression residuals
s_x = standard deviation of independent variable in the regression

Since, in the regression used to estimate the slope, the independent variable, x, is the year (or quarter), s_x only depends on the number of years (or quarters) used to estimate the slope.

Note that the critical slope or threshold is below the population mean slope according to the null hypothesis (i.e., zero) by an amount that depends on the significance level (i.e., α or risk of Type I error), the variability of the residuals (i.e., the standard deviation s_e), and the sample size (i.e., the number of years or quarters of data).

So if

$$\hat{b} < \hat{b}*$$

then improvement has been detected. But if

$$\hat{b} \geq \hat{b}*$$

then improvement has <u>not</u> been detected. This threshold is illustrated in Figure 1. The blue curve represents the expected distribution of the estimated slopes, assuming that the null hypothesis is correct, i.e., there has been no improvement. The threshold is shown as a black line. The blue area represents the risk of Type I error – detecting improvement where there has been no real improvement.

Now if the null hypothesis is incorrect and the alternative hypothesis is correct, there has been real improvement. How likely is it that the improvement will be detected? That is the question that statistical power answers. How likely is it that the real improvement will not be detected? That is the risk of Type II error – false negatives. Statistical power is the complement of the risk of Type II error:

Statistical Power = 1 - β

where β = risk of Type II error

If the alternative hypothesis is correct, then the population slope is less than zero. Let us assume that the population mean slope is μ_{Ha}. In Figure 1, the red curve represents the expected distribution of the estimated slopes, assuming that the alternative hypothesis is correct, i.e., there has been improvement. The red area represents the risk of Type II error.

We can compute the statistical power (1-β) from:

$$t\{(1-\beta),(n-2)\} = \frac{\mu_{Ha} - \hat{b}*}{\left(\frac{s_e}{\sqrt{n-1} \cdot s_x}\right)}$$

and can also determine the risk of Type II error (β) from:

$$t\{\beta,(n-2)\} = \frac{\hat{b}^* - \mu_{Ha}}{\left(\frac{s_e}{\sqrt{n-1}\cdot s_x}\right)}$$

If we replace $\hat{b}^*$ by its equivalent from above, then:

$$t\{\beta,(n-2)\} = \frac{\mu_{Ho} - \mu_{Ha}}{\left(\frac{s_e}{\sqrt{n-1}\cdot s_x}\right)} - t\{\alpha,(n-2)\}$$

From t{β,(n-2)}, we can obtain β, and from β, we can find the power, 1- β. Note that β, the risk of a false negative, depends on the amount of improvement we want to be able to detect (i.e., μHa - μHo) relative to the standard deviation of the residuals (i.e., s_e), the risk of false positives (i.e., α), and the samples size (i.e., n), which also determines s_x.

3) Illustrative Examples: Using national coefficients for HDD and CDD only, the standard deviation of the regression residuals for each state for the period 1970 to 2005, about 95% of the standard deviations of residuals range from 0.3 to 3.0 MBtu/cap/yr. For a few states in a few years, the standard deviations are larger with the highest being less than 10 MBtu/cap/yr. In the examples here, we have used the mean standard deviation of 1.6 MBtu/cap/yr.

A) Annual aECI Values: In the first set of examples, we will assume that annual values of the aECI are available to estimate the rate of change in the aECI (i.e., the slope). We will consider values of (μHa-μHo) (i.e., the rate of change we want to be able to detect) from 0.01 to 1.0 (Mbtu/cap/yr)/yr. The risk of Type I error, the risk of false positives, is fixed at 20%.

Table 1 shows how power varies with (μHa-μHo) and sample size. Not surprisingly, as either sample size increases, the power (i.e., the chance of successfully detecting an improvement) also increases. For n = 5 years and (μHa-μHo) = 0.25 (Mbtu/cap/yr)/yr, the power is only 33.1%. That makes the risk of Type II error 66.9%, so that the odds of detecting a real improvement of that magnitude is about 1:2. For a value of (μHa-μHo) = 0.50 and n = 5 years, the power increases to 50.4%, so there is a 50:50 chance of detecting a real improvement of that magnitude.

Figure 2 presents the results from Table 1. The power increases as magnitude of the real improvement increases and as the sample size increases. It is possible to detect an increase of 0.5 (MBtu/cap/yr)/yr with powers of 26%, 50%, 75%, and 96% for sample sizes of 3, 5, 7, and 10, respectively.

B) Quarterly aECI Values: In this set of examples, we will assume that quarterly values of the aECI are available for 2 to 5 years so that n might range from 8 to 20. We will consider

values of (μHa-μHo) from 0.01 to 1.0 (Mbtu/cap/yr)/yr. The risk of Type I error, the risk of false positives remains fixed at 20%.

Table 2 shows how power varies with (μHa-μHo) and sample size. As above, as either sample size increases, the power (i.e., the chance of successfully detecting an improvement) also increases. For n = 8 quarters and (μHa-μHo) = 0.1 (Mbtu/cap/yr)/yr, which is much lower than in the example for annual data, the power is only 25.5%. That makes the risk of Type II error 74.5%, so that the odds of detecting a real improvement of that magnitude is about 1:3. For a value of (μHa-μHo) = 0.1 and n = 20 quarters, the power increases to 75.5%, the odds have reversed so there is now a 3:1 chance of detecting a real improvement of that magnitude.

Figure 3 presents the results from Table 2. The power increases as magnitude of the real improvement increases and as the sample size increases. It is possible to detect an increase of 0.1 (MBtu/cap/yr)/yr with powers of 25.5%, 41.6%, 58.7%, and 75.5% for sample sizes of 8, 12, 16, and 20 quarters, respectively.

4) Comments: There is clearly a large increase in the chance of detecting a real improvement in going from annual to quarterly values. It is also true that it is unlikely that we would be able to detect very small improvements even using quarterly data and small sample sizes such as 8 quarters. The fewer the number of data points used to estimate the slope, the less likely it is that small to modest rates of improvement can be successfully detected.

   For cases with greater scatter in the regression residuals, the estimates of power provided here would be too high.

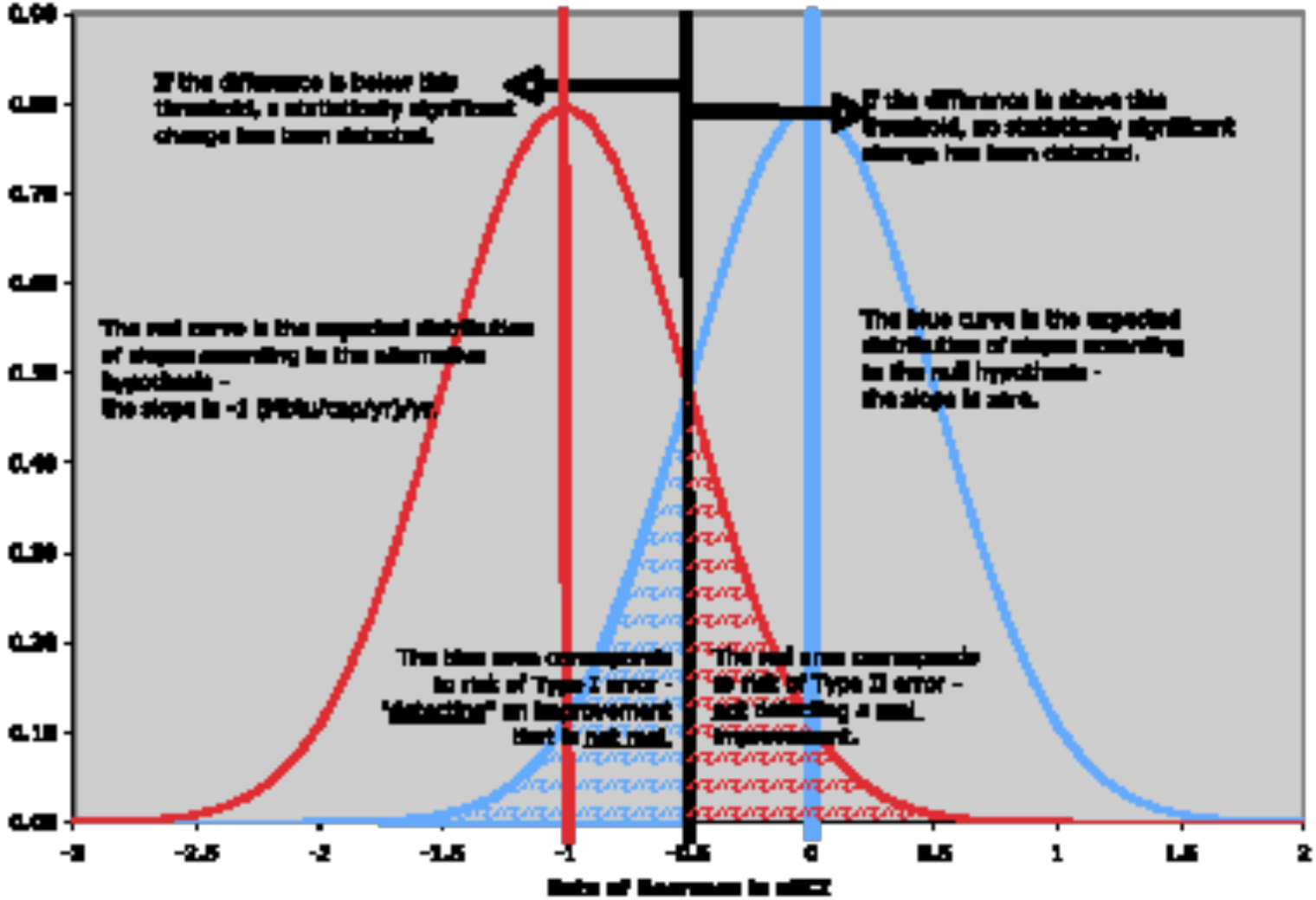

Figure 1. Hypothesis Testing to Detect Improvements in aECI

Table 1. Probability of Successfully Detecting an Improvement of from 0.01 to 1.00 (MBtu/cap/yr)/yr, α = 20%, and Samples Sizes of 2, 3, 5, and 10 Years

(μho-μha) [(Mbtu/cap/yr)/yr]	n=3	n=5	n=7	n=10
0.01	20.1%	20.4%	20.8%	21.5%
0.10	21.0%	24.6%	29.1%	37.8%
0.20	22.1%	30.0%	40.3%	59.4%
0.30	23.3%	36.3%	52.8%	78.0%
0.40	24.6%	43.1%	64.8%	89.8%
0.50	26.1%	50.4%	75.2%	95.6%
0.60	27.6%	57.6%	83.2%	98.2%
0.70	29.4%	64.4%	88.9%	99.2%
0.80	31.2%	70.5%	92.8%	99.7%
0.90	33.2%	75.9%	95.3%	99.9%
1.00	35.4%	80.4%	96.9%	99.9%

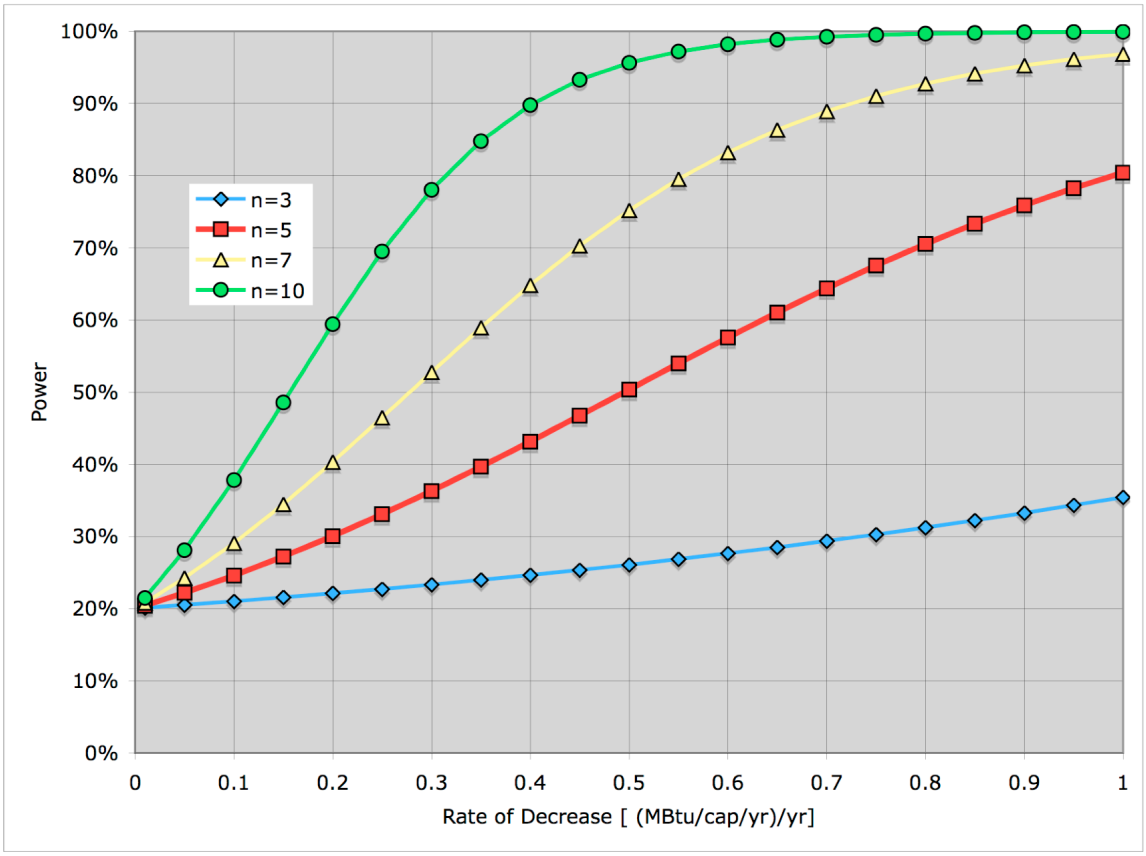

Figure 2. Power vs. Sample Size and Rate of Decrease in aECI for Annual Data

Table 2. Probability of Successfully Detecting an Improvement of from 0.01 to 1.00 (MBtu/cap/yr)/yr, α = 20%, and Samples Sizes of 8, 12, 16, and 20 Quarters

(μho-μha) [(Mbtu/cap/yr)/yr]	n=8	n=12	n=16	n=20
0.01	20.5%	21.6%	22.9%	24.4%
0.10	25.5%	41.6%	58.7%	75.5%
0.20	33.6%	67.9%	88.8%	97.6%
0.30	44.9%	85.2%	97.4%	99.8%
0.40	57.6%	93.1%	99.3%	100.0%
0.50	68.3%	96.5%	99.8%	100.0%
0.60	75.8%	98.0%	99.9%	100.0%
0.70	80.9%	98.8%	100.0%	100.0%
0.80	84.3%	99.2%	100.0%	100.0%
0.90	86.8%	99.5%	100.0%	100.0%
1.00	88.6%	99.6%	100.0%	100.0%

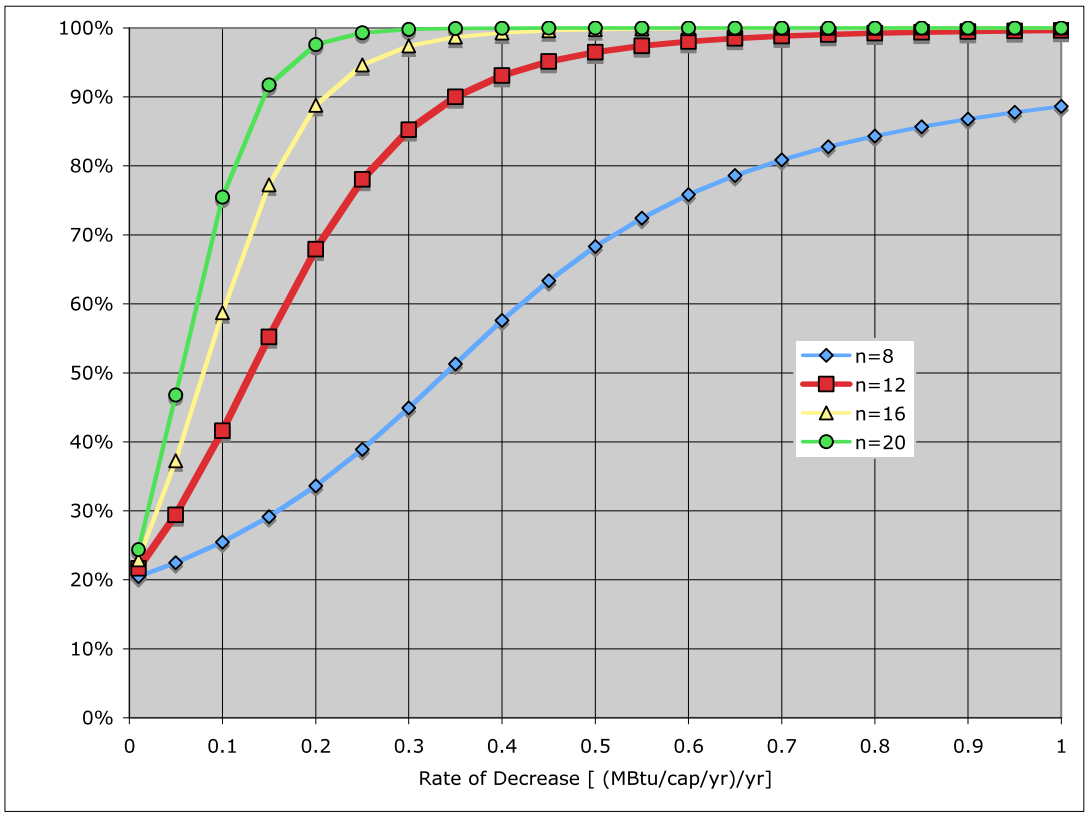

Figure 3. Power vs. Sample Size and Rate of Decrease in aECI for Quarterly Data

Appendix C - Calculation of Heat Rates in SEDS and by the Revised Method

Current SEDS Heat Rate Methodology

The State Energy Data System (SEDS) reports the electricity sales to the residential sector in terms of MkWh (10^6 kWh) and converts these to BBtus (10^9 Btus) using the unit conversion of 3.412 BBtu/MkWh. To account for the primary energy associated with these electricity sales, SEDS calculates a "Losses" term (LORCB). To determine the value of LORCB for each state, SEDS first calculates a total electricity losses term for the US (LOTCBUS) by subtracting the total electricity sales (ESTCBUS) from the total energy consumed by the electric power sector (TEEIBUS):

$$\text{LOTCBUS} = \text{TEEIBUS} - \text{ESTCBUS}$$

The total energy term (TEEIBUS) is calculated after applying a high heat rate to renewables, nuclear and geothermal energy. Electricity generated from renewable sources (hydroelectric, wind and solar) is converted from its physical units of kWh to units of Btu by multiplying by heat rates ranging between 10,760 Btu – 9,884 Btu per kWh, depending on the year. These rates are based on the fossil-fuel steam-electric power plant conversion factor (FFETKUS), which is an average heat rate of all fossil fuel steam-electric power plants in the US. The heat rate can be considered comparable to a measure of the efficiency of fossil fuel steam-electric power plants. A similar process is done with nuclear and geothermal generation using the national average nuclear steam-electric power plant heat rate (NUETKUS) and the national average geothermal steam-electric power plant heat rate (GEETKUS).

After determining the total electricity losses (LOTCBUS), the losses for just the lower 48 states (LOTCB48) are calculated by subtracting the losses for Alaska and Hawaii:

$$\text{LOTCB48} = \text{LOTCBUS} - (\text{LOTCBAK} + \text{LOTCBHI})$$

In addition to accounting for the primary energy associated with the electricity sales, the calculation attempts to account for the likelihood of interstate sales of electricity throughout the lower 48 states by calculating a "losses to sales ratio" (ELLSS48) for the lower 48 states:

$$\text{ELLSS48} = \frac{\text{LOTCB48}}{\text{ESTCB48}} = \frac{\text{TEEIB48} - \text{ESTCB48}}{\text{ESTCB48}} = \frac{\text{TEEIB48}}{\text{ESTCB}} - 1$$

The value of ELLSS48 ranges from 2.15 to 2.47 over the period from 1960 to 2007. This national "losses to sales ratio" is then used to calculate the losses associated with electricity in each state for each sector by simply multiplying the ratio by the electricity sales to that sector in that state. For the residential sector, the electricity losses associated with electricity sales to the residential sector (LORCBZZ) are equal to the electricity sales to the residential sector (ESRCBZZ) multiplied by the "losses to sales" ratio (ELLSS48):

$$\text{LORCBZZ} = \text{ESRCBZZ} * \text{ELLSS48}$$

Finally, when calculating the total energy used by the residential sector (TERCB), SEDS adds the energy use in BBtus from all sources of energy, along with energy in the form of electricity sales (ESRCB) and the losses associated with the electricity (LORCB):

TERCB = CLRCB + NGRCB + PARCB + WDRCB + GERCB + SORCB + ESRCB + LORCB

Total Res. Energy = Coal + Natural Gas + Petroleum Products + Wood + Geothermal + Solar + Electricity Sales + Electricity Loses

In summary, because the electricity sales and the losses are accounted for separately, the total energy associated with electricity is essentially calculated by multiplying the electricity sales by a factor between 3.47 and 3.15 (ELLSS48 + 1), depending on the year. This factor is the same for all states, regardless of their production or consumption grid mix, and includes large heat rates applied to renewables, geothermal and nuclear electricity production.

Revised Heat Rate Methodology

We propose that these high heat rates on renewables, hydropower, and nuclear electricity should not be incorporated into the calculation of primary energy associated with electricity use. Additionally we propose that an overall heat rate should be calculated for each state based on the state's electricity grid mix. To recalculate the total primary energy for the residential sector, using state specific heat rates, we used the following methodology.

The first step in determining a state specific heat rate is to determine the grid mix of the residential electricity use. Because residential electricity sales are represented by a single term and not divided according to generation source, the grid mix is based on the state's generation grid mix for all sectors rather than the consumption grid mix. Our definition of the grid mix is therefore the percentage of the state's total electricity generation contributed by each generation source.

Quantities of fuel used for total electricity generation are reported in SEDS in physical units (short tons, cubic feet, million kWh,etc.). These quantities are then converted to BBtu using the conversion factors listed in SEDS. This number now represents the total primary energy associated with each electricity generation source. The primary energy used for each generation source is then divided by an appropriate heat rate to determine the electricity generated (in GWh) by each generation source. The national average fossil fuel steam-electric power plant heat rate (FFETKUS) is applied to natural gas, coal and petroleum products, while no heat rate (only the 3.412 BBtu/GWh unit conversion) is applied to renewables, geothermal, and nuclear generation. In our current analysis, the amount of electricity generated in GWh is again multiplied by 3.412 to determine the equivalent energy in BBtu. Using coal and hydroelectric as examples, where CLEIP is the physical amount of coal used by the electric power industry in short tons, CLEIK is the conversion factor from short tons to BBtu and HYEGP is the electricity generated using hydropower in GWh:

BBtu of electricity generated using coal = ((CLEIP * CLEIK)/FFETKUS)*3.412

BBtu of electricity generated using hydroelectric power = ((HYEGP*3.412)/3.412)*3.412
= HYEGP*3.412

The values of BBtu of electricity generated for each generation type are summed to determine the total BBtu of electricity generated by the electric power industry. The value of BBtu of electricity generated by each generation type is then divided by the total electricity generated to determine the grid mix percentage for each generation type. These percentages are then used to create a weighted average heat rate for the state. Each percentage of a generation source is multiplied by its associated heat rate (again, these are FFETKUS for fossil fuel sources and 3.412 for renewable and nuclear). These terms are then summed to determine the average heat rate for the state:

State-specific heat rate = %Coal*FFETKUS +%Natural Gas*FFETKUS + %Petroleum*FFETKUS +%Hydro*3.412 + %Wind*3.412 + %Solar*3.412 + %Geothermal*3.412 + %Nuclear*3.412

This heat rate is then divided by 3.412 BBtu/MkWh to create a dimensionless heat rate for the state. The dimensionless heat rate determined for Washington ranged from 1.00 – 1.46 over the period from 1960 to 2007. These values can be compared to the dimensionless "heat rate" used by SEDS (ELLSS48+1), which ranged from 3.15 – 3.47 over the same period.

Once a heat rate is established, this heat rate can be multiplied by the electricity sales to the residential sector (ESRCB) to determine the primary energy associated with the electricity consumption in the residential sector. Because this method no longer accounts for transmission and distribution losses, an estimate of these losses is added to the primary energy term.

Primary Energy for Residential Electricity = ESRCB*State-specific heat rate + T&D losses

To then calculate the total energy used by the residential sector, the electricity sales (ESRCB) and electricity losses (LORCB) are subtracted from the total energy term (TERCB) reported in the SEDS database and the new value of primary energy associated with electricity use is added. To determine the per capita energy use, this value is divided by the population reported by the Census in the SEDS database.

Revised Total Energy = TERCB – ESRCB – LORCB + Revised Primary Energy for Residential Electricity

The Revised Total Energy per capita can then be used in the established analysis to create an aECI and track progress for the state.

Appendix D – Estimation of Population Weighted Degree Days for Hawaii and Alaska

The population weighted degree day data used in the analysis presented in this report came from the National Climatic Data Center (NCDC), a data publishing arm of the National Oceanographic and Atmospheric Administration (NOAA). While NCDC provides up-to-date, population weighted, heating and cooling degree day data for the continental U.S., it does not provide these data for the states of Hawaii and Alaska[14]. These data do exist for HI and AK as published by the National Weather Service Climate Prediction Center[15], however, the period of record extends back only to 1998. Our analysis requires data back to 1975.

For the period from 1975-1997, our team chose to generate population weighted degree day data based on monthly measurements of degree days at weather stations in larges cities throughout Hawaii and Alaska. We downloaded monthly heating and cooling degree day data from an online weather almanac service called the Weather Underground[16] for the 15 weather stations listed in Table D.1 over the period from 1960-2009. The choice of these stations was based on population size and availability of data.

Table D.1: Weather stations used to estimate population degree day data for Hawaii and Alaska.

Weather Station	City	2000 Population (% of total state population)[17]
PHNL	Honolulu, HI	371,657 (30.7%)
PHTO	Hilo, HI	40,759 (3.4%)
PHNG	Kaneohe, HI	34,970 (2.9%)
PHHI	Waipaku, HI	33,108 (2.7%)
PHOG	Kahului, HI	20,146 (1.7%)
PAMR	Anchorage, AK	278,700 (44.5%)
PAFB	Fairbanks, AK	31,142 (5.0%)
PAJN	Juneau, AK	30,737 (4.9%)
PASI	Sitka, AK	8,920 (1.4%)
PAEN	Kenai, AK	7,533 (1.2%)
PAKT	Katchitkan, AK	7,446 (1.2%)
PAAQ	Palmer, AK	7,443 (1.2%)
PADQ	Kodiak, AK	6,259 (1.0%)
PABE	Bethel, AK	6,356 (1.0%)
PAHO	Homer, AK	5,524 (0.9%)

[14] NCDC, 2010. http://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp#
[15] National Weather Service Climate Prediction Center, 2010. http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/cdus/degree_days/.
[16] Weather Underground, wunderground.com, 2010. Example page view containing degree day data: http://www.wunderground.com/history/airport/PHNL/2005/01/01/MonthlyHistory.html?req_city=NA&req_state=NA&req_statename=NA.
[17] U.S. Department of Commerce, Bureau of the Census, 2010.

The following steps were taken to estimate the annual degree day data for HI and AK:

- All stations were missing Weather Underground data from March and April of 2000. These missing values were replaced with the mean March and April estimates from all remaining years in the data set.

- For each year from 1960-2009, the population weighted mean of the summed degree days were calculated. However, if a station was missing data for that year, the following adjustment was employed: estimate the average deviation from the 30 year norms of the remaining cities and apply that fraction to the 30 year average of the complete data. As a formula:

  DD_yr_state_incomplete = DD_30yr_state_complete * Mean_remaining_cities((DD_yr_city - DD_30yr_city) / DD_30yr_city)

  Where DD_yr_state_incomplete is the estimated annual DD value for the year missing data, DD_30yr_state_complete is the 30 year normal DD value for the whole state using only years where no data are missing, Mean_remaining_cities is the average over all of the cities/stations in the given year that are not missing data, DD_yr_city is the DD value from a city for the given year, and DD_30yr_city is the 30 year normal DD value for that city.

- The resulting annual population weighted degree day values are biased due to the fact that the weather stations used in the estimate do not adequately cover the geographic extent of the state populations. In order to adjust for this bias, the data are correlated to the National Weather Service (NWS) estimates and this relationship is used to correct the Weather Underground (WU) estimates.

- For Alaska, over the concurrent years between the reference (WU) and target (NWS) data sets (1998-2009), perform a simple linear regression with the NWS value as the dependent variable and the WU value as the predictor. Use the period of record from the WU to predict the degree day values from 1960-1997. See table D.2 for a listing of the regression results.

Table D.2: Simple linear regression statistics when modeling HDD in AK. Data from the National Weather Service served as the dependent variable and data from the Weather Underground served as the independent variable.

Model	Intercept (p-value) units: DD	Slope (p-value) units: DD/DD	Adjusted R-Squared
AK – HDD	3055 (0.0068)	0.7581 (1.01e-5)	0.8847
AK – CDD	6.41 (0.0047)	1.585 (1.55e-5)	0.8732

- For Hawaii, the annual population weighted HDD in Hawaii is zero every year from 1998-2009 according to the NWS. While the WU data set yields some non-zero years, the highest of all had a value of 20 HDD and most of the remaining non-zero years were less than 10 HDD. We chose to accept the NWS data set as appropriate and assume that

Hawaii always has 0 HDD each year. For CDD, there was a large difference in variance in the NWS time series and the WU data set. Under these circumstances, basing a prediction off of a simple linear regression can lead to a substantial underestimation of the variance in the predicted values. To avoid this pitfall, the variance ratio method[18] was used, the method employs a linear model that ensures that the variance of the predicted data set is equal to the variance of the target data set.

The resulting HDD and CDD values for AK and HI are shown in Figures D.1 through D.4.

[18] Rogers, A. L., J. W. Rogers, and J. F. Manwell. 2005a. Comparison of the performance of four measure-correlate-predict algorithms. Journal of Wind Engineering and Industrial Aerodynamics, 93:243–264.

Figure D.1: Annual population weighted heating degree day values for Alaska from the National Weather Service (red, 1998-2009) and as estimated by SERC (black, 1960-1997).

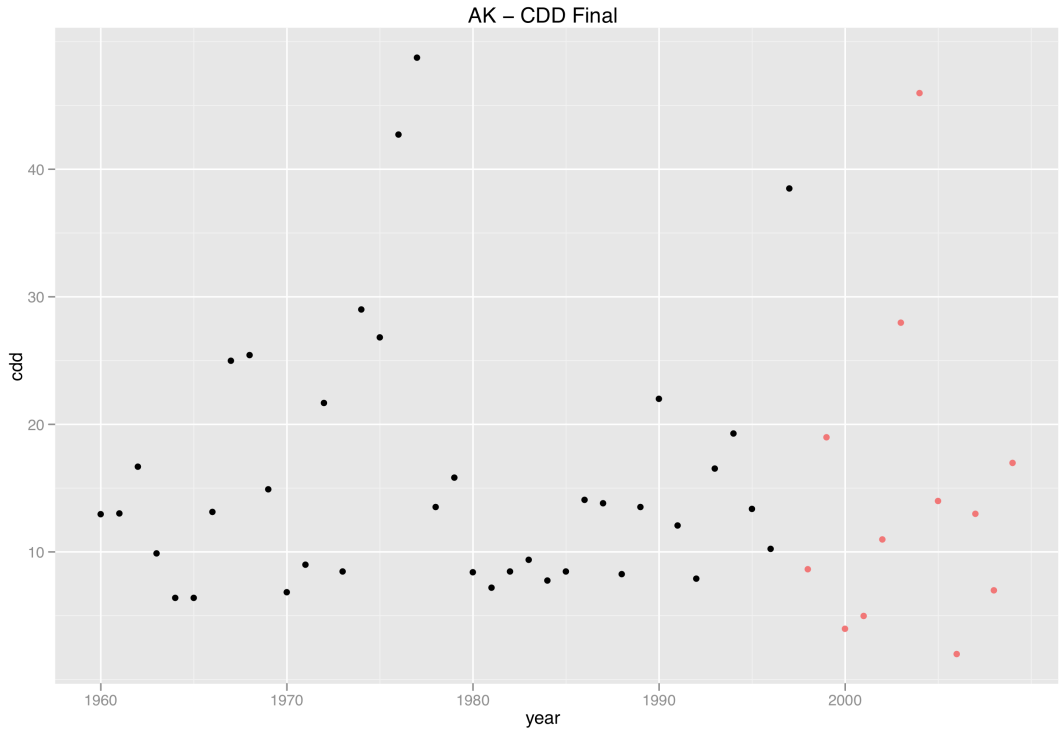

Figure D.2: Annual population weighted cooling degree day values for Alaska from the National Weather Service (red, 1998-2009) and as estimated by SERC (black, 1960-1997).

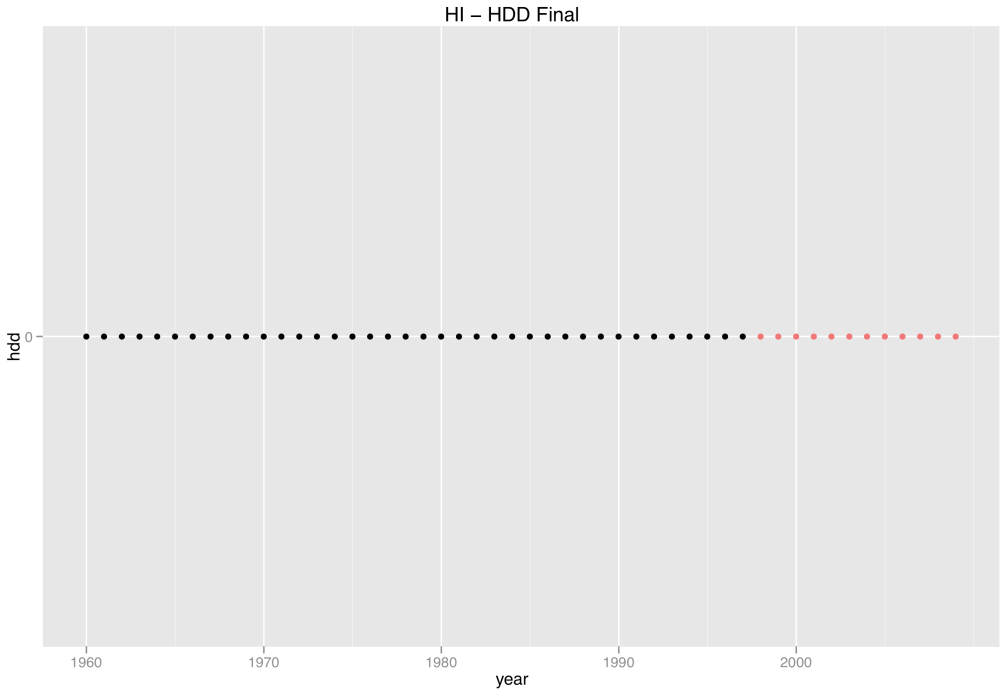

Figure D.3: Annual population weighted heating degree day values for Hawaii from the National Weather Service (red, 1998-2009) and as assumed by SERC (black, 1960-1997).

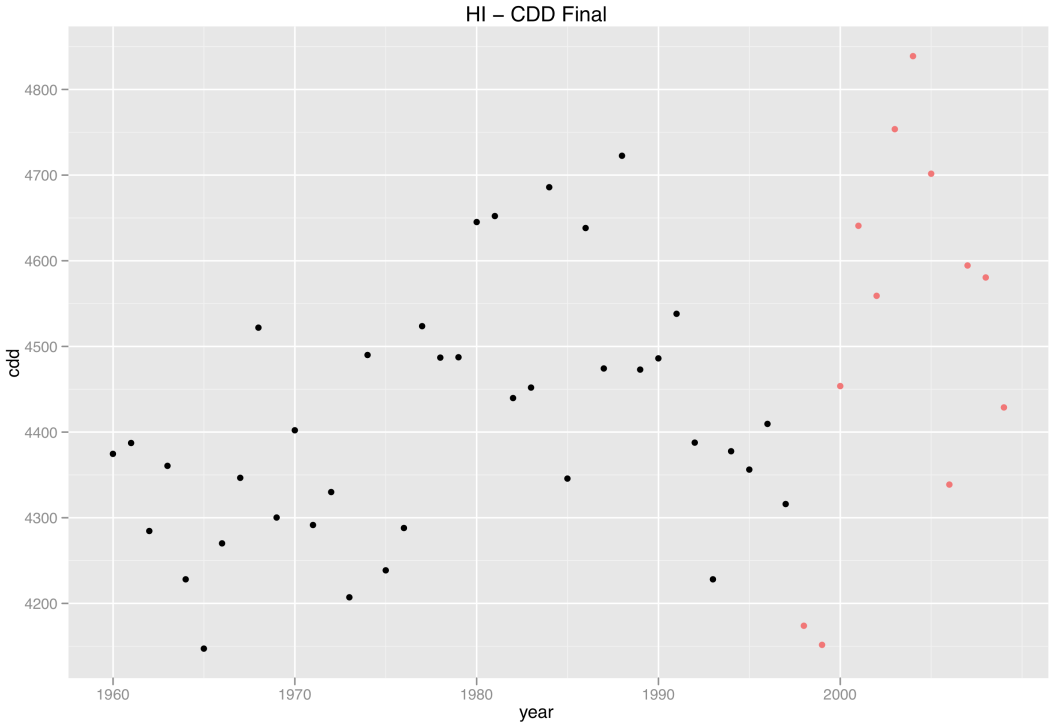

Figure D.4: Annual population weighted cooling degree day values for Hawaii from the National Weather Service (red, 1998-2009) and as estimated by SERC (black, 1960-1997).

Appendix E – Impact of Age Distribution on ECI

We have identified that a demographic shift, particularly an increase in the population's average age, can increase per capita residential energy use. This effect is outside the influence of energy policy makers, and it may therefore be reasonable to correct the ECI trend to account for demographic changes in age distribution within a state.

To investigate the impact of age, we perform a multiple linear regression on ECI from the 2005 RECS data set as explained by the mean age in a household as well as several other factors that were determined to be statistically significant: heating and cooling degree days, household income, area of heated space, and age of the house. The results of this analysis are presented in Table E.1. We then perform a comparable regression, but only include average age as a predictor (Table E.2), the resulting coefficient is only 2% different from the coefficient as determined in the first model. This robust result leads us to the conclusion that the relationship between ECI and age is relatively insensitive to other parameters.

Table E.1: Regression coefficients and statistics modeling per capita total energy consumption based on 2005 RECS data.

	Estimate	Units	Std. Error	t value	Pr(>|t|)	
(Intercept)	-56470.0	1000Btu/(cap*yr)	3666.0	-15.4	<2e-16	***
hdd	8.1	1000Btu/(cap*yr*DD)	0.4	19.2	<2e-16	***
cdd	6.3	1000Btu/(cap*yr*DD)	0.9	6.7	0.00	***
avg.age	1015.0	1000Btu/(cap*yr*yr)	32.4	31.4	<2e-16	***
hh.income	0.2	1000Btu/(cap*yr*$)	0.0	10.3	<2e-16	***
heated.space	7.6	1000Btu/(cap*yr*ft^2)	0.6	12.6	<2e-16	***
house.age	368.5	1000Btu/(cap*yr*yr)	29.7	12.4	<2e-16	***

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Table E.2: Regression coefficients and statistics modeling per capita total energy consumption based on 2005 RECS data.

	Estimate	Units	Std. Error	t value	Pr(>|t|)	
(Intercept)	21319.7	1000Btu/(cap*yr)	1807.8	11.8	<2e-16	***
avg.age	1035.9	1000Btu/(cap*yr*yr)	36.2	28.6	<2e-16	***

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

In order to adjust for the structural changes in age demographics within a state, we follow an alternative route to arrive at a similar place. The RECS data set specifies the age of every household member in the survey, however, the reported energy is aggregated over all members. We assume that every member shares equally in the energy consumption for that household, then we generate a new data set of all individuals in the RECS data containing their age and ECI. We choose a log linear formula to model the relationship because it explains slightly more variation

than the linear or quadratic models (0.1832 r^2 for the log model versus 0.1778 for the linear and 0.1786 for the quadratic).

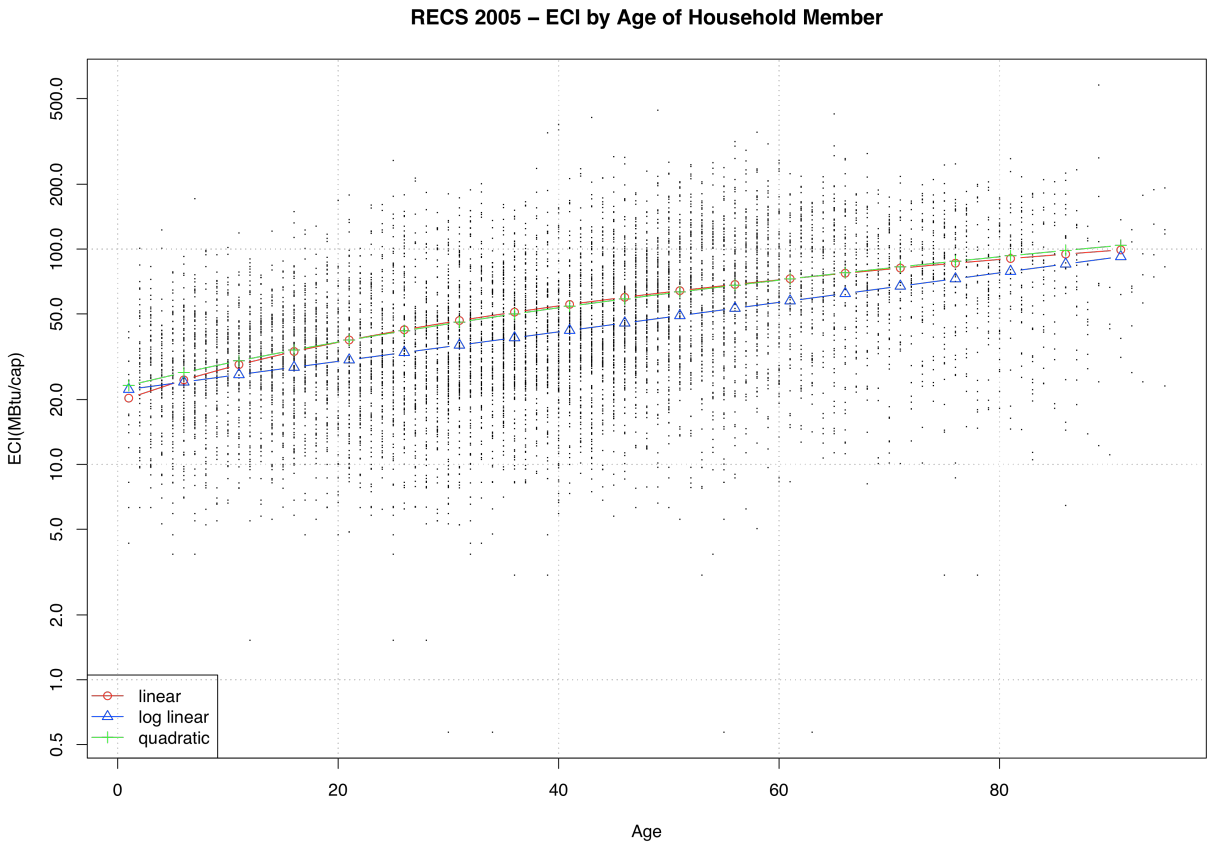

Figure E.1: Log linear and alternative relationships between ECI and age based on 2005 RECS data.

Based on the estimated relationship between ECI and age, we simulate what the impact of shifts in age distribution would be for each state between 1990 and 2008 assuming that ECI would have otherwise been constant. The shifts in age distribution are based on data from the U.S. Bureau of the Census. To summarize the results, we calculate the average impact of age on ECI over any 5-year period and present the averages in Figure E.2.

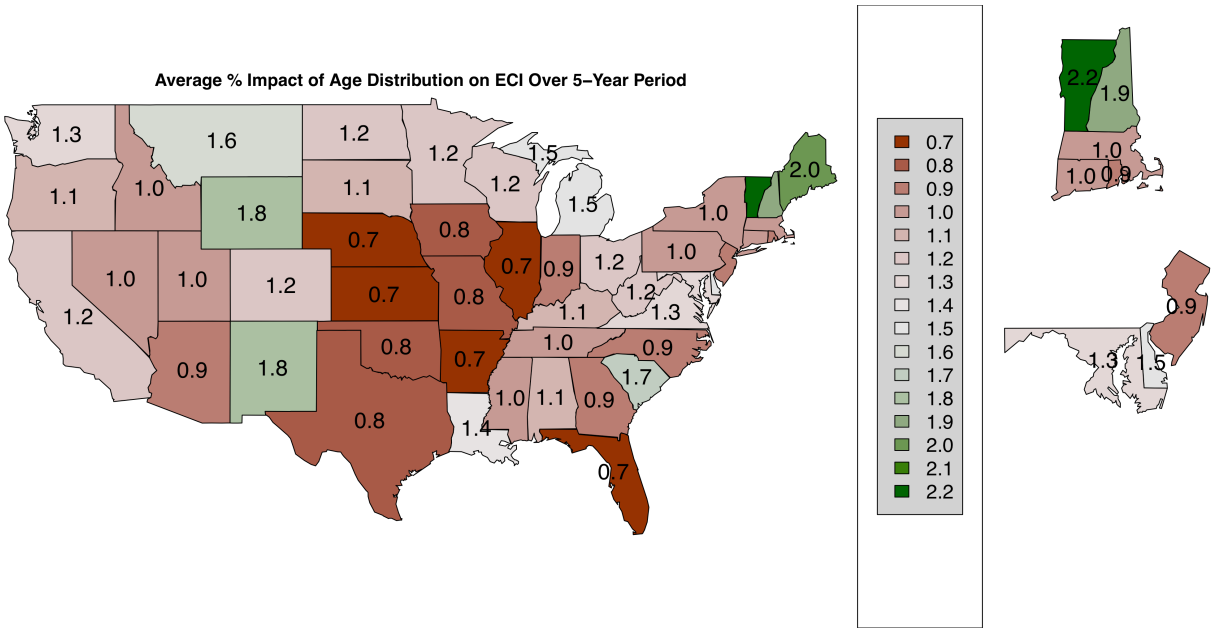

Figure E.2: Average % impact of age distribution on ECI over a 5-year period for the 48 continental U.S. states.

The effect is relatively large in a few states, particularly in Vermont where the increase in the average age in the population is larger than in any other state (Figure E.3). These shifts in the age distribution of Vermont's population could account for an 8% increase in the aECI from 1990-2007. A correction for the age distribution effect has not yet been incorporated into the PSEP method, but it may be included in a future version of the metric.

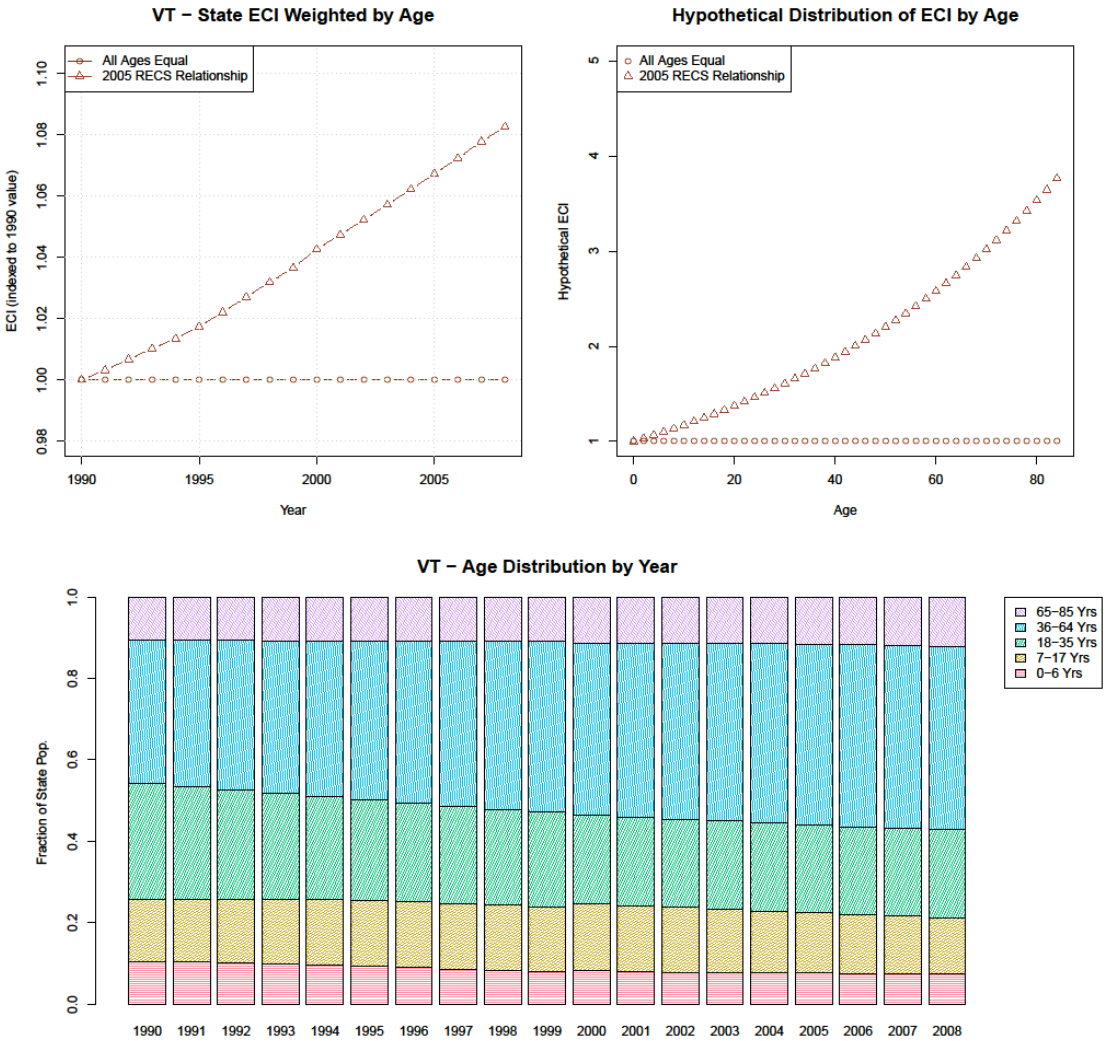

Figure E.3: Distribution of Vermont citizens by age (bottom); relationship between age and dimensionless ECI based on analysis of RECS 2005 data set (top right); impact of changes in the age distribution on ECI (top left) demonstrating that from 1990-2007 ECI would have increased by ~8% due to shifts in the age of the state's population.