To Be Competitive, America Requires NEEDC: A National Energy Efficiency Data Center

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ABSTRACT

The current quantity, quality, and scope of national energy efficiency data is inadequate for energy planning and policymaking. Without a centralized storehouse of detailed information, it is likely that as time goes on there will be fewer opportunities to carefully track the energy-related performance of national industries or to enact sensible policies that help U.S. industries remain competitive in the global economy. One solution to this dilemma is to create a national organization whose purpose will be to collect, organize, disseminate, and archive energy efficiency data, particularly those related to public policies and programs. The organization might be named the National Energy Efficiency Data Center (NEEDC).

Introduction

Energy and environmental concerns, from reducing greenhouse gas emissions to enhancing national security, are demanding increasingly serious attention and are motivating local, national, and international initiatives of ever-widening scope. To even begin to appreciate the consequences of these initiatives, good reliable data is a must. Data provides an historical record and like all records, has many uses. Sometimes the record speaks plainly for itself, and sometimes the record, or the facts in that record, provide feedstock and insights for more complex analyses. In all cases, data are needed to help policymakers anticipate the intended consequences, and the side effects, of policy actions or inaction.

Unfortunately, energy, environmental, and economics professionals that study energy efficiency labor under a significant handicap; while policy discussions are increasing in intensity and importance, the data needed for informing decisionmakers about energy efficiency-related policies are simply absent. Although the past three decades have produced thousands of studies on the subject of energy efficiency, they come mainly from local utilities and agencies who seem to lose interest with their most recent studies as as soon as one funding cycle ends and another one begins. In other words, every year tens of millions of dollars of energy efficiency studies end up with shelf lives more befitting pulp fiction than hard science.

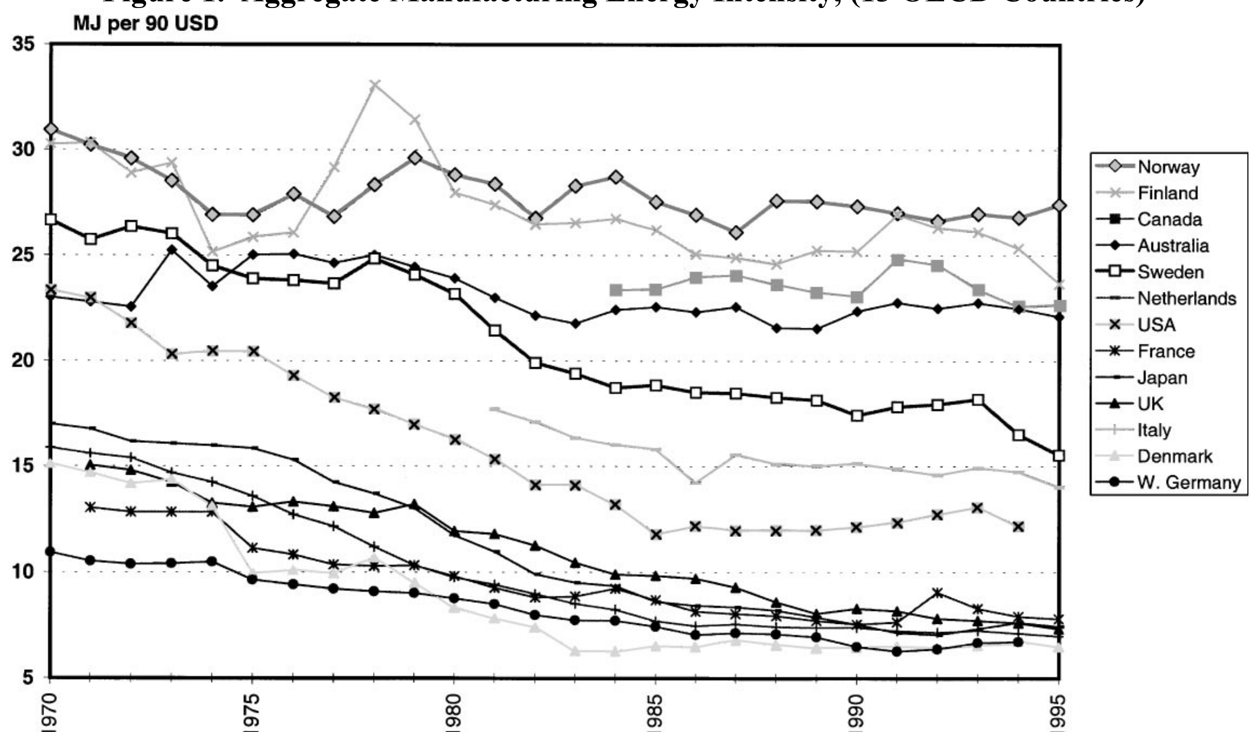
One of the outcomes of the lack of good data is that the realized, and potential, supply of energy efficiency in the United States goes largely unappreciated by much of the public and many of our policymakers. Despite the tremendous increase in energy efficiency and economic growth over the last 15 years, energy efficiency is perceived by many to be a negative drag on the economy. Why does this bias exist, when there is no empirical evidence that energy efficiency brings harm to national income?

The controversy over energy efficiency has many sources, not the least of which is the fact that energy savings, unlike energy production, is invisible. Savings is not seen with the naked eye, and its effects are not measurable except by logical inference of what would have transpired in its absence. This means that accepting the benefits of energy efficiency requires, at least initially, a leap of faith. Of course, eventually, to gain full acceptance faith must be replaced by facts. Unfortunately, the energy savings industry has neglected to develop the institutions and mechanisms that produce the kind of data that turns energy efficiency into visible fact.

Without a centralized storehouse of detailed information, it is likely that as time goes on there will be fewer opportunities to carefully track the energy-related performance of national industries or to enact sensible policies that help U.S. industries remain competitive in the global economy. As the trends in national manufacturing energy intensity reveal in Figure 1, the U.S. has achieved substantial progress in reducing energy intensity in the manufacturing sector, but remains somewhat in the middle of the pack compared to other OECD countries. Energy intensity is but one element in total productivity, and yet gains in energy productivity are likely to also affect the productivity of labor and capital. Hence, monitoring and improving energy productivity must be part and parcel of an overall national strategy for competing in the global economy. Such monitoring is not possible without high quality energy efficiency data.

One solution to this dilemma is to create a national organization whose purpose will be to collect, organize, disseminate and archive energy efficiency data, particularly those related to public policies and programs. The organization might be named the National Energy Efficiency Data Center (NEEDC). The aim of NEEDC will be to create databases that permit energy efficiency to be studied and understood, thereby placing energy efficiency resources on the same footing as other energy supply resources.

Figure 1. Aggregate Manufacturing Energy Intensity, (13 OECD Countries)



Unander, Fridtjof and Sohbet Karbuz, Lee Schipper, Marta Khrushch and Michael Ting (1999). "Manufacturing Energy Use in OECD Countries: Decomposition of Long-Term Trends," *Energy Policy*, (27)13:745 - 812.

National Electricity Data Examples

There is no reason why detailed national data on energy efficiency cannot be collected alongside all the other energy data that is collected regularly by trade organizations and the federal government. For example, electricity data is extensive and centralized, and yet electricity efficiency data is piecemeal and uncoordinated. These shortcomings are made all the more ironic because it now appears that the existing on-line supply of energy efficiency is substantial. Based on the findings of a just-published study, I estimate that publicly-funded electricity efficiency programs have reduced total retail electricity sales in the U.S. in the treatment period from 1992 to 2003 by about 6.8 percent annually. This estimate is derived from a counterfactual analysis using aggregate data. Some of the findings of this study are displayed in Table 1.

Table 1. U.S. Electricity Savings in 2006 (due to E.E. Programs beginning in 1992)

U.S. Electricity Savings in 2006 (due to E.E. Programs beginning in 1992)[1]			
Sector	**Industrial**	**Commerical**	**Residential**
Factual change since 1991 (n=36)	19.5%	49.6%	41.9%
Counterfactual change (n=36)	52.0%	63.7%	26.1%
Net change since 1991 (n=36)	-32.5%	-14.2%	15.8%
Impact on 2006 MWh (n=36)	-27.2%	-9.5%	11.1%
% Total 2006 MWh w/o Programs (n=48)	31.5%	36.5%	31.9%
% Sector 2006 MWh w/o Programs (n=36)	80.9%	83.6%	84.1%
% Weighted 2006 Savings (n=48)	-6.9%	-2.9%	3.0%
2006 Net Impact of Energy Efficiency Programs (3 Sectors, 48 States): -6.8%			

[1] calculated based on Horowitz, Marvin J. (2007). "Changes in Electricity Demand in the United States from the 1970s to 2003," *The Energy Journal*, 28(3):87 – 113.

Compare this supply of electricity savings to the supply of electricity generated by various fuels, as found in Table 2. According to the statistics, the energy efficiency encouraged by public programs exceeded petroleum as a fuel source for electricity, and provides close to the same level of electricity generation as hydroelectric dams. Only coal, nuclear and natural gas resources contributed substantially more to U. S. electricity supplies. Note also in Table 2 that fuel proportions have remained roughly the same over the reported years. Due to the lag times in planning and construction, these proportions will change slowly, if at all. Yet, because a large share of energy efficiency is behavior-driven, it is possible for large supplies of energy efficiency to come on-line relatively rapidly.

Of course, collecting data and measuring the physical volume of a resource is only half the story, the other being the cost of the resource. Naturally, the federal government closely monitors the costs of fuels as well as the other variable costs associated with generating electricity. In Table 3, the dollar cost per kilowatthour for the inputs that are required for generating electricity are reported, by type of generation.

Table 2. U. S. Electricity Generation, by Fuel Source

Generation Fuel	2003 GWh	2003 Percent	2004 GWh	2004 Percent	2005 GWh	2005 Percent
Coal	1,973,737	50.8%	1,978,620	49.8%	2,013,179	49.6%
Nuclear	763,733	19.7%	788,528	19.8%	781,986	19.3%
Natural Gas	649,908	16.7%	708,979	17.8%	757,974	18.7%
ENERGY EFFICIENCY PROGRAMS 2006:						6.8%
Hydro	275,806	7.1%	268,417	6.8%	269,587	6.6%
Petroleum	119,406	3.1%	120,646	3.0%	122,522	3.0%
Other Renewables	87,410	2.2%	90,408	2.3%	94,932	2.3%
Other Gases	15,600	0.4%	16,766	0.4%	16,317	0.4%
Other	6,121	0.2%	6,679	0.2%	4,749	0.1%
Total	**3,891,721**	**100%**	**3,979,043**	**100%**	**4,061,246**	**100%**

Source: EIA, Electric Power Annual

Table 3. U. S. Electricity Generation Variable Costs (Nominal $/kWh)

Sectors of the Economy	2003	2004
Sales to Ultimate Customers (thousand MWh)		
Residential	1,273,597	1,293,587
Commercial	1,197,199	1,229,045
Industrial	1,011,617	1,018,522
All Sectors	3,489,223	3,548,218
Revenue From Ultimate Customers (million $)		
Residential	110,794	116,037
Commercial	95,759	100,255
Industrial	51,794	53,661
All Sectors	258,861	270,456
Average Retail Price (nominal cents/kWh)		
Residential	$0.0870	$0.0897
Commercial	$0.0800	$0.0816
Industrial	$0.0512	$0.0527
All Sectors	$0.0742	$0.0762

Source: EIA, various forms

As can be seen, the total variable costs associated with nuclear generation are relatively small compared to those of fossil steam, gas turbine, and small scale generating plants such as photovoltaic and solar. Only the variable costs for hydroelectric power are less expensive, and this is due to the absence of fuel costs. Further, fuels costs are only a small part of the costs associated with delivering electricity to its end use. In Table 4, average national retail prices are provided, by sector.

Table 4. U. S. Electricity Retail Sales and Revenues, by Sector

Plant Type	2004	2005
Operations		
Nuclear	$0.0083	$0.0084
Fossil Steam	$0.0027	$0.0030
Hydroelectric	$0.0051	$0.0053
Gas Turbine and Small Scale	$0.0027	$0.0030
Maintenance		
Nuclear	$0.0054	$0.0052
Fossil Steam	$0.0030	$0.0030
Hydroelectric	$0.0036	$0.0036
Gas Turbine and Small Scale	$0.0022	$0.0022
Fuel		
Nuclear	$0.0046	$0.0045
Fossil Steam	$0.0182	$0.0218
Hydroelectric	--	--
Gas Turbine and Small Scale	$0.0452	$0.0537
Total		
Nuclear	$0.0183	$0.0182
Fossil Steam	$0.0239	$0.0277
Hydroelectric	$0.0087	$0.0089
Gas Turbine and Small Scale	$0.0501	$0.0589

Source: EIA, FERC Form 1

Given that prices are largely regulated, these reflect the average costs of producing and delivering electricity. In 2004, these average prices ranged from a little over 5 cents per kilowatthour in the industrial sector to a little less than 9 cents per kilowatthour in the commercial sector. The overall average was 7.6 cents per kilowatthour. Given the variable cost data and the retail sales data, it can be deduced that the combined fixed costs for power plant construction, transmission facilities, distribution facilities, and administrative services roughly averages about 5 cents per kilowatthour.

Most of the data presented in these three tables are available by year and by state. Were comparable kinds of data collected for publicly-funded energy efficiency savings, e.g., by year, economic sector, end use, or technology, it would be possible to compare the cost-effectiveness of the different energy resources, as well as the cost-effectiveness of energy efficiency vis-à-vis conventional fuels. Moreover, it would be possible to determine where energy efficiency would be most cost-effective and could do the most good, and what the cost thresholds might be for adding different energy resources. Unfortunately, at this time almost no data of this kind exists for energy efficiency.

Modeling Pitfalls

Inadequate current and historical energy efficiency data affect economic research in many different ways, all of which can end up prejudicing future energy policies, investments, and behavior. Three potential problems that arise in statistical models are: (a) missing variables; (b) missing observations; and (c) coefficient transformation. The following is a brief description of each problem.

Missing Variables

The consequences within an econometric model of omitting and important explanatory variable are well known; it is equivalent to setting stating that the variable has no effect on the outcome variable. Setting a relevant variable to zero in a conventional regression model violates the assumption that the error term is independent. For illustrative purposes, if a true model of energy demand, Y, is

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X' + \varepsilon$$

where β_1 is a parameter associated with a policy-related independent variable X_1; β_2 is a parameter vector associated with a vector of market-related variables X'; and, ε is a classical error term, then omitting X_1 will cause the equation to become

$$Y = \beta_0 + \beta_2 X' + \varepsilon^*$$

where the error term of this misspecified equation is now

$$\varepsilon^* = \beta_1 X_1 + \varepsilon .$$

To the extent that X_1 is correlated with X', its absence from the estimated model will cause ε^* to be dependent on the movements of the remaining explanatory variables. Consequently, all of the model's estimates will be biased and inconsistent.

A vivid example of the seriousness of model specification error is provided by an analysis contained in a recent study. In it, a fixed effects model of commercial sector electricity intensity was estimated for 42 states over a 13 year period, from 1989 through 2001. In addition to various other market-related determinants, the model contained a national time trend variable, referred to as *INFOX*. It is the actual Federal Reserve Board market group index of production of information processing equipment for businesses. It is included in the model to account for the variations in annual commercial sector electricity intensity caused by the adoption of electronic business equipment. Table 5 contains the commercial sector electricity intensity model coefficients related to *INFOX* as well as two public program variables, referred to as *DSMX1* and *MTX*.

The former is the mnemonic for annual state-level energy savings due to commercial sector demand-side management programs, and the latter is the mnemonic for an annual, national-level index representing energy savings from publicly-funded market transformation programs. The columns marked 1, 2, 3, and 4 contain the variables' coefficients estimated under different model specifications, with the standard errors of the coefficients in italics.

As can be seen, each of the model specifications attain a virtually identical R-squared compared to the full, correctly-specified model, designated as model (4). However, in model (1) both public program variables were excluded, and in models (2) and (3) one of the two public program variables is excluded. This suggests that the R-squared statistic is not a reliable indication of the quality of the models or of specification error. What is telling is that the coefficient of *INFOX* -- which measures the impact of electronic equipment on electricity intensity – changes dramatically in models (1), (2), and (3) when one or both public policy variables is dropped from the full model. As well as switching signs in two of the three abbreviated models, the statistical significance of the coefficient changes back and forth. Equally noteworthy, the magnitudes of the public policy coefficients change when one or the other is excluded from the model.

Table 5. Effects of Dropping Key Determinants

DV: MWh/GCP	**Specifications**			
	(1)	**(2)**	**(3)**	**(4)**
INFOX	-0.006	-0.0037	0.0077	0.0048
	-0.003	*-0.0033*	*-0.0041*	*-0.0046*
DSMX1	--	-0.0033	--	-0.0025
	--	*-0.0006*	--	*-0.0007*
MTX	--	--	-0.0076	-0.005
	--	--	*-0.0014*	*-0.0018*
R 2	0.69	0.68	0.69	0.68

Horowitz, Marvin J. (2004). "Electricity Intensity in the Commercial Sector: Market and Public Program Effects," *The Energy Journal* , (25)2:115 – 137.

Missing Observations

The consequences within an econometric model of dropping a substantial fraction of observations in a population, or from a sample, are so well-known that they do not warrant a technical exposition in this paper. The central issue, of course, is one of random versus systematic sampling. Losing observations due to random sampling has, in theory, little effect on anything other than the precision of the estimates; however, losing observations based on one or more factors that are related to the outcome in question can lead to bias and inconsistency in the estimates.

One of the inadequacies in the current state of energy efficiency data is that units of analysis or observation, be they state-level, local, or time-related, tend to go missing. Depending on the dataset that is being used for analyzing energy consumption, there could be years that are missing or cross-sections. A dramatic example of this problem can be found in a recent study that used a sample of electric utilities to estimate the impacts of annual demand-side management expenditures on changes in total electricity sales. The central element of this study was a time series cross section reduced form model whose specification or sample was altered in five different ways. As shown in Table 6, alteration in the sample size produced changes in the model coefficients, as shown in the rightmost column.

The predicted cost per DSM kilowatthour, displayed in the last row of Table 7, is the single most important statistic to emerge from the model. As can be seen, losing observations clearly leads to dramatically opposing policy conclusions. Note that the only difference in the two estimated equations is that the sample in model (4) is restricted to those electric utilities with positive energy efficiency expenditures in every year in the time frame. In other words, models (1) and (4) are identical save that model (4) has 1,041 fewer observations, or only 42 percent of the original sample.

Table 6. Effects of Dropping Many Observations

DV: Dt Utility MWh Sales	**Model (1)**	**Model (4)**	**Change (t-stat)**
DSM_E	0.0003	-0.0027	0.003
	-0.001	*-0.0018*	*1.457*
DSM_E(-1)	-0.0007	0.0016	-0.002
	-0.0011	*-0.0021*	*-0.970*
DSM_E(-2)	-0.0005	-0.0007	0.000
	-0.0005	*-0.0011*	*0.166*
Dt CUST	**0.9691**	**0.7756**	0.194
	-0.1493	*-0.0926*	*1.101*
Dt MWH_I	**0.6784**	0.5734	0.105
	-0.2021	*-0.3436*	*0.263*
Dt MWH_C	0.371	0.3249	0.046
	-0.1987	*-0.3107*	*0.125*
Dt GSP	**0.0322**	**0.0492**	-0.017
	-0.0164	*-0.0195*	*-0.667*
Dt P_ES	-0.1012	-0.1298	0.029
	-0.0553	*-0.0721*	*0.315*
Dt P_NG	-0.0233	-0.0629	0.040
	-0.0229	*-0.0344*	*0.958*
Dt P_CL	-0.0278	0.0143	-0.042
	-0.0215	*-0.027*	*-1.220*
Dt P_PA	0.0887	**0.1493**	-0.061
	-0.0509	*-0.0574*	*-0.790*
Dt CLIMATE	**0.1496**	**0.211**	-0.061
	-0.0359	*-0.0408*	*-1.130*
Year effects	x	x	
n	1,815	774	1,041
R 2	0.54	0.60	-0.06
Predicted $DSM_E /kWh	0.137	0.064	0.073

Loughran, David S. and Jonathan Kulick (2004). "Demand Side Management and Energy Efficiency in the United States." *The Energy Journal*, 25(1):19-43.

The result is not only that the predicted cost of energy efficiency differs by more than a factor of two -- in the model using the larger sample, the predicted cost per kWh is 13.7 cents, whereas in the model with the smaller sample the predicted cost per kWh is 6.4 cents – but that, as can be seen in the final column of the table, individual coefficients change signs and/or magnitudes. The fact that none of these changes is statistically significant (t-statistics are in italics) speaks more to the weakness of the model's variables than to the similarity of the coefficient estimates; four of the twelve variables in either model have statistically significant coefficients, as indicated in bold.

The divergence in these estimates is another strong argument for creating energy efficiency databases that are uniform and complete. Moreover, before leaving this example it should be noted that unlike many studies, in this particular study the smaller sample is actually the more valid sample, since the observations that are dropped are ones suspected of having substantial data reporting error. Again, this is a further argument for producing and compiling high quality, consistent energy efficiency data.

Coefficient Transformation

A final example of how inadequate national energy efficiency data handicaps modeling efforts and fosters biases against energy efficiency can be drawn from the study cited at the beginning of this paper. In this study I show that changes in the demand for electricity in the commercial, industrial, and residential sectors are associated with energy efficiency programs, and furthermore, that changes in the behavioral responses to economic variables that drive energy demand are associated with energy efficiency programs. This empirical finding, which I refer to as *demand transformation*, is often overlooked in policy research despite in-depth theoretical explorations of this subject in such studies as Gary S. Becker and Kevin M. Murphy (1993), "A Simple Theory of Advertising as a Good or Bad," *Quarterly Journal of Economics*, 108, No. 4:941-964, and Justin P. Johnson and David P. Myatt (2006), "On the Simple Economics of Advertising, Marketing, and Product Design," *American Economics Review*, Vo. 96, No. 3, pp. 757-789. These studies describe the pathways through which government programs, advertising, or any form of societal persuasion, can alter price, income, and other elasticities by transforming the underlying utility function of consumers.

In Table 7 the changes in the coefficients of time series cross section reduced form electricity demand equations, with electricity intensity as the dependent variables, are reported. These sector-level coefficients are estimated in a base period taken to be 1977 to 1991, and a treatment period taken to be 1992 to 2003. The observations in each sector are the twelve states that appear to have shown the strongest commitment to both voluntary and mandatory energy efficiency programs since 1992. The values in italics indicate that the change, based on the t-test, is statistically significant at the 95 percent level or better. Inspection of these statistics reveal what has happened to demand behavior from one period to the next. Of particular interest is how they have changed for three key economic variables, i.e., electricity price, per capita income/GSP, and technology trend.

Table 7. Changes in Coefficients from Base to Treatment Period

DV: MWh Intensity	Sector of the U. S. Economy (48 States)		
	Residential	Commercial	Industrial
constant	0.715	*-2.043*	*5.793*
Electricity Price	*-0.283*	-0.140	*-0.384*
Natural Gas Price	-0.039	*0.068*	0.030
Per Capita Inc/GSP	*-0.310*	*-0.347*	0.462
Technology Trend	*-0.029*	-0.047	*-0.151*
Heating Degree Days	*0.134*	*0.134*	*-0.278*
Cooling Degree Days	0.034	0.033	-0.033

Horowitz, Marvin J. (2007). "Changes in Electricity Demand in the United States from the 1970s to 2003," *The Energy Journal*, 28(3):87 – 113.

With respect to energy prices, economic theory suggests that if programs intended to lower electricity demand are successful, energy price elasticity will increase as consumers become more sensitive to the possibility of substituting capital, in the form of more energy efficient equipment, for fuel. Of course, other pathways for increased price elasticity are possible, too, such as altered equipment operation. As can be seen in Table 7, demand has, in fact, become more price elastic from the base to the treatment period for across all three sectors, and this change is statistically significant in the residential and industrial sector. The finding of an income effect in the expected negative direction is an equally important indicator of demand transformation. Greater income inelasticity will occur if programs encourage consumers with rising incomes to substitute higher energy efficiency equipment for existing equipment, thereby turning energy use from a superior good into a normal one, all things being equal. Other pathways, such as sophisticated operations and maintenance, are possible too. As also can be seen in Table 7, a statistically significant change in the expected direction, as expressed through the GSP/income coefficient, occurs for both the residential sector and the commercial sector. The change is in the opposite direction in the industrial sector, however it is not statistically different from zero. Lastly, a third important indicator is the technology growth coefficients. This continuous variable varies by sectors and years, but not by state, and it is to be expected that successful programs will reduce the elasticity of demand with respect to technology growth. As can be seen in Table 7, demand becomes more inelastic from the base to the treatment period in all three sectors, and the changes are statistically significant in all but the commercial sector.

The point of this exhibit is to demonstrate that without good reliable energy efficiency data series, it is difficult to assess the extent to which behavioral coefficients may have transformed, and may transform in the future, due to energy efficiency. By ignoring this issue, models are likely to show statistical bias against energy efficiency, and this bias is likely to affect the views of policymakers and the public.

Conclusion

Energy data and statistics are feedstock for research that informs the actions of private industry, not to mention government legislation and regulation. With regards to public planning and policymaking, the end result of energy research tends to be laws and rules that reward some companies or consumers, and punish others. With regard to privately-owned businesses, the end result of energy research tends to be investment decisions that are intended to optimize their use of resources, their competitiveness, and their profits. In short, energy data and statistics are part of the foundation of economic productivity and progress; without good information, it is highly unlikely that the best of all energy-related public policies, and business decisions, will be made.

It has not been the purpose of this paper to enumerate the multitude of shortcomings in the way in which energy efficiency data is collected and analyzed. Rather, it has been to discuss a potential improvement to the status quo. While there is no magic formula for seeing into the future, if the public, the business community, and policymakers are to believe in the value of any energy efficiency at all, then the least they ought to do is demand better and more accurate energy efficiency data. NEEDC can meet this demand by providing detailed information on this large and cost-effective resource, one that thus far has not received the attention and respect that it deserves. A major reason for this, and for widespread skepticism regarding energy efficiency among professional economists, is the dearth of continuous, standardized data with which to study this resource. This oversight has direct implications for industrial competitiveness, not to mention environmental management.