DISCUSSION PAPER

# Understanding Errors in EIA Projections of Energy Demand

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RESOURCES
FOR THE FUTURE

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## Abstract

This paper investigates the potential for systematic errors in the Energy Information Administration's (EIA) widely used Annual Energy Outlook, focusing on the near- to midterm projections of energy demand. Based on analysis of the EIA's 22-year projection record, we find a fairly modest but persistent tendency to underestimate total energy demand by an average of 2 percent per year after controlling for projection errors in gross domestic product, oil prices, and heating/cooling degree days. For 14 individual fuels/consuming sectors routinely reported by the EIA, we observe a great deal of directional consistency in the errors over time, ranging up to 7 percent per year. Electric utility renewables, electric utility natural gas, transportation distillate, and residential electricity show significant biases on average. Projections for certain other sectors have significant unexplained errors for selected time horizons. Such independent evaluation can be useful for validating analytic efforts and for prioritizing future model revisions.

**Key Words:** EIA, energy forecasting, bias

**JEL Classification Numbers:** Q43, C53

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# Understanding Errors in EIA Projections of Energy Demand

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## Introduction

Since 1982 the U.S. Energy Information Administration (EIA) has published projections of future energy demands in its Annual Energy Outlook (AEO). These projections are widely used by business, governments, and others concerned with energy markets. The EIA also conducts its own retrospective of its projection performance (EIA 2006). Aggregating across short-, medium-, and long-term projections, the EIA analysis reveals quite small errors in the estimates of the total quantity of energy demanded and other relatively aggregate quantity–based measures.

Independent evaluation of these projections can be valuable for validating ongoing analytic activities and for prioritizing future model revisions. In fact, several independent researchers have found indications of bias in the projections, especially for longer time periods. The present paper addresses these issues with a focus on near- to medium-term projections, based on an analysis of the EIA's 22-year projection record. In order to identify where model revisions are most needed, we examine the accuracy of the energy demand projections for the 14 individual fuels/consuming sectors routinely reported by the EIA as well as the more aggregate results. While we cannot observe policy changes from the reference scenario, we take care in controlling for unexpected changes in real output, oil prices, and key weather variables, which are often cited as drivers of energy demand. Particular attention is paid to the development of historical data that are consistent with the variable definitions and price deflators used at the time the original projections were made.

Overall, we find a fairly persistent tendency to underestimate total energy demand by an average of 2 percent per year over the one- to five-year projection horizon after controlling for projection errors in gross domestic product (GDP), oil prices, heating degree days (HDDs), and

cooling degree days (CDDs). For the 14 individual fuels/consuming sectors we observe a great deal of directional consistency in the error patterns over time and significant biases in a number of individual sectors, ranging up to 7 percent per year.

## Background

Since 1994, the *AEO* projections have been based on the National Energy Modeling System (NEMS), a partial equilibrium model of the U.S. economy developed and maintained by the Office of Integrated Analysis and Forecasting of the EIA. Although NEMS has evolved considerably over the years, it has consistently emphasized a market-based approach to energy analysis. For each fuel and consuming sector it balances energy supply and demand, accounting for economic competition among the various fuels and sources, and explicitly includes regional differences in energy markets. NEMS contains four demand modules, one each for the residential, commercial, industrial, and transportation sectors. The supply side is characterized by four separate modules for oil and gas, renewable energies, natural gas transmission and distribution, and coal. Two additional modules characterize conversion into electricity and the refining of petroleum. A separate macroeconomic module explicitly models interactions between domestic aggregates and energy prices. Further, the model allows for feedback between world and U.S. oil markets. The primary flow of information among the modules is via the delivered prices of energy to end users and the quantities consumed by product, region, and sector. NEMS calls each supply, conversion, and end-use demand module in sequence until the delivered prices of energy and the quantities have converged within tolerance. Prior to NEMS, similar projections were made using the Intermediate Future Forecasting System (IFFS) and, for a three-year period, Personal Computing–AEO (PC-AEO). PC-AEO is described as a simplified spreadsheet representation of the basic IFFS methodology (EIA 1998).

*AEO* projections are made for various time horizons, in some cases as long as 15 years. It is important to note that the EIA characterizes its estimates as "policy-neutral reference cases that can be used to analyze policy initiatives" (EIA 2006). These projections are described as business-as-usual estimates, given existing technologies, technological and demographic trends, and current laws and regulations. Pending or proposed legislation, regulations, or standards are not generally reflected in the projections.

Although NEMS, PC-AEO, and IFFS have been the EIA's primary long-term projection models, the first few years of *AEO* projections are benchmarked to the *EIA's Short-Term Energy Outlook* (*STEO*) projections. Benchmarking applies to select variables, including the fuel/sector categories relevant to our analysis, since NEMS covers a broader set of indicators than the *STEO*

models. These variables are gradually transitioned back to NEMS/IFFS projected values over five years or less; in more recent editions, most indicators are transitioned back within a two-year projection horizon. Apparently, this transition pattern has varied over time. Thus we cannot attribute any of our results to the effectiveness of a particular EIA model. Instead, we evaluate the broader *AEO* projection process.

The *STEO* projections to which the *AEO* is benchmarked were produced using the Short-Term Integrated Forecasting System (STIFS), a massive system of interrelated regressions.[1] STIFS has been used in creating *STEO* forecasts since at least the first quarter of 1983. The model generates short-term national-level forecasts of several fundamental U.S. energy indicators. The historical data used in the regressions are drawn from EIA publications such as *Quarterly Coal Report*, *Petroleum Supply Monthly*, *Petroleum Marketing Monthly*, *Electric Power Monthly*, *Natural Gas Monthly*, and *Monthly Energy Review*. Since August 2005, *STEO* has presented projections generated by a new Regional Short-Term Energy Model (RSTEM). However, our sample does not include editions of *AEO* from this time period, so we defer any detailed discussion of RSTEM.

In its own *Annual Retrospective Review*, the EIA examines relatively aggregate measures of energy demand, calculating the average absolute percent error for several major price and quantity variables across the entire range of projection horizons. In recent years they have also projected energy intensity for the economy as a whole. While offering a fair indication of the absolute magnitude of the errors, such calculations have several important limitations: they ignore the direction of bias; they fail to reveal how error patterns may change over different projection horizons; they disregard potentially persistent biases for a given horizon; and they ignore the possibility that projection error variance may increase with the length of the projection horizon.

Several independent analyses have been published over the past decade that examine the accuracy of EIA projections; most of them focus on the aggregate-level analyses. A relatively early paper by Shlyakhter and his colleagues (1994), who did look at some disaggregate measures of fuel/consuming sectors, combined the results for *AEO* projections made in three separate years (1983, 1985, and 1987) for low-, reference-, and high-scenario projections, with an emphasis on extreme outliers. The authors developed a simple one-parameter model to

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[1] Description draws heavily on EIA (2002).

estimate a probability distribution for future projections. Lutter (2000) examined the EIA's projection accuracy for carbon dioxide ($CO_2$), a related but somewhat different measure than the Btu-based measures used in other papers, including the present one. On the basis of simple arithmetic calculations, Lutter found that the absolute $CO_2$ projection error rises from about 1 to 2 percent in the one- or two-year projections to between 4.6 and 7 percent for the projections that are 12 or 14 years in the future. On average, the $CO_2$ projections tend to be less than the realized values. Using a more sophisticated modeling approach, O'Neill and Desai (2005) also found that long-run projections of energy consumption tend to underestimate future demand. Further, they show consistent long-run overprojections of GDP, a finding of particular interest for the present analysis. Auffhammer (2007) tested for the rationality of aggregate EIA projections under symmetric and asymmetric loss functions by using long-term data. He finds strong empirical evidence of asymmetric loss for natural gas consumption, GDP, and energy intensity, but no systematic bias in total demand projections. Auffhammer does not examine the accuracy of projections of individual fuels/consuming sectors.

## Data

While other researchers have focused on the EIA's projections of several variables, including energy prices and energy intensity of the overall economy, we are concerned with energy demand expressed in physical quantities. We compare projection and actual data for total energy demand and fourteen fuel/consuming categories from 1985 through 2006 with projections made between 1984 and 2004.[2] As noted, we restrict our analysis to projection horizons of one to five years, dropping the limited number of long-range projections in order to provide a larger sample size for each time horizon studied. Overall, the resulting sample size for fuel/sector groups is 64 or 66, while for total energy there are 95 observations. The historical energy

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[2] Prior to 1989, the *AEO* was dated with the year prior to the year of publication; as a result of this change in nomenclature, the *EIA* did not publish a report titled "*AEO 1988*," although no years were actually skipped. EIA projections used in this analysis are taken from EIA (2006), EIA *AEO* (various years), and EIA *Annual Energy Review* (various years).

consumption data used for comparison purposes are from the EIA's *Annual Energy Review* (*AER*).[3]

To develop a consistent series for output, some adjustments are required. EIA real output figures are used as derived from Wade (2007) and remain in the "publication base year" as found in the relevant edition of the *AEO*. Due to changes in accounting methods, EIA output projections prior to 1993 are for gross national product (GNP) as opposed to GDP. For convenience, we refer to our real GNP/GDP hybrid output series as real output.

Our task of comparing output projections to historical values is complicated by the BEA's revision regime. Every five years or so, a so-called comprehensive, or benchmark, revision is undertaken. These may entail changes in definitions, statistical methods, and deflators. Since the definitions and deflators used in constructing estimates of real output have drastically changed over time, we cannot simply match EIA projections to the most recent BEA historical series. Accordingly, historical real output figures are drawn from the real-time real output series constructed by Croushore and Stark (2001). This series presents real output data based on the variable definitions and price deflators used at the time the data were actually released. Data representing years prior to a revision are recalculated for each "vintage." However, output figures for a year after a revision are not revised backward to match pre-revision definitions. Thus, a projection made in a year prior to a benchmark revision that purports to predict output for a year after the revision cannot be compared directly to any historical number. We extrapolate growth ratios to construct hypothetical versions of these

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[3] We use the projected energy consumption figures from the 2006 EIA *AEO Retrospective Review* and actual energy consumption figures from various editions of the EIA *Annual Energy Review*. The obvious issue with constructing this time-series is that the inclusion of renewable energy changed in the 1990 *AEO*; thus, the concepts of total energy in recent *AER* editions are not comparable. After correspondence with *Annual Retrospective Review* contact Steven Wade (2007), we follow the methodology used in the *Retrospective*. That is, we observe the difference between 1998 and 1997 *AER* historical figures, thus inferring the difference in methods. We assume no error in renewable projection and add the realized renewables figure to past projections to construct comparable time-series.

backward revisions.[4] Any observations that cross two benchmark revisions are omitted from our analysis.

As noted, *AEO* projections are designed as policy-neutral, business-as-usual estimates. While policy changes are one explanation for projection deviations, their influence is more likely to be felt in the long-term than the short-term. For the horizons we are considering, economic surprises are likely to play a larger role. In particular, the EIA singles out the importance of output projections:

"Because GDP is a good indicator of the economic activity which drives energy consumption, the differences between projected energy consumption and actual consumption are often similar to the differences between the GDP projections and actual GDP" (EIA 2006, 2).

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[4] Consider two vintages, *I* being the last vintage before some comprehensive revision at the end of year *t*, and *II* the last vintage prior to the next comprehensive revision; these are Croushore and Stark's (2001) so-called benchmark vintages. This choice allows for as many annual revisions within a comprehensive revision period as possible and also allows much of the relevant data to stabilize at a generally accepted value. Averaging the annualized quarterly data, we derive annual series for years *t–6* through *t–1* since the fourth quarter of year *t* is not included in vintage *I* in our real-time dataset. Using our annual series for *t–6* through *t–1*, we find annual average growth rates, denoted $g_I$ and $g_{II}$. The ratio $g^* = g_I/g_{II}$ represents the five-year average growth rate ratio between vintages *I* and *II*. We use these five years because they cover a reasonable period of time while representing a U.S. economy similar to that existing in years shortly after year *t*. For years after *t–1* we calculate growth rates for vintage *II*, multiply them by $g^*$, and apply the results to vintage *I* to construct our extrapolated series.

**Figure 1. Percent Error: EIA Real Output and EIA Total Energy
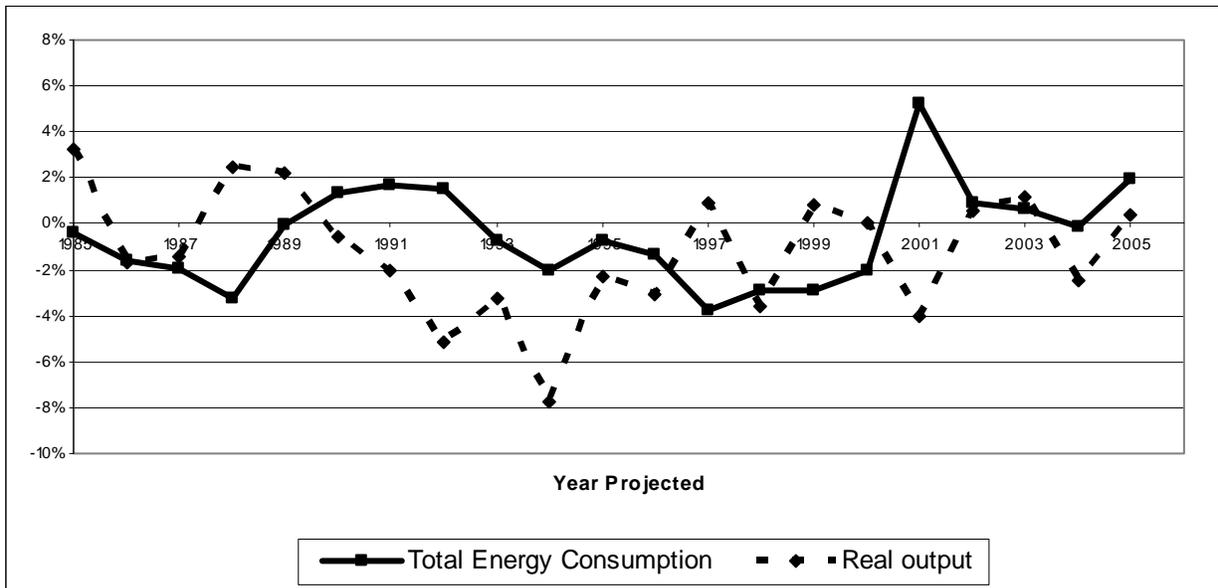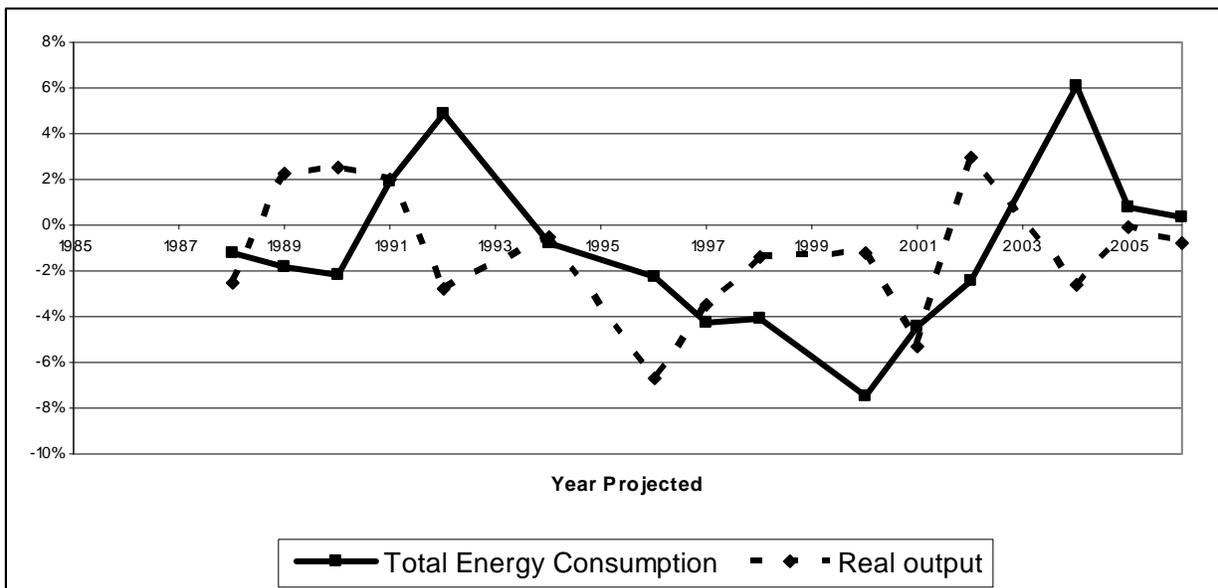(Two-Year Projections for 1985–2005)**



**Figure 2. Percent Error: EIA Real Output and EIA Total Energy
(Five-Year Projections for 1988–2006)**



Figures 1 and 2 display the available time-series for the percentage error in output projections made by the EIA over the two-year and five-year horizons, respectively, along with

the percentage error in total energy demand. Data are plotted for the year predicted. For most of the time period, the EIA underpredicted output. In the past decade, however, the trend seems to shift toward zero error. Mixing longer-term horizons with the nearer-term ones—as the EIA and other researchers have done—can confound one's understanding of the direction and magnitude of EIA output projection errors.

The EIA (2006) singles out the important role of oil price projections in energy demand, particularly in the transportation sectors. As a further check on the importance of identifying key factors that affect projection accuracy, we will control for the possible role of errors in these projections.5 As shown in Figure 3, although EIA projections have underpredicted oil prices in recent years, the pattern prior to 2000 was a tendency to overprojection.

**Figure 3. Mean Percent Error for EIA Oil Price Projection**



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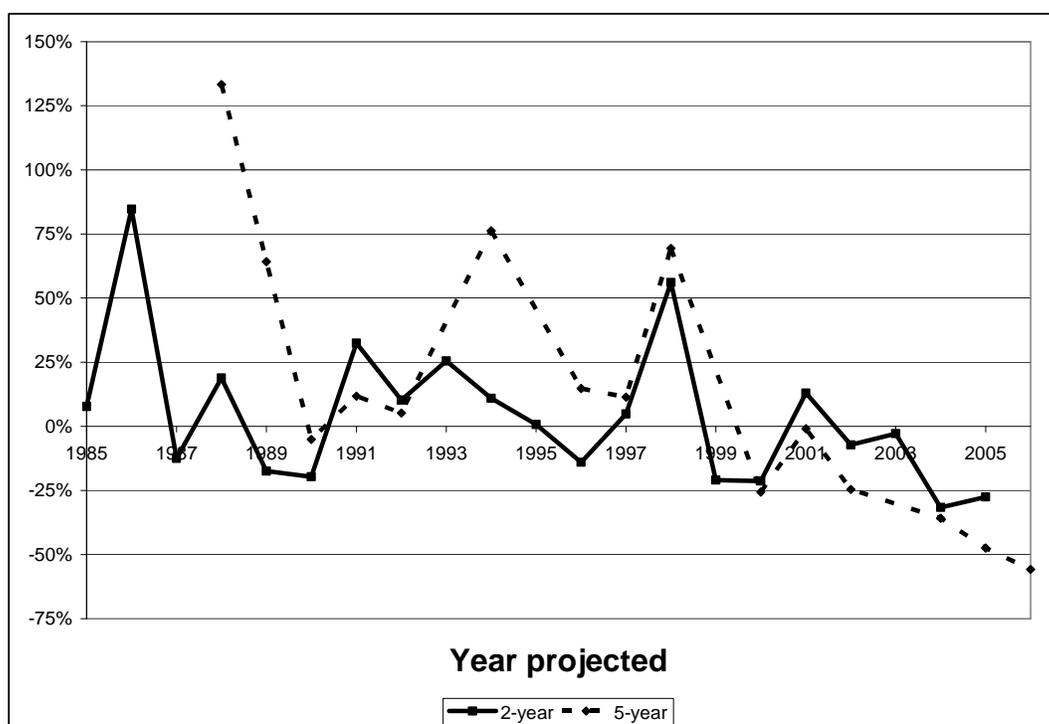
5 EIA oil price projections come from the *AEO* nominal series as cited in the *Annual Retrospective Review*.

Weather is also a key factor. An unexpectedly cold or warm year could significantly affect the EIA's ability to accurately project energy consumption. Accordingly, we include in our analysis measures of projection errors in HDDs and CDDs.6 Error is derived where we define the projection to be the average over the previous 30 years. We compare this to the actual value for the year projected to derive a percentage error. We do not attribute this error to the EIA; we simply wish to include an important variable while keeping interpretation consistent. Since weather patterns tend to be regional in nature, a spatially disaggregated model would be preferred to the use of national aggregates, especially for the commercial and residential sectors. However, the AEO only reports these projections on a national basis.

## Results

### *Analysis of Total Energy Consumption Projections*

We seek to examine residual bias in the EIA's projection of total energy consumption using the following specification:

$$C_{th} = \beta_0 + \beta_1 Y_{th} + \beta_2 oilprice_{th} + \beta_3 HDD_{th} + \beta_4 CDD_{th} + \sum_{h=1}^{5} \gamma_h$$

where Cth is energy consumption projection error, Yth is output projection error, HDDth and CDDth are measures of HDD and CDD projection error,7 all in year t with projection horizon h (i.e., for year t + h – 1). The projection horizon fixed effects, $\gamma_h$, are measures of mean residual bias controlling for the explanatory variables. We also constrain $\beta_0 = 0$ for ease of interpretation; each projection horizon has a unique constant term in the form of the $\gamma_h$'s. We run generalized least squares with a Prais–Winsten transformation to address concerns of serial correlation (test statistics are shown in Table 1) and adjust the standard errors for contemporaneous correlation within the year a projection was made.

Table 2 presents the regression results from this specification. Focusing on the projection horizon indicator variables, there are statistically significant residual errors on the order of 2 percent in the first four projection horizons. The errors peak at the two-year horizon and are not

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6 The basic data are from Tables 1.7 & 1.8 in the *2006 EIA Annual Energy Review*.

7 Degree-day deviation.

significant for the five-year horizon. Although four of the five horizon coefficients are statistically discernable from zero, we cannot with confidence claim that any particular coefficient is significantly different from another.8 The mean bias over these projection horizons, a linear combination of the five horizon coefficients weighted by number of observations, is 2 percent and is statistically significant at the 1 percent level. This result suggests that, accounting for our control vector, the AEO is significantly underestimating total energy consumption during our sample period.

We also experimented with an alternative specification, testing for a structural break by including a period dummy based on the year a projection was made. We found that splitting the sample at the first year that NEMS was used in tandem with STEO in the AEO led to a significant difference, with estimated residual bias being higher in the later portion of the sample. However, the Quandt likelihood ratio (QLR) test found a more significant break elsewhere.9 Thus, we cannot determine whether NEMS has had an impact on projection quality or if the later period is simply more prone to projection error due to omitted factors. This is in keeping with O'Neill and Desai (2005), who could not find a clear difference between projections from NEMS versus its predecessor, IFFS.

### *Analysis of Specific Fuel Consumption Projections by End-Use Sector*

At the outset, it is useful to examine the actual error patterns for total energy demand and its 14 fuel/consuming sector components for different projection horizons. Figure 4 displays the mean percentage projection error by energy demand type for the one- through five-year projection horizons.

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[8] We ran Wald F-tests of equality on each pair of projection horizon coefficients. The pair with the most significant test statistic was the one-year and two-year coefficients, with an F-statistic of 3.95 and a corresponding p-value of 0.061.

[9] The time period indicator coefficient was significant at 5 percent when the early period ended at any year between 1989 and 1993. Our QLR statistic (10.77) was from a 1991 break; subjected to the proper critical values (Stock and Watson 2003), it is significant at the 5 percent level.

**Figure 4. Mean Percentage Error by Projection Horizon for Total Energy and for Significant Energy Fuel/Consuming Categories**
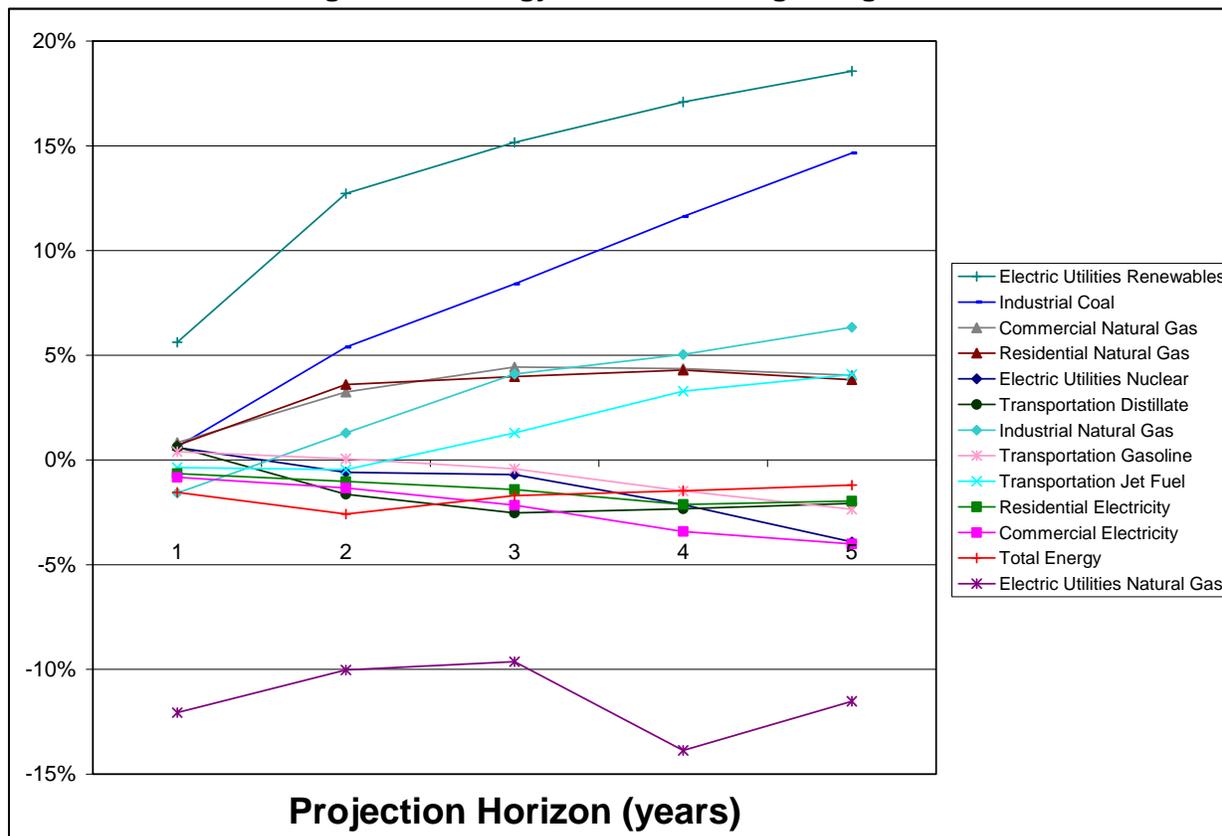


Perusal of Figure 4 confirms the EIA view that the mean errors in the projection of total energy use are relatively small, at least for the one- to five-year time horizon. At the same time, Figure 4 illustrates that projection errors for specific fuel/consuming sectors can be considerably larger, either positive or negative, and they can vary by time horizon, reflecting the notion that projection errors may increase with the projection horizon. Overall, the errors appear to be directionally consistent over the one- to five-year projection horizons. Residential and commercial electricity demands are consistently underpredicted, as is the electricity sector's demand for natural gas. Demand for transportation gasoline is underpredicted in four out of five projection horizons. Other forms of natural gas demand are consistently overpredicted. The reason behind some of the inaccuracy in electric utility and industrial natural gas projections is the reclassification of independent power producers (IPPs), an issue that is addressed later in this section. Industrial electricity and coal demand are increasingly overpredicted over longer horizons. Finally, demand for renewables seems to suffer from the greatest upward bias overall.

To examine projection bias for consumption of specific fuels in particular end-use sectors, we adopt the basic model specification used to analyze total energy consumption projections. A regression is run independently for each sector–fuel combination. For the transportation, residential, and commercial sectors, we use the following specification:

$$C_{th} = \beta_0 + \beta_1 Y_{th} + \beta_2 oilprice_{th} + \beta_3 HDD_{th} + \beta_4 CDD_{th} + \sum_{h=1}^{5} \gamma_h$$

For the electric utility and industrial sectors, we include a variable to reflect the EIA's reclassification of IPPs. That is,

$$C_{th} = \beta_0 + \beta_1 Y_{th} + \beta_2 oilprice_{th} + \beta_3 HDD_{th} + \beta_4 CDD_{th} + \beta_5 IPP_{th} + \sum_{h=1}^{5} \gamma_h$$

where IPPth is a dummy variable reflecting the reclassification. Based on discussions with Steven Wade (2007) and examination of the AEO and AER, we determined that the switch of IPPs from the industrial to the electric utility sector first occurred in the AEO 2002. However, it seems that the data necessary to make the revision were only available for years after 1988. Thus, we set IPP equal to unity only for projections made prior to the AEO 2002 edition, which sought to predict consumption for a year after 1988.

Table 3a shows the coefficients from the control vector from these regressions; Table 3b presents the projection horizon coefficients. Examining these control variables allows us to draw some conclusions about the validity of our analysis. First, as one would expect, oil price projection error has a significant negative coefficient for all three fuels in the transportation sector. As they are all refined petroleum products, we would expect low consumption projections of these fuels if oil prices were projected to be too high.

The weather variables are similarly telling in the residential sector. For HDDs, both the electricity and natural gas regressions display a positive relationship between deviations and consumption. If the 30-year average projected more HDDs than actually occurred, we would expect consumption projections to be too high as well due to the overprojection of residential heat use. A similar story goes for CDDs and electricity through the use of fans and air conditioners.

In investigating the status of IPPs, we concluded that the sectoral switch would be a serious issue only for natural gas; this is reflected in the fact that IPP is only significant in the electric utility natural gas and industrial natural gas regressions. The negative coefficient for the electric utility sector and positive coefficient for the industrial sector reflect the fact that for

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observations where IPP = 1, projections were made as though IPPs would be counted in the industrial sector. However, in the historical AER data (realized after the sectoral switch), they are instead included in the electric utility sector. Hence, these observations for which IPP = 1 systematically underpredict natural gas consumption in the electric utility sector and overpredict it in the industrial sector.

Table 3b presents the projection horizon coefficients, which are an indication of residual bias accounting for the control vector. We find substantial variation across fuel/sector combinations. If we consider the observation-weighted mean coefficient, only four fuel/consuming sector combinations show a significant bias. Consistent with the simple average error reported in Figure 4, the regression analysis confirms that the consumption of electricity from renewables is significantly overprojected, while consumption of residential electricity and transportation tend to be underprojected. At the same time, although electric utility natural gas was the most underprojected sector on average, when we control for errors in macroeconomic projections and other factors, we find a significant bias toward overprojection in this sector. This is an artifact of the IPP switchover; once we control for their reclassification, we find a tendency to overprojection. However, focusing on the mean coefficient merely aggregates across projection horizons, an issue that has characterized several earlier studies.

When we look at the individual horizon coefficients, five more fuel/consuming sector combinations show significant bias in either the first or last of the projection horizons examined. Commerical electricity and transportation motor gasoline are both underpredicted, as one might have expected from Figure 4. Industrial natural gas also displays a negative bias that is significant in the one-year horizon and insignificant for longer horizons, although demand in this sector had on average been overpredicted after the first year. While industrial consumption of coal was on average the second most overpredicted sector, when we control for the explanatory variables it is significantly overpredicted only in the five-year projection horizon. Electric utility nuclear is significantly overprojected for the one-year horizon, but this shifts to underprojection (albeit to a statistically insignificant extent) when we look at the longer four- and five-year horizons, underscoring the value of disaggregating by horizon length.

## Conclusions

Our analysis investigates bias in the EIA's AEO, focusing on the near- to mid-term energy projections in this widely used document. Overall, based on an analysis of the EIA's 22-year projection record, we find a fairly persistent tendency to underestimate total energy demand by an average of 2 percent per year over the one- to five-year projection horizon. In the

individual fuel/consuming sectors, the residual projection errors range up to 7 percent. Since these calculations control for errors in projections of GDP, oil prices, HDDs, and CDDs, the estimated bias must be found elsewhere, most likely within individual demand or supply side modules. Of course, some portion of these residual errors might be explained by unobservable policy, technological, and institutional changes that are not, by definition, considered in the EIA's projection techniques.

Prime candidates for attention can be found in those individual modules where our analysis reveals significant biases across the full five-year horizon: electric utility renewables, electric utility natural gas, residential electricity, and transportation distillate. Next on the list are those fuel/consuming sectors that exhibit significant biases in one or more of the time horizons: commercial electricity, electric utility nuclear, industrial coal, industrial natural gas, and transportation gasoline.

Projecting the future is an inherently difficult task fraught with many uncertainties. The EIA is a respected statistical agency with a well deserved reputation for professional competence, political independence, and transparency. The fact that the EIA's models are subject to frequent updating and that our analysis spans both NEMS and non-NEMS periods of AEO projections are potentially limiting factors of our work. At the same time, it is our expectation that findings of the type developed here will themselves be subject to evaluation and, if sustained, will serve as valuable input to the EIA's ongoing efforts to revise and improve its modeling capabilities.

Finally, we echo a point made by Auffhammer (2007): users of EIA projections would benefit from greater clarity regarding the EIA's objectives in preparing its projections. Does the EIA prefer to err on the side of underprojection or overprojection? Apart from any technical changes made to the models, even qualitative information about the objectives of the EIA or, perhaps, individual modelers, would have considerable value to the user community as the EIA projections are applied in real-world circumstances.

**Table 1. Results of Woolridge (2002) Test for Panel Serial Correlation**

| Sector–Fuel | F-statistic | p-value |
|---|---|---|
| Total demand | 0.895 | 0.356 |
| Commerical electricity | 20.082 | 0.001 |
| Commercial natural gas | 8.958 | 0.012 |
| Electric utility coal | 2.418 | 0.148 |
| Electric utility natural gas | 0.671 | 0.430 |
| Electric utility nuclear | 4.583 | 0.056 |
| Electric utility renewables | 2.400 | 0.150 |
| Industrial coal | 0.026 | 0.875 |
| Industrial electric | 1.324 | 0.274 |
| Industrial natural gas | 11.538 | 0.006 |
| Residential electricity | 1.260 | 0.286 |
| Residential natural gas | 1.109 | 0.315 |
| Transportation distillate | 26.253 | 0.000 |
| Transportation motor gasoline | 5.988 | 0.032 |
| Transportation jet fuel | 15.180 | 0.003 |

$H_0$: No first-order autocorrelation.

**Table 2. Percentage Total Energy Consumption Projection Error**

| Regressor | Coefficient |
|---|---|
| Real output error | 0.162 |
|  | (0.161) |
| Oil price error | –0.004 |
|  | (0.007) |
| HDD deviation | 0.027 |
|  | (0.064) |
| CDD deviation | –0.068 |
|  | (0.048) |
| 1-Year projection horizon | –0.018* |
|  | (0.007) |
| 2-Year projection horizon | –0.029** |
|  | (0.008) |
| 3-Year projection horizon | –0.020* |
|  | (0.009) |
| 4-Year projection horizon | –0.018* |
|  | (0.007) |
| 5-Year projection horizon | –0.013 |
|  | (0.010) |
| Mean projection horizon | –0.020** |
|  | (0.006) |

\**Significant at 1 percent; *significant at 5 percent.

Mean projection horizon is a postestimate frequency-weighted linear combination of the other five projection horizon variables and is not included in the actual regression specification. Standard errors are clustered by year projection was made and are presented in parentheses. The constant term is constrained to equal zero.

**Table 3a. Sector/Fuel Energy Consumption Regression, Control Vector Coefficients**

| Sector/Fuel | Real output error | Oil price error | HDD error | CDD error | IPP |
|---|---|---|---|---|---|
| Commerical electricity | 0.831** | 0.006 | –0.116 | 0.009 | |
| | (0.270) | (0.023) | (0.081) | (0.104) | |
| Commercial natural gas | 0.375 | –0.006 | 0.093 | –0.272 | |
| | (0.447) | (0.038) | (0.210) | (0.199) | |
| Electric utility coal | 0.515* | –0.009 | 0.108 | –0.017 | –0.009 |
| | (0.186) | (0.017) | (0.072) | (0.052) | (0.018) |
| Electric utility natural gas | 0.842* | 0.070 | –0.329 | 0.255 | –0.193** |
| | (0.326) | (0.043) | (0.221) | (0.248) | (0.026) |
| Electric utility nuclear | 0.141 | 0.080** | –0.152 | 0.055 | –0.010 |
| | (0.170) | (0.016) | (0.173) | (0.189) | (0.009) |
| Electric utility renewables | –0.078 | 0.032 | –0.453 | –0.172 | –0.073 |
| | (0.339) | (0.048) | (0.335) | (0.297) | (0.049) |
| Industrial coal | 1.512** | 0.026 | –0.765 | –0.678** | 0.048 |
| | (0.512) | (0.046) | (0.393) | (0.209) | (0.048) |
| Industrial electric | 0.582* | –0.008 | –0.161 | –0.186 | 0.036 |
| | (0.230) | (0.016) | (0.137) | (0.114) | (0.022) |
| Industrial natural gas | –0.076 | 0.016 | –0.641 | –0.740 | 0.126** |
| | (0.736) | (0.041) | (0.436) | (0.400) | (0.043) |
| Residential electricity | 0.156 | –0.014* | 0.118** | 0.149** | |
| | (0.105) | (0.006) | (0.025) | (0.024) | |
| Residential natural gas | –0.056 | 0.005 | 0.350** | –0.148 | |
| | (0.224) | (0.016) | (0.108) | (0.088) | |
| Transportation distillate | 0.735* | –0.084* | 0.301* | 0.001 | |
| | (0.282) | (0.033) | (0.135) | (0.104) | |
| Transportation motor gasoline | 0.311 | –0.075** | 0.058 | –0.047 | |
| | (0.151) | (0.012) | (0.075) | (0.041) | |
| Transportation jet fuel | 0.183 | –0.115** | –0.019 | –0.225 | |
| | (0.351) | (0.026) | (0.286) | (0.156) | |

**Significant at 1 percent; *significant at 5 percent.

Regression also included dummy variables for projection horizon (see Table 3b for results). Standard errors are clustered by year projection was made and are presented in parentheses. The constant term is constrained to equal zero.

**Table 3b. Sector/Fuel Energy Consumption Regression, Projection Horizon Coefficients**

| Sector/Fuel | 1-Year | 2-Year | 3-Year | 4-Year | 5-Year | Mean |
|---|---|---|---|---|---|---|
| Commerical electricity | –0.004 (0.010) | –0.007 (0.012) | –0.011 (0.014) | –0.020 (0.013) | –0.031** (0.011) | –0.013 (0.011) |
| Commercial natural gas | –0.015 (0.017) | 0.009 (0.021) | 0.024 (0.022) | 0.029 (0.021) | 0.033 (0.024) | 0.014 (0.019) |
| Electric utility coal | –0.007 (0.011) | –0.003 (0.013) | –0.001 (0.014) | –0.001 (0.014) | 0.004 (0.016) | –0.002 (0.013) |
| Electric utility natural gas | 0.006 (0.021) | 0.026 (0.018) | 0.053* (0.023) | 0.045 (0.024) | 0.081* (0.033) | 0.040* (0.018) |
| Electric utility nuclear | 0.024** (0.007) | 0.009 (0.009) | 0.004 (0.012) | –0.006 (0.012) | –0.020 (0.011) | 0.004 (0.008) |
| Electric utility renewables | 0.077 (0.044) | 0.154** (0.044) | 0.183** (0.048) | 0.214** (0.055) | 0.231** (0.059) | 0.167** (0.047) |
| Industrial coal | –0.020 (0.039) | 0.030 (0.044) | 0.058 (0.050) | 0.090 (0.055) | 0.137* (0.051) | 0.052 (0.044) |
| Industrial electric | –0.029 (0.018) | –0.026 (0.016) | –0.013 (0.018) | –0.001 (0.021) | 0.024 (0.023) | –0.012 (0.018) |
| Industrial natural gas | –0.099* (0.035) | –0.075 (0.041) | –0.061 (0.046) | –0.053 (0.050) | –0.035 (0.050) | –0.067 (0.041) |
| Residential electricity | –0.005 (0.004) | –0.007 (0.004) | –0.011 (0.005) | –0.016* (0.006) | –0.018** (0.005) | –0.011** (0.003) |
| Residential natural gas | –0.017 (0.009) | 0.012 (0.010) | 0.016 (0.010) | 0.016 (0.010) | 0.018 (0.012) | 0.008 (0.009) |
| Transportation distillate | –0.007 (0.012) | –0.026 (0.018) | –0.032* (0.015) | –0.028 (0.014) | –0.024 (0.013) | –0.023* (0.013) |
| Transportation motor gasoline | –0.000 (0.004) | –0.003 (0.006) | –0.005 (0.005) | –0.013 (0.007) | –0.021* (0.008) | –0.007 (0.004) |
| Transportation jet fuel | –0.010 (0.013) | –0.009 (0.015) | 0.013 (0.021) | 0.035 (0.024) | 0.053 (0.025) | 0.013 (0.017) |

**Significant at 1 percent; *significant at 5 percent.

Regression also included output projection error, oil price projection error, heating and cooling degree days deviations, and (for industrial and electric utility sectors) a dummy for the IPP classification switch as discussed in the text (see Table 3a for results). Mean projection horizon is a postestimate frequency-weighted linear combination of the other five projection horizon variables and is not included in the actual regression specification. Standard errors are clustered by year projection was made and are presented in parentheses. The constant term is constrained to equal zero.

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