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August 15, 2007

The Honorable Nancy Pelosi
Speaker
U.S. House of Representatives
235 Cannon House Office Building
Washington, DC 20515

Dear Madam Speaker:

Given the importance of cost effective climate change legislation, the attached article by Public Utilities Fortnightly entitled, “Betting on Bad Numbers” is of critical importance. The article, written by two Penn State University professors, illustrates beyond doubt that the Energy Information Administration (EIA) computer model that is used to calculate the cost of climate legislation consistently produces systematically flawed data that significantly underestimates the cost of climate legislation. We urge you to read this article and take action to improve the accuracy of EIA’s modeling.

Key conclusions of the study are: The EIA model systematically over-estimates natural gas production; underestimates natural gas consumption by the electricity utility sector; over estimates LNG imports; and underestimates prices.

The analysis is focused on natural gas and for good reason. Under a carbon constrained economy natural gas will become the “bridge fuel.” And, because natural gas supply has fallen by 4% since 2000, even a small increase in demand can significantly drive up the price. Please keep in mind that consumers paid $76 billion more in 2006 versus 2000 for natural gas and $65 billion more for electricity. There is much at stake.

As consumers, our worse fear is that if carbon caps are established, electric utilities will fuel switch from coal to natural gas. According to testimony before the Senate Energy and Natural Resources Committee on March 26, 2007, this is exactly what happened in Europe with the implementation of the EU Emissions Trading Scheme. Testimony from the panel comprised of Europeans who said the bulk of the CO_2 emission reductions came from utility fuel switching from coal to natural gas.

Sincerely,

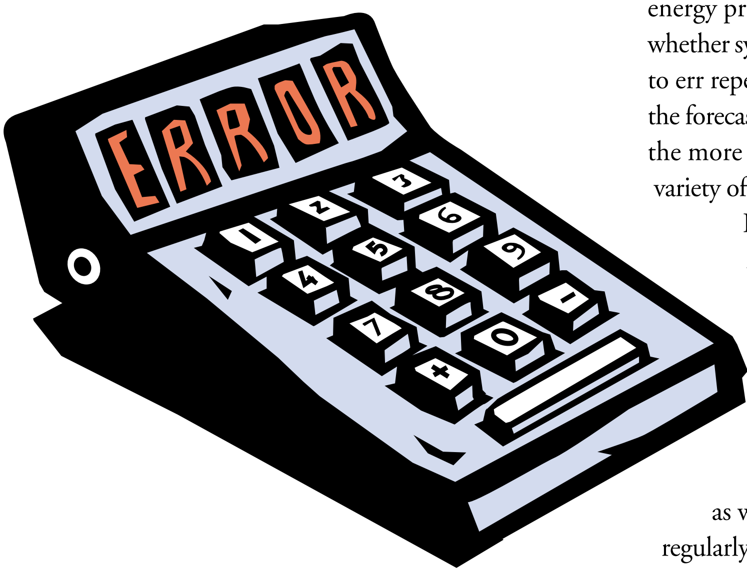
Paul N. Cicio
President

cc: The Honorable Samuel W. Bodman
The Honorable Guy Caruso

Gas-Market Forecasts

BETTING ON BAD NUMBERS

Why predictions from the Energy Information Administration may contain systematic errors.



The difficulties of predicting future trends in energy are widely recognized (*see Reference [4], p. 61*). Even the most sophisticated of forecasting models cannot account fully for a myriad of complex and generally uncontrollable variables. Thus, energy policy-makers necessarily must anticipate a wide range of possible outcomes in formulating energy plans.

The issue here, however, is not how difficult it is to predict energy prices, supply, and demand. Our question, rather, is whether systematic biases are built into forecasts, causing them to err repeatedly in the same direction. And the more visible the forecast (and the more likely also that it will be used), then the more likely it is that the error will be compounded in a variety of settings.

In the case of the U.S. Energy Information Administration (EIA), for example, natural gas (NG) data and projections are used widely in regulatory proceedings, energy planning, scientific research, investment decisions, litigation, and legislation. In such cases, systematic bias can have profound socioeconomic implications—not only within the United States but in other nations as well. Indeed, the National Energy Board of Canada regularly includes EIA NG forecasts in its projections. Even OPEC scholars use EIA projections as a benchmark in their research.

This widespread use of EIA forecasts follows the organization's own view of its nature and purpose. In fact, the EIA has

By Timothy J. Considine, Ph.D. and Frank A. Clemente, Ph.D.

indicated that it designs its forecasts specifically to aid policymakers by providing "a policy-neutral reference case that can be used to analyze policy initiatives." However, while the EIA may strive to make its reference case forecasts "policy neutral," the question still remains: Are they "substantively neutral" in a forecasting sense? In other words, are they removed from the sort of systematic bias in which predictions deviate from actual observations in a distinct pattern?

Over the past decade, it increasingly has become apparent that EIA forecasts for NG differ substantially from actual outcomes. Some commentators [1] have suggested that EIA forecasts present a consistently "optimistic" view of NG that, for instance, underestimate price and overestimate supply. On the surface, this concern has face validity based upon forecasts from the EIA's *Annual Energy Outlook* series:

- In 2002, the EIA projected the cost of NG to electric generators in 2006 would be $ 3.82 per thousand cubic feet (Mcf). Actual cost per Mcf was $7.15 (all in 2006 dollars)
- In 2003, the EIA overestimated domestic NG production in 2006 by almost 2 trillion cubic feet—more than the annual production of Oklahoma.
- In 2005, the EIA projected liquefied natural gas (LNG) imports would reach 1,140 bcf in 2006. Actual imports in 2006 were only 583 Bcf—off by more than 550 Bcf just one year out.

To shed light upon the question of bias, we conducted an error decomposition analysis of EIA NG projections of key variables—price, supply, and consumption—from 1998 to 2006. Error-decomposition analysis is used commonly to evaluate economic forecasting models by identifying those components of the forecast errors or the proportions attributed to bias, the model, or randomness. A reliable model would display random errors with no discernable pattern of consistent under- or over-predictions. Thus, the proportions of forecast errors attributed to bias and model components would be minimal.

In our case, we evaluated one-, two-, three-, and four-year-ahead forecasts made by EIA from 1998 to 2006 for six key variables: (1) wellhead price; (2) price to electric generators; (3) consumption by electric generators; (4) domestic production; (5) imports from Canada; and (6) LNG imports.

Selecting Data for Review

Bolinger and Wiser [5] provides a graphical illustration of how EIA wellhead-gas prices forecasts going back to 1985 track actual prices. Their graph clearly illustrates that price forecasts during the 1980s turned out to be too high while forecasts made during the early 2000s appear too low. Graphical techniques, however, do not quantify the size or systematic tendencies of these forecasts errors. This study attempts to extend their analysis by applying the error decomposition methods discussed above.

During December of each year, EIA publishes a forecast that forms the basis of the *Annual Energy Outlook,* or *AEO*, [8] for the subsequent year. (Note: The EIA each year releases its reference case in December. Then in the following February, the EIA releases its full report, with sensitivity cases.)

So, for example, the 2006 *AEO* report released in December 2005 [9] contains a forecast of 2006 prices. This study examines their forecasts published from 1998 to 2006 because EIA posts the detailed forecast tables on its Web site, which is accessible to the public. Auffhammer [2] uses a larger sample and finds that the EIA forecasts of NG consumption, production, imports, and prices do not exhibit the necessary conditions for rationality under symmetric loss. (*Note: The EIA uses the National Energy Modeling System, or NEMS. See "Appendix: Methods of Forecast Evaluation," p. 58, describing our evaluation of EIA's forecasting methods.*)

While each EIA forecast extends 20 years or more, the maximum length of the forecast horizon examined in this study is four years. A three- to four-year forecast for prices is likely of most interest to industry because natural-gas-fired electricity generating plants take roughly three years to build. Moreover, going any more than four years out would not be meaningful given the small size of our sample. Given the sample of forecasts from 1998 to 2006, there are nine one-year-ahead forecasts, eight two-year forecasts, seven three-year forecasts, and six four-year forecasts. While comparing each published *AEO* forecast with actual data over its entire forecast horizon is insightful, economists typically stratify forecasts by length of time not necessarily when they are made. Hence, the forecasts are sorted by length of forecast horizon.

Evaluating the EIA Forecasts

To keep the analysis manageable and comprehensible, our decomposition analysis is conducted for three pairs of variables in the natural-gas market involving prices, domestic flows, and imports. The two prices are the average wellhead price and prices paid for natural gas by electricity producers. The flow variables include dry natural-gas production and consumption by electricity producers. The later was selected because the electricity sector comprises the most dynamic, market-sensitive component of natural-gas consumption along with industrial sector use. Imports include those from Canada and imports of LNG.

Prices. The EIA forecasts natural-gas prices in constant dollars. To establish a consistent basis for comparison, these constant price forecasts are inflated by the corresponding forecasts for the price deflator for gross domestic product (GDP). Once the forecasts are sorted, the prices are converted back to 2006 dollars using the latest GDP price deflator.

The forecast evaluation metrics for the one- through four-year-ahead forecasts from 1998 to 2006 appear in Table 1. On average, the one-year-ahead average percentage forecast error for the wellhead natural-gas price is 16 percent with an absolute error of $1/Mcf. These errors steadily rise and reach more than 45 percent with the four-year-ahead forecast and $2.60/Mcf.

The RMSE (root mean squared error), which penalizes large errors more severely than the average percentage error (*see "Appendix," p. 58 for full explanation*), is almost 35 percent for the one-year-ahead forecast. Like the average percentage error, it too rises with the forecast horizon, reaching more than 57 percent with the four-year-ahead forecasts.

The decomposition of the MSE (mean squared error) for the one-year-ahead wellhead natural-gas price forecast errors indicates that 54.7 percent of the errors can be attributed to systematic bias. This bias crests to almost 88 percent for the three-year-ahead forecasts. While random disturbances are substantial for the one-year-ahead forecast, the large proportion attributed to bias is noteworthy. A plot of the actual time series for wellhead natural-gas prices and the four different forecasts appears in Fig. 1 and illustrates the tendency of the EIA price forecasts to systematically under-predict actual prices. The results for electric generator's natural-gas costs are very similar to those for wellhead natural-gas prices.

TABLE 1 EVALUATION OF EIA NATURAL GAS-PRICE FORECASTS, 1998-2006

	Years Ahead			
	One	Two	Three	Four
	Average Wellhead NG Prices			
Average Percentage Error	-16.0%	-30.3%	-41.8%	-45.5%
Average Absolute Error ($/Mcf)	1.055	1.749	2.340	2.652
Root Mean Squared Error	34.9%	48.9%	54.3%	57.3%
Decomposition of MSE (proportion)				
Bias	0.547	0.651	0.876	0.845
Model	0.006	0.013	0.029	0.027
Random	0.447	0.336	0.095	0.128
	Electric Generator's NG Prices			
Average Percentage Error	-16.0%	-29.1%	-39.5%	-43.0%
Average Absolute Error ($/Mcf)	1.153	1.893	2.537	2.861
Root Mean Squared Error	33.4%	44.8%	50.8%	52.5%
Decomposition of MSE (proportion)				
Bias	0.565	0.672	0.868	0.854
Model	0.024	0.006	0.022	0.014
Random	0.412	0.322	0.110	0.131

Source: Annual Energy Outlook (annually, 1998-2006), U.S. Energy Information Administration, Table 14.

TABLE 2 EVALUATION OF EIA GAS CONSUMPTION AND PRODUCTION FORECASTS, 1998-2006

	Years Ahead			
	One	Two	Three	Four
	Electric Generator's NG Consumption			
Average Percentage Error	-15.3%	-15.0%	-14.6%	-14.7%
Average Absolute Error (TCF)	0.913	0.871	0.800	0.816
Root Mean Squared Error	19.7%	21.4%	20.1%	17.9%
Decomposition of MSE (% Contribution)				
Bias	0.575	0.548	0.577	0.704
Model	0.353	0.390	0.348	0.234
Random	0.072	0.062	0.075	0.062
	Dry NG Production			
Average Percentage Error	1.6%	4.1%	5.5%	7.8%
Average Absolute Error (TCF)	0.590	1.053	1.152	1.527
Root Mean Squared Error	3.9%	6.1%	7.0%	9.2%
Decomposition of MSE (% Contribution)				
Bias	0.189	0.444	0.615	0.707
Model	0.472	0.417	0.285	0.221
Random	0.340	0.139	0.100	0.07

Source: Annual Energy Outlook (annually, 1998-2006), U.S. Energy Information Administration, Table 13.

Market Flows. Table 2 shows the forecast errors for natural-gas consumption by electricity generators and for dry natural-gas production. The forecast errors are much smaller than those associated with the forecast errors for prices, which is a common phenomenon. Price forecasting often is more difficult than forecasting demand and production series, which often contain a sizeable trend component or signal. Nevertheless, the forecast errors for these two key natural-gas market flows are substantial.

The EIA forecasts for natural-gas consumption in electricity generation consistently are below actual observations of gas use in this sector (*see the average percentage errors in Table 2*). This is somewhat counter-intuitive because given that EIA under-estimates prices paid for natural gas by electric generators, it would seem that lower prices would imply higher, not lower, natural-gas consumption, all other things held equal. One of the big changes affecting the electricity sector's use of fuels has been the sulfur-dioxide emissions-trading program. That program has exerted a dramatic effect on the opportunities for fuel substitution in power generation, as shown by Considine and Larson [6]. Whether the NEMS correctly mod-

Table 3 **Evaluation of EIA Natural Gas Import Forecasts, 1998-2006**

	Years Ahead			
	One	Two	Three	Four
	NG Imports from Canada			
Average Percentage Error	-4.4%	-3.1%	2.0%	4.9%
Average Absolute Error (TCF)	0.184	0.245	0.285	0.347
Root Mean Squared Error	8.1%	8.9%	8.8%	10.9%
Decomposition of MSE (% Contribution)				
Bias	0.464	0.126	0.044	0.205
Model	0.246	0.613	0.669	0.625
Random	0.290	0.261	0.287	0.170
	LNG Imports			
Average Percentage Error	-11.2%	-5.6%	-7.1%	-25.1%
Average Absolute Error (TCF)	0.146	0.160	0.193	0.155
Root Mean Squared Error	65.6%	53.4%	67.4%	59.8%
Decomposition of MSE (% Contribution)				
Bias	0.151	0.104	0.093	0.420
Model	0.455	0.255	0.515	0.036
Random	0.394	0.641	0.393	0.544

Source: *Annual Energy Outlook* (annually, 1998-2006), U.S. Energy Information Administration, Table 13.

els the role of permits in power-sector fuel demand and fuel switching could be an important question.

The absolute error for the one-year-ahead forecast for electric generators natural-gas consumption is more than 900 billion cubic feet, which is more than 15 percent of consumption in this sector. In addition, the RMSEs are around 20 percent, nearly four times the errors found in econometric forecasting models of energy demand. [7] Like prices, the error decomposition analysis for natural-gas consumption by electric generators reveals a substantial bias across all four forecast horizons.

The forecast errors for dry natural-gas production reveal further problems. As the average percentage errors indicate, EIA consistently over-predicts dry natural-gas production. The absolute errors are quite sizeable in relation to marginal supplies of gas, specifically imports of LNG. For example, the one-year-ahead forecast error for production is 590 billion cubic feet, which is about equal to LNG imports in 2006. The two- through four-year-ahead forecast errors exceed one trillion cubic feet.

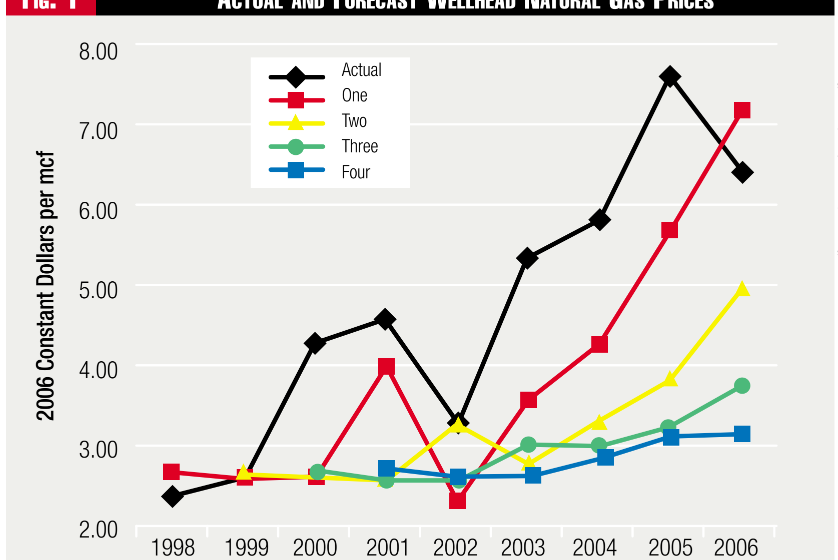
The mean squared error decomposition for natural-gas production also reveals sizeable bias, especially for the three- and four-year forecasts. Unlike prices and consumption forecast errors, the model component of the errors is more than 40 percent for the one- and two-year forecasts. This fact suggests that the model itself is generating systematic errors for the near-term forecast horizon. The time path of each forecast depicted in Fig. 2 illustrates that even though EIA has been scaling back its projections of natural-gas production, the model still portrays an upward track for production albeit from a lower base during each forecast year.

Imports. Another important factor influencing natural-gas markets is imports. The largest external source of natural gas into the United States is Canada, although EIA expects imports of LNG to become significant in the future. Among the forecast errors examined in this study, those associated with EIA's projection of imports from Canada are the lowest. Similar to the other forecast errors, however, the forecasts contain either bias or systematic errors arising from the model.

The projections of LNG imports are not as accurate as those for Canadian imports. The RMSEs are quite large and, while the bias components are relatively small, the proportion of the forecast errors associated with the model remains substantial, especially for the first and third year-ahead forecasts. This finding could be associated with the rather idiosyncratic nature of the LNG import forecasts.

To understand what is happening in the LNG forecast error decomposition, a scatter plot of the actual versus predicted LNG imports appears in Fig. 3. A perfect forecast in which the predictions are equal to the actual observations is plotted on the solid line. A "good" forecasting model should generate

Fig. 1 **Actual and Forecast Wellhead Natural Gas Prices**



Note: Forecast published in January

Fig 1 Source: *Annual Energy Outlook* (annually, 1998-2006), U.S. Energy Information Administration, Table 14.

forecasts close to the line of perfect forecasts and randomly scattered around it. As Fig. 3 illustrates, there are several very large over-predictions of LNG imports. The small number of these very large errors most likely accounts for the erratic swings in the mean squared error components reported above in Table 3. Indeed, as Fig. 4 illustrates EIA substantially over-estimated LNG imports in each of the preceding three years.

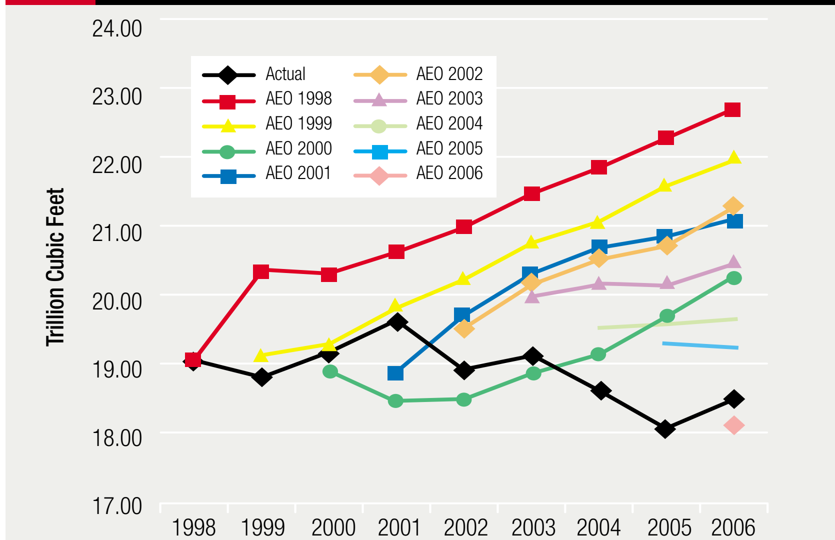
Policy Implications

As the independent research branch of the Department of Energy, the EIA forecasts for NG possess an imprimatur that stretches across the panorama of energy policy and analysis. Thus, the socioeconomic implications of systematic bias are profound indeed.

Several important conclusions can be drawn from this research. First, the NEMS model used by EIA to generate the *AEO* forecasts tends to over-estimate NG production and to under-estimate NG consumption by electricity producers. While EIA forecasts of NG imports from Canada fare somewhat better, projections of LNG imports are over-estimated substantially. These errors are associated with significant under-predictions of market prices. Hence, the overall optimistic picture of ample NG supplies, and growing consumption with either falling or constant real prices has not been supported by actual experience.

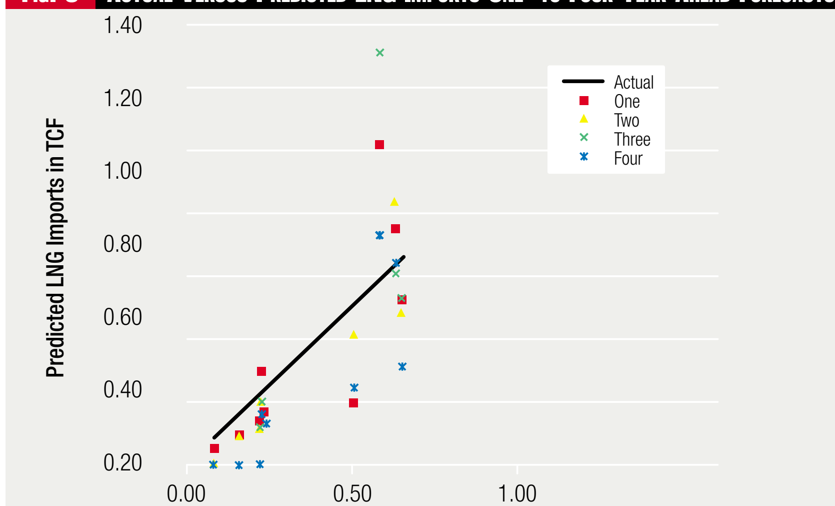
Moreover, an error-decomposition analysis demonstrated that the variation in EIA's forecast errors generally are not reflective of random chance but instead contain evidence of systematic bias, either arising from a fixed, linear bias or

FIG. 2 **ACTUAL AND FORECAST DRY NATURAL-GAS PRODUCTION**



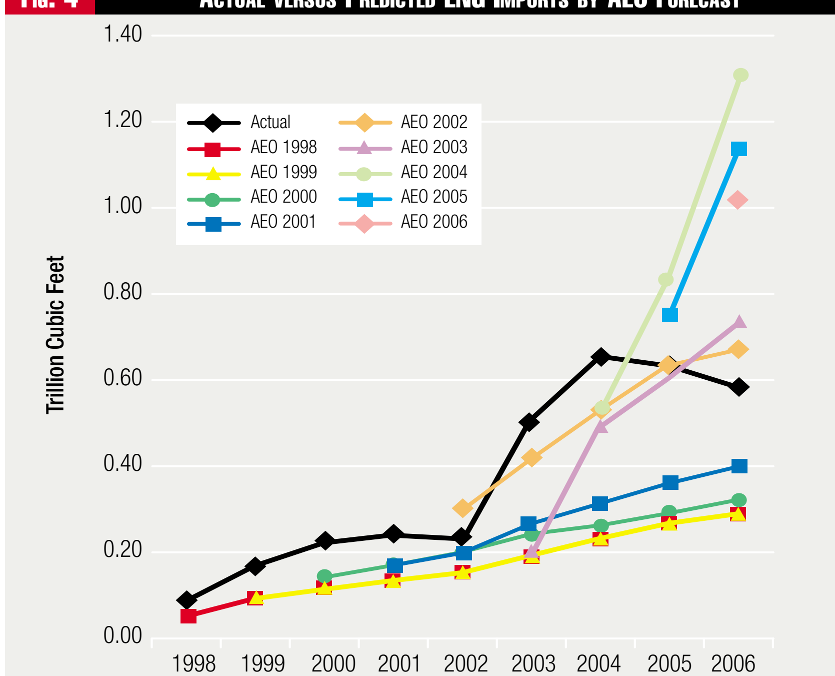
Source: Annual Energy Outlook (annually, 1998-2006), U.S. Energy Information Administration, Table 13.

FIG. 3 **ACTUAL VERSUS PREDICTED LNG IMPORTS ONE- TO FOUR-YEAR-AHEAD FORECASTS**



Source: *Annual Energy Outlook* (annually, 1998-2006), U.S. Energy Information Administration, Table 13.

FIG. 4 **ACTUAL VERSUS PREDICTED LNG IMPORTS BY AEO FORECAST**



Source: *Annual Energy Outlook* (annually, 1998-2006), U.S. Energy Information Administration, Table 13.

APPENDIX

Methods of Forecast Evaluation

There are a variety of metrics available to evaluate forecasts. No one measure tells the complete story but rather a suite of metrics and graphics must be employed to evaluate forecasts.

Since the National Energy Modeling System (NEMS) used by EIA to generate its forecasts equilibrates supply and demand, it seems most appropriate here to employ methods of economic-forecast evaluation in order to evaluate EIA forecasts of natural-gas markets. These methods all involve the computation of a variety of metrics that compare actual observations with predicted values.

The first metric is the average percentage error defined as:

$$APE_t = \frac{1}{n}\sum_{t=1}^{n} 100 * \frac{(P_t - A_t)}{A_t}$$

where t denotes the time period for a forecast horizon of n periods, P_t is the prediction from the model for period t, and A_t is the actual realized value of the variables in that period. As Auffhammer (*see Reference [2], p. 61*) observes, the problem with this metric is that large positive and negative values can cancel each other out. A similar metric is the average absolute error:

$$AAE = \frac{1}{n}\sum_{t=1}^{n} |A_t - P_t|,$$

which provides an estimate of the average magnitude of the forecast errors.

The third measure employed in this study is the mean squared error, which is defined as

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{(P_t - A_t)}{A_{t-1}}\right)^2 = \frac{1}{n}\sum_{t=1}^{n}(p_t - a_t)^2$$

where $p_t = (P_t - A_{t-1})/A_{t-1}$ and $a_t = (A_t - A_{t-1})/A_{t-1}$. Notice unlike the common average percent error, the mean square error compares predicted versus actual changes. In addition, squaring the errors has the effect of disproportionately penalizing large errors, either negative or positive. The square root of the mean squared error, often referred to as the root mean squared error (RMSE), is more commonly reported because the square root operator on changes closely approximates percent change.

Ideally, model forecast errors should be random, displaying no discernible tendencies to either over or under-predict, or no patterns of either getting smaller or larger over time. Economists and statisticians have developed a variety of methods to determine whether forecast errors exhibit randomness or systematic bias. These methods involve decomposing the mean squared error into various error components. There are a variety of methods to decompose the MSE into its various components. An approach devised by Theil [14], and later recommended by Maddalla [13], and subsequently used in many studies since involves the computation of the following three components:

$$B = Bias = \frac{(\bar{p} - \bar{a})^2}{MSE}$$

$$M = Model = \frac{(S_p - rS_a)^2}{MSE}$$

$$R = Random = \frac{(1 - r^2)S_a^2}{MSE}$$

where S_p is the population standard deviation of p, r is the correlation coefficient between p and a and S_a is the standard deviation of a, and all three measures sum to one, *i.e.* $B + M + R = 1$. Maddalla and Theil note that the bias and the model components measure what can be called "systematic" errors. If B is large, then the average predicted change deviates substantially from the actual average change. This is a serious error because forecasters should be able to reduce such errors in the course of time. In short, if B is close to 1, the forecast is considered biased. The model component of the forecast error reflects the linear association between the actual and predicted values. If M is relatively large then this would suggest that the model itself is generating systematic errors. In a perfect forecast, both M and B would be zero so that if the following regression was estimated:

$$A_t = \alpha + \beta P_t$$

$\hat{\alpha} = 0$ and $\hat{\beta} = 1$ so that $A_t = P_t$. A regression model is not estimated in this study because our sample of forecasts is relatively small. Therefore, we do not attempt to estimate statistical confidence intervals around our forecast evaluation metrics because the power of these tests would be weak given the small sample.—***TJC, FAC***

from a systematic error coming from the model itself. This evidence of forecast bias arising from perhaps the most comprehensive energy market forecasting system in the world illustrates the enormous difficulty of forecasting these markets. The emergence of a natural-gas cartel will add even greater uncertainty to the forecasting.

These results offer several lessons and suggest certain concerns about current and future forecasts at EIA:

1. Gas Production. First, the consistent over-predictions of NG production in the United States should raise serious questions about the reliability of the premise that large supplies would become available with higher prices.

2. Gas Use for Generation. Second, the under-prediction of NG use in electric-power production even with unrealistically low prices suggests that other factors, such as sulfur-dioxide pollution permit costs, may be stimulating NG use in this sector. (This lesson suggests that the NEMS may not be adequately modeling factors that determine the electric-power sector's consumption of NG.)

3. LNG Imports. Third, the large over-estimates of LNG imports suggest fundamental problems with the trade side of the model. Each of these three problems presents daunting challenges for energy market modelers.

4. A Bias Toward Optimism. Current EIA forecasts exhibit a continuing optimism. In the 2007 *AEO*, for example, NG prices are forecasted to decline over the next decade—despite the fact that wellhead prices have increased more than 100 percent in the last five years and that the EIA did not project the vast bulk of those increases. Further, the EIA forecasts that NG production will increase 11 percent by 2020. Yet the EIA has overestimated production substantially in virtually every forecast since 1998.

5. A Failure to Recognize the Problem. Despite the biased divergence between their NG forecasts and actual outcomes, the EIA has published virtually nothing on the question of asymmetrical error. In fact, EIA's model evaluation methodology may itself camouflage the problem. For example, Auffhammer [2] has commented that, "The EIA conducts its own forecast evaluation…[but] this type of evaluation ignores potentially persistent biases in the forecasting model."

The analysis reported here suggests that considerable caution should be exercised when using EIA forecasts relating to the future price, supply, and consumption of NG. Similar caution should be exercised when using NEMS to assess the broader economic impacts of energy policy initiatives, *e.g.*, carbon cap-and-trade programs.

Climate-change proposals currently before Congress [3] depend heavily on predictions of the response of natural-gas supply and prices to carbon-permit prices. The actual capability of the NG supply network both here and abroad will be a critical factor in how economies adjust to such climate-change policies. Overestimating the supply capabilities of this network (as EIA has done over the past decade) could lead to underestimating the costs of carbon regulations.

Tim Considine is a member of the Energy and Mineral Engineering Department. Frank Clemente is a senior member of the graduate faculty at Penn State and former director of the university's Environmental Policy Center. Contact Clemente at 814-237-0787 or fac226@psu.edu. *The authors would like to express their appreciation for suggestions from Professor Maximilian Auffhammer (UC-Berkeley).*

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