The Rationality Of EIA Forecasts Under Symmetric and Asymmetric Loss.

Maximilian Auffhammer*

Department of Agricultural and Resource Economics &
International Area Studies

University of California Berkeley

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Abstract

The United States Energy Information Agency publishes annual forecasts of nationally aggregated energy consumption, production, prices, energy intensity and GDP. These government issued forecasts often serve as reference cases in the calibration of simulation and econometric models which climate and energy policy are based on. This note shows that under the assumption of a class of symmetric loss functions some EIA forecasts are not rational. If we extend the class of loss functions considered for these series to asymmetric ones, we show that most observed forecasts are rational. Using this framework we provide evidence that the consistent underprediction of energy intensity is not due to an asymmetric loss function over energy intensity, but rather GDP.

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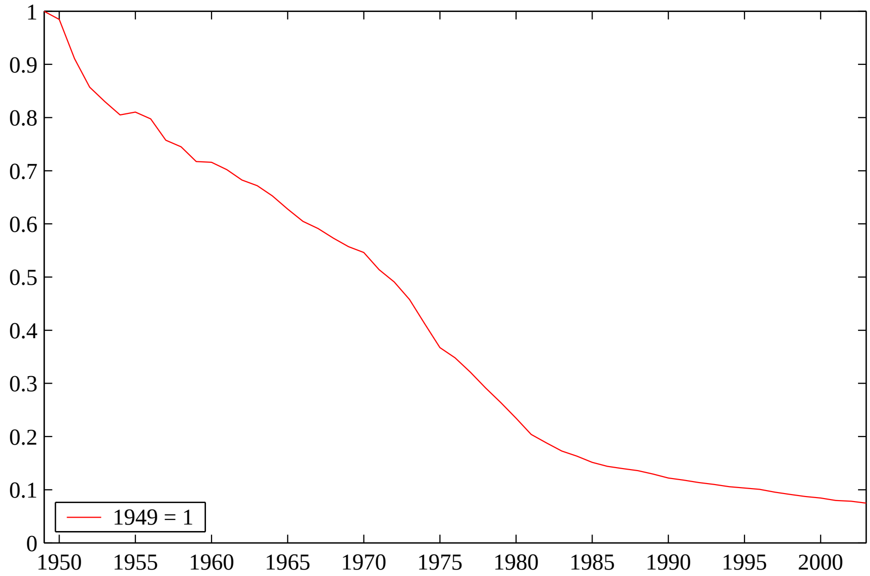
1. Introduction

Since the quest for the crystal ball has proven to be a hopeless endeavor, forecasting of random sequences has become increasingly important in economics. Forecasts of *i.e.* asset returns are used by investors to make portfolio decisions. Point and density forecasts of macroeconomic variables are used by government and central bank decision makers to determine optimal intervention (*e.g.* the Bank of England uses inflation forecasts to guide monetary policy). Recently forecasts have taken on a central role in the debate surrounding global climate change. The Intergovernmental Panel on Climate Change (2000) has published a volume called the Special Report on Emission Scenarios, which provides forecasts of global greenhouse gas emissions by geographic regions. These forecasts are used as benchmarks to estimate the future costs of regulating the emissions of greenhouse gases. The IPCC forecasts are constructed assuming no policy intervention.

The withdrawal of the United States from the Kyoto Protocol in 2001 has put into question the future success of the climate treaty. President George W. Bush has cited extensive costs of meeting the encoded reductions and the comparative advantage of developing countries due to their exemption from cutbacks as the main reasons for current US non-participation. This puts the evolution of factors, which decrease the costs of meeting reductions at the center of the debate. Invoking the traditional IPAT (Impact = Population · Affluence · Technology) identity (Ehrlich and Holdren, 1971), it is argued that emissions are decreasing in technological progress. A frequently invoked indicator of technological progress is the energy intensity of an economy. As shown in figure 1, energy intensity for the United States has decreased almost monotonically since 1949. Future drops in energy intensity, ceteris paribus, will partially determine the magnitude of additional measures and related costs necessary to decrease carbon emissions. Expectations of future drops in this ratio are therefore closely tied to expected costs of regulation.

For the United States, the Energy Information Agency (EIA) annually publishes forecasts of energy consumption, production and prices. Recently these forecasts have included energy intensity of the economy in British Thermal Units per US$ of GDP. These are provided since "the EIA has seen more public interest in energy intensity, particularly as public policy issues such as carbon dioxide emissions, technological development, impacts of structural changes on the economy, and national energy security, are more openly discussed and evaluated" (Energy Information Agency, 2004). The energy intensity forecasts are thought to reflect government expectations and are used directly or indirectly by modelers. The EIA forecasts are used both for the calibration of economic simulation models

Figure 1: Energy Intensity in BTU per US$ of GDP (1949=1)



and for benchmarking engineering-based energy scenario analyses (Sands, 2004; Interlaboratory Working Group on Energy-Efficient and Low-Carbon Technologies, 2000). Reduced form econometric models, such as Yang and Schneider (1998) use energy intensity trends as "right hand side" variables to forecast emissions. Finally, these quasi official EIA forecasts, including the predictions of production, consumption, prices, imports, and GDP are frequently cited as benchmarks to provide direct comparability of model performance, since they are issued by a US government agency. This makes assessing their quality important.

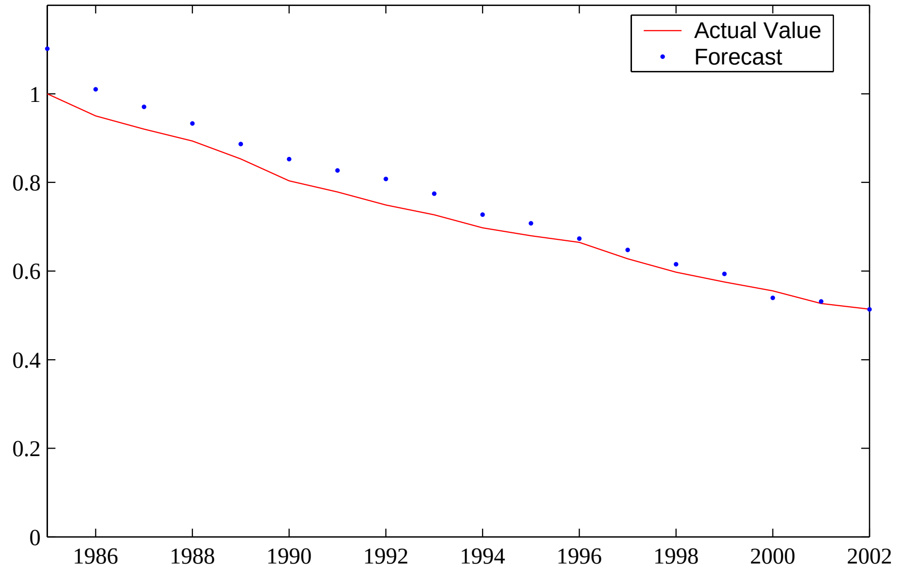
It is the task of the forecaster to evaluate how well the employed forecasting model performed once the realization of the series in question is observed. The forecasting model is constructed or revised according to the *cost* from erroneous forecasting. The forecaster's cost of over- and underpredictions is summarized in a loss function, which is used to assess forecast performance of the particular forecasting model. Traditionally used loss functions are Mean Square Forecast Error (MSFE) or Mean Absolute Forecast Error (MAFE) Loss. Under the most frequently used MSFE class of loss functions, testing for rationality amounts to testing for mean zero forecast errors and no serial correlation in the forecast errors beyond the prediction horizon. As Granger and Newbold (1986) point out, the assumption of a symmetric cost function is not reasonable in all settings, since in many circumstances overpredictions are considered to be more costly than underpredictions and vice versa. A classic example is forecasts of a firm's sales, where overpredictions lead to buildup of inventory and underpredictions of sales may lead to a potentially very costly loss of business and damages in reputation.

It is the purpose of this note to evaluate the forecasts published by the EIA. Specifically we will test whether the forecasts are rational given a traditional class of symmetric loss functions. In cases where we reject the notion of rationality under symmetric loss, we extend the class of considered loss functions to include lin-lin and quad-quad asymmetric loss. Instead of assuming a specific asymmetry of the loss function, we will employ the Generalized Method of Moments estimator proposed by Elliott, Komunjer and Timmermann (2004) to back out an asymmetry parameter given a class of loss functions, which is consistent with the observed forecasts being rational. This note is not a critique of the EIA's forecasting methodology, but an attempt to understand the loss function of its forecasters. Although we are mostly interested in the forecasts of energy intensity, we provide estimates of asymmetry and test results for all forecast series provided by the EIA. The next section provides background information and describes the estimator. Section 3 presents data and results. Section 4 concludes.

2. Asymmetric Loss and Forecast Rationality

The goal of the forecaster is to predict the realization of Y_t, the variable of interest, τ periods from now, which we denote $Y_{t+\tau}$. We call τ the forecasting horizon. At time t the forecaster constructs his/her forecast of $Y_{t+\tau}$ conditional on the information set $\Im_t$ which we will denote $f_{t+\tau}$. The forecaster only observes the forecast error $\varepsilon_{t+\tau} = Y_{t+\tau} - f_{t+\tau}$ at time $t + \tau$. For the purposes of this note we will limit ourselves to the case where $\tau = 1, 2$. When the forecaster constructs his rational forecast of Y_t his objective is to minimize the cost of forecast error. This cost of over/under prediction is summarized in a loss function, which is defined over forecast error and denoted by $L(\varepsilon_{t+\tau}, \boldsymbol{\psi})$, where $\boldsymbol{\psi}$ is a vector of parameters governing the shape of the loss function. The overwhelming majority of traditionally used loss functions are symmetric, such as the mean square forecast error cost function or the mean absolute deviation forecast error cost function. Patton and Timmermann (2004) show that under a squared error loss function $L(\varepsilon_{t+\tau}, \psi) = \psi\,(\varepsilon_{t+\tau})^2$, where the scalar $\psi > 0$, the rational forecast of $Y_{t+\tau}$ is $E_t[Y_{t+\tau}]$, the rational forecast error is unbiased and the forecast error does not exhibit any serial correlation beyond lag τ. These properties of rational forecasts rely on the assumption of this most frequently used loss function. Testing for forecast rationality under MSFE Loss can be achieved by

Figure 2: EIA Energy Intensity Forecasts (1985=1)



testing for a zero intercept and unity slope in a Mincer and Zarnowitz (1969) regression of $Y_{t+\tau} = \alpha + \beta f_{t+\tau} + \varepsilon_{t+\tau}$.

MSFE and MAEF loss functions imply that a one unit positive forecast error is as costly as a one unit negative forecast error. If we relax the symmetry assumption, these properties of rational forecasts no longer hold. Under asymmetric loss, it is likely to be rational to observe non-zero mean forecasts errors.

Figure 2 shows the one step ahead forecasts and forecast errors for the energy intensity series. Upon casual inspection the forecast errors do not look like they are rational under symmetric loss (mean zero and serially uncorrelated). The energy intensity series are over predicted at the one period forecast horizon for all years except for the year 2000.

Elliott et al. (2004) make use of the information contained in a sequence of observed forecasts and the realization of the series to estimate an asymmetry parameter governing the shape of the loss function of the forecaster consistent with the observed forecasts being rational. They further provide a joint J-test of forecast rationality conditional on a given asymmetry of the loss function. The class of loss functions they consider is restricted to the family:

$$L(p, \alpha, \theta) \equiv [\alpha + (1 - 2\alpha) \cdot 1(Y_{t+\tau} - f_{t+\tau}(\theta) < 0)] \, |Y_{t+\tau} - f_{t+\tau}(\theta)|^p \qquad (1)$$

where $\alpha \, \epsilon \, (0, 1)$ is the parameter governing the relative cost of over versus underprediction, which we will refer to as the asymmetry parameter and will be the goal of our estimation. p in theory can be any positive integer, but we will restrict it to be either one (lin-lin loss) or two (quad-quad loss). The underlying forecasting model does not need to be known, but is restricted to the type $f_{t+\tau} = \boldsymbol{\theta} W_t$, where W_t is a set of variables observed by the forecaster at time t thought to help forecast Y_t.[1] The forecaster solves the minimization problem:

$$\min_{\boldsymbol{\theta}} E\left[L(p_o, \alpha_o, \boldsymbol{\theta})\right] \tag{2}$$

where p_o and α_o are the true values observed by the forecaster only. Assuming this class of loss functions and optimizing behavior on behalf of the forecaster gives rise the following moment condition(s), which have to hold for forecast rationality:

$$E[V_t(1(Y_{t+\tau} - f_{t+\tau}(\theta) < 0) - \alpha_o)]|Y_{t+\tau} - f_{t+\tau}(\theta)|^{p_o - 1} = 0 \tag{3}$$

V_t is a $k \times 1$ observed vector and a subset of the W_t. The estimation strategy is to assume a value of $p_o \; \epsilon \; (0, 1)$ and $\alpha_o = 0.5$. We will test whether the k moment conditions above hold. If they do not, we assume a value of p_o and estimate $\hat{\alpha}$. For overidentified cases, where the number of moment conditions is greater than the number of estimated parameters, we apply the Elliott et al. (2004) J-Test for overidentification, which allows for the joint test of rationality under a given loss function. Assuming symmetric loss and a value for p allows application if this test for any k. Under asymmetric loss, this test only applies for this class of loss functions if $k > 1$.

3. Data and Results

The Energy Information Agency in their publication "Annual Energy Outlook" publishes forecasts for the 17 series listed in table 3. The publication appears in January of each year and includes forecasts for the anticipated value of each series by the end of the calendar year, as well as annual forecasts for each year up to 22 years into the future.[2] The first

[1] Elliott et al. (2004) do not assume that the model is correctly specified. Further, the linearity assumption is not crucial to the estimation procedure. It is a strong assumption implicit in our analysis, that the NEMS forecasting model employed by the EIA can be approximated by this class of models.

[2] Over the history of the publication the forecasting horizon has gradually grown. The Annual Energy Outlook in 1982 included forecasts of up to 8 years, which was extended to 15 years in 1986 and finally 22 years in 1998. It would be interesting to evaluate forecast rationality for short versus long range forecasts, yet the data do not support this at the current time.

Table 1: EIA Annual Energy Outlook Forecast Series

Code	EIA Series Title
ENC	Total Energy Consumption
PEC	Total Petroleum Consumption
NGC	Total Natural Gas Consumption
COC	Total Coal Consumption
ELS	Total Electricity Sales
OIP	Crude Oil Production
NGP	Natural Gas Production
COP	Coal Production
PEI	Net Petroleum Imports
NGI	Net Natural Gas Imports
OI$	World Oil Prices
NG$	Natural Gas Wellhead Prices
CO$	Coal Prices to Electric Generating Plants
EL$	Average Electricity Prices
GDP	Gross Domestic Product
CO2	Total Carbon Dioxide Emissions
ENI	Energy Intensity

available year of these forecasts is 1982, although the only forecasts available for that year start at the 3 year ahead horizon. We have a consistent series of same year forecasts from 1985 until 2003. True one step ahead forecasts are available for the same period. This means that we have 18 usable observations for the end of year series and 17 usable observations for the true one step ahead forecasts. We do observe the level forecast and the realization of the series, which allows us to calculate the forecast error. These samples are admittedly very small, and the results should be interpreted keeping the shortness of the series in mind.[3] Further, the first Carbon Dioxide forecasts were published in 1992, which does not provide us with a sufficient sample size to test for rationality on this rather important series. Overall, this is the best data set the authors are aware of in the energy context. It would be desirable to conduct this exercise on IPCC forecasts of Carbon Emissions, yet unfortunately there are only two sets of forecasts available and an update will not be available until the fifth assessment report, which is likely to be published only in another decade.

Due to the brevity of the series we only consider $\tau = 1, 2$, for the same year and next

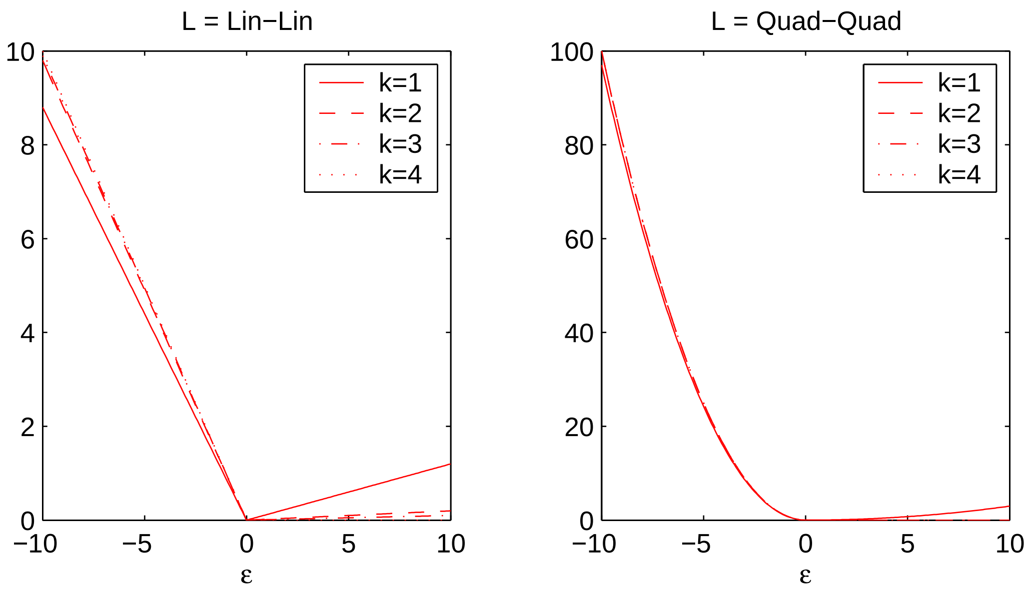
[3]Elliott et al. (2004) use government forecasts of budget deficits as their empirical application, for which they have 25 observations. Clearly applications in finance allow for much larger samples.

year forecasts respectively. In order to apply the method proposed by Elliott et al. (2004), we require Y_t to be a stationary series. We apply a series of tests for stationarity around a deterministic trend, using the Elliott, Rothenberg and Stock (1996) (ERS) procedure, which has better power properties than the test proposed by Dickey and Fuller (1979). It has been shown that tests using the null of a non-stationary process tend to fail to reject the null too frequently. If the p-value of the test statistic for the ERS test is less than 0.3, we apply the Kwiatkowski, Phillips and Schmidt (1992) test, which poses a stationary series as the null. If we fail to reject the null for the KPS test, we break in favor of the KPP result. For series, which are stationary around a deterministic trend, we detrend the series and forecasts based on information available up to 1985. Following this procedure, we cannot conclude that NGC, NGP and OIP are stationary series. We report the results for all series for completeness. Forecast errors in the estimation are realizations minus the calculated forecast. In the case of energy intensity, a positive forecast error is therefore an over prediction of the variable, which implies that the energy intensity of the economy has fallen by more than expected.

In the empirical test of forecast rationality we assume that $p_o = 1$, which is a lin-lin loss function and a good approximation for a large class of asymmetric loss function. We follow Elliott et al. (2004) and report results for $p_o = 2$, which is a quad-quad loss function. We use four different combinations of instruments for the V_t: an intercept; an intercept and the lagged forecast error; an intercept and Y_{t-1}; and an intercept, the lagged forecast error and Y_{t-1}.

The top panel of table 2 reports the estimated asymmetry parameter $\hat{\alpha}$, assuming rationality and lin-lin loss for the same year forecasts. The bottom panel reports the parameters for the true one year ahead forecasts. The standard errors are reported in brackets under the estimates for $\hat{\alpha}$. For the same year forecasts, we reject the null of symmetric loss for Net Gas Imports, Coal Prices, Electricity Prices, GDP and Energy Intensity. This is true irrespective of what combination of instruments are used. The parameter estimates on Coal Consumption, Electricity Sales and Petroleum Imports are closer to zero than they are to 0.5, yet not statistically different from 0.5. For the true one year ahead forecasts Net Gas Imports, Coal Prices, Electricity Prices, GDP and Energy Intensity we again reject the null hypothesis of symmetric lin-lin loss. Table 2 displays the parameter estimates under nonlinear quad-quad loss, under which large errors are generally more costly than small errors. The results from lin-lin loss are echoed in the results for quad-quad loss. The same series show statistically significant evidence of asymmetric loss.

Figure 3: Estimated Loss Functions for Energy Intensity



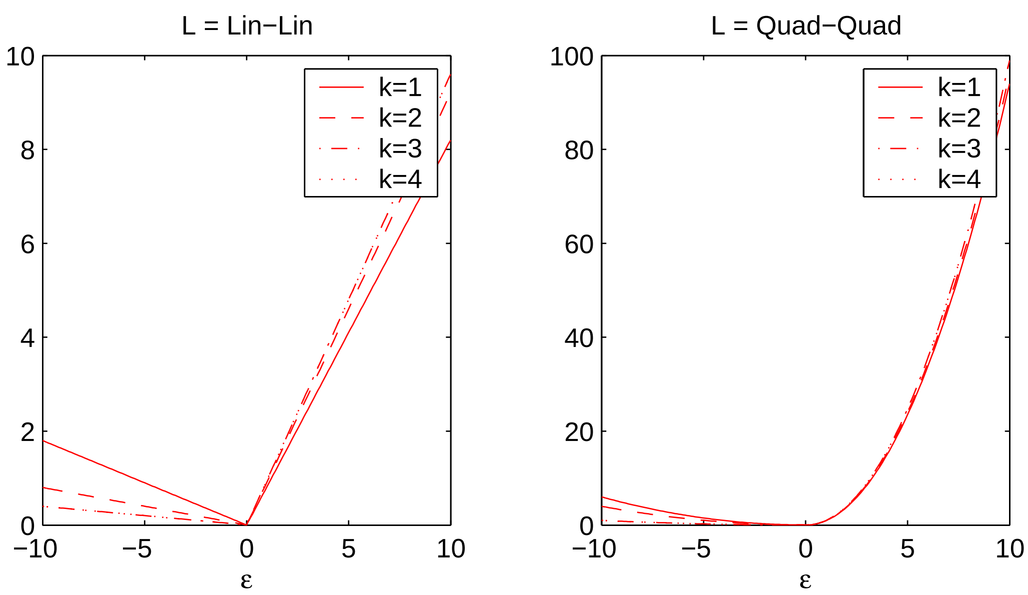
For energy intensity (ENI) the asymmetry parameter is very close to one, suggesting that positive errors are considered much less costly than negative forecast errors. The parameter is significantly different from 0.5 at the 1% level in all estimations. This is consistent across loss functions and instruments considered. Figure 3 displays the estimated loss function over energy intensity forecasts for lin-lin and quad-quad loss for the four instruments used. This visualization demonstrates nicely the implicit extreme cost of underprediciting the future energy intensity of the economy. Since $\hat{\alpha}$ is at the boundary of the space for some scenarios, this leads us to believe that in the most conservative estimate the EIA finds overpredictions seven times more costly than underpredictions of energy intensity. At the upper end the ratio is roughly 400.[4]

Although the above results provide some evidence of asymmetric loss for energy intensity, the results do not provide any explanation why this may be so. We do not observe the internal decision making process the EIA undergoes until it agrees to release one specific set of forecasts. Further we do not observe the potential political pressures which lead to one set of forecasts over another.

Further inquiry into the actual method of forecasting energy intensity employed by the EIA provided an interesting, although less behavioral, explanation for the observed sequence of overpredicted energy intensity values. Forecasts and rudimentary forecast

[4]Due to rounding the parameter estimate is not exactly one.

Figure 4: Estimated Loss Functions for U.S. Gross Domestic Product



evaluation are posted on the EIA website.[5] From the posted calculation it is apparent that energy intensity is not forecast directly, yet constructed from the ratio of the forecast for energy consumption and gross domestic product. This implies that the implicit loss for energy intensity forecast error is the ratio of the loss for energy consumption over the loss for GDP:

$$L\left(\varepsilon_{t+\tau,t}^{ENI}\right) = \frac{L(\varepsilon_{t+\tau,t}^{ENC})}{L(\varepsilon_{t+\tau,t}^{GDP})} \tag{4}$$

Tables 2 and 3 show that we cannot reject the null of a symmetric loss function for energy consumption for quad-quad or lin-lin loss using any combination of instruments. We do, however reject the null of symmetric loss for the GDP forecasts at the 3% level for all 16 cases. The implicit loss function for GDP is depicted in figure 4.

Energy consumption forecasts, as well as all of the other series with the exception of GDP are calculated from using the EIA National Energy Modeling System (NEMS). GDP is forecast by assuming an annual growth rate. The published forecasts underpredict GDP growth for a majority of the observed time periods at the one and two period horizon. Admittedly, GDP growth is very difficult to forecast. A naive forecast would on average be expected to be as likely to overstate as to understate GDP growth. The repeated un-

[5] http://www.eia.doe.gov/oiaf/analysispaper/tables2_18.html

derprediction of GDP growth may just reflect a conservative forecasting approach, which we here interpret as asymmetric loss. We take this as evidence that the consistent over-predictions of energy intensity for the US economy have their source in asymmetric loss over GDP.

The degree of asymmetry of the forecasters' loss function is interesting, yet ultimately we are interested in testing whether the observed forecasts are rational. The top panels in tables 4 and 5 display the results for the joint hypothesis test of forecast rationality under symmetric loss.[6] The results presented in these top panels are especially interesting, since symmetric loss is assumed in the vast majority of forecast rationality tests. Therefore the top panels indicate a "traditional" test for forecast rationality. Overall we reject rational forecasts for energy intensity and GDP for all considered sets of instruments, forecast horizons and loss functions at the 1% level. This is not surprising given the previous estimates for α. We further reject rationality in most scenarios for coal consumption, electricity sales, net petroleum import, natural gas imports, coal prices and average electricity prices for both lin-lin and quad-quad symmetric loss.

The bottom panels of table 4 and 5 provide the J-tests under asymmetric loss, which allows us to check whether the rejection of forecast rationality is due the assumed shape of the loss function. For energy intensity we fail to reject the null of rationality and asymmetric loss for all cases considered at the 10% level. GDP forecasts are rational with the exception of the three instrument case for the end of year forecasts under lin lin loss and and the three and four instrument case for the end of year forecasts under quad-quad loss as well as the three instrument case for the one year ahead forecasts for quad-quad loss.

Overall we reject forecast rationality for 68 out of 96 valid cases under lin-lin symmetric loss and 65 out of 96 valid cases for quad-quad symmetric loss. Once we relax the symmetry restriction, we reject rationality for 12 out of 72 valid cases for lin-lin loss and 14 out of 72 valid cases for quad-quad loss. It is to be noted that we fail to reject forecast rationality for energy consumption for all cases under quadratic loss and the majority of cases for lin-lin loss.

[6] This case is overidentified for all k since we are "Fixing" the asymmetry parameter and p.

4. Conclusions

This paper provides tests of forecast rationality under a class of symmetric and asymmetric loss functions, which nest the frequently used Mean Squared Forecast Error Loss and Mean Absolute Forecast Error Loss. The series at the center of analysis are short term forecasts for energy consumption production, prices, GDP and energy intensity published by the Energy Information Agency. Using the loss function parameter estimator provided by Elliott et al. (2004) we demonstrate that forecasts for energy intensity are only rational under a highly asymmetric loss function. Further investigation shows that the asymmetric loss function over energy intensity is due to asymmetric loss over GDP, since the EIA does not forecast energy intensity directly.

Since these quasi-official EIA forecasts are used both for the calibration of economic simulation models and for benchmarking engineering-based energy scenario analyses understanding the implicit loss function of the forecasters who constructed them is crucial. Overall the forecasts of energy intensity reflect very conservative expectations of future drops in energy intensity. Overpredicting the future energy intensity ratio understates autonomous drops in efficiency and therefore overstates expected costs of regulation. The rejection of rationality of energy intensity forecasts is likely due to the GDP forecasts, while the energy consumption forecasts are judged to be rational. We therefore advise modelers to use the energy consumption forecasts in combination with more reliable forecasts of GDP in order to construct a series of energy intensity expectations, which can be used to calibrate models.

Table 2: Parameter Estimates under Lin-Lin Loss and Symmetry Test

Current Year		ENC	PEC	NGC	COC	ELS	OIP	NGP	COP	PEI	NGI	OI$	NG$	CO$	EL$	GDP	ENI
Inst=1	$\hat{\alpha}$	0.35	0.35	0.18	0.35	0.24	0.59	0.29	0.53	0.35	0.24	0.88	0.53	0.82	0.88	0.18	0.88
	s..e.	0.23	0.23	0.15	0.23	0.18	0.24	0.21	0.25	0.23	0.18	0.10	0.25	0.15	0.10	0.15	0.10
	p-value	0.52	0.52	0.03	0.52	0.14	0.72	0.32	0.91	0.52	0.14	0.00	0.91	0.03	0.00	0.03	0.00
Inst=2	$\hat{\alpha}$	0.30	0.34	0.11	0.35	0.23	0.60	0.29	0.53	0.26	0.22	0.91	0.54	0.90	0.95	0.08	0.98
	s..e.	0.21	0.22	0.10	0.23	0.21	0.24	0.21	0.26	0.20	0.17	0.08	0.25	0.10	0.05	0.08	0.02
	p-value	0.36	0.48	0.00	0.52	0.21	0.69	0.30	0.91	0.23	0.11	0.00	0.88	0.00	0.00	0.00	0.00
Inst=3	$\hat{\alpha}$	0.35	0.35	0.16	0.35	0.23	0.59	0.29	0.55	0.32	0.22	0.89	0.53	0.97	0.96	0.04	0.99
	s..e.	0.23	0.23	0.14	0.23	0.18	0.24	0.21	0.25	0.22	0.17	0.10	0.25	0.05	0.05	0.08	0.01
	p-value	0.52	0.52	0.01	0.50	0.14	0.71	0.30	0.85	0.42	0.11	0.00	0.90	0.00	0.00	0.00	0.00
Inst=4	$\hat{\alpha}$	0.30	0.34	0.12	0.35	0.18	0.60	0.27	0.55	0.25	0.21	0.91	0.54	0.97	0.96	0.04	1.00
	s..e.	0.21	0.22	0.11	0.23	0.15	0.24	0.20	0.25	0.19	0.17	0.08	0.25	0.04	0.05	0.08	0.01
	p-value	0.36	0.47	0.00	0.50	0.04	0.69	0.25	0.85	0.21	0.08	0.00	0.89	0.00	0.00	0.00	0.00
One Year Ahead																	
Inst=1	$\hat{\alpha}$	0.56	0.50	0.25	0.44	0.19	0.63	0.31	0.56	0.56	0.38	0.56	0.56	0.94	0.88	0.13	0.94
	s..e.	0.25	0.25	0.19	0.25	0.15	0.23	0.21	0.25	0.25	0.23	0.25	0.25	0.06	0.11	0.11	0.06
	p-value	0.80	1.00	0.18	0.80	0.04	0.59	0.38	0.80	0.80	0.59	0.80	0.80	0.00	0.00	0.00	0.00
Inst=2	$\hat{\alpha}$	0.58	0.50	0.25	0.40	0.14	0.73	0.30	0.58	0.62	0.37	0.53	0.58	1.00	0.98	0.10	0.99
	s..e.	0.24	0.25	0.19	0.78	0.15	0.21	0.21	0.74	0.24	0.23	0.31	0.24	0.01	0.03	0.09	0.01
	p-value	0.74	1.00	0.18	0.90	0.01	0.28	0.34	0.91	0.63	0.59	0.91	0.75	0.00	0.00	0.00	0.00
Inst=3	$\hat{\alpha}$	0.57	0.50	0.10	0.41	0.12	0.63	0.19	0.59	0.56	0.36	0.60	0.56	1.00	0.95	0.02	1.00
	s..e.	0.25	0.25	0.12	0.24	0.11	0.23	0.17	0.24	0.25	0.24	0.24	0.25	0.01	0.05	0.04	0.00
	p-value	0.77	1.00	0.00	0.72	0.00	0.59	0.07	0.71	0.80	0.55	0.69	0.80	0.00	0.00	0.00	0.00
Inst=4	$\hat{\alpha}$	0.59	0.50	0.10	0.41	0.10	0.73	0.17	0.60	0.62	0.36	0.60	0.56	1.00	0.99	0.02	1.00
	s..e.	0.24	0.25	0.12	0.24	0.10	0.21	0.17	0.24	0.24	0.24	0.24	0.25	0.00	0.03	0.04	0.00
	p-value	0.70	1.00	0.00	0.70	0.00	0.27	0.05	0.68	0.62	0.55	0.69	0.80	0.00	0.00	0.00	0.00

Table 3: Parameter Estimates under Quad-Quad Loss and Symmetry Test

Current Year		ENC	PEC	NGC	COC	ELS	OIP	NGP	COP	PEI	NGI	OI$	NG$	CO$	EL$	GDP	ENI
Inst=1	$\hat{\alpha}$	0.41	0.35	0.10	0.28	0.24	0.66	0.28	0.70	0.23	0.18	0.94	0.38	0.98	0.90	0.06	0.97
	s..e.	0.46	0.41	0.09	0.26	0.29	0.30	0.23	0.33	0.25	0.15	0.03	0.32	0.01	0.10	0.03	0.02
	p-value	0.84	0.72	0.00	0.39	0.37	0.58	0.32	0.54	0.29	0.03	0.00	0.71	0.00	0.00	0.00	0.00
Inst=2	$\hat{\alpha}$	0.42	0.36	0.01	0.13	0.26	0.66	0.28	0.70	0.14	0.16	0.94	0.33	0.99	0.97	0.04	1.00
	s..e.	0.37	0.40	0.02	0.13	0.45	0.30	0.22	0.32	0.17	0.13	0.03	0.30	0.00	0.03	0.02	0.00
	p-value	0.83	0.72	0.00	0.00	0.59	0.59	0.33	0.53	0.04	0.01	0.00	0.57	0.00	0.00	0.00	0.00
Inst=3	$\hat{\alpha}$	0.38	0.35	0.10	0.26	0.21	0.68	0.27	0.75	0.16	0.15	0.96	0.34	1.00	0.97	0.01	1.00
	s..e.	0.38	0.39	0.08	0.24	0.21	0.29	0.22	0.30	0.20	0.13	0.02	0.30	0.00	0.03	0.01	0.00
	p-value	0.76	0.71	0.00	0.31	0.18	0.55	0.31	0.39	0.08	0.01	0.00	0.60	0.00	0.00	0.00	0.00
Inst=4	$\hat{\alpha}$	0.40	0.35	0.01	0.24	0.16	0.67	0.27	0.76	0.15	0.14	0.97	0.30	1.00	0.97	0.01	1.00
	s..e.	0.37	0.39	0.02	0.23	0.18	0.29	0.22	0.30	0.18	0.13	0.02	0.27	0.00	0.03	0.01	0.00
	p-value	0.79	0.71	0.00	0.27	0.06	0.55	0.31	0.38	0.06	0.00	0.00	0.45	0.00	0.00	0.00	0.00
One Year Ahead																	
Inst=1	$\hat{\alpha}$	0.54	0.54	0.22	0.38	0.23	0.60	0.25	0.61	0.51	0.38	0.58	0.34	0.97	0.89	0.11	0.99
	s..e.	0.39	0.42	0.23	0.35	0.25	0.38	0.23	0.32	0.32	0.31	0.31	0.29	0.02	0.09	0.11	0.00
	p-value	0.91	0.93	0.23	0.73	0.28	0.80	0.28	0.73	0.98	0.70	0.80	0.57	0.00	0.00	0.00	0.00
Inst=2	$\hat{\alpha}$	0.52	0.46	0.09	0.21	0.19	0.66	0.23	0.74	0.47	0.35	0.55	0.29	1.00	0.99	0.12	1.00
	s..e.	0.39	0.39	0.09	0.48	0.25	0.37	0.21	0.96	0.32	0.29	0.34	0.27	0.00	0.03	0.10	0.00
	p-value	0.95	0.93	0.00	0.55	0.21	0.66	0.19	0.81	0.93	0.60	0.89	0.42	0.00	0.00	0.00	0.00
Inst=3	$\hat{\alpha}$	0.53	0.49	0.06	0.29	0.21	0.59	0.13	0.66	0.52	0.40	0.63	0.27	1.00	0.96	0.01	1.00
	s..e.	0.39	0.40	0.12	0.31	0.23	0.38	0.17	0.30	0.32	0.35	0.29	0.24	0.00	0.05	0.03	0.00
	p-value	0.94	0.99	0.00	0.49	0.21	0.81	0.03	0.59	0.96	0.77	0.66	0.33	0.00	0.00	0.00	0.00
Inst=4	$\hat{\alpha}$	0.53	0.48	0.05	0.29	0.14	0.66	0.12	0.68	0.45	0.42	0.66	0.26	1.00	0.99	0.01	1.00
	s..e.	0.39	0.39	0.11	0.31	0.20	0.36	0.16	0.30	0.31	0.34	0.26	0.22	0.00	0.02	0.03	0.00
	p-value	0.94	0.96	0.00	0.49	0.07	0.65	0.02	0.56	0.88	0.80	0.55	0.27	0.00	0.00	0.00	0.00

Table 4: Tests of Joint Hypothesis of Quad-Quad Loss and Forecast Rationality

		ENC	PEC	NGC	COC	ELS	OIP	NGP	COP	PEI	NGI	OI$	NG$	CO$	EL$	GDP	ENI
$\alpha = 0.5$		$\hat{f}_{t+1,t}$															
Inst=1	j-stat	0.33	0.92	30.03	3.29	3.91	1.54	3.73	2.09	4.82	11.64	106.70	0.77	586.73	27.24	102.20	249.13
	p-value	0.57	0.34	0.00	0.07	0.05	0.21	0.05	0.15	0.03	0.00	0.00	0.38	0.00	0.00	0.00	0.00
Inst=2	j-stat	0.34	0.93	215.18	20.48	2.81	1.68	3.88	2.13	16.04	15.68	106.52	3.21	1354.03	118.24	170.83	3156.72
	p-value	0.56	0.33	0.00	0.00	0.09	0.20	0.05	0.14	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00
Inst=3	j-stat	0.69	0.94	34.45	4.40	6.78	2.28	4.21	5.58	14.44	16.94	174.85	4.15	1509.63	119.46	326.47	4602.50
	p-value	0.41	0.33	0.00	0.04	0.01	0.13	0.04	0.02	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00
Inst=4	j-stat	1.18	0.96	235.12	5.91	12.54	2.31	4.83	6.30	15.70	17.92	225.23	6.30	1761.34	120.33	328.49	4870.52
	p-value	0.55	0.62	0.00	0.05	0.00	0.31	0.09	0.04	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00
		$\hat{f}_{t+2,t}$															
Inst=1	j-stat	0.07	0.05	5.48	0.68	4.66	0.39	4.32	0.61	0.00	0.75	0.32	1.48	191.37	27.19	21.46	1886.30
	p-value	0.79	0.82	0.02	0.41	0.03	0.53	0.04	0.43	0.96	0.39	0.57	0.22	0.00	0.00	0.00	0.00
Inst=2	j-stat	1.97	3.18	30.44	4.12	7.10	6.93	6.14	1.89	6.81	1.90	0.68	6.15	1949.54	152.24	22.31	11406.24
	p-value	0.16	0.07	0.00	0.04	0.01	0.01	0.01	0.17	0.01	0.17	0.41	0.01	0.00	0.00	0.00	0.00
Inst=3	j-stat	2.29	1.76	29.65	5.85	6.72	0.49	16.67	4.91	0.71	5.07	4.85	7.73	2101.40	68.41	125.55	34367.31
	p-value	0.13	0.18	0.00	0.02	0.01	0.48	0.00	0.03	0.40	0.02	0.03	0.01	0.00	0.00	0.00	0.00
Inst=4	j-stat	3.48	3.25	34.29	7.81	13.84	7.00	18.57	7.86	8.42	5.33	5.82	8.76	2320.09	159.84	125.83	39307.47
	p-value	0.18	0.20	0.00	0.02	0.00	0.03	0.00	0.02	0.01	0.07	0.05	0.01	0.00	0.00	0.00	0.00
$\alpha = \hat{\alpha}$		$\hat{f}_{t+1,t}$															
Inst=2	j-stat	0.03	0.04	2.18	2.45	0.65	0.18	0.22	0.03	3.43	0.30	0.20	1.59	1.51	1.28	1.23	1.10
	p-value	0.87	0.84	0.14	0.12	0.42	0.67	0.64	0.86	0.06	0.58	0.66	0.21	0.22	0.26	0.27	0.29
Inst=3	j-stat	0.09	0.00	0.00	0.24	0.18	0.48	0.32	1.85	4.29	0.50	0.38	2.73	2.19	1.46	2.76	1.11
	p-value	0.77	0.96	0.97	0.62	0.68	0.49	0.57	0.17	0.04	0.48	0.54	0.10	0.14	0.23	0.10	0.29
Inst=4	j-stat	0.75	0.04	2.26	1.18	1.53	0.56	0.99	2.50	4.40	0.55	1.08	3.72	2.19	1.47	2.82	1.11
	p-value	0.69	0.98	0.32	0.56	0.46	0.76	0.61	0.29	0.11	0.76	0.58	0.16	0.33	0.48	0.24	0.57
		$\hat{f}_{t+2,t}$															
Inst=2	j-stat	1.95	3.12	1.60	1.35	0.86	5.81	0.35	0.96	6.78	0.63	0.56	3.39	1.05	2.21	0.07	0.91
	p-value	0.16	0.08	0.21	0.25	0.35	0.02	0.56	0.33	0.01	0.43	0.45	0.07	0.30	0.14	0.79	0.34
Inst=3	j-stat	2.25	1.76	3.67	3.53	0.83	0.15	3.86	3.48	0.70	4.61	3.94	4.19	1.04	1.70	2.14	1.00
	p-value	0.13	0.19	0.06	0.06	0.36	0.70	0.05	0.06	0.40	0.03	0.05	0.04	0.31	0.19	0.14	0.32
Inst=4	j-stat	3.44	3.24	3.69	5.45	3.28	5.82	3.98	6.21	8.31	5.00	4.33	4.50	1.05	2.34	2.60	1.01
	p-value	0.18	0.20	0.16	0.07	0.19	0.05	0.14	0.04	0.02	0.08	0.12	0.11	0.59	0.31	0.27	0.60

Table 5: Tests of Joint Hypothesis of Lin-Lin Loss and Forecast Rationality

		ENC	PEC	NGC	COC	ELS	OIP	NGP	COP	PEI	NGI	OI$	NG$	CO$	EL$	GDP	ENI
$\alpha = 0.5$		$\hat{f}_{t+1,t}$															
Inst=1	j-stat	1.61	1.61	12.24	1.61	6.62	0.55	3.47	0.06	1.61	6.62	23.94	0.06	12.24	23.94	12.24	23.94
	p-value	0.20	0.20	0.00	0.20	0.01	0.46	0.06	0.81	0.20	0.01	0.00	0.81	0.00	0.00	0.00	0.00
Inst=2	j-stat	5.71	2.69	26.66	1.69	6.33	1.42	3.95	0.10	9.76	8.01	35.02	2.23	28.74	63.20	39.01	162.84
	p-value	0.02	0.10	0.00	0.19	0.01	0.23	0.05	0.75	0.00	0.00	0.00	0.14	0.00	0.00	0.00	0.00
Inst=3	j-stat	1.65	1.61	14.72	2.09	6.74	0.66	3.94	3.55	3.84	8.24	28.01	0.30	83.54	73.57	47.92	317.00
	p-value	0.20	0.20	0.00	0.15	0.01	0.42	0.05	0.06	0.05	0.00	0.00	0.58	0.00	0.00	0.00	0.00
Inst=4	j-stat	5.80	2.74	25.54	2.23	12.84	1.50	5.43	3.55	10.29	9.85	35.74	3.79	88.53	74.33	48.13	362.93
	p-value	0.05	0.25	0.00	0.33	0.00	0.47	0.07	0.17	0.01	0.01	0.00	0.15	0.00	0.00	0.00	0.00
		$\hat{f}_{t+2,t}$															
Inst=1	j-stat	0.25	0.00	5.33	0.25	10.26	1.07	2.62	0.25	0.25	1.07	0.25	0.25	52.27	20.57	20.57	52.27
	p-value	0.61	1.00	0.02	0.61	0.00	0.30	0.11	0.61	0.61	0.30	0.61	0.61	0.00	0.00	0.00	0.00
Inst=2	j-stat	2.81	2.40	5.39	0.59	14.93	10.26	3.49	0.33	7.90	1.08	1.09	2.57	750.64	134.32	27.93	254.87
	p-value	0.09	0.12	0.02	0.44	0.00	0.00	0.06	0.57	0.00	0.30	0.30	0.11	0.00	0.00	0.00	0.00
Inst=3	j-stat	1.18	0.28	26.17	6.15	22.06	1.23	15.15	3.41	0.26	6.13	3.22	3.49	696.86	60.69	94.14	1107.49
	p-value	0.28	0.59	0.00	0.01	0.00	0.27	0.00	0.06	0.61	0.01	0.07	0.06	0.00	0.00	0.00	0.00
Inst=4	j-stat	3.99	2.48	27.41	7.21	27.22	10.32	16.66	4.49	8.32	6.32	3.21	3.52	857.01	146.20	94.52	1235.53
	p-value	0.14	0.29	0.00	0.03	0.00	0.01	0.00	0.11	0.02	0.04	0.20	0.17	0.00	0.00	0.00	0.00
$\alpha = \hat{\alpha}$		$\hat{f}_{t+1,t}$															
Inst=2	j-stat	2.63	0.75	1.53	0.07	0.53	0.76	0.24	0.04	4.87	0.42	0.64	2.14	1.88	1.41	1.66	2.07
	p-value	0.10	0.39	0.22	0.80	0.47	0.38	0.63	0.83	0.03	0.52	0.42	0.14	0.17	0.24	0.20	0.15
Inst=3	j-stat	0.03	0.00	0.38	0.34	0.04	0.10	0.24	3.40	1.44	0.56	0.26	0.24	3.71	1.65	4.58	2.29
	p-value	0.86	0.97	0.54	0.56	0.85	0.75	0.63	0.07	0.23	0.46	0.61	0.62	0.05	0.20	0.03	0.13
Inst=4	j-stat	2.77	0.79	1.58	0.44	1.65	0.84	0.95	3.40	4.97	1.05	0.66	3.71	3.78	1.66	4.58	2.33
	p-value	0.25	0.67	0.45	0.80	0.44	0.66	0.62	0.18	0.08	0.59	0.72	0.16	0.15	0.44	0.10	0.31
		$\hat{f}_{t+2,t}$															
Inst=2	j-stat	2.37	2.40	0.02	0.38	0.73	6.32	0.47	0.19	7.00	0.01	1.03	2.16	1.11	2.18	0.46	0.89
	p-value	0.12	0.12	0.89	0.54	0.39	0.01	0.49	0.67	0.01	0.91	0.31	0.14	0.29	0.14	0.50	0.35
Inst=3	j-stat	0.86	0.28	5.30	5.64	1.80	0.13	5.89	2.88	0.00	4.77	2.61	3.23	1.09	1.61	2.70	1.08
	p-value	0.35	0.59	0.02	0.02	0.18	0.72	0.02	0.09	0.95	0.03	0.11	0.07	0.30	0.20	0.10	0.30
Inst=4	j-stat	3.42	2.48	5.50	6.63	2.32	6.33	6.44	3.84	7.38	4.94	2.61	3.27	1.11	2.43	2.70	1.09
	p-value	0.18	0.29	0.06	0.04	0.31	0.04	0.04	0.15	0.03	0.08	0.27	0.20	0.58	0.30	0.26	0.58

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