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The United States Energy Information Administration publishes annual forecasts of nationally aggregated energy consumption, production, prices, 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 study tests for rationality of published EIA forecasts under symmetric and asymmetric loss. We find strong empirical evidence of asymmetric loss for oil, coal and gas prices as well as natural gas consumption, GDP and energy intensity.

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Keywords: Forecasting, Asymmetric Loss, Energy Intensity, Energy Information Administration

JEL Codes: Q43, C53

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1. Introduction

Expectations of future energy prices are a key factor in public and private capital investment decisions. This is especially true in the energy sector, but also carries over to energy intensive industries as well as household durable goods investment decisions. Expectations of future aggregate domestic energy production and consumption are important to policymakers concerned with domestic energy security. These variables are also crucial factors determining the need for investment in large scale energy infrastructure, such as refineries and additional power generation facilities which take a long time to construct and are very costly. Expectations of future energy imports and exports have repercussions for foreign policy decisions. Further, future realizations of these random sequences along with expectations of future carbon dioxide (CO_2) emissions and energy intensity have taken on a prime role in the discussion on global climate change. Since the United States has withdrawn from the Kyoto Protocol in 2001, citing excessive current *and* future costs of reducing emissions, a debate on the expected future costs reducing greenhouse gas emissions has emerged. At the center of this debate is the anticipated future trajectory of carbon intensity of the economy, which is closely related to the energy intensity of the economy. This indicator of carbon saving technological change, is often cited as the key variable determining whether economies will be able to maintain economic growth while reducing aggregate emissions, ceteris paribus.[1] The energy intensity of the economy is of indirect interest to the climate change debate and of central interest to energy planners (Rosenfeld, McAuliffe and Wilson, 2004).

The process by which individuals form expectations of future realizations of these sequences is a key area of study in economics. Firms and policymakers often form their expectations based on forecasts made by government agencies or *experts*. Forecasts of *i.e.* asset returns constructed by equity research firms (e.g. Bloomberg) are used by investors to make portfolio allocation decisions. Point and density forecasts of macroeconomic variables

[1]The composition effect, which indicates a transition from a manufacturing to a service based economy would have the same effect on carbon/energy intensity of an economy. The difference is that emissions in this case may migrate to another country, although empirical evidence of this is limited.

are used by government and central bank decision makers to determine optimal monetary policy intervention. When taking these forecasts as exogenous inputs to the decision making process, it is important to have an assessment of their quality. If the forecasts used are constructed by rational forecasters, it is important to understand how costly the producer of the forecasts finds over predictions relative to under predictions of the variable of interest. This relative cost of forecast errors is captured in a loss function.[2] A given forecast is only optimal for a forecast user when the loss function of the user matches that of the forecast producer. This is the case if the producer and the user are one and the same person, yet not necessarily the case if the user and producer are separate individuals or organizations. Often users assume that forecast producers use symmetric loss functions, which may not be the case. This misperception would result in a suboptimal outcome for the forecast user.

This paper is an empirical attempt to shed light on the loss function of the most important forecaster of energy related sequences for the United States - the Energy Information Administration (EIA), which is the research branch of the Department of Energy. The forecasts produced by the EIA are widely used by policymakers, industry and modelers - often under the assumption of a symmetric loss function. We will test the null hypothesis of symmetric loss and if it is rejected provide estimates of asymmetry parameters. These estimates of asymmetry parameters will allow forecast users to get a fuller understanding of the loss function of the EIA.

The next section provides an overview of the EIA's forecasts and the model used to construct them. Section 3 describes the empirical model and approach. Section 4 presents the estimation results and discussion. Section 5 contains some concluding remarks.

2. Background

The EIA annually publishes forecasts of energy consumption, production, prices, imports, gross domestic product and energy intensity of the US economy. Modelers use these

[2] Sometimes the loss function is referred to as the utility function of the forecast producer.

EIA forecasts to calibrate economic simulation models and to benchmark engineering-based energy scenario analyses (Sands, 2004; Interlaboratory Working Group on Energy-Efficient and Low-Carbon Technologies, 2000). Since 1982, these forecasts have been published annually in the widely cited Annual Energy Outlook (AEO) (Energy Information Agency, 1982-2005a). 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, to 22 years in 1998 and this year to 25 years out. The AEO includes five different scenarios of forecasts: a reference case, a high and low economic growth case and a high and low oil price case. These forecasts are to be considered "business-as-usual trend forecasts, given known technology, technological and demographic trends, and current laws and regulations. Thus, they provide a policy-neutral reference case that can be used to analyze policy initiatives." (Energy Information Agency, 2005b).

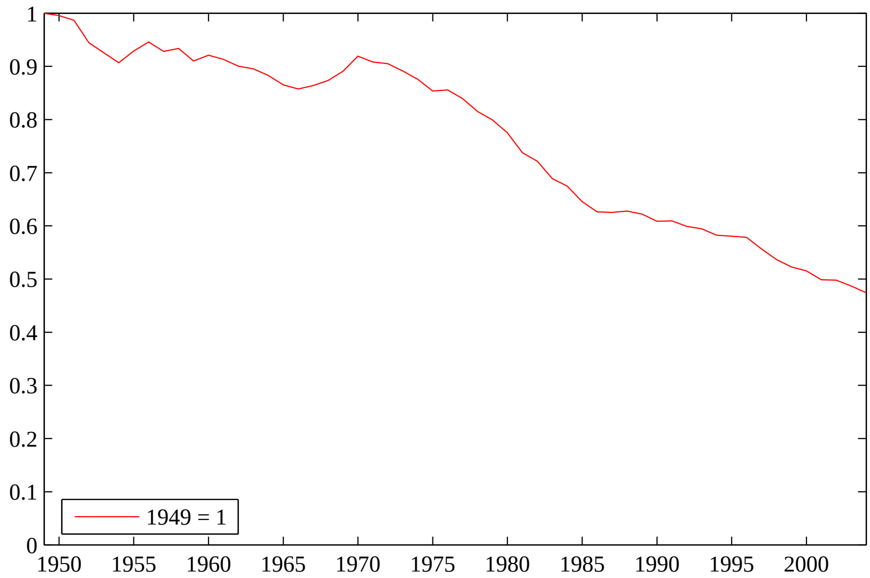
The model employed to construct all energy related forecasts is the National Energy Modeling System (NEMS).[3] This partial equilibrium model of the economy divides the US into the nine census regions and one non-US region. Ten modules are used to model the entire US energy system. There are four demand modules, one each for the residential, commercial, industrial and transportation sector. The supply side is characterized by four separate modules for oil and gas, renewable energies, natural gas transmission and distribution, and coal. The final two modules are so called conversion modules for 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 US oil markets.

The AEO forecasts have included energy intensity of the economy in British Thermal Units per US$ of GDP only recently.[4] These are provided since "the EIA has seen more public interest in energy intensity, particularly as public policy issues such as CO_2 emissions, technological development, impacts of structural changes on the economy, and

[3]Kydes (1999) provides an accessible description of the NEMS model and its predecessor, the Intermediate Future Forecasting System (IFFS), and its sensitivities to different assumptions regarding technological innovations.

[4]Explicit forecasts of Carbon Intensity are not provided by the EIA.

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



national energy security, are more openly discussed and evaluated" (Energy Information Agency, 2004). Figure 1 shows that energy intensity for the United States has decreased almost monotonically since the first energy crisis in 1973. Future drops in energy intensity, ceteris paribus, will partially determine the magnitude of additional measures and related costs necessary to decrease carbon emissions and slow growth in aggregate energy consumption as advocated by some policymakers (Leonhardt, Mouawad, Sanger and Hulse, 2005).[5] Expectations of future drops in this ratio are therefore one of the main drivers of expected costs from regulating energy consumption and carbon emissions. Further, 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.

[5] Carbon Intensity measures units of carbon per dollar of output, while energy intensity measures BTUs per unit of output, which includes carbon free sources of energy such as solar, hydro and nuclear. If there is a drastic shift in fuel mix towards these fuels, energy intensity may stay constant while carbon intensity falls.

This paper is not the first paper evaluating forecasts made by the EIA. The EIA conducts its own forecast evaluation and publishes these results (Energy Information Agency, 2004). As a measure of forecast performance they calculate the average percent error made for the forecast of a given year across AEOs, therefore averaging forecast errors made at different horizons. They call this measure the average absolute [forecast] error. This type of evaluation ignores potentially persistent biases in the forecasting model for a given horizon. By mixing forecasts made over different horizons this approach to forecast evaluation ignores the fact that forecast error variance usually increases with the forecasting horizon. Further this approach allows no insight into the performance of the NEMS model over different horizons. Shlyakhter, Kammen, Broido and Wilson (1994) examine forecast errors and show that a normal error density cannot account for the large number of extreme outliers. They suggest using an asymmetric distribution of forecast errors with fat tails. O'Neill and Desai (2005) provide an in depth evaluation of the long term forecasts from the Annual Energy Outlook. They provide a formal evaluation of the forecast errors and attempt to identify sources of inaccuracies, finding that long run projections of energy consumption have tended to underestimate future demand. They further show consistent long run overpredictions of GDP and underpredictions of energy intensity for the US economy. The authors find no evidence of improvements in these EIA forecasts since 1982. They call for further detailed studies explaining the source of these persistent inaccuracies, which is the goal of the current paper.

It is the task of the econometrician 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 by 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. Both of these are symmetric around zero, indicating that the forecaster considers an overprediction as costly as an equidistant underprediction. For MSFE, the cost of forecast errors increases nonlinearly in the absolute value of the forecast error, whereas under MAFE this cost increases linearly. 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 loss 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 unlikely that in this case the cost of forecast errors is symmetric around zero. When using forecasts for model calibration or as benchmarks, it is important to understand what loss function was applied to arrive at the employed prediction. Forecasts not produced by the user are only optimal for the forecast user if the loss function of the forecast producer is identical to that of the forecast user. If one assumes that EIA forecasts are constructed using symmetric loss when using them and this is indeed not the case, using these EIA forecasts is not optimal from the user's perspective.

It is the purpose of this study to provide an insight as to what loss function the EIA uses when it constructs the forecasts reported as the reference case in the Annual Energy Outlook. The strategy we will follow involves two steps. First we will test whether the forecasts are rational given a traditional class of symmetric loss functions, specifically the MSFE and MAFE loss functions. If we reject the notion of rationality under symmetric loss, we extend the class of considered loss functions to include asymmetric loss functions. In this second step, instead of considering all possible types of loss functions, we restrict the class of considered loss functions to the class of asymmetric linear (lin-lin) loss as well as asymmetric quadratic loss (quad-quad). Instead of assuming a particular asymmetry given these loss functions, we attempt to empirically estimate an asymmetry parameter by applying the Generalized Method of Moments estimator proposed by Elliott, Komunjer and Timmermann (2005). This approach will provide some insight into the implicit loss function of the Energy Information Administration for each of the published series.

This study is not meant as a critique of the EIA's forecasting methodology, but an attempt to show statistically what type of implicit loss function is consistent with the observed forecasts being rational. From a climate change perspective, the results concerning the energy intensity series are of special interest, although the consumption, production and import series are of potentially greater significance to policymakers and energy planners.

3. 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 observed at time t, which includes a set of variables observed at time t, denoted W_t. The forecast of $Y_{t+\tau}$ made at time t is denoted $f_{t+\tau}(W_t, \boldsymbol{\theta})$, where $\boldsymbol{\theta}$ is a vector of parameters of the forecasting model. The forecaster only observes the forecast error $\varepsilon_{t+\tau}(W_t, \boldsymbol{\theta}) = Y_{t+\tau} - f_{t+\tau}(W_t, \boldsymbol{\theta})$ at time $t + \tau$. Given this definition, an overprediction of the series of interest is therefore equivalent to a negative forecast error. When the forecaster constructs his/her rational forecast of $Y_{t+\tau}$ his/her 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 the forecast error and denoted by $L(\varepsilon_{t+\tau}(W_t, \boldsymbol{\theta}), \boldsymbol{\psi})$, where $\boldsymbol{\psi}$ is a vector of parameters governing the shape of the loss function. The overwhelming majority of traditionally used loss functions is symmetric, such as the mean square forecast error loss function or the mean absolute deviation forecast error loss function. Patton and Timmermann (2004) show that under a squared error loss function $L(\varepsilon_{t+\tau}(W_t, \boldsymbol{\theta}), \psi) = \psi\,(\varepsilon_{t+\tau}(W_t, \boldsymbol{\theta}))^2$, 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 testing for a zero intercept and unity slope in a Mincer and Zarnowitz (1969) regression of $Y_{t+\tau} = \alpha + \beta f_{t+\tau}(W_t, \boldsymbol{\theta}) + \varepsilon_{t+\tau}$.

MSFE and MAFE 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. As mentioned in the previous section, Shlyakhter et al. (1994) show that an assumed normal error density fails to adequately predict the number of extreme events and argue that an asymmetric error density with fat tails is more consistent with the observed forecast errors. An alternate explanation for the observed large number of extreme events on one side of the error distribution is the possible asymmetry of the forecaster's loss function.

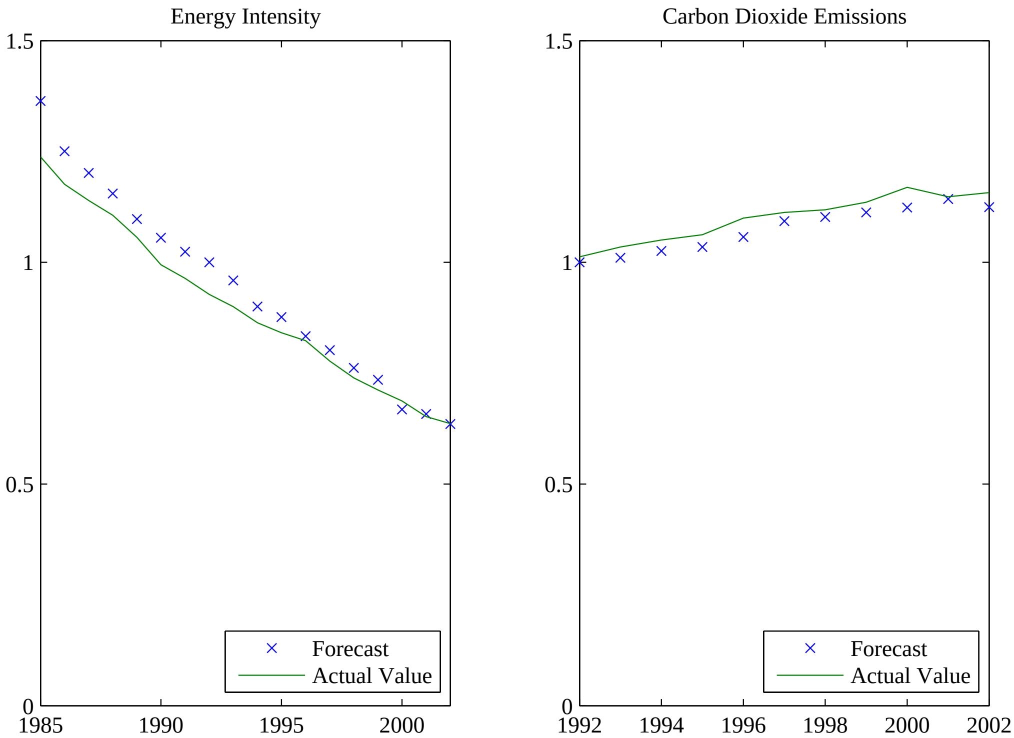
Figure 2 shows the one step ahead forecasts and realizations for the energy intensity and total CO_2 emissions series in the left and right panel respectively. Upon casual inspection the forecast errors do not look like they are rational under symmetric loss (mean zero and serially uncorrelated) for either series. The energy intensity series are over predicted at the one period forecast horizon for all years except for the year 2000. Table 1 in the next section shows the mean forecast errors and correlation coefficients of the examined forecast errors for the first, second and third lag. The energy intensity series displays non-zero mean forecast errors as well as statistically significant autocorrelations at lags 1, 2 and 3. The CO_2 series is underpredicted for each year in the sample. The mean forecast error is also statistically different from zero, with the opposite sign.

The Elliott et al. (2005) estimator we employ, makes use of the information contained in a sequence of observed forecast errors 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:

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

where $\boldsymbol{\psi} = (p, \alpha)$ and $\alpha \; \epsilon \; (0, 1)$ is the parameter governing the relative cost of over

Figure 2: EIA Energy Intensity and CO_2 Forecasts (1992=1)



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 assumed to be a linear forecasting rule of the type $f_{t+\tau}(W_t, \boldsymbol{\theta}) = W_t\boldsymbol{\theta}$, where W_t is a set of variables observed by the forecaster at time t thought to help forecast Y_t.[6] The forecaster solves the minimization problem:

$$\min_{\boldsymbol{\theta}} E\left[L(\varepsilon_{t+\tau}(W_t, \boldsymbol{\theta}), \boldsymbol{\psi_o})\right] \tag{2}$$

where the true shape parameters of the loss function $\boldsymbol{\psi}_o = (p_o, \alpha_o)$ are observed by the forecaster only. Assuming this class of loss functions and optimizing behavior on behalf of

[6] Elliott et al. (2005) 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.

the forecaster gives rise the following moment condition, which have to hold for forecast rationality:

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

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 $p_o \,\epsilon\, (1, 2)$ 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. (2005) 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 $k > 1$.

4. Data and Results

The Energy Information Administration publication 'Annual Energy Outlook' 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 25 years into the future, although the long range forecasts have only become available recently. The first 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. A complete series of true one step ahead forecasts is 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.

The 17 series for which forecasts are provided are listed in table 4. The table reports the means of end of same year forecast errors as well as the autocorrelations at the first, second and third lag. A simple test for forecast rationality under symmetric loss, is to see whether the mean forecast error is statistically not different from zero and the second and third order autocorrelations are equal to zero. Nine of the series have forecast error means which are statistically different from zero. Further the energy intensity series as well as the natural gas production series have significant autocorrelations beyond the first lag, indicating that the forecasts are not rational under symmetric MSFE loss. Estimation of the specific asymmetry of the loss function for each of these series is likely to provide some interesting insights.

It would be appealing to use our framework to analyze long range forecasts of the EIA, yet there are two reasons why this is not a feasible exercise. First, due to the brevity of the series, extending the forecasting horizon past one year ahead, decreases the size of our sample by the forecasting horizon, which is already very small. Second, using the reported long range forecasts does not allow one to conduct true forecast model performance evaluation. Conversations with the EIA modelers showed that definitions of many series have changed over time, so that looking at the long term forecasts is not a valid exercise. Short run forecasts incorporate the slight changes in definitions, and therefore do not suffer from this change in definitions. For the above reasons, we consider two forecasting horizons in our models, which are forecasts for end of current calendar year made at the time of publication, and forecasts for the following calendar year ($\tau = 0, 1$).

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.[7]

Further, the first CO_2 forecasts were first published in 1992, which does not provide us with a sufficient sample size to test for rationality on this rather important series. The consistent underpredictions of CO_2 emissions, as is evident by the statistically significant mean of the forecast error reported in table 4, leads us to believe that analyzing this series for loss function asymmetries may be a valuable exercise once sufficient data are available.[8] It would be desirable to conduct the same exercise on the quasi-official country

[7]In the original application of this estimator, Elliott et al. (2005) use government forecasts of budget deficits as their empirical application, for which they have 25 observations.

[8]Carbon Intensity is not forecast by the EIA directly. Using the available, yet very short series, we can construct a measure of Carbon Intensity of the economy by dividing CO_2 by GDP. The mean forecast error of this series is statistically not different from zero and serially uncorrelated up to three lags. This is due to the consistent overpredictions of CO_2 and underpredictions of GDP, which cancel each other out. This somewhat surprising result is quite different from the result for energy intensity.

Table 1: EIA AEO Forecast Series Titles, Mean Forecast Error and Autocorrelations

Code	Series Name	Mean ε_{t+1}	ρ_{t-1}	ρ_{t-2}	ρ_{t-3}
ENC	Total Energy Consumption	0.05	0.08	-0.06	-0.41
PEC	Total Petroleum Consumption	0.04	-0.05	0.21	-0.30
NGC	Total Natural Gas Consumption	0.45**	0.33	-0.03	-0.21
COC	Total Coal Consumption	7.25	0.22	0.04	-0.21
ELS	Total Electricity Sales	16.21**	-0.33	0.39	-0.38
OIP	Crude Oil Production	-0.02	0.14	0.08	0.21
NGP	Natural Gas Production	0.13	0.16	-0.44**	-0.17
COP	Coal Production	-7.01	0.21	0.04	-0.38
PEI	Net Petroleum Imports	0.20	0.62**	0.35	0.42
NGI	Net Natural Gas Imports	0.05**	-0.05	0.08	0.00
OI$	World Oil Prices	-0.55**	-0.04	0.06	-0.16
NG$	Natural Gas Wellhead Prices	0.02	-0.28	0.34	0.19
CO$	Coal Prices to Electric Generating Plants	-0.08**	0.14	0.00	-0.11
EL$	Average Electricity Prices	-0.13**	0.30	-0.03	0.18
GDP	Gross Domestic Product	235.75**	0.67**	0.36	0.05
ENI	Energy Intensity	-0.61**	0.79**	0.69**	0.50**
CO_2	Carbon Dioxide Emissions	34**	-0.42	-0.13	-0.06

level forecasts of CO_2 emissions issued by the Intergovernmental Panel on Climate Change (IPCC), 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. Overall, the set of data we employ is the best data set we are aware of in the energy context.

Following the method outlined in the previous section, we will test for rationality of the forecasts by assuming MSFE and MAFE loss functions, which is equivalent to setting $\alpha = 0.5$ and $p = 1, 2$ respectively. We then conduct the J-Test to test for whether we have sufficient evidence to reject the null of forecast rationality under symmetric loss. In the second step, we obtain an estimate of $\alpha_o = \hat{\alpha}$ and then again test for forecast rationality under the estimated degree of asymmetry. The employed J-Test and GMM estimator provided by Elliott et al. (2005) 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. We fail to reject the null of nonstationarity for most series, which may still be due to the weak power properties of the test for the small sample employed. We therefore estimate the model in predicted growth rates, which amounts to converting the forecast of $Y_{t+\tau}$ into a growth rate, which is more likely to be stationary. The forecast growth rate for horizon τ made at time t is given by: $\dot{f}_{t+\tau}(W_t, \boldsymbol{\theta}) = (\frac{f_{t+\tau}(W_t,\boldsymbol{\theta})}{Y_t} - 1)/\tau$, where the dot indicates the growth rate. In order to not lose another observation due to this conversion, we went back to hard copies of the Annual Energy Outlook and collected actual realizations of all series for 1984. We run ERS tests on these series again and for series, for which the p-value of the test statistic is greater than 0.1, 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 KPS result. Using this procedure we argue that the growth rates are stationary. Forecast errors in the estimation are also realizations minus the calculated forecast. A negative forecast error is therefore an over prediction of the variable. In the case of energy intensity this implies that the energy intensity of the economy has fallen by more than expected.

We conduct the empirical test of forecast rationality for $p_o = 1$ first, which is a lin-lin loss function and a good approximation for a large class of asymmetric loss functions. We then 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}.

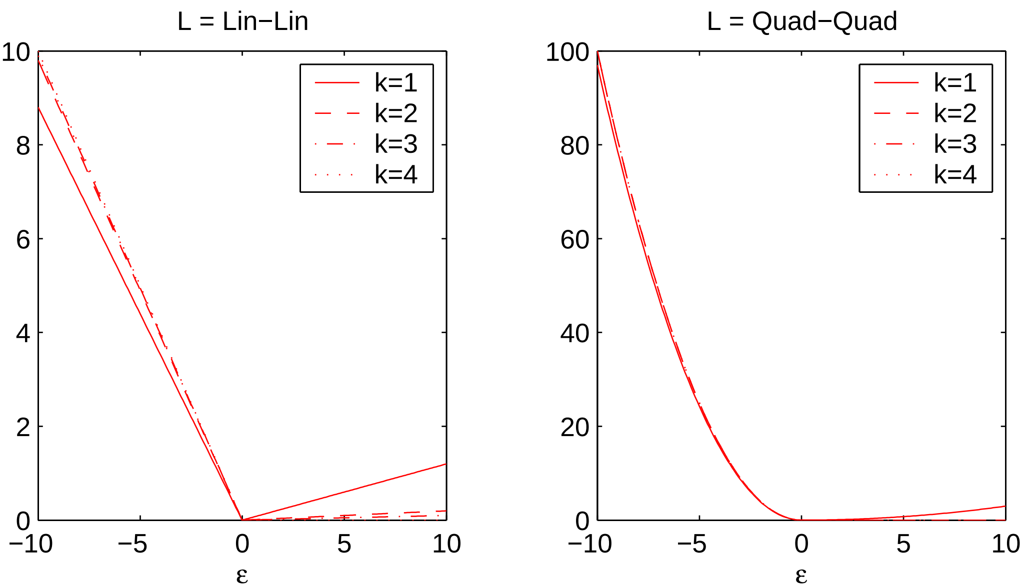
The top panel of table 2 reports the estimated asymmetry parameter $\hat{\alpha}$, assuming rationality and lin-lin loss for the same year forecasts. The bottom panel reports the parameters for the true one year ahead forecasts. The standard errors and two-tailed p-values are reported in brackets under the estimates for $\hat{\alpha}$. For the same year forecasts, we reject the null of symmetric loss for the following series: natural gas consumption, electricity sales, natural gas imports, world oil price, coal prices to electric generating plants, GDP and energy intensity. This mirrors the results from table 1, which is not surprising. The estimated lin-lin loss functions display asymmetry at the 10% level of significance irrespective of what combination of instruments is used.[9] According to these estimates, the EIA considers overpredictions NGC, ELS, NGI and GDP as very costly, while regarding underpredictions of OI$, CO$, EL$ and ENI as relatively more costly.

For the true one year ahead forecasts a similar picture emerges, although the natural gas consumption estimate is closer to 0.5 and only statistically different from 0.5 for the four instruments case. The one step ahead oil price series no longer display asymmetric loss. The estimated coefficient for the natural gas import series is also no longer statistically different from 0.5 - although the point estimate is closer to zero than one. For electricity sales, coal prices, electricity prices, GDP and energy intensity we again reject the null hypothesis of symmetric lin-lin loss. Overall, the results are almost identical to the $\tau = 0$ case.

Table 3 displays the parameter estimates under nonlinear quad-quad loss, under which large errors are relatively more costly than small errors compared to MAFE loss. 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. For energy intensity and coal prices to electric generating plants as well as electricity prices, the asymmetry parameter is very close to or equal to one, suggesting that positive errors are considered much less costly than negative forecast errors. Since the estimated coefficient is at the boundary of the parameter space, one should be careful with inference. The results using the quad-quad loss function for natural gas consumption display a statistically significant degree of asymmetry at both forecasting horizons we consider. The estimated degree of asymmetry for coal prices, electricity prices, GDP and energy intensity is different from 0.5 for all combinations of instruments, forecasting horizons and loss functions considered. Figure 3 displays the estimated loss function over energy intensity forecasts for lin-lin and quad-quad loss for each of the four combinations of instruments used. This visualization demonstrates the implicit extreme cost of underpredicting 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

[9] $\hat{\alpha}$ for Electricity Sales and Natural Gas Imports using one instrument are only significantly different from 0.5 at the 14% level.

Figure 3: Estimated Loss Functions for Energy Intensity



underpredictions of energy intensity. At the upper end the ratio is roughly 400.[10]

Although the above estimation results provide strong evidence of asymmetric loss for natural gas consumption, electricity sales, natural gas imports, GDP, oil, coal and electricity prices as well as energy intensity, they do not provide any explanation *why* this may be so. If the Energy Information Administration uses an explicitly asymmetric loss function for some series, but not others, this is not reported in the Annual Energy Outlook and therefore observable to the econometrician or more importantly so - the forecast user. Further, we do not observe the internal decision making process the EIA undergoes until it agrees to release one specific set of forecasts. One potential political economy explanation may be that political pressures are applied, which lead to one set of forecasts over another being chosen. For example, an explanation of conservatively forecasting drops in the energy intensity ratio of the economy may have to do with planning for sufficient fuel supply for coming years. Should a predicted large drop in this ratio not be realized, allocated fossil fuels may not be sufficient to meet demand and have severe economic and political consequences.

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

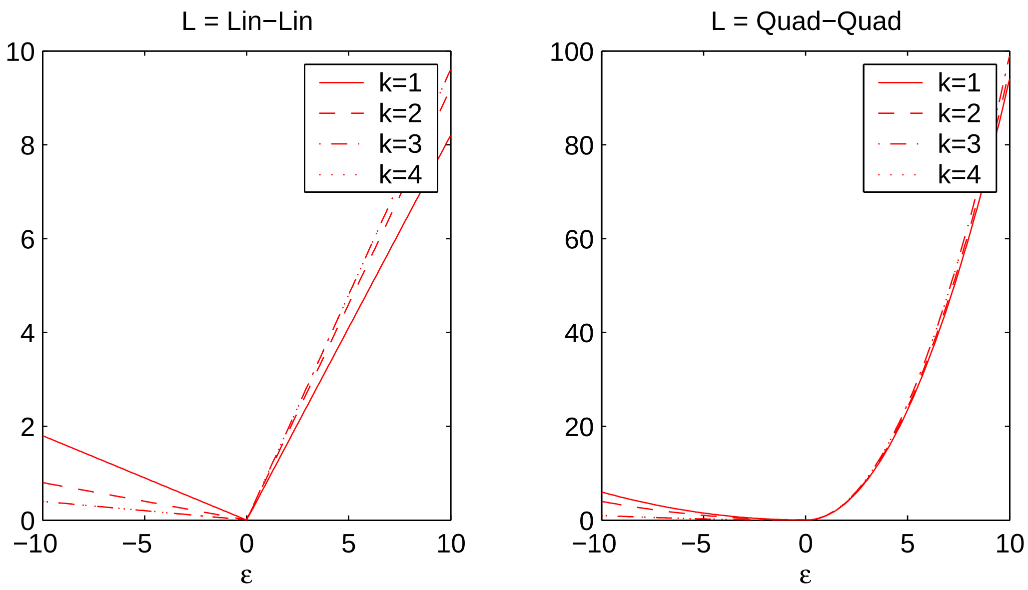
We pursued two routes of inquiry to gain a better understanding of how the EIA arrives at choosing a set of forecasts out of the many possible scenarios emerging due to a particular parametrization of the NEMS model. First, through conversations with the relevant contacts at EIA for a subset of the modules, an interesting picture emerged. The individual(s) responsible for each of the NEMS modules work on parameterizing each module for the next set of forecasts separately. In a series of meetings, these modelers discuss the assumptions, which go into the new set of forecasts produced by each module and then go back to incorporate any agreed upon changes. Ultimately, later rounds of forecasts are handed up to higher levels in the administration, but explicit questioning showed that the modelers are to a large extent responsible for choosing a particular set of forecasts, which get released in a particular volume of the Annual Energy Outlook. The conversations suggest that the estimated asymmetries in loss are likely due to heterogeneous loss functions of individual modelers, rather than a generally applied loss function decided on by higher levels of authority within the administration.

The second line of inquiry specifically dealt with the actual method of forecasting energy intensity employed by the EIA. The publicly available forecast evaluation materials (Energy Information Agency, 2004) provided an interesting, although less behavioral, explanation for the observed sequence of overpredicted energy intensity values. Forecasts and rudimentary forecast evaluation are posted on the EIA website in spreadsheet form.[11] 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. 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.

As discussed above, 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). The GDP forecasts are supplied to the EIA by an outside consulting firm

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

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



and then modified by the modelers in charge of the macroeconomic module. Historically, Standard & Poor's DRI GDP forecasts were used, who have since merged with their main competitor (the WEFA group) to form Global Insight, who now supply the GDP forecasts. The EIA uses the Global Insight forecasts as a guideline and then modifies these forecasts. Inquiries into how these modification are conducted, revealed a non-structural approach. The Global Insight forecasts are compared to other popular forecasts available in the literature and adjusted accordingly.[12] A rudimentary forecast comparison of the short run GDP forecasts made by the EIA, versus the WEFA and DRI forecasts as well as a forecast issued by the Congressional Budget office indicates that the EIA forecasts predict slightly higher growth rates than any of the three other providers.[13] The resulting published forecasts underpredict GDP growth for a majority of the observed time periods for both forecasting horizons. Admittedly, GDP growth is very difficult to forecast. A naive forecast of the GDP growth rate, however, would on average be expected to be as likely to overstate as to understate future GDP. The repeated underprediction of GDP

[12] This was described as the 'looking over our shoulder' approach.
[13] Available at http://www.eia.doe.gov/oiaf/economy/energy_price.html

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

The degree of asymmetry of the forecasters' loss function is interesting, yet we are also interested in testing whether the observed forecasts are rational, given a specific loss function. The top panels in tables 4 and 5 display the results for the joint hypothesis test of forecast rationality under symmetric loss.[14] 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. We reject rational forecasts for natural gas consumption, electricity sales, coal and electricity prices, GDP and energy intensity for all considered sets of instruments, forecast horizons and loss functions at the 3% level. This is not surprising given the previous estimates for α. We further reject rationality in most scenarios for the remainder of the series. Petroleum consumption and natural gas prices are the only two series, which for the majority of cases pass the test of rationality under symmetric loss. For the quad-quad loss case, we reject forecast rationality under symmetry for 95 out of the possible 128 tests conducted. For the lin-lin loss function we reject for 79 out of the 128 conducted tests.

The bottom panels of table 4 and 5 provide the J-tests under asymmetric loss, which allow 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 two instrument case for the end of year forecasts under lin-lin loss. Once we relax the symmetry restriction, we reject rationality for 10 out of 96 valid cases for lin-lin loss and 13 out of 96 valid cases for quad-quad loss. Overall, the results from estimation suggest that the majority of the AEO forecasts considered in this paper are not consistent with a symmetric loss function of the forecaster producing them - the Energy Information Administration.

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

5. Conclusions

Using forecasts produced by others is only optimal for the forecast user if the loss function of the forecast producer is identical to that of the forecast user. This paper provides empirical evidence that a majority of the most important national level energy related forecasts published by the Energy Information Administration are only rational/optimal under highly asymmetric loss function. The forecasts of oil, coal and gas prices as well as natural gas consumption, GDP and energy intensity are shown to be consistent with highly asymmetric loss functions.

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. Using these forecasts under the assumption that they were constructed using a symmetric loss function will result in suboptimal outcomes for the user. We argue that the observed asymmetric loss functions are likely to reflect loss functions of individual modelers at the EIA, rather than an overall loss function of the EIA as an organization or its top administrators.

Interestingly, 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 consistent overprediction of energy intensity is due to asymmetric loss over Gross Domestic Product forecast errors. The GDP forecasts, which are provided by an outside consulting firm and are modified by EIA modelers drive the energy intensity forecasts. Other GDP forecasts considered by the EIA seem to do underpredict future GDP even more.

On interesting line of future research is taking a closer look at CO_2 forecasts from NEMS. It is possible that underpredictions of GDP, reflecting economic activity, may be responsible for the underpredictions of CO_2 emissions. When constructing a frequently used measure of technological progress (Carbon Intensity) from these two series, the biases cancel each other out and the forecasts of Carbon intensity seem to be consistent with symmetric loss, although the available series are too short to formally test this at the current time.

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

Same Year	($\tau = 0$)	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	0.12	0.35	0.21	0.60	0.29	0.53	0.25	0.18	0.91	0.53	0.89	0.95	0.05	0.96
	s..e.	0.21	0.23	0.11	0.23	0.16	0.24	0.20	0.25	0.20	0.15	0.08	0.25	0.10	0.05	0.07	0.04
	p-value	0.35	0.48	0.00	0.51	0.08	0.67	0.30	0.91	0.21	0.03	0.00	0.89	0.00	0.00	0.00	0.00
Inst=3	$\hat{\alpha}$	0.27	0.34	0.09	0.35	0.22	0.61	0.28	0.53	0.34	0.22	0.90	0.53	0.88	0.97	0.13	0.90
	s..e.	0.20	0.23	0.09	0.23	0.17	0.24	0.20	0.25	0.23	0.17	0.09	0.25	0.11	0.04	0.12	0.09
	p-value	0.27	0.49	0.00	0.52	0.10	0.64	0.27	0.90	0.49	0.09	0.00	0.90	0.00	0.00	0.00	0.00
Inst=4	$\hat{\alpha}$	0.27	0.32	0.09	0.35	0.21	0.64	0.28	0.53	0.25	0.18	0.91	0.54	0.91	0.97	0.05	0.96
	s..e.	0.20	0.22	0.09	0.23	0.16	0.23	0.20	0.25	0.20	0.15	0.08	0.25	0.09	0.04	0.07	0.04
	p-value	0.26	0.42	0.00	0.50	0.08	0.54	0.26	0.90	0.20	0.03	0.00	0.89	0.00	0.00	0.00	0.00
One Year Ahead	($\tau = 1$)																
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	0.43	0.14	0.72	0.30	0.57	0.61	0.37	0.57	0.58	1.00	0.98	0.07	0.94
	s..e.	0.24	0.25	0.19	0.24	0.12	0.21	0.21	0.25	0.24	0.23	0.25	0.24	0.01	0.03	0.07	0.06
	p-value	0.74	1.00	0.18	0.76	0.00	0.28	0.34	0.78	0.64	0.57	0.79	0.75	0.00	0.00	0.00	0.00
Inst=3	$\hat{\alpha}$	0.60	0.50	0.23	0.42	0.15	0.64	0.30	0.57	0.59	0.37	0.57	0.58	1.00	0.96	0.08	0.98
	s..e.	0.24	0.25	0.18	0.24	0.13	0.23	0.21	0.25	0.24	0.23	0.24	0.24	0.00	0.04	0.07	0.02
	p-value	0.69	1.00	0.13	0.76	0.00	0.55	0.34	0.78	0.70	0.59	0.77	0.75	0.00	0.00	0.00	0.00
Inst=4	$\hat{\alpha}$	0.60	0.50	0.21	0.42	0.14	0.76	0.30	0.57	0.61	0.32	0.58	0.58	1.00	0.98	0.07	0.98
	s..e.	0.24	0.25	0.17	0.24	0.12	0.20	0.21	0.25	0.24	0.22	0.24	0.24	0.00	0.03	0.07	0.02
	p-value	0.68	1.00	0.09	0.75	0.00	0.19	0.33	0.78	0.65	0.42	0.74	0.75	0.00	0.00	0.00	0.00

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

Same Year	($\tau = 0$)	ENC	PEC	NGC	COC	ELS	OIP	NGP	COP	PEI	NGI	OI$	NG$	CO$	EL$	GDP	ENI
Inst=1	$\hat{\alpha}$	0.40	0.35	0.10	0.27	0.24	0.68	0.27	0.69	0.27	0.15	0.94	0.42	0.97	0.90	0.04	0.96
	s.e.	0.43	0.41	0.08	0.25	0.26	0.28	0.22	0.34	0.28	0.12	0.04	0.35	0.01	0.09	0.01	0.03
	p-value	0.82	0.72	0.00	0.36	0.31	0.53	0.31	0.58	0.42	0.00	0.00	0.83	0.00	0.00	0.00	0.00
Inst=2	$\hat{\alpha}$	0.43	0.35	0.02	0.25	0.15	0.68	0.28	0.69	0.21	0.08	0.94	0.39	0.99	0.97	0.01	1.00
	s.e.	0.38	0.40	0.03	0.24	0.17	0.28	0.22	0.33	0.26	0.07	0.04	0.33	0.00	0.03	0.01	0.00
	p-value	0.85	0.72	0.00	0.30	0.04	0.52	0.32	0.57	0.26	0.00	0.00	0.74	0.00	0.00	0.00	0.00
Inst=3	$\hat{\alpha}$	0.40	0.32	0.01	0.27	0.19	0.76	0.25	0.69	0.26	0.15	0.94	0.41	0.99	0.97	0.03	0.98
	s..e.	0.43	0.38	0.02	0.25	0.23	0.24	0.21	0.30	0.27	0.12	0.04	0.34	0.00	0.02	0.01	0.01
	p-value	0.83	0.64	0.00	0.36	0.18	0.27	0.24	0.53	0.38	0.00	0.00	0.80	0.00	0.00	0.00	0.00
Inst=4	$\hat{\alpha}$	0.35	0.31	0.01	0.25	0.15	0.80	0.25	0.69	0.20	0.07	0.94	0.38	0.99	0.97	0.01	1.00
	s..e.	0.35	0.32	0.02	0.24	0.16	0.23	0.19	0.30	0.26	0.06	0.04	0.33	0.00	0.02	0.01	0.00
	p-value	0.67	0.57	0.00	0.28	0.03	0.19	0.19	0.53	0.25	0.00	0.00	0.72	0.00	0.00	0.00	0.00
One Year Ahead	($\tau = 1$)																
Inst=1	$\hat{\alpha}$	0.52	0.52	0.20	0.36	0.22	0.59	0.24	0.59	0.52	0.24	0.53	0.40	0.96	0.90	0.08	0.99
	s.e.	0.39	0.41	0.20	0.32	0.24	0.37	0.22	0.34	0.32	0.20	0.32	0.35	0.02	0.08	0.06	0.00
	p-value	0.95	0.96	0.13	0.65	0.24	0.80	0.22	0.78	0.96	0.18	0.93	0.77	0.00	0.00	0.00	0.00
Inst=2	$\hat{\alpha}$	0.51	0.47	0.09	0.31	0.15	0.65	0.21	0.60	0.54	0.24	0.52	0.36	1.00	0.99	0.07	0.99
	s.e.	0.39	0.40	0.10	0.31	0.19	0.36	0.19	0.34	0.32	0.20	0.32	0.34	0.00	0.03	0.06	0.00
	p-value	0.99	0.93	0.00	0.53	0.07	0.68	0.13	0.77	0.90	0.18	0.94	0.68	0.00	0.00	0.00	0.00
Inst=3	$\hat{\alpha}$	0.51	0.45	0.10	0.36	0.18	0.59	0.23	0.60	0.54	0.24	0.53	0.37	1.00	0.97	0.07	1.00
	s.e.	0.39	0.38	0.10	0.32	0.22	0.36	0.21	0.34	0.32	0.20	0.32	0.34	0.00	0.04	0.06	0.00
	p-value	0.97	0.90	0.00	0.66	0.15	0.80	0.20	0.76	0.90	0.19	0.94	0.71	0.00	0.00	0.00	0.00
Inst=4	$\hat{\alpha}$	0.52	0.46	0.09	0.31	0.15	0.73	0.22	0.60	0.53	0.24	0.53	0.39	1.00	0.99	0.06	1.00
	s.e.	0.39	0.38	0.10	0.30	0.17	0.33	0.19	0.34	0.32	0.20	0.31	0.33	0.00	0.02	0.05	0.00
	p-value	0.96	0.91	0.00	0.54	0.04	0.48	0.14	0.77	0.92	0.19	0.93	0.73	0.00	0.00	0.00	0.00

Table 4: 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
$\alpha = 0.5$	$\tau = 0$																
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	6.13	2.47	23.34	1.75	9.79	2.13	4.03	0.09	11.34	13.77	35.04	1.52	28.42	63.11	54.67	85.35
	p-value	0.01	0.12	0.00	0.19	0.00	0.14	0.04	0.77	0.00	0.00	0.00	0.22	0.00	0.00	0.00	0.00
Inst=3	j-stat	8.90	2.34	34.24	1.66	8.22	3.10	4.81	0.20	2.42	8.71	29.60	0.26	24.89	93.95	21.47	28.47
	p-value	0.00	0.13	0.00	0.20	0.00	0.08	0.03	0.65	0.12	0.00	0.00	0.61	0.00	0.00	0.00	0.00
Inst=4	j-stat	9.03	4.21	34.69	1.98	9.80	6.54	4.96	0.43	11.38	14.02	35.23	1.78	35.26	103.76	54.76	88.76
	p-value	0.01	0.12	0.00	0.37	0.01	0.04	0.08	0.81	0.00	0.00	0.00	0.41	0.00	0.00	0.00	0.00
$\alpha = 0.5$	$\tau = 1$																
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	2.63	2.49	5.54	1.75	18.34	10.20	3.61	0.96	7.02	1.65	0.78	2.43	753.81	122.87	41.67	52.57
	p-value	0.11	0.11	0.02	0.19	0.00	0.00	0.06	0.33	0.01	0.20	0.38	0.12	0.00	0.00	0.00	0.00
Inst=3	j-stat	5.12	1.65	7.13	2.11	17.01	2.07	3.55	0.92	4.81	1.11	1.50	2.48	897.67	84.49	39.00	178.21
	p-value	0.02	0.20	0.01	0.15	0.00	0.15	0.06	0.34	0.03	0.29	0.22	0.12	0.00	0.00	0.00	0.00
Inst=4	j-stat	5.43	2.56	9.15	2.26	18.47	14.51	3.95	1.06	7.03	5.69	2.87	2.53	906.66	135.07	42.91	179.30
	p-value	0.07	0.28	0.01	0.32	0.00	0.00	0.14	0.59	0.03	0.06	0.24	0.28	0.00	0.00	0.00	0.00
$\alpha = \hat{\alpha}$	$\tau = 0$																
Inst=2	j-stat	2.99	0.60	1.41	0.10	0.92	1.38	0.28	0.03	5.96	1.87	0.61	1.44	1.86	1.42	3.22	1.76
	p-value	0.08	0.44	0.23	0.76	0.34	0.24	0.60	0.86	0.01	0.17	0.44	0.23	0.17	0.23	0.07	0.18
Inst=3	j-stat	4.62	0.51	2.27	0.03	0.48	2.22	0.65	0.14	0.57	0.62	0.34	0.20	1.56	1.85	1.23	0.28
	p-value	0.03	0.48	0.13	0.86	0.49	0.14	0.42	0.71	0.45	0.43	0.56	0.65	0.21	0.17	0.27	0.60
Inst=4	j-stat	4.69	1.77	2.30	0.26	0.92	5.09	0.72	0.37	5.98	1.92	0.62	1.69	2.33	1.95	3.22	1.80
	p-value	0.10	0.41	0.32	0.88	0.63	0.08	0.70	0.83	0.05	0.38	0.73	0.43	0.31	0.38	0.20	0.41
$\alpha = \hat{\alpha}$	$\tau = 1$																
Inst=2	j-stat	2.21	2.49	0.07	1.39	1.24	6.35	0.55	0.66	6.20	0.45	0.50	2.03	1.11	2.24	1.08	0.01
	p-value	0.14	0.11	0.79	0.24	0.26	0.01	0.46	0.42	0.01	0.50	0.48	0.15	0.29	0.13	0.30	0.94
Inst=3	j-stat	4.49	1.65	0.61	1.73	1.07	0.77	0.52	0.63	4.22	0.03	1.17	2.08	1.13	1.92	0.99	0.79
	p-value	0.03	0.20	0.43	0.19	0.30	0.38	0.47	0.43	0.04	0.85	0.28	0.15	0.29	0.17	0.32	0.37
Inst=4	j-stat	4.77	2.56	1.23	1.87	1.26	8.91	0.73	0.76	6.23	3.40	2.44	2.12	1.13	2.31	1.12	0.79
	p-value	0.09	0.28	0.54	0.39	0.53	0.01	0.69	0.68	0.04	0.18	0.30	0.35	0.57	0.32	0.57	0.67

Table 5: 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
$\alpha = 0.5$	$\tau = 0$																
Inst=1	j-stat	0.37	0.92	31.71	3.57	4.53	1.93	3.86	1.81	3.06	17.78	90.32	0.29	441.22	32.25	251.86	128.55
	p-value	0.54	0.34	0.00	0.06	0.03	0.16	0.05	0.18	0.08	0.00	0.00	0.59	0.00	0.00	0.00	0.00
Inst=2	j-stat	0.44	0.92	139.16	5.63	13.37	2.84	4.11	1.82	8.96	44.99	92.99	2.01	1008.31	127.36	625.24	862.86
	p-value	0.51	0.34	0.00	0.02	0.00	0.09	0.04	0.18	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00
Inst=3	j-stat	2.90	1.66	235.65	3.60	7.71	7.36	5.71	2.00	4.27	17.92	90.77	0.79	1001.44	155.57	290.29	343.28
	p-value	0.09	0.20	0.00	0.06	0.01	0.01	0.02	0.16	0.04	0.00	0.00	0.38	0.00	0.00	0.00	0.00
Inst=4	j-stat	4.12	2.12	250.10	6.24	14.49	11.46	6.26	2.04	9.31	49.37	93.06	2.32	1148.16	155.69	673.66	863.87
	p-value	0.13	0.35	0.00	0.04	0.00	0.00	0.04	0.36	0.01	0.00	0.00	0.31	0.00	0.00	0.00	0.00
$\alpha = 0.5$	$\tau = 1$																
Inst=1	j-stat	0.02	0.02	7.34	1.03	5.32	0.38	5.15	0.42	0.01	5.65	0.04	0.46	146.46	30.24	49.56	1037.17
	p-value	0.88	0.90	0.01	0.31	0.02	0.54	0.02	0.52	0.91	0.02	0.85	0.50	0.00	0.00	0.00	0.00
Inst=2	j-stat	2.21	3.38	28.43	5.10	11.59	6.54	7.48	4.42	5.35	5.69	0.25	3.49	1501.98	149.46	55.76	1446.01
	p-value	0.14	0.07	0.00	0.02	0.00	0.01	0.01	0.04	0.02	0.02	0.62	0.06	0.00	0.00	0.00	0.00
Inst=3	j-stat	3.24	3.13	27.99	2.30	8.46	0.38	6.59	3.11	2.75	6.51	0.31	4.18	1865.18	98.34	52.17	3407.99
	p-value	0.07	0.08	0.00	0.13	0.00	0.54	0.01	0.08	0.10	0.01	0.58	0.04	0.00	0.00	0.00	0.00
Inst=4	j-stat	3.42	3.44	29.46	5.11	13.10	10.88	7.80	4.63	5.74	8.12	0.33	4.26	1908.83	165.60	63.52	3444.26
	p-value	0.18	0.18	0.00	0.08	0.00	0.00	0.02	0.10	0.06	0.02	0.85	0.12	0.00	0.00	0.00	0.00
$\alpha = \hat{\alpha}$	$\tau = 0$																
Inst=2	j-stat	0.21	0.01	2.25	1.19	1.40	0.84	0.28	0.01	3.44	1.59	0.13	1.36	1.49	1.28	2.20	1.15
	p-value	0.65	0.92	0.13	0.28	0.24	0.36	0.60	0.91	0.06	0.21	0.72	0.24	0.22	0.26	0.14	0.28
Inst=3	j-stat	2.55	0.27	2.04	0.03	0.82	2.47	0.70	0.00	0.63	0.03	0.23	0.41	0.91	1.47	0.92	0.64
	p-value	0.11	0.60	0.15	0.86	0.37	0.12	0.40	0.98	0.43	0.86	0.63	0.52	0.34	0.23	0.34	0.42
Inst=4	j-stat	3.06	0.31	2.32	1.61	1.41	4.89	0.71	0.02	3.55	1.79	0.25	1.61	1.49	1.48	2.65	1.19
	p-value	0.22	0.86	0.31	0.45	0.49	0.09	0.70	0.99	0.17	0.41	0.88	0.45	0.47	0.48	0.27	0.55
$\alpha = \hat{\alpha}$	$\tau = 1$																
Inst=2	j-stat	2.21	3.34	1.75	3.20	1.58	5.56	0.44	3.98	5.27	0.00	0.22	2.58	1.06	2.27	0.94	0.33
	p-value	0.14	0.07	0.19	0.07	0.21	0.02	0.51	0.05	0.02	0.97	0.64	0.11	0.30	0.13	0.33	0.57
Inst=3	j-stat	3.23	3.03	1.51	1.31	1.20	0.01	0.99	2.60	2.67	1.15	0.27	3.42	1.07	1.96	0.66	0.76
	p-value	0.07	0.08	0.22	0.25	0.27	0.93	0.32	0.11	0.10	0.28	0.60	0.06	0.30	0.16	0.42	0.38
Inst=4	j-stat	3.40	3.37	1.75	3.27	1.59	8.29	1.04	4.16	5.70	2.69	0.29	3.63	1.07	2.30	1.11	0.77
	p-value	0.18	0.19	0.42	0.19	0.45	0.02	0.59	0.13	0.06	0.26	0.87	0.16	0.59	0.32	0.57	0.68

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