Testing the rationality of DOE's energy price forecasts under asymmetric loss preferences*

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Abstract

This paper examines the rationality of the Energy Information Administration (EIA) of the United States Department of Energy's (DOE) forecasts given a loss function. The underlying loss function has some unknown shape parameters that provide information regarding the preferences of the forecaster. Even without observing the DOE's forecasting model we examine for asymmetries in preferences. Empirical results show the existence of asymmetries in DOE's loss function, revealing preferences that lean towards optimism. In turn, these preferences imply irrationality.

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1. Introduction

The Energy Information Administration (EIA thereafter) of the United States Department of Energy (DOE thereafter) provides official energy statistics to the US government. Moreover, DOE publishes every month the Short-Term Energy Outlook (STEO) that provides quarterly energy price forecasts. The main aim of DOE is to improve market efficiency by providing accurate forecasts and thus enhancing the predictability of highly volatile energy prices. Effectively, DOE’s forecasts are of great importance as they provide the main source of information for setting a yardstick regarding future movements in energy prices for the US market but also world wide markets.

DOE opts for a complex forecasting model. Moreover, it employs a large system of equations so as to forecast energy prices. DOE produces forecasts for petroleum, natural gas, coal, electricity, and other power sectors. Interestingly, DOE’s forecasts incorporate some subjective elements, though to a certain degree an adjustment is carried out at a regional level (DOE, 2008). This adjustment together with the subjective elements could assert an impact on the shape of the DOE’s underlying loss function. This paper bridges a gap in the literature by estimating for the first time this shape parameter. To this end, the methodology of this paper departs from the standard analysis of forecast error in energy prices (for a review see Sanders et al. 2009) and employs instead the modelling of the DOE’s loss function as in Elliott et al. (2005).

There have been numerous studies that provide an assessment of DOE’s forecasts. Bentzen and Linderoth (2005) show that DOE’s forecasts perform better for shorter forecast horizons. Sanders et al. (2008) examine DOE’s energy price forecasts for bias and efficiency. They employ tests for bias, beta efficiency, and rho efficiency to show that the DOE forecasts perform well as a group, though natural gas forecasts are biased and coal and crude oil forecasts are inefficient. However, over all Sanders et al. (2008) argue that DOE's forecasts perform well in terms of biasedness and efficiency, even if they could gain by using all available information. In another study, Sanders et al. (2009) show that in most cases the DOE's energy price forecasts provide incremental information even in longer forecast horizons, whereas coal forecasts suffer from inefficiency and as a result their performance could substantially improve.

The above studies have done a good job in evaluating the performance of DOE's energy forecasts using a plethora of available tests for multiple horizons. Overall, it is reported that DOE's forecasts perform well with some notable exceptions, i.e. coal prices. However, a criticism to the literature concerns the common assumption that DOE's forecasts are based on a symmetric underlying loss function with respect to positive vs. negative forecast errors. This paper augments the previous findings of Sanders et al. (2009) and Sanders et al. (2008) by providing estimates of the shape parameters of DOE's loss function and thus revealing preferences over rationality. Specifically, this paper employs an up to date sample of Sanders et al. (2009) for one to five quarters ahead forecasts for crude oil, retail gasoline, retail diesel fuel, coal, natural gas, and electricity. Without imposing a specific preference structure in the underlying DOE's loss function we use a model that both symmetric and asymmetric loss functions are present as special cases.

Mincer and Zarnowitz (1969) were the first to develop a method to evaluate forecasts based on the assumption of a loss function that mirrors symmetric preferences and rational behaviour.[1] It is customary to further assume that such forecasts have a Mean Square Error (MSE) that is unbiased and does not suffer from serial correlation. Our objective in this paper is to empirically test the validity of these hypotheses. To this end, we depart from the typical tests developed by Mincer and Zarnowitz (1969) and by Diebold and Lopez (1998) and opt instead for the methodology of Elliott et al. (2005) that allows testing the joint hypothesis of an asymmetric loss function and rationality.[2]

Moreover, the loss function is indexed by a single unknown shape parameter, *'α'*, that measure whether the loss function is symmetric or not. Estimating the shape parameter *'α'* of the forecast error loss function allows identifying any asymmetries in the underlying loss function, whether it takes a linear or a non-linear form. Then, we define the null hypothesis of rationality in terms of a symmetric loss function as in Mincer and Zarnowitz (1969) that is tested using GMM methodology and a X^2-test. To this end, this paper provides for the first time estimates of the shape parameter of the DOE's underlying loss function.

Empirical results show that for most energy prices forecasts the loss function is asymmetric. Asymmetry in the loss function reveals that DOE's preferences lean towards optimism and thus irrationality. Specifically, overall DOE's energy price forecasts assign higher loss for the case that the forecast exceeds realization, especially for longer time horizons. These empirical findings come in line with Ito (1990) who reports the tendency of price forecasts to be optimistic, arguing that market participants form what he calls *'wishful expectations'*, i.e. exporters expect currency depreciation.

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[1] For a recent review of forecast error assessment see Elliott and Timmermann (2008).
[2] For the first forecast rationality test under asymmetric loss see Bachelor and Peel (1998).

He further argues that in the presence of *'wishful expectations'* rationality is compromised, in particular in the case of long-term forecasts. Present findings show that DOE's energy price forecasts are based on *'wishful expectations'* along the lines of Ito's (1990), as they clearly lean towards optimism, associated with a systematic under-prediction. As a consequence, DOE's underlying loss function is not associated with rational preferences.

The next section the paper presents an analysis of the track record of DOE's forecasts. Section 3 presents the empirical methodology, while Section 4 provides information regarding the data set. Section 5 reports the results and last Section 6 offers some concluding statements and policy considerations.

2. The Track Record of DOE's energy price forecasts

DOE provides quarterly price forecasts for the main energy commodities and is the source of official energy statistics of US government. Moreover, DOE publishes every month the Short-Term Energy Outlook (STEO) that provides US monthly projections. In addition, DOE publishes quarterly energy price forecasts in the Short-Term Energy Outlook (STEO thereafter). The forecasting exercise of STEO is dynamic and highly complex.[3]

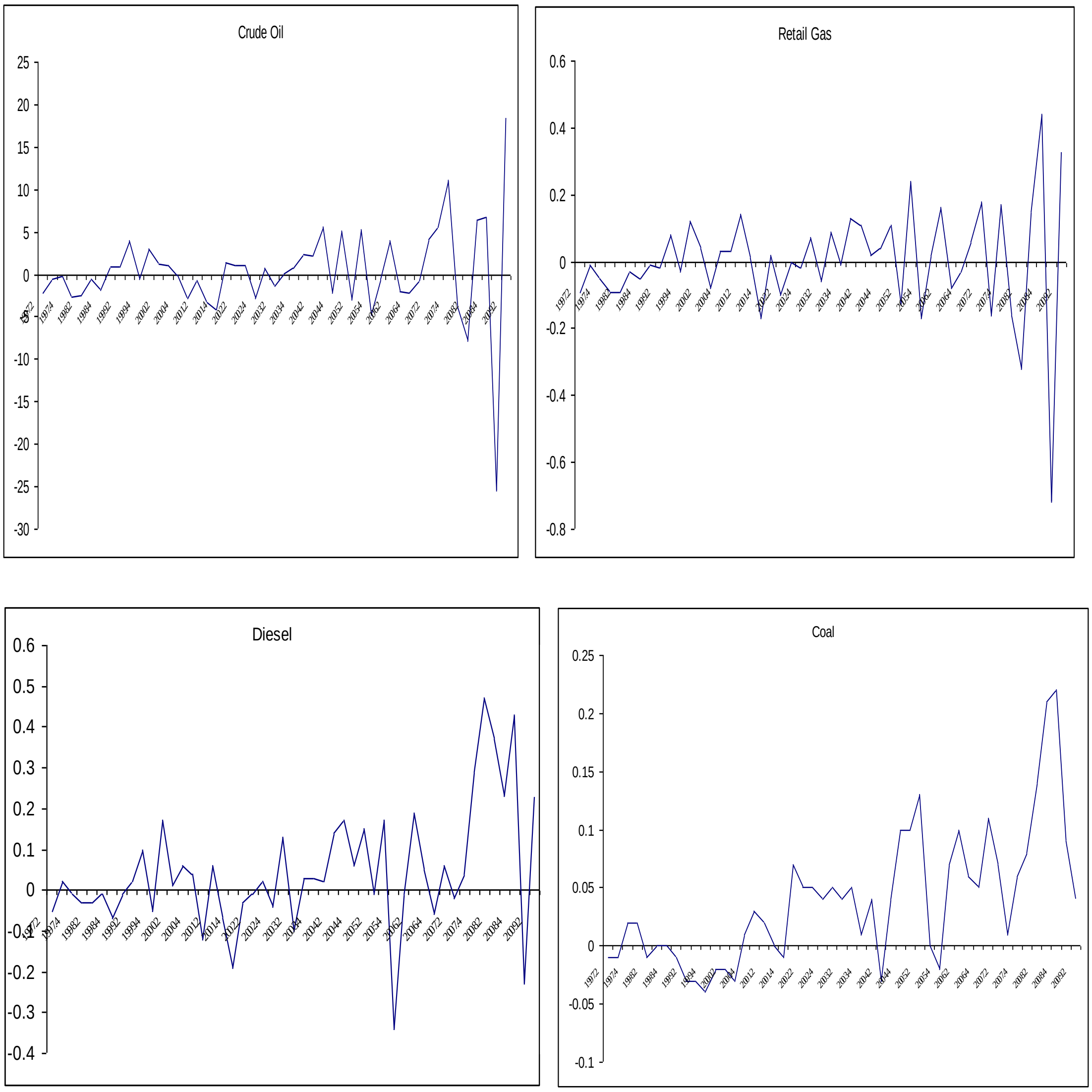
[3]The DOE employs a complex forecasting procedure, which includes structural econometric equations and time series analysis. Moreover, over 300 forecasting equations and many exogenous variables, such as world crude oil production and usage, U.S. domestic crude oil production, macroeconomic forecasts, and weather forecasts are part of DOE's forecasting modeling (for a comprehensive review see DOE, 2008 and Sanders et al. 2009). This modelling approach was set at a national level prior to 2005. Since then DOE opts for an even more complicated regional short term energy model to improve the accuracy of national forecasts in a parallel process of providing regional forecasts.

Diagram 1 presents the one quarter ahead forecast errors, defined as realization minus forecast, for crude oil, retail gas, diesel, and coal. The time period spans from the second quarter in 1997 till the second quarter in 2009. The key underlying common hypothesis in the literature (see Sanders et al. 2009 and Sanders et al. 2008) is that DOE forms forecasts using a symmetric underlying loss function. This, in turn, implies that forecast errors whether positive or negative are equally costly. In terms of diagrammatic analysis, symmetry in the loss function could imply that forecast errors hover around zero without exhibiting any persistence, especially for positive forecast errors.

However, note that forecast errors exhibit some variation around zero, whilst there exist periods when forecast errors largely deviate from zero, in particular later in the sample when they take large positive values (see Diagram 1). Positive values in forecast errors are of interest as they suggest under-prediction that is the case when the actual, realization, of energy price is higher than the forecast. Such forecast errors can hardly be viewed as prudent, especially in periods of energy price hikes.[4] However, with the exception of coal, there is not strong evidence of persistence in positive forecast errors over the whole sample period as fluctuations earlier in the sample show that there are also quarters with large negative forecast errors, thus implying over-prediction. An interesting case appears to be the forecast error of coal, taking positive values since late in 2005. This implies that DOE has systematically under-predicted coal as prices turn out higher than forecasted.

[4]Note that an *'over-prudent'* economic agent may exhibit higher aversion to positive forecast errors versus negative ones of the same size. This would essentially imply that there might be lower costs associated with over-prediction, and thus pessimism, that is the case when the realization is less than the forecast, against the case of an equal size under-prediction.

Diagram 1. One Quarter -Ahead Forecast Errors for Crude Oil, Retail Gas, Retail Diesel, and Coal.



Source: DOE Quarterly Energy Prices.

Overall, the above diagrammatic analysis suggests that DOE may form its forecasts based on an underlying asymmetric loss function. Of course, one can not draw final conclusions using diagrammatic analysis. It is up to the empirical evidence to reveal any possible asymmetries in the loss function.

3. Empirical Methodology

Following Mincer and Zarnowitz, (1969) an optimal forecast is defined as both unbiased and efficient. An unbiased forecast does not systematically over or under estimate the actual value, whilst an efficient forecast takes into account all available information, and is also the most accurate forecast in terms of mean squared error.

In addition, and crucially for the purpose of the current paper, an optimal forecast is also considered as a rational forecast (Mincer and Zarnowitz, 1969, Diebold and Lopez, 1998 and Sanders et al., 2009). However, for this statement to be true, one important assumption must be valid. An optimal forecast is rational if the forecaster has a symmetric underlying loss function.

In the evaluation of DOE's forecasts (Sanders et al., 2008), examine rationality, and thus optimality, using regression techniques of the actual values against the forecasts along the lines of Mincer and Zarnowitz, (1969):

$$P_{t+1} = \alpha_0 + \beta_0 f_{t+1} + u_{t+1} \qquad (1)$$

where P_{t+1} are the actual values and f_{t+1} are the forecasts and u_{t+1} is the random error term. Forecast rationality is tested under the joint null hypothesis that $\alpha_0=0$ and $\beta_0=1$. If the null is not rejected the forecast is rational, unbiased ($\alpha_0=0$), and efficient ($\beta_0=1$).

The above simple regression framework has attracted criticism from Granger and Newbold (1986) that show that the joint null is a necessary and a sufficient condition for efficiency, but not necessary for unbiasedness. As a result, rejecting the joint null hypothesis may not necessarily imply that forecasts are rational. Sanders et al. (2008) in an evaluation of DOE's forecasts follow the methodology of Pons (2000) focusing strictly on forecast errors that deals with the criticism of Granger and Nwebold (1986). They argue that that DOE's energy forecasts have only limited evidence of bias and inefficiency. In another paper Sanders et al. (2009) examine forecast rationality in multiple *k* periods ahead forecasts using the methodology similar to Vuchelen and Gutierrez (2005). Their evidence shows that DOE's energy price forecasts contain information at multiple horizons and thus are rational, though some variability is also observed. One limitation of such analysis is that crucially depends upon the assumption that the forecaster has a symmetric underlying loss function and thus unbiasedness and efficiency would imply rationality. The present paper tests the validity of this assumption.

As in Elliott et al. (2005) f_{t+1} is the forecast of P_{t+1}. f_{t+1} is conditional on the information set F_t and takes the form:

$$f_{t+1} \equiv \theta' W_t \qquad (2)$$

where θ is an unknown k-vector of parameters, $\theta \in \Theta$, with Θ compact in R^k, and W_t is an h-vector of variables. These variables are part of the information set F_t.

Now, given P_{t+1} and W_t, the forecast f_{t+1} is based on an underlying generalized flexible loss function L defined by

$$L(p,\alpha) \equiv [\alpha + (1-2\alpha)1(P_{t+1} - f_{t+1})]\left|P_{t+1} - f_{t+1}\right|^p \qquad (3)$$

where p=1 or 2, counting for a linear and non-linear loss function respectively, $\alpha \in (0,1)$, the shape parameter of the loss function, **1** is an indicator and $(P_{t+1} - f_{t+1})$ is the forecast error. Herein the forecast error is defined as the actual value, that is the realization, minus the forecast.

The above loss function is considered as flexible given that it can take a linear form, for p=1, or a non-linear form, for p=2. What is of importance, however, in the present analysis is the shape parameter *'α'* of the loss function. In the case that α=0.5, the loss function is symmetric. This is the standard assumption in the literature and goes back to Mincer and Zarnowitz (1969). However, if $\alpha \neq 0.5$ this would imply the existence of asymmetric preferences in the loss function and thus behavior that deviates from symmetry. Moreover, for α<0.5 the asymmetric loss function implies that the loss associated with positive forecast errors, that is the case of under-prediction where the realization is higher than the forecast, is lower compared to the loss associated with the case where the forecast over-predicts the realization. Thus, an asymmetric loss function with α<0.5 reveals preferences that lean towards under-prediction, given that in this case the loss is lower than in the case of over-prediction. This, in turn, would imply that forecasts are optimistic. Equivalently, for α>0.5 the loss function shows asymmetric preferences as the loss for negative forecast errors that is the case of over-prediction is lower compared to the case of under-prediction. Thus, in this case the forecaster's loss function leans towards over-prediction.

Diagram 2 draws the non-linear loss function for three different shape parameters. That is *'α'* takes the value of 0.5 for a symmetric loss function and *'α'* takes the value 0.2 and 0.8 for an asymmetric loss. Moreover, in the case of α=0.2 the forecaster assigns higher loss to negative forecast errors, that is the case of over-prediction where the forecast exceeds actual values, compared to positive forecast errors. In this case, forecasts underlying preferences are characterized by optimism. The opposite is true for α=0.8.

<<Diagram 2 about here>>

From the above discussion it becomes clear the importance of accurately estimating the parameter of asymmetry, α. As in Elliott et al. (2005) we use a simple linear GMM Instrumental Variable estimator by observing the sequence of forecasts $\{f_{t+1}\}$, $\tau \le t < T+\tau$ to estimate 'α' as follows:

$$\hat{\alpha} = \frac{\left[\frac{1}{T}\sum_{t=\tau}^{T+\tau-1} v_t \left|P_{t+1} - f_{t+1}\right|^{p_0-1}\right]' \hat{S}^{-1} \left[\frac{1}{T}\sum_{t=\tau}^{T+\tau-1} v_t \mathbf{1}(P_{t+1} - f_{t+1} < 0)\left|P_{t+1} - f_{t+1}\right|^{p_0-1}\right]}{\left[\frac{1}{T}\sum_{t=\tau}^{T+\tau-1} v_t \left|P_{t+1} - f_{t+1}\right|^{p_0-1}\right]' \hat{S}^{-1} \left[\frac{1}{T}\sum_{t=\tau}^{T+\tau-1} v_t \left|P_{t+1} - f_{t+1}\right|^{p_0-1}\right]} \quad (4)$$

where $\hat{\alpha}_T$ is the estimate of α, v_t is a dx1 vector of instruments which is a subset of the information set used to generate f.[5]

Now from equation (4) one can not fail to notice that we need the estimate of $\hat{S}$. As in Elliott et al. (2005) $\hat{S}$ is given by:

[5]Following Elliott et al. (2005) we use three instruments in the empirical application. In particular, we use a constant and lagged forecast error as well as the lagged actual data.

$$\hat{S} = \frac{1}{T}\sum_{t=\tau}^{T+\tau-1} v_t v_t' (\mathbf{1}(P_{t+1} - f_{t+1} < 0) - \hat{\alpha}_\tau)^2 \left|P_{t+1} - f_{t+1}\right|^{2p_0-2} \tag{5}$$

Given that $\hat{S}$ depends on α_T in the estimation we use a series of iterations. Moreover, as in Elliott et al. (2005) in the first iteration it is assumed that that $\hat{S}$ =I. Thus, we estimate α_T until convergence is achieved. Elliott et al. (2005) show that the estimator of α_T is asymptotically normal.

Elliott et al. (2005) also employ a J-statistic which under the joint null hypothesis of rationality and flexible loss function is distributed as a $X^2(d-1)$ variable for d>1 and takes the form:

$$J = \frac{1}{T}\left[\begin{array}{l}\left(\sum_{t=\tau}^{T+\tau-1} v_t\left[\mathbf{1}(Pt+1-ft+1<0)\right]\left|P_{t+1}-f_{t+1}\right|^{p_0-1'}\right)\hat{S}^{-1} \\ \times\left(\sum_{t=\tau}^{T+\tau-1} v_t\left[\mathbf{1}(Pt+1-ft+1<0)-\hat{\alpha}_T\right]\left|P_{t+1}-f_{t+1}\right|^{p_0-1}\right)\end{array}\right] \sim X^2_{d-1} \tag{6}$$

Given the above analysis the parameter estimate of 'α', whether exhibiting a symmetric or an asymmetric loss function, reveals the preferences of the forecaster rather than model biases. This point is of importance as model bias could impair our analysis. Elliott et al. (2005) clearly demonstrate that the general loss function of equation (3) reflects actual preferences. Moreover, they show that the loss function analysis does not extract the underlying model of the forecaster as it is based on the following general linear model:

$$f_{t+1} = \Theta(a)' W_t \tag{7}$$

where Θ is a Kx1 vector of parameters, an implicit function of the loss asymmetry parameter (a), W_t is the full set of information.

Given the generalised loss function of equation (3), f_{t+1} is a rational forecast if and only if the first order forecast optimality condition holds:

$$E\left[W_t\left(\mathbf{1}_{(P_{t+1}-f_{t+1}<0)} - a\right)\left|P_{t+1} - f_{t+1}\right|^{p-1}\right] = 0 \tag{8}$$

Given the values of the shape parameter, 'a', and both for the linear and non-linear case, the forecaster uses the first order optimisation condition to forecast f_{t+1}. Elliott et al (2005) proves that this first order condition leads to a unique solution. Moreover, given f_{t+1} they use the first order condition to uniquely estimate the parameter of interest 'a'.

An interesting case that it may emerge is the one of model misspecification. Elliott et al (2005) demonstrate this case by assuming that the forecaster observes only V_t, which is a sub-vector of the full information set at period t, W_t. Then, the forecast is based on the following general linear model:

$$f_{t+1} = \tilde{\Theta}(a)' V_t \,. \tag{9}$$

The first order forecast optimality condition is:

$$E\left[V_t\left(\mathbf{1}_{(P_{t+1}-f_{t+1}<0)} - a\right)\left|P_{t+1} - f_{t+1}\right|^{p-1}\right] = 0 \quad (10)$$

Elliott et al. (2005) show that this first order condition is sufficient to estimate '*a*'.[6] This is strong result and shows that model misspecification may not be a concern in identifying the shape parameter, '*a*'. In this paper we opt for the GMM estimator of Elliott et al. (2005) to estimate the unique shape parameter, '*a*', of the generalised loss function in equation (4) that minimises the variation of the first order condition also under model misspecification. To this end, possible model misspecification may not be of concern here.

3. Data

We use an update sample of Sanders et al. (2009). Moreover, DOE energy price forecasts for crude oil, retail gasoline, diesel, coal, natural gas, and electricity are included in the current sample. As in Sanders et al. (2009) crude oil prices are measured in dollars and represent the refiner acquisition cost (RAC) of imported crude oil. The retail gasoline and diesel fuel prices are in dollars per gallon. The coal and natural gas prices represent dollars per million British thermal units (BTU). These data are collected from the STEO, published monthly. Each monthly report contains quarterly forecasts for one to five quarters ahead.

This paper uses forecasts for one-quarter ahead, two-quarters ahead, three-quarters ahead, four-quarters ahead as in Sanders et al. (2009). To account also for longer forecast horizons we also include in the analysis forecasts for five-quarters ahead. The

[6] Proposition 1 and Lemma 2 in Elliott et al. (2005) proves this point.

actual or realized prices are taken from subsequent releases of the STEO reports. The sample period is from the second quarter of 1997 (1997.2) to the second quarter of 2009 (2009.2), resulting in 49 observations of one to five quarters ahead forecasts and realized values.

4. Results

In what follows we report the parameter estimates of *'α'* and accompanied J-stats for testing rationality of the DOE's energy commodities prices. Moreover, we estimate equations (3) and (4) for both the linear (p=1) and non-linear case (p=2) using three instruments, in particular a constant and lagged forecast error as well as the lagged realization.[7]

The reporting results concern energy prices for: crude oil, retail gas, retail diesel, coal, natural gas and electricity up to five quarters (see Tables 1 to 5).[8] In detail, Table 1 reports results for energy price forecasts one quarter ahead. Our estimated loss function parameters are all statistically different from zero, but coal in the linear case and electricity in the non-linear case. It is striking that only for crude oil the parameter *'α'* is centred around symmetry, indicating neutral and thus rational preferences in terms of the typical forecasting testing of Mincer and Zarnowitz, 1969. Interestingly, for all the rest energy price forecasts the shape parameter, *'α',* of the underlying loss function

[7] All estimations were carried out employing standard programming code for estimating both equations (3) and (4) with standard GMM. Also, for a comprehensive analysis of applying GMM estimation techniques on rational expectations models see Hansen and Singleton (1982).

[8]In this paper we deal with multiple k periods ahead forecasts along the lines of Sanders et al. (2009) who argue that DOE's energy forecasts at multiple horizons are rational, but there is some variability. Thus, in examining the shape parameter *'α'* we ought to take into account that at different horizons there might exist differences in the information set that could affect preferences and thus the shape of the loss function.

that reflects preferences of DOE takes values less than 0.5, indicating optimistic preferences both in the linear and the non-linear case.

Moreover, for $\alpha<0.5$ the loss function is asymmetric as the loss associated with negative forecast errors, that is the case of over-prediction where actual values are lower than forecast, is higher compared to forecasts that under-predict actual values. Thus, an asymmetric loss function with $\alpha<0.5$ reveals preferences that lean towards under-prediction. This would imply that DOE's forecasts are not rational even for short time horizons of one quarter ahead. Instead, the loss function asymmetry reveals preferences towards optimism. In terms of the analysis of Ito (1990), present results appear to confirm what he calls *'wishful expectations'*, and thus a clear violation of rationality in energy forecasts of DOE.

Note that for the non-linear case estimates of the asymmetry parameter *'α'* shows optimism also for crude oil. These results reconfirms the ones for the linear loss function and demonstrate that DOE's energy price forecasts assign higher loss for over-prediction compared to under-prediction, implying irrationality.

Table 2 presents parameter estimates for *'α'* for two quarters ahead. Note that as the forecast horizon increases the parameter *'α'* gains in terms of statistical significance, presenting evidence also of higher degree of asymmetry in the underlying loss function. At two quarter forecasts ahead crude oil, also in the linear case, shows an asymmetric loss function that leans towards optimism.

<<Tables 1-2 about here>>

Given the evidence of asymmetry in the underlying loss function of DOE's forecasts, we perform *J-statistics* for three null hypotheses, $H_0 : a = \hat{a}$ (from the estimation), $\alpha=0.2$, and $\alpha=0.8$, the latter two representing optimistic and pessimistic preferences respectively. Under both linear and non-linear loss functions it is shown that for alphas which are statistically different from 0.5 the likelihood to reject the null of 0.5 or 0.8 is higher. Moreover, we find strong evidence against the hypothesis of pessimism that is the hypothesis of assigning higher loss in under-prediction of energy prices as the asymmetric *J-stat* of the null of $\alpha=0.8$ is rejected in all cases. This is not case for optimistic preferences that is $\alpha=0.2$.

Note that in one particular case, that of coal, it is striking that the parameter *'α'* is close to zero, indicating large deviations from rational behaviour. Moreover, coal forecasts are generated based on an asymmetric underlying loss function that assigns very large loss for over-prediction, which is the case when forecast is higher than actual data. This in turn implies the existence of extreme optimism. Previous research highlighted the special case of coal. Sanders et al. (2008) and Sanders et al. (2008) argue that coal forecasts do not incorporate all information available in an efficient way. They show that forecast errors in the case of coal are negatively related to the forecast and are inefficient. This implies that inefficient forecasts exhibit the tendency to repeat errors. In terms of our findings, DOE appears to present very optimistic coal forecasts and thus irrational forecasts based on *'wishful expectations'* (see Ito, 1990).

Note that assigning higher cost to under-prediction compared to over-prediction implies that the forecaster could serve the market to be better prepared to deal with energy price hikes. Therefore, a pessimistic loss function could be considered, certainly in periods of price hikes, to reflect prudent preferences whereas the underlying loss function is not symmetric. Alas, on the other hand, over-prediction could do little to easy price hikes and could prolong speculative spells. Thus, as there is no one size fits all case and preferences reflect behaviour that only ex-post can be evaluated, judgement on what is prudent forecast away from a symmetric loss function must be applied with extreme caution. Note, however, that persistent asymmetric preferences highlight deviation from rationality.

Tables 3-4 present parameter estimates for *'α'* for three and four quarters ahead. Once more, in long forecast horizon the parameter *'α'* gains in terms of statistical significance whilst presenting evidence of high degree of asymmetry in the underlying loss function. However, in the linear case it is striking that for crude oil and four quarters ahead a symmetric loss function is reported, insinuating the existence of rationality. Also note that for four quarters ahead the loss function for electricity reports that *'α'* equals to 0.54, though the J-stat shows that *'α'* is not significantly different from 0.5. These results insinuate that symmetric preferences are at play, implying that for these particular cases the forecast could be viewed as rational as it assigns equal loss to both the case of over and under-prediction.

<<Tables 3-4 about here>>

Thus, it appears that at four quarters ahead and for two cases, crude oil and electricity, a correction towards rationality in the shape parameter of the loss function is reported. However, these two exemptions can hardly reverse the domination of smaller than 0.5 values of '*alphas'* across forecast horizons. These results are complemented with the *J-statistic* for the joint null of rationality and flexible loss function. Once more, we find strong evidence against pessimism, which means rejection of the null α=0.8, in favour of optimism.

<<Tables 5 about here>>

Finally, Table 5 presents parameter estimates for *'α'* for five quarters ahead. For this long forecast horizon case the parameter *'α'* present even higher, than in shorter time horizons, degree of asymmetry towards optimism. Moreover, for five quarters crude oil presents a case of an asymmetric underlying loss function, insinuating the existence of optimism. In fact, at longer forecast horizons it appears that alphas decline providing further evidence of an asymmetric loss that assigns higher loss to over-prediction compared to under-prediction thus implying optimism. In addition, *J-statistics* under both linear and quadratic loss functions reject the null of alphas taking the values of 0.5 and 0.8. This presents strong evidence against the hypothesis of pessimism that is the hypothesis of assigning higher loss in under-prediction of future energy prices.

To reveal a comprehensive picture of the shape parameters Diagram 2 presents the histogram of the *'alphas'* for the DOE's energy price forecasts. It appears that the average shape parameter of the loss function, *'α'*, takes a value around 0.34 that is associated with an asymmetric loss that clearly leans towards optimism, and thus it is more costly to over-predict compared to under-predict. This apparent asymmetry casts in doubt the perception of a symmetric loss function in DOE's energy price forecasts assumed in the literature (see Sanders et al. 2009 and 2008, and Bentzen and Linderoth, 2005) across various forecast horizons.

These results provide a useful source of information as understanding DOE's underlying preferences is a crucial component of economic policy decision making (Artis, 1996 and Elliott and Timmermann, 2008). The role of the DOE is to provide high-quality energy price information to government, industry and the public that in turn would promote sound policymaking and overall market efficiency, as well as raise agents' understanding of the functioning of energy markets (Caruso, 2005). Specifically, energy price forecasts are often used to guide private investment projects (Taal et al., 2003), whilst they also play an important role in the budgeting and planning process of government. Therefore, it is imperative that both the government and market participants are aware of the shape parameters of the loss function of the forecaster so as to apply better judgment in their decision making whether it concerns budgeting, planning, investment or the efficient allocation of resources.

In terms of economic policy advice, a clear message emerges; forecasts must not persistently under-predict energy prices. DOE's underlying loss function is asymmetric, leans towards optimism and thus not rational. Persistency in assigning high losses to negative forecast errors, which is the case when the forecast is higher than actual data, would not seem appropriate to facilitate markets and smooth out price variations. Moreover, the underlying optimism in DOE's energy price forecasts, to the extent that it is anticipated by the markets, could do little to reduce uncertainty.

4. Conclusion

In this paper we examine the structure of loss preferences and the rationality of DOE's energy forecast prices in the context of asymmetric flexible loss functions. We follow

Elliott *et al* (2005) and present estimates for the asymmetry parameter of the DOE's loss function.

Moreover, this paper provides empirical estimates of the shape parameter of the underlying DOE's loss function for crude oil, retail gas, retail diesel, coal, natural gas, and electricity up to five quarters. Results show that in all cases, but crude oil and electricity for four quarters ahead, there is evidence of high degree of asymmetry in the loss function, and thus irrationality. DOE appears to assert preferences that lean towards optimism. Optimism in the DOE's preferences may hardly be seen as applying prudent behavior. Systematic under-prediction in energy prices across short and long time forecasting horizons could essentially enhance uncertainty and forfeit rationality.

The provided evidence of the existence of asymmetry in DOE's loss function is of quite importance for market participant and policy makers alike. The existence of an asymmetric loss function with preferences that lean towards under-prediction insinuate that forecasts are not rational even for short time horizons of one quarter ahead. Instead, the loss function asymmetry reveals preferences towards optimism. Ito (1990) argue that price forecasts are often based on *'wishful expectations'*. We provide evidence that *'wishful expectations'* are present in energy forecasts of DOE.

In terms of economic policy, DOE's energy price forecasts could benefit by the knowledge that its underlying loss function is indeed asymmetric. Thus, less optimism in the loss preference structure could enhance rationality, also in view of recent incidents of intense hikes in energy prices.

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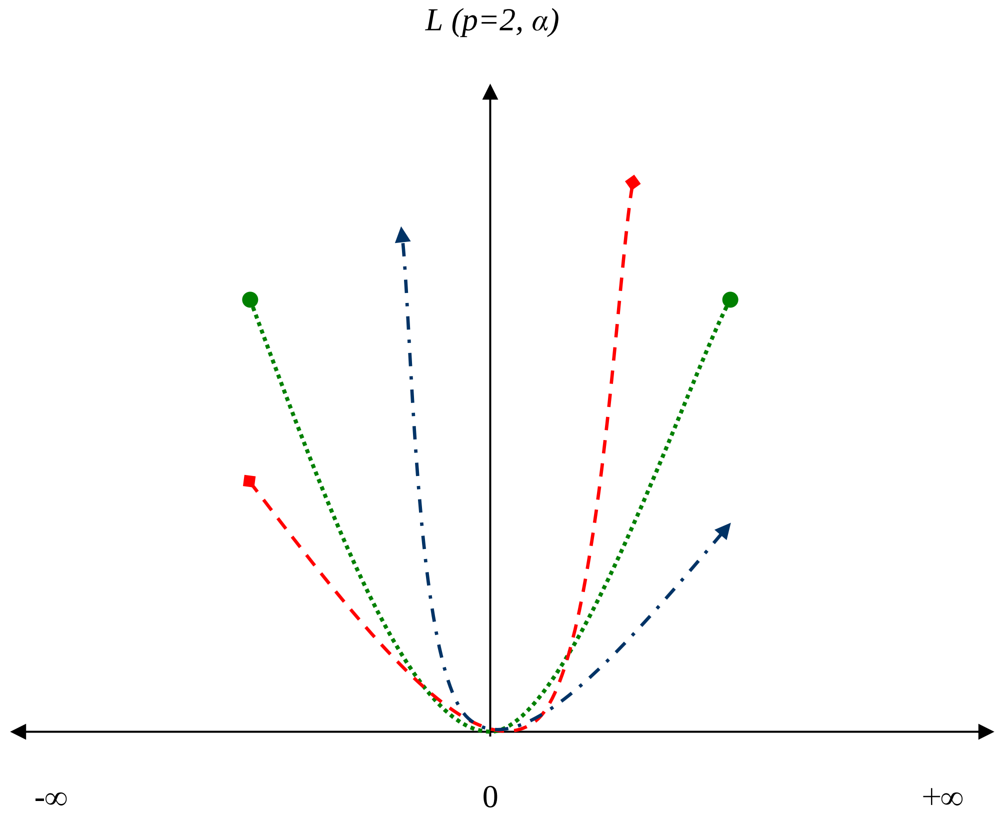
Diagram 1: Symmetry (‘*α’*=0.5, green line) and asymmetry (‘*α’*=0.2 blue line and ‘*α’*=0.8 red line) for the quadratic loss functions.



Note: horizontal axis shows ‘forecast error = actual data– forecast’, whilst vertical axis is the quadratic loss function, *L(p=2,α)*. For *‘α’*=0.5 (green line) there is symmetry, whilst for *‘α’*=0.2 (blue line) and *‘α’*=0.8 (red line) there is asymmetry.

TABLE 1: DOE's energy prices under asymmetric loss function, 1 quarter ahead forecast.

Linear case

	$\hat{a}$	SE	$J_{\hat{a}}$	$J_{\alpha=0.2}$	$J_{\alpha=0.5}$	$J_{\alpha=0.8}$
Crude Oil	0.500	0.072	1.256	13.075	1.256	12.852
Retail Gas	0.474	0.072	4.726	12.912	4.605	14.535
Retail Diesel	0.405	0.071	3.032	8.791	4.006	18.338
Coal	0.035	0.027	11.101	18.527	19.914	30.063
Natural Gas	0.394	0.071	0.487	6.756	2.619	19.568
Electricity	0.321	0.067	1.699	4.543	6.535	23.842

Non-Linear case

	$\hat{a}$	SE	$J_{\hat{a}}$	$J_{\alpha=0.2}$	$J_{\alpha=0.5}$	$J_{\alpha=0.8}$
Crude Oil	0.4753	0.1149	2.116	4.4336	2.0189	7.4408
Retail Gas	0.4215	0.0978	2.7148	5.5184	3.1646	8.238
Retail Diesel	0.1783	0.0742	8.3822	7.9092	5.9362	13.9501
Coal	0.0064	0.0069	9.2794	9.3679	16.1995	22.5651
Natural Gas	0.3499	0.0851	1.3439	3.8989	3.8757	11.2114
Electricity	0.0286	0.0182	9.0292	4.167	6.0192	8.2653

Estimates are based on D=3 instruments.

J-statistics are distributed as X^2(D-1) or $J_{\hat{a}}$ and X^2(D) for the remaining J.

TABLE 2: DOE's energy prices under asymmetric linear loss function, 2 quarters ahead forecast.

Linear case

	$\hat{a}$	SE	$J_{\hat{a}}$	$J_{\alpha=0.2}$	$J_{\alpha=0.5}$	$J_{\alpha=0.8}$
Crude Oil	0.4789	0.0721	0.2879	11.4945	0.3646	14.052
Retail Gas	0.4354	0.0716	0.7724	9.1594	1.4761	16.7861
Retail Diesel	0.3803	0.0701	3.1201	7.7755	4.7426	19.7107
Coal	0.0946	0.0423	6.7314	8.4341	19.8518	32.7962
Natural Gas	0.4365	0.0716	0.3963	9.0339	1.1551	16.7659
Electricity	0.3481	0.0688	4.2507	7.4035	6.5904	21.2201

Non-Linear case

	$\hat{a}$	SE	$J_{\hat{a}}$	$J_{\alpha=0.2}$	$J_{\alpha=0.5}$	$J_{\alpha=0.8}$
Crude Oil	0.4556	0.1051	1.112	4.684	1.1081	8.41
Retail Gas	0.4477	0.0946	0.7538	5.8089	1.0278	10.2935
Retail Diesel	0.2425	0.0681	4.468	5.6723	6.4605	14.4043
Coal	0.0124	0.0115	6.8736	7.9571	16.3756	21.8458
Natural Gas	0.3793	0.0837	2.6328	5.5663	3.9883	11.4359
Electricity	0.2559	0.0745	4.5873	5.6683	5.3477	12.0661

Estimates are based on D=3 instruments.

J-statistics are distributed as X^2(D-1) or $J_{\hat{a}}$ and X^2(D) for the remaining J.

TABLE 3: DOE's energy prices under asymmetric linear loss function, 3 quarters ahead forecast.
Linear case

	$\hat{a}$	SE	$J_{\hat{a}}$	$J_{\alpha=0.2}$	$J_{\alpha=0.5}$	$J_{\alpha=0.8}$
Crude Oil	0.4545	0.0719	2.0093	10.7581	2.2186	15.5596
Retail Gas	0.4782	0.0721	1.0745	11.6553	1.142	14.1586
Retail Diesel	0.329	0.0678	6.4587	8.2245	8.61	21.3844
Coal	0.1962	0.0573	2.6043	2.6058	15.8136	31.2166
Natural Gas	0.4151	0.0711	0.4401	7.8943	1.7488	18.1301
Electricity	0.4432	0.0717	6.3887	11.9004	6.5167	16.1745

Non-Linear case

	$\hat{a}$	SE	$J_{\hat{a}}$	$J_{\alpha=0.2}$	$J_{\alpha=0.5}$	$J_{\alpha=0.8}$
Crude Oil	0.4177	0.0955	0.4247	4.6997	0.9772	11.0278
Retail Gas	0.4049	0.0873	0.1078	5.1867	1.1302	11.2586
Retail Diesel	0.2556	0.0688	2.6208	3.8986	6.9392	15.2806
Coal	0.0554	0.0283	5.6834	6.3236	14.8734	21.3304
Natural Gas	0.3581	0.0826	1.4491	4.4083	3.1923	11.7322
Electricity	0.3621	0.0847	3.5859	6.4339	4.1161	10.971

Estimates are based on D=3 instruments.
J-statistics are distributed as X^2(D-1) or $J_{\hat{a}}$ and X^2(D) for the remaining J.

TABLE 4: DOE's energy prices under asymmetric linear loss function, 4 quarters ahead forecast.
Linear case

	$\hat{a}$	SE	$J_{\hat{a}}$	$J_{\alpha=0.2}$	$J_{\alpha=0.5}$	$J_{\alpha=0.8}$
Crude Oil	0.5	0.0722	3.6572	13.6746	3.6572	13.2525
Retail Gas	0.4581	0.0719	0.1553	10.1984	0.4914	15.3761
Retail Diesel	0.3695	0.0697	1.0122	5.8595	4.062	21.0084
Coal	0.1753	0.0549	3.9811	4.1071	16.8167	31.2741
Natural Gas	0.5	0.0722	1.5442	12.9219	1.5442	13.0409
Electricity	0.5419	0.0719	0.1059	15.3861	0.4491	10.1849

Non-Linear case

	$\hat{a}$	SE	$J_{\hat{a}}$	$J_{\alpha=0.2}$	$J_{\alpha=0.5}$	$J_{\alpha=0.8}$
Crude Oil	0.3937	0.0903	0.091	4.4958	1.3635	12.542
Retail Gas	0.3695	0.0887	0.4166	3.7004	1.9707	11.2264
Retail Diesel	0.246	0.0688	2.5863	3.4095	7.1983	15.9145
Coal	0.065	0.033	4.9434	5.8481	17.0698	23.3604
Natural Gas	0.3877	0.0879	1.1724	5.1597	2.0782	9.7042
Electricity	0.3443	0.0846	3.0204	6.3159	3.9865	9.2434

Estimates are based on D=3 instruments.
J-statistics are distributed as X^2(D-1) or $J_{\hat{a}}$ and X^2(D) for the remaining J.

TABLE 5: DOE's energy prices under asymmetric linear loss function, 5 quarters ahead forecast.

Linear case

	$\hat{a}$	SE	$J_{\hat{a}}$	$J_{\alpha=0.2}$	$J_{\alpha=0.5}$	$J_{\alpha=0.8}$
Crude Oil	0.4489	0.0718	4.4428	11.896	4.4635	15.8611
Retail Gas	0.4545	0.0719	1.9982	10.6244	2.3194	15.6438
Retail Diesel	0.3028	0.0663	11.3223	11.3786	12.8416	20.6443
Coal	0.1156	0.0461	4.4899	6.4313	21.2336	34.2446
Natural Gas	0.4088	0.071	2.0679	8.2179	3.6393	18.4582
Electricity	0.3942	0.0705	0.3813	6.8786	2.3491	19.4984

Non-Linear case

	$\hat{a}$	SE	$J_{\hat{a}}$	$J_{\alpha=0.2}$	$J_{\alpha=0.5}$	$J_{\alpha=0.8}$
Crude Oil	0.381	0.0912	0.3776	4.6444	1.9572	13.4355
Retail Gas	0.3881	0.0876	0.5589	4.5557	1.8795	13.967
Retail Diesel	0.2489	0.0713	3.2123	4.0785	7.1337	15.5053
Coal	0.0293	0.0196	6.5534	6.8908	19.2458	24.7073
Natural Gas	0.3791	0.0882	3.5324	5.4639	4.3756	11.5501
Electricity	0.1797	0.0709	3.4279	3.1406	4.3692	7.6793

Estimates are based on D=3 instruments.

J-statistics are distributed as X^2(D-1) or $J_{\hat{a}}$ and X^2(D) for the remaining J.

Diagram 2: Histogram of *'α'* shape parameters of the DOE's forecast loss function.