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Why did the historical energy forecasting succeed or fail? A case study on IEA's projection

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A B S T R A C T

Medium-to-long term energy prediction plays a widely-acknowledged role in guiding national energy strategy and policy but could also lead to serious economic and social chaos when poorly executed. A consequent issue may be the effectiveness of these predictions, and sources that errors can be traced back to. The International Energy Agency (IEA) has published its annual World Energy Outlook (WEO) concerning energy demand based on its long term world energy model (WEM) under specific assumptions towards uncertainties such as population, macroeconomy, energy price and technology. Unfortunately, some of its predictions succeeded while others failed. We in this paper attempt to decompose the leading source of these errors quantitatively. Results suggest that GDP acts as the leading source of demand forecasting errors while fuel price comes thereafter, which requires extra attention in forecasting. Gas, among all fuel types witness the most biased projections. Ignoring the catch-up effect of acquiring rapid economic growth in developing countries such as China will lead to huge mistake in predicting global energy demand. Finally, asymmetric cost of under- and over-estimation of GDP suggests a potentially less conservative stance in the future.

1. Introduction

Medium and long term energy demand forecast, which is fundamental to strategic decision making throughout governments and corporates, plays a widely-acknowledged role in guiding national policy and production arrangement. It is most useful and insightful for ‘clearly articulating underlying principles and fundamental driving forces’ according to Koomey et al. (2003) and Craig et al. (2002).

As a result, forecasts from influential analysts are all over the map every year, seeking to draw a clear blueprint for our future world. Two of the most well-known institutions in predicting global energy demand are IEA (International Energy Agency) and EIA (Energy Information Administration) of DOE (Department of Energy) of the US.

However, energy projections turn out to be rather difficult and prone to be poorly executed in the past few decades. False prediction of investment in China's electricity market since 2002 brings about long-enduring supply shortage in the last century, putting an awkward end to our Tenth Five-year Plan. Things can be even worse when it comes to long term energy forecast which is, more often than not, incorrect in both quantitative and qualitative terms according to Smil (2000) due to fluctuating social and economic conditions, unexpected events and technology breakthrough.

So now comes the question: why did these forecasts sometimes succeed or fail? Are they really helpful in heading for a more promising future? This paper is, upon initial steps in an attempt to answer these questions, seeking to review IEA's historical medium-to-long term projections and their errors and quantitatively investigate the key factors driving these errors, in a bid to shed light on future energy demand projections.

This is our line of thinking: all predictions are made on the basic assumptions of several major drivers containing economic growth, population growth, energy price, technology advancement and particular government policy. So accuracy of these assumptions can be well accounted for the accuracy and preciseness of corresponding prediction results which is our major concern.

Our analysis differs from previous work in several ways. First off, few studies has been done to review IEA's annual forecasts due to its poor data comparability. IEA's annual forecast appears to be less comparable and inconsistent compared with that of EIA in both content and data range (reference can be made in Appendix A).Secondly, previous analyses turn out to be either simple descriptive statistics or merely qualitative assessment. Instead we apply econometric methods in decomposing forecasting errors for different fuels in different countries and regions. Thirdly, further in-depth analysis is done to deal with asymmetric costs in projections which are ignored by most of previous studies. Asymmetric cost in this paper is defined ad hoc as different levels

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of forecasting error induced by upward or downward biases of major assumptions. More specifically, underestimation (or overestimation) of certain “driver” makes predicted energy demand much more/less severely deviated from their true value, hence aggravating the original situation. This paper is organized as follows: Section 2 introduces some relevant backgrounds of IEA's energy forecast as well as previous evaluations. Section 3 covers methodology of decomposition and data used in this paper. In Section 4, econometric tools are used to figure out the deep-rooted source of forecast errors. Sections 5 briefly introduces the asymmetric response of energy projection bias to under- and over-estimation of major sources. Section 6 concludes with a discussion and directions for future work. Appendix A contains some data processing supplements.

2. Literature review

2.1. IEA's energy forecast

The International Energy Agency (IEA) has been initiating its energy forecasting published as *World Energy Outlook* (*WEO*) since 1993. IEA is reluctant to be labeled as a forecaster and emphasizes that they are providing some outlooks for the future. But actually they are making predictions under different scenarios. These medium-to-long term projections are generated and updated every year based on its world energy model (WEM) covering major sovereign states (latest 2014 version covers 25 regions with 12 countries being individually modeled). The comprehensive forecast model consists of three major molecules including final energy consumption (divided by residential, services, agriculture, industry, transport and non-energy use); energy transformation including power generation and heat, refinery and other transformation; and energy supply. Outputs from the model include energy flows by fuel, investment needs and costs, CO_2 emissions and end-user pricing according to WEM 2014 edition Documentation IEA (2014). Considering possible huge policy variation concerning future energy demand, three cases are considered containing *Current Policies Scenario* (also named as business as usual capacity constraint case/reference case in earlier years), *New Policies Scenario* and *450 Scenario* in agreement with the goal of controlling greenhouse gas. We will in this paper concentrate only on *Current Policies Scenario* described as “an illustration of how energy demand, supply and prices are likely to develop if recent trends and current policies continue” according to IEA (1998). We are concerned with the accuracy of forecast in that national strategic decisions based on wrongly-predicted prospects will bring extremely heavy cost for the whole society. This is exactly why retrospective analysis is valuable in making models and forecasts ‘better’, especially for model users.

2.2. Previous evaluations of energy forecasts

Some more existing work has been done to compare and analyze the varying outcomes of various models concerning future energy demand and carbon dioxide emission such as the Energy Modeling Forum (EMF) at Stanford University, which concentrates on the use of several large macroeconomic models to uncover the differences or similarities upon them (Auffhammer, 2007).

Suganthi and Samuel (2012) review and summarize various models in predicting energy demand. EIA itself publishes Annual Energy Outlook Forecast Evaluation for the purpose of reviewing its historical forecasts. O'Neill and Desai (2005) analyze EIA's energy forecasts between 1982 and 2000 and prove that 10 to 13 years' forecasts have an average error of about 4% while shorter time horizons are half as much. Fischer et al. (2009) found an average of 2% per year underestimation of total energy demand based on EIA's Annual Energy Outlook. Linderoth (2002) compares projections in 1985, 1990 and 1995 to actual data for IEA countries and find out a “not so nice” subsector error even when total error is small due to the sum of positive and negative forecast errors. Holte (2001); Sanders et al. (2008); Sakva (2005) and Winebrake and Sakva (2006) employ error decomposition analysis to examine its short-term forecasts' ability towards different industries in the US. Results prove that outstanding projection biases in industry and transportation have not been alleviated during the whole projection period. Bezdek and Wendling (2002) assess the long-term energy forecast conducted over the past two decades and prove that lessons can be learned in helping to avoid repeated mistakes and doing a better work in the future. Lady (2010), compares the projections using actual values with that using assumed values for model assumptions and finds out −2.225% of difference unaccounted for by models. Other methods are still used here. Chang et al. (2012) compare their predictions based on historical trends with EIA using both classical and kinked experience curve models. Kemp-Benedict (2008) uses a self-consistent estimator to measure the gaps between observed and modeled values. Auffhammer (2007) tests rationality of EIA's forecasts under symmetry and asymmetric loss and proving the existence of asymmetric loss.

Many scholars focus their prediction review on particular kinds of fuels. Huntington (2011) backcasts 10-year projections of US petroleum consumption that began in 2000 and allows asymmetric reactions of oil demand to the ups and downs of oil price. Baumeister et al. (2014); Baghestani (2015) and Bastianin et al. (2014) compare several methods in forecasting short-term real-time oil price and gasoline prices. Clemente and Considine (2007) investigate IEA's oil price forecasts released from 1998 and 2006 by distinguishing three different kinds of errors, namely random chance, linear bias and model bias. Donkor et al. (2012) review various methods and models in forecasting urban water demand. Bludszuweit et al. (2008) recorrect the wind power forecast error using a more appropriate probability density function.

There are also some attempts in getting to the deep-rooted source of prediction biases. Utgikar and Scott (2006) use the Delphi technique to decompose four drivers of prediction errors containing improper technique, technology barrier, social and political considerations as well as economic considerations. O'Neill and Desai (2005) find out two critical points leading to inaccurate projections including abrupt events and unexpected changes in model variables: misprediction of GDP growth rate and unforeseen changes in energy price and energy policy. Fye et al. (2013) evaluate nine attributes that influence forecasting accuracy. Smil (2000) summarizes 5 major contributors containing major energy conversions, primary energy requirements, sectoral needs, exhaustion of energy resources, and energy substitutions. Laitner et al. (2003) articulate that false assumptions towards economic agents and technology progress can be well accountable for most of the biases. Simoes et al. (2015) seeks to quantify the impact of certain assumptions on the results of different scenarios.

3. Forecasting error estimator

In order to quantitatively measure the accuracy of IEA's historical projections, We calculate “the difference between the projected energy consumption and actual energy consumption” (O'Neill and Desai, 2005), intuitively it is $\hat{Y}_{t_i}^j - Y_{t_i}^j$. However regional and fuel aggregation in WEOs varied with time passing by, making different years of forecasting error (calculated with $\hat{Y}_{t_i}^j - Y_{t_i}^j$) incomparable due to inconsistent scope of statistics. For example Czech Republic, Hungary, Poland, Mexico and Korea aren't OECD countries in earlier versions of WEO but turn out to acquire their membership in later years. So we transform the physical quantity of all data used in this paper into the form of average growth rate. The metric defined to determine forecasting error is as follows:

$$PE_{t_i}^j = \left(\hat{Y}_{t_i}^j \Big/ Y_{t_0}^j\right)^{[1/(t_i - t_0)]} - \left(Y_{t_i}^j \Big/ Y_{t_0}^j\right)^{[1/(t_i - t_0)]} \tag{3.1}$$

where t_0 and t_i respectively stand for the latest year that actual data is available (e.g. the latest year that actual data is available for projection year 1993 is 1990) and projection year; Y is the actual growth rate of