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Hua Liao
Jia-Wei Cai
Dong-Wei Yang
Yi-Ming Wei

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Center for Energy and Environmental Policy Research
Beijing Institute of Technology
No.5 Zhongguancun South Street, Haidian District
Beijing 100081
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Yi-Ming Wei
Director of Center for Energy and Environmental Policy Research, Beijing Institute of Technology

<u>For more information, please contact the office:</u>

Address:
Director of Center for Energy and Environmental Policy Research
Beijing Institute of Technology
No.5 Zhongguancun South Street
Haidian District, Beijing 100081, P.R. China

Access:
Tel: +86-10-6891-8551
Fax: +86-10-6891-8651
Email: ceeper@vip.163.com
Website: http://ceep.bit.edu.cn/english/index.htm

Why Did the Historical Energy Forecasting Succeed or Fail?

A Case Study on IEA's Projection

Hua Liao[1, 2, 3], Jia-Wei Cai[1, 2, 3], Dong-Wei Yang[1, 2, 3],Yi-Ming Wei[1, 2, 3, *]

1. Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing 100081, China;

2. School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China;

3. Collaborative Innovation Center of Electric Vehicles in Beijing, Beijing 100081, China.

Correspondence Information:

Yi-Ming Wei, PhD., Professor
Director, Center for Energy and Environmental Policy Research,Beijing Institute of Technology
Dean, School of Management and Economics,Beijing Institute of Technology

5 South Zhongguancun Street, Haidian District
Beijing 100081 China
Tel./ Fax: +86-10-68918651
Email: wei@bit.edu.cn
ymwei@deas.harvard.edu
Website: www.ceep.net.cn

ABSTRACT: 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, macro economy, energy price and technology etc. Unfortunately, some of its predictions succeeded while others failed. We in this paper attempts 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.

Key words: energy demand; Medium-to-long term prediction; forecast error; social development

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 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 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 are, 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 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 work 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 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 deep-rooted source of forecast errors. Sections 5 briefly introduce 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 is some data processing supplements.

2. Literature review

2.1 IEA's energy forecast

The International Energy Agency (IEA) initiated its energy forecasting published as *World Energy Outlook (WEO)* since 1993. IEA is reluctant to be labelled as a forecaster and emphasize that they are providing some outlooks for the future. But actually they are making predictions under different scenarios. This 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 modelled). 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, CO2 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 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 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 percent 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 errors 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 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 proves that lessons can be leaned 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) test 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 et al. Clemente and Considine (2007) investigates 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 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, *et al.* (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 form of average growth rate. The metric defined to determine forecasting error is as follows:

$$PE_{t_i}^j = \left(\hat{Y}_{t_i}^j \big/ Y_{t_0}^j \right)^{\left[1/(t_i - t_0)\right]} - \left(Y_{t_i}^j \big/ Y_{t_0}^j \right)^{\left[1/(t_i - t_0)\right]} \qquad \text{Eq. (3.1)}$$

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 energy consumption, economic and population size while ŷ is the calculated growth rate of IEA's corresponding predictions and assumptions. *PE* namely percentage error can be either positive or negative indicating whether over- or under-estimation has taken place accordingly. Typically the extent of value of percentage error deviated from 0 measures the magnitude of relative error. Projections for 2000 and 2010 in WEOs are used in this paper to measure IEA's forecasting ability. GDP can be a proper proxy for macroeconomic prospects while IEA's crude oil import price is chosen to represent the overall level of fuel price considering its fundamental role in formulating international energy price system. Detailed data processing will be omitted here for limited space but can be obtained in appendix A.

Following above analysis, we graph forecasting error of different fuel type for year 2010 in 2004. As shown in fig.1 and 2, some projections turned out to closely match the actual situation evidenced by OECD and world as a whole whose forecasting error is small in absolute value, while others seems to achieve bad performance. China stands out with the highest level of prediction error in total primary energy supply (TPES) which is up to 5.68%. Things get more complicated as prediction quality varies among different types of fuels in different regions. Generally speaking, oil demand forecasting errors are relatively small and stable compared with coal and gas. Percentage error of gas demand prediction even rises up to nearly 10 percent in China thus is far from successful.

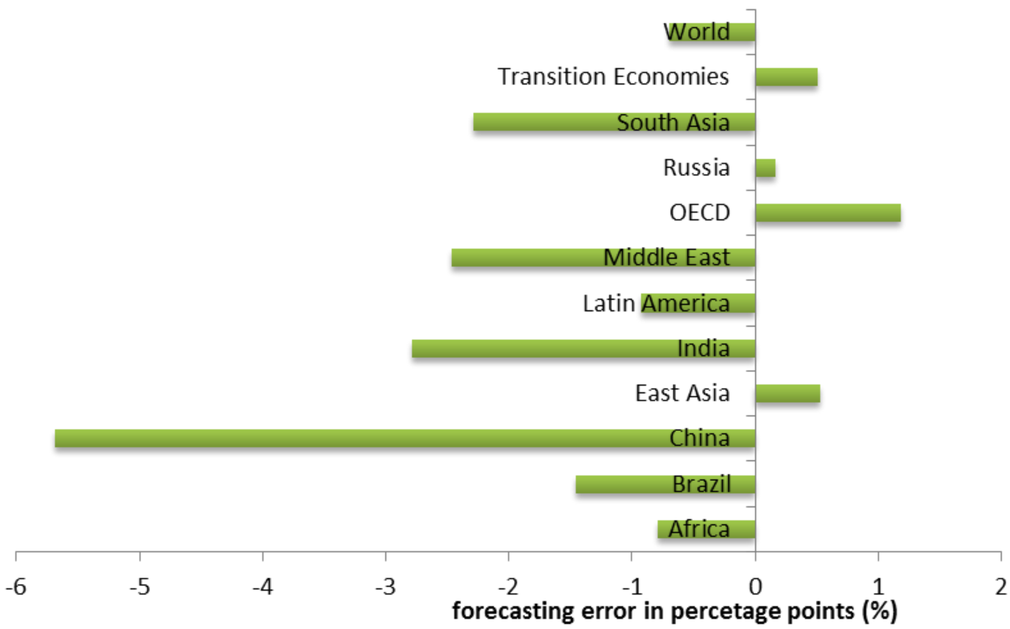

Fig.1: forecasting error of total primary energy in different countries for year 2010 in 2004

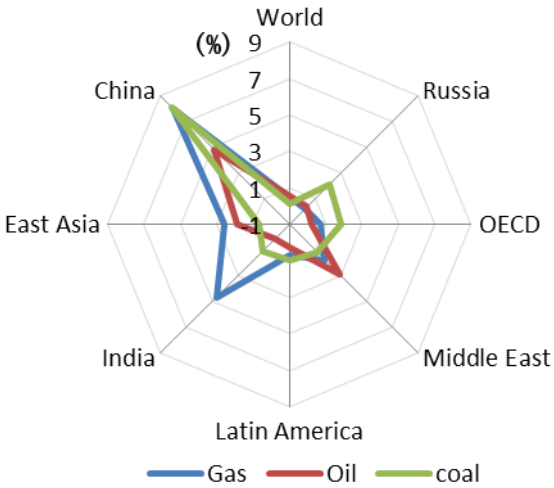

Fig.2: forecasting error of different fuel type for year 2010 in 2004 (in percentage)

4. Analysis of source of IEA's forecasting error

4.1 Empirical model

All years' forecasts in WEOs are based on IEA's complicated and mysterious WEM (The World Energy Model). Unfortunately, the whole model is a mysterious "black box" and we can have no idea what it exactly looks like. But one thing we can be sure of is that model is formulated based on assumptions of several exogenous and independent variables of paramount importance in deciding energy consumption. Three major assumptions considered here include macroeconomic prospects, population growth and international energy price. Therefore failure in estimation shall be resulted from wrong projections on these factors. Econometric techniques will be used to decompose these "sources" in contributing to IEA's medium-to-long term energy projections. Regression equation is as followed:

$$De_{i,j,t} = \alpha_0 + \alpha_1 gdp_{i,t} + \alpha_2 pop_{i,t} + \alpha_3 price_t + \alpha_4 \ln(length_t) + \sum_i \beta_i fuel_i + \sum_j \gamma_j region_j + \varepsilon_{i,j,t} \quad \text{Eq. (4.1)}$$

Where *De* is the demand forecasting error of kind *i* of fuel for region *j* in year *t*. *GDP, POP* and *Price* respectively represent for percentage forecasting error of GDP, population and oil price.. *Length* represents projection horizons which equals projected year (namely 2010) minus projection year. For example *Length* for 1993 equals 2010 minus 1993, which is 17. We take its logarithmic form to reduce possible heteroscedasticity in regression process. *Fuel* stands for dummy vector set for different fuels. Crude oil is taken as baseline group while other four types of fuels including TPES, gas, coal, and hydro power are added each as a dummy variable. *Fuel*=1 if it is for fuel i and Fuel=0 if it is not. We dropped "other primary energy" due to its small sample sizes as well as multicollinearity and "nuclear" for repeated 0-value for many observations (thinking of nuclear power hasn't been put into wide use in many countries). *Region* is the dummy vector set for different countries. Notice that stable economic growth and IEA's relatively mature forecast technology towards OECD countries can well explain the outstanding performance in predicting their energy demand. So we choose OECD as the benchmark for country groups and add all the other regions as dummy variables in this model. As a result, *region* is defined to be 1 if it is percentage error for region j and 0 otherwise. ε_{ijt} is the residual term which absorbs all the other unobservable factors excluded from the regression.

4.2 Forecasting error driven by three major assumptions

We first perform the fixed effect regression model with only three basic assumptions biases to test their impact on the accuracy of prediction. We also add projection horizon to control possible trends of percentage error with time getting near to 2010. (Data summary can be obtained from appendix B.2.) Results with heteroscedasticity-robust White standard error are presented in table 1 below, Sets I through V are processes of stepwise regression to insure robustness. GDP projections alone account for 13.1% of projection bias in energy demand forecast. R-square witnesses no big improvement after containing population and oil price variables but rises up to 19.9% when projection horizon is controlled. The corresponding coefficient for GDP is statistically significant all the time with a coefficient of 0.638 which illustrates the strong positive relationship between forecast error of GDP growth rate and regional demand. One percentage point overestimation of assumed economic growth will lead to 0.638 percent of upward bias of energy demand after controlling other variables.

Coefficient of oil price is -0.341 which means one percentage point overestimation of oil price will lead to 0.341 percentage points of underestimation in energy demand forecast. The different positive and negative relationship can be well explained by basic economic principles that higher economic growth as well as lower fuel price will induce more energy demand. Population variable fail to pass t-test even under 10% confidence level which suggested that population forecast error is not a major factor leading to bias of demand forecast. Unfortunately, coefficient of length is positive and statistically significant no matter which form, either original (in the fourth regression) or logarithmic (in the fifth regression) is taken. It gives no proof that percentage error shows any trend of convergence with time getting near to the projected year. All these conclusions are in accordance with our expectations in the aforementioned analysis. Strongly positive *length* variable shed light on its trend of convergence because forecasting error diminish with projection horizon getting shorter.

Table 1

Stepwise regression of three major assumptions.

	I	II	III	IV	V
gdp	0.662***	0.640***	0.504**	0.638***	0.731***
	(3.24)	(0.219)	(0.201)	(2.99)	(4.07)
pop		0.649**	0.329	0.129	0.226
		(0.298)	(0.412)	(0.31)	(0.60)
price			0.050	-0.341***	-36.19**
			(0.039)	(-3.01)	(-3.24)
ln(*length*)				3.220***	3.217***
				(3.51)	(3.61)
R-square (%)	13.1	14.0	14.7	19.9	19.8
obs	360	315	315	315	315
Fe/Re	Fe	Fe	Fe	Fe	Re

Note: (1) Fe stands for fixed effect regression and Re refers to random effect model. (2) Figures in parentheses are standard errors. (3) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (4) *gdp, pop, price* respectively represent for their corresponding prediction bias upon growth rate of GDP, population and oil price; *length* equals projection horizon.

To check the robustness of such relationships, we also apply several more regressions using the PPE form (namely proportional percentage error) which takes the form of PE divided by actual average growth rate. Relationship between GDP and demand projection bias is robust but R-square is much lower in such condition indicating its poor quality in goodness of fit as PPE form can dilute some part of errors But it still can be well-functioned in examining the robustness of each assumptions in generating corresponding demand forecast errors. Results will not be listed here due to space limitation.

4.3 Fuel & region specific errors in forecasting

Review that we have seen the varied magnitude of forecasting error for different fuels above. Econometric approach is employed in this part to testify such difference. Dummy variables are added to define each type of fuels. We also control binary variables concerning different regions. Crude oil and OECD are picked out as the benchmark for the two groups of binary variables. Regression results are listed as follows (table 2), Sets VI and VII are processes of stepwise regressions to insure robustness. Coefficients for gas, hydro, coal and TPES are -1.412, -0.125, -1.090 and -0.592 respectively while gas, coal and TPES partially or totally significant under the significance level of 0.95. These four coefficients reflect the statistically significant bias of each type of fuel compared with oil demand forecasts. We can infer that forecasts of demand for coal and gas experience maximum forecast errors from their relatively higher absolute value of coefficients (which is greater than 1 percent). Further t-test is applied here to compare the coefficients value of coal and gas. Null hypothesis is no dramatic differences between gas and coal. We cannot reject the null hypothesis that coefficients of gas and coal variables differ significantly with each other (*P* value is 0.5514).

Table 2

Regression for different fuel type and country group.

	VI		VII	
gdp	0.737***	(4.25)	0.638***	(2.92)
pop	0.233	(0.63)	0.129	(0.31)
price	-0.363***	(-3.27)	-0.341***	(-2.94)
ln(*length*)	3.213***		3.220***	(3.42)
Dummy variables by fuel type (crude oil as benchmark)				
gas	-1.412***	(-3.93)	-1.410***	(-5.24)
hydro	-0.125	(-0.19)	-0.132	(-0.24)
coal	-1.090**	(-2.21)	-1.084**	(-2.55)
tpes	-0.592**	(-2.16)	-0.586**	(-2.10)
Dummy variables by country group (OECD as benchmark)				
China			-2.120**	(-2.43)
East Asia (excluding China)			-1.303***	(-2.78)
Russia			1.179*	(1.92)
Other regions are statistically insignificant therefore omitted due to limited space				
R square (%)	19.8		19.9	
obs	315		315	

Note: (1) Column VI is OLS regression while column VII is GLS regression result. (2) Figures in parentheses are standard errors. (3) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (4) *gdp, pop, price* respectively represent for their corresponding prediction bias upon growth rate of GDP, population and oil price; *length* equals projection horizon.

We will then examine the source of forecasting error by different country group. Columns (VI) and (VII) list related regression results. China, with the largest value of coefficient -2.120 is also statistically significant, demonstrating that accuracy of projections concerning China is greatly deviated from that of OECD. That is to say some more parts of projection biases are unexplained for China even if the "quadra drivers" variables are controlled. East Asia comes right after with a highly significant coefficient of -1.303 while coefficient for Russia is 1.179 with a relatively weaker significance. It suggests the serious underestimation of energy use in East Asia and high expectation on Russia's demand forecast.

To grasp the institution of the aforementioned relationship, we graph the percentage error of total primary energy demand, GDP, population and oil price forecast for two typical country groups: OECD and China. As shown in fig.3 and 4, GDP for both countries share same trend and magnitude of projection with energy demand while population forecasting error is rather small and weakly related with energy demand bias. Serious misprediction in GDP and oil price acts as major source of IEA's energy projection biases.

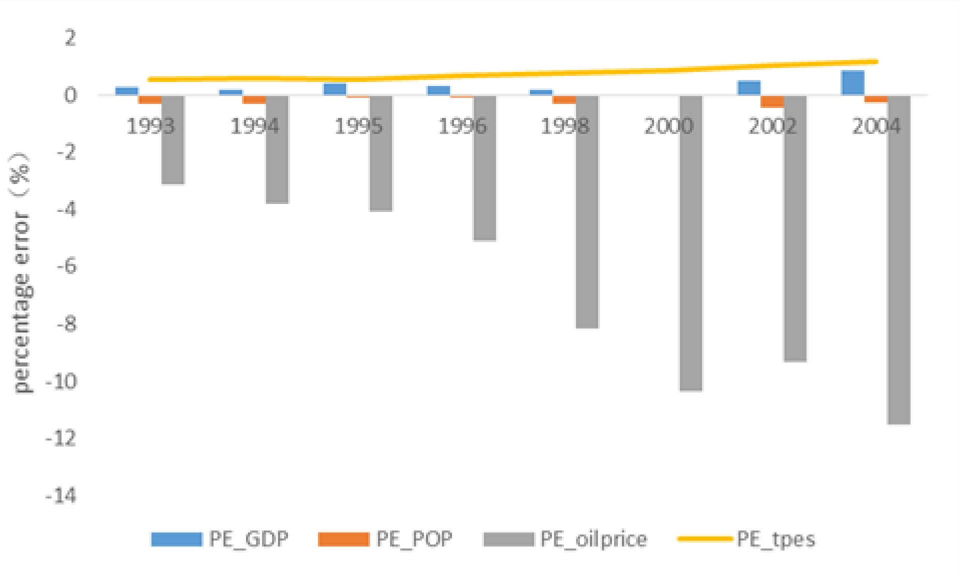

Fig.3: forecasting error of OECD's energy demand, GDP, population and oil price

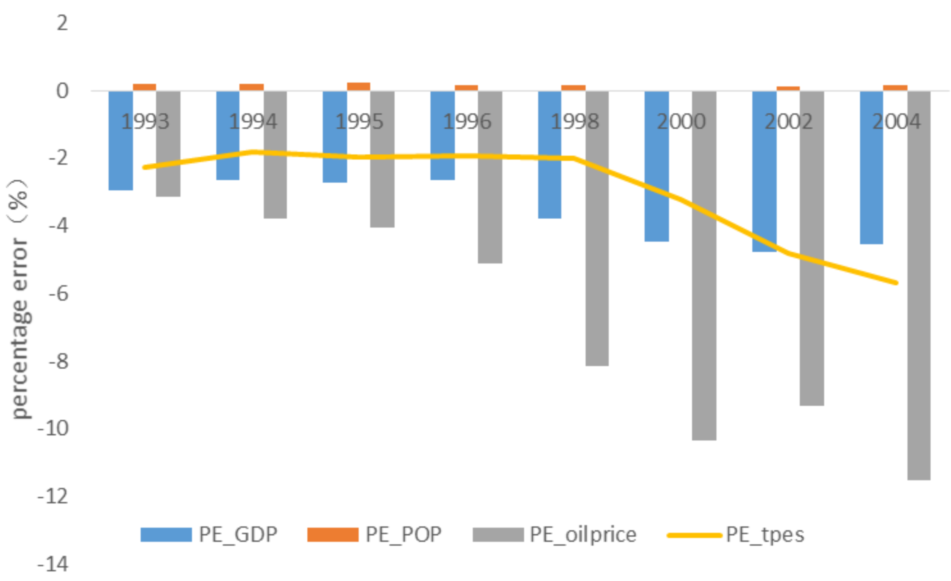

Fig.4: forecasting error of China's energy demand, GDP, population and oil price

5. Asymmetric response of demand projection bias to error sources

Another interesting topic concering IEA's prediction outcomes is asymmetric response of demand projection bias to above error sources. The concept is firstly put forward by Granger and Newbold (1974) indicating that "symmetric loss function is not reasonable in all settings". Asymmetric cost in this paper is defined ad hoc as different levels of forecasting errors induced by upward and downward biases of major assumptions. More specifically, underestimation (or overestimation) of certain "driver" makes predicted energy demand much more or less severely deviated from actual ones, thus inducing more serious and costly consequences. Consider the example of production arrangement of one particular enterprice,company owners will tend to produce more goods than order requirements because centain invetory cost is no big deal compared to possible breach of commercial cause and ruins of reputation when they fail to tender their goods in time. It can surely be a different story when invetory cost gets extremely high.

Therefore over- and under-estimation of sources can result in quite different magnitudes of demand projection biases. When oil price is overestimated, for example, oil demand react firstly to the basic law of supply and demand. Then high price of crude oil will trigger birth of technology and expansion of other fuels such as biomas and other renewable fuels which will further cutting down needs for crude oil. Such technology encouragement effect is not obvious when oil price is underestimated.The most famous oil embargo conducted by OPEC countries can be a good proof when high oil price triggered technology breakthrough. however, so far wecan only theorectically prove the exisistence of asymmetric cost in oil priceinstead of statistically tesitifying it because IEA keeps underestimating oil price during the whole projection period.

We then further this anaysis to examine different reactions of demand forecasting error to GDP assumptions. It is rather intuitive to conclude that pessimistic expectation for GDP is more costly than optimistic ones considering bad consequences of production cut-off and economic recession. To testify this hypothesis, we divided total sample size into two groups: overestimation with percentage error of GDP greater than 0 and underestimation otherwise. We compare the two groups of coeffcients related to these two groups to testify the asymmtric response because each coeffcient measures the reaction of demand forecasting biases to errors of forecasting assumed drivers. Before running the regression, we summerize all dummy variables as shown in appendix B.2. Percentage errors for different countries and regions show great consistency in direction of bias during this period. Developing countries like Brazil China India and Russia are always underestimated while OECD is always overestimated . For example, all OECD samples are included in group PE<0. Then in the group PE<0 there is too few sample to derive the coeffcient of

OECD dummy variable. So it is meaningless to include country group variables again in this regression. Columns in table 3 are group regression results. Interesting thing is the underprediction group is strongly significant with its aboslute coefficient value greatly larger than that of overprediction group. Aboslute value of coefficients for underestimated group is around 1%, grealtly larger than that of another group even if it is far from being statistically significant. we can now make the conclusion that postive and negative biases of GDP assumptions contribute differently to percentage error of demand forecast. More specifically, one percent of downward bias will cause nearly twice as many demand forecasting bias resulted by one percent of upward bias. Accordingly, forecasters can be more positive when considering GDP growth rate as major input to derive energy demand. On fuel side, gas is the one and only type of fuel significant for either group demostrating its similarly symmetric underestimation effect under each circumstance-one percent of over- and under-estimation cause statistically indifferent extent of bias in energy demand.Unfortunatelly, we truly cannot go any further because this comparisom illustrates only closer relationship between underestimated GDP and biased demand forecast but shall, in some ways prove the exsistence of asymmetric cost.

Table 3

Asymmetric cost analysis for GDP.

	GDP forecasting error			
	PE>0		PE<0	
gdp	-0.523*	(-1.71)	1.036***	(4.66)
pop	1.304***	(2.71)	0.0320	(0.07)
price	-0.121	(-0.65)	-0.506***	(-3.51)
ln(*length*)	-0.0673	(-0.05)	4.662***	(4.17)
gas	-1.573***	(-3.64)	-1.297***	(-3.41)
hydro	-1.391***	(-2.71)	0.224	(0.31)
coal	-0.669	(-1.29)	-1.270**	(-2.36)
tpes	-0.595**	(-2.25)	-0.622*	(-1.93)
R square (%)	9.9		30.8	
obs	105		210	

Note: (1) All regressions use GLS with White robust standard error. (2) Figures in parentheses are standard errors. (3) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (4) *gdp, pop, price* respectively represent for their corresponding prediction bias upon growth rate of GDP, population and oil price; length equals projection horizon.

6. Conclusions and policy implications

Medium-to-long term energy prediction is of great importance but failed in many times. A consequent issue may be the sources that errors can be traced back to. This paper systemically investigates IEA's annual projections towards energy consumption based on its historical forecasts up to 2010.

We first calculate the percentage error for energy forecast of different fuel type by region and find out that IEA appears to be well-functioned in predicting energy demand for the world as a whole and OECD countries ——within two percent in all times, due to stable economic and social development as well as high achievability data; While China, acting as the outlier all the time, remains to be underestimated up to eight percent Failure to foresee the variation in energy consumption projections since 2000 can be attributed to the rapid economic development and structural changes of developing countries such developing countries as India, Brazil and Russia since the new millennium.

Secondly, econometric tools are applied to explain why energy demand for some fuel is more accurate than that for others; and why forecasts concerning certain region face extraordinarily greater bias than others (e.g. China). We focus on three major assumptions which projections are generally based on (i.e. GDP, population and fuel price) and add in projection horizon variable as control variable. Results show that GDP is one leading source with good robustness in explaining to demand forecast errors. Fuel price, when being overestimated by one percent, will lead to 0.341 percent of underestimation in energy demand forecast. Population, however, shows no clear relationship with demand forecasting errors. It can be explained by either high-quality population projection or relatively blurred error transmission mechanism. In consistent with this analysis, researchers should focus its effort in improving accuracy of projections concerning basic assumptions, especially GDP. But we also notice that GDP and projection horizon only account for around 20% of demand forecasting bias while the rest 80% shall require further analysis in inner structure and parameters of the model.

Thirdly, gas appears to be the most severely biased among all fuel types (crude oil as benchmark). It suggests that extra attention should be drawn to evaluate demand for cleaner fuels such as natural gas. Regressions with regional dummy variables consolidate earlier results of China, being outstanding outlier is underestimated more seriously than any other country groups. Opposite trend of overestimation can be seen in Russia demonstrating IEA's relatively higher expectation after the collapse of Soviet Union. Unexpected structural changes usually occur in these none- mature economies which needs extra effort in future work of forecast.

Finally, we explore the asymmetric response of demand projection bias to GDP misprediction and find the differentiated reactions of biases towards GDP forecasts. The relatively more serious consequence of underestimation can be meaningful enlightenment for IEA being less conservative in their future work.

In conclusion, researchers should improve their prediction ability on basic assumptions, especially in terms of GDP and fuel price. Cleaner fuels such as natural gas have witnessed rapid development，to which extra attention should be drawn. Also, developing countries including China enjoy the advantage of backwardness and are expected to acquire rapid economic growth rate and narrow the gap between them and developed ones. Ignoring trend like this will lead to huge mistake in predicting global energy demand. Therefore IEA may need to pay more attention to the actual needs for energy consumption by developing countries with great potential in the future.

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Appendix A: Data processing

So far until this paper is finished, only predictions for year 2000 and 2010 can be compared to actual data values (the latest projection year since 2006 is 2015). However compared with EIA, IEA's annual forecast appears to be less comparable in the following two aspects.

(1) Inconsistent content: We seek to investigate the trend of IEA's annual forecasting errors but WEO1999, WEO2001, WEO2003 each focus on special issue containing energy subsidiary, supply and investment while WEO2005 is a detailed middle-east project. So demand forecasts are unavailable in these years which leads to data inconsistency.

(2) Inconsistent data range: annual forecasting is difficult to compare among different years due to changing classification of country groups and fuel type.

As a result projections for 2000 in WEO1993-1996 and projections for 2010 in WEO1993-1996, WEO1998, WEO2000, WEO2002 and WEO2004 are used in this paper to measure IEA's forecasting ability. For simplify, we take few consideration to different policies adopted by each government and ignore forecasting error of technology breakthrough for data availability reasons. Core projection errors under reference case are tested for seven groups of countries covering OECD, Africa, East Asia (excluding China), Latin America, Middle East, South Asia, Transition Economies (namely Central and Eastern Europe and Former Soviet Union) and four sovereign states of China, Brazil, Russia, India plus the world as a whole. Restricted by data availability, data for Brazil, Russia and India can only be traced since 2000. Prediction error of three major assumptions containing GDP, population size and crude oil price are also traced and compared in form of growth rate during this period.

Actual energy consumption data for all years are collected from IEA's annual energy balances. Data concerning total primary energy supply, GDP and population are obtained from IEA's CO2 Emissions from Fuel Combustion published in 2014 and WDI as supplement. Crude oil price in 2010 which can be traced in latter version of outlook is 78.1 US dollars while projected oil price of all years are adjusted at 2010 constant US dollars using CPI Inflation calculator from US Bureau of Labor Statistics, all in form of percentage error of growth rates.

Appendix B: Tables

Table B.1

Results of descriptive statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
de	405	-0.325	1.997	-9.559	4.512
gdp	360	-0.931	1.425	-4.781	1.497
pop	315	0.101	0.253	-0.442	0.741
price	405	-0.073	0.031	-0.115	-0.032
length	405	11.778	3.779	6	17

Note: Obs is full sample size for all observations.

Table B.2

Subgroup descriptive description.

	PE>0		PE<0	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
gdp	0.564	0.380	-1.588	1.202
pop	0.086	0.335	0.109	0.200
price	-6.741	2.951	-7.671	3.168
length	12.774	3.170	11.160	3.995
gas	0.200	0.401	0.200	0.401
hydro	0.200	0.401	0.200	0.401
oil	0.200	0.401	0.200	0.401
coal	0.200	0.401	0.200	0.401
tpes	0.200	0.401	0.200	0.401
Africa	0.032	0.177	0.140	0.348
Brazil	0.000	0.000	0.060	0.238
China	0.000	0.000	0.160	0.367
East Asia	0.226	0.419	0.020	0.140
India	0.000	0.000	0.060	0.238
Latin America	0.194	0.396	0.040	0.196
Middle East	0.032	0.177	0.140	0.348
OECD	0.258	0.439	0.000	0.000
Russia	0.000	0.000	0.060	0.238

South Asia	0.065	0.246	0.120	0.326
Transition Economies	0.161	0.369	0.060	0.238
World	0.032	0.177	0.140	0.348
obs	155		250	

Note: Obs is full sample size for all observations.

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