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Comparisons of Chinese and Indian Energy Consumption Forecasting Models

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Abstract
I evaluate the out-of-sample forecasting performance of five models of Chinese and Indian energy consumption. The results are mixed, but in general the auto-regressive distributed lag and unobserved components models perform the best over multiple evaluation criteria. I then use these two models and generate long-term forecasts [2010-2040] for comparison with the International Energy Outlook of the U.S. Energy Information Administration and other similar publications. For both countries the forecasting models predict higher levels and growth rates of energy consumption than the published estimates.

The analysis and conclusions expressed here are those of the author and not necessarily those of the U.S. Energy Information Administration. I have benefited from the comments and suggestions of Linda Doman, Peter Gross, Brian Murphy, Elizabeth Sendich, and Kay Smith.
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1 Introduction

In 2010 China and India accounted for over 36% of the world's population but less than 25% of its total primary energy consumption. In contrast, the Organization for Economic Cooperation and Development (OECD) countries made up approximately 18% of the world's population and nearly half of its total primary energy consumption. Given their relatively low energy consumption per capita, it is safe to assume that China and India are central to future global energy consumption. While longer-term model-based projections of energy consumption in these countries are common, there are few comparisons of the forecasting performance of different econometric models either in the short or long-term (Bhattacharyya and Timilsina, 2009). And there remain questions about the levels and dynamics of energy consumption for either country in these longer-term projections (Wolfram et al., 2012).[1]

In this paper I evaluate the out-of-sample forecasting performance of five different econometric models of Chinese and Indian energy consumption. I then use two of the models to generate long-term forecasts and compare them against different published long-term projections for both countries. The primary goal is to evaluate the performance of relatively simple forecasting models for energy consumption in these two important countries. I also seek to compare their longer-term forecasts with projections generated using more complicated models.

In the forecasting exercises I use two different data-sets, total primary energy consumption from the U.S. Energy Information Adminstration (EIA) and total primary energy supply from the International Energy Agency (IEA). Although these series are attempting to measure the same thing, there are substantial differences in levels and growth rates between them in either country, and they cover different time periods. The five models are used to generate two different out-of-sample forecasts in each country using each data-set. For the EIA data the forecast periods are 2005-2009 and 2000-2009, while the periods are 2006-2010 and 2001-2010 for the IEA data. The forecasting results are mixed, but in general the autoregressive distributed lag (ADL) and unobserved components (UC) models perform the best across the countries and time periods over multiple evaluation criteria.

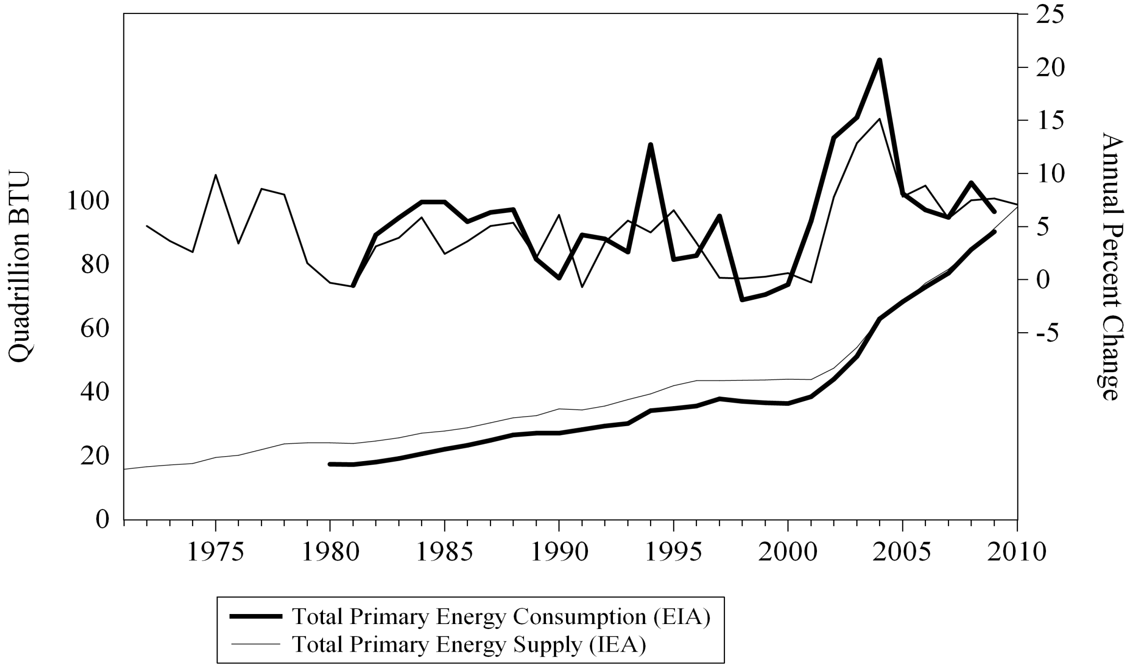
I then use the ADL and UC models to generate long-term forecasts [2010-2040] based on EIA data for comparison with the International Energy Outlook (IEO) of 2011 and 2013. The forecasting models predict higher levels and growth rates of energy consumption than the IEO for both countries over the entire period, but the differences are greatest after 2020. The same is true in comparison to other published reports as well for either country. Primarily this is because the relatively simple models used here do not consider energy supply, and are based on historical relationships between total primary energy consumption, its lags, and GDP per capita. There is also a concern that the forecasting models presented in this paper are estimated on data for periods shorter than the long-run forecasts.

2 Data and Descriptive Statistics

Annual data on real gross domestic product (GDP) and energy consumption are used in generating the forecasts for both China and India. The GDP data is available for either country between 1971 and 2040 from IHS/Global Insight and is real GDP per capita in 2005 U.S. dollars at purchasing power parity (PPP). Historical GDP and energy consumption data are used for estimation, and certain out-of-sample energy consumption forecasts rely on past and projected GDP data as well. These energy consumption forecasts are based on two different series for both China and India.

[1] Examples of longer-term projections include the International Energy Outlook of the U.S. Energy Information Adminstration, the World Energy Outlook of the International Energy Agency, the Energy Outlook of British Petroleum corporation, and the Outlook for Energy of Exxon Mobil corporation.

Figure 1: Comparison of EIA and IEA energy consumption data for China.



One measure of energy consumption is based on total primary consumption from the U.S. Energy Information Administration as of February 2013. This series is available for each country from 1980 to 2009 in quadrillion British thermal units (BTUs).[2] The other measure of energy consumption is total primary energy supply from the non-OECD energy balances of the International Energy Agency as of October 2012.[3] Total primary energy supply is equivalent in the IEA's formulations to total primary energy demand. The data is available from 1971 through 2010 in kilotonnes of oil equivalent (ktoe).

Figures (1) and (2) plot the level and growth rate of each energy consumption series in the respective countries. Figure (1) shows that there are broad similarities in the EIA and IEA data for energy consumption with respect to China. This is especially true for the levels after 2004, although the growth rates do vary somewhat. There are substantial differences, however, for India as shown in Figure (2). In this case the EIA energy consumption series has a lower level and greater volatility in growth rates, particularly before 1997.

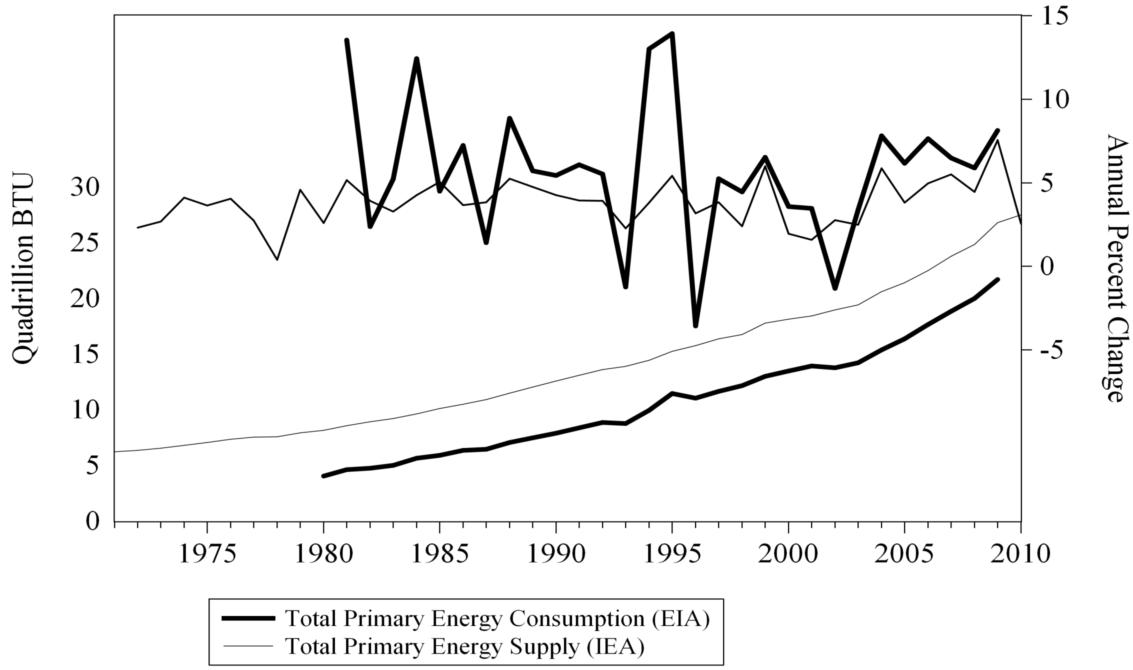
These features of the two energy consumption series are further highlighted in Table (**??**), which shows descriptive statistics for the annual growth rates of each series along with that of GDP per capita.[4] Over the period 1971 to 2010, panel (a) of Table (**??**) shows that real GDP growth (Δ_{GDP}) averages over 7.5% in China, with a little less than half that level of volatility. The distribution is negatively skewed, indicating relatively few low values, and also diverges from the normal distribution in its peak as evidenced by the kurtosis value above four. Panel (b) of Table (**??**) shows similar results for the growth rate of real Indian GDP per capita over this time period, except that the average rate of growth is less then half that of China.

[2] See `http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm`. EIA defines primary energy consumption as consumption of energy in the form that it is first accounted for in a statistical energy balance, before any transformation to secondary or tertiary forms of energy.

[3] The IEA defines primary energy as that which is either extracted or captured directly from natural resources.

[4] Growth rates are shown because unit root tests indicate that each series has a stochastic trend. Specifically, the KPSS test [see Kwiatkowski et al. (1992)] is able to reject the null of stationarity at the 5% level for each series.

Figure 2: Comparison of EIA and IEA energy consumption data for India.



In terms of energy consumption, the EIA data on total primary energy consumption (Δ_{TPC}) has a faster growth rate and higher volatility than IEA data on total energy supply (Δ_{TPS}) for either country. Consistent with Figure (2), the differences are largest for India. For example, the growth rate of the total primary energy consumption series for India is over three times as volatile as that of total primary energy supply [0.042 vs. 0.014]. The skewness and kurtosis results differ between the energy consumption series in either country, but all are positively skewed, indicating relatively few high values, and each series except for Chinese total primary energy consumption has kurtosis values similar to the standard normal distribution.

3 Models

The energy consumption forecasts are based on five different models, each of which are estimated for both countries with the EIA and IEA energy consumption data. These include: exponential smoothing (EXP), autoregressive integrated moving average (ARIMA), autoregressive distributed lag (ADL), and two unobserved components (structural) models.[5] In what follows the conditional expectations operator has been dropped for notational simplicity.

3.1 Exponential Smoothing

The exponential smoothing model is a Holt-Winters type with no seasonal variation. This method extends basic exponential smoothing to take account of a possible linear trend. The estimates of the level (a_t) and

[5]The software used for all estimations is EViews, and the specifications outlined below are based in part on the EViews user guide.

Table I: Descriptive statistics for the first difference of the natural logarithm of each data series in China and India. The real GDP per capita (Δ_{GDP}) and total primary energy supply (Δ_{TPS}) series range from 1971-2010, and the total primary energy consumption (Δ_{TPC}) series covers 1980-2009.

(a) China

	Mean	Standard Deviation	Skewness	Kurtosis
Δ_{GDP}	0.076	0.034	-0.958	4.06
Δ_{TPS}	0.047	0.037	0.600	3.30
Δ_{TPC}	0.057	0.051	0.960	4.17

(b) India

	Mean	Standard Deviation	Skewness	Kurtosis
Δ_{GDP}	0.034	0.032	-1.18	5.33
Δ_{TPS}	0.038	0.014	0.125	3.35
Δ_{TPC}	0.058	0.042	0.018	3.19

linear trend (b_t) of energy consumption (y_t) at t are given by:

$$a_t = \alpha y_t + (1-\alpha)[a_{t-1} + b_{t-1}] \tag{1}$$

$$b_t = \beta_t [a_t - a_{t-1}] + 1 - \beta b_{t-1} \tag{2}$$

where the α and β are smoothing constants. These equations can be used to generate smoothed estimates of y_t:

$$y_t = a_{t-1} + b_{t-1} \tag{3}$$

and h-step ahead forecasts of energy consumption from T are computed as:

$$y_{T+h} = a_T + b_T h \tag{4}$$

3.2 Autoregressive Integrated Moving Average

The ARIMA model is specified as an ARIMA(p,1,0), and the autoregressive lag length varies depending on the energy consumption series and country. The estimating equation for the growth rate of energy consumption (Δy_t) follows:

$$\Delta y_t = \lambda + \sum_{k=1}^{j} \gamma_k \Delta y_{t-k} + \varepsilon_t \tag{5}$$

with the λ a constant, the γ_k different coefficients, and ε_t a white noise error term. For this model h-step ahead forecasts of energy consumption from T are computed as:

$$\Delta y_{T+h} = \lambda + \sum_{k=1}^{j} \gamma_k \Delta y_{T+h-k} \tag{6}$$

3.3 Autoregressive Distributed Lag

The ARIMA model is extended to an ADL model by adding contemporaneous and lagged values of real GDP per capita in either country (x_t). The estimating equation has the following form:

$$\Delta y_t = \lambda + \sum_{k=1}^{j} \gamma_k \Delta y_{t-k} + \sum_{i=0}^{n} \kappa_i \Delta x_{t-i} + \varepsilon_t \tag{7}$$

where the κ_i are different coefficients. The h-step ahead forecasts of energy consumption from T are computed as:

$$\Delta y_{T+h} = \lambda + \sum_{k=1}^{j} \gamma_k \Delta y_{T+h-k} + \sum_{i=0}^{n} \kappa_i \Delta x_{T+h-i} \tag{8}$$

3.4 Unobserved Components

The unobserved components model specifies the level of energy consumption in either country as a linear function of GDP per capita and a stochastic trend. In the state space representation of this model the signal equation takes the form:

$$y_t = \mu_t + \sum_{i=0}^{n} \kappa_i x_{t-i} + \varepsilon_t \tag{9}$$

where μ_t is a stochastic trend. Two different formulations of the state equation for μ_t are estimated. The first specifies it as a random walk:

$$\mu_t = \mu_{t-1} + u_t \tag{10}$$

with the u_t white noise. The alternative specification is that the stochastic trend is a random walk with drift:

$$\mu_t = \theta + \mu_{t-1} + u_t \tag{11}$$

In this case the θ is a drift term, and the other variables are as above. For details on forecasting with these types of models see Harvey (2006).

4 Results

This section presents the results of dynamic out-of-sample forecasts based on the models outlined above. For each country the models are applied to both EIA and IEA energy consumption series over two different time periods. In either case the models are estimated until the year before each period begins and use forecasted values of energy consumption, exogenous values of GDP per capita, and the estimated parameters thereafter. The forecasting performance of each model is evaluated based on standard metrics, including: the root mean squared error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), and Theil's inequality coefficient (TIC).

4.1 Forecasts with EIA Data

EIA data on total primary energy consumption ranges from 1980 through 2009 for both China and India, and the forecast periods are 2005-2009 and 2000-2009. The second column of each table in Figure (3) shows the out-of-sample forecasting results for either country from 2005-2009 based on this data set. For China, the unobserved components models are clearly superior to the others in terms of forecasting performance. They have the lowest errors across any of the measures, as well as lower values of the inequality coefficient. The structural model with a random walk does slightly better than the model which takes the trend to be a random walk with drift, and the largest difference between these two is in the RMSE.

The second column of the second table in Figure (3) shows the results for India over the same time period. The ADL and ARMA models have the lowest RMSE values (with ADL less than half the RMSE of the ARMA), but the ADL and unobserved components model (random walk with drift) have lower MAE, MAPE, and TIC. Across each measure the ADL model outperforms all of the others. Particularly notable is that the ADL model has half of the MAPE of the unobserved components model, and this value is almost 7 times smaller than that generated by the exponential forecast.

The fifth column of the China table in Figure (3) highlights the strength of the ADL model in forecasting total primary energy consumption from 2000-2009. The ADL model has the lowest forecast errors and TIC value of the models, although the unobserved components model (random walk) has values that are only slightly higher. Interestingly, the errors for each of the unobserved components models are substantially higher than with the shorter-term forecasts of 2005-2009. The results for India for the period 2000-2009 presented in the fifth column of the India table in Figure (3) change as well. It is now the exponential smoothing model with the lowest forecasting errors and TIC. The unobserved components model (random walk with drift) has the next lowest errors of the remaining models.

In summary, there is no clearly superior method when forecasting total primary energy consumption in China or India over these time periods. However, the ADL and unobserved components models (random walk for China, random walk with drift for India) have lower forecasting errors than the others across three of the four time periods for both countries. These differences are most pronounced in either country over the 2005-2009 period.

4.2 Forecasts with IEA Data

IEA data on total primary energy supply ranges from 1971 through 2010 for both China and India, and the forecast periods are 2006-2010 and 2001-2010. The second column of each table in Figure (4) shows the out-of-sample forecasting results for either country from 2006-2010 based on this data set. For China, the exponential model has the lowest errors and TIC of all the models. The ADL model also forecasts relatively well, with errors that are only slightly higher than the exponential model. The differences between the two are relatively consistent between RMSE, MAE, and MAPE.

The second column of the second table in Figure (4) shows the results for India over the same time period. As with the EIA data, the ADL and ARMA models have the lowest RMSE values but in this case they both also have the lowest values for MAE, MAPE, and TIC. And the ADL model outperforms all of the others across the metrics for this time period in forecasting total primary energy supply for India.

The fifth column of the China table in Figure (4) shows the results for IEA data from 2001-2010. The unobserved components model (random walk) has the lowest values for RMSE, MAE, MAPE, and TIC. The next lowest errors are split between the other unobserved components model (random walk with drift) and the ADL model. The ADL has a lower RMSE value, but this other unobserved components model has lower values of MAE and MAPE. Both have the same TIC value. The results for India for the period 2001-2010 presented in the fifth column of the India table in Figure (4) are similar to that of China. The unobserved components model (random walk) has the lowest errors and TIC, and the next lowest errors are for the other unobserved components model. The differences are most pronounced with MAPE, where the unobserved components model (random walk) is over one percent lower than the next best model (unobserved components, random walk with drift).

In summary, as with EIA data there is no clearly superior method when forecasting total primary energy supply in China or India over these time periods. The structural models have lower errors in the longer forecasts of either country, while the ADL is preferred in India for the shorter time period.

4.3 Comparisons with Long-Term Projections

Because of their relatively strong out-of-sample forecasting performance, the ADL and unobserved components model (random walk with drift) are used to generate long-run forecasts of total primary energy consumption in China and India. To generate the forecasts each model is estimated over the period 1980-2009, and these estimated parameter values along with forecasts of real GDP per capita from IHS/Global Insight are used to generate total primary energy consumption forecasts from 2010-2040. These are compared against projections from the 2011 and 2013 International Energy Outlook of the EIA in Figures (5) and (6).

Figure (5) plots the levels and percent changes for each projection or forecast for China. In terms of levels, the ADL has the largest value in 2040, while both IEO series are on the lower end. The IEO 2011 projection ends in 2035 and is the lowest at that time. The forecast from the unobserved components model (random walk with drift) falls in the middle range. The real differences manifest themselves after 2020. This becomes clearer when looking at the annual growth rates of each series in the same graph. The IEO series show steadily declining rates of growth throughout the sample period. The forecast model rates of growth also fall, but at a much slower pace, especially towards the end of the sample.

Figure (6) plots the same data for India from 2010-2040. The differences in these series appear to be much larger than for China. In terms of levels, both forecasting models grow at a faster pace than the IEO projections. This pattern begins about 2015 and then accelerates through 2040. The annual growth rates show that the forecast models predict growth in Indian total primary energy consumption that is about 3 percent higher on average per year throughout the entire period. By 2040 the forecast models show total consumption that is almost three times greater than either IEO projection.

These forecasts can also be compared to longer-term projections from the IEA and Exxon-Mobil for energy consumption. For China, average annual growth from 2010-2040 is 4.2% for the ADL model, 3.7% for the unobserved components model, and 2.6% for the IEO 2013. The IEO 2011 has annual average growth in total primary energy consumption as 2.5%. Exxon Mobil projects much lower energy demand in China, with an annual average growth rate of 1.3%.[6] The IEA's 2012 World Energy Outlook (WEO) current policies scenario is higher, at 2.4% growth in total primary energy supply on average from 2010-2035.[7]

With respect to India, average annual growth from 2010-2040 is 6.2% for the ADL model, 6.1% for the unobserved components model, and 2.8% for the IEO 2013. The IEO 2011 projects annual average growth in India from 2010-2035 to be 3.0%. This is the same as Exxon-Mobil's projection of 3.0% per year from 2010-2040, but lower than the 3.6% per year projected by the IEA's WEO 2012 for India.

5 Conclusion

In this paper I evaluate the out-of-sample forecasting performance of five different models of Chinese and Indian energy consumption. The forecasting results are mixed, but in general the autoregressive distributed lag (ADL) and unobserved components models perform the best across the countries and time periods over multiple evaluation criteria. I then use these two models and generate long-term forecasts [2010-2040] based on EIA data for comparison with the International Energy Outlook (IEO) of 2011 and 2013. For both

[6]See http://www.exxonmobil.com/Corporate/energy_outlook.aspx.

[7]See http://www.worldenergyoutlook.org/publications/weo-2012/.

countries the forecasting models predict higher levels and growth rates throughout the entire period than either IEO, but particularly after 2020. The differences are largest for India, where the forecasts are nearly 3 times greater than the IEO by 2040. The same is true in comparison to other published reports as well for either country. This is because the models used here do not consider energy supply, and are based on historical relationships between total primary energy consumption, its lags, and GDP per capita. There is also a concern that the forecasting models presented in this paper are estimated on data for periods shorter than the long-run forecasts.

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Appendix 1: Tables and Figures

Figure 3: Results of out-of-sample forecasts of EIA total primary energy consumption for China and India across various metrics for the specified periods. Sample runs from 1980 to the year before the forecast period begins.

EIA Data

China

Root Mean Squared Error				
Model	*2005-2009*		*Model*	*2000-2009*
ADL	20.02		ADL	19.26
ARMA	19.84		ARMA	21.04
EXP	21.03		EXP	25.93
UC (RW)	1.18		UC (RW)	19.50
UC (RWD)	1.39		UC (RWD)	19.66

Mean Absolute Error				
Model	*2005-2009*		*Model*	*2000-2009*
ADL	18.21		ADL	15.86
ARMA	18.17		ARMA	17.13
EXP	19.17		EXP	20.98
UC (RW)	0.98		UC (RW)	16.04
UC (RWD)	0.96		UC (RWD)	16.22

Mean Absolute Percentage Error				
Model	*2005-2009*		*Model*	*2000-2009*
ADL	22.33		ADL	21.85
ARMA	22.32		ARMA	23.43
EXP	23.51		EXP	28.52
UC (RW)	1.23		UC (RW)	22.09
UC (RWD)	1.24		UC (RWD)	22.35

Theil's Inequality Coefficient				
Model	*2005-2009*		*Model*	*2000-2009*
ADL	0.113		ADL	0.170
ARMA	0.112		ARMA	0.189
EXP	0.118		EXP	0.242
UC (RW)	0.007		UC (RW)	0.173
UC (RWD)	0.009		UC (RWD)	0.175

India

Root Mean Squared Error				
Model	*2005-2009*		*Model*	*2000-2009*
ADL	0.47		ADL	2.16
ARMA	1.05		ARMA	1.68
EXP	2.65		EXP	1.10
UC (RW)	1.14		UC (RW)	2.74
UC (RWD)	0.85		UC (RWD)	1.56

Mean Absolute Error				
Model	*2005-2009*		*Model*	*2000-2009*
ADL	0.36		ADL	1.98
ARMA	0.92		ARMA	1.58
EXP	2.38		EXP	0.88
UC (RW)	0.99		UC (RW)	2.28
UC (RWD)	0.73		UC (RWD)	1.46

Mean Absolute Percentage Error				
Model	*2005-2009*		*Model*	*2000-2009*
ADL	1.77		ADL	11.66
ARMA	4.67		ARMA	9.56
EXP	12.09		EXP	5.13
UC (RW)	5.06		UC (RW)	12.75
UC (RWD)	3.65		UC (RWD)	8.93

Theil's Inequality Coefficient				
Model	*2005-2009*		*Model*	*2000-2009*
ADL	0.013		ADL	0.061
ARMA	0.028		ARMA	0.048
EXP	0.075		EXP	0.033
UC (RW)	0.029		UC (RW)	0.076
UC (RWD)	0.023		UC (RWD)	0.045

Figure 4: Results of out-of-sample forecasts of IEA total primary energy supply for China and India across various metrics for the specified periods. Sample runs from 1971 to the year before the forecast period begins.

IEA Data

China

Root Mean Squared Error				
Model	*2006-2010*		*Model*	*2001-2010*
ADL	2.67		ADL	19.15
ARMA	6.55		ARMA	21.17
EXP	2.11		EXP	25.74
UC (RW)	5.58		UC (RW)	18.93
UC (RWD)	6.50		UC (RWD)	19.24

Mean Absolute Error				
Model	*2006-2010*		*Model*	*2001-2010*
ADL	2.07		ADL	16.08
ARMA	5.65		ARMA	17.53
EXP	1.66		EXP	21.29
UC (RW)	4.71		UC (RW)	15.77
UC (RWD)	5.69		UC (RWD)	15.93

Mean Absolute Percentage Error				
Model	*2006-2010*		*Model*	*2001-2010*
ADL	2.27		ADL	20.32
ARMA	6.31		ARMA	22.00
EXP	1.84		EXP	26.69
UC (RW)	5.24		UC (RW)	19.86
UC (RWD)	6.38		UC (RWD)	19.99

Theil's Inequality Coefficient				
Model	*2006-2010*		*Model*	*2001-2010*
ADL	0.016		ADL	0.151
ARMA	0.040		ARMA	0.169
EXP	0.012		EXP	0.212
UC (RW)	0.034		UC (RW)	0.148
UC (RWD)	0.039		UC (RWD)	0.151

India

Root Mean Squared Error				
Model	*2006-2010*		*Model*	*2001-2010*
ADL	0.49		ADL	1.52
ARMA	0.77		ARMA	1.16
EXP	1.83		EXP	1.47
UC (RW)	1.07		UC (RW)	0.69
UC (RWD)	1.28		UC (RWD)	0.71

Mean Absolute Error				
Model	*2006-2010*		*Model*	*2001-2010*
ADL	0.39		ADL	1.22
ARMA	0.61		ARMA	0.90
EXP	1.60		EXP	1.07
UC (RW)	0.83		UC (RW)	0.42
UC (RWD)	1.12		UC (RWD)	0.61

Mean Absolute Percentage Error				
Model	*2006-2010*		*Model*	*2001-2010*
ADL	1.51		ADL	4.98
ARMA	2.34		ARMA	3.79
EXP	6.14		EXP	4.38
UC (RW)	3.14		UC (RW)	1.68
UC (RWD)	4.30		UC (RWD)	2.70

Theil's Inequality Coefficient				
Model	*2006-2010*		*Model*	*2001-2010*
ADL	0.010		ADL	0.034
ARMA	0.015		ARMA	0.026
EXP	0.038		EXP	0.033
UC (RW)	0.022		UC (RW)	0.015
UC (RWD)	0.026		UC (RWD)	0.016

Figure 5: Comparison of EIA IEO projections and model forecasts for China.

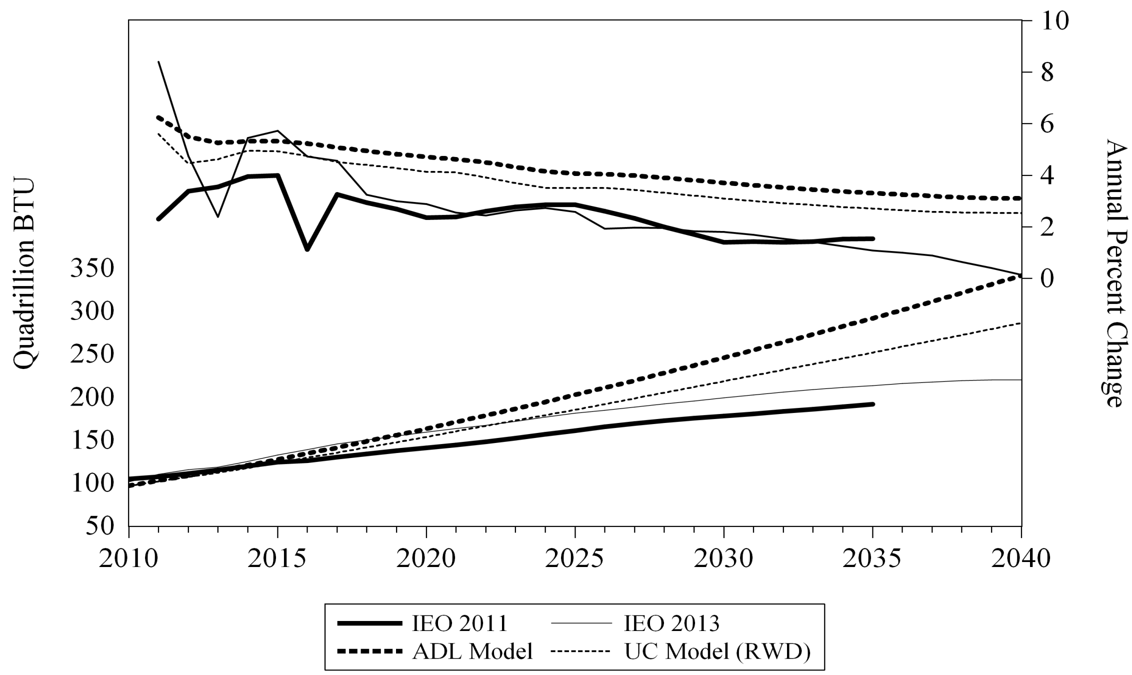

Figure 6: Comparison of EIA IEO projections and model forecasts for India.