Assessing the Accuracy of Electricity Demand Forecasts in Developing Countries*

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January 24, 2017

Abstract

This study assesses the accuracy of time-series econometric methods in forecasting electricity demand in developing countries. The analysis of historical time series for 106 developing countries over the period 1960-2012 demonstrates that econometric forecasts are highly accurate for the majority of developing countries. These forecasts significantly outperform predictions of simple heuristical models, which assume that electricity demand grows at an exogenous rate or is proportional to real GDP growth. The quality of demand forecasts, however, diminishes for the countries of Subsaharan Africa region, the low-income countries, and the countries with small electricity generation systems.

JEL: Q47

Keywords: electricity demand forecasting, time-series econometric models

*Acknowledgments: The author thanks Deb Chattopadhyay, Vivien Foster, Arthur Kochnakyan, Herman Stekler, Joeri de Wit and the seminar participants at the Oxford Institute for Energy Studies and the World Bank for their helpful suggestions and comments. Responsibility for the content of the paper is the author's alone and does not necessarily reflect the views of his institution or member countries of the World Bank.

1 Introduction

Forecasting the future demand of electricity is a significant problem for the utility companies, policy-makers and private investors in the developing countries. Reliable electricity demand forecasts are essential for both short-term load allocation and long-term planning for future generation facilities and transmission augmentation. In the short term, high-quality forecasts allow the utilities to optimize the amount of generated power, i.e., maximize their revenue and minimize operational (including environmental) costs. Over the longer term, accurate forecasts are even more important, as they help to reduce dynamic inefficiencies. As excess power is not easily storable, underestimating electricity demand results in supply shortages and forced power outages, which have detrimental effects on productivity and economic growth (Calderón and Servén 2004; Fisher-Vanden, et al., 2015; Allcott et al., 2016). However, overestimating demand may result in overinvestment in generation capacity and ultimately even higher electricity prices. Forecasting electricity demand is a challenging problem as it is subject to a range of uncertainties, which include, among other factors, underlying population growth, changing technology, economic conditions, and prevailing weather conditions (and the timing of those conditions). This problem can be particularly challenging in developing countries, where data is often elusive, political influences are often brought to bear, and historical electricity demand itself is more volatile owing to macroeconomic or political instability.

Despite the enormous significance of having accurate and reliable electricity demand forecasts for utilities, investors and policy makers, the electricity demand forecasting literature comprises of a handful of studies. Table 1 summarizes this limited research on electricity production and consumption econometric forecasts.[1] Most of the studies focus on developed economies. Only five studies (Abdel-Aal and Al-Garni 1997, Sadownik and Barbosa 1999, Saab et al. 2001, Inglesi 2010, and El-Shazly 2013) forecast electricity demand for developing countries (Saudi Arabia, Brazil, Lebanon, South Africa, and Egypt, respectively). As regards data frequency, these studies are almost evenly split between short-term forecasts based on monthly data and long-term forecasts based on yearly data. The largest part of these studies employs univariate time

[1] This summary focuses on medium- to long-term econometric projections and does not include high-frequency forecast studies of day-ahead electricity demand. It also omits non-econometric forecast studies based on soft computing techniques such as fuzzy logic, genetic algorithm, and neural networks, and bottom-up computational models such as MARKAL and LEAP. For a comprehensive review of these methods and their applications to energy forecasting, please refer to Suganthi and Samuel (2012).

Table 1: Summary of Previous Studies of Electricity Consumption Forecasts

Author	Country	Frequency	Sample	Forecast	Method
Abdel-Aal and Al-Garni (1997)	Saudi Arabia	Monthly	1987-1993	12 months	ARIMA
Bianco et al. (2009)	Italy	Yearly	1970-2007	5 years	ARDL
Baltagi et al. (2002)	United States	Yearly	1970-1990	1-5 years	ARDL
Harris and Liu (1993)	United States	Monthly	1969-1990	3 years	ARIMA
Dilaver and Hunt (2011)	Turkey	Yearly	1960-2008	12 years	UCM
El-Shazly (2013)	Egypt	Yearly	1982-2010	2 years	ARDL / ECM
Inglesi (2010)	South Africa	Yearly	1980-2005	15 years	ECM
Joutz et al. (1995)	United States	Monthly	1977-1991	10 months	VAR / VECM
Mohamed and Bodger (2005)	New Zealand	Yearly	1965-1999	15 years	Linear Regression
Narayan and Smyth (2005)	Australia	Yearly	1966-1999	10 years	ARDL / ECM
Pao (2009)	Taiwan	Yearly	1980-2007	1-6 years	State Space Models
Saab et al. (2001)	Lebanon	Monthly	1970-1999	10 years	ARIMA
Sadownik and Barbosa (1999)	Brazil	Monthly	1990-1994	1 month	UCM
Tserkezos (1992)	Greece	Monthly	1975-1989	24 months	ARIMA
Zachariadis (2010)	Cyprus	Yearly	1960-2007	43 years	ARDL

Notes. ARIMA: Autoregressive integrated moving average model. ARDL: Autoregressive distributed lag model. VAR: Vector autoregressive model. (V)ECM: (Vector) error correction model. UCM: Unobserved components model.

series methods with exogenous regressors. Few other studies use multivariate time series methods or state space econometric models. With the exception of Baltagi et al. (2002), none of these studies attempt to compare the forecast accuracy of different forecasting models.[2] Given significant variation in country coverage, time frame, forecast horizons, and econometric methods, the results of these studies are difficult, if not impossible, to reconcile.

The purpose of this study is to assess the accuracy of different econometric methods in forecasting electricity demand in developing countries. Based on the time series econometrics literature we first develop an econometric framework for forecasting electricity demand. We then obtain a number of electricity demand forecasts based on historical time series of 106 developing countries over the period 1960-2012. Finally, we evaluate the accuracy of the electricity demand forecasts resulting from different econometric methods and model specifications.

Our results demonstrate that time-series econometric forecasts yield highly accurate predictions for the evolution of electricity demand in the majority of developing countries. The forecasts based on the best performing method do significantly improve over the predictions of two heuristical models, commonly used by development practitioners, which assume that electricity demand grows at an exogenous rate or is proportional to real GDP growth. The quality of demand forecasts, however, diminishes for the countries of Subsaharan Africa region, the low-income countries, and the countries with small power generation systems.

2 Forecasting Methods and Accuracy Tests

This section briefly documents the econometric framework for forecasting electricity demand and evaluating its forecast accuracy. It first discusses implications of the stationarity property on forecastability of electricity demand time series. It then summarizes econometric methods employed for forecasting electricity demand. Finally, it describes measures of forecast errors for assessing forecast accuracy and comparing the quality of different forecasting methods.

[2] Baltagi et al. (2002) only focus on a small set of estimators within Autoregressive distributed lag (ARDL) model.

2.1 Testing for Data Stationarity

As electricity generation and consumption data series are typically nonstationary (i.e., their mean and/or variance are varying with time), an important aspect of forecasting model selection concerns the appropriate treatment of nonstationary data. The difference-stationary processes contain stochastic trends that are integrated of order k, so that differencing k times yields a stationary series. The difference stationary processes have poor forecastability as forecast error variances grow linearly in the forecast horizon for these processes (Clements and Hendry 2001). Establishing whether the data generating process is the difference stationary one is therefore of particular concern.

To test whether the data are the difference stationary we perform the modified Dickey–Fuller test (also known as the DF-GLS test) proposed by Elliott et al (1996).[3] The test involves fitting a regression of the form

$$\Delta y_t = \alpha + \beta y_{t-1} + \sum_{i=1}^{k} \delta_k \Delta y_{t-k} + \varepsilon_t \tag{1}$$

where y_t are the electricity production series, ε_t is the error term, α, β and δ are the parameters to be estimated, k is the lag order of time t, and Δ is the difference operator. The DF-GLS test is performed on detrended data by Generalized Least Squares (GLS) and involves testing the null hypothesis $H_0 : \beta = 0$. If the test cannot reject the null hypothesis, this implies that y_t is a random walk, possibly with drift and the data are difference stationary. Our choice of lag order in regression (1) is based on the modified Akaike information criterion developed by Ng and Perron (2000).

2.2 Forecasting Methods

Table 2 summarizes econometric methods employed for forecasting electricity demand. A brief formal representation of these methods is documented in Appendix A.1. For advanced textbook treatment of these methods, please refer to Harvey (1989), Hamilton (1994), Lütkepohl (2005), and Enders (2010).

[3] For robustness purposes we have also performed other tests for data stationarity, such as Augmented Dickey–Fuller test and Phillips and Perron (1988) unit root test. The results were little changed.

Table 2: Methods for Assessing Electricity Production Forecasts

Method	Description
VAR3/VECM3	Trivariate vector autoregressive model / Vector error correction model
VAR2/VECM2	Bivariate vector autoregressive model / Vector error correction model
ARIMA	Autoregressive integrated moving average model
GARCH	Generalized autoregressive conditional heteroskedasticity model
Holt-Winters	Holt–Winter's linear smoothing model
UCM-RWD	Unobserved components model: Random walk with a drift
UCM-LLTM	Unobserved components model: Local level with deterministic trend
UCM-RWSC	Unobserved components model: Random walk with a stochastic cycle

These methods can be broadly grouped into three categories. Vector autoregressive model (VAR) and Vector error correction model (VECM) are the multivariate time series forecasting methods that are most appropriate when electricity demand is closely related to other macroeconomic fundamentals. Over the long term, electricity demand is influenced by economic and demographic growth, changes in energy intensity, and shifting input prices. Among these drivers, gross domestic product (GDP) is often the strongest correlate of electricity demand (Steinbuks et al., 2017). And the data for input prices and structural fundamentals affecting energy intensity are scarce for most of the developing countries. In light of the above, we employ trivariate methods, which assume that a country's electricity demand is co-determined by GDP and population growth and bivariate methods, which assume that the country's electricity demand is co-determined by its GDP growth only.

Autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH) models are univariate time series forecasting methods that work best when other drivers of electricity demand are exogenous and have a small effect on electricity demand. These models assume that the best predictors of electricity demand are its past realizations. Additionally, the GARCH model is particularly helpful for forecasting electricity demand in countries, where electricity supply is highly volatile.

Finally, Holt-Winters and unobserved components methods are the most suitable for forecasting electricity demand that evolves around a linear trend, which can be either deterministic or stochastic. Additionally, the random walk with a stochastic cycle model (RWSC) may further improve forecasting accuracy in countries, where electricity demand exhibits cyclical behavior.

Autoregressive time series models (both multivariate and univariate) and the Holt-Winters method are applied to forecast both stationary and non-stationary electricity demand time series. Unobserved components models are only applied to forecast non-stationary electricity demand series. For all autoregressive time series models, we also estimate different specifications, assuming different lag structures (for details, please refer to Appendix). Altogether we estimate 33 model specifications for stationary electricity demand series and 36 model specifications for non-stationary series.

2.3 Measures of Forecast Accuracy of Individual Methods

We employ two popular measures of forecast errors for assessing forecast accuracy of an individual method: symmetric mean absolute percent error (sMAPE) and root mean squared error (RMSE). sMAPE is defined as the average absolute percent error of electricity consumption forecasts, y^F, minus actuals divided by the average of absolute values of forecasts and actuals across all forecasts made for a given horizon:

$$sMAPE = \frac{1}{T}\sum_{t=1}^{T}\left[\frac{\left|y_t^F - y_t\right|}{\left(\left|y_t^F\right| + \left|y_t\right|\right)/2}\right] \tag{2}$$

By using the symmetric MAPE, we avoid the problem of large errors when the actual values are close to zero, and the problem of the large difference between the absolute percentage errors when actuals are greater than forecasts and vice versa (Makridakis and Hibon, 2000).

The RMSE is a quadratic scoring rule which measures the average magnitude of the error. RMSE is defined as the difference between forecast and corresponding observed values that are each squared and then averaged over the sample:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}\left(y_t^F - y_t\right)^2}{T}} \tag{3}$$

As forecast errors are squared before they are averaged, the RMSE gives a relatively high weight to larger errors. The RMSE is, therefore, most useful when large errors are particularly undesirable.

2.4 Measures of Forecast Accuracy of Competing Methods

An important question that occurs in assessing the accuracy of electricity demand forecasts is how to formally compare the quality of different forecasting methods. Makridakis and Hibon (2000, p. 457) argue that "the absolute accuracy of the various methods is not as important as how well these methods perform relative to some benchmark." We choose two benchmarks, the random walk model (Näıve), and the fixed GDP multiplier model (Näıve2). The former is a standard benchmark in the forecasting literature, which sets predicted electricity demand to the last available data value of stationary series. The latter benchmark assumes that electricity demand grows at the exogenous rate, which is the same rate as country's GDP growth.[4] The choice of this benchmark is motivated by common practices by development professionals. Given the paucity of data and the methodological challenges, they frequently derive electricity demand forecasts from GDP-based demand growth forecasts as proxies for the growth in demand for electricity (Bhattacharyya and Timilsina 2010, Steinbuks et al. 2017).

To assess the accuracy of electricity demand forecasts, we calculate the median relative absolute error (MdRAE), which is the absolute error for the proposed model relative to the absolute error for a random walk model. It is defined as

$$MdRAE = p_{50}\left\{\frac{\left|y_t^{F,i} - y_t\right|}{\left|y_t^{F,Naïve} - y_t\right|}\right\} \tag{4}$$

It ranges from 0 (a perfect forecast) to 1.0 (equal to the random walk), to greater than 1 (worse than the random walk). The RAE is similar to Theil's U2, except that it is a linear rather than a quadratic measure. It is designed to be easy to interpret, and it lends itself easily to summarizing across horizons and series as it controls for scale and the difficulty of forecasting. The median RAE is recommended for comparing the accuracy of alternative models as it also controls for outliers (for information on the performance of this measure, see Armstrong and Collopy, 1992). We also compute the median percentage better measure, which reports the median of the percentage difference between sMAPE forecasting error of proposed model and one of the two benchmark

[4]For a more detailed description of these models, please refer to Appendix A.2.

models. Finally, we perform the Diebold and Mariano (1995) test to assess whether differences between competing forecasts are statistically significant or simply due to sampling variability.[5]

3 Electricity Demand Measurement, Data and the Forecast Horizon

The ultimate goal of this study is to forecast electricity demand, i.e., the total final consumption.[6] However, in many developing countries, particularly in South Asia and Subsaharan Africa regions, these data are either not available or available for a relatively short time frame due to difficulties with an accurate accounting of electricity at the end use level.[7] In light of these limitations, we have to rely on the more accurate electricity production (output) data for forecasting purposes. As electricity is a nonstorable and poorly tradable commodity, the output is a reasonable proxy for the total final consumption. However, we have to acknowledge that using electricity output data may lead to biased forecasts in a handful of developing countries with high exposure to electricity trade.

As regards data sources, the electricity generation (output) data come from the OECD/IEA Extended World Energy Balances database (IEA, 2016). The data on population and real GDP come from Penn World Tables, version 8 (Feenstra et al., 2013). The resulting dataset covers 106 developing countries over the period between 1960 and 2012.

Finally, we have to specify the within sample forecast horizons for assessing the accuracy of the forecasting methods. These are set to five and ten years, conditional on at least ten observations in the forecast validation sample. Additionally, we report out of sample forecasts over the period 2013-2022. For each country in the dataset, the out of sample forecasts are chosen based on the fore-

[5]For a more detailed description of the Diebold and Mariano (1995) test please refer to appendix section A.3.

[6]Bhattacharyya and Timilsina (2010) point out that the reliance on consumption data for the demand forecasting implies that only the satisfied demand is captured the suppressed demand is not taken into consideration. This problem can be potentially important in the presence of electricity market distortions and, correspondingly, unrealized demand (e.g., load shedding). As estimating unrealized demand typically requires high-quality micro-level panel data of enterprises and households, which are typically not available, addressing this problem is beyond the scope of this paper.

[7]These difficulties include the inaccurate recording of electricity consumption due to the poor technical capacity of electric utilities (Jamasb 2006), the absence of reliable electricity meters (Victor and Heller 2007), and large unaccounted losses from electricity theft (Smith 2004, Joseph 2010).

casting method corresponding to lowest within sample 5 year forecast horizon sMAPE. Appendix Table A3.1 shows the historical and forecasted electricity demand growth rates for each country. Country-specific forecast plots are also shown in the appendix.

4 Evaluating Accuracy of Different Methods

This section describes the evaluation of different forecasting methods' accuracy. In subsection 4.1 we compare different forecasting methods based on the chosen measures of predictive accuracy (for a description of these measures see subsection 2.3). In subsection 4.2 we examine the effectiveness of the best performing method across different categories of developing countries.

4.1 Comparisons across error measures

Tables 3 and 4 report frequencies of best-performing methods according to sMAPE and RFSE criteria, respectively.[8] For both measures of forecasts accuracy, the GARCH model has the highest incidence of delivering best predictions over both 5- and 10-year forecast horizons, followed by the bivariate VAR / VEC model over the 5-year forecast horizon and the trivariate VAR / VEC model over the 10-year forecast horizon. None of the chosen forecasting methods appears clearly superior to other methods. However, VAR/VEC and ARIMA/GARCH models cumulatively account for a dominant share of best performing models. Other methods (Holt-Winters and Unobserved Components models) tend to perform better in a relatively small number of cases.

[8]For VAR/VEC and ARIMA/GARCH models, the best performing method is a specification with the number of lagged terms that minimizes sMAPE and RFSE forecast errors.

Table 3: Frequency Tabulation of Best Performing Methods: sMAPE criterion

Model	5 year forecast horizon		10 year forecast horizon	
	Count	Frequency	Count	Frequency
VAR3 / VEC3	15	14.15%	30	28.57%
VAR2 / VEC2	21	19.81%	20	19.03%
GARCH	39	36.79%	34	32.35%
ARIMA	13	12.25%	9	8.55%
HOLT-WINTERS	6	5.66%	8	7.62%
UCM-RWD	3	2.83%	2	1.90%
UCM-RWC	9	8.49%	2	1.90%
Total	106	100%	105	100%

Table 4: Frequency Tabulation of Best Performing Methods: RMSE criterion

Model	5 year forecast horizon		10 year forecast horizon	
	Count	Frequency	Count	Frequency
VAR3 / VEC3	15	14.15%	33	31.41%
VAR2 / VEC2	23	21.69%	19	18.09%
GARCH	29	27.35%	33	31.41%
ARIMA	17	16.02%	7	6.65%
HOLT-WINTERS	7	6.60%	10	9.52%
UCM-RWD	5	4.72%	2	1.90%
UCM-LLTM	1	0.94%	0	0.00%
UCM-RWC	9	8.49%	1	0.95%
Total	106	100%	105	100%

Tables 5 and 6 show how well the forecasting methods perform compared to benchmark models, Näıve and Näıve2. For each forecast horizon, these tables report the median percentage better measure (see subsection 2.4) as well as the percentage of times the difference between the forecast errors is statistically significant based on the Diebold and Mariano (1995) forecast accuracy test.

Table 5 compares the accuracy of forecasting methods relative to the Näıve model, which assumes that electricity demand is a random walk. We see that the best performing model based on sMAPE criterion yields considerable improvement over Näıve model. The median sMAPE forecast error of the Näıve model is 77 percent higher than forecast error of the best performing model over the 5-year forecast horizon and 74 percent higher over the 10 year forecast

Table 5: Comparison of various methods with Näıve as the benchmark

Model	5 year forecast horizon		10 year forecast horizon	
	Median % Better	% significant ($p = 0.05$)	Median % Better	% significant ($p = 0.05$)
Lowest sMAPE	77%	85.0%	74%	67.5%
VAR3 / VEC3	19%	83.3%	16%	68.3%
VAR2 / VEC2	7%	96.5%	11%	72.5%
GARCH	37%	84.6%	10%	69.3%
ARIMA	13%	83.9%	-8%	70.1%
HOLT-WINTERS	-2%	86.0%	-11%	78.1%
UCM-RWD	-9%	86.8%	-22%	82.5%
UCM-LLTM	-10%	88.4%	-23%	82.5%
UCM-RWC	-40%	94.8%	-58%	87.9%

horizon. And the difference between forecast errors is statistically significant (assuming 5 percent level) for 85 percent of countries over the 5 year forecast horizon and for 67.5 percent of countries over the 10-year forecast horizon. As regards specific forecasting methods, VAR/VEC and GARCH methods yield more accurate forecasts than the Näıve model over both 5- and 10-year forecast horizons, with median accuracy improvement ranging between 7 and 37 percent. To the contrary, the Holt-Winters method and Unobserved Components Models yield less accurate forecasts over both 5- and 10-year forecast horizons, with median accuracy decline ranging between 2 and 58 percent. Finally, the ARIMA model produces more accurate forecasts than the Näıve model over the 5-year forecast horizon, with median accuracy improvement of 13 percent. However, the ARIMA model yields less accurate forecasts than the Näıve model over 10-year forecast horizon, with median accuracy decline of 8 percent. Regardless of the direction of forecast error differences, they are mostly statistically significant across all methods, ranging between 83.3 to 96.5 percent of countries over the 5-year forecast horizon, and between 68.3 and 87.9 percent of countries over the 10-year forecast horizon.

Table 6 compares the accuracy of forecasting methods relative to Näıve2 model, which assumes that electricity demand grows at the same rate as GDP. The results are qualitatively similar to those reported in Table 5, and the quantitative improvements over forecasts of Näıve2 model are even more pronounced. The median sMAPE forecast error of the Näıve2 model is 184% percent higher than forecast error of the best performing model over the 5-year forecast hori-

Table 6: Comparison of various methods with Näıve2 as the benchmark

Model	5 year forecast horizon		10 year forecast horizon	
	Median % Better	% significant ($p = 0.05$)	Median % Better	% significant ($p = 0.05$)
Lowest sMAPE	184%	88.0%	124%	73.0%
VAR3 / VEC3	68%	91.2%	52%	73.5%
VAR2 / VEC2	57%	95.2%	43%	73.7%
GARCH	121%	85.1%	54%	74.5%
ARIMA	69%	91.8%	23%	76.3%
HOLT-WINTERS	45%	90.2%	17%	81.7%
UCM-RWD	35%	90.5%	1%	79.5%
UCM-LLTM	31%	90.8%	0%	77.1%
UCM-RWC	-16%	94.2%	-40%	91.2%

zon and 124 percent higher over the 10-year forecast horizon. The performance of specific forecasting methods over the Näıve2 forecasting model is also improved. Specifically, VAR/VEC, GARCH, ARIMA, and Holt-Winters methods all yield more accurate forecasts than the Näıve2 model over both 5- and 10-year forecast horizons, with median accuracy improvement ranging between 17 and 121 percent. As regards Unobserved Components models, both RWD and LLTM methods deliver more accurate forecasts over the 5-year forecast horizon, whereas their forecast accuracy over the 5 year forecast horizon is of the same magnitude as that of the Näıve2 model. Finally, the RWC model yields less accurate forecasts than the Näıve2 model over both 5- and 10-year forecast horizons, with median accuracy decline between 16 and 40 percent. Similar to results reported in Table 5, the differences in predicted forecasts between forecasting methods and the Näıve2 model are mostly statistically significant across all methods, ranging between 85.1 to 95.2 percent of countries over the 5-year forecast horizon, and between 73 and 91.2 percent of countries over the 10-year forecast horizon.

4.2 Comparisons across developing country groups

Tables 7 - 10 compare effectiveness of the best performing method (based on sMAPE criterion) across developing countries based on their regional, income, generation capacity and energy intensity characteristics. Table 7 reports the average sMAPE and MdRAE measures of forecast accuracy across regions over

Table 7: Comparison of Forecast Errors across Regions

Region	5 year forecast horizon		10 year forecast horizon	
	sMAPE	MdRAE	sMAPE	MdRAE
AFR	0.09	0.44	0.11	0.63
EAP	0.05	0.54	0.05	0.53
ECA	0.06	0.45	0.07	0.49
LAC	0.05	0.52	0.08	0.62
MENA	0.05	0.42	0.08	0.52
SAR	0.02	0.25	0.05	0.41

the 5- and 10-year forecast horizons. All in all, the best performing method is highly accurate with average sMAPE varying between 2 and 9 percent over the 5-year forecasting horizon and between 5 and 11 percent over the 10-year forecasting horizon, respectively. Consistent with the results from the previous section, the best performing method is also more accurate than the Näıve model, with average MdRAE varying between 0.25 and 0.54 over the 5-year forecasting horizon, and between 0.41 and 0.63 over the 10-year forecasting horizon, respectively.

It follows from Table 7 that the forecast accuracy is the highest for the countries of the South Asia region over both 5- and 10-year forecasting horizons and across both types of error accuracy measures. The forecast accuracy is the lowest for the Subsaharan Africa region based on the sMAPE criterion over both 5- and 10- year forecasting horizons, with other regions having broadly comparable forecast errors. The forecast accuracy based on the MdRAE criterion is the lowest for the East Asia and Pacific and the Latin America regions over the 5-year forecasting horizon, and for the Subsaharan Africa and the Latin America regions over the 10-year forecasting horizon.

To frther elucidate the observed differences in the forecast accuracy across regions, this study also reports the average sMAPE and MdRAE measures of forecast accuracy for individual countries, grouped across regions over the 5- and 10-year forecast horizons (see Appendix Table A3.2). For most countries, both sMAPE and MdRAE errors are small, which indicates that the best performing method is both highly accurate and yields considerable improvements over the Näıve model. However, the forecasting accuracy is greatly diminished for countries that have recently undertaken major investments (Ethiopia, Cameroon, Myanmar) or disinvestments (Lithuania) in electricity generation assets; countries that have volatile electricity demand and / or rely heavily on electricity imports (Albania, Benin, Botswana); or countries affected by major conflicts (Iraq, Libya, Syria) or environmental disasters (Haiti).

Table 8 shows the average sMAPE and MdRAE measures of forecast accuracy across country income groups over the 5- and 10-year forecast horizons. It follows from Table 8 that electricity demand forecasts are less accurate for the lower income countries. For low income countries, the average sMAPE is 9 and 12 percent over the 5- and 10-year forecast horizons, respectively. These errors are twice as high compared to high-income countries. The accuracy of forecasting methods relative to the Näıve model is also considerably diminished for lower income countries. For low-income countries, the value of MdRAE is 0.79 over the 10-year forecast horizon, which indicates that the best performing method is just 21 percent more accurate than the Näıve model.

Table 8: Comparison of Forecast Errors across Income Groups

Income	5 year forecast horizon		10 year forecast horizon	
	sMAPE	MdRAE	sMAPE	MdRAE
Low	0.09	0.49	0.12	0.79
Low-Middle	0.05	0.39	0.07	0.44
Upper-Middle	0.06	0.50	0.08	0.59
High	0.05	0.46	0.06	0.49

Table 9 shows the average sMAPE and MdRAE measures of forecast accuracy across installed capacity categories over the 5 and 10 year forecast horizons. Forecast accuracy is the highest for the countries with large installed capacity and diminishes significantly as the size of the installed capacity falls. For countries with the largest installed capacity (over 100GW), the average sMAPE is 3 and 4 percent over the 5 and 10 year forecast horizons, respectively. These errors are twice as low as compared to countries with medium installed capacity size (1 to 10 GW). For countries with the smallest installed capacity (less than 1GW), electricity generation is particularly difficult to forecast, with the average sMAPE of 9 and 10 percent over the 5- and 10-year forecast horizons, respectively. The countries with large installed capacity also have higher accuracy of forecasting methods relative to the Näıve model. The value of MdRAE for countries with the largest installed capacity (over 100GW) is 0.34 and 0.23 over the 10-year forecast horizon, which is 1.5-2 times smaller as compared to countries with the smallest installed capacity size (less than 1GW).

Table 9: Comparison of Forecast Errors across Installed Capacity Categories

Installed Capacity	5 year forecast horizon		10 year forecast horizon	
	sMAPE	MdRAE	sMAPE	MdRAE
less than 1GW	0.09	0.50	0.10	0.57
1GW-10GW	0.06	0.47	0.08	0.59
10GW-100GW	0.02	0.41	0.04	0.47
more than 100GW	0.03	0.34	0.04	0.23

Table 10 shows the average sMAPE and MdRAE measures of forecast accuracy across energy intensity categories over the 5 and 10 year forecast horizons. Forecast accuracy is the highest for the most energy intensive countries (more than 12\$/kgoe) with average sMAPE of 2 and 4 percent over the 5 and 10 year forecast horizons, respectively. Compared to other countries these errors are 2 to 3 times smaller over the 5 year forecast horizon and 1.5 to 2 times smaller over the 10 year forecast horizon. However, the more energy intensive countries also have the lower accuracy of forecasting methods relative to the Näıve model, at least for the shorter term forecast horizon. The value of MdRAE for the most energy intensive countries is 0.75 over the 5 year forecast horizon, which is twice as high as compared to the most energy efficient countries. To the contrary, the most energy efficient countries have the lowest forecast accuracy relative to the Näıve model over the 10 year forecast horizon, with MdRAE of 0.68.

Table 10: Comparison of Forecast Errors across Energy Intensity Categories

Energy Intensity	5 year forecast horizon		10 year forecast horizon	
	sMAPE	MdRAE	sMAPE	MdRAE
<3\$/kgoe	0.04	0.34	0.09	0.68
3\$/kg-6\$/kgoe	0.06	0.41	0.08	0.47
6\$/kg-9\$/kgoe	0.07	0.43	0.09	0.56
9\$/kg-12\$/kgoe	0.06	0.50	0.06	0.46
>12\$/kgoe	0.02	0.75	0.04	0.52

5 Conclusions

Accurate projections of electricity demand are essential for planning power systems and appraising investment projects in developing countries. Nonetheless, demand forecasting issues are not rigorously studied and are not always given adequate attention among development practitioners. This study demonstrates that time-series econometric methods yield highly accurate forecast predictions for the majority of developing countries. Econometric forecasts significantly outperform simple heuristical rules used by practitioners, who frequently assume that electricity demand grows at some exogenous rate or is proportional to real GDP growth. These improvements notwithstanding, relying on time-series econometric methods alone may produce inaccurate forecasts in some developing countries. We show that econometric forecasts of electricity demand are challenging for developing countries that are in the process of rapid economic and structural transformation or are prone to conflicts and environmental disasters. These include, among other, the countries in Subsaharan Africa region, the low-income countries, and the countries with small electricity generation systems. For those countries, in particular, a more rigorous forecasting approach, using a combination of micro-econometric and computational modeling methods would be preferred.

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Appendix

A.1 Description of Forecasting Methods

A.1.1 VAR / VEC Model

Vector autoregressive model (VAR) is a commonly used tool for forecasting multivariate stationary time series that are simultaneously determined, e.g., electricity demand, and its drivers such as GDP, population, etc. The structure of VAR model is that each variable is a linear function of past lags of itself and past lags of the other variables. The VAR model with lag order p with k endogenous and m exogenous variables can be written as

$$\mathbf{y_t} = \mathbf{A}\mathbf{Y_{t-1}} + \mathbf{B_0}\mathbf{x_t} + \varepsilon_\mathbf{t}, \tag{A1.1}$$

where $\mathbf{y_t}$ is the $K \times 1$ vector of endogenous variables, $\mathbf{A}$ is a $K \times Kp$ matrix of coefficients, $\mathbf{Y_t}$ is the $Kp \times 1$ matrix of endogenous variables of lag order p, $\mathbf{B}_0$ is a $K \times M$ matrix of coefficients, $\mathbf{x_t}$ is the $M \times 1$ vector of exogenous variables, and $\varepsilon_\mathbf{t}$ is the $K \times 1$ vector of white noise innovations.

Vector error correction model (VECM) provides a framework for estimation, inference, and forecasting of difference stationary multivariate time series, when these variables are simultaneously determined. VECM representation of VAR model of lag order p defined by equation (A1.1) is given by

$$\mathbf{\Delta y_t} = \Pi\mathbf{y_{t-1}} + \sum_{i=1}^{p-1}\Gamma_\mathbf{i}\mathbf{\Delta y_{t-i}} + \mathbf{B_0}\mathbf{x_t} + \varepsilon_\mathbf{t} \tag{A1.2}$$

where $\mathbf{\Pi} = \sum_{j=1}^{j=p}\mathbf{A_j} - \mathbf{I_k}$, $\mathbf{\Gamma_i} = -\sum_{j=i+1}^{j=p}\mathbf{A_j}$, and other terms are same as in equation (A1.1). If the variables $\mathbf{y_t}$ are difference stationary, the matrix Π in A1.2 has rank $0 \leq r < K$, where r is the number of linearly independent cointegrating vectors. As matrix Π has reduced rank the cointegrating vectors are not identified without further restrictions. We apply standard normalization restrictions suggested by Johansen (1995). For both VAR and VECM models we set the maximum number of lagged terms, p, equal to four.

A.1.2 ARIMA Model

AutoRegressive Integrated Moving Average (ARIMA) models are appropriate if there is a reason to believe that other drivers of electricity consumption are exogenous or have little effect on electricity demand forecasts. They provide a parsimonious description of a weakly stationary stochastic processes in terms of two polynomials, one for the auto-regression and the second for the moving average. Pure ARMA models can be written as autoregressions in the dependent variable. An ARIMA*(p,d,q)* model can be written as

$$\Delta^d y_t = \alpha + \sum_{i=1}^{p} \rho_i \Delta^d y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t, \tag{A1.3}$$

where y_t is the dependent variable, α is a constant term, ρ and θ are the coefficients of autoregressive and moving average processes of lag orders p and q, d is the order of time-series integration (zero for stationary series), and ε_t is the error term that is assumed to be a white noise. We set the maximum number of lagged autoregressive terms, p, equal to four and the maximum number of lagged moving average terms, q, equal to two.

A.1.3 GARCH Model

Generalized autoregressive conditional heteroskedasticity (GARCH) models are frequently used for forecasting univariate time series when there is reason to believe that the error terms have a characteristic size or variance. This model is particularly relevant for developing countries with highly volatile electricity demand. The variance equation in the GARCH*(p,q)* model can be written as

$$\mathrm{Var}\left(\varepsilon_t\right) = \beta + \sum_{i=1}^{p} \mu_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \delta_i \sigma_{t-i}^2, \tag{A1.4}$$

where p is the length of squared innovations (ARCH terms) lags and p is the length of variances (GARCH terms) lags. The GARCH model simultaneously combines equations (A1.3) and (A1.4).

A.1.4 Holt-Winters Method

Holt-Winters method is used for forecasting time series that can be modeled as a linear trend in which the intercept and the coefficient on time vary over time. The method was shown to produce optimal forecasts for the ARIMA(0,2,2) model and some local linear models (Gardner, 1985). The Holt-Winters method forecasts series of the form

$$\widehat{y}_{t+1} = a_t + b_t t \tag{A1.5}$$

where $\widehat{y}_t$ is the forecast of the original series y_t, and a_t and b_t are coefficients that drift over time. Given starting values, a_0 and b_0, the updating equations are recursively formulated as

$$a_t = \alpha y_t + (1 - \alpha)(a_{t-1} + b_{t-1}) \tag{A1.6}$$

and

$$b_t = \beta(a_t - a_{t-1}) + (1 - \beta)b_{t-1} \tag{A1.7}$$

where smoothing parameters α and β are chosen by an iterative process to minimize the in-sample sum-of-squared prediction errors.

A.1.5 Unobserved Components Models

The Random Walk with a Drift (RWD) and the Local Level with Deterministic Trend (LLTD) models are most appropriate for forecasting difference-stationary time series that evolve around a linear appearing trend. Mathematical representation of the RWD and LLDT models is given by equations

$$y_t = \mu_t$$

$$\mu_t = \mu_{t-1} + \alpha + \varepsilon_t, \tag{A1.8}$$

(RWD) and

$$y_t = \mu_t + u_t$$

$$\mu_t = \mu_{t-1} + \alpha + \varepsilon_t, \tag{A1.9}$$

(LLDT), where μ_t is the conditional expectation of electricity demand series, y_t, α is a drift parameter, and ε_t and u_t are the white noise error terms.

The Random Walk with a Stochastic Cycle Model (RWSC) is most appropriate for forecasting difference-stationary time series that exhibit cyclical behaviour. Mathematical representation of the RWSC model is given by

$$y_t = \mu_t + \psi_t$$

$$\mu_t = \mu_{t-1} + \varepsilon_t,$$

$$\psi_t = \psi_{t-1}\rho\text{cos}\lambda + \widetilde{\psi}_{t-1}\rho\text{sin}\lambda + \omega_t,$$

$$\widetilde{\psi}_t = -\psi_{t-1}\rho\text{sin}\lambda + \widetilde{\psi}_{t-1}\rho\text{cos}\lambda + \widetilde{\omega}_t, \tag{A1.10}$$

where λ is a frequency of the cyclical component, ρ is a unit less scaling (or dampening) factor, $\widetilde{\psi}_t$ is auxiliary variable, and ε_t, ω_t, and $\widetilde{\omega}_t$ are the white noise error terms.

A.2 Description of Benchmark Models

A.2.1 Naïve Model

The forecasts of the Näıve model for covariance stationary data are simply the last available data value. It is defined as follows:

$$y_{t+i} = y_t, \tag{A1.11}$$

where $i = 1, 2, ..., m$, and $m = 5$ for 5-year ahead forecasts and $m = 10$ for 10-year ahead forecasts. In statistical terms the Näıve model is a random walk model, which assumes that the trend in the data cannot be predicted, and that the best forecast for the future is their own most recent value.

The forecasts of the Näıve model for difference stationary data are the difference of the last available data value summed over the forecast period, and added to the last available data value. It is defined as follows:

$$y_{t+i} = y_t + \sum_{i=t+1}^{t+m} (y_t - y_{t-1}), \tag{A1.12}$$

where $m = 5$ for 5-year ahead forecasts and $m = 10$ for 10-year ahead forecasts. In statistical terms the Näıve model holds the same interpretation as a random walk model.

A.2.2 Naïve2 Model

The Näıve2 model assumes that electricity demand grows at exogenous rate, which is the same rate as country's GDP growth. It is defined as follows:

$$y_{t+i} = (1+k)^i y_t, \tag{A1.13}$$

where k is the expected growth in GDP. In this study we assume it is equal to the historical GDP growth average over last 5 years in the sample.

A.3 Diebold-Mariano (1995) Test

The Diebold and Mariano (1995) (DM) parametric test is a well-known procedure for testing the null hypothesis of no difference in the accuracy of two competing forecasts.

Let $\{(e_{1t}, e_{2t})\}_{t=1}^{T}$ be a bivariate time series vector of competing forecast errors. The quality of the forecasts is to be evaluated according to a specified loss function, $g(\cdot)$. Let us assume that the loss function depends only on the forecast errors, and let $d_t = g(e_{1t}) - g(e_{2t})$ be the loss differential. Then, the null hypothesis of unconditional equal forecast accuracy is

$$H_0 \ : \ \mathbb{E}[d_t] = 0, \tag{A1.14}$$

i.e., the errors associated with the two forecasts are, on average, of equal magnitude. If the null is rejected, the forecasting method that yields the smallest loss will be chosen. Given a series of loss differentials, $\{d_t\}_{t=1}^{T}$, a test of (A1.14) is based on their sample mean:

$$\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t. \tag{A1.15}$$

The DM test it is given by

$$DM = \frac{\bar{d}}{\sqrt{\hat{V}(\overline{d})}} \tag{A1.16}$$

where $\hat{V}(\overline{d})$ is an estimate of the asymptotic variance of $\overline{d}$. Whenever an optimal forecast is produced from a proper information set, the resulting h-step forecast errors will follow a moving-average (MA) process of order $(h-1)$ of the form $e_t = \theta_0\varepsilon_t + \theta_1\varepsilon_{t-1} + ... + \theta_{h-1}\varepsilon_{t-h+1}$. Diebold and Mariano (1995) propose estimating the variance using the truncated kernel with a bandwidth of $(h-1)$ for h-step forecasts:

$$\hat{V}(\bar{d}) = \frac{1}{T}\left[\hat{\gamma}_0 + 2\sum_{k=1}^{h-1}\hat{\gamma}_k\right], \tag{A1.17}$$

where $\hat{\gamma}_k$ is an estimate of the kth auto covariance of d_t , given by

$$\hat{\gamma}_k = \frac{1}{T}\sum_{t=k+1}^{T}(d_t - \bar{d})(d_{t-k} - \bar{d}) :$$

Luger (2004, p. 2) argues that "if the loss-differential series satisfies some regularity assumptions such as covariance stationarity, short memory, and the existence of moments that ensure the applicability of a central limit theorem, then the DM test statistic has an asymptotic standard normal distribution under the null hypothesis."

Tables

Table A3.1: Historical and Forecast Rates of Electricity Demand Growth

country	Historical growth			Forecast growth, 2015-2020		
	2000-2004	2005-2009	2010-2014*	5% CI	Mean	95% CI
Sub-Saharan Africa						
Angola	18.6%	19.1%	3.5%	-2.1%	3.2%	7.0%
Benin	5.5%	8.0%	1.2%	-7.5%	0.0%	2.3%
Botswana	-1.7%	-7.7%	-2.0%	-20.0%	-10.0%	-4.9%
Cameroon	3.0%	9.5%	2.1%	1.3%	1.5%	1.7%
Congo	9.3%	16.3%	14.2%	-20.0%	4.3%	8.7%
DRC	4.7%	1.3%	0.1%	-2.1%	0.1%	1.5%
Eritrea	7.4%	1.6%	5.2%	4.3%	4.1%	3.8%
Ethiopia	14.0%	15.0%	22.3%	23.2%	24.4%	25.4%
Gabon	3.8%	5.3%	2.8%	1.6%	2.1%	2.6%
Ghana	-1.2%	10.0%	3.3%	1.6%	1.4%	1.2%
Ivory Coast	3.7%	1.0%	2.1%	2.0%	1.9%	1.8%
Kenya	8.6%	5.0%	4.8%	4.1%	4.4%	4.6%
Mauritius	5.6%	3.7%	2.2%	1.4%	2.2%	2.8%
Mozambique	7.4%	5.1%	1.1%	-5.1%	-1.1%	1.1%
Namibia	3.6%	-4.3%	1.5%	0.3%	0.4%	0.5%
Nigeria	12.0%	2.2%	2.3%	3.3%	3.0%	2.8%
Senegal	11.7%	4.2%	3.9%	3.6%	3.5%	3.4%
South Africa	3.3%	1.2%	0.1%	-1.0%	0.2%	1.1%
Sudan	9.8%	19.2%	22.0%	26.6%	26.3%	26.0%
Tanzania	8.8%	9.2%	0.5%	-20.0%	0.5%	71.1%
Togo	1.6%	-1.1%	-4.2%	n/a	-2.8%	5.7%
Zambia	2.9%	5.3%	5.3%	6.6%	8.5%	9.7%
Zimbabwe	6.8%	-1.6%	0.7%	-9.6%	-3.3%	0.1%
East Asia and Pacific						
Brunei	5.7%	3.2%	1.6%	1.4%	2.4%	3.2%
Cambodia	23.0%	0.6%	-0.5%	-11.3%	-1.6%	1.2%
China	16.9%	13.5%	17.1%	12.1%	12.4%	12.7%
Indonesia	7.4%	6.6%	7.8%	6.5%	6.9%	7.3%
Malaysia	3.9%	10.2%	5.8%	-2.7%	-1.4%	-0.2%
Mongolia	3.2%	5.2%	6.4%	3.9%	5.8%	7.4%
Myanmar	3.5%	5.1%	21.4%	n/a	3.4%	203.3%
North Korea	3.6%	-1.1%	0.8%	n/a	4.0%	212.8%
Philippines	5.0%	4.0%	2.7%	2.3%	2.7%	3.0%
Singapore	4.1%	3.7%	2.2%	1.6%	2.2%	2.7%
Thailand	7.5%	4.1%	1.3%	2.1%	2.0%	2.0%
Vietnam	20.4%	15.4%	13.9%	12.8%	12.9%	13.0%

Notes. * - includes mean forecasts for 2013-2014. CI: Confidence Interval

Table A3.1 Historical and Forecast Rates of Electricity demand Growth (continued)

country	Historical growth			Forecast growth, 2015-2020		
	2000-2004	2005-2009	2010-2014*	5% CI	Mean	95% CI
Europe and Central Asia						
Albania	3.0%	7.9%	-4.5%	-4.1%	0.7%	2.0%
Armenia	1.2%	0.6%	7.9%	n/a	6.8%	8.6%
Azerbaijan	4.5%	-3.6%	5.0%	-20.0%	-1.3%	-0.7%
Belarus	3.7%	2.5%	-2.3%	-0.5%	-1.1%	-1.5%
Bosnia and Herzegovina	4.2%	7.2%	-1.6%	1.6%	3.3%	4.4%
Bulgaria	1.6%	0.9%	2.8%		1.8%	
Croatia	3.1%	2.7%	0.8%	1.0%	1.6%	2.0%
Cyprus	6.0%	4.3%	-1.5%	-1.5%	0.0%	1.2%
Georgia	-0.4%	7.9%	9.2%	13.6%	12.6%	11.8%
Hungary	0.3%	0.9%	-0.7%	-1.4%	0.2%	1.5%
Kazakhstan	6.4%	4.4%	4.3%	-3.5%	3.3%	7.6%
Kyrgyzstan	-0.1%	-3.7%	0.8%	-0.7%	0.1%	0.7%
Latvia	3.7%	7.0%	-6.1%		-0.2%	
Lithuania	5.9%	-13.1%	8.1%	37.3%	15.1%	14.6%
Macedonia	0.4%	0.9%	0.5%	1.4%	1.2%	1.1%
Malta	3.4%	-1.1%	0.8%	-1.9%	-0.2%	1.1%
Moldova	1.4%	0.4%	0.4%	0.4%	0.4%	0.4%
Poland	1.7%	0.2%	1.2%	-1.2%	0.5%	1.8%
Romania	2.9%	0.4%	1.7%		1.0%	
Russia	1.7%	1.8%	1.3%	1.4%	1.9%	2.4%
Serbia	1.4%	0.5%	0.4%	0.9%	0.5%	0.3%
Tajikistan	4.0%	-0.8%	-0.4%	-0.3%	-0.3%	-0.2%
Turkey	5.9%	6.1%	7.0%	-20.0%	2.8%	53.4%
Turkmenistan	6.0%	6.0%	2.6%	1.4%	1.4%	1.3%
Ukraine	1.7%	0.3%	0.2%	-2.8%	-2.5%	-2.2%
Uzbekistan	1.0%	1.0%	2.9%	3.6%	3.4%	3.3%
Latin America and Caribbean						
Argentina	3.7%	3.7%	4.2%	3.4%	3.8%	4.1%
Bolivia	5.2%	8.4%	6.4%	6.3%	7.1%	7.8%
Brazil	3.1%	5.6%	4.1%	3.8%	4.0%	4.2%
Chile	6.2%	3.0%	3.9%	-1.0%	1.6%	3.8%
Colombia	3.3%	3.6%	2.4%	2.2%	2.1%	2.0%
Costa Rica	3.9%	3.2%	2.3%	n/a	2.0%	n/a
Cuba	0.4%	2.7%	0.0%	-0.8%	0.5%	1.4%
Dominican Republic	9.7%	4.2%	2.6%	2.3%	2.1%	1.9%
Ecuador	4.0%	10.7%	3.7%	-0.6%	2.9%	6.0%
El Salvador	8.6%	4.8%	-0.6%	-2.0%	-0.2%	1.2%
Guatemala	6.6%	2.1%	2.2%	1.8%	1.8%	1.7%
Haiti	0.3%	1.1%	13.6%	3.3%	2.7%	2.3%
Honduras	10.7%	4.2%	3.5%	2.2%	2.1%	2.1%
Jamaica	2.5%	-8.4%	1.7%	2.3%	2.0%	1.8%

Table A3.1 Historical and Forecast Rates of Electricity Demand Growth (continued)

country	Historical growth			Forecast growth, 2015-2020		
	2000-2004	2005-2009	2010-2014*	5% CI	Mean	95% CI
Latin America and Caribbean (continued)						
Mexico	3.9%	2.2%	3.6%	2.1%	2.0%	2.0%
Nicaragua	6.0%	4.0%	3.6%	3.1%	2.9%	2.8%
Panama	3.8%	5.5%	5.0%	3.0%	2.9%	2.8%
Paraguay	-0.9%	1.1%	3.5%	-0.4%	2.2%	2.8%
Peru	5.6%	8.2%	9.1%	7.0%	8.8%	10.4%
Trinidad & Tobago	5.9%	4.0%	5.2%	n/a	6.5%	n/a
Uruguay	0.2%	8.6%	3.7%	2.3%	3.1%	3.7%
Venezuela	4.7%	2.4%	2.3%	1.7%	2.2%	2.7%
Middle East and North Africa						
Algeria	6.7%	7.0%	6.3%	5.1%	5.8%	6.3%
Bahrain	8.0%	4.2%	2.3%	0.6%	2.2%	3.5%
Egypt	7.8%	7.0%	6.3%	4.7%	4.7%	4.6%
Iran	9.3%	6.2%	2.9%	2.2%	2.2%	2.3%
Iraq	-0.9%	13.0%	3.9%		2.1%	
Israel	2.8%	4.1%	2.1%	2.1%	2.0%	1.9%
Jordan	6.2%	10.6%	0.7%	-20.0%	1.3%	20.7%
Kuwait	7.1%	6.1%	3.2%	3.4%	3.3%	3.3%
Lebanon	5.5%	5.3%	0.7%	1.6%	2.5%	3.1%
Libya	9.3%	8.9%	-6.9%	n/a	17.6%	86.7%
Morocco	10.0%	4.5%	6.0%	2.2%	3.8%	5.1%
Oman	7.8%	11.3%	13.6%	13.6%	14.3%	15.1%
Qatar	11.5%	19.1%	13.5%	14.1%	13.9%	13.7%
Saudi Arabia	7.9%	7.3%	6.3%	5.1%	6.0%	6.8%
Syria	7.7%	6.6%	-14.6%	-20.0%	-20.0%	-20.0%
Tunisia	3.9%	6.4%	3.1%	3.2%	3.7%	4.1%
United Arab Emirates	10.4%	12.2%	1.8%	2.1%	2.1%	2.0%
Yemen	7.9%	12.5%	-1.1%	2.5%	2.3%	2.1%
South Asia						
Bangladesh	13.5%	11.6%	10.0%	10.3%	10.4%	10.5%
India	5.1%	7.4%	9.2%	9.7%	9.2%	8.6%
Nepal	10.5%	5.3%	7.3%	6.1%	6.0%	5.9%
Pakistan	7.5%	0.2%	0.2%	-1.6%	-0.1%	1.0%
Sri Lanka	6.6%	3.2%	3.8%	2.2%	2.1%	2.0%

Table A3.2: Comparison of Forecast Errors across Countries

Country	5 year forecast horizon		10 year forecast horizon	
	sMAPE	MdRAE	sMAPE	MdRAE
Sub-Saharan Africa				
Angola	0.09	0.34	0.08	0.26
Benin	0.29	0.7	0.2	0.44
Botswana	0.34	0.66	0.15	0.51
Cameroon	0.01	0.08	0.22	0.88
Congo	0.38	0.89	0.24	0.39
DRC	0.02	0.17	0.08	0.58
Eritrea	0.02	0.23	0.07	0.68
Ethiopia	0.06	0.26	0.38	1.38
Gabon	0.04	0.86	0.03	0.98
Ghana	0.19	0.71	0.13	0.97
Ivory Coast	0.03	0.29	0.03	0.38
Kenya	0.03	0.45	0.15	1.08
Mauritius	0.01	1.02	0.01	0.07
Mozambique	0.06	1.14	0.07	0.78
Namibia	0.07	0.26	0.07	0.99
Nigeria	0.08	0.14	0.08	0.31
Senegal	0.02	0.37	0.03	0.26
South Africa	0.02	0.23	0.03	0.46
Sudan	0.04	0.18	0.13	0.6
Tanzania	0.02	0.16	0.06	0.31
Togo	0.19	0.36	0.15	0.61
Zambia	0.02	0.18	0.05	1.09
Zimbabwe	0.04	0.51	0.08	0.58
East Asia and Pacific				
Brunei	0.01	0.44	0.04	0.3
Cambodia	0.17	0.84	n/a	n/a
China	0.04	0.38	0.06	0.3
Indonesia	0.02	0.13	0.02	0.26
Malaysia	0.03	0.23	0.05	0.36
Mongolia	0.05	0.47	0.04	0.43
Myanmar	0.11	0.84	0.14	2.29
North Korea	0.06	0.62	0.08	0.71
Philippines	0.02	0.49	0.02	0.22
Singapore	0.02	1.03	0.01	0.61
Thailand	0.02	0.96	0.02	0.2
Vietnam	0.02	0.07	0.02	0.09

Table A3.3: Comparison of Forecast Errors across Countries (continued)

Country	5 year forecast horizon		10 year forecast horizon	
	sMAPE	MdRAE	sMAPE	MdRAE
Europe and Central Asia				
Albania	0.17	0.3	0.26	0.85
Armenia	0.05	0.29	0.07	0.35
Azerbaijan	0.06	0.57	0.09	0.59
Belarus	0.06	0.74	0.08	0.33
Bosnia and Herzegovina	0.08	0.16	0.07	0.21
Bulgaria	0.03	0.73	0.03	0.56
Croatia	0.1	0.66	0.09	1.08
Cyprus	0.05	0.2	0.05	0.31
Georgia	0.04	0.33	0.09	0.35
Hungary	0.08	0.64	0.04	0.34
Kazakhstan	0.02	0.23	0.02	0.08
Kyrgyzstan	0.09	0.6	0.11	0.57
Latvia	0.07	0.29	0.11	0.39
Lithuania	0.28	0.43	0.23	0.79
Macedonia	0.05	0.66	0.06	0.64
Malta	0.04	0.4	0.06	1.02
Moldova	0.02	0.1	0.02	0.05
Poland	0.03	0.42	0.03	0.96
Romania	0.04	0.49	0.03	0.48
Russia	0.02	0.3	0.02	0.17
Serbia	0.01	0.6	0.02	0.33
Tajikistan	0.04	0.46	0.07	0.71
Turkey	0.05	1.06	0.09	0.63
Turkmenistan	0.01	0.06	0.02	0.05
Ukraine	0.05	0.8	0.04	0.22
Uzbekistan	0.01	0.12	0.02	0.68
Latin America and Caribbean				
Argentina	0.03	0.29	0.09	0.66
Bolivia	0.02	0.12	0.11	0.83
Brazil	0.01	0.08	0.11	1.22
Chile	0.03	0.52	0.04	0.16
Colombia	0.01	0.58	0.02	0.46
Costa Rica	0.01	0.65	0.02	0.44
Cuba	0.03	0.64	0.03	0.9
Dominican Republic	0.02	0.94	0.08	0.53
Ecuador	0.04	0.31	0.17	1.25
El Salvador	0.03	0.41	0.07	0.53
Guatemala	0.02	0.58	0.07	0.39
Haiti	0.39	0.92	0.2	1.14
Honduras	0.02	0.95	0.12	0.63
Jamaica	0.2	0.4	0.27	0.86

Table A3.3: Comparison of Forecast Errors across Countries (continued)

Country	5 year forecast horizon		10 year forecast horizon	
	sMAPE	MdRAE	sMAPE	MdRAE
Latin America and Caribbean (continued)				
Mexico	0.02	0.65	0.02	0.31
Nicaragua	0.04	0.68	0.02	0.3
Panama	0.04	0.54	0.03	0.39
Paraguay	0.02	0.47	0.03	0.52
Peru	0.02	0.19	0.02	0.13
Trinidad & Tobago	0.01	0.22	0.07	0.56
Uruguay	0.06	0.94	0.15	0.51
Venezuela	0.01	0.42	0.05	0.82
Middle East and North Africa				
Algeria	0.08	0.58	0.14	1.24
Bahrain	0.01	0.99	0.07	0.47
Egypt	0.01	0.22	0.02	0.12
Iran	0.01	0.15	0.02	0.21
Iraq	0.26	0.95	0.16	0.66
Israel	0.02	0.61	0.02	0.55
Jordan	0.02	0.51	0.15	0.82
Kuwait	0.01	0.22	0.04	0.32
Lebanon	0.05	0.31	0.06	0.99
Libya	0.07	0.3	0.22	1.15
Morocco	0.05	0.76	0.05	0.35
Oman	0.05	0.24	0.06	0.38
Qatar	0.02	0.11	0.03	0.17
Saudi Arabia	0.06	0.49	0.04	0.36
Syria	0.1	0.07	0.07	0.06
Tunisia	0.02	0.29	0.05	1.13
United Arab Emirates	0.05	0.21	0.05	0.17
Yemen	0.08	0.46	0.09	0.21
South Asia				
Bangladesh	0.01	0.05	0.07	0.27
India	0.02	0.18	0.06	0.52
Nepal	0.02	0.18	0.03	0.3
Pakistan	0.01	0.06	0.04	0.47
Sri Lanka	0.03	0.8	0.07	0.51