Metropolitan Econometric Electric Utility Forecast Accuracy

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Abstract
El Paso Electric Company (EPEC) is the sole commercial electricity provider for two metropolitan economies in the southwestern desert region of the United States: El Paso, Texas and Las Cruces, New Mexico. A publicly traded corporation, EPEC employs a structural econometric system of equations model to forecast energy sales for various customer classes. Although the modeling system has provided reliable inputs to annual corporate planning efforts at EPEC, its historical track record has not previously been formally assessed for forecast accuracy. Both descriptive and inferential statistics are used to evaluate the EPEC model's forecasting performance. Results indicate that accurate prediction of electricity usage in this service area is an elusive target. Those results are similar to what has been documented for other regional economic variables.

Key Words: Energy forecasting, Regional forecasting, Disaggregation, Statistical tests, Forecast accuracy evaluation

1. Introduction

Electricity sales forecasts are typically utilized for planning of generation capacity as well as for revenue and expenditure planning at electric utility companies. It has long been recognized that sales volumes are affected by numerous factors such as income growth, prices, and weather (Taylor, 1975; Lee and Chiu, 2011). For border economies, currency market fluctuations plus international, regional, and local business cycles also influence the demand for electricity (Fullerton, 1998). The service territory of EPEC, the Rio Grande Valley of far west Texas and southern New Mexico, is affected by all of these factors. Weather often affects energy sales in this region during summer months when maximum daily temperatures can exceed 100 degrees Fahrenheit (37.8 degrees Celsius) for multiple consecutive days throughout the EPEC service area.

Similar to many public utilities, EPEC has long utilized econometric models to forecast its customer base and energy sales. Those forecasts are employed in annual corporate budgeting exercises as well as medium- and long-term generation, transmission, and distribution network capacity planning efforts. Separate models and forecasts are developed for each of the metropolitan economies in the EPEC service area: El Paso, Texas and Las Cruces, New Mexico. Although econometric forecasts have been prepared by corporate economists at EPEC for more than 35 consecutive years, the historical track record of this ongoing enterprise has not previously been formally assessed. EPEC and other electric utilities are not unique in this regard and a similar paucity of empirical evidence also exists for natural gas companies and municipal water utilities (one recent attempt to address this issue for water is Fullerton and Molina, 2010).

This paper attempts to partially fill this gap in the applied economics literature by analyzing the predictive accuracy associated with the annual econometric forecasts developed by the corporate planning department at El Paso Electric Company. EPEC is an investor-owned private utility whose service area covers parts of Texas and New Mexico with a long history of econometric forecasting analysis. Because of its multi-state service area, the data set analyzed is a fairly broad one. It includes residential, small commercial and industrial, large commercial and industrial, and non-profit categories. That results in eight different sets of megawatt hour (MWH) electricity usage forecasts, one for each customer category in each of the two states. These forecasts can then be combined to estimate aggregate regional electricity demand. The sample is also interesting because it encompasses both a large metropolitan economy (El Paso, Texas) and a small metropolitan economy (Las Cruces, New Mexico). The latter is potentially useful because prior studies have shown that regional differences in electricity consumption patterns within countries and among sectors may be substantial (Chern and Just, 1980; Badri, 1992; Winebrake and Sakva, 2006; Contreras et al., 2009).

Subsequent sections of the study are organized as follows. The next section provides an overview of prior electricity demand and regional econometric studies. Data and methodology are discussed next. Empirical results are summarized in the fourth section. Concluding observations and suggestions for future research make up the final part of the paper.

2. Literature Review

Research on the demand for electricity occurs in a wide variety of contexts. Businesses rely on the accuracy of these models to help improve planning efforts while public institutions use both estimation and simulation results from these models to help design more effective policies (Brown and Koomey, 2003). Many research efforts support generation, transmission, and distribution grid investment decisions and management efforts (Fatai et al., 2003; Mohamed and Bodger, 2005; Bogetic and Fedderke, 2006). Much of this research has been conducted using national data aggregates (Contreras et al., 2009; Athukorala and Wilson, 2010), but a fair amount has also been directed toward regional and metropolitan electricity markets, as well (Roth, 1981; Fullerton et al., 2012).

Favorable forecasting results have been documented for many of the regional models (Leung and Miklius, 1994; Arsenault et al., 1995; Sharma and Nair, 2002). Econometric evidence generally supports breaking down total electricity demand into residential, commercial, industrial, and non-profit or similar categories (Winebrake and Sakva, 2006). As noted above, explanatory regressor variables frequently include population, personal income, average price of electricity, average price of natural gas as a substitute good, climate variables, and other economic indicators. Predictive accuracy is influenced by a wide variety of factors that include technological change as well as reverberative simulation errors associated with regressor series forecasts (Smil, 2000; Craig et al., 2002; Linderoth, 2002; O'Neill and Desaib, 2005). Industrial electricity use may generally be more difficult to predict than either residential or commercial demand (Thoma, 2004; Dilaver and Hunt, 2011).

El Paso Electric Company has a fairly long history of short-, medium-, and long-range econometric forecasting analysis in support of its corporate planning efforts. Those exercises involve developing load forecasts for one large metropolitan economy (El Paso, Texas) and one small metropolitan economy (Las Cruces, New Mexico). To date, the historical accuracy of those projections has not been formally assessed. Because both urban economies are characterized by relatively high unemployment rates and fairly substantial historical population estimate revisions, accurate econometric forecasts for this region may be difficult to obtain (Charney and Taylor, 1984; West, 2003; Fullerton and Molina, 2010). The track record of EPEC as a privately owned electric utility is also of interest because most of the prior electricity forecast records analyzed have been for either academic research centers or public sector agencies. It is also of interest because data sets of this nature are very difficult to assemble (Lady, 2010). Although some internal company documentation may exist, corporate sector econometric predictive accuracy for electricity demand remains largely uncharted. This paper attempts to at least partially fill that gap in the energy economics literature.

3. Data and Methodology

This study analyzes the accuracy of load forecasts produced for the 1999-2010 period using the El Paso Electric econometric modeling system. Each year during the sample period a complete set of 10-year forecasts is produced by EPEC for short- and medium-range planning purposes. To provide sufficient observations for statistical analysis of the data, the sets of forecasts produced each year are pooled together, resulting in a sample of 78 previously utilized structural econometric forecast observations for each variable included in the empirical accuracy analysis. The EPEC service area is a challenging one to model and analyze. A key feature of the region is that it is geographically adjacent to an international border and measurably influenced by economic conditions in Mexico (Fullerton, 2001; Fullerton and Novela, 2010).

Table 1 lists the variables for which the forecast accuracy assessments are carried out. In all, there are nine variables included in the sample. Four of the variables are for the El Paso portion of the EPEC service area, four are for the Las Cruces portion of the service area, and one is for both areas combined. For each geographic segment, the usage data are measured in MWH for each of four customer categories. From a utility planning perspective, separate examination of the out-of-sample simulation performances of the MWH usage projections are generally utilized for short- and medium-range budget and operational management exercises. Medium- and long-term transmission and generation capacity planning efforts also rely upon usage forecasts. As has been documented for other public utilities, the relative predictive accuracies of each modeling category may vary (Fullerton and Molina, 2010).

Table 1. Variable Names and Units of Measure

Variable	*Definition and Unit of Measure*
ERMWH	El Paso Residential Electricity Usage in Megawatt Hours
ESMWH	El Paso Small Commercial & Industrial Elec. Usage in Megawatt Hours
ELMWH	El Paso Large Commercial & Industrial Elec. Usage in Megawatt Hours
EGMWH	El Paso Govt. & Non-Profit Electricity Usage in Megawatt Hours
LRMWH	Las Cruces Residential Electricity Usage in Megawatt Hours
LSMWH	Las Cruces Small Commercial & Ind. Elec. Usage in Megawatt Hours
LLMWH	Las Cruces Large Commercial & Ind. Elec. Usage in Megawatt Hours

LGMWH	Las Cruces Govt. & Non-Profit Electricity Usage in Megawatt Hours
TMWH	Total Combined EPEC Electricity Usage in Megawatt Hours

Table 2 summarizes the historical values for each of the variables in the sample. Period coverage is from 1980 through 2010. Good variability is observed among the different variables comprising the sample. The greatest annual average MWH consumption category in El Paso is small commercial and industrial. The fastest growing MWH categories in that urban economy are residential consumption and government and non-profit consumption. In Las Cruces, the largest annual average MWH consumption category is residential. It is also the most rapidly growing consumption category in that metropolitan economy.

Table 2. Historical Usage Data Descriptive Statistics

Series	*Mean*	*Std. Dev.* [a]	*Maximum*	*Minimum*	*CV* [b]	*CAGR* [c]
ERMWH	1,179,799	775,688	1,853,887	752,005	0.657	0.0293
ESMWH	1,367,694	690,513	1,795,593	819,059	0.505	0.0256
ELMWH	919,334	295,142	1,267,038	604,047	0.321	0.0171
EGMWH	715,921	468,819	1,119,842	456,246	0.655	0.0293
LRMWH	385,098	310,968	654,947	214,482	0.808	0.0366
LSMWH	328,998	236,068	499,944	166,094	0.718	0.0362
LLMWH	52,674	34,042	108,685	16,043	0.646	0.0431
LGMWH	348,327	140,406	427,755	223,983	0.403	0.0207
TMWH	5,297,845	2,951,647	7,434,173	3,259,915	0.557	0.0269

Notes:
[a] Std. Dev.is the standard deviation of the variable.
[b] CV is the coefficient of variation calculated as the ratio of the standard deviation to the mean.
[c] CAGR is the 1980-2010 compound annual growth rate of the variable.

The accuracy performances of the nine different sets of MWH econometric forecasts recorded by El Paso Electric are assessed relative to random walk and random walk with drift forecasts for each variable in the sample. Random walk forecasts have frequently been shown to provide stiff competition for structural econometric model projections of regional variables. The latter circumstance has also been documented for the Borderplex region that comprises the EPEC service area (Fullerton and Molina, 2010; Fullerton and Novela, 2010). Given the high rates of joblessness in El Paso and Las Cruces, plus the degree to which preliminary population data are revised, it is very possible that the random walk forecasts may outperform the annual econometric forecasts generated by the utility (Charney and Taylor, 1984; West, 2003).

The descriptive metrics utilized to assess the accuracy of the EPEC econometric forecasts relative to the random walk benchmarks are root mean square error (RMSE) statistics and Theil inequality coefficients. RMSE provides a measure of the deviation of forecasted values from the actual values for a particular variable (Pindyck and Rubinfeld, 1998). RMSE can be hard to interpret because it is unbounded from above. Given that, the Theil inequality coefficient and its three second moment proportions are also employed due to ease of interpretation (Stekler, 1968). Based on RMSE calculations, the Theil inequality coefficient ranges in value from zero to one. Zero indicates absolute forecast accuracy (Leuthold, 1975). The calculation of RMSEs is shown in Equation (1). In Equation (1), Y_n^s represents the out-of-sample forecast value of a variable Y in period n and Y_n^a represents its actual value. N is the number of forecast observations in the sample. For purposes of this study, Y is MWH consumption for a given rate class.

$$\text{RMSE} = \sqrt{1/N \sum_{n=1}^{N} (Y_n^s - Y_n^a)^2} \tag{1}$$

Theil inequality coefficients are also known as U-statistics. The manner in which they are calculated forces them to range from zero to one. The closer U is to zero, the better the predictive accuracy of the model, while the closer it is to one, the worse its predictive performance (Leuthold, 1975). Equation (2) shows how to calculate a U-statistic.

$$U = \sqrt{1/N \sum_{n=1}^{N} (Y_n^s - Y_n^a)^2} \,/ \left(\sqrt{1/N \sum_{n=1}^{N} (Y_n^s)^2} + \sqrt{1/N \sum_{n=1}^{N} (Y_n^a)^2}\right) \tag{2}$$

Theil U statistic second moments can be decomposed into 3 separate proportions of inequality: U^M, U^S, and U^C. They, respectively, represent bias, variance, and covariance proportions. As indicated in Equation (3), the inequality coefficient proportions sum to one.

$$U^M + U^S + U^C = 1 \tag{3}$$

The bias proportion, U^M, measures systematic error based on the difference between the average forecast values from the model and the actual values for the dependent variable. The optimal value of U^M is zero, in which case no bias is present in the out-of-sample simulations for the variable of interest. Equation (4) summarizes the formula for the bias proportion of the U-statistic.

$$U^M = (\overline{Y^s} - \overline{Y^a})^2 / (1/N \sum_{n=1}^{N} (Y_n^s - Y_n^a)^2) \tag{4}$$

The variance proportion, U^S, shown in Equation (5) measures the ability of the projections to mimic the variability of the actual values. The standard deviations of Y_n^s and Y_n^a are represented by σ_s and σ_a respectively. The optimal value of U^S is zero, in which case the fluctuations of the simulated values are identical to those of the actual value. The covariance proportion, U^C, shown in Equation (6), measures unsystematic forecast errors. The correlation coefficient between Y_n^s and Y_n^a is represented by ρ. U^C is rarely expected to be zero since out-of-sample simulations will probably never be perfect. Given that, the optimal value for U^C is one so that U^M and U^S can equal zero. Thus, the preferred values of the proportions are: $U^M = U^S = 0$ and $U^C = 1$ (Pindyck and Rubinfeld, 1998).

$$U^S = (\sigma_s - \sigma_a)^2 / (1/N \sum_{n=1}^{N} (Y_n^s - Y_n^a)^2) \tag{5}$$

$$U^C = (2(1-\rho)\sigma_s \sigma_a) / (1/N \sum_{n=1}^{N} (Y_n^s - Y_n^a)^2) \tag{6}$$

Theil inequality statistics are useful, but are descriptive, only. In general, error structures associated with forecasting make statistical inference difficult, so descriptive measures are frequently utilized. When degree of freedom constraints are not binding, some formal tests can be employed (Ashley et al., 1980; Diebold and Mariano, 1995). The error differential regression is designed to test a null hypothesis of mean square error (MSE) equality between competing sets of forecasts (Ashley et al., 1980). This test helps further assess the accuracy performance of the structural forecasts relative to the random walk benchmark. The null hypothesis tested is shown in Equation (7).

$$H_0\text{: MSE}(e_1) = \text{MSE}(e_2), \tag{7}$$

where MSE refers to the respective mean-squared error of two competing forecast errors, e_1, e_2. In this regard, MSE(e_1) represents the mean square error for a random-walk benchmark and MSE(e_2) represents the mean square error for the EPEC electricity usage and customer forecasts.

By defining

$$\Delta_t = e_{1t} - e_{2t} \text{ and } \sum{}_t = e_{1t} + e_{2t}, \tag{8}$$

Equation (7) can be re-expressed in the following manner,

$$\text{MSE}(e_1) - \text{MSE}(e_2) = [\text{cov}\ (\Delta,\textstyle\sum)] + [\text{m}(e_1)^2 - \text{m}(e_2)^2], \tag{9}$$

where cov denotes sample covariance for the simulation period and m denotes sample mean. Forecasts from the EPEC econometric model will be judged as superior if the joint null hypothesis that $\mu(\Delta) = 0$ and cov $(\Delta,\sum) = 0$ can be rejected in favor of the alternative hypotheses discussed below.

Two regression equations can be extracted from (7) to test if the MSEs differ significantly in value. The structure of the regression equation used to test the null hypothesis depends on the signs of the error means. When the error means have the same sign, the following regression equation is used to test the joint null hypothesis:

$$\Delta_t = \beta_1 + \beta_2[\textstyle\sum_t - \text{m}(\sum_t)] + u_t, \tag{10}$$

where u_t is a randomly distributed error term. The test for $\mu(\Delta) = 0$ depends on the interpretation of β_1, while the test for cov $(\Delta,\sum) = 0$ is determined by the interpretation of β_2.

A positive value for β_2 will always indicate that the variance of the random walk forecast errors (e_1) is larger than the variance of the EPEC structural equation model forecast errors (e_2). Given that, a significantly positive β_2 will indicate EPEC structural equation model superiority. The interpretation of β_1 will depend on the signs of the error means. When both error means are positive, EPEC econometric forecast superiority results when the joint null hypothesis that $\beta_1 = \beta_2 = 0$ is rejected in favor of the alternative hypothesis that both are non-negative and at least one is positive. If either β_1 or β_2 are significantly negative, the EPEC econometric forecast cannot be considered more accurate than its random walk benchmark. If one of the estimates is insignificantly negative and the other is positive, a one tailed t-test can be performed to test for significance. Lastly, if both estimates are positive, an F-test can be used to test if they are jointly different from zero. However, because the F-test does not take sign into account on 4-pronged test results, the true significance that both estimates are positive will not be more than half the probability obtained from the F distribution (Ashley et al., 1980).

When both error means are negative, (10) is still used to test (7) but the interpretation of β_1 changes. In this case, if β_1 is found to be significantly negative, and

β_2 is either insignificant or significantly positive, the EPEC structural equation forecasts are most accurate. Conversely, a significantly positive β_1 will indicate random walk superiority.

If the error means of the forecasts have opposite signs, a different regression equation must be employed to test (7). For such a case, the dependent variable becomes the sum of the forecast errors and the regression equation is:

$$\sum_t \;=\; \beta_1 + \beta_2[\mathit{\Delta}_t - \mathrm{m}(\mathit{\Delta}_t)] + u_t \tag{11}$$

Once again, if $\beta_1 = \beta_2 = 0$, the test fails to reject (7). As before, interpretation of the β_2 coefficient is the same, but interpretation of the β_1 depends on which of the error means is positive and which is negative. One possibility is that the random walk counterpart has a negative error mean and the EPEC forecast has a positive error mean. In this case, β_1 significantly negative, with β_2 insignificant or significantly positive, points to superior EPEC structural equation model forecast accuracy. Further, if β_1 is insignificant while β_2 is significantly positive, the EPEC structural model is still deemed superior. Lastly, if β_1 is significantly positive, or β_2 is significantly negative, the random walk forecasts are most accurate. The final case is when the random walk extrapolation has a positive error mean and the EPEC forecast has a negative error mean. Under these circumstances, a significantly positive β_1 with a significantly positive or insignificant β_2 points to EPEC accuracy. Alternatively, if either of the equation parameters is significantly negative, the random walk predictions are favored (Ashley et al., 1980; Kolb and Stekler, 1993).

Tables 3 and 4 can be used to determine which, if either, of two sets of forecasts is more accurate based on error differential regression results. To make a determination, it is necessary to know the algebraic sign of the mean of the random walk (RW) forecast errors. If the mean is positive, then Table 3 should be used; if it is negative then Table 4 is applicable. The block of cells on the lower right-hand side of the tables indicates which forecasting model dominates given the signs and statistical significance of both estimated parameters.

Table 3. Decision Rules when the Random Walk Error Mean is Positive

$m(e_1) > 0$		$\beta_1 > 0$		$\beta_1 < 0$	
		β_1 *significant*	β_1 *insignificant*	β_1 *significant*	β_1 *insignificant*
$\beta_2 > 0$	β_2 *significant*	EPEC	EPEC	Indeterminate	EPEC
	β_2 *insignificant*	EPEC	Indeterminate	RW	Indeterminate
$\beta_2 < 0$	β_2 *significant*	Indeterminate	RW	RW	RW
	β_2 *insignificant*	EPEC	Indeterminate	RW	Indeterminate

Table 4. Decision Rules when the Random Walk Error Mean is Negative

$m(e_1) < 0$		$\beta_1 > 0$		$\beta_1 < 0$	
		β_1 *significant*	β_1 *insignificant*	β_1 *significant*	β_1 *insignificant*
$\beta_2 > 0$	β_2 *significant*	Indeterminate	EPEC	EPEC	EPEC
	β_2 *insignificant*	RW	Indeterminate	EPEC	Indeterminate
$\beta_2 < 0$	β_2 *significant*	RW	RW	Indeterminate	RW
	β_2 *insignificant*	RW	Indeterminate	EPEC	Indeterminate

4. Empirical Results

As shown in Table 5, only one of the eight customer category econometric forecasts is judged as superior using the descriptive statistics described above. In four cases, the random walk with drift forecasts are most accurate. In the remaining three categories, the random walk extrapolations have the lowest RMSE and U-statistics. However, when electricity consumption is aggregated across customer categories and states, the EPEC forecasts outperform the random walk benchmarks. The relative accuracy of the aggregate, region-wide econometric forecasts of electricity demand likely constitutes an important consideration for EPEC corporate planners in assessing the overall performance of the forecasting model. While electricity demand must be disaggregated into jurisdictional components for reasons related to regulatory oversight, EPEC administrators also evaluate system-wide demand when making decisions about expanding generation capacity and purchasing inputs.

In all nine cases, the U-statistics for the EPEC econometric forecasts are fairly low, less than 0.3. Bias is not found to be a problem, with UM statistics greater than 0.5 occurring in only three instances. Beyond that, the EPEC forecasts do a very good job of replicating cyclical upswings and downswings in electricity usage in both metropolitan economies, never exceeding 0.3 for any of the variables in the sample. The majority of the EPEC structural econometric forecast errors are, thus, attributable to unpredictable sources of variation in the two service areas. The relatively good performance of the random walk benchmarks is similar to what has been previously documented for other regional econometric forecasts (Fullerton et al., 2001; Fullerton and Molina, 2010; Fullerton and Novela, 2010). The lesson for EPEC economists, and analysts at other utilities, is that recent trends are important to monitor both quantitatively and qualitatively. Reliance on random walk forecasting is probably not a viable strategy because scenario analyses are not really feasible and no single random walk procedure is dominant.

RMSE and U-statistics are also calculated for a reduced sample of forecasts that includes only periods of pronounced business cycle fluctuations marked by distinct turning points in United States economic activity. During the sample period, macroeconomic activity peaked twice, first in March 2001 and again in December 2007. Troughs occurred in November 2001 and June 2009. Because some of these turning points occurred during the first or last quarter of a particular year, the reduced sample includes the contiguous years of 2000, 2002, and 2008 in addition to those years that include at least one peak or trough. The results are largely similar to those reported in Table 5. The only noteworthy difference is that the EPEC forecasts become slightly more accurate than the random walk alternatives in the case of El Paso area electricity sales to governmental and non-profit entities.

Table 5. Theil Inequality Coefficient Accuracy Comparisons [a]

Variable	*Model*	*RMSE*	*U*	U^M	U^S	U^C
ERMWH	EPEC	108,789	0.035	0.504	0.049	0.447
	RW	282,922	0.095	0.698	0.006	0.296
	RW Drift	**59,801**	**0.019**	0.159	0.091	0.750
ESMWH	EPEC	130,566	0.037	0.574	0.212	0.215
	RW	**113,355**	**0.034**	0.672	0.004	0.324
	RW Drift	139,865	0.040	0.463	0.296	0.241
ELMWH	EPEC	109,909	0.051	0.281	0.022	0.697
	RW	**103,145**	**0.047**	0.402	0.018	0.580
	RW Drift	197,615	0.087	0.687	0.031	0.282
EGMWH	EPEC	71,717	0.037	0.000	0.053	0.947
	RW	162,630	0.090	0.660	0.065	0.275
	RW Drift	**64,555**	**0.034**	0.125	0.113	0.762
LRMWH	EPEC	45,988	0.042	0.544	0.002	0.455
	RW	116,743	0.112	0.711	0.003	0.286
	RW Drift	**40,775**	**0.035**	0.896	0.010	0.094
LSMWH	EPEC	**23,316**	**0.025**	0.105	0.300	0.596
	RW	65,087	0.074	0.696	0.013	0.290
	RW Drift	39,950	0.042	0.116	0.386	0.498
LLMWH	EPEC	40,775	0.222	0.008	0.218	0.774
	RW	**36,931**	**0.209**	0.188	0.082	0.731
	RW Drift	37,414	0.219	0.024	0.138	0.838
LGMWH	EPEC	25,872	0.031	0.145	0.192	0.664
	RW	37,542	0.048	0.653	0.001	0.347
	RW Drift	**18,119**	**0.022**	0.060	0.116	0.824
TMWH	EPEC	**211,220**	**0.015**	0.084	0.167	0.749
	RW	710,680	0.054	0.701	0.002	0.297
	RW Drift	332,497	0.024	0.626	0.097	0.277

[a] Boldface type indicates best predictive accuracy.

Of course, the accuracy results in Table 5 are descriptive. Estimation results for the error differential regression analyses for the random walk (without drift) comparative forecasts are summarized in Table 6. A 5-percent significance criterion is used to classify the regression results as favoring either the random walk (RW) or the EPEC forecasts. The statistical test results favor the EPEC forecasts in six of the nine categories for which the MWH projections are analyzed. In two categories the analysis yields indeterminate results and in only one is the random walk judged to be more accurate by a statistically significant margin. For total MWH forecast accuracy, the EPEC econometric forecasts are also found to be most accurate by a statistically significant margin.

Table 6. Structural Econometric vs. Random Walk Forecasts
Mean Square Error differential regression results [a, b, c, d]

Variable	*β_1 (t-statistic)*	*β_2 (t-statistic)*	*F-statistic (prob.)*	*Most accurate*
ERMWH (Both error means negative)	-159,138.5 (-23.370)	0.367 (12.041)	144.995 (0.000)	EPEC
ESMWH (EPEC error mean positive; RW error mean negative)	5,945.2 (0.729)	-0.176 (-2.846)	8.099 (0.006)	RW
ELMWH (Both error means positive)	7,108.2 (0.670)	-0.109 (-1.500)	2.249 (0.138)	Indeterminate
EGMWH (EPEC error mean positive; RW error mean negative)	-130,740.7 (-8.410)	0.478 (2.758)	7.605 (0.007)	EPEC
LRMWH (Both error means negative)	-64,569.4 (-23.260)	0.365 (11.855)	140.534 (0.000)	EPEC
LSMWH (EPEC error mean positive; RW error mean negative)	-46,774.7 (-10.725)	0.462 (4.405)	19.405 (0.000)	EPEC
LLMWH (Both error means negative)	-12,390.3 (-6.939)	-0.104 (4.199)	17.635 (0.000)	Indeterminate
LGMWH (EPEC error mean positive; RW error mean negative)	-20,499.4 (-4.599)	-0.139 (-0.763)	0.582 (0.448)	EPEC
TMWH (EPEC error mean positive; RW error mean negative)	-533,917.8 (-11.791)	0.769 (6.424)	41.264 (0.000)	EPEC

Notes:
[a] Ordinary least squares is utilized for parameter estimation.
[b] The sample includes 78 observations.
[c] Dependent variable is $\Delta_t = e_{1t} - e_{2t}$ when the signs of the forecast error means are the same.
[d] Dependent variable is $\sum_t = e_{1t} + e_{2t}$ when the signs of the forecast error means are opposite.

Table 7. Structural econometric vs. random walk with drift forecasts
Mean Square Error differential regression results [a, b, c, d]

Variable	*β_1 (t-statistic)*	*β_2 (t-statistic)*	*F-statistic (prob.)*	*Most accurate*
ERMWH	53,346.4	-0.223	11.355	RW with Drift
(Both error means negative)	(7.102)	(-3.370)	(0.001)	
ESMWH	-3,742.9	0.122	3.478	EPEC
(Both error means positive)	(-0.351)	(1.865)	(0.066)	
ELMWH	105,456.8	0.121	2.719	EPEC
(Both error means positive)	(8.380)	(1.649)	(0.103)	
EGMWH	-21,471.6	-0.195	2.309	RW w/ Drift
(Both error means positive)	(-1.912)	(-1.519)	(0.133)	
LRMWH	4,682.8	-0.804	73.665	RW w/ Drift
(EPEC error mean negative; RW Drift error mean positive)	(1.593)	(-8.583)	(0.000)	
LSMWH	6,077.6	0.333	32.709	EPEC
(Both error means positive)	(1.981)	(5.719)	(0.000)	
LLMWH	330,413.9	0.748	335.115	EPEC
(EPEC error mean negative; RW Drift error mean positive)	(47.737)	(18.306)	(0.000)	
LGMWH	-5,404.5	-0.214	9.112	RW w/ Drift
(EPEC error mean negative; RW Drift error mean positive)	(-2.173)	(-3.019)	(0.003)	
TMWH	201,809.0	0.005	0.003	EPEC
(Both error means positive)	(7.008)	(0.054)	(0.957)	

Notes:
[a] Ordinary least squares is utilized for parameter estimation.
[b] The sample includes 78 observations.
[c] Dependent variable is $\Delta_t = e_{1t} - e_{2t}$ when the signs of the forecast error means are the same.
[d] Dependent variable is $\sum_t = e_{1t} + e_{2t}$ when the signs of the forecast error means are opposite.

The estimation results for the error differential regression equations using random walk with drift benchmarks are shown in Table 7. In four of the categories, the random walk with drift prediction errors are found to be smaller than those of the EPEC econometric forecasts. In the remaining five categories, the EPEC econometric forecasts exhibit statistically superior track records over the course of the sample period. The latter include total MWH sales forecasts for the EPEC system as a whole.

Taken together, the results in Tables 6 and 7 indicate that there are only two individual categories, Las Cruces small commercial and industrial demand and total aggregate electricity consumption, for which EPEC forecast accuracy is statistically superior to that of both random walk benchmarks. This is not an uncommon outcome for other types of regional econometric forecasts, but is one of the first times it has been documented for metropolitan electricity usage customer class projections. While that raises a cautionary flag for utilities employing econometric models for planning purposes, the error differential regression outcomes also document overall statistical superiority by the EPEC structural forecasts relative to both benchmarks. While any given rate class may be difficult to model and simulate, the aggregate econometric track record at EPEC compares favorably to those of the selected benchmarks.

Results for the EPEC econometric forecasts among customer classes for El Paso and Las Cruces indicate that this utility faces many of the same regional and sectoral forecast difficulties that confront analysts shouldering similar planning challenges. Although there are some areas in regional forecasting in which econometric models do comparatively well (employment and income), metropolitan electricity projections seem to be an area in which relative accuracy for individual customer categories is somewhat elusive. In the case of EPEC, however, total MWH sales forecasts have been anticipated with a fair amount of relative accuracy. Whether the results reported above are representative of other electric utilities is not known at this juncture, but this is a question that probably merits more scrutiny. Long standing regulatory and utility planning requirements effectively mean that econometric and other statistical means of forecasting electricity usage will be employed for many years (Gloze, 1973). Additional assessment of the historical track records for these efforts, including those for utilities whose services areas are not located along international borders, would be useful.

5. Conclusion

Electricity sales forecasts are commonly utilized for generation planning and budget year planning activities. While many utility companies have formal forecasting programs that date back several years or more, very few of these efforts have been assessed for historical accuracy relative to competitive benchmarks. This study attempts to partially fill that gap in the energy economics literature by taking advantage of well-documented forecast records across multiple customer categories in two service areas where El Paso Electric Company operates.

The service areas are the metropolitan economies of El Paso, Texas and Las Cruces, New Mexico. The customer classes for which historical forecast data are assembled are residential, small commercial and industrial, large commercial and industrial, and government and non-profit. Benchmarks utilized are random walks and random walks with drift. The latter are selected because they have generally been found to provide exacting competition to regional forecasts and are not difficult to generate.

Two methods are employed to assess the El Paso Electric track record. One is descriptive and the other has formal hypothesis tests associated with it. In both cases, random walk benchmarks are found to be more accurate than structural econometric forecasts for many of the customer categories in El Paso and Las Cruces. The strong performance of random walk forecasts suggests the importance of closely monitoring recent trends when developing corporate outlooks. From an overall system planning perspective, it is also important to note that the EPEC structural econometric projections are found to be more accurate than those of the benchmarks for aggregate electricity demand in the entire service region.

Given the accuracy patterns documented for other categories of regional economic forecasts, the results obtained in this effort are in agreement with what is indicated by prior research. There have been, to date, however, relatively few accuracy assessments such as this one conducted for specific electric utilities. It is not known, therefore, whether the results discussed above are representative of the industry at large. Additional research regarding historical forecasting efforts at other electric companies will prove helpful in examining this topic.

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