Do Electricity Prices Reflect Economic Fundamentals?: Evidence from the California ISO

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Abstract

In a truly smart grid, system load would be known, in advance, with a high degree of confidence. Currently, this goal of "smart forecasting" is far from being realized. In the Pacific Gas and Electric (PG&E) aggregation area managed by the California Independent System Operator (ISO), the root mean squared day-ahead forecast error was about 3.8 percent of actual load over the period 1 April 2009 through 31 March 2010. This error may appear small except for the inconvenient fact that the stability of the power system requires that electricity demand and supply of electricity match at all times, not merely on average.

This paper contends that if day-ahead markets for electricity are efficient, then the day-ahead prices will reflect the load forecast generated by the system operator along with the information processed by and the consequent insights of all market participants. For example, suppose a system operator fails to account for the effect of a holiday in its load forecast but that market participants know that the holiday in question will boost demand. The market participants will incorporate the holiday induced demand into their economic calculations so that the impact of the holiday on electricity demand will be reflected in the day-ahead prices. Consequently, one can hypothesize that if day-ahead prices reflect the processed information and expectations of all market participants regarding day-ahead demand, then descriptive measures of the day-ahead prices may be useful in explaining the forecast errors by the system operator. We test this hypothesis using data for the PG&E aggregation area in the California ISO. The results indicate that the load forecasting errors have a significant systematic component. A portion of this systematic component is accounted for by the "shape" of the day-ahead forecasted load profile, the "shape" of the day-ahead price profile, and the day-ahead hourly price relative to the price of natural gas, natural gas being one of the primary fuels used to produce electricity in California. Evidence is presented that the root-mean-squared errors of the day-ahead load forecasts can be significantly reduced when the load forecasts are modified using the day-ahead information.

Keywords: Electricity Markets, Load Forecasting, California ISO

JEL Codes : L5, L9, Q4, D8

1. Introduction

To neoclassical economists, market prices are the primary signals ensuring efficient resource allocation. While many might concede that markets "work" in the abstract, events like the California power crisis of 2000/2001, the oil price spike of 2008, and the 2008/2009 global financial crisis have undeniably and seriously undermined people's confidence in the ability of markets to adequately address important resource allocation issues.

Opposition to the use of the price mechanism is particularly fierce in the case of electricity. For instance, Blumsack and Lave (2006) have argued that the restructuring of the electricity sector has been a failure because of market manipulation. Van Doren and Taylor (2004) have also concluded that electricity restructuring has been a failure and that "vertical integration may be the most efficient organizational structure for the electricity industry." (Van Doren and Taylor 2004, p 9). And in a review of several restructuring studies, Kwoka (2008) adds his voice to the chorus of critics of the use of markets in the electricity sector.

Regardless of one's views on the use of markets to allocate resources, the minimization of generation costs requires highly accurate day-ahead forecasts of electricity demand. In a truly smart grid, system load would be known in advance with a high degree of confidence. This goal of "smart forecasting" is currently far from being realized. In the Pacific Gas and Electric (PG&E) aggregation zone managed by the California Independent System Operator (ISO), the root mean squared forecast error was approximately 450 MW over the period 1 April 2009 through 31 March 2010 corresponding to about 3.8 percent of average load. This error level may appear small except for the inconvenient fact the stability of the power system requires that the supply of electricity match demand at all times, not merely on average.

One of the load forecasting challenges that the California ISO faces is known as the "Delta Breeze" phenomenon (SIO and SAIC, 2004), a sea breeze that carries the cool air from the ocean into the San Francisco Bay area and up to 100 miles inland (SIO and SAIC, 2004, p. 15). The breeze is most prevalent between May and September and thus the breeze lowers the cooling component of the electric load. The absence of the breeze can lead to significantly higher electricity load. The California ISO has reported that the Delta Breeze is difficult to predict (SIO and SAIC, 2004, p. 27). Analyses of weather forecasts by NOAA confirm this view with the errors in forecasted temperatures being systematically positive (forecasted temperatures minus actual temperatures are greater than zero) when the Delta Breeze is blowing and systematically negative (forecasted temperatures minus actual temperatures are less than zero) when it is not (SIO and SAIC, 2004, p. 11). Because load is temperature sensitive, these errors have contributed to significant load forecasting errors. For example, on May 28 2003, the day-ahead forecasted load was 35,012 MW while the actual load was 39,577 MW. As a result, a stage 1 alert had to be declared (SIO and SAIC, 2004, p. 7). The California ISO is not the only balancing area to experience nontrivial load forecasting errors. Preliminary analyses of the load forecast errors for the French Power Grid, the New York ISO, and the PJM RTO reveal that the day–ahead load forecast errors in these balancing areas are nontrivial as well. For example, over the period 1 January 2000 through 31 December 2008, approximately 16 percent of the days in New York City, the New York ISO's leading zone in terms of electricity consumption, had a root-mean-day-ahead-forecast-error in excess of five percent of daily mean load. In the case of the French power grid, over the period 1 November 2003 through 31 December 2007, approximately seven percent of the days in France had a root-mean-day-ahead-forecast-error in excess of five percent of daily mean load.

This paper assesses the efficiency of markets with what we think is a novel test of the informational content of prices in electricity markets. Following Bachelier (1900), the first to recognize what has become known as the efficient market hypothesis, we begin with the proposition that if day-ahead markets for electricity are efficient, then day-ahead prices will reflect the load forecast generated by the system operator as well as the information processed by and the consequent insights of all market participants. For example, suppose a system operator has failed to account for the effect of a holiday in its load forecast but that market participants know that the holiday in question will boost demand. The market participants will incorporate the holiday induced demand into their economic calculations and thus the impact of the holiday on electricity demand will be reflected in the day-ahead prices. As for the system operator, the holiday will give rise to a load forecasting error. Consequently, to the extent that there are many of these holidays, the load forecasting errors and day-ahead prices will be correlated. More importantly, if the market is efficient, the day-ahead prices will reflect all available meteorological information including the forecasts by any proprietary models that are more accurate than that employed by the system operator. Hence, one can hypothesize that if day-ahead prices accurately reflect the processed information and expectations of all market participants regarding day-ahead demand, then descriptive measures of the various distributional characteristics of day-ahead prices will be useful in predicting the day-ahead load. We also believe that the errors will be related to the complexity of the load profile and thus we include measures of the "shape" of the day-ahead forecasted load profile as explanatory variables.

The remainder of the paper is organized as follows. Section 2 provides some background material on the California ISO. Section 3 presents and estimates a model that seeks to explain the load forecasting errors in the PG&E Load Aggregation Point (LAP). Section 4 summarizes the results and presents a roadmap for future research.

2. The California ISO

The California Independent System Operator (ISO) launched a Market Redesign and Technology Upgrade (MRTU) on Wednesday, April 1, 2009. Under the new system, there are three load aggregation points (LAPs) that correspond to the service territories of Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDGE). The LAP prices are the load weighted average price of all the location marginal prices (LMPs) located inside the LAP. Figure 1 depicts the service territory of PG&E. Inspection of the figure reveals that the area affected by the "Delta Breeze" largely lies within the PG&E service territory.

Figure 1. PG&E's Service Territory

Figure 2 depicts a histogram of the day-ahead forecast errors for the PG&E LAP over the period 1 April 2009 through 31 March 2010 where the error is defined as forecasted load minus actual load. [1] Inspection of the figure reveals that there were a nontrivial number of hours in which the forecast error was more than 1,000 MW.

[1] The California ISO reports load by transmission access charge (TAC) areas. There are currently three TACs in the control area: TAC_NORTH, TAC_ECNTR, and TAC_SOUTH. . According to CAISO personnel, there is a very close correspondence between the TACs and the demand LAPs with TAC NORTH being like the PG&E demand LAP. The essential difference between the TACs and the demand LAPs is that the TACs also include external transmission facilities that have been placed under CAISO operational control. These facilities have no bearing on the levels of forecasted and actual load since the reported values by TAC region only reflect electricity consumption that is internal to the California ISO. Consistent with this interpretation, the load data sets from the California OASIS identifies load by the TAC areas PGE, SCE, and SDG&E. We are grateful to Darren Lamb of the California ISO for his clarification of this issue.

In terms of supply costs, the price of electricity in the California ISO is highly dependent on the delivered price of natural gas and the heat rates of the marginal generating unit. When load is low, only the most efficient plants are dispatched and thus prices will reflect the natural gas purchasing costs of these low heat rate units. When loads are high, less efficient generating units will be the marginal source of supply and the day-ahead market price of electricity will reflect the gas purchasing costs of these higher heat rate units to the extent that the day-ahead electricity market is efficient. As a result, there is a positive relationship between the day-ahead electricity/gas price ratio and load. In this paper, we refer to this day-ahead price ratio as the "sparks ratio". It is calculated under the assumption of no energy losses and thus increases as generating units with higher heat rates are expected to be dispatched. The relationship between this ratio and load for the PG&E LAP is depicted in Figure 3.

Figure 2. A Histogram of the Day-Ahead Load Forecasting Errors for the PG&E LAP by the California ISO, 1 April 2009 – 31 March 2010

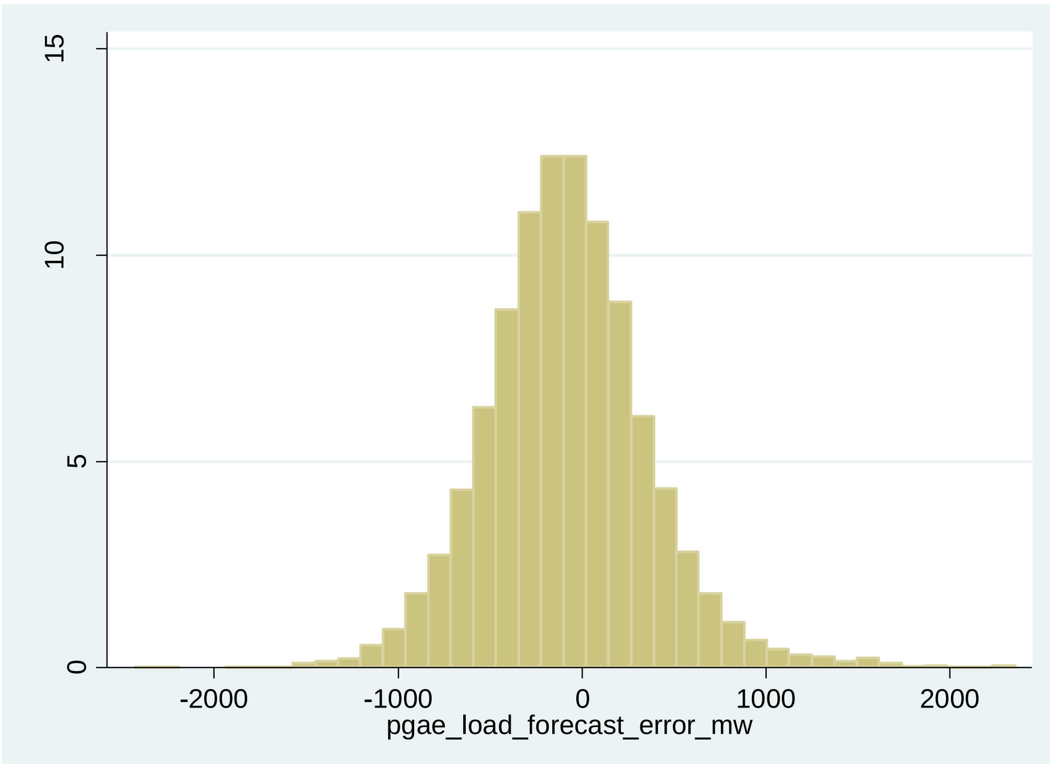
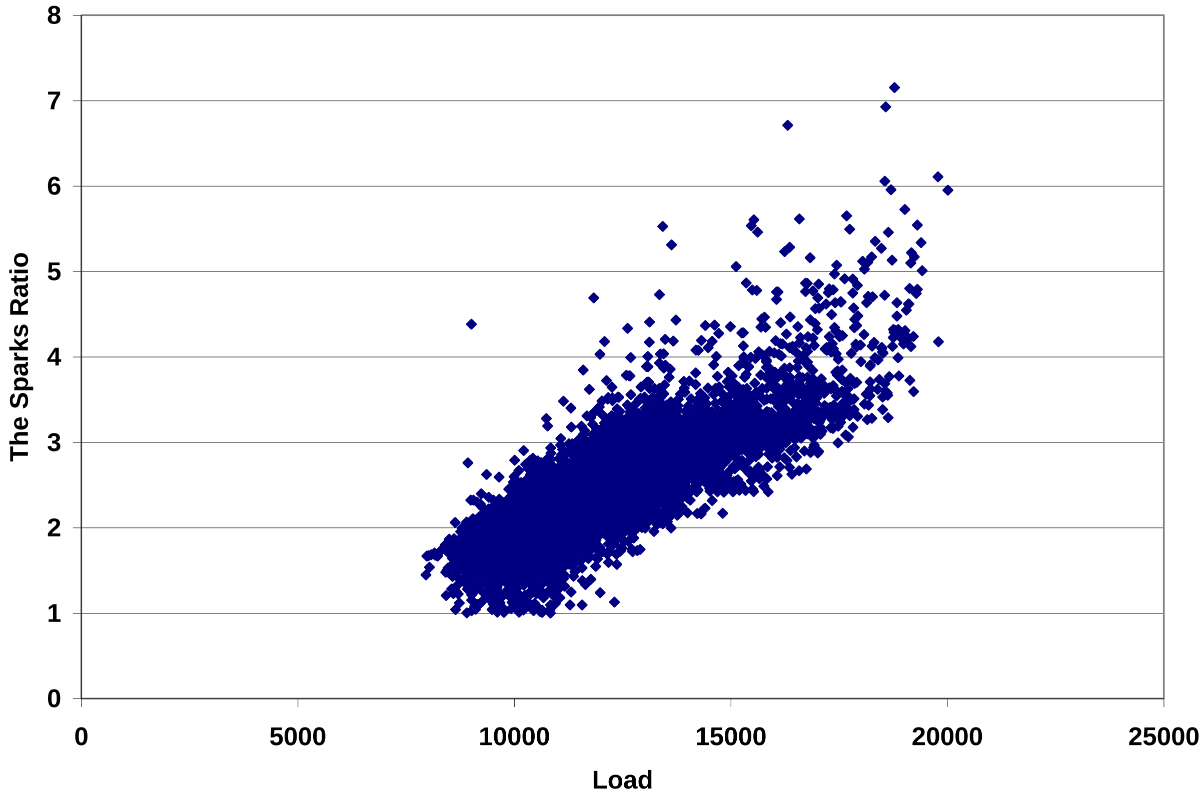


Figure 3. The Day-Ahead "Sparks Ratio" and the Actual Level of Load for the PG&E LAP in the California ISO, 1 April 2009 – 31 March 2010



Notes: The "Sparks Ratio" is calculated under the assumption of no energy losses, i.e. that 1 MWh is equivalent to 3.412 MMBTU. To facilitate the presentation of the data, the ratio in the figure is reported for the range of one through ten. This range accounts for over 98 percent of the observations.

3. A Model of Load Forecasting Errors

Given the discussion of the previous sections, our econometric model presumes that the load forecasting error is a function of the day-ahead sparks ratio, the day-ahead price profile, the day-ahead profile of forecasted load, and the hourly forecasted load relative to the forecasted profile. The day-ahead price profile is comprised of the coefficient of variation and skewness in the day-ahead prices. The day-ahead load profile consists of the coefficient of variation and skewness in the day-ahead forecasted load, the forecasted peak load, and the forecasted minimum load. The hourly forecasted load relative to the forecasted load profile is measured by the hourly forecasted load relative to both the peak and minimum forecasted levels of load. Finally, we include binary variables for the hour of the day, the day of the week, the month of the year, and if the hour in question occurs between sunrise and sunset.

It is also presumed that the marginal impact of each explanatory variable on the error measured in MW depends on the values of the other explanatory variables. For example, we expect that the marginal impact of an increase in SparksRatio on the error measured in MW will likely depend on the hour of the day and on the forecasted peak hourly load. For this reason, we model the forecast error as the natural logarithm of the actual load relative to the forecasted load.[2] Under this formulation, the marginal impact each independent variable on the error measured in MW is contingent on the values of the other independent variables.

[2] The ratio of actual to forecasted load is used in place of the difference since the natural logarithms of negative numbers are undefined.

In its most general form, the model is given by:

$$
\begin{aligned}
\ln ForecastError_{hd} = f(&Hour_j, Day_k, Month_i, Daylight_{hd}, SparksRatio_{hd}, CVP_d, PosSkewP_d, \\
&NegSkewP_d, FLPeakRatio_d, FLNadirRatio_d, FLPeak_d, FLNadir_d, \\
&CVFL_d, PosSkewFL_d, NegSkewFL_d)
\end{aligned} \tag{1}
$$

where:

$lnForecastError_{hd}$ is the natural logarithm of the ratio of actual to forecasted load for hour *h* in day *d*;

$Hour_i$ are binary variables representing each hour of the day excluding hour one (*j* = 2 to 24);.

Day_k are binary variables representing each day of the week excluding Monday (*k* = 2 to 7);

$Month_i$ are binary variables representing each month excluding January(*i* = 2 to 12);

$Daylight_{hd}$ is a binary variable that is equal to one if hour *h* in day *d* occurs between sunrise and sunset;

$SparksRatio_{hd}$ equals the day-ahead Apnode price for hour *h* in day *d* for the PG&E LAP divided by the price of natural gas reported by California ISO for the PG&E LAP the day prior to the closing of the day-ahead electricity market. The Apnode price for the PGE LAP is the locational marginal price for the PGE aggregated pricing node. The price of natural gas is normalized to its MWh equivalent under the assumption of zero energy losses. This is done by multiplying the price per MMBtu by 3.412 .

CVP_d is the coefficient of variation in the 24 hourly day-ahead prices in day *d*. Specifically, for each day both the average hourly price and the standard deviation in the prices are calculated. The ratio of the latter to the former is defined as *CVP* .

$PosSkewP_d$ equals the skewness in the 24 day-ahead hourly prices in day *d* when the skewness in the hourly prices is positive. It is equal to zero otherwise.

$NegSkewP_d$ equals the absolute value of skewness in the 24 day-ahead hourly prices in day *d* when the skewness in the prices is negative. It is equal to zero otherwise.

$FLPeakRatio_{hd}$ equals the ratio of the forecasted load in hour *h* relative to the forecasted peak load in day *d*

$FLNadirRatio_{hd}$ equals the ratio of the forecasted load in hour *h* relative to the forecasted minimum load level in day *d*

$FLPeak_d$ is the forecasted peak hourly load in day d

$FLNadir_d$ is the forecasted minimum hourly load in day d

$CVFL_d$ is the coefficient of variation in the 24 hourly day-ahead prices in day d. Specifically, for each day both the average hourly price and the standard deviation in the prices are calculated. The ratio of the latter to the former is defined as $CVFL_d$;

$PosSkewFL_d$ equals the skewness in the 24 day-ahead hourly prices in day d when the skewness in the day-ahead forecasted hourly load is positive. It is equal to zero otherwise.

$NegSkewFL_d$ equals the absolute value of skewness in the 24 day-ahead hourly levels of forecasted load in day d when the skewness in the forecasted hourly load is negative. It is equal to zero otherwise.

Data to calculate the "daylight" variable were obtained from http://www.timeanddate.com/worldclock/sunrise.html . All remaining data were obtained from California's ISO website (http://oasis.caiso.com/mrtu-oasis/home.jsp?doframe=true&serverurl=http%3a%2f%2farptp10.oa.caiso.com%3a8000&volume=OASIS). In five cases, the calculated SparksRatio was more than five standard deviations above its mean of 2.43. These observations were considered to be extreme outliers and were dropped from the analysis. The transition days between standard and daylight savings time (and back again) are also dropped from the analysis.

In many markets, prices exhibit unit roots which preclude conventional regression analysis. For all non-binary variables in this study, Augmented Dickey-Fuller tests were performed. The results are reported in Table 1. Inspection of the table shows that the null hypothesis of a unit root can be rejected at the five percent level for all variables. In all but one case, the null hypothesis of a unit root can be rejected at the one percent level. Accordingly, our regression results are not expected to be plagued by non-stationarity issues.

Table 1
Augmented Dickey-Fuller Tests for Unit Root

Variable	**Test Statistic**	**1 Percent Critical Value**	**5 Percent Critical Value**
$SparksRatio_{hd}^{2}$	-20.814	-3.430	-2.860
CVP_{d}^{-1}	-7.062	-3.430	-2.860
$PosSkewP_{d}$	-12.523	-3.430	-2.860
$NegSkewP_{d}$	-9.452	-3.430	-2.860
$FLPeakRatio_{d}^{.5}$	-15.869	-3.430	-2.860
$FLNadirRatio_{d}^{.5}$	-14.947	-3.430	-2.860
$FLPeak_{d}$	-4.407	-3.430	-2.860
$FLNadir_{d}$	-3.416	-3.430	-2.860
$CVFL_{d}^{3}$	-5.786	-3.430	-2.860
$PosSkewFL_{d}$	-12.088	-3.430	-2.860
$NegSkewFL_{d}$	-9.074	-3.430	-2.860

The estimation of (1) was conducted using the multivariable fractional polynomial (MFP) model, a useful technique when one suspects that some or all of the relationships between the dependent variable and the explanatory variables are non-linear (Royston and Altman, 2008) but there is little or no basis, theoretical or otherwise, on which to select particular functional forms. The MFP approach begins by estimating a model that is strictly linear in the explanatory variables. Subsequent estimations then cycle through a battery of nonlinear transformations of the explanatory variables (positive and negative powers, natural logarithms, etc.) until it finds the MFP model that best predicts the dependent variable. In our case, the analysis provided support for including five of the explanatory variables with powers other than unity. Specifically, the MFP model obtained is given by:

$$
\begin{aligned}
\ln ForecastError_{hd} = const &+ \sum_{j=2}^{24} \alpha_j Hour_j + \sum_{k=2}^{7} \delta_k Day_k + \sum_{i=2}^{12} \mu_i Month_i \\
&+ \beta_1 Daylight_{hd} + \beta_2 SparksRatio_{hd}^2 + \beta_3 CVP_d^{-1} + \beta_4 PosSkewP_d \\
&+ \beta_5 NegSkewP_d + \beta_6 FLPeakRatio_d^{0.5} + \beta_7 FLNadirRatio_d^{0.5} + \beta_8 FLPeak_d \quad (2) \\
&+ \beta_9 FLNadir_d + \beta_{10} CVFL_d^3 + \beta_{11} PosSkewFL_d + \beta_{12} NegSkewFL_d
\end{aligned}
$$

where *const* represents the overall constant term. Parameter estimates, t-statistics, p-values, and diagnostics are provided in Table 2.

Consistent with the conjecture that a significant proportion of the load forecast error is systematic, the adjusted R-squared of the estimated equation is approximately 0.48. Almost all binary variables representing the hour of the day, day of the week, and month of the year are statistically significant. The binary variable for daylight is also statistically significant. It may appear odd that these variables are statistically significant since the systematic hourly, daily, and monthly variations in load would seem to be essential pieces of information that experienced load forecasters would possess. Surprisingly, however, preliminary analyses of load forecast errors for several other power grids indicate that this may not be an isolated finding.

The estimated coefficients on the variables $NegSkewP_d$, $PosSkewFL_d$, and $NegSkewFL_d$ are statistically insignificant. Estimated coefficients on the remaining continuous variables are statistically significant at all standard levels. For example, the coefficient on $SparksRatio_{hd}^2$ while small in value is highly statistically significant indicating that the forecast error will be larger, ceteris paribus, the higher the day-ahead price of electricity relative to the price of natural gas. Another notable result is the coefficient on $CVFL_d^3$. Its positive coefficient is consistent with our expectation that increases in expected load variability over the course of the day makes load more difficult to forecast.

Table 2
Equation 2 Regression Results

Variable	Estimated Coefficient	t- Statistic	P value
const	0.5576	12.99	< 0.001
$Hour_2$	0.0075	5.98	< 0.001
$Hour_3$	0.0171	10.25	< 0.001
$Hour_4$	0.0242	13.14	< 0.001
$Hour_5$	0.0312	16.9	< 0.001
$Hour_6$	0.0446	25.31	< 0.001
$Hour_7$	0.0590	29.72	< 0.001
$Hour_8$	0.0516	19.31	< 0.001
$Hour_9$	0.0517	14.73	< 0.001
$Hour_{10}$	0.0521	13.47	< 0.001
$Hour_{11}$	0.0506	12.34	< 0.001
$Hour_{12}$	0.0452	10.75	< 0.001
$Hour_{13}$	0.0472	11.23	< 0.001
$Hour_{14}$	0.0463	10.91	< 0.001
$Hour_{15}$	0.0443	10.51	< 0.001
$Hour_{16}$	0.0449	10.69	< 0.001
$Hour_{17}$	0.0541	12.18	< 0.001
$Hour_{18}$	0.0577	12.5	< 0.001
$Hour_{19}$	0.0517	11.52	< 0.001
$Hour_{20}$	0.0515	11.9	< 0.001
$Hour_{21}$	0.0425	10.57	< 0.001

$Hour_{22}$	0.0153	4.66	< 0.001
$Hour_{23}$	-0.0049	-2.04	0.042
$Hour_{24}$	-0.0100	-6.51	< 0.001
Tuesday (d = 2)	-0.0041	-0.89	0.374
Wednesday (d = 3)	-0.0001	-0.02	0.987
Thursday (d = 4)	0.0047	1.02	0.307
Friday (d = 5)	0.0047	1.05	0.293
Saturday (d = 6)	0.0073	1.63	0.102
Sunday (d = 7)	0.0016	0.46	0.645
February (i = 2)	-0.0019	-0.58	0.561
March (i = 3)	-0.0063	-1.86	0.062
April (i = 4)	-0.0144	-3.6	< 0.001
May (i = 5)	-0.0085	-2.03	0.042
June (i = 6)	-0.0135	-2.62	0.009
July (i = 7)	0.0032	0.53	0.596
August (i = 8)	0.0028	0.51	0.613
September (i = 9)	-0.0090	-1.75	0.08
October (i = 10)	-0.0033	-0.89	0.374
November (i = 11)	-0.0049	-1.64	0.101
December (i = 12)	0.0015	0.43	0.665
$Daylight_{hd}$	0.0044	2.69	0.007
$SparksRatio_{hd}^{2}$	0.0016	5.24	< 0.001
CVP_{d}^{-1}	-0.0013	-2.56	0.011
$PosSkewP_{d}$	0.0051	2.67	0.008

$NegSkewP_d$	0.0003	0.1	0.921
$FLPeakRatio_d^{.5}$	-1.2149	-6.27	< 0.001
$FLNadirRatio_d^{.5}$	0.6110	4.07	< 0.001
$FLPeak_d$	0.0000	-5.65	< 0.001
$FLNadir_d$	0.0000	3.75	< 0.001
$CVFL_d^3$	11.9449	4.01	< 0.001
$PosSkewFL_d$	-0.0047	-0.51	0.613
$NegSkewFL_d$	0.0044	0.75	0.456
Adjusted R^2	0.4814		
Number of Observations	8585		

Following Newey and West (1987), the reported p-values are robust to heteroskedasticity and autocorrelation.

Based on the fitted values of the dependent variable, a revised forecast series for the sample period was calculated. This is easily calculated by multiplying the anti-log of the fitted value by the day-ahead forecasted load. Because the predicted anti-log values are not an unbiased predictor of ratio of actual load relative to forecasted load, the predicted anti-log values were then rescaled using the procedure presented by Wooldridge (2009, p. 211). The root-mean-squared-error of the revised forecast series is 2.98 percent of mean load which is significantly below the actual root-mean-squared error of 3.8 percent of load. An out of sample analysis for the period 1 April 2010 through 31 March 2011 was also performed. Using the parameters reported in Table 2, the root mean squared error of the revised out-of-sample forecast is approximately 352 MW (about 2.94 percent of mean load) as compared to 489 MW (about four percent of mean load. This represents an approximately 28 percent reduction. The out-of-sample results for selected hours are presented in Table 3. While the reduction in the RMSE is modest in some hours (e.g. hour 13), the error is significantly lower during the critical morning ramp-up hours. For example, for hour 7, the RMSE of the revised forecast is 343 MW (3.01 percent) as compared to 696 MW (6.12 percent). The error is also nontrivially lower in the late afternoon and evening. For instance, in hour 17, the RMSE of the revised forecast is 476 MW (3.60 percent) as compared to 585 MW (4.43 percent). In hour 22, the error is about 45 percent lower (287 MW vs. 521 MW; Table 3).

Table 3
Out of Sample Forecasting Results for Selected Hours, 1 - April 2010- 31 March 2011

Hour Ending	RMSE of the Revised Forecasts as a Percent of Mean Actual Load	RMSE of CAISO's Forecasts as a Percent of Mean Actual Load	RMSE of the Revised Forecasts in MW	RMSE of CAISO's Forecasts in MW
6	3.08	6.07	325	641
7	3.01	6.12	343	696
8	2.67	4.38	315	517
9	2.21	3.25	268	396
10	2.11	2.76	263	344
11	2.38	2.61	302	330
12	2.40	2.54	306	324
13	2.67	2.79	340	356
14	2.85	2.90	365	372
15	3.01	3.14	388	405
16	2.94	3.38	381	439
17	3.60	4.43	476	585

18	**3.49**	**4.28**	**474**	**581**
19	**2.91**	**3.43**	**396**	**467**
20	**2.76**	**3.24**	**374**	**439**
21	**2.44**	**2.91**	**325**	**388**
22	**2.29**	**4.15**	**287**	**521**
23	**2.19**	**4.81**	**252**	**554**
24	**2.51**	**4.08**	**267**	**435**
All Hours	**2.94**	**4.08**	**352**	**489**

The out-of-sample results by month are presented in Table 4. In every case, the revised forecast yields a significant reduction in the forecast error. The months with the largest percentage reductions in the forecast errors are the winter months of December and January and the "Delta Breeze" months of May, July, and August. In each of these cases, the RMSE is more than 30 percent lower under revised forecast. The month with the lowest reduction is September which is also a "Delta Breeze" month. Even here, however, the reduction is a nontrivial 19 percent (418 MW vs. 518 MW; Table 4).

Table 4
Out of Sample Forecasting Results by Month, 1 - April 2010 - 31 March 2011

Month	RMSE of the Revised Forecasts as a Percent of Mean Actual Load	RMSE of CAISO's Forecasts as a Percent of Mean Actual Load	RMSE of the Revised Forecasts in MW	RMSE of CAISO's Forecasts in MW
January	2.53	3.83	294	444
February	2.35	3.25	269	372
March	2.43	3.44	273	386
April	2.73	3.54	295	383
May	2.64	3.94	293	437
June	3.92	4.94	500	630
July	3.26	4.80	445	657
August	2.63	3.83	350	508
September	3.26	4.04	418	518
October	2.77	3.93	323	457
November	318	4.25	369	494
December	2.60	4.10	304	479

To assess further the performance of the revised forecast, the 100 worst forecasts using the existing method were identified. The RMSE for these 100 hours using the existing methodology is 1,516 MW. Using the revised forecast, the RMSE for these same hours is approximately 28 percent smaller at 1,096 MW. We then identified the 100 worst revised forecasts. The RMSEs for these 100 hours are 1,342 MW and 1,289 MW for the existing methodology and revised forecast, respectively.

4. Summary and Conclusions

This paper has presented evidence that a substantial portion of the day-ahead load forecast errors in the PG&E LAP of the California ISO are systematic in nature. Specifically, the findings indicate that the day-ahead load forecasting errors are statistically related with the hour of the day, the day of the week, the month of the year, the shape of the day-ahead forecasted load profile, the shape of the day-ahead price profile, and the day-ahead electricity price relative to the natural gas price.

An out of sample analysis indicates that it is possible to reduce substantially the load forecasting errors by revising the forecasts based on the systematic component of the errors. More generally, the results are consistent with the view that market prices in California's electricity market are determined by economic fundamentals. In general, the results suggest that there is merit in using markets to allocate scarce resources efficiently.

In terms of methodology, the framework of analysis presented here can be expected to facilitate the analysis of disturbances on the power grid such as those that give rise to the deployment of emergency power. To the extent that the circumstances associated with an unusual event are expected by market participants, they will be reflected in the day-ahead prices.

We suspect that the explanatory power of the model can be significantly improved. The fact that the coefficient on the "daylight" variable is statistically significant leads us to believe that it may be possible to further reduce the load forecast errors by improved modeling of the relationship between forecasted meteorological outcomes and load.

It will be very interesting to see whether the findings reported here are confirmed or not in other ISOs where natural gas is not the primary fuel (e.g. PJM, New York, and France). And it will be especially interesting to see whether the findings are conditional on the electricity market being administered by the system operator. In the case of California, the ISO operates the market and has the right to impose price caps to mitigate the perceived exercise of market power. In contrast, spot markets in most of Europe (e.g. UK, France, and Germany) are not managed by system operators.

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