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THE EFFECT OF EARLY DAYLIGHT SAVING TIME ON CALIFORNIA ELECTRICITY CONSUMPTION: A STATISTICAL ANALYSIS

STAFF REPORT

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ABSTRACT

The extension of Daylight Saving Time (DST) to March 2007 had little or no effect on energy consumption in California, according to a statistical analysis. The most likely approximation is a 0.2% decrease during these three weeks. Given the natural variation in consumption, however, the margin of electricity use change associated with early DST could have been one and a half percent of increase or decrease without such effects showing up statistically. Formally, weather- and lighting-corrected savings from DST were estimated at 0.18% with a 95% confidence interval ranging from 1.5% savings to a 1.4% increase.

BACKGROUND

The Energy Policy Act of 2005 extended Daylight Saving Time (DST) by three weeks in the spring and one week in the fall, beginning on March 11 of this year, in the hope that the extension would save energy. This paper will examine whether and how much it changed daily electricity consumption in California from March 11 through 31, 2007.

How early DST affects electricity use depends on what parts of electricity use respond to time-of-day and daylight conditions. Agricultural processes follow a diurnal schedule and account for approximately eight percent of the total electricity consumption in California,[1] Daylight Saving Time should not affect agricultural electricity consumption, nor should it affect total electricity consumption of most industrial processes (20% of the state's electricity use).

Many other activities are driven by time schedules of work, school and family, but one cannot separate out their effects without detailed records of electrical appliances, building envelope characteristics, commercial and industrial processes, and electricity consumption choices. These consumption characteristics, which may vary from state to state, influence response to DST. As a result, it is difficult to extrapolate results of this California study to the United States as a whole.

DATA

Staff used data from the California Independent System Operator (ISO) to assess the effect of early DST on total daily electricity use in the state. (Other California control areas have not all released their March 2007 electricity use.)

[1] http://www.energy.ca.gov/2005publications/CEC-400-2005-034/CEC-400-2005-034-SF-ED2.PDF

The California ISO oversees grid operations that represent approximately 80 percent of the population in the state, located in 13 climate zones.
Because California is a coastal state with a large diversity of micro-climates, the overall weather-dependent electricity load must be characterized by numerous weather stations within the state. Staff combined weather information from nine weather stations, weighting each station's contribution to heating degree days by the population size of its region and each station's contribution to cooling degree days by the number of air conditioners.[2] Still, weather corrections will remain imperfect and increase the uncertainty of statistical results.

Analysis

Staff compared daily total electricity use in the early DST weeks of March 2007 to usage in comparable days of preceding years, using the statistical tool of regression analysis. The analysis began with year 2000 electricity use but excluded year 2001 because the energy crisis in that year in California produced atypical conservation behavior. Observations for the months of January, February and March were included, while April was not yet available for 2007.

A regression of daily megawatt hours (MWh) on a binary DST variable would establish the average difference in electricity use between DST and non-DST days. When one adds other independent variables, such as weather, to the regression one controls for their effects, and the coefficient of the DST variable becomes the average difference in weather-corrected electricity use. The independent variables one chooses therefore depend on what effects one needs to correct for. Staff's variable choices were:

Weather Effects

Electricity use responds differently to weather in March than it does in winter months, so the following independent variables were used:

- MarHDD = Heating Degree Days in the month of March, a measure of how cold it was for heating purposes. This is a binary-continuous interaction variable which is zero for January and February days, and shows heating degree days with a base of 65°F during March.
- MarHDD2 = MarHDD squared. This combines with MarHDD, to produce a nonlinear response of electricity use to HDD, something suggested by scatter plots of the data and supported by regression results.
- MarCDD = Cooling Heating Degree Days in the month of March, a measure of how hot it was for cooling purposes, with a base of 65°F.

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[2] The weather stations used are Eureka, Sacramento, Riverside, Long Beach, San Diego, Fresno, San Jose, San Francisco, Burbank

- JanFebHDD,JanFebHDD2,JanFebCDD: These are just like the March weather variables, but measured on January and February days.

As one would expect, MarCDD had a clearly positive effect, while JanFebCDD had a statistically insignificant positive effect. Electricity use increased with HDD in winter and in March, with positive MarHDD2 and JanFebHDD2 coefficients. Negative MarHDD and JanFebHDD coefficients added curvature to the effect without reversing its direction.

Staff also ran the regressions without separating the weather effects between midwinter and March and still obtained the ultimate result of no statistically significant March DST effect, shown in Table 3.

Daylight

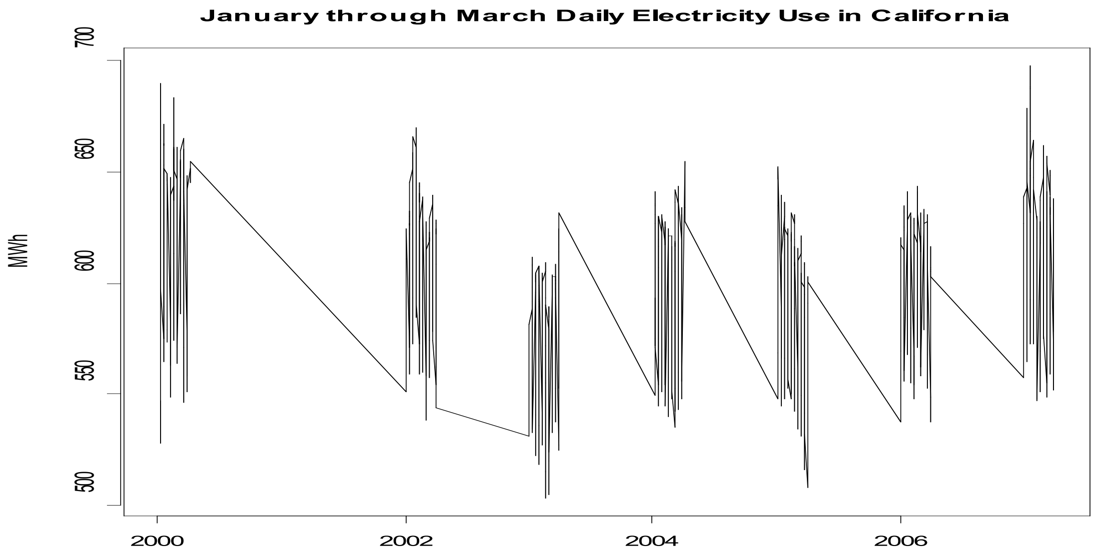
The regressions included two different variables indicating hours of daylight in a given day: MarDaylight for March days and JanFebDaylight for midwinter days. As expected, longer days led to less electricity use, with the effect more marked in midwinter.

Weekends and holidays

Two binary variables: JanFebWeekend and MarWeekend take the value 1 during weekends and holidays of the months in question, and 0 during work days, since electricity use is higher on work days. JanFebWeekend and MarWeekend had the expected negative effects.

Yearly binary indicator variables

Electricity use responds to population, to economic activities, and to societal attitudes and choices so that 2007 electricity use cannot be compared directly to previous year's electricity use. The following graph shows electricity use for January through March of the years' data studied:



Variables for economic activity and population corrected only partially for the difference between different years' weather-corrected electricity use, so staff chose the common approach of having a binary indicator variables for each year (and no constant term in the regression).

Staff had considered doing the same regressions on March data only, comparing March usage of different years, but then the DST indicator variable – which takes the value one rather than zero only for the last 20 days of 2007 – would be confounded with the 2007 indicator variable, which takes the value one for all of March 2007. Put differently, only 10 data points would define the difference between the 2007 effect and the DST effect, and results would be far from accurate. Thus, January and February data were included to better identify and control for the year 2007 effect. The Mar- and JanFeb- interaction variables noted above allowed for seasonal differences in weather and daylight responses, while the yearly dummies to represent economic, demographic and social effects. Appendix 2 lists alternative regressions on March-only data without 2007 or other year indicator variables.

DST

This is the binary indicator variable that represents the effect of March DST on total daily MWh of electricity used in the California ISO. It takes the value one for the early DST days in March 2007 and zero for all other days in the dataset.

FINAL REGRESSION RESULTS

Regression results are listed in boxed Table 1 below. Early DST effects were uncertain and statistically indistinguishable from zero in the main model presented in Table 1, as well as alternative models (see Appendix 2).

Table 1 shows that the most likely effect of early DST is negative but negligible. DST's coefficient of -0.104 is only 0.02% of average daily electricity use. In addition, the p-value of .98 signifies only 2% confidence that one can reject the null hypothesis that early DST had no effect whatsoever on total daily electricity use.

Still, it is important to understand that the absence of statistical confidence does not mean there is no effect. It is entirely possible that early DST saved electricity as people used less light and heat in the evenings. It also could have increased electricity use, with morning increases outweighing evening savings. A 95% confidence interval would have the early DST effect lie somewhere between a 1.5% savings and a 1.4% increase in electricity use.

For a technical explanation of the treatment of the regression in light of the data's time series nature and the correlation between electricity use from one day to the next, see Appendix 1. Appendix 2 describes other regression approaches tested, all supporting the conclusion that effects were small and uncertain.

Table 1: How early DST and other variables affected daily electricity use in California ISO areas

dependent variable: daily MWH used in ISO area

	coefficient	std error	t stat	p value
janfebCDD	0.7426237	1.67917095	0.44225619	6.584632e-01
janfebHDD	-2.3736915	0.88528227	-2.68128212	7.535809e-03
janfebHDD2	0.1996831	0.03613033	5.52674521	4.869326e-08
janfebWeekend	-62.9484703	1.19407666	-52.71727715	0.000000e+00
janfebDaylight	-3.4918489	1.16230467	-3.00424578	2.773435e-03
marCDD	3.6083967	1.37101017	2.63192557	8.708663e-03
marHDD	-3.3437844	1.05027010	-3.18373757	1.529149e-03
marHDD2	0.2278225	0.05489072	4.15047471	3.798178e-05
marWeekend	-68.0273937	1.68838752	-40.29133881	0.000000e+00
marDaylight	-2.8623690	1.13908910	-2.51285790	1.223681e-02
d2000	688.1089080	12.66703493	54.32280811	0.000000e+00
d2002	669.6234699	12.70055924	52.72393578	0.000000e+00
d2003	639.7783801	12.68507516	50.43552144	0.000000e+00
d2004	659.5695076	12.78602168	51.58520172	0.000000e+00
d2005	656.9791003	12.72949762	51.61076423	0.000000e+00
d2006	664.3227083	12.69760834	52.31872731	0.000000e+00
d2007	675.6853741	12.70368552	53.18813764	0.000000e+00
DST	**-0.1038382**	**4.52775757**	**-0.02293369**	**9.817108e-01**

R^2 = .895 *autocorrelation coefficients:* $\hat{\rho}_1 = 0.08007$, $\hat{\rho}_2 = 0.2405$

Appendix 1:
Dealing with Correlation Across Time

To test for serial correlation, staff regressed the residuals of an ordinary least squares regressions on their lags – meaning the residuals attributed to the day before, 2 days before, 3 days before, and 4 days before. The first three days in each year were excluded to prevent erroneous lag values between years. Staff found autocorrelation to be significant in the first and especially second orders, as shown by the following tables of results.

Regressing residuals on their 1st 4 lags, no constant:

```
      Estimate Std. Error t value Pr(>|t|)
elag   0.10184    0.04509   2.259   0.0244 *
elag2  0.26457    0.04476   5.911   6.55e-09 ***
elag3  0.03703    0.04406   0.841   0.4010
elag4 -0.01405    0.04342  -0.324   0.7463
```

Regressing residuals on their 1st 3 lags, no constant:

```
      Estimate Std. Error t value Pr(>|t|)
elag   0.10254    0.04402   2.330   0.0202 *
elag2  0.25277    0.04143   6.101   2.08e-09 ***
elag3  0.02185    0.04128   0.529   0.5969
```

Regressing residuals on their 1st 2 lags, no constant

```
      Estimate Std. Error t value Pr(>|t|)
elag   0.08211    0.04003   2.051   0.0407 *
elag2  0.22385    0.03860   5.799   1.12e-08 ***
```

Regressing residuals on their 1st lag, no constant

```
     Estimate Std. Error t value Pr(>|t|)
elag  0.15189    0.03882   3.913 0.000101 ***
```

This suggested the process was autocorrelated of the second order, and corrections were needed in order to obtain accurate confidence intervals and accurate tests of significance, as well as to obtain efficient (low variance) estimates. Letting ρ_1 and ρ_2 be the first and second order autocorrelation coefficients, respectively, and letting the « ^ » symbol signify regression estimates and the "*" represent transformed variables, staff transformed the data in the standard fashion by quasi-differencing as follows:

$$\underbrace{y_t - \hat{\rho}_1 y_{t-1} - \hat{\rho}_2 y_{t-2}}_{y_t^*} = \beta_1 \underbrace{\left(x_{1t} - \hat{\rho}_1 x_{1,t-1} - \hat{\rho}_2 x_{1,t-2}\right)}_{x_{1t}^*} + \ldots + \beta_k \underbrace{\left(x_{kt} - \hat{\rho}_1 x_{k,t-1} - \hat{\rho}_2 x_{k,t-2}\right)}_{x_{kt}^*} + \underbrace{e_t - \hat{\rho}_1 e_{t-1} - \hat{\rho}_2 e_{t-2}}_{u_t}$$

To get maximum likelihood estimates, staff iterated this process until the $\hat{\rho}$'s converged. The following Table 2 shows the Ordinary Least Squares results. Table 1 above shows final results after transforming for autocorrelation.

Table 2. Ordinary Least Squares model results

dependent variable: daily MWH used in ISO area

	coefficient	std error	t stat	p value
janfebCDD	0.6474764	1.83570173	0.3527133	7.244244e-01
janfebHDD	-2.9356150	0.86454117	-3.3955757	7.290332e-04
janfebHDD2	0.2248746	0.03462209	6.4951199	1.714680e-10
janfebWeekend	-63.4711955	1.38987250	-45.6669195	0.000000e+00
janfebDaylight	-3.1913201	1.01924967	-3.1310484	1.824603e-03
marCDD	3.5621085	1.49744728	2.3787872	1.767446e-02
marHDD	-4.5266491	1.08426889	-4.1748400	3.413354e-05
marHDD2	0.2908946	0.05631070	5.1658853	3.239289e-07
marWeekend	-68.8366187	2.02851852	-33.9344296	0.000000e+00
marDaylight	-2.4067254	1.03687630	-2.3211307	2.060632e-02
d2000	685.9495240	11.28561473	60.7808738	0.000000e+00
d2002	668.9623708	11.31004879	59.1476114	0.000000e+00
d2003	638.9450481	11.31943109	56.4467457	0.000000e+00
d2004	657.7959231	11.43102965	57.5447657	0.000000e+00
d2005	656.5797368	11.35271999	57.8345751	0.000000e+00
d2006	663.9038485	11.29982688	58.7534531	0.000000e+00
d2007	674.2236015	11.33069569	59.5041664	0.000000e+00
DST	**1.0772056**	**3.55843973**	**0.3027185**	**7.622069e-01**

R^2 = .875   *autocorrelation coefficients*: $\hat{\rho}_1 = 0.08007$, $\hat{\rho}_2 = 0.2405$

The expected effect of DST is positive but close to zero: 1.08 only 0.17 of average daily electricity use. In addition, the p-value of .76 suggests that one cannot rule out the hypothesis that the effect is exactly zero. However, the standard errors and hence the p-values and confidence intervals are biased in this regression with autocorrelated errors, so staff proceeded to the AR2 model in Table 1 to correct these shortcomings.

Appendix 2. Results Confirmed by Other Model Specifications

Staff tested the robustness of our results by trying alternative specifications, including a regression without separate midwinter lighting and weather effects, and a set of regressions on March-only data with economic and demographic data replacing the yearly indicator variables. The tables below show that DST effect remained small and statistically indistinguishable from zero.

Table 3 shows a regression where weather, daylight and weekend effects are estimated only once over the 3 month period, rather than having separate January-February and March values.

Table 3. AR2 model results without interaction variables

dependent variable: daily MWH used in ISO area

	b	se	tstat	pvalue
CDD	2.7754025	1.03851511	2.6724719	7.732437e-03
HDD	-2.9606694	0.62844306	-4.7111179	3.058888e-06
HDD2	0.2208243	0.02777725	7.9498263	9.103829e-15
Weekend	-64.5936762	0.97331431	-66.3646628	0.000000e+00
Daylight	-3.3803509	0.78824862	-4.2884324	2.094095e-05
d2000	690.9409167	9.80478915	70.4697374	0.000000e+00
d2002	672.1573833	9.88667656	67.9861811	0.000000e+00
d2003	642.2558582	9.79860941	65.5456128	0.000000e+00
d2004	663.5383105	9.83302437	67.4805925	0.000000e+00
d2005	659.9807750	9.83333853	67.1166535	0.000000e+00
d2006	666.5846225	9.95049306	66.9901098	0.000000e+00
d2007	678.5355108	9.72250553	69.7901903	0.000000e+00
DST	**1.1022287**	**4.58764902**	**0.2402600**	**8.102101e-01**

R^2 = .893 $\hat{\rho}_1 = 0.0863, \quad \hat{\rho}_2 = 0.252$

The effect of DST is near zero again, although seemingly positive this time: 1.098 is only 0.18% of average daily electricity use and one can only be 19% confident the effect is not exactly zero.

Tables 4 through 6 show regressions on March-only data, dropping the yearly dummies and instead using population to capture time trends and load factors. March-only data will be better if March is so different from the midwinter months that their inclusion in the regression adds more variability than information. In these regressions, the DST effect remained insignificant.

Table 4. AR2 Model using March data in years 2006 and 2007

	b	se	tstat	pvalue
constant	-825.0790786	300.84120525	-2.7425734	7.538871e-03
CDD	2.1231903	2.02528364	1.0483422	2.976777e-01
HDD	-2.7747878	1.31390014	-2.1118711	3.785772e-02
HDD2	0.1960946	0.06482657	3.0249107	3.354759e-03
Weekend	-67.1130690	2.03670824	-32.9517344	0.000000e+00
Daylight	4.1128995	4.71989173	0.8713970	3.861779e-01
Pop	38.6482781	8.09951901	4.7716757	8.229833e-06
DST	**-1.8939444**	**6.13914185**	**-0.3085031**	**7.585116e-01**

R2 = 0.94 $\hat{\rho}_1 = 0.196, \quad \hat{\rho}_2 = 0.285$

One can only be 24% confident of a nonzero result of DST. A 95% confidence interval ranges from 2.3% savings to a 1.7% increase in electricity use attributable to early DST.

Table 5. AR2 model using March data in years 2005 through 2007

	b	se	tstat	pvalue
constant	-108.0708733	783.63875961	-0.1379090	0.8905690962
CDD	4.4919148	1.19317148	3.7646850	0.0002716895
HDD	-1.2881091	1.12225420	-1.1477873	0.2535925031
HDD2	0.1299280	0.05729733	2.2676096	0.0253431888
Weekend	-68.1223244	1.57191171	-43.3372460	0.0000000000
Daylight	3.9476770	4.44205940	0.8887042	0.3761371572
Pop	18.9775329	21.66812637	0.8758271	0.3830678037
DST	**-14.2516670**	**9.16461090**	**-1.5550761**	**0.1228535764**

R2 = 0.94 $\hat{\rho}_1 = 0.396, \quad \hat{\rho}_2 = 0.510$

Increasing the sample size and including another year, one is 88% confident of a nonzero result, with the savings centering at 2.3% of electricity use, and a 95% confidence interval ranging from 5.4% savings to an 0.65% increase in electricity use. However, this savings is a comparison of March 12-31, 2007 to all of March in 2005-2006 plus early March 2007. So it could reflect a general decrease in weather-adjusted electricity use since 2005, rather than a daylight saving effect. It could also be due to random statistical variation: extending the analysis to 2002, confidence of a nonzero result drops again:

Table 6: AR2 model using March data in years 2002- 2007

	b	se	tstat	pvalue
constant	467.5287379	276.55428848	1.6905496	9.279970e-02
CDD	4.6461080	1.01573847	4.5741184	9.316787e-06
HDD	-0.5910725	0.89298886	-0.6619036	5.089508e-01
HDD2	0.0810832	0.04622894	1.7539490	8.128469e-02
Weekend	-66.1642375	1.23861780	-53.4177997	0.000000e+00
Daylight	0.8322097	3.52464793	0.2361114	8.136373e-01
Pop	3.9522755	7.67021566	0.5152757	6.070459e-01
DST	-7.7752184	8.19865468	-0.9483530	3.443284e-01

R2 = 0.95 $\hat{\rho}_1 = 0.391, \quad \hat{\rho}_2 = 0.473$

Confidence of a nonzero result drops to 66%, as the 95% confidence interval around the DST effect extends from 4% savings to a 1.4% increase, with the point estimate of DST-induced savings being 1.3% of electricity use.

In summary, the Ordinary Least Squares regression suggested that DST had uncertain effect, small and statistically indistinguishable from zero. However, Ordinary Least Squares could not prove that result because the standard errors and hence the confidence interval sizes were biased so staff ran second order autoregressive models. The autoregressive models in a variety of specifications verified that DST effects had no statistically significant effect on total daily electricity use in the month of March 2007 in the parts of California subject to the California ISO. The regressions did not and cannot rule out small savings, nor can they rule out an electricity use increase.