Impact of Extended Daylight Saving Time on National Energy Consumption

TECHNICAL DOCUMENTATION FOR REPORT TO CONGRESS

Energy Policy Act of 2005, Section 110

Prepared for

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Executive Summary

The Energy Policy Act of 2005 (Pub. L. No. 109-58; EPAct 2005) amended the Uniform Time Act of 1966 (Pub. L. No. 89-387) to increase the portion of the year that is subject to Daylight Saving Time. (15 U.S.C. 260a note) EPAct 2005 extended the duration of Daylight Saving Time in the spring by changing its start date from the first Sunday in April to the second Sunday in March, and in the fall by changing its end date from the last Sunday in October to the first Sunday in November. (15 U.S.C. 260a note) EPAct 2005 also called for the Department of Energy to evaluate the impact of Extended Daylight Saving Time on energy consumption in the United States and to submit a report to Congress. (15 U.S.C. 260a note)

This report presents the detailed results, data, and analytical methods used in the DOE Report to Congress on the impacts of Extended Daylight Saving Time on the national energy consumption in the United States. It describes in detail, the different statistical and other analysis methods conducted in support of the study.

The key findings are:

- The total *electricity* savings of Extended Daylight Saving Time were about 1.3 Tera Watt-hour (TWh). This corresponds to 0.5 percent per each day of Extended Daylight Saving Time, or 0.03 percent of electricity consumption over the year. In reference, the total 2007 electricity consumption in the United States was 3,900 TWh.
- In terms of national *primary energy* consumption, the electricity savings translate to a reduction of 17 Trillion Btu (TBtu) over the spring and fall Extended Daylight Saving Time periods, or roughly 0.02 percent of total U.S. energy consumption during 2007 of 101,000 TBtu.
- During Extended Daylight Saving Time, electricity savings generally occurred over a three- to five-hour period in the evening with small increases in usage during the early-morning hours. On a daily percentage basis, electricity savings were slightly greater during the March (spring) extension of Extended Daylight Saving Time than the November (fall) extension. On a regional basis, some southern portions of the United States exhibited slightly smaller impacts of Extended Daylight Saving Time on energy savings compared to the northern regions, a result possibly due to a small, offsetting increase in household air conditioning usage.
- Changes in national *traffic volume* and *motor gasoline consumption* for passenger vehicles in 2007 were determined to be statistically insignificant and therefore, could not be attributed to Extended Daylight Saving Time.

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Acronyms

AEO	Annual Energy Outlook
AZN	Arizona/ New Mexico/ Southern Nevada Power Area
Btu	British thermal unit
CDD	Cooling Degree-days
CEC	California Energy Commission
CNV	California/Mexico Power Area
DDST	Double Daylight Saving Time
DID	Difference-in-Difference Regression
DOE	Department of Energy
DOE-2	Department of Energy Residential Building Model
DOT	Department of Transportation
DST	Daylight Saving Time
ECAR	East Central Area Reliability Coordination Agreement
EDST	Extended Daylight Saving Time
EERE	Office of Energy Efficiency and Renewable Energy
EIA	DOE Energy Information Administration
ELCAP	Load and Consumer Assessment Program
ERCOT	Electric Reliability Council of Texas
ES&D	Electricity Supply and Demand Database
FERC	Federal Energy Regulatory Commission
FHWA	Federal Highway Administration
FRCC	Florida Reliability Coordinating Council
GWh	Giga Watt-hours
HDD	Heating Degree-days
HELM	Hourly Electric Load Model
ISO	Independent System Operator
ISO-NE	Independent System Operator – New England
LADWP	Los Angeles Department of Water and Power
LCD	Local Climatological Data
MAAC	Mid-Atlantic Area Council
MAIN	Mid-America Interconnected Network
MMBtu	Million British thermal units
MRO	Midwest Reliability Organization
MWh	Mega Watt-hours
NBS	National Bureau of Standards
NCDC	National Climatic Data Center
NEL	Net Energy for Load
NEMass	Northeast Massachusetts
NEMS	National Energy Modeling System
NERC	North American Electric Reliability Council
NPCC	Northeast Power Coordinating Council
NPCC-NY	Northeast Power Coordinating Council – New York
NPCC-NE	Northeast Power Coordinating Council – New England
NWP	Northwest Power Pool Area

O&M	Operations and Maintenance
OLS	Ordinary Least Squares
RECS	Residential Energy Consumption Surveys
RFC	ReliabilityFirst Corporation
RMP	Rocky Mountain Power Area
S.E.	Standard Error
SERC	Southeastern Electric Reliability Council
SERC-CENT	SERC Reliability Corporation – Central
SERC-DEL	SERC Reliability Corporation – Delta
SERC-GAT	SERC Reliability Corporation – Gateway
SERC-SE	SERC Reliability Corporation – Southeastern
SERC-VAC	SERC Reliability Corporation – VACAR
SPP	Southwest Power Pool
ST	Standard Time
SUR	Seemingly Unrelated Regressions
TBtu	Trillion British thermal units
TRE	Texas Regional Entity
TVA	Tennessee Valley Authority
TWh	Tera Watt-hours
UC	University of California
VMT	Vehicle-Miles of Travel
WECC	Western Electricity Coordinating Council
WECC-AZN	Western Electricity Coordinating Council – AZ-NM-SNV
WECC-CA	Western Electricity Coordinating Council – CA
WECC-NWP	Western Electricity Coordinating Council – NWPP
WECC-RMP	Western Electricity Coordinating Council – RMPA

1. Introduction

This report presents the detailed results, data, and analytical methods used in the DOE Report to Congress (DOE, 2008) on the impact of Extended Daylight Saving Time on national energy consumption in the United States.[1] It fully documents the data used, and the different statistical and other analysis methods conducted, in support of the study.

Section 110 of EPAct 2005 amended the Uniform Time Act of 1966 (Pub. L. No. 89-387) to increase the portion of the year that is subject to Daylight Saving Time (DST). (15 U.S.C. 260a note) EPAct 2005 extended DST in the spring from the first Sunday in April to the second Sunday in March (three or four weeks earlier than the previous law), and in the fall from the last Sunday in October to the first Sunday in November (one week later than the previous law). Section 110(c) of EPAct directed the Department of Energy to prepare a report on the energy impacts of EDST.

Previous analyses by the Federal Government of the impact of DST on energy consumption indicated that the largest effect was on lighting (Department of Transportation, 1975; DOE, 2006). Assuming that businesses and households maintain their daily schedules (with respect to clock time) after the transition to EDST, extra evening daylight hours may lower electricity consumption because of the delayed need for lighting. Morning electricity use could increase, as people awaken to darker homes and the need for electric lighting is greater. Some parts of the country enjoy cooler or warmer evening weather, and EDST could result in changes in the amount of electricity used for heating and air conditioning.

Daylight Saving Time also provides people with the opportunity to pursue more outdoor activities during the lighter (and warmer) late-afternoon/evening hours. Consequently, while reducing electricity consumption in homes, extra daylight might lead to more driving, which would likely translate into more vehicle-miles-of-travel (VMT) – thus resulting in higher motor gasoline consumption and higher energy use.

Table 1-1 lists some of the possible energy effects of EDST. Some are potentially quantifiable, while others require a significant amount of behavioral analysis to understand their potential impact.

[1] The main report can be found on the DOE Office of Energy Efficiency and Renewable Energy's website at http://www.eere.energy.gov/ba/pba/pdfs/epact_sec_110_edst_report_to_congress_2008.pdf.

Table 1-1. Potential Energy Effects of EDST

Energy Use	Potential Effect
Home Lighting	• Some lighting use will be reduced in early evening, and total evening amounts will be reduced if bedtimes are not delayed • Some lighting use will increase in rooms normally sunlit in the morning
Commercial Lighting	• Outdoor lighting use will decrease if the need for lights is delayed during the evening (e.g., parking lot lighting in retail establishments) • The need for Indoor lighting for businesses that employ daylighting in the late afternoon and evening hours will decrease
Heating and Cooling	• Heating needs may increase in daytime morning hours as more people are active before sunshine-induced heating • Residential cooling needs may increase with more people home during warmer daylight hours in the late afternoon and evening • Commercial and industrial space heating and cooling needs may fluctuate depending on outside temperature and internal heating demand
Appliance Use	• Indoor appliance use may be delayed or reduced as people engage in more outdoor activities or other activities outside the home
Total Electricity	• Increases and decreases from the different end uses will have either a net negative or positive change in electricity needs • Amounts of these changes will depend on the region and time
Total Fuel for Electricity	• Shift and reduction in electricity use may change the type and quantity of total fuel used for generation
Electricity Capacity	• Shifts in electricity requirements may lower the daily peak demand and consequent electric capacity requirements • Because the extensions are in March and November, which are typically periods of low demand, insufficient capacity is generally not a problem
Transportation	• Increased evening daylight may increase the amount of driving for discretionary activities • Increased evening daylight may spread the amount of travel at peak times, reducing congestion and decreasing energy use • Increased evening trips while already traveling may consolidate activities and reduce weekend travel, reducing overall trip miles • Net change in traffic patterns could be positive or negative

The next section of this report presents the key findings (Chapter 2). Chapter 3 describes the rationale for the analysis methods used in the study, followed by Chapters 4 and 5 reporting on the detailed results. These two chapters present the results for electricity and motor gasoline use, and total energy. Appendix A provides a summary of previous studies. Appendices B and C give detailed descriptions of the data and analysis approaches. Appendices D and E present selected electricity demand curves and regression results.

2. Key Findings: Changes in National Energy Consumption

Using both heuristic[2] and statistical analysis methods for measuring the national pattern of electricity changes, the study found:

- For the heuristic analysis, total savings of electricity during the four weeks of EDST time in 2007 was 1.29 TWh and the total primary energy saved associated with the changes in electricity consumption was 17 TBtu.
- For the statistical analysis, total savings of electricity during the four weeks of EDST in 2007 was 1.24 TWh. This also corresponds to a total primary energy savings of 17 TBtu. The statistical variation on this result is ±40 percent (at a 95 percent level of confidence).

The electricity savings are small compared to the national total for the year, representing about 0.03 percent of the total national electricity consumption of 3,900 TWh in 2007.[3] On a daily basis, the total electricity savings due to EDST was 0.46 to 0.48 percent per each day of EDST.

Electricity savings generally occurred over a period of three to five hours in the evening, offset slightly by small increases in energy consumption in several morning hours—typically the hours ending at 7:00 a.m. and 8:00 a.m. in the morning, and ending 5:00 p.m. through 9:00 p.m. in the evening. On a daily percentage basis, electricity savings were slightly greater during the March (spring) extension of DST (0.50 percent) than the November (fall) extension (0.38 percent).

Regionally, areas of the southern United States exhibited smaller impacts of EDST compared to areas of the North. The study found:

- Based on the heuristic analysis, electricity savings in the South as a percent per day were the same as in the North regions, 0.48 percent.
- Based on the statistical analysis, the average daily percent savings in electricity consumption for the North were 0.51 percent, while in the South the savings were 0.42 percent.

There is insufficient statistical evidence that the EDST period has had any measurable impact on motor gasoline consumption for passenger vehicles or traffic volume in 2007.

- A comparison of average motor gasoline consumption over the past 10 years (1998 to 2007) shows that the difference in average motor gasoline consumption during the two weeks before and two weeks after daylight saving time was not statistically significant.
- A 0.06 percent increase in the daily total traffic volume (i.e., counting all hours of the day) was observed in the week after EDST in the spring. This is equivalent to a

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[2] A pragmatic approach that compares the average changes in the pattern of electricity consumption between 2006 and 2007 during the periods of EDST in March and November, without use of formal modeling.

[3] Total net electric load for 2006 was 3,900 TWh as reported by the North American Electric Reliability Corporation (NERC). The DOE Energy Information Administration (EIA) has projected the national total net generation for 2007 at 3,990 TWh, while consumer demand was 3,900 TWh. The differences are due to electrical losses, generation for self-use, and imports.

> *"maximum possible increase of 5.5 thousand barrels per day in motor gasoline consumption that could occur during the late afternoon/evening hours, when EDST is expected to have the greatest impact on traffic volume in the spring 2007."* However, there is insufficient statistical evidence to indicate this percent change in traffic and corresponding gasoline use were attributable to increased afternoon/evening daylight. Other influencing factors, such as weather conditions, traffic incidents/accidents, and special events may have also led to the observed changes in traffic during those hours.

Although this study did not examine changes in traffic volume in the fall, a steady pattern of annual miles of vehicular travel for 2005, 2006, and 2007 suggests that EDST-induced traffic and associated motor gasoline consumption for the fall, if any, would likely be similar to results found in the spring.

3. Analysis Methods

The study used four methods of analysis to calculate changes in national energy consumption.

- A "heuristic" method compared the average changes in the pattern of electricity consumption between 2006 and 2007 during the periods of EDST in March and November;
- A statistical method applied a regression model to daily and hourly consumption for a sample of utilities;
- Examination of the two-week averages of "motor gasoline supplied" information[4] for periods before and after daylight saving time, over 10 years, to determine if there was any statistical evidence of DST and EDST impacts on consumption; and
- Comparison of differences in average week-to-week national traffic volume to determine if there were statistically significant differences in the averages for the weeks before, during, and after the 2007 EDST.

Section 3.1 describes the first two methods, while Section 3.2 describes the last two. Appendices B and C provide the methodological details on the electricity and transport analysis methods, respectively.

3.1 Analysis of Electricity Use across Extended Daylight Saving Time Transitions

Due to the complex interaction between additional daylight hours and hourly temperature, there is no single best method for analyzing EDST impacts on electricity consumption. The study used several methods to evaluate the impact of EDST on changes in electricity consumption, each with different strengths and limitations. Taken together, their findings provide greater insight into EDST electricity effects than examining only a single method.

3.1.1 Heuristic analysis of electricity demand curves

The heuristic (hourly consumption pattern) analysis used data collected from 67 electric utilities from across the United States. The heuristic method examined hourly electricity consumption patterns in 2007 relative to 2006 and used 21-day averages (for the spring period) for each hour of the day. The fall analysis used seven-day averages.[5] This approach is heuristic in the sense

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[4] Motor gasoline supplied" information is used as a proxy for gasoline consumption. In a longer timeframe, "gasoline supplied" equals gasoline consumption, provided that the motor gasoline rolling stock remains constant. DOE's Energy Information Administration (EIA) states: "Products supplied approximately represent consumption of petroleum products because it measures the disappearance of these products from primary sources, i.e., refineries, natural gas processing plants, blending plants, pipelines, and bulk terminals. In general, the product supplied value of each product in any given period is computed as follows: field production, plus refinery production, plus imports, plus unaccounted for crude oil, (plus net receipts when calculated on a Petroleum Administration for Defense (PAD) District basis), minus stock change, minus crude oil losses, minus refinery inputs, minus exports." [U.S. DOE Energy Information Administration (EIA) *Weekly Petroleum Status Report*, 2008]

[5] The spring extension of DST moved the date from the first Sunday in April to the second Sunday in March. For 2007, that totaled 21 days. The fall extension was from the last Sunday in October to the first Sunday in November, seven days.

that it seeks to predict the 2007 *pattern* of the average electricity consumption profile that would have occurred without EDST, without use of formal modeling.

The observed deviations from a smooth pattern of ratios (in defined ranges of morning and evening hours) are taken as evidence of the impact of EDST. By interpolating between hours deemed to be unaffected by EDST, one can estimate the average change in consumption over the spring and fall EDST periods.

<u>Illustrative example of heuristic method for Boston, spring EDST</u>

Figure 3-1 provides an illustration of the approach for Boston.[6] Figure 3-1 shows the 2007 to 2006 ratio, over 21 days, of average hourly electricity consumption for each hour in a day for the spring EDST period. Looking at the ratio of 2007/2006 consumption, it is possible to see that for Boston, EDST is likely responsible for the sharp increase in the consumption in the morning around 7:00 a.m. and a substantial reduction during several evening hours.

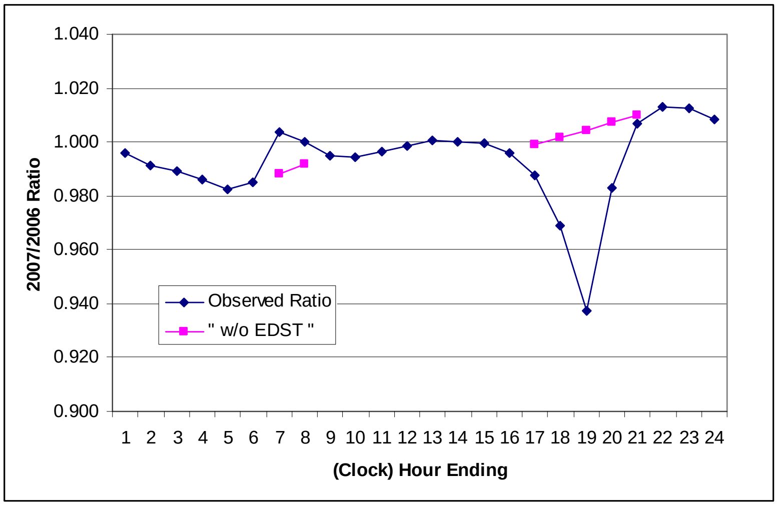

Figure 3-1. Illustration of heuristic approach to estimating impacts, Boston

The lines with squares are the linearly inserted values of the ratios of consumption for the morning and evening periods. In the morning period, the analysis interpolates the ratios between the hours ending at 6:00 a.m. and 9:00 a.m. In the evening, the analysis interpolates the ratios between the hour ending at 4:00 p.m. and the hour ending at 10:00 p.m.[7]

While the procedure illustrated in Figure 3-1 is straightforward, it suffers from two major limitations. The ratios shown are all based on the average consumption patterns during the full 21 days of the spring EDST period. On a day-to-day basis, the ratios will fluctuate based on a variety of factors. This variability influences the statistical confidence of any estimate of the average change. Thus, while the interpolation method provides an estimate of the mean change, it offers no information as to its statistical confidence. The second limitation is that this simple method does not take into account statistical significance of differences in weather (i.e., temperature effects) between 2006 and 2007. Temperature effects in March and November could reduce or enhance the differences observed in the energy consumption ratio curves. The idea behind the heuristic method is that it covers short-term effects over a few hours, while

[6] The data used in the Boston illustrative example comes from the Northeast Massachusetts-Boston subregion of the New England ISO. As a shorthand descriptor, the study refers to this area as Boston.

[7] Based on Figure 3.1, one may question the choice of 4:00 p.m., rather than 3:00 p.m. as the first “boundary” hour of the evening interpolation. For most utilities, 4:00 p.m. appears to be the most appropriate choice. In the Boston case, the estimates of daily electricity savings based upon the 4:00 p.m. hour would be slightly conservative.

temperature effects would be more gradual over the entire day. Appendix B.2 discusses details on the heuristic method.

3.1.2 Statistical models: focus on lighting and appliance use

To address the limitations of the heuristic approach, we developed a statistical approach, using detailed regression models of daily and hourly electricity consumption for as many as 35 utilities located across the United States.[8] The statistical models account for:

- Electricity consumption growth between 2006 and 2007;
- Seasonal change;
- Day of week (Saturday, Sunday, weekday) and holidays;
- Temperature (degree-days for both heating and cooling)[9]; and
- Indicator variables to distinguish between the (March and November) EDST and (April and October) DST time periods in 2007 and 2006.

A statistical measure of confidence was determined for the calculated impacts.

Appendix B.3 discusses details of the model specifications. To study spring EDST impacts, the models analyzed February through April. For the analysis of the EDST week in the fall, the estimation covered the months of October and November.

The analysis focused on the specific hours expected to be most influenced by EDST. Typically, we assumed the influenced hours in the morning were the hours ending at 7:00 a.m. and 8:00 a.m.[10] In the evening, we assumed the influenced hours extended from those ending at 5:00 p.m. through 9:00 p.m.

Table 3-1 provides the estimated hourly impacts for Boston, again with this city taken as an illustrative example. Consistent with Figure 3-1, both of the morning hours show increased electricity use — 1.5 percent from 6:00 a.m. to 7:00 a.m. and 0.9 percent from 7:00 a.m. to 8:00 a.m. During the two-hour period, the average percentage change was 1.2 percent.

In the evening, the maximum reduction of 6.7 percent occurs at the hour ending at 7:00 p.m. During the five-hour period, the average hourly change was -2.9 percent.

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[8] Thirty-five utilities, for which data was available, for the spring analysis, and 29 for the fall analysis.

[9] A “degree-day” is a measure of heating or cooling. For example, if the actual temperature is above 65 degrees, the number of heating degrees for that day is zero.

[10] In about one-third of the utilities analyzed, the morning hours displaying the most influence from EDST (based upon the 2007/2006 ratios from the heuristic method) were those ending at 8:00 a.m. and 9:00 a.m.

Table 3-1. Estimated Impacts of Spring EDST by Hour, Boston

Time Period	Percent Change	Standard Error (S.E.)	Uncertainty Range Upper	Uncertainty Range Lower
Morning				
7 (6 – 7 a.m.)	1.5%	0.6%	0.3%	2.7%
8 (7 – 8 a.m.)	0.9%	0.6%	-0.2%	1.9%
Average	1.2%	0.5%	0.2%	2.1%
Evening				
17 (4 – 5 p.m.)	-1.8%	0.9%	-3.5%	-0.1%
18 (5 – 6 p.m.)	-3.6%	1.1%	-5.7%	-1.5%
19 (6 – 7 p.m.)	-6.7%	1.1%	-8.9%	--4.6%
20 (7 – 8 p.m.)	-2.2%	0.9%	-4.0%	-0.4%
21 (8 – 9 p.m.)	0.2%	0.8%	-1.3%	1.7%
Average	-2.9%	0.7%	-4.2%	-1.5%
Changes with respect to Daily Consumption				
Morning	0.10%	0.04%	0.0%	0.2%
Evening	-0.68%	0.16%	-1.0%	-0.4%
Total for Day	-0.58%	0.16%	-0.9%	-0.3%

The bottom of the table shows the net effect of the morning and evening periods, both compared to average daily consumption. For Boston, less daylight during the same (clock) hours in the morning yields an average 0.10 percent increase in daily electricity use. The evening decrease is more than offsetting, contributing a 0.68 percent decline in electricity use. Taken together, the net effect is about a 0.6 (0.58) percent decline in electricity use per day.

The third column of the table shows the standard errors associated with each of the estimates. Assuming that the uncertainty of the estimates follows a normal distribution, the expected value of the impact would have a probability of about 68 percent of being between one standard error on either side of the computed estimate (in first column). The 95 percent uncertainty ranges are shown in the last two columns of the table.[11]

The uncertainty ranges indicate that by using standard statistical tests, most of the impacts at the hourly level are statistically significant at the 95 percent level of confidence. For the entire day, the results for Boston indicate an uncertainty range of between -0.9 percent and -0.3 percent. The estimated daily impacts and associated uncertainty ranges for all utilities for which statistical models were estimated are shown in several tables in Section 4.2.

[11] For this study, the standard errors are subsequently translated into uncertainty ranges at the 95 percent level of confidence. Given the number of observations used to develop the estimates, a constant factor of about 1.98 is an appropriate value to translate the standard error into an uncertainty range. The lower bound of the uncertainty range is thus equal to the point estimate of the impact minus 1.98 times the standard error. The upper bound is found by adding (1.98 times the standard error) to the estimate.

3.1.3 Statistical model: consideration of space conditioning

The study also considered impacts on electricity consumption that may occur outside the morning and evening periods. These more diffuse effects of daylight saving time may reflect changes in the amount of electricity used for heating and cooling in buildings. To estimate these effects, statistical models covering all 24 hours of the day were estimated, but they yielded mixed results across the utilities investigated. The models suggest that EDST may have led to some increased consumption from air conditioning in some southern locations, but that there may also have been reductions in electricity for heating in northern locations. Across utilities, the results appear to be dependent on the range of daily temperatures during which the EDST occurred, and the prevalence of electricity as a heating energy source in a particular utility service area. Because we judged the statistical models to be insufficiently robust to yield uniformly unbiased estimates of these effects, the estimated impacts from this aspect of the study were not included as part of the national savings shown above. Selected results from these investigations are included in Appendix E.

3.2 Approaches Used to Examine Traffic Volume and Motor Gasoline Consumption

This section briefly describes the analysis considerations and analytical approaches used to examine both weekly "motor gasoline supplied" information for spring and fall and national traffic volume data. For traffic volume analysis, we analyzed both late-afternoon/evening traffic and daily total traffic before, during, and after EDST in the spring. The results from these two analysis approaches provide insight on changes in transportation energy consumption that could be the result of EDST.

"Motor gasoline supplied" data analysis

The study used weekly "motor gasoline supplied" information from the DOE Energy Information Administration (EIA). It used weekly "motor gasoline supplied" data as a proxy for motor gasoline consumption. The study also examines two-week average "motor gasoline supplied" information for the two weeks before and the two weeks after the daylight saving time transitions in the spring and fall, for the time period from 1998 to 2007. Statistical tests were applied in examination of the before and after "motor gasoline supplied" data for both spring and fall time periods. The statistical testing evaluated the hypothesis that the means of weekly "motor gasoline supplied" were the same (at the 95 percent confidence level) across the transition to or from DST. Estimated energy savings was determined by the week-to-week percentage change between the before (pre-DST) and after (post-DST) weekly "motor gasoline supplied" information.

Traffic volume analysis using pair-wise statistical tests

Analysts usually measure aggregate travel activity by vehicle-miles traveled (VMT), which is a function of the number of vehicles on the road and the average trip length. The VMT on a given segment of a roadway is estimated by multiplying the traffic volume on the segment by its length. Total VMT of the entire roadway is the summation of VMT from its individual segments. The total fuel consumption can then be estimated by dividing total VMT by the average vehicle fuel efficiency (i.e., miles per gallon). Therefore, a higher traffic volume will yield more motor fuel consumption, provided the traffic volume increases are uniform among roadway segments, and the roadway segment lengths and average fuel consumption rates are constant.

This analysis also employed traffic volume information from the Federal Highway Administration (FHWA) publication, *Traffic Volume Trends*. More than 4,000 continuous traffic-counting locations collect traffic data nationwide. The study used traffic information during the two weeks before and after EDST in spring 2007 as well as traffic data for the same period in 2006. Using only two weeks of traffic data before and after EDST minimizes potential influences from long-term trends and seasonal variations within the traffic data series. The study analyzed both daily total traffic and late-afternoon/evening traffic before and after EDST using a statistical Pair-wise t-test. For traffic volume analysis, both late-afternoon/evening traffic and daily total traffic before and after EDST in spring were analyzed.

The EDST for 2007 started on March 11, 2007. Four weeks for both 2006 and 2007 are from February 25 and March 24. Because the 2006 DST started on April 2, 2006, the four weeks of 2006 traffic data taken for the period from February and March were not under the influence of EDST. Thus, the 2006 data was assembled is viewed as the baseline for comparison in this study.

This report used the week number assignments contained in Table 3-2 to refer to the specific weeks in the four-week period while discussing the analysis and results from the traffic count data.

The four weeks in 2007 start on Sunday and end on Saturday. However, to match the dates with 2007 data, the four weeks in 2006 start on Saturday and end on Friday.

Table 3-2. Specific Weeks for Daily Traffic Counts Data Used in the Analysis

Week	2006 Dates	2007 Dates
Week 1	Feb 25 – Mar 3	Feb 25 – Mar 3
Week 2	Mar 4 – Mar 10	Mar 4 – Mar 10
Week 3	Mar 11 – Mar 17	Mar 11 – Mar 17
Week 4	Mar 18 – Mar 24	Mar 18 – Mar 24

Before and after analysis

This analysis sought to determine whether traffic volume during late-afternoon/evening and daily totals before EDST were different from the comparable time periods after the transition to EDST. To avoid a potential bias that might be introduced because of the difference in weekdays and weekends, daily traffic totals on the same day of the week in the targeted weeks are used for comparisons. This forms a set of pair-wise comparisons that can be expressed as:

$$\textit{Traffic Difference} = \textit{DailyTraffic Volume}_{station,Date} - \textit{DailyTraffic Volume}_{station,Date+7}$$

Where,

Station = *AutomaticTraffic Recorder ID Number*

Date = *From February* 25 *to March* 3 *(Week* 1 *vs. Week* 2*)*
From March 4 *to March* 10 *(Week* 2 *vs. Week* 3*)*
From March 11 *to March* 17 *(Week* 3 *vs. Week* 4*)*

This comparison scheme allows the statistical Pair-wise t-tests to be used to determine whether a difference is significant or not. The Pair-wise t-tests concern a comparison of the same group of individuals, or matched pairs, being measured before and after an "intervention." The null hypothesis is that the means of these daily traffic volume pairs are the same (at the 95 percent confidence level). Alternatively, the hypothesis can be viewed as a test of whether the changes between two groups differ significantly from zero.

The study conducted this analysis for all states that have EDST.[12] It used traffic volume information from two states that do not observe daylight saving time, i.e., Hawaii and Arizona, as the baseline condition for the comparisons.

One could conclude that EDST has a statistically significant influence on the late-afternoon/ evening daily traffic volume nationally, if:

1) The means of traffic volumes are significantly different from Week 2 to Week 3 in 2007;
2) No significant differences can be found between the pair of Week 1 and Week 2, as well as between the pair of Week 3 and Week 4 in 2007;
3) No significant difference can be found between any pairs for the 2006 time periods (i.e., Week 1 to Week 2, Week 2 to Week 3, and Week 3 to Week 4); and
4) No significant differences can be found between the weeks for Hawaii and Arizona in 2007.

On the other hand, one could conclude that EDST has *no* significant influence on the late-afternoon/evening daily traffic volume nationally, if there were:

1) No significant traffic differences from Week 2 to Week 3 in 2007;
2) No significant differences between the pair of Week 1 and Week 2, Week 3 and Week 4 in 2007;
3) No significant differences between any pairs for the 2006 time periods (i.e., Week 1 to Week 2, Week 2 to Week 3, and Week 3 to Week 4); and
4) No significant differences between the weeks for Hawaii and Arizona in 2007.

Otherwise, it is inconclusive that EDST has influence on traffic volume nationally.

The study did not examine national traffic data collected in the fall. The VMT information from *Traffic Volume Trends* by FHWA shows steady annual VMT patterns for 2005, 2006, and 2007. For this reason, we assumed that if the fall analysis were carried out, it would most likely lead to similar conclusions that were found in the spring analysis.

[12] Within the United States and its territories, Hawaii, American Samoa, Guam, Puerto Rico, the Virgin Islands, the Commonwealth of Northern Mariana Islands, and Arizona do not observe DST. The Navajo Nation within Arizona, however, does participate in DST.

3.3 Aggregation to Determine Changes in National Energy Consumption

We determined the national energy savings from electricity reduction by the regional results, which were determined by scaling the individual utilities' results within each region. We used 16 regions in the analysis to cover the country (minus Hawaii and Alaska). Their boundaries follow the classification used by the National Electricity Reliability Council (NERC). Appendix B.1.1 more fully describes these regions. For each utility analyzed, we divided the amount of electricity savings from EDST by the total electricity consumption for each month where EDST is applicable, March, April, October, and November. When more than one utility in a NERC region was analyzed, their savings and consumption results were combined. Dividing the savings by the consumption and multiplying by the NERC region's consumption gave the savings applicable to the entire region. Each region's monthly electricity consumption was available from NERC. Finally, summing the results for the 16 regions gave the national savings from EDST. The equations are:

For each month:

$$\text{Savings}_{\text{Region}} = \sum \text{Savings}_{\text{utility}} / \sum \text{Consumption}_{\text{utility}} * \text{Consumption}_{\text{Region}}$$

$$\text{Savings}_{\text{Nation}} = \sum \text{Savings}_{\text{Region}}$$

For the year:

$$\text{Savings}_{\text{Annual}} = \sum \text{Savings}_{\text{Month}}$$

Another key metric is the savings per day for a utility, region, or the Nation. To find a utility's savings, divide the utility-specific EDST savings by the consumption during the same EDST period (three weeks in the spring, one week in the fall). To find a region's consumption during EDST, use the equation above, replacing "Savings" with "Consumption during the EDST period."

In some regions, we conducted an analysis on both individual utilities and ISO regions that included the utilities' results. Examples include the cities of Memphis and Chattanooga as a subset of the results from Tennessee Valley Authority (TVA). In the heuristic analysis, we used the larger region's results to capture a higher percentage of the region's consumption. The statistical analysis focused only on the smaller subsets because it required temperature data for a single location. (We also applied the statistical approach to a smaller set of entities.) Because of the different set of data used, the heuristic and statistical methods could yield slightly different estimates of the amount of savings in a region.

The impacts of EDST may be different in various parts of the country, due to weather, lifestyle, or other factors. To best assess the country as a whole, the analysis used data from regionally representative electric utilities. We selected these electric utilities from across the United States, based on the coverage of electricity load, geographic location of service area and climate zone.[13]

[13] The selection of electric utilities for this study aimed to result in a regionally representative collection of utilities, although they were not randomly selected.

The utilities (and regional ISOs) included in this report represent 66 percent of U.S. electricity consumption in the heuristic analysis and 32 percent of consumption in the statistical analysis (See Table B-2 in Appendix B). Appendix B.1 shows maps of the locations and a list of the utilities and ISOs used in the study.

To estimate the national savings, the utility-level results must be weighted by the proportion of total national electricity consumption that each utility represents. The weight for a particular utility is based, in part, upon its proportion of electricity consumption within one of the Nation's 16 NERC regions. Appendix B discusses the construction of the weighting factors.

4. Detailed Results: Changes in Electricity Use

Before presenting the numerical estimates of EDST impacts upon electricity use, several graphical illustrations are presented that depict how EDST impacted the utilities' 2007 hourly electricity demand. These graphical presentations provide some useful background to help understand the quantitative results on electricity use presented later in this Chapter.

The availability of hourly electricity consumption data for the EDST periods in 2007 and for the comparable periods in 2006 facilitates a visual examination of the effect of extended daylight time in 2007. As an illustration of this comparison, the study employed electricity consumption from the area around Boston. The average hourly consumption was computed over the 21 days of the spring EDST period in 2007 (March 11 through March 31). We applied a similar procedure to the same period in March of 2006. For 2006, the 21-day period began on March 12 in order to line up the days of the week (so that both series began on a Sunday and ended on a Saturday). Figure 4-1 shows the average hourly consumption levels for both years. Clearly, the evening consumption in hour 19 (hour ending at 7:00 p.m.) during 2007 is relatively lower than during 2006; the peak evening consumption is shifted from the hour ending at 7:00 p.m. to the following hour.

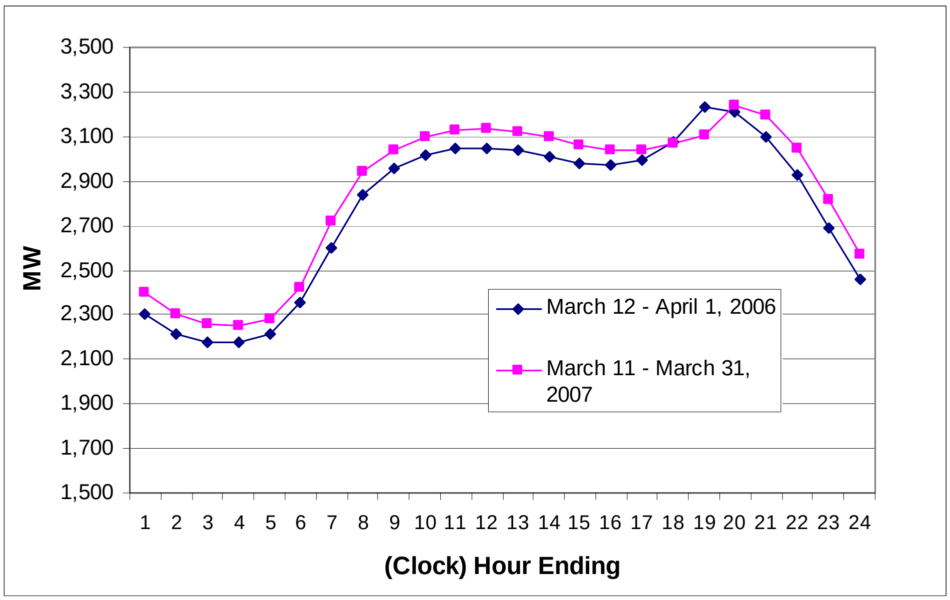

Figure 4-1. Average hourly electricity consumption, 2006 and 2007 spring EDST periods, Boston

More revealing than a comparison of the absolute hourly consumption levels is the *ratio* of the 2007 average consumption to the 2006 average consumption at the corresponding hours of the day, as shown in Figure 4-2. Note that, just as one might increase the magnification on a microscope to see previously unnoticed details, the choice of scaling for the vertical axis is very important. (Figure 4-2 employs a minimum y-axis value of 0.9 rather than zero.) By focusing upon the ratio of the consumption values, it is clear that EDST appears to affect a number of hours in the morning and evening. Particularly pronounced is the sharp increase in the ratio in the morning hour ending at 7:00 a.m. Clearly, viewed in this manner, the reduction in electricity use during the evening hours appears to more than offset the increase in use during several morning hours.

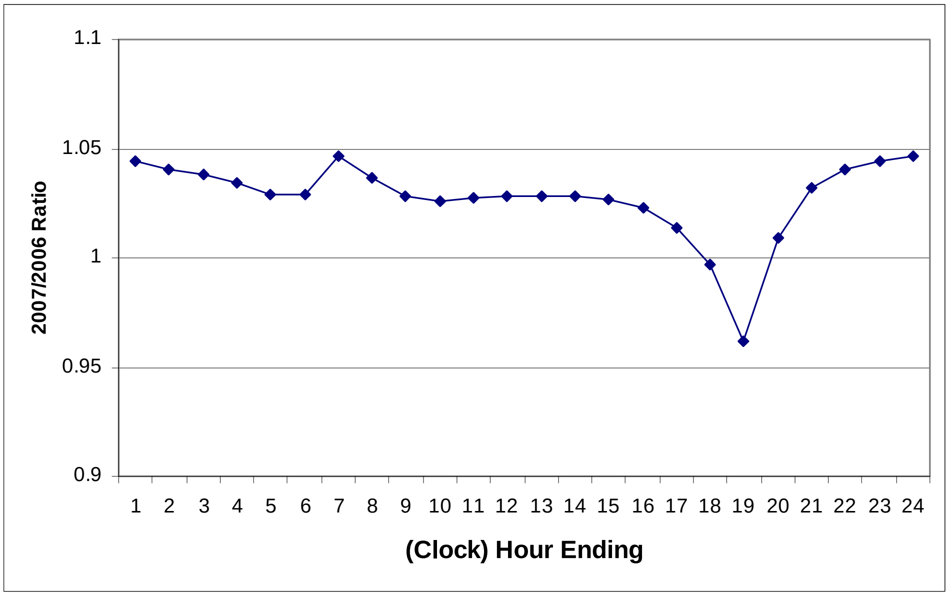

Figure 4-2. Ratio of 2007 average hourly consumption to 2006 average hourly consumption, Boston

A natural question is whether the pattern of ratios can really be attributed to EDST. Figure 4-3, as a simple means of supporting that supposition, shows the ratios of hourly consumption for weeks immediately preceding and following the spring EDST period for Boston. The figure clearly shows that the both the morning and evening deviations in the ratios are not present in either the week before or the week after the EDST period.

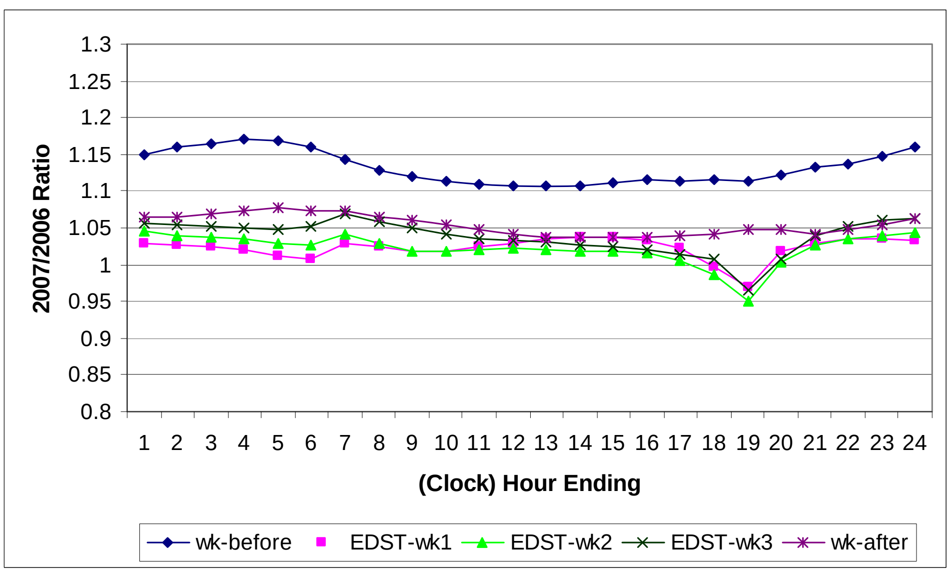

Figure 4-3. Ratio of 2007 to 2006 average hourly consumption, spring EDST period and adjacent weeks

The examination of hourly electricity consumption from utilities all across the United States revealed that the general pattern illustrated in Figure 4-2 for Boston was pervasive. While the ratios of energy consumption for some cities were not as stable during the middle portion of the day as those for Boston, all the plots show a small increase in energy consumption from the prevailing trend and a larger reduction during the evening hours. Appendix D includes spring and fall curves for 19 utilities across all regions of the country as examples. Deviations from the clear pattern for Boston fell into two categories. First, in a number of utilities, the increase in morning consumption was not as discernable as that in Boston. Second, for locations in the south, the presence of air conditioning appears to make the reduction during the evening occur later and with less intensity. We observed the same general pattern for both the spring and fall extensions of DST.

4.1 Findings from Heuristic Method Comparing Average Electricity Consumption Profiles

Nationally, total savings for electricity from the heuristic method was 1.29 TWh, with a marginal cost savings of $84 million. Using the state and regional fuel prices for the spring and fall months, the total primary energy saved was 17 TBtu. Table 4-1 shows the savings by NERC region. Appendix B.1.1 describes these regions in more detail. The lowest energy savings per day were in the Mid-South regions (0.27 percent, on average), while the greatest was in California (0.93 percent). The national average was 0.48 percent electricity savings per each day of EDST.

Table 4-1. Energy Savings by Region from Electricity Reductions Using the Heuristic Method[14]

NERC Region*	Location	Savings (GWH)	Avg. Savings per Day (%)	Primary Energy Savings (TBtu)
RFC	North	336	0.46%	5.3
NPCC-NY	North	49	0.41%	0.7
NPCC-NE	North	68	0.68%	0.7
MRO	North	58	0.37%	0.9
SERC-GAT	North	20	0.36%	0.3
WECC-NWP	North	111	0.64%	1.6
WECC-RMP	North	19	0.43%	0.3
North Subtotal		660	0.48%	9.9
FRCC	South	60	0.40%	0.7
SERC-DEL	South	25	0.26%	0.2
SERC-SE	South	111	0.67%	1.4
SERC-CEN	South	40	0.29%	0.5
SERC-VAC	South	114	0.52%	1.4
SPP	South	33	0.24%	0.5
TRE	South	54	0.29%	0.6
WECC-AZN	South	20	0.61%	0.2
WECC-CNV	South	172	0.93%	2.1
South Subtotal		629	0.48%	7.4
Total		1,290	0.48%	17.3

Note: Details on the NERC regions listed are found in Appendix B.1 of the supporting Technical Documentation (Belzer, et al., 2008).

[14] The national energy savings from electricity reduction are determined by the regional results, which are determined by scaling the individual utilities' results within each region. Appendix B describes the construction of the weighting factors and calculation of national energy savings.

The total savings of 1.29 TWh represents 0.033 percent of the Nation's 3,900 TWh of electricity demand for 2006.[15] The cost savings includes both fuel and a small amount of variable operating costs for power plants. It is based on the marginal cost of production at the time of the savings and represents the reduction in fuel purchases or other avoided operating costs. This net value includes both savings (typically in the evening) and extra production in the morning. The average cost of this saved production is $65/MWh, though the amount can vary depending on the time of day, region, type of fuel, and efficiency of the power plant.

The study aggregated the 16 NERC regions into broad North and South portions of the country, as shown in Table 4-1. The savings in the South as a percent per day are the same as in the North regions, 0.48 percent. However, this is largely because of the results in California, which were both higher than all other regions and represent 14 percent of the Southern electricity demand.

We analyzed 67 utilities or control areas using the heuristic method. Figure 4-4 shows the percentage reductions for each, with the relative size of each circle based on the percentage savings over the combined spring and fall EDST periods. Savings were between 0.96 percent (California ISO) and 0.2 percent (ERCOT North and Southwestern Public Service). Two utilities showed gains (in brown) rather than savings (in green), but these were generally small and had unusual electricity load shapes for either the spring or fall series. Table 4-2 lists each utility with its spring, fall, and annual savings in GWh and percent per day.

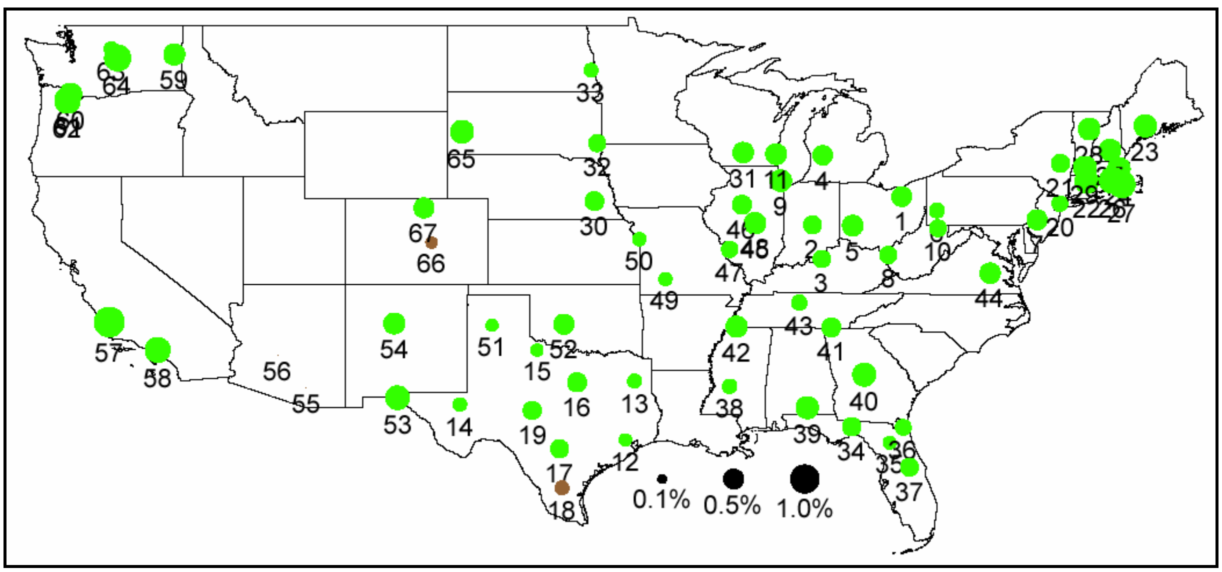

Figure 4-4. EDST percent savings of electricity per day for each utility studied using the heuristic method

[15] Total net electric load for 2006 was 3,900 TWh as reported by NERC. EIA has projected the national total net generation for 2007 at 3,990 TWh while consumer demand was 3,900 TWh, as reported elsewhere in this report. The differences are due to electrical losses, generation for self-use, and imports. Because 2006 data was more complete (national totals and hourly costs), we based the scaling up to national totals in this report on what would have been saved in 2006 with EDST rather than what would have been consumed in 2007 without EDST. However, because we based the percentage changes on hourly ratios between the two years, the results should be essentially the same.

Table 4-2. EDST Savings in GWh and Percent per Day of EDST for Utilities, Regions, and Nation Using the Heuristic Method

	Utility	Region	Spring Savings (GWh)	Spring Savings (%/day)	Fall Savings (GWh)	Fall Savings (%/day)	Annual Savings (GWh)	Annual Savings (%/day)
1	FirstEnergy Corporation	RFC	-19	-0.48	-7	-0.51	-26	-0.49
2	Indianapolis Power & Light Company	RFC	-4	-0.40	-1	-0.41	-5	-0.41
3	Louisville Gas & Electric and Kentucky Utilities	RFC	-6	-0.32	-4	-0.57	-10	-0.38
4	Midwest ISO East Region	RFC*	-67	-0.47	-24	-0.48	-90	-0.47
5	PJM Interconnection AEP-Dayton Hub	RFC	-6	-0.54	-2	-0.55	-7	-0.54
6	PJM Interconnection Duquesne Hub	RFC	-2	-0.23	-1	-0.46	-3	-0.28
7	PJM Interconnection Eastern Hub	RFC	-69	-0.45	-34	-0.68	-103	-0.51
8	PJM Interconnection LLC (AEP Hub)	RFC	-21	-0.26	-19	-0.71	-39	-0.37
9	PJM Interconnection North Illinois Hub	RFC	-29	-0.53	-9	-0.51	-38	-0.52
10	PJM Interconnection Western Hub	RFC	-8	-0.28	-5	-0.56	-13	-0.35
11	Wisconsin Electric Power Company	RFC	-9	-0.51	-4	-0.64	-12	-0.54
12	ERCOT COAST	TRE	-12	-0.28	1	0.06	-11	-0.19
13	ERCOT EAST	TRE	-2	-0.33	0	-0.01	-2	-0.24
14	ERCOT FAR_WEST	TRE	-1	-0.20	-1	-0.31	-2	-0.23
15	ERCOT NORTH	TRE	0	-0.07	-1	-0.55	-1	-0.19
16	ERCOT NORTH_C	TRE	-23	-0.46	-7	-0.45	-30	-0.46
17	ERCOT SOUTH_C	TRE	-10	-0.46	-2	-0.25	-12	-0.41
18	ERCOT SOUTHERN	TRE	1	0.04	3	0.82	4	0.24
19	ERCOT WEST	TRE	-2	-0.40	-1	-0.43	-2	-0.41
20	Consolidated Edison Co. of NY Inc.	NPCC-NY*	-11	-0.34	-2	-0.22	-13	-0.31
21	New York Independent System Operator, Inc.	NPCC-NY	-32	-0.37	-16	-0.54	-48	-0.41
22	ISO-New England - Connecticut	NPCC-NE	-12	-0.69	-4	-0.69	-17	-0.69
23	ISO-New England - Maine	NPCC-NE	-4	-0.69	-1	-0.44	-5	-0.62
24	ISO-New England - NE Massachusetts	NPCC-NE	-9	-0.66	-3	-0.61	-12	-0.65
25	ISO-New England - New Hampshire	NPCC-NE	-4	-0.59	-1	-0.58	-5	-0.58
26	ISO-New England - Rhode Island	NPCC-NE	-4	-0.87	-1	-0.78	-5	-0.85
27	ISO-New England - SE Massachusetts	NPCC-NE	-7	-0.87	-2	-0.81	-9	-0.86
28	ISO-New England - Vermont	NPCC-NE	-2	-0.56	-1	-0.68	-3	-0.59
29	ISO-New England - W Central	NPCC-NE	-7	-0.65	-2	-0.66	-9	-0.65

	Utility	Region	Spring Savings (GWh)	Spring Savings (%/day)	Fall Savings (GWh)	Fall Savings (%/day)	Annual Savings (GWh)	Annual Savings (%/day)
	Massachusetts							
30	Lincoln Electric System	MRO*	-1	-0.51	0	-0.22	-1	-0.44
31	Madison Gas & Electric Company	MRO	-1	-0.54	0	-0.49	-1	-0.53
32	Midwest ISO West Region	MRO	-19	-0.32	-11	-0.51	-29	-0.36
33	Otter Tail Power Company	MRO*	-1	-0.31	0	-0.05	-1	-0.24
34	City of Tallahassee	FRCC	-1	-0.50	0	-0.22	-1	-0.43
35	Gainesville Regional Utilities	FRCC	0	-0.17	0	-0.31	0	-0.21
36	Jacksonville Energy Authority	FRCC	-3	-0.42	-1	-0.31	-4	-0.39
37	Progress Energy (Florida Power Corp.)	FRCC	0	0.00	-3	-0.40	-3	-0.40
38	Entergy Corporation/Services (Entergy System)	SERC-DEL	-17	-0.28	-4	-0.20	-21	-0.26
39	Alabama Electric Cooperative	SERC-SE	-3	-0.62	0	0.00	-3	-0.62
40	Oglethorpe Power Company	SERC-SE	-11	-0.62	-5	-0.80	-16	-0.67
41	Electric Power Board of Chattanooga	SERC-CEN*	-1	-0.41	-1	-0.51	-2	-0.44
42	Memphis Light, Gas and Water	SERC-CEN*	-4	-0.52	-2	-0.69	-5	-0.56
43	Tennessee Valley Authority	SERC-CEN	-17	-0.18	-20	-0.63	-37	-0.29
44	PJM Interconnection Dominion Hub	SERC-VAC	-24	-0.49	-10	-0.64	-34	-0.52
45	Ameren (Illinois Power Co. Control Area)	SERC-GAT*	-6	-0.58	0	0.00	-6	-0.58
46	Ameren CILCO	SERC-GAT	-1	-0.45	0	0.00	-1	-0.45
47	Ameren Corporation Control Area	SERC-GAT	-11	-0.33	0	0.00	-11	-0.33
2	Indianapolis Power & Light Company	SERC-GAT**	-4	-0.40	-1	-0.41	-5	-0.41
48	Midwest ISO Central Region	SERC-GAT*	-54	-0.45	-16	-0.46	-70	-0.45
49	Empire District Electric Company	SPP	0	0.00	0	-0.22	0	-0.22
50	Kansas City Board of Public Utilities & Wyandotte County	SPP	0	-0.21	0	-0.28	0	-0.23
51	Southwestern Public Service Company (Xcel)	SPP	-3	-0.19	0	0.00	-3	-0.19
52	Western Farmers Electric Cooperative	SPP	-2	-0.50	0	0.00	-2	-0.50
53	El Paso Electric Company	WECC-AZN	-3	-0.77	-1	-0.52	-4	-0.70
54	Public Service Company of New Mexico	WECC-AZN	-3	-0.58	-1	-0.46	-4	-0.55
55	Tucson Electric Power Company	WECC-AZN***	0	0.00	0	0.00	0	0.00

	Utility	Region	Spring Savings (GWh)	Spring Savings (%/day)	Fall Savings (GWh)	Fall Savings (%/day)	Annual Savings (GWh)	Annual Savings (%/day)
56	Western Area Power Administration - Lower Colorado control area (Desert Southwest)	WECC-AZN***	0	0.00	0	0.00	0	0.00
57	California Independent System Operator	WECC-CNV	-121	-0.96	-41	-0.95	-162	-0.96
58	Los Angeles Department of Water and Power	WECC-CNV	-11	-0.79	-2	-0.42	-13	-0.69
59	Avista Corporation	WECC-NWP	-4	-0.52	-2	-0.68	-5	-0.56
60	Bonneville Power Administration, USDOE	WECC-NWP	-17	-0.58	-8	-0.77	-25	-0.63
61	PacifiCorp - Part II Sch 2	WECC-NWP	-18	-0.59	0	0.00	-18	-0.59
62	Portland General Electric Company	WECC-NWP	-10	-0.82	0	0.00	-10	-0.82
63	PUD No. 1 of Chelan County	WECC-NWP	-1	-0.29	0	-0.20	-1	-0.26
64	PUD No. 1 of Douglas County	WECC-NWP	-1	-0.88	0	-0.82	-1	-0.86
65	Black Hills Corporation	WECC-RMP	-1	-0.66	0	0.00	-1	-0.66
66	Colorado Springs Utilities	WECC-RMP	0	0.16	0	0.00	0	0.16
67	Western Area Power Administration - Colorado-Missouri Control Area (Rocky Mtn Region)	WECC-RMP	-6	-0.51	-2	-0.51	-8	-0.51
		Total	-913	-0.45	-377	-0.56	-1290	-0.48

* Results are not included in scaling up to the region because they are already included in another utility or ISO result.
** Indianapolis Power and Light results for the fall were applied to neighboring SERC-GAT, even though the utility is in the RFC region.
*** Arizona utilities have no savings since Arizona does not use DST.

Most utilities saved between 0.2 percent and 0.9 percent each day of EDST. No NERC region had lower savings for all utilities, but Texas and the South-Central regions generally appeared to have lower savings. There is some speculation that this may be caused by increased afternoon demands for cooling. Other reasons may simply be due to the weather in 2007 versus 2006 in those parts of the country.

As described in Chapter 3 and Appendix B, a key metric used in the heuristic analysis is the deviation of the hourly average 2007 electricity demand as compared to the 2006 demand. Figure 4-5 and Figure 4-6 show the ratio of 2007 hourly electricity loads to 2006 loads for California ISO during the spring and fall, respectively. The red line indicates the actual ratio of 2007 to 2006 consumption during the EDST period. The green line indicates the estimated path of hourly electricity loads if EDST were not in effect.

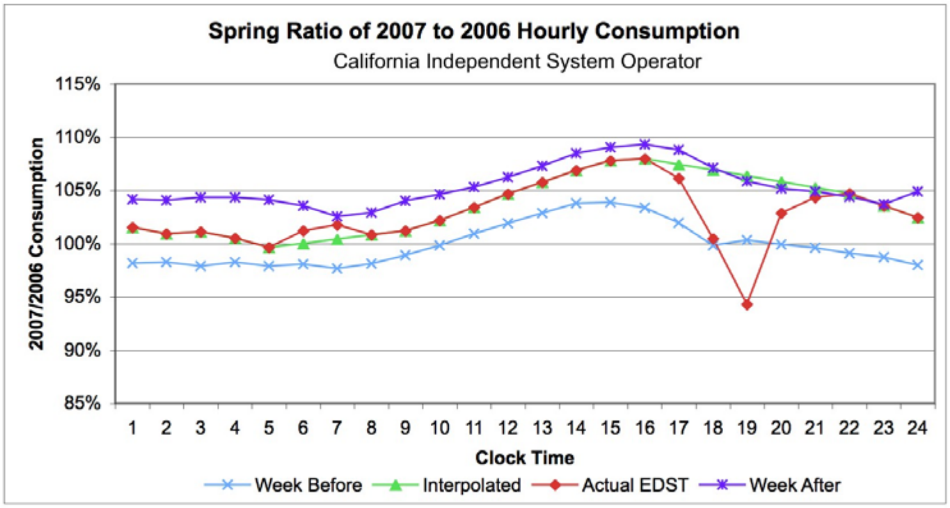

Figure 4-5. Comparison of California ISO spring 2007 to 2006 electricity loads

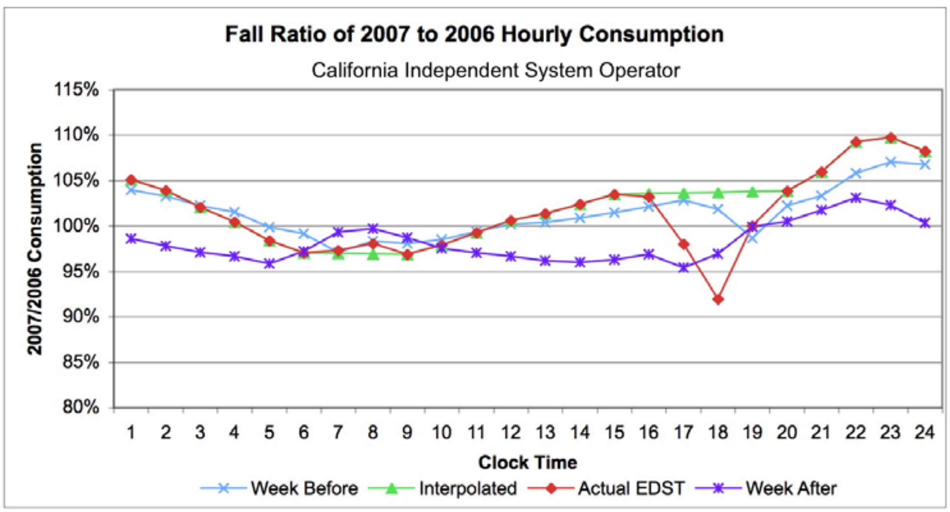

Figure 4-6. Comparison of California ISO fall 2007 to 2006 electricity loads

The California ISO results had the highest response to DST in its hourly curves. There are large decreases in electricity consumption in the evening hours that extend for a number of hours. The morning hours show an increased electricity use, but on a much smaller scale. Based on these curves, the California ISO saved 0.96 percent per day of electricity in the spring and 0.95 percent in the fall, giving an annual daily savings for those four weeks of 0.96 percent. Most utilities had curves similar to the California ISO curves although less extreme in total savings.

4.2 Findings from Statistical Model Applied to Morning and Evening Periods

Summary results for utilities: spring EDST

Table 4-3 summarizes the results from the statistical model, described in general terms in Section 2.1, applied to 35 utilities for which spring electricity consumption data were analyzed. The table shows all values as the average percentage change for the hours considered in the period—two hours in the morning and five hours in the evening. The impacts during the morning hours show wide variation across utilities, ranging from a reduction of 0.2 percent to an increase of 4 percent.

This reflects a situation where other factors in addition to electric lighting affect morning loads. The variability in the evening is not as great, but still substantial. On an average hourly basis, the impacts during the evening generally fall between a reduction of 1 percent and 4 percent.

Table 4-3. Morning and Evening Impacts by Utility, Spring EDST

Utility*	Morning Average Hourly Pct. Chg.	Morning Std. Error[16]	Evening Average Hourly Pct. Chg.	Evening Std. Error
Indianapolis Power & Light	2.4%	0.9%	-3.8%	1.3%
Louisville Gas & Elec	1.7%	1.0%	-2.6%	1.3%
Dayton Hub - PJM	1.6%	0.7%	-3.4%	1.1%
Duquesne Hub - PJM	0.6%	0.6%	-2.6%	0.9%
No. Illinois Hub - PJM	1.9%	0.7%	-3.6%	0.8%
ERCOT - Coast	0.4%	0.9%	-0.8%	1.0%
ERCOT - S. Central	0.5%	1.3%	-1.7%	1.5%
Con Ed - New York	0.9%	0.3%	-1.9%	0.5%
ISO-NE - Connecticut	1.1%	0.6%	-3.3%	0.8%
ISO-NE - NE Mass (Boston)	1.2%	0.5%	-2.9%	0.7%
Lincoln Electric System	1.2%	0.8%	-3.2%	1.4%
Madison Gas & Elec	1.8%	0.5%	-2.8%	0.7%
Otter Tail Power Co.	4.0%	1.6%	-2.5%	1.6%
City of Tallahassee	1.6%	1.4%	-2.1%	1.3%
Gainesville Regional Utility	2.0%	1.3%	-1.8%	1.3%
Jacksonville Energy Authority	1.4%	1.2%	-2.2%	1.5%
Entergy Corp.	1.1%	0.8%	-1.9%	1.4%
Alabama Electric Coop	-0.1%	1.9%	-1.2%	2.3%
Oglethorpe Power Co.	0.7%	1.7%	-1.7%	1.8%
Electric Power - Chattanooga	0.3%	1.2%	-2.8%	1.3%
Memphis Light, Gas & Water	1.9%	0.9%	-2.2%	1.4%
Dominion Hub - PJM	0.6%	1.3%	-3.1%	1.3%
Ameren Control Area	1.7%	0.8%	-3.1%	1.1%
Kansas City Public Utilities	1.2%	1.0%	-1.2%	1.3%
Southwestern Public Service	0.6%	0.7%	-1.0%	1.1%
Western Farmers Elec Coop	-0.2%	1.4%	-2.5%	1.7%
El Paso Electric	2.6%	0.9%	-2.2%	1.0%
Public Service of N. Mexico	2.2%	0.6%	-4.1%	0.6%
California ISO	1.7%	0.5%	-4.0%	0.6%
Los Angeles DWP	2.4%	0.6%	-3.7%	0.9%
Avista Corp	1.1%	0.7%	-2.8%	0.9%
Portland General Electric	0.6%	0.8%	-1.9%	0.9%
Chelan County PUD	2.1%	0.8%	-1.0%	0.8%
Black Hills Corporation	1.0%	1.1%	-3.5%	1.5%
WAPA - Rocky Mountain	1.9%	0.7%	-3.3%	0.8%

* Note: The utilities listed are a combination of individual utilities (investor-owned or consumer-owned) and regional entities -- Independent System Operators, or ISOs. Details are provided in Appendix B.1 of the supporting Technical Documentation (Belzer, et al., 2008).

[16] "Std Error" is the standard deviation associated with the estimated change in electricity use, based upon the results of the statistical model. It is a statistical measure that reflects the uncertainty of the estimated change with respect to its expected (or average) value (as shown in the highlighted columns of Tables 2-2 and 2-3).

Table 4-4 combines the morning and evening impacts into the impact for the day. Columns four and five present the (95 percent) uncertainty ranges for each utility.

Table 4-4. Daily Impacts and Uncertainty Bounds by Utility, Spring EDST

Utility	Average Daily Pct. Chg.	Std. Error	Uncertainty Range Lower	Uncertainty Range Upper	Sample Weight	North/ South
Indianapolis Power & Light	-0.6%	0.3%	-1.2%	-0.1%	0.022	N
Louisville Gas & Elec	-0.5%	0.3%	-1.0%	0.1%	0.051	N
Dayton Hub - PJM	-0.6%	0.3%	-1.2%	-0.1%	0.026	N
Duquesne Hub - PJM	-0.5%	0.2%	-0.9%	-0.1%	0.021	N
No. Illinois Hub - PJM	-0.7%	0.2%	-1.1%	-0.3%	0.144	N
ERCOT - Coast	-0.1%	0.3%	-0.6%	0.4%	0.046	S
ERCOT - S. Central	-0.4%	0.4%	-1.1%	0.4%	0.024	S
Con Ed - New York	-0.4%	0.1%	-0.6%	-0.2%	0.044	N
ISO-NE - Connecticut	-0.7%	0.2%	-1.1%	-0.3%	0.020	N
ISO-NE - NE Mass (Boston)	-0.6%	0.2%	-0.9%	-0.3%	0.016	N
Lincoln Electric System	-0.7%	0.3%	-1.3%	0.0%	0.017	N
Madison Gas & Elec	-0.5%	0.2%	-0.8%	-0.2%	0.018	N
Otter Tail Power Co.	-0.2%	0.4%	-0.9%	0.6%	0.022	N
City of Tallahassee	-0.4%	0.3%	-1.0%	0.3%	0.009	S
Gainesville Regional Utility	-0.3%	0.3%	-1.0%	0.3%	0.006	S
Jacksonville Energy Authority	-0.4%	0.4%	-1.1%	0.3%	0.042	S
Entergy Corp.	-0.3%	0.3%	-1.0%	0.3%	0.036	S
Alabama Electric Coop	-0.3%	0.6%	-1.5%	0.9%	0.012	S
Oglethorpe Power Co.	-0.4%	0.5%	-1.3%	0.6%	0.048	S
Electric Power - Chattanooga	-0.6%	0.3%	-1.3%	0.0%	0.015	S
Memphis Light, Gas & Water	-0.4%	0.4%	-1.1%	0.3%	0.035	S
Dominion Hub - PJM	-0.7%	0.3%	-1.3%	0.0%	0.079	S
Ameren Control Area	-0.6%	0.3%	-1.1%	-0.1%	0.019	N
Kansas City Public Utilities	-0.2%	0.3%	-0.7%	0.4%	0.003	S
Southwestern Public Service	-0.2%	0.2%	-0.6%	0.3%	0.037	S
Western Farmers Elec Coop	-0.6%	0.4%	-1.4%	0.2%	0.008	S
El Paso Electric	-0.3%	0.2%	-0.8%	0.2%	0.012	S
Public Service of N. Mexico	-0.8%	0.2%	-1.1%	-0.5%	0.017	S
California ISO	-0.8%	0.2%	-1.1%	-0.5%	0.063	S
Los Angeles DWP	-0.7%	0.2%	-1.1%	-0.3%	0.007	S
Avista Corp	-0.5%	0.2%	-1.0%	-0.1%	0.021	N
Portland General Electric	-0.4%	0.2%	-0.8%	0.1%	0.037	N
Chelan County PUD	0.0%	0.2%	-0.3%	0.3%	0.006	N
Black Hills Corporation	-0.7%	0.4%	-1.4%	0.0%	0.002	N
WAPA - Rocky Mountain	-0.6%	0.2%	-1.0%	-0.2%	0.014	N
National Average	-0.50%	0.07%	-0.64%	-0.36%	1.000	
North (17 utilities)	-0.54%	0.08%	-0.70%	-0.38%		
South (18 utilities)	-0.46%	0.11%	-0.68%	-0.24%		

NOTE: “N” = North; “S” = South

As explained in Section 2.1 and Appendix B, the study estimated national savings from the utility-level results by using weights set in proportion of total national electricity consumption that each utility represents. The weights shown in column six of Table 4-4 were used to develop the estimate of national average daily electricity savings in the spring of 0.50 percent, as shown in the last line of the table.

While the uncertainty ranges for individual utilities are large, the pervasive finding of electricity savings in every utility yields a significantly smaller uncertainty range when computed for the entire United States. [17] The standard error of 0.07 percent for the national impact is considerably smaller than any of those shown for the utilities on an individual basis. Converted to an uncertainty range, the analysis shows that the 2007 national electricity savings from spring EDST, due primarily from impacts on lighting and appliances in the morning and evening hours, was between about -0.65 percent and -0.35 percent with a 95 percent level of confidence.

As shown at the bottom of the table, the average savings are somewhat higher in those utilities located in the northern portion of the United States as compared to those in the south. Most of this difference can be attributed to an offsetting increase in electricity for air conditioning in some of the most southern utilities.

Summary results for utilities: fall EDST

Tables 4-5 and 4-6 show the same results from the models used to estimate the impacts from the one-week extension of EDST in the fall for 29 utilities, for which we analyzed fall electricity consumption data. Table 4-5 shows the average hourly impacts during the morning and evening periods. Table 4-6 presents the daily impacts and associated uncertainty ranges.

Electricity consumption data were not available in October and November for a number of utilities in the fall, as shown by the NA entries in Tables 4-5 and 4-6. The national average results were based on renormalizing the sample weights for the utilities from which data were available.

The impacts during the fall EDST period are somewhat smaller than those in the spring. The national average reduction in daily electricity use in the fall EDST period is 0.38 percent as compared to the 0.50 percent estimated for the spring. An examination of the impact in both the morning and evening indicates that the impacts (both positive and negative) are generally smaller in the fall than in the spring.

The findings may result from two factors. First, even under standard time, some portion of the morning hours during which many people prepare for work or school is already dark at the end of October. Thus, the extension of daylight time, which provides later sunrises in terms of clock time, will have a smaller effect on lighting use than in March. Second, the cooler (colder)

[17] The method for developing the standard error of the national estimate is described in Appendix B.5. The method considers the standard errors (variance) of the individual utility estimates and as well as the correlation of the standard errors across utilities (covariance).

temperatures at the end of October are less conducive to outdoor activities (e.g., gardening, youth sports activities, etc.) regardless of daylight conditions. Thus, a smaller impact in the evening during the fall EDST period, as compared to the spring, is not surprising.

Table 4-5. Morning and Evening Impacts by Utility, Fall EDST

	Morning		Evening	
Utility*	Average Hourly Pct. Chg.	Std. Error	Average Hourly Pct. Chg.	Std. Error
Indianapolis Power & Light	2.3%	1.1%	-3.4%	1.9%
Louisville Gas & Elec	1.4%	1.6%	-3.9%	1.4%
Dayton Hub - PJM	0.5%	1.1%	-3.6%	1.4%
Duquesne Hub - PJM	0.5%	1.0%	-3.1%	1.3%
No. Illinois Hub - PJM	2.0%	0.6%	-3.2%	1.0%
ERCOT - Coast	2.9%	1.1%	-1.1%	1.3%
ERCOT - S. Central	3.3%	2.4%	-1.7%	2.5%
Con Ed - New York	1.3%	0.7%	-1.4%	0.7%
ISO-NE - Connecticut	0.5%	1.0%	-3.5%	1.2%
ISO-NE - NE Mass (Boston)	1.0%	0.8%	-2.8%	1.1%
Lincoln Electric System	2.9%	0.8%	-2.5%	1.3%
Madison Gas & Elec	1.0%	0.6%	-2.6%	1.2%
Otter Tail Power Co.	0.9%	2.4%	-2.5%	2.5%
City of Tallahassee	-0.2%	1.6%	-1.0%	1.4%
Gainesville Regional Utility	1.1%	1.5%	-1.3%	1.9%
Jacksonville Energy Authority	NA	NA	0.0%	0.0%
Progress Energy (Florida)	0.6%	1.5%	-1.5%	1.8%
Entergy Corp.	1.8%	1.0%	-1.7%	1.1%
Alabama Electric Coop	NA	NA	0.0%	0.0%
Oglethorpe Power Co.	NE	NE	-1.4%	2.0%
Electric Power - Chattanooga	1.3%	1.4%	-3.1%	1.7%
Memphis Light, Gas & Water	0.7%	1.1%	-3.5%	1.6%
Dominion Hub - PJM	0.3%	1.8%	-3.7%	1.3%
Ameren Control Area	NA	NA	0.0%	0.0%
Kansas City Public Utilities	1.7%	1.3%	-1.3%	1.3%
Southwestern Public Serv.	NA	NA	0.0%	0.0%
Western Farmers Elec Coop	NA	NA	0.0%	0.0%
El Paso Electric	1.8%	1.7%	-3.2%	1.2%
Public Service of N. Mexico	1.8%	0.7%	-3.3%	0.9%
California ISO	1.2%	0.8%	-3.8%	1.4%
Los Angeles DWP	2.5%	0.5%	-3.6%	0.9%
Avista Corp	1.0%	1.0%	-3.0%	1.2%
Portland General Electric	NA	NA	0.0%	0.0%
Chelan County PUD	1.4%	1.3%	-1.5%	1.2%
Black Hills Corporation	NA	NA	0.0%	0.0%
WAPA - Rocky Mountain	2.0%	1.0%	-3.7%	0.9%

* Note: The utilities listed are a combination of individual utilities (investor-owned or consumer-owned) and regional entities -- Independent System Operators, or ISOs. Details are provided in Appendix B.1 of the supporting Technical Documentation (Belzer, et al., 2008).

Table 4-6. Daily Impacts and Uncertainty Bounds by Utility, Fall EDST

Utility	Average Daily Pct. Chg.	Std. Error	Uncertainty Range Lower	Uncertainty Range Upper	Sample Weight	North/ South
Indianapolis Power & Light	-0.4%	0.4%	-1.1%	0.3%	0.042	N
Louisville Gas & Elec	-0.6%	0.3%	-1.1%	0.0%	0.049	N
Dayton Hub - PJM	-0.6%	0.3%	-1.2%	-0.1%	0.026	N
Duquesne Hub - PJM	-0.5%	0.3%	-1.0%	0.0%	0.020	N
No. Illinois Hub - PJM	-0.4%	0.2%	-0.8%	-0.1%	0.141	N
ERCOT - Coast	0.0%	0.3%	-0.5%	0.5%	0.049	S
ERCOT - S. Central	-0.1%	0.5%	-1.1%	1.0%	0.026	S
Con Ed - New York	-0.2%	0.2%	-0.5%	0.1%	0.043	N
ISO-NE - Connecticut	-0.7%	0.25%	-1.1%	-0.2%	0.020	N
ISO-NE - NE Mass (Boston)	-0.5%	0.2%	-0.9%	0.0%	0.016	N
Lincoln Electric System	-0.2%	0.3%	-0.7%	0.3%	0.017	N
Madison Gas & Elec	-0.4%	0.2%	-0.9%	0.0%	0.017	N
Otter Tail Power Co.	-0.4%	0.5%	-1.3%	0.6%	0.023	N
City of Tallahassee	-0.2%	0.3%	-0.8%	0.4%	0.003	S
Gainesville Regional Utility	-0.2%	0.4%	-1.0%	0.6%	0.002	S
Jacksonville Energy Authority	0.0%	0.0%	0.0%	0.0%	0.013	S
Progress Energy (Florida)	-0.3%	0.4%	-1.0%	0.5%	0.042	S
Entergy Corp.	-0.2%	0.2%	-0.6%	0.3%	0.035	S
Alabama Electric Coop	NA	NA	NA	NA	0.000	S
Oglethorpe Power Co.	-0.3%	0.4%	-1.1%	0.6%	0.061	S
Electric Power - Chattanooga	-0.5%	0.3%	-1.1%	0.2%	0.015	S
Memphis Light, Gas & Water	-0.6%	0.3%	-1.2%	0.0%	0.035	S
Dominion Hub - PJM	-0.7%	0.3%	-1.2%	-0.1%	0.078	S
Ameren Control Area	NA	NA	NA	NA	0.000	N
Kansas City Public Utilities	-0.1%	0.3%	-0.6%	0.4%	0.050	S
Southwestern Publc Service	NA	NA	NA	NA	0.000	S
Western Farmers Elec Coop	NA	NA	NA	NA	0.000	S
El Paso Electric	-0.5%	0.3%	-1.0%	0.1%	0.013	S
Public Service of N. Mexico	-0.5%	0.2%	-0.8%	-0.1%	0.019	S
California ISO	-0.7%	0.3%	-1.2%	-0.1%	0.058	S
Los Angeles DWP	-0.5%	0.2%	-0.9%	-0.1%	0.007	S
Avista Corp	-0.5%	0.2%	-0.9%	0.0%	0.051	N
Portland General Electric	NA	NA	NA	NA	0.000	N
Chelan County PUD	-0.1%	0.2%	-0.6%	0.3%	0.014	N
Black Hills Corporation	NA	NA	NA	NA	0.000	N
WAPA - Rocky Mountain	-0.5%	0.2%	-0.8%	-0.2%	0.016	N
National Average	-0.38%	0.09%	-0.6%	-0.2%	1.000	
North (14 utilities)	-0.42%	0.08%	-0.6%	-0.3%		
South (15 utilities)	-0.34%	0.11%	-0.6%	-0.1%		

NOTE: “N” = North; “S” = South

5. Detailed Results: Changes in Motor Gasoline Use and Traffic Volume

The analysis of EDST and motor gasoline use examined weekly “motor gasoline supplied” information for both spring and fall, looking over a 10-year period for each season. The study also analyzed national traffic volume data for the spring to estimate the changes in energy consumption from EDST. For traffic volume analysis, both late-afternoon/evening traffic and daily total traffic before and after DST in spring were analyzed.

5.1 Changes of Two-Week Average “Motor Gasoline Supplied”

The “motor gasoline supplied” information is used as a proxy for motor gasoline fuel consumption data. There is a time lag between when motor gasoline is supplied and when it is actually consumed by the driving public. Therefore, we use a two-week average of “motor gasoline supplied” information, before and after the daylight saving time, to allow the “motor gasoline supplied” to be consumed. Two-week average “motor gasoline supplied” before and after the transitions to daylight saving time for spring from 1998 to 2007 were assembled. Similar information for the fall was also prepared. There were large variations in the changes in two-week average “motor gasoline supplied” before and after daylight saving time.

Table 5-1 presents the weekly two-week average “motor gasoline supplied” before and after the daylight saving time for spring from 1998 to 2007. Table 5-3 presents similar information for the fall. As seen from Tables 5-1 and 5-2, changes in weekly “motor gasoline supplied” before and after daylight saving time range from -3.85 percent to 3.79 percent and -3.39 percent to 3.33 percent during spring and fall, respectively. The 10-year average change before and after the daylight saving time was 0.83 percent for the spring and 0.25 percent for the fall. Small compared to the seasonal variations and long-term growth rate in “motor gasoline supplied.”

Table 5-1. Two-Week Average “Motor Gasoline Supplied” before and after DST and EDST for Spring, 1998 to 2007

Two-Week Average Before		Two-Week Average After		
Two-Week Period	Thousand Barrels per Day	Two-Week Period	Thousand Barrels per Day	Percent Change
21-Mar-98 to 3-Apr-98	8,494	4-Apr-98 to 17-Apr-98	8,167	-3.85%
20-Mar-99 to 2-Apr-99	8,148	4-Apr-99 to 16-Apr-99	7,972	-2.16%
18-Mar-00 to 31-Mar-00	8,140	1-Apr-00 to 14-Apr-00	8,606	5.72%
17-Mar-01 to 30-Mar-01	8,491	31-Mar-01 to 13-Apr-01	8,372	-1.40%
23-Mar-02 to 5-Apr-02	8,626	6-Apr-02 to 19-Apr-02	8,762	1.58%
22-Mar-03 to 4-Apr-03	8,371	5-Apr-03 to 18-Apr-03	8,689	3.79%
20-Mar-04 to 2-Apr-04	8,990	3-Apr-04 to 16-Apr-04	9,156	1.84%
19-Mar-05 to 1-Apr-05	9,085	2-Apr-05 to 15-Apr-05	9,130	0.49%
18-Mar-06 to 31-Mar-06	9,059	1-Apr-06 to 14-Apr-06	9,199	1.55%
24-Feb-07 to 9-Mar-07	9,175	10-Mar-07 to 23-Mar-07	9,245	0.77%
Average	8,658		8,730	0.83%

Table 5-2. Two-Week Average "Motor Gasoline Supplied" before and after DST and EDST for Fall, 1998 to 2007

Two-Week Average Before		Two-Week Average After		
Two-Week Period	Thousand Barrels per Day	Two-Week Period	Thousand Barrels per Day	Percent Change
10-Oct-98 to 23-Oct-98	8,074	24-Oct-98 to 6-Nov-98	8,278	-3.85%
16-Oct-99 to 29-Oct-99	8,527	30-Oct-99 to 12-Nov-99	8,375	-2.16%
14-Oct-00 to 27-Oct-00	8,773	28-Oct-00 to 10-Nov-00	8,498	5.72%
13-Oct-01 to 26-Oct-01	8,661	27-Oct-01 to 9-Nov-01	8,784	-1.40%
12-Oct-02 to 25-Oct-02	8,838	26-Oct-02 to 8-Nov-02	9,042	1.58%
11-Oct-03 to 24-Oct-03	9,084	25-Oct-03 to 7-Nov-03	9,156	3.79%
16-Oct-04 to 29-Oct-04	8,930	30-Oct-04 to 12-Nov-04	9,227	1.84%
15-Oct-05 to 28-Oct-05	9,013	29-Oct-05 to 11-Nov-05	9,199	0.49%
14-Oct-06 to 27-Oct-06	9,505	28-Oct-06 to 10-Nov-06	9,183	1.55%
20-Oct-07 to 2-Nov-07	9,361	3-Nov-07 to 16-Nov-07	9,205	0.77%
Average	8,877		8,895	0.25%

Pair-wise t-tests were applied to statistically analyze the before and after motor gasoline data, and the results are presented in Table 5-3. The two-week average "motor gasoline supplied" changes before and after the daylight saving time are not significantly different in both the spring and fall cases. In other words, daylight saving time had no statistically significant impact on "motor gasoline supplied."

Table 5-3. Results for Pair-wise t-Test

	Mean of Changes in Two-week Average "Motor Gasoline Supplied"*	Standard Error of the Mean Change	Change in Means Statistically Significant (Yes/No)
Spring	72	74	No (t = 0.97; Pr>|t|=0.36)
Fall	18	71	No (t = 0.25; Pr>|t|=0.80)

* Unit of measurement is thousand barrels per day.

This finding was confirmed when we analyzed the average changes before transition into daylight saving time in the spring and after transition back into standard time in the fall. Theoretically, the average changes should have opposite positive and negative signs, if daylight saving time has an influence on the "motor gasoline supplied." In other words, the "motor gasoline supplied" should increase in spring but decrease in fall, or vice versa, if daylight saving time has a noticeable influence on "motor gasoline supplied." However, the average changes before and after daylight saving time during spring and fall are both increasing. Therefore, we did not detect an energy impact due to daylight saving time from the analysis of the weekly "motor gasoline supplied" data.

5.2 Traffic Volume Data Analysis

Theoretically, EDST will lead to more traffic volume if longer daylight hours encourage people to stay out later. Statistical Pair-wise t-tests were performed for weekly traffic changes from 3:00

p.m. to 9:00 p.m. to test this theory. Statistical Pair-wise t-tests were also performed for weekly traffic changes from the daily total.

As discussed in Chapter 3, we used the following week number assignments for 2006 and 2007 (see Table 3-2).

- Week 1: February 25 – March 3
- Week 2: March 4 – March 10
- Week 3: March 11 – March 17
- Week 4: March 18 – March 24

5.2.1 Results for changes in late-afternoon/evening traffic volume

The Pair-wise t-test under this option tests the null hypothesis that the mean of the traffic volume pairs collected from 3:00 p.m. to 9:00 p.m. are the same (at the 95 percent confidence level) by testing whether the sum of the changes between the two groups differs significantly from zero.

Table 5-4 presents the results from the Pair-wise t-test on the weekly traffic changes (from 3:00 p.m. to 9:00 p.m.) for four weeks in 2006 and 2007. As shown in the table, there is a statistically significant, but small, increase (0.17 percent) in traffic from 3:00 p.m. to 9:00 p.m. after EDST for Week 2 to Week 3. There is no statistically significant difference between Week 3 and Week 4 for traffic that occurred during the same period. However, traffic during this 3:00 p.m. to 9:00 p.m. time period increased by 1.68 percent from Week 1 to Week 2.

Week-to-week traffic comparisons for Arizona, Hawaii, and the rest of the United States in 2006 are not influenced by EDST. Among these week-to-week traffic differences, 6 out of 15 show no significant differences between the respective weeks. The other 9 comparisons show changes ranging from -3.90 percent to 2.59 percent.

Traffic from 3:00 p.m. to 9:00 p.m. is only a portion of the daily total traffic. By calculating the total daily traffic and traffic from 3:00 p.m. to 9:00 p.m. from traffic volume in Week 2, the proportion can be estimated. Traffic from 3:00 p.m. to 9:00 p.m. accounts for about 37 percent of the daily total traffic in Week 2.[18]

Thus, based on the results reported in Tables 5-4, the 0.17 percent increase of late-afternoon/evening traffic is equivalent to about 0.06 percent increase of the daily total traffic.[19]

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[18] Based on the traffic information by hours of the day for some 4,000 traffic counters, the traffic from 3:00 p.m. to 9:00 p.m. was about 37 percent of the total daily traffic for 24 hours for all counters during the week of March 4 to March 10, 2007. Thirty-seven percent of 0.17 percent equals 0.06 percent.

[19] i.e., 37 percent of 0.17 percent = 0.06 percent.

Table 5-4. Summary Results for Traffic from 3:00 p.m. to 9:00 p.m., Spring

Year	Region	Comparison	Mean Change	Standard Error of the Mean Change	Percent of Change	Difference in Means, Statistically Significant (Yes/No)
2007	US (Exclude AZ, DC, HI, WY)	Week 1 vs. Week 2	157	6	1.68%	Yes(t=24,56; Pr>|t|<0.0001)
		Week 2 vs. Week 3	16	7	0.17%	Yes(t=2.26; Pr>|t|=0.0241)
		Week 3 vs. Week 4	-7	6	-0.08%	No(t=-1.33; Pr>|t|=0.185)
	AZ	Week 1 vs. Week 2	-30	27	-0.52%	No(t=-1.11; Pr>|t|=0.2673)
		Week 2 vs. Week 3	77	29	1.20%	Yes(t=2.63; Pr>|t|=0.0089)
		Week 3 vs. Week 4	-140	40	-2.08%	Yes(t=-3.5; Pr>|t|=0.0005)
	HI	Week 1 vs. Week 2	-116	87	-0.85%	No(t=-1.33; Pr>|t|=0.189)
		Week 2 vs. Week 3	-2	66	-0.01%	No(t=-0.03; Pr>|t|=0.9781)
		Week 3 vs. Week 4	-262	79	-3.90%	Yes(t=-3.33; Pr>|t|=0.0012)
2006	US (Exclude AZ, DC, HI, WY)	Week 1 vs. Week 2	32	5	0.34%	Yes(t=6.29; Pr>|t|<0.0001)
		Week 2 vs. Week 3	89	5	0.91%	Yes(t=16.6; Pr>|t|<0.0001)
		Week 3 vs. Week 4	-50	5	-0.51%	Yes(t=-9.42; Pr>|t|<0.0001)
	AZ	Week 1 vs. Week 2	52	29	0.88%	No(t=1.78; Pr>|t|=0.076)
		Week 2 vs. Week 3	181	49	2.59%	Yes(t=3.73; Pr>|t|=0.0002)
		Week 3 vs. Week 4	-100	41	-1.50%	Yes(t=-2.43; Pr>|t|=0.0158)
	HI	Week 1 vs. Week 2	133	108	1.75%	No(t=1.23; Pr>|t|=0.2240)
		Week 2 vs. Week 3	34	80	0.28%	No(t=0.43; Pr>|t|=0.6709)
		Week 3 vs. Week 4	-253	94	-3.77%	Yes(t=-2.71; Pr>|t|=0.0078)

*Note: Arizona (AZ) and Hawaii (HI) are two states that do not observe Daylight Saving Time. Traffic volume data was not available for the District of Columbia (DC) and Wyoming (WY).

More traffic volume will yield more motor fuel consumption, provided the traffic volume increases are uniform among roadway segments, and the roadway segment lengths and average fuel consumption rate are constant. Assuming the daily total traffic increase is uniformly distributed, the 0.06 percent increase in daily traffic translates to a motor gasoline consumption increase of about 5.5 thousand barrels per day for each day of EDST.[20]

Based on the above test results, we made the following conclusions. There is a small (0.17 percent) increase in traffic during the late-afternoon/evening time for the week after EDST begins. This small increase in traffic could not be directly attributed to EDST for the following reasons:

- There are large variations of changes (ranging from -3.90 percent to 2.59 percent) between weeks that are not influenced by EDST.
- Other factors may have influenced the changes in daily traffic volume during those hours (e.g., weather conditions, roadway construction, traffic accidents/incidents, and special events/festivals).[21]
- There is a statistically noticeable change in traffic the week prior to EDST, when traffic increased by 1.68 percent from the week of "February 25 – March 3" compared to "March 4 – March 10." In addition, there is no statistically significant difference from the week of "March 11 – March 17" to "March 18 – March 24" (the second week after EDST).
- The week-to-week traffic differences are statistically noticeable for the same time frame in 2006—the February 25 to March 24 period. Although these four weeks of traffic in 2006 were not under the influence of EDST, the week to week traffic differences ranged from -0.51 percent to 0.91 percent. This further supports the evidence that observed traffic variations in 2007 were the result of an array of traffic influencing factors, and cannot be attributed to EDST.

5.2.2 Results for changes in daily total traffic volume

The Pair-wise t-test under this option tests the null hypothesis that the means of these daily total traffic volume pairs are equal (at the 95 percent confidence level). Alternatively, the Pair-wise t-test can test if the sum of the changes between the two groups differs statistically significantly from zero.

Table 5-5 presents the results from the Pair-wise t-test on the weekly changes in daily total traffic for four weeks in 2006 and 2007. As shown in the table, there is a statistically significant

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[20] Weekly motor gasoline supplied was 9,158 thousand barrels per day for the week ending on March 9, 2007. Therefore, 0.06 percent of 9,158 thousand barrels is roughly 5.5 thousand barrels per day. The EIA collects weekly motor gasoline supplied information from Saturday to Friday. However, the extended daylight saving time started on Sunday.

[21] Gasoline prices did not appear to have been one of the factors. The average retail gasoline price was determined to not have had an influence on the week-to-week differences in traffic volume in the spring of 2007 (February 26 to March 19) and in the spring of 2006 (February 27 to March 20). During those 2007 and 2006 periods, the national weighted average retail price for all grades and all formulations of gasoline ranged from 2.43 to 2.62 dollars per gallon (February 26 to March 19, 2007) and from 2.30 to 2.55 dollars per gallon (February 27 to March 20, 2006). There was no statistical relationship between traffic volume and retail gasoline price, as measured by the correlation coefficient of 0.005. Therefore, gasoline price was not a factor in explaining the short-term changes in traffic from February 26 to March 19 of 2007.

increase (1.05 percent) in daily total traffic after EDST for Week 2 to Week 3. Based on previous test results, there is a very small traffic increase (0.17 percent of the later-afternoon and evening traffic or 0.06 percent of the daily total traffic) during later afternoon and evening, from Week 2 to Week 3. Thus, the majority of daily increase (1.05 percent - 0.06 percent) is from traffic outside the later-afternoon/evening. Because EDST-induced traffic, if any, would most likely take place in the later-afternoon/evening, the majority of a traffic increase could not be attributed to EDST. The difference between Week 3 and Week 4 traffic is not statistically significant. However, the daily total traffic significantly increases, by 1.68 percent, from Week 1 to Week 2, which is prior to EDST.

Table 5-5. Summary Results for Daily Total Traffic, Spring

<table>
<tr><th>Year</th><th>Region</th><th>Comparison</th><th>Mean Change</th><th>Standard Error of the Mean Change</th><th>Percent of Change</th><th>Difference in Means, Statistically Significant (Yes/No)</th></tr>
<tr><td rowspan="9">2007</td><td rowspan="3">US (Exclude AZ, DC, HI, WY)</td><td>Week 1 vs. Week 2</td><td>426</td><td>16</td><td>1.68%</td><td>Yes(t=26.81; Pr>|t|<0.0001)</td></tr>
<tr><td>Week 2 vs. Week 3</td><td>260</td><td>15</td><td>1.05%</td><td>Yes(t=17.07; Pr>|t|<0.0001)</td></tr>
<tr><td>Week 3 vs. Week 4</td><td>-24</td><td>13</td><td>-0.10%</td><td>No(t=-1.88; Pr>|t|=0.0604)</td></tr>
<tr><td rowspan="3">AZ</td><td>Week 1 vs. Week 2</td><td>-83</td><td>103</td><td>-0.50%</td><td>No(t=-0.81; Pr>|t|=0.4192)</td></tr>
<tr><td>Week 2 vs. Week 3</td><td>560</td><td>81</td><td>3.04%</td><td>Yes(t=6.95; Pr>|t|<0.0001)</td></tr>
<tr><td>Week 3 vs. Week 4</td><td>-390</td><td>99</td><td>-2.03%</td><td>Yes(t=-3.94; Pr>|t|<0.0001)</td></tr>
<tr><td rowspan="3">HI</td><td>Week 1 vs. Week 2</td><td>-383</td><td>514</td><td>-0.94%</td><td>No(t=-0.74; Pr>|t|=0.4601)</td></tr>
<tr><td>Week 2 vs. Week 3</td><td>-237</td><td>283</td><td>-0.62%</td><td>No(t=-0.84; Pr>|t|=0.4046)</td></tr>
<tr><td>Week 3 vs. Week 4</td><td>-686</td><td>228</td><td>-3.58%</td><td>Yes(t=-3.01; Pr>|t|=0.0033)</td></tr>
<tr><td rowspan="9">2006</td><td rowspan="3">US (Exclude AZ, DC, HI, WY)</td><td>Week 1 vs. Week 2</td><td>173</td><td>13</td><td>0.67%</td><td>Yes(t=13.22; Pr>|t|<0.0001)</td></tr>
<tr><td>Week 2 vs. Week 3</td><td>333</td><td>13</td><td>1.26%</td><td>Yes(t=25.1; Pr>|t|<0.0001)</td></tr>
<tr><td>Week 3 vs. Week 4</td><td>-124</td><td>13</td><td>-0.47%</td><td>Yes(t=-9.26; Pr>|t|<0.0001)</td></tr>
<tr><td rowspan="3">AZ</td><td>Week 1 vs. Week 2</td><td>182</td><td>79</td><td>1.08%</td><td>Yes(t=2.31; Pr>|t|=0.0212)</td></tr>
<tr><td>Week 2 vs. Week 3</td><td>493</td><td>117</td><td>2.51%</td><td>Yes(t=4.2; Pr>|t|<0.0001)</td></tr>
<tr><td>Week 3 vs. Week 4</td><td>-197</td><td>97</td><td>-1.01%</td><td>Yes(t=-2.04; Pr>|t|=0.0423)</td></tr>
<tr><td rowspan="3">HI</td><td>Week 1 vs. Week 2</td><td>-149</td><td>125</td><td>-0.72%</td><td>No(t=-1.2; Pr>|t|=0.2368)</td></tr>
<tr><td>Week 2 vs. Week 3</td><td>353</td><td>190</td><td>1.03%</td><td>No(t=1.85; Pr>|t|=0.066)</td></tr>
<tr><td>Week 3 vs. Week 4</td><td>-856</td><td>280</td><td>-4.37%</td><td>Yes(t=-3.06; Pr>|t|=0.0028)</td></tr>
</table>

Week-to-week traffic comparisons for Arizona, Hawaii and the rest of the United States in 2006 are not influenced by EDST. Among these week-to-week traffic differences, 5 out of 15 show no significant differences between the respective weeks. The remaining 10 with significant differences show changes ranging from -4.73 percent to 3.04 percent.

Based on the test results, we can make the following conclusions. There is a (1.05 percent) increase in daily total traffic in the week after EDST. Most of this 1.05 percent increase could not be attributed to EDST. There are large variations of changes (ranging from -4.73 percent to 3.04 percent) between weeks that are not influenced by the EDST change. Based on the analysis of daily traffic data, there is insufficient evidence of attribution for similar reasons as found for the hourly traffic analysis.

Retail gasoline influence on week-to-week traffic

We used gasoline price information collected by the Energy Information Administration (EIA) to examine the influence of retail gasoline prices on national traffic. The gasoline price includes all taxes and is the pump price paid by a consumer as of 8:00 a.m. on Monday. The average retail gasoline price for two Mondays before and after EDST in the spring of 2007 and the same time frame in 2006 is presented in Table 5-6. All of the week-to-week differences show increases. The magnitude of these increases is larger than the week-to-week differences in traffic. There is no relationship between the week-to-week increases of average retail gasoline prices and the week-to-week traffic differences. The correlation coefficient between the two data series is 0.005. The average retail gasoline price has no influence on the week-to-week traffic differences.

Table 5-6 U.S. Average Retail Gasoline Prices

Mondays	U.S. Average Retail Gasoline Prices (Cents per Gallon)	Week-to-Week Differences
Feb 26, 2007	242.8	
Mar 5, 2007	255.1	5.07%
Mar 12, 2007	260.5	2.12%
Mar 19, 2007	262.3	0.69%
Feb 27, 2006	229.8	
Mar 6, 2006	237.3	3.26%
Mar 13, 2006	240.8	1.47%
Mar 20, 2006	254.8	5.81%

5.2.3 Changes in National Traffic Volume and Motor Gasoline for the fall EDST

This study did not examine national traffic data collected in the fall. However, the VMT information from *Traffic Volume Trends* by FHWA shows steady annual VMT patterns for 2005, 2006, and 2007. The estimated monthly VMT information is presented in Figure 5-1.[22] This

[22] Federal Highway Administration, Department of Transportation, *Traffic Volume Trends, December 2007*, Washington DC, 2008. Federal Highway Administration, Department of Transportation, *Traffic Volume Trends, December 2006*, Washington DC, 2007.

implies that national traffic volume data is relatively stable provided average trip length remains constant. Expert opinion concluded that if we were to carry out the fall analysis, it would most likely lead to similar conclusions as found in the spring analysis.

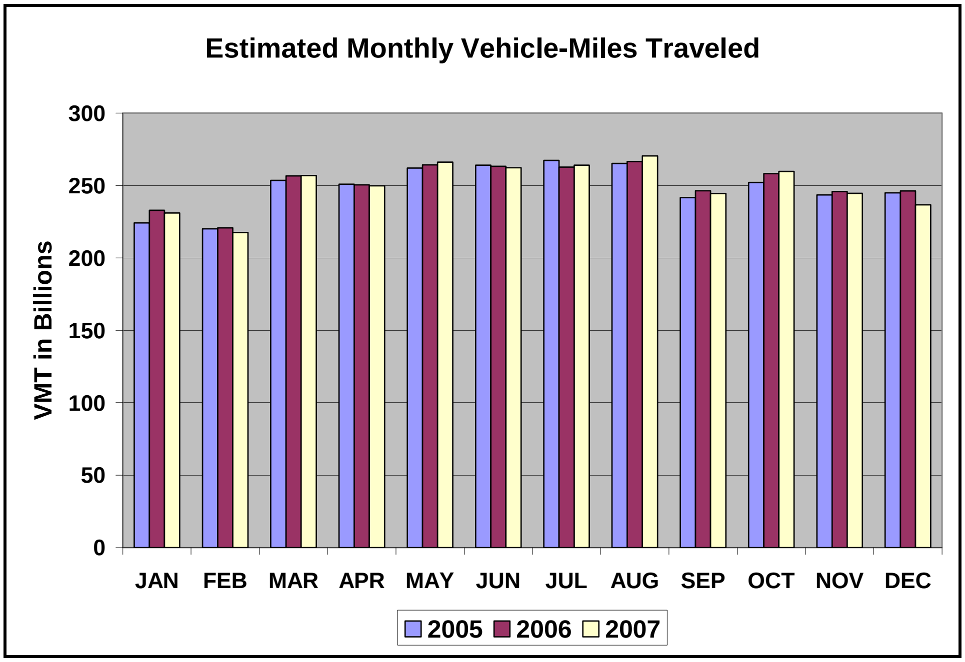

Figure 5-1. Estimated monthly VMT for 2005, 2006, and 2007

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Appendix A. Highlights of Previous U.S. Studies on Energy Use and Daylight Saving time

Few comprehensive analyses have been conducted to estimate potential energy impacts of Daylight Saving Time (DST) or Extended Daylight Saving Time (EDST) for the United States. The Department of Transportation (DOT) conducted the most comprehensive study in 1975. A 1996 study by a researcher at the University of Kansas evaluated the effect of EDST on residential buildings, with a focus on the temperature shift induced by the change to the clocks. The California Energy Commission (CEC) conducted a detailed econometric analysis for proposing state-level changes in Double Daylight Saving Time (DDST) in 2001. In 2007, the CEC conducted a detailed econometric analysis examining the impact of EDST in California. Both the DOT study and CEC study recognized that the largest energy-saving potential was in the form of electricity, and that other fuels may be impacted, but to a smaller degree. The University of California, Santa Barbara, conducted a more recent study of electricity impacts of EDST for Indiana.

While there have been several studies of the energy impacts of DST, none have looked specifically at national level energy impacts of the current DST extension (three weeks in the spring, one in the fall). Several studies have looked at year-round DST or at eight-month schedules (March-October); others have looked at adding a second hour of DST, called DDST, during summer months. Some of the analyses provided information on a monthly or seasonal basis. The CEC study (Adrienne and Metz, 2001) provides results on a monthly basis, but only applies the analysis to its own state.

We used the results of these studies to inform our analysis and their methodologies were helpful in determining appropriate strategies; however, most of the results are not directly comparable.

A.1 1975 U.S. Department of Transportation Study

When Congress enacted the Emergency Daylight Saving Time Energy Conservation Act of 1973, they required that the Secretary of Transportation prepare interim and final reports on the operation and effects of the Act. The interim report recommended that Congress amend the Act to revert to Standard Time for the months of November 1974 through February 1975.

While energy savings was the main purpose for DST, the DOT study also considered other benefits such as safety and crime as possible effects. Table A-1, taken from the study’s executive summary, provides a digest of the study’s results.

The electric-use analysis involved comparing the hourly electricity data from 15 utilities across the United States, both with and without DST at certain points in the year. The analysis used a procedure of “equivalent day normalization” to isolate the effects of DST from other effects such as weather or economic changes. It separated each day into two parts: one where a potential DST influence is hypothesized (i.e., morning and evening), and one where no DST influence would occur (i.e., midday and night). Similar days were compared (e.g., the first Monday before a DST transition versus the first Monday afterward). For each pair of days, the DST-influenced parts were compared, and the parts uninfluenced by DST were compared. If the value of a parameter had a greater change in the DST-influenced part of the day than in the uninfluenced part, then DST was assumed to be the cause. (Department of Transportation, 1975)

Table A-1. 1975 U.S. DOT Results of DST Impact Studies: The Experimental Eight–Four (Months) System vs. the Historical Six–Six System (Department of Transportation, 1975)

Area	DST Impact	Comments
Travel	None perceived by [DOT] techniques; technique would not perceive effect of less than 1.0 percent.	Seasonal changes in travel obscure DST effects at DST transitions.
Electricity Use	Approximate savings of 1 percent or 49,200 megawatts per day for March and April; no evidence of significant peak shaving.	Savings related to DST measured at transitions in October (1973 and 1974), in April (1973), and January (1974).
Gasoline Consumption	None perceived by [DOT] techniques. Estimated maximum possible <u>undetected</u> impact of 0.5 percent of total daily gasoline consumption.[23]	Statistical analysis revealed a small DST effect (0.4 percent), which was not statistically significant.
Home Heating Fuel Consumption	Saving of less than 0.1 percent of national demand.	A maximum savings of 3,000 barrels of oil and the equivalent of 5,000 barrels of natural gas per day might occur in Southern and Southwestern states only.
Fatal Motor Vehicle Accidents	Reduction of approximately 0.7 percent or about 50 lives and 2,000 injuries for March and April.	Reduction is observed in a comparison between March and April 1974 (DST) and March and April 1973 (non-DST). Also, spring and fall transition analysis of 1973 provide consistent results.
Fatal Motor Vehicle Accidents of School-Age Children	No special hazard to children compared to the total population at any time of day.	Two studies were conducted. The findings were that during the DST period of January to April 1974, school-age children did not suffer greater fatalities than those of the total population in accidents involving pedestrian/ pedal-cyclists, motor vehicles.
A.M. Radio Broadcasting	0.01 percent loss per station.	
Crime	Evidence of 10 percent to 13 percent reduction in violent crimes in Washington, D.C.	
Advance in School Hours	Essentially no change.	A few schools in two Western and Midwestern states advanced hours where bus routes were long.
Election Day	Increases daylight during existing polling hours in almost all states.	A nine-month system of DST would be required to cover all election days.

[23] Page 99 of the 1975 DOT report, “Based on this analysis, DST appears to have had no discernible effect on travel demand. If there are subtle influences, which DST exerts on travel demand, they are so small, so diffuse, and so intermixed with the effects of other factors that it was not possible for our analytical technique to detect and measure them by using the automatic traffic recorder data furnished by the states. It has been estimated that if there were any effect of DST on travel demand, it would not be greater than plus or minus ½ percent to 1 percent. Such an amount is less than the normally expected week-to-week variation in traffic; but would be significant, if it exists, in analyzing the total energy effect due to DST.”

Table 6-2. Effect of DST on Electricity Use from 1975 DOT Study. Positive Values Reflect Removal of DST (Department of Transportation, 1975)

From DST Transition	Percent Change in Usage, after vs. before	
	Volume I	Volume II
January 1974	- 0.74	- 0.74
February 1975		- 0.65
April 1973	- 1.32	- 0.86
October 1972	+ 0.91	+ 0.91
October 1974	+ 1.76	+ 1.73

Volume I of the report describes the analysis of four transitions to and from DST: January 1974, April 1973, October 1972, and October 1974. Volume II provides more detail and lists five transitions (and gives different values for some). The January 1974 analysis used the hourly demand for the four days prior and four days subsequent to DST, while the other transitions evaluated seven days of data. Table 6-2 reprinted from the DOT report shows the percentage change in use they found for each transition. Note that use went down when entering DST and up when exiting DST. The average of the four values in Volume I is 1.18 percent, and the five values in Volume II is 0.98 percent, which the authors of the study rounded off to report that "electricity usage is consistently less during the DST period at each transition by an average amount of about 1 percent."

It is unclear how the authors arrived at the often-repeated estimate of saving 100,000 barrels of oil per day. The Executive Summary table in the DOT report (Table 6-1) lists savings of 49,200 MWh per day, while the report mentions 38,000 MWh per day for the January 1974 transition. Converting electricity savings to oil equivalents, assuming an efficiency of 28 percent (12,000 Btu/kWh) and 6 MMBtu/barrel of oil, the 49,200 MWh per day translates into roughly 100,000 barrels per day.

The study also attempted to analyze the effect of DST on gasoline consumption. Three approaches were attempted: estimates based on behavior and climate, an equivalent-day normalization study, and linear-regression models. All of these techniques led to estimates of a few tenths of a percent for the magnitude of the DST effect and were statistically insignificant.

The study examined several modes of home heating-system operation for which savings or losses in fuel consumption are possible because of DST. However, there was insufficient information concerning people's operation of their heating systems or the complementary demographic, climatological, and sociological data required. The report states that a detailed questionnaire to a statistical sampling of households would be required, but an order-of-magnitude estimate of the savings or losses would be very small and not warrant the necessary complete analysis.

National Bureau of Standards review of DOT study

In 1976, Congress requested the National Bureau of Standards (NBS) to review the results of the 1975 DOT study. The review was to focus on four topics: the regional effects of DST, the statistical treatment of school-age children fatal accidents, the DOT analysis of fatal motor-vehicle accidents, and the DOT calculations of electricity savings. (National Bureau of Standards, 1976)

The first major NBS finding was a strong confirmation with the DOT study for extreme caution in drawing even tentative conclusions, because of the substantial technical effort and reliance on extensive data (sometimes faulty) for analyses. The major findings that the review had with regard to the electricity savings were (to quote from the report—(National Bureau of Standards, 1976):

- *The DOT database, derived from hourly electricity-demand records of 14 power companies (producing approximately 1/3 of the Nation's electrical energy), was found faulty in several respects, and corrections were required;*
- *Applying the analyses used by DOT to the corrected database, NBS finds no conclusive evidence for decreased production of electrical energy during DST.*
- *Results from equivalent-day normalization (a technique used by DOT to compare electrical demand between DST and Standard Time periods) were found to be highly sensitive to the choice of morning and evening periods considered to show the influence of DST.*

As part of the examination of the data used by the DOT study, NBS found that DOT examined 14 rather than 15 utilities. NBS found errors in approximately 1 percent of the data from the Federal Power Commission and arithmetical errors in weekly totals. When corrected, the NBS analysis found that rather than an approximate 1 percent savings from DST, the data analysis gave "a totally inconclusive result."

Furthermore, NBS recommended against the "equivalent-day normalization" technique used by DOT in the absence of definite information on the actual hours of the day that DST might influence. They found that changing the hours of influence and non-influence could alter the results significantly. DOT assumed an influence period of 11 hours (5:00 a.m. to 10:00 a.m. and 3:00 p.m. to 9:00 p.m.). Using a smaller influence period (such as 6:00 a.m. to 9:00 a.m. and 4:00 p.m. to 7:00 p.m.) could give greater savings, while a larger influence period in the equation could show an increase in demand due to DST. When NBS used the smaller influence period above, they got a 50 percent increase in savings. As an example, they provided a graph showing the percentage change in energy for Tennessee Valley Authority and Southern California Edison using the October 1972 transition data (Figure A-1). They admitted that other utilities may have different curves, depending on their demand, but used these to show the sensitivity.

DOT had an opportunity to respond to the NBS review in a Congressional hearing on June 8, 1976 (Testimony of Robert H. Binder, 1976). They attached, with their testimony, additional analysis of the data based on the findings of NBS. They found that correction to data and selection of any reasonable influence period in the equivalent-day normalization still gave savings due to DST.

In summary, when errors (pointed out by NBS) in the electricity data used by DOT were removed and the equivalent-day normalization was applied to the corrected data, the small changes in the results did not alter the original conclusions that:

1) There is a saving in electricity use due to DST at DST transitions, and
2) The magnitude of this DST saving is about 1 percent (Testimony of Robert H. Binder, 1976).

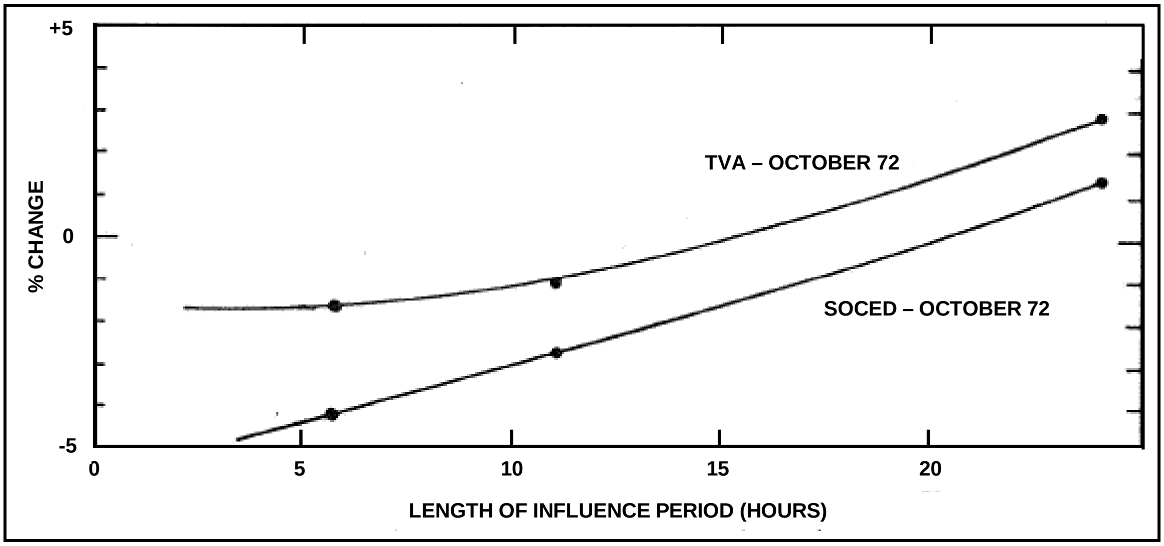

Figure A-1. Coefficient of influence as a function of the length-of-influence period

A.2 1996 University of Kansas Study on Residential Energy Use

In 1996, Brian Rock of the University of Kansas School of Architectural Engineering used the DOE-2 residential building demand model to calculate the potential impact of DST on a typical residential house in different parts of the country (Rock, 1997).

The DOE-2 code is a well-recognized hour-by-hour simulation model of residential buildings. It can track the annual electrical energy use, electrical cost, natural gas quantity, natural gas cost, and total energy cost. The house modeled was a five-bedroom house built in 1992 in Lawrence, Kansas; and its actual characteristics, operation schedules, and utility bills were used in the preparation of the energy model. Its construction and floor area were typical of many houses built at the time, with a main floor area of 1,100 ft^2, an upper level of 500 ft^2, and a finished basement of 1,000 ft^2. Specifics for the house, such as a heating, ventilating, and air conditioning system; windows and wall construction; and number of residents were all based on values for the house.

The code allowed the house to be modeled in 224 locations around the United States. Weather data for each site included hour-by-hour dry bulb, wet bulb, wind speed and direction, cloud cover, and solar data. They ran the DOE-2 code in three modes: with Standard Time (ST) year-round, DST only during the summer, and DST year-round. The results showed that for summer-only DST, average annual costs were slightly higher than year-round ST, 0.147 percent. Both electricity and natural gas use increased. Costs for year-round DST were essentially the same as for year-round ST, - 0.0004 percent, with electricity use declining but gas use increasing. Going from summer-only DST to year-round DST saved 0.148 percent in cost, with most savings being in electricity. Table A-3 shows the electricity, natural gas, and cost differences among the three scenarios. The paper did not provide finer resolution of the results.

Table A-2. Average Annual Percentage Difference between Scenarios (Rock, 1997)

	ST to ST w/Summer DST	ST to Year-Round DST	ST w/Summer DST to Year-Round DST
Electrical energy (kWh)	0.244	- 0.022	- 0.267
Electricity cost (US$)	0.228	- 0.012	- 0.241
Natural gas (therms)	0.051	0.024	- 0.027
Natural gas cost (US$)	0.047	0.015	- 0.032
Total energy cost (US$)	0.147	- 0.0004	- 0.148

Source: (Rock, 1997)

A.3 2001 California Energy Commission Study

During the California energy crisis of 2000-2001, the California Energy Commission studied the potential impact of changing the period of DST in California (Adrienne and Metz, 2001). The study examined both a lengthening of the period of conventional DST (characterized by a one-hour shift from ST) as well as moving to a two-hour shift from ST during the summer months (so-called DDST).

The study, undertaken by the CEC, indicated that the energy savings from moving DST up to the beginning of March would be about 0.6 percent of electricity consumption during that period. These estimates were specific to California, and different weather characteristics in other regions of the country—as well as different end-use patterns of electricity use—may yield higher or lower-percentage savings.

The analysts included energy, economic, and weather variables in a statistical formula that evaluated “seemingly unrelated regression” parameters to determine a best-fit approximation of hourly energy use. It is a system of 24 linear equations, one for each hour of the day. According to the authors, “This method was chosen because it allows the estimated relationship between the independent variables and energy use to change throughout the day while taking into account the correlation between energy use over the hours of the day.”

As part of the analysis, the report provided monthly graphs of the weekday electricity profile both with and without the proposed DST. The graph for March (Figure A-2) is applicable to this study, because it is similar to the time frame of the springtime DST extension. The peak demand between 6:00 p.m. and 7:00 p.m. drops 8 percent, with about 2 percent reductions in the hour before and after. The overall system peak shifts to one hour later and drops 3.5 percent, from 32.6 GW to 31.4 GW. Because California was significantly capacity-constrained (the major reason behind the study), a 3.5 percent reduction in peak demand could make a significant difference in the amount of capacity required. The 1,149 MW difference is equal to about one large nuclear plant.

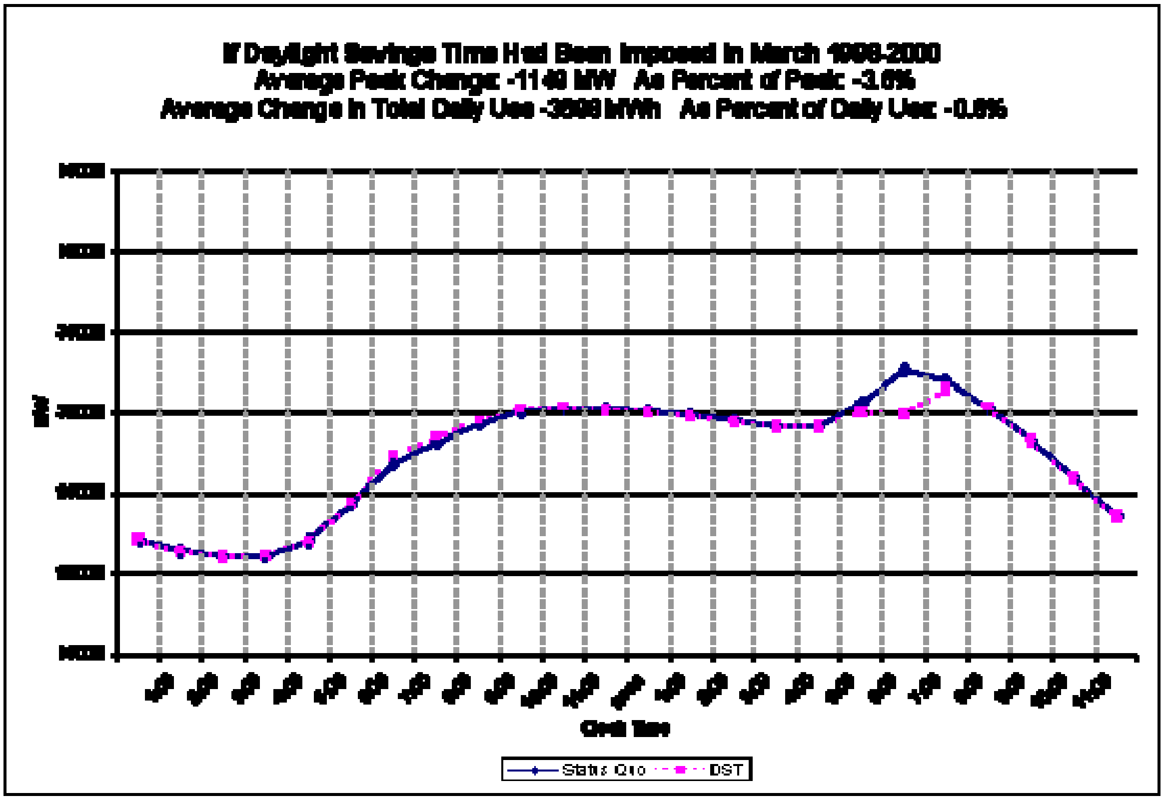

Figure A-2. Results of California DST study for March (Adrienne and Metz, 2001)

Also of interest for this study were the results for November (FigureA-3). Extending DST through November had less effect on overall energy use, a 0.4 percent reduction, than the March results. The daily peak demand was reduced by 2.8 percent. The reductions were more concentrated in the 5:00 p.m. to 6:00 p.m. period than the 6:00 p.m. to 7:00 p.m. hour, reflecting that November is well past the Autumnal equinox, while March is during the Vernal equinox. Sunsets are an hour earlier; e.g., for Los Angeles the sunset on Nov. 4, 2006, was 4:58 p.m., but for March 12, 2006, was 5:59 p.m.

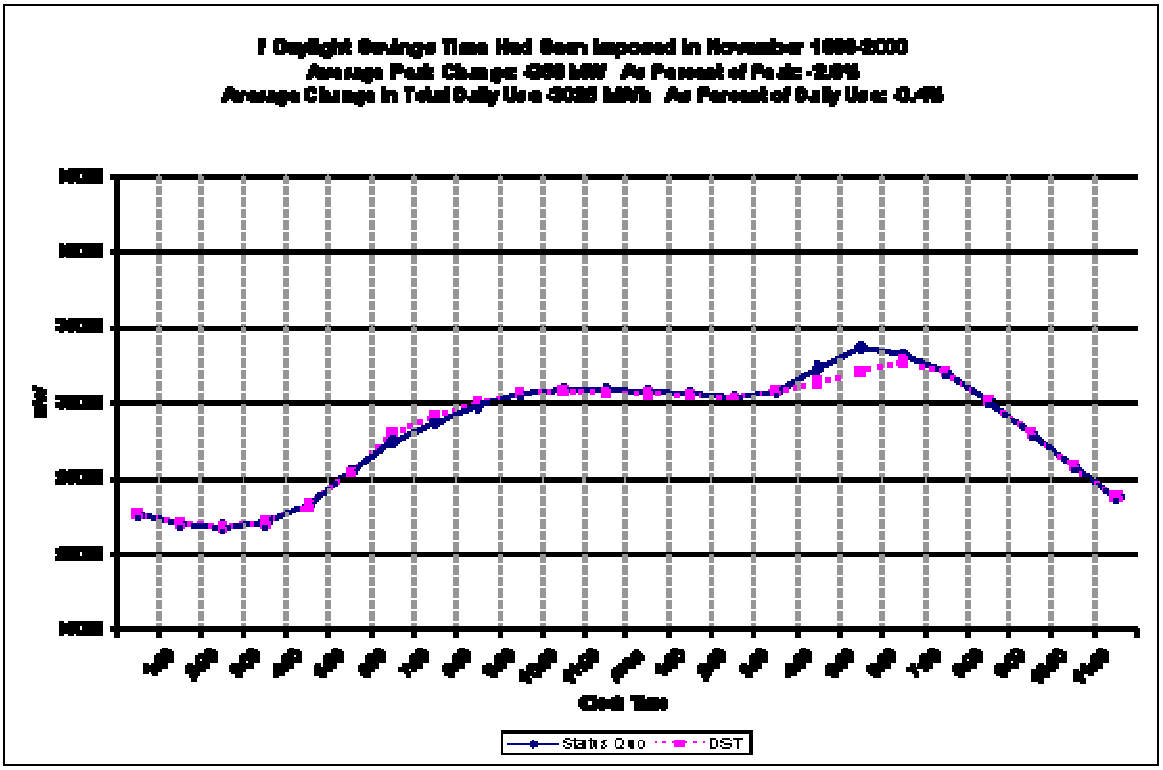

Figure A-3. Results of California DST study for November (Adrienne and Metz, 2001)

EIA review of the CEC study

In the summer of 2001, Congress asked the EIA to analyze the CEC study, with an eye to the feasibility of carrying out this analysis nationwide. EIA provided a letter report and three enclosures in response (Letter from Mary J. Hutzler, 2001). The first enclosure was a review of the CEC analysis from a technical perspective. EIA was very complimentary of the CEC effort, recognizing it as an excellent effort at modeling, performed in a relatively short period of time. They identified the following technical questions:

- *The CEC study may understate the uncertainty of the model predictions. (CEC has told EIA that it is pursuing the development of more complete estimates of the uncertainty.)*
- *EIA concluded that the theoretical model underlying the CEC analysis is based on the assumption that the "residuals" (unobserved "shocks" that cause consumption to be higher or lower than normal) from day-to-day are independent. This is not the case, as is acknowledged in the CEC report. When CEC tried to incorporate day-to-day correlation in their model, it was unable to obtain convergence from the estimation program. This does not bias results, but does increase the variance of predictions.*
- *The CEC model explains consumption in California as a linear function of variables that include weather for six sites and hours of daylight for three sites. While CEC was very careful in their selection of the sites, this high level of aggregation in the consumption data makes it difficult to accurately account for variation due to weather and daylight. The standard error of the residuals for the 24 hourly models range from about 5 percent to 0 percent of estimated consumption. EIA believes that a major contributor to the lower*

> *level of accuracy in the CEC model is the high level of aggregation. Additionally, in other modeling work, EIA has found that using weighting of input variables (such as weather and daylight in the CEC analysis) to reflect the size of the population exposed to those conditions provides better explanatory power in models.*

They also noted that the analysis was based on historical demands from 1998-2000. With changes in consumption patterns due to conservation, especially considering the energy crisis in California, it may be difficult to apply the historical data to future uses.

The second report provided details on possible options to conduct a broader, national study on energy savings. They provided three options with costs ranging from $50,000 to more than $2 million. The first and largest would apply the California methodology to between 100 and 150 randomly selected utility service areas across the country. This would be the most exhaustive method and would still face methodological issues raised with the CEC study. The second option would conduct case studies of a small number of utility service areas to illustrate possible extremes in weather and daylight. It may provide ranges of savings, but not a national estimate. The third method would be a comparison of several "paired regions" in adjacent time zones. This was the simplest option, but it would not provide a national estimate. The EIA conducted a paired-region analysis in the third enclosure, comparing the electricity use for Indianapolis, Indiana (in the Eastern Time Zone and no DST) to Springfield, Illinois (in the Central Time Zone and with DST). The results showed no appreciable electricity savings due to DST during the year. However, the analysis did not address the issue of whether a small extension of DST in the spring and fall might result in savings.

EIA concluded: "After reviewing the CEC analysis and considering the alternative approaches, EIA does not believe that any reasonable amount of data collection and analysis would yield estimates of [national] electricity savings from daylight-saving time that would be significant and statistically credible."

Some of these criticisms may apply to this study and should be considered in future efforts.

A.4 2007 California Energy Commission Study

In May 2007, the California Energy Commission released a brief report (California Energy Commission, 2007) dealing with the estimated impact of the spring 2007 EDST on electricity sales in the area served by California Independent System Operator (ISO). The California ISO manages the electrical grid representing approximately 80 percent of the population in the state.

The CEC performed a statistical analysis of daily electricity consumption over the months of January through March and for years from 2000 through 2007 (excluding the energy crisis year of 2001). The model included variables for daily hours of daylight, weekends and holidays, cooling and heating degree-days, binary indicator variables to represent different years, and a binary indicator variable for the days in March 2007 for the EDST period. Separate sets of degree-day variables were used for the January-February time periods and for March.

The statistical results from the CEC study suggested a very small amount of electricity savings in the spring EDST period. The specific estimate from the CEC's primary model specification was a 0.02 percent savings in daily electricity use. The end points of the associated 95 percent confidence interval developed from the analysis were a 1.5 percent savings to a 1.4 percent increase in daily electricity use. Other model specifications yielded estimates ranging between an increase of 0.2 percent and declines of 2.3 percent.[24]

A.5 2006 DOE Preliminary Analysis of EDST

In 2006, the Department of Energy made a preliminary analysis of the potential impacts of EDST (DOE 2006). The DOE study used 2004 hourly system electricity consumption from eleven utilities across the United States. The methodology involved statistical models of the changes in the morning and evening hourly consumption before and after the transitions to and from DST in the spring and fall. These models were designed to predict normalized consumption in specific hours of the morning and evening. The normalization used the two adjacent hours before and after the hours of interest as the control hours. Explanatory variables in the models included the fraction of daylight in each hour and current and lagged temperatures.

The estimated models were used to predict the impact upon electricity that might be expected given the amount of daylight in each hour under the then pending DST schedule under the 2005 EPAct legislation. Thus, the models predicted changes in electricity consumption for the three-week period beginning in the second week in March and for the week ending the first week of November. When aggregated to a national basis, the results of this prediction process indicated daily average electricity savings of about 0.4 percent (and a total national primary energy savings of 1 Tera Watt-hour). Across the utilities analyzed, daily savings ranged between 0.4 percent to 0.6 percent in the north (six utilities) and between 0.2 percent and 0.4 percent in the south (five utilities). The predicted savings were somewhat greater in the spring than the fall.

A.6 2001 Indiana Energy Use and Daylight Saving Time Study

Prior to 2006, most of Indiana did not follow DST. However, they have often evaluated the issues. In late 2001, the Indiana Fiscal Policy Institute attempted to use the analytical methods of the California study to determine the energy savings in the state (Indiana Fiscal Policy Institute, 2001). They had difficulty getting the original Seemingly Unrelated Regression equations, based on California's model, to give credible results. They modified the equations to take the general form:

$$\text{Megawatts} = c + b^*(\text{Workday}) + b^*(\text{Employment}) + b\,^*(\text{Temperature}) + b\,^*(\text{Humidity}) + b\,^*(\text{Barometric Pressure}) + b\,^*(\text{Wind}) + b\,^*(\text{Visibility}) + b\,^*(\text{Sunrise}) + b\,^*(\text{Sunset}) + b\,^*(\text{Morning Twilight}) + b\,^*(\text{Evening Twilight}) + e$$

Where each italicized letter represented a solved-for weighting factor (generically represented by *b*).

[24] In the specification most similar to the current study, using data from March for only 2006 and 2007, the estimated EDST impact was a savings of 0.3 percent per day.

Their energy-savings results were in contrast with California, in that electricity consumption appeared to drop during the morning hours due to DST and increase during the additional hour of daylight in the evening. They admitted that the results in their report were neither definitive nor conclusive, and so could not infer that DST in Indiana would either increase or decrease electricity consumption.

A.7 2008 Indiana Daylight Saving Time Study

This recent Indiana study (Kotchen and Grant, 2008) used more than seven million monthly meter readings from Duke Energy Corp., covering nearly all the households in southern Indiana over a three-year period from 2004 through 2006. In 2006, for the first time, the entire state of Indiana observed daylight saving time beginning in April. Thus, the time period for the study included household electricity before and after a number of Indiana counties began observing daylight-saving time.

Indiana counties that observed daylight saving time prior to 2006 were used as a control group, which enabled adjustments for changes in weather from one year to the next. The study by Kotchen and Grant concluded that daylight saving time increased residential electricity consumption from between 1.0 and 4.0 percent, primarily due increased cooling in the late afternoon and evening.

In contrast to the 2006 DOE study, which included electricity consumption in residential and commercial buildings as part of total system electricity consumption, the Indiana study addressed only residential electricity use using billing data. Thus, while the Indiana study determined that DST increases residential air conditioning use, any change in cooling requirements in commercial buildings was not assessed. The Indiana study also considered the impact of DST over the entire six-month period from April through the end of October, as contrasted to the spring and fall extensions of DST under EPAct 2005.

Appendix B. Methodological Details in Support of Electricity and Energy Analysis

B.1 Data Sources and Construction

To understand the effects of EDST across the United States, it was necessary to obtain data from a broad array of utilities across the country. The main factors used in the selection were location of electricity demand and geographic location of utilities with respect to the electricity reliability region and climate zone. Size of utility was also a factor, but not a primary one. The selection aimed to result in a regionally representative collection of utilities, although they were not randomly selected.

B.1.1 NERC region and subregion data

The map below (Figure B-1) shows the reliability regions as of 2006 as defined by the North American Electric Reliability Council (NERC). These regional reliability councils provide summary data for their regions and offer an appropriate mechanism for segmenting the country's electricity demands. Some of the regions are quite large, but have been further divided into subregions, notably the Western Electricity Coordination Council (WECC), the Southeast Electric Reliability council (SERC), and the Northeast Power Coordinating Council (NPCC).

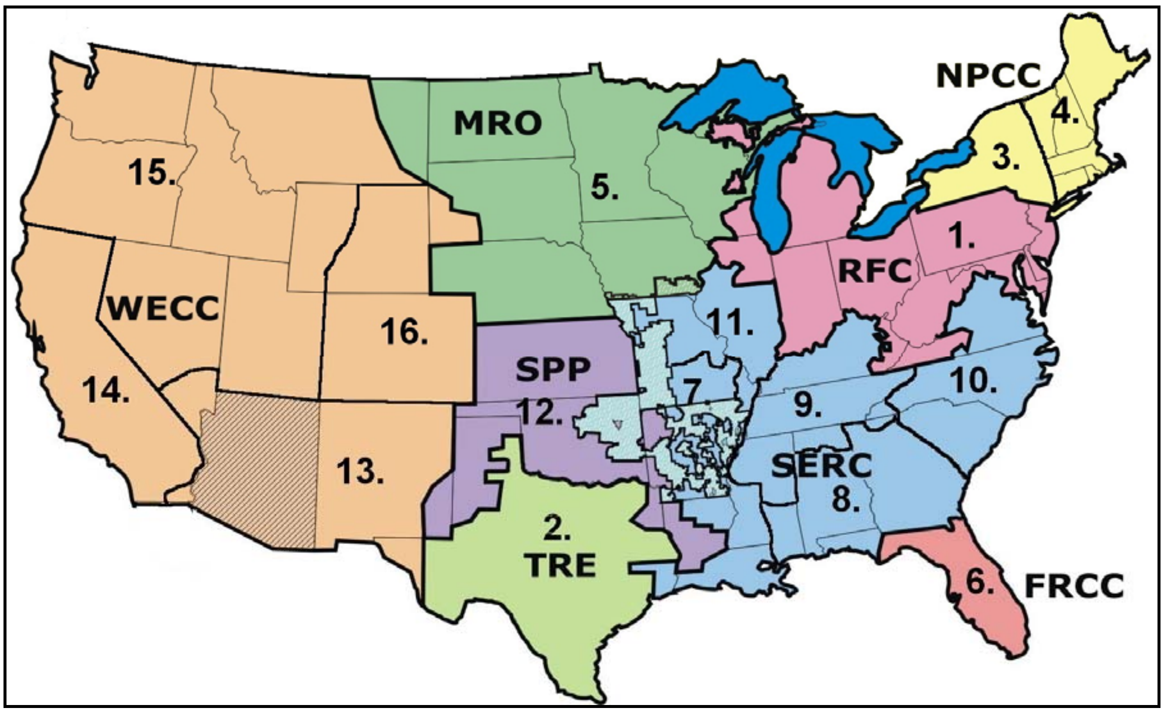

Figure B-1. NERC Regions

Arizona is shaded in the map because that state does not follow DST. In later calculations extrapolating and aggregating results by region, we adjusted the demands for its region to compensate.

Table B-1 lists the 16 regions or subregions used for the study along with their annual net electric load in TWh. Note that ReliabilityFirst has the largest load; however, NERC data no longer separates it into separate regions. In previous years, this area was included in the Mid-Atlantic Area Council, the East Central Area Reliability Coordination Agreement, and the Mid-America Interconnected Network. On the map, the SERC-DELTA region shows some confusion in its boundaries because Southwest Power Pool (SPP)-related entities control some transmission within its area.

Table B-1. NERC Regional Entities with Abbreviation and Net Electric Load

	Region	Abbreviation	2006 Net Electric Load (TWh)	Fraction of National Total (less AK and HI)
1.	ReliabilityFirst Corporation	RFC	1,005	26%
2.	Texas Regional Entity	TRE	299	8%
3.	Northeast Power Coordinating Council – New York	NPCC-NY	167	4%
4.	Northeast Power Coordinating Council – New England	NPCC-NE	136	3%
5.	Midwest Reliability Organization	MRO	217	6%
6.	Florida Reliability Coordinating Council	FRCC	227	6%
7.	SERC Reliability Corporation – Delta	SERC-DEL	142	4%
8.	SERC Reliability Corporation – Southeastern	SERC-SE	241	6%
9.	SERC Reliability Corporation – Central	SERC-CENT	191	5%
10.	SERC Reliability Corporation – VACAR	SERC-VAC	309	8%
11.	SERC Reliability Corporation – Gateway	SERC-GAT	79	2%
12.	Southwest Power Pool	SPP	202	5%
13.	Western Electricity Coordinating Council – AZ-NM-SNV	WECC-AZN	127	3%
14.	Western Electricity Coordinating Council – CA	WECC-CA	266	7%
15.	Western Electricity Coordinating Council – NWPP	WECC-NWP	234	6%
16.	Western Electricity Coordinating Council – RMPA	WECC-RMP	59	2%
	Total		3,900	100%

B.1.2 FERC Form 714 data for 2006

The initial source of hourly load data for many utilities is from Part II of the Federal Energy Regulatory Commission's FERC Form-714 data. Balancing authorities must submit this data by June 1 of each year, although there was an extension provided in 2007. FERC personnel then include these submissions as electronic files in the FERC eLibrary. Many utilities acted as their own balancing authority and, thus, turned in forms that included the hourly loads. However, many utilities have transferred their balancing authority to another entity such as a power pool, holding company, or independent system operator.

All 276 of the FERC-714 submissions to FERC in 2007 were downloaded. Many of these were revisions from earlier submittals, leaving 199 separate entities submitting data. However, of these, many did not include hourly data. Approximately 90 of the submittals included hourly load data in MWh for 2006.

The hourly data within the FERC form is 11 tables with a combined 365 rows and the date, time zone, and 24 hours in 26 columns. To get the data in a meaningful form, we had to extract, combine, and convert it from the electronic file into a single column of 8,760 values. Some utilities submitted their forms with the data representing the prevailing or "clock" time, meaning that when the table showed a value for the 0400 hour, this represented the total megawatt-hours demanded between 0300 and 0400, according to the clock at that time. These utilities would typically have a zero value on April 2, 2006, either in hours 0200, 0300, or 2400. They also may have a doubled value on October 29, 2006, to represent the turning back of the clocks. However, not all utilities followed this practice.

Other utilities used solar or "standard" time. They did not adjust the data to show the advance for DST in April and drop back in October, so the load they showed at 0400 during the summer months would have been between 0400 and 0500, according to the clocks at that time.

To determine the method used by each utility, we had to compare their daily load shapes for several days before and after DST. Figures B-2 and B-3 show the hourly loads in the days before and after the spring DST shift on April 2—Figure B-2 is used if the utility turned in data based on clock time, and Figure B-3 is used if based on standard time. For this utility (New York State Electric & Gas), the data was submitted using clock time. Because most morning profiles show a rapid increase that should largely be determined by the clock time, it would be unusual for loads during DST to be dramatically different. Also, the evening peak would be more likely to shift one hour as in Figure B-2 rather than hours. We also inspected the fall curves for each utility to corroborate the timing for the data. We placed the resulting column of 8,760 hourly values in the model for further analysis.

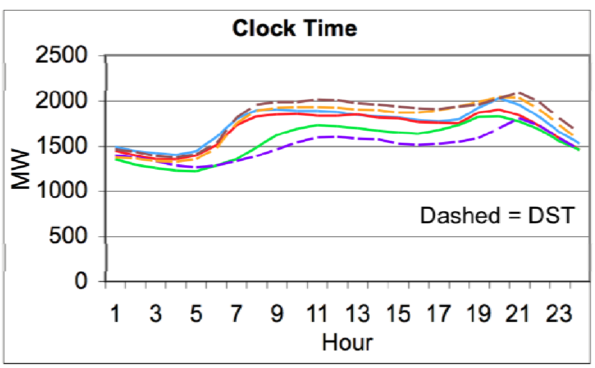

Figure B-2. Utility daily loads before and after spring DST assuming clock time

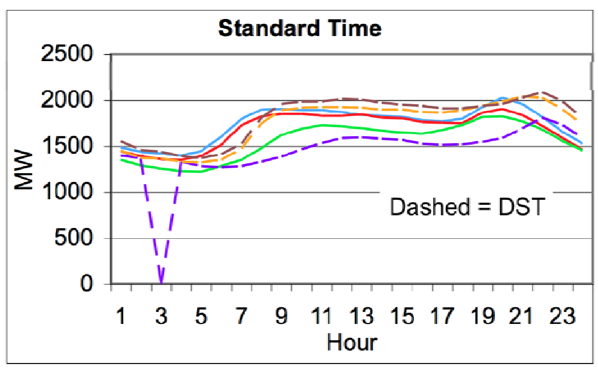

Figure B-3. Utility daily loads before and after spring DST assuming standard time

Seventy utilities had their 2006 data analyzed in this way. These are listed below and were selected based on their location, relative size, and previous analysis. Figure B-4 shows their approximate location and relative sales level (utilities with data from FERC are in blue). The area of each circle represents the annual net electric load for each.

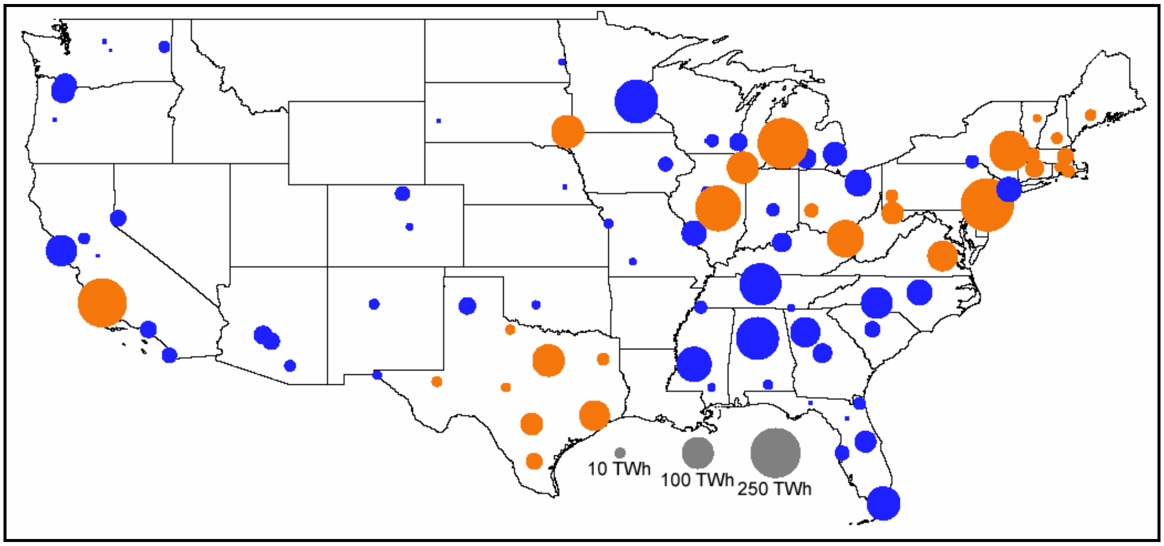

Figure B-4. Utilities or regions available for the study showing 2006 loads by size

Note: The circle size represents 2006 consumption. FERC source data is in blue, Region source data in orange.

The FERC Form 714 also has a place for the hourly marginal cost or "system lambda" for the utility. These are in the same format as the hourly loads (11 tables for a total of 365 rows by 24 columns). Many utilities did not include this information because they no longer use internally generated system lambdas for dispatch calculations. Instead, they rely on the larger regional wholesale market and on independent system operators to set the dispatch order based on bid prices. We collected this data from the utilities that made it available and used it to calculate the marginal cost of electricity saved, and the consequent implied heat rate and primary energy used.

B.1.3 ISO regional data for 2006 and 2007

Separately, several of the regional independent system operators (ISO) post historical hourly data on their Web sites. These included the ISO for New England (ISO-NE), New York ISO, California ISO, PJM, ERCOT, and Midwest ISO—Web sites are shown below:

http://www.iso-ne.com/markets/hstdata/znl_info/hourly/index.html

http://www.nyiso.com/public/market_data/load_data.jsp

http://oasis.caiso.com/

http://www.pjm.com/markets/jsp/loadhryr.jsp

http://www.ercot.com/gridinfo/load/load_hist/index.html

http://www.midwestmarket.org/publish/Folder/32bf3f_114f0892511_-7ffd0a48324a?rev=2

While the California ISO provides data only for their entire region, the others break down the data into multiple subregions. These data are for both 2006 and 2007. The PJM regions are all in the ReliabilityFirst NERC region except one that is in the SERC-VACAR region. The Midwest ISO separates its territory into three broad regions. One is entirely inside the MRO NERC region but the other two overlap other NERC reliability regions. Figure B-4 shows the size of these regions as well, with the regions shown in orange. (New York ISO data was not broken down further for the analysis.)

B.1.4 Data for 2007 from utilities

Comparing the locations of utilities with data and the regional maps, and attempting to get a mixture of urban and rural locations, we selected a number of utilities for further analysis. We sent requests to 72 utilities for 2007 hourly data. Of these, 39 responded with spring data, while 33 responded with fall data. (Three utilities provided fall but not spring data.) The percent of U.S. electricity consumption met by participating utilities was 23.3 percent.

B.1.5 Construction of final utility list

Combining the utility-submitted and regional data, the analysis included 67 utilities total: 64 utilities in the spring and 56 utilities in the fall. Figure B-5 shows the utilities that provided data for both spring and fall in green, those with just spring data in red, and those with just fall data in blue. The numbers correspond to the utilities in Table B-3.

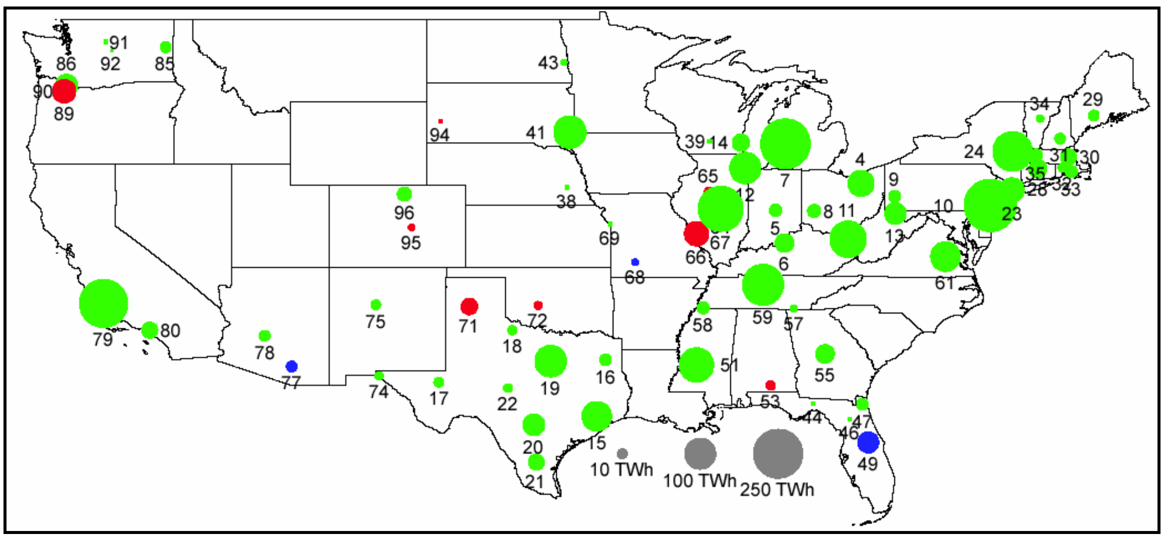

Figure B-5. Sixty-seven utilities or regions with 2007 data available (both spring and fall in green, just spring in red, just fall in blue) (Numbers correspond to utilities in Table B-3.)

Figure B-6 shows the 67 utilities overlaid on a climate zone map. All but climate zone 1 have several utilities within its zone. Some utilities are near a border and have parts of their territory within two or more zones. The most notable example is Entergy, which stretches from the Arkansas-Missouri border to New Orleans, and has some of its territory in zones 2, 3, and 4.

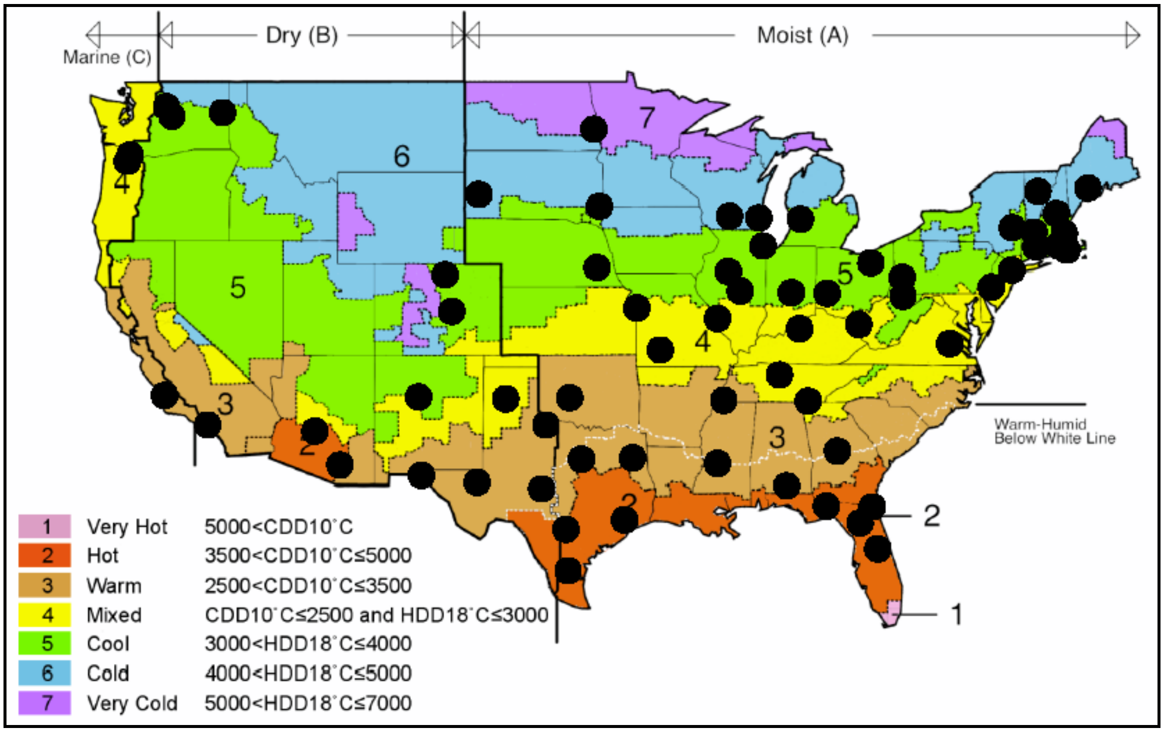

Figure B-6. Sixty-seven utilities with 2007 data overlaid on climate zone map

We applied the heuristic method to all 67 utilities. We performed a more detailed statistical analysis on a subset of 36 of these utilities, ensuring that we had all regions of the United States represented.[25] Figure B-7 shows the utilities selected with the numbers corresponding to the utilities in Table B-3.

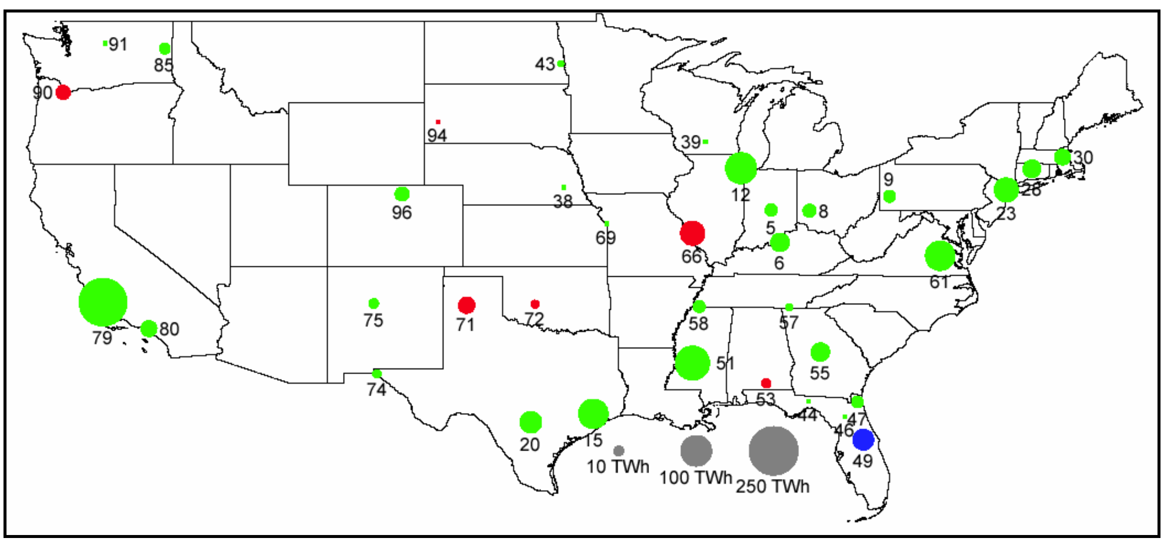

Figure B-7. Thirty-six utilities or subregions used for statistical analysis (both spring and fall in green, just spring in red, just fall in blue) (Numbers correspond to utilities in Table B-3)

[25] There were 36 separate utilities considered in the statistical analysis. Thirty-five were available for spring. The missing one for spring was available for the fall. However, 7 other utilities were not - leaving 29.

Figure B-8 shows these same 36 utilities on the climate zone map. Again, all regions have some coverage in the analysis despite the lower number of utilities.

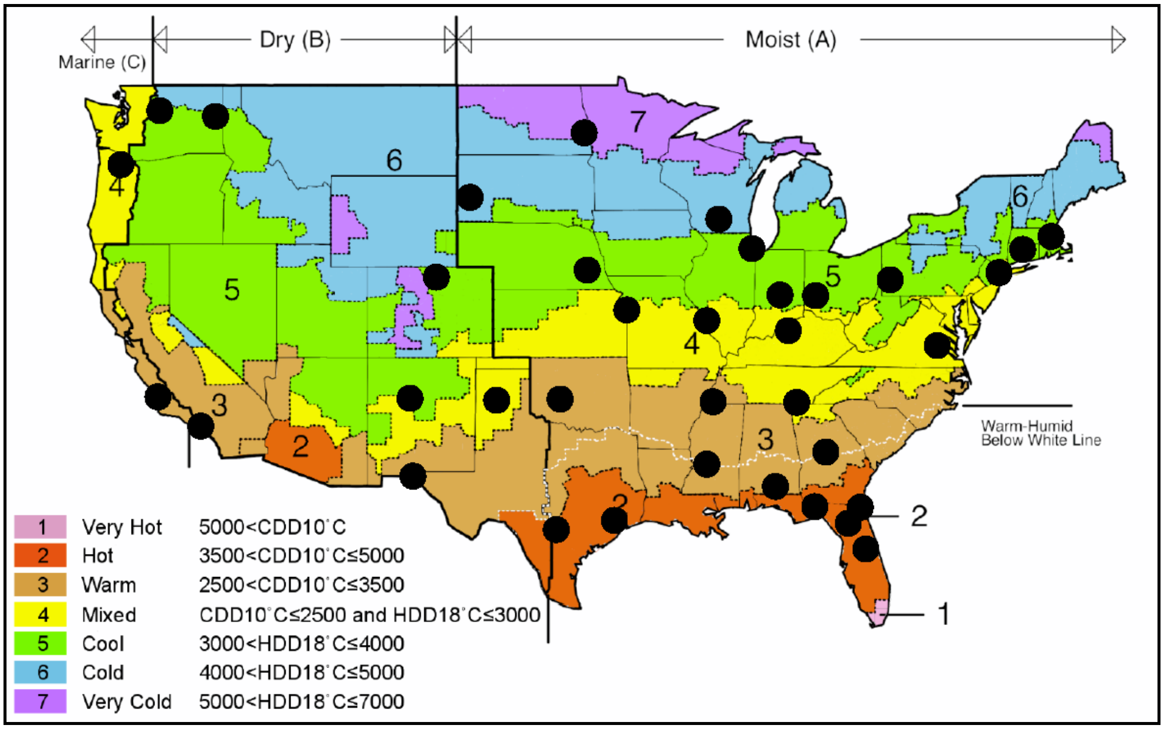

Figure B-8. Thirty-six utilities used for statistical analysis on climate zone map

Table B-2 shows the percentage of each region's annual system load included in the utilities used for the heuristic and statistical analysis. As mentioned above, we only analyzed some of the

Table B-2. Fraction of NERC 2006 Regional Loads Collected and Analyzed by Each Method

	Region	2006 Data Collected	Heuristic	Statistical
1	RFC	85%	75%	19%
2	TRE	104%	104%	47%
3	NPCC-NY	97%	97%	36%
4	NPCC-NE	95%	95%	43%
5	MRO	52%	52%	5%
6	FRCC	90%	29%	29%
7	SERC-DEL	90%	86%	86%
8	SERC-SE	94%	19%	19%
9	SERC-CEN	92%	92%	11%
10	SERC-VAC	90%	30%	30%
11	SERC-GAT	85%	85%	77%
12	SPP	25%	21%	19%
13	WECC-AZN	81%	33%	14%
14	WECC-CNV	105%	101%	101%
15	WECC-NWP	79%	62%	16%
16	WECC-RMP	47%	47%	39%
	Total	84%	66%	32%

utilities for the spring or fall. The percentages are only approximate because we collected the NERC regional data and other sources (FERC or utility) using separate methods. For example, the Texas Regional Entity has more than 100 percent of their NERC-reported net electric load collected. We adjusted the numbers in the table to avoid double counting where we have both individual utility data and their regional totals.

Table B-3 shows the utilities and regions with their 2006 annual loads. The cities listed are not necessarily their headquarters, but were selected to be representative of their territory.

Table B-3. Utilities and Regions Used for EDST Analysis, 2006 Data is from FERC Form-714, Utility Websites, or Directly from Utilities

No.	Utility	City Used for Mapping	NERC Region	2006 TWh	Spring 07 Data	Fall 07 Data	Statistic Analysis
1	Consumers Energy Company	Jackson, MI	RFC	39			
2	Dayton Power & Light Company	Dayton, OH	RFC	16			
3	Detroit Edison Company	Detroit, MI	RFC	56			
4	FirstEnergy Corporation	Wadsworth, OH	RFC	71	✓	✓	
5	Indianapolis Power & Light Company	Indianapolis, IN	RFC	16	✓	✓	✓
6	Louisville Gas & Electric and Kentucky Utilities	Louisville, KY	RFC	36	✓	✓	✓
7	Midwest ISO East Region	Grand Rapids, MI	RFC	257	✓	✓	
8	PJM Interconnection AEP-Dayton Hub	Dayton, OH	RFC	18	✓	✓	✓
9	PJM Interconnection Duquesne Hub	Pittsburgh, PA	RFC	15	✓	✓	✓
10	PJM Interconnection Eastern Hub	Philadelphia, PA	RFC	284	✓	✓	
11	PJM Interconnection LLC (AEP Hub)	Huntington, WV	RFC	138	✓	✓	
12	PJM Interconnection North Illinois Hub	Chicago, IL	RFC	102	✓	✓	✓
13	PJM Interconnection Western Hub	Morgantown, WV	RFC	48	✓	✓	
14	Wisconsin Electric Power Company	Milwaukee, WI	RFC	31	✓	✓	
15	ERCOT COAST	Houston, TX	TRE	91	✓	✓	✓
16	ERCOT EAST	White Oak, TX	TRE	14	✓	✓	
17	ERCOT FAR_WEST	Barstow, TX	TRE	10	✓	✓	
18	ERCOT NORTH	Crowell, TX	TRE	9	✓	✓	
19	ERCOT NORTH_C	Cresson, TX	TRE	104	✓	✓	
20	ERCOT SOUTH_C	San Antonio, TX	TRE	49	✓	✓	✓
21	ERCOT SOUTHERN	Benavides, TX	TRE	26	✓	✓	
22	ERCOT WEST	Eden, TX	TRE	8	✓	✓	
23	Consolidated Edison Co. of NY Inc.	New York, NY	NPCC-NY	61	✓	✓	✓
24	New York Independent System	Albany, NY	NPCC-	162	✓	✓	

No.	Utility	City Used for Mapping	NERC Region	2006 TWh	Spring 07 Data	Fall 07 Data	Statistic Analysis
	Operator, Inc.		NY				
25	New York State Electric & Gas Corporation	Binghamton, NY	NPCC-NY	16			
26	Orange & Rockland Utils., Inc.	Spring Valley, NY	NPCC-NY	6			
27	Boston Edison Company (NSTAR)	Boston, MA	NPCC-NE	16			
28	ISO-New England - Connecticut	Hartford, CT	NPCC-NE	33	✓	✓	✓
29	ISO-New England - Maine	Augusta, ME	NPCC-NE	12	✓	✓	
30	ISO-New England - NE Massachusetts	Boston, MA	NPCC-NE	26	✓	✓	✓
31	ISO-New England - New Hampshire	Concord, NH	NPCC-NE	12	✓	✓	
32	ISO-New England - Rhode Island	Providence, RI	NPCC-NE	8	✓	✓	
33	ISO-New England - SE Massachusetts	New Bedford, MA	NPCC-NE	15	✓	✓	
34	ISO-New England - Vermont	Montpelier, VT	NPCC-NE	6	✓	✓	
35	ISO-New England - W Central Massachusetts	Northampton, MA	NPCC-NE	18	✓	✓	
36	Alliant Energy - East	Madison, WI	MRO	15			
37	Alliant Energy - West	Cedar Rapids, IA	MRO	20			
38	Lincoln Electric System	Lincoln, NE	MRO	3	✓	✓	✓
39	Madison Gas & Electric Company	Madison, WI	MRO	3	✓	✓	✓
40	Mid-Continent Area Power Pool	Roseville, MN	MRO	189			
41	Midwest ISO West Region	Sioux Falls, SD	MRO	109	✓	✓	
42	Minnesota Municipal Power Agency	Minneapolis, MN	MRO	1			
43	Otter Tail Power Company	Fargo, ND	MRO	4	✓	✓	✓
44	City of Tallahassee	Tallahassee, FL	FRCC	3	✓	✓	✓
45	Florida Power & Light Company	Miami, FL	FRCC	113			
46	Gainesville Regional Utilities	Gainesville, FL	FRCC	2	✓	✓	✓
47	Jacksonville Energy Authority	Jacksonville, FL	FRCC	14	✓	✓	✓
48	Orlando Utilities Commission	Orlando, FL	FRCC	6			
49	Progress Energy (Florida Power Corp.)	Orlando, FL	FRCC	45		✓	✓
50	Tampa Electric Company	Tampa, FL	FRCC	20			
51	Entergy Corporation/Services (Entergy System)	Jackson, MS	SERC-DEL	122	✓	✓	✓
52	South Mississippi Electric Power	Hattiesburg, MS	SERC-	6			

No.	Utility	City Used for Mapping	NERC Region	2006 TWh	Spring 07 Data	Fall 07 Data	Statistic Analysis
	Association		DEL				
53	Alabama Electric Cooperative, Inc.	Andalusia, AL	SERC-SE	9	✓		✓
54	Georgia Power Company	Atlanta, GA	SERC-SE	89			
55	Oglethorpe Power Company	Macon, GA	SERC-SE	36	✓	✓	✓
56	Southern Company	Birmingham, AL	SERC-SE	183			
57	Electric Power Board of Chattanooga	Chattanooga, TN	SERC-CEN	6	✓	✓	✓
58	Memphis Light, Gas and Water	Memphis, TN	SERC-CEN	15	✓	✓	✓
59	Tennessee Valley Authority	Nashville, TN	SERC-CEN	175	✓	✓	
60	Duke Energy Carolinas, LLC	Charlotte, NC	SERC-VAC	98			
61	PJM Interconnection Dominion Hub	Richmond, VA	SERC-VAC	92	✓	✓	✓
62	Progress Energy (Carolina Power & Light Company)	Raleigh, NC	SERC-VAC	64			
63	South Carolina Electric & Gas	Columbia, SC	SERC-VAC	24			
64	Ameren (Illinois Power Co. Control Area)	Decatur, IL	SERC-GAT	22	✓		
65	Ameren CILCO	Peoria, IL	SERC-GAT	6	✓		
66	Ameren Corporation Control Area	St. Louis, MO	SERC-GAT	61	✓		✓
67	Midwest ISO Central Region	Decatur, IL	SERC-GAT	211	✓	✓	
68	Empire District Electric Company (the)	Springfield, MO	SPP	5		✓	
69	Kansas City Board of Public Utilities & Wyandotte County	Kansas City, KS	SPP	3	✓	✓	✓
70	Missouri Public Service	Kansas City, MO 641085	SPP	8			
71	Southwestern Public Service Company (Xcel)	Amarillo, TX	SPP	28	✓		✓
72	Western Farmers Electric Cooperative	Oklahoma City, OK	SPP	7	✓		✓
73	Arizona Public Service Company	Phoenix, AZ	WECC-AZN	33			
74	El Paso Electric Company	El Paso, TX	WECC-AZN	7	✓	✓	✓

No.	Utility	City Used for Mapping	NERC Region	2006 TWh	Spring 07 Data	Fall 07 Data	Statistic Analysis
75	Public Service Company of New Mexico	Albuquerque, NM	WECC-AZN	10	✓	✓	✓
76	Salt River Project	Tempe, AZ	WECC-AZN	28			
77	Tucson Electric Power Company	Tucson, AZ	WECC-AZN	12		✓	
78	Western Area Power Administration - Lower Colorado control area (Desert Southwest)	Phoenix, AZ	WECC-AZN	12	✓	✓	
79	California Independent System Operator	San Luis Obispo, CA	WECC-CNV	240	✓	✓	✓
80	Los Angeles Department of Water and Power	Los Angeles, CA	WECC-CNV	27	✓	✓	✓
81	Pacific Gas and Electric Company	San Francisco, CA	WECC-CNV	95			
82	Sacramento Municipal Utility District (& City of Redding Electric Utility)	Sacramento, CA	WECC-CNV	12			
83	San Diego Gas & Electric Company	San Diego, CA	WECC-CNV	22			
84	Turlock Irrigation District	Turlock, CA	WECC-CNV	2			
85	Avista Corporation	Spokane, WA	WECC-NWP	12	✓	✓	✓
86	Bonneville Power Administration, USDOE	Vancouver, WA	WECC-NWP	51	✓	✓	
87	Eugene Water & Electric Board	Eugene, OR	WECC-NWP	3			
88	Nevada Power Company	Reno, NV	WECC-NWP	25			
89	PacifiCorp - Part II Sch 2	Portland, OR	WECC-NWP	56	✓		
90	Portland General Electric Company	Portland, OR	WECC-NWP	21	✓		✓
91	PUD No. 1 of Chelan County	Wenatchee WA	WECC-NWP	3	✓	✓	✓
92	PUD No. 1 of Douglas County	Wenatchee, WA	WECC-NWP	1	✓	✓	
93	Sierra Pacific Resources	Reno, NV	WECC-NWP	12			
94	Black Hills Corporation	Rapid City, SD	WECC-RMP	2	✓		✓
95	Colorado Springs Utilities	Colorado Springs, CO	WECC-RMP	5	✓		
96	Western Area Power Administration - Colorado-Missouri Control Area (Rocky Mtn Re)	Loveland, CO	WECC-RMP	21	✓	✓	✓

B.2 Specification for Heuristic Method Comparing Average Electricity Load Profiles

A utility's hourly loads for 2006 and 2007 during the time of EDST typically show a shift in the afternoon peak for 2007 and a smaller impact in the morning hours. Figure B-9 is an example curve from Indianapolis Power & Light. The graph shows the three-week average load in MW for each hour. The first point for the 2006 line is the sum of demands between midnight and 1:00 a.m. for the 21 days between March 12, 2006, and April 1, 2006, divided by 21. The second point would be for the loads between 1:00 a.m. and 2:00 a.m., etc. The equivalent curve for 2007 is for the 21 days between March 11, 2007, and March 31, 2007.

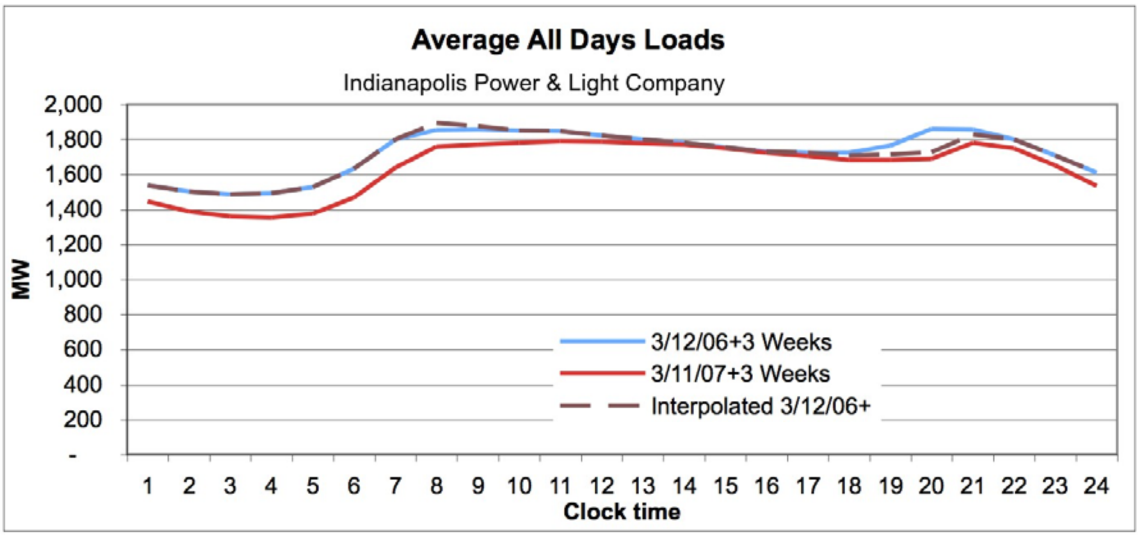

Figure B-9. Hourly average load shapes for Indianapolis Power & Light for spring 2006 and 2007

Plotting the ratio between the 2007 and 2006 values for each hour gives a better view of the difference between the two years. For example, during the three-week spring EDST for the time between midnight and 1:00 a.m. (Hour 1 in Figure B-9), the 2007 average value is 1,448 MW, while the average value for the corresponding days in 2006 is 1,539 MW. The consequent ratio is 0.941. Figure B-10 shows the ratio for each hour. The large dip in the evening and slight increase in the morning are presumed evidence of the impact of DST. To corroborate that, the analysis examined ratio curves for the weeks previous to and subsequent to these weeks as well. In addition, the study looked at 2006/2005 ratios during these same weekly periods for a limited set of utilities.

A simple mechanism for quantifying the amount of savings or extra production was to draw a line from two points to interpolate across the bump or dip. These beginning and ending hours represented the points where DST began and finished having an effect on loads. Using the example below, the interpolation line in the morning implies that there was no difference due to DST between 6:00 a.m. and 7:00 a.m.; but between 7:00 a.m. and 8:00 a.m., the 2007/2006 ratio would have equaled 93 percent without DST in 2007, rather than 95 percent. (Alternatively, the ratio would have been 93 percent if 2006 had also had DST.) Similarly, there was a roughly 1 percent difference in demand in the 8:00 a.m. to 9:00 a.m. hour. The 9:00 a.m. to 10:00 a.m. hour would have seen no difference. The evening interpolated curve implies that the ratio would have been higher if 2006 had DST or 2007 did not have DST.

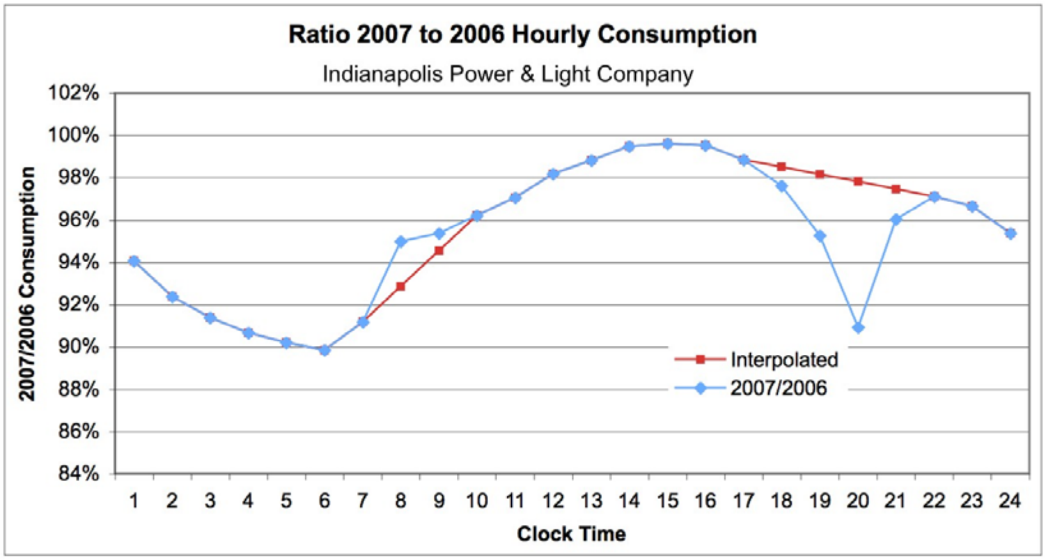

Figure B-10. Ratio of Indianapolis Power & Light 2007 to 2006 demands during the spring EDST period showing the interpolated line

For some utility load ratios, it was more difficult to identify the proper location. As a first step, an algorithm was created that calculated the least-squares fit of a line using different potential starting and ending hours plus the hourly points immediately to the left and right of the straight line. The initial analysis then selected the hours that had the minimized least squares. After that, the analysts visually examined each utility's curve and the starting and ending hours were adjusted to best match the data—there was some subjectivity involved. The ratio curves for the week before and the week after EDST were also plotted (Figure B-11) to better understand the utility's loads.

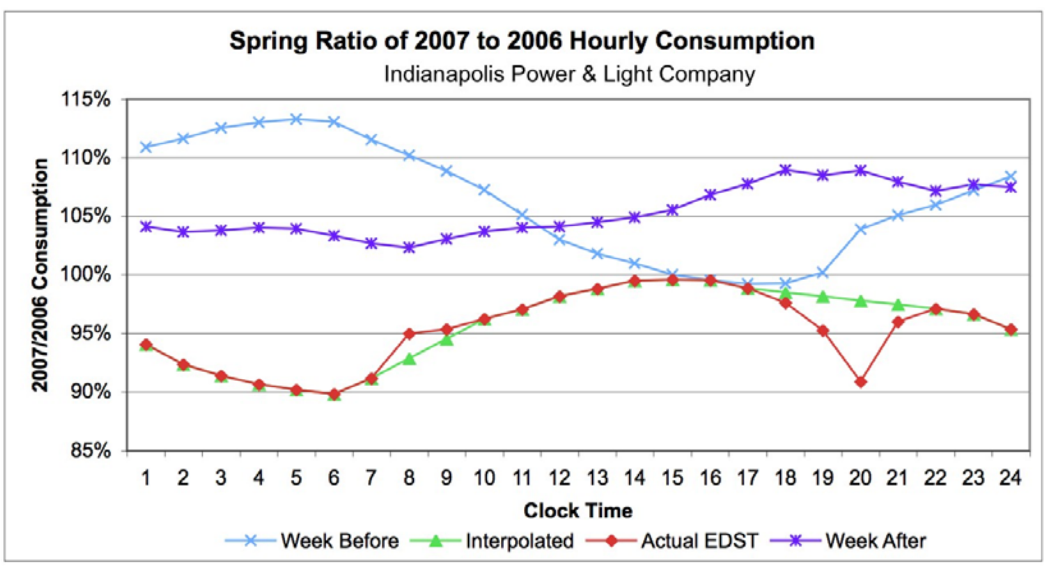

Figure B-11. Ratio of spring 2007 to 2006 hourly loads for Indianapolis Power & Light

Note how individual weeks can have more variation because of the unpredictability of weather or other activities. We similarly analyzed the fall curves and had starting and ending hours assigned for the heuristic lines. Because the fall EDST period was only one week rather than three weeks long, it had more variation in its shape for many utilities.

Finally, analysts had to calculate the percent of savings for each hour. As mentioned above, the interpolated lines represent the load 2007 would have been without DST, or the load 2006 would have been with DST. Because the marginal cost data for the 2006 loads was available, it was more appropriate to calculate the amount 2006 would have changed with DST so that the ratio of 2007 to 2006 would match the interpolated curve. We then applied these hourly percentage changes to that hour of each day over the EDST period. This approximation meant that each week's average curve might not necessarily show a straight line. Figure B-12 shows the weekly curves before, during, and after the spring EDST period.

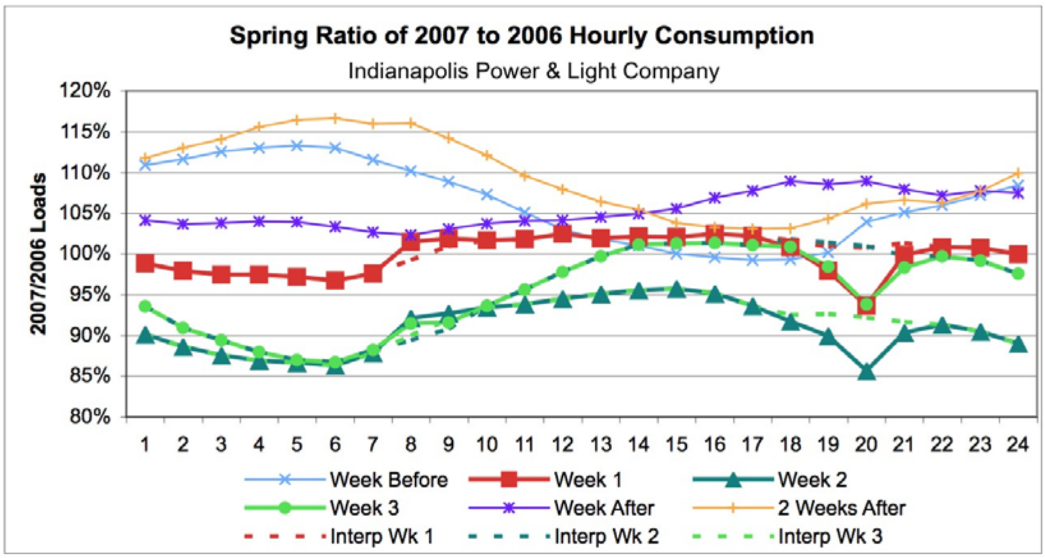

Figure B-12. Weekly ratio of spring 2007 to 2006 hourly loads for Indianapolis Power & Light

Once these percentage changes were determined, we could apply them to the 2006 loads to create a simulated load curve as if 2006 had EDST in place. Figure B-9 above (on page 59) includes this new curve as a brown-dashed line along with the original 2006 curve and the 2007 curve. The difference between it and the original 2006 curve in blue represents the electricity savings due to EDST for that utility. We can convert this to MWh of electricity in each hour, which can then be used in conjunction with the marginal cost of power and fuel prices to find the amount of energy saved. Appendix B.4 describes the method for this calculation.

B.3 Specifications for Daily and Hourly Electricity Regression Models

B.3.1. Introduction

As in the heuristic model, the basic methodological approach for the regression analysis compares 2006 and 2007 system consumption for the same periods (three weeks in the spring, one week in the fall) that were impacted by EDST. Analysts developed several model specifications that seek appropriately to account for other influences on the system load between the two years. Based on the empirical results from the preliminary 2006 EDST study (DOE, 2006), the amount of daylight in each hour of the day has a considerable influence on the load, separate from temperature effects. Because the amount of daylight during the evening will change by approximately 25 minutes during the three-week period beginning March 12, we considered this natural increase in daylight as part of the empirical specifications.

The general strategy employed several specifications, beginning with the simplest and moving toward those that are more complex. The simplest specifications focus on the system electricity consumption for the entire day or for selected hours in the morning or evening expected to be directly influenced by DST. The more complex specifications seek to explain hourly loads for all hours of the day. The final regression methodology combined elements of both the daily and hourly models.

B.3.2 Daily model specification

One principal methodological approach of the study targeted the estimation of the impacts of EDST on average daily electricity consumption within a given utility service area. We designed the specification of this daily model to reflect the major factors assumed to affect daily consumption patterns during a period of several months. It employs a regression model that incorporates what is termed a “Difference-in-Difference” (DID) specification. The DID specification seeks to isolate the impact of EDST during March 2007 by including a separate, additional variable for the same period during 2006, which accounts for systematic factors that may apply to both years. We designed this approach to provide a more robust strategy for isolating the independent impact of EDST in 2007. The details of this specification are discussed further below.[26]

The complete model is expressed as

$$\begin{aligned} L_{dy} = {} & b_0 + b_1\, Time_d + b_2\, Growth_y + b_3\, Saturday + b_4\, Sunday + \\ & b_5\, HDDVW_{dy} + b_6\, HDDVSQRW_{dy} + b_7\, CDDVW_{dy} + b_8\, CDDVSQRW + \\ & b_9\, EDST\text{-}C + b_{10}\, EDST\text{-}I + b_{11}\, DST + u \end{aligned} \qquad \text{Eq. (B.1)}$$

Where,

L_{dy}	=	System electricity consumption in day *d* in year *y*,
$Time_d$	=	Time trend as measured by day number in year y (i.e., Feb. 1 = 0, Feb 2 = 1, … , April 30 = 88)
$Growth_y$	=	Binary variable to measure overall annual consumption growth; = 0 for 2006, = 1 for 2007
Saturday	=	Binary indicator variable: = 1 if Saturday, 0 otherwise

[26] With the exception of the DID framework, the daily model specification described below is similar to the that used by the California Energy Commission in a recent preliminary study of the effects of the 2007 EDST in California (California Energy Commission, 2007). The CEC study used data for six years prior to 2007 and over the months of January through March. They defined both the heating and cooling degree variables with a reference (or base) temperature of 65 degrees F, as compared to the variable reference temperatures used in this analysis (as discussed below).

Sunday	=	Binary indicator variable: = 1 if Sunday, 0 otherwise
$HDDVW_{dy}$	=	Heating Degrees for day *d* in year *y*,[27]
$HDDVSQRW_{dy}$	=	Squared value of Heating Degrees for day *d* in year *y*,
$CDDVW_{dy}$	=	Cooling Degrees for day *d* in year *y*,
$CDDVSQRW_{dy}$	=	Squared value of Cooling Degrees for day *d* in year *y*,
EDST-C	=	Binary indicator variable for periods of EDST in *both* 2006 and 2007 (= 1 from March 12 – March 30, 2006, and from March 12 – March 31, 2007, 0 otherwise) 2007 (= 1 from March 11 through March 31, 0 otherwise)
EDST-I	=	Binary indicator variable for EDST in 2007 (= 1 from March 11 through March 31, 0 otherwise)
DST	=	Binary indicator variable for conventional DST (= 1 from first Sunday in April and later in both 2006 and 2007, 0 otherwise)
Holiday	=	Binary indicator variable(s) for holidays (see text below).

We classified the variables in model specification (B.1) into three groups: 1) trend and general indicator variables, 2) weather variables, and 3) daylight time indicator variables. These three groups are discussed below.

Trend and general indicator variables

We intended for the time trend to pick up the influence of longer daylight and other seasonal effects during the February – April period. Because the spring equinox is roughly in the middle of this period, the daily *change* in the amount of daylight is nearly constant during this period. The time trend will also reflect other seasonal changes in overall electricity consumption such as changes in the operating hours of seasonal businesses.

We can expect electricity consumption to change from one year to the next because of changes in population or economic activity. While the difference from one year to the next cannot be expected to be uniform over any given set of time intervals (e.g., intervals involving weeks or months), it is still necessary to take some account of the underlying change. We used the binary indicator variable "Growth" to account roughly for the (typically positive) change in daily consumption between 2006 and 2007.

We intended for the day-type binary variables, Saturday and Sunday, to account for the typically lower amounts of electricity used on those days as compared to weekdays. For the model for the spring EDST period, a binary indicator variable was included for President's Day in both 2006 and 2007.[28] In the fall regression model, we included separate binary variables to account for the below-normal electricity consumption on Thanksgiving and the following day ("Black Friday")

[27]See discussion below about weighting of minimum and maximum daily temperature to compute heating and cooling degrees.

[28] The inclusion of a binary variable for President's Day was a late modification of the specification for the spring EDST period. The reduction in electricity consumption on President's Day (as compared to a normal weekday) was the greatest for the utilities serving the heavily urban utilities in the Northeast and for California. As a Federal holiday, President's Day is observed nationwide, but the decline in financial institution activity in these areas (e.g., national banking, NYSE) may contribute to a relative larger decline in electricity use in these areas.

Temperature and degree-day variables

Typically, we represent temperature effects on aggregate energy consumption (fossil fuel as well as electricity) in terms of heating and cooling degrees. A brief description of this approach may be helpful. Looking first at heating, we computed the number of heating degrees in a day as the difference between the observed temperature and a reference temperature. The reference temperature underlying the conventional heating and cooling degree statistics reported by the U.S. National Climatic Data Center (NCDC) is 65 degrees F. If the actual temperature is above 65 degrees, the number of heating degrees for that day is zero. We based this convention on an assumption that for most buildings, heating will not be required when the daily average temperature is above 65 degrees. For degree-days published by the NCDC, the daily average temperature is defined as the simple average of the daily maximum and daily minimum temperature. Formally, the definition of heating degree-days can be described as

$$\text{HDD} = (65 - \text{Tave}) \text{ if} > 0\text{, otherwise } 0, \qquad \text{(B.2)}$$

In Equation (B.1), the name degree-day variable begins with "HDD," following conventional terminology. As the variable in the daily model is defined for only a single day, heating degrees and heating degree-days are equal. For periods longer than a day, the sum of heating degrees for each day of the period is termed heating degree-days.

The analogous situation applies for conversion of temperatures into cooling degrees (or cooling degree-days). For a reference temperature of 65 degrees, the definition in this case is

$$\text{CDD} = (\text{Tave} - 65) \text{ if} > 0\text{, otherwise } 0, \qquad \text{(B.3)}$$

As shown in Equation (B.1), the influence of temperature on system electricity consumption, as represented in this study, is made entirely through the use of heating and cooling degree variables. However, the empirical implementation relaxes the key assumptions made in the construction of the conventional heating and degree-day measures. In essence, the data are employed to select the values for the three major parameters used to construct heating and cooling degrees:

- Reference temperature for heating;
- Reference temperature for cooling; and
- Weighting of daily minimum and maximum temperatures.

We considered the weighting of the observed daily maximum and minimum temperatures first. Generally, one can expect heating loads to be more strongly related to the daily minimum temperature, and cooling loads to be more strongly related to the daily maximum temperature. Of course, this association is not exclusive. On cold days, the maximum temperatures will influence heating demands during the day. On warm days, particularly in commercial buildings, minimum temperatures will influence the amount of electricity used for cooling.

The estimation procedure used in this analysis allows the data to determine weighting for temperatures that best explain the observed daily consumption. Depending on the location and amount of electricity used for heating as compared to other end uses, the procedure estimates a single weight parameter (between zero and one) that we used to adjust both temperatures. Thus, letting this weight be denoted as *wt*, the construction of an "adjusted" maximum temperature can be defined as

$$TADJ_{max} = wt\ T_{max} + (1 - wt)\ T_{min} \tag{B.4}$$

We applied a converse weighting to define an adjusted minimum temperature. Thus, the "adjusted" minimum temperature is

$$TADJ_{min} = wt\ T_{min} + (1 - wt)\ T_{max} \tag{B.5}$$

We defined heating and cooling degrees with respect to these adjusted minimum and maximum temperatures. The estimated weight allows the daily temperatures used in the construction of heating and cooling degree variables to differ from a single daily average temperature computed with weights of 0.5 on both the minimum and maximum temperatures.

The estimation procedure also lets the reference temperatures, here denoted as *TRH* and *TRC*, be derived from the data in the same way. Given a reference temperature for heating, *TRH,* heating degrees are then computed in the conventional manner, where if the weighted daily temperature (adjusted daily minimum temperature) is greater than the reference temperature, the number of heating degrees for the day is set equal to zero. Formally, this construction is:

$$HDDV = (TRH - TADJ_{min})\ \text{if} > 0,\ 0\ \text{otherwise} \tag{B.6}$$

The construction for the cooling degrees is analogous, with the provision that cooling degrees are zero for days in which the weighted daily temperature (adjusted maximum temperature) is less than the cooling reference temperature (*TRC*). Thus,

$$CDDV = (TADJ_{max} - TRC\ \text{if} > 0,\ 0\ \text{otherwise} \tag{B.7}$$

The squared values of both the heating and cooling degree variables are also included in the specification. Generally, the squared terms reflect the notion that as temperatures fall (rise) an increasing fraction of the building stock begins to use electricity for heating (cooling). Thus, while the relationship for a single building may be roughly linear below or above the reference temperature, a nonlinear response at the system level is due, in part, to the fact that there is a distribution of reference temperatures across buildings. In addition, in areas where heat pumps are common, the nonlinear response of electricity for heating may result from the need for (less-efficient) electric resistance heating at very cold temperatures.

The final component in the construction of the temperature variables involves time lags. Initial testing showed that the inclusion of effects from the degree-day variables for the previous day (and sometimes for the day before that) considerably improved the empirical prediction of the system loads.[29] The construction of some buildings with "mass" walls (concrete or brick) leads to considerable lags between changes in temperature and heating or cooling demands. To maintain tractability of the estimation procedure, and to reflect the notion that the lagged response in a given building should be similar across a wide range of temperature, the inclusion of the prior days' degree-day variables is handled by two parameters. The lag weights for the heating and cooling degree variables are constrained to be the same. Formally, we constructed an "effective" or "day-weighted" variable as the weighted average of the values for the current and previous two days. Thus, for example, we define the day-weighted heating degree variable as

$$HDDVW_d = wd(0)\ HDDV_d + wd(1)\ HDDV_{d-1} + wd(2)\ HDDV_{d-2} \qquad \text{(B.8)}$$

As part of the estimation procedure, the weighted heating degree variables are normalized to sum to 1.0 (and, as such, only *wd(0)* and *wd(1)* need to be estimated). In addition, all weights are constrained to be non-negative.

Daylight saving indicator variables

The DID approach involves the incorporation of two separate binary variables that cover the EDST time frame of the last three weeks of March. The first variable (EDST-C) is termed "EDST Control;" it is used to control special factors that may have affected electricity consumption during this period in *both* 2006 and 2007. An example of such an influence is a school spring vacation that reduces the load in a specific utility during this period in March. Such an effect is not represented in other model variables (e.g., in the included time trend variable). Operationally, this variable is included as a binary indicator variable that takes on the value of 1 during the relevant 21 days of March in both 2006 and 2007 and zero for all other days.

The key variable of interest, EDST-I, represents the estimated Impact of EDST during March 2007. Even if there is some systematic change in the load during this period, we designed the regression model to allow this effect to be captured by the EDST-C variable. The coefficient on EDST-I represents the available statistical evidence of whether EDST had a measurable impact on daily consumption and whether that impact can be viewed as statistically significant.[30]

Finally, as the estimation period extends into April in both 2006 and 2007, the model specification must allow for a separate effect for DST as observed prior to 2007. A DST variable takes on the value of 1 from (Sunday) April 2 through April 30 in 2006, and from (Sunday) April 1 through April 30 in 2007. Because we presumed there were relatively small changes in overall consumption between 2006 and 2007, we used a single DST variable for both years. In essence, the estimated coefficient on this variable reflects the average effect over both years.

Estimation procedure

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[29] As will be discussed in Appendix E the decision to include a two-day lag of the degree-day variables was motivated by the initial regression modeling for several southern climates.

[30] A more complete discussion of the Difference-in-Difference procedure is included as part of the following section dealing with hourly models.

We performed the initial estimation of Equation (B.1) with an automated search procedure involving ordinary least squares. As discussed in the section on weather variables, we used four parameters to construct the heating and cooling degree variables. The parameters were: 1) the weight to adjust the daily maximum and minimum on the maximum daily temperature (*w*) as shown in Equation (B.2), 2) the heating reference temperature *TRH*, and 3) and the cooling reference temperature *TRC*. Beginning with an initial choice of values for each of these parameters, analysts performed a linear regression using the daily observations for the spring of 2006 and 2007. The automated optimization procedure then searched for alternative parameter sets of (*wt, wd(o), wd(1), TRH, and TRC*) to maximize the percentage of explained variance of the daily consumption.

To facilitate graphical analysis, variable construction, and potential exchange with other analysts, we carried out the daily model estimation entirely within the Excel spreadsheet environment. Within Excel, the process used the LINEST matrix function to compute the linear regression, and the SOLVER add-in utility to search the parameters used to define the degree-day variables. For SOLVER, the instruction involves maximizing the value of the regression model R^2 by changing the values of *wt, wd, TRH,* and *TRC*.

We estimated the daily model during the period of February 2 through April 30 for both 2006 and 2007 (88 days in each year). We performed some very limited testing with a shorter estimation period covering nine weeks—three weeks before EDST, three weeks during EDST, and three weeks after EDST. In general, the results were deemed to be less satisfactory in terms of reasonable coefficients on the EDST-C and EDST-I variables. In many areas of the United States, the last two weeks during March 2007 were abnormally warm followed by unusually cold weather through much of April. We judged the longer estimation period more suitable in distinguishing weather effects from the effects of daylight time.

For the fall analysis, we estimated the daily regressions for the period from October 2 through November 30.

B.3.3 Implementation of hourly regression models

We also developed models to estimate EDST impacts across various hours of the day for each utility in the sample. At the outset, we need to state that the development of the hourly models for this study received a different emphasis as compared to the daily model. We primarily based our decision on two considerations. The available studies using hourly models suggest that it is very difficult to derive a statistically robust estimate of the DST impact (and the associated confidence intervals) on daily consumption by aggregating the results across hours. For the study here, the primary question is whether the implementation of EDST saved, on net, any electricity for the additional days in 2007 in which DST was implemented. We initially judged that objective to be better accomplished by a model that directly addressed daily electricity consumption.

A satisfactory hourly model would include hourly temperature and daylight variables as well as detailed assessment of appropriately lagged effects of temperature on the system electricity consumption.

In spite of this limitation, somewhat simplified versions of the hourly models were used to generate the final estimates of the EDST impacts in 2007. Drawing upon the construction of the heating and cooling degree-day variables from the daily model, the hourly models employed a more complex DID framework to generate estimated impacts.

The second consideration involved the availability of time and resources to build robust hourly models for the large sample of utilities considered in this study. A satisfactory hourly model would include hourly temperature and daylight variables as well as detailed assessment of appropriately lagged effects of temperature on the system load.

In spite of these limitations, somewhat simplified versions of the hourly models were used to generate the final estimates of the EDST impacts in 2007. Drawing upon the construction of the heating and cooling degree-day variables from the daily model, the hourly models employed a more complex DID framework to generate estimated impacts.

The estimation of both daily and hourly models served several useful purposes. First, to the extent possible, there should be general congruence between the daily and hourly model results. The hourly models also provide evidence regarding potential contamination of the estimated EDST impact and temperature. In such cases, one could use the hourly model to provide an alternative (conservative) estimate of the impacts of EDST. Finally, because the hourly models indicate which hours are most impacted by EDST, the effects on the electricity utilities can be assessed. This utility assessment provides measures of how the changes in electricity use were translated into changes in primary energy consumption.

Hourly models were constructed for three separate time periods: morning, evening, and 24-hour day. The morning and evening models essentially are regression-based analogues to the heuristic approach presented in Section B.2. We used these models to evaluate the magnitude and statistical confidence of the differences in the hourly system-consumption profiles between 2006 and 2007. As a rough approximation, one can view these models as measuring the impacts of EDST on lighting and appliance electricity use.

A third hourly model specification covered all 24 hours of the day. We used this specification to try to assess the more diffuse effects that DST may have on the amount of electricity used for space conditioning.

As the use of the DID approach was fundamental to the results produced by all three of these hourly models, the next section discusses this methodology in some depth. Readers familiar with the use of the method in other statistical studies may wish to skip to Section B.3.3.2.

The DID approach and its application to hourly models

The hourly models also employ the DID approach to estimating the impacts of EDST. The approach considers differences across two time frames – one annual and the other hourly. At the annual time frame, the differences in system consumption are examined at the same hour during the corresponding weeks of the EDST period between 2006 and 2007. Thus, for example, the first week in the 2007 EDST period extended from Sunday, March 11 through Saturday, March 17. The corresponding week in 2006 began on March 12 and ended on March 19. Thus, one variable in the regression model is used to essentially measure the mean difference between 2007 and 2006 for a particular hour for the seven days during these weeks (holding other factors including weather constant). At this point, the approach is identical to the daily model with the exception that the consumption in a particular hour is compared across both years rather the average across all hours of the day.

A second difference looks at changes *between* hours of the day. Thus, if the one variable measures the difference between 2006 and 2007 at 6:00 a.m. in morning, we use a second variable to measure the average difference between 6:00 a.m. and 7:00 a.m. between the two years. As will be discussed below, the approach provides a method of estimating by means of a regression model hourly impacts similar in magnitude to those generated by the heuristic model.

Motivation for the DID approach and implementation issues

As a starting point in how we employed the DID approach in the hourly models, consider the most basic regression model of hourly electricity consumption. We can represent the consumption in each hour (h) for day *d* by

$$L(h)_d = b_0(h) + b_1(h)\ Time_d + b_3(h)\ W(h)d \qquad \text{(B.9)}$$

We can estimate this model for any *single* hour (*h*) of the day (e.g., hour ending at 6:00 a.m.) across all the days of the sample period. In this simple model, we assume the system consumption in hour h is a function only of seasonal changes and weather. As in the daily model, seasonal changes are captured by a time trend ($Time_d$) that changes by a constant amount each day over the sample period. We represent the effect of weather in this simple formulation as a composite variable *W*, measured at hour *h*, but which varies from one day to the next. Note that the constant term, and the coefficients on the trend and weather variables are specific to the particular hour *h* for which the model is estimated [designated by "*(h)*"].

DST (or, in this case, the extension of DST) is presumed to change the amount of electricity consumed at different hours of the day. Assuming this effect is constant for those days observing EDST, a conventional procedure is to add a binary indicator variable to Equation (B.9) as follows:

$$L(h)_d = b_0(h) + b_1(h)\ Time_d + b_3W(h)d + b_4(h)\ EDST(h) \qquad \text{(B.10)}$$

EDST(h), as an indicator variable, takes on the value of one during the EDST period and zero for all other days. As an initial estimate of the impact of EDST, the model in Equation (B.10) could be estimated over a number of weeks preceding, and then including, the three weeks of EDST in March 2007. Thus, the sample period might include all the days of February and March of 2007.

However, this particular model assumes that the only factor explaining the differential consumption during the EDST time period in 2007 is the influence of DST.[31] This may or may not be true. As an example, a large university in a particular utility service area may schedule

[31] As used here and in the subsequent discussion, the generic term "EDST time period" means either the last three weeks in March or the week ending the first Sunday in November, in *either* 2006 or 2007.

spring break during the third week of March every year. With no consideration of that factor in Equation (B.10), the coefficient b_4 would be biased, as it would include the effects of both daylight time and the reduction in electricity consumption at the university.

The only viable solution to this problem in this case is to identify another year, without EDST, from which the average effect of the university's spring break can be estimated. If data for 2006 are available for example, then we can estimate Equation (B.10) separately for 2006. While the variables in the equation are exactly the same for both years, the b_4 coefficient in the model for 2006 has a different interpretation, as it represents any special factors that cause consumption to be different during the EDST time period as compared to other days in the sample period.

If one assumes that these same special factors equally influenced system level consumption during 2007, the best available measure of the influence of daylight time in 2007 is obtained by taking the difference between coefficient b_4 in the 2007 model and the same coefficient in the 2006 model. The computation of the standard error (or associated confidence interval) around this difference in the two coefficients is more complicated, as it must consider the variances of both coefficients.

While the model in Equation (B.10) can be estimated separately for each year (in this case 2006 and 2007), a more efficient approach is to pool the information across both years into a single regression model. Before considering the averaging of effects across years, it is useful to point out that "pooling" by simply stacking the observations in 2007 below those in 2006 and keeping the explanatory variables separate for 2006 and 2007 will yield the same results as estimating the equations for each year individually. Table B-4 shows a schematic of the variable layout in this type of regression framework.

Table B-4. Schematic of Variable Layout with Stacked 2006 and 2007 Data

Dependent Variable	Independent Variables (2006)	Independent Variables (2007)
Y(2006)	X(2006)	0
Y(2007)	0	X(2007)

Clearly, merely stacking the data in this manner is not what we mean by pooling the data across years. By combining some of the explanatory variables (e.g., weather) for both years as a single variable, the accuracy of the estimated coefficients is likely to be improved.

With regard to the binary indicator variables for the EDST periods in both years [distinguished as EDST(2006) and EDST(2007)], we undertook the following procedure as part of the DID approach. In the stacked framework, we constructed a new variable as the sum of the separate EDST variables for 2006 and 2007. Operationally, this results in a binary indicator variable for which the value is one in both 2006 and 2007 during the EDST time periods. We retained the original binary indicator variable for 2007 in the model. However, the coefficient on this variable now represents the *difference* between the coefficients in the original models.

We can demonstrate this fact more rigorously. Let the coefficient on the indicator variable in EDST [EDST(2006)] in 2006 be represented as b_4' and that for 2007 as b_4" (For simplicity, the designation of a particular hour has been omitted). For the stacked regression model, the effects during both EDST periods can be represented by $b4'$ EDST(2006) + $b4''$ EDST(2007). Mathematically, we can show the introduction of the new combined variable as:

$$b4' \text{ EDST(2006)} + b4'' \text{ EDST(2007)} = \\ b4' \text{ [EDST(2006)} + \text{EDST(2007)]} + (b4'' - b4') \text{ EDST(2007)} \tag{B.11}$$

Note that the explanatory power of the pooled model is exactly the same as when the models were estimated separately.[32] However, we can interpret the coefficient on the combined variable on the right hand side of Equation B.11 as the influence of systematic factors present in both 2006 and 2007, but identified by means of the data for 2006. The coefficient on the EDST(2007) can now be interpreted as the difference between a possible systematic effect, measured by the 2006 data (i.e., b_4'), and the total effect originally estimated for 2007 (i.e., b_4''). For this application, this technique is designed to produce a more robust estimate of the separate and independent effect of daylight time during the EDST time period in 2007.

This discussion hopefully provides further insight into the terminology used in Section B.3.3.1 in regard to the daily model. The EDST-C variable in that model is simply a combination of binary indicator variables during the EDST time periods for both years. This variable essentially controls for the influence of other factors that may be present in both years in the EDST *time periods*. The EDST-I variable, whose values are 1 only in the appropriate days in 2007, reflects the difference in the estimated effects between the two years and is presumed to reflect the impact of DST in 2007.

DID applied to hours within each day

The previous discussion was concerned only with measuring differences between years for the same hour of the day. We next discuss how that framework is extended to differences between hours.

We can show an illustration of the extension of the method in terms of a subset of the binary indicator variables used in the regression model. Table B-5 shows the indicator variables used to construct the first-order DID model—the model seeking to explain only changes between corresponding hours between 2006 and 2007.

Table B-5 shows the values of the binary indicator variables for the first day of three sub-periods used in the spring EDST estimating models:

1) February 2 – first day in sample period, standard time;
2) March 12, 2006, and March 12, 2007, – first days in EDST time periods, but implemented only in 2007, DST; and

[32] This result holds under the unrealistic assumption that the coefficients for all other variables are exactly the same for the 2006 sample as for the 2007 sample. In practice, the pooled model will always show some deterioration of the regression fit, but the increase in the number of observations will improve their statistical reliability. For the discussion here, the concern is only with the binary indicator variables used to measure the influence of daylight saving time.

3) April 2, 2006, and April 1, 2007, – first day of DST as observed prior to 2007.

Table B-5. EDST Binary Indicator Variable Layout for Pooled Hourly Model A

		Control for Systematic Effects in Specific Hours between 2006 and 2007 EDST Periods				*Estimated Impacts from EDST by Hour in 2007*			
	Variables ---------->	Hour 6-C	Hour 7-C	Hour 8-C	Hour 9-C	Hour 6-I	Hour 7-I	Hour 8-I	Hour 9-I
Date	Hour of Day	(EDST period =1, 0 otherwise	(EDST period =1, 0 otherwise	(EDST period =1, 0 otherwise	(EDST period =1, 0 otherwise	EDST Period in 2007 =1, 0 otherwise	EDST Period in 2007 =1, 0 otherwise	EDST Period in 2007 =1, 0 otherwise	EDST Period in 2007 =1, 0 otherwise
2-Feb-06	6	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0
:									
12-Mar-06	6	1	0	0	0	0	0	0	0
	7	0	1	0	0	0	0	0	0
	8	0	0	1	0	0	0	0	0
	9	0	0	0	1	0	0	0	0
:									
2-Apr-06	6	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0
:									
:									
2-Feb-07	6	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0
:									
11-Mar-07	6	1	0	0	0	1	0	0	0
	7	0	1	0	0	0	1	0	0
	8	0	0	1	0	0	0	1	0
	9	0	0	0	1	0	0	0	1
:									
1-Apr-07	6	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0

In this case, the data are stacked in two time dimensions. The top half of the data matrix relates to 2006, the bottom half to 2007. Within each year, the data for four consecutive hours for each day are included in the dataset.

We used the variables shown in the figure to estimate EDST during four morning hours. As in the heuristic model, the typical period used in the model extends from 5:00 a.m. through 9:00 a.m. (four hours ending at 6:00, 7:00, 8:00, and 9:00 a.m.). Motivated by the earlier discussion, the first four variables in this portion of the model can be considered “control” variables (indicated in the figure with the suffix “-C”). One variable is included for each hour in the morning.

Each of these variables is included in the model for both 2006 and 2007. Thus, using the same example as above, if the local university “spring break” affects the system consumption at 6:00

a.m. in the morning during the second week of March every year, the coefficient on the variable "Hour6-C" would reflect that reduction. Thus, all the variables ending with "-C" control for systematic changes in total electricity consumption that occurred at the same hour during the March EDST period in both 2006 and 2007.

We used the second set of four variables to measure the differences that pertain to 2007 as compared to 2006. These variables take on a value of 1 only during 2007. Thus, the coefficients on the variables ending with the suffix "-I" are used to reflect the impact of EDST, assuming other variables that would account for such changes are included elsewhere in the model (i.e., temperature variables) or are quantitatively insignificant.

Both sets of variables only take on non-zero values during the March EDST periods. For the days before and after these periods, the values are all zero.

The block diagonal structure shown in Table B-5 implies that the coefficients on all variables will be the same if we estimate the hourly equations separately *or* as a system. (Table B-5 is simply a more detailed view of the generic layout in Table B-4). However, the standard errors associated with the coefficients will differ as the system estimation assumes a constant error variance across all observations. As will be discussed later, some means of accounting for the differences in the variance in the error terms for different hours of the day must be taken into account to generate appropriate standard errors for the coefficient estimates.

The extension of the DID model to estimating differences across hours of the morning is shown in Table B-6. This particular version shows a model (Model B) in which we estimated the *differences* between hour 6 and the three subsequent hours. In essence, the model combines variables to force the coefficients to show differences across hours as well as differences between 2006 and 2007. Consider the difference between hour 7 and hour 6. Letting coefficients on the Hour6-I and Hour7-I binary variables be represented as *a6* and *a7*, one can rearrange the effects over both hours as:

$$a6 \text{ Hour6-I} + a7 \text{ Hour7-I} = a6 \text{ (Hour6-I + Hour7-I)} + (a7 - a6) \text{ (Hour7-I)} \qquad \text{(B.12)}$$

Thus, by combining the binary variables for hour 6 and hour 7 and then including (or retaining) a separate binary variable for hour 7, the linear regression model in the revised framework will convert the coefficient on hour 7 to be the *difference* between the original coefficients on hours 6 and 7.[33] In terms of explaining the variation of the hourly consumption over the entire time period, the two models are mathematically equivalent.[34] However, in the revised structure, the

[33] Combining variables in any linear regression framework is a simple method of restricting the coefficients to be the same for each variable. The coefficient of the new combined variable typically reflects the contribution of the separate variables as a weighed average. However, by retaining one of the original variables used to develop the combined variable, the coefficient on the combined variable will depend only upon the original variable(s) not separately included elsewhere. In this example, the combined variable of Hour 6 and Hour 7 will have the same coefficient as Hour 6 in the unrestricted model.

[34]One could argue that models A and B are really the same as they produce the same predictions of the dependent variable, hourly system consumption. Because the explanatory variables have been rearranged to yield a different parameterization, they are considered two models for the purpose of this discussion.

statistical significance of the (difference) coefficient on hour 7 can be now be evaluated directly in terms of its standard error.

In the revised framework shown in Table B-6, the coefficient on Hour6-I continues to show the difference between that hour in 2007 versus 2006. In turn, the coefficients on hours 7, 8, and 9 (Hour7-I, Hour8-I, and Hour9-I) now represent estimated differences between these hours and hour 6 for 2007. Again, the model is functionally equivalent to the structure shown in the previous figure (in terms of explanatory power), but with a different interpretation of the coefficients for the last three variables. An important point is that to yield this revised interpretation, one must estimate the equations for all four hours together.

Table B-6. EDST Binary Indicator Variable Layout for Pooled Hourly Model B

		Control for Systematic Effects in Specific Hours between 2006 and 2007 EDST Periods				*Estimated Impacts from EDST by Hour in 2007*			
	Variables ---------->	Hour 6-C	Hour 7-C	Hour 8-C	Hour 9-C	Hour 6-I	Hour 7-I	Hour 8-I	Hour 9-I
Date	Hour of Day	(EDST period =1, 0 otherwise	(EDST period =1, 0 otherwise	(EDST period =1, 0 otherwise	(EDST period =1, 0 otherwise	EDST Period in 2007 =1, 0 otherwise	EDST Period in 2007 =1, 0 otherwise	EDST Period in 2007 =1, 0 otherwise	EDST Period in 2007 =1, 0 otherwise
2-Feb-06	6	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0
:									
12-Mar-06	6	1	0	0	0	0	0	0	0
	7	0	1	0	0	0	0	0	0
	8	0	0	1	0	0	0	0	0
	9	0	0	0	1	0	0	0	0
:									
2-Apr-06	6	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0
:									
:									
2-Feb-07	6	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0
:									
11-Mar-07	6	1	0	0	0	1	0	0	0
	7	0	1	0	0	1	1	0	0
	8	0	0	1	0	1	0	1	0
	9	0	0	0	1	1	0	0	1
:									
1-Apr-07	6	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0

The final model (Model C) is shown in Table B-7. In this model, the coefficients on hours 6 and 9 are constrained to take on the same value. We accomplished this by simply dropping the variable, Hour 9-I, from the model. The coefficient under the column headed by “Hour6-I” now can be roughly interpreted as the average impact of the original variables Hour6-I and Hour9-I. At this point, it should be noted that imposing this constraint does not imply that the model is not forcing the actual consumption to be same in hours 6 and 9. Other coefficients in the model represent the average changes in the hourly profile of consumption that is present over the entire sample period. (Thus, electricity consumption always rises between 6:00 a.m. and 9:00 a.m. as households and businesses begin their normal daily activities.) Instead, the coefficient on this combined variable reflects the average difference in system electricity use in hours 6 and 9 that one can *attribute to EDST*. Based upon visual examination of the ratios of average hourly consumption between 2007 and 2006 (as illustrated through the heuristic approach) the assumption is that the influence of EDST is small during these particular hours).

Table B-7. EDST binary indicator variable layout for pooled hourly Model C

		Control for Systematic Effects in Specific Hours between 2006 and 2007 EDST Periods				Estimated Impacts from EDST by Hour in 2007		
Variables ---------->		Hour 6-C	Hour 7-C	Hour 8-C	Hour 9-C	Hour 6-I	Hour 7-I	Hour 8-I
Date	Hour of Day	(EDST period =1, 0 otherwise	(EDST period =1, 0 otherwise	(EDST period =1, 0 otherwise	(EDST period =1, 0 otherwise	EDST Period in 2007 =1, 0 otherwise	EDST Period in 2007 =1, 0 otherwise	EDST Period in 2007 =1, 0 otherwise
2-Feb-06	6	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0
:								
12-Mar-06	6	1	0	0	0	0	0	0
	7	0	1	0	0	0	0	0
	8	0	0	1	0	0	0	0
	9	0	0	0	1	0	0	0
:								
2-Apr-06	6	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0
:								
:								
2-Feb-07	6	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0
:								
11-Mar-07	6	1	0	0	0	1	0	0
	7	0	1	0	0	1	1	0
	8	0	0	1	0	1	0	1
	9	0	0	0	1	1	0	0
:								
1-Apr-07	6	0	0	0	0	0	0	0
	7	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0

The coefficients of interest are for hours 7 and 8. These coefficients provide measures of the differences between each of these hours and the (approximately) average effect involving hours 6 and 9. Under the strong assumption that the "treatment" effect of EDST is zero in hours 6 and 9, the coefficients on hour 7 and hour 8 then provide measures of changes in consumption due to

EDST in these intervening hours. Thus, these coefficients can be expected to be very similar to impacts that are generated by the heuristic method that simply interpolates between the 2007/2006 ratios for hours 6 and 9. The advantage of the regression model framework is that it takes into account the variability of the differences due to weather changes and yields measures of the statistical confidence of the estimated impacts.

Hourly model specifications

With the exception of the more complex application of the DID approach, the hourly model is similar in structure to the daily model. For each hour of the day, we specified a separate equation with explanatory variables appropriate to that hour.

For the spring hourly models, binary indicator variables for EDST are included for each week during March. The weekly variables are designed pickup changes in the system consumption that may result from changes in daylight that occur over this three-week period. Thus, representing the hour of the day with the superscript *h*, we can write the hourly specification for the spring as:

$$\begin{aligned} L_{hdy} = {} & b_0 + b_1\,Growth_y + b_2\,Time\text{-}PreDST_d + b_3\,Time\text{-}DST_d + b_4\,Saturday + \\ & b_5\,Sunday + b_6\,HDDVW_{dy} + b_7\,HDDVSQRW_{dy} + b_8\,CDDVW_{dy} + \\ & b_9\,CDDVSQRW_{dy} + b_{10}\,EDST\text{-}Wk1\text{-}C + b_{12}EDST\text{-}Wk2\text{-}C + \\ & b_{13}\,EDST\text{-}Wk3\text{-}C + b_{14}\,EDST\text{-}Wk1\text{-}I + b_{15}\,EDST\text{-}Wk2\text{-}I + \\ & b_{16}\,EDST\text{-}Wk3\text{-}I + b_{17}\,DST + b_{18}\,Holiday + u \end{aligned} \qquad \text{(B.13)}$$

Many of the same variables in the daily model are included in the hourly model. However, in the hourly model, we allowed the coefficients on each variable to vary according to the particular hour of the day. Thus, for example, one could expect that consumption in the morning hours of Saturday and Sunday shows a greater difference from weekday consumption as compared to other hours during the day. As a second example, differences in the load that we could attribute to economic growth between 2006 and 2007 are more likely to be reflected during the daytime hours.

A key difference between the daily and hourly models is in the inclusion of an additional trend variable to capture the effects of changing daylight in different hours of the day. Two separate time trends are included in the hourly model. The first, Time-PreDST, is a linear time trend that begins at the start of the sample and extends through the onset of (conventional) DST in April. We designed this variable to pick up changes in consumption during this period, prompted by either increased daylight or other seasonal factors.[35] The second time trend (Time-DST) is included to capture the effects of changing daylight in a given hour during the month of April.

Some discussion about an explicit inclusion of the amount of daylight in each hour is useful at this point. In the preliminary study of EDST conducted by DOE in 2006, all of the model specifications employed a daylight variable. The estimated historical effects of daylight for the

[35] For example, the hour between 6:00 p.m. and 7:00 p.m. may be just beginning to exhibit significant daylight around the second week of March under the pre-EDST calendar. The negative impact on the system load from this effect would be captured more accurately by this second time trend, rather than blurring the effects from a single time trend.

load in a given hour were required in order to *predict* the impact of the change in daylight that would occur under the 2007 EDST (daylight was measured as the fraction of clock hour with daylight). In the work for this *ex post* analysis, the aim was to find specifications that do not require a daylight variable for each hour. In essence, if one can account for weather and overall consumption growth between 2006 and 2007, we can attribute the remaining changes in the consumption to the change in daylight without an explicit measure of daylight. This approach considerably simplifies the analytical framework as binary (or "dummy") variables can be used to represent the shift in consumption patterns caused by EDST.

We used the heating and cooling degree temperature variables, derived from the daily model, without modification for each of the hourly models. As such, the coefficients on the various heating and cooling degree variables reflect the diurnal pattern of space conditioning. Early morning hours are likely to involve heating and thus the coefficients on the heating degree variables will be larger than during other hours of the day. We would expect a similar result for afternoon hours with respect to the cooling degree variables. As the degree-day variables in the daily model incorporate the temperature effects from both the current and previous two days, hourly responses are viewed as sufficiently stable from one day to the next to utilize this approach.[36] As stated above, one purpose of the hourly models is to corroborate the daily model and to provide an approximate distribution of EDST impacts across different hours. Thus, we did not consider a complex treatment of hourly weather impacts in the study.

Binary indicator variables for EDST are included for each of the three weeks during the EDST period in 2007. We designed the separate variables to capture the influence of changes in the daylight (in a step function fashion) in specific morning and evening hours over the three-week EDST period. Following the approach illustrated in Table B-5, we included separate "control" and "impact" variables for each week.

The hourly specification for the fall is similar to that used for the spring, with two key differences: 1) the EDST-related binary variables are required for only one week; and 2) the holiday variable is comprised of two separate binary indicator variables for Thanksgiving and the following day ("Black Friday"). We observed system consumption for most utilities to be distinctly lower than normal for both of these days.

The model specification shown in Equation (B.13) can be run separately for each hour of the day or as system combining a number of hours. When estimated separately, the coefficients on the EDST-Wk-I variables provide estimates of the influence of daylight time in those hours as derived from the difference between 2006 and 2007. As discussed in the previous section, when the hourly models are combined as a system, the DID approach allows the estimation of differences in system consumption between hours (or combinations of hours) to be generated.

Final outputs from hourly models

The final estimation strategy produced four separate models: 1) morning, 2) evening, 3) 24 hours

[36] In essence, the approach also relies upon the stability of the pattern of temperature changes between the daily maximum and daily minimum temperature. The lagged response of space conditioning demand to temperatures also helps to reduce the impacts from any significant deviations in the normal diurnal temperature profile.

independently estimated, and 4) 24 hours with a mid-day normalization. These models are described briefly below.

Morning Model. We estimated the morning model as the regression counterpart to the morning procedure under the heuristic method. Using the DID approach shown in the Figure B-.16, this model typically estimated the impacts of EDST for the hours ending at 7:00 a.m. and 8:00 a.m. The model included the hours ending at 6:00 a.m. and 9:00 a.m., which we assumed to have negligible impact from daylight time.

Evening Model. The evening model followed the same approach as the morning model. Based upon visual examination of ratios of the system loads, we assumed that EDST had negligible influence on the hours ending at 4:00 p.m. and 10:00 p.m. (ending 9:00 p.m. in the fall). The DID procedure was used to estimate the differences between the average influence from daylight time in these hours (if any) and each of the intervening hours. We designed both the morning and evening models to capture the effect on the system consumption that is likely due to changes in lighting and appliance consumption.

24-Hour Model – Separately Estimated Hourly Equations. In reality, this “model” is nothing more than a procedure to estimate all 24 hourly equations (as in Equation B.13) in some automated fashion. The coefficients on the EDST-Wk-I variables represent the model-derived impacts of DST for each hour. We can use this less restrictive model to determine whether there may be effects from EDST in hours other than the morning or the evening. More specifically, this model may provide a means of determining whether EDST has any significant effects on electricity used for space conditioning.

24-Hour Model – DID Procedure with Mid-Day Normalization. This final model estimates all 24 hourly equations as a system. Employing the same DID approach as both the morning and evening models, this model assumes that the influence of DST is negligible in the middle hours of the day. The specific assumption is that the hours ending at noon, 1:00 p.m., and 2:00 p.m. are unlikely to be strongly affected by daylight time. Accordingly, we then used the DID approach to measure differences in the estimated DST impacts in the other 21 hours of the day from that in this period. We based this assumption upon two factors: 1) in several locations where temperature conditions were similar between 2006 and 2007, these hours displayed little impact from DST, and 2) an Australian study that examined electricity consumption before and after DST transitions over a number of years used a similar restriction (Kellogg and Wolff, 2008). (Using half-hourly data, the Australian study assumed no influence from DST between noon and 2:30 p.m.) By formally restricting the influence of DST to be zero in these hours, the specification helps identify those utilities where one may assume that other special factors may be affecting the system consumption during March of 2007.[37]

Software implementation

While the daily model and the independent estimation of the hourly models could be handled in Excel, it was infeasible to estimate the DID hourly model in a spreadsheet environment. In the

[37] As discussed in Appendix E, in one utility a decrease in system electricity consumption of between two and three percent in this mid-day period could be attributed to extensive maintenance in the last several weeks of March in 2007 of a large continuous process industrial plant.

24-hour DID model, over 450 coefficients were required to be estimated. We estimated these models via Gauss, a high-level matrix programming language that is used extensively in econometric applications. With its large array of built-in matrix and scalar functions, Gauss facilitated the variable construction for each of hourly regression models and the subsequent calculation of standard errors for the metrics of interest.

Error structure and adjustments

We estimated the coefficients in all of the DID hourly models using ordinary least squares (OLS). OLS assumes that the error terms for each hour have the same variance (homoskedastic) and are uncorrelated across time periods (no autocorrelation). One does not typically meet these conditions in the statistical models of electricity consumption.

In this analysis, we retained the estimated coefficients generated by OLS for generating point estimates of the impacts of EDST. We adjusted the standard errors, however, by the estimation procedure developed by Whitney Newey and Kenneth West (Newey, et al., 1987). The Newey-West procedure is an extension of White's Heteroskedasticity Consistent Covariance Matrix estimator, which provides improved estimates of the coefficient covariances in the presence of heteroskedasticity (i.e., non-uniform variances in the error term) in unknown form (White, 1980). The Newey-West procedure is more general in that it is consistent in the presence of both heteroskedasticity and autocorrelation in unknown form.

The Newey-West procedure requires an assumption about the number of the autocorrelations that are present in the OLS residuals. Based upon a series of regressions in which the error terms are regressed on their lagged values (up to 24 hours in the 24-hour model), the truncation parameter used for the Newey-West covariance estimator was set to two.

B.3.4 Weather data

Weather information for specific locations was taken from the Local Climatological Data (LCD) files constructed by the National Climatic Data Center (NCDC). Daily and hourly weather data for each month for about 800 locations in the United States are available from this source. Text files for the months of February, March, April, October, and November for both 2006 and 2007 were downloaded from the NCDC Web site.[38] Key variables in each file are temperature, humidity, cloud conditions, wind speed, and precipitation.

In this assessment, the statistical analysis considered only a single weather variable—the outdoor temperature. The daily minimum and maximum temperatures were converted to degree-days during the estimation process, as discussed in Section B.3.1.

For each utility examined in the statistical analysis, the temperature data from a single location was chosen as representative of the utility service area. These locations are the same as those shown in Table B-3 as the "City Used for Mapping."[39] Because the estimation procedure for the

[38] The NCDC Web site for this information is http://cdo.ncdc.noaa.gov/ulcd/ULCD.

[39] Due to lack of weather data for Andalusia (Alabama Electric Cooperative), data for Montgomery was substituted.

daily model selects the reference temperatures for heating and cooling along with other parameters, the use of a single location to represent temperatures throughout the utility (or ISO area) was deemed an acceptable method. Generally, variations in day-to-day temperatures are highly correlated across large regions of the United States. Thus, if a selected weather location is somewhat different from what where a more rigorous analytical framework might identify, the use of model-determined reference temperatures will help to compensate for such differences.

B.4 Computation of National Electrical and Energy Consumption

B.4.1 Conversion of marginal cost data to fuel use

Each year, utilities report their hourly "system lambda" values to Form 714 on the same form as was used for reporting their hourly demands. The system lambda is the marginal cost of increasing generation by one MW over any given hour. The definition for system lambda on Form 714 is:

> *For control areas where load following is primarily performed by thermal generating units, the system lambda is derived from the economic dispatch function associated with automatic generation control performed at the controlling utility or pool control center. Excluding transmission losses, the fuel cost ($/hr) for a set of on-line and loaded thermal generating units (steam and gas turbines) is minimum* [40] *when each unit is loaded and operating at the same incremental fuel cost ($/MWh)*[41] *with the sum of the unit loadings (MW) equal to the system demand plus the net of interchange with other control areas. This single incremental cost of energy is the system lambda. System lambdas are likely recalculated many times in one clock hour. However, the indicated system lambda occurring on each clock hour would be sufficient for reporting purposes.* (FERC, 2007)

Not all utilities submit their system lambda data to FERC, often because they operate in a wholesale market system where dispatching is done by bidding and clearing the market. Some of the utilities that were used for calculating the DST potential impacts did not have their system lambdas posted on the FERC Web site. However, there were frequently utilities nearby that did, or the region's hourly market clearing prices were posted on their website.

As described above, the system lambda is the marginal cost of production at any given hour of operation. Applying the system lambda schedules to the corresponding energy savings for each utility provides an approximation of the costs that those utilities would save. The hourly costs ranged from $8/MWh to $155/MWh, depending on the region, date, and time of the energy savings.

A more difficult calculation is to determine the amount of total energy saved that would have generated the electricity saved by EDST. At any point in time, utilities will have one or more power plants available to raise or lower production to meet demands. As described in the

[40] Some utilities may also include variable operation and maintenance costs that they consider "dispatchable." Therefore, the costs to be minimized could include a variable O&M component as well as the fuel costs.

[41] Because unit heat rates and fuel costs vary, some units may not be able to operate at the same incremental fuel cost as the other units and, thus, those units may be loaded differently.

definition of system lambda, these plants will be dispatched based on the marginal cost to produce additional power. The consequent cost is a function of the cost of the fuel, the efficiency of the plant, and any other variable operations and maintenance (O&M) costs.

$$\text{Cost (\$/MWh)} = \text{Fuel Price (\$/MMBtu)} * \text{Heat Rate (Btu/kWh)} / 1000 + \text{Variable O\&M (\$/MWh)} \quad \text{(B.14)}$$

Or,

$$\text{Heat Rate (Btu/kWh)} = (\text{Cost} - \text{Variable O\&M}) / \text{Fuel Price} \quad \text{(B.15)}$$

The heat rate is a common term used to depict the efficiency of a power plant. Because one kWh equals 3,412 Btu, the equation to find the efficiency in percentage of “energy out” to “energy in” is:

$$\text{Efficiency (percent)} = 3412 \text{ (Btu/kWh)} / \text{Heat Rate (Btu/kWh)} * 100 \text{ percent} \quad \text{(B.16)}$$

Any power plant may have different fuel prices and variable O&M costs. However, fuel prices will tend toward the average and, for lack of more specific information, we found the state, regional, and national average prices for each month (March, April, October, and November 2006) from EIA’s *Electric Power Monthly* data sets (EIA, 2007). The value for the state is preferentially used, but if it is not available (either no information or because the price is protected from disclosure for proprietary reasons) then the regional price is used. Lastly, if neither a state nor a region value is available, then the national price is used.

Plants use three main fuel types that are likely on the margin at this time: coal, natural gas, and petroleum fuels. Each fuel actually has multiple subcategories, such as distillate versus residual oil, or different qualities of coal; and fuel prices can vary across the country—but the cost data were not readily available to provide further disaggregation. Furthermore, regional average fuel prices would still have the problem that they would not necessarily represent the actual fuel price of the facilities on the margin. Tables B-8, B-9, and B-10 show the average fuel prices to electric utilities for each month of interest in 2006. Natural gas prices were typically \$6 - \$8/MMBtu, while oil products were higher. Coal prices were only around \$1.70/MMBtu.

Table B-8. Average Cost of Natural Gas Delivered for Electricity Generation by State

(Dollars per Million Btu) Census Division and State	Mar-06	Apr-06	Oct-06	Nov-06
New England	7.9	7.66	5.85	7.86
Connecticut	7.66	7.65	6.26	7.88
Maine	W	W	W	W
Massachusetts	8.24	7.7	5.87	7.74
New Hampshire	W	W	W	W
Rhode Island	7.83	7.54	5.4	7.81
Vermont	8.03	7.91	5.16	8.18
Middle Atlantic	7.94	7.81	5.88	8.08
New Jersey	W	8.1	6.08	8.07
New York	7.82	7.78	5.85	8.13
Pennsylvania	W	7.63	5.74	7.73
East North Central	6.78	6.63	5.9	7.3
Illinois	7.24	7.01	5.45	7.45
Indiana	W	W	W	W
Michigan	5.86	6.18	5.15	6.22
Ohio	11.74	W	W	W
Wisconsin	W	7.89	5.99	7.44
West North Central	W	W	W	W
Iowa	8.05	8.38	6.08	8.29
Kansas	6.73	6.46	4.88	6.48
Minnesota	W	W	W	W
Missouri	W	W	W	W
Nebraska	8.2	7.31	6.14	8.34
North Dakota	11.81	10.00	15.53	6.7
South Dakota	--	--	--	--
South Atlantic	8.32	W	W	8.89
Delaware	W	W	W	W
District of Columbia	--	--	--	--
Florida	8.39	8.48	7.54	9.15
Georgia	7.5	7.42	5.17	W
Maryland	8.01	8.31	5.9	8.44
North Carolina	W	W	W	W
South Carolina	W	W	W	W
Virginia	8.12	9.76	5.64	8.19
West Virginia	W	9.02	6.89	W
East South Central	W	7.57	W	W
Alabama	7.34	7.6	6.05	6.75
Kentucky	W	W	W	W
Mississippi	W	W	5.74	W
Tennessee	--	--	--	W
West South Central	6.72	6.68	5.05	6.87
Arkansas	W	6.93	4.65	W
Louisiana	7.73	7.53	5.8	7.7
Oklahoma	W	6.27	4.97	W
Texas	6.58	6.63	4.97	6.73

(Dollars per Million Btu) Census Division and State	Mar-06	Apr-06	Oct-06	Nov-06
Mountain	6.5	6	4.74	6.58
Arizona	W	6.34	5.02	6.84
Colorado	6.45	W	4.46	6.36
Idaho	W	--	W	W
Montana	W	W	W	W
Nevada	6.41	5.46	4.4	6.53
New Mexico	W	W	W	W
Utah	W	4.87	W	W
Wyoming	7.16	7.11	5.5	15.13
Pacific	6.14	6.18	5.22	6.49
California	6.41	6.36	5.36	6.84
Oregon	W	W	5.33	6.28
Washington	W	W	4.68	6.61
Alaska	3.42	3.68	3.79	1.61
Hawaii	--	--	--	--
United States Total	7.14	7.09	5.61	7.29

W = Withheld to avoid disclosure of individual company data.

Table B-9. Average Cost of Petroleum Liquids Delivered for Electricity Generation by State

(Dollars per Million Btu) Census Division and State	Mar-06	Apr-06	Oct-06	Nov-06
New England	8.79	W	7.89	7.62
Connecticut	W	14.53	8.02	W
Maine	W	W	W	W
Massachusetts	W	W	W	W
New Hampshire	13.6	10.15	8.96	7.62
Rhode Island	--	--	--	--
Vermont	--	--	--	--
Middle Atlantic	8.18	8.55	7.67	7.75
New Jersey	10.96	W	W	W
New York	8	W	7.64	W
Pennsylvania	13.6	12.91	W	9.56
East North Central	10.22	W	9.11	11.39
Illinois	14.92	W	11.18	W
Indiana	5.73	11.56	4.14	6.82
Michigan	9.78	8.92	9.83	13.05
Ohio	W	W	W	W
Wisconsin	W	14.22	W	15.18
West North Central	9.28	10.75	13.58	13.48
Iowa	13.64	14.84	13.54	14.63
Kansas	7.53	7.08	13.5	13.9
Minnesota	11.5	10.13	10.1	10.06
Missouri	13.16	15.37	14.04	14.58
Nebraska	14.19	16.44	13.94	15.19
North Dakota	14.37	14.63	14.36	14.66
South Dakota	--	--	--	--

(Dollars per Million Btu) Census Division and State	Mar-06	Apr-06	Oct-06	Nov-06
South Atlantic	8.17	7.65	7.04	7.6
Delaware	12.21	W	W	W
District of Columbia	W	W	W	--
Florida	W	6.72	W	7.08
Georgia	10.4	16.07	W	W
Maryland	9	12.08	12.21	11.56
North Carolina	13.12	13.68	W	W
South Carolina	14.04	14.88	12.29	12.68
Virginia	W	13.76	W	W
West Virginia	14.2	15.35	10.67	3.79
East South Central	13.48	W	W	W
Alabama	13.67	W	12.56	12.38
Kentucky	13.77	W	W	W
Mississippi	11.1	14.15	8.91	8.69
Tennessee	13.74	14.5	13.29	13.55
West South Central	W	13.25	W	10.35
Arkansas	13.7	13.74	14.09	14.16
Louisiana	W	W	W	W
Oklahoma	13.78	14.5	12.21	11.68
Texas	W	W	W	W
Mountain	W	W	W	W
Arizona	15.2	15.64	14.29	14.91
Colorado	13.26	W	13.74	12.15
Idaho	--	--	--	--
Montana	W	W	W	W
Nevada	12.38	14.5	12.21	11.76
New Mexico	16.8	17.34	16.3	17.86
Utah	14.41	19.11	13.33	14.18
Wyoming	14.57	17.61	16.14	14.44
Pacific	11.88	W	W	10.82
California	W	W	W	W
Oregon	12.38	14.5	--	11.76
Washington	--	--	--	W
Alaska	--	--	--	--
Hawaii	W	W	--	W
United States Total	8.84	9.11	7.87	8.12

Table B-10. Average Cost of Coal Delivered for Electricity Generation by State

(Dollars per Million Btu)

Census Division and State	Mar-06	Apr-06	Oct-06	Nov-06
New England	2.65	2.83	2.71	2.72
Connecticut	W	W	W	W
Maine	W	W	W	W
Massachusetts	2.74	2.82	W	W
New Hampshire	2.42	2.9	2.54	2.51
Rhode Island	--	--	--	--
Vermont	--	--	--	--
Middle Atlantic	1.97	1.97	1.93	1.99
New Jersey	2.69	2.64	2.91	2.8
New York	2.4	2.41	2.29	2.36
Pennsylvania	1.83	1.81	1.75	1.81
East North Central	1.54	1.52	1.5	1.51
Illinois	1.29	1.24	1.25	1.25
Indiana	W	W	W	W
Michigan	1.71	W	W	W
Ohio	W	W	W	W
Wisconsin	1.43	1.43	1.56	W
West North Central	1.07	1.07	1.1	1.1
Iowa	0.98	1.04	1.08	1.02
Kansas	1.18	1.23	1.21	1.19
Minnesota	1.19	1.2	1.26	1.29
Missouri	1.13	1.1	1.14	1.11
Nebraska	0.85	0.8	0.8	0.8
North Dakota	0.85	0.84	0.89	0.98
South Dakota	1.59	1.48	1.65	1.53
South Atlantic	2.3	2.32	2.35	2.31
Delaware	W	W	W	W
District of Columbia	--	--	--	--
Florida	2.56	2.54	2.54	2.54
Georgia	2.39	2.33	2.43	2.39
Maryland	2.05	2.08	1.98	1.95
North Carolina	W	W	W	W
South Carolina	2.24	2.32	2.37	2.34
Virginia	2.38	2.5	2.44	2.44
West Virginia	1.67	1.67	1.66	1.61
East South Central	W	W	W	1.87
Alabama	2.14	2.02	2.35	2.14
Kentucky	W	W	W	W
Mississippi	W	W	W	W
Tennessee	1.65	1.55	1.75	1.74
West South Central	1.48	1.43	1.4	1.4
Arkansas	1.64	1.38	1.54	1.45
Louisiana	W	W	W	W
Oklahoma	W	W	W	W
Texas	W	W	W	W

(Dollars per Million Btu) Census Division and State	Mar-06	Apr-06	Oct-06	Nov-06
Mountain	W	W	W	W
Arizona	1.44	1.47	1.44	1.38
Colorado	1.19	1.18	1.25	1.25
Idaho	--	--	--	--
Montana	W	W	W	W
Nevada	1.73	1.73	1.73	1.7
New Mexico	1.62	1.58	1.42	1.55
Utah	W	W	W	W
Wyoming	1.02	0.92	0.98	1.05
Pacific	1.8	1.63	1.66	W
California	W	W	W	2.41
Oregon	--	1.25	1.33	1.3
Washington	W	W	W	W
Alaska	--	--	--	--
Hawaii	W	W	W	2.99
United States Total	1.7	1.7	1.7	1.68

Variable O&M prices can also differ significantly by plant. The EIA uses a large data set of all existing and planned power plants in the operation of its model used for the Annual Energy Outlook (AEO). The variable operating cost can vary for each, but we can make aggregations to find typical values for different plant types and fuel. In addition, the simulation model can add plants of various types to meet demands in the future, and these plants have assumed variable costs.

From the data set used by the National Energy Modeling System (NEMS), we calculated the ranges for the variable costs from coal-, gas- and oil-fired plants for the preliminary EDST study as shown in Table B-11. Because the gas- and oil-fired production could be from a combined-cycle plant, combustion turbine, or steam plant, it becomes more difficult to select the proper values to apply to the plants on the margin. The percent of generation (found by multiplying the capacity and capacity factor for each plant within the database) helps to identify the more likely production types. Typically, plants use turbines at higher demand periods, because of their higher heat rates (lower efficiencies). However, with recent increases in gas and oil prices, combined-cycle plants have become more widely used for load following. Higher variable O&M cost will mean a lower relative fuel cost for the same marginal cost, hence a lower heat rate and therefore less total energy used. Final results, though, are more complex because the answer depends on the type of fuel that ends up being assigned to a system lambda value.

Table B-11. O&M Costs and Minimum Heat Rate Used

	Gas	Oil	Coal
O&M Cost ($/MWh)	2.3	2.8	2.4
Min Heat Rate (Btu/kWh)	6,500	8,000	7,500

At any given system lambda marginal cost value, it is unknown whether the marginal plant was using coal, oil, or natural gas. For example, a marginal price of $40/MWh could be from an efficient gas-fired plant (with high-cost fuel) or inefficient coal plant (with low-cost fuel). One means of differentiation is that there are minimum heat rates below which it is unlikely that plants can operate. A plant with a heat rate below 6,824 Btu/kWh is operating at greater than 50 percent efficiency. Only a few modern combined-cycle plants can approach that.

The process used to determine which fuel a given system lambda corresponds to was to calculate the resulting heat rate assuming each of the fuels. If the heat rate assuming natural gas was above 6,500 Btu/kWh, then gas was the assumed fuel. If the heat rate assuming gas was below 6,500 Btu/kWh, but the heat rate was above 8,000 Btu/kWh for oil, then oil was the assumed fuel. (The oil threshold was set higher to reflect the paucity of oil-fired combined-cycle plants.) If the heat rate met neither of these thresholds, then the production was assumed to be from a coal-fired plant.

B.4.2 Aggregation and extrapolation to regional loads

The monthly Net Energy for Load (NEL) (defined as system generation plus energy received from others, less energy delivered to others through interchange) for each region is listed in NERC's ES&D database (NERC, 2007). Table B-12 lists the amount of electrical demand for the two spring and two fall months, plus the annual total for each region. We scaled the electrical demands of the representative utilities analyzed above in each region to match the total demand for each region. We used only the two spring and two fall months as scaling factors, to minimize distortions due to varying summer or winter energy demand.

Table B-12. 2006 Net Energy for Load in NERC Regions (TWh) (NERC, 2007)

NERC Region	Mar	Apr	Oct	Nov	Annual
RFC	82	72	77	77	1,005
TRE	21	20	24	21	299
NPCC-NY	14	12	13	13	167
NPCC-NE	11	10	11	10	136
MRO	17	16	17	17	217
FRCC	17	16	19	16	227
SERC-DEL	11	10	10	10	142
SERC-SE	18	17	19	18	241
SERC-	16	14	15	15	191
SERC-VAC	25	21	24	23	309
SERC-GAT	6	5	6	6	79
SPP	15	14	15	15	202
WECC-AZN	9	9	10	9	127
WECC-CNV	21	20	18	21	266
WECC-NWP	19	18	18	20	234
WECC-RMP	5	4	5	5	59
Total	305	278	300	295	3,900

Each utility or control area modeled is located in one of the 16 NERC regions or subregions. Because the regional NEL is only available on a monthly basis, it is necessary to calculate the percent of electricity saved for each utility (or combination of utilities) over each of the months, March, April, May, and June. We can then multiply the regional NEL by these percentages to determine the regional electricity savings for each region.

In some regions, the data collected from the regional authority included the demands from an individual utility for which we also had data. For example, we collected the NEL from the New York ISO as well as Consolidated Edison. Rather than double-count the smaller utility's data, we only used the larger of the utilities that were located in that region. There were three regions where this applied: New York, Tennessee, and the upper plains states in the western region of the Midwest ISO. We did not use the other two regions of the Midwest ISO because they straddle multiple NERC regions. Table 4-2 in the main body lists the regions that each utility was assigned to and includes an asterisk by those that were not included in the scaling calculation for the region as a whole.

B.5 Standard Errors for National-Level Electricity Impacts from EDST

This section discusses the development of standard errors associated with national-level impacts, in view of the fact that total variability includes both measurement errors from the utility-specific regression models as well as the variation of expected effects from DST across utilities.

B.5.1. Methodology to combine variances

To consider the total variation, we must consider both the *precision* of the predictions yielded by the regression models for the individual utilities as well as the variation of the predictions *across* the utilities in the sample. Formally, to begin to construct a measure of total variation, one may consider that a prediction of the EDST impact (represented generically by Y) for a utility can be represented as

$$YP_i = \widehat{Y}_i + u_i \qquad \text{(B.17)}$$

Where,

YP_i = predicted value of Y for utility i
$\widehat{Y}_i$ = expected value of Y
u_i = stochastic error term for utility i

Typically, the prediction for Y for utility i (YP_i) is taken to be the expected value of Y ($\widehat{Y}_i$), under the assumption that the expected value of u is zero. For a sample of N utilities, the mean is thus calculated as the mean of the individual values of $\widehat{Y}_i$.

The derivation of variability for the entire sample must account for both terms on the right-hand side of Equation (B.17). In essence, the total variance across the sample is the sum of the variances:

$$\text{Total variance} = \text{Var}(\widehat{Y}_i) + \text{Var}(u) \qquad \text{(B.18)}$$

We can calculate the variation of the expected values of $\widehat{Y}_i$ in a conventional manner as a variance or standard deviation. In the application here, we computed the variance of the estimated change in consumption due to EDST across the sample of approximately 30 utilities.

The stochastic error term in Equation (B.17) results from the imprecision of the individual regression models, as reflected in the standard error of the regression coefficients on the binary indicator variables associated with EDST. Using the formula for the variance for the mean (where the variance for each utility is equal to the square of the standard error), we have

$$\text{Variance of } u \text{ (sample)} = [\text{se}(u_1)^2 + \text{se}(u_2)^2 + \ldots.. + \text{se}(u_n)^2] / \text{n}) \qquad \text{(B.19)}$$

In Equation (B.19), se(u_i) is the estimated standard error associated with a particular metric for utility *i*.

We can then sum the two variances on the right side of Equation (B.18). The square root of this value is the standard error associated with the sample. In essence, this standard error reflects the variability of the estimate of any single utility's savings due to EDST—taking into account the variation in expected savings across the complete sample as well as imprecision in estimating those expected savings.[42]

For the national average, one can draw upon the fact that we can estimate the standard error of the mean from a single sample of size N as:

$$\text{Std error (mean)} = \text{Std. error/sqrt(N)} \qquad \text{(B.20)}$$

The expression in Equation (B.20) rests upon the assumption that the impact estimates are not (spatially) correlated across utilities.

Example of methodology applied to estimated daily savings from spring EDST

The application of this procedure to a portion of the results discussed in Section 4 may help to make this procedure more transparent. Table B-13 shows an expanded version of Table 4-3 with the estimated daily impacts of EDST by utility in the spring. The first column of numbers shows the expected value of savings [$\widehat{Y}_i$ in terms of Equation (B.17)]. Column (2) shows the standard errors associated with the estimated percentage changes.

Column (3) shows the sample weight associated with each utility, based upon electricity sales [see Section B.1 for a general discussion of sources].

[42] One way to assess the reasonableness of this approach is to consider two polar cases. If resources were available to estimate EDST impacts for only a single utility, the best available evidence of the national impact would be based solely on the that utility. Thus, the uncertainty for the national average would pertain only to the regression model error for that utility. On the other hand, if metered electricity data or some other approach were available to generate very precise estimates of impacts for a number of utilities, the uncertainty or standard error for national impact would involve only the variation across the sampled utilities.

Table B-13. Numerical Illustration of Adjusted Variance Procedure

Number	Utility	(1) Average Daily Pct. Change	(2) Std. Error.	(3) Sample Weight	(4) Variance	(5) Weighted Variance	
1	Indianapolis Power & Light	-0.6%	0.3%	0.022	0.0000084	1.873E-07	
2	Louisville Gas & Elec	-0.5%	0.3%	0.051	0.0000090	4.551E-07	
3	Dayton Hub - PJM	-0.6%	0.3%	0.026	0.0000068	1.789E-07	
4	Duquesne Hub - PJM	-0.5%	0.2%	0.021	0.0000040	8.386E-08	
5	No. Illinois Hub - PJM	-0.7%	0.2%	0.144	0.0000040	5.746E-07	
6	ERCOT - Coast	-0.1%	0.3%	0.046	0.0000063	2.900E-07	
7	ERCOT - S. Central	-0.4%	0.4%	0.024	0.0000137	3.339E-07	
8	Con Ed - New York	-0.4%	0.1%	0.044	0.0000012	5.292E-08	
9	ISO-NE - Connecticut	-0.7%	0.2%	0.020	0.0000036	7.392E-08	
10	ISO-NE - NE Mass (Boston)	-0.6%	0.2%	0.016	0.0000026	4.046E-08	
11	Lincoln Electric System	-0.7%	0.3%	0.017	0.0000116	1.995E-07	
12	Madison Gas & Elec	-0.5%	0.2%	0.018	0.0000026	4.504E-08	
13	Otter Tail Power Co.	-0.2%	0.4%	0.022	0.0000137	3.024E-07	
14	City of Tallahassee	-0.4%	0.3%	0.009	0.0000109	9.354E-08	
15	Gainesville Regional Utility	-0.3%	0.3%	0.006	0.0000109	6.613E-08	
16	Jacksonville Energy Authority	-0.4%	0.4%	0.042	0.0000137	5.717E-07	
17	Progress Energy (NA)			0.000			
18	Entergy Corp.	-0.3%	0.3%	0.036	0.0000109	3.916E-07	
19	Alabama Electric Coop	-0.3%	0.6%	0.012	0.0000348	4.150E-07	
20	Oglethorpe Power Co.	-0.4%	0.5%	0.048	0.0000221	1.062E-06	
21	Electric Power - Chattanooga	-0.6%	0.3%	0.015	0.0000102	1.521E-07	
22	Memphis Light, Gas & Water	-0.4%	0.4%	0.035	0.0000123	4.320E-07	
23	Dominion Hub - PJM	-0.7%	0.3%	0.079	0.0000102	8.074E-07	
24	Ameren Control Area	-0.6%	0.3%	0.019	0.0000068	1.293E-07	
25	Kansas City Public Utilities	-0.2%	0.3%	0.003	0.0000084	2.865E-08	
26	Southwestern Publc Service	-0.2%	0.2%	0.037	0.0000058	2.122E-07	
27	Western Farmers Elec Coop	-0.6%	0.4%	0.008	0.0000160	1.355E-07	
28	El Paso Electric	-0.3%	0.2%	0.012	0.0000058	7.097E-08	
29	Public Service of N. Mexico	-0.8%	0.2%	0.017	0.0000026	4.450E-08	
30	California ISO	-0.8%	0.2%	0.063	0.0000023	1.418E-07	
31	Los Angeles DWP	-0.7%	0.2%	0.007	0.0000044	3.175E-08	
32	Avista Corp	-0.5%	0.2%	0.021	0.0000048	1.013E-07	
33	Portland General Electric	-0.4%	0.2%	0.037	0.0000048	1.785E-07	
34	Chelan County PUD	0.0%	0.2%	0.006	0.0000029	1.594E-08	
35	Black Hills Corporation	-0.7%	0.4%	0.002	0.0000130	1.945E-08	
36	WAPA - Rocky Mountain	-0.6%	0.2%	0.014	0.0000036	5.181E-08	
	National Average	**-0.50%**	**0.06%**	1.000		0.0000080	< ---- Mean Variance of Model Error
			Variance across sample ------------>			0.0000037	
				Std Deviation		0.0019	
				Sum of Variances ----->		0.0000116	
				Std. Error		0.0034121	
				Std. Error (mean)		0.0005767	= **0.06%**

Column (4) shows the variance of the measurement error (or, in the context of this study, regression model error) for each utility, calculated as the square of the standard error (but displayed in the table in decimal form). The last column shows the weighted variance for each utility. The weighted mean variance is then simply the sum of these values, shown as the highlighted value of 0.0000080.

The highlighted value of 0.0000037 is the variance of estimated percentage changes in system consumption attributable to EDST across the sample of 35 utilities. The standard deviation of 0.0019, converted to percentage terms, is 0.22 percent. Thus, assuming a roughly normal distribution of impacts, about 70 percent of the utilities would show point estimates of percentage savings between about 0.3 percent and 0.7 percent.

The sum of the two variances, one for the model error and the other for sample variation, is 0.0000116, as labeled near the bottom of the table. Taking the square root generates the adjusted standard error of 0.0034 (0.34 percent). In this case, the variance associated with the measurement error of the individual utilities is about 65 percent of the total variance as defined in Equation (B.18). This proportion implies that taking account of the measurement error yields an adjusted standard error for the overall sample that is significantly higher than would have been calculated using only the expected values (point estimates) of the sampled utilities.

Standard error of the mean values

The final highlighted entry at the bottom of Table B-13 shows the standard error (se) for the sample mean using the conventional formula:

$$\text{se}\,[(\text{Mean}(Y)] = \text{se}\,(Y) / \text{sqrt}\,(N) \qquad \text{(B.21)}$$

Because this study considered a reasonably large number of utilities (N = 35) for the spring analysis, the standard error of the mean (national average) value is relatively small as compared to the results for any specific utility. For the mean percentage changes in electricity consumption of 0.5 percent, the associated standard error is approximately 0.06 percent (rounded up from a value 0.058 percent).

This approach provides a statistically rigorous approach to incorporating the variability of expected savings across the utilities in the sample together with the uncertainty inherent in the regression models used to estimate those savings.

B.5.2. Methodology to account for covariances across utilities

The procedure described in the previous section is appropriate under the assumption that the measurement errors inherent in the utility-specific regression models are statistically *independent*. However, it is not unreasonable to expect that excluded factors in these models would influence more than a single utility, especially for utility service areas that are geographically close to one another. These excluded factors suggest that the statistical distributions describing the variance of the EDST impacts are not independent, and thus the procedure outlined in Section B.5.1 is likely to understate the *variance* of the national average savings.

The only robust method of accounting for the interrelated nature of the EDST impacts is to estimate simultaneously the models described in Section B.3 across all utilities (or as regional subsets). An appropriate simultaneous estimation procedure in this situation is termed Seemingly Unrelated Regressions (SUR), a technique that was originally developed to account for the covariance in the disturbance terms in regression models that appear to be unrelated (e.g. , no parameters whose values are restricted to be the same in each model). For the hourly DID models, a complete SUR system estimation involving the thirty or more utilities is computationally infeasible. However, for this study, a reduced form of the statistical models was employed in an effort to develop an approximate measure of the influence that the excluded covariances (across utilities) might have upon the calculated variance of the *national* average electricity savings from EDST.

The reduced form model employed in this study uses two composite variables for each utility. The composites are based upon linear combinations of variables used in the individual utility regression—the linear combinations are constructed with estimated coefficients from these models. The first composite includes all variables *except* the EDST binary variables. Let this composite vector be denoted as X1. The second composite pertains the EDST binary variables (X2). Then within a SUR system, we have for each utility:

$$Y = b_0 + b_1\, X1 + * \, b_2\, X2 + e \tag{B.22}$$

In this formulation, the regression for each utility (on a stand-alone basis) should yield a coefficient of 0 for b_0 and 1.0 for b_1 and b_2. Thus, the composite variables retrieve most of the information that was originally in the separate variables (as shown in Equation B.13).

The simple two-variable model in Equation (B.22) is developed for each utility. These models are then reestimated as system within the SUR framework. Of interest in the system estimation is the covariance of the b_2 coefficients related to the EDST impacts. If the total *covariance* is relatively high compared to the total of the *variances* of the b_2 coefficients, the assumption is made that a similar result would have obtained if the original, full-blown models had been estimated in the same fashion.

Even with reduced form models, a complete SUR framework still requires the ability to invert very large matrices to compute the estimated coefficients. As such, two approaches were taken to further reduce the computational requirements of the problem. The first approach involved estimating the evening model, pertaining to the fall EDST impacts, for a reduced sample period for all 29 utilities for which fall data were available. The second approach used the entire sample period, but performed the SUR estimation for five regional groupings of utilities. The two approaches are outlined below.

In the first approach, using a reduced sample period, two separate estimations were undertaken, each having a sample period of 28 days. In the first estimation, the sample period included one week *prior* to the EDST period and the one-week EDST period, for both 2006 and 2007. In the second estimation, the sample period included the EDST period and the *following* week, again for both 2006 and 2007.

The SUR procedure requires an estimate of the correlation of the disturbances across utilities in the same time period. The residuals from the first-stage, individual, OLS models were used to compute the variance-covariance matrix of disturbances across equations (utilities).

The objective of both approaches to develop an overall adjustment factor that can be applied to the mean of the variances of the estimated EDST impacts that result from the separately estimated utility models. This adjustment factor was intended to reflect the additional effect of covariances of the EDST impacts across utilities that were not included in the utility-by-utility estimation process. Using the SUR regression, the adjustment factor was defined as the ratio of the total variance and covariance of the EDST coefficients using the SUR to the total variance of the EDST coefficients when estimated individually with OLS.

Table B-14 shows these derivations of these ratios using the first approach where all 29 utilities are include in the SUR. The total variance (i.e., the summed variances of the 29 b_2 coefficients) is shown in column (1). Column (3) shows the total variance, plus covariance, of the same coefficients, estimated with SUR. As shown in the last column, the ratios are almost the same for the two sample periods tested. The adjustment factor derived from this method was just under 1.5.

Table B-14. Covariance Adjustment Factors Based upon Reduced Sample Period

	(1)	(2)	(3)	(4)
	Independent - OLS	GLS (SUR)		
Estimation Period	Total Variance	Total Variance	Total Variance + Covariance	Ratio (Col 3/Col 1)
Week before+EDST	1.8200	1.2217	2.7120	1.4901
Week after+EDST	1.8080	1.2170	2.7120	1.5000
			Average ±	1.4951

The second approach, as discussed above uses the full sample period, but with a smaller number of utilities to be estimated simultaneously. The regional grouping of utilities for this approach is shown in Table B-15.

Table B-16 shows the results of the SUR estimations with respect to the total variance and covariance of the ESDT coefficients.[43] The ratios between column (4) [total variance + covariance using SUR] and column (1) [total variance using single-equation OLS] range from about 1.2 to 2.2. The ratios will depend upon the correlations of the errors among the utilities as well as the correlations of included variables. Further analysis would be required to try to provide a quantitative analysis of these differences. Across the five regions estimated, the average adjustment factor is just over 1.6, corresponding well with the results from first approach.

[43]As mentioned above, the expected value of the coefficients on the composite EDST variables was 1.0, owing to the particular construction of the variable from the first-stage OLS regressions. Using SUR, these coefficients typically ranged between 0.98 and 1.02. Thus, any adjustment to the individual utility regression estimates of the EDST impacts was judged unnecessary. The objective of the SUR methodology was to account for the missing covariance across these parameter estimates for use in aggregating to a national impact.

Table B-15. Regional Grouping of Utilities for SUR Estimation

Group 1 - Northeast/Mid-Atlantic (4)

- Con Ed – New York
- ISO-NE – Connecticut
- ISO-NE – NE Mass (Boston)
- Dominion Hub – PJM (Virginia)

Group 2 - North Central (6)

- Indianapolis Power & Light
- Dayton Hub – PJM
- Duquesne Hub – PJM
- No. Illinois Hub – PJM
- Madison Gas & Elec
- Otter Tail Power Co.

Group 3 - South (7)

- City of Tallahassee
- Gainesville Regional Utility
- Progress Energy (Florida)
- Entergy Corp.
- Oglethorpe Power Company
- ERCOT – Coast (Houston)
- ERCOT – S. Central

Group 4 - Mid-America (5)

- Louisville Gas & Elec
- Lincoln Electric System
- Electric Power – Chattanooga
- Memphis Light, Gas & Water
- Kansas City Public Utilities

Group 5 - West (7)

- El Paso Electric
- Public Service of N. Mexico
- California ISO
- Los Angeles DWP
- Avista Corp
- Chelan County PUD
- WAPA – Rocky Mountain

Table B-16. Covariance Adjustment Factors Based Upon Regional Grouping of Utilities

	(1)	(2)	(3)	(4)	(5)
	Independent - OLS	GLS (SUR)	GLS (SUR)		
Regional Group	Total Variance	Total Variance	Total Variance + Covariance	Ratio (Col 3/ Col. 1)	Sum of Sample Weights
Group 1	0.1216	0.1142	0.2613	2.1488	0.157
Group 2	0.2113	0.1728	0.3304	1.5637	0.264
Group 3	0.9927	0.8516	1.3500	1.3599	0.218
Group 4	0.2712	0.2236	0.3164	1.1667	0.166
Group 5	0.1057	0.0971	0.1922	1.8184	0.177
Total	1.7025		Average ±	1.6115	

As a conservative approach, the higher value of 1.6 was selected as the overall adjustment factor (leading to a somewhat larger uncertainty bound for the national average EDST savings. Table B-17 illustrates the use of this adjustment factor, by showing some of the comparable results from the bottom of Table B-13. In terms of Table B-17 (based upon B-13) the mean variance of the model error, shown as 0.0000080, is multiplied by 1.6. This resulting value 0.0000128 is then added to the variance of the point estimates of the EDST estimates, as explained in the previous subsection. In this case, the adjustment has the effect of increasing the variance of the national average savings from 0.058 percent to 0.069 percent, an adjustment of approximately 20 percent.[44]

Table B-17. Implementation of Covariance Adjustment Factor

Mean variance of model error	0.0000080		
x Covariance Adjustment Factor	1.6		
= Adjusted variance from model error	0.0000128		
Variance across sample	0.0000037		
Std. deviation	0.0019		
Sum of Variances	0.0000164		
Std. Error	0.0040528		
Std. Error (mean)	0.0006850	=	0.07%

[44] The smaller size of the fall regression models (fewer observations and variables) allowed the SUR procedure to be conducted on a larger percentage of observations and utilities than a similar analysis using the spring data. The adjustment factor of 1.6, based upon the fall analysis, was also applied to the development of the national average savings for spring.

Appendix C. Data Sources and Characteristics for Transportation and Gasoline Impacts Estimation

Weekly "motor gasoline supplied" data series

The study used weekly "motor gasoline supplied" information prepared by DOE's Energy Information Administration (EIA). We assembled weekly "motor gasoline supplied" information for two weeks before and two weeks after DST during spring and fall from 1998 to 2007. We used the weekly "motor gasoline supplied" information as a proxy for transportation gasoline consumption.

It would have been desirable to use weekly motor gasoline consumption information to study the energy effects of DST during spring. However, only weekly finished "motor gasoline supplied" information is available from the EIA's Weekly Petroleum Supply Reporting System,[45] which is comprised of six surveys. The weekly "motor gasoline supplied" information is not consumption data. However, in a longer timeframe, "gasoline supplied" equals gasoline consumption, provided that rolling stock remains constant.

Trend and seasonal variations

The weekly finished "motor gasoline supplied" data exhibits a long-term increasing trend. Between 1996 and 2006, transportation petroleum consumption increased at the average annual percentage rate of 1.6 percent[46]. In addition, we also found seasonal cycles in the long-term data series. Comparing weekly "motor gasoline supplied" that ended on January 19, 2007, to the week that ended on July 12, 2007; the seasonal variation in 2007 weekly "motor gasoline supplied" can be as high as 7.8 percent. In order to minimize the influence of a long-term increasing trend and seasonal variation, we examined only four weeks (two weeks before and two weeks after EDST) of weekly finished "motor gasoline supplied" data.

Week definition

The EIA collects weekly "motor gasoline supplied" information from Saturday to Friday. However, the EDST started on Sunday. Thus, the "after" weekly "motor gasoline supplied" includes one-day "motor gasoline supplied" information for Saturday, which is before DST.

Factors Motivate People to Travel

Many factors could motivate people to travel. To understand the complex trip making decisions, one could look at trip statistics by trip purposes. Trip statistics by trip purposes is presented in Table C-1. This information is based on the 2001 National Household Transportation Surveys

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[45] Energy Information Administration, Department of Energy, Weekly Petroleum Status Report, Report Number DOE/EIA-0208(2008-14), Washington DC, 2008.

[46] Stacy C. Davis and Diegel, 2007, S. W. *Transportation Energy Data Book*, 26th Edition, Report Number ORNL-6978. Tennessee.

conducted by the U.S. DOT.[47] If DST induced any additional trips, most likely they would be discretionary trips with purposes categorized as shopping, visiting friends/relatives, and other social/recreational activities in the late-afternoon/evening hours. Instead of other trips that take place during the day, the induced trips most likely would take place in the later-afternoon/evening. As shown in Table B-1, these discretionary trips account for about 41 percent of the total number of trips and about 37 percent of the total vehicle-miles of travel (VMT). Furthermore, trip length for shopping trips is relatively short while vacation trips have the longest trip length. Not surprisingly, trip duration is correlated with trip length.

Table C-1. Trip Statistics by Trip Purposes

Trip Purpose	Share of Trips	Share of Trip Vehicle-miles Traveled	Trip Length (miles)	Duration (minutes)
To/from work	22.1%	27.0%	12.1	22.3
Work-related business	4.1%	8.4%	20.3	30.9
Shopping	21.1%	14.5%	6.7	14.4
Other family/personal business	24.7%	18.7%	7.5	15.2
School/church	4.9%	3.7%	7.5	15.8
Medical/dental	2.2%	2.2%	9.9	20.7
Vacation	0.4%	1.8%	47.4	59.6
Visit friends/relatives	6.3%	9.4%	14.9	24.4
Other social/recreational	13.7%	13.2%	9.6	18.2
Other	0.5%	1.0%	18.1	31.4
All	99.9%	100.0%	9.9	18.7

NOTE: Annual data for 2001, (Davis and Diegel, 2007; Table 8-8)

National traffic volume data

For the study, we used traffic volume information from the Office of Highway Policy Information (OHPI), Federal Highway Administration (FHWA) publication, *Traffic Volume Trends*. We used traffic data collected at over 4,000 continuous traffic-counting locations nationwide. We prepared traffic information during the two weeks before and after DST during spring from both 2006 and 2007.

Traffic data counters

For this study, we used hourly traffic count data from the *Traffic Volume Trends* for the two weeks before, and the two weeks after, DST. This covers the time period between February 25,

[47] U.S. Department of Transportation, Bureau of Transportation Statistics, *NHTS 2001 Highlights Report*, BTS03-05, Washington, DC: 2003.

2007, and March 24, 2007. Specifically, data for this four-week period was available from 4,705 traffic-counting locations in the United States. No traffic information, however, is available from Washington DC during this four-week period in 2007. Note that data available for the 2006 time period was collected from 4,447 traffic-counting locations. There is no traffic data from Wyoming during March, for both 2006 and 2007.

Functional classification distribution of traffic counters

Table C-2 presents the distribution of the traffic counters by their corresponding roadway functional classification. One can observe that roadways in both Interstates and other arterials, for both urban and rural areas, are well represented.

Table C-2. Traffic Counter Distribution

	2006		2007	
	Urban	Rural	Urban	Rural
Interstates/Expressway	958	604	987	620
Other Arterials	813	1,571	853	1,712
Others	101	400	98	435

Missing traffic data

Although automatic traffic recorders have been in use for quite some time, the reliability of these traffic counters is still a challenge. Consequently, there are missing data within the traffic volume database. Because of the nature of this study, we made no data imputation for the missing data. This is because most data imputation methodologies utilize generalization processes (e.g., averaging or trending) which are typically based on historical or related data. The imputation process could inherit any trends and patterns imbedded in the historical data. Because this study is looking at a specific short time period, such imputation might cause the conclusion from this study to be somehow biased. Thus, this study used only non-missing pair-wise traffic data collected during the specific time periods.

Traffic counter location information

The Bureau of Transportation Statistics has made efforts to geo-reference the locations of these traffic counters. Unfortunately, location information in terms of longitude and latitude is only available for about two-thirds of the traffic counters. For most of the remaining traffic counters, the next best available geographic location information is the county where the counter is located (1,367 counters). The other 286 traffic counters have no location information except for the name of the state in which they are located (see Figure C-1).

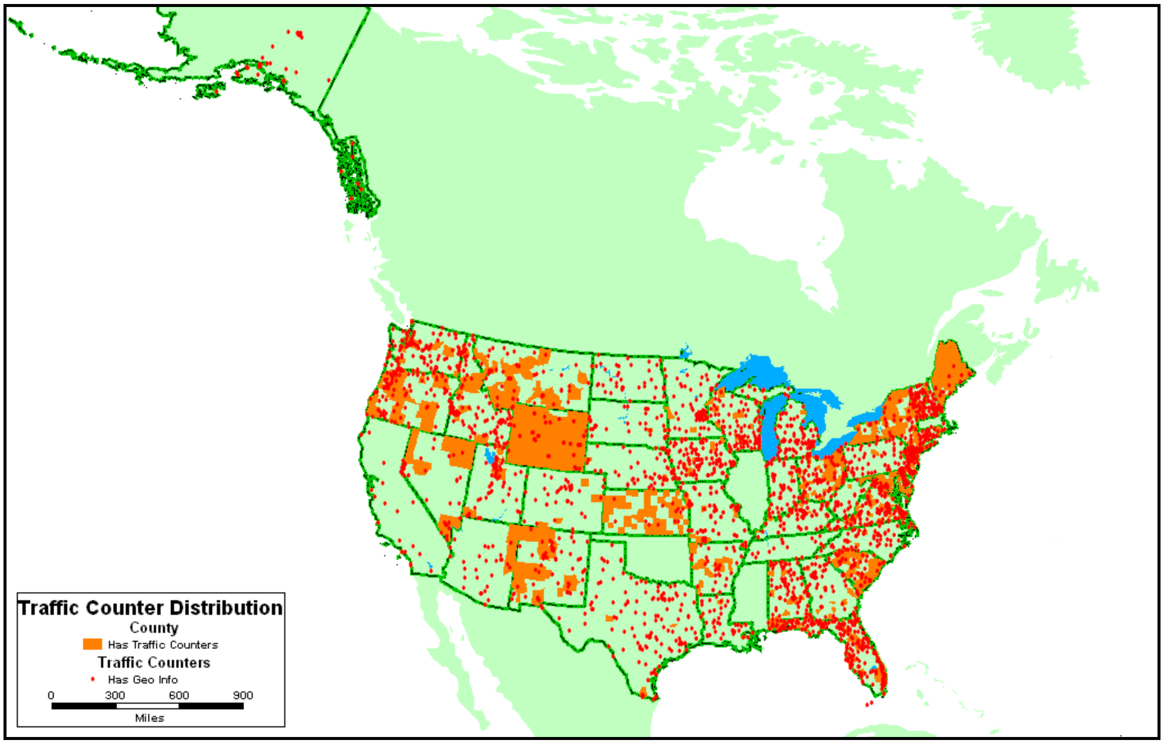

Figure C-1. Traffic counter locations

Traffic volume adjustment

Many factors influence traffic volumes. These include traffic counter malfunctions, roadway construction, traffic incidents/accidents, and special events, such as local festivals and inclement weather conditions. It is difficult to associate these conditions to significant changes in traffic volume from one week to the next for more than 4,000 traffic counters. There are no records of these traffic-changing events except for weather conditions. There are no well-established quantitative relationships on traffic volume behavior under these traffic volume-influencing events. Lacking location information for one third of the traffic counters makes matching traffic counters with weather stations impossible. Thus, we could not make any adjustments for other events that effect traffic volumes.

Induced traffic is expected to be small

We expect the increase in travel, if any, to be small. DST induced trips, if any, involve only certain types of trips that take place in the late-afternoon/evening. DST most likely would induce discretionary trips with purposes categorized as shopping, visiting friends/relatives, and other social/recreational activities in the late-afternoon/evening hours. Instead of other trips that take place during the day, the induced trips most likely would take place in the late-afternoon/ evening.

To take full advantage of longer daylight, some people get off from work as early as 3:30 pm during the summer. In order to include most induced after work travel activities; this study concentrates on travel during the late-afternoon/evening time period from 3:00 pm to 9:00 pm.

Figures C-2 and C-3 present VMT shares for discretionary trips and all trip purposes by hour of the day[48] for February-March and October-November, respectively. Discretional trip VMT during late-afternoon/evening (from 3:00 pm to 9:00 pm) accounted for 15.98 percent and 17.15 percent the total daily VMT for all trip purposes for February-March and October-November, respectively.

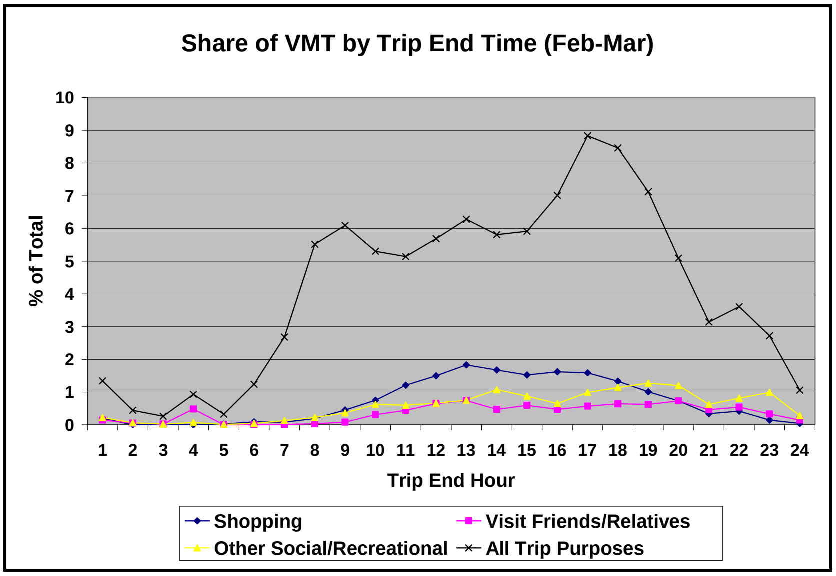

Figure C-2. Share of VMT by trip end time (Feb-Mar)

Thus, for example, each percentage change of VMT (induced by DST) for these three trip purposes, during the late-afternoon/evening hours, would yield only a small percentage of change to the total VMT by all activities (e.g., 1.0 percent of 15.98 percent or 1.0 percent of 17.15 percent) for the spring and fall. Based on the weekly "motor gasoline supplied" information, the gasoline supplies are 9,158 and 9,367 thousand barrels per day before DST transitions in spring and fall, respectively. Assuming the motor gasoline consumption is equal to "motor gasoline supplied," each percentage change of VMT (induced by DST) would translate into motor gasoline consumption rate changes of 15 and 16 thousand barrels per day in spring and fall. We base this on the assumption that a one percent increase in overall VMT translated into a one percent increase in motor gasoline consumption and travel patterns by trip purpose and by hour of the day for 2007 is the same as 2001.

Exclusion of extreme values

As discussed, we expected the DST induced traffic, if any, to be small. In this study, we assumed that any traffic increases or decreases of more than twenty percent are not caused by the 2007 EDST and are excluded in the daily traffic comparisons performed under this study. Other factors such as incidents, roadway construction, special events, and inclement weather impact traffic volume more significantly than DST.

[48] U.S. Department of Transportation, Bureau of Transportation Statistics, *NHTS 2001 Highlights Report*, BTS03-05 Washington, DC: 2003.

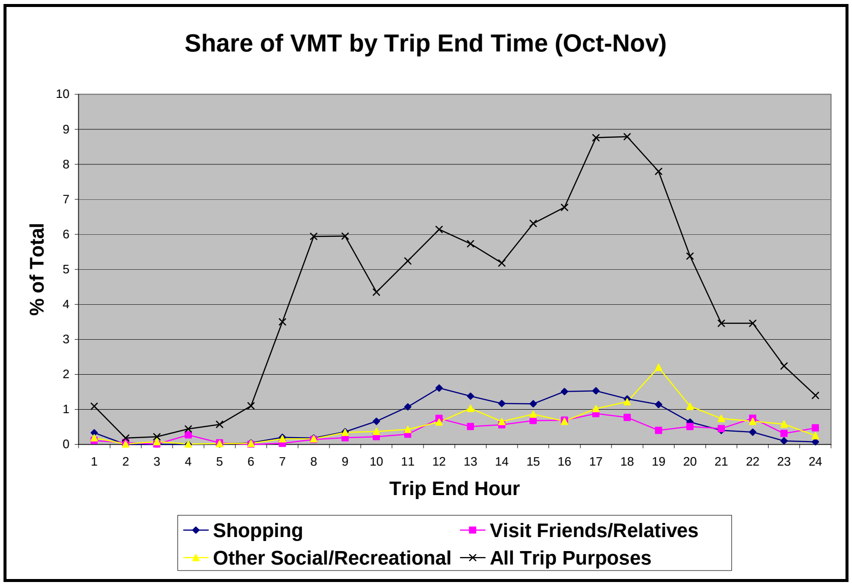

Figure C-3. Share of VMT by Trip End Time (Oct-Nov)

Figure C-4 presents the histogram of the percentage of differences of daily traffic from Week2 to Week3 in 2007. As shown in Figure C-4, the exclusion of the extreme values (i.e., those over 20 percent) only eliminated a small portion of the data and posted no impact to the overall distribution.

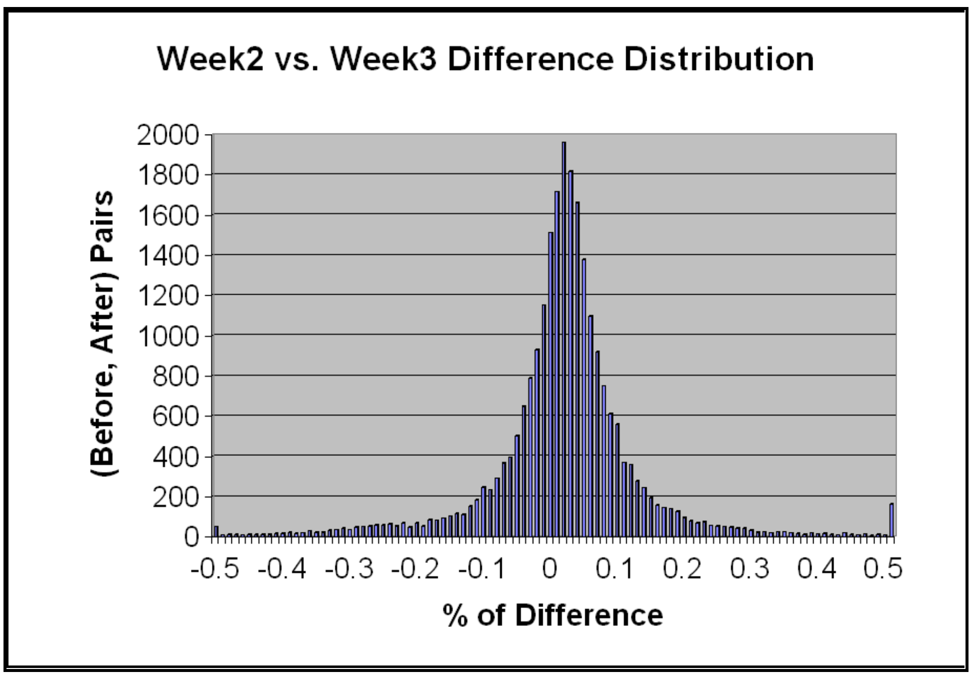

Figure C-4. Distribution of the percent of difference between Weeks 2 and 3 in 2007

Appendix D. Electricity Demand Curves During EDST Transitions

Shown in the figures below are graphs of the ratio of 2007 to 2006 hourly loads for the week before EDST, the EDST period, and the week after, for major utilities in each NERC region. The figures show the actual ratio during the EDST period, the ratio for the interpolated heuristic model, and, for those utilities that also had statistical analysis, the ratio based on the regression results. Both spring and fall graphs are included for those utilities that provided data for both seasons.

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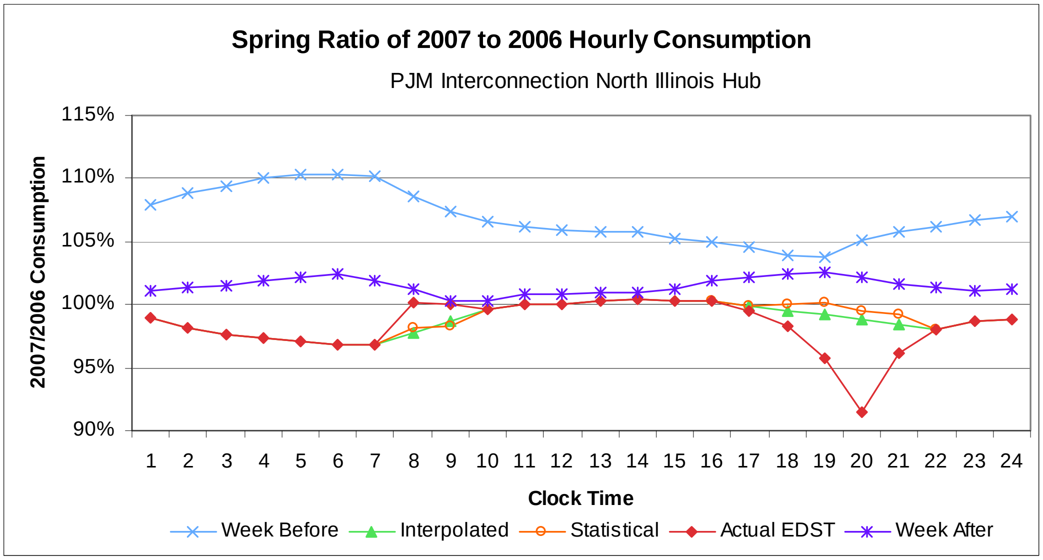

Figure D-1. PJM North Illinois Hub spring ratio of 2007 to 2006 hourly consumption

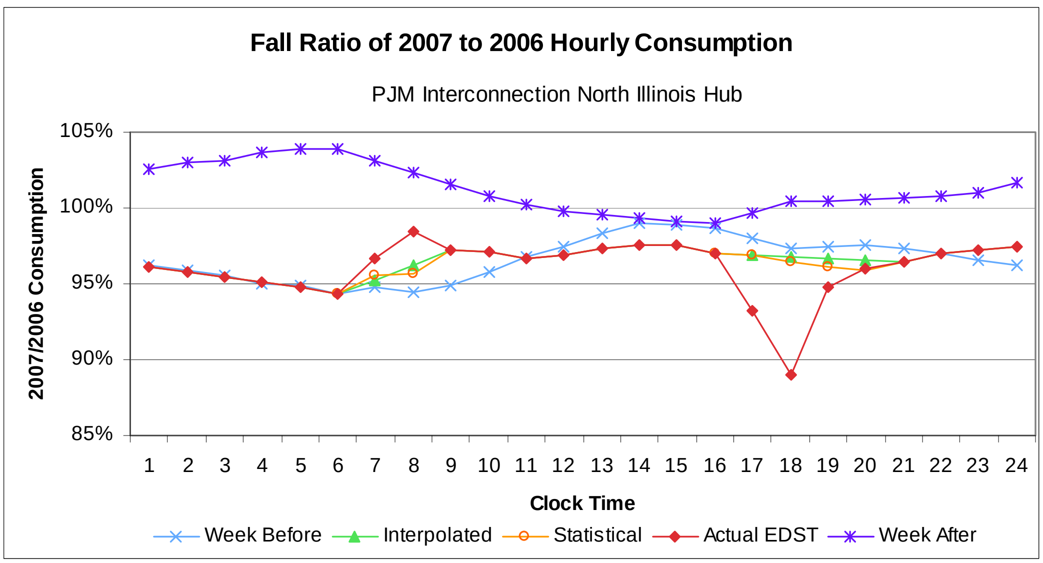

Figure D-2. PJM North Illinois Hub fall ratio of 2007 to 2006 hourly consumption

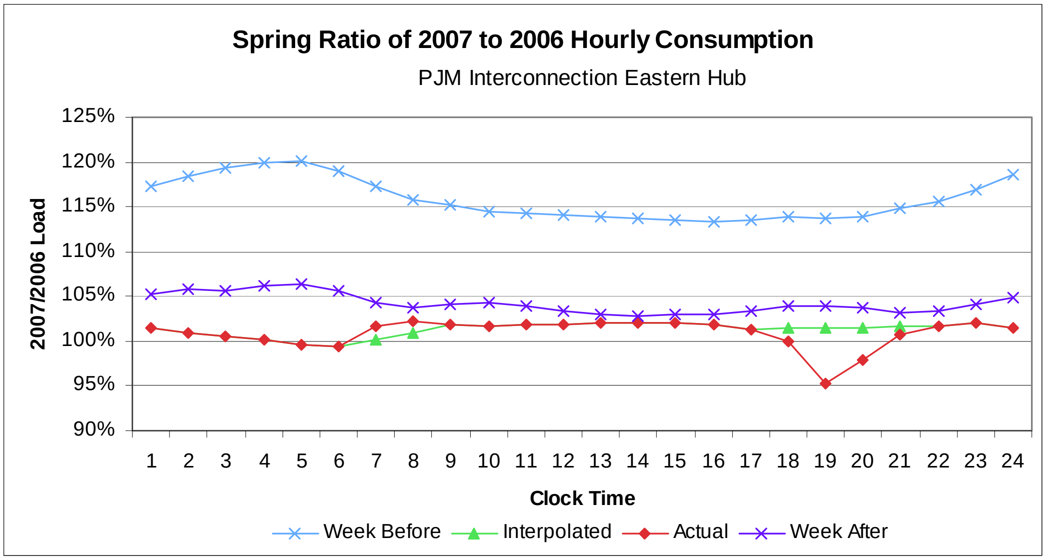

Figure D-3. PJM Eastern Hub spring ratio of 2007 to 2006 hourly consumption

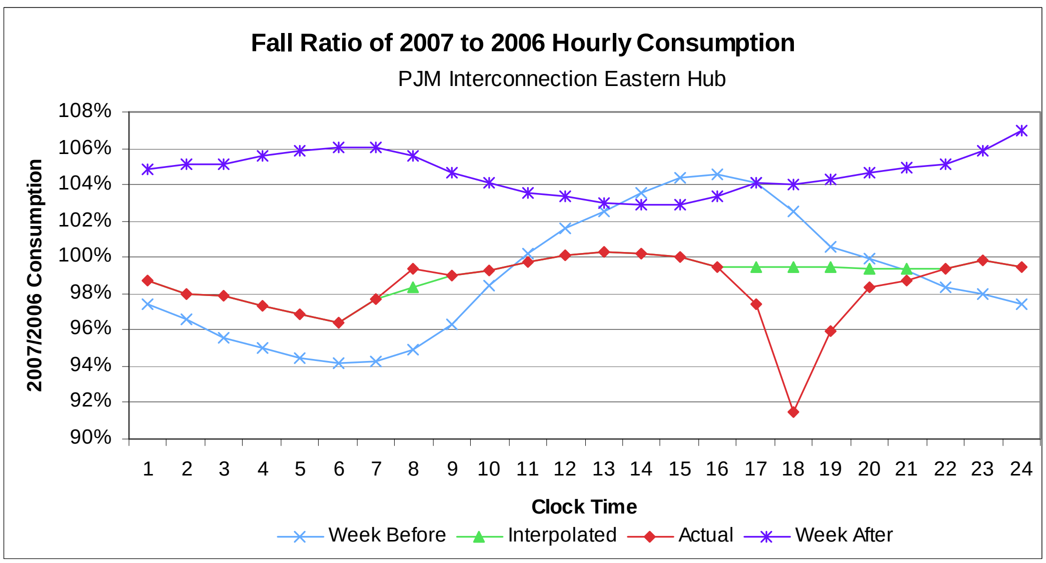

Figure D-4. PJM Eastern Hub fall ratio of 2007 to 2006 hourly consumption

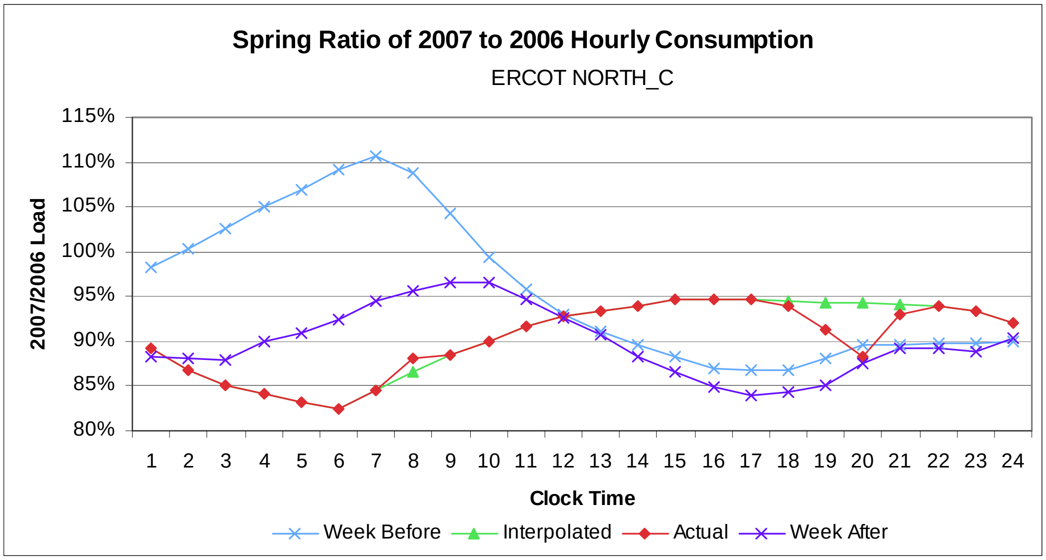

Figure D-5. ERCOT North Central (Dallas-Ft. Worth) spring ratio of 2007 to 2006 hourly consumption

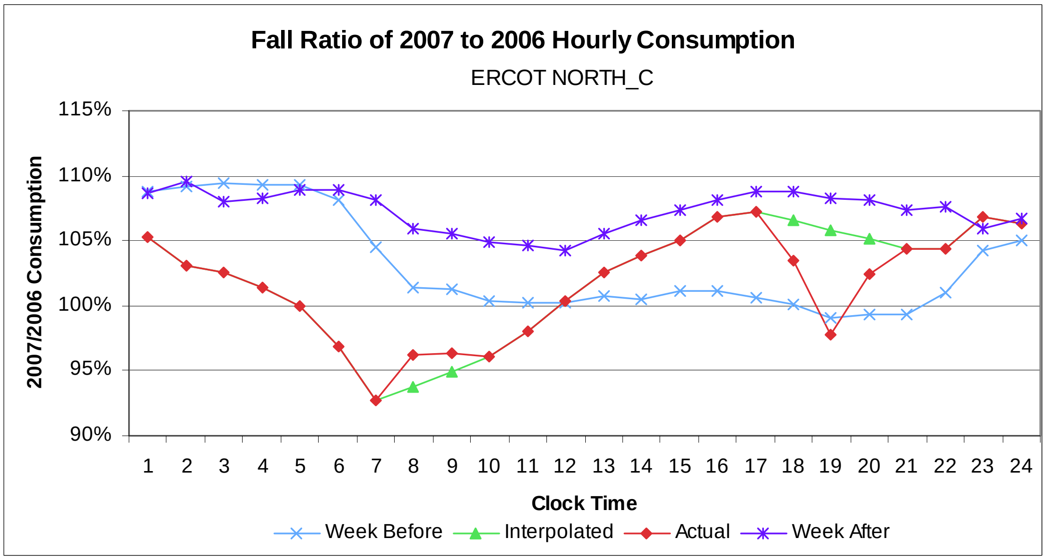

Figure D-6. ERCOT North Central (Dallas-Ft. Worth) fall ratio of 2007 to 2006 hourly consumption

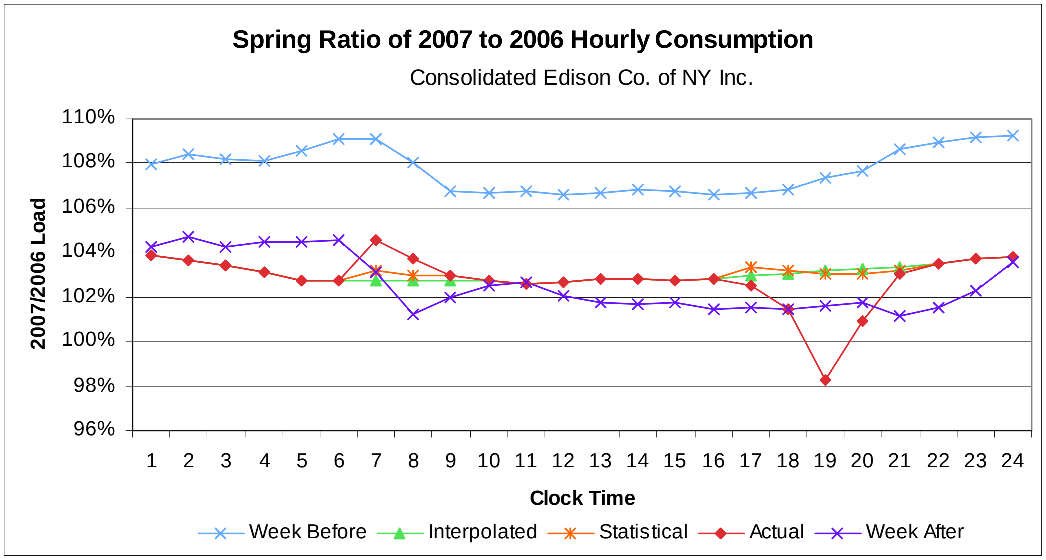

Figure D-7. Consolidated Edison Co. spring ratio of 2007 to 2006 hourly consumption

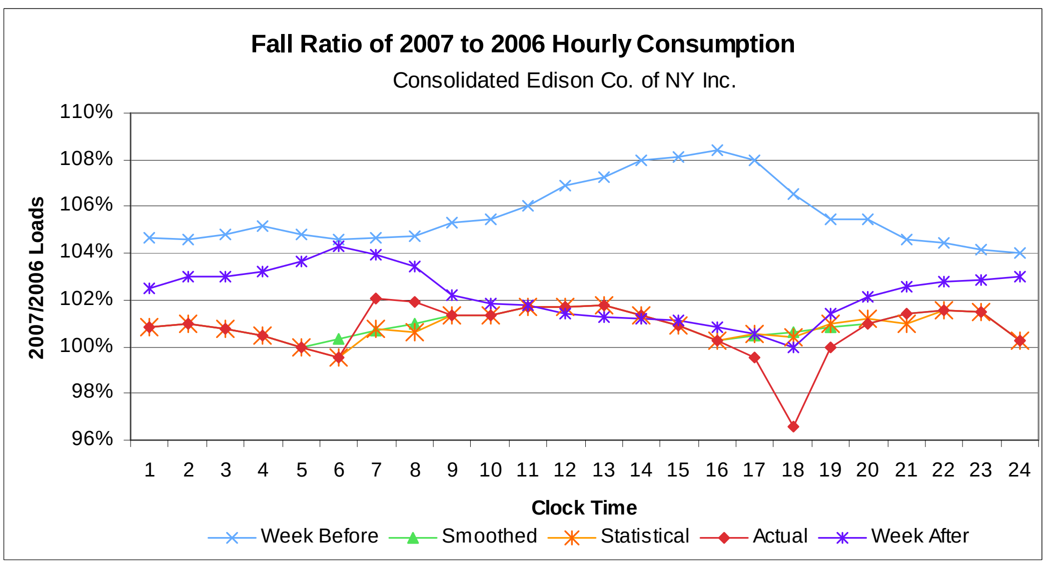

Figure D-8. Consolidated Edison Co. fall ratio of 2007 to 2006 hourly consumption

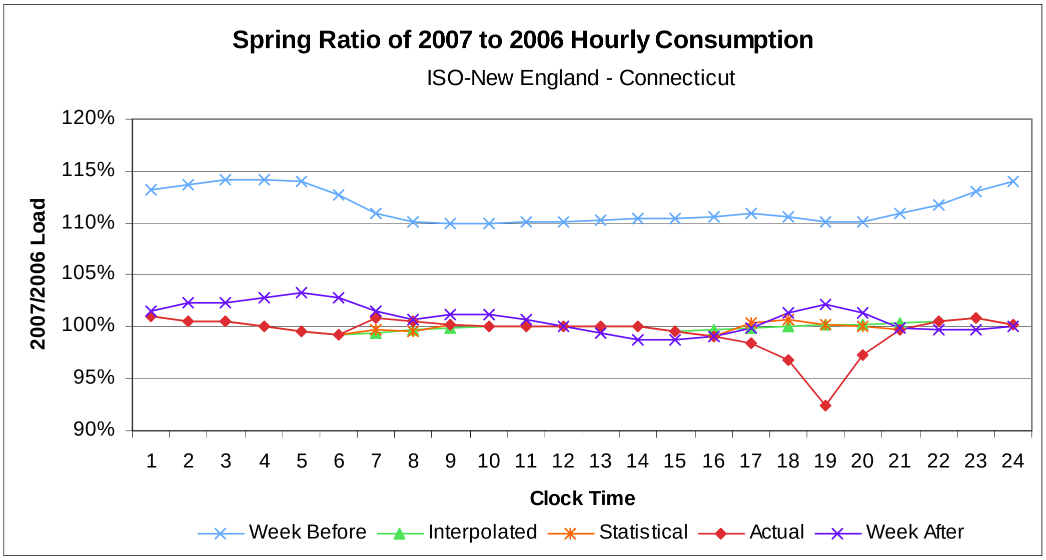

Figure D-9. ISO-New England - Connecticut spring ratio of 2007 to 2006 hourly consumption

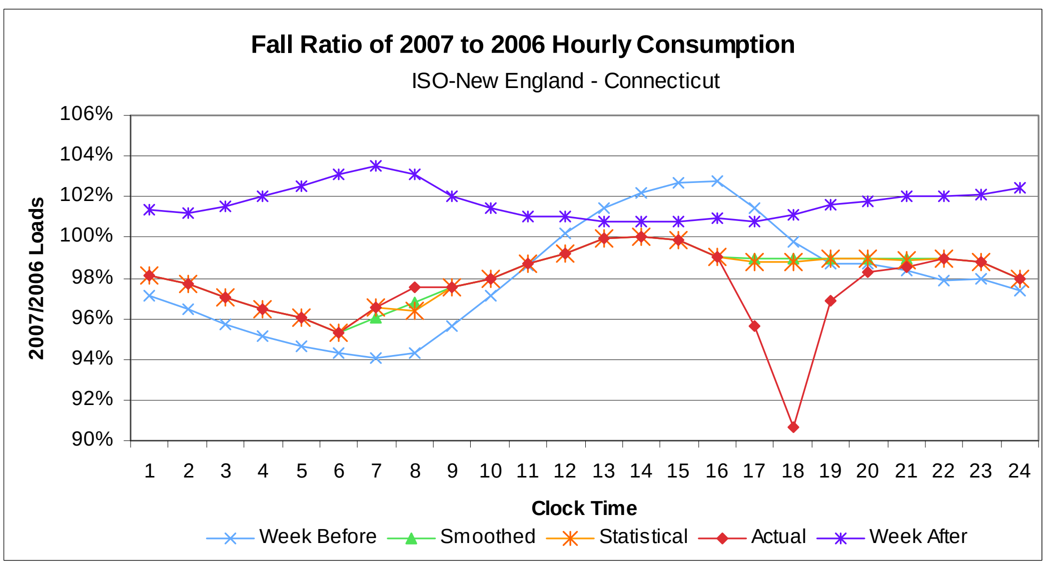

Figure D-10. ISO-New England - Connecticut fall ratio of 2007 to 2006 hourly consumption

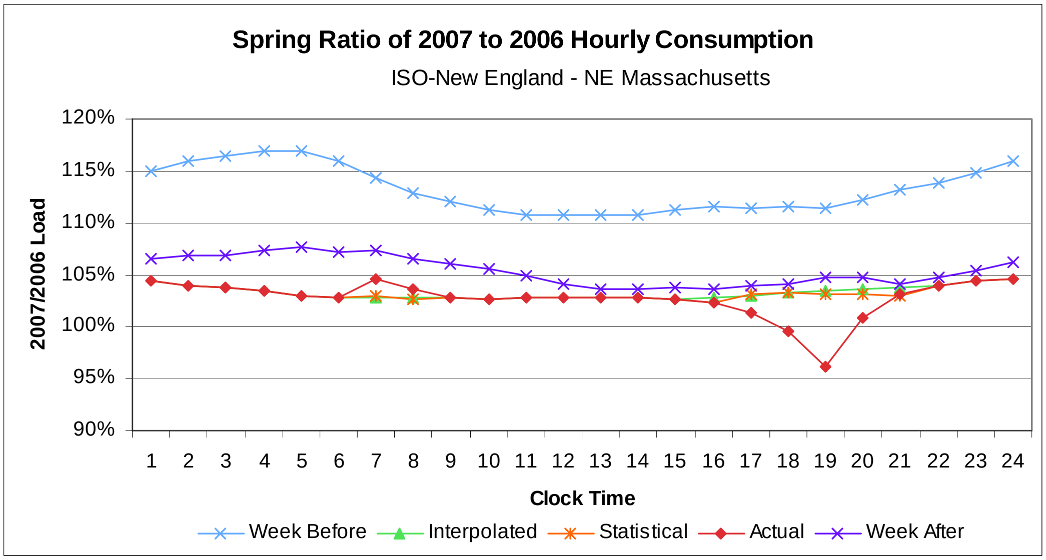

Figure D-11. ISO-New England – NE Massachusetts spring ratio of 2007 to 2006 hourly consumption

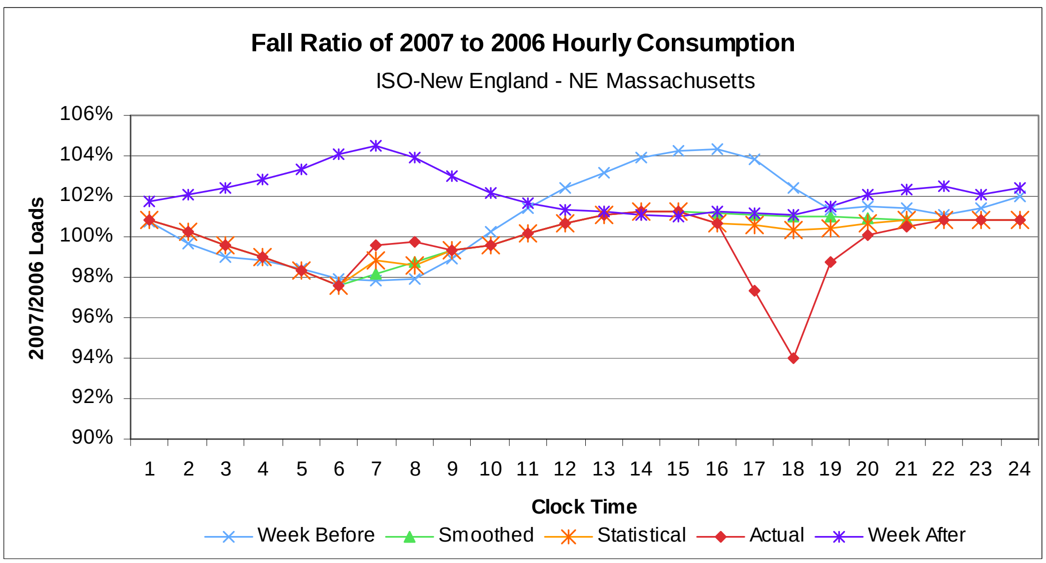

Figure D-12. ISO-New England – NE Massachusetts fall ratio of 2007 to 2006 hourly consumption

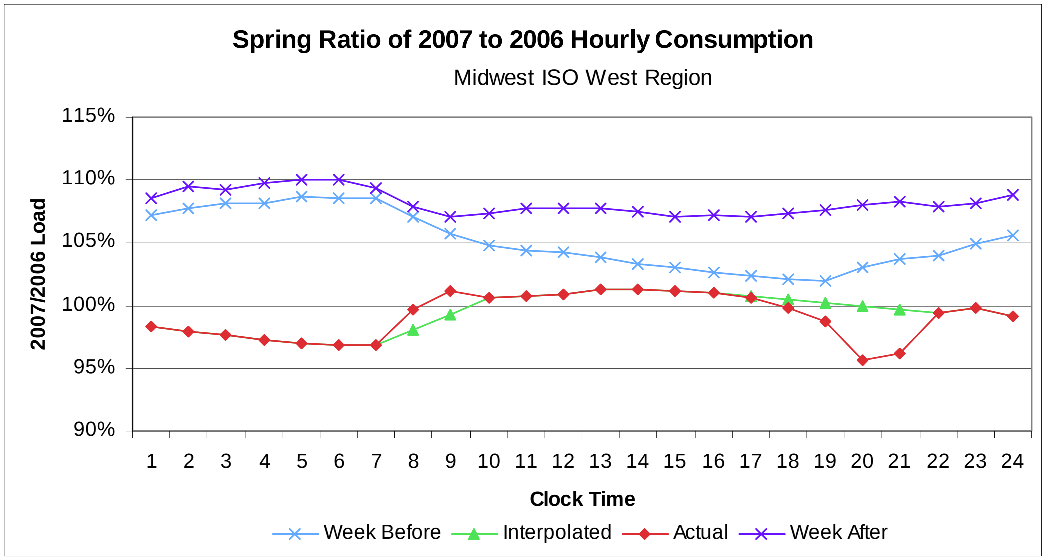

Figure D-13. Midwest ISO West Region spring ratio of 2007 to 2006 hourly consumption

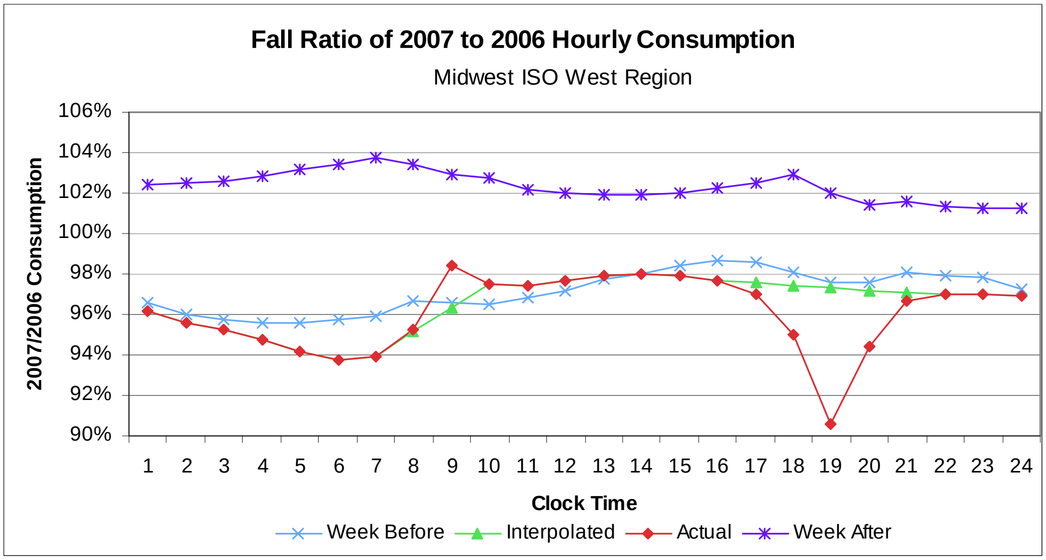

Figure D-14. Midwest ISO West Region fall ratio of 2007 to 2006 hourly consumption

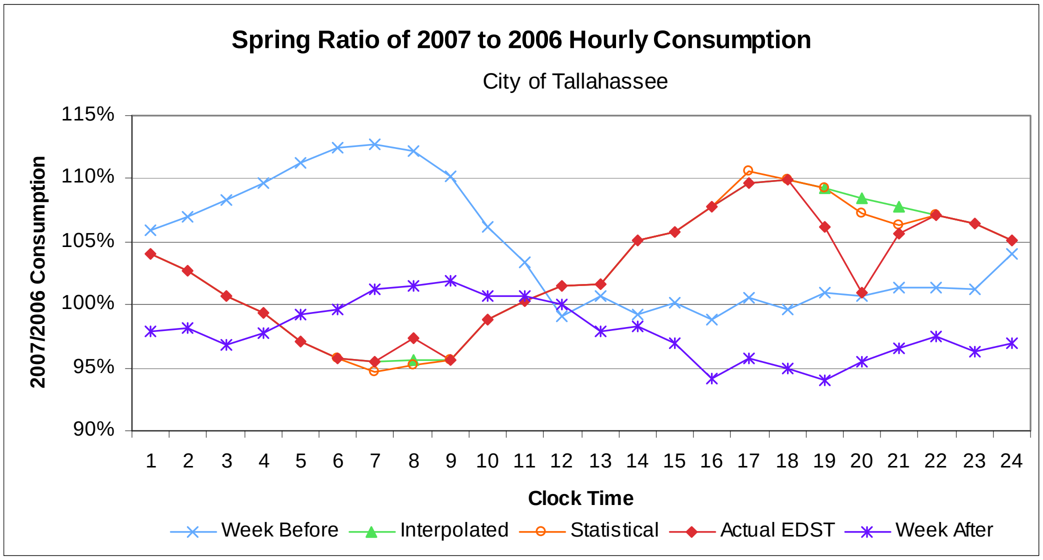

Figure D-15. City of Tallahassee spring ratio of 2007 to 2006 hourly consumption

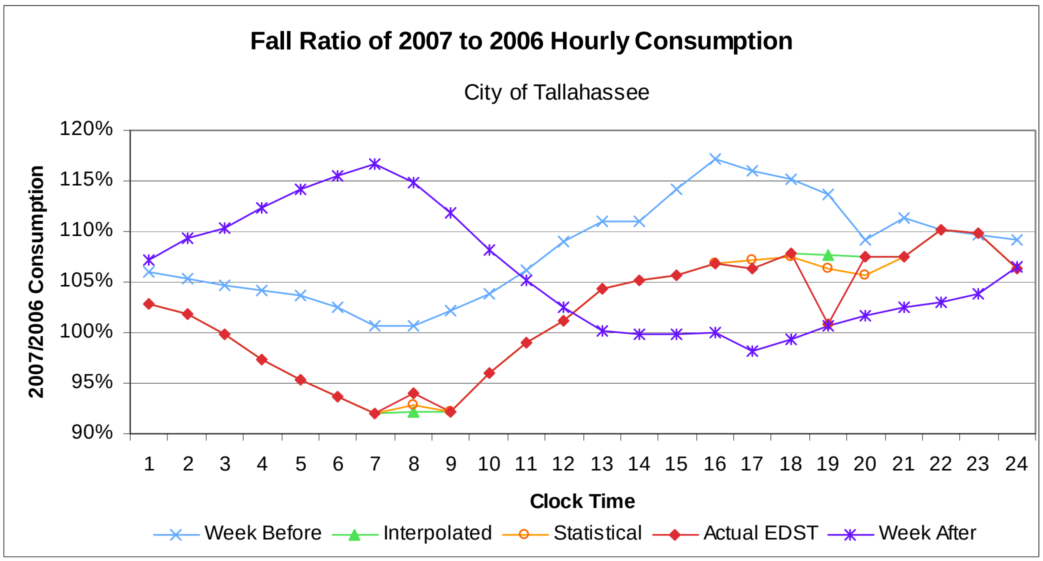

Figure D-16. City of Tallahassee fall ratio of 2007 to 2006 hourly consumption

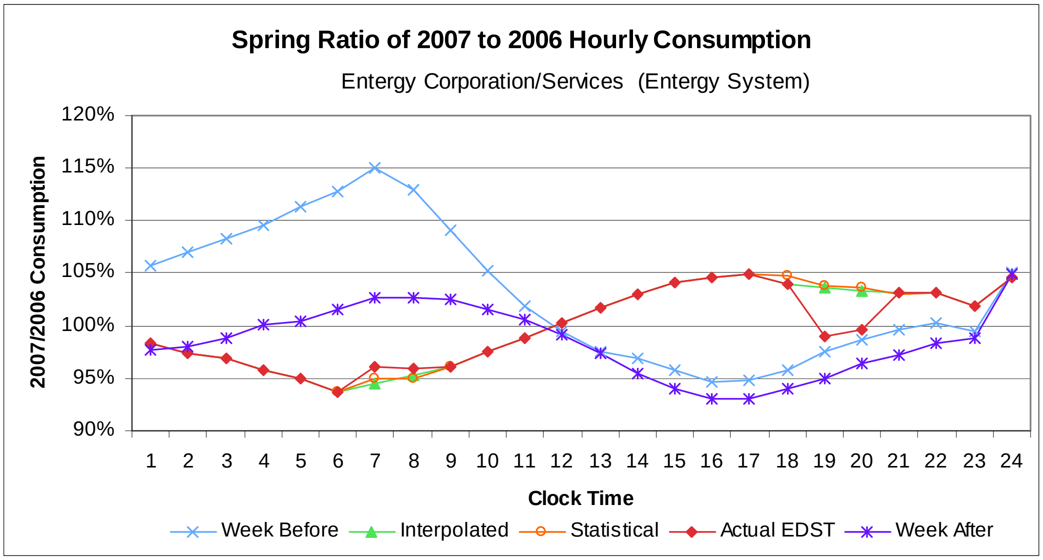

Figure D-17. Entergy Corporation spring ratio of 2007 to 2006 hourly consumption

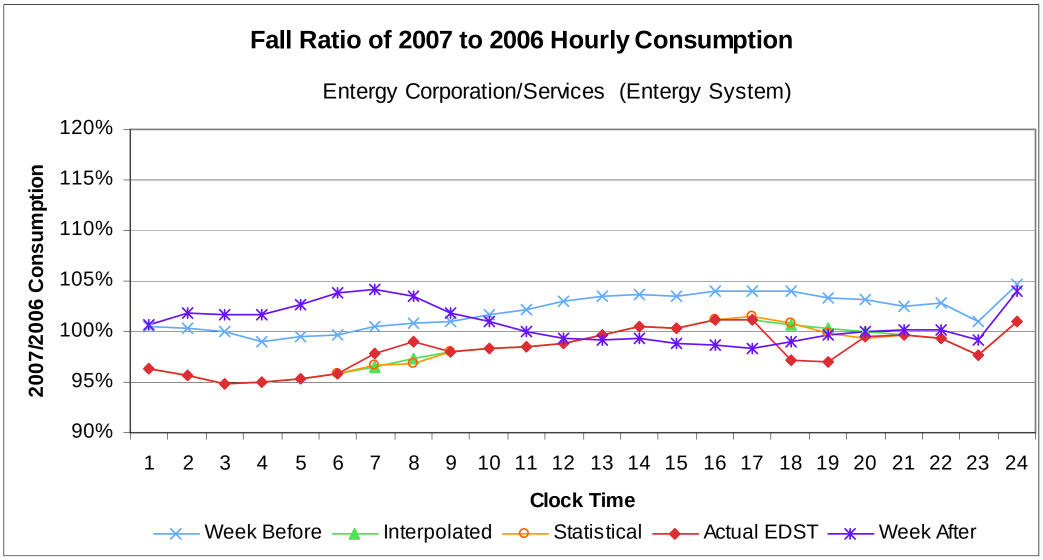

Figure D-18. Entergy Corporation fall ratio of 2007 to 2006 hourly consumption

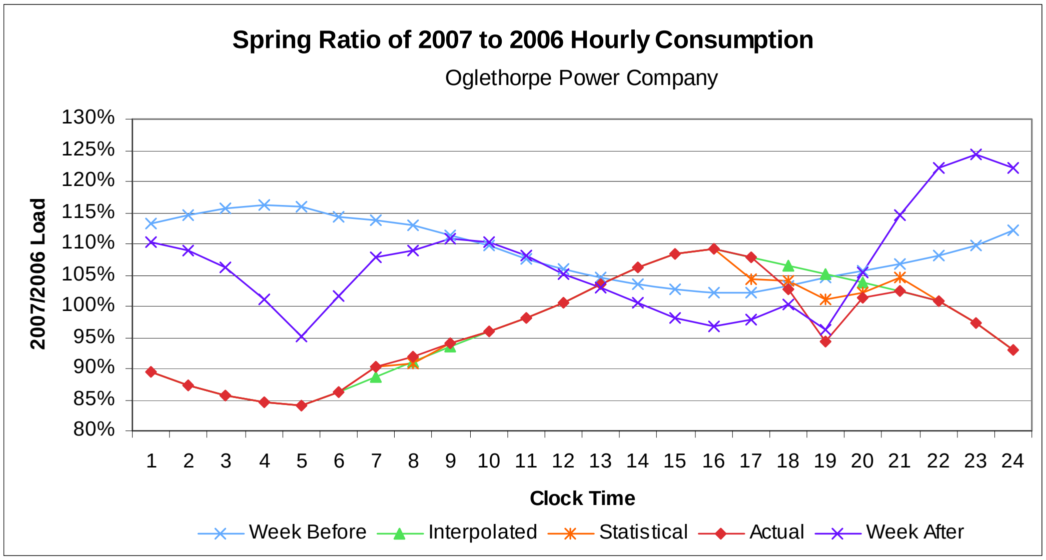

Figure D-19. Oglethorpe Power Company spring ratio of 2007 to 2006 hourly consumption

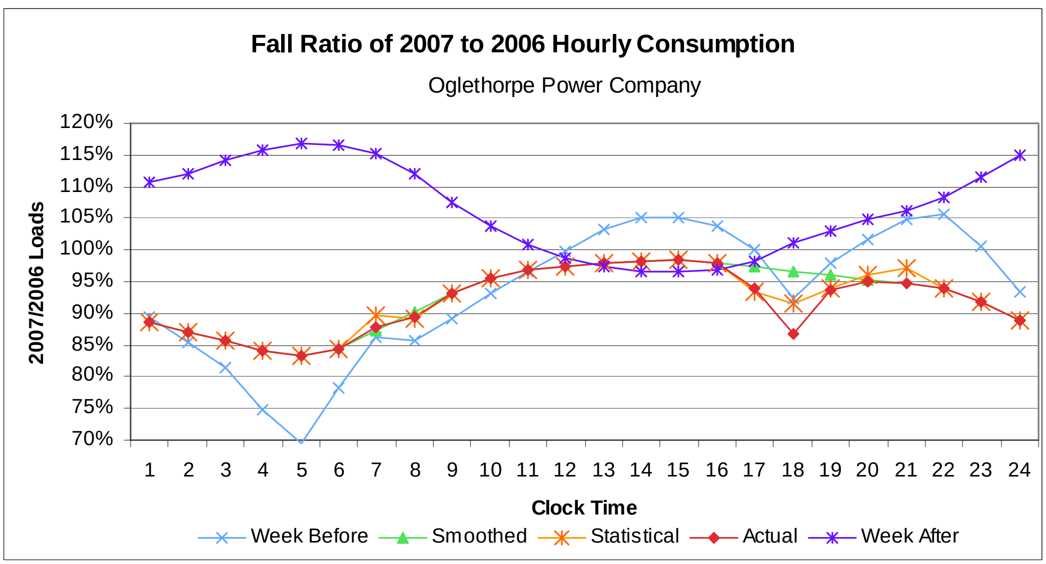

Figure D-20. Oglethorpe Power Company fall ratio of 2007 to 2006 hourly consumption

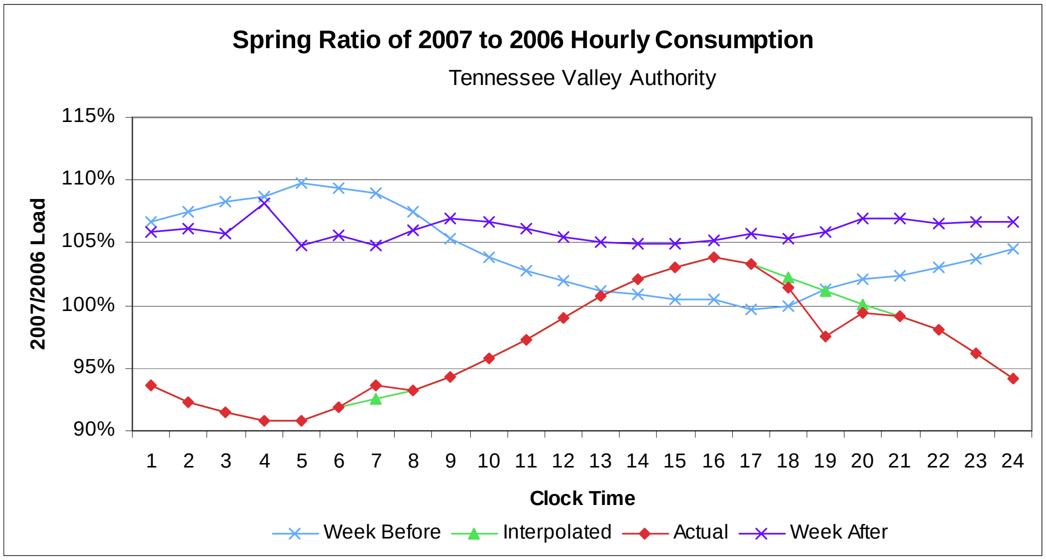

Figure D-21. Tennessee Valley Authority spring ratio of 2007 to 2006 hourly consumption

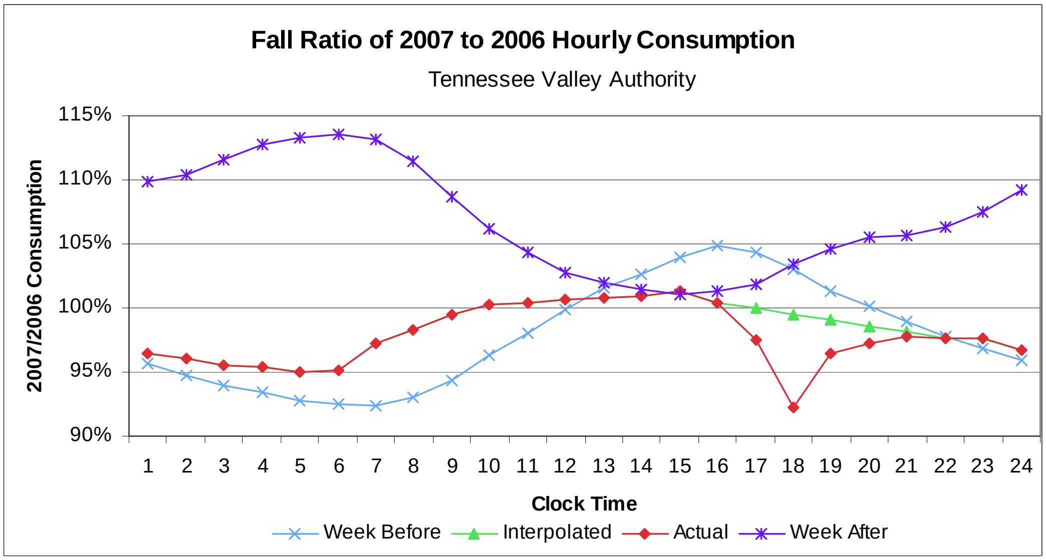

Figure D-22. Tennessee Valley Authority fall ratio of 2007 to 2006 hourly consumption

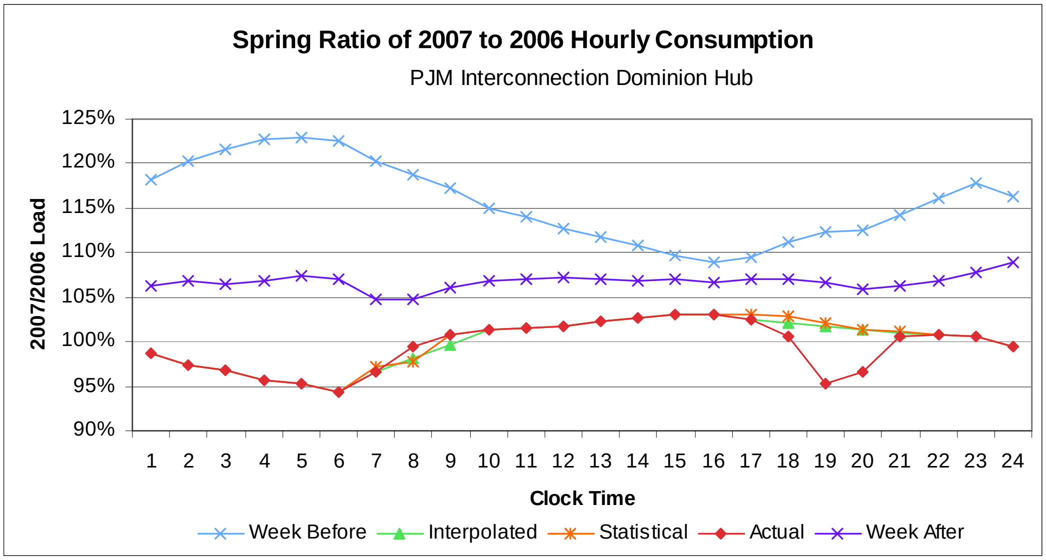

Figure D-23. PJM Dominion Hub spring ratio of 2007 to 2006 hourly consumption

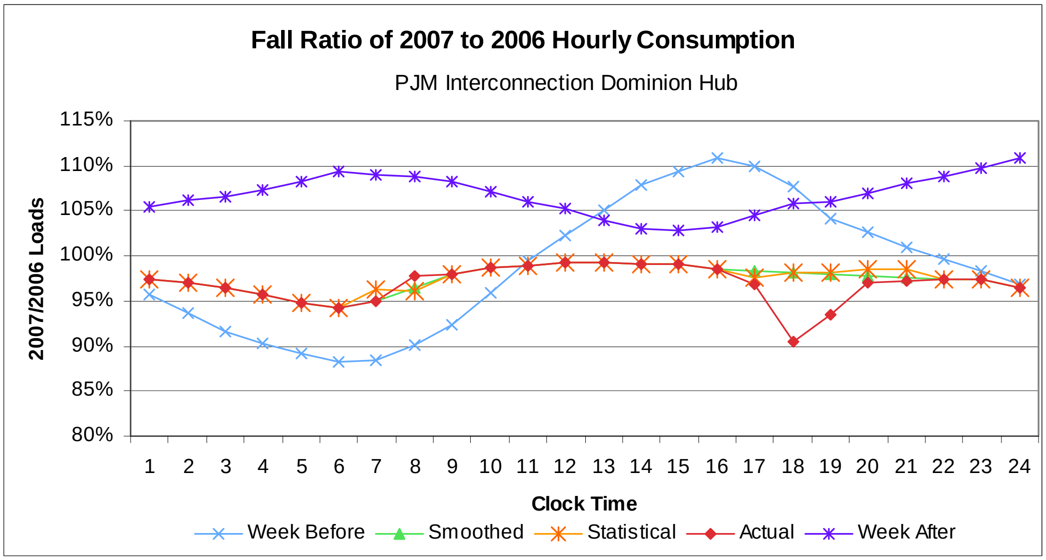

Figure D-24. PJM Dominion Hub fall ratio of 2007 to 2006 hourly consumption

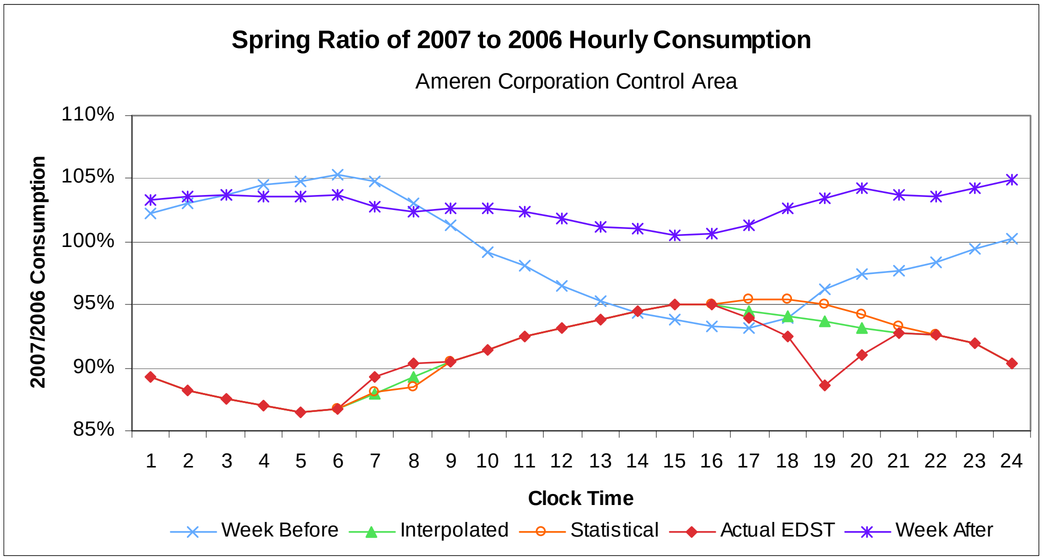

Figure D-25. Ameren Corporation spring ratio of 2007 to 2006 hourly consumption

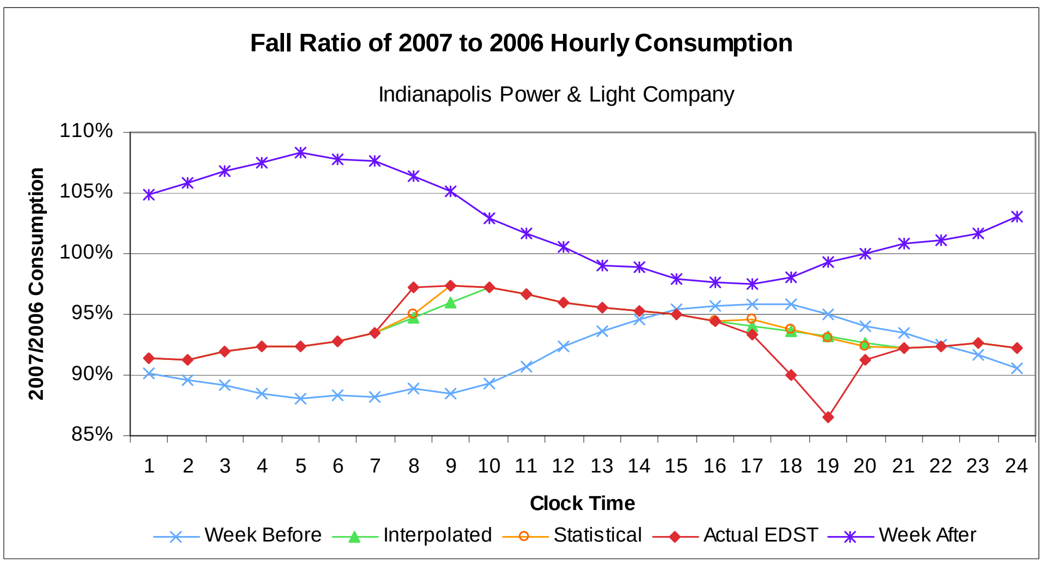

Figure D-26. Indianapolis Power & Light fall ratio of 2007 to 2006 hourly consumption (Indianapolis Power & Light results used for the fall in SERC-GAT despite in neighboring region because no SERC-GAT utility provided fall data)

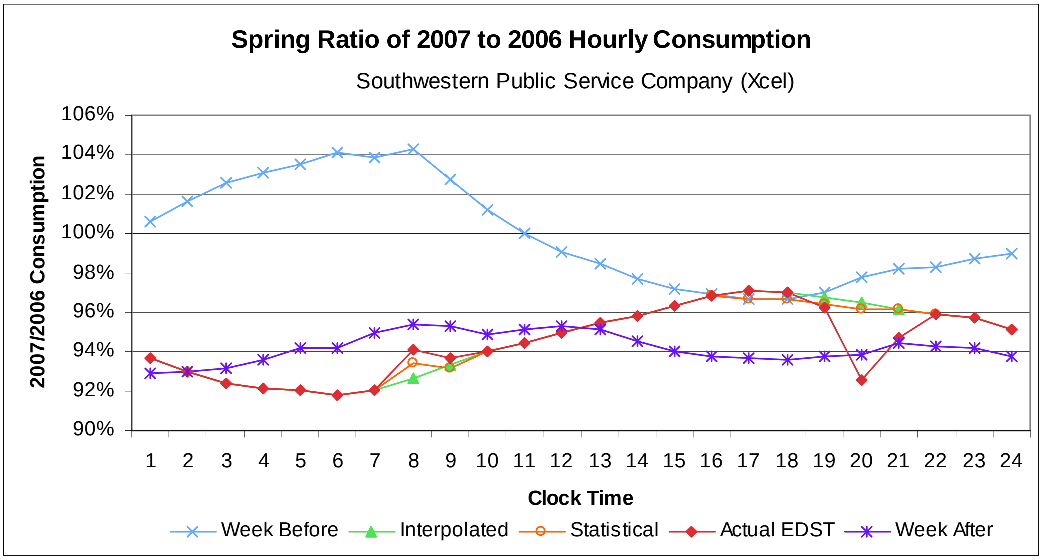

Figure D-27. Southwestern Public Service Company spring ratio of 2007 to 2006 hourly consumption

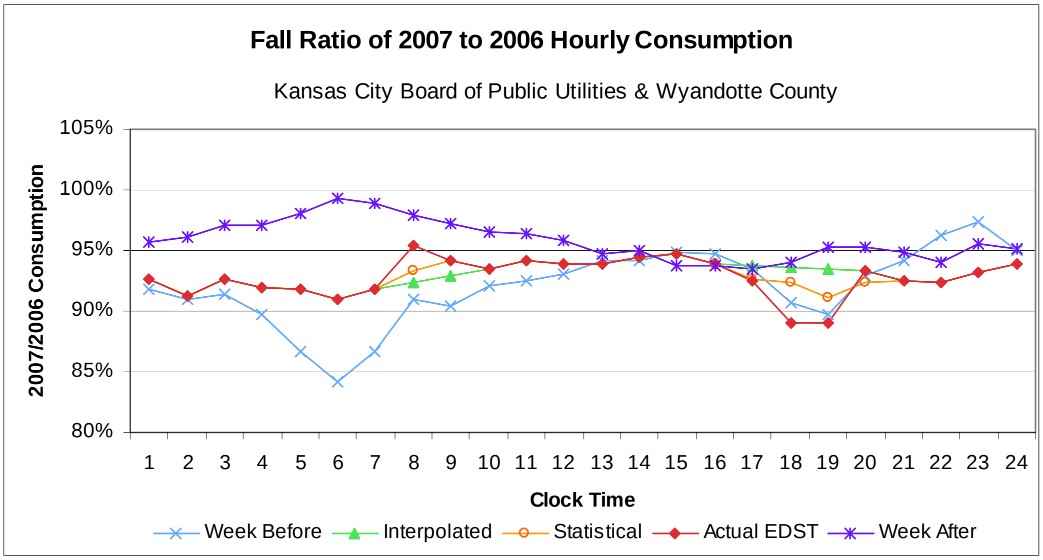

Figure D-28. Kansas City Board of Public Utilities fall ratio of 2007 to 2006 hourly consumption

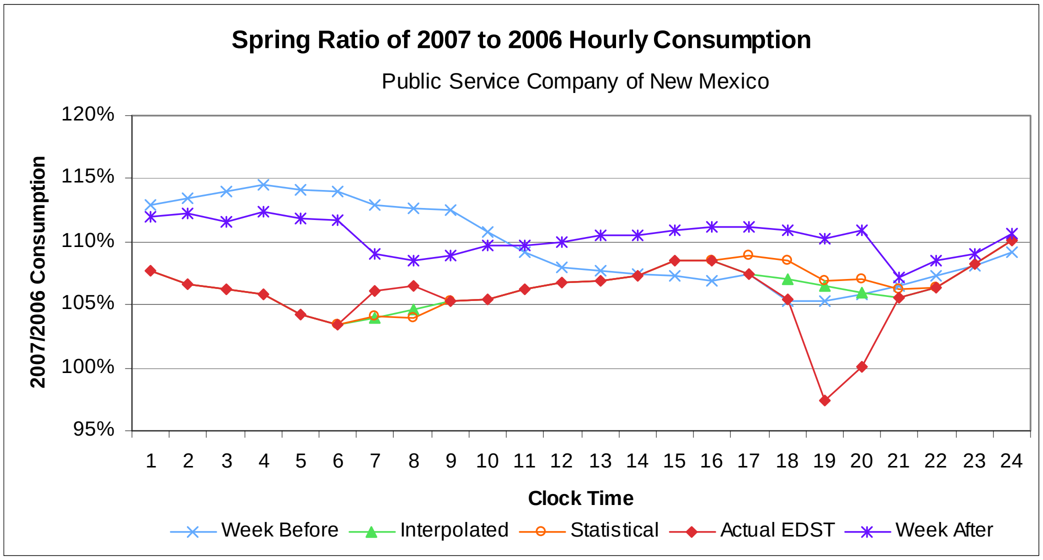

Figure D-29. Public Service Company of New Mexico spring ratio of 2007 to 2006 hourly consumption

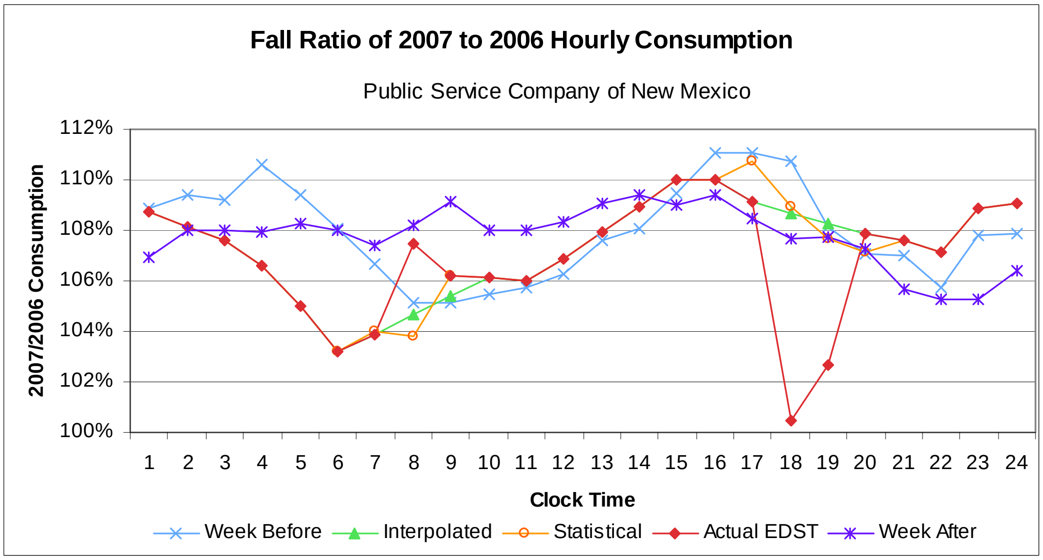

Figure D-30. Public Service Company of New Mexico fall ratio of 2007 to 2006 hourly consumption

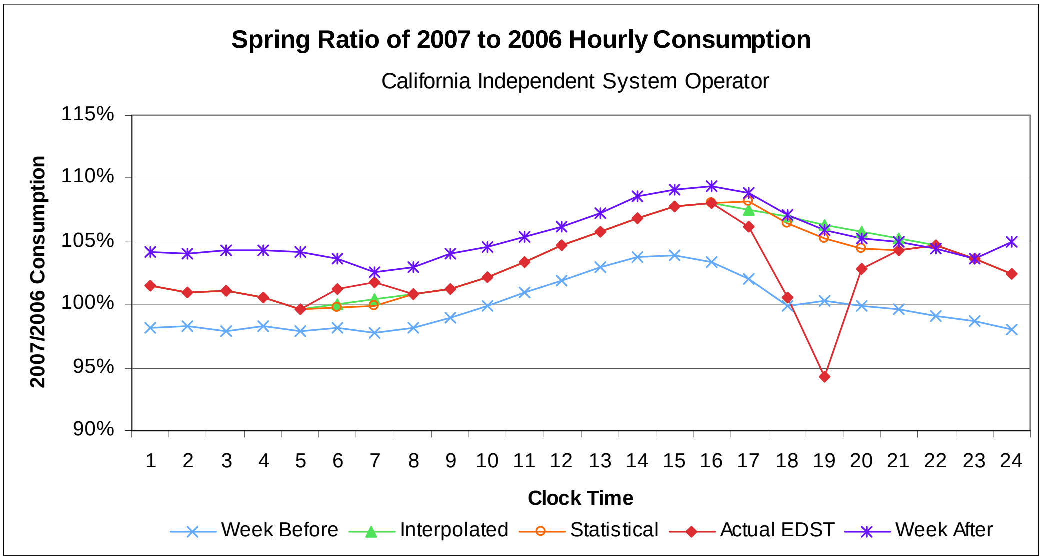

Figure D-31. California ISO spring ratio of 2007 to 2006 hourly consumption

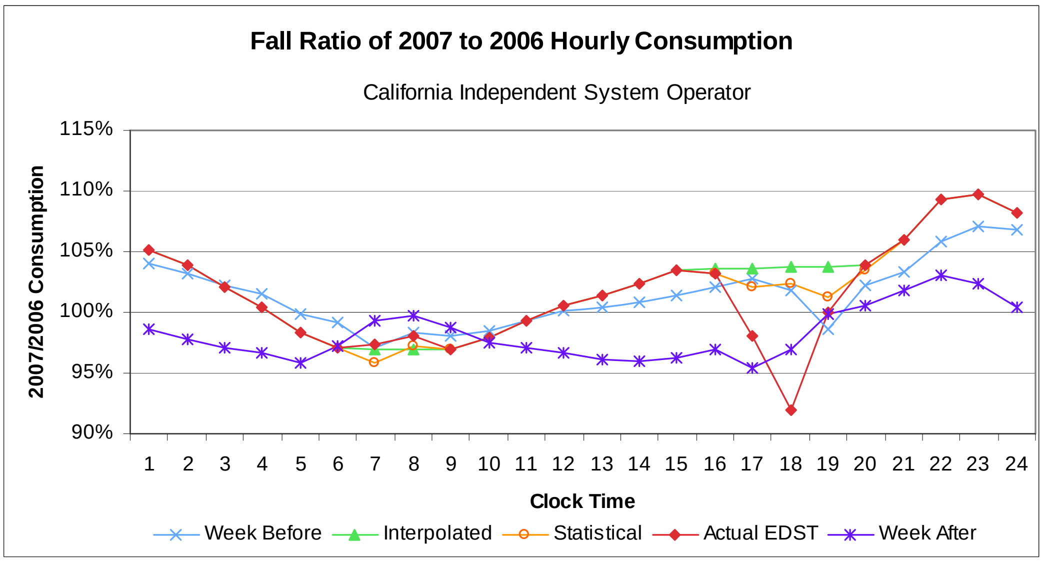

Figure D-32. California ISO fall ratio of 2007 to 2006 hourly consumption

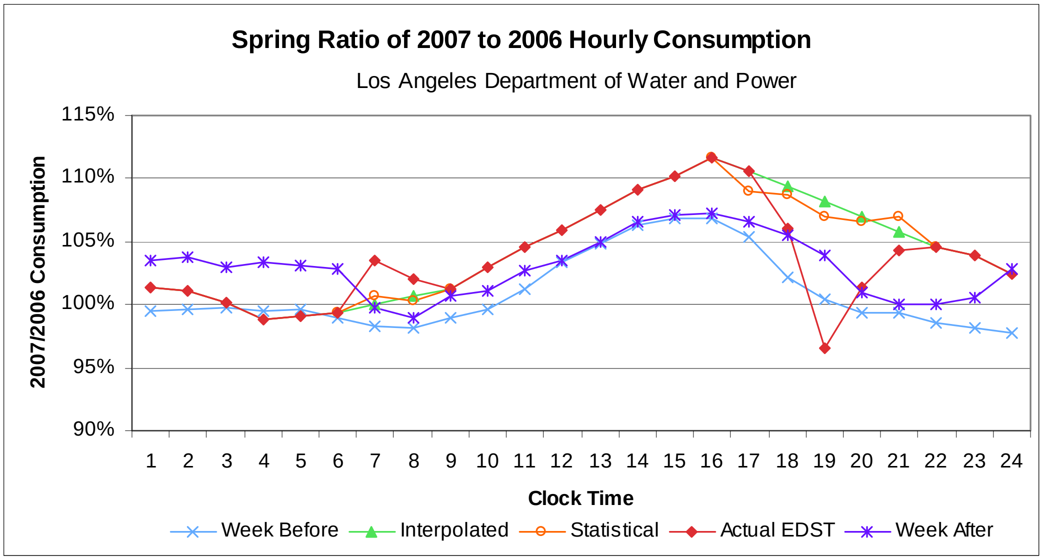

Figure D-33. Los Angeles Dept of Water and Power spring ratio of 2007 to 2006 hourly consumption

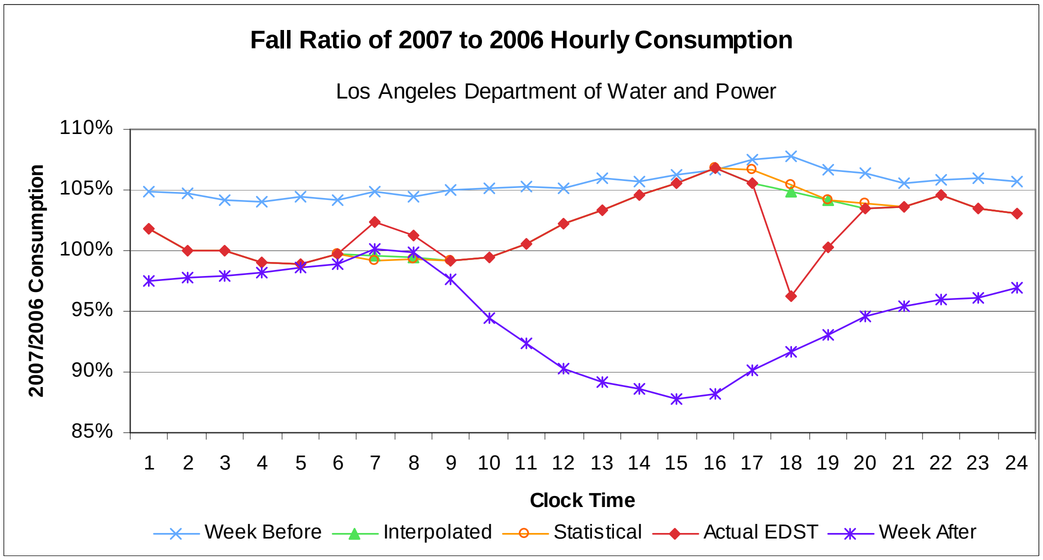

Figure D-34. Los Angeles Dept of Water and Power fall ratio of 2007 to 2006 hourly consumption

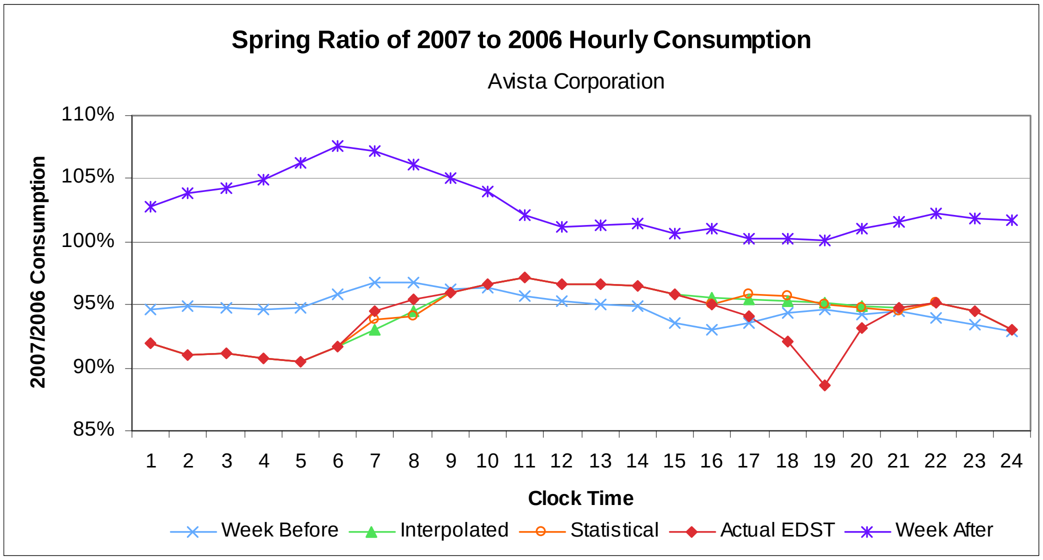

Figure D-35. Avista Corporation spring ratio of 2007 to 2006 hourly consumption

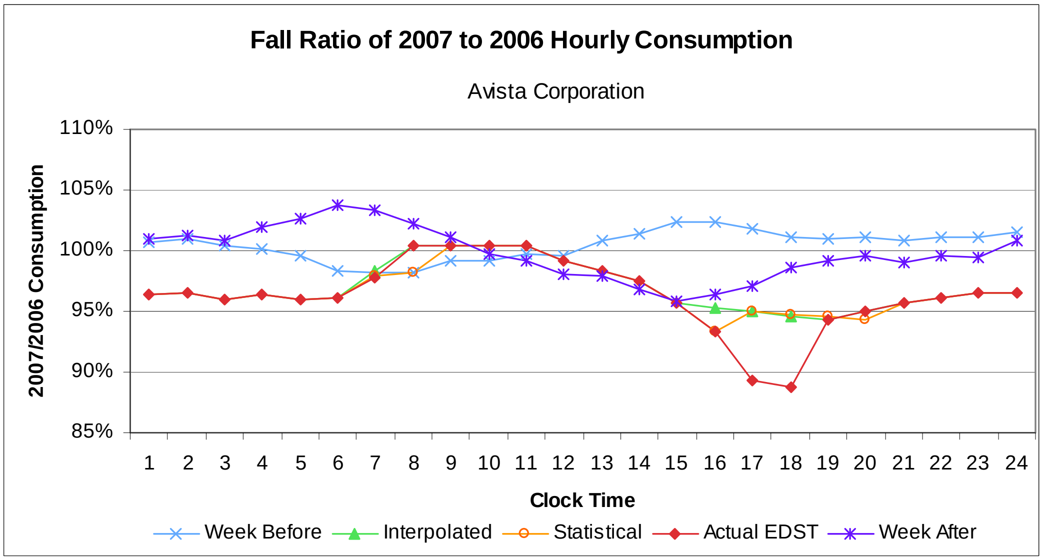

Figure D-36. Avista Corporation fall ratio of 2007 to 2006 hourly consumption

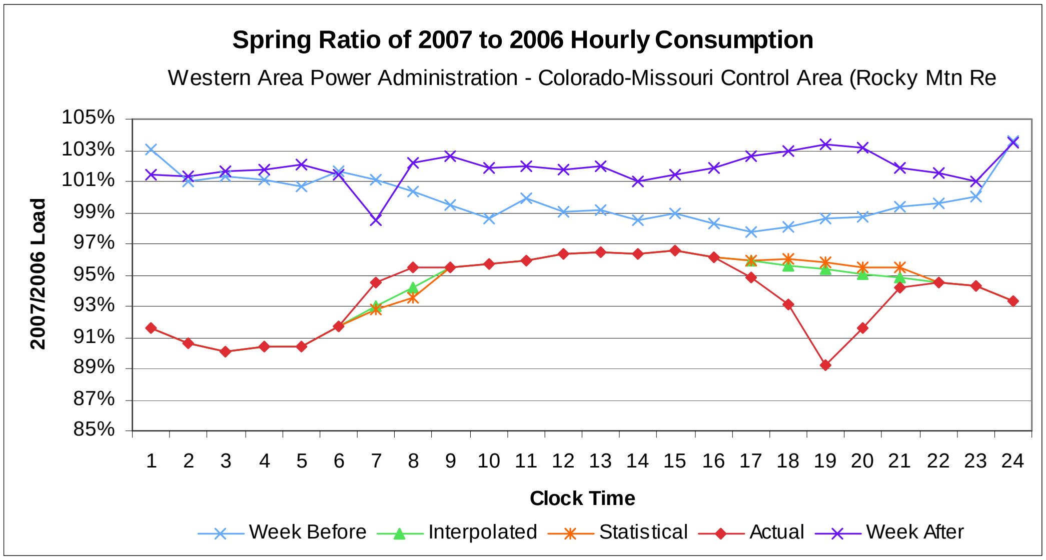

Figure D-37. WAPA Colorado-Missouri Control Area spring ratio of 2007 to 2006 hourly consumption

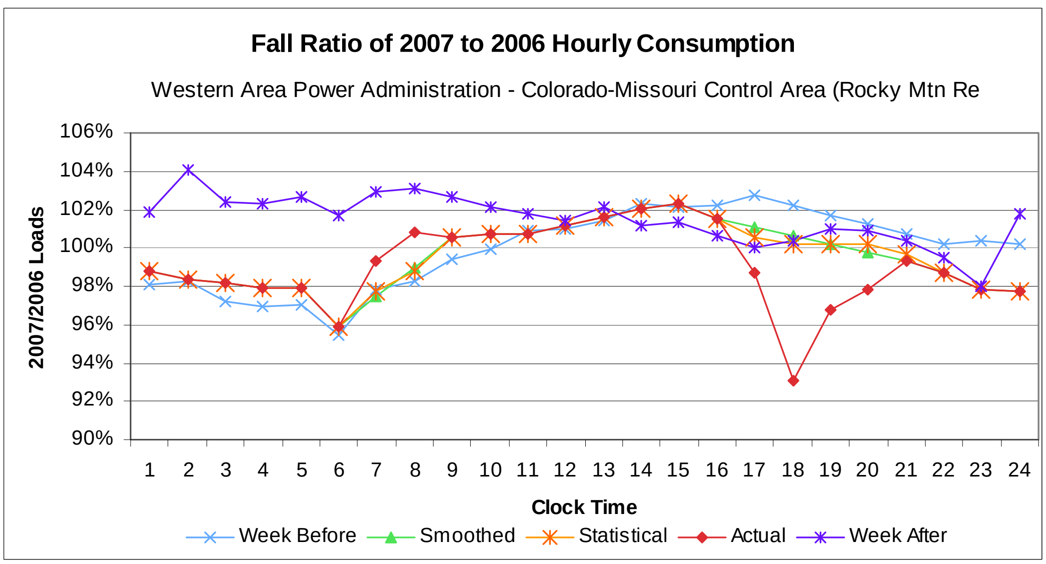

Figure D-38. WAPA Colorado-Missouri Control Area fall ratio of 2007 to 2006 hourly consumption

Appendix E. Electricity Consumption Regression Results for Selected Utilities

E.1 Impacts across the Entire Day: Consideration of Space Conditioning

We based the estimates derived in the statistical model specification in Appendix B.3 on the assumption that the primary impacts of EDST are related to lighting and appliance use and, thus, the analysis can be restricted to estimating changes in energy consumption during specific morning and evening hours. A broader question is whether EDST has additional impacts on heating and cooling use that are more diffuse and may extend to other hours of the day.

Several observations, all related to daylight time and air conditioning use, prompted an examination of this issue. First, Arizona has never implemented DST. While that fact may stem from the desire of Arizona residents to enjoy cooler evening weather (with sunsets occurring earlier in terms of clock time), the likely reduction of evening air-conditioning consumption may also play a role in maintaining year-around standard time in that state. Second, as summarized in Appendix A, a recent study of DST in Indiana indicated that household electricity bills increased after the implementation of DST in 2006, as compared to what would have occurred under standard time (Kotchen and Grant, 2008). However, while suggestive, the Indiana study was concerned only with residential buildings and covered the entire period of daylight time from April through October.

Finally, in support of the study, we undertook some very cursory building energy simulations for several prototypical buildings in San Antonio, Texas in the spring.[49] The building simulations involved the use of typical hourly patterns of electricity use in a single-family house and a small office building in this location. For both types of buildings in March, the DST simulation was conducted by shifting the normal schedule of electricity consumption (for lights and appliances) one hour earlier. For the residential buildings, we also reduced lighting consumption over several evening hours, with a maximum percentage reduction of 30 percent in the hour ending at 7:00 p.m. In a Texas climate, with temperatures approximating the long-term averages for March, the simulations suggested some small increase in overall residential electricity consumption, primarily occurring as a sharper spike in air-conditioning use from 5:00 p.m. to 7:00 p.m.

The situation was somewhat different in the commercial building—in that simulated electricity use actually declined. Most of the normal operation of a typical office building is conducted during portions of the day that are actually cooler under DST. In other types of commercial buildings (e.g., retail or schools), the impact would likely be different. Unfortunately, any type of simulation analysis required us to make a variety of assumptions about both the use pattern of electricity (for non-space-conditioning equipment) over the day and night as well as occupant behavior influencing indoor temperatures. However, these two very limited simulations suggest that DST could affect overall electricity use, but that the effect is likely to be influenced by the

[49] These simulations were undertaken by David Belzer, one of principal investigators of the study, in October of 2007. The building energy simulation tool was EnergyPlus. EnergyPlus has the capability of running the simulation in either standard time or daylight saving time.

occupant behavior, the differences between indoor and outdoor temperatures, and the thermal properties related to the construction of the particular building.

In consideration of the available, and admittedly disparate, evidence suggesting a link between DST and space-conditioning energy use, this study made a concerted effort to estimate the magnitude of such impacts. Because this effect may occur over many hours during the day, statistical models of daily electricity use and hourly electricity use—across all 24 hours of the day—were developed.

This second set of statistical models dealt with the possible effects of EDST on space conditioning by using a system of hourly equations, one for each hour of the day. We imposed a normalizing restriction during the estimation of these models—namely, that the effects of EDST were likely to be small during the hours around noon. The restriction was motivated by an examination of the hourly results for locations where temperature changes between 2006 and 2007 were not large as well as an extensive study of DST in Australia (Kellogg and Wolff, 2008).[50]

Temperature "Shift" under EDST and its potential influence

Assessing the changes in electricity consumption due to EDST over two periods of time is confounded by other effects, primarily weather conditions that can be expected to influence electricity consumption differently in each hour of the day. However, the effect of weather, and particularly temperature, occurs with a lagged effect over a number of hours and so the hour-to-hour changes in total consumption typically follow a fairly smooth pattern. In general, the hourly *difference* between total electricity consumption averaged over two time periods (e.g., over a week or longer) can be expected to also show a relatively smooth pattern.

Before turning to the 24-hour model results, it is useful to illustrate the pattern of temperatures may change between DST and ST. Figure E-1 shows the average hourly temperature in Boston for the third week of EDST, under both DST and ST. We generated the values for ST by simply shifting all of the hourly temperatures under DST one hour earlier. Clearly, the major influence of DST seen in this context is to produce warmer temperatures in the evening and early morning (after midnight) hours.[51]

[50] Additional discussion of the motivation for this restriction is provided in Sections E.2 and E.3, where results for a small sample of utilities in which the restriction was not imposed are presented. As discussed in Section B.3, the specific restriction imposed in this study was that the impacts of EDST were zero in the three hours between 11 a.m. and 2 p.m.

[51] The concept of temperature shifts in time may seem peculiar. The daily pattern of temperatures is primarily influenced by the position of the sun and the resulting heat transfer to and from the earth, which obviously do not abruptly shift at 2:00 a.m. on the transition day to DST. By "springing forward" into daylight time, the typical time pattern of business and household activity shifts one hour earlier relative the to the sun ("solar" time) and the normal rise and fall of temperatures throughout the day. However, because we conducted this analysis from the perspective of users of electricity, the discussion here refers to the temperatures under DST lagging those under ST by one hour.

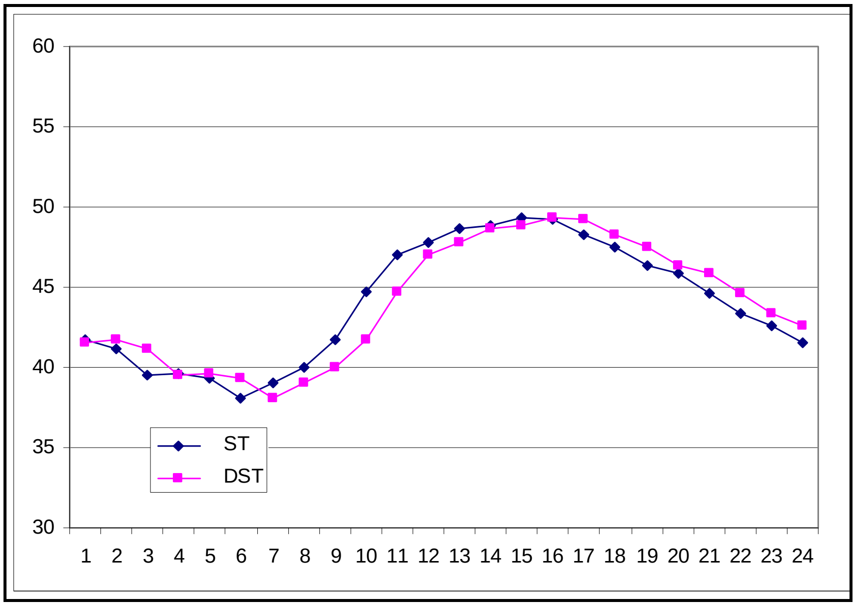

Figure E-1. Average hourly temperatures in DST and standard time (ST), third week of 2007 EDST, Boston

Figure E-2 shows the comparable situation in Tallahassee during the same week at 8 p.m., the average temperatures under DST were more than 4 degrees warmer than had standard time been in effect. These warmer temperatures throughout the evening are reflected as higher consumption for air conditioning for both the evening and much of the night.

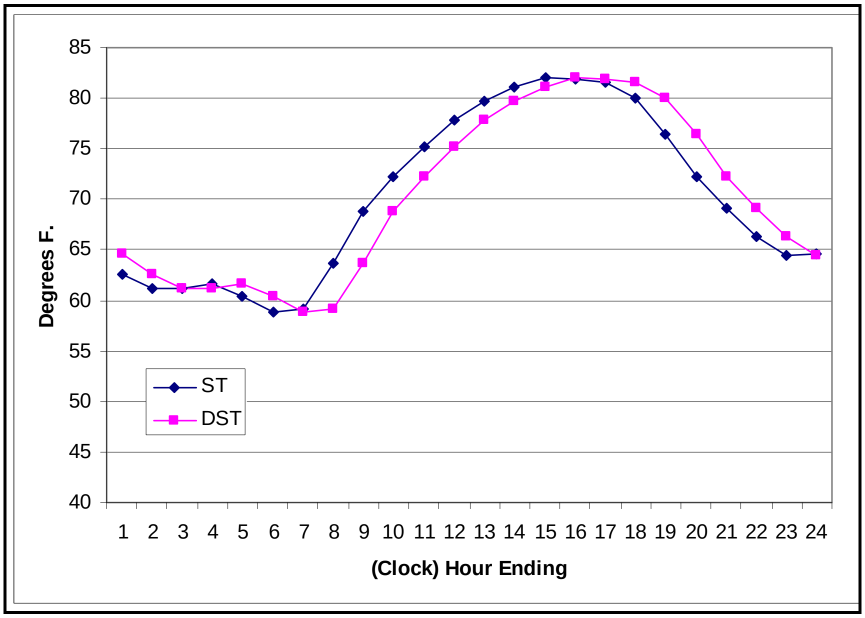

Figure E-2. Average hourly temperatures in DST and standard time (ST), third week of 2007 EDST, Tallahassee

Results from 24- hour statistical models for examining space conditioning and EDST

Figure E-3 shows the results of running the 24-hour statistical models for each hour of the day for Boston for the spring EDST period. The pattern of estimated impacts looks very similar to the ratios of the average 2007 and 2006 consumption shown in Figure 4-2. In that instance, that result stems from the similar weather conditions during the last three weeks in March in both 2006 and 2007.[52] In that case, we did not impose the normalizing restriction that assumes a zero impact during the hours of 11:00 a.m. through 2:00 p.m. The results here support that assumption, and the estimated effects during these hours are very small in this case.

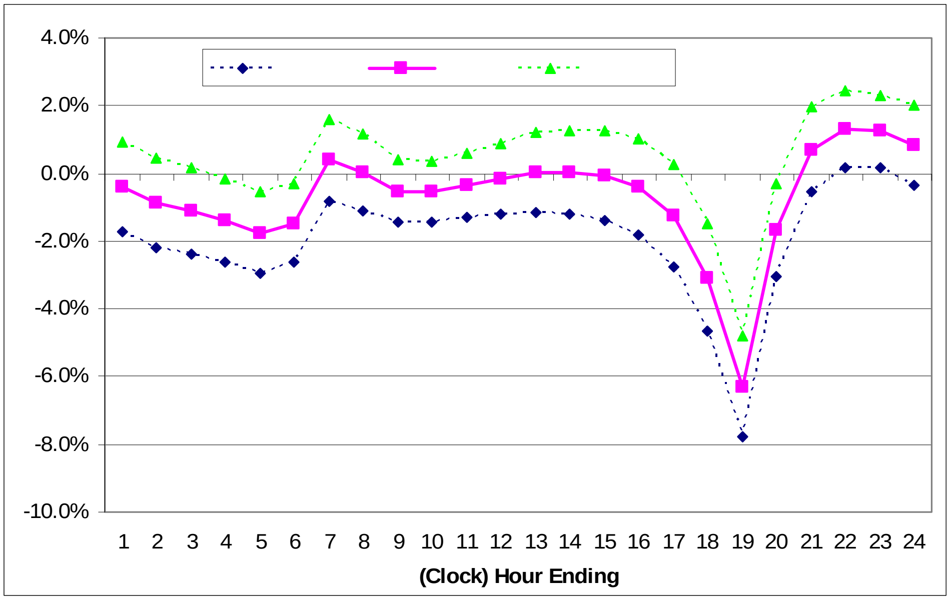

Figure E-3. Estimated percentage changes in hourly consumption due to EDST during spring 2007, Boston

From Table 3-1 in Chapter 3 the average daily impact of the spring EDST period for Boston, based upon the models estimated for the morning and evening hours, was 0.6 percent. Using the hourly model results plotted in Figure E-3, the savings are somewhat larger—summed across all hours the daily savings is estimated to be 0.7 percent. The additional savings appear to come in the late evening and night hours. As temperatures shown in Figure E-1 are slightly higher in these hours under DST as compared to ST, the electric-heated buildings in this area may consume just slightly less electricity. However, the confidence intervals associated with these impacts indicate very weak statistical support for this supposition.

Figure E-4 shows the results of the hourly model applied to the system consumption for the municipal utility serving Tallahassee, Florida. While the hourly pattern of responses is more erratic than for Boston, the general features of the pattern are consistent with the expectation of the impact of EDST in this climate. The estimated impacts spike upward in the late afternoon and extend, with the exception of the declines likely due to lighting and appliance use in the evening, throughout the night.

[52] This statement is in reference to average temperatures over these two years. Readers from the Northeast may recall that a major snowstorm struck the area at the end of the first week of EDST in 2007.

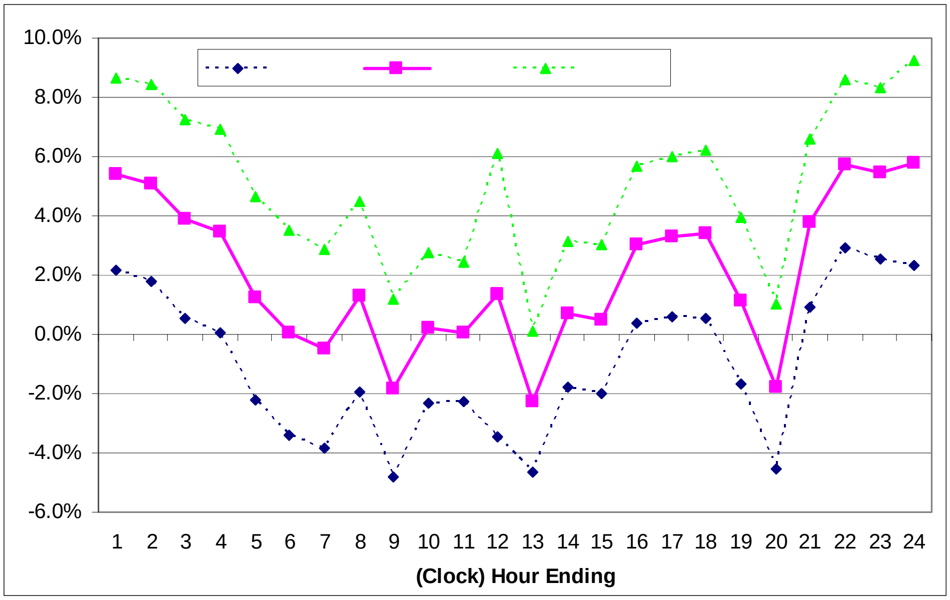

Figure E-4. Estimated percentage changes in hourly consumption due to EDST during spring 2007, Tallahassee

Compared to standard time, temperature will be warmer in the evening and through most of the night until sunrise. The previously shown Figure E-2 shows the average hourly temperatures for the third week of EDST Tallahassee, under both DST and ST. We generated the values for standard time by simply shifting all of the hourly temperatures under DST one hour earlier. At 8:00 p.m., the average temperatures under DST were more than 4 degrees warmer than had standard time been in effect. These warmer temperatures throughout the evening are reflected as higher consumption for air conditioning for both the evening and much of the night.

While the regression results for the models indicate insignificant change on purely statistical grounds [with a standard error exceeding the point estimate of daily savings as shown in Table E-1 (Tallahassee)], for this utility, the results support the notion that EDST may increase overall consumption in some climates and under a given set of weather conditions. (On the other hand, in northern locations, the warmer night temperatures may result in less electricity for heating, illustrated by the slight impact shown above for Boston.)

With regard to the spring EDST period, Table E-1 summarizes the results of the statistical models involving all hours of the day (24-hour model). Clearly, the range of impacts is considerably larger than that implied by examination of just morning and evening hours. In some utilities, the estimated changes in electricity consumption suggest savings of up to 3 percent per day, while for others, EDST indicates increased consumption by greater than 3 percent.

Table E-1. Daily Impacts and Uncertainty Bounds Based on 24-Hour Model, Spring EDST

Utility	Average Daily Pct. Change	Std. Error	Uncertainty Range Lower	Uncertainty Range Upper	Sample Weight	North/ South
Indianapolis Power & Light	-1.9%	1.1%	-4.1%	0.2%	0.022	N
Louisville Gas & Elec	-1.4%	1.1%	-3.6%	0.8%	0.051	N
Dayton Hub - PJM	-1.5%	1.0%	-3.4%	0.4%	0.026	N
Duquesne Hub - PJM	-0.4%	0.7%	-1.9%	1.0%	0.021	N
No. Illinois Hub - PJM	-1.4%	0.8%	-2.9%	0.2%	0.144	N
ERCOT - Coast	-0.6%	1.0%	-2.6%	1.3%	0.046	S
ERCOT - S. Central	-0.2%	1.3%	-2.7%	2.3%	0.024	S
Con Ed - New York	-0.3%	0.5%	-1.1%	0.6%	0.044	N
ISO-NE - Connecticut	-0.9%	0.7%	-2.4%	0.5%	0.020	N
ISO-NE - NE Mass (Boston)	-0.62%	0.6%	-1.8%	0.6%	0.016	N
Lincoln Electric System	-1.9%	1.2%	-4.3%	0.5%	0.017	N
Madison Gas & Elec	-1.0%	0.6%	-2.1%	0.1%	0.018	N
Otter Tail Power Co.	-2.4%	1.3%	-4.9%	0.1%	0.022	N
City of Tallahassee	1.9%	1.4%	-0.9%	4.7%	0.009	S
Gainesville Regional Utility	2.6%	1.1%	0.4%	4.7%	0.006	S
Jacksonville Energy Auth.	1.3%	1.3%	-1.2%	3.8%	0.042	S
Entergy Corp.	-0.1%	1.2%	-2.6%	2.3%	0.036	S
Alabama Electric Coop	-3.0%	2.2%	-7.4%	1.4%	0.012	S
Oglethorpe Power Co.	-4.0%	1.5%	-7.0%	-1.0%	0.048	S
Electric Power - Chattanooga	-2.0%	1.2%	-4.3%	0.4%	0.015	S
Memphis Light, Gas & Water	0.3%	1.1%	-1.9%	2.4%	0.035	S
Dominion Hub - PJM	-2.3%	1.1%	-4.4%	-0.2%	0.079	S
Ameren Control Area	-0.7%	1.0%	-2.7%	1.3%	0.019	N
Kansas City Public Utilities	-1.4%	1.0%	-3.4%	0.6%	0.003	S
Southwestern Publc Service	-1.0%	1.0%	-3.0%	0.9%	0.037	S
Western Farmers Elec Coop	-1.8%	1.4%	-4.5%	0.9%	0.008	S
El Paso Electric	-0.4%	0.9%	-2.2%	1.4%	0.012	S
Public Service of N. Mexico	-0.9%	0.5%	-1.8%	0.1%	0.017	S
California ISO	-0.4%	0.6%	-1.5%	0.8%	0.063	S
Los Angeles DWP	-3.2%	0.7%	-4.7%	-1.8%	0.007	S
Avista Corp	-1.2%	0.8%	-2.8%	0.5%	0.021	N
Portland General Electric	0.3%	0.7%	-1.2%	1.7%	0.037	N
Chelan County PUD	-0.9%	0.7%	-2.3%	0.6%	0.006	N
Black Hills Corporation	-3.1%	1.4%	-5.8%	-0.3%	0.002	N
WAPA - Rocky Mountain	-3.1%	0.7%	-4.5%	-1.8%	0.014	N
National Average (weighted)	-1.09%	0.27%	-1.6%	-0.6%	1.000	
North (17 utilities)	-1.17%	0.27%	-1.7%	-0.6%		
South (18 utilities)	-1.01%	0.45%	-1.9%	-0.1%		

NOTE: “N” = North; “S” = South

Using the same procedure as described for Tables 4-4 and 4-6, we estimated the national average impact to be -1.1 percent with a standard error of 0.27 percent. The (95 percent) uncertainty range for electricity *savings* is between 0.7 and 1.5 percent.

Given the magnitude and variability of these results, one of the major issues in this study related to electricity use was whether we can consider the estimates shown in Table E-1 robust estimates of the overall impact of (spring) EDST during 2007. As discussed briefly below, the basic judgment was that the answer is no. We can summarize several reasons for that conclusion as follows:

1) As shown in Figures E-1 and E-2, DST only shifts the hourly pattern of temperatures with respect to the operating schedule of businesses and households. As shown in those figures, the changes in temperature for a *specific* hour of the day would only be in the neighborhood of a few degrees (although as high as 4 degrees in a southern location such as Tallahassee. However, based on the daily model estimates as part of the study, the impacts are more consistent with the *average daily* temperature changing by several degrees or more. Thus, the magnitude of the effect estimated by the 24-hour model is implausible from the standpoint of the response of typical buildings to changes in temperature.
2) For some of the utilities, the hourly pattern of EDST impacts is implausible. Again, in reference to Figures E-1 and E-2, the effect of daylight time is to defer peak afternoon temperatures. Thus, a credible pattern of responses to EDST would show increased consumption occurring in only the very late afternoon, evening, and early morning hours. However, in more than a few utilities, the implied impacts from EDST begin to occur in mid-afternoon, a period that is cooler under daylight time than under standard time. This behavior is only consistent with the statistical models that include the response to the warmer temperatures experienced during 2007 as compared to 2006 as part of the EDST impact.

From a larger perspective, a robust statistical decomposition of weather effects from those of DST in the spring of 2007 is complicated by the sharp differences in 2007 temperature conditions as compared to 2006. The last few weeks of March in 2007 were considerably warmer than normal (and 2006) in many parts of the United States. As illustrated earlier, average high temperatures during the last two weeks in March were as much as 10 to 20 degrees warmer in 2007 as compared to 2006 in some utility service areas.

Perhaps the most telling statistical evidence about the particular effects of temperature changes can be obtained from the published degree-days by region of the country (EIA, 2006 and 2007b). Figure E-5 shows a chart of heating degree-days by census region for March under normal conditions (30-year average) and for 2006 and 2007. Only in the Northeast were temperature conditions similar between 2006 and 2007. In the three other regions of the United States, the number of degree-days were at least 15 percent lower in 2007 than in 2006 (35 percent lower in the West). Based upon the temperature data collected for this study, most of this difference occurred in the last several weeks of March.[53]

[53] Thus, if HDD data were available only for the EDST period, the percentage changes would likely be greater than those shown in the chart for the entire month.

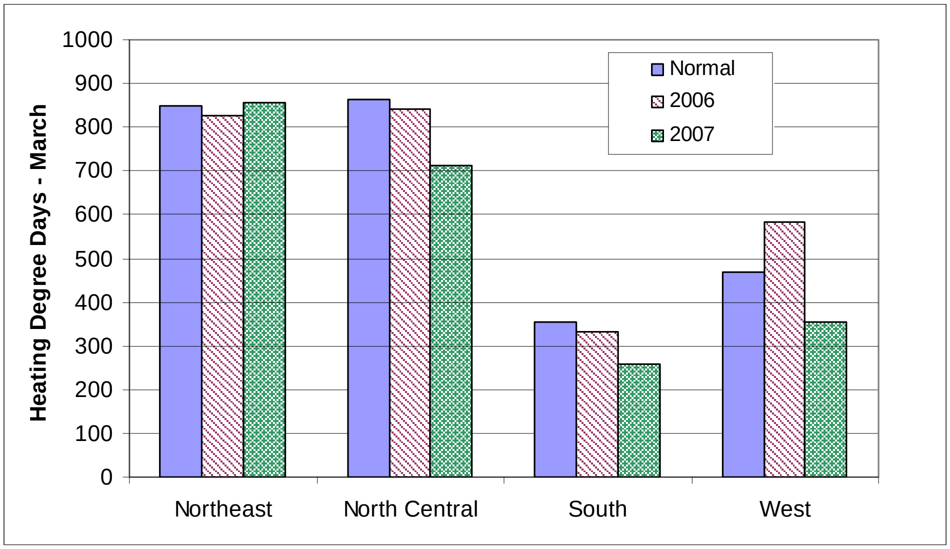

Figure E-5. Heating degree-days by census region for March: normal, 2006, and 2007

Figure E-6 shows the cooling degree-days for the same periods and regions. Based upon a reference temperature of 65 degrees, the number of cooling degrees is normally zero or negligible in both the Northeast and North Central regions of the United States.[54] The South and West show a considerably higher number of cooling degree-days for 2007 as compared to 2006, particularly in the West.

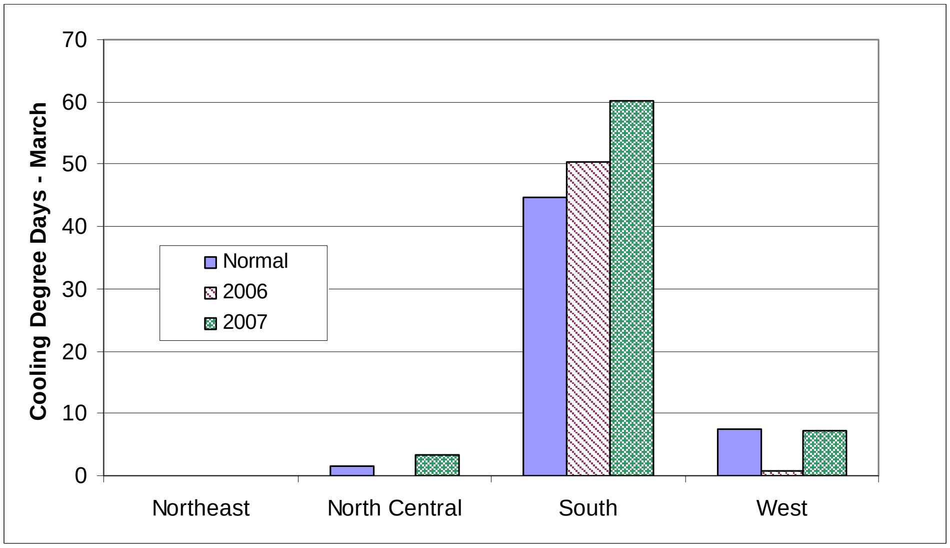

Figure E-6. Cooling degree-days by census region for March: normal, 2006, and 2007

[54] A discussion of degree-days and reference temperatures is included in Appendix (Section) B.3. The use of 65 degrees F. for the cooling reference temperature leads to a measures of cooling degree-days that understates the demand for cooling by many commercial buildings.

E.2 Detailed Results for Selected Utilities

This section presents the empirical results for six utilities, selected to illustrate the range of estimated impacts from EDST for the spring of 2007. Tables and graphics were prepared to show both regression results and temperature differences between 2006 and 2007. An abbreviated set of empirical results for the fall EDST analysis is included for three of the utilities.

For each of the six utilities, the results from the 24-hour model are shown in both graphical and tabular form. In this subsection, the results from an unrestricted 24-hour model are shown; this model does not impose the mid-day restriction (i.e., normalization) used to develop the results in Table E-1. In this regard, the results in this section illustrate cases where the restriction may be appropriate and other cases where the restriction may not be sufficient to identify credible estimates of EDST impacts.

E.2.1 Results for Boston (ISO-NE, Northeastern Massachusetts)

Descriptive summary

Figure E-7 shows the ratio of the 2007 consumption to the 2006 consumption during each of hour of the EDST period, averaged over all three weeks of the EDST period in the spring. The ratios in the figure clearly indicate a relative increase in consumption during several hours in the morning in 2007 and the sharp decline in consumption spread across four or five hours in the evening. For the remaining hours, the ratios might suggest an increase in consumption in 2007. However, by themselves, these ratios reflect no adjustment for differences in weather between 2006 and 2007 or changes in the overall consumption between 2006 and 2007 from population growth or economic activity. Pending these adjustments, the graph can only suggest a relative increase in consumption for several morning hours and a larger decline in evening consumption after the implementation of EDST.

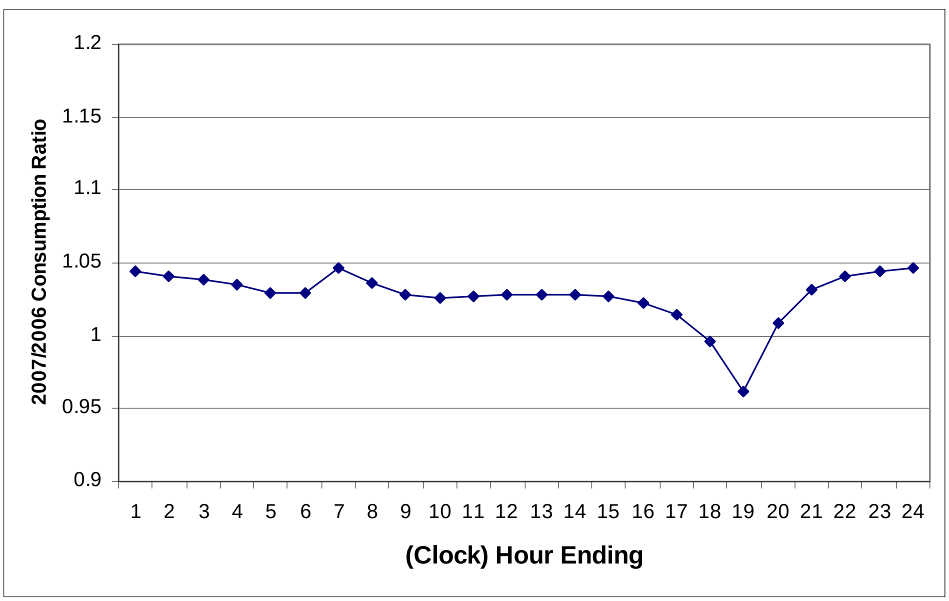

Figure E-7. Ratio of 2007 hourly consumption to 2006 hourly consumption during spring EDST period, NE-ISO N.E. Massachusetts (Boston)

Figure E-8 provides a more detailed look at the 2007/2006 consumption ratios by hour, by computing the average ratios for each of the three weeks in the Spring EDST period.[55] The purpose of these graphs is show how stable the pattern of the ratios are from one week to the next. For Boston, the three week-long profiles of hourly ratios are very similar, all showing an uptick in morning electricity use at 7:00 a.m. and reductions during the evening hours that are similar for the three separate weeks

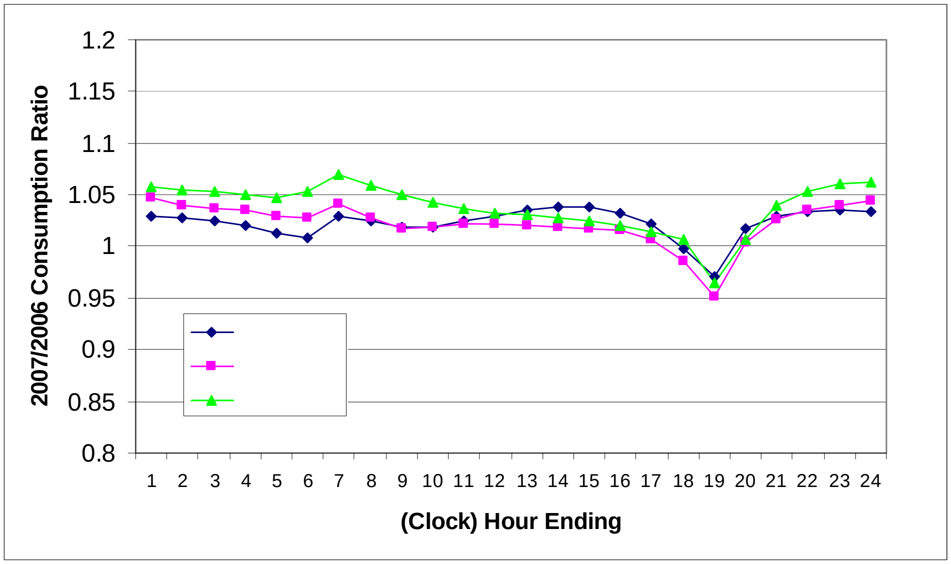

Figure E-8. Ratio of 2007 to 2006 average hourly consumption by week during spring EDST, NE-ISO N.E. Massachusetts (Boston)

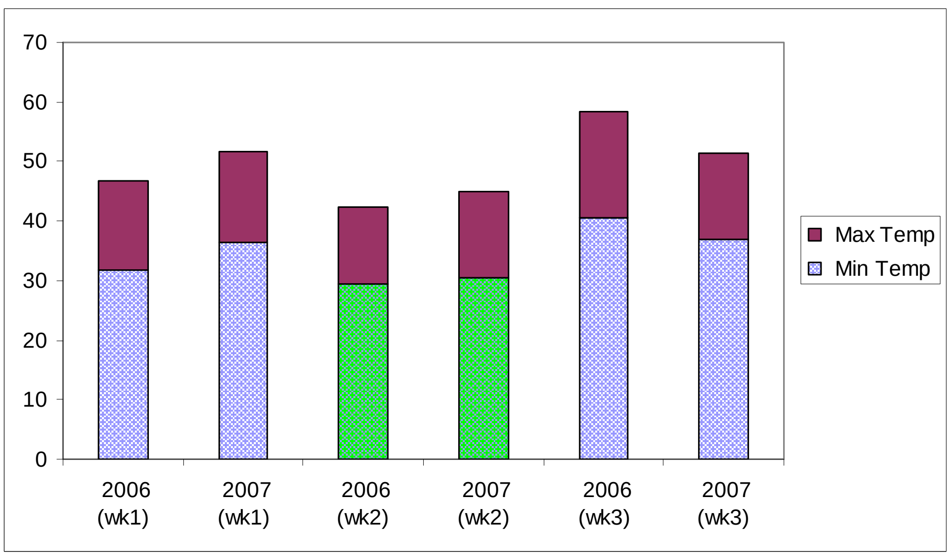

Figure E-9. Average Maximum and Minimum Temperatures by Week during spring EDST periods, 2006 and 2007, ISO-NE Northeast Massachusetts (Boston)

[55] The weeks include the consumption from Sunday through the following Saturday. The first week begins March 11, 2007, as compared to the week in 2006 beginning on March 12. Similarly, the second week begins March 18, 2007 and third week begins March 25, 2007.

In part, the stability of the hourly consumption changes across the weeks during the last three weeks of March stems from the similar weather conditions during 2006 and 2007, at least as measured by average temperatures. Figure E-9 compares the weekly averages of maximum and minimum temperatures for both 2006 and 2007 during the spring EDST period. For the first two weeks, the average maximum temperature between 2006 and 2007 differed by five degrees or less. In the third week, the average maximum temperature was almost ten degrees colder, but the average minimum temperature shows a somewhat smaller difference.

Regression Model Results

Daily Model

Table E-2 presents the estimated coefficients for the daily model (Equation B.1 above) for Boston. The results suggest a very satisfactory model in the explanation of the variation of daily system loads.[56] On the top right of the panel, the fraction of explained variance (RSQ = R^2) is over 97 percent. The mean absolute percentage error (MAPE) is 1.19 percent.

Table E-2. Daily Model Regression Results for the Spring – ISO New England (Boston)

Utility	ISO New England - NE Mass	Estimation Period:	Day	Sample Period:	Feb. 2 - April 30 2006
Location (weather):	Boston				Feb. 2 - April 30 2007

Temperature Parameters			Reference Temperature		Goodness of Fit		Autocorrelation		Average Daily Consumption (MWh)	
Adj. Wgt.	Period	Lag Wgt	HDD-Ref	CDD-Ref	R^2	0.973	D.W.	1.287	2006	2,806
(wt)	day(0)	0.690	52.9	56.1	MAPE	1.19%	rho	0.357	2007	2,964
0.43	day(-1)	0.293								
	day(-2)	0.018								

OLS	Constant	Time	Load Grow	Saturday	Sunday	HDD-Ref	HDDSqr	CDD-Ref	CDDSqr	EDST-C	EDST-I	DST	Pres_Day
Coef.	2813.7	-2.2	106.5	-253.9	-320.8	9.24	0.23	-1.45	2.91	8.7	-23.5	-15.7	-176.9
S. E. (OLS)	18.2	0.4	8.4	10.0	9.9	1.48	0.039	14.17	2.10	16.8	16.6	22.8	33.3
S. E. (N-W)	17.8	0.4	10.3	10.0	10.7	1.48	0.04	9.52	1.22	17.5	18.5	27.9	
AR1	*First-order autocorrelation rho (iterative) =*				0.340								
Coef.	2807.0	-2.2	107.8	-246.6	-318.3	9.89	0.21	12.01	1.12	13.9	-26.4	-13.0	-146.4
S.E.	21.9	0.5	11.4	9.0	9.0	1.65	0.04	13.55	1.92	21.9	22.0	29.2	29.2

The top left portion of the table shows the parameters used to construct the temperature variables. The weighting factor to adjust the maximum and minimum temperatures (wt) is selected by the statistical optimization process as 0.43. This result likely reflects some dominance of heating (rather than cooling) electricity use during the sample period – a result not surprising for a northern and marine, location such as Boston. Thus, in the construction of the heating degree-day variable, somewhat more weight is actually on the maximum temperature for the day than on the minimum temperature for the day.[57] The lag weights (wd) indicates that the

[56] The dependent variable in the daily model is the *average hourly* consumption for each calendar day. Thus, the daily consumption may be considered in terms of average megawatts rather than a total of megawatt-hours over the day. This convention makes the magnitudes of daily consumption comparable to those graphed in Figure 4-1 and the hourly consumption values used in the hourly models.

[57] From the discussion in Section B.3, a weight of 1.0 for this variable indicates that using the minimum temperature to define heating degrees and the maximum temperature to define cooling degrees yields the best in-sample predictions. Equal weights suggest that minimum and maximum temperatures have equal importance for both degree-day measures. In some locations, the weight selected by optimization procedure is greater than 0.5. The different behavior for Boston over this time period may result from its coastal climate where cold, relatively humid, conditions may lead to the daily maximum temperature being slightly more important in explaining the amount of electricity used for heating.

day-to-day variation in electricity consumption is best explained by weighting the current day's heating and cooling degrees by about 70 percent (0.69) and the previous day's by about 30 percent (1 – 0.69). Relative to the adjusted minimum and maximum temperatures, the reference temperatures to compute daily heating and cooling degrees are 52.9 degrees F. and 56.1 degrees F., respectively.

The degree of temporal or autocorrelation between the model errors (residuals) is significant. Autocorrelation involves a statistical dependence of the model errors (which reflect random factors not included in the model) from one time period to the next. The presence of such autocorrelation does not bias the coefficient estimates, but tends to understate their computed standard errors with OLS. The Durbin-Watson statistic of 1.29 suggests a modest degree of autocorrelation.[58] The "rho" value shown in the table is the first-order autocorrelation coefficient obtained by regressing the model errors on their values for the previous day.

The first set of the rows in the lower portion of the table shows model coefficients (as described in Equation B.1 above) as estimated with standard regression (ordinary least squares, OLS). The values immediately beneath the estimated coefficients are the standard errors produced by OLS. The second set of standard errors is computed by the Newey-West procedure developed in 1987. The Newey-West (N-W) standard errors are considered to be more robust estimates of the true standard errors in the presence of autocorrelated errors.

The second set of coefficient estimates are developed by assuming a first-order autocorrelation process [commonly termed AR(1)] and using an iterative process to develop revised estimates of the coefficients and associated standard errors. Given the assumption of first-order autocorrelation, all of the model variables are transformed by the equation $x(t)' = x(t) - rho * x(t-1)$ and the model using the transformed data is re-estimated using OLS. The iterative technique involves searching for the appropriate value of rho that maximizes the explained variance of the transformed model.[59] The resulting standard errors are less likely to be understated than those derived under OLS. The AR(1) model results are included as part of the overall estimation strategy, as this device is often used to correct for autocorrelation. However, the construction of the heating and cooling degree-day variables is based solely upon minimizing the unexplained variance with OLS.

The first two coefficients relate to the time trend and the overall growth in system electricity consumption between 2006 and 2007. The coefficient of time trend variable (measured by days) is -2.2. Relative to the average hourly consumption per day of 2,806 MW, this coefficient reflects increasing daylight and other seasonal effects and implies about a 0.08 percent reduction per day in average consumption over the months of February through April. In terms of overall load growth, the model suggests about a three percent increase in the average consumption in

[58] The Durbin-Watson statistic is a commonly used measure of the degree of autocorrelation of the error terms in an econometric model. In this particular model, values below 1.5 generally denote a statistically significant degree of autocorrelation.

[59] This technique is known as the Hildreth-Lu correction process, after the two econometricians who proposed the technique in 1960. With the number of observations in the study, the estimation approach is equivalent to a maximum likelihood method. See any introductory econometrics text for a more complete discussion. See, for example, Kennedy 2000.

2007 as compared to 2006. The value of the binary indicator variable (Load Grow) for 2007 is 106.5, with a relatively small standard error (implying a t-statistic over 10, computed as the coefficient of 106.6 divided by the standard error of 8.4.)

As expected, the estimated coefficients on the indicators for Saturday and Sunday are both negative and statistically significant. Comparing the Saturday coefficient to the average daily load, electricity consumption on Saturdays is about 9 percent less than the weekday average. That percentage decline is greater on Sundays, with more than an 11 percent decline. The variables labeled as “HDD-Ref” and “HDD-sqr” represent the heating degree variables (defined in Equation B.1 above) and its squared value. The estimated coefficients for both variables are highly significant, as indicated by their relatively smaller standard errors. The coefficient on the squared term suggests a nonlinear (increasing) response of heating to colder temperatures.

Given that average high temperatures during these months seldom exceeded 60 degrees, the amount of air conditioning is very small. Neither coefficient on cooling degrees nor its squared value exceeded its standard error.

The last three variables in the model related to estimation of impacts from daylight saving time. The coefficient for the control period for EDST (EDST-C) suggests that there were no significant factors other than weather that affected the loads during the last three weeks in March in both 2006 and 2007. The value of the coefficient is only 8.7, with a standard error of 16.8.

For this analysis, the key variable of interest is EDST-I. The coefficient of -23.5 suggests a reduction per day of about 0.7 percent to 0.8 percent over the 2007 EDST period. However, the (Newey-West) standard error is only marginally smaller (+/- 18.5). During April, during which daylight time was observed in both 2006 and 2007, the model indicates a reduction of about 16 MW per day as compared to time periods on standard time. However, the statistical significance of this finding is even lower than for the EDST period, given that the standard error exceeds the value of the coefficient.

Hourly Model

As described in Section B.3, the hourly model was initially run as separate OLS regressions for each hour of the day. The dependent variable is the reported system electricity consumption for that hour. The weather variables, as developed for the daily model, are used for each hourly equation. The key assumption is that the hour-specific pattern and magnitude of electricity consumption responses to daily minimum and maximum temperatures is stable over the sample period. Thus, the variability in weather effects is captured in the differential coefficients on the weather variables.

Figure E-3 (shown in the previous subsection) summarizes the results for the key variable of interest—the estimated impact on the system load derived from the EDST variables in Equation (B.13). The impacts derived from the EDST coefficients for the three separate weeks have been aggregated for this figure. The figure shows the percentage changes along a confidence defined by plus or minus one standard error. If one considers the confidence interval—loosely measured by one standard deviation on either side of the estimated mean impact—only evening hours display changes statistically significant different from zero.

Table E-3 summarizes the results from the daily and hourly models in terms of the estimated change in daily electricity consumption. Depending upon the choice of the OLS or AR1 models,[60] daily consumption is estimated to have fallen by between 0.8 and 0.9 percent per day. Given the sample size of 186 observations, a 90 percent confidence interval can be estimated by multiplying the standard error shown by a factor of 1.65.[61] Thus, in terms of the statistical model employed here (OLS), the confidence interval would range between a reduction of 1.85 percent and an increase of 0.24 percent of the daily electricity consumption.

Table E-3. Comparison of Daily Consumption Changes from Alternative Models, Boston

	Daily Model		Hourly Model (24-hr sum)
	OLS	AR(1)	OLS
Chg. (MW)	-23.5	-26.4	-25.3
S.E.	18.5	22.0	NA
% Chg.	-0.8%	-0.9%	-0.9%
S.E.	0.6%	0.8%	NA

When the separate impacts from the 24 hourly models are averaged, the resulting mean change in the daily electricity consumption is slightly greater than that from the daily model (-25.3 MW vs. -23.5). This provides a measure of confidence that both models are adequately explaining the observed consumption. It also provides some measure of confidence that the pattern of the 2007/2006 consumption ratios shown in Figures E-7 and E-8 are indeed reflecting changes primarily due to EDST.

E.2.2 Results for Dayton (Dayton Hub of PJM)

Descriptive summary

As was done for Boston, it is useful to gain perspective by illustrating changes in the consumption profiles and average temperatures between 2006 and 2007 over the last three weeks of March. Figure E-10 shows the ratios of hourly loads by week during the EDST period. Figure E-11 compares the average weekly maximum and minimum temperatures across the two years. In the first week of the EDST period, temperatures were comparable between the two years. This similarity is reflected in the plot of ratios in Figure E-10, where the ratios during the night hours are near 1.0 (indicating roughly similar absolute loads for these two years). Week 2 during 2006 was very cold, with average low temperatures in the mid 20s, and highs only about 40 degrees.

[60] In the final set of hourly models, only the OLS estimates were retained. The hourly models discussed in this section were estimated individually for each hour. Thus, the lagged error term relates to the corresponding hour for the previous day. The degree of autocorrelation in these model was typically very small, precluding the need to estimate separate AR(1) models.

[61] This factor is taken from a table of percentiles for the 0.90 significance level for the t-distribution. For a sample of 120 observations, the tabulated value is 1.658 and, for an infinite sample, the value is 1.645. The value of 1.65 was chosen as appropriate for the purpose here.

The weather pattern in the same week during 2007 was quite different with temperatures nearly 15 degrees higher. The profile of the ratios is consistent with less electric heating in 2007, especially at night. The hourly ratio of the loads (2007/2006) increases from about 0.90 to 0.97 from the early morning hours to mid-afternoon.

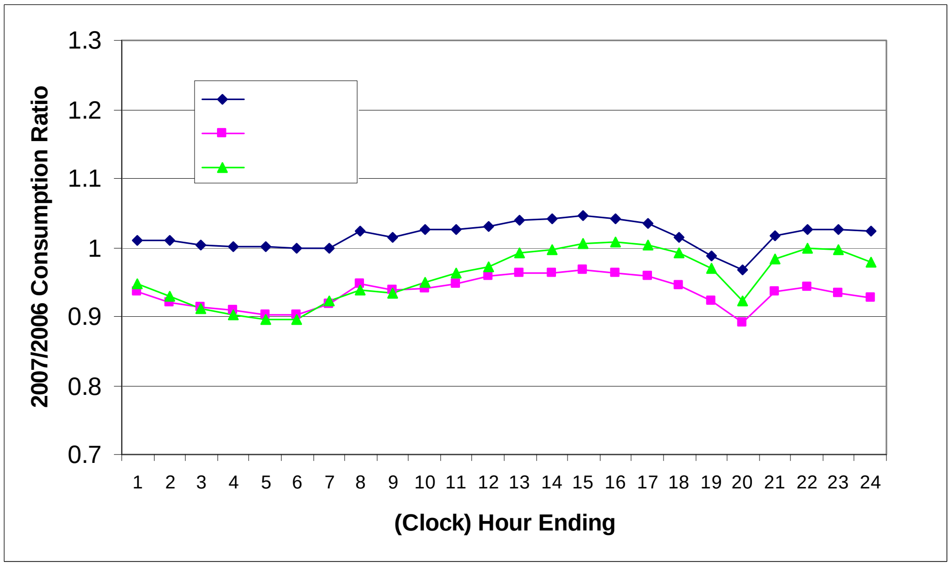

Figure E-10. Ratio of 2007 to 2006 average hourly consumption by week during spring EDST, Dayton Hub - PJM

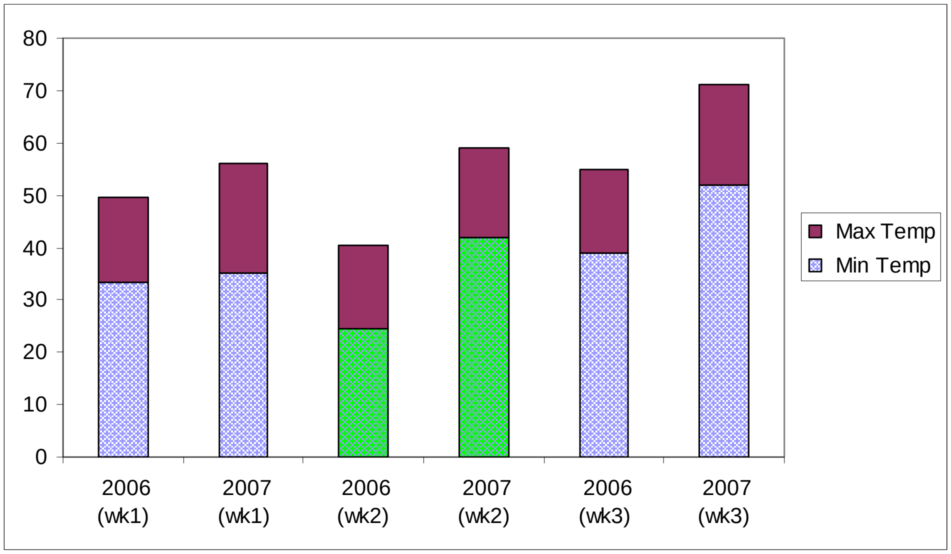

Figure E-11. Average maximum and minimum temperatures by week during spring EDST periods, 2006 and 2007, Dayton Hub, PJM

The third week during EDST (last full week in March) was also much warmer in 2007 than in 2006. The ratios here suggest some cooling was taking place (perhaps concentrated in commercial buildings) during 2007, as average temperatures reached 70 degrees. The ratios of hourly system consumption continued to increase during the mid-afternoon and evening hours as compared to the pattern of the ratios for week 2.

The data displayed in Figures E-10 and E-11 clearly indicate the importance of temperature effects upon the profile of hourly loads. However, the presumed impacts of daylight time can still be discerned from the ratio plots, with slight morning deviations from trend and the larger negative changes during the evening hours.

Regression Model Results

Daily model

Table E-4 presents the estimated coefficients for the daily model for Dayton Ohio. Again, the statistical fit is very good with a R^2 exceeding 0.96 and a MAPE of just under 2 percent. Again, there is an indication of autocorrelation of the errors, but not as pronounced as for Boston.

Table E-4. Daily Model Regression Results for the Spring – Dayton Hub - PJM

Utility	PJM Interconnection AEP-Dayton Hu	Estimation Period:	Day	Sample Period:	Feb. 2 - April 30	2006
Location (weather):	Dayton				Feb. 2 - April 30	2007

Temperature Parameters			Reference Temperature		Goodness of Fit		Autocorrelation		Average Daily Consumption (MWh)	
Adj. Wgt.	Period	Lag Wgt	HDD-Ref	CDD-Ref	R^2	0.961	D.W.	1.567	2006	2,030
(wt)	day(0)	0.765	61.8	53.7	MAPE	1.87%	rho	0.220	2007	2,142
0.49	day(-1)	0.230								
	day(-2)	0.005								

OLS	Constant	Time	Load Grow	Saturday	Sunday	HDD-Ref	HDDSqr	CDD-Ref	CDDSqr	EDST-C	EDST-I	DST	Pres_Day
Coef.	2010.0	-1.6	55.2	-266.8	-343.4	6.66	0.10	-0.17	0.24	1.7	-21.2	-31.4	-37.8
S. E. (OLS)	34.4	0.5	10.5	12.0	12.1	1.76	0.026	6.46	0.41	19.9	21.5	27.1	39.4
S. E. (N-W)	36.8	0.5	11.7	11.5	12.7	2.00	0.03	6.90	0.44	17.4	16.2	27.9	
AR1	*First-order autocorrelation rho (iterative) =*				0.261								
Coef.	2004.9	-1.7	56.1	-253.4	-338.9	7.11	0.09	0.71	0.23	4.4	-22.3	-25.4	-32.3
S.E.	39.5	0.6	13.4	11.4	11.7	2.01	0.03	6.69	0.40	24.9	26.6	33.5	36.8

The coefficients on the temperature variables indicate the dominance of heating over cooling during the sample period. The weight used to adjust the daily maximum and minimum temperatures conforms more to expectations than for Boston, as it is near 0.5. Thus, the temperatures used in the computation of daily heating degrees have about equal weights attached to the both the minimum and maximum temperatures. The reference temperature for cooling is lower than that for heating, reflecting the behavior of commercial buildings that will begin to cool under lower outside temperatures, combined with their higher internal heat gains, as compared to residential buildings. Finally, the lag weights to combine the current and lagged daily degree-day variables are roughly the same as for Boston (wt = 0.77, implying 77 percent of weight on the current day, 23 percent on the previous day).

The coefficient on the binary control variable for EDST (EDST-C) is negligible, suggesting no unidentified factors were systematically influencing the average consumption during the EDST period in both 2006 and 2007. The coefficient of the variable of interest, EDST-I, is negative (-21.2), but of marginal statistical significance. The coefficient on the DST binary variable is also negative (-31.2), but is only slightly greater than its estimated standard error.

Hourly Model

Figure E-12 (Dayton) plots the estimated percentage impacts from EDST over the 24 hourly periods. The extended 2-hour upward spike in morning consumption shows up very clearly. The graph shows negligible impacts during the later morning hours. While the morning impact is somewhat greater in Dayton as compared to Boston, so is the evening impact. For the hour ending at 8:00 p.m., consumption is reduced by nearly 8 percent. For Dayton, the inconvenience of darkness in the morning may be partially offset by having daylight for additional outdoor activities well into the evening.

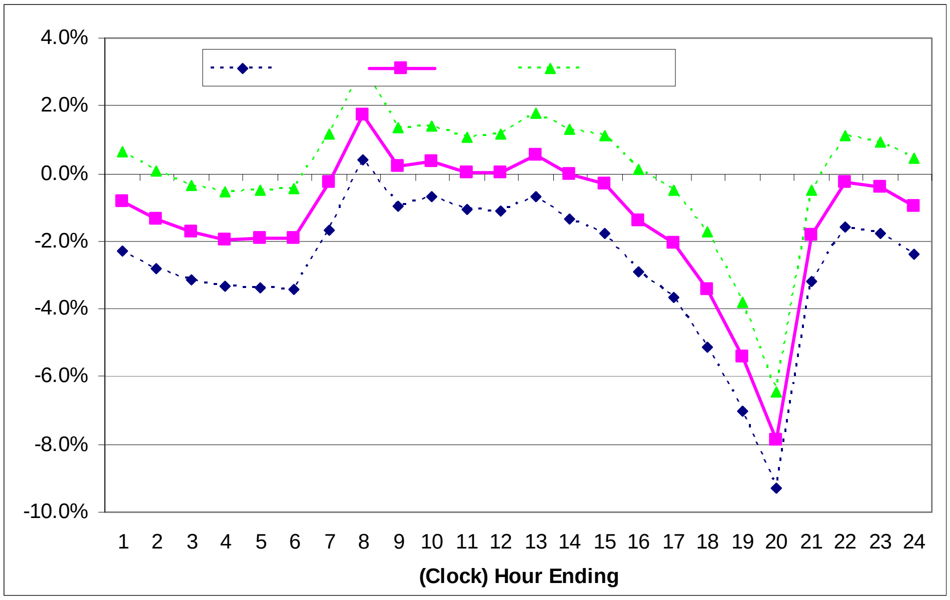

Figure E-12. Estimated percentage changes in hourly consumption due to daylight saving time during spring EDST, Dayton Hub – PJM.

Table E-5 compares the estimates of daily electricity change from the various model specifications. All of the methods produce similar point estimates of impacts—savings of between 1.1 and 1.3 percent per day. The aggregated results from the hourly model again are very consistent with those from the single regression used to explain the daily consumption. The standard errors, however, show more variability.

Table E-5. Comparison of Daily Consumption Changes from Alternative Models, Dayton Hub - PJM

	Daily Model		Hourly Model (24-hr sum)
	OLS	AR(1)	OLS
Chg. (MW)	-21.2	-22.3	-24.9
S.E.	16.2	26.6	NA
% Chg.	-1.1%	-1.1%	-1.3%
S.E.	0.8%	1.4%	NA

E.2.3 Results for Memphis (Memphis Light, Gas, and Water)

Descriptive summary

For the municipal utility serving Memphis, Figures E-13 and E-14 provide some insight with respect to air conditioning use during the EDST period in 2007. As shown in Figure E-13, in the first week of the EDST period, temperatures were very similar between the two years. This similarity is reflected in the plot of ratios in Figure E-14 where the ratios fall in a fairly narrow band of 1.0 to 1.10.

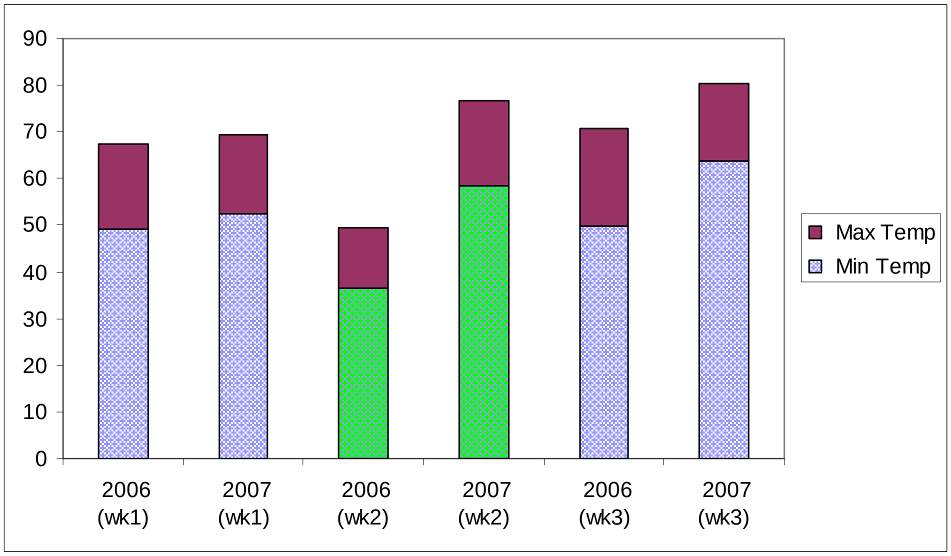

Figure E-13. Average maximum and minimum temperatures by week during spring EDST periods, 2006 and 2007, Memphis Gas, Light, and Water

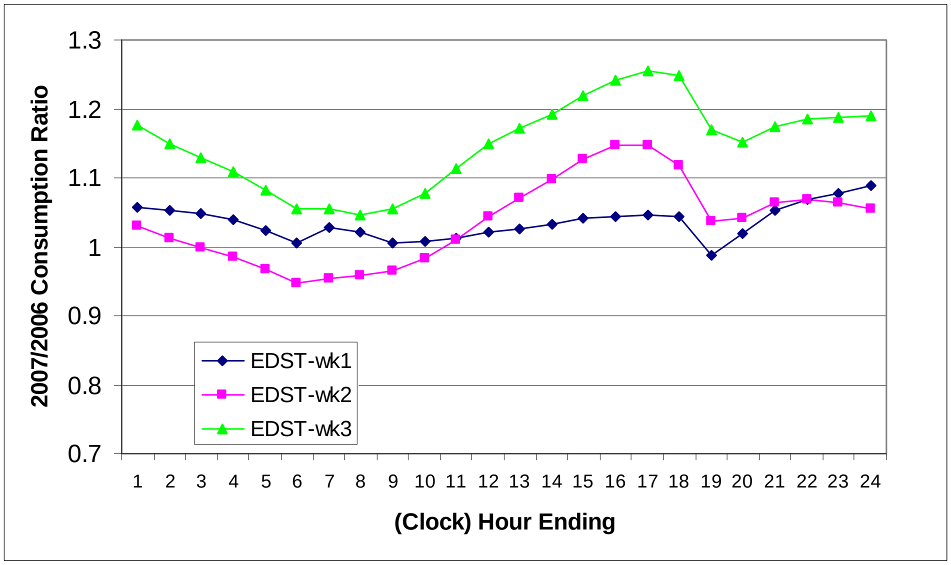

Figure E-14. Ratio of 2007 to 2006 average hourly consumption by week during spring EDST, Memphis Gas, Light, and Water

As in Dayton, week 2 of the spring EDST period during 2006 was relatively cold, with average low temperatures in the high 30s, and highs only about 50 degrees. A comparison of 2006-2007 temperatures for this week show greater year-over-year change than in Dayton, as 2007 temperatures were roughly twenty degrees higher as compared to the previous year. The plot of the ratios suggests that there was both less electricity used for heating in the morning as well as more electricity used for cooling in the afternoon in 2007. This supposition is based on the observation that the increase in morning consumption in the 7:00 a.m. and 8:00 a.m. hours is not evident in the plot of the ratios for the second week. In essence, the reduced heating during the morning due to higher temperatures roughly offsets the increased need for electric lighting over the course of this week and the following week. The significant increase in the ratios during the afternoon is clearly related to cooling demand where maximum temperatures were near 80 degrees in 2007.

Regression Model Results

Daily model

Table E-6 presents the estimated coefficients for the daily model for Memphis. Again, the statistical fit is very good with an R^2 exceeding 0.90 and MAPE of just over 2 percent.

Table E-6. Daily Model Regression Results for the Spring – Memphis Gas, Light, and Water PJM

Utility	Memphis Light, Gas and Water	Estimation Period:	Day	Sample Period:	Feb. 2 - April 30	2006
Location (weather):	Memphis				Feb. 2 - April 30	2007

Temperature Parameters			Reference Temperature		Goodness of Fit		Autocorrelation		Average Daily Consumption (MWh)	
Adj. Wgt.	Period	Lag Wgt	HDD-Ref	CDD-Ref	R^2	0.910	D.W.	0.895	2006	1,507
(wt)	day(0)	0.729	63.0	61.0	MAPE	2.20%	rho	0.552	2007	1,524
0.74	day(-1)	0.153								
	day(-2)	0.118								

OLS	Constant	Time	Load Grow	Saturday	Sunday	HDD-Ref	HDDSqr	CDD-Ref	CDDSqr	EDST-C	EDST-I	DST	Pres_Day
Coef.	1486.8	-0.6	22.7	-90.2	-137.7	-7.72	0.43	-12.18	1.61	-48.1	19.8	35.8	-33.8
S. E. (OLS)	37.5	0.4	8.0	9.8	9.9	2.88	0.058	4.10	0.14	16.5	17.9	22.2	32.7
S. E. (N-W)	45.6	0.5	9.7	10.5	11.9	3.52	0.07	4.56	0.14	19.4	20.0	28.7	
AR1	*First-order autocorrelation rho (iterative) =*				0.712								
Coef.	1429.8	-0.7	30.5	-79.4	-126.6	-1.00	0.26	-3.04	1.24	-28.0	-2.7	27.8	-16.0
S.E.	38.0	0.7	19.2	6.7	7.0	2.49	0.05	3.72	0.14	27.9	30.4	35.1	20.7

In comparison to Boston and Dayton, there was considerable autocorrelation present after the model was estimated with OLS. A possible explanation for this difference could be the effects of extended periods of warmer weather experienced in this mid-South climate. In an effort to account for this factor, the initial daily model regression specification in Equation (B.1) was modified to include the effects of heating and cooling degrees in the preceding *two* days, in addition to that from the current day. While the relative response from the current day's temperature variables is about the same as for Boston and Dayton (a weight of about 0.7), the lagged effects show up for both of the preceding two days. As shown in the top left portion of the table, the weight for the one-day lag was estimated to be 0.15 and that for the two-day lag was about 0.12.

The coefficients on the degree-day variables clearly indicate that both electric heating and cooling are present over the sample period for this utility. For the OLS results, the coefficients on the squared values of the heating and cooling degree variables both exceed their estimated standard errors by multiples of 6 or larger. The weight used to adjust the maximum and minimum temperatures is 0.74 (upper left corner of Table E-6), also reflecting the importance of both heating and cooling in the sample period. In this formulation, the maximum daily temperature has three times the influence on cooling as does the minimum temperature (as the weighted average temperature using for the heating degree calculation is weighted by 0.74 on Tmax and 0.26 on Tmin). The opposite holds for the temperature used in computing heating degrees. The reference temperatures for both heating and cooling are both just above 60 degrees.

The continuing presence of autocorrelation in the model, even after extending the lagged effects of the degree-day variables by an additional day, has a pronounced effect on the coefficients in AR(1) specification. Compared to the OLS results, the coefficients on the squared terms for degree-days are considerably smaller, as well as the coefficient on the EDST control variable.

For the estimate of the impact of EDST, the coefficient on the EDST-I variable using OLS is positive, with a magnitude suggesting about a 1.3 percent increase in average daily consumption. After correcting for serial correlation, the estimated impact becomes slightly negative. However, in the AR(1) model, there is no support of the statistical validity of this result, as the estimated standard error for this coefficient is 30 (or 2.0 percent in percentage terms).[62] The key result is that the daily statistical models provide very uncertain evidence of a strong effect of EDST on heating and cooling demands, when aggregated over the entire day.

Hourly model

The estimated impacts from spring EDST by hour are plotted in Figure E-15. The pattern of hourly impacts is considerably different from Boston and Dayton. The night and early morning hours display a positive consumption impact from EDST. The evening impacts of daylight time are clearly discernable, but the magnitude of the reduction (from 3 to 5 percent in the 7:00 p.m. hour) is not nearly as large as for the two previous locations. An unresolved issue is the extent to which daylight saving time is responsible for the increased consumption between 10:00 p.m. and 5:00 a.m.

Table E-7 compares the estimates of daily electricity change from the various model specifications. As mentioned above, the AR(1) model shows a much different result with respect to the daily impact. The OLS daily and hourly models show very close correspondence, suggesting an increase of over one percent in daily electricity use per day.

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[62] The effect of adding the two-day lag of the degree-day variables had the effect of reducing the autocorrelation coefficient from 0.76 to 0.70, as estimated via the Hi-Lu procedure. This change had a significant effect on the point estimates of the EDST impacts, from OLS and especially with AR(1). Without the second-day lag, the estimated effect of EDST from OLS was +1.6 percent (s.e. = 1.4 percent) and with the second-day lag the estimate was +1.3 percent (s.e. = 1.4 percent). For the AR1 specification, the omission of the second-day lag yielded at point estimate of -1.4 percent (s.e. 2.1 percent), and with the second-day lag, the estimate was -0.1 percent (s.e. = 2.0 percent).

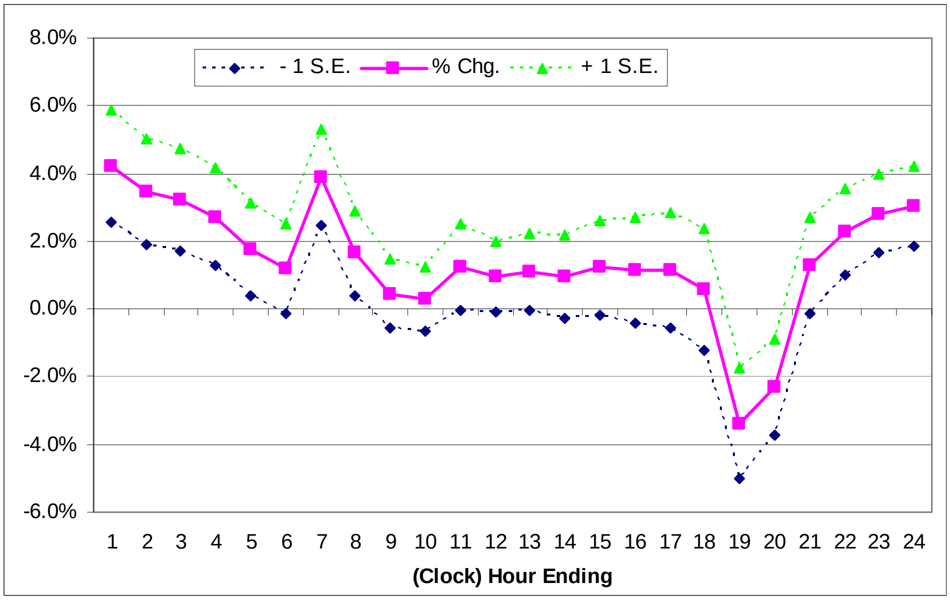

Figure E-15. Estimated percentage changes in hourly consumption due to daylight saving time during spring EDST, Memphis Gas, Light, and Water

Table E-7. Comparison of Daily Consumption Changes from Alternative Models, Memphis Gas, Light, and Water

	Daily Model		Hourly Model (24-hr sum)
	OLS	AR(1)	OLS
Chg. (MW)	19.8	-2.7	19.7
S.E.	20.0	30.4	NA
% Chg.	1.3%	-0.2%	1.3%
S.E.	1.3%	2.0%	NA

E.2.4 Results for City of Tallahassee

Descriptive summary

Similar to Memphis, the plots of average temperatures and the 2007/2006 hourly consumption for municipal utility serving Tallahassee suggest some impact on cooling from EDST. As shown in Figure E-16, in the first week of the spring EDST period, temperatures were very similar between the two years. This similarity is reflected in the plot of ratios in Figure E-17 where the ratios fall in a fairly narrow band of 0.95 to about 1.07.

The occurrence of temperatures above 80 degrees during the last week in March 2007 (as compared to just above 70 degrees in 2006) may explain why the pattern of ratios of the 2007 to 2006 consumption was much different from the previous two weeks. The (green) triangle-shaped points in Figure E-17 show this behavior.

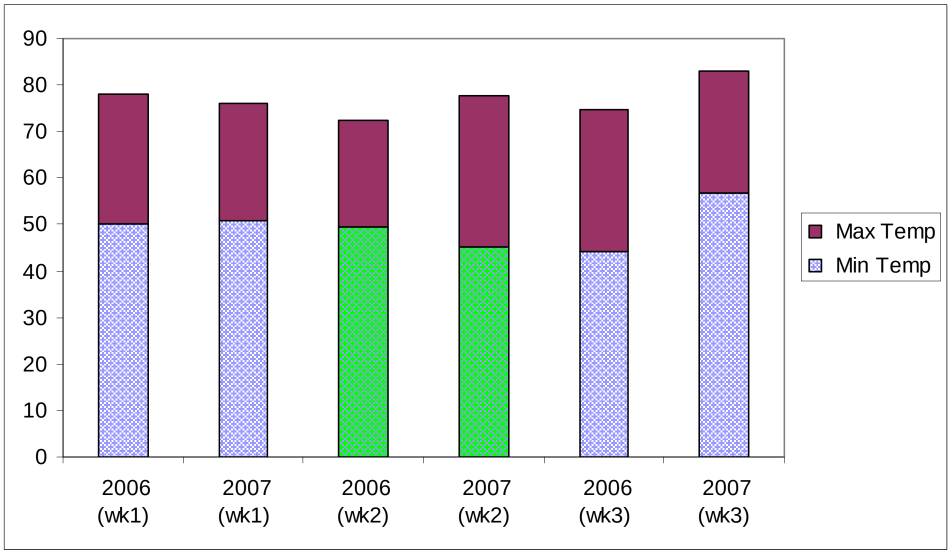

Figure E-16. Average maximum and minimum temperatures by week during spring EDST periods, 2006 and 2007, Tallahassee

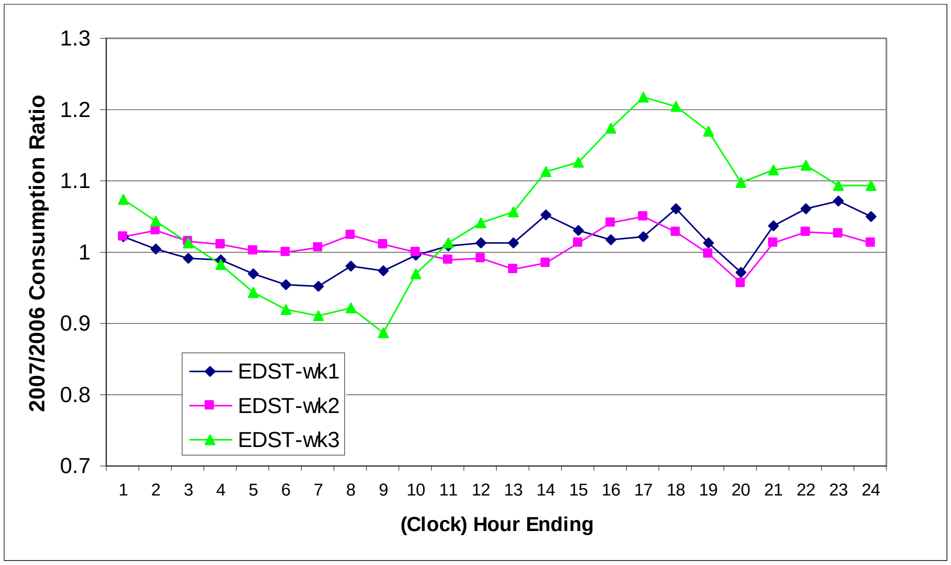

Figure E-17. Ratio of 2007 to 2006 average hourly consumption by week during spring EDST, Tallahassee

Regression Model Results

Daily model

Table E-8 presents the estimated coefficients for the daily model for the city of Tallahassee municipal utility. The OLS regressions have a bit more difficulty in explaining the variation in daily consumption as compared to the larger utilities discussed earlier, but the R^2 of just over 0.9 is still a satisfactory value.

Table E-8. Daily Model Regression Results for the Spring – Tallahassee

Utility	City of Tallahassee	Estimation Period:	Day	Sample Period:	Feb. 2 - April 30 2006
Location (weather):	Tallahassee				Feb. 2 - April 30 2007

Temperature Parameters			Reference Temperature		Goodness of Fit		Autocorrelation		Average Daily Consumption (MWh)	
Adj. Wgt.	Period	Lag Wgt	HDD-Ref	CDD-Ref	R^2	0.902	D.W.	1.148	2006	299
(wt)	day(0)	0.759	62.8	44.3	MAPE	2.72%	rho	0.430	2007	299
0.72	day(-1)	0.171								
	day(-2)	0.070								

OLS	Constant	Time	Load Grow	Saturday	Sunday	HDD-Ref	HDDSqr	CDD-Ref	CDDSqr	EDST-C	EDST-I	DST	Pres_Day
Coef.	378.9	-0.2	0.4	-31.5	-34.5	-1.46	0.11	-8.77	0.22	-0.5	5.0	11.5	2.4
S. E. (OLS)	11.7	0.1	2.0	2.5	2.5	0.54	0.020	0.79	0.02	4.1	4.1	5.8	8.2
S. E. (N-W)	11.1	0.1	2.5	2.4	2.4	0.60	0.02	0.90	0.02	5.1	4.4	7.2	
AR1	*First-order autocorrelation rho (iterative) =*				0.538								
Coef.	364.6	-0.1	-0.6	-28.3	-33.1	-0.67	0.09	-8.22	0.21	1.7	4.8	12.6	4.1
S.E.	12.4	0.2	3.6	2.0	2.0	0.55	0.02	0.78	0.02	6.3	6.7	8.4	6.3

Similar to Memphis, the data suggest that temperatures lagged by two days have some influence on the current day's consumption, although the weight on the second lagged day is not as high. The degree of autocorrelation of the errors is somewhat less than shown for Memphis. For the final AR(1) estimates, the first-order autocorrelation coefficient was estimated to be a little over 0.5.

Again, as was the case for Memphis, the coefficients on the temperature variables clearly indicate that both electric heating and cooling are present over the sample period for this utility. For the OLS results, the coefficients on the squared values of the heating and cooling degree variables both exceed their estimated standard errors by multiples by 5 or larger. In contrast to Memphis, the AR(1) specification yields coefficient estimates that are similar to those yielded by OLS. The standard error on the squared cooling degree variable implies a t-statistic greater than 10, the highest statistical confidence of any model variable with the exception of the constant term and the day type variables.

For the estimate of the impact of EDST, the OLS-derived coefficient on EDST-I is positive, with a magnitude suggesting about a 1.7 percent increase in average daily consumption. However, even after correcting for autocorrelation, the estimated impact remains positive and at about the same level, although its statistical significance is weak.

Hourly model

The estimated impacts from EDST by hour are plotted in Figure E-18.[63] From Figure E-18, it is clear that there are excluded (unidentified) factors not considered by the model. The average consumption for this utility is about 300 MW, only about 20 percent as large as for Memphis. Thus, individual large consumers that changed their consumption patterns over these few weeks will impact the estimated coefficients in the model.

While the hourly pattern of responses is somewhat erratic, the general features of the pattern accord with an expectation of the impact of EDST in this climate. The impact spikes upward in the late afternoon and extends, with the exception of the declines due to lighting and appliance use in the evening, throughout the night. Compared to standard time, temperatures will be

[63] Figure E-18 is the same as Figure E-4. It is repeated here for convenience.

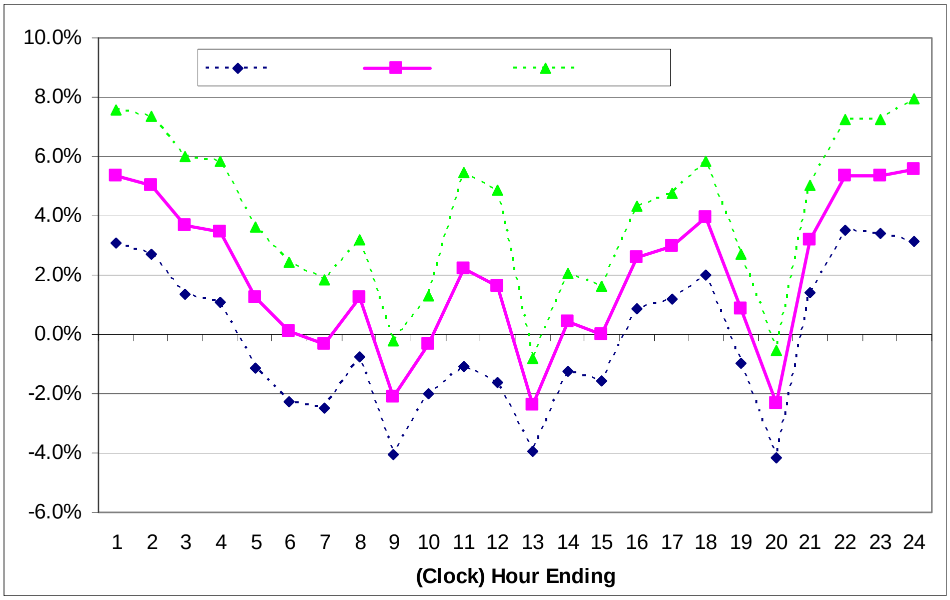

Figure E-18. Estimated percentage changes in hourly consumption due to daylight saving time during spring EDST, Tallahassee

warmer in the evening and through most of the night until sunrise. As shown in the previous sub-section , Figure E-2 plots the average hourly temperatures for the third week of EDST, under both DST and ST. The values for standard time were generated by simply shifting all of the hourly temperatures under DST one hour earlier. At 8:00 p.m., the average temperatures under DST were more than 4 degrees warmer than had standard time been in effect. These warmer temperatures throughout the evening are reflected as higher consumption for air conditioning for both the evening and much of the night.

While the regression results for the models indicate insignificant change on purely statistical grounds (as shown in Table E-8), for this utility, the results taken together suggest that EDST may increase overall consumption in some climates and under a given set of weather conditions. However, further analysis and more experience with EDST is required before any definitive quantitative estimates can be developed.

Table E-9 compares the estimated impacts across the two variants of the daily model and the hourly model. For this utility, the agreement across all three models is very good.

Table E-9. Comparison of Daily Consumption Changes from Alternative models, Tallahassee

	Daily Model		Hourly Model (24-hr sum)
	OLS	AR(1)	OLS
Chg. (MW)	5.0	4.8	5.2
S.E.	4.4	6.7	NA
% Chg.	1.7%	1.6%	1.8%
S.E.	1.5%	2.3%	NA

E.2.5 Results for Lincoln Electric System

Descriptive summary

Figure E-19 vividly illustrates the dramatic differences in temperature that were experienced in some portions of the United States between the 2006 and 2007 EDST time periods. In the second week of the spring EDST, the average 2007 high temperature was more than thirty degrees higher than in the previous year. While the temperature difference in the second week is most pronounced, temperatures were also higher in 2007 in the first and third weeks as well.

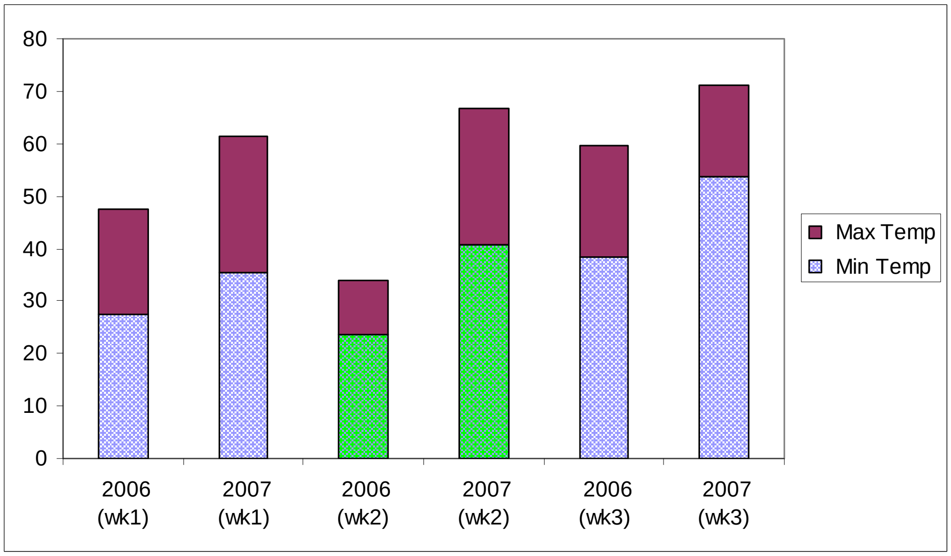

Figure E-19. Average maximum and minimum temperatures by week during spring EDST periods, 2006 and 2007, Lincoln Electric System

These temperature differences are reflected in the ratios of the 2007 to 2006 average hourly consumption. The distinctly higher minimum temperatures in the second EDST week in 2007 (compared to 2006) show up as considerably lower consumption ratios in the nighttime hours after midnight [lower (pink) line with squares]. The highest temperatures occur in the third EDST week in 2007. Compared to the same week in 2007, these temperatures appear to influence air conditioning, as the ratios grow steadily throughout the day.

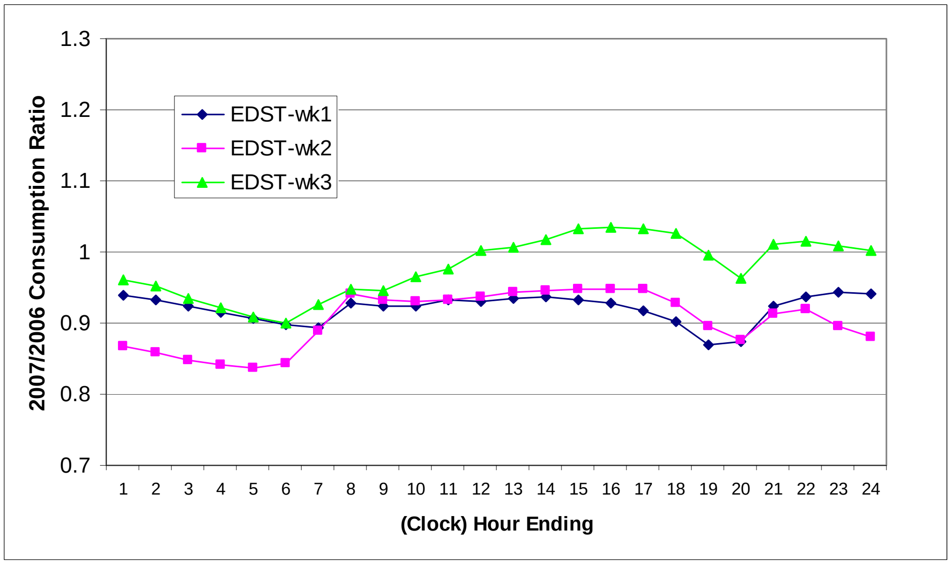

Figure E-20. Ratio of 2007 to 2006 average hourly consumption by week during spring EDST, Lincoln Electric System

Regression model results

Daily model

Table E-10 presents the estimated coefficients for the daily model for the Lincoln Electric System. The OLS regression does a very good job in explaining the variation in daily electricity use, with an R2 of about 0.95.

Table E-10. Daily Model Regression Results for the Spring – Lincoln Electric System

Utility	Lincoln Electric System	Estimation Period:	Day	Sample Period:	Feb. 2 - April 30	2006
Location (weather):	Lincoln				Feb. 2 - April 30	2007

Temperature Parameters			Reference Temperature		Goodness of Fit		Autocorrelation		Average Daily Consumption (MWh)	
Adj. Wgt.	Period	Lag Wgt	HDD-Ref	CDD-Ref	R^2	0.947	D.W.	1.212	2006	360
(wt)	day(0)	0.781	45.4	54.9	MAPE	1.87%	rho	0.395	2007	366
0.48	day(-1)	0.063								
	day(-2)	0.156								

OLS	Constant	Time	Load Grow	Saturday	Sunday	HDD-Ref	HDDSqr	CDD-Ref	CDDSqr	EDST-C	EDST-I	DST	Pres_Day
Coef.	367.0	-0.3	2.9	-37.9	-48.3	1.83	0.02	-1.72	0.32	0.8	-14.6	-2.4	-8.5
S. E. (OLS)	3.1	0.1	1.6	1.9	1.9	0.25	0.007	0.77	0.06	3.3	3.7	4.4	6.3
S. E. (N-W)	4.1	0.1	2.0	1.7	1.9	0.32	0.01	0.63	0.06	3.9	4.0	5.3	
AR1	*First-order autocorrelation rho (iterative) =*				0.505								
Coef.	367.8	-0.3	3.6	-35.3	-46.4	2.03	0.01	-1.01	0.25	3.1	-14.0	1.2	-5.5
S.E.	4.2	0.1	2.7	1.6	1.6	0.28	0.01	0.69	0.05	5.0	5.4	6.5	5.0

Again, as was the case for other utilities, the coefficients on the temperature variables clearly indicate that both electric heating and cooling are present over the sample period for this utility. For the OLS model results, the coefficient on the heating degree variable exceeds its standard error by a factor of five. The coefficient on the squared cooling degree variable is also estimated with high statistical significance.

For the estimate of the impact of EDST, the OLS-derived coefficient on EDST-I is negative, with a magnitude suggesting just over four percent decrease in average daily consumption. However, even after correcting for autocorrelation, the estimated impact remains negative and at about the same level, and its statistical significance is strong.

Hourly model

The estimated impacts from EDST by hour for the Lincoln Electric System are shown in Figure E-21. Clearly, there are significant negative deviations from the zero line for most hours of the day, but the early morning hours from midnight to 6:00 a.m. show significant declines. The reductions in the evening hours are consistent with reduced lighting requirements, but the estimated impacts begin as early as 1:00 p.m. in the afternoon.

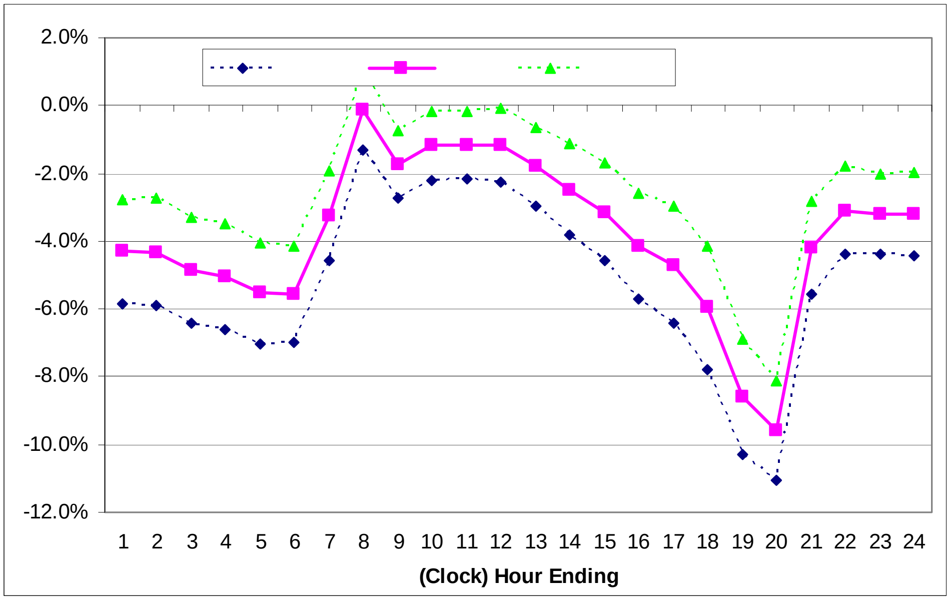

Figure E-21. Estimated percentage changes in hourly consumption due to daylight saving time during spring EDST, Lincoln Electric System

Table E-11 compares the estimated impacts across the two variants of the daily model and the hourly model. Again, for this utility, the agreement across all three models is very good.

Table E-11. Comparison of Daily Consumption Changes from Alternative Models, Lincoln Electric System

	Daily Model		Hourly Model (24-hr sum)
	OLS	AR(1)	OLS
Chg. (MW)	-14.6	-14.0	-13.4
S.E.	4.0	5.4	NA
% Chg.	-4.1%	-3.9%	-4.08%
S.E.	1.1%	1.5%	NA

E.2.6 Results for Avista Corporation (Spokane)

Descriptive summary

The Avista Corporation is an investor-owned utility that serves the northeastern portion of Washington State and northern Idaho. Located on the western side of the Rocky Mountains, the temperature differences between the 2006 and 2007 spring EDST periods were not as pronounced as in the middle sections of the United States.

As shown in Figure E-22, the major temperature difference between the 2006 and 2007 spring EDST period occurred in the first week, where average maximum temperatures were nearly 10 degrees warmer in 2007 compared to 2006. In the last week in March (third week of EDST), average temperatures were nearly the same in 2006 and 2007.

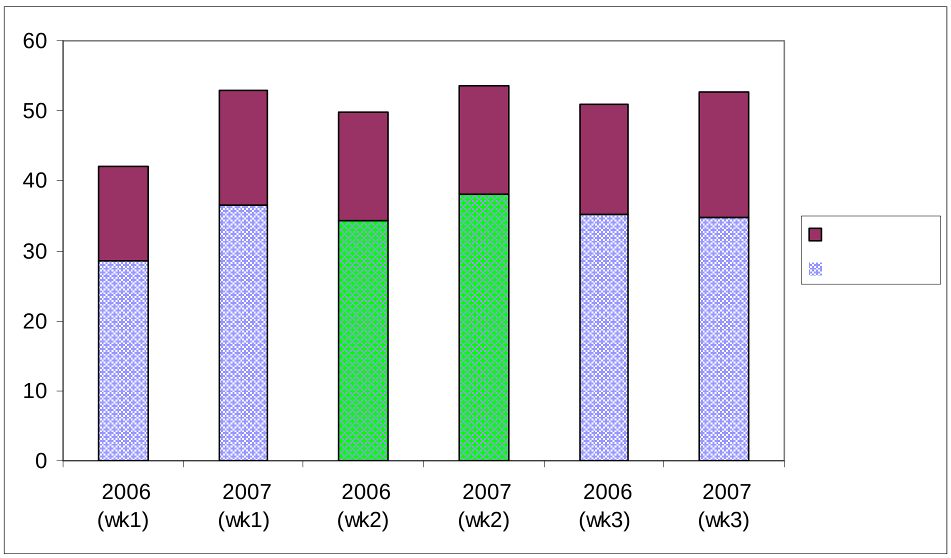

Figure E-22. Average maximum and minimum temperatures by week during spring EDST periods, 2006 and 2007, Spokane (Avista Corporation)

The 2007/2006 ratios of hourly electricity consumption reflect these temperatures, at least qualitatively. The lowest ratios, as shown in Figure E-23, occur in the first week, with consumption nearly twelve percent lower in 2007 (compared to 2006) in the early morning hours and roughly eight percent lower during the middle portion of the day. In the third week, with very comparable temperatures, the ratios during the middle portion of the day are close to one.

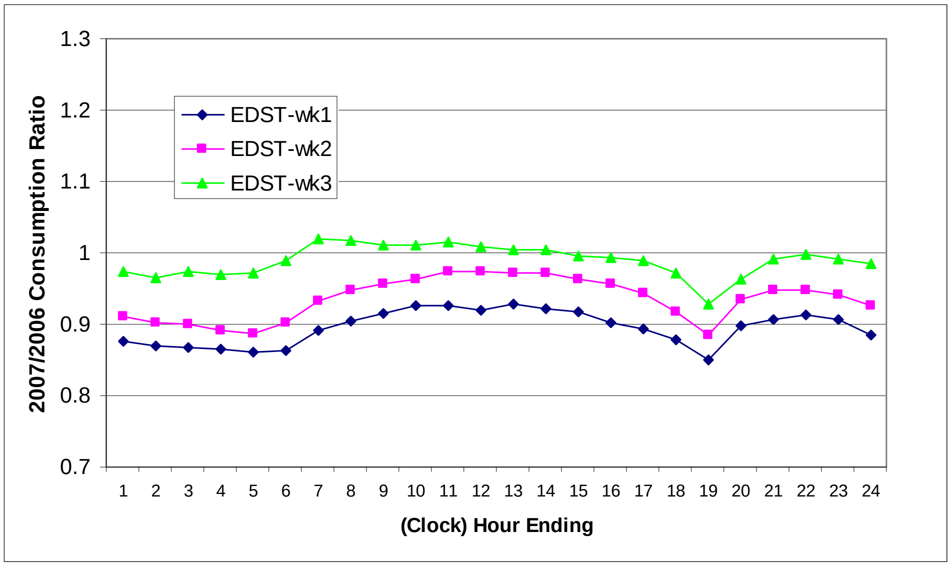

Figure E-23. Ratio of 2007 to 2006 average hourly consumption by week during spring EDST, Avista Corporation

Regression model results

Daily model

Table E-12 presents the estimated coefficients for the daily model for the Avista Corporation's electricity sales. The OLS regression does a very good job in explaining the variation in daily electricity use, with an R^2 greater than 0.96.

Table E-12. Daily Model Regression Results for the Spring – Avista Corporation

Utility	Avista Corporation	Estimation Period:	Day	Sample Period:	Feb. 2 - April 30 2006
Location (weather):	Spokane				Feb. 2 - April 30 2007

Temperature Parameters			Reference Temperature		Goodness of Fit		Autocorrelation		Average Daily Consumption (MWh)	
Adj. Wgt.	Period	Lag Wgt	HDD-Ref	CDD-Ref	R^2	0.960	D.W.	1.182	2006	1,403
(wt)	day(0)	0.666	62.6	54.4	MAPE	1.52%	rho	0.408	2007	1,380
0.43	day(-1)	0.284								
	day(-2)	0.050								

OLS	Constant	Time	Load Grow	Saturday	Sunday	HDD-Ref	HDDSqr	CDD-Ref	CDDSqr	EDST-C	EDST-I	DST	Pres_Day
Coef.	1314.0	-0.7	17.3	-100.5	-113.2	3.71	0.15	27.62	-4.06	-16.7	-54.5	-47.6	7.0
S. E. (OLS)	21.6	0.2	4.9	6.2	6.1	1.39	0.026	24.52	9.93	10.1	10.1	13.5	19.9
S. E. (N-W)	25.6	0.3	6.2	5.2	5.9	1.63	0.03	18.00	5.34	10.4	12.4	15.6	
AR1	*First-order autocorrelation rho (iterative) =*				0.481								
Coef.	1333.4	-1.1	16.2	-90.8	-112.9	2.69	0.17	20.98	-4.92	-3.8	-50.0	-28.5	1.2
S.E.	25.9	0.4	8.0	5.2	5.1	1.62	0.03	21.35	7.42	15.0	15.6	19.7	16.1

For this utility, the regression model indicates a clear predominance of electricity use for heating over cooling during the February-April sample period. The coefficients on both heating degree variables show high statistical significance, whereas the coefficients on the cooling variables do not exceed their standard errors.

For the estimate of the impact of EDST, the OLS-derived coefficient on EDST-I is negative, with a magnitude suggesting just over four percent decrease in average daily consumption. The

OLS coefficient (-54.5) exceeds its standard error by a factor greater than five. After making a correction for autocorrelation, the estimated impact remains negative and at about the same level, and its statistical significance remains strong.

Hourly model

The estimated impacts from EDST by hour on the Avista Corporation's electricity consumption are shown graphically in Figure E-24. There are significant negative deviations from the zero line for all hours of the day, but the early morning hours from midnight to 6:00 a.m. show significant declines. The reductions in the evening hours are consistent with reduced lighting requirements, but the estimated impacts begin as early as 1:00 p.m. in the afternoon (similar to the pattern shown for the Lincoln Electric System)..

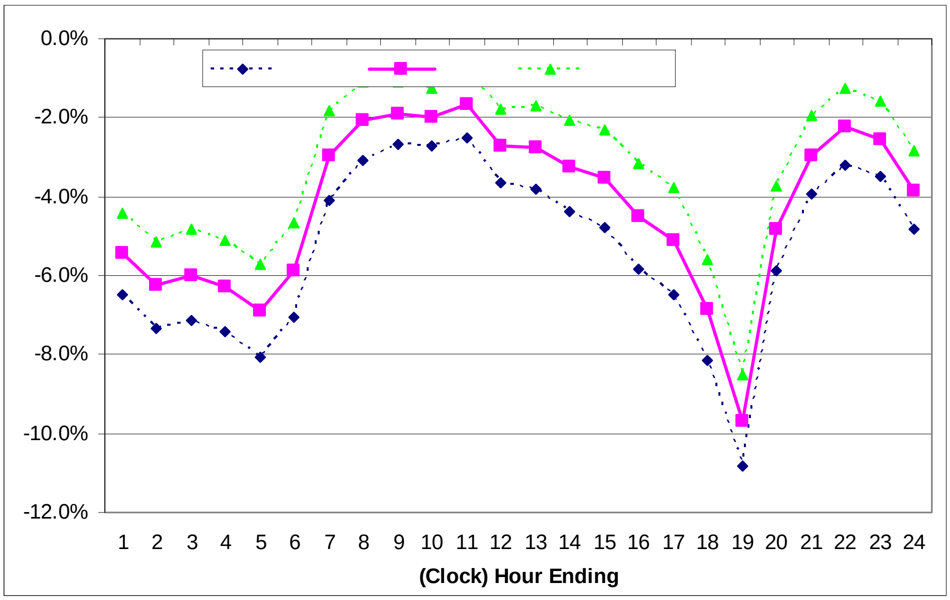

Figure E-24. Estimated percentage changes in hourly consumption due to daylight saving time during spring EDST, Avista Corporation

Table E-13 compares the estimated impacts across the two variants of the daily model and the hourly model. Again, for this utility, the agreement across all three models is very good.

Table E-13. Comparison of Daily Consumption Changes from Alternative Models, Avista Corporation

	Daily Model		Hourly Model (24-hr sum)
	OLS	AR(1)	OLS
Chg. (MW)	-54.5	-50.0	-56.7
S.E.	12.4	15.6	NA
% Chg.	-4.0%	-3.7%	-4.4%
S.E.	0.9%	1.2%	NA

Special information

For this particular utility, the study was fortunate to gain some special insight as to a major factor helping to explain the apparent large negative impact from EDST shown in Table E-13. During the first two weeks of the 2007 EDST period, annual maintenance for portions of a large continuous process industrial plant in Avista's service area resulted in lower electricity usage.[64] This situation reduced Avista's overall electricity consumption by approximately two percent or more during this period.

As shown in Figure E-24, the reduction in electricity consumption from this particular factor corresponds quite well with the estimates of a mid-day reduction of between two and three percent (two percent in the hours before noon, about three percent in the early afternoon hours). In this particular case, the specification of the regression model would have been able to account for such annual maintenance had it occurred at the same time of the year (i.e., in early March 2006 as well).[65] In this particular case, circumstances prompted the maintenance outage to be undertaken earlier than normal for this particular facility.

E.2.7 Fall results for Dayton Hub - PJM

An abbreviated set of results is shown for Dayton (Dayton Hub – PJM) for the fall EDST period. Figure E-25 shows the average maximum and minimum temperatures for three weeks: 1) prior week [-1], 2) EDST week, and the subsequent week [+1]. Average high temperatures were about seven degrees higher in 2007 as compared to 2006 for the EDST week.

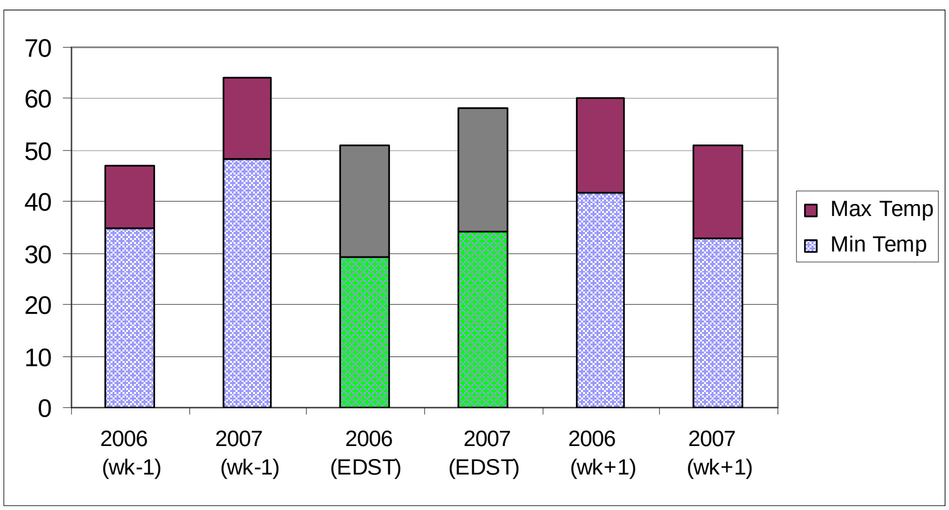

Figure E-25. Average maximum and minimum temperatures during weeks adjacent to and including the EDST week in the fall, Dayton (Dayton Hub - PJM)

Table E-14 shows the OLS regressions for the daily model for months of October and November (2006 and 2007). The overall fit is good, with over 96 percent of the daily variation explained by the model. The coefficients on the temperature (degree-day) variables reflect the presence of

[64] Personal communication with Randy Barcus, chief economist, Avista Corporation, April 25, 2008.

[65] This is the purpose of the EDST "control" variables that were discussed in Section B.3.

heating and cooling over the sample period. The EDST-I coefficient suggests a significant decrease in daily electricity use during the EDST period. Compared to the average consumption during the week of EDST, the coefficient implies about a 2.5 percent decrease in electricity use.

Table E-14. Daily Model Regression Results for the Fall – Dayton Hub - PJM

Utility	PJM Interconnection AEP-Dayton Hub	Estimation Period:	Day	Sample Period:	Oct. 2 - Nov. 30	2006
Location (weather):	Dayton				Oct. 2 - Nov. 30	2007

Temperature Parameters			Reference Temperatures		Goodness of Fit		Autocorrelation		Average Daily Consumption (MWh)	
Adj. Wgt.	Period	Lag Wgt	HDD-Ref	CDD-Ref	R^2	0.963	D.W.	1.537	2006	2007.78
(wt)	day(0)	0.690	61.3	36.1	MAPE	1.49%	rho	0.235	2007	2016.32
0.54	day(-1)	0.202								
	day(-2)	0.036								

OLS	Constant	Time	Load Grow	Saturday	Sunday	HDD-Ref	HDDSqr	CDD-Ref	CDDSqr	EDST-C	EDST-I	DST
Coef.	2106.1	0.9	-22.4	-290.71	-362.5	17.59	-0.47	-30.50	1.03	23.5	-42.6	-31.5
S. E. (OLS)	125.1	0.6	7.9	10.9	10.6	4.09	0.083	6.36	0.09	19.5	23.3	19.0

Figure E-26 shows the estimated EDST impacts by hour. The hourly pattern of impacts is somewhat different from that shown during the spring (Figure E-12). In this case, the reductions in the electricity use occur primarily in the afternoon and evening hours. With the exception of the early morning (hours ending 4:00 a.m. through 7:00 a.m.), there is no period for which the coefficients are relative constant over an extended period of hours.

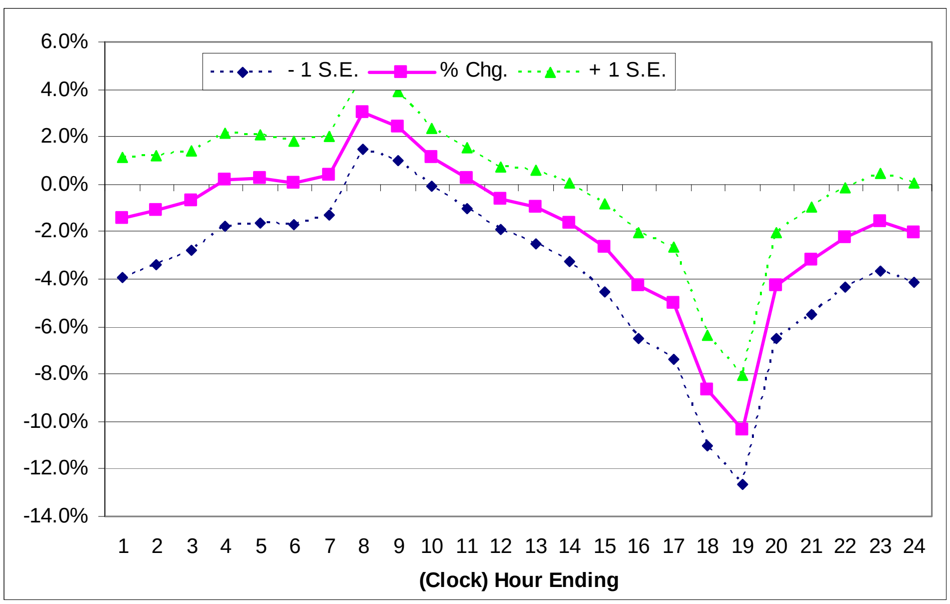

Figure E-26. Estimated percentage changes in hourly consumption due to daylight saving time during fall EDST, Dayton Hub – PJM

E.2.8 Fall results for Tallahassee

As for Dayton, an abbreviated set of results is shown for the Tallahassee municipal utility for the fall EDST period. Figure E-27 shows the average maximum and minimum temperatures for three weeks: 1) prior week [-1], 2) EDST week, and the subsequent week [+1]. While maximum temperatures in 2007 were about the same as the corresponding period (EDST) in 2006, minimum temperatures were nearly ten degrees higher on average.

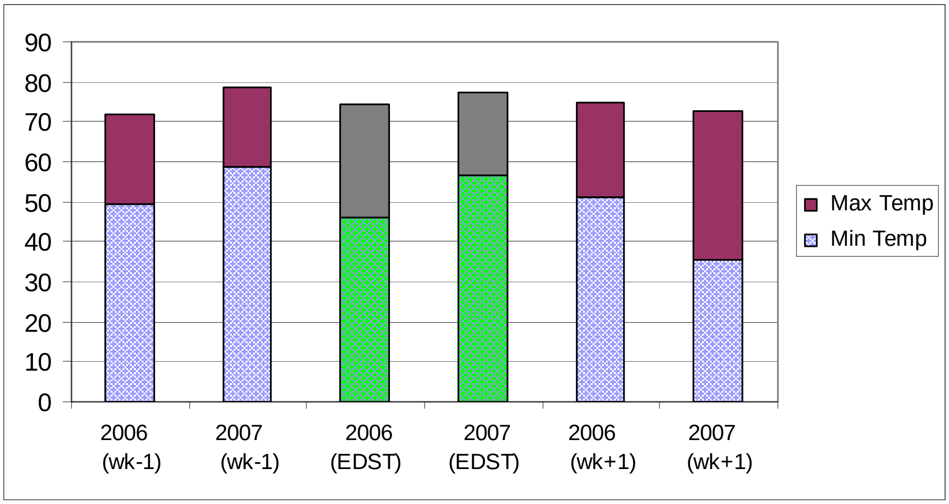

Figure E-27. Average maximum and minimum temperatures during weeks adjacent to and including the EDST week in the fall, Tallahassee

Table E-15 shows the OLS regressions for the daily model for months of October and November (2006 and 2007). The overall fit is very high, with nearly 98 percent of the daily variation explained by the model. As for Dayton, the coefficients on the degree-day variables indicate significant use of electricity for both heating and cooling over the sample period. In this case, the EDST-I coefficient suggest a large decrease in electricity use during the EDST period. Compared to the average consumption during the week of EDST, the coefficient implies over a four percent decrease in electricity use.

Table E-15. Daily Model Regression Results for the Fall – Tallahassee

Utility City of Tallahassee	Estimation Period: Day	Sample Period: Oct. 2 - Nov. 30	2006
Location (weather): Tallahassee		Oct. 2 - Nov. 30	2007

Temperature Parameters			Reference Temperatures		Goodness of Fit		Autocorrelation		Average Daily Consumption (MWh)	
Adj. Wgt.	Period	Lag Wgt	HDD-Ref	CDD-Ref	R^2	0.963	D.W.	1.735	2006	302.70
(wt)	day(0)	0.696	68.8	50.4	MAPE	1.89%	rho	0.143	2007	283.00
0.80	day(-1)	0.261								
	day(-2)	0.036								

OLS	Constant	Time	Load Grow	Saturday	Sunday	HDD-Ref	HDDSqr	CDD-Ref	CDDSqr	EDST-C	EDST-I	DST
Coef.	349.1	0.3	4.1	-25.92	-28.6	-3.65	0.12	-6.86	0.21	5.6	-11.5	2.2
S. E. (OLS)	10.9	0.1	1.5	2.1	2.0	0.42	0.012	0.54	0.01	3.5	4.4	4.0

Figure E-28 shows the estimated EDST impacts by hour. The sharply warmer temperatures during the night during the 2007 appear to be reflected in the EDST coefficients for hours between midnight at 9:00 a.m. The estimated impacts remain negative for much of the rest of day, climbing above the zero line only by 10 p.m. The increases in the morning and evening that could likely be attributed to lighting impacts of DST are significant but extend only a limited period of time.

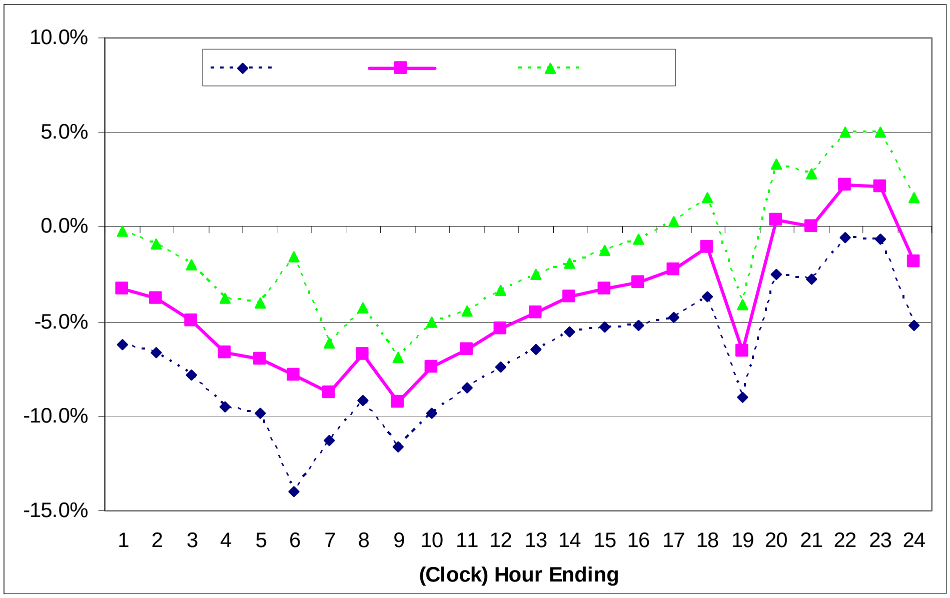

Figure E-28. Estimated percentage changes in hourly consumption due to daylight saving time during fall EDST, Tallahassee

E.2.9 Fall results for Avista Corporation

The final set of results is shown for the Avista Corporation for the fall EDST period. Figure E-29 shows the average maximum and minimum temperatures for three weeks: 1) prior week [-1], 2) EDST week, and the subsequent week [+1]. Average high temperatures were considerably warmer in the 2007 EDST period as compared to the same time period in 2006.

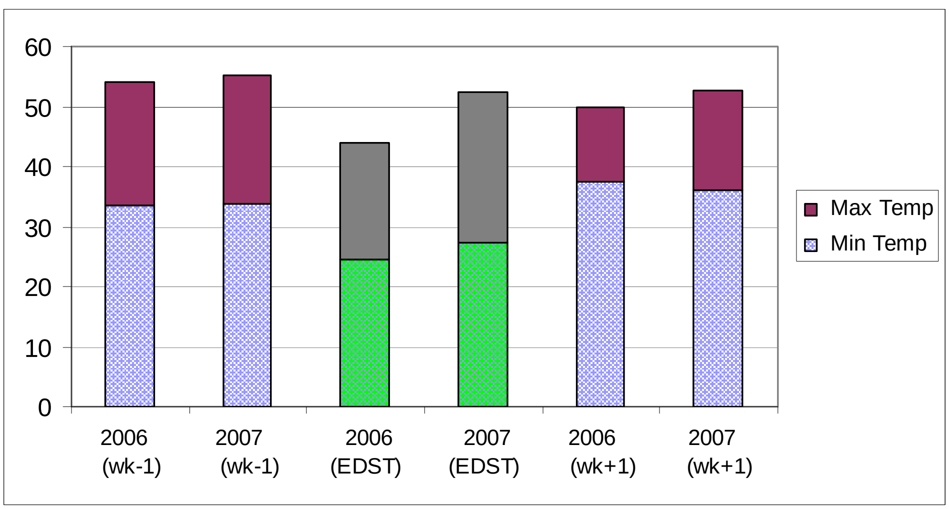

Figure E-29. Average maximum and minimum temperatures during weeks adjacent to and including the EDST week in the fall, Spokane (Avista Corporation)

Table E-16 shows the OLS regressions for the daily model for months of October and November (2006 and 2007). The overall fit is very high, with nearly 98 percent of the daily variation explained by the model. The coefficients on the temperature variables indicate a dominance of heating over cooling over the sample period, although both cooling coefficients have marginal statistical significance. The EDST-I coefficient suggest an increase in daily electricity use during the EDST period. Compared to the average consumption during the week of EDST, the coefficient implies about a 1.3 percent increase in electricity use.

Table E-16. Daily Model Regression Results for the Fall – Avista Corporation

Utility	Avista Corporation	Estimation Period:	Day	Sample Period:	Oct. 2 - Nov. 30	2006
Location (weather):	Spokane				Oct. 2 - Nov. 30	2007

Temperature Parameters			Reference Temperatures		Goodness of Fit		Autocorrelation		Average Daily Consumption (MWh)	
Adj. Wgt.	Period	Lag Wgt	HDD-Ref	CDD-Ref	R^2	0.979	D.W.	2.353	2006	1354.09
(wt)	day(0)	0.565	48.9	53.0	MAPE	1.04%	rho	-0.195	2007	1459.11
0.56	day(-1)	0.409								
	day(-2)	0.036								

OLS

	Constant	Time	Load Grow	Saturday	Sunday	HDD-Ref	HDDSqr	CDD-Ref	CDDSqr	EDST-C	EDST-I	DST
Coef.	1314.8	0.6	1.7	-99.26	-89.8	8.13	0.13	-11.78	1.97	-32.7	14.9	-30.9
S. E. (OLS)	14.2	0.4	3.9	5.5	5.5	0.96	0.026	5.94	1.16	10.7	11.5	10.1

Figure E-30 shows the estimated EDST impacts by hour. The hourly pattern of impacts is broadly consistent with that shown above for the spring. However, the increase in morning consumption occurs later in the morning (as expected with a later sunrise in late October as compared to March). In this case, the most stable period of impacts occur during the late night and early morning hours. After the peak impact at 8:00 a.m., the magnitude of the estimated impacts falls steadily through 5:00 p.m. The presumed impacts on lighting electricity use occur most strongly in the hours ending between 5:00 p.m. and 6:00 p.m.

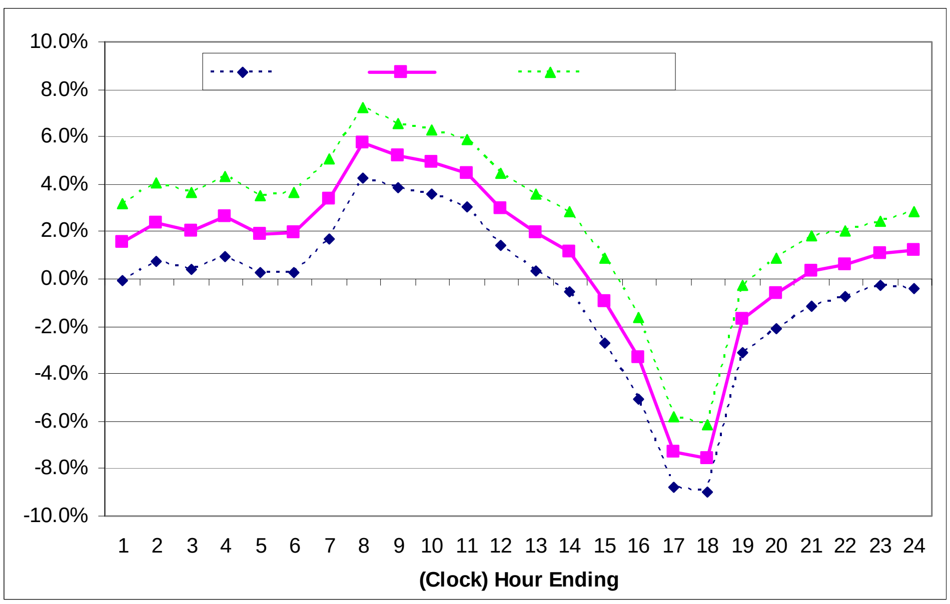

Figure E-30. Estimated percentage changes in hourly consumption due to daylight saving time during fall EDST, Avista Corporation

E.3 Concluding Remarks – 24-Hour Models

The results shown for the six utilities during the spring generally support the notion that the effects of daylight saving time are likely to be the smallest during the mid-day hours. For the unrestricted models for Boston and Dayton, the results clearly support the view that the EDST impacts are near zero for these hours (see Figures E-3 and E-12). Moreover, in these cases the impacts are relatively constant for a period of three to five hours in this portion of the day.

This pattern was also observed in the two southern locations. For Memphis, the pattern of EDST impacts is relatively constant between 11:00 a.m. and 5:00 p.m. (Figure E-15). The magnitude of the coefficients over this period (approximately a one percent decline in hourly consumption) may be due special factors that are independent of EDST. Such factors may be similar to that observed for Avista, where a particularly large consumer reduced its consumption during the EDST period in 2007 as compared to 2006. The fluctuations in the estimated impacts for Tallahassee make this generalization somewhat more tenuous, but as shown in Figure E-18, the average impact over the period from about 10:00 a.m. through 3:00 p.m. is roughly zero.

For the Lincoln Electric System, a period of relatively constant impacts was observed in the late morning hours, but at a level of about a one percent decline relative to the corresponding EDST period in 2006 (Figure E-18). Finally, for Avista , the general pattern of impacts over the entire day was similar to Lincoln, reflecting a dominant space heating use of electricity in influencing the hourly consumption profile (Figure E-21). However, the magnitude of the negative impacts during the mid-day hours (somewhat over two percent) has a specific explanation owing to the partial maintenance outage in the large industrial facility, as cited above.

Table E-17 compares the estimated impacts, in terms of the change in daily electricity consumption, between the alternative specifications of the 24-hour model. The estimates from the unrestricted model were shown in the separate figures and tables in the previous subsection (E.2). The restricted estimates, using the DID model described in Section B.3 and reported in Table E-1 in Section E.1, are shown in the last column of the table. Clearly, the mid-day restriction reduces the absolute level of savings in several utilities. As noted above, the apparent savings for Avista in the unrestricted model are more related to the situation with a single large customer than with daylight saving time. Clearly, similar types of circumstances affecting normal electricity consumption patterns may have influenced the estimated impacts of EDST in Memphis and Lincoln as well.

Table E-17. Comparison of Estimated Impacts from Spring EDST from Unrestricted and Restricted 24-Hour Models

Utility	EDST Impact – 24 Hour Model (no restriction)	EDST Impact – 24-Hour Model with mid-day restriction
Boston (ISO-NE Ne Mass.)	-0.9%	-0.7%
Dayton Hub – PJM	-1.3%	-1.4%
Memphis Gas, Light, & Water	1.3%	0.3%
City of Tallahassee	1.8%	2.0%
Lincoln Electric System	-4.0%	-1.8%
Avista Corporation	-4.4%	-1.1%

However, even after the imposition of the mid-day restriction (normalization), the magnitude of the EDST impacts from the 24 hour and daily model are large. Adding to the discussion in Section E.1, the detailed results shown in Section E.2 highlight the apparent correlation between estimated impacts and the specific temperatures experienced in 2006 and 2007. While the specification of the degree-day variables in the daily models yielded generally very good predictions of system consumption for most utilities, the concern is that, given only 2006 and 2007 data, the current specification appears not able to disentangle the effects of EDST and temperatures.[66] A more robust approach may require estimating these models with additional years of data (e.g., 2005 and 2008) to try to better identify these effects. Without conducting this additional analysis, the primary results from study (described in the body of this report) were restricted to the morning and evening hours during which the primary influence of DST is likely to be lighting and appliance use.

Finally, the example results for 24-hour model applied to fall data illustrate the difficulty in seeking to identify accurately EDST impacts by hour for such limited number of data points (seven days). With the three examples shown, the magnitude of impacts using the daily or 24-hour regression models are implausibly large. Moreover, in none of the three examples shown do the plots of the impacts suggest that a mid-day normalization is appropriate. In all these cases, the pattern of impacts was either rising or falling during this period. Again, additional experience with EDST or analysis of fall hourly consumption data across the transition from daylight saving time to standard time in earlier years is needed to develop more satisfactory models.

[66] As a conceptual issue, it should also be noted that the effects of DST and temperature are not really independent influences upon energy consumption. For example, if DST tends to increase evening and late night temperatures, the magnitude of an effect will depend upon the range of temperatures occurring at the same time. In some range of temperatures, the influence of DST will be just sufficient to induce some use of air conditioning that would have not occurred otherwise. On the other hand, in somewhat colder climates, DST may eliminate some hours of heating that might have otherwise taken place. With more data points, model specifications incorporating specific interaction effects might be feasible. It should be noted, however, that even with a highly robust statistical model, the impacts of DST upon space conditioning use could be expected to be different from one year to the next (and vary significantly by region).