Does Daylight Saving Time Save Energy? Evidence from a Natural Experiment in Indiana*

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---very preliminary and comments welcome---

Abstract

The history of Daylight Saving Time (DST) has been long and controversial. Throughout its implementation during World Wars I and II, the oil embargo of the 1970s, and more regular practice today, the primary rationale for DST has always been to promote energy conservation. Nevertheless, there is surprisingly little evidence that DST actually saves energy. This paper takes advantage of a natural experiment in the state of Indiana to provide the first empirical estimates of DST effects on electricity consumption in the United States since the mid-1970s. Focusing on residential electricity demand, we conduct the first-ever study that uses micro-data on households. The dataset consists of more than 7 million observations on monthly billing data for nearly all households in southern Indiana for three years. Our main finding is that—contrary to the policy's intent—DST increases residential electricity demand. Estimates of the overall increase range from 1 to 4 percent, but we find that the effect is not constant throughout the DST period. There is some evidence of electricity savings during the spring, but the effect lessens, changes sign, and appears to cause the greatest increase in consumption near the end of the DST period in the fall. These findings are consistent with simulation results that point to a tradeoff between reducing demand for lighting and increasing demand for heating and cooling. Based on the dates of DST practice before the 2007 extensions, we estimate a cost of increased electricity bills to Indiana households of $8.6 million per year. We also estimate social costs of increased pollution emissions that range from $1.6 to $5.3 million per year.

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1. Introduction

The well-known mnemonic of "spring-forward, fall-back" describes the annual ritual of Daylight Saving Time (DST): turn clocks forward one hour in the spring and turn them back one hour in the fall. Less well known is the primary rationale for DST as a policy to conserve energy. Benjamin Franklin (1784) first proposed the idea after observing that people were sleeping during sunlit hours in the early morning and burning candles for illumination in the evening. He argued that if we simply pushed the clocks forward at certain times of the year, an immense sum of tallow and wax could be saved by the "economy of using sunshine rather than candles." It took more than 130 years for Franklin's idea to take hold during World War I, when the need for energy prompted Germany to institute the first DST policy in 1916. By taking advantage of sunlight for an additional hour each day, the aim was to reduce demand for electrical lighting so that more coal could be diverted to the war effort. The United States soon followed Germany's lead, but then repealed DST after World War I ended. Decades later, a more ambitious, year-round DST was reinstated for three years during World War II.

The Uniform Time Act of 1966 was the first federal DST law in the United States that was not part of a wartime initiative. The Act established that DST would begin on the last Sunday in April and end on the last Sunday in October.[1] The Arab oil embargo of the early 1970s prompted further changes to federal DST policy, when the Emergency Daylight Saving Time Energy Conservation Act of 1973 imposed year-round DST for 15 months. A more enduring change, again with the intent of energy conservation, occurred in 1986, when the start date was moved forward by three weeks. Most recently, the Energy Policy Act of 2005 extended DST yet again; as of 2007, DST begins three weeks earlier, on the second Sunday in March, and lasts one week longer, until the first Sunday in November.

In debates leading up to Act's passage, members of Congress speculated that the extension would save the equivalent of 100,000 barrels of oil per day (Congressional Record 2005a, 2005b). But the Act requires that research be conducted to estimate the actual

[1] While individual states could choose to be exempt, only Arizona, Hawaii, Indiana, and a few U.S. territories have done so in various ways over time.

conservation benefits, and Congress retains the right to repeal the extensions if the intended benefits are not realized. Despite the long history and current practice of DST as a conservation policy—in the United States and more than 70 other countries worldwide—surprisingly little research has been conducted to determine whether DST actually saves energy.[2] Even among the few studies that do exist, which we review in the next section, the evidence is inconclusive.

In this paper, we investigate whether DST does in fact save energy, with a focus on residential electricity consumption.[3] Our research design takes advantage of the unique history of DST in the state of Indiana, combined with a dataset of monthly billing cycles for nearly all households in the southern portion of the state for the years 2004 through 2006. While some counties in Indiana have historically practiced DST, the majority have not. This changed with a state law that required all counties to begin practicing DST in 2006. The initial heterogeneity of DST among Indiana counties and the policy change in 2006 provides unique opportunities—with treatment and control groups of counties—to empirically identify the relationship between DST and residential electricity demand.

Our results provide the first empirical estimates of DST effects on electricity demand in the United States since the mid-1970s. The study is also the first to use residential micro-data to estimate an overall DST effect and date-specific effects throughout the DST period. Another contribution of the study is that we estimate changes in pollution emissions due to DST and quantify the associated social costs and/or benefits.

We find that the overall DST effect on electricity consumption runs counter to conventional wisdom: DST results in an overall increase in residential electricity demand, and the effect is highly statistically significant. Based on two distinct identification strategies—a difference-in-differences approach for 2004-2005 and a natural experiment in 2006—we find

[2] Other effects of DST have been studied in more detail. These include studies that investigate the effects on safety (e.g., Coate and Markowitz 2004, Sullivan and Flannagan 2002, Coren 1996a 1996b), economic coordination (Hamermesh *et al* 2006), and stock market performance (Kamstra *et al* 2000 2002, Pinegar 2002).

[3] Although we focus exclusively on residential electricity consumption, it is likely to be the portion of aggregate electricity demand that is most sensitive to DST. Changes in the timing of sunrise and sunset occur when people are more likely to be at home, where and when behavioral adjustments might occur. Commercial electricity demand, in contrast, is likely to be greatest at inframarginal times of the day and generally less variable to changes in the timing of daylight.

estimates for the overall effect of DST that range from a 1-percent to a 4-percent increase in consumption. We also find that the effect is not constant throughout the DST period. There is some evidence of electricity savings during the spring, but the effect lessens, changes sign, and appears to cause the greatest increase in consumption near the end of the DST period in the fall. To help interpret these results, we simulate the effect of DST for an Indiana household with the U.S Department of Energy model for residential electricity demand (eQuest). Consistent with Benjamin Franklin's original conjecture, DST is found to save on electricity used for illumination, but there are increases in electricity used for heating and cooling. Both the empirical and simulation results suggest that the latter effect is larger than the former. A final component of our analysis is calculation of the costs associated with DST. We find that the policy costs Indiana households an average of $3.19 per year in increased electricity bills, which aggregates to approximately $8.6 million over the entire state. We also calculate the social costs in terms of increased pollution emissions, and these estimates range from $1.6 to $5.3 million per year.

2. Existing Evidence

The most widely cited study of the DST effect on electricity demand is the U.S. Department of Transportation (1975) report that was required by the Emergency Daylight Saving Time Energy Conservation Act of 1973. The most compelling part of the study is its use of the 'equivalent day normalization technique,' which is essentially a difference-in-differences (DD) approach. Using hourly electricity load data from 22 different utilities for a period of days before and after transitions in and out of DST, days are partitioned into DST-influenced periods (morning, evening) and uninfluenced periods (midday, night). It is then assumed that differences in the difference between influenced and uninfluenced periods, before and after the transition are due to the DST effect. The results indicate an average load reduction of approximately 1 percent during the spring and fall transition periods, but a subsequent evaluation of the study, conducted by the National Bureau of Standards (cited in Gurevitz 2006), concludes that the energy savings are insignificant.

The California Energy Commission (CEC 2001) conducts a simulation-based study to estimate the effects of DST on statewide electricity consumption. A system of equations is estimated to explain hourly electricity demand as a function of employment, weather, temperature, and sunlight. The Commission then simulates electricity use under different DST practice regimes. The results indicate that practicing winter DST reduces consumption by 0.5 percent, and DST as currently practiced leaves electricity consumption virtually unchanged between May and September, but may reduce consumption between 0.15 and 0.3 percent during April and October.[4] More recently, the CEC modeling approach is used to consider the actual extensions to DST that occurred in 2007 (CEC 2007). Based on the spring and fall extensions, the simulation predicts a decrease in electricity consumption of 0.56 percent, but the 95-percent confidence interval includes zero and ranges from a decrease of 2.2 percent to an increase of 1.1 percent.

Kellogg and Wolff (2007) take advantage of a quasi-experiment that occurred in Australia with the extension of DST in conjunction with the Sidney Olympic Games in 2000. Using a comparison of electricity load data from two different states, where only one experienced the extension of DST, they find that DST increases demand for electricity in the morning and decreases demand in the evening. While in some cases the net effect is an increase in demand, the combined results are not statistically different from zero. Kellogg and Wolff also apply the CEC simulation technique to determine whether it reasonably predicts what actually occurred with the Australian DST extension. They find that the simulation fails to predict the morning increase in consumption and overestimates the evening decrease. Their study thus provides the first empirical study that brings into question whether DST policies actually produce the intended effect of reducing electricity demand.

Using an engineering simulation model, Rock (1997) also finds evidence that DST might increase, rather than decrease, electricity consumption. He calibrates a model of energy

[4] The Indiana Fiscal Policy Institute (2001) attempts to replicate the CEC approach and estimate the potential effects of DST in Indiana; however, the results are not conclusive. While the statistical models are reported as very preliminary, and to our knowledge have never been completed, the results indicate that DST in Indiana could either increase or decrease electricity consumption.

consumption for a typical residence using actual utility records, while accounting for construction, residential appliances, heating and cooling systems, lighting requirements, and number of occupants. In order to account for differences in weather and geographic location, the model is used to simulate DST scenarios for 224 different locations within the United Sates. The results indicate that DST, as it is currently practiced, increases electricity consumption by 0.244 percent when averaged over the different locations. Other results indicate that extending DST year-round would save an average of 0.267 percent, but the overall effect of year-round DST compared to no DST would leave electricity consumption virtually unchanged.

A similar methodology is employed in two recent studies that take place in Japan, where DST is continually debated but not currently practiced. Fong *et al*. (2007) use a simulation model to investigate the effects of DST on household lighting, and they find a reduction in electricity consumption that differs by region. Shimoda *et al*. (2007) conduct a similar exercise, with the added consideration of DST's effect on residential cooling. When considering both effects, they find that implementing DST results in a 0.13-percent increase in residential electricity consumption. The underlying mechanism for the result is that residential cooling is greater in the evening than in the morning, and implementing DST creates an additional hour of higher outdoor air temperature and solar radiation during the primary cooling times of the evening.

This review of existing studies suggests that the evidence to date is inconclusive about the effect of DST on electricity consumption. None of the empirical studies finds an overall effect that is statistically different from zero, and the simulation-based studies find mixed results. Hence, given the widespread practice of DST, its conservation rationale, and the recent changes to policy, there is a clear need for more research that informs the question of whether DST actually saves energy.

3. Research Design and Data Collection

Our study takes advantage of the unique history of DST in the state of Indiana. The practice of DST has been the subject of long-standing controversy in Indiana, due in large part to the importance of agriculture in the state, and to Indiana's location at the border between the Eastern and Central Time Zones.[5] For more than 30 years prior to 2006, the result has been three different time scenarios within the state: (*i*) 77 counties on Eastern Standard Time (EST) that did not practice DST, (*ii*) 10 counties clustered in the north- and south-western corners of the state on Central Standard Time (CST) that did practice DST, and (*iii*) 5 counties in the south-eastern portion of the state on EST that did practice DST.[6] The different time scenarios changed in 2006 when the entire state began practicing DST as required by a vote that passed the state legislature in 2005. Also beginning in 2006, a handful of counties switched from EST to CST.

Let us now be more precise about time and timing in the southern portion of Indiana, which is the geographic focus of our study. Figure 1 distinguishes four sets of counties. The SE and SW counties experienced no change; they both practiced DST prior to 2006 and have remained on EST and CST, respectively. The NE counties began practicing DST for the first time in 2006, but remained on EST. The NW counties also began practicing DST for the first time in 2006, but changed time zones from EST to CST simultaneously at the spring transition into DST. In effect, the NW counties did not advance clocks one hour in April 2006, but did turn them back one hour at the end of October 2006.

Given the pattern of time and timing in figure 1, we have two main empirical strategies for identifying the effect of DST on residential electricity consumption. Both rely on having monthly billing data for households located within the different sets of counties. The first strategy uses only data for years prior to 2006 and is based on a comparison between DST and non-DST periods of the year, between counties that did and did not practice DST. This is a standard difference-in-differences (DD) approach. Consider the difference in electricity consumption between the DST and non-DST periods of the year, after controlling for observables such as differences in climate. If one is willing to assume that this difference would have been the same for the set of north (NE, NW) and south (SE, SW) counties in figure 1—

[5] It is a common misperception that DST is an agricultural policy. Farmers have historically been one of the most organized groups against the practice of DST, as it requires them to work in the morning darkness for an extra hour in order to coordinate with the timing of markets. See Prerau (2005) for an extended discussion.

[6] These differences in the practice of DST were possible because of a 1972 amendment to the Uniform Time Act of 1966 (15 U.S.C. 260-67). The amendment was a direct response to Indiana's ongoing time regime debate, and it permitted states with multiple time zones to allow exemptions from the practice of DST.

were it not for the practice of DST in the south counties—then the effect of DST can be identified from the empirical DD in electricity demand between the DST and non-DST periods of the year.

The second identification strategy takes advantage of the natural experiment created by the policy change in 2006. Considering only the DST periods of each year, we can partition electricity demand into pre-2006 and 2006 periods. Among the different counties, we thus have treatment and control groups for the before and after periods. The NE counties serve as a treatment group because they began practicing DST for the first time in 2006. The other sets of counties serve as a control group because their clock time never changed during the DST period of the year, before and after the policy change.[7] In this case, the key identification assumption is that, after controlling for changes in observables such as weather and the practice of DST, changes from year to year in electricity demand would otherwise be the same for the treatment and control groups of counties. With this assumption, identification of the DST effect comes from a DD estimate between the two groups, before and after the policy change.

Table 1 shows selected variables from the 2000 U.S. Census by the four sets of counties. Comparisons among the counties are of interest because our empirical strategy relies on comparisons among them based on electricity consumption. The majority of people in our study area live in the eastern sets of counties. The northern counties have a larger fraction of the population classified as rural and farm, although the overall proportion of people living on farms in small. All four sets of counties are similar with respect to median age and average household size. Electric heat is more common in the eastern counties, and income is higher in the southern counties, where average commute times are also somewhat higher.

We obtained data on residential electricity consumption from Duke Energy, which provides electrical service in southern Indiana to nearly all households in the sets of counties shown in figure 1.[8] The dataset consists of monthly billing information for all households in the

[7] Recall that clock time did not change for the three sets of counties in the control group, but for different reasons. The policy had no effect on the SE and SW counties, but clock time did not change for the NW counties because the first practice of DST and the switch in time zones occurred simultaneously.

[8] Cinergy formerly provided electrical service in southern Indiana but was acquired by Duke Energy in 2005.

study area from January 2004 through December 2006. All households in the service area faced the same standard residential rate, and there were no rate changes between 2004 and 2006. Several variables are important for our analysis. The *meter position* is a unique number for each electric meter that is read for billing purposes. We refer to these positions as residences, and for each one, we have data for its *zip code* and *county*. For each monthly observation at each residence, we also have codes that identify which ones belong to the same *tenant*. This enables us to account for the fact that people move and to identify the observations that belong to the same tenant within each residence.[9] Each observation includes *usage amount*, which is electricity consumption in kilowatt-hours (kWh), and *number of days*, which is the number of calendar days over which the usage amount accumulated. With these two variables, we are able to calculate *average daily consumption* (ADC). Finally, each monthly observation includes a *transaction date*, which is the date that the usage amount was recorded in the utility company's centralized billing system.

The actual read-date of each meter occurs roughly every 30 days and is determined according to assigned billing cycles. Residences are grouped into billing cycles and assigned a cohort number for one of 21 monthly read-dates (i.e., the weekdays of a given month). Meters are read for billing cycle 1 on the first weekday of each month, billing cycle 2 on the second weekday, and so forth throughout the month. This staggered system allows the utility company to collect billing information and provide 12 bills to customers on an annual basis. In a separate file, we obtained data on the assigned billing cycle for each meter position. We then merged these datasets so that each monthly observation could be associated with its assigned *read-date*, according to Duke Energy's billing-cycle schedule.

We also collected and merged data on weather and day-length. Data on average daily temperature were obtained from the National Climatic Data Center.[10] We collected these data for every day in 2004 through 2006 from 60 different weather stations in southern Indiana and

[9] The data does not permit us to follow tenants from one residence to another, but this is not a limitation for our analysis here.
[10] These data are available online at the National Climatic Data Center webpage: www.ncdc.noaa.gov/oa/ncdc.html.

neighboring Kentucky. For each day and all 60 weather stations, we calculated heating and cooling degree days, as these provide standard metrics for explaining and forecasting electricity demand. The reference point for calculating degree days is 65° Fahrenheit (F). When average daily temperature falls below 65° F, the difference is the number of heating degrees in a day. When average daily temperature exceeds 65° F, the difference is the number of cooling degrees in a day. We then matched each residence to a climate station using a nearest-neighbor GIS approach, and for each observation, we collected the exact days corresponding to the dates of the billing cycle. Heating degrees in each day were summed over the days in the billing cycle to yield the heating degree days variable for each monthly observation. A parallel procedure was used to create the cooling degree days variable. We then used used the number of days for each observation to calculate variables for *average heating degree days* (AHDD) and *average cooling degree days* (ACDD). This approach gives nearly residence-specific weather data corresponding to each billing cycle.

The variable for average day length corresponding to each billing cycle at each residence was created with similar precision. We calculated the latitude and longitude at the centroid of each county in the dataset. At each of these points, we obtained sunrise and sunset times for each day of the year from the Astronomical Applications Department of the U.S. Naval Observatory.[11] We then calculated day length for each day in each county, matched the exact days with billing cycles for each residence by its county, and calculated the corresponding *average day length* (ADL) for each billing cycle at each residence.

The original dataset included 7,949,207 observations, 229,818 residences, and 413,802 tenants; however, several steps were taken, in consultation with technical staff at Duke Energy, to clean and prepare the data. In order to focus on the most regular bills, we first dropped all observations that had a number of days less than 27 and greater than 35 (2.7 percent of the data).[12] We also dropped all of the observations for which the transaction date did not align with

[11] These data are available online at aa.usno.navy.mil/data/docs/RS_OneYear.php.

[12] A consequence of focusing on the most regular bills is that we lose observations that are associated with tenants moving in or moving out. These may be observations with fewer than 27 days. Although we do not expect that it will have a large impact on our results, we are currently in the process of redoing much of the analysis to include

the scheduled billing cycle. The vast majority of transaction dates fall within 0 to 3 days after the scheduled read-date, as meter readers typically enter data into the system on the following workday. Those with transaction dates that were more than one day earlier than the scheduled read date or more than 5 days later were deemed irregular and dropped (and additional 4.9 percent of the data). Finally, we considered irregular and dropped all observations that had less than 1 kWh for average daily consumption (an additional 2.1 percent of the data). The final dataset includes 7,181,877 observations, 223,878 residences, and 374,186 tenants.

Table 2 reports descriptive statistics disaggregated into the different sets of counties and combined. The majority of data come from the NE counties, followed by those in the SE, with fewer in the western counties. Average daily consumption—at approximately 35 kWh/day—is very similar among all sets of counties. Average heating degree days is higher in the north counties, while average cooling degree days is higher in the south counties. Not surprisingly, average day length is virtually identical for all counties.

4. Empirical Analysis

We report the methods and results of our empirical analysis in three parts. First we consider the estimates of the overall effect of DST on residential electricity consumption that comes from a DD approach using data from 2004 and 2005, that is, the years before DST policy changed in Indiana. Then we report comparable estimates that come from an alternative identification strategy: the natural experiment caused by the policy change in 2006. Finally, we investigate how the effect of DST on electricity demand varies throughout the year, with estimates that differ by month, are broken down into billing cohorts, and take place at the spring and fall transitions.

Difference-in-Differences Estimates 2004-2005

As described briefly in the previous section, one approach for estimating the effect of DST relies on a comparison between the “north” and “south” counties in figure 1 for the years 2004 and

these “movers.” We plan to set the cutoff at 15 days, which has been used in other research (see Reiss and White 2003).

2005. Recall that while the south counties practiced DST for both of these years, the NE counties did not, and the NW counties effectively did not because of the simultaneous change in DST practice and time zone. Within a DD framework, therefore, the north and south counties can serve as "control" and "treatment" groups, respectively. Identification of the DST effect comes from the assumption that, after controlling for changes in other observables, the difference in electricity demand between non-DST and DST periods would be the same between tenants in the north and south counties, were it not for the practice of DST in the south counties. With this assumption, any difference in the difference between the two groups is attributable to the effect of DST.

We begin with a graphical display of the data. Figure 2 plots the natural log of ADC for the north and south counties separately. The figure also plots AHDD and ACDD for each month and both groups of counties. The first thing to note, which is to be expected, is the close correspondence between ADC and the weather variables. Electricity demand is greater in months with high AHDD and ACDD. Of greater interest for our purposes here, however, are the differences between the two groups of counties. Inspection of the trends for ADC reveals that the south counties tend to have greater electricity demand during the DST periods, while the north counties tend to have greater electricity demand during the non-DST periods. It appears that differences in HDD and CDD influence this pattern, as the south counties tend to be hotter during the DST periods, and the north counties tend to be colder during the non-DST periods.

In order to compare the trend in electricity demand between the north and south counties controlling for differences in weather, we apply the following procedure. For each of the 24 month-years, we estimate the following regression:

$$(1) \qquad lnADC_i = \alpha + \beta_i ACDD_i + \beta_2 AHDD_i + \varepsilon_i \,.$$

We then calculate $\alpha + \varepsilon_i$ for all observations i in each month-year and report them separately for those in the north and south counties. These results are plotted in figure 3 and can be interpreted as weather-detrended ADC. These trends follow each other more closely than those in figure 2, but there still appears to be a difference between the non-DST and DST periods. While the north and south counties have very similar ADC in the non-DST periods, the south counties still appear to have somewhat greater electricity demand during the DST periods. Under our identification assumption, this suggests that DST may increase electricity demand.

To formally estimate the overall effect of DST on electricity demand, we estimate models with the following general specification:

$$(2)\qquad lnADC_{it} = \delta DSTperiod_t \times South_i + \gamma DSTperiod_t + \beta_1 ACDD_{it} + \beta_2 AHDD_{it} + \beta_3 ADL_{it} + \theta_t + \nu_i + \varepsilon_{it}\,,$$

where subscripts i denote tenants, $DSTperiod_t$ is a dummy variable for whether the observation occurs during the DST period, $South_i$ is a dummy variable for whether the residence is in one of the south counties, θ_t is a time-specific intercept, and ν_i is a tenant-specific intercept. The estimate of δ is of primary interest, as it indicates how the south counties differ in their difference between non-DST and DST periods. When estimating equation (2), we include only observations that are entirely contained within either the DST or non-DST period of the year. In other words, we dropped all monthly bills that straddle the transition date in or out of DST.[13]

Table 3 reports the fixed-effects estimates of specification (2). We report three models that account for the time trend differently: an average year effect, month and year dummies, and month-year dummies. Note that we include average day length only in the model that does not have monthly controls. The variable is omitted from the other models with month controls because average day length is identical for a given month from year to year. All standard errors are clustered as the tenant level to account for potential serial correlation. The estimate of δ is similar across all three specifications and highly statistically significant. The estimate of δ at roughly 3.3 percent is very similar in models (a) and (c). Based on the identification strategy employed here, these estimates imply that DST results in a 3.3-percent increase in electricity

[13] Later in this section we use these dropped observations to estimate the DST effect at the transitions in and out of DST in the spring and fall.

demand over the whole DST period. Model (b) produces a higher estimate of 4.2 percent, but the three estimates are not statistically different from each other according to the overlapping 95-percent confidence intervals (not reported).

The finding here—that DST results in more than a 3-percent increase in residential electricity demand—depends crucially on the assumption that, after controlling for differences in weather and average day length, the difference between non-DST and DST period electricity demand would have been the same in the north and south counties in the absence of DST practice in the south. While this assumption may be reasonable, there are potential concerns. One potentially confounding effect could be more widespread adoption of air-conditioners in the south counties, which we have seen tend to be more urban. If this were the case, our estimate of the DST effect might be an overestimate because it would also capture the effect of air-conditioner use. While we do not have data on the presence of air-conditioners, we can look to figure 3 for evidence that the air-conditioner effect may not be very large. If air-conditioners were having a large effect, one might expect the difference between the trend lines to be greatest during the hottest summer months of June through August. But the difference appears to be at least as great, or greater, during September and October, when air-conditioner use is far lower and DST is still in effect.

There are, of course, other potentially confounding variables, for which we do not have data, that could imply over- or under-estimates of the DST effect. Nevertheless, these results are highly suggestive. If one is willing to make this particular identifying assumption, we find that DST results in more than a 3-percent increase in electricity demand over the entire DST period from the first Sunday in April until the last Sunday in October. We now turn to an alternative identification strategy that produces comparable estimates.

Natural Experiment 2006

Indiana's 2006 change to DST policy provides a natural experiment and entirely different approach for identifying the effect of DST on residential electricity consumption. The approach is once again based on a comparison between a set of treatment and control counties, but the two groups differ somewhat from those used for the previous estimates. Referring back to in figure 1, recall that the NE counties began practicing DST for the first time in 2006. The other sets of counties either practiced DST for all the years 2004 through 2006, or had no change in clock time in 2006 due to the offsetting effects of DST and the change in time zone. Our identification strategy thus comes from a DD comparison between the two groups, before and after the DST policy change. The key assumption here is that, after controlling for differences in weather, the difference between before an after electricity demand would have been the same in the two sets of counties were it not for the change in DST policy.

We begin with a simple comparison of means for average daily consumption. Consider first only the DST periods of the year. The first two columns of table 4 report *lnADC* for both the treatment and control groups, before and after the policy change. These means are calculated by first averaging within tenants and then averaging between tenants in order to account for the unbalanced panel. We also report the before-after difference and the DD between groups. Based on this simple comparison of means, we find that electricity demand increased in the treatment group (NE counties) by approximately 1.8 percent compared to the control group (all other counties). As a point of comparison, we conduct the same procedure for the non-DST periods and also report the results in table 4. This can be thought of as a quasi-counterfactual because it provides an estimate of how the two groups differ in their difference before and after 2006, but during the non-DST period of the year. With this comparison, we find that the treatment group of counties decreased, rather than increased, electricity demand by 1.2 percent. While these results provide preliminary evidence that DST increases electricity demand, the simple comparison of means is not a formal test, nor does it control for other variables that may be changing differentially over time between the two groups, namely weather.

Turning now to a DD regression analysis, we estimate models with the following specification:

$$(3) \qquad lnADC_{it} = \delta Year2006_t \times NE_i + \beta_1 ACDD_{it} + \beta_2 AHDD_{it} + \beta_3 ADL_{it} + \theta_t + \nu_i + \varepsilon_{it} \, ,$$

where δ is the coefficient of primary interest. It captures the average DD of electricity demand in 2006 between the treatment and control groups of counties. In parallel with the simple comparison of means, we estimate equation (3) first using only data from the DST period for all years, and then using only data from the non-DST period for all years. In each case, we once again drop the monthly observations that straddle to date of transition in or out of the DST period.

Table 5 reports the fixed-effects estimates of equation (3). We again estimate models that account for the time trend in three different ways, and we exclude *ADL* from the models with monthly controls. The estimates of δ for all three DST period models are positive, highly statistically significant, and of nearly identical magnitudes of 0.009. The interpretation is that DST caused approximately a 1-percent increase in electricity demand over the whole DST period. These estimates are smaller in magnitude than those from the previous section, but both provide strong evidence that DST increases electricity consumption. We consider these natural-experiment estimates to be more conservative and reliant on what is perhaps a more reasonable assumption. The estimates in the previous section are based on the assumption that the comparison groups would have the same difference in electricity consumption between different times of the year. The natural-experiment estimates, in contrast, are based on the assumption that the comparison groups would have the same difference in consumption between different years at the same time of year. Essentially we think that it is more reasonable to assume that the comparison groups would have the same trend from year to year rather than within different times of the year.

Table 5 also reports the non-DST period models. All of these quasi-counterfactual estimates of δ are negative, have relatively small magnitudes, and are not statistically different from zero. These results provide support for the identification assumption that the trend in electricity demand is similar between the treatment and control groups of counties, other than for the change in DST policy. For the negative results that we find here occur despite having close to 2.3 million observations upon which to estimate the models.

Disaggregated Natural Experiment 2006

Our estimates thus far have focused on the overall DST effect on electricity consumption. We now examine the extent to which the effect of DST differs throughout the DST period. As discussed above, we prefer the identification strategy that exploits the natural experiment of 2006 and therefore proceed with this identification strategy in what follows.

We begin with a model specification that is a special case of equation (3) and can be written as

$$(4) \qquad lnADC_{it} = \delta Year2006_t \times NE_i + \beta_1 ACDD_{it} + \beta_2 AHDD_{it} + \gamma_1 Year2005_t + \gamma_2 Year2006_t + \nu_i + \varepsilon_{it} ,$$

where we estimate a separate equation for each month within both the DST and non-DST periods of the year. Following the same practice, we exclude monthly observations that straddle the DST transitions, meaning that we do not have monthly models for April or November. Rather than report each of the 10 equations, we focus on the estimates of δ. We illustrate these results graphically in figure 4, along with the 95-percent confidence intervals. The findings suggest that DST decreases electricity consumption in May, with a magnitude of approximately 0.5 percent. The effect is not statistically different from zero in June, but for all of the other DST months, it is positive and statistically significant, with magnitudes ranging between 1 and 2 percent. In the non-DST (i.e., quasi-counterfactual) months the effect is not statistically different from zero for 3 out of the 4 months.

The fact that monthly billing data is structured around billing cycles—with consistent read-dates within each month—allows us to decompose the estimates even further. We separate the observations into billing cohorts where the month is divided into three segments: those with read-dates in the first third of the month, the second third of the month, and the last third of the month.[14] We then estimate equation (4) for each cohort in each month. In effect, this

[14] Because there are 21 billing cycles in each month, this procedure means that there are 7 billing cycles in each

disaggregates the monthly estimates in third-of-month estimates. These results are shown in figure 5. We again find some evidence for a decrease in electricity consumption for the early May read-dates, but through the DST period, there is a clear upward trend. In the later half of the DST period, nearly every estimate indicates that DST causes an increase in electricity consumption, with the effect appearing to be strongest during the October read-dates, when one estimate is approximately 4 percent. In the non-DST periods, most of the coefficients are not statically different from zero, and this is what should be expected if we are in fact identifying the effect of DST.

The final set of models that we estimate take advantage of the monthly observations that straddle the transition dates in and out of the DST period. We have thus far dropped these observations from the analysis, but we now use them to focus on estimates of the DST effect at the time of transition. In parallel with specification (4), we estimate models for the spring and fall transitions that have the following form:

$$(5) \qquad lnADC_{it} = \delta DSTfrac \times Year2006_t \times NE_i + \beta_1 ACDD_{it} + \beta_2 AHDD_{it} + \gamma_1 Year2005_t + \gamma_2 Year2006_t + \nu_i + \varepsilon_{it} ,$$

where the only difference is the interaction with *DSTfrac* in the treatment effect variable. This new term is the fraction of the number of days in the billing cycle that are in the DST period. Once again, the coefficient δ is of primary interest, and its interpretation remains the same: the percentage change in average daily consumption due to the practice of DST. But here the effect is identified off of one day's change within the billing cycle. Table 6 reports the fixed-effects estimates of equation (5) for both the spring and fall models. For the spring transition, we find a positive and statistically significant effect, with a magnitude of approximately 1 percent. The coefficient estimate for the fall transition model is also positive, but has a very small magnitude

cohort. In principle, we could estimate the DST effect for each billing cycle separately, rather than combining them into cohorts. But there is a tradeoff between having more precisely timed estimates and having less data upon which to estimate the effect. We thus follow the segmentation in Reiss and White (2003), whereby 7 billing cycles are combined into one cohort.

and is not statistically different from zero. While both of these transition results are of interest, they should be interpreted with caution because they are based on an attempt to extract a daily effect out of inherently monthly data. This, of course, makes it difficult to precisely estimate the effect. The same caution does not apply, however, to the estimates reported previously, where the models are based on data for which all days in the monthly billing cycle are subject to the same treatment effect.

5. Discussion

In this section we consider two questions. First, what are the underlying mechanisms that give rise to the estimates of the DST effect on residential electricity consumption? To answer this question we provide evidence from an engineering simulation model. Second, given that DST causes an overall increase in electricity consumption, what are the costs? We answer this question in terms of increased residential electricity costs and the social costs of increased pollution emissions.

Engineering Simulations

We ran simulations on eQuest, an interface program based on a versatile U.S. Department of Energy simulation model of a building's energy demand, including electricity.[15] The program has standardized design parameters for various building types, but all parameters can be altered by the user. We modeled a single-family residence: single-story, wood-frame construction, front and rear entry points with appropriate square footage for a family of four (~2000 sq ft). Heating in the residence is forced-air electric, and cooling is typical Freon-coil air conditioning. We kept all other pre-specified parameters. The software includes hourly weather data for the specified location and year of analysis. We report simulations for southern Indiana in 2005, and our aim is to demonstrate the simulated changes in electricity demand due to DST.

[15] The program description and download can be found at www.doe2.com. eQuest has the complete DOE-2 (version 2.2) building energy use simulation program embedded. Rock (1997) uses an older version of DOE-2.

We ran simulations for the DST periods of the year, with and without implementation of DST. The first column of table 7 reports the simulated percentage change in electricity consumption by month. Electricity consumption increases in 5 out of the 7 months. The only months associated with a savings are June and July, and the magnitudes are both just under 2 percent. The increased consumption that occurs in the spring months of April and May are both under 1 percent. The magnitudes in the late summer and fall are larger, especially in September and October, where the increased consumption is close to 4 and 3 percent, respectively. Note that the pattern of these results is similar in many respects to our estimates in the previous section. Referring back to figure 5, we find evidence of some electricity savings in early summer, and the largest increases in consumption occur in the fall. In particular, the October read-dates, which reflect half of September's consumption, have magnitudes of increased electricity consumption that are very similar to the predictions of the simulation model.

Beyond corroboration of our findings, the value of the simulation exercise is that we can decompose electricity consumption into its component parts. The last three columns in table 7 report the simulated change in average daily consumption by month for lighting, heating, and cooling separately. In all months, other than October, DST saves on electricity used for lighting; therefore, it appears that the "Benjamin Franklin effect" is occurring. But when it comes to heating and cooling, the clear pattern is that DST causes an increase in electricity consumption. The changes in average daily consumption are far greater for cooling, which follows because air-conditioning tends to draw more electricity and DST occurs during the hotter months of the year. These results indicate that the findings of Shimoda *et al*. (2007) for Japan apply to Indiana as well. Moving an hour of sunlight from the early morning to the evening (relative to clock time) increases electricity consumption for cooling because (*i*) demand for cooling is greater in the evening and (*ii*) the build-up of solar radiation throughout the day means that the evening is hotter. In some months, the cooling effect out weights the Benjamin Franklin effect. There is also some evidence for a heating effect that causes an increase in electricity consumption. When temperatures are such that heating is necessary, having an additional hour of darkness in the morning, which is the coldest time of day, increases electricity consumption. Kellogg and Wolff

(2006) find evidence for the heating effect in their study of DST extensions in Australia. While the magnitude of the heating effect does no appear to be a large in our Indiana simulation results, it is likely to be more substantial when considering extensions to DST, which push further into the colder times of year when the days are also shorter.

Costs of DST in Indiana

To begin calculating the costs of DST in Indiana, we need to establish the baseline of what electricity consumption would be without the practice of DST. We take advantage of all the data during the DST period to establish the baseline. For all observations that were subject to DST, we subtract the conservative estimate of 0.93 percent that comes from the models in table 5. Average daily consumption is then calculated from these adjusted observations and all others that were not subject to DST, yielding an overall estimate of 30.15 kWh/day. It follows that the effect of DST—under the pre-2007 dates of practice—is an increase in consumption for the average residence of 59.16 kWh/year (i.e., 0.0093×30.15 kWh/day $\times$ 211 days/year). Extrapolating this estimate to all 2,724,429 households in the state of Indiana implies that DST increases statewide residential electricity consumption by 161,177 megawatt hours per year (MWh/year).

With this estimate, it is straightforward to derive the increased residential electricity costs per year. The average price paid for residential electricity service from Duke Energy in southern Indiana is $0.054/kWh. Multiplying this price by the change in a household's consumption implies a residential cost of $3.19 per year. Extrapolating once again to the entire state yields a cost of $8,690,928 per year in residential electricity bills due to the practice of DST.[16]

The statewide increase in electricity consumption of 161,177 MWh/year also provides the basis for calculating the social costs of pollution emissions. We follow the general approach used in Kotchen *et al*. (2006). The first step is to determine the fuel mix for electricity generation. According to the Energy Information Administration (EIA 2006), the fuel mix for generation in Indiana is 94.8 percent coal, 2 percent natural gas, 0.1 percent petroleum, and 4.9 percent from

[16] A more precise estimate, which we are in the process of obtaining, would account for price differences in different areas of the state.

other sources (gases, hydroelectric, and other renewables). We assume the change in generation due to DST comes entirely from coal, as it accounts for such a vast majority of the state's electricity generation.[17] Emission rates—in tons of emissions per MWh of electricity generation from coal—are taken from Ecobilan's Tool for Environmental Analysis and Management (TEAM) model, which is a life-cycle assessment engineering model (Ecobilan 1996). The first column in table 8 reports the marginal emissions for carbon dioxide, lead, mercury, methane, nitrogen oxides, nitrous oxide, particulates, and sulfur dioxide. The second column reports the change in emissions for each pollutant, which is simply the product of marginal emissions and the change in overall electricity generation.

The next step is to quantify the marginal damages of each pollutant. For this we use a benefits transfer methodology and report low- and high-marginal damage scenarios where possible. The two exceptions are mercury and sulfur dioxide. We have only one estimate for mercury, and the values for sulfur dioxide are the tradable permit price in 2007, rather than the marginal damages. The reason for using the sulfur permit price is that total emissions are capped, so the marginal costs are reflected in the permit price, as the increase in emissions due to DST must be abated somewhere because of the binding cap. Table 8 reports the range of values in 2007 dollars for all pollutants, and we refer readers to Kotchen *et al*. (2006) for details on the specific references for each estimate.

The final step is to simply multiply the marginal damages by the change in emissions for each pollutant. The last two columns of table 8 report these total damage costs for each pollutant, for the low and high scenarios. After summing the results across all pollutants, the low and high estimates for the social costs of emissions are approximately \$1.6 million and \$5.3 million per year. In the low scenario, increases in carbon dioxide, particulates, and sulfur dioxide account for the vast majority of the costs. In the high scenario, increases in carbon dioxide account for a

[17] This assumption could be important because emissions differ substantially for different fuel sources, and coal is the dirtiest. If, for example, electric utilities in Indiana meet peak demand with natural gas, rather than coal, we would be overestimating the change in emissions, as changes in electricity demand due to DST are most likely to occur during peak times. While we are currently looking into this, the fact that 95 percent of the state's generation comes from coal suggests that coal is also being used to meet peak demand.

much greater share of the costs, with the difference reflecting uncertainty about the economic impacts of climate change. In both scenarios the costs of increases in lead, mercury, and methane are negligible.

6. Conclusion

The history of DST has been long and controversial. Throughout its implementation during World Wars I and II, the oil embargo of the 1970s, and more regular practice today, the primary rationale for DST has always been to promote energy conservation. Nevertheless, there is surprisingly little evidence that DST actually saves energy. This paper takes advantage of a natural experiment in the state of Indiana to provide the first empirical estimates of DST effects on electricity consumption in the United States since the mid-1970s. We focus on residential electricity demand and conduct the first study that uses micro-data on households.

Our main finding is that—contrary to the policy's intent—DST results is an overall increase in residential electricity demand. Estimates of the overall increase in consumption range from 1 to 4 percent. We also find that the effect is not constant throughout the DST period, with evidence for electricity savings in the spring and increases that are greatest in the fall. These findings are generally consistent with simulation results that point to a tradeoff between reducing demand for lighting and increasing demand for heating and cooling. According to the dates of DST practice prior to 2007, we estimate a cost to Indiana households of $8.6 million per year in increased electricity bills. Estimates of the social costs due to increased pollution emissions range from $1.6 to $5.3 million per year.

The results of this research should inform ongoing debate about the recent extensions to DST that took place in 2007. The Energy Policy Act of 2005 requires that research be conducted to evaluate whether the extensions yield conservation benefits. While our results suggest that the extensions to DST are most likely to increase, rather than decrease, demand for residential electricity, further research is necessary to examine the effects of the extensions themselves. Future research should also investigate whether the findings here generalize to other locations throughout the United States. While we find that the longstanding rationale for DST is questionable, and that if anything the policy seems to have the opposite of its intended effect, there are other arguments made in favor of DST. These range from increased opportunities for leisure, enhanced public health and safety, and economic growth. In the end, a full evaluation of DST should account for these multiple dimensions, but the evidence here suggests that continued reliance on Benjamin Franklin's old argument alone has become misleading.

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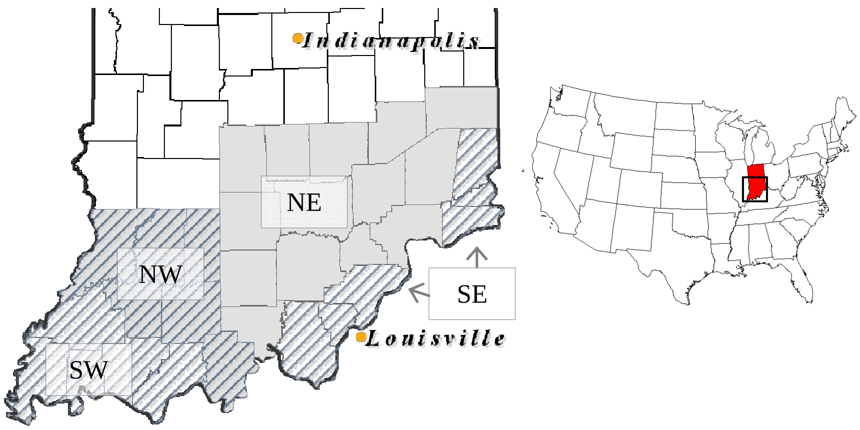

Region	Pre-2006	Starting 2006
NE	EST and no DST	EST and DST
SE	EST and DST	EST and DST
SW	CST and DST	CST and DST
NW	EST and no DST	CST (Fall start) and DST

Figure 1: Sets of Indiana counties in the study area with different time zones and differential practice of daylight saving time.

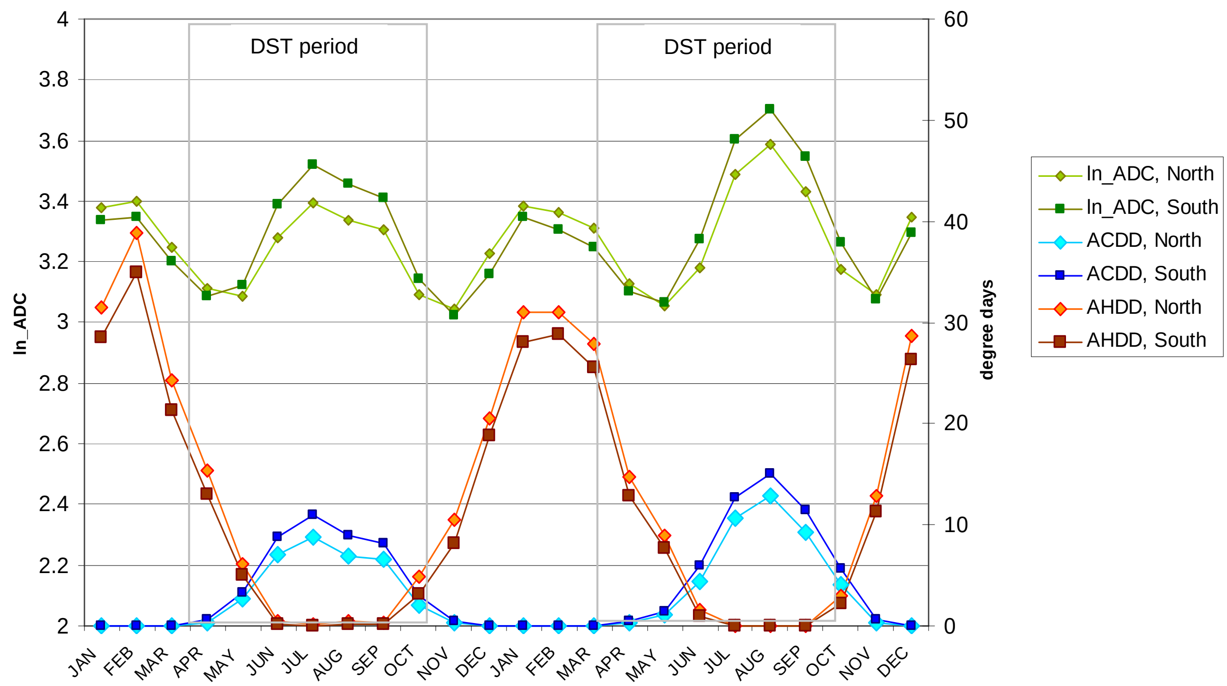

Figure 2: 2004-2005 average daily consumption, average cooling degree days, and average heating degree days by month for the north and south counties separately

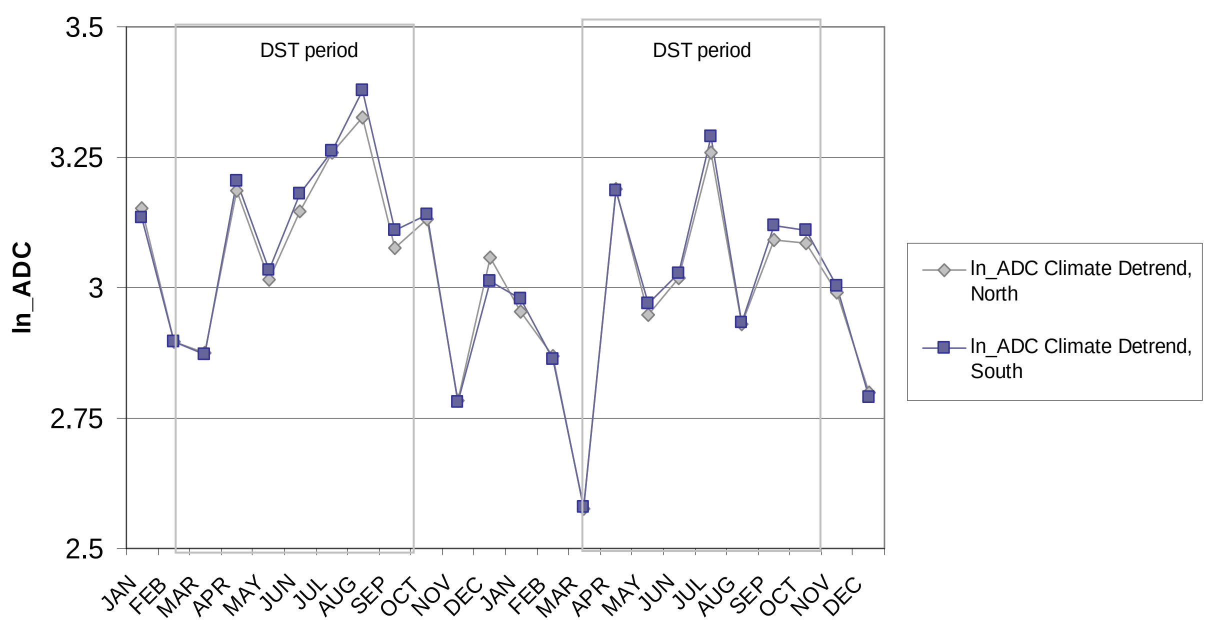

Figure 3: Weather-detrended average daily consumption by month for the north and south counties separately

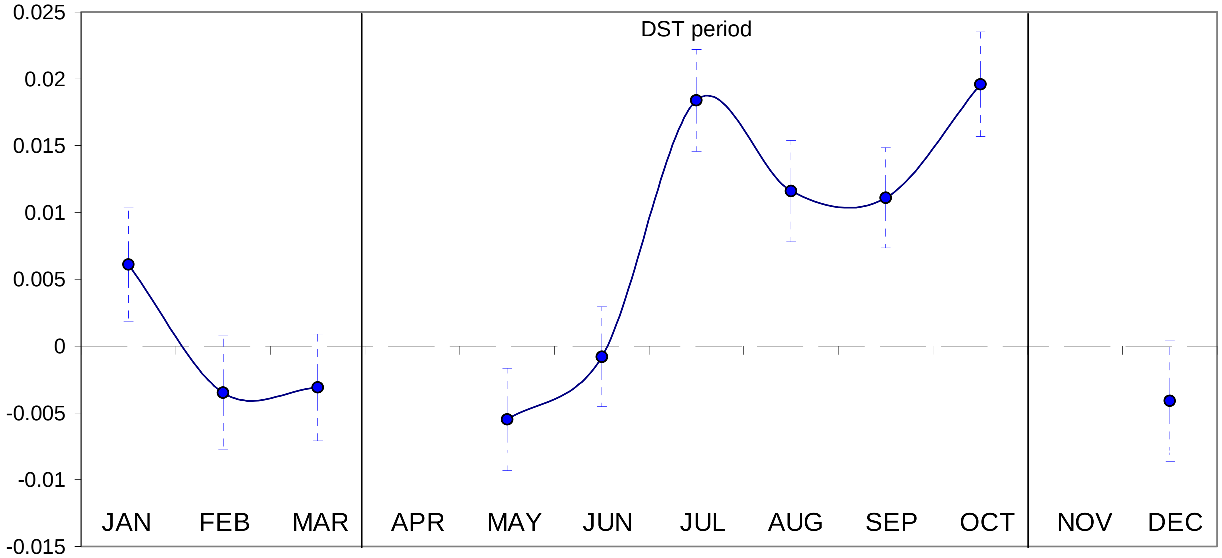

Figure 4: Monthly estimates and 95-percent confidence intervals for the DST effect and the quasi-counterfactual

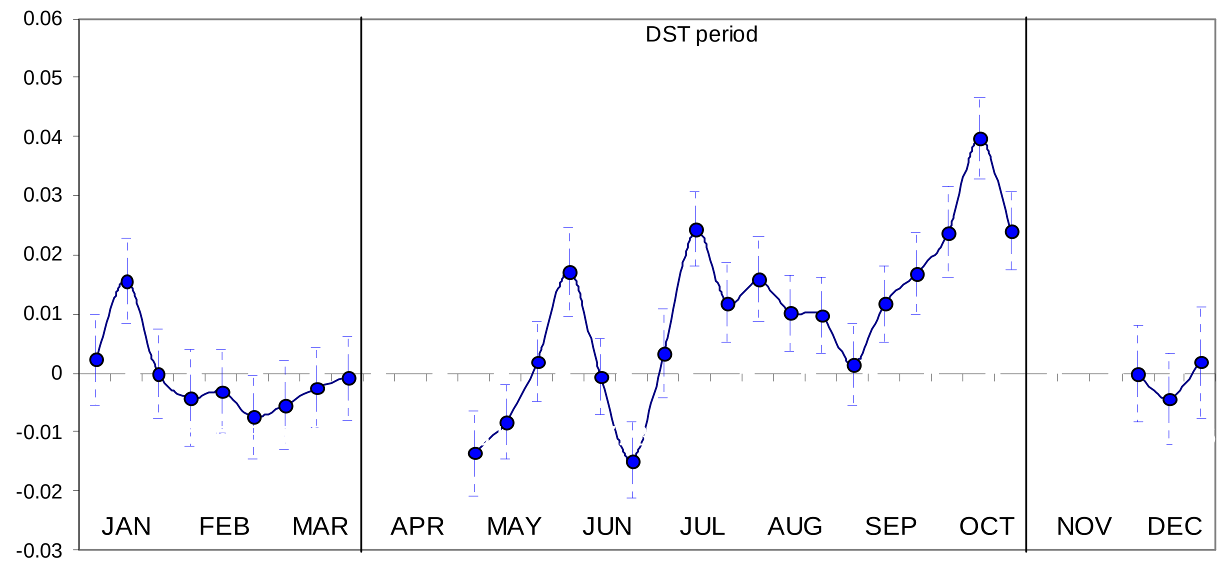

Figure 5: Third-of-month estimates and 95-percent confidence intervals for the DST effect and the quasi-counterfactual

Table 1: U.S. Census data for different sets of counties in southern Indiana

Census variable	Set of counties SE	SW	NE	NW	Total
Number of counties	3	3	14	4	24
Total population	176,906	111,944	506,932	92,282	958,887
Proportion of population rural	0.461	0.456	0.493	0.537	0.466
Proportion of population rural and farm	0.023	0.029	0.032	0.063	0.031
Median age	36.4	37.6	35.9	37.4	36.4
Number of households	68,500	42,490	195,597	35,748	369,846
Average household size	2.5	2.6	2.5	2.5	2.5
Proportion households with electric heat	0.322	0.284	0.334	0.218	0.311
Median household income in 1999	$42,613	$43,505	$38,076	$33,717	$39,553
Average per capita commute time (minutes)	12.63	11.18	10.58	9.56	10.92

Notes: All data taken from the 2000 U.S. Census. Cells weighted appropriately by either population or number of households.

Table 2: Descriptive statistics for different sets of counties in the dataset

Variable	Set of counties SE	SW	NE	NW	Total
Number of counties	3	3	14	4	24
Observations	1,278,519	314,598	5,036,552	552,208	7,181,877
Residences	39,646	9,595	157,469	17,173	223,878
Tenants	64,230	14,086	269,315	26,555	374,186
Average daily consumption (kWh/day)	35.21	35.99	35.98	35.09	35.77
	(25.28)	(26.09)	(29.02)	(26.96)	(28.11)
ln average daily consumption	3.30	3.31	3.29	3.27	3.29
	(0.79)	(0.82)	(0.83)	(0.82)	(0.82)
Average heating degree days	11.20	11.86	12.94	12.47	12.54
	(11.30)	(11.81)	(12.44)	(12.31)	(12.23)
Average cooling degree days	4.01	3.88	3.13	3.60	3.36
	(5.09)	(4.92)	(4.17)	(4.54)	(4.43)
Average day length (hours)	12.25	12.24	12.25	12.24	12.25
	(1.81)	(1.79)	(1.83)	(1.82)	(1.83)

Notes: Standard deviations are reported in parentheses.

Table 3: Fixed-effects models for difference-in-difference estimates 2004-2005

	Model		
	(a)	(b)	(c)
DSTperiod × South counties	0.0325**	0.0421**	0.0334**
	(0.0028)	(0.0028)	(0.0028)
DSTperiod	-0.0777**	--	--
	(0.0015)		
Average cooling degree days	0.0578**	0.0509**	0.0566**
	(0.0001)	(0.0002)	(0.0003)
Average heating degree days	0.0116**	0.0124**	0.0123**
	(0.0001)	(0.0001)	(0.0001)
Average day length	-0.0132**	--	--
	(0.0002)		
Year 2005	-0.0012*	0.0042**	--
	(0.0006)	(0.0006)	
Month dummies	--	Yes	--
Month-year dummies	--	--	Yes
Number of observations	3,843,759	3,843,759	3,843,759
Number of residents	315,251	315,251	315,251
R-squared (within)	0.152	0.154	0.154

Notes: The left-hand side variables is *lnADC* for each resident. Standard errors, clustered at the tenant level, are reported in parentheses. ** and * indicate statistical significance at the 99- and 95-percent levels, respectively.

Table 4: Differences in average daily consumption between 2004-2005 and 2006

	DST period		Non-DST period	
	Treatment: NE	Control: SE, SW, NW	Treatment: NE	Control: SE, SW, NW
Years 2004-2005	3.1395	3.2402	3.2841	3.2142
Year 2006	3.1864	3.2695	3.2983	3.2404
Difference	0.0469	0.0292	0.0142	0.0262
Difference-in-difference (DD)	0.0176		-0.0120	

Notes: Average daily consumption reported as *lnADC*. Difference is interpreted as the percentage change from years 2004-2005 to year 2006. Difference-in-difference is the percentage difference in the treatment group compared to the control group.

Table 5: Fixed-effects models for changed average daily consumption in 2006, DST and Non-DST periods

	DST period models			Non-DST period models		
	(a)	(b)	(c)	(d)	(e)	(f)
Year 2006 $\times$ Treatment group	0.0097**	0.0093**	0.0093**	-0.0019	-0.0014	-0.0023
	(0.0014)	(0.0014)	(0.0014)	(0.0015)	(0.0015)	(0.0015)
Average cooling degree days	0.0505**	0.0465**	0.0487**	-0.0170**	-0.0072	0.0038
	(0.0001)	(0.0001)	(0.0001)	(0.0058)	(0.0059)	(0.0063)
Average heating degree days	0.0013**	0.0039**	0.0034**	0.0132**	0.0140**	0.0144**
	(0.0001)	(0.0001)	(0.0002)	(0.0000)	(0.0001)	(0.0001)
Average day length	-0.0076**	--	--	-0.0316**	--	--
	(0.0002)			(0.0003)		
Year 2005	-0.0072**	-0.0019	--	0.0144**	0.0134**	--
	(0.0007)	(0.0007)		(0.0007)	(0.0007)	
Year 2006	-0.0236**	-0.0246**	--	0.0193**	0.0194**	--
	(0.0013)	(0.0013)		(0.0014)	(0.0014)	
Month dummies	--	Yes	--	--	Yes	--
Month-year dummies	--	--	Yes	--	--	Yes
Number of observations	3,623,370	3,623,370	3,623,370	2,289,640	2,289,640	2,289,640
Number of residents	335,509	335,509	335,509	332,032	332,032	332,032
R-squared (within)	0.312	0.313	0.314	0.075	0.075	0.076

Notes: The left-hand side variables is *lnADC*. Standard errors, clustered at the tenant level, are reported in parentheses. ** and * indicate statistical significance at the 99- and 95-percent levels, respectively.

Table 6: Fixed-effects models for the spring and fall transitions in and out of DST

	Transition model	
	Spring	Fall
Fraction DST days × Year 2006 × Treatment group	0.0106**	0.0014
	(0.0028)	(0.0032)
Average cooling degree days	0.0360**	0.0537**
	(0.0022)	(0.0028)
Average heating degree days	0.0118**	0.0132**
	(0.0004)	(0.0004)
Year 2005	0.0112**	0.0036**
	(0.0011)	(0.0016)
Year 2006	0.0131**	0.0261**
	(0.0025)	(0.0032)
Number of observations	574,821	578,430
Number of residents	279,893	278,078
R-squared (within)	0.007	0.035

Notes: The left-hand side variables is *lnADC*. Standard errors, clustered at the tenant level, are reported in parentheses. ** and * indicate statistical significance at the 99- and 95-percent levels, respectively.

Table 7: Simulation results for changes in monthly electricity demand with and without DST

		Difference in average daily consumption (no DST – DST)		
	DST Effect	Lighting	Heating	Cooling
April	0.22%	-10	1	9
May	0.98%	-18	7	14
June	-1.84%	-19	1	11
July	-1.97%	-20	0	12
August	1.03%	-16	0	20
September	3.92%	-5	3	14
October	2.93%	5	-2	8
Overall	0.32%			

Notes: Simulation results based on 2005 weather in southern Indiana. Quantities reported in the last three columns are differences in average daily consumption for the category and month indicated. DST effect percent differences do not exactly reflect the percentage change in light, heating, and cooling because they capture relatively small changes in electricity consumption due to DST in other categories as well.

Table 8: The social costs to Indiana of pollution emissions from DST

	Emissions (tons/MWh)	Δ emissions (tons)	Marginal damages		Total damages	
			Low	High	Low	High
Carbon dioxide	1.134E-00	182774.72	\$2.82	\$20.55	\$515,370	\$3,755,143
Lead	6.752E-07	0.11	\$572.52	\$2,457.32	\$62	\$267
Mercury	2.490E-08	0.00	\$58.90	\$58.90	\$0	\$0
Methane	1.336E-05	2.15	\$79.96	\$343.16	\$172	\$739
Nitrogen oxides	5.275E-03	850.21	\$77.20	\$179.41	\$65,633	\$152,534
Nitrous oxide	4.868E-05	7.85	\$853.54	\$7,690.35	\$6,697	\$60,339
Particulates	8.540E-04	137.65	\$954.91	\$3,282.86	\$131,438	\$451,869
Sulfur dioxide	1.060E-02	1708.48	\$518.98	\$518.98	\$886,665	\$886,665
Total					\$1,606,038	\$5,307,557

Notes: Emissions (tons/MWh) taken from Ecobilan's TEAM model, copyright 2006. Δ emissions are the product of emissions and the DST change in electricity consumption of 161,177 MWh/year. All dollars values are reported in 2007 dollars.