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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, consistent practice today, and recent extensions, 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 to estimate an overall DST effect. The dataset consists of more than 7 million observations on monthly billing data for the vast majority of 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 are approximately 1 percent, but we find that the effect is not constant throughout the DST period. DST causes the greatest increase in electricity consumption in the fall, when estimates range between 2 and 4 percent. These findings are consistent with simulation results that point to a tradeoff between reducing demand for lighting and increasing demand for heating and cooling. We estimate a cost of increased electricity bills to Indiana households of $9 million per year. We also estimate social costs of increased pollution emissions that range from $1.7 to $5.5 million per year. Finally, we argue that the effect is likely to be even stronger in other regions of the United States.

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1. Introduction

Daylight Saving Time (DST) is currently practiced in 76 countries and directly affects more than 1.6 billion people worldwide. The well-known mnemonic of “spring-forward, fall-back” describes the annual ritual: turn clocks forward one hour in the spring, and turn them back one hour in the fall. Less well known is that DST is a policy designed to conserve energy.[1] Benjamin Franklin (1784) is credited with the basic 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 people adjusted their schedules to earlier in the day during summer months, when day length is longest, an immense sum of tallow and wax could be saved by the “economy of using sunshine rather than candles.” To encourage the behavior, Franklin satirically proposed the firing of cannons to awaken people at dawn and a tax on window shutters that keep out sunlight.[2]

More than a century later, William Willet (1907) proposed the simple advancement of clock time during summer months in order to avoid “The Waste of Daylight.” But it was not until World War I that the idea finally took hold. Germany was the first country to implement a DST policy, with the aim of reducing demand for electrical lighting so that more coal could be diverted to the war effort. Thirty-one other nations, including the United States, soon followed with their own DST policies, but the practice was generally repealed after the war ended. Decades later, and for the same reason, 52 countries again implemented various DST policies during World War II. In the United States, year-round DST was practiced for three years and then repealed entirely.

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[1] A common misperception is 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 morning darkness for an extra hour in order to coordinate with the timing of markets. See Prerau (2005) for a detailed discussion of DST’s long and controversial history.

[2] Interestingly, Franklin also recognized that his calculations of the economic savings during the summer were an underestimate because of general equilibrium effects. He wrote that “… I have calculated upon only one half of the year, and much may be saved in the other, though the days are shorter. Besides, the immense stock of wax and tallow left unconsumed during the summer, will probably make candles much cheaper for the ensuing winter, and continue them cheaper as long as the proposed reformation shall be supported.”

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.[3] Then, the oil embargo of the early 1970s prompted temporary 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. The DST regime in practice today includes a further extension authorized within the Energy Policy Act of 2005. Having begun in 2007, DST now starts three weeks earlier, on the second Sunday in March, and lasts one week longer, until the first Sunday in November. Figure 1 shows the sunrise and sunset times, the time shifting of DST, the 2007 extensions on both ends, and the day length throughout the year (the middle line) for a representative location in southern Indiana.

Congressional debate about the most recent extension to DST focused on the potential energy savings. It was forecasted that each additional day of DST would save the equivalent of 100,000 barrels of oil per day (Congressional Record 2005a, 2005b). But the 2005 Energy Policy Act specifically requires that research be conducted to estimate the actual effects on energy demand, and Congress retains the right to repeal the extensions if the conservation benefits are not realized. Despite the conservation rationale for DST's current and historical practice, surprisingly little research has been conducted to determine whether DST actually saves energy.[4] Even among the few studies that do exist, which we review in the next section, the evidence is inconclusive. Hence, the need to better understand the DST effect on energy consumption is immediately policy relevant. What is more, with worldwide energy demand expanding rapidly, along with concerns about climate change, it is increasingly important to know whether DST,

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[3] Individual states could opt for exemption, but only Arizona, Hawaii, Indiana, and a few U.S. territories have done so in various ways over the years.

[4] 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), health (e.g., Kantermann et al 2007), economic coordination (Hamermesh et al 2006), and stock market performance (Kamstra et al 2000, 2002; Pinegar 2002).

which is among the most uniformly applied policies on the planet, has its intended effect of energy conservation.

In this paper, we investigate whether DST does in fact save energy, with a focus on residential electricity consumption. Our research design takes advantage of the unique history of DST in the state of Indiana, combined with a data set of monthly billing cycles for the majority of 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 a natural experiment—with treatment and control sets 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 ever to use residential microdata. A unique feature of the research design, due to the natural experiment, is that we are able to estimate, for the first time, an overall DST effect and different effects throughout the year over the entire DST period, including the periods of transition. We also run an engineering model that simulates the effect of DST on household electricity demand. These results are comparable with our empirical estimates and highlight seasonal differences in the quantity and timing of electricity demand for lighting, heating, and cooling. A further contribution of the paper 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 a 1-percent overall increase in residential electricity demand, and the effect is highly statistically significant. We also find that the effect is not constant throughout the DST period. In particular, DST causes the greatest increase in consumption later in the year, with October estimates ranging from an increase of 2 to nearly 4 percent. To help interpret these results, we simulate the effect of DST for an Indiana household with a 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 the calculation of costs associated with DST. We find that the policy costs Indiana households an average of \$3.29 per year in increased electricity bills, which aggregates to approximately \$9 million over the entire state. We also calculate the social costs in terms of increased pollution emissions, and these estimates range from \$1.7 to \$5.5 million per year.

The remainder of the paper proceeds as follows: The next section reviews existing evidence on the effect of DST on electricity consumption. Section 3 describes the research design and data collection. Section 4 contains the empirical analysis. Section 5 provides a discussion of the results with comparisons to engineering simulations and cost estimates. Section 6 concludes with a brief summary and remarks about the generalizability of our results.

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 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 (Filliben 1976), concludes that the energy savings are questionable and statistically 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 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.[5] 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.

The U.S. Department of Energy (DOE 2006) also conducts a study to estimate the potential energy saving impacts of the 2007 DST extensions. Using hourly electricity data immediately before and after the DST transitions in 2004, the study estimates DST effects and extrapolates them into the extension periods to predict what might happen beginning in 2007. The results of most relevance here are the actual DST effects. The main findings of the study include the following: a decrease in electricity demand of 0.4 percent at the points of transition, but the estimate is very imprecise; morning increases in demand that are more than offset by evening decreases; southern regions of the United States experience lower energy savings; and energy savings are slightly greater during the spring transition compared to the fall transition.[6]

Kellogg and Wolff (in press) 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 experi-

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[5] 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 appear to have never been completed, the results indicate that DST in Indiana could either increase or decrease electricity consumption.

[6] Currently underway, but not yet released, is the official U.S. DOE report to Congress required by the Energy Policy Act of 2005. The report will use 2007 data to estimate the actual, rather than potential, energy savings due to extended DST.

enced 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 provides the first empirical results that 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 consumption for a typical residence using utility records and chosen parameters for construction type, 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 simulates 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. Results for alternative scenarios 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.[7] 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

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[7] Aries and Newsham (2008) review other studies, many of which are technical reports not published in peer-reviewed journals, that focus on lighting energy use in the United States and other countries. They find no clear DST effect other than some evidence for a reduction in evening peak demand for electricity.

greater in the evening than in the morning, and implementing DST aligns an additional hour of higher outdoor air temperature and solar radiation with 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 further 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 the state, due in large part to the importance of agriculture in Indiana, and the state's location split between the Eastern and Central Time Zones. For more than 30 years prior to 2006, the resultant policy has been three different time scenarios within the state: 77 counties on Eastern Standard Time (EST) that did not practice DST; 10 counties clustered in the north- and south-western corners of the state on Central Standard Time (CST) that did practice DST; and 5 counties in the south-eastern portion of the state on EST that did practice DST.[8] The different time scenarios changed in 2006 when the entire state began practicing DST as required by a law 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, where our study takes place. The shaded counties in Figure 2 are those included in the study. It is useful to partition the counties into four sets, as shown in the figure. The SE and SW counties experienced no change; they practiced DST prior to 2006 and have remained on EST and CST,

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[8] 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.

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. [9]

The pattern of time and timing in southern Indiana creates a natural experiment to identify the effect of DST on residential electricity demand. The empirical strategy relies on having monthly billing data for households located within the different sets of counties before and after 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 when moving from the before to after period. 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.[10] 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 difference-in-differences estimate between the two groups, before and after the policy change.

Table 1 shows selected variables from the 2000 U.S. Census for the different sets of counties and in total. The majority of people live in the eastern counties. The northern counties have a larger fraction of the population classified as rural and farm, although the overall pro-

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[9] Specific counties included in the study are the following: (NE) Bartholomew, Brown, Crawford, Decatur, Franklin, Jackson, Jefferson, Jennings, Lawrence, Monroe, Orange, Scott, Ripley, Washington; (SE) Clark, Dearborn, Flyod, Harrison; (SW) Gibson, Posey, Warrick; (NW) Daviess, Knox, Martin, Pike. Counties in southern Indiana not included in the study because data were not available from Duke Energy are the following: (SE) Ohio, Switzerland; (SW) Spencer, Vanderburgh; (NW) Dubois, Perry.

[10] Recall that clock time did not change for all 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.

portion of people living on farms is 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 the majority of households in the counties shown in Figure 2.[11] The dataset consists of monthly billing information for all households serviced by Duke Energy in the 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 electricity meter. 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.[12] 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

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[11] Cinergy formerly provided electrical service in southern Indiana but was acquired by Duke Energy in 2005. Alternative electrical service providers are the investor-owned utility Vectren and rural electric membership cooperatives.

[12] The data does not permit us to follow tenants from one residence to another, but this is not a limitation for our analysis.

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 is associated with its assigned *read-date*, according to Duke Energy's billing-cycle schedule.

We also collected and merged data on weather. Data on average daily temperature were obtained from the National Climatic Data Center.[13] We collected these data for every day in 2004 through 2006 from 60 different weather stations in southern Indiana and 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 its zip code and 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 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 for each billing cycle.

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 15 and greater than 35 (1.52 percent of the

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[13] These data are available online at www.ncdc.noaa.gov/oa/ncdc.html.

data).[14] We also dropped all of the observations for which the transaction date did not closely align with 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 (an additional 5.20 percent of the data). Finally, we considered irregular and dropped all observations that had less than 1 kWh for average daily consumption (an additional 1.76 percent of the data). The final dataset includes 7,267,392 observations, 223,889 residences, and 384,083 tenants.

Table 2 reports descriptive statistics disaggregated into the different sets of counties and combined. Reflecting the relative populations, the majority of data come from the NE counties, followed by those in the SE, with fewer in the western counties. Average daily consumption—between 35 and 36 kWh/day—is very similar among all sets of counties. As expected, average cooling degree days is higher in the south counties, while average heating degree days is higher in the north counties.

Figure 3 illustrates average daily consumption and the weather variables graphically for each month in the dataset. We show the natural log of ADC separately for the control and treatment sets of counties, along with AHDD and ACDD. 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. Also worth noting are the differences between the treatment and control groups. Inspection of the trends for ADC reveals that the control group tends to have greater electricity demand during the DST periods, while the treatment group tends to have greater electricity demand during the non-DST periods. It appears that differences in AHDD and ACDD influence this pattern, as the control group tends to be hotter during the DST periods, and the treatment group tends to be colder during the non-DST

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[14] The cutoff at 15 days is standard in econometric analysis of residential electricity demand (e.g., Reiss and White 2003), and Duke Energy considers bills with more than 35 days irregular.

periods. These patterns underscore the importance of accounting for weather when trying to explain variation in electricity demand.

4. Empirical Analysis

Indiana's 2006 change to DST policy provides a natural experiment for identifying the effect of DST on residential electricity demand. As mentioned previously, the approach is based on a comparison between the treatment and control groups of counties. 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 during the DST period in 2006 due to the offsetting effect of changing time zones. Our identification strategy thus comes from a difference-in-differences (DD) comparison between the two groups, before and after the DST policy change.[15]

We begin with a simple comparison of means for average daily consumption. First consider only the monthly electricity bills with start- and end-dates entirely within the DST period of each year. The first two columns of Table 3 report *lnADC* for both the treatment and control groups, before and after the policy change. We also report the before-after difference and the DD between groups. These comparisons indicate that electricity demand increased for both groups, but demand increased 1.9 percent more in the treatment group. While this result suggests that DST may increase electricity demand, the simple comparison of means does not provide a formal test, nor does it control for other variables that may be changing differentially over time between groups, namely weather.

As a point of comparison, we conduct the same procedure using electricity bills with start- and end-dates entirely outside the DST period of each year. This calculation can be

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[15] An alternative identification strategy is to compare the DST and non-DST periods with a DD approach in the years prior to the policy change. This strategy relies on the assumption that different sets of counties would have the same differences in consumption at different times of the year, if not for the differential practice of DST. We find this assumption less plausible because of the potential confounders of differences in the distribution of air conditioning and/or electric heat. Although not reported in the paper, we estimate models using this approach and find results with magnitudes nearly twice as large as those presented here. The following estimates should therefore be considered conservative.

thought of as a quasi-counterfactual because it provides an estimate of how the two groups differ in their differences to 2006 during the non-DST period of the year, when there was no policy change.[16] We again find that electricity demand increased for both groups, but in this case, demand increased 0.91 percent less in the treatment group. The fact that this result, when there was no policy change, has a lower magnitude and the opposite sign provides further evidence that DST may increase electricity demand.

To more rigorously investigate the DST effect on residential electricity demand, we estimate standard DD, treatment-effects models. We once again begin using only electricity bills that fall entirely within the DST period of each year.[17] Our regression models have the following general specification:

$$(1) \qquad lnADC_{it} = \delta Year2006_t \times NE_i + f(ACDD_{it}, AHDD_{it}, NE_i) + \theta_t + \nu_i + \varepsilon_{it} \, ,$$

where subscripts i denote tenants, $Year2006_t$ is a dummy variable for whether the observation occurs during 2006, NE_i is a dummy variable for whether the residence is in the NE set of counties, θ_t is a time-specific intercept, ν_i is a tenant-specific intercept, and ε_{it} is the error term. Equation (1) does not specify a particular functional form for the weather variables because we try several different specifications, some of which allow the effect of weather to differ between the treatment and control groups. The estimate of δ is of primary interest, as it captures the average DD in electricity demand for 2006 between the treatment and control groups. Again, the key identification assumption here is that, after controlling for differences in weather and time-invariant unobserved heterogeneity among tenants, electricity demand would have followed the same trend in the treatment and control groups, but for the effect of the change in DST.

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[16] For this calculation, we exclude electricity bills in the NW counties during November and December of 2006, when and where there is the confounding effect of a time-zone change.

[17] To be even more specific, for these DST and non-DST models, we drop the monthly electricity bills that straddle the date of transition in or out of DST; however, later in this section we use these dropped observations to estimate the DST effect at the spring and fall transitions.

All standard errors are clustered at the billing-cycle within each county in order to make statistical inference robust to potential serial and spatial correlation. The importance of considering serial correlation in DD estimation is well known (see Bertrand et al 2004), and clustering at this level accounts for potential serial correlation of household electricity demand. Clustering at the billing-cycle also has the advantage of accounting for potential serial correlation due to the timing of meter reads earlier or later in the month, which is not captured with month-year dummies used to control for the time trend in specification (1). The relatively broad level of clustering should also ally concerns about potential spatial correlation. Within counties, billing cycles are closely aligned with neighborhoods because they are designed as meter-reading walking routes. The clustering thus account for spatial correlation that may arise because of neighborhood characteristics, such as the density of housing, type and date of construction, and possibly socio-economic characteristics.

Table 4 reports the fixed-effects estimates of equation (1). We include four specifications that account for weather in different ways. The variables ACDD and AHDD enter linearly in models (a) and (b). The only difference is that model (b) includes interactions with the treatment group so that weather is allowed to affect electricity demand differently in the treatment and control groups. The models in columns (c) and (d) are more flexible, with dummy variables for ACDD and AHDD binned at each integer. This includes 18 dummies for ACDD and 16 dummies for AHDD. In parallel, the only difference in model (d) is that each weather dummy variable is also interacted with the treatment group to allow differences in the effect of weather between groups. The estimate of δ for all four models is positive, highly statistically significant, and of similar magnitude. The estimates fall between 0.008 and 0.0103. The interpretation is that DST causes an increase in electricity demand that ranges from 0.8 to 1.03 percent over the entire DST period.

Table 5 reports the fixed-effects estimates for the quasi-counterfactual experiment. Using only data for the non-DST period of each year, we estimate a slightly modified version of equation (1). To take advantage of all the data, we include an additional dummy variable, *NWchg2006,* to account for the time-zone change that occurred in the NW counties at end of 2006. Another difference is that models (c) and (d) do not include dummy variables for ACDD, as there are exceedingly few cooling degree days in Indiana during the non-DST period of the year. These models do, however, include 32 dummy variables for AHDD, which are also interacted with the treatment group in model (d). All estimates of the quasi-counterfactual DST effect are negative and have relatively small magnitudes, ranging from 0.3 percent to 0.6 percent. While three of the four estimates are not statistically distinguishable from zero, despite having close to 2.4 million observations, the coefficient in model (c) is marginally, statistically significant. Generally, we interpret these results in support of our key 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 and differences due to weather.

We now disaggregate our estimate of the overall DST effect into monthly estimates in order to investigate whether the effect of DST differs throughout the year. In particular, we estimate equation (1) separately for each month of the year based on the meter-read date. Following the same practice, we estimate equations for both the DST and non-DST periods, and we continue to exclude observations that straddle the DST transitions, meaning that we do not have monthly models for April or November. For simplicity, we report disaggregated estimates consistent with inclusion of the weather variables in column (a) in Tables 4 and 5.[18] Rather than report each of the 10 equations, we focus on estimates of δ, that is, the DST and quasi-counterfactual effects. We illustrate these results graphically in Figure 4, along with the 95-percent confidence intervals (standard errors are again clustered at the county × billing-cycle level). We find that the effect of DST is not statistically different from zero in May and June. It is, however, positive and statistically significant for the months July through October, with magnitudes ranging from 1 to 2 percent. As expected, during the non-DST months, we find no statistically significant differences between the treatment and control groups.

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[18] Alternative specifications of the weather variables have little affect on the estimate interest.

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.[19] We then estimate parallel models for each cohort in each month. In effect, this disaggregates the monthly estimates into third-of-month estimates. These results are shown in Figure 5. We again do not find consistent evidence for DST effects in May and June, yet 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 estimates range between 2 and 4 percent. In the non-DST periods, all coefficients except one are not statically different from zero, as one would expect if the DST periods are identifying the effect of changing the clock.

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 equation (1), we estimate models for the spring and fall transitions that have the following form:

$$(2) \qquad lnADC_{it} = \delta DSTfrac \times Year2006_t \times NE_i + \beta_1 ACDD_{it} + \beta_2 AHDD_{it} + \gamma_1 Year2005_t + \gamma_2 Year2006_t + \nu_i + \varepsilon_{it} ,$$

where the main difference is the interaction of *DSTfrac* with the treatment-effect variable.[20] This new term is the fraction of the number of days in the billing cycle that are in the DST pe-

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

[20] We again report only specifications in which the weather variables enter linearly and without interactions with the treatment group.

riod. 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 marginal changes in the number of days in DST.

Table 6 reports the fixed-effects estimates of equation (2) for both the spring and fall models. For the spring transition, we find a positive and statistically significant effect, with a magnitude of approximately 1.2 percent. The coefficient estimate for the fall transition model is also positive, but has a very small magnitude 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 residential 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.

A. 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.[21] The program has standardized design parameters for various building types, but all parameters can be altered

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[21] 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.

by the user. We ran many simulations with different sets of parameters based on advice we received from program experts. While the numerical estimates differ among simulations, the general pattern of results remains the same. Here we report the results for a single family residence in southern Indiana with parameter settings thought to be most representative.[22] Embedded in the software is hourly weather data averaged from 1961 through 1990. Using 2006 as the calendar year, we ran simulations for the DST periods of the year, with and without the option to implement DST.

The first column of Table 7 reports the simulated percentage change in electricity consumption by month. Electricity consumption increases in 6 out of the 7 months. The only month associated with a savings is July, and the magnitude is less than half of a percent. The increased consumption that occurs in the spring months of April and May, at approximately 0.7 and 1.7 percent, respectively, tapers off in mid-summer. By September and October the simulated increase in consumption is well over 2 percent. Note that the pattern of these results is similar in many respects to our estimates in the previous section. We found some evidence, based on the model presented in Table 6, of an increase in electricity consumption at the time of transition in April. Referring back to Figure 5, we also found that the largest increases in consumption occur in late summer and early fall. In particular, the October read-dates, which reflect half of September's consumption because there is nearly a 30-day lag on average, have magnitudes of increased electricity consumption that are very similar to the predictions of the simulation model.

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[22] Details about the program settings for the results presented here are the following: We use the multi-family, low-rise schematic to model a single-family dwelling in Evansville, IN. The dwelling is a single-story, wood-frame construction, front and rear entry points with appropriate square footage for a family of four (~1800 sq ft). The rectangular footprint (35' x 51') is oriented N-S in the lengthwise direction, with doors on both N and S sides. We modify the roof to 'pitched' with recommended default settings. Day lighting controls are set at 100 percent to simulate electricity-use change due to daylight relative to clock-time. Occupancy schedules are default, based on daytime work and leisure outside of the home. Heating in the residence is forced-air resistance electric, and cooling is typical Freon-coil air conditioning. Seasonal thermostat set points to initiate the HVAC system for occupied are 76F for cooling and 68F for heating, for unoccupied 80F and 65F, respectively. Fans are cycled intermittently at night, except are shut off from midnight to 4am. Further details about the simulations and results are available upon request.

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, cooling, and heating 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 cooling and heating, 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. Though not shown here, this is precisely the pattern that we find in the simulated daily electricity profiles for each month. In some months, as can be seen in Table 7, the cooling effect out weights the Benjamin Franklin effect.

There is also 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 not appear to be as large in our Indiana simulation results, it is likely to be more substantial when considering extensions to DST, which push further into the colder and shorter days of the year.

B. 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 estimate of 0.96 percent that comes from model (a) in Table 4. Average daily consumption is then calculated from these adjusted observations and all others that were not subject to DST, yielding an overall estimate of 30.12 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 61.01 kWh/year (i.e., 0.0096 × 30.12 kWh/day × 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 166,217 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 $3.29 per year. Extrapolating once again to the entire state yields a cost of $8,963,371 per year in residential electricity bills due to the practice of DST.[23]

The statewide increase in electricity consumption of 166,217 MWh/year also provides the basis for calculating the social costs of pollution emissions.[24] 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 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. Emission rates—in tons of emissions per MWh of electricity generation from coal—are taken from Ecobilan's Tool for Environmental Analysis and Man-

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[23] A more precise estimate would account for price differences in different areas of the state. But the estimate presented here should be treated as an underestimate. According to the Energy Information Administration (EIA 2006) the average retail price of electricity throughout Indiana in 2006 was $0.0646/kWh. At this price, the increased cost to residential electricity bills is $10,737,645 per year.

[24] The focus on changes in consumption rather than generation means that we do not take account of transmission and distribution loses, which can be substantial. This is one respect in which the social costs of pollution emissions reported here should be treated as conservative.

agement (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 $1.7 million and $5.5 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 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, more consistent practice today, and recent extensions, the primary rationale for DST has always been the promotion of energy conservation. Nevertheless, there is surprisingly little evidence that DST actually saves energy. This paper takes advantage of a unique 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. The results are also the first-ever empirical estimates of DST's overall effect.

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 are approximately 1 percent and highly statistically significant. We also find that the effect is not constant throughout the DST period: there is some evidence for an increase in electricity demand at the spring transition into DST, but the real increases come in the fall when DST appears to increase consumption between 2 and 4 percent. 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 \$9 million per year in increased electricity bills. Estimates of the social costs due to increased pollution emissions range from \$1.7 to \$5.5 million per year.

Although this paper focuses exclusively on residential electricity consumption, it is likely to be the portion of aggregate electricity demand that is most responsive 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. But future research that accounts for commercial and industrial electricity demand would be useful.

It is also worth considering how the results reported here might generalize to other locations in the Unites States. Answers to this question are, of course, limited by the fact that Indiana is the only place where such a natural experiment has occurred. There are nevertheless several reasons we might infer that DST increases electricity demand across a much broader area.

First, existing simulations suggest that DST increases electricity consumption on average over 224 different locations throughout the United States (Rock 1997). Our results also corroborate the results of such simulation exercises. Second, even when prior research finds little or no electricity savings from DST in the United States, the effect is smaller in more southern regions (DOE 2006). Finally, the fact that we identify the underlying tradeoff between artificial illumination and primarily air-conditioning suggests that the DST effect that we estimate is likely to be even stronger in the more populated, southern regions of the Unites States. Further south, the days are shorter during the summer, meaning that decreases in electrical use from lighting are likely to be smaller, and air conditioning is more common and intensively used, meaning that increases in electricity for cooling are likely to be bigger.

The results of this research should inform ongoing debate about the recent extensions to DST that took place in 2007. As mentioned earlier, 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. At present, we are still awaiting release of the official Department of Energy study.

In conclusion, we find that the longstanding rationale for DST is questionable, and if anything, the policy seems to have the opposite of its intended effect. Nevertheless, 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 is now misleading.

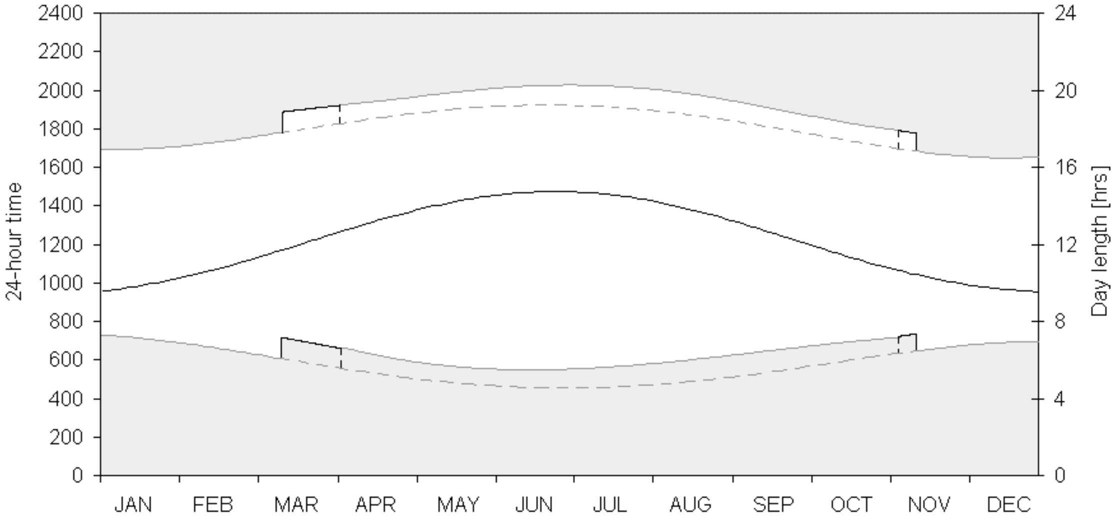
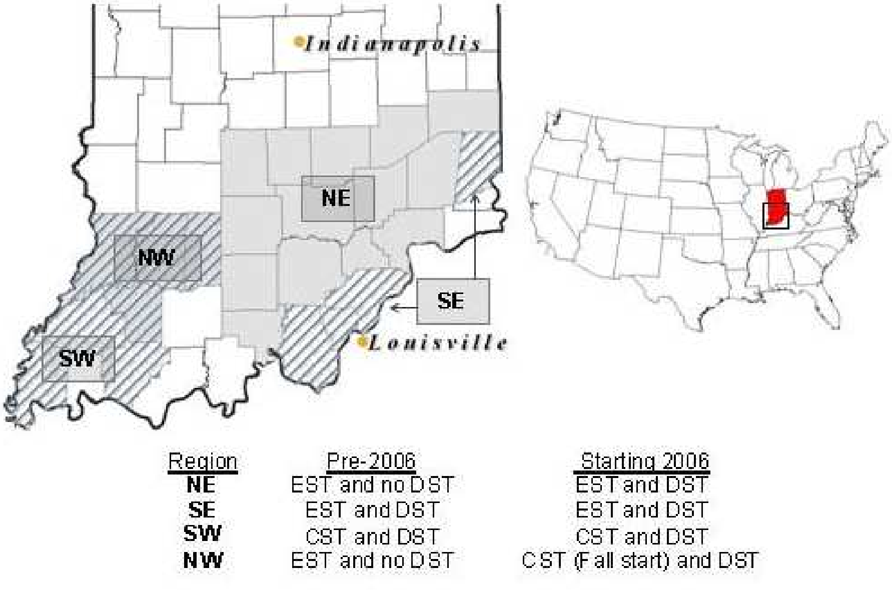


Figure 1: Sunrise and sunset times with daylight saving time and 2007 extensions in southern Indiana



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 2: Sets of Indiana counties included in the study with different time zones and differential practice of daylight saving time

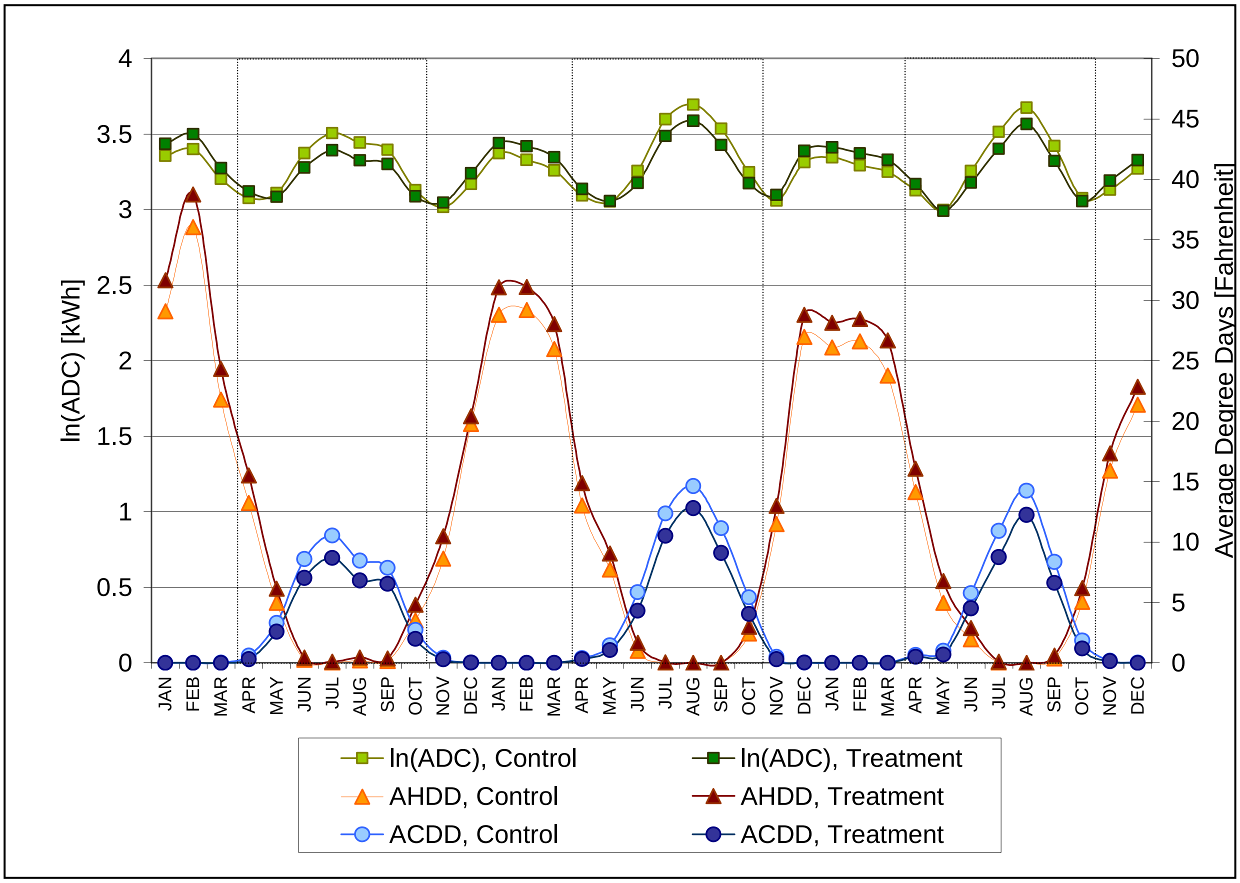


Figure 3: Average daily consumption, average heating degree days, and average cooling degree days by month 2004-2006 for the control and treatment sets of counties

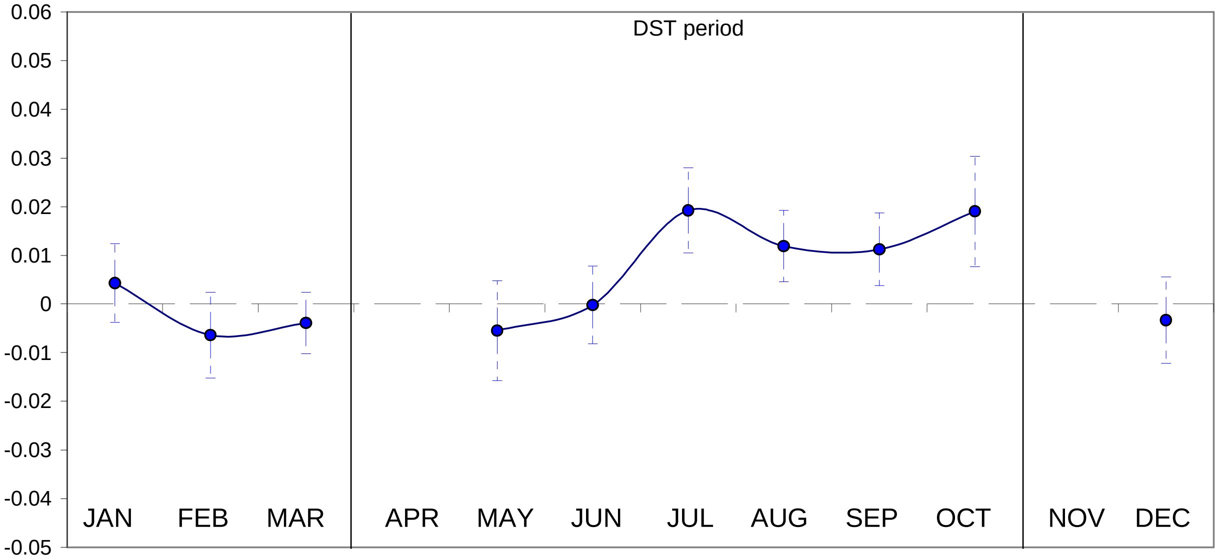


Figure 4: Monthly estimates and 95-percent confidence intervals for the DST effect and the quasi-counterfactual

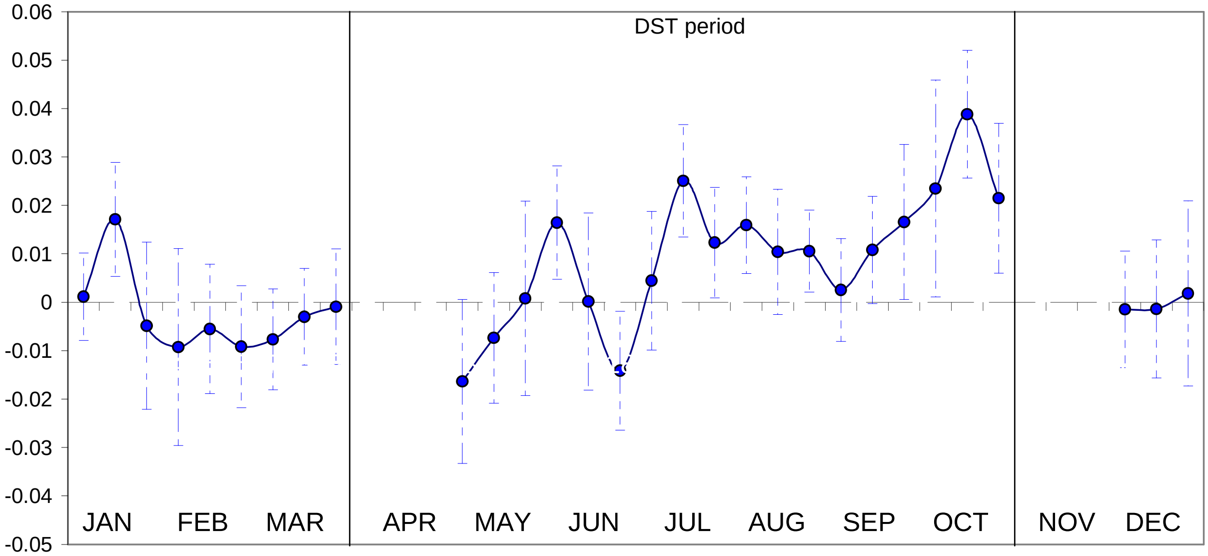


Figure 5: Third-of-month estimates and 95-percent confidence intervals for the DST effect and the quasi-counterfactual

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

	Set of counties				
Census variable	SE	SW	NE	NW	Total
Number of counties	4	3	14	4	25
Total population	247,729	111,944	506,932	92,282	958,887
Proportion of population rural	0.389	0.456	0.493	0.537	0.466
Proportion of population rural and farm	0.018	0.029	0.032	0.063	0.031
Median age	36.5	37.6	35.9	37.4	36.4
Number of households	96,011	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	0.313	0.284	0.334	0.218	0.311
Median household income in 1999	$42,964	$43,505	$38,076	$33,717	$39,553
Average per capita commute time (minutes)	12.00	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 data set

	Set of counties				
Variable	SE	SW	NE	NW	Total
Observations	1,295,108	316,746	5,097,035	558,503	7,267,392
Residences	39,643	9,595	157,477	17,174	223,889
Tenants	66,148	14,387	276,339	27,209	384,083
Average daily consumption (kWh/day)	35.10	35.91	35.86	35.00	35.66
	(25.26)	(26.08)	(28.99)	(26.95)	(28.08)
Average cooling degree days	4.01	3.88	3.14	3.59	3.36
	(5.09)	(4.92)	(4.18)	(4.53)	(4.43)
Average heating degree days	11.19	11.86	12.91	12.47	12.53
	(11.29)	(11.82)	(12.44)	(12.30)	(12.23)

Notes: Standard deviations reported in parentheses.

Table 3: 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	3.1256	3.2239	3.2940	3.2147
Year 2006	3.1814	3.2607	3.3068	3.2366
Difference	0.0558	0.0368	0.0128	0.0219
Difference-in-difference (DD)	0.0191		-0.0091	

Notes: Average daily consumption reported as *lnADC*. In order to account for the unbalanced panel, we first calculate averages within tenants and then average between tenants. 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. Differences may not compute exactly due to rounding. For the non-DST control group, we exclude electricity bills in the NW counties during Nov. and Dec. of 2006, when and where there was a policy change due to the shifting of time zones

Table 4: Natural experiment DST period fixed-effects models for changed average daily consumption in 2006

	(a)	(b)	(c)	(d)
Year 2006 × Treatment group	0.0096** (0.0030)	0.0080** (0.0029)	0.0103** (0.0027)	0.0089** (0.0029)
Average cooling degree days (ACDD)	0.0487** (0.0012)	0.0481** (0.0013)	--	--
Average heating degree days (AHDD)	0.0035** (0.0011)	0.0005 (0.0013)	--	--
ACDD × Treatment group	--	-0.0004 (0.0009)	--	--
AHDD × Treatment group	--	0.0029* (0.0013)	--	--
ACDD dummies	--	--	Yes	Yes
AHDD dummies	--	--	Yes	Yes
ACDD dummies × Treatment group	--	--	--	Yes
AHDD dummies × Treatment group	--	--	--	Yes
Month-year dummies	Yes	Yes	Yes	Yes
Observations	3,685,287	3,685,287	3,685,287	3,685,287
Tenants	343,530	343,530	343,530	343,530
R-squared (within)	0.310	0.310	0.310	0.310

Notes: The left-hand side variable is *lnADC*. Standard errors, reported in parentheses, are clustered at the billing-cycle × county level, of which there are 388 clusters. Models (c) and (d) include 18 categories for ACDD and 16 categories for AHDD. All weather dummies are also interacted with the treatment group in model (d). ** and * indicate statistical significance at the 99- and 95-percent levels, respectively.

Table 5: Quasi-counterfactual non-DST period fixed-effects models for changed average daily consumption in 2006

	(a)	(b)	(c)	(d)
Year 2006 × Treatment group	-0.0030 (0.0029)	-0.0004 (0.0028)	-0.0064* (0.0031)	-0.0029 (0.0031)
Average cooling degree days (ACDD)	0.0065 (0.0292)	-0.0483** (0.0178)	0.0244 (0.0248)	-0.0060 (0.0211)
Average heating degree days (AHDD)	0.0150** (0.0004)	0.0144** (0.0005)	--	--
ACDD × Treatment group	--	0.1008* (0.0494)	--	0.0453 (0.0424)
AHDD × Treatment group	--	0.0008 (0.0005)	--	--
ACDD dummies	--	--	--	--
AHDD dummies	--	--	Yes	Yes
ACDD dummies × Treatment group	--	--	--	--
AHDD dummies × Treatment group	--	--	--	Yes
NWchg2006	0.0062 (0.0077)	0.0039 (0.0076)	0.0041 (0.0079)	0.0015 (0.0076)
Month-year dummies	Yes	Yes	Yes	Yes
Observations	2,374,790	2,374,790	2,374,790	2,374,790
Tenants	340,328	340,328	340,328	340,328
R-squared (within)	0.080	0.080	0.080	0.081

Notes: The left-hand side variable is *lnADC*. Standard errors, reported in parentheses, are clustered at the county × billing-cycle level, of which there are 387 clusters. Models (c) and (d) include 31 categories for AHDD, and each of these dummy variables is interacted with the treatment group in model (d). ** 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	0.0123**	0.0048
	(0.0060)	(0.0069)
Average cooling degree days (ACDD)	0.0347**	0.0501**
	(0.0040)	(0.0066)
Average heating degree days (AHDD)	0.0126**	0.0131**
	(0.0007)	(0.0009)
Year 2005	0.0130**	0.0043
	(0.0020)**	(0.0029)
Year 2006	0.0148**	0.0257**
	(0.0029)	(0.0065)
Number of observations	580,888	603,253
Number of residents	282,703	283,964
R-squared (within)	0.008	0.036

Notes: The left-hand side variable is *lnADC*. Standard errors, reported in parentheses, are clustered at the county × billing-cycle level, of which there are 374 and 277 clusters for the spring and fall models, respectively. ** and * indicate statistical significance at the 99- and 95-percent levels, respectively.

Table 7: Simulation results for changes in monthly electricity demand due to DST

		Difference in average daily consumption (DST – no DST)		
	DST effect	Lighting	Cooling	Heating
April	0.73%	-4.1	6.8	2.2
May	1.69%	-6.0	10.5	4.4
June	0.03%	-7.5	6.8	0.4
July	-0.05%	-7.5	6.7	0.0
August	0.60%	-5.7	9.7	0.0
September	2.31%	-1.9	11.7	2.6
October	2.39%	2.4	10.4	1.8
Overall	0.98%	-4.5	9.1	1.7

Notes: Simulation results based on 2006 simulations in southern Indiana. Quantities reported in the last three columns are changes in average daily consumption (kWh/day) due to DST for the period indicated. DST effect is the percentage change and does not correspond exactly to the percentage change in lighting, cooling, and heating, as the overall effect also captures other relatively small changes in electricity consumption.

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	188,490.08	$2.82	$20.55	$531,485	$3,872,566
Lead	6.752E-07	0.11	$572.52	$2,457.32	$64	$276
Mercury	2.490E-08	0.00	$58.90	$58.90	$0	$0
Methane	1.336E-05	2.22	$79.96	$343.16	$178	$762
Nitrogen oxides	5.275E-03	876.79	$77.20	$179.41	$67,686	$157,304
Nitrous oxide	4.868E-05	8.09	$853.54	$7,690.35	$6,906	$62,226
Particulates	8.540E-04	141.95	$954.91	$3,282.86	$135,548	$465,999
Sulfur dioxide	1.060E-02	1,761.90	$518.98	$518.98	$914,391	$914,391
Total					$1,656,259	$5,473,524

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 166,217 MWh/year. All dollars values are reported in 2007 dollars.

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