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Daylight saving all year round? Evidence from a national experiment

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Abstract
We study the effects of staying on daylight saving time (DST) permanently on electricity consumption, generation, and emissions. In October 2016, Turkey chose to stay on DST all year round. Employing alternative identification methods, we find a negligible overall impact on consumption. However, the policy has a strong intra-day distributional effect, increasing consumption in the early morning and reducing it in the late afternoon. This change in the load shape reduced generation by dirtier fossil fuel plants and increased it by cleaner renewable sources that can more easily satisfy peak load generation. Emissions from generation decreased as a result.

Keywords: daylight saving time; electricity consumption; power generation; greenhouse gas emission

JEL Classification: O13, Q40, Q48

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1 Introduction

Daylight saving time (DST) – also called "daylight time" or "summer time" – refers to the practice of temporarily moving clocks forward during summer months in order to benefit from sunlight exposure in the evening hours. Many countries have followed DST over the past century with the goal of reducing energy consumption.[1] Existing research on whether the practice actually helps achieve this goal remains inconclusive (Aries and Newsham, 2008; Irsova et al., 2017), while popular opinion is divided on its potential benefits versus costs. For instance, in March 2019, the European Parliament voted to stop the obligatory practice of DST across the European Union (EU).[2] This will allow EU member countries to opt for either DST or standard time permanently from 2021 onward. Subsequently, there is renewed interest in understanding whether continuing or scrapping the DST practice helps save energy.

In this paper, we study a novel and nationwide policy experiment from Turkey, which has recently opted to permanently stay on DST. Having moved its clocks forward during summer months and back during winter months since 1972, Turkey stopped turning back its clocks to standard time on October 30, 2016, with the intention to make more use of daylight during winter. The country has effectively stayed on DST all year round since then. We exploit variation in hourly electricity demand on dates before and after the policy change, and between hours that are most and least affected by exposure to sunlight within a day, to identify the impact of this policy change on electricity consumption, generation, and emissions from electricity generation.

To preview our results, we find that permanently staying on DST neither increases nor decreases aggregate daily electricity consumption. However, we find a strong intra-day distributional effect of staying on DST during winter months: while electricity consumption increases considerably in the morning, it is reduced in the late afternoon and early evening. In particular, electricity consumption is 3.4% *higher* on average in the early morning hours of winter months after October 2016 compared with the early morning hours on the same dates previously, when Turkey used to set its clocks back. In contrast, consumption is 3.5% *lower* on average in the late afternoon hours of winter months following the policy change compared

[1] Around seventy countries follow DST in at least a portion of the country, affecting more than 1.6 billion people, for energy conservation and reduction of greenhouse gas emissions (Kellogg and Wolff, 2008; Choi et al., 2017).

[2] See https://www.bbc.com/news/world-europe-47704345. There has also been a heated debate on DST in the United States: see https://www.nytimes.com/roomfordebate/2014/03/06/daylight-saving-time-at-what-cost. Most recently, in March 2018, Florida's Senate approved the Sunshine Protection Act, which asks Congress to allow the state to observe DST all year round (https://www.npr.org/sections/thetwo-way/2018/03/08/591925587/sunshine-daydream-florida-bill-would-make-daylight-saving-time-year-round).

with earlier periods. Hence, energy savings targeted by the policy change to make more use of daylight in the later hours of the day are cancelled out by the increase in consumption in the early hours.

We show that this change in the intra-day variation in demand – captured by the change in the daily "load curve" or "load profile", which reflects the hour-by-hour electricity load in a day – affects the fuel mix used for electricity generation. In particular, the policy change significantly reduces the amount of electricity provided by power plants that use fossil fuels as their source input, especially during early morning hours. At the same time, electricity generation from renewable sources, such as hydropower, significantly increases. Using data on emission factors by source, we estimate the impact of the policy change on total carbondioxide (CO_2) emissions from electricity generation.[3] We find that staying on DST during winter months may have led to a reduction in CO_2 emissions of between 1,500 and 8,200 tons per day. Hence, the policy change has an unforeseen but beneficial effect of reducing greenhouse gas (GHG) emissions, as generation by "cleaner" power plants substitutes generation from "dirtier" ones to satisfy changes in intra-day demand.

To study the effects on electricity consumption due to the policy change, we use variants of a traditional difference-in-differences (DiD) approach as in Kellogg and Wolff (2008) for our identification strategy. The first source of variation for our approach comes from Turkey's decision to adopt DST permanently in late 2016. This allows us to compare earlier dates when standard (winter) time was implemented and clocks set back (8 November 2015 – 27 March 2016) to those when it would continue to be applied if the policy change had not happened (30 October 2016 – 26 March 2017). The second source of variation comes from intra-day changes in electricity demand, under the assumption that staying on DST permanently does not affect demand during midday hours, since any resulting shift in daylight is marginal within those hours. We validate this assumption by studying discontinuities in hourly electricity demand around the days when Turkey switched from standard (winter) time to DST in the years prior to its policy change.

We subject our findings to a battery of robustness checks and follow an alternative identification strategy to derive estimates. This alternative approach relaxes the assumption that electricity demand during midday hours is unaffected by changes to DST, and instead uses summer months as an alternative control period. We again find strong intra-day redistribution of consumption, with a peak increase in electricity use of 3.1% at 7:00 in the morning and a decrease of 2.6% at 17:00 in the evening.[4] The overall daily effect is statistically

[3]We focus on CO_2 emissions, which constitute the bulk of greenhouse gas emissions from electricity generation. According to IEA (2020), electricity generation has long been the primary source of CO_2 emissions worldwide. In the Appendix, we also present results on SO_2 and NO_x emissions.

[4]We use a 24-hour time scale throughout the paper to avoid confusion.

indistinguishable from zero, confirming our earlier result.

Our results are consistent with Turkish policy makers' goal of reducing electricity consumption in the evening hours of winter months by taking advantage of more sunlight. However, they are also consistent with waking and sleeping habits of the Turkish population that are tied to the clock instead of natural daylight. Before Turkey adopted DST permanently, electricity demand during winter months typically peaked in the morning as people travelled to work and school, and again in the evening as they returned home. We show below that the policy change eliminated peak demand in the evening but increased it in the morning, as would be expected from a shift to permanent DST and no changes to individuals' daily schedules of work and sleep. However, the morning peak demand occurs much more frequently than earlier, thereby leading to an increase in electricity consumption and cancelling out reductions later in the day. Hence, aggregate electricity consumption in Turkey is not reduced as a result of staying on DST permanently.

The increase in the morning peak demand has led to an overall increase in intra-day demand variability and affected the market for electricity generation. Prices in the intra-day wholesale electricity markets have peaked more frequently in the morning hours than in the evening hours following the decision to stay on DST permanently. We find that these two facts – greater intra-day variability and higher prices in the morning hours – favoured generators in Turkey that can more easily meet peak morning demand. In particular, using our identification strategy of summer months as a control period, we find that daily electricity production from coal-powered plants *decreased* by 4.5%, while electricity production from hydro power *increased* by 12.4% on average due to the policy change. This finding is consistent with the fact that hydropower and other renewable sources can ramp up their generation capacity to meet increased demand very quickly – typically in less than five minutes – while coal- and natural gas-powered plants can take up to several hours to reach full capacity.

We contribute to the literature on the impact of DST on electricity consumption and generation in three ways. First, we provide the first evidence from a nationwide change in DST policy on both electricity demand and generation. Earlier contributions rely on temporary policy changes affecting a few regions of a country to document the impact of DST extension on electricity consumption. For instance, Kellogg and Wolff (2008) study the temporary extension of DST in parts of Australia to facilitate the Sydney Olympics in 2000, while Kotchen and Grant (2011) study a change in Indiana state law that requires all counties of the state to practice DST in 2006.[5] Our setting of a nationwide policy change helps us document the effect on a country's aggregate electricity demand and its generation markets, as aggregate demand is almost fully met by a single nationwide grid.

[5]See also Kandel and Sheridan (2007); Mirza and Bergland (2011); Rivers (2016).

Second, we provide new evidence on how DST affects electricity generation, related emissions by source, and the underlying mechanism. Earlier studies provide estimates for the environmental impact of DST by multiplying the estimated change in overall electricity consumption with average emission rates of energy sources employed in the relevant electricity grid (Hill et al., 2010; Kotchen and Grant, 2011; Hancevic and Margulis, 2016). In contrast, we use a difference-in-differences model to directly test how a DST policy change influences electricity generation by source. This allows us to estimate the hourly and daily impact on emissions due to changes in the intra-day electricity load, helping us to pinpoint the mechanisms through which DST affects electricity markets.

Specifically, we show that the change in intra-day demand induced by the extension of DST has important effects on electricity generation and consequent emissions. As first emphasised by Holland and Mansur (2008), changes in intra-day demand variance can affect emissions based on what sources are used for peak demand generation. We find that permanent DST increases demand variance during winter months and shifts peak demand to early morning hours. This favours zero-emission hydropower sources over dirtier base load fossil generation, because hydropower has low marginal production costs and quick ramping rates (Holland and Mansur, 2008), which makes it better suited to meet the early morning peak demand.

Third, our empirical approach offers important advantages relative to earlier work. Existing research typically uses a small window of a few days or weeks of DST extension to derive estimates (Kandel and Sheridan, 2007; Kellogg and Wolff, 2008; Momani et al., 2009; Rivers, 2016). Extrapolating from these windows to the overall impact of DST may be misleading if these samples differ from longer periods during which DST is typically followed, for example with respect to weather conditions (Mirza and Bergland, 2011; Choi et al., 2017), exposure to sunlight or seasonal economic activity. In this study, we exploit a permanent change in DST practice and compare longer time periods. This allows greater confidence in the generality of the findings and enables us to run a number of placebo tests. We use alternative treatment and control definitions to mitigate concerns that our findings are driven by how we define our treatment and control windows.

Our work relates to earlier studies on changes to DST policy, which found mixed effects on electricity consumption. Belzer et al. (2008) analyse the impact of a DST extension on national energy consumption in the US and estimate respective total electricity savings of about 0.5% per each day of extended DST. Similarly, Mirza and Bergland (2011) find a 1% decrease in annual electricity demand in Southern Norway and Sweden due to DST. In contrast, using a natural experiment in Indiana from 2006 and monthly data on household-level consumption, Kotchen and Grant (2011) find an overall increase in electricity demand by around 1%. Hancevic and Margulis (2016) also find that DST increases electricity consumption in the case of Argentina. Our findings are instead consistent with studies by Kellogg and Wolff (2008) and Choi et al. (2017), who find a negligible effect of extending DST.

Our work also relates to studies on how policies in electricity markets affect greenhouse gas emissions. Cullen (2013) and Novan (2015) discuss emissions offset by wind power generation in Texas and the roles of production subsidies to different renewable sources. Graff Zivin et al. (2014) study how intra-day electricity-shifting policies affect emissions across the US. In relation to these studies, we show how changes to DST policies affect the role that renewable sources play in generation-related emissions.

The remainder of this paper is structured as follows. Section 2 describes the background for the policy change and an overview of the Turkish electricity market. Section 3 describes the dataset we use and shows preliminary and visual evidence. Section 4 discusses alternative identification strategies and reports the estimated effects of permanent DST on electricity consumption. Section 5 presents estimates for electricity generation and the associated environmental impacts. Section 6 concludes.

2 Institutional background

Turkey has traditionally used the GMT+2 time zone on grounds of its close ties with European countries. It started practising DST in 1972 nationwide and turned back its clock by one hour on the last Sunday of every October and moved it forward on the last Sunday of every March. We should note one exception to this pattern, which occurred in 2015 as clocks were set back on 8 November instead, in order to avoid confusion when local elections took place on 1 November.

The Turkish Ministry of Energy and Natural Resources (MENR) first floated the idea of staying permanently on DST in March 2012. It cited confusion and concerns by citizens that an early sunset during winter months contributed to general unhappiness, especially in the country's eastern provinces.[6] The ministry argued that staying on DST – or summer time – all year round would help reduce electricity consumption by making greater use of daylight in the evening also during winter months. Although the Turkish Council of Ministers released a decree in October 2013 to permanently stay on DST, this was not implemented at the

[6]Turkey lies between longitudes 26° and 45° East, which translates into a time difference of 76 minutes between its easternmost and westernmost points. Given this large time difference, sunrise and sunset hours vary considerably across the country's eastern and western cities. In comparison, the time difference between the easternmost and westernmost points is 12 minutes in Portugal, 30 minutes in Germany, and 48 minutes in Spain.

time. The policy change was finally enacted on 7 September 2016. It came into force on 30 October 2016, meaning that the country stopped turning back its clock and chose to stay on DST permanently. We will refer to this policy change as *permanent DST* to help our exposition below.[7]

As DST policy is observed nationwide, the change affected all Turkish provinces since late October 2016. In the following analysis, we study nationwide electricity consumption and generation, focusing on two time periods most affected by the policy change. The first period spans 8 November 2015 – 27 March 2016 and serves as our *control period*; it covers dates when clocks were set back and standard (winter) time was observed. The second period spans 30 October 2016 – 26 March 2017 and serves as our *treatment period*; it includes all dates where Turkey would have had standard time in the absence of the policy change, but stayed on DST instead.

Extending DST to winter months meant that both sunrise and sunset occurred an hour later during the treatment period when compared with the same dates in earlier years. For instance, sunrise (sunset) in the capital city of Ankara took place at 7:00 (16:36) on 21 December 2015, but at 8:00 (17:36) on 21 December 2016. We show in Figure A.1 of the Appendix how exposure to sunlight early in the mornings and evenings changed between the control and treatment periods for all 81 provinces of Turkey. While most provinces woke up to sunlight at 7:00 almost every day during the control period, the switch to permanent DST meant that all provinces now woke up to dark mornings almost every day. This pattern is reversed for the early evening hours: sunset occurred before 18:00 almost every day for all provinces during the control period, but with the change in policy, sunset occurred after 18:00 on most days. Hence, the policy change effectively shifted an hour of sunlight from morning to early evening, especially for the western provinces of the country where the vast majority of the Turkish population lives. Sunrise and sunset times are unaffected during summer months, which run from end of March until end of October for our purposes.

The electricity market in Turkey is mostly privately operated. Electricity generation is carried out by public and private companies, with the latter controlling around three quarters of total installed capacity. The country is divided into 21 electricity distribution regions, which are served by private utilities that are also responsible for maintaining distribution lines and reading the meters of the end users. Regulations allow for commercial electricity trade with other nations; however, there is little cross-border trade in electricity in practice.

Energy Exchange Istanbul (EXIST) is responsible for managing and operating the wholesale electricity market in Turkey. EXIST provides an exchange-based platform to utilities and generators in which energy companies trade in the day-ahead and the intra-day markets

[7] The policy change means that Turkey has technically changed its time zone to GMT+3.

at prices that clear the market absent central optimisation. The day-ahead market involves participants who place bids and offers for each hour of the next day, which are financially binding. The intra-day market allows real-time trading between participants in response to demand fluctuations and determines prices paid by utilities to generators throughout the day. Because these are market prices, and not the regulated prices that households pay utilities, they do not affect electricity demand during the day. There is also no real-time pricing for households, so that retail prices of electricity do not vary with the level of demand in the system.

3 Data and graphical evidence

We collect detailed data at the hourly level on electricity demand, planned and actual generation, installed capacity by source, and intra-day market prices from EXIST.[8] Because electricity demand can be heavily influenced by weather conditions, we collect hourly data from Open Weather Map for a number of variables. In particular, we use the average hourly air temperature, pressure, relative humidity, wind speed, and cloudiness across all city centers of Turkey's 81 provinces, where the vast majority of the country's population lives and economic activity takes place. To account for the different sizes of these provinces, we use population-weighted averages for each variable.[9] We complement these data with information on public holidays.

We collect all previously mentioned data points for our control and treatment periods, which form our main dataset. To conduct additional analyses and run placebo tests, we also collect data from previous years when clocks were set back and the summer months of 2016 and 2017. Table 1 presents descriptive statistics for each of the variables used in the analysis by control and treatment periods in columns (1)-(2) and for the summer months of 2016 and 2017 in columns (3)-(4).

Our first goal is to understand the effect of staying on DST permanently on electricity consumption. Figure 1 gives us an immediate insight by depicting the load curve, which shows average hourly electricity demand, during winter months of 2012–2017. There is a clear daily pattern in electricity consumption in all years; but evidently, the hourly load shape differs between our treatment period – depicted by the top line in the figure – and earlier periods. In the years prior to the policy change, daily consumption patterns appear to be almost identical: demand is low overnight, increases strongly after 7:00, reaches a peak first at 11:00 and then again at 17:00, before it declines during evening hours. In contrast,

[8] EXIST data are available at `https://seffaflik.epias.com.tr/transparency/index.xhtml`.

[9] See Appendix A.1 for a detailed description of the variable construction.

during the winter months of October 2016 – March 2017, electricity demand starts rising sharply at 6:00 and reaches a single peak at 11:00 before falling gradually later in the day. The single peak at 11:00 seems to occur at a much higher level compared with earlier years, while there is a notable drop in demand at 17:00.

Our second goal is to understand whether staying on DST permanently has direct effects for the environment via generation-related emissions. Figure 2 shows the average hourly fuel mix of electricity generation for the treatment and control periods. First, it illustrates that the average daily peak generation that occurred at 17:00 during the control period was shifted towards the morning hours, resulting in an average daily peak generation at 11:00 during the treatment period. Second, it shows that Turkey mostly relies on coal to satisfy its daily base load generation.[10] Peak load generation, in turn, is mostly met by power plants that run on natural gas and hydropower. Each of these three major sources of power generation – coal, natural gas and hydropower – accounts for around 30% of total generation, with the remaining generation provided by renewables other than hydro, liquid fuels or imports.

Both Figures 1 and 2 point to a change in the load shape that is consistent with the expected effect of permanent DST during winter months. An hour of sunlight is shifted from morning to evening, which leads to higher demand for lighting and heating in the morning hours and to less demand in the evening hours. This eliminates the bimodal load shape we observe in earlier years as peak consumption at 17:00 is dampened.

Figures 3 and 4 show when peaks in demand and intra-day market prices, respectively, occur most frequently during the control and treatment dates. During the control period, peak demand occurs at 11:00 in around half of the days and at 17:00 in nearly 40% of the days (Figure 3). In contrast, during the treatment period, peak demand occurs at 11:00 in more than 80% of the days and in the evening hours in less than 15% of the days. Figure 4 shows a similar picture with respect to the intraday electricity market. During the control period, intra-day market prices peak before noon on around 40% of the days, whereas during the treatment period, they peak before noon on 55% of the days. Interestingly, the distribution of peak prices in the intra-day market is more uniform across different hours of the day during the control period than during the treatment period, when this distribution seems to follow an almost bimodal shape.

Apart from depicting changes to the load shape, Figure 1 shows a clear and positive trend in average hourly electricity demand across the years for each hour. Electricity demand may change due to a number of observable factors, such as weather conditions, changes

[10] In what follows, we refer to imported coal, lignite, black coal, and asphaltite together as "coal". Similarly, we refer to natural gas and LNG together as "natural gas", and we refer to dams and run-of-the-river units as "hydropower".

in population or economic activity, public holidays, or changes to retail prices (Kellogg and Wolff, 2008; Choi et al., 2017). Admittedly, our visualisation cannot account for these observable factors or unobservable ones that may be specific to our treatment and control periods. We therefore turn to the following econometric analysis to isolate the effect of permanent DST on electricity demand from potential confounders.

4 Electricity consumption

4.1 Identification strategy

Our main identification strategy uses variation in demand for electricity across our control and treatment periods, and across hours within dates of each period. As the previous discussion indicates, electricity demand can vary throughout the day for a variety of reasons. It is relatively easy to control for observable factors with our dataset. However, capturing shifts in demand specific to certain dates, which could take place irrespective of any changes in DST policy, is much more difficult.

To account for these unobservable and potentially confounding factors, we follow earlier research and use hours in the midday as an additional control dimension (Kellogg and Wolff, 2008; Mirza and Bergland, 2011; Verdejo et al., 2016; Rivers, 2016). This strategy is built on a simple assumption: the one hour time shift implied by permanent DST should not affect electricity demand during midday hours, given that the resultant shift in daylight is minimal within those hours. Any differences in midday demand levels between the treatment and control periods that are not due to observables can therefore be explained by unobservable confounders unrelated to DST policy (Kellogg and Wolff, 2008; Mirza and Bergland, 2011).

To implement this strategy, we use the hours between 12:00 and 13:59 as control hours. We assume that total electricity consumption would be similar whether local time is set to 12:00–13:59 (with permanent DST policy in place) or 11:00–12:59 (in the absence of the policy). We follow Kellogg and Wolff (2008) and Rivers (2016) in verifying this assumption for the Turkish case. Specifically, we conduct a regression discontinuity analysis using data around the shift to DST that occurred in late March of 2013, 2014, 2015, and 2016; that is, in the four years immediately before the policy change. We report results from this analysis for each hour of the day in Appendix A.2, which confirm our intuition and justify the choice of 12:00–13:59 as control hours. We will refer to this strategy as the *intra-day control* approach below.

Our baseline identification assumption can be summarised as follows. Conditional on fixed effects and observable factors, and in the absence of the policy change, electricity demand at non-midday hours during the treatment dates would have exhibited the same consumption pattern relative to midday hours as the relative demand observed during the control dates. The resulting model can then be written as:

$$ln(Demand_{dh}) = \alpha + \beta_h D_{dh} + \gamma_d + \lambda_h + \boldsymbol{\vartheta_h W_{dh}} + \varepsilon_{dh} \tag{1}$$

where $ln(Demand_{dh})$ is the natural logarithm of the aggregate electricity consumption at hour h on date d. D_{dh} is the difference-in-differences (DiD) estimator, for which we measure hourly treatment effects β_h. It is equal to 1 during the treatment period between 3:00 on 30 October 2016 and 3:00 on 26 March 2017 for all non-midday hours, and 0 otherwise. The control period covers the period from 3:00 on 8 November 2015 to 3:00 on 27 March 2016. γ_d and λ_h are date and hour fixed effects, respectively. Hour fixed effects account for systematic variation in demand specific to a particular hour of the day irrespective of the date. Date fixed effects, in turn, capture date-specific differences in electricity usage that are due to unobservable shocks or seasonal factors, including day of the week, day of the year, or public holidays. The percentage change in electricity consumption in each hour h is given by $100 * (exp(\beta_h) - 1)$. We cluster standard errors by date to account for serial correlation and within-date heteroskedasticity.

We control for a vector of weather variables, $\boldsymbol{W_{dh}}$, which includes hourly temperature, air pressure, humidity, wind speed, and cloudiness. Temperature is a key determinant of demand for heating or cooling. We follow earlier research and calculate a measure of heating degrees, defined as the difference between the actual temperature and 18.33 °C (Kandel and Sheridan, 2007; Kellogg and Wolff, 2008; Kotchen and Grant, 2011; Choi et al., 2017). We also include a quadratic term for this variable to capture any nonlinear effects of demand for heating or cooling. All weather controls are further interacted with hour dummies to allow for hour-specific effects of weather conditions.

Note that our treatment and control periods in Equation (1) cover two sets of winter months. Our intra-day control approach, which "normalises" the treatment effect of permanent DST to zero for midday hours, enables us to identify the effect on non-midday hours using winter months only. However, an alternative identification strategy to control for unobservables is to extend the sample and use summer months as control dates instead. One could estimate a DiD model using the difference in the hourly electricity demand during the summer months of 2016 and 2017 as the counterfactual consumption pattern. This strategy has the advantage that we can relax the assumption of a non-existent DST effect during midday hours. However, it comes at the cost of dropping date fixed effects, and it assumes that unobservable shocks to electricity demand are persistent across several months (Kellogg and

Wolff, 2008).[11] We refer to this alternative strategy as the *intra-year control* approach. We prefer the intra-day control approach for the demand analysis, because it allows us to capture all unobservable date-specific shocks. Nevertheless, we present results of the intra-year control strategy in subsection 4.4 below and confirm our baseline results.

4.2 Results

Figure 5 presents hourly treatment effects, in percentages, from estimating Equation (1). We find that staying on DST during winter months leads to a sizable intra-day redistribution of electricity demand. During the treatment period of October 2016 – March 2017, demand increases substantially between 6:00 and 8:00 in the morning, whereas it declines around 17:00 in the evening, compared with the control period of November 2015 – March 2016. Both of these effects are statistically significant and economically substantial, even after controlling for other relevant factors affecting demand. The increase in electricity demand in the morning hours reaches a peak of 3.4% at 7:00, as people wake up with less daylight and lower temperatures during winter months when days become shorter. In contrast, the additional hour of daylight shifted from the morning to the evening leads to a decrease in hourly electricity consumption by 3.5% at 17:00, as people can better take advantage of sunlight for lighting or heating purposes.

Does this redistribution decrease total daily consumption as the policy originally intended? We find that it does not. We aggregate β_h in equation (1) to assess the overall effect of permanent DST on electricity demand. The point estimate is -0.2%, which is very small in magnitude, and with a standard error of 0.4, it fails to reach statistical significance at all conventional levels. Hence, the effect of extending DST during the winter does *not* lead to a change in overall electricity consumption. This is because the decrease in demand during evening hours due to the extra hour of sunlight is offset by a large increase in demand during the morning. This finding is consistent with existing studies that find a similar intra-day redistribution in electricity consumption (Kellogg and Wolff, 2008; Choi et al., 2017). Unlike existing studies, we provide the first piece of evidence from a nationwide experiment.

4.3 Robustness checks

Our findings of a null effect of permanent DST on aggregate demand and a substantial intra-day redistribution are robust to a number of alternative specifications. We discuss three of

[11] In other words, unobservable factors that cause electricity consumption to be particularly high or low during the treatment dates from October 2016 to March 2017 must alter demand during the period from April to October 2017 in a similar way, irrespective of changes to DST.

these in this subsection, before we turn to our alternative identification strategy.

First, we re-estimate equation (1) using different hours as controls. Recall that our baseline estimation assumes that permanent DST leaves demand during the midday hours of 12:00–13:59 unchanged. We now shift the midday control hours slightly and normalise the hours of 11:00–11:59 and 11:00–12:59 in two alternative specifications. The resultant hourly effects are depicted in the top panel of Figure 6. In each case, we continue to observe a spike in demand in the early morning hours of 6:00–7:00 and a drop in demand in the evening at 17:00. Next, we use the midnight hours between 0:00 and 1:59 as "non-treated" hours. The bottom-left panel of Figure 6 continues to indicate a large increase in demand around 6:00-7:00 hours and a decline in demand at 17:00. Finally, we include both midnight hours 0:00–1:59 and midday hours 12:00–13:59 as control hours. The bottom-right panel of Figure 6 depicts a similar picture as before, and it also displays statistically significant estimates for a drop in demand overnight (2:00–5:00) and an increase in the evening (19:00-21:00) hours.

Across the four specifications in Figure 6, the estimated increase in demand during morning hours ranges from 3.4% to 4.3%, whereas the estimated drop in demand during evening hours lies between 2.6% and 3.7%. Overall, they point to substantial redistribution of intraday demand and a small, insignificant effect on aggregate electricity consumption due to permanent DST. Table 2 provides point estimates for the aggregated daily effect for each of the four specifications. These range from a reduction of 0.4% in column (1) to an increase of 0.8% in column (3), but none of these point estimates are significant at conventional levels of statistical testing.

Second, we restrict our sample to the same days of the year in the treatment and control periods. Given that our treatment period is over a week longer than our control period, one may be concerned that differences in the hours of sunlight during those periods bias the estimation. Restricting the sample to overlapping days of the year ensures that we only include days with similar hours of sunrise and sunset in our sample. Figure A.4 depicts the estimated hourly effects using this sample. As before, we observe an increase in demand at 6:00–7:00 and a decrease at 17:00. The point estimates in each case now stand around 4%, which are slightly larger than our baseline estimates. When we aggregate the hourly effects, we find an aggregate reduction of 0.1% in daily electricity consumption, which is again very small in magnitude and statistically insignificant.

Third, we estimate equation (1) for the summer months of 2016–2017 and the winter months in earlier years when Turkey used to switch its clock back in October and forward in March. These serve as placebo checks. To compare differential behaviour over summer months, we compare hourly electricity consumption between 27 March and 30 October 2016 to the period from 26 March to 29 October 2017. Given that Turkey observed DST in both of these periods, the hourly electricity consumption should be comparable when controlling for factors such as weather conditions and date-specific shocks. Additionally, we estimate differences in hourly electricity demand between winter time periods prior to the policy change, when Turkey stayed on standard time in all years.

Table A.3 reports the estimates of the respective pooled regressions and the results for the hourly effects are shown in Figure A.5. We find that the DST impact on electricity consumption is very small in magnitude and remains statistically insignificant for all placebo regressions. Additionally, the hourly estimates fluctuate around 0 and are also mostly statistically insignificant. One major exception is the positive and significant increase for the early morning hours during the summer months of 2017. However, we observe a similar spike in the evening hours as well, which is at odds with a change in behaviour due to the shift in daylight from morning to evening hours.

4.4 Alternative identification strategy

In our alternative identification strategy, we estimate the effect of permanent DST on electricity demand using the intra-year approach instead of the intra-day approach. Specifically, we use electricity demand during the summer months of 2017 and 2016 as the control dimension in our DiD regressions, instead of consumption during midday hours of winter months. Hence, the sample now includes all dates between 8 November 2015 and 29 October 2017. The advantage of this alternative empirical strategy is that we do not have to impose a zero effect of DST on electricity consumption during the middle of the day. However, as indicated in section 4.1, it is more difficult to control for potential time-varying shocks to electricity usage that are specific to the treatment or control periods. To alleviate this concern, we use the following DiD equation including multiple sets of fixed effects and control variables:

$$\begin{aligned} ln(Demand_{dh}) &= \alpha + \theta_h postpolicy_{dh} + \delta_h affectedperiod_{dh} \\ &\quad + \beta_h postpolicy_{dh} * affectedperiod_{dh} \\ &\quad + \lambda_h + \boldsymbol{\vartheta_h W_{dh}} + \boldsymbol{\varphi_h X_{dh}} + \varepsilon_{dh} \end{aligned} \tag{2}$$

where $ln(Demand_{dh})$ is the natural logarithm of electricity demand in hour h on date d. $postpolicy_{dh}$ is a binary indicator equal to 1 if the hour and date follow the policy change; i.e. after 3:00 on 30 October 2016, and 0 otherwise. The variable $affectedperiod_{dh}$ equals 1 in periods that are potentially affected by keeping DST all year round; i.e. between 3:00 on 8 November 2015 and 3:00 on 27 March 2016, as well as between 3:00 on 30 October 2016 and 3:00 on 26 March 2017. We are interested in the hour-specific coefficients of the

DiD estimator, $postpolicy_{dh} * affectedperiod_{dh}$, which equals 1 if both $postpolicy_{dh}$ and $affectedperiod_{dh}$ are equal to 1, and 0 otherwise.

In equation (1), we include a set of hour fixed effects, λ_h, a vector of weather variables, $\boldsymbol{W_{dh}}$, and a vector of fixed effects, $\boldsymbol{X_{dh}}$, to account for trends in electricity consumption. Specifically, $\boldsymbol{X_{dh}}$ includes hourly effects for day of the year, day of the week, and holiday dummies. Standard errors are clustered at the date level to allow for serial correlation in demand across hours within a day.

Figure 7 shows hourly effects of permanent DST on electricity demand. Reassuringly, we find a strong intra-day redistribution of electricity consumption, but no change in aggregate daily consumption. The policy change leads to a peak increase in demand of 3.1% at 7:00 and a significant decrease of 2.6% at 17:00, due to the one hour shift in sunlight exposure from the morning to the evening. The estimated overall effect of DST during winter months is slightly larger than our baseline results and has the opposite sign. It equals 0.5%, but with a clustered standard error of 0.5, it is again statistically indistinguishable from 0.

Overall, our two main findings from this section – namely, that permanent DST led to a significant redistribution in intra-day demand, while the effect on the country's aggregate consumption did not change materially – prove robust to several alternative specifications and identification strategies.

5 Electricity generation and emissions

5.1 The role of load variance

The preceding analysis suggests that staying on DST permanently is unlikely to cut down GHG emissions from electricity generation. Because overall electricity consumption is not reduced, notable reductions in emissions are therefore unlikely (Kellogg and Wolff, 2008). However, the policy's impact on the intra-day load shape could have substantial consequences for the environment. Holland and Mansur (2008) show that changes to the variance of intra-day electricity demand affect fossil generation and emissions, even after controlling for average daily base load. This is because fluctuations in demand throughout the day are met by generation units that use different fuel sources for electricity production. In particular, during hours of very high or low demand, electricity generation is met by sources that ramp up and down flexibly rather than by slower base load generation units. If a country's peak generation units are relatively cleaner (dirtier) than base load technologies, then increases in within-day variance of electricity load can lead to a decrease (increase) in emissions (Holland and Mansur, 2008; Kellogg and Wolff, 2008).

Which energy sources meet demand throughout the day is determined by two factors. First, electricity generation firms typically use generating units in order of their marginal costs (Holland and Mansur, 2008). Grid operators try to minimise the cost of electricity production, therefore calling on low-cost generating units to ramp up production whenever there is excess demand. Second, differences in the age and technology of generation units connected to the grid affect the fixed costs of running generation units. For instance, coal power stations have high fixed costs because they typically take several hours to reach full capacity. They are therefore more economical to operate at constant production levels; they provide base load power and generally do not change their production to match fluctuations in demand. In contrast, natural gas turbines take only around half an hour to reach full capacity, although electricity generation from natural gas tends to have higher marginal costs than generation from coal.[12] Hydropower units have the lowest marginal cost – as do other renewable generators, such as windpower, which practically have zero marginal costs – and can be utilised in full capacity in less than five minutes.

Figure 8 reveals that the decision to adopt permanent DST increased within-day load variability. It plots the average daily ratio of maximum-to-minimum electricity load for the treatment period and previous winter time periods. While the average within-day variability of the load curve steadily decreased over time up to and including the control period, it increased significantly during the treatment period by about 3 percentage points. In unreported results, we find similar patterns when we use alternative summary statistics of variability, such as the coefficient of variation or the relative mean deviation.

We expect the increase in intra-day load variability to affect generation units through two mechanisms. First, higher uncertainty during the day, especially regarding the level of the minimum load, means that base load supplying plants may plan to produce and therefore deliver a lower share of the base load. As it is especially costly for coal-fired power plants to ramp their production up and down, we expect that they may scale back their generation to avoid having to supply the grid at negative prices if they overproduce.

Second, peak demand that occurs earlier in the morning is more likely to be met by more flexible and lower marginal cost producers, such as hydropower and gas-fired power plants. This is because on days with more within-day variation, generation firms are likely to use technologies that ramp up and down quickly rather than slower base load technologies (Holland and Mansur, 2008). We expect that hydropower can benefit especially in this case, as its marginal cost of production is lowest.

[12] For the same reason that a car that rapidly starts and stops burns more fuel per mile than one going at constant speed, a natural gas-fired generation unit (or more generally, generation units that run on fossil fuels) that rapidly increases and decreases output consumes more natural gas to produce a megawatt-hour (MWh) of energy than the same unit operating at a constant level (Anderson et al., 2019).

5.2 Identification strategy

We analyse the effect of the DST policy change on actual, hourly gross generation by coal, gas and hydropower plants, given that these sources account for over 90% of Turkey's electricity generation. We use the intra-year DiD approach rather than the intra-day normalisation for this analysis. This is because the assumption that the policy change does not affect electricity generation around midday is difficult to substantiate. Unlike electricity consumption, the amount dispatched by specific sources at noon likely depends on the fuel mix used in other hours of the day. If, for example, base-load coal generation is reduced due to stronger intra-day load variability and pronounced peaks in demand in the morning, this likely affects the load satisfied by inflexible coal-fired plants throughout the entire day.

We therefore estimate an equation similar to equation (2) for each source, where the dependent variable is (log) gross generation in MWh for source s. Consider:

$$\begin{aligned} ln(generat_{sdh}) \; = \; & \alpha + \theta_{sh} postpolicy_{dh} + \delta_{sh} affectedperiod_{dh} \\ & + \beta_{sh} postpolicy_{dh} * affectedperiod_{dh} \\ & + \lambda_h + \boldsymbol{\vartheta_{sh} W_{dh}} + \boldsymbol{\varphi_{sh} X_{dh}} + \theta_{sh} C_{sdh} + \varepsilon_{dh} \end{aligned} \tag{3}$$

where $ln(generat_{sdh})$ captures actual electricity production by coal, gas, or hydropower plants on date d and hour h. As before, we have hourly fixed effects and controls for day of the year, day of the week, and holiday fixed effects, all of which are interacted by hour. Additionally, we control for hourly installed capacity of each source, C_{sdh}. Controlling for installed capacity on an hourly level accounts for unobserved trends in the management of the Turkish electricity grid.

We include further controls that may affect the marginal costs of production by generation units. In estimating the effect on production by coal power plants, we include the (log) price of the import price index for coal, since a large share of generation by coal power plants uses imported coal. For regressions on production by natural gas, we include the (log) price of natural gas in the retail market.[13] Finally, hydropower in Turkey typically comes in two types: run-of-river dams and storage reservoirs. Holland and Mansur (2008) note that the first type depends on the natural flows of the river, and the second on seasonal runoff (a fixed stock of water). The marginal opportunity costs of hyropower units therefore include the scarcity cost of the exhaustible stock. As the scarcity of water is directly a function of weather conditions, we include a vector of weather variables, $\boldsymbol{W_{dh}}$, as before that are fully

[13] During the control and treatment periods, generators that use natural gas as their primary source of fuel faced the same price as retail consumers and users in industry.

interacted by hour. Since weather conditions are an important determinant of electricity demand throughout the day, we include $\boldsymbol{W_{dh}}$ also in our regressions for coal and gas.

5.3 Results

Figure 9 presents hourly coefficients from estimating Equation (3) for each source. The top panel shows that generation by coal-fired plants decreased substantially in each of hour of the day, but especially so in the evening hours, following the switch to permanent DST. The average estimated reduction in hourly generation by coal over the treatment period ranges from 3.5% at 13:00 to 6.5% at 18:00 in the evening when compared with generation over the control period. The middle panel suggests that generation by gas was higher following the switch to permanent DST, but this impact is not precisely estimated except for a few hours later in the day. In contrast, the bottom panel shows that generation by hydropower increased strongly due to higher intra-day load variability. This is especially the case overnight and in the early morning hours when hydro units are ramped up by nearly 40% more in the treatment period relative to the control period, in order to absorb the surge in early morning demand. We see that hydropower is used again relatively more in the evening hours, when demand is high, alongside gas-powered generation units.

We present the estimated treatment effects from pooling the hourly coefficients in Table 3. We find that, when summed across the 24 hours in a day, electricity generation from coal decreased by 4.6% on average during the treatment period when compared with a year earlier (column 1). At the same time, generation from hydropower increased by 12.4% on average due to the switch to permanent DST (column 3). We find a statistically insignificant 4.0% increase in generation by gas power plants when hourly estimates are aggregated (column 2).

These results suggest that a higher intra-day variability of electricity load due to permanent DST increased generation from cleaner hydropower at the expense of generation from dirtier fossil fuels. This result seems to be a combination of two phenomena.

First, generation units that use coal as their input have cut back on production on all hours of the day during the treatment period when compared with the control period. This is likely because coal-powered generators aim to minimise the frequency of restarting their units and ramping production up or down in anticipation of greater intra-day variance. To test this mechanism, we re-estimate equation (3) with hourly planned production figures submitted in the day-ahead market as a dependent variable. Table 4 shows the pooled hourly coefficients from this regression. Following the switch to permanent DST, coal-powered generators' total planned production for the next day dropped by 8.3% on average. In contrast, planned production by gas and hydropower plants were up by 5.6% and 25.2%, respectively.

Second, hydropower is utilised at a much higher rate during peak demand hours in the morning thanks to their low marginal cost and speed at which they can ramp up production. This enables hydropower units to replace dirtier generators at the margin whenever there is excess demand. To see this, we re-estimate equation (3) with realisation of planned generation as the dependent variable, defined as the ratio of actual production to planned production from the day-ahead market. Table 5 shows the pooled hourly coefficients. We estimate that, during our treatment period, the ratio of actual to planned generation for coal-powered units has actually dropped by 6.2 percentage points on average on a daily basis when compared with the control period. At the same time, the same ratio for hydropower units was on average 6.3 percentage points higher due to permanent DST on a daily basis.

We can provide additional evidence on the mechanisms underlying the above compositional changes in power generation. To do so, we first collapse the hourly generation data to the daily level and then relate daily generation to within-day load variability. We carry out two exercises separately for coal, gas and hydropower over the period January 2012 – October 2016. The estimates therefore capture the existing technology just before the change in DST policy took place.[14]

In the first exercise, presented in Table 6, we regress the average daily production (in logs) by each source on the max-to-min demand ratio. This provides the elasticity of different generation units' production to the volatility in intra-day demand at the daily level. We find that coal-powered plants have very low elasticity to changes in demand variability, gas-fired plants have intermediate levels of elasticity, and hydropower units have very high elasticity.

In the second exercise, presented in Table 7, we regress average hourly actual production (in logs) by each source on a dummy variable that equals 1 for days on which peak demand occurs before noon, and 0 otherwise. This exercise presents us with the pecking order in which generation sources meet early peak demand. We find that on days when peak demand occurs before noon, generation by hydropower units is 9.0% higher when compared with days when peak demand occurs after noon. The estimates for coal- and gas-powered generators are 1.8% and 8.3%, respectively, indicating that dirtier coal-powered generators are the least susceptible to hikes in electricity demand that occur earlier in the day.

[14] Each regression includes month fixed effects. Limiting the sample to more recent time periods before October 2016, or controlling additionally for a linear time trend, has minimal impact on the size of the estimates. These results are available upon request.

5.4 Emissions

To quantify the effects of these changes in electricity generation in terms of CO_2 emissions, we first need to establish the counterfactual of what electricity generation from coal and gas would have been without the practice of DST during winter months. For each generation source, we divide all hourly production observations that were subject to DST by one plus the estimates shown in Figure 9. Average hourly generation for each source is then calculated from these counterfactuals, which we multiply with the respective treatment effect to obtain the change in electricity generation in MWh for an average hour. We report these estimates in columns 2 and 5 of Table 8 (and similarly in columns 2 and 4 of Table 9). The product of these estimates and an hourly emissions factor yields the estimated change in CO_2 emissions.

Emissions per MWh of electricity produced vary greatly between electricity generators due to differing fuel types, generator efficiencies, and installed abatement technologies (Cullen, 2013). Studies typically use average emission factors (AEFs), which are often readily available, to estimate changes in emissions due to changes in generation. However, if the switch to permanent DST affects production by generators differently by hour of the day, then using marginal emission factors (MEFs) by generator will be more accurate. This is because MEFs reflect the emissions intensities of the marginal generators in the system – that is, the last generators needed to meet demand at a given time, and the first to respond given an intervention – and can by by time of day or year (Siler-Evans et al., 2012).

As MEFs for Turkey's generators are unavailable, we use two alternative measures for the emissions factors in our analysis. First, we use AEFs by generation source as reported by Turkey's MENR. The ministry reports total electricity generation and CO_2 emissions by source on a weekly basis, which yields a source-specific AEF that is constant over our sample period.[15] We obtain AEFs – or CO_2 intensities – for generation units that use lignite (1.65 tons/MWh), imported coal (1.09 tons/MWh), hard coal (0.59 tons/MWh), and natural gas (0.48 tons/MWh). Since our generation model for coal combines three separate sources, we use the average AEF for coal, which equals 1.11 tons/MWh. Notably, these AEFs are very similar to those reported by Novan (2015) in his study of the Texas electricity market.[16]

We believe that average AEFs are unlikely to deviate much from MEFs in our case because: (i) almost all consumption is met by power plants within a single, nationwide generation network; and (ii) marginal generators in the system are likely to be natural gas

[15]Turkey follows the Intergovernmental Panel on Climate Change (IPCC) guidelines and uses production-based emissions factors to compile its emission inventory for reporting to the United Nations Framework Convention on Climate Change (UNFCCC), which it ratified in May 2004.

[16]Novan (2015) reports an average CO_2 intensity of 1.06 tons/MWh and 0.46 tons/MWh for coal and combined cycle gas, respectively.

sources or renewables.[17] This means that our calculations based on AEFs likely provide an upper bound on estimated emissions reductions.

Second, we use hourly average MEFs for the US reported by Graff Zivin et al. (2014), who estimate MEFs for several regions based on the North American Electric Reliability Corporation (NERC) classifications. As US regions tend to vary in the fuel mix of their power generation sources, we use the average estimate across all regions. Specifically, we use the hourly coefficient estimates from the last column of Table 2 (p. 257) in Graff Zivin et al. (2014).[18] Marginal emissions are determined not only by the fuel source of generation units, but also how clean their technologies are. If US generation units operate with cleaner technologies than their Turkish counterparts do, then our estimates based on MEFs likely provide a lower bound on emissions prevented by the policy change.

Table 8 reports the estimated change in emissions due to permanent DST based on AEFs in columns (3) and (6) for coal and gas, respectively. Column (3) shows that permanent DST leads to an average reduction of 522 tons of CO_2 emissions per hour by dampening the need for coal power generation supplying the base load. The emissions reduction from coal generation is partly offset by an increase in emissions from gas-powered generators. However, gas has a much lower emissions factor than coal, meaning that the estimated total reduction in CO_2 emissions is 344 tons on average per hour (column 7). This figure translates into a reduction of around 8,200 tons of CO_2 emissions on a daily basis.

We report the estimated changes in emissions based on hourly MEFs in Table 9. Column (7) shows that the average hourly reduction in CO_2 emissions due to permanent DST is 62 tons, but this effect varies substantially throughout the day. The maximum decreases in emissions occur first at around 05:00 in the morning and then at 17:00 in the evening, when estimated reductions reach 465 tons and 292 tons, respectively. These are the times when hydropower offsets generation from fossil fuels the most. At other times in the day when gas-powered generators are ramped up to meet excess demand, we observe small increases in emissions. On a daily basis, permanent DST seems to have helped prevent nearly 1,500 tons of CO_2 emissions, when we use MEFs in our calculations.

In the Appendix, we also provide estimates for reductions in SO_2 and NO_x emissions based on AEFs reported by Novan (2015) and MEFs reported by Graff Zivin et al. (2014) (see Tables A.6-A.9). Accordingly, we find that change in policy to stay on DST all year round may have led to reductions in SO_2 emissions between 5 tons and 32 tons, and in NO_x

[17] Siler-Evans et al. (2012) and Graff Zivin et al. (2014) find that AEFs and MEFs in most US regions do not deviate from each other consistently, especially where coal plays a smaller role. They also find that MEFs do not vary substantially across different hours of the day or across months, except in regions heavily reliant on coal-powered generation such as the Midwest.

[18] We reproduce MEF estimates by Graff Zivin et al. (2014) in column 6 of Table 9.

emissions between 1.3 and 12 tons, on a daily basis.

6 Conclusion

We use unique data and a nationwide policy change in Turkey to estimate the impact of year-round daylight savings time on hourly electricity consumption, generation and emissions. Using several strategies with different identifying assumptions, we show that the change in Turkey's DST policy does not affect overall electricity consumption. However, keeping DST during winter months increases electricity consumption in the early morning hours and reduces it in the late afternoon hours. This intra-day redistribution of electricity consumption leads to significant changes in the sources of electricity generation and related greenhouse gas emissions. We find that the rise in intra-day variability of electricity load increases peak hydro and reduces dirtier base-load fossil generation. Although the policy change falls short of its goal to save energy in aggregate, it has positive – but unintended – implications with respect to emissions reductions related to generation.

We should note the following in terms of the external validity of our results. When there is greater intra-day load variability, there is an appealing element to generating electricity from hydropower instead of other renewables to meet unforeseen demand. For instance, unlike wind and solar energy, which are intermittent providers that supply to the grid when weather conditions allow, hydropower can be called upon at any time during the day, provided there is sufficient water. This makes hydropower ideally situated to meet peak demand, especially on days that have low base load. In other settings where the existing capacity of renewable generators may not allow them to easily replace fossil fuel powered generators, changes to the intra-day load variability due to permanent DST may actually end up increasing emissions.

We should also note that the emissions reductions due to the change in DST policy may have come at a cost. Specifically, an increase in intra-day load variability may have affected the wholesale prices of electricity, especially in the intra-day market. We leave the question of whether there were any adverse impacts on wholesale prices, and if so, whether these were passed on to end-consumers, to future research.

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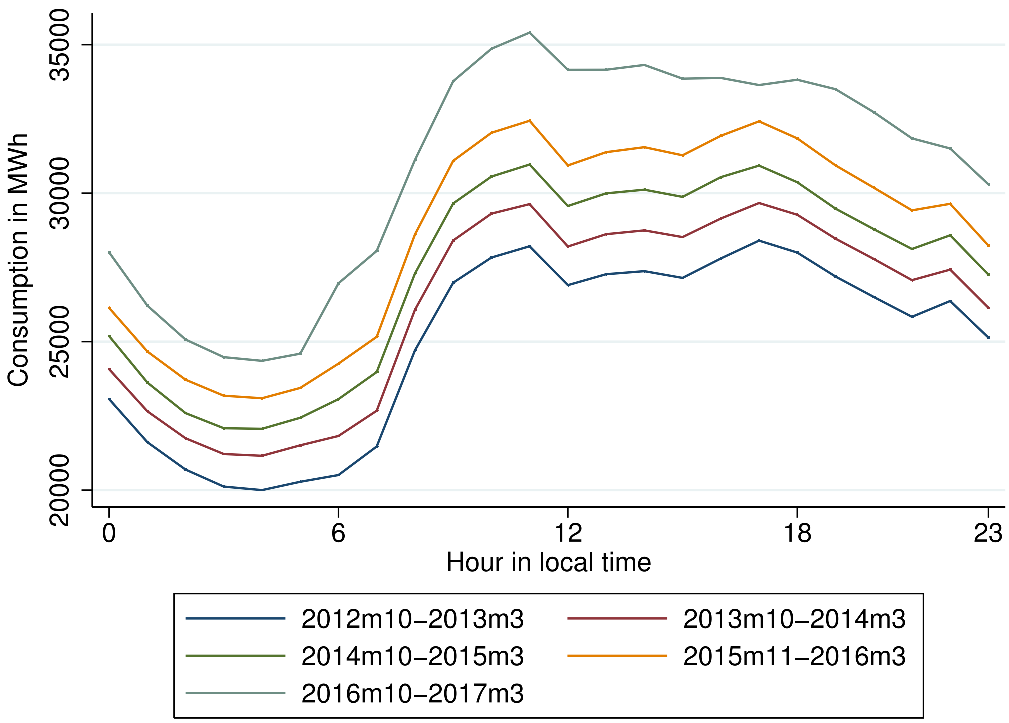
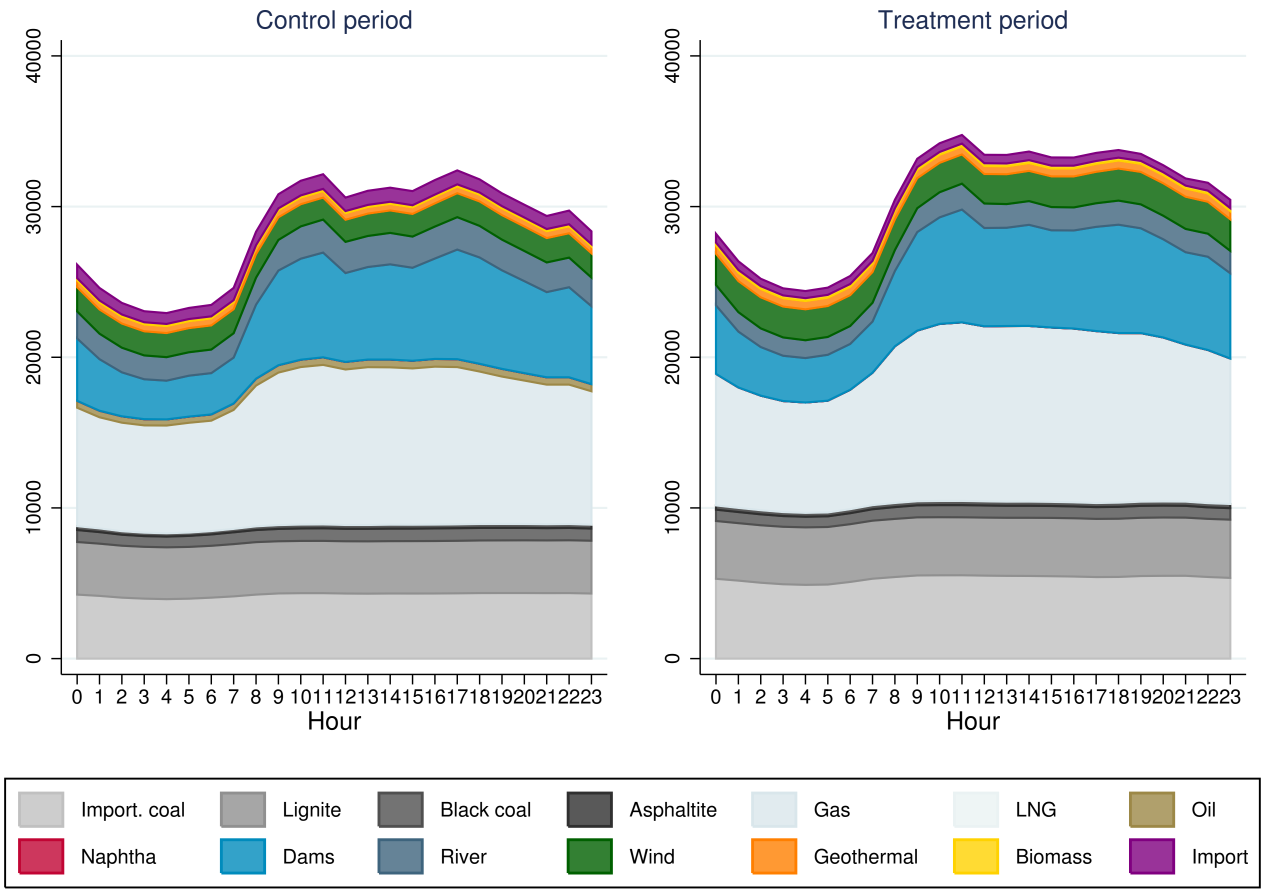
Figures and Tables

Figure 1: Average hourly electricity consumption during treatment, control and placebo periods



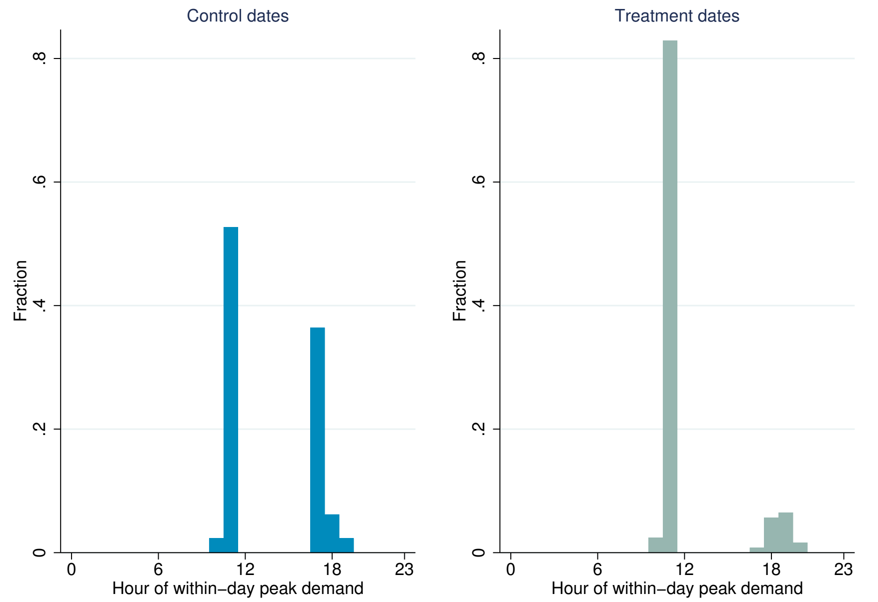
Notes: The figure shows the average hourly electricity consumption in MWh for five periods: (i) 28 October 2012 – 31 March 2013, (ii) 27 October 2013 – 31 March 2014, (iii) 26 October 2014 – 29 March 2015, (iv) 8 November 2015 – 27 March 2016, and (v) 30 October 2016 – 26 March 2017.

Figure 2: Average hourly fuel mix in treatment and control periods (in MWh)



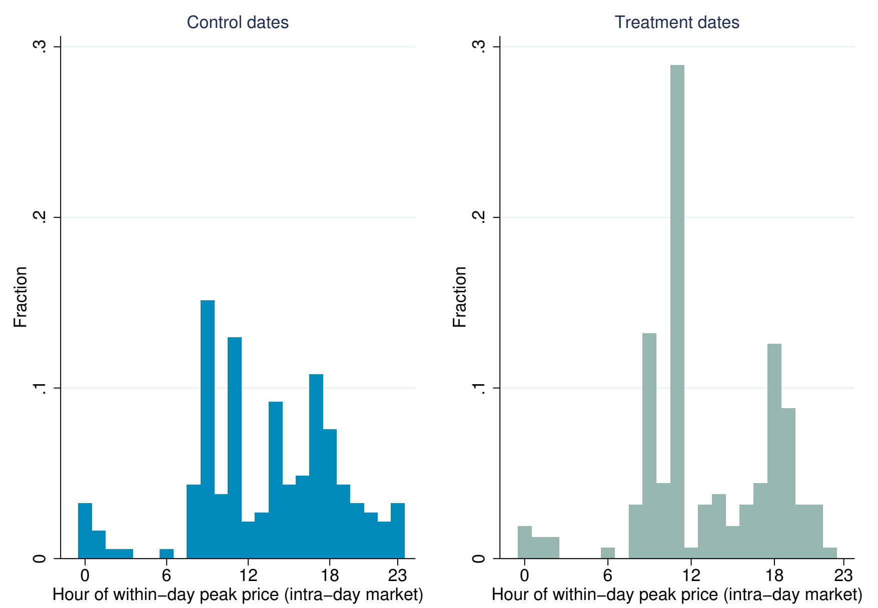
Notes: The figure shows the hourly fuel mix in MWh for the treatment period (30 October 2016 - 25 March 2017) and the control period (8 November 2015 - 26 March 2016).

Figure 3: Frequency of peak demand hours over control and treatment periods



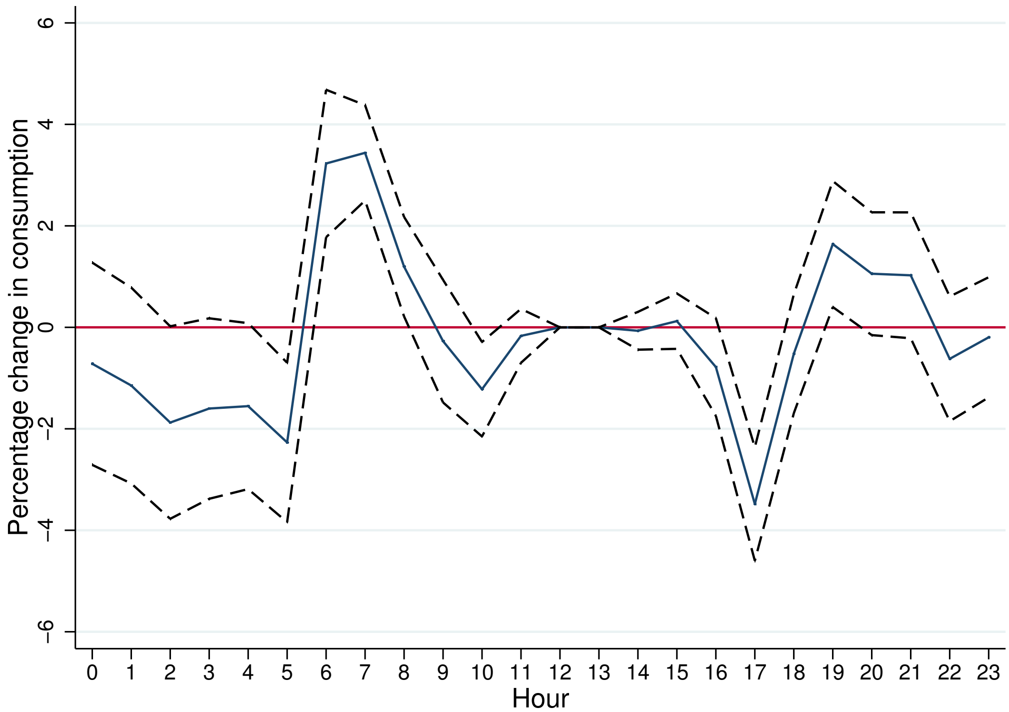
Notes: The figure shows histograms of within-day peak demand hours for control (8 November 2015 - 26 March 2016) and treatment dates (30 October 2016 - 25 March 2017) on the left and right panels, respectively.

Figure 4: Frequency of peaks in prices of the intraday market over control and treatment periods



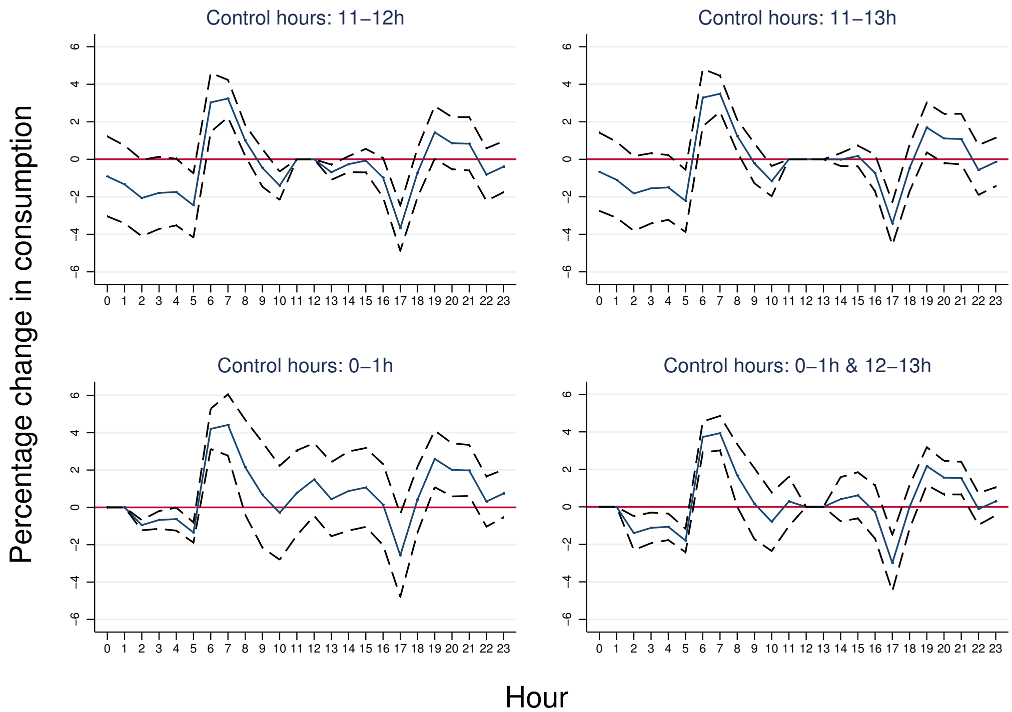
Notes: The figure shows histograms of within-day peak hours for prices of the Turkish intraday electricity market for control (8 November 2015 - 26 March 2016) and treatment dates (30 October 2016 - 25 March 2017) on the left and right panels, respectively.

Figure 5: Hourly effects of permanent DST on electricity demand



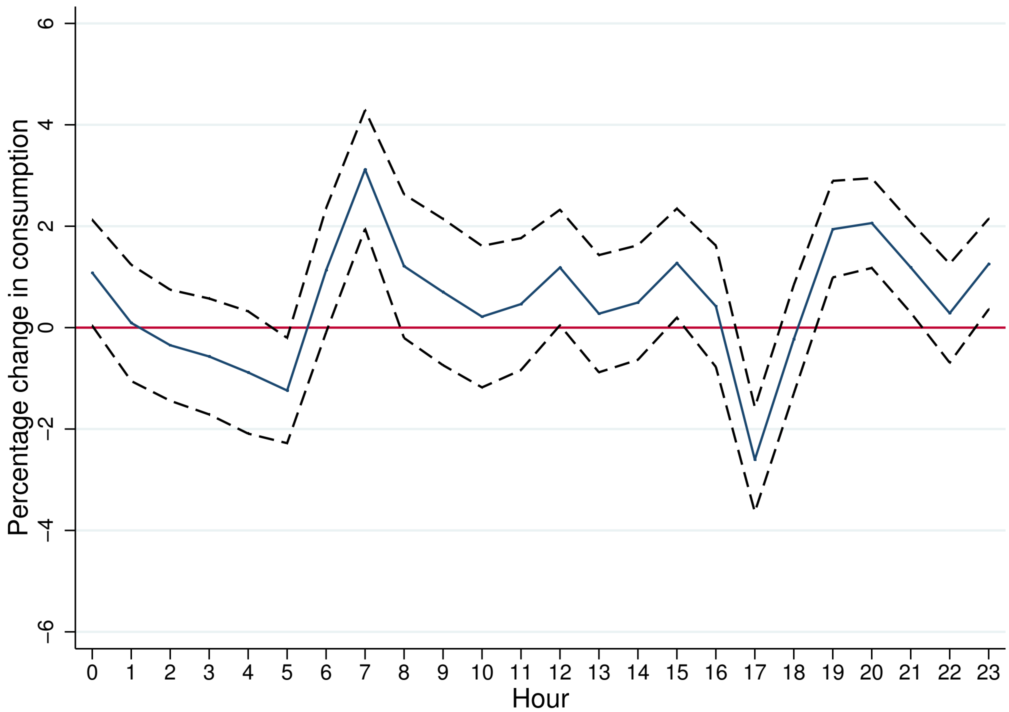
Notes: The figure shows hourly estimates of staying on DST during the treatment period on electricity consumption, using midday control hours in Equation (1). 95% confidence intervals are indicated, with standard errors clustered by date. Effects during mid-day hours (12:00 and 13:59) are zero by assumption. The sample includes 8 November 2015 – 26 March 2016 and 30 October 2016 – 25 March 2017 ($N = 6,889$). Estimates are based on Equation (1). The underlying model includes weather controls interacted by hour, date FE, hour FE, and a constant. Weather controls include population-weighted national aggregates of heating degrees, heating degrees squared, pressure, humidity, wind speed, and cloudiness.

Figure 6: Hourly effects of permanent DST on electricity demand with different control hours



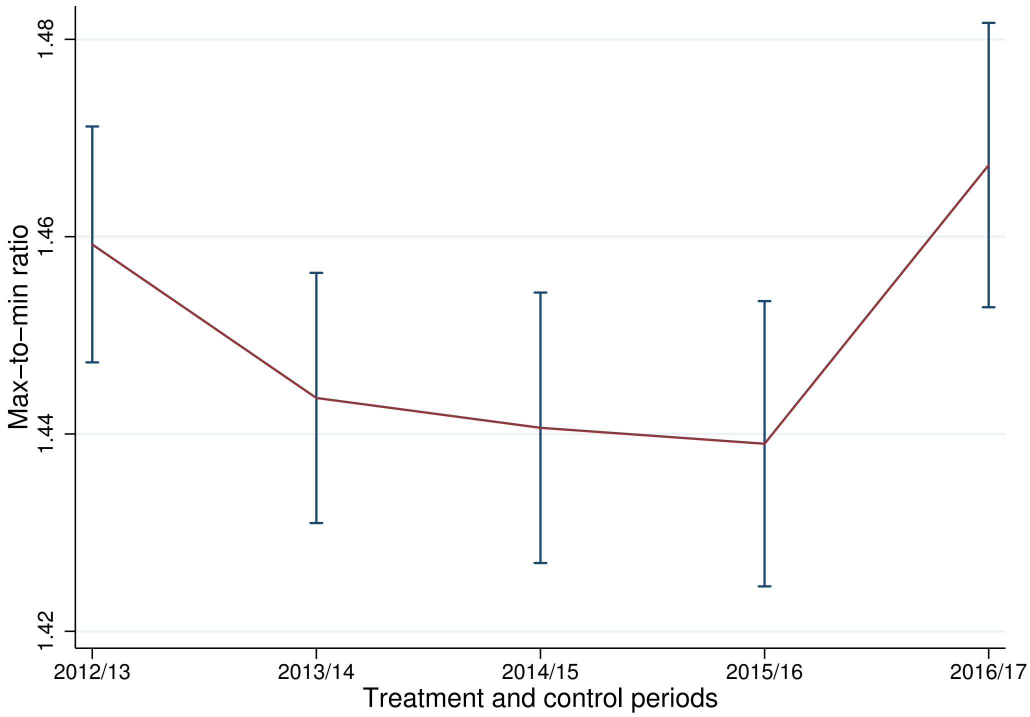
Notes: The figure show hourly estimates of staying on DST during the treatment period on electricity consumption, using different control hours in Equation (1). 95% confidence intervals are indicated, with standard errors clustered by date. The sample includes 8 November 2015 – 26 March 2016 and 30 October 2016 – 25 March 2017 ($N = 6,889$). All underlying models include weather controls interacted by hour, date FE, hour FE, and a constant. Weather controls include population-weighted national aggregates of heating degrees, heating degrees squared, pressure, humidity, wind speed, and cloudiness.

Figure 7: Hourly effects of permanent DST on electricity demand, using intra-year control approach



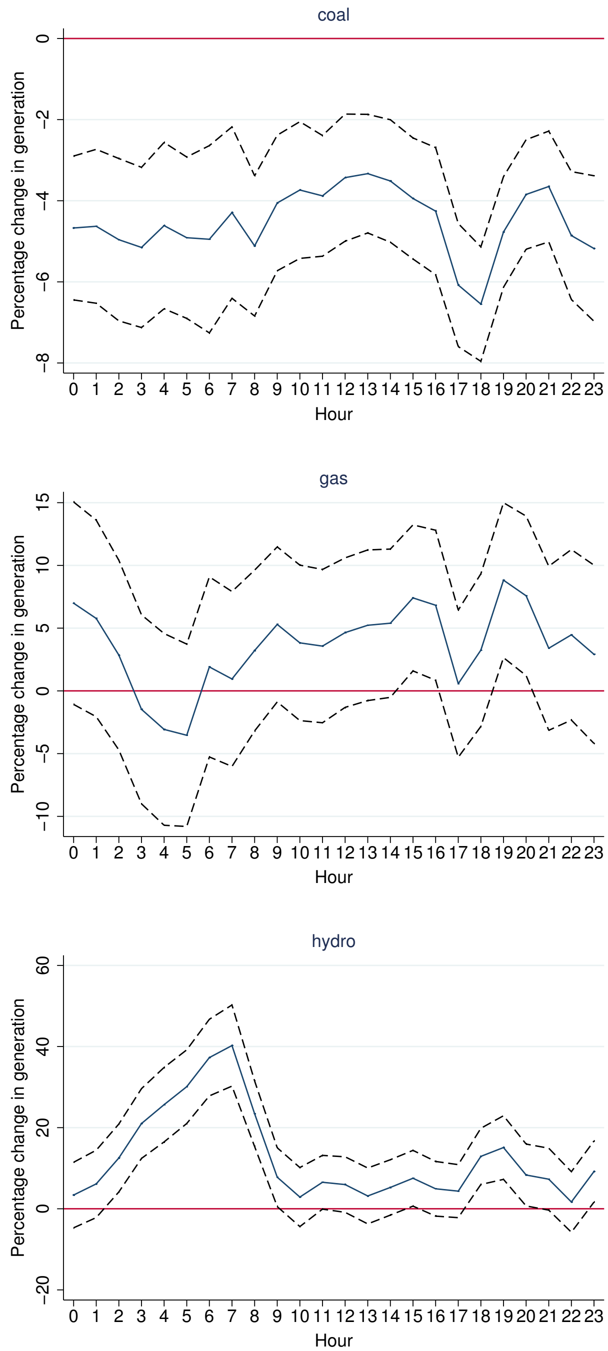
Notes: The figure shows hourly estimates from Equation (2) of staying on DST during the treatment period on electricity consumption, using summer months (27 March – 30 October 2016 and 26 March – 29 October 2017) as our control period. 95% confidence intervals are indicated, with standard errors clustered by date. The sample includes 8 November 2015 – 29 October 2017 ($N = 17,302$). The underlying model includes hourly estimates for weather controls, day of the year FE, day of the week FE, holiday FE, hour FE, and a constant. Weather controls include population-weighted national aggregates of heating degrees, heating degrees squared, pressure, humidity, wind speed, and cloudiness.

Figure 8: Development of intra-day variability of electricity load



Notes: The figure shows average max/min ratios (daily maximum to minimum ratio of load) for the treatment period (30 October 2016 - 25 March 2017), the control period (8 November 2015 - 26 March 2016) and earlier winter time periods (26 October 2014 - 28 March 2015; 27 October 2013 - 30 March 2014; 28 October 2012 - 30 March 2013) together with 95% confidence intervals of the mean.

Figure 9: Hourly effects of DST on electricity generation



Notes: The figures depict hourly estimates of DST on electricity generation from coal, gas and hydro power plants during the treatment period, using generation during summer time periods (27 March – 30 October 2016 and 26 March to 29 October 2017) as control. 95% confidence intervals are indicated, with standard errors clustered by date. The sample includes 8 November 2015 - 29 October 2017 ($N = 17,302$). Estimates are based on Equation (3).

Table 1: Summary statistics by treatment and control periods

		(1)	(2)	(3)	(4)
Variable	Unit	Control (Winter 2015/16)	Treatment (Winter 2016/17)	Control (Summer 2016)	Control (Summer 2017)
Demand	MWh	28649.58	30856.92	29234.00	31262.87
		(4077.18)	(4490.92)	(4746.70)	(5094.57)
Generation	MWh	28463.76	30537.95	28916.84	31112.18
		(4084.99)	(4439.30)	(4736.71)	(5222.09)
Generation from coal	MWh	8513.97	9955.82	8755.24	9118.22
		(761.69)	(966.10)	(1186.37)	(1598.65)
Generation from gas	MWh	9123.91	10058.16	8976.56	11484.99
		(2514.06)	(2703.27)	(2579.65)	(2995.09)
Generation from hydropower	MWh	7071.78	6926.08	7798.10	6965.09
		(2533.26)	(2764.60)	(2355.95)	(3239.52)
Installed capacity	MWh	43122.26	50039.42	50031.19	50664.53
		(2170.78)	(1904.71)	(3257.83)	(2705.81)
Installed capacity: coal	MWh	9677.74	11551.59	10178.29	10313.85
		(650.72)	(1010.07)	(1122.38)	(1459.18)
Installed capacity: gas	MWh	16077.96	16085.25	16407.74	16342.17
		(1442.81)	(1774.55)	(1420.03)	(1908.20)
Installed capacity: hydropower	MWh	15140.45	17655.78	18923.74	19152.31
		(1702.13)	(1046.81)	(1786.63)	(1476.07)
Intra-day price	TRY/MWh	125.60	169.78	125.03	149.99
		(68.41)	(89.12)	(68.11)	(45.37)
Coal import price index	base=1	1.09	1.51	0.93	1.62
		(0.08)	(0.19)	(0.06)	(0.08)
Natural gas price	TRY/KWh	0.08	0.07	0.09	0.07
		(0.00)	(0.00)	(0.00)	(0.00)
Heating degrees	°C	-11.41	-13.31	1.64	1.49
		(5.23)	(5.24)	(6.35)	(6.69)
Pressure	hPa	999.90	1006.42	981.94	1004.44
		(7.30)	(15.02)	(17.57)	(5.33)
Humidity	%	73.83	73.18	63.90	59.34
		(9.99)	(11.45)	(14.66)	(14.34)
Wind speed	m/s	2.63	2.90	2.72	3.03
		(1.07)	(1.12)	(1.02)	(1.11)
Cloudiness	%	38.34	40.14	22.47	24.25
		(21.60)	(22.09)	(16.74)	(18.13)
Public holiday	% of days	0.01	0.01	0.07	0.07
		(0.08)	(0.08)	(0.25)	(0.25)
Observations		3,360	3,529	5,207	5,207

Notes: This table shows means and standard deviations (in brackets) for variables included in the analysis. Columns 1 and 2 present summary statistics for the control period (8 November 2015 – 26 March 2016) and treatment period (30 October 2016 – 25 March 2017), respectively. Columns 3 and 4 present statistics for the summer months in 2016 and 2017.

Table 2: Overall effects of DST on electricity consumption with different control hours

	(1)	(2)	(3)	(4)
	Control hours: 11:00-12:59h	Control hours: 11:00-13:59h	Control hours: 0:00-1:59h	Control hours: 0:00-1:59h and 12:00-13:59h
Permanent DST (pooled β_h)	-0.004	-0.001	0.008	0.003
	(0.004)	(0.004)	(0.007)	(0.003)
Observations	6,889	6,889	6,889	6,889
R^2	0.940	0.940	0.940	0.940

Notes: This table shows pooled estimates of staying on DST during the treatment dates on electricity consumption, using different control hours in Equation (1) (hourly estimates are reported in Figure 6). All models include weather controls interacted by hour, date FE, hour FE, and a constant. Weather controls include population-weighted national aggregates of heating degrees, heating degrees squared, pressure, humidity, wind speed, and cloudiness. Standard errors are clustered at the date level. * p<0.05; ** p<0.01; *** p<0.001

Table 3: Overall effects of DST on actual electricity generation

	(1)	(2)	(3)
	Coal	Gas	Hydro
Post policy (Pooled θ_{sh})	0.025***	-0.005	-0.119***
	(0.008)	(0.035)	(0.018)
Affected period (Pooled δ_{sh})	0.044***	0.220***	0.049
	(0.012)	(0.042)	(0.038)
Post policy * affected period (Pooled β_{sh})	-0.046***	0.040	0.124***
	(0.005)	(0.028)	(0.033)
Observations	17,302	17,302	17,302
R^2	0.948	0.882	0.833

Notes: This table shows pooled estimates of staying on DST during treatment dates on electricity generation by source. Estimates are based on Equation (3). All models include hourly (log) installed capacity of each source, hourly weather controls, day of the year FE, day of the week FE, holiday FE, hour FE, and a constant. Column 1 controls additionally for (log) import coal price index, and column 2 for (log) natural gas price. Weather controls include population-weighted national aggregates of heating degrees (difference to 18.33°C), heating degrees squared, pressure, humidity, wind speed, and cloudiness. Coal includes generation from imported coal, lignite and hard coal, gas includes generation from natural gas, and hydro includes generation from dams and rivers. Standard errors are clustered at the date level. * p<0.05; ** p<0.01; *** p<0.001

Table 4: Overall effects of DST on day-ahead generation plans

	(1)	(2)	(3)
	Coal	Gas	Hydro
Post policy	0.042***	-0.037	-0.261***
	(0.007)	(0.037)	(0.017)
Affected period	0.081***	0.152***	-0.097**
	(0.017)	(0.030)	(0.045)
DiD indicator (post policy * affected period)	-0.083***	0.056*	0.252***
	(0.005)	(0.029)	(0.032)
Observations	17,302	17,302	17,302
R^2	0.956	0.865	0.834

Notes: This table shows pooled estimates of staying on DST during treatment dates on day-ahead planned electricity generation by source. Estimates are based on Equation (3). All models include hourly (log) installed capacity of each source, hourly weather controls, day of the year FE, day of the week FE, holiday FE, hour FE, and a constant. Column 1 controls additionally for (log) import coal price index, and column 2 for (log) natural gas price. Weather controls include population-weighted national aggregates of heating degrees (difference to 18.33°C), heating degrees squared, pressure, humidity, wind speed, and cloudiness. Coal includes generation from imported coal, lignite and hard coal, gas includes generation from natural gas, and hydro includes generation from dams and rivers. Standard errors are clustered at the date level. * p<0.05; ** p<0.01; *** p<0.001

Table 5: Overall effects of DST on realisation of day-ahead generation plans

	(1)	(2)	(3)
	Coal	Gas	Hydro
Post policy	0.043***	-0.013	-0.075***
	(0.006)	(0.023)	(0.005)
Affected period	0.049***	0.087***	-0.014
	(0.012)	(0.017)	(0.013)
DiD indicator (post policy * affected period)	-0.062***	0.027	0.063***
	(0.004)	(0.017)	(0.007)
Observations	17,302	17,302	17,302
R^2	0.664	0.831	0.827

Notes: This table shows pooled estimates of staying on DST during treatment dates on the realisation of day-ahead planned electricity generation by source. The dependent variable is defined as the ratio of actual generation to day-ahead planned generation. Estimates are based on Equation (3). All models include hourly (log) installed capacity of each source, hourly weather controls, day of the year FE, day of the week FE, holiday FE, hour FE, and a constant. Column 1 controls additionally for (log) import coal price index, and column 2 for (log) natural gas price. Weather controls include population-weighted national aggregates of heating degrees (difference to 18.33°C), heating degrees squared, pressure, humidity, wind speed, and cloudiness. Coal includes generation from imported coal, lignite and hard coal, gas includes generation from natural gas, and hydro includes generation from dams and rivers. Standard errors are clustered at the date level. * p<0.05; ** p<0.01; *** p<0.001

Table 6: Effect of load variability on actual generation

	(1)	(2)	(3)
	Coal	Gas	Hydro
Mean max-to-min load	0.082***	0.679***	0.745***
	(0.024)	(0.042)	(0.052)
Month*Year FE	Yes	Yes	Yes
Observations	1,982	1,982	1,982
R^2	0.862	0.590	0.789

Notes: This table shows results from regressions of daily actual production on intra-day variability by source. All models include month-by-year FE and a constant. Standard errors are clustered at the date level. * p<0.05; ** p<0.01; *** p<0.001

Table 7: Effect of early peak in demand on actual generation

	(1)	(2)	(3)
	Coal	Gas	Hydro
Early peak in demand	0.018***	0.083***	0.090***
	(0.005)	(0.008)	(0.010)
Month*Year FE	Yes	Yes	Yes
Observations	1,982	1,982	1,982
R^2	0.862	0.557	0.776

Notes: This table shows results from regressions of daily actual production on a dummy equal to 1 for days with early peak loads, and 0 otherwise, by source. Early peak is defined as a day on which maximum hourly load occurs before noon. All models include month-by-year FE and a constant. Standard errors are clustered at the date level. * p<0.05; ** p<0.01; *** p<0.001

Table 8: Effects of DST on CO_2 emissions using average emissions factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hour	Coal			Gas			Total
	DST effect	ΔMWh	ΔEmissions	DST effect	ΔMWh	ΔEmissions	ΔEmissions
0	-0.047	-484.47	-537.76	0.070	570.35	273.77	-264.00
1	-0.046	-472.26	-524.21	0.058	436.29	209.42	-314.79
2	-0.050	-499.87	-554.86	0.029	210.73	101.15	-453.70
3	-0.052	-513.80	-570.32	-0.015	-109.88	-52.74	-623.06
4	-0.046	-455.36	-505.45	-0.031	-231.92	-111.32	-616.77
5	-0.049	-487.74	-541.39	-0.035	-271.81	-130.47	-671.86
6	-0.049	-502.52	-557.80	0.019	148.59	71.32	-486.47
7	-0.043	-444.50	-493.40	0.010	82.69	39.69	-453.70
8	-0.051	-541.94	-601.55	0.032	324.03	155.53	-446.02
9	-0.041	-429.92	-477.21	0.053	569.80	273.51	-203.71
10	-0.037	-395.34	-438.83	0.038	433.02	207.85	-230.98
11	-0.039	-411.14	-456.37	0.036	408.23	195.95	-260.41
12	-0.034	-360.94	-400.64	0.046	515.39	247.39	-153.26
13	-0.033	-349.61	-388.07	0.052	579.16	278.00	-110.07
14	-0.035	-369.33	-409.96	0.054	596.61	286.37	-123.58
15	-0.039	-415.88	-461.63	0.074	798.30	383.18	-78.44
16	-0.043	-449.00	-498.39	0.068	736.74	353.63	-144.76
17	-0.061	-650.67	-722.24	0.006	64.93	31.17	-691.08
18	-0.065	-705.83	-783.47	0.032	354.09	169.96	-613.51
19	-0.048	-507.75	-563.60	0.088	906.51	435.13	-128.48
20	-0.038	-406.01	-450.67	0.076	766.23	367.79	-82.88
21	-0.036	-384.08	-426.33	0.034	342.44	164.37	-261.96
22	-0.049	-512.72	-569.12	0.045	434.63	208.62	-360.50
23	-0.052	-545.21	-605.18	0.029	273.26	131.16	-474.02

Notes: This table shows the estimated effects of permanent DST on CO2 emissions by hour and source of electricity generation using AEFs. Emissions are in tons of CO2. Columns 1 and 4 report the treatment effects depicted in Figure 9 for coal and gas, respectively. Columns 2 and 5 show the change in MWh due to DST. Columns 3 and 6 include the corresponding change in CO2 emissions, and Column 7 shows the sum of these hourly changes in emissions.

Table 9: **Effects of DST on CO_2 emissions using marginal emissions factors**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hour	Coal		Gas		Total		
	DST effect	ΔMWh	DST effect	ΔMWh	ΔMWh	MEF (kg/kWh)	ΔEmissions
0	-0.047	-484.47	0.070	570.35	85.88	0.581	49.86
1	-0.046	-472.26	0.058	436.29	-35.97	0.594	-21.38
2	-0.050	-499.87	0.029	210.73	-289.14	0.617	-178.37
3	-0.052	-513.80	-0.015	-109.88	-623.68	0.621	-387.57
4	-0.046	-455.36	-0.031	-231.92	-687.28	0.617	-423.97
5	-0.049	-487.74	-0.035	-271.81	-759.55	0.612	-465.11
6	-0.049	-502.52	0.019	148.59	-353.93	0.590	-208.70
7	-0.043	-444.50	0.010	82.69	-361.81	0.553	-200.22
8	-0.051	-541.94	0.032	324.03	-217.91	0.531	-115.64
9	-0.041	-429.92	0.053	569.80	139.88	0.535	74.87
10	-0.037	-395.34	0.038	433.02	37.68	0.549	20.68
11	-0.039	-411.14	0.036	408.23	-2.91	0.553	-1.61
12	-0.034	-360.94	0.046	515.39	154.45	0.544	84.07
13	-0.033	-349.61	0.052	579.16	229.55	0.535	122.86
14	-0.035	-369.33	0.054	596.61	227.28	0.522	118.56
15	-0.039	-415.88	0.074	798.30	382.42	0.508	194.28
16	-0.043	-449.00	0.068	736.74	287.74	0.503	144.87
17	-0.061	-650.67	0.006	64.93	-585.74	0.499	-292.25
18	-0.065	-705.83	0.032	354.09	-351.74	0.494	-173.90
19	-0.048	-507.75	0.088	906.51	398.76	0.494	197.15
20	-0.038	-406.01	0.076	766.23	360.22	0.494	178.10
21	-0.036	-384.08	0.034	342.44	-41.64	0.503	-20.97
22	-0.049	-512.72	0.045	434.63	-78.09	0.517	-40.38
23	-0.052	-545.21	0.029	273.26	-271.95	0.549	-149.26

Notes: This table shows the estimated effects of permanent DST on CO2 emissions by hour and source of electricity generation using MEFs. Emissions are in tons of CO2. Columns 1 and 3 report the treatment effects depicted in Figure 9 for coal and gas, respectively. Columns 2 and 4 show the change in MWh due to DST. Column 5 shows the total change in MWh due to DST. Column 6 reproduces the average hourly MEF reported by Graff Zivin et al. (2014). Column 7 shows the corresponding change in CO2 emissions.

Online Appendix for

Daylight Saving All Year Round? Evidence from a National Experiment

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A Appendix

A.1 Data Appendix

This section describes the construction of the weather variables used in this study in more detail. Hourly weather data between 1 October 2012 and 2 January 2018 for the central districts of all 81 Turkish provinces is provided by the history bulk of Open Weather Map.[19] For some city-day-hour observations, we observe more than one entry in the data set due to changing weather conditions within these particular dates, hours, and provinces. We collapse those duplicates using the simple average for all weather variables.

Given that our main database contains information on hourly electricity consumption and production on the *national* level, we then construct a measure for aggregate average hourly temperature, pressure, humidity, wind speed and cloudiness. Hourly temperature is measured in degrees Celsius, the pressure is given in hPa per hour, and wind speed reports the hourly average speed in meter per seconds. The degree of both humidity and cloudiness is measured in percentage. As we are interested in the effect of the DST policy change on total demand, we account for the different sizes of the Turkish provinces and weight the province-level data by population figures, using data from the address based population registration system of the Turkish Statistical Institute.[20]

A.2 Justification for using midday control hours

Our main identification strategy relies upon the assumption that electricity demand and production during midday hours is unaffected by changes to DST policy. This appendix section presents regression results from regression discontinuity analyses (RDD) in the spirit of Kellogg and Wolff (2008) and Rivers (2016) to substantiate this assumption and justify our choice of the window from 12:00 pm to 13:59 as control hours in our DiD analysis.

For the RDD analysis we leverage four "normal" switches from standard time to DST that occurred in late March of 2013-2016. In each year, we use eight weeks before and after the time switch, including the same days of the week as the date of the time change only. For example, if the switch to summer time happened on a Monday, such as in 2014, we include hourly demand observations during eight Mondays before and eight Mondays after the time change.[21] This ensures that we compare dates that are similar in terms of people's daily routine and levels of electricity consumption. Figure A.2 plots the log consumption near the

[19] https://openweathermap.org/history-bulk

[20] See http://www.turkstat.gov.tr/PreTablo.do?alt_id=1059.

[21] Note that results remain largely unchanged if we change this time frame to seven or nine weeks. Results are available on request.

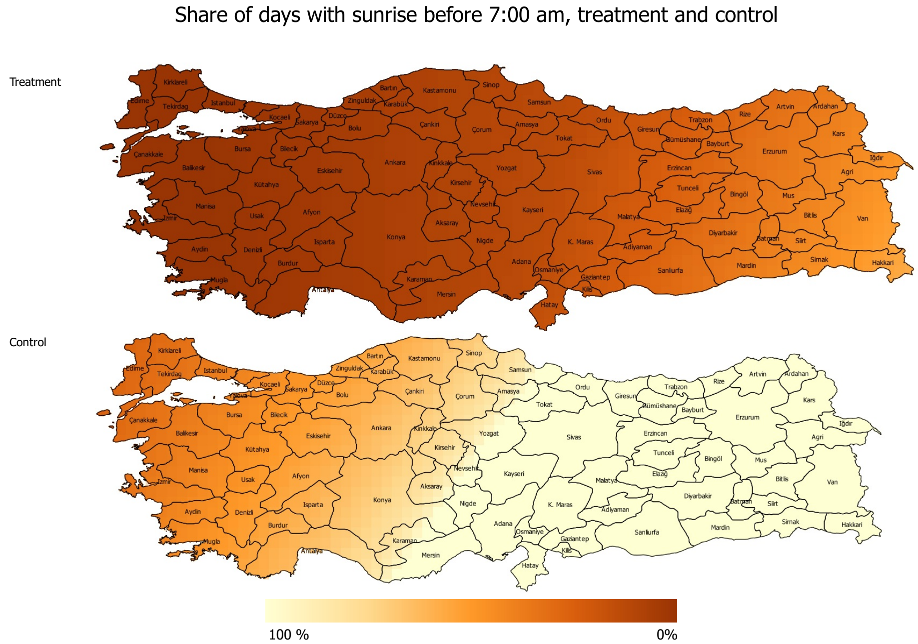
time switch by hour. While we do not observe a significant discontinuity for several hours, including those around midday, there seems to be a small jump in electricity consumption around the time change at 6:00 and a drop in demand at 17:00 and 18:00. To assess the effect of the switch to DST on electricity demand, we estimate the following equation for each hour separately:

$$ln(consump_{dy}) = \alpha + \beta_0 D_{dy} + \beta_1 \widetilde{X}_{dy} + \beta_2 \widetilde{X}_{dy} * D_{dy} + \delta_y + \gamma_{dy} + \vartheta W_{dy} + \varepsilon_{dy} \tag{4}$$

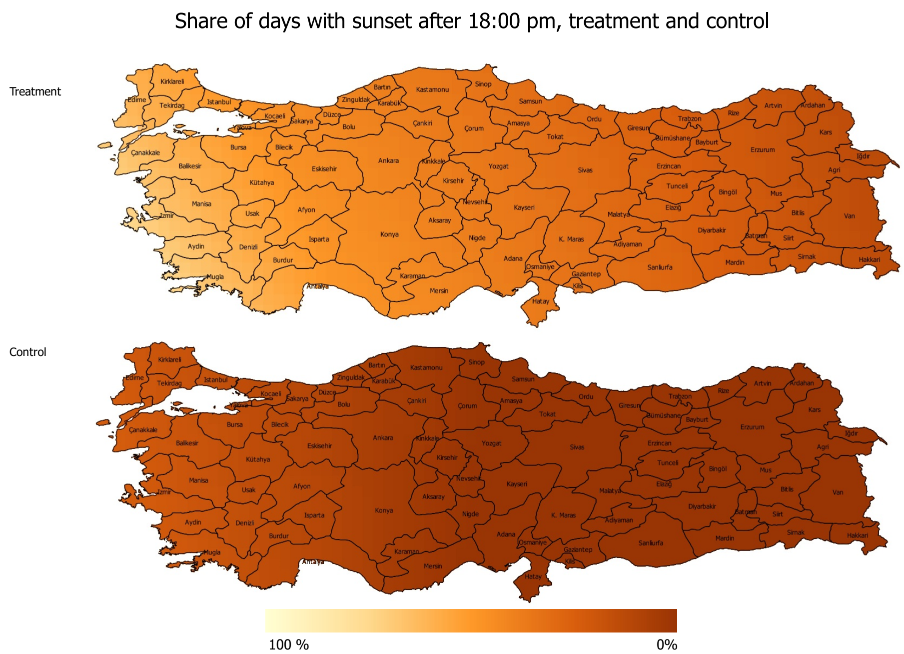
where D_{dy} is an indicator variable for whether DST is in place and $\widetilde{X}_{dh}$ is the "running" variable which is centered at the date of the time switch and counts the days from and to the cutoff. We interact these two variables in order to allow for different linear slopes before and after the discontinuity. Additionally, we include year fixed effects δ_y, a binary indicator for public holidays γ_{dy} and the weather variables W_{dh} already included in the main analysis.

Figure A.3 graphically presents the estimates of the DST effect $(100 * (exp(\beta_0) - 1))$ from equation 4 for each hour. In line with existing research (Kellogg and Wolff, 2008; Rivers, 2016) and consistent with intuition, we find that following the switch from standard time to DST electricity consumption increases on average by 3.8% at 6:00 (with a standard error of 1.2%), while electricity demand in Turkey significantly declines between 17:30 and 19:00 with estimated decreases of more than 9% at 18:00. During midday including our control hours between 12:00 and 13:59, in contrast, the estimated effect of switching to summer time is moderate and statistically insignificant. These results are robust to different RDD specifications, such as fitting equal linear slopes on both sides of the cutoff, allowing for year-specific linear slopes and comparing simple averages of electricity consumption before and after the time change. Similarly, when we run the RDD regression specified in equation 4 for rolling two hour windows, the estimate for the interval between 12:00 and 13:59 is 0.011, which is again statistically indistinguishable from 0 despite a considerably larger number of observations ($N = 136$). Hence, these supplementary analyses support our assumption that the one hour time change due to DST does not affect consumption during mid-day hours and justify normalising the DST effect during the 12:00 - 13:59 interval to 0 in our main analysis.

Figure A.1: Exposure to sunlight by treatment vs. control dates



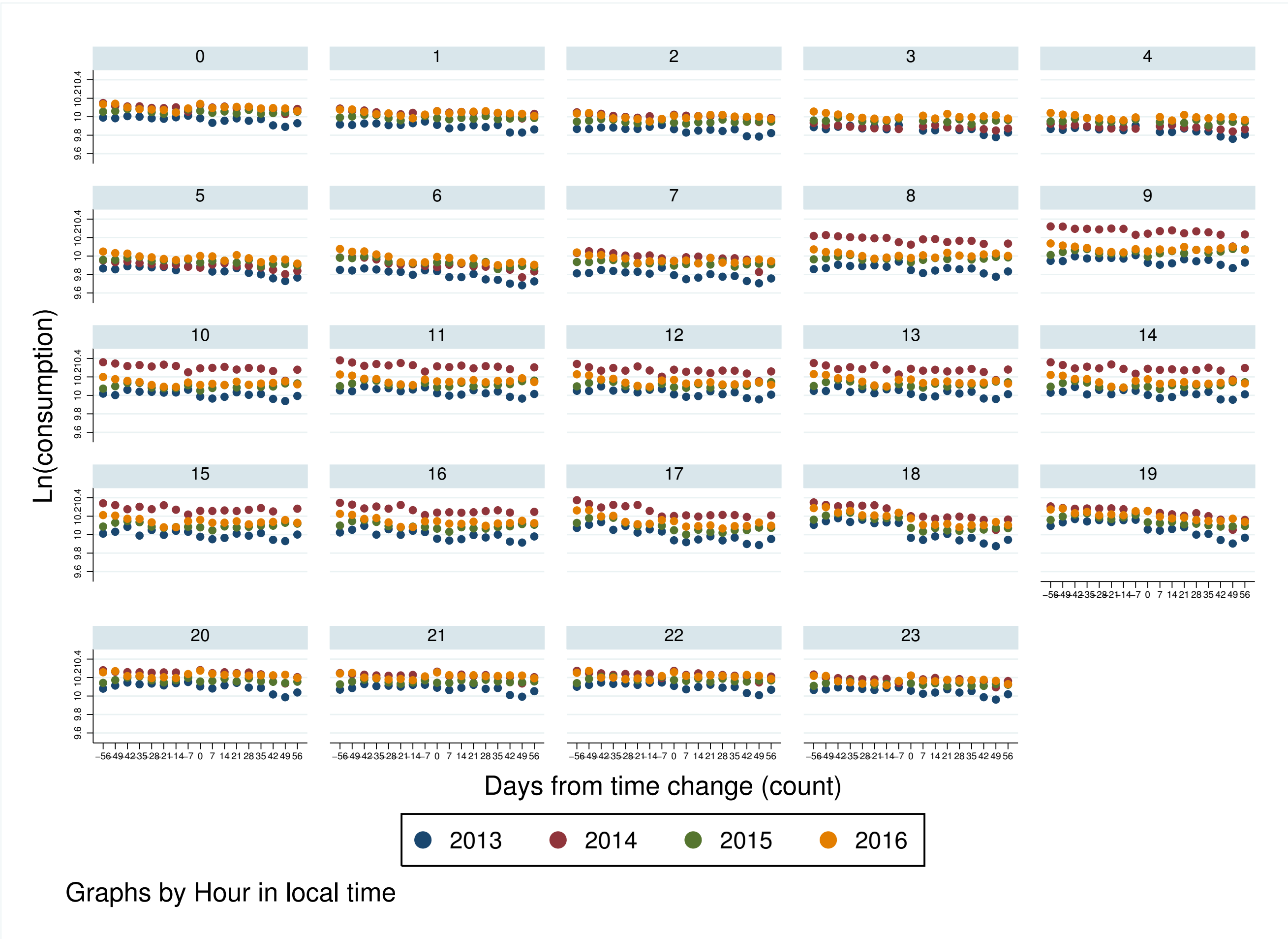
(a) Sunlight in early morning hours



(a) Sunlight in early evening hours

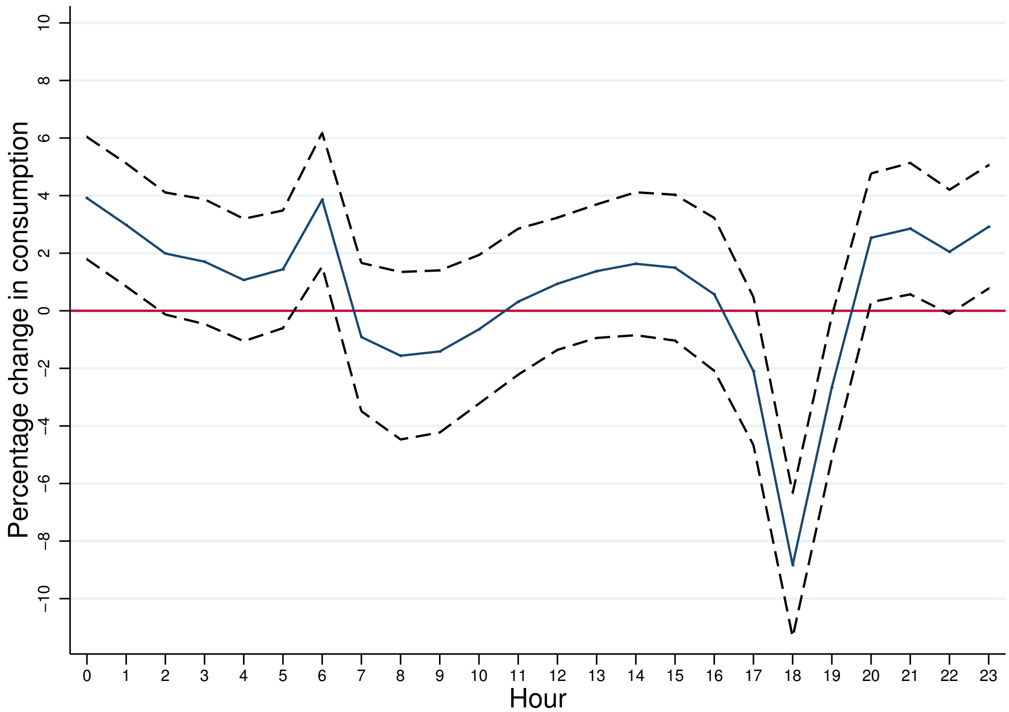
Notes: This figure shows, for each of Turkey's 81 provinces, the share of days when the sun rises before 07:00 in Panel A and when the sun sets after 18:00 in Panel B over control and treatment periods. Lighter tones indicate a greater share of days during the corresponding period. The control period includes 8 November 2015 – 26 March 2016 and the treatment period includes 30 October 2016 – 25 March 2017. Sunrise and sunset times for each province is sourced from OpenWeatherMap.

Figure A.2: Electricity consumption shortly before and after the switch to DST in March 2013-2016



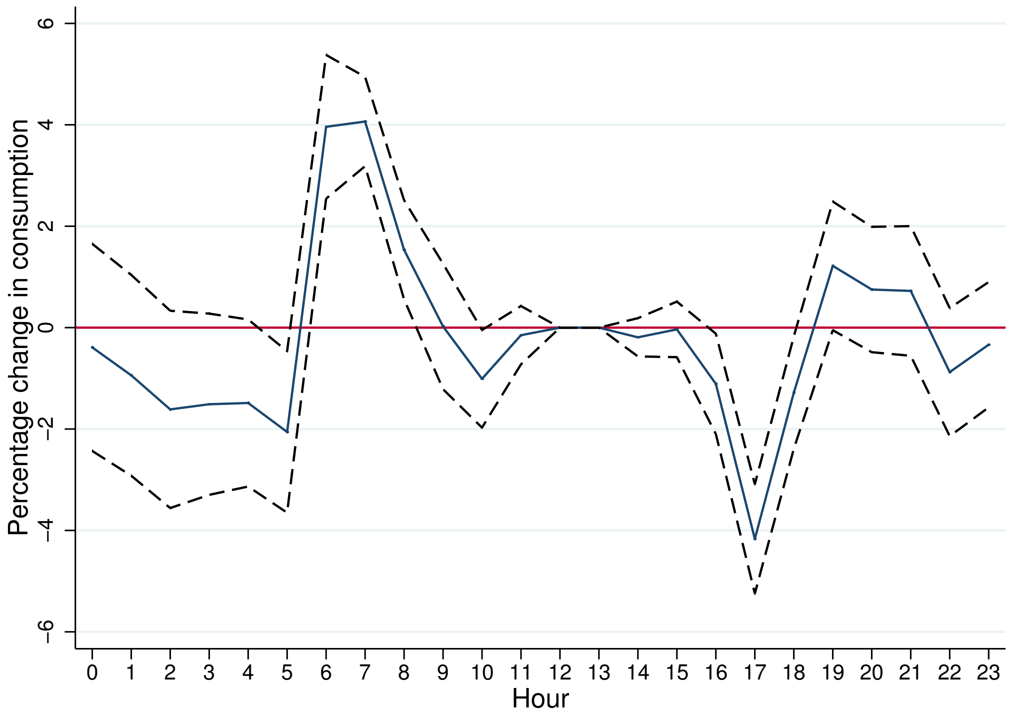
Notes: This figure shows the natural logarithm of electricity consumption by hour eight weeks before and after the time change from standard time to DST. Switches to summer time occurred on 31 March 2013, 31 March 2014, 29 March 2015 and 27 March 2016.

Figure A.3: RDD regression results



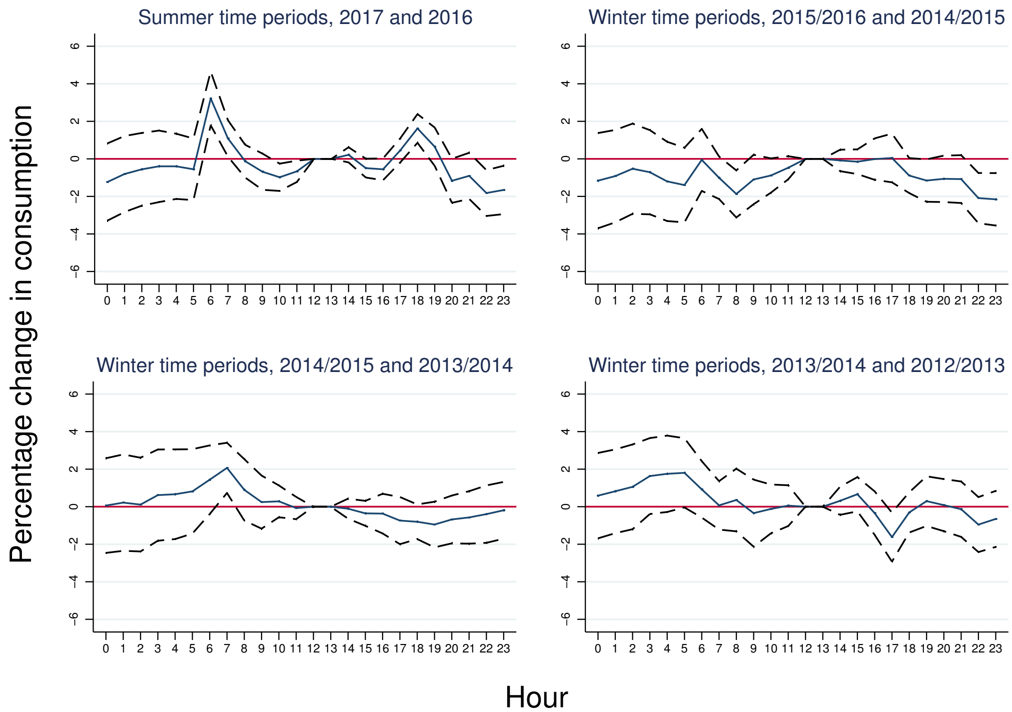
Notes: This figure shows the estimated effect of switching from standard time to DST, using data on electricity consumption eight weeks before and after the time change in late March of 2013-2016 ($N = 68$). 95% confidence intervals are indicated. Switches to summer time occurred on 31 March 2013, 31 March 2014, 29 March 2015 and 27 March 2016.

Figure A.4: Hourly effects of permanent DST on electricity demand: restricting the sample to days with same amount of sunlight



Notes: The figure shows hourly estimates of staying on DST during the treatment period on electricity consumption as in Equation (1). 95% confidence intervals are indicated, with standard errors clustered by date. The sample is restricted to equivalent days of the year in the treatment and control year: 9 November 2015 – 24 March 2016 and 8 November 2016 – 25 March 2017 ($N = 6,600$). All underlying models include weather controls interacted by hour, date FE, hour FE, and a constant. Weather controls include population-weighted national aggregates of heating degrees, heating degrees squared, pressure, humidity, wind speed, and cloudiness.

Figure A.5: Hourly effects for placebo regressions



Notes: The figure shows hourly estimates for placebo regressions of Equation (1) with midday control hours. 95% confidence intervals are indicated, with standard errors clustered by date. Effects during mid-day hours are zero by assumption. The samples in each model include: (1) 27 March 2016 – 30 October 2016 and 26 March 2017 – 29 October 2017 ($N = 10,413$), (2) 26 October 2014 – 28 March 2015 and 8 November 2015 – 26 March 2016 ($N = 7,056$), (3) 27 October 2013 – 30 March 2014 and 26 October 2014 – 28 March 2015 ($N = 7,416$), (4) 28 October 2012 – 30 March 2013 and 27 October 2013 – 30 March 2014 ($N = 7,416$). The underlying model includes weather controls interacted by hour, date FE, hour FE, and a constant. Weather controls include population-weighted national aggregates of heating degrees, heating degrees squared, pressure, humidity, wind speed, and cloudiness.

Table A.1: Hourly effects of DST on electricity demand

DST at hour 0	-0.007	DST at hour 12	-
	(0.010)		-
DST at hour 1	-0.012	DST at hour 13	-
	(0.010)		-
DST at hour 2	-0.019	DST at hour 14	-0.001
	(0.010)		(0.002)
DST at hour 3	-0.016	DST at hour 15	0.001
	(0.009)		(0.003)
DST at hour 4	-0.016	DST at hour 16	-0.008
	(0.008)		(0.005)
DST at hour 5	-0.023**	DST at hour 17	-0.035***
	(0.008)		(0.006)
DST at hour 6	0.032***	DST at hour 18	-0.005
	(0.007)		(0.006)
DST at hour 7	0.034***	DST at hour 19	0.016*
	(0.005)		(0.006)
DST at hour 8	0.012*	DST at hour 20	0.011
	(0.005)		(0.006)
DST at hour 9	-0.003	DST at hour 21	0.010
	(0.006)		(0.006)
DST at hour 10	-0.012*	DST at hour 22	-0.006
	(0.005)		(0.006)
DST at hour 11	-0.002	DST at hour 23	-0.002
	(0.003)		(0.006)

Notes: This table shows hourly estimates of keeping summer time during treatment dates on electricity consumption, as shown in Figure 5. Effects during mid-day hours (12:00 and 13:59) are zero by assumption. The sample includes 8 November 2015 - 26 March 2016 and 30 October 2016 - 25 March 2017 ($N = 6,889$). The underlying model, as presented in Equation (1), includes weather controls interacted by hour, date FE, hour FE and a constant. Weather controls include population-weighted national aggregates of heating degrees (difference to 18.33°C), heating degrees squared, pressure, humidity, wind speed and cloudiness. Standard errors are clustered on the date level. * p<0.05; ** p<0.01; *** p<0.001

Table A.2: Hourly effects of DST on electricity demand for placebo regressions

	Summer time periods, 2017 and 2016	Winter time periods, 2015/2016 and 2014/2015	Winter time periods, 2014/2015 and 2013/2014	Winter time periods, 2013/2014 and 2012/2013	Restricted sample (days of same length)
DST at hour 0	-0.012	-0.012	0.001	0.006	-0.004
	(0.010)	(0.013)	(0.013)	(0.012)	(0.010)
DST at hour 1	-0.008	-0.009	0.002	0.008	-0.009
	(0.010)	(0.012)	(0.013)	(0.011)	(0.010)
DST at hour 2	-0.006	-0.005	0.001	0.011	-0.016
	(0.010)	(0.012)	(0.013)	(0.011)	(0.010)
DST at hour 3	-0.004	-0.007	0.006	0.016	-0.015
	(0.010)	(0.011)	(0.012)	(0.010)	(0.009)
DST at hour 4	-0.004	-0.012	0.007	0.017	-0.015
	(0.009)	(0.011)	(0.012)	(0.010)	(0.008)
DST at hour 5	-0.006	-0.014	0.008	0.018	-0.021*
	(0.008)	(0.010)	(0.011)	(0.009)	(0.008)
DST at hour 6	0.032***	-0.001	0.014	0.009	0.039***
	(0.007)	(0.008)	(0.009)	(0.008)	(0.007)
DST at hour 7	0.011*	-0.010	0.02**	0.001	0.040***
	(0.005)	(0.006)	(0.007)	(0.007)	(0.004)
DST at hour 8	-0.001	-0.019**	0.009	0.004	0.015**
	(0.004)	(0.006)	(0.008)	(0.008)	(0.005)
DST at hour 9	-0.007	-0.011	0.002	-0.003	0.000
	(0.005)	(0.007)	(0.007)	(0.009)	(0.006)
DST at hour 10	-0.010**	-0.009	0.003	-0.001	-0.010*
	(0.004)	(0.005)	(0.004)	(0.007)	(0.005)
DST at hour 11	-0.007*	-0.005	-0.001	0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)
DST at hour 14	0.002	-0.001	-0.001	0.003	-0.002
	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)
DST at hour 15	-0.005	-0.002	-0.004	0.007	-0.000
	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)
DST at hour 16	-0.006	-0.000	-0.004	-0.003	-0.011*
	(0.003)	(0.006)	(0.005)	(0.006)	(0.005)
DST at hour 17	0.005	0.000	-0.007	-0.016*	-0.043***
	(0.003)	(0.007)	(0.006)	(0.007)	(0.005)
DST at hour 18	0.016***	-0.009	-0.008	-0.003	-0.013*
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)
DST at hour 19	0.006	-0.012*	-0.010	0.003	0.012
	(0.005)	(0.06)	(0.006)	(0.007)	(0.006)
DST at hour 20	-0.012	-0.011	-0.007	0.001	0.007
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
DST at hour 21	-0.009	-0.011	-0.006	-0.001	0.007
	(0.006)	(0.06)	(0.007)	(0.008)	(0.007)
DST at hour 22	-0.018**	-0.021**	-0.004	-0.010	-0.009
	(0.006)	(0.007)	(0.008)	(0.007)	(0.006)
DST at hour 23	-0.017*	-0.022**	-0.002	-0.007	-0.003
	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)
Observations	10,413	7,056	7,416	7,416	6,600
R^2	0.954	0.937	0.936	0.940	0.942

Notes: This table shows hourly estimates of keeping summer time for placebo regressions, as shown in Figures A.5 and A.4. Effects during mid-day hours (12:00 and 13:59) are zero by assumption. The samples in each model include: (1) 27 March 2016 - 30 October 2016 and 26 March 2017 - 29 October 2017 ($N = 10,413$), (2) 26 October 2014 - 28 March 2015 and 8 November 2015 - 26 March 2016 ($N = 7,056$), (3) 27 October 2013 - 30 March 2014 and 26 October 2014 to 28 March 2015 ($N = 7,416$), (4) 28 October 2012 - 30 March 2013 and 27 October 2013 - 30 March 2014 ($N = 7,416$), (5) 9 November 2015 - 24 March 2016 and 8 November 2016 - 25 March 2017 ($N = 6,600$). The underlying model includes weather controls interacted by hour, date FE, hour FE and a constant. Weather controls include population-weighted national aggregates of heating degrees (difference to 18.33°C), heating degrees squared, pressure, humidity, wind speed and cloudiness. Standard errors are clustered on the date level. * p<0.05; ** p<0.01; *** p<0.001

Table A.3: Overall effects of DST on electricity consumption for placebo periods

	(1)	(2)	(3)	(4)
	Summer time periods, 2017 and 2016	Winter time periods, 2015/2016 and 2014/2015	Winter time periods, 2014/2015 and 2013/2014	Winter time periods, 2013/2014 and 2012/2013
Permanent DST (pooled β_h)	-0.002	-0.009	-0.001	0.002
	(0.004)	(0.005)	(0.004)	(0.005)
Observations	10,413	7,056	7,416	7,416
R^2	0.954	0.937	0.936	0.940

Notes: This table shows pooled estimates of Equation (1) for placebo regressions with midday control hours (hourly estimates are reported in Figure A.5). All models include weather controls interacted by hour, date FE, hour FE, and a constant. Weather controls include population-weighted national aggregates of heating degrees, heating degrees squared, pressure, humidity, wind speed, and cloudiness. Standard errors are clustered at the date level. * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table A.4: Hourly effects of DST on electricity demand with different control hours

	Control hours: 11:00-12:59h	Control hours: 11:00-13:59h	Control hours: 0:00-1:59h	Control hours: 0:00-1:59h and 12:00-13:59h
DST at hour 0	-0.009	-0.007	-	-
	(0.011)	(0.011)	-	-
DST at hour 1	-0.013	-0.011	-	-
	(0.011)	(0.010)	-	-
DST at hour 2	-0.021*	-0.018	-0.010***	-0.014**
	(0.010)	(0.010)	(0.001)	(0.005)
DST at hour 3	-0.018	-0.016	-0.007**	-0.011**
	(0.010)	(0.010)	(0.002)	(0.004)
DST at hour 4	-0.018	-0.015	-0.006*	-0.011**
	(0.009)	(0.009)	(0.003)	(0.004)
DST at hour 5	-0.025**	-0.022**	-0.014***	-0.018***
	(0.009)	(0.008)	(0.003)	(0.003)
DST at hour 6	0.030***	0.032***	0.041***	0.037***
	(0.008)	(0.008)	(0.006)	(0.004)
DST at hour 7	0.032***	0.034***	0.043***	0.039***
	(0.005)	(0.005)	(0.008)	(0.005)
DST at hour 8	0.010*	0.012**	0.021	0.017
	(0.040)	(0.004)	(0.013)	(0.008)
DST at hour 9	-0.005	-0.002	0.007	0.002
	(0.005)	(0.005)	(0.014)	(0.010)
DST at hour 10	-0.014***	-0.012**	-0.003	-0.008
	(0.004)	(0.004)	(0.013)	(0.008)
DST at hour 11	-	-	0.008	0.003
	-	-	(0.012)	(0.007)
DST at hour 12	-	-	0.015	-
	-	-	(0.010)	-
DST at hour 13	-0.007***	-	0.004	-
	(0.002)	-	(0.010)	-
DST at hour 14	-0.003	-0.000	0.009	0.004
	(0.002)	(0.002)	(0.011)	(0.006)
DST at hour 15	-0.001	0.002	0.011	0.006
	(0.003)	(0.003)	(0.011)	(0.006)
DST at hour 16	-0.010	-0.007	0.002	-0.003
	(0.005)	(0.005)	(0.011)	(0.007)
DST at hour 17	-0.037***	-0.035***	-0.026*	-0.030***
	(0.006)	(0.006)	(0.011)	(0.008)
DST at hour 18	-0.007	-0.005	0.004	-0.000
	(0.007)	(0.006)	(0.009)	(0.006)
DST at hour 19	0.014*	0.017*	0.026***	0.022***
	(0.007)	(0.007)	(0.008)	(0.005)
DST at hour 20	0.009	0.011	0.020**	0.015***
	(0.007)	(0.007)	(0.007)	(0.005)
DST at hour 21	0.008	0.011	0.020**	0.015***
	(0.007)	(0.007)	(0.007)	(0.004)
DST at hour 22	-0.008	-0.006	0.003	-0.001
	(0.007)	(0.007)	(0.007)	(0.004)
DST at hour 23	-0.004	-0.001	0.007	0.003
	(0.007)	(0.007)	(0.006)	(0.004)
Observations	6,889	6,889	6,889	7,416
R^2	0.942	0.942	0.942	0.940

Notes: This table shows hourly estimates of keeping summer time during the treatment period on electricity consumption with different control hours, as shown in Figure 6. The sample includes 8 November 2015 - 26 March 2016 and 30 October 2016 - 25 March 2017 ($N = 6,889$). The underlying model includes weather controls interacted by hour, date FE, hour FE and a constant. Weather controls include population-weighted national aggregates of heating degrees (difference to 18.33°C), heating degrees squared, pressure, humidity, wind speed and cloudiness. Standard errors are clustered on the date level. * p<0.05; ** p<0.01; *** p<0.001

Table A.5: Hourly effects of DST on electricity demand, using intra-year DiD estimation

DST at hour 0	0.011*	DST at hour 12	0.011*
	(0.004)		(0.004)
DST at hour 1	0.000	DST at hour 13	0.003
	(0.005)		(0.004)
DST at hour 2	-0.006	DST at hour 14	0.006
	(0.005)		(0.004)
DST at hour 3	-0.007	DST at hour 15	0.013**
	(0.004)		(0.004)
DST at hour 4	-0.010*	DST at hour 16	0.008
	(0.004)		(0.005)
DST at hour 5	-0.015***	DST at hour 17	-0.021***
	(0.004)		(0.005)
DST at hour 6	0.001	DST at hour 18	-0.005
	(0.006)		(0.005)
DST at hour 7	0.023***	DST at hour 19	0.013**
	(0.005)		(0.004)
DST at hour 8	0.009	DST at hour 20	0.020***
	(0.005)		(0.004)
DST at hour 9	0.006	DST at hour 21	0.015***
	(0.006)		(0.004)
DST at hour 10	0.003	DST at hour 22	0.007
	(0.005)		(0.004)
DST at hour 11	0.006	DST at hour 23	0.015***
	(0.005)		(0.004)
Observations	17,302		17,302
R^2	0.972		0.972

Notes: This table shows hourly estimates of keeping summer time during the treatment period on electricity consumption , using consumption during summer time periods (27 March – 30 October 2016 and 26 March to 29 October 2017) as control. The results are also shown in Figure 7. The sample includes 8 November 2015 - 29 October 2017 ($N = 17,302$). The underlying model includes hourly estimates for weather controls, day of the year FE, day of the week FE, holiday FE, hour FE, and a constant. Weather controls include population-weighted national aggregates of heating degrees (difference to 18.33°C), heating degrees squared, pressure, humidity, wind speed and cloudiness. Standard errors are clustered on the date level. * p<0.05; ** p<0.01; *** p<0.001

Table A.6: **Effects of DST on SO_2 emissions using average emissions factors**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hour	Coal			Gas			Total
	DST effect	ΔMWh	ΔEmissions	DST effect	ΔMWh	ΔEmissions	ΔEmissions
0	-0.047	-484.47	-1,371.25	0.070	570.35	2.59	-1,368.66
1	-0.046	-472.26	-1,336.69	0.058	436.29	1.98	-1,334.71
2	-0.050	-499.87	-1,414.84	0.029	210.73	0.96	-1,413.88
3	-0.052	-513.80	-1,454.27	-0.015	-109.88	-0.50	-1,454.77
4	-0.046	-455.36	-1,288.86	-0.031	-231.92	-1.05	-1,289.91
5	-0.049	-487.74	-1,380.51	-0.035	-271.81	-1.23	-1,381.74
6	-0.049	-502.52	-1,422.34	0.019	148.59	0.67	-1,421.67
7	-0.043	-444.50	-1,258.12	0.010	82.69	0.38	-1,257.74
8	-0.051	-541.94	-1,533.91	0.032	324.03	1.47	-1,532.44
9	-0.041	-429.92	-1,216.85	0.053	569.80	2.58	-1,214.27
10	-0.037	-395.34	-1,118.98	0.038	433.02	1.96	-1,117.01
11	-0.039	-411.14	-1,163.70	0.036	408.23	1.85	-1,161.84
12	-0.034	-360.94	-1,021.61	0.046	515.39	2.34	-1,019.27
13	-0.033	-349.61	-989.54	0.052	579.16	2.63	-986.91
14	-0.035	-369.33	-1,045.36	0.054	596.61	2.71	-1,042.65
15	-0.039	-415.88	-1,177.11	0.074	798.30	3.62	-1,173.49
16	-0.043	-449.00	-1,270.86	0.068	736.74	3.34	-1,267.51
17	-0.061	-650.67	-1,841.67	0.006	64.93	0.29	-1,841.37
18	-0.065	-705.83	-1,997.79	0.032	354.09	1.61	-1,996.19
19	-0.048	-507.75	-1,437.14	0.088	906.51	4.11	-1,433.03
20	-0.038	-406.01	-1,149.18	0.076	766.23	3.48	-1,145.70
21	-0.036	-384.08	-1,087.11	0.034	342.44	1.55	-1,085.55
22	-0.049	-512.72	-1,451.21	0.045	434.63	1.97	-1,449.24
23	-0.052	-545.21	-1,543.17	0.029	273.26	1.24	-1,541.93

Notes: This table shows the estimated effects of permanent DST on SO2 emissions by hour and source of electricity generation using AEFs. Emissions are in kg of SO2. We use AEFs for SO2 from Novan (2015). Columns 1 and 4 report the treatment effects depicted in Figure 9 for coal and gas, respectively. Columns 2 and 5 show the change in MWh due to DST. Columns 3 and 6 include the corresponding change in SO2 emissions, and Column 7 shows the sum of these hourly changes in emissions.

Table A.7: Effects of DST on SO_2 emissions using marginal emissions factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hour	Coal		Gas		Total		
	DST effect	ΔMWh	DST effect	ΔMWh	ΔMWh	MEF (kg/MWh)	ΔEmissions
0	-0.047	-484.47	0.070	570.35	85.88	1.65	141.35
1	-0.046	-472.26	0.058	436.29	-35.97	1.68	-60.41
2	-0.050	-499.87	0.029	210.73	-289.14	1.82	-526.21
3	-0.052	-513.80	-0.015	-109.88	-623.68	1.87	-1,166.79
4	-0.046	-455.36	-0.031	-231.92	-687.28	1.91	-1,315.90
5	-0.049	-487.74	-0.035	-271.81	-759.55	2.01	-1,527.01
6	-0.049	-502.52	0.019	148.59	-353.93	2.04	-721.36
7	-0.043	-444.50	0.010	82.69	-361.81	1.92	-695.48
8	-0.051	-541.94	0.032	324.03	-217.91	1.87	-406.79
9	-0.041	-429.92	0.053	569.80	139.88	1.77	248.09
10	-0.037	-395.34	0.038	433.02	37.68	1.81	68.04
11	-0.039	-411.14	0.036	408.23	-2.91	1.73	-5.03
12	-0.034	-360.94	0.046	515.39	154.45	1.57	242.56
13	-0.033	-349.61	0.052	579.16	229.55	1.48	339.90
14	-0.035	-369.33	0.054	596.61	227.28	1.42	323.60
15	-0.039	-415.88	0.074	798.30	382.42	1.43	548.33
16	-0.043	-449.00	0.068	736.74	287.74	1.40	402.28
17	-0.061	-650.67	0.006	64.93	-585.74	1.34	-786.73
18	-0.065	-705.83	0.032	354.09	-351.74	1.35	-474.20
19	-0.048	-507.75	0.088	906.51	398.76	1.38	549.66
20	-0.038	-406.01	0.076	766.23	360.22	1.33	478.38
21	-0.036	-384.08	0.034	342.44	-41.64	1.34	-55.72
22	-0.049	-512.72	0.045	434.63	-78.09	1.36	-106.14
23	-0.052	-545.21	0.029	273.26	-271.95	1.52	-414.20

Notes: This table shows the estimated effects of permanent DST on SO2 emissions by hour and source of electricity generation using MEFs. Emissions are in kg of SO2. Columns 1 and 3 report the treatment effects depicted in Figure 9 for coal and gas, respectively. Columns 2 and 4 show the change in MWh due to DST. Column 5 shows the total change in MWh due to DST. Column 6 reproduces the average hourly MEF reported by Graff Zivin et al. (2014). Column 7 shows the corresponding change in SO2 emissions.

Table A.8: **Effects of DST on NOx emissions using average emissions factors**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hour	Coal			Gas			Total
	DST effect	ΔMWh	ΔEmissions	DST effect	ΔMWh	ΔEmissions	ΔEmissions
0	-0.047	-484.47	-564.76	0.070	570.35	67.26	-497.50
1	-0.046	-472.26	-550.53	0.058	436.29	51.45	-499.08
2	-0.050	-499.87	-582.71	0.029	210.73	24.85	-557.86
3	-0.052	-513.80	-598.95	-0.015	-109.88	-12.96	-611.91
4	-0.046	-455.36	-530.83	-0.031	-231.92	-27.35	-558.18
5	-0.049	-487.74	-568.57	-0.035	-271.81	-32.06	-600.63
6	-0.049	-502.52	-585.80	0.019	148.59	17.52	-568.28
7	-0.043	-444.50	-518.17	0.010	82.69	9.75	-508.42
8	-0.051	-541.94	-631.76	0.032	324.03	38.21	-593.54
9	-0.041	-429.92	-501.17	0.053	569.80	67.20	-433.97
10	-0.037	-395.34	-460.86	0.038	433.02	51.07	-409.79
11	-0.039	-411.14	-479.28	0.036	408.23	48.14	-431.13
12	-0.034	-360.94	-420.76	0.046	515.39	60.78	-359.98
13	-0.033	-349.61	-407.55	0.052	579.16	68.30	-339.25
14	-0.035	-369.33	-430.54	0.054	596.61	70.36	-360.18
15	-0.039	-415.88	-484.80	0.074	798.30	94.15	-390.66
16	-0.043	-449.00	-523.41	0.068	736.74	86.89	-436.53
17	-0.061	-650.67	-758.51	0.006	64.93	7.66	-750.85
18	-0.065	-705.83	-822.81	0.032	354.09	41.76	-781.05
19	-0.048	-507.75	-591.90	0.088	906.51	106.91	-484.99
20	-0.038	-406.01	-473.30	0.076	766.23	90.36	-382.93
21	-0.036	-384.08	-447.73	0.034	342.44	40.39	-407.35
22	-0.049	-512.72	-597.69	0.045	434.63	51.26	-546.44
23	-0.052	-545.21	-635.57	0.029	273.26	32.23	-603.34

Notes: This table shows the estimated effects of permanent DST on NOx emissions by hour and source of electricity generation using AEFs. Emissions are in kg of NOx. We use AEFs for NOx from Novan (2015). Columns 1 and 4 report the treatment effects depicted in Figure 9 for coal and gas, respectively. Columns 2 and 5 show the change in MWh due to DST. Columns 3 and 6 include the corresponding change in NOx emissions, and Column 7 shows the sum of these hourly changes in emissions.

Table A.9: Effects of DST on NOx emissions using marginal emissions factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hour	Coal		Gas		Total		
	DST effect	ΔMWh	DST effect	ΔMWh	ΔMWh	MEF (kg/MWh)	ΔEmissions
0	-0.047	-484.47	0.070	570.35	85.88	0.460	39.47
1	-0.046	-472.26	0.058	436.29	-35.97	0.475	-17.10
2	-0.050	-499.87	0.029	210.73	-289.14	0.508	-146.89
3	-0.052	-513.80	-0.015	-109.88	-623.68	0.524	-326.90
4	-0.046	-455.36	-0.031	-231.92	-687.28	0.556	-382.40
5	-0.049	-487.74	-0.035	-271.81	-759.55	0.615	-467.02
6	-0.049	-502.52	0.019	148.59	-353.93	0.697	-246.69
7	-0.043	-444.50	0.010	82.69	-361.81	0.705	-254.92
8	-0.051	-541.94	0.032	324.03	-217.91	0.720	-156.94
9	-0.041	-429.92	0.053	569.80	139.88	0.726	101.52
10	-0.037	-395.34	0.038	433.02	37.68	0.711	26.77
11	-0.039	-411.14	0.036	408.23	-2.91	0.678	-1.97
12	-0.034	-360.94	0.046	515.39	154.45	0.632	97.54
13	-0.033	-349.61	0.052	579.16	229.55	0.616	141.37
14	-0.035	-369.33	0.054	596.61	227.28	0.613	139.29
15	-0.039	-415.88	0.074	798.30	382.42	0.622	238.03
16	-0.043	-449.00	0.068	736.74	287.74	0.604	173.88
17	-0.061	-650.67	0.006	64.93	-585.74	0.574	-336.24
18	-0.065	-705.83	0.032	354.09	-351.74	0.564	-198.37
19	-0.048	-507.75	0.088	906.51	398.76	0.558	222.48
20	-0.038	-406.01	0.076	766.23	360.22	0.560	201.88
21	-0.036	-384.08	0.034	342.44	-41.64	0.533	-22.18
22	-0.049	-512.72	0.045	434.63	-78.09	0.465	-36.32
23	-0.052	-545.21	0.029	273.26	-271.95	0.450	-122.40

Notes: This table shows the estimated effects of permanent DST on NOx emissions by hour and source of electricity generation using MEFs. Emissions are in kg of NOx. Columns 1 and 3 report the treatment effects depicted in Figure 9 for coal and gas, respectively. Columns 2 and 4 show the change in MWh due to DST. Column 5 shows the total change in MWh due to DST. Column 6 reproduces the average hourly MEF reported by Graff Zivin et al. (2014). Column 7 shows the corresponding change in NOx emissions.