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When does daylight saving time save electricity? Weather and air-conditioning

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ABSTRACT

Previous research on the effects of daylight saving time (DST) on electricity consumption has provided mixed results. We use daily state-level panel data on electricity consumption in Australia between 1998 and 2015, during which period there was considerable variation in the presence and timing of DST implementation, as well as in weather conditions and cooling usage within and between states. This provides us with a unique opportunity to study the interaction effects of DST with exogenous variation in daily weather conditions and cooling usage over two decades. Our results show that the effect of DST on electricity consumption depends strongly on weather conditions and cooling usage. Forward DST increases the electricity consumption when temperatures and air conditioner ownership are higher. We provide simulations for countries in the European Union that need to decide on DST adoption in the coming year. Our findings are policy-relevant given rising temperatures and worldwide increases in cooling usage during summer.

1. Introduction

Several countries have implemented daylight saving time (DST) with the aim of saving electricity and reducing greenhouse gas emissions. However, recent notable studies have provided mixed evidence on the effects of DST on electricity consumption and challenged the long-held view that DST reduces electricity consumption. Differences in findings across studies can be attributed to differences in estimation methods, countries, time periods, and control variables (Havranek et al., 2018). Indeed, weather conditions, basic patterns of energy use, and the energy efficiency of buildings and equipment change over time. In addition, the National Oceanic and Atmospheric Administration reported that July 2019 was 1.71 degrees Fahrenheit (0.95 degrees Celsius) warmer than the average of 56.9 degrees Fahrenheit. The record-setting July followed the hottest June on record, which was 0.71 degrees Fahrenheit (0.95C) above the average temperature for that month. Regions across the world experienced record-breaking temperatures: the continent of Africa experienced its hottest month on record, and countries across Europe — including France, Belgium, Germany, Netherlands, and Luxembourg — experienced the hottest days in their nations' histories (Global Climate Report, July 2019). Thus, it is vital that future energy policy decisions regarding changes to DST be based on research that uses appropriate techniques and longer longitudinal data that can provide information on changes in weather conditions and household behaviours that will affect energy use.

In this vein, we depart from the existing literature, which has focused on the net effect of DST on electricity consumption, controlling for weather and other conditions. Instead, we study the interaction effects of DST with temperature and cooling usage using a panel fixed effects approach. Previous findings have suggested that forward DST could have two opposing effects on electricity consumption: it might decrease electricity consumption due to a lower demand for lighting, or increase electricity consumption due to a higher demand for cooling. We hypothesize that forward DST will increase the electricity consumption when the temperatures are quite high and cooling usage is quite prevalent, meaning that the increase in the demand for cooling will outweigh the decline in the demand for lighting.

We test this hypothesis using daily state-level panel data on electricity consumption from Australia between 1998 and 2015. Indeed, Australia makes for an important case study to test this hypothesis because of the wide range of climatic conditions coupled with different adoption rates of air conditioner (AC) and variations in DST across and

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within states. The minimum and maximum daily temperatures were − 7 °C and 44 °C, while air conditioner penetration in Australia increased from 35% to 65% over the study period. In addition, this period showed large variations in the presence and timing of DST implementation across and within states in Australia. Tasmania, Victoria, New South Wales, South Australia, and the Australian Capital Territory have implemented DST continuously over the last 20 years, while Queensland and Western Australia have implemented DST only for a few years during that period. Northern Territory has never observed DST. Overall, this provides us with a unique opportunity to study the interaction effects of DST with exogenous variation in daily weather conditions and cooling usage across and within Australian states over two decades.

We make several novel contributions to the literature. First, we focus on a previously unexplored question: does the effect of DST on electricity consumption depend on weather conditions and cooling usage? To the best of our knowledge, this is the first empirical study in the literature to explore this question. It is made possible by using a very long panel dataset from Australia and utilizing an identification strategy based on the variations in DST implementation, weather conditions and cooling usage within and between states. Second, the range of weather conditions and cooling usage in the regression sample ensures that our estimates have external validity, and thus can be used by other countries/states which are deciding whether or not to adopt DST. More than 140 countries have used DST at some point, but about half of them have since abolished it. Around the world, 75 countries currently implement DST, of which 49 are in Europe. Indeed, there is an ongoing debate regarding the implementation of DST around the world. For instance, DST was abolished in Turkey in 2016, but has since been made permanent in 2018. The state of Western Australia abandoned DST in March 2009. The DST adoption decision is particularly important for Europe at present because the *European Union* recently abolished daylight saving time, leaving individual members to make the decision for themselves.[1] Accordingly, we provide simulation results on the effect of DST for countries in Europe, should they choose to apply them.

We have collected data on the daily electricity consumption of seven Australian states and territories (Australian Capital Territory, New South Wales, Northern Territory, Queensland, South Australia, Tasmania and Victoria) between 1998 and 2015; the state of Western Australia is excluded from our analysis due to missing electricity data. We calculate daily weather indicators for each of these states by weighting station-level weather data by postcode populations. We also have a unique dataset of annual AC ownership and penetration by state during the period of our regression sample.

We use this information to estimate daily panel fixed effects regressions where we estimate the DST effect and its interaction with weather indicators within a 1-month window from the forward DST implementation date. Our focus is on the maximum temperature, which is what matters most in explaining the demand for cooling. We estimate OLS regressions that control for variables that include midday electricity consumption, dummy variables for school and public holidays, fixed effects for day of the week, month of the year, state and year, and state-specific time trends. We cluster standard errors by state–month. We find that the diff-in-diff estimate of forward DST is significant and negative but its interaction with the maximum temperature is positive and significant. In addition, the interaction effect seems to be non-linear, as the forward DST increases the electricity consumption further at very high temperatures. The results show that the forward DST leads to increases in electricity consumption when the maximum temperature is above 31 °C in the full sample (this number is 22 °C when we focus only on states that implement DST every year in our sample). We find similar results when we divide the maximum temperature into three terciles: the total forward DST effect is negative in the second tercile (18.71 °C–25.31 °C) but positive in the third tercile (above 25.32 °C). These regressions implicitly assume that cooling usage is at the mean level (AC ownership of 0.76 or AC penetration of 0.54%), as we do not include this variable in our models.

Therefore, we include the cooling usage variable in the model explicitly by including the interaction between DST and maximum temperature and AC ownership. We find that the triple interaction term is positive and highly significant, as expected. Again, the effect is found to be non-linear, as the coefficient is significantly larger at high temperatures. Overall, our findings suggest that the net effect of DST depends on the weather conditions and cooling usage among Australian states. The results are robust to replacing the maximum temperature with the minimum temperature or sunshine duration, which are correlated positively with the maximum temperature. This suggests that potential errors or changes over time in measuring the maximum temperature cannot explain our findings.

One threat to our identification is the potential selection of DST adoption in such a way that states that implement DST could be different from non-DST states in their electricity consumption trends or weather conditions before and after DST. However, our sensitivity checks show that it is unlikely that such a possibility is driving our findings because the evolution of weather conditions before and after DST implementation dates do not differ across states. In addition, the results remain similar when we focus only on states that implement DST uninterrupted in all years, confirming that our results cannot be attributed to selection effects. Our results are also robust across different specifications: alternative methods of calculating state-level weather indicators, not controlling for midday-electricity consumption and controlling for midnight consumption, considering alternative measures of cooling usage, and clustering standard errors using the wild bootstrap method. Furthermore, we carry out placebo exercises using DST and rainfall interaction, applying placebo DST implementation dates and using electricity prices as the outcome variable. These results also confirm that our overall results cannot be attributed to alternative explanations. It is possible that differences in daylight hours could lead to bias in our estimates. We investigate this possibility by adding sunshine hours or day of the year fixed effects as independent variables in the models. The results show that our findings cannot be explained by potential differences in daylight hours. We also check our results using backwards DST implementation rather than forward DST, because backwards DST dates are generally the same across DST-implementing states, while forward DST dates can differ a lot. The results are as expected: the backwards DST effect is positive and significant while the interaction effect with temperature is negative and highly significant, and the size of the interaction coefficient is twice as high as the value obtained using the forward DST date. We also consider controlling for heating degrees hours and cooling degrees hours along with their squared values in the regression models and find that our findings remain similar in these specifications.

Our study is related to the literature on the effects of DST adoption on electricity consumption, which has reported mixed results. Kellogg and Wolff (2008) evaluate the effect of DST by exploiting the extension of DST in 2000 to facilitate the Sydney Olympics. Using half-hourly panel data for Victoria, New South Wales and South Australia between 1999 and 2001 and employing a difference-in-difference-in-difference (DDD) method, they find that DST has no significant effect on reducing electricity consumption and greenhouse gas emissions. They show that DST significantly reduces electricity demand in the evening but has the opposite effect in the morning (between 07:00 and 08:00), which offsets its intended benefit. That is, the decrease in electricity consumption in the evening did not outweigh the increase in the morning. The authors find that the DST extension did not reduce the overall electricity consumption, but did cause a substantial intraday shift in electricity consumption.

[1] The EU voted in 2019 to abolish the practice of daylight saving time in the coming year and leave the decision to each member but this decision is postponed in 2020 due to coronavirus crisis. Instead, all EU countries switched to winter time for perhaps the final time in 2020 but concrete plans on what comes next remain elusive due to continuing coronavirus crisis.

Choi et al. (2017) recently examined the effect of DST on the electricity demand in Western Australia using data from September 2006 to March 2013 and employing the difference-in-differences (DD) approach. They find results similar to those of Kellogg and Wolff (2008), namely that DST has little effect on the overall electricity consumption. They suggest that DST leads to redistribution by reducing the evening electricity consumption and increasing the morning consumption. Similarly, Kandel and Sheridan (2007) examine the impact of a 1-month DST extension on electricity consumption in California and find a near-zero impact.

Kotchen and Grant (2011) exploit a natural experiment in the state of Indiana in the United States in order to estimate the effects of DST on electricity consumption. The authors examine the effect of Indiana's DST implementation policy that required a number of counties in the state to adopt DST. Focusing on residential electricity demand, the authors find that DST increases the residential electricity demand by approximately 1%, which suggests a trade-off between reducing the demand for lighting and increasing the demand for heating and cooling. A similar conclusion is reached by earlier studies (e.g. Rock, 1997), which show that residential electricity consumption increases slightly when summer daylight saving time is used rather than using standard time year-round.

On the other hand, Mirza and Bergland (2011) show an annual reduction in electricity consumption of at least 1% for Southern Norway and Sweden due to DST. They find that DST causes a small but significant reduction in electricity consumption in the morning and a steep decline in the evening in both countries. Momani et al. (2009) provide further support on the benefits of DST and show that DST decreases the electricity demand by 0.2% in Jordan. A recent study supports this line of evidence: Rivers (2018) uses a natural experiment approach and finds that DST reduces the demand for electricity in Ontario by approximately 1.5%.

Aries and Newsham (2008) provide a review of the literature on the effect of DST on electricity use. Their estimates suggest a reduction in national electricity use of around 0.5% due to reductions in residential lighting. Along these lines, Havranek et al. (2018) conduct a meta-analysis over 162 estimates from 44 studies and find that DST reduces electricity consumption by an average of 0.34%. There is a consensus that DST does contribute to an evening reduction in the demand for electricity; however, this may be offset by an increase in the morning (i.e. Sexton and Beatty, 2014).

Our study is also related to the broader literature on the effects of DST adoption on different areas of life. Putting clocks forward may benefit retailing, sports, and other activities that exploit sunlight after working hours, but can cause problems for evening entertainment and activities that are tied to sunlight, such as farming (Alonso and Ogle, 2009). DST clock shifts can complicate timekeeping and disrupt travel, billing, record keeping, medical devices, heavy equipment and sleep patterns (Hamermesh et al., 2008; Harrison, 2013). Sleep deprivation and circadian rhythm disturbances due to DST could have adverse health effects (Kantermann et al., 2007; Toro et al., 2015), reduce life satisfaction (Kountouris and Remoundou, 2014), increase absenteeism from work (Markussen and Røed, 2015), and increase workplace injuries (Barnes and Wagner, 2009). On the other hand, a recent study by Doleac and Sanders (2015) found that DST increases daylight exposure and therefore leads to dramatic reductions in criminal activity such as robberies. There is also a well-established body of literature on the effects of DST on traffic accidents (i.e. Sood and Ghosh, 2007) and on stock market and other financial assets (i.e. Kamstra et al., 2000; Kamstra et al., 2003).

Our findings are also related to the literature on the social and economic effects of climate change (Carleton and Hsiang, 2016; Hsiang et al., 2017). It is reported that higher temperatures are correlated with higher levels of energy consumption (i.e. Auffhammer and Mansur, 2014). Higher minimum temperatures are correlated with higher mortality rates in Europe (Analitis et al., 2008), while higher humidity is correlated with higher mortality rates in the USA (Barreca, 2012). Higher maximum temperatures are also correlated with higher mortality rates in the US, but there have been some adaptation effects, due mainly to the increased availability of indoor cooling in recent decades (Barreca et al., 2015; Heutel et al., 2017). Climate change and temperature changes also affect time allocation (Graff Zivin and Neidell, 2014) and economic productivity (Tol, 2009; Burke et al., 2015).

The remainder of this paper is structured as follows. Section 2 presents a brief background on the history of DST in Australia. Section 3 describes the data used in this study. Section 4 presents the empirical approach, while Section 5 presents the empirical results and discussions. Section 6 focuses on robustness specifications, and Section 7 concludes the paper.

2. Background

Daylight saving time (DST) is the practice of advancing clocks forward by 1 h during the summer months so that the extra hour of evening daylight can save electricity consumption on lighting. Typically, people who live in regions where DST is practiced adjust their clocks forward by 1 h around the start of spring and adjust them back to standard time in the autumn. New Zealander George Hudson proposed the modern idea of daylight saving in 1895, while Germany and Austria-Hungary organized the first implementation, starting on 30 April 1916. Many countries have used it at various times since then, particularly since the energy crisis of the 1970s.

In Australia, the states and territories have been allowed to decide for themselves whether to adopt DST, except during the two World Wars, when all states and territories had daylight saving. In 1968, Tasmania became the first state to observe DST in post-WWII. In 1971, a number of states, including Victoria, Queensland, South Australia, and the Australian Capital Territory, also adopted DST. After a year, though, Queensland abandoned DST. Since then, Queensland and Western Australia have observed DST from time to time on trial bases.

Since the summer of 2008/09, all DST-observing states except Western Australia have agreed to common starting and finishing dates, where DST commences on the first Sunday in October and ends on the first Sunday in April.[2] Between December 2006 and March 2009, Western Australia observed daylight saving from the last Sunday in October to the last Sunday in March, but from then on it ceased to observe DST at all. Tasmania, Victoria, New South Wales, South Australia, and the Australian Capital Territory have implemented DST continuously over the last 20 years, while Queensland and Western Australia have implemented DST only for a few years during that period. Northern Territory has never observed DST. The transition to DST took place at 02:00 Local Standard Time on the day concerned, and that from DST to standard time at 03:00.

3. Data

We use state-level data on the electricity demands and prices for the period between 1998 and 2015, obtained from the Australian Energy Market Operator (AEMO). AEMO is responsible for operating Australia's largest gas and electricity markets and power systems. The dataset provides details of the electricity demands and market prices for half-hour intervals for Victoria, Tasmania, New South Wales, ACT, South Australia and Northern Territory while we calculate and use daily indicators in this paper. Data are not available for Western Australia because the suppliers have not yet joined the AEMO fully. Our key identification comes from variation in the DST implementation over time between states and within states. DST transition dates have also changed over time for some states. This information is available from the Bureau of Meteorology (Appendix Table 1).

We also use data on the daily maximum temperature, minimum temperature, sunshine duration and rainfall from the same source as independent variables in our estimations. We accessed information on

[2] The DST starting and finishing dates could differ across years during this period as presented in Appendix Table 1.

daily weather indicators on all weather stations in Australia between 1998 and 2009, along with information on the longitude and latitude of each weather station. Then, we matched each postal code to its closest weather station using the latitude and longitude information. Next, from the Australian Bureau of Statistics website we accessed population information at the postal code from the 2016 census. Finally, we weighted each weather indicator with the postal code population and calculated state-level data.

As a robustness check, we also calculated alternative measures of weather indicators as simple state-level averages and capital city metro region averages. Data on AC ownership (number of air conditioners per household) and AC penetration (proportion of households with at least one air conditioner) are accessed through Energy Efficient Strategies Technical Papers (2006, 2008), which provide estimated values for each state and year during our regression period.[3] Our main regressions use ownership because the data are available for all years, whereas penetration data are available only until 2010. For a similar reason, we use penetration data only for our simulations for European countries while penetration data for Europe were provided recently by Jakubcionis and Carlsson (2017).

3.1. Descriptive statistics

Table 1 presents the descriptive statistics of our data. The table shows that there is a significant difference in daily electricity consumption between DST and non-DST periods for DST-implementing states. Specifically, the logs of the daily total electricity consumption are about 11.89% and 11.95% in the DST and non-DST periods, respectively. As Panel B of Table 1 shows, the difference in daily total electricity consumption between DST and non-DST periods is insignificant for states where DST is not observed. We observe increases in electricity demand in the morning and reductions in the evening for DST-observing states, while no such difference exists for states that do not observe DST. Significant differences in weather conditions (maximum temperature, minimum temperature, sunshine duration) between DST and non-DST periods exist across all states, while rainfall differs only for DST non-implementing states. There are also significant differences between DST and non-DST periods for all states in terms of school holidays, while public holidays differ only for DST non-implementing states. Panel C shows that there is considerable variation in terms of cooling usage in our dataset, with the AC penetration ranging from 3% to 88% for DST adopting states and from 23% to 93% for non-adopting states.

4. Empirical methodology

We examine the interaction effects of DST with weather conditions on electricity consumption by exploiting the discontinuous nature of the DST treatment and employing a panel fixed effects approach. This is a generalized version of the differences-in-differences method, and exploits the variations across and within states in terms of DST adoption and timing, as well as exogenous variations in weather conditions. Our first econometric model investigates the interaction effect of DST with weather indicators as follows[4]:

$$\begin{aligned}\log(\mathit{ElecricityDemand})_{ity} = \alpha &+ \beta_1 \mathrm{DSTafter}_{ity} + \beta_2 \mathrm{DSTstate}_{ity} \\ &+ \beta_3 \mathrm{DSTafter}_{ity} * \mathrm{DSTstate}_{ity} \\ &+ \beta_4 \mathrm{DSTafter}_{ity} * \mathrm{DSTstate}_{ity} \\ &* \mathrm{WeatherIndicator}_{ity} \\ &+ \beta_5 \mathrm{WeatherIndicator}_{ity} + \beta_6 \mathrm{X}_{ity} + \varepsilon_{ity}, \end{aligned} \quad (1)$$

where $\log(\mathit{ElecricityDemand})_{ity}$ is the log of total electricity consumption in Gigawatt hours in state i on date t of year y. $\mathrm{DSTafter}_{ity}$ is the variable that indicates whether the day is 1 month after or before DST.[5] Throughout the paper, in each year we use the dates which are adopted by most states. However, we also check for earliest and latest adoption dates in the unreported regressions (results available from authors upon request) and find similar results. $\mathrm{DSTstate}_{ity}$ indicates DST adoption and takes the value of one if a state implemented DST in that year, and zero otherwise. $\mathrm{DSTafter}_{ity} * \mathrm{DSTstate}_{ity}$ is the interaction between $\mathrm{DSTafter}_{ity}$ and $\mathrm{DSTstate}_{ity}$, which is labelled **Forward DST** in the regression tables.[6] $\mathrm{WeatherIndicator}_{ity}$ is the weather indicator (maximum temperature, minimum temperature or sunshine duration) that is measured on the same day as a state's electricity consumption. Our main variable of interest is the triple interaction term $\mathrm{DSTafter}_{ity} * \mathrm{DSTstate}_{ity} * \mathrm{WeatherIndicator}_{ity}$, which is labelled **Forward DST* MaximumTemperature, Forward DST* MinimumTemperature,** or **Forward DST* Sunshine Duration** in the regressions, depending on the weather indicator. We expect β_4 to be positive, because the electricity consumption is expected to increase due to higher cooling usage when there are higher temperatures and daylight saving time (longer daytime).

X_{ity} denotes a vector of control variables that include midday electricity consumption, dummy variables for school and public holidays, and fixed effects for day of the week, month of the year, state, year and state by year (state-specific time trend). We can control for any unobserved factors that affect the demand for electricity in any day of the year using these fixed effects and controlling for midday electricity demand. This model treats weather indicators as linear variables. However, previous research has found that there can be non-linear effects. Therefore, we estimate the same model by dividing the weather indicators into three quantiles (terciles) to check for non-linear effects that can be labelled as (Eq. (2)). The terciles of the weather indicators are measured as follows: maximum temperature (first [2.93 °C–18.70 °C], second [18.71 °C–25.31 °C] and third [25.32 °C–44.08 °C]); minimum temperature (first [−7.06 °C–8.29 °C], second [8.30 °C–13.67 °C] and third [13.68 °C–28.70 °C]); and sunshine duration (first [0–6.16], second [6.17–9.25] and third [9.26–13.91]).

We examine the interaction effects of DST with weather conditions and cooling usage on electricity consumption by estimating our second model as follows:

$$\begin{aligned}\log(\mathit{ElecricityDemand})_{ity} = \alpha &+ \beta_1 \mathrm{DSTafter}_{ity} + \beta_2 \mathrm{DSTstate}_{ity} \\ &+ \beta_3 \mathrm{DSTafter}_{ity} * \mathrm{DSTstate}_{ity} \\ &+ \beta_4 \mathrm{DSTafter}_{ity} * \mathrm{DSTstate}_{ity} \\ &* \mathrm{WeatherIndicator}_{ity} + \beta_5 \mathrm{DSTafter}_{ity} \\ &* \mathrm{DSTstate}_{ity} * \mathrm{Cooling}_{iy} \\ &+ + \beta_6 \mathrm{DSTafter}_{ity} * \mathrm{DSTstate}_{ity} \\ &* \mathrm{WeatherIndicator}_{ity} * \mathrm{Cooling}_{iy} \\ &+ + \beta_7 \mathrm{WeatherIndicator}_{ity} + \beta_8 \mathrm{X}_{ity} \\ &+ \varepsilon_{ity}, \end{aligned} \quad (3)$$

where $\mathrm{Cooling}_{iy}$ is the cooling usage for state i in year t, proxied by AC ownership or AC penetration. Our main coefficient of interest in this model is β_6, which is expected to be positive because we expect a higher electricity consumption during daylight saving times when there are higher temperatures and a greater usage of cooling. We estimate the same model by dividing the weather indicators into three terciles to check for non-linear effects that can be labelled as (Eq. (4)). These models are estimated using OLS, and we cluster robust standard errors at the state by month level and present standard errors in parentheses in all tables. Importantly, the regressions estimating Eq. (3) and 4 are our preferred models because we can control for the non-linear weather effects on electricity consumption and get unbiased estimates.

[3] Indeed, these sources included forecasts for some variables from 2010 to 2015. However, these numbers have been revised later with relevant data.

[4] This equation is for the full sample baseline regression, while $\mathrm{DSTstate}_{ity}$ is subsumed in the state FE in the subsample of states with consistent adoption.

[5] Indeed, the DSTafter variable do not vary by state by design but varies only by year and date.

[6] The focus in this paper is on forward DST implementation, i.e., the adjusting the clock forward in the spring. However, we also investigate backward adjustments where DST is reverted back to standard time. As Appendix Table 10 reports, we find quantitatively similar results with opposite effects.

Table 1
Descriptive statistics.

Panel A: DST implementing states

Variables	1 month before forward DST	1 month after forward DST	Difference	*t*-statistics
Electricity consumption (in log):				
Daily	11.947	11.875	−0.072	2.59
Half-hourly	8.067	7.998	−0.069	2.46
6–9	8.033	8.144	0.111	1.39
9–12	8.117	7.990	−0.127	1.61
12–15	8.218	8.077	−0.141	1.72
15–18	8.013	8.051	0.038	0.47
18–21	8.146	8.113	−0.033	0.42
21–24	8.144	7.927	−0.217	2.73
Midday	11.764	11.777	0.013	3.16
Midnight	11.629	11.578	−0.051	16.32
Weather indicators				
Population weighted maximum temperature (°C)	18.787	20.595	1.808	12.99
Population weighted minimum temperature (°C)	7.151	8.907	1.756	17.31
Population weighted sunshine duration (hours)	7.677	8.235	0.558	6.58
Population weighted rainfall (mm)	1.978	1.973	−0.005	0.04
Other variables				
Public holiday (dummy)	0.012	0.010	−0.002	0.54
School holiday (dummy)	0.341	0.087	−0.254	24.28

Panel B: DST non-implementing states

Variables	1 month before forward DST	1 month after forward DST	Difference	*t*-statistics
Electricity consumption (in log):				
Daily	12.468	12.471	0.003	0.56
Half-hourly	8.594	8.601	0.007	0.63
6–9	8.560	8.569	0.009	0.40
9–12	8.283	8.669	0.386	0.60
12–15	8.637	8.684	0.047	2.26
15–18	8.675	8.708	0.033	1.51
18–21	8.714	8.710	−0.004	0.24
21–24	8.615	8.600	−0.015	0.84
Midday	11.756	11.758	0.002	0.50
Midnight	11.642	11.571	−0.071	15.57
Weather indicators				
Population weighted maximum temperature (°C)	29.921	31.439	1.518	8.63
Population weighted minimum temperatuRE (°C)	17.705	20.517	2.812	15.06
Population weighted sunshine duration (hours)	9.437	9.294	−0.143	1.61
Population weighted rainfall (mm)	0.894	2.599	1.705	8.44
Other variables				
Public holiday (dummy)	0.002	0.000	−0.002	1.53
School holiday (dummy)	0.317	0.045	−0.272	18.81

Panel C: Annual variables

	DST implementing states		DST non-implementing states	
	Air conditioner ownership (stock/households)	Air conditioner penetration (%)	Air conditioner ownership (stock/households)	Air conditioner penetration (%)
Mean	0.706	0.557	0.945	0.498
Standard deviation	0.244	0.204	0.348	0.148
Minimum	0.026	0.025	0.345	0.234
Maximum	1.065	0.883	2.396	0.933

Notes: Descriptive statistics are presented for state-level variables which are measured from 1998 to 2015. Air conditioner ownership is available between 1998 and 2015 while air conditioner penetration is available from 1998 to 2010. DST implemeting states are Tasmania, Victoria, Australian Capital Territory, New South Wales and South Australia. DST non-implemeting states are Northern Territory and Queensland. Western Australia is not included in the analysis due to missing electricity data.

4.1. Our empirical model compared to previous studies

Our empirical model differs from the existing literature on DST because our main independent variables of interest are not only Forward DST, but also its interaction effects with temperature and cooling usage. That means that some of the previous empirical analyses are not relevant to our study. First, Choi et al. (2017), Kellogg and Wolff (2008), and Rivers (2018) transform the raw data on the minimum and maximum temperatures into cooling degree hours and heating degree hours, to control for the effects of extremely cold and hot days on the electricity demand. Indeed, these papers used half-hourly or hourly data and were interested in the net effect of the DST. On the other hand, we use daily data and are interested in the interaction effects of DST with weather and importantly with cooling usage. Acknowledging the fact that this method is more flexible than the linear weather method, we preferred not to use this method in our baseline specification because i) it will be very hard to interpret the double and triple interaction coefficients using heating degree hours and cooling degree hours compared to linear weather or terciles, ii) interactions using heating degree hours and cooling degree hours do not allow us to make policy recommendations and provide simulation exercises in Table 7 for the European Union countries, iii) we use tercile temperature dummies in our baseline specifications which deals with the non-linear weather effects where the interaction coefficients are easier to interpret. Nevertheless, we control for heating degree hours, cooling degree hours and their squared values in the Appendix and find that our results are robust to these specifications. We explain these analyses below in the robustness section.

Moreover, the previous literature, which has used hourly data, has considered permutation tests in order to examine the effects of DST for each day. However, this is not suitable for us, as we use a monthly window for our regressions using daily data. Even though we carry out this test, estimates of interaction effects will be very hard to interpret in our context. Third, we do not estimate regression discontinuity models because we are interested in the interaction effects that are identified through the variation in weather and cooling usage over time, and this method would simply average the temperature and cooling usage across time, thus destroying the variation.

5. Empirical results

5.1. Potential selection

Our empirical models assume implicitly that daily weather changes are exogenous to the adoption and timing of daylight saving. We check for possible endogeneity using event study methods and graph the evolution of weather indicators over the 60 days before and after DST for both DST implementing and non-implementing states. Fig. 1A–C show that weather indicators follow the same trend before and after DST among DST implementing states, implying that it is highly unlikely that DST adoption decisions are related to weather changes. Fig. 2A–C present the same graphs for DST non-implementing states and show that the trends for maximum temperature, minimum temperature and sunshine before and after DST are similar, and are also similar to the trends observed among DST implementing states. However, rainfall appears to increase after the DST dates for these states. Nevertheless, we hedge against such selection problems by controlling for state-specific time trends, along with fixed effects for the day of the week, month of the year, state and year in the regression models.

It is not likely that selection could occur by AC ownership, as it is an annual variable in our data, while we examine daily electricity consumption. However, Fig. 3A and B shows that there is considerable variation in AC ownership and penetration in Australia that is essential for identification in our models. For instance, the percentage of Australian households with ACs increases from 25% to 65% during our regression period.

Selection could also occur based on electricity demand, such that states could simply choose to adopt DST because of an increasing electricity demand. Indeed, we already control for state-specific time trends in our models that should control for this selection. Nevertheless, we

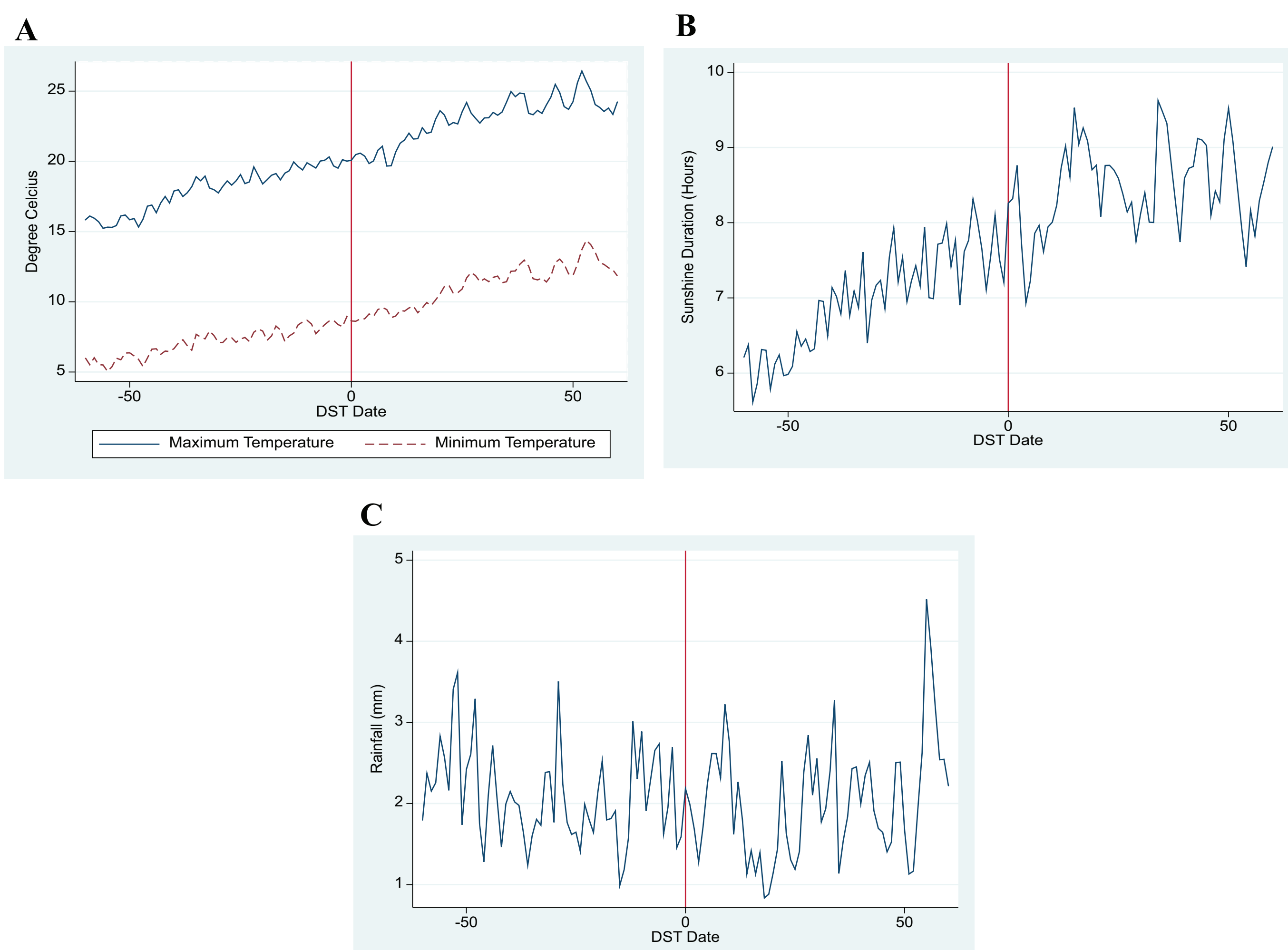

Fig. 1. (A) evolution of population weighted temperature around DST for DST implementing states. (B) Evolution of population weighted sunshine duration around DST for DST Implementing States. (C) Evolution of population weighted rainfall around DST for DST implementing states.

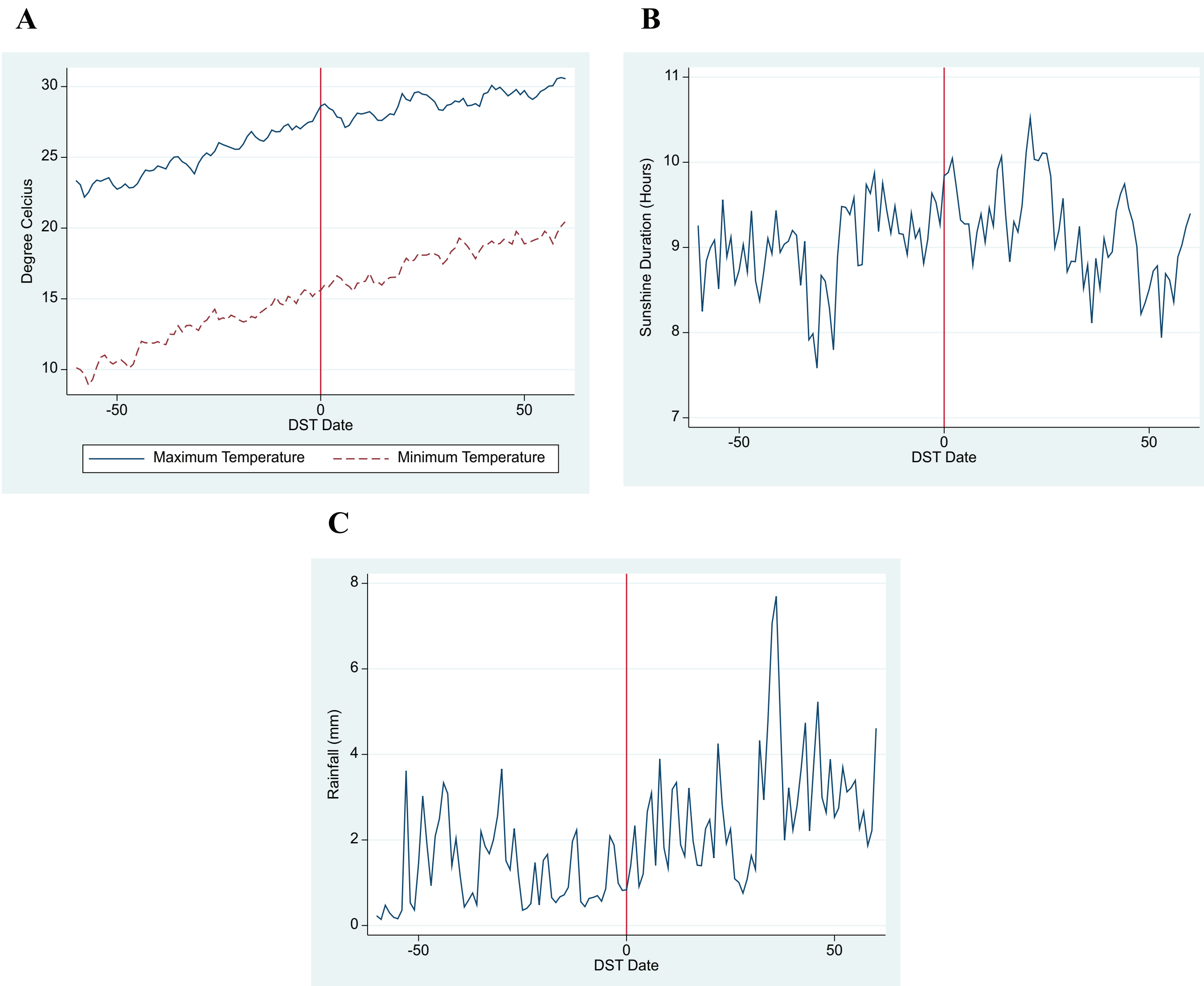

Fig. 2. (A) Evolution of population weighted temperature around DST for DST non-implementing states. (B) Evolution of population weighted sunshine duration around DST for DST non-implementing states. (C) Evolution of population weighted rainfall around DST for DST non-implementing states.

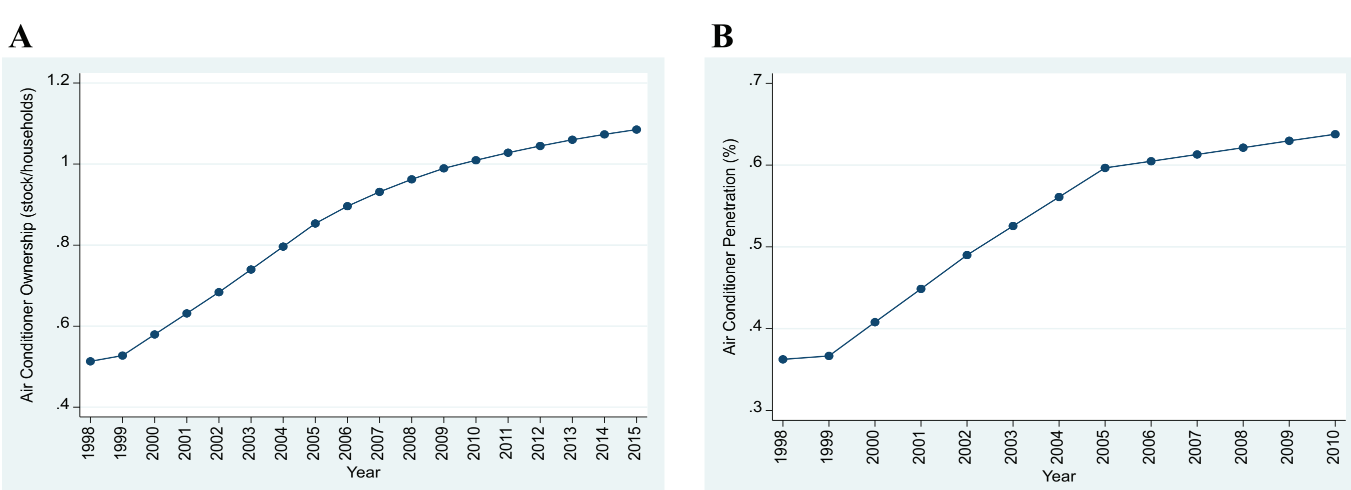

Fig. 3. (A) Evolution of air conditioner ownership in australia. (B) Evolution of air conditioner penetration (%) in australia.

address this issue specifically by excluding Northern Territory (which never implemented DST) and Queensland (which implemented DST only three times), thus focusing only on states which implemented DST in every year.

5.2. Interaction of DST with weather

Table 2 presents the estimates for Eq. (1) using the full sample period in Columns 1–3. Panel A uses the maximum temperature as the weather indicator. Column 1 shows that the forward DST decreases the electricity consumption by around 13 percentage points. However, the interaction effect with the maximum temperature is positive and significant. The results suggest that the total forward DST effect becomes positive when the maximum temperature is above 31 °C for the full sample. When we exclude Northern Territory from the regression in Column 2, the results stay the same, as expected. However, excluding both the Northern Territory and Queensland in Column 3, to completely remove the potential selection bias, changes the results slightly. This is our preferred specification, and suggests that the electricity consumption increases due to DST when the maximum temperature is above 22 °C (close to the sample mean). Columns 4–6 restrict the sample to 2009–2015, when DST implementation dates are the same for all implementing states, and the results in this specification are slightly stronger or similar. Overall, the results suggest that the effect of forward DST on the electricity consumption depends strongly on the maximum temperature. Electricity consumption declines during the forward DST period when the maximum temperature is low, but increases at high temperatures.

We also check the results using other weather indicators that are correlated with the maximum temperature. Simple correlations (Appendix Table 2) show that the minimum temperature is correlated highly (0.86) with the maximum temperature, and therefore is expected to provide results similar to those reported in Panel A. The correlation of sunshine duration with the maximum temperature is 0.41. Nevertheless, the results in Panels B and C using these alternative weather indicators in Columns 3 (most preferred) are similar to those reported in Panel A. These findings provide further support for our argument that the total effect of DST on electricity consumption depends on the weather conditions, with the total DST effect being positive rather than negative during high maximum temperatures.

Previous research (Choi et al., 2017; Kellogg and Wolff, 2008; Rivers, 2018) has shown that weather can have non-linear effects on the electricity consumption. Whether these non-linear effects show up in the interaction with DST is an empirical question that we would like to test next in Table 3, which estimates Eq. (2). We calculate three quantiles for the weather indicators and enter them in our estimations as categorical variables (low, medium, high). In each column, the first quantile (low) and the interaction of the first quantile (low) with Forward DST are the reference groups. Column 1 in Panel A finds that forward DST decreases the electricity consumption by around 5%, while the interaction with medium (high) maximum temperatures is 1.4 (4.8) percentage points. Thus, it is clear that non-linear effects exist. Column 3, our preferred specification, finds that the total effect of forward DST is negative and significant during low and medium maximum temperatures, but positive and significant during high maximum temperatures. The results for the sample 2009–2015 are similar, with Column 6 finding that forward DST implementation increases the electricity consumption by around 4.5% during high maximum temperatures. The findings in Panels B and C using the minimum temperature and sunshine duration provide somewhat similar results and again confirm the existence of non-linear weather effects.

Table 2
Does the effect of forward DST depend on weather conditions? Linear weather indicators.

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Panel A: Population weighted maximum temperature						
Forward DST	−0.125***	−0.125***	−0.108***	−0.140***	−0.140***	−0.123***
	(0.038)	(0.038)	(0.037)	(0.029)	(0.029)	(0.030)
Forward DST*Maximum Temperature	0.004**	0.004**	0.005**	0.005***	0.005***	0.006***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	4620	4620	3660	2040	2040	1680
Panel B: Population weighted minimum temperature						
Forward DST	−0.062***	−0.062***	−0.044**	−0.075***	−0.075***	−0.054***
	(0.021)	(0.021)	(0.018)	(0.022)	(0.022)	(0.013)
Forward DST*Minimum Temperature	0.002	0.002	0.005**	0.004	0.004	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	4620	4620	3660	2040	2040	1680
Panel C: Population weighted sunshine duration						
Forward DST	−0.057***	−0.057***	−0.027**	−0.062***	−0.062***	−0.035**
	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)
Forward DST*Sunshine Duration	0.002*	0.002*	0.003**	0.003*	0.003*	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	4620	4620	3660	2040	2040	1680

Notes: State-level OLS regressions estimating Eq. (1) using daily data. The full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. Forward DST time is the same for all states 2009–2015. The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3
Does the effect of forward DST depend on weather conditions? Non-linear weather indicators.

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Panel A: Population weighted maximum temperature						
Forward DST	−0.052***	−0.052***	−0.019**	−0.058***	−0.058***	−0.027**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
Forward DST*2nd Tercile Maximum Temperature	0.014*	0.014*	0.013*	0.024***	0.024***	0.021***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)
Forward DST*3rd Tercile Maximum Temperature	0.048***	0.048***	0.053**	0.059***	0.059***	0.072***
	(0.017)	(0.017)	(0.018)	(0.014)	(0.014)	(0.016)
Observations	4620	4620	3660	2040	2040	1680
Panel B: Population weighted minimum temperature						
Forward DST	−0.038***	−0.038***	−0.010	−0.040***	−0.040***	−0.013**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
Forward DST*2nd Tercile Minimum Temperature	0.005	0.005	0.006	0.013*	0.013*	0.012*
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)
Forward DST*3rd Tercile Minimum Temperature	0.024*	0.024*	0.030**	0.029**	0.029**	0.070***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.021)
Observations	4620	4620	3660	2040	2040	1680
Panel C: Population weighted sunshine duration						
Forward DST	−0.050***	−0.050***	−0.016**	−0.052***	−0.052***	−0.022**
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
Forward DST*2nd Tercile Sunshine Duration	0.009	0.009	0.010	0.008	0.008	0.009
	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)
Forward DST*3rd Tercile Sunshine Duration	0.015*	0.015*	0.021**	0.021*	0.021*	0.028**
	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.012)
Observations	4620	4620	3660	2040	2040	1680

Notes: State-level OLS regressions estimating Eq. (2) using daily data. The full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. Forward DST time is the same for all states 2009–2015. The terciles of the weather indicators are measured as follows: maximum temperature (first [2.93 °C–18.70 °C], second [18.71 °C–25.31 °C] and third [25.32 °C–44.08 °C]); minimum temperature (first [−7.06 °C–8.29 °C], second [8.30 °C–13.67 °C] and third [13.68 °C–28.70 °C]); and sunshine duration (first [0–6.16], second [6.17–9.25] and third [9.26–13.91]). The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator tercile dummies, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

However, these regression models do not take into account the role of cooling usage in each state explicitly, meaning that the estimates of the interaction between forward DST and temperature are calculated implicitly at the sample mean of cooling usage. This assumes that around 50% of households have access to ACs throughout the entire sample. Using a unique dataset on AC ownership, we enter the cooling usage specifically in the next regression model, which should provide much better estimates.

5.3. Interaction effects of DST with weather and cooling

Table 4 estimates Eq. (3), where we use AC ownership as a proxy for cooling usage. Panel A again provide estimates using the population-weighted maximum temperature as the weather indicator. Column 1 shows that the interaction of forward DST with maximum temperature and AC ownership is positive and significant, while both the interaction with maximum temperature and the interaction with AC ownership are significant and negative. The results are similar in our preferred specification (Column 3), where we focus on states that adopted DST in all years. The significance and sizes of the coefficients remain similar in Columns 4–6 using data between 2009 and 2015. These results suggest that the potential benefits of DST depend not only on the temperature but also on the usage of cooling. This finding is especially important as maximum temperatures and the usage of cooling rise around the world. It also implies that merely examining the effects of DST on electricity consumption over a few years or for a few states/countries can be misleading. Estimates using longer panels could provide conclusions that can be generalized more readily for policy makers. These findings are supported by alternative specifications. The triple interaction term is also positive and significant in Column 3 of Panels B and C, where we use the minimum temperature and sunshine duration as the weather indicator.

Table 5 presents the estimates for Eq. (4), where we check the case of non-linearity in weather effects while examining the roles of daily weather conditions and cooling usage. The measurement of categorical variables and the reference groups are similar to regression models in Table 3. Panel A, Column 3 shows that the triple interaction term is positive and significant only for the third tercile of temperature, suggesting that cooling usage is most prevalent when the temperature is above 25 °C during the forward DST period. However, when we use the minimum temperature in Panel B across all columns, we again find that the triple interaction is positive and significant only for the third tercile of temperature. Likewise, when using sunshine duration in Columns 3 and 6 of Panel C, the triple interaction terms are significant and positive only for the third tercile.

5.4. Estimates using half-hourly data

Thus far, this paper has confirmed that the effects of DST on electricity consumption depend on temperature and cooling usage using daily

Table 4
Does the effect of forward DST depend on weather conditions and cooling usage? Linear weather indicators.

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Panel A: Population weighted maximum temperature						
Forward DST	0.061	0.061	0.102	0.012	0.012	0.099
	(0.062)	(0.062)	(0.067)	(0.055)	(0.055)	(0.060)
Forward DST*Maximum Temperature	−0.005*	−0.005*	−0.006*	−0.002	−0.002	−0.006*
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Forward DST*Air Conditioner Ownership	−0.257**	−0.257**	−0.293**	−0.202*	−0.202*	−0.297***
	(0.123)	(0.123)	(0.132)	(0.101)	(0.101)	(0.095)
Forward DST*Maximum Temperature*Air Conditioner Ownership	0.013**	0.013**	0.014**	0.009	0.009	0.015**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Observations	4620	4620	3660	2040	2040	1680
Panel B: Population weighted minimum temperature						
Forward DST	−0.023	−0.023	0.022	−0.065***	−0.065***	0.011
	(0.030)	(0.030)	(0.033)	(0.016)	(0.016)	(0.016)
Forward DST*Minimum Temperature	−0.004	−0.004	−0.006	0.003	0.003	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Forward DST*Air Conditioner Ownership	−0.054	−0.054	−0.095	0.003	0.003	−0.079**
	(0.056)	(0.056)	(0.060)	(0.041)	(0.041)	(0.033)
Forward DST*Minimum Temperature*Air Conditioner Ownership	0.009	0.009	0.014*	0.001	0.001	0.013**
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.004)
Observations	4620	4620	3660	2040	2040	1680
Panel C: Population weighted sunshine duration						
Forward DST	−0.055***	−0.055***	−0.003	−0.090***	−0.090***	−0.028*
	(0.017)	(0.017)	(0.017)	(0.014)	(0.014)	(0.015)
Forward DST*Sunshine Duration	−0.002	−0.002	−0.004	0.004	0.004	−0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Forward DST*Air Conditioner Ownership	0.002	0.002	−0.030	0.045	0.045	−0.004
	(0.032)	(0.032)	(0.034)	(0.031)	(0.031)	(0.030)
Forward DST*Sunshine Duration*Air Conditioner Ownership	0.005	0.005	0.010*	−0.002	−0.002	0.006
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	4620	4620	3660	2040	2040	1680

Notes: State-level OLS regressions estimating Eq. (3) using daily data. The full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. The forward DST time is the same for all states 2009–2015. The dependent variable is daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

regressions. We expect that the interaction effects would be higher during the day when the temperature is higher and should be insignificant in the evening when there is no sunlight. Table 6 estimates Eq. (1) using half-hourly data and shows that the triple interaction term is positive and significant from 6 am until 8 pm and is not significant between 9 and 11 pm. The results suggest that electricity consumption would go up from early morning until early evening during forward DST when there are high temperatures and high cooling usage.

5.5. Robustness and placebo tests

We carry out several robustness checks to validate our findings in this paper. First, Appendix Table 3 considers alternative methods of calculating state-level weather indicators, where Panel A uses the simple average of all weather stations in a state, while Panel B uses the simple average of all weather stations in metro regions of capital cities as the state-level weather indicator. The findings remain similar in these specifications. Second, Appendix Table 4 tests the robustness of controlling for midday electricity consumption in the models, where Panel A excludes midday control from the regression models and Panel B replaces midday electricity consumption (12:00 pm to 3:00 pm) with midnight electricity consumption (0:00 am to 3:00 am). The results are similar and again confirm our findings.

Third, Appendix Table 5 uses an alternative measure of cooling usage, where we replace AC ownership with AC penetration. The results are consistent with our previous findings: the triple interaction term between forward DST, maximum temperature and AC penetration is positive and significant consistently across all columns 1–6. Fourth, we carry out an alternative method of clustering standard errors because Cameron and Miller (2015) suggest that cluster groups of less than 50 might be problematic with regular clustering and would require the bootstrapping of standard errors. Therefore, Appendix Table 6 presents estimates of Table 2, Column 1 by clustering standard errors using the Wild Bootstrap, and presents *p*-values and confidence intervals. Overall, the significance of our estimates remains similar using this alternative way of clustering standard errors.

We also carry out some placebo tests to confirm that our results cannot be explained by alternative theories. First, we test whether the interaction between DST and temperature is capturing the role of cooling or something else. As has been indicated, the correlation between rainfall and maximum temperature is quite low, and therefore we test the inclusion of forward DST and rainfall interaction in the regression (Appendix Table 7). The results show that the interaction of

Table 5
Does the effect of forward DST depend on weather conditions and cooling usage? Non-linear weather indicators.

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Panel A: Population weighted maximum temperature						
Forward DST	−0.044***	−0.044***	−0.012	−0.046***	−0.046***	−0.019
	(0.013)	(0.013)	(0.010)	(0.011)	(0.011)	(0.011)
Forward DST*2nd Tercile Maximum Temperature	−0.015	−0.015	−0.003	−0.020	−0.020	0.005
	(0.018)	(0.018)	(0.017)	(0.024)	(0.024)	(0.021)
Forward DST*3rd Tercile Maximum Temperature	−0.057	−0.057	−0.077	−0.038	−0.038	−0.178**
	(0.038)	(0.038)	(0.046)	(0.058)	(0.058)	(0.075)
Forward DST*Air Conditioner Ownership	−0.015	−0.015	−0.013	−0.015	−0.015	−0.014
	(0.025)	(0.025)	(0.023)	(0.016)	(0.016)	(0.015)
Forward DST*2nd Tercile Maximum Temperature*Air Conditioner Ownership	0.042	0.042	0.026	0.055	0.055	0.025
	(0.027)	(0.027)	(0.024)	(0.032)	(0.032)	(0.030)
Forward DST*3rd Tercile Maximum Temperature*Air Conditioner Ownership	0.133*	0.133*	0.165*	0.116	0.116	0.276**
	(0.066)	(0.066)	(0.079)	(0.068)	(0.068)	(0.090)
Observations	4620	4620	3660	2040	2040	1680
Panel B: Population weighted minimum temperature						
Forward DST	−0.051***	−0.051***	−0.022**	−0.054***	−0.054***	−0.029**
	(0.011)	(0.011)	(0.009)	(0.010)	(0.010)	(0.009)
Forward DST*2nd Tercile Minimum Temperature	−0.022	−0.022	−0.020	0.004	0.004	0.004
	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
Forward DST*3rd Tercile Minimum Temperature	−0.058*	−0.058*	−0.057	−0.043	−0.043	−0.244***
	(0.030)	(0.030)	(0.037)	(0.049)	(0.049)	(0.052)
Forward DST*Air Conditioner Ownership	0.018	0.018	0.018	0.022	0.022	0.021*
	(0.015)	(0.015)	(0.014)	(0.013)	(0.013)	(0.012)
Forward DST*2nd Tercile Minimum Temperature*Air Conditioner Ownership	0.035	0.035	0.033	0.007	0.007	0.006
	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)
Forward DST*3rd Tercile Minimum Temperature*Air Conditioner Ownership	0.106**	0.106**	0.111*	0.101*	0.101*	0.339***
	(0.047)	(0.047)	(0.062)	(0.048)	(0.048)	(0.063)
Observations	4620	4620	3660	2040	2040	1680
Panel C: Population weighted sunshine duration						
Forward DST	−0.062***	−0.062***	−0.020**	−0.072***	−0.072***	−0.033***
	(0.010)	(0.010)	(0.007)	(0.008)	(0.008)	(0.009)
Forward DST*2nd Tercile Sunshine Duration	−0.013	−0.013	−0.018	−0.003	−0.003	−0.007
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)
Forward DST*3rd Tercile Sunshine Duration	−0.015	−0.015	−0.032	0.036	0.036	−0.041
	(0.015)	(0.015)	(0.019)	(0.029)	(0.029)	(0.033)
Forward DST*Air Conditioner Ownership	0.019	0.019	0.006	0.031**	0.031**	0.017
	(0.016)	(0.016)	(0.015)	(0.012)	(0.012)	(0.012)
Forward DST*2nd Tercile Sunshine Duration*Air Conditioner Ownership	0.027	0.027	0.039	0.009	0.009	0.018
	(0.021)	(0.021)	(0.023)	(0.019)	(0.019)	(0.020)
Forward DST*3rd Tercile Sunshine Duration*Air Conditioner Ownership	0.037	0.037	0.068*	−0.023	−0.023	0.075*
	(0.029)	(0.029)	(0.033)	(0.039)	(0.039)	(0.040)
Observations	4620	4620	3660	2040	2040	1680

Notes: State-level OLS regressions estimating Eq. (4) using daily data. The full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. The forward DST time is the same for all states 2009–2015. The dependent variable is daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator tercile dummies, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

forward DST with rainfall is insignificant and does not make any change to our results. This confirms that the interaction between DST and temperature probably captures cooling usage rather than some other unobserved variable. Second, we test whether the forward DST dummy captures the effect of a specific date or some other event (Appendix Table 8) by replacing the actual forward DST date each year with a placebo date. The results show that the coefficient on forward DST and its interaction with the maximum temperature are insignificant in all specifications, suggesting that our results cannot be explained by any event other than DST adoption. Third, it is possible that electricity consumption might change due to price changes. Indeed, daily electricity prices in Australia are driven by supply rather than demand (Kellogg and Wolff, 2008). In any event, when we replace the electricity demand with electricity prices in Eq. (2) (Appendix Table 9), we find that the coefficient on forward DST and its interaction with maximum temperature are insignificant in all specifications, suggesting that our results cannot be explained by changes in electricity prices.

It is possible that month and day of the week fixed effects will not capture the differences in daylight hours in our empirical models entirely, which could lead to bias in our estimates. We investigate this possibility by estimating two alternative models in Appendix Table 10. Our first method adds sunshine hours as an independent variable in the models (Panel A), while examining the role of DST interactions with the maximum and minimum temperature. We do not present regressions for DST and sunshine duration interactions in this panel because sunshine hours have been included as an independent variable in our

Table 6
Estimates using half-hourly electricity consumption. All states, 1998–2015.

Outcome: electricity consumption time interval→	6:00–8:59	9:00–11:59	12:00–14:59	15:00–17:59	18:00–20:59	21:00–23:59
Forward DST	0.11*	−0.00088	0.051	0.12	0.059	−0.047
	(0.052)	(0.072)	(0.076)	(0.074)	(0.083)	(0.070)
Forward DST*Maximum Temperature	−0.0059**	−0.0039	−0.0060	−0.0078*	−0.0065	0.00039
	(0.0025)	(0.0036)	(0.0039)	(0.0038)	(0.0042)	(0.0035)
Forward DST*Air Conditioner Ownership	−0.12	−0.18	−0.30*	−0.37**	−0.38**	−0.25*
	(0.098)	(0.15)	(0.15)	(0.14)	(0.16)	(0.14)
Forward DST*Maximum Temperature*Air Conditioner Ownership	0.0096**	0.011*	0.016**	0.018**	0.017**	0.0086
	(0.0044)	(0.0069)	(0.0071)	(0.0065)	(0.0076)	(0.0065)
Observations	27720	27720	27716	27720	27720	27720
Adjusted *R*-squared	0.996	0.996	0.996	0.996	0.996	0.997

Notes: State-level OLS regressions using half-hourly data. All states consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. The dependent variable is half-hourly electricity consumption in logs. The population-weighted maximum temperature is used in all regressions. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for half-hour, day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

baseline models already (Table 2). Our second method (Panel B) adds day of the year fixed effects to the models in order to control for such differences in daylight duration (see Shaffer, 2019; Rivers, 2018; Smith, 2016). In these regressions, the coefficients on the forward DST change only marginally, while the coefficients on the interaction terms remain similar. These results show that our findings cannot be explained by potential differences in daylight hours, and thus differ from previous studies of the role of daylight hours in explaining the effects of DST on electricity consumption.

We also test the validity of our results using backwards DST dates rather than forward DST dates (Appendix Table 11). Appendix Table 1 shows that the DST starting dates differ significantly across and within states in Australia, whereas the finishing dates are very similar across states and do not change much over time within states. Thus, we expect that our findings could be stronger using backwards DST. The results confirm our expectation and show that the backwards DST coefficient is positive and significant, while the interactions between the backwards DST and weather indicators are negative and significant across all columns and panels. The coefficients are stronger than those using the forward DST. For instance, the double interaction term in Panel A, Column 3 (−0.012) is twice as large as that reported in Panel A, Column 3 of Table 2 (0.05).

Finally, we test the non-linear weather effects with an alternative method by controlling for heating degree hours, cooling degree hours and their squared values in Appendix Tables 12 and 13. We would like to note that previous literature which controlled for these indicators were using hourly or half-hourly data but we use daily data. Nevertheless, in line with the previous literature, we convert the population weighted daily maximum temperature (T) data into heating degree hours and cooling degree hours, to reflect the idea that both extremely hot days and extremely cold days can drive electricity demand. Cooling degree hours (cdh) and heating degree hours (hdh) are calculated in each day as the difference between the actual temperature and 18 degrees Celsius or 20 degrees Celcius as follows: $hdh = \max(0, 18 - T)$ or and $cdh = \max(0, T - 18)$ or $hdh = \max(0, 20 - T)$ or and $cdh = \max(0, T - 20)$. Appendix Table 12 tests the inclusion of hdh and cdh as well as their squared values using 18 and 20 degree Celsius definitions. We find that our findings remain similar in all specifications. Indeed, the coefficient of interest (Forward DST*Maximum Temperature) in Panels A-D is very similar to the values presented in Table 2 Panel A. Similarly, Appendix Table 13 finds that our findings remain similar when we include hdh and cdh (defined either using 18 or 20 degree Celsius) as well as their squared values in the regressions. Indeed, the coefficient of interest (Forward DST*Maximum Temperature*Air Conditioner Ownership) in Panels A-D is similar in significance and magnitude to the values presented in Table 4 Panel A. As a result, our findings are robust to this alternative method of controlling for non-linear weather effects in our models.

Table 7
Simulations of the total effect of DST in EU capital cities.

(1) Capital city of	(2) DST adoption	(3) Average maximum temperature during July	(4) Air conditioner penetration	(5) Total effect of forward DST (in logs)
Austria	1	23	0.582	−0.054
Belgium	1	22	0.404	−0.062
Bulgaria	1	25	0.803	−0.029
Croatia	1	27	0.74	−0.022
Cyprus	1	37	0.973	0.112
Czech Republic	1	22	0.548	−0.058
Denmark	1	20	0.231	−0.060
Estonia	1	20	0.287	−0.061
Finland	1	20	0.163	−0.059
France	1	25	0.597	−0.047
Germany	1	25	0.461	−0.058
Greece	1	32	0.957	0.056
Hungary	1	28	0.694	−0.023
Ireland	1	18	0	−0.042
Italy	1	29	0.825	0.004
Latvia	1	21	0.35	−0.063
Lithuania	1	21	0.398	−0.062
Luxembourg	1	21	0.39	−0.062
Malta	1	30	0.973	0.038
Netherlands	1	20	0.341	−0.061
Poland	1	22	0.445	−0.061
Portugal	1	29	0.82	0.003
Romania	1	29	0.7	−0.017
Slovakia	1	25	0.537	−0.052
Slovenia	1	28	0.567	−0.041
Spain	1	30	0.847	0.015
Sweden	1	21	0.117	−0.065
United Kingdom	1	21	0.169	−0.064

Notes: Simulations are based on Appendix Table 5 Column (1): Total Effect of Forward DST (in logs) = 0.102Forward DST – 0.08(Forward DST*Maximum Temperature) – 0.389(Forward DST*Air Conditioner Penetration) + 0.019(Forward DST*Maximum Temperature*Air Conditioner Penetration). Data on average maximum temperature during 2019 July are obtained from weather-and-climate.com. Data on air conditioner penetration are obtained from Jakubcionis and Carlsson (2017).

6. Simulations of DST effects for European countries

The biggest advantage of using a long panel dataset is the ability it gives to provide predictions for other countries, because our identification depends on large variations in temperatures and cooling usages within and across states. Thus, our results have external validity and can help other states and countries to decide whether or not to adopt DST given their own conditions. In this vein, we provide predictions of the effects of DST for countries in Europe because *European Union* member countries need to decide in the coming year whether or not they will adopt DST. Our simulations are based on the regression results in

Appendix Table 5, where we use AC penetration as the measure of cooling usage because such data were made available recently by Jakubcionis and Carlsson (2017) for European countries. For simplicity, we used the average maximum temperatures reported during July 2019 for capital cities in Europe. The results of this simulation are reported in Table 7, with the total effect of forward DST on electricity consumption (in logs) being provided in column 5. Our simulations show that countries such as Germany, Netherlands, Sweden and United Kingdom would benefit from DST adoption in terms of lower electricity consumption, whereas countries such as Greece, Spain and Portugal would experience higher electricity consumption with DST. Overall, our simulations show that DST will be costly in countries with higher summer temperatures and higher levels of AC penetration. The temperature values used in this table are probably very conservative, but provide an indication of the potential effects of DST adoption across European countries.

7. Conclusion

We examine a previously unexplored question: does the effect of DST on electricity consumption depend on weather conditions and cooling usage? We hypothesize that forward DST will increase the electricity consumption when the temperatures are quite high and cooling usage is quite prevalent, meaning that the increase in the demand for cooling will outweigh the decline in the demand for lighting. We test this hypothesis using daily state-level panel data on electricity consumption from Australia between 1998 and 2015, when there was considerable variation in the presence and timing of DST implementation, weather conditions and cooling usage within and between states. The minimum and maximum daily temperatures were − 7 °C and 44 °C, while air conditioner (AC) penetration has increased from 35% to 65% in Australia over the study period. This provides us with a unique opportunity to study the interaction effects of DST with exogenous variation in daily weather conditions and cooling usage across and within Australian states over a period of two decades.

We estimate daily panel fixed effects regressions and find that forward DST leads to increases in electricity consumption when the maximum temperature is above 31 °C in the full sample, while this number is 22 °C when focusing on the states that implemented DST in each year during the regression sample. When we include the interaction of DST with the maximum temperature and AC ownership, we find that this triple interaction term is positive and highly significant, as expected. Overall, our findings suggest that the total effect of DST depends strongly on the weather conditions and cooling usage. These results are confirmed when we replace the maximum temperature with the minimum temperature or sunshine duration, which are correlated positively with the maximum temperature. Our results cannot be explained by endogenous selection of DST adoption, and our findings are supported by robustness and placebo tests.

There is an ongoing debate regarding the implementation of DST around the world. For instance, the *European Union* recently abolished daylight saving time, leaving the decision to be made by individual members in the coming year. Accordingly, we provide simulation results for countries in Europe on the effects of adopting DST. Our simulations show that countries such as Germany, Netherlands, Sweden and the United Kingdom would benefit from DST adoption in terms of lower electricity demand, whereas countries such as Greece, Spain and Portugal would experience higher electricity consumption with DST. Overall, our simulations show that DST will be costly in countries with higher summer temperatures and higher levels of AC penetration.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

All authors contributed to this manuscript equally.

Appendix Table 1
Implementation dates of daylight saving time within Australia.

Season	State(s) and territories affected	Starting date	Finishing date
1997–98	Tas	05-Oct-97	29-Mar-98
	Vic, ACT, NSW, SA	26-Oct-97	29-Mar-98
1998–99	Tas	04-Oct-98	28-Mar-99
	Vic, ACT, NSW, SA	25-Oct-98	28-Mar-99
1999–2000	Tas	03-Oct-99	26-Mar-00
	Vic, ACT, NSW, SA	31-Oct-99	26-Mar-00
2000–01	Vic, ACT, NSW, Tas	27-Aug-00	25-Mar-01
	SA	29-Oct-00	25-Mar-01
2001–02	Tas	07-Oct-01	31-Mar-02
	Vic, ACT, NSW, SA	28-Oct-01	31-Mar-02
2002–03	Tas	06-Oct-02	30-Mar-03
	Vic, ACT, NSW, SA	27-Oct-02	30-Mar-03
2003–04	Tas	05-Oct-03	28-Mar-04
	Vic, ACT, NSW, SA	26-Oct-03	28-Mar-04
2004–05	Tas	03-Oct-04	27-Mar-05
	Vic, ACT, NSW, SA	31-Oct-04	27-Mar-05
2005–06	Tas	02-Oct-05	02-Apr-06
	Vic, ACT, NSW, SA	30-Oct-05	02-Apr-06
2006–07	Tas	01-Oct-06	25-Mar-07
	Vic, ACT, NSW, SA	29-Oct-06	25-Mar-07
2007–08	Tas	07-Oct-07	06-Apr-08
	Vic, ACT, NSW, SA	28-Oct-07	06-Apr-08
2008–09	Tas, Vic, ACT, NSW, SA	05-Oct-08	05-Apr-09
2009–10	Tas, Vic, ACT, NSW, SA	04-Oct-09	04-Apr-10
2010–11	Tas, Vic, ACT, NSW, SA	03-Oct-10	03-Apr-11
2011–12	Tas, Vic, ACT, NSW, SA	02-Oct-11	01-Apr-12
2012–13	Tas, Vic, ACT, NSW, SA	07-Oct-12	07-Apr-13
2013–14	Tas, Vic, ACT, NSW, SA	06-Oct-13	06-Apr-14
2014–15	Tas, Vic, ACT, NSW, SA	05-Oct-14	05-Apr-15
2015–16	Tas, Vic, ACT, NSW, SA	04-Oct-15	03-Apr-16

Notes: Information accessed from http://www.bom.gov.au/climate/averages/tables/dst_times.shtml.

Appendix Table 2
Descriptive statistics of population weighted weather indicators.

Panel A: Summary statistics

	Mean	Standard deviation	Minimum	Maximum
Maximum temperature	22.96	7	5.28	37.83
Minimum temperature	11.39	6.54	−3.86	27.67
Sunshine duration	8.37	2.85	0	13.6
Rainfall	2.01	4.3	0	52.88

Panel B: Correlation matrix

	Maximum temperature	Minimum temperature	Sunshine duration	Rainfall
Maximum temperature	1.000			
Minimum temperature	0.861	1.000		
Sunshine duration	0.404	0.134	1.000	
Rainfall	−0.131	0.069	−0.245	1.000

Notes: Weather indicators are state-level population weighted daily variables. Summary statistics and correlations are provided during the period 30 days before and 30 days after Forward DST across all Australian states considered (Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland) between 1989 and 2015.

Appendix Table 3
Alternative methods of calculating weather indicators.

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: Keeping States which implemented DST every year
Panel A: Simple average of all weather stations in a state						
Forward DST	−0.127***	−0.127***	−0.108***	−0.139***	−0.139***	−0.120***
	(0.037)	(0.037)	(0.036)	(0.028)	(0.028)	(0.028)
Forward DST*Maximum Temperature	0.004**	0.004**	0.005***	0.005***	0.005***	0.006***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Forward DST	−0.070***	−0.070***	−0.049**	−0.081***	−0.081***	−0.060***
	(0.023)	(0.023)	(0.019)	(0.024)	(0.024)	(0.015)
Forward DST*Minimum Temperature	0.003	0.003	0.005**	0.004*	0.004*	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Forward DST	−0.064***	−0.064***	−0.033***	−0.072***	−0.072***	−0.045**
	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.015)
Forward DST*Sunshine Duration	0.003**	0.003**	0.004***	0.004**	0.004**	0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Panel B: Simple average of all weather stations in capital city metro region in a state						
Forward DST	−0.109***	−0.109***	−0.088**	−0.124***	−0.124***	−0.103***
	(0.033)	(0.033)	(0.033)	(0.027)	(0.027)	(0.029)
Forward DST*Maximum Temperature	0.003**	0.003**	0.004**	0.004***	0.004***	0.005***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Forward DST	−0.066***	−0.066***	−0.046**	−0.077***	−0.077***	−0.055***
	(0.021)	(0.021)	(0.018)	(0.020)	(0.020)	(0.016)
Forward DST*Minimum Temperature	0.002	0.002	0.004**	0.003*	0.003*	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Forward DST	−0.054***	−0.054***	−0.026***	−0.054***	−0.054***	−0.033**
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)
Forward DST*Sunshine Duration	0.002**	0.002**	0.002**	0.002**	0.002**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: State-level OLS regressions estimating Eq. (1) using daily data. The full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. The forward DST time is the same for all states 2009–2015. The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table 4
Robustness of controlling for midday electricity consumption.

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Panel A: No midday/midnight control						
Forward DST	-0.150^{***}	-0.150^{***}	-0.132^{***}	-0.167^{***}	-0.167^{***}	-0.142^{***}
	(0.043)	(0.043)	(0.044)	(0.035)	(0.035)	(0.038)
Forward DST*Maximum Temperature	0.005^{**}	0.005^{**}	0.006^{***}	0.006^{***}	0.006^{***}	0.007^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Forward DST	-0.078^{***}	-0.078^{***}	-0.058^{**}	-0.094^{***}	-0.094^{***}	-0.064^{***}
	(0.026)	(0.026)	(0.024)	(0.028)	(0.028)	(0.019)
Forward DST*Minimum Temperature	0.004	0.004	0.007^{**}	0.006^{*}	0.006^{*}	0.009^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Forward DST	-0.059^{***}	-0.059^{***}	-0.026^{**}	-0.067^{***}	-0.067^{***}	-0.033^{**}
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Forward DST*Sunshine Duration	0.002^{*}	0.002^{*}	0.003^{**}	0.003^{**}	0.003^{**}	0.004^{**}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: Control for midnight electricity consumption						
Forward DST	-0.133^{***}	-0.133^{***}	-0.093^{**}	-0.152^{***}	-0.152^{***}	-0.102^{**}
	(0.040)	(0.040)	(0.038)	(0.035)	(0.035)	(0.037)
Forward DST*Maximum Temperature	0.004^{**}	0.004^{**}	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Forward DST	-0.062^{**}	-0.062^{**}	-0.018	-0.077^{***}	-0.077^{***}	-0.025
	(0.022)	(0.022)	(0.018)	(0.026)	(0.026)	(0.019)
Forward DST*Minimum Temperature	0.002	0.002	0.005^{**}	0.004	0.004	0.007^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Forward DST	-0.057^{***}	-0.057^{***}	-0.002	-0.064^{***}	-0.064^{***}	-0.002
	(0.011)	(0.011)	(0.009)	(0.012)	(0.012)	(0.009)
Forward DST*Sunshine Duration	0.002^{*}	0.002^{*}	0.003^{**}	0.003^{**}	0.003^{**}	0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: State-level OLS regressions estimating Eq. (1) using daily data. The full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. The forward DST time is the same for all states 2009–2015. The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and midnight electricity consumption (only Panel B). All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table 5
Alternative measure of cooling usage.

	1998–2010			2009–2010		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Forward DST	0.102	0.102	0.099^{*}	0.039	0.039	0.059
	(0.065)	(0.065)	(0.054)	(0.056)	(0.056)	(0.040)
Forward DST*Maximum Temperature	-0.008^{**}	-0.008^{**}	-0.005^{*}	-0.004	-0.004	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Forward DST*Air Conditioner Penetration	-0.389^{***}	-0.389^{***}	-0.356^{**}	-0.280^{**}	-0.280^{**}	-0.297^{***}
	(0.138)	(0.138)	(0.130)	(0.114)	(0.114)	(0.087)
Forward DST*Maximum Temperature*Air Conditioner Penetration	0.019^{***}	0.019^{***}	0.017^{**}	0.013^{*}	0.013^{*}	0.014^{**}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Observations	3180	3180	2460	600	600	480

Notes: State-level OLS regressions estimating Eq. (3) using daily data. The air conditioner penetration data are obtained from Energy Efficient Strategies (2008) and Energy Efficient Strategies (2006). Note that this variable has observations between 1998 and 2010. Full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. The forward DST time is the same for all states 2009–2010. The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table 6
Clustering standard errors using the wild bootstrap.

Sample: Table 2 Column 1			
	Coefficient	p-value	95% Confidence interval
Forward DST	−0.122	0.04	[−0.19021955, −0.05494533]
Forward DST*Maximum Temperature	0.004	0.04	[0.00058261, 0.00594276]
Forward DST	−0.061	0.84	[−0.10469929, −0.02484474]
Forward DST*Minimum Temperature	0.001	0.08	[−0.00231289, 0.0046066]
Forward DST	−0.066	0.04	[−0.09633853, −0.04039907]
Forward DST*Sunshine Duration	0.002	0.2	[−0.00057825, 0.00337684]

Notes: State-level OLS regressions estimating Eq. (1) using daily data and the cgmwildboot command in STATA. Regressions are estimated for the full sample that includes the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters.

Appendix Table 7
Placebo exercise using rainfall.

	1998–2015			2009–2015		
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Forward DST	-0.123^{***}	-0.123^{***}	-0.106^{**}	-0.141^{***}	-0.141^{***}	-0.125^{***}
	(0.039)	(0.039)	(0.038)	(0.030)	(0.030)	(0.031)
Forward DST*Rainfall	−0.000	−0.000	−0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Forward DST*Maximum Temperature	0.004^{**}	0.004^{**}	0.005^{**}	0.005^{***}	0.005^{***}	0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	4620	4620	3660	2040	2040	1680

Notes: State-level OLS regressions using daily data. The full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. The forward DST time is the same for all states 2009–2015. The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicators (population weighted state-level daily variables), fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{**}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table 8
Placebo forward DST implementation dates. All states.

Months before/after actual forward DST date		1998–2015	2009–2015
1 month before	Forward DST	0.053	0.046
		(0.084)	(0.11)
	Forward DST*Maximum Temperature	−0.0026	−0.0024
		(0.0041)	(0.0055)
1 month after	Forward DST	0.0083	−0.012
		(0.070)	(0.083)
	Forward DST*Maximum Temperature	−0.00053	0.00036
		(0.0026)	(0.0033)

Notes: State-level OLS regressions using daily data. The Population Weighted Maximum Temperature is used in all regressions. All states include the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. The forward DST time is the same for all states 2009–2015. The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table 9
Placebo exercise using the electricty price as the outcome variable.

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Forward DST	−6.734	−6.734	−3.422	1.226	1.226	2.687
	(8.986)	(8.986)	(9.513)	(5.730)	(5.730)	(5.713)
Forward DST*Maximum Temperature	0.308	0.308	0.344	−0.032	−0.032	−0.021
	(0.410)	(0.410)	(0.413)	(0.255)	(0.255)	(0.260)
Observations	4620	4620	3660	2040	2040	1680

Notes: State-level OLS regressions using daily data. Population Weighted Maximum Temperature is used in all regressions. Full sample includes the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. Forward DST time is the same for all states 2009–2015. The dependent variable is the daily average electricity price in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table 10
Controlling for potential differences in daylight hours.

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Panel A: Add control for sunshine hours						
Forward DST	-0.125^{***}	-0.125^{***}	-0.107^{**}	-0.139^{***}	-0.139^{***}	-0.122^{***}
	(0.038)	(0.038)	(0.037)	(0.028)	(0.028)	(0.029)
Forward DST*Maximum Temperature	0.004^{**}	0.004^{**}	0.005^{**}	0.005^{***}	0.005^{***}	0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Forward DST	-0.061^{**}	-0.061^{**}	-0.043^{**}	-0.071^{***}	-0.071^{***}	-0.051^{***}
	(0.022)	(0.022)	(0.018)	(0.022)	(0.022)	(0.013)
Forward DST*Minimum Temperature	0.002	0.002	0.005^{**}	0.003	0.003	0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Panel B: Add control for day-of-year fixed effects						
Forward DST	-0.123^{***}	-0.123^{***}	-0.089^{***}	-0.137^{***}	-0.137^{***}	-0.112^{**}
	(0.034)	(0.034)	(0.029)	(0.029)	(0.029)	(0.037)
Forward DST*Maximum Temperature	0.004^{**}	0.004^{**}	0.005^{***}	0.005^{***}	0.005^{***}	0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Forward DST	-0.065^{***}	-0.065^{***}	-0.036^{**}	-0.076^{***}	-0.076^{***}	-0.062^{**}
	(0.021)	(0.021)	(0.017)	(0.022)	(0.022)	(0.021)
Forward DST*Minimum Temperature	0.002	0.002	0.005^{***}	0.004^{*}	0.004^{*}	0.007^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)

Notes: State-level OLS regressions using daily data. The full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. The forward DST time is the same for all states 2009–2015. The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table 11
Effects of backwards DST.

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Panel A: Population weighted maximum temperature						
Backwards DST	0.314^{***}	0.314^{***}	0.293^{***}	0.304^{***}	0.304^{***}	0.276^{***}
	(0.053)	(0.053)	(0.054)	(0.045)	(0.045)	(0.046)
Backwards DST*Maximum Temperature	-0.013^{***}	-0.013^{***}	-0.012^{***}	-0.012^{***}	-0.012^{***}	-0.012^{***}
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	4530	4530	3570	2040	2040	1680
Panel B: Population weighted minimum temperature						
Backwards DST	0.165^{***}	0.165^{***}	0.155^{***}	0.174^{***}	0.174^{***}	0.153^{***}
	(0.030)	(0.030)	(0.036)	(0.024)	(0.024)	(0.027)
Backwards DST*Minimum Temperature	-0.013^{***}	-0.013^{***}	-0.012^{***}	-0.013^{***}	-0.013^{***}	-0.012^{***}
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Observations	4530	4530	3570	2040	2040	1680
Panel C: Population weighted sunshine duration						
Backwards DST	0.088^{**}	0.088^{**}	0.076^{**}	0.093^{***}	0.093^{***}	0.073^{***}
	(0.033)	(0.033)	(0.026)	(0.024)	(0.024)	(0.015)
Backwards DST*Sunshine Duration	-0.007^{**}	-0.007^{**}	-0.008^{**}	-0.006^{***}	-0.006^{***}	-0.007^{***}
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	4530	4530	3570	2040	2040	1680

Notes: State-level OLS regressions estimating Eq. (1) using daily data. The full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. The backwards DST time is the same for all states 2009–2015. The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption. All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table 12
Does the effect of forward DST depend on weather conditions? Controlling for heating and cooling degrees.

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Panel A: HDH and CDH added as controls. Threshold is 18 degrees celcius.						
Forward DST	−0.089***	−0.089***	−0.078**	−0.108***	−0.108***	−0.096**
	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)	(0.034)
Forward DST*Maximum Temperature	0.003**	0.003**	0.004**	0.004**	0.004**	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4620	4620	3660	2040	2040	1680
Panel B: HDH, CDH, HDH-squared and CDH-squared are added as controls. Threshold is 18 degrees celcius.						
Forward DST	−0.077***	−0.077***	−0.061**	−0.094***	−0.094***	−0.079**
	(0.023)	(0.023)	(0.024)	(0.025)	(0.025)	(0.029)
Forward DST*Maximum Temperature	−0.002**	−0.002**	−0.003**	−0.003***	−0.003***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4620	4620	3660	2040	2040	1680
Panel C: HDH and CDH are added as controls. Threshold is 20 degrees celcius.						
Forward DST	−0.082***	−0.082***	−0.071**	−0.101***	−0.101***	−0.088**
	(0.028)	(0.028)	(0.028)	(0.030)	(0.030)	(0.032)
Forward DST*Maximum Temperature	−0.003**	−0.003**	−0.003**	−0.003**	−0.003**	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4620	4620	3660	2040	2040	1680
Panel D: HDH, CDH, HDH-squared and CDH-squared are added as controls. Threshold is 20 degrees celcius.						
Forward DST	−0.077***	−0.077***	−0.061**	−0.094***	−0.094***	−0.079**
	(0.023)	(0.023)	(0.024)	(0.025)	(0.025)	(0.029)
Forward DST*Maximum Temperature	−0.002**	−0.002**	−0.003**	−0.003***	−0.003***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	4620	4620	3660	2040	2040	1680

Notes: State-level OLS regressions estimating Eq. (1) using daily data. The full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. Forward DST time is the same for all states 2009–2015. The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption, heating degrees hours (HDH) and cooling degrees hours (CDH) and their squared values (Panels B and D). All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix Table 13
Does the effect of forward DST depend on weather conditions and cooling usage? Controlling for heating and cooling degrees.

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Panel A: HDH and CDH added as controls. Threshold is 18 degrees celcius.						
Forward DST	0.088*	0.088*	0.134**	0.027	0.027	0.121**
	(0.047)	(0.047)	(0.052)	(0.054)	(0.054)	(0.054)
Forward DST*Maximum Temperature	−0.007***	−0.007***	−0.007**	−0.003	−0.003	−0.007*
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)
Forward DST*Air Conditioner Ownership	−0.260**	−0.260**	−0.309**	−0.204*	−0.204*	−0.304***
	(0.108)	(0.108)	(0.115)	(0.098)	(0.098)	(0.086)
Forward DST*Maximum Temperature*Air Conditioner Ownership	0.013**	0.013**	0.015**	0.010	0.010	0.016***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Observations	4620	4620	3660	2040	2040	1680
Panel B: HDH, CDH, HDH-squared and CDH-squared are added as controls. Threshold is 18 degrees celcius.						
Forward DST	0.066*	0.066*	0.106**	0.014	0.014	0.087
	(0.036)	(0.036)	(0.040)	(0.046)	(0.046)	(0.054)
Forward DST*Maximum Temperature	−0.005***	−0.005***	−0.006***	−0.002	−0.002	−0.005*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Forward DST*Air Conditioner Ownership	−0.207**	−0.207**	−0.240**	−0.160**	−0.160**	−0.235**
	(0.076)	(0.076)	(0.084)	(0.073)	(0.073)	(0.080)
Forward DST*Maximum	0.011***	0.011***	0.012***	0.008*	0.008*	0.012**

Appendix Table 13 (*continued*)

	1998–2015			2009–2015		
	Full sample	Addressing potential selection		Full sample	Addressing potential selection	
	(1) All states	(2) Exclude NT which never implemented DST	(3) Exclude NT and Queensland: keeping states which implemented DST every year	(4) All states	(5) Exclude NT which never implemented DST	(6) Exclude NT and Queensland: keeping states which implemented DST every year
Temperature*Air Conditioner Ownership	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	4620	4620	3660	2040	2040	1680
Panel C: HDH and CDH are added as controls. Threshold is 20 degrees celcius.						
Forward DST	0.076	0.076	0.118**	0.027	0.027	0.111*
	(0.045)	(0.045)	(0.049)	(0.051)	(0.051)	(0.053)
Forward DST*Maximum Temperature	−0.006**	−0.006**	−0.007**	−0.003	−0.003	−0.007*
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)
Forward DST*Air Conditioner Ownership	−0.231**	−0.231**	−0.274**	−0.188*	−0.188*	−0.280***
	(0.100)	(0.100)	(0.108)	(0.092)	(0.092)	(0.084)
Forward DST*Maximum Temperature*Air Conditioner Ownership	0.012**	0.012**	0.014**	0.009	0.009	0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	4620	4620	3660	2040	2040	1680
Panel D: HDH, CDH, HDH-squared and CDH-squared are added as controls. Threshold is 20 degrees celcius.						
Forward DST	0.067*	0.067*	0.107**	0.010	0.010	0.082
	(0.035)	(0.035)	(0.039)	(0.044)	(0.044)	(0.052)
Forward DST*Maximum Temperature	−0.005***	−0.005***	−0.006***	−0.002	−0.002	−0.005*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Forward DST*Air Conditioner Ownership	−0.209**	−0.209**	−0.242***	−0.154**	−0.154**	−0.229**
	(0.076)	(0.076)	(0.083)	(0.071)	(0.071)	(0.079)
Forward DST*Maximum Temperature*Air Conditioner Ownership	0.011***	0.011***	0.013***	0.007*	0.007*	0.012**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	4620	4620	3660	2040	2040	1680

Notes: State-level OLS regressions estimating Eq. (1) using daily data. The full sample consists of the following states: Tasmania, Victoria, Australian Capital Territory, New South Wales, South Australia, Northern Territory and Queensland. Forward DST time is the same for all states 2009–2015. The dependent variable is the daily electricity consumption in logs. All specifications include the following covariates: DSTafter dummy, DSTstate dummy, weather indicator, fixed effects for the day of the week, month, state and year, state-specific linear time trend, public holiday dummy, school holiday dummy and mid-day electricity consumption, heating degrees hours (HDH) and cooling degrees hours (CDH) and their squared values (Panels B and D). All specifications correct robust standard errors for state by month clusters. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105216.

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