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The Importance of Time Zone Assignment: Evidence from Residential Electricity Consumption

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Abstract
This paper presents the first nationwide empirical assessment of residential electricity use in response to the timing of daylight. Employing Geographical Information Systems (GIS) solar times of sunrise and sunset are calculated for all geographical locations in mainland USA. This is used to uncover the non-standard variation in sunrise times in standard local time over space, depending on time zone, daylight saving time, and geographical position within time zone. This variation is subsequently used to uncover county-level responses in residential electricity consumption to changes in sunlight. I find no robust overall effect of sunrise times, but early sunrise is associated with lower residential electricity use in the North, but higher consumption in the South. These results would suggest that additionally splitting the USA into time-zones horizontally could reduce the total annual residential electricity bill, but further research is needed to examine the behavioral channels that could give rise to these effects.

Keywords: time-use, time zones, daylight saving, energy consumption, GIS
JEL Classifications Nos. H4, Q4

1 Introduction

There are many reasons to believe that the timing of daylight matters for individual utility and welfare. Humans do not usually derive joy from sitting in the dark and we know that daylight has important impacts on health outcomes, i.e. van den Berg (2005). This study estimates the effect of the timing of daylight on electricity consumption. Electricity consumption presents an interesting case because US households spent 125 billion US-$ for electricity in 2005 alone (USdOT, 2010), which corresponds to about one per cent of total GDP. I argue that a better understanding of the effect of the timing of daylight on electricity consumption could potentially result in significant cost savings and welfare improvements.

Surprisingly, we know very little about the economic effects of local time and daylight on human activity. This is because for a given location, local times of sunrise and sunset only vary in a very smooth pattern over the year, which makes credible empirical estimation difficult. In terms of variations in local time, the exceptions are changes due to daylight-savings time (DST), and this variation has indeed been used to estimate effects on residential energy consumption (USdOT, 1975; Rock, 1997; CEC, 2001; Kandel, 2007; Kotchen and Grant, 2012; Kellogg and Wolff, 2008).[1] The latter two are empirical studies that focus on local changes in DST regimes in Australia and the state of Indiana and use a local difference-in-difference approach for estimation. Overall the results are inconclusive.

Contrary to Kotchen and Grant (2012) and Kellogg and Wolff (2008), I argue that rather than focussing on local changes in DST regimes, nationwide geo-temporal variation in local times of sunrise can be used for estimation. My approach has the advantage that I can fully examine the heterogeneity in the response of residential energy consumption across different latitudes and climate zones.

To obtain credible estimates for the elasticity of residential energy consumption with respect to local sunrise times, I use geo-temporal variation that has never, to my knowledge, been used before. To do this, I use Geographical Information Systems (GIS) to calculate the exact solar time for each county of the mainland US. This allows me to com-

[1]Economists have developed an interest in time zones/DST to understand the costs of coordination (Hamermesh et al., 2008), effects on trade and FDI (Marjit, 2007), on financial markets (Kamstra et al., 2000), and car accidents (Sood and Ghosh, 2007).

pute the length of the solar day (sunrise to sunset) and seasonal patterns in daylight for each county. Using additional information on time zones and daylight saving[2], I demonstrate that local standard times of sunrise and sunset depend on solar time, time zone, daylight savings regime, and the position within the time zone. Building on these stylised facts, I show in a simple model that these geographic and institutional patterns generate two different sources of variation that can be used to estimate the effect of the timing of daylight on residential electricity consumption. In principle both variation within time zone and across its boundaries can be used for estimation.

The mainland US presents a very good case study for the effects of the timing of daylight on residential electricity consumption because it is large enough to span four time zones, yet all counties share common institutional factors. Moreover, the US Department of Energy publishes panel data on residential electricity sales for each year between 2001 and 2009 for the entire country. This data contains information on annual retail revenue, sales, and customer counts, by state and by class of service[3], for each electric distribution utility, or energy service provider in all 50 states. In total, over 3,400 providers generate and sell electricity to residential customers in the US, which can be mapped into the counties of operation. The resulting data is a county-level panel of average annual residential electricity consumption, which can be directly used for estimation of the effects of the timing in daylight.

The coefficient for averaged annual sunrise time is insignificant for the US overall. However, this results masks stark heterogeneity across latitude and climate. In the North, later sunrise is associated with increases in residential electricity consumption, whereas in the hot South the effect goes the opposite direction. These patterns are remarkably robust. In the most demanding specification I include controls for geographical latitude, time-varying county-level industry structure and employment, and county-level census data on climate, land area, population, educational attainment, median age and poverty, and state fixed effects, and my general conclusions remain unaffected. I include this rich set of controls to hopefully capture all the unobserved geographically correlated factors that might otherwise invalidate the approach. I also test the robustness of these findings against a number of potential threats, including measurement error and specification of

[2] A synonym for 'British Summer Time'.

[3] including the Transportation sector, new in 2003.

the functional form.

This paper offers a first explanation of the channels that could give rise to differences in the effects of the timing of daylight in the North and the South. As I show, people living in the North and the South get the same overall amount of daylight over the year in principle. However, the North is much colder and has a larger seasonal variation in sunrise times. A simple analysis suggests that in the hot South later sunrise could lead to lower residential electricity consumption if this shifts the hours of human activity into the colder morning hours. Such a change could result in a reduced demand for cooling, which is one of the major sources of residential electricity consumption in hot areas. However, in the North, temperature-related arguments cannot explain why early sunrise would reduce electricity consumption since most heating uses fossil fuels. I argue that the extent of people's waking hours at home (versus at work) can generate a situation where early daylight is associated with lower residential electricity consumption through changes in the demand for lighting in the dark mornings.

The finding of this heterogeneity in the effect of the timing of daylight on residential electricity consumption is completely novel and has potentially important welfare consequences. This is because the timing of daylight is determined by institutional factors which policymakers can directly influence. However, further work is required to gain a better understanding of the economic channels that give rise to these effects. While this paper offers a first attempt to explain potential behavioural channels, it is left to future research to examine these in detail.

The rest of the paper is structured as follows. The next section reviews the literature and explains where the approach taken here differs from the existing literature on electricity savings and daylight savings time. Section 3 presents stylised facts about the geo-temporal variation in local daylight times that results from geography, time zones and daylight savings regimes. A short historical discussion highlights the roles that (exogenous) geography and (endogenous) institutions play in the generation of this variation. Next, section 4 presents a simple model to show how this geo-temporal variation can be used to estimate the effect of the timing of daylight on residential electrify consumption. Section 5 presents the data. In section 6, I discuss the results obtained from two different sources of variation. Section 7 presents a series of robustness checks, before I offer a first explanation of the behavioural channels that could explain the new set of stylised facts in section 8. Finally, section 9, concludes and outlines directions for future research on this topic.

2 Literature Review

To my knowledge, there exists no direct evidence for a link between electricity savings and time zones. However, the existing literature on the effect of daylight savings time regimes on electricity consumption can be seen as an indirect test of the general effect of time zone assignment on electricity consumption. This is because standard time varies across time zones by exactly one hour, equivalent to the variation around DST time changes, when clocks are adjusted one hour forward or backward. As a result, observing DST can be interpreted as changing time zones for the summer period.

While DST was originally established to reduce energy demand as first advocated by Benjamin Franklin in 1784, there is a lack of empirical evidence as to whether it achieves this aim. Aries and Newsham (2008) conclude in their literature on DST and electricity savings that we are far from an understanding. They write: "There is general consensus that DST does contribute to an evening reduction in peak demand for electricity, though this may be offset by an increase in the morning." (p. 1858). This is in line with the most recent study by Kotchen and Grant (2012), who present the only microeconometric study in the field using US data to study DST and electricity consumption in the state of Indiana. They use the fact that some counties in Indiana changed their DST policies in 2006 and track changes in electricity consumption using household level data. They find that for Indiana DST in fact increased residential energy consumption, as there is a trade-off between electricity consumption in the evening, and energy consumption for heating in the morning. The only other recent econometric study looking at DST and energy consumption is by Kellogg and Wolff (2008), who use a natural experiment in Australia, where some regions altered their DST patters for the Sydney Olympics. Their main finding is that morning and evening reductions and increases in electricity consumption offset each other.

However, studies comparing DST regimes across contiguous localities ignore the effects of synchronisation. By this I mean that the existing literature on daylight and electricity consumption neglects (or assumes away) the fact that we derive benefits from coordinating activities across space. If a neighbouring locality, but not my own, changes its DST policy and I happen to work there, for example, I will need to adjust my work patterns in accordance with this locality's time policy, regardless of my own. As a result, work schedules or national TV schedules do not necessarily change in line with DST policies for each locality (i.e. holding solar time constant). Indeed, Hamermesh et al. (2008) demonstrates that there are large benefits to synchronising economic activity over space. They show that national TV scheduling has large effects on the timing of economic activity. Hamermesh et al. (2008) shows that if your locality just changed to Summer time, for example, whether your neighbour also changes time affects when you get up. As a result, it is unclear to what extent any local differences in DST, as in Kotchen and Grant (2012) for example, result in changes of behaviour that in turn effect energy consumption. This is a general problem of difference-in-difference DST studies, as localities with different DST regimes must be otherwise as similar as possible for credible estimation.

The alternative is to compare electricity consumption before and after the actual DST change, in Spring and Autumn. This is, of course, also not a viable approach, as any results would be the local effects found around the dates of clock changes. Since DST is introduced to generate summer savings, we would in fact expect the local effect around the DST-changing dates to be close to zero, if DST was set optimally. Therefore, in order to answer more general questions regarding year-round timing of sunlight and electricity consumption, using the DST time-discontinuity would not be useful.

The existing literature holds daylight constant and examines changes in local times, thus exposing itself to the issue of synchronization. As I show later, the variation that I am using in this study is not affected by these issues. I can control for synchronisation by holding local current times constant but varying daylight. A further problem of local studies is that they cannot uncover potentially heterogeneous effects across different climates. For these reasons, it is unclear whether the local effects of DST can be generalised. To my best knowledge, this study is the first to use nationwide data on electricity consumption to fully examine heterogeneity across different climates and latitudes.

The next section describes the geo-temporal variation in sunrise times that is used for estimation.

3 A short primer in astronomy and time zones: variation in local time of sunrise

3.1 Sunrise and sunset of the solar day

Sunrise and sunset of the solar day and seasonal variations are geographically determined for each location depending on the exact position of that location on the surface of the earth and the position of the earth with respect to the sun. As a result it is possible to calculate these two variables for any location directly using a mathematical approximation for the shape of the globe and the path around the sun[4]. Figure 1 shows the resulting spatial variation in annual daylight for summer (June) and winter (December). Seasonal differences in daylight depend on latitude offset over the year. The North gets shorter days during December, but longer days in summer. Over the whole year, differences in total minutes of daylight are negligible[5]. Independent of the season, patterns in solar day-length only differ on the vertical axis, as can be seen by the horizontal layers in Figure 1. This means that any two locations on the same latitude experience exactly the same seasonal patterns of solar day-length. Ignoring cloud cover, for any given day of the year, all locations on the same latitude band have the same number of minutes of sunshine. Overall, each location in the US gets about 734 minutes of daylight per day on average, annually. These facts are exogenously determined by geography.

3.2 A short history of time zones and daylight savings time (DST)

In order to derive local standard times of sunrise and sunset, i.e. the time shown on local clocks, it is necessary to combine solar information with the respective time zone (off-set from GMT) and daylight savings regime. Even if we regard time zones as daily reality, they are only a relatively recent phenomenon. Historically, local timekeeping

[4]The U.S. Department of Commerce, National Oceanic & Atmospheric Administration, provides a solar calculator that is highly accurate for locations within the US at URL: `http://www.srrb.noaa.gov/highlights/sunrise/NOAA_Solar_Calculations_day.xls, whichIuseforcounty-levelcalculation`

[5]Note that I ignore differences due to local weather or cloud cover, which are negligible over the long run according to Hamermesh et al. (2008).

only emerged with the development of mechanical clocks, and the word 'punctuality' only emerged in the English language in the late 18th century (Levine, 1998). During the 19th century, villages would each have their clock tower and set noon to the highest point of the sun. As a result, over 70 different time zones are recorded for the 1860s in the US alone (ibid.). The four time zones in the mainland US as we know them today were only introduced in 1883 and formally established in 1918, and only marginally changed thereafter (see Levine (1998) for a fully-fledged historical discussion).

Daylight saving time is defined as temporarily advancing the time by one hour during summertime, which is referred to as British Summer Time in the UK. This procedure was first advocated in the US by Benjamin Franklin in 1784 and in the UK by William Willett in 1907 (Aries and Newsham, 2008). The idea was to shift human activity one hour backwards to save energy used for lighting. DST was first introduced during WW1 by Germany and subsequently adopted by other European countries. The US first introduced DST in 1918. Contrary to time zones, daylight-savings time has continuously been modified. The US, for instance, was on 'year round DST time (YRDST)' in 1974-1975. The current British Prime Minister, David Cameron, wants to put the UK on double-DST, effectively putting the United Kingdom into the GMT+1 time zone, for a trial period. Regarding the US, the last change in DST policies was in 2007, when it was lengthened, and Indiana started observing DST in 2006 (all from Aries and Newsham (2008) who discusses the historical background of DST in more detail).

3.3 Variations in local standard time or sunrise

Combining local information on solar time, time zone and daylight saving, the local standard time for sunrise can be calculated for each geographical location in the mainland US. In order to do this, I augment the mathematical model that calculates solar times with county-level information on time zone and daylight savings policy, by year[6]. Figure 2 shows the local standard time for sunrise in summer (June), winter (December) and annually (lower panel). Contrary to the previous exercise, time zones and daylight-savings regimes matter here in the sense that they influence the spatial pattern. The four time zones are clearly visible. Further, the local standard time for sunrise changes discontinu-

[6]This program is written in visual basic, building on the solar times calculator used in section 3.1.

ously at the borders of time zones. Within each zone, local standard time for sunrise increases smoothly as we move from the east to the west. This is because the sun rises on the eastern horizon in the morning, and hence rises earlier in the east, depending on the time zone. On average the sun rises at 6:49am, and one standard deviation in the average annual sunrise time is about eighteen minutes. Strong differences in seasonality are displayed in the upper panel of Figure 2. These arise because the sun rises from the northeast in summer and from the southeast in winter. Again, these differences cancel each other out over the year, so that time-bands for local standard sunrise time run vertically through the time zones in the lower panel. The total 'width' of each time zone corresponds roughly to one hour. That is, at the eastern border of each time zone, the sun rises about one hour earlier than close to the western border, for any two locations within the same time zone[7]. Finally, Arizona and large parts of Indiana did not observe daylight savings time, which is clearly visible in both the annual figure and also the top left-hand panel, showing sunrise times for June. In December, on the other hand, Arizona and Indiana do not stand out, as everyone is on standard time now[8].

In a nutshell, local standard time for sunrise exhibits a non-standard variation across space, depending on solar time, geographical location, and on position within time zone and daylight saving. While the former is geographically determined, the latter are policy variables, and daylight savings regimes have frequently changed over recent decades for reasons not related to robust empirical evidence. This is important to note, since it shows that policy can indeed affect the timing of daylight, which makes the question of timing of daylight and electricity consumption relevant from a policy perspective.

4 A simple model of annual residential electricity consumption

4.1 Intuition for the model

Figure 3 illustrates how the geo-temporal patterns described in the previous section can be used for the estimation of the effect of the timing of daylight on residential electricity

[7]This is this norm, given that there are 24 time zones for 24 hours on the globe. However, in other parts of the world time zones follow actual solar time less closely. Europe has a single time zone at GMT+1 that is spanning a region from eastern Poland to western Spain (about two and a half hours differences in sunrise-times), and China is on a single time zone.

[8]This map is drawn for the year 2003.

consumption in a stylised way. The two boxes represent two time zones which have a one-hour difference in local time. For example, the right (eastern) box could represent the Central time zone, and the left box Mountain time. The smaller white boxes inside show the sunrise times for people living close to the western or eastern border within each time zone. Focussing on the left box, someone who lives close to the western border observes local sunrise at 7am. Another person living in the same time zone but close to the eastern border observes sunrise (and sunset) one hour earlier in local time: here, the sun rises at 6am. This pattern is the same in the other box (Central time zone). As a result, two sources of variation in the local time of sunrise emerge. First, moving within time zone, it is possible to compare the electricity consumption of people living close to the western versus the eastern border. Generally, moving horizontally within each time zone, daylight occurs later in local time. For now, assuming that everyone gets up at 7am local time, this would generate a variation of one hour in the timing of daylight.

The second source of variation comes from moving across time zone boundaries. A person who lives close to the eastern border of the Mountain time zone in Figure 3 observes sunrise at 6am local time, whereas a person living close to the western border of the Central time zone observes sunrise one hour later in local time, at 7am. In principle, both sources could be used for estimation.

There are some important factors to consider. First, within time zones actual solar time is changing but local time is constant. Everyone in the same time zone has the same local time. In contrast, at the boundary actual solar time does not change (the sun rises 'at the same time') but local times differ by one hour. As we will see, this has important consequences for the interpretation of the estimates. So far we assumed that everyone always gets up at 7am local time. Indeed, different sunrise times can only have real economic effects on electricity consumption if they are not mirrored by an exact behavioural response of getting up in the morning and going to bed in the evening. For example, if people living in a county towards the western border of a time zone get up about one hour later than people living in counties that are close to a time zone boundary to the east, we would not expect to find any impact on electricity consumption because their work-sleep patterns would not be different with respect to solar time.

Indeed, the assumption that has always been implicit - but never tested - in the existing literature is that people perfectly adjust their behaviour according to their local current time. This assumption implies that people always get up at the same local time regardless of the position of the sun, i.e. solar time. Similarly, issues such as coordination costs across space have been ignored. At the boundary, or when comparing counties that observe DST with neighbouring counties that do not, it is usually assumed that there are no coordination costs across space (Kotchen and Grant, 2012). However, these arise if people commute across a county or time zone boundary to get to work, or simply because people watch live events on television at the same time. Hamermesh et al. (2008) show that coordination costs across boundaries are non-trivial, and we should therefore not assume them away without knowing the consequences.

4.2 Setup

In order to understand how these different behavioural responses to changes in the timing of daylight could affect reduced form effects, I present a simple model of local times of waking and sunrise in the following[9].

Sunrise in current time $SRCT$

$$SRCT = f(longitude, TZ) \tag{1}$$

From Figure 2 we learn that sunrise in current time is a function of geographical longitude and time zone. Sunrise in current time defines the actual time that is shown on the clocks in each location. Accordingly, $SRCT$ is a function of longitude and time zone, denoted by the term TZ. We ignore differences in daylight savings regimes for simplicity.

Waking time in current time WCT

$$WCT = g(longitude, X) \tag{2}$$

As discussed, the effect of the current time of sunrise on electricity consumption also

[9] I continue to refer to sunrise times and waking times in the morning rather than the evening. While sunrise in local time in the morning and sunset in the evening change symmetrically as we move across longitude, there is the possibility that people who, say, get up earlier do not go to bed earlier by the same time difference. For simplicity, we shall assume that the total hours people are awake does not vary depending on geographical location within a time zone. However, this is an important assumption that should be tested using the American Time Use Survey in future research.

depends on how waking behaviour changes with sunlight. This is why waking in current time, WCT, is a function of longitude to capture the potential response to sunlight. The term X captures other influences over space that might affect the time people get up in the morning. A potential candidate for X is coordination costs across space, which will be discussed in more detail in section 6.2. Finally, WCT is not a function of time zone. This implies the assumption that people in different time zones in principle get up at the same time (i.e. at 7am). Taken together, residential electricity consumption then depends on how daylight changes, controlling for changes in waking times.

Specifically, differencing equations 1 and 2 we get:

Residential electricity consumption REC

$$REC = f(SRCT) - g(WCT) \tag{3}$$

Assuming linearity:

$$REC = [(\alpha_1 longitude + \alpha_2 TZ) - (\beta_1 longitude + \beta_2 X)] \tag{4}$$

We can now partially differentiate equation 4 at the time zone boundary and within time zones to shed some light on potential behavioural responses to changes in current sunrise times. Imposing linearity is a potentially strong assumption, which will be tested later on. Here, we keep the linear notation for simplicity.

4.2.1 Partial derivative: Variation within time zone

Using equation 4 and taking the derivative with respect to longitude within time zone, we get:

$$\frac{\partial REC}{\partial longitude} = [\alpha_1 - \beta_1] \tag{5}$$

where α_1 is how much SRCT changes when we move within TZ and β_1 how much WCT changes with changes in sunlight.

We can clearly see that if β_1 is positive the reduced form effect will be a combination of the effect of position within time zone on sunrise times and waking behaviour.

4.2.2 Partial derivative: Variation at the time zone boundary

Using equation 4 and taking the derivative with respect to longitude at the time zone boundary, we get

$$\frac{\partial REC}{\partial boundary} = [\alpha_2 - \beta_2] \tag{6}$$

where α_2 is equal to one since current time changes by one hour for each TZ in the US. α_1 is close to zero since latitudes of counties close to the time zone boundary are similar. What this highlights, however, is that some measure that captures longitude should be included as running variable in regression analysis that exploits the boundary discontinuity.

More importantly, β_2 depends on coordination costs/changes in conventions in WCT at the boundary. If people commute across the boundary to get to work, they effectively need to live on the neighbouring time schedule. There might be other reasons why people on both sides of the boundary would get up at different local times, and hence simultaneously. As shown by Hamermesh et al. (2008) air times of popular television programs have a significant effect on the time people get up in the morning and go to bed in the evenings. This is important because all major television channels air their programs simultaneously in the Eastern and Central time zone, for example. This pattern is less clear at the other time zone boundaries and depends on actual channels, but naturally all live events are aired simultaneously throughout the US. Therefore, the assumption that β_2 equals zero is a strong one and we have reasons to believe that β_2 is positive. If this is the case, again the reduced form estimate would be a combination of the time change at the boundary and the behavioural response and would go towards zero. In the extreme, if coordination costs at the boundary were prohibitive, and people got up simultaneously, there would be no effect on electricity consumption.

4.3 Summary

In this section we have seen that, in principle, two different sources of variation emerge from the spatial patterns described in section 3. Reduced form estimates of electricity consumption on sunrise times can be estimated using either within-time-zone variation across longitude, or the boundary discontinuity. However, effects of daylight timing on electricity consumption also depend on how people adjust their sleep patterns with respect to changes in the timing of daylight. I have shown that the effects of the two sources of variation will thus differ depending on the behavioural responses of waking time. Since the behavioural response is due to different reasons at the boundary versus within the boundary, it is not clear a priori why reduced form estimates should be comparable in magnitude and significance.

For example, if coordination costs across space are high, the behavioural adjustment in waking times within time zones should be minimal. This is because when coordination matters, people who live close to the eastern border of a time zone will need to get up simultaneously with other people living further west in the same time zone. As a result, local clock time will determine when people get up, and not the position of the sun. In contrast, behavioural adjustment with respect to local time at the boundary would be large. This is because if two people living on opposite boundaries of a time zone need to get up simultaneously, they will in fact get up with a one-hour difference in their local times. As shown by the model, the estimated effects would vary accordingly. I will return to these important considerations when comparing the estimates obtained from the two distinct sources of variation later in section 6.[10]

5 Data

5.1 Residential electricity consumption

The U.S. Energy Information Administration (EIA) requires all energy utilities in the USA to report their annual residential electricity sales. Specifically, the form called 'EIA-861' contains information on annual retail revenue, sales, and customer counts, by state and class of service (including the Transportation sector, new in 2003), for each electric distribution utility, or energy service provider in all 50 states. Each utility or service provider also lists all counties of operation. Therefore, combining this information, it is possible to

[10]The sum of β_1 and β_2 define the total time budget available, i.e. the total difference in waking times that we can find across the whole of mainland US. If, for example, people in the Pacific time zone get up exactly three hours later on average than people in the Eastern time zone, β_1 and β_2 needed to sum to one. Whether this equality needs to hold is something that future research should examine using geo-coded data from time use surveys.

extract annual per-consumer (which is per electricity-meter) residential energy sales. [11]

In total, 3,420 different energy utilities sold electricity to residential customers in the US between 2001 and 2009. Over ninety per cent of energy utilities both produce and sell electricity. However, about six per cent of utilities do only produce and not sell electricity to residential customers themselves. This electricity is sold through the other providers or a small number of sales-only providers, on which information is available, as well. Since we are interested in the location of residential electricity consumption (and not production), we need to drop the six per cent of utilities that do not directly sell to end consumers themselves [12].

The EIA also collects seasonal information on residential electricity consumption[13], however this information is only collected for a subsample of energy providers. Therefore seasonal electricity consumption data is available for a sample of counties as well.

Table 1 shows descriptive statistics for annual county level per-customer electricity consumption in MWh. The first two columns show descriptive statistics for all counties in mainland US, and the remaining columns split the US into time zones. The first row gives averages for all latitudes, whereas the remaining rows split the US into quintiles based on latitude of county centroid. The first quintile includes the twenty per cent of counties furthest North, for example. All data is averaged over the period from 2001 to 2009 and weighted by county population according to the 2001 census.

Turning to the statistics, the first entry in column (1) is average annual per-customer residential electricity consumption, which is 12.1 MWh. The remaining rows in column (1) show how this consumption varies over five latitude quintiles. We can clearly see that electricity consumption is higher in the South than in the North. In the most southerly quintile, per-customer electricity consumption averages 13.82MWh, compared to 10.63MWh in the most northern quintile. However, as the standard deviations in column (2) show, there is substantial variation within these geographical bands. As a result, these differences do not turn out to be statistically significant at conventional levels.

Looking at time zones individually, it is interesting to see that the North-South pattern documented in column (1) is not present in all four time zones. In fact, in the Pacific

[11] All power-utilities are required to provide this information through an online portal knows as 'Single sign-on'.

[12] Many thanks to Paul Hesse from the EIA for helpful explanations.

[13] This is done through the form EIA-862.

and the Mountain time zones, overall consumption is higher in the North than in the South. The overall pattern is thus driven by the Central and Eastern time zones. In the Eastern zone in particular, there is a clear pattern of higher electricity consumption in the North than in the South. The most northerly counties in the Eastern time zone have an average electricity consumption of about 7.85MWh per customer, compared to 14.12MWh in the South. These differences turn out to be significant, as we can see from the standard deviations reported in column (10).

To conclude this section, overall there is a North-South pattern in residential electricity sales. Splitting the US into latitude quintiles, we can see that electricity use is somewhat higher in the South. As I will argue in section 8.1 this is probably because the use of air conditioning for cooling is very electricity-intensive in the hot South. Patterns are somewhat different in the Mountain and Pacific time zones. These differences could be partly driven by climatic patterns. The next section describes data on climatic variables in detail.

5.2 Climate: Cooling Degree Days and Heating Degree Days

Different climates might affect energy consumption, and the effects of daylight might be different depending on climate. Table 2 shows indexes for Heating Degree Days (HDD) and Cooling Degree Days (CDD) for the four time zones of the mainland US and by latitude percentile. HDD and CDD are common measures in the energy sector. As we can see from column (1) in table 2, the South has significantly more CDD than the North, which has significantly more heating degree days. This is unsurprising, of course. Indeed, the correlation between geographical latitude and these measures is very high. The correlation coefficient for latitude and HDD is 0.9357 and for latitude and CDD -0.8737.

Turning to columns (3) to (10), CDD and HDD measures are shown for each time zone individually. The general North-South pattern of increases in CDD and decreases in HDD as we more further South is present in all four time zones. Interestingly, the South in the Central and Eastern time zones have a much higher index for CDD compared to the other time zones. For the most southern quintile, for example, the CDD index is 7.21 and 7.18 for the Central and Eastern time zones respectively, and significantly lower at 5.88 and 5.40 in the Pacific and Mountain time zones. The way the CDD index is constructed, this difference translates into a factor of about two, meaning that the Central and Eastern time zones have a much higher potential absolute demand for cooling. Since cooling is very demanding in electricity, these patterns might explain the overall higher electricity consumption in the south in these time zones, which we detected in section 5.1.

5.3 Further control variables

Appendix table A.1 shows descriptive statistics of additional county-level variables. The table shows data in the first five panels on population (measured in 2001), land area (square miles), median age, educational attainment (high school graduate or higher in 1990 and the number of persons below poverty level. This data is taken from the ICPSR 2896 Historical, Demographic, Economic and Social Data DS81:2000 County Data Book, and I will include these variables as additional control variables in some of the specifications that I discuss in the next section. The lower part of the table further shows statistics on county-level industry specialisation and overall employment and the information on these two variables is extracted from the County Business Pattern dataset for every year between 2001 and 2009. Since this is county-level data, again all entries are weighted by county population as recorded by the 2001 census.

Overall, the table shows some regional variation across both time zones and latitude, but these patterns do not seem significant. For example, there is a clear North-South pattern for both educational and poverty levels. Column (1) shows that in the North people are on average better educated and less poor. However, there is also substantial variation within the latitude bands and these differences are not significant. Similarly, differences across time zones are not remarkable.

6 Regression Analysis, main results

This section presents regression results from using two different sources of geographical variation in the timing of daylight. Section 6.1 presents results from using geographical variation across longitude and within latitude bands for estimation. Section 6.2, on the other hand, uses variation in the timing of daylight that arises because of different current times on opposing sides of inland time zone boundaries in the mainland US. Before turning to the specific analysis, let us first discuss two technical notes that apply to all regression specifications presented below.

First, in all specifications I cluster the error term at the county level to account for the fact that each county is observed in nine consecutive years and that the residual is likely to be correlated within a county over time. Alternatively, I can use robust standard errors to control for heteroscedasticity only, which results in similar estimates. Since my treatment varies across geographical latitude I also clustered at the state*year-level result, which results in even smaller standard errors. I also estimated most specifications using two-way clustering to simultaneously control for potential autocorrelation in the residual over time and across geographical latitude[14]. In particular, I clustered the error at the county level and additionally along twenty-four latitude bands, which I constructed based on the integer values of the geographical county-centroid latitude coordinates. This two-way clustering also only marginally changed the estimated standard errors and never changed the interpretation of my coefficients. I therefore concluded that autocorrelation in the error term across latitude is not a major concern and cluster all standard errors only at the county level in all of the analysis below.

Secondly, I will use county-level averages in residential electricity consumption as dependent variable throughout. In principle, however, we want to make claims about population electricity consumption. In order to do this we would ideally use individual-level data. However, as explained in section 5 my data is only available on the aggregated county level. Since counties differ in population, treating them all as equal would not make it possible to make statements about overall electricity consumption. Stated intuitively, this is because a change in the average electricity consumption in a county with a very large population would result in a larger change in national electricity consumption than a similar change in average electricity consumption in a county with smaller population.[15]

We can solve this problem by using weighted least squares and assigning analytic weights to the county-level regression. This can be done with the command 'aweight' in STATA, which I use to scale the assumed variance of the county-level data by the inverse

[14] Two-way clustering was implemented in STATA using the cluster-command of the ï£¡ivreg2'-routine, which allows for multiple level clustering of the error term.

[15] This is similar to Angrist (1998) who estimates the labour market impact of military service using averaged data on earnings, see Angrist and Pischke (2008), p. 40 for a discussion.

of the county population. The data on county population is taken from the 2001 Census as described in section 5. Notice that using WLS is justified solely because I have grouped data. This is different to issues of heteroscedasticity or frequency weighting because of non-random sampling. For notational simplicity I will ignore the weighting matrix in the specifications spelled out below, but all results presented are based on WLS using analytic weighting as described here.

6.1 Analysis using within time zone spatial variation in the timing of daylight

6.1.1 Specification

The most basic specification that I estimate is the following:

$$\begin{aligned} lnY_{c,t} =& \gamma_0 + \gamma_1(avsunrise)_{c,t} + \gamma_2(timezone)_c \\ &+ \gamma_3(year)_t + \gamma_4(timezone)(year)_{c,t} + \varepsilon_{c,t} \end{aligned} \tag{7}$$

In this specification, the term $Y_{c,t}$ represents annual per-household electricity consumption for county c in year t. Sunrise times are in local current times. Further, time zone and year dummies are included to capture any potentially unobserved time zone year specific shocks. The coefficient γ_1 is the main coefficient of interest.

If the within-time-zone variation in local sunrise times were truly exogenous to other factors that determine electricity consumption, then this simple specification should already reveal an unbiased estimate of the reduced form relationship of timing of daylight on electricity consumption as discussed in the model in section 4. However, there is the potential that historical time zone assignment has not been truly random, or that firms or people sorted themselves into specific geographical locations in ways that would confound causal interpretation. In order to alleviate these concerns I also estimate specifications including additional controls. Specifically, I include variables on the geographical latitude of the county centroid, Cooling and Heating Degree Days (CDD, HDD), industry specialisation and employment numbers, land area, population, a poverty measure and education[16]. These controls are included to capture factors that potentially correlate with

[16]For descriptive statistics on controls see Appendix Table A.1

local time of sunrise and residential electricity consumption over space. If unobserved, these factors could induce omitted variables bias. Since it is not clear a priori which variables are likely candidates to capture such geographical patterns, I follow a 'kitchen sink' approach and include this wide range of controls. The hope is that conditional on general control variables on education, production and climate, there are no relevant unobserved factors correlated with local times of sunrise and electricity consumption.[17]

To further alleviate potential concerns of omitted variable bias I also estimate regressions that include state-by-year fixed effects. This is to control for any institutional differences of states that could affect electricity consumption and also correlate to within time zone geography. Estimating the effect of the timing of daylight on electricity consumption within states is very demanding because state fixed effects alone explain about 44 per cent of the variation in annual electricity consumption conditional on year and time zone.[18].

6.1.2 Estimation results

Table 3 shows the estimates for the main coefficients of interest for specifications that try to explain residential electricity consumption as a function of local times of sunrise using the spatial variation of local sunrise times within time zones. The first column presents the γ_1 estimate of specification 7 above. In the second column controls are added to the specification, and the third column further includes state and state-times-year fixed effects. Columns (4) to (6) and (7) to (9) repeat these regressions on a subset of counties, splitting the US into two equal halves based on geographic latitude of county centroids.

What we can see from the estimates in the first column of table 3 is that there is a positive association between sunrise times and residential electricity consumption across the whole US. The estimated effect is significant at the one-per cent level, and very large: A one-hour-later sunrise is associated with about twenty per cent higher annual residential electricity consumption in column (1). However, this estimate is almost halved once we include a rich set of control variables in column (2). The fact that the estimate

[17]Since it is hard to see these general control variables as outcomes themselves, the hope is that including these variables does not cause 'bad control' issues, i.e. bias in the main coefficient of interest, as explained by Angrist and Pischke (2008).

[18]Obtained by keeping the residual of the specification in column (2) with explanatory variable *avsunrise* excluded. Over 43 per cent of the remaining variation in the residual is between states.

is sensitive to the inclusion of controls shows that the regression in column (1) suffered from omitted variable bias. Jointly, the additional control variables included in column (2) correlate with within-time-zone geography and electricity consumption. Indeed, the adjusted R2 rises to 0.45 in this specification, a dramatic increase compared to the previous specification with an adjusted R2 of 0.16. Further, adding state fixed effects in column (3) completely removes any association between average annual sunrise times and residential electricity consumption across the US. Controlling for state-by-year averages in residential electricity consumption makes it possible to predict almost 80 per cent of the variation in residential electricity consumption. At the same time the estimated standard error in column (3) remains unaffected. This suggests that the insignificance of the estimate for the effect of the timing of daylight on residential electricity consumption is not driven by lack of within-state variation in the outcome or explanatory variables. Taken at face value, this estimate means that shifting existing time zone boundaries towards the East or West would not result in any overall residential electricity savings.

Moving to columns (3) to (9), where the US is split into North and South, it becomes evident that there is substantial heterogeneity across geographical latitude. We should note that the US is split into two halves crudely based on geographical latitude of county centroid and ignoring any other boundaries or location-specific features.

The estimate in column (4) shows that in the North an one-hour-later annual average sunrise is associated to about a thirty-five per cent increase in electricity consumption in the unconditional specification. This is an unrealistically large effect and once the rich set of control variables is included the estimated coefficient reduces from 0.341 to 0.250. Again, this suggests that the control variables are not randomly distributed over the within-time-zone geography. Adding state fixed effects in column (6) further reduces the effect to a sixteen percentage-point change in residential electricity consumption. Overall, this set of results demonstrates that while the estimates are sensitive to the inclusion of controls, the estimates remain large in size and highly significant even in the most demanding specification.

Columns (7) to (9) show the estimates for the southern half of the United States. Here, the results are opposite to the North. In the South, a one-hour-later average annual sunrise is associated with a reduction in residential energy sales of about sixteen per cent in the unconditional specification. Notice that this effect in the South is very robust to the inclusion of a wide range of control variables. Indeed the point estimate remains virtually identical in column (8). Here, even including state fixed effects does not significantly alter the estimated coefficient. The unconditional estimate in column (7) is estimated at -161, including state fixed effects reduces the coefficient only to -0.131. This difference in estimates between the unconditional and most demanding specification is not significant at the five-per cent level.

To recap, using the spatial variation within time zones to estimate the relationship between residential electricity consumption and the timing of daylight we found two results: first, there is no robust evidence for an overall association between average annual sunrise times and electricity consumption. However, this overall result masks significant heterogeneous effects across latitude. Splitting the US into two halves along county latitude, in the North a delay in sunrise is associated with an increase in residential electricity sales, whereas later sunrise with lower electricity consumption in the South. While the estimated effect is sensitive to the inclusion of controls for the North, the estimates for the South are remarkably robust to the inclusion of a wide range of controls variables. We can even include additional state fixed effects, which take out over 40 per cent of the variation used in the estimation, and the estimates remain unchanged compared to the unconditional specification.

6.2 Analysis using time zone boundary spatial variation in the timing of daylight

An alternative approach to estimating the effect of daylight on residential electricity consumption is to focus on time zone boundaries.

In order to implement regression analysis of boundary counties it is necessary to first identify all counties that are close to the boundary. Initially, I focussed on counties that are contingent to a time zone boundary only. However, it turned out that using counties that share a border with the time zone boundary resulted in large estimates of the standard errors due to the small sample size. Also, since counties in the eastern US tend to be smaller than counties in the West, the overall area included was not balanced across space. Therefore I now focus on 612 counties that lie within a 100km buffer around a time zone boundary. Figure 4 shows these counties divided into 'treatment' and 'control' groups. First, note that a few counties, mainly around Arizona, are not grouped into control or treatment group, because they followed different daylight-savings regimes for at least one year of the study period. While this is taken care of in the construction of the average sunrise variable, it is less clear what would happen to the discontinuity. In particular, it is not clear which would be a control county and which ones would be treated. To be on the safe side, I exclude these counties from the control and treatment groups for the boundary analysis. The remaining counties are grouped into a treatment and control group, where the treatment group consists of counties that lie east of the respective time zone boundary. These counties have a local time one hour later than the control group, hence the estimated coefficient can be interpreted as adding one hour, or as sunlight beginning one hour later under the following two conditions.

Firstly, when using this variation it is only possible to estimate the coefficients of interest on a subset of counties, namely counties that are close to a time zone boundary. One concern is that these counties might not be representative and it might not be possible to examine heterogeneity because of small numbers. Appendix Tables A.2, A.3, and A.4 replicate Table 1, 2 and Table A.1 previously described in section 3, but for the sample of boundary counties only. Notice that since counties around the state of Arizona could not be included, there are some missing entries for the southern quintiles in the Pacific time zone in these tables.

First turning to Appendix table A.2, which shows the average residential electricity consumption the counties that lie within 100 km of an inland time zone boundary, what we see is promising: the boundary counties are quite similar to the rest of the US. Again, there is the overall North-South pattern with higher electricity consumption in the South, as shown by column (1): the average customer in the most northern boundary country uses about 9.57MWh, whereas this figure is 13.37MWh for the most southern quintile. Notice that I again split the US into five latitude quintiles based on the latitude of the county centroid. The climate variables on Cooling and Heating Degree Days also follow a similar pattern, and they are tabulated in Appendix Table A.3.

However, Appendix Table A.4 shows the descriptive statistics for the boundary counties. Focussing on column (1), comparing numbers across to table A.1 it becomes clear that the boundary counties are indeed not representative. The first column, for example, shows that the average boundary county has a population of about 100,000, which compares to 150,000 in the full sample. This is a potential caveat when trying to generalise results from the boundary estimation.

A second concern, which I already pointed out in section 4, is that at a time zone boundary daylight does not change much. Indeed, very close to the boundary the real change in solar time is negligible. Instead, local current time changes by one hour. We know from Hamermesh et al. (2008), who study time use in adjacent counties in Arizona that followed different daylight savings regimes, that there is extremely little impact on behaviour in terms of waking time when clocks are changed but neighbours remain in a different time zone. The key problem is that it is not daylight that varies across the boundary, but local current time. While we can probably assume that people get up at the same local time within a time zone, it is harder to assume that they get up with a one-hour time difference at the boundary. This would imply that β_2 in Equation 6 is likely to be greater than zero. In fact, in order to compare estimates to the previous exercise, one would need to assume an elasticity of waking up with respect to local time of one at the boundary. If this is not met, the reduced form estimate will be lower depending on β_1 and β_2 of equation 6, as shown in section 4.

6.2.1 Specification

The simplest specification that I estimate is the following:

$$\begin{aligned} Y_{c,t} = \delta_0 + \delta_1(treatment)_c + \delta_2(tzboundary)_{c,t} \\ +\delta_3(year)_t + \delta_4(longitude)_c + v_{c,t} \end{aligned} \tag{8}$$

Here, δ_1 is the main coefficient of interest and should capture the effect of being in the treatment group, i.e. a one hour later local time, on electricity consumption. δ_2 is an estimate for the difference between the group of boundary counties shown in figure 4 overall, compared to all other counties which are still included in the regression to reduce the Residual Sum of Squares. A significant coefficient here would indicate that boundary counties are on average significantly different to the average other county in the US. Note that it is now not possible to include time zone fixed effects but time fixed effects are still included to capture any overall differences in annual electricity consumption. As highlighted by the theoretical discussion in section 4 a measure of longitude is included as running variable, here the longitudinal coordinate of the county centroids. I continue to cluster the residual at the county level and weight each county by its overall population using weighted regressions.

6.2.2 Results

Column (1) of table 4 shows the estimates for specification 8. Here, all latitudes and time zones are bunched together. First, note that the estimate for β_2, reported in the second row, is negative and significant. This raises important concerns from an external validity perspective as this shows that boundary counties have lower residential electricity sales compared to the rest of the mainland US. The main coefficient of interest reported in the first row is also significant (and positive), but these are only the unconditional results.

However, it turns out that the inclusion of the usual set of control variables in column (2) does not change much, and even state fixed effects (column (3)) do not change the message: using the boundary variation there seems to be an overall positive association between sunrise times and electricity consumption. The finding of a positive effect in the most robust specification in column (3) especially seems to contradict the earlier finding that there is no significant overall effect. However, recall that we had to drop a significant number of counties in the South due to the changing DST regimes around Arizona from the control and treatment groups. In the within-time-zone analysis, splitting the US into two halves by county centroid ensured an equal number of counties in the North and South in the previous analysis. Here, more counties in the North are treated than in the South. Therefore, these results are less informative. This becomes clearer when looking at the effects for northern and southern counties separately.

Columns (4) to (6) show estimates for the same regressions but using counties in the northern half only, and (7) to (9) are for the South. Again, the estimates in the second row all turn out significant and negative. Counties close to the boundary are non-representative as they have lower per-customer annual electricity consumption.

Turning to the estimates for the treatment, later sunrise is significantly associated with higher electricity consumption. The estimated effect is always significant at the one-per cent level. The unconditional estimate reported in column (4) is 0.094, which is only reduced to 0.089 by the inclusion of the usual set of control variables. Further including state fixed effects reduces the coefficient to 0.060. To summarise, the estimated effect in the North is robust to the inclusion of controls, though it does decrease by about three percentage points. However, this reduction is not significant at the five-per cent level.

Columns (7) to (9) show the respective estimates for southern counties. In the South, there seems to be less of a problem in terms of representativeness, which documents itself in the fact that the 'tzboundary'-estimate is insignificant in two of the three specifications, and also smaller in absolute terms. In contrast, the treatment coefficients are consistently estimated at negative values. The unconditional estimate in column (7) is -0.024, which is significant at the five-per cent level. Including control variables in column (8) reduces the coefficient to -0.021, which makes it just non-significant. However, including state fixed effects increases the estimated effect to -0.030, which is precisely estimated due to the reduction in the residual and therefore significant at the one per cent level. Again, we conclude that there is a negative association between average sunrise time and electricity consumption that is robust to the inclusion of a rich set of control variables, and even state fixed effects.

Summarising the boundary estimates, overall the results point in a similar direction to the findings using the within-time-zone variation. The estimates again suggest that the North could benefit from earlier sunrise, while the South would benefit from later sunrise. As before, the estimated effects are remarkably robust against the inclusion of controls, especially in the South. This is exactly what we previously found using the totally different variation in average sunrise times within time zones.

However, the results of the boundary counties should be taken with a pinch of salt. First, as the significant estimates for the dummy variable indicating boundary status indicates, these boundary counties are significantly different to the rest of the US in terms of electricity consumption. Therefore it is not clear if these results can be generalised across the US.

In addition, in order to interpret the estimate as the effect of sunlight on electricity consumption at the boundary, we have to make the unrealistic assumption that the elasticity of getting up with respect to local time equals one. As argued before, this is not very likely to be the case due to coordination costs across the boundary. For both of these reasons, the magnitudes of these results are not directly comparable to those obtained from the within-time-zone variation.

Keeping these caveats in mind, we do find the same overall pattern using both completely orthogonal sets of variation: the North benefits from early light, whereas the South suffers.

7 Robustness checks

7.1 Functional form

All findings so far come from specifications assuming linearity. As already mentioned in section 4 this is a potentially strong assumption, which is relaxed in table 5. Here, I estimate nine different regressions and the first three columns present results from regressions for the mainland US, columns (4) to (6) for the North and (7) to (9) for the South. Note that these results estimate the effect using within-time-zone variation in the timing of daylight, as in section 6 only. This is because the 'treatment' close to the boundary is not continuous, which makes it impossible to consider alternative functional forms.[19]

In contrast to the results presented in table 3, the explanatory variable for average local sunrise time is now also included as a quadratic and first two rows show the respective estimates. Since it is difficult to compare these results to the previous linear specifications directly, table 5 also reports computed marginal effects at variable means in the third row.

The first thing to note is that most estimates of both the linear and quadratic term are significant at the one-percent level. In principle, this would suggest that the quadratic term should be included. It is only in columns (7) and (8) that the estimates are non-significant. However, when turning to the marginal effects, the results are very close to the linear specification results presented in table 3, both in terms of magnitudes and significance. Indeed, the estimated marginal effects are almost identical and never different from the linear model in any of the specifications at any conventional significance level. Comparing the most robust specifications that include state fixed effects, the estimated

[19] Technically, this is not possible simply because the boundary treatment is captured by a dummy variable, and a dummy is equal to its own square.

marginal effects are -0.008, 0.174** and -0.158**, which compares with -0.002, 0.163** and -0.131** in table 3. Therefore I conclude that the linearity assumption is defensible on grounds of simplicity.

7.2 A closer look at heterogeneity by latitude

The findings so far suggest that there is heterogeneity across latitude in the effect of average local sunrise times on residential electricity sales. This section examines this finding in more detail, splitting the US not only into North and South but into five latitude bands based on quintile of county centroid. This is again only possible when looking at variation within time zones. Around the boundary, there are not enough observations for each quintile to obtain precise estimates.

Columns (1) to (3) of table 6 mimic the regressions of the first three columns of table 3, but coefficients are estimated separately for each latitude *quintile*. All effects are estimated from running separate regressions for each quintile, thus table 3 reports results obtained from fifteen different regressions. As before, in columns (2) and (3) we subsequently add control variables and state fixed effects.

Turning to the results, column (1) shows estimates for specification (7) broken down by latitude quintile. Moving from the North to the South, there is a strong and similarly-sized positive estimated effect in the northern two quintiles, which then turns negative in the third quintile to -0.011, but not significantly different to zero at conventional levels. Moving further south, the fourth and fifth quintile both have large negative associations between average sunrise and residential electricity sales. In fact, the coefficient for the most southern quintile is somewhat smaller than for the fourth quintile. However, these are only the unconditional results.

In column (2) the usual set of control variables is included. Here, there are some marginal changes in the coefficients resulting in a smooth pattern as we move from the North to the South. The inclusion of additional state-times-year fixed effects again does not change much. As we can see in column (3), here the magnitudes of the effects are reduced in the North, but amplified in the South, resulting in a very similar overall pattern.

To summarise the findings so far, breaking up the US into latitude quintiles confirms the previous finding that the effect of average sunrise times on residential electricity sales is heterogeneous by latitude. The results in table 3 for the North and South of the US are not driven by some outliers or few counties, but there is evidence for an overall North-South pattern across latitude quintiles. For the middle quintile of the US there is no evidence for a significant association between sunrise times and electricity consumption in any of the specifications. Therefore, we can conclude that this pattern is robust and the later sunrise is indeed associated with higher electricity consumption in the North, and lower consumption in the South.

7.3 Measurement error

There is no measurement error in the timing of daylight variable but as explained in section 5, some power utilities serve more than one county, and whenever this has been the case, per-customer sales have been averaged over the entire service area. Theoretically, it is unclear why measurement error in the dependent variable should bias my results. Nevertheless, table 7 reports the main results relying only on county level electricity consumption data that was derived using utilities that serve at most 10 counties $PanelA$, or exactly one county $PanelB$. While these restrictions result in a loss of up to 65 per cent of the counties for which electricity data is available, none of these changes significantly affects the main results.

8 Interpretation

Due to the lack of empirical evidence it has not been clear a priori what to expect in terms of findings. Equally there are no clear theoretical predictions of the effect of the timing of daylight on electricity consumption. This is because it is difficult to generate clear theoretical predictions without any empirical guidance, and the relationship is further complicated by the fact that people do not maximize their daily schedules with respect to sunlight and electricity consumption only. Indeed, the timing of daylight certainly matters for individual utility and welfare in many other dimensions.

This study presents the first nationwide empirical assessment of the timing of daylight and residential electricity consumption. Guided by these new empirical results I present a first attempt to rationalism the findings in the following. In particular, I am proposing two different mechanisms to explain the documented associations between daylight and electricity consumption in the North and the South. In any case, I acknowledge that more research is needed to examine these, and potentially other, channels in more detail.

8.1 The demand for cooling in the hot South

According to the US Annual Energy Review (USdOT, 2010), American households used electricity equivalent to 0.88 quadrillion Btu[20] for cooling in 2005, which constituted 20 per cent of overall household electricity consumption. Unfortunately, regional data is not available, but given that the South has a much higher demand for cooling, it follows that electricity use for cooling is responsible for a high share of overall electricity consumption in the hot South.

One possible explanations for the finding that later sunrise could reduce electricity consumption in the South is illustrated by figure 5: the functions show a typical relationship between air temperature and daytime. In particular, the coldest point of the day just after sunrise, whereas the hottest time of the day is in the afternoon.[21] Further assuming that demand cooling is higher when people are awake during daytime, shifting daylight later can result in electricity savings. For instance, if people get up at 7am and go to bed at 11pm and only demand cooling during this time, the area between 7am and 11pm that lies under curve (A) represents potential total demand for cooling. Shifting daylight later, the temperature schedule also shifts as shown by function (B). Since it is colder in the morning than in the evening, the area between 7am and 11pm under function (B) is strictly smaller compared to function (A). Put simply, a relatively later sunrise shifts the hours of human activity into the cooler times of the day, which can potentially result in savings for cooling demand. These effects are exacerbated if people are at work from 9am to 6pm and only demand cooling when at home as the savings from the early morning hours would be a larger proportion of overall consumption of cooling.

This diagram can be used to generate a number of predictions that should be brought back to the data in future research: in particular, a critical assumption is that demand for

[20] One kilowatt-hour=3.412 Btu

[21] Source: http://www.wisegeek.com/what-is-the-coldest-time-of-the-day.htm

cooling is lower when people are asleep. This could imply that the association between timing of daylight and electricity consumption should not hold in the South in months when it is so hot that people leave the air conditioning running 24 hours a day. Future research should address this prediction using seasonal data on electricity consumption in hot areas.

8.2 The demand for lighting in dark mornings in the North

The demand for cooling cannot possibly explain the findings for the North since the overall demand for cooling is low in cold places. Instead, heating mainly relies on fossil fuels rather than electricity, which only makes up about 6.5 per cent of total energy use for residential space heating. Again, no regional information is available, but it seems plausible to assume that colder areas are less likely to use electricity for space heating since fossil fuel is more efficient. As a result it seems unlikely that a temperature-related story gives rise to the patterns documented for the North of the mainland US.

Figure 2 shows that the sun rises at the same local time in the North and South in the annual average. However, what the lower panel of figure 2 does not show is that there is much larger variation in sunrise and sunset times in the North. In the summer, the sun raises extremely early and days are very long, as we can see in the upper panel. During winter days are very short and the sun raises after people would normally get up.

Figure 6 shows that in situations when people get up (and switch on the light) before the sun raises, early sunrise can result in savings. Making a few additional assumptions, this is because the equivalent 'loss' of daylight in the evenings occurs at a point in time when people are still at work. To see this, notice that the top part of figure 6 shows total hours of daylight over the time of the day. Two situations are compared, when the sun rises after people get up in scenario (A) and when the sun rises exactly when people get up, scenario (B). Assuming that people do not consume electricity for lighting when at work, the lower part of the figure backs out the hours when people would need to switch on the light under both regimes. If the sun rises late (A), people consume lighting before going to work and after coming back. In contrast, if the sun is already up when people get up in the morning, they only consume lighting after work (B). Again, future research should examine these channels and test whether, for example, effects only emerge where and when people get up before sunrise.

9 Discussion of results and concluding remarks

In this paper I have shown that the variation in local standard times of sunrise are non-standard across space, and depend on geographical position, time of the year, time zone, daylight savings regime, and position within the time zone. Building on these stylised facts I have demonstrated that two different sources of geographical variation in the timing of daylight can be used in order to estimate the effects on residential electricity consumption. First, variation in the timing of daylight that arises along latitude bands within time zones can be used. Alternatively, we can use differences in local current times that arise in counties in proximity to either side of inland time zone boundaries.

Using the within-time-zone variation in the timing of daylight along geographical latitude bands for estimation, I find no evidence for an overall effect of average sunrise times on residential electricity sales in the most robust specification. However, this finding masks substantial heterogeneity along geographical latitude. In particular, I show that a one-hour-later sunrise in the annual average is associated to an about 16-per cent increase in residential electricity sales in the North. Contrary, in the South a one-hour-later average annual sunrise is associated with a reduction in residential electricity sales of about 13 per cent in the most demanding specification. Especially for the South these estimates are insensitive to the inclusion of a rich set of county level control variables, including industry specialisation, industry employment, population, area, educational levels, median age, climate variables, latitude, a poverty index, and state-times-year fixed effects. Further, the heterogeneity across latitude is shown to be a general pattern that is present throughout latitude quintiles.

Next, the variations in local times across time zone boundaries are used for estimation. Using this totally different source of variation, I can confirm the general pattern of the previous findings. In the most robust specification a one-hour-later average annual sunrise is associated to a six-per cent higher electricity consumption, whereas the effect in the South is estimated to be negative at three per cent in the most demanding specification.

I have also shown in a theoretical discussion of these two sources of variation that the reduced form estimates from within-time-zone variation and at the boundary capture different behavioural responses towards the solar position of the sun and local time. In particular, coordination costs at the boundary could explain why the estimates coming from the boundary variation are lower than those from the analysis that uses the within-time-zone variation in daylight for estimation. Therefore I am not overly concerned by differences in the point estimates, but future research should examine the proposed behavioural responses to explain the differences in findings. This could be done using geographically localised time use data, for example.

In this paper, I also present a first attempt to highlight potential channels that could give rise to this new set of stylised facts, namely that early daylight is associated with increased electricity consumption in the South and lower consumption in the North. I argue that later sunrise in the hot South could shift human activity into the cooler hours of the day, which would then result in electricity savings. In the North, additional assumptions about work times are necessary to generate a situation where earlier sunrise can reduce electricity demand if people get up before sunrise otherwise. I believe that testing these theoretical channels or finding better explanations is a fruitful path for future research.

Finally, another potentially important channel that should be examined by future research are supply side reactions to changes in electricity demand. If we believe my results that early sunrise creates long-term higher demand in the South, for example, then in principle this can be used to estimate the slope of the long-run supply curve of electricity production in the South. This is because a change in demand induced by the timing of daylight is unlikely to enter the production function of electricity directly. As a result, both the within-time zone and the time zone boundary variation in the timing of daylight should be valid instruments for estimating long-run electricity supply.

As a final note of caution, the supply side also matters for the interpretation of the results presented so far. If electricity production, for example, exhibits increasing returns to scale, this would affect the interpretation of the reduced form results that I estimated here. This is because people who live in counties with lower electricity demand would potentially pay higher prices for their electricity, thus further reducing their demand depending on the exact slope of the demand curve. Once the slopes of the supply and demand curves are known, the reduced form effects of daylight on electricity consumption could be decomposed into a price and pure quantity effect.

With all these precautionary notes in mind, interpreting my reduced form findings at face value my results would imply that introducing a new time zone boundary which splits the US horizontally along the median latitude could result in substantial residential electricity savings. In 2005 annual residential electricity sales totalled 124.74 billion US dollars (USdOT, 2010) (Table 2.5). Taking my estimates, this means that introducing a horizontal time zone boundary would result in residential electricity savings of about 13 billion US dollars annually, which is equivalent to over 0.1 per cent of GDP in 2005. However, changing the timing of daylight is likely also to affect other outcomes, in particular expenditure for fossil fuel heating, and these should be examined. Future work should also validate the behavioural channels that give rise to the large effects documented here, either using seasonal, or even better micro-data, as I outlined above.

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Table 1: Residential Electricity Consumption in MWh

	All		Pacific		Mountain		Central		Eastern	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Electricity Cons.	12.10	2.70	10.86	3.46	9.70	2.13	12.85	2.20	11.96	2.75
North (1)	10.63	2.86	13.84	1.82	11.68	1.60	11.04	2.32	7.85	1.55
(2)	10.42	2.05	9.90	2.23	9.45	1.31	11.31	1.65	10.18	2.13
(3)	12.29	2.51	7.44	1.48	8.54	0.92	12.39	1.47	13.48	1.71
(4)	13.28	2.31	7.94	2.48	7.85	2.10	13.85	1.76	13.75	1.25
South (5)	13.82	1.86	8.74	2.32	9.26	1.92	14.09	1.65	14.12	0.83
N	26891		1527		2744		12389		10231	

Notes Average per-customer residential energy sales in MWh. Data from the U.S. Department of Energy, forms EIA-f826 and EIA-f861 and utility-level residential energy sales from 2001 to 2009 are matched to US counties based on area of operation of respective utility. Number of counties matched: over 2600, about 1300 in Central TZ, 900 in Eastern, 250 in Mountain and 100 in the Pacific TZ. The first row gives averages for all mainland counties. NORTH (1) to SOUTH (5) divide the USA into five latitude-bands based on the percentile of county centriod. Counties weighed by 2001 census population.

Table 2: Cooling and Heating Degree Days

	All		Pacific		Mountain		Central		Eastern	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Cooling Degree Days	4.56	1.81	2.77	1.47	2.98	1.37	5.38	1.64	4.33	1.65
NORTH (1)	2.46	0.69	1.83	0.68	2.41	0.80	2.89	0.50	2.30	0.49
(2)	3.42	0.85	2.45	0.75	2.43	0.83	4.21	0.59	3.25	0.67
(3)	4.39	0.96	3.28	1.02	2.54	0.99	5.11	0.26	4.37	0.68
(4)	5.20	1.01	4.39	1.33	3.42	1.17	5.75	0.57	4.96	0.92
SOUTH (5)	7.10	0.87	5.88	1.93	5.40	1.13	7.21	0.66	7.18	0.84
Heating Degree Days	5.39	2.02	5.92	1.65	7.10	1.49	5.00	2.11	5.40	1.89
NORTH (1)	7.86	0.74	6.92	0.94	8.08	0.67	8.18	0.40	7.90	0.48
(2)	6.87	0.66	6.62	0.89	7.75	0.73	6.96	0.55	6.76	0.60
(3)	5.54	0.86	5.09	1.51	7.49	0.78	5.42	0.39	5.46	0.58
(4)	4.35	0.82	4.32	1.15	6.13	1.07	4.21	0.45	4.28	0.82
SOUTH (5)	2.55	0.77	2.64	0.70	4.25	0.76	2.64	0.54	2.19	0.82
N	2617		108		250		1317		942	

Notes: Index for heating and cooling degree days in the USA by latitude and time zone. HDD and CDD are indexed from 1 to 7. (HDD: 1 under 1001, 2 1001-2000, 3 2001-3000, 4 3001-4000, 5 4001-5000, 6 5001-6 > 000, 7 6001+. CDD: 1 under 101, 2 100-400, 3 701-1000, 4 701-1000, 5 1001-1500, 6 1501-2000, 7 2001-2500). Source: U.S. Department of Commerce, National Climatic Data Centre, NOAA Satellite and Information Service, NNDC Climate Data, GIS map in ESRI shapefile format, county-level data calculated using the ï£¡zonal statisticsï£¡ tool. The first row for each panel gives averages for all mainland counties. NORTH (1) to SOUTH (5) divide the USA into five latitude-bands based on the percentile of county centriod. Counties weighed by 2001 census population..

Table 3: Within-TZ analysis: the timing of daylight and residential electricity use

	All latitudes			North			South		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Av. Sunrise Time	0.198**	0.114**	-0.002	0.341**	0.250**	0.163**	-0.161**	-0.162**	-0.131**
	(0.020)	(0.017)	(0.017)	(0.022)	(0.023)	(0.026)	(0.016)	(0.015)	(0.023)
N	26891	26891	26891	13511	13511	13511	13380	13380	13380
Adj. R2	0.16	0.45	0.79	0.24	0.38	0.74	0.64	0.70	0.80
Controls		✓	✓		✓	✓		✓	✓
State FX			✓			✓			✓

Sunrise-time is annual average in local time. All regressions include dummy variables for the year of observation interacted with time zone. Data is for mainland USA countries from 2001 to 2009. Residential energy consumption measure as before. Controls are: year-specific ln(employment), [ln(emp)]2, and index of industry specialisation (which is the number of employees in dominant two-digit industry divided by overall employment), also entered squared, and average Heating Degree Days (HDD), average Cooling Degree Days (CDD), latitude for county centroid, land area, population on 1st July 2001, median age of population in 2000, educational attainment, high school graduate or higher (rate from 1990), persons below poverty level, persons under 18 years of age (percent). North-South split is by latitude-median of county centroids. Standard errors in parentheses and clustered at county level.

** $p < 0.01$

Table 4: TZ boundary analysis: the timing of daylight and residential electricity use

	All latitudes			North			South		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	0.055**	0.042**	0.033**	0.094**	0.089**	0.060**	-0.024*	-0.021	-0.030**
	(0.023)	(0.018)	(0.012)	(0.027)	(0.023)	(0.019)	(0.014)	(0.013)	(0.012)
Boundary Dummy	-0.033*	-0.030**	-0.052**	-0.095**	-0.122**	-0.096**	0.008	0.029**	0.017
	(0.019)	(0.014)	(0.010)	(0.017)	(0.016)	(0.015)	(0.013)	(0.011)	(0.011)
Controls		✓	✓		✓	✓		✓	✓
State FX			✓			✓			✓
N	26891	26891	26891	13511	13511	13511	13380	13380	13380
Adj. R2	0.01	0.45	0.79	0.11	0.36	0.74	0.45	0.67	0.81

Sunrise-time is annual average in local time. For definition of *tzboudnary* and *treatment* look at Figure 4. Data is for mainland USA countries from 2001 to 2009. Residential energy consumption measure as before. Controls are: year-specific ln(employment), [ln(emp)]2, and index of industry specialisation (which is the number of employees in dominant two-digit industry divided by overall employment), also entered squared, and average Heating Degree Days (HDD), average Cooling Degree Days (CDD), latitude for county centroid, land area, population on 1st July 2001, median age of population in 2000, educational attainment, high school graduate or higher (rate from 1990), persons below poverty level, persons under 18 years of age (percent). North-South split is by latitude-median of county centroids. Standard errors in parentheses and clustered at county level.

* $p < 0.05$, ** $p < 0.01$

Table 5: Main results robustness: Including a quadratic term for average sunrise time

	All latitudes			North			South		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Av. Sunrise Time	3.206**	3.725**	3.927**	5.470**	7.177**	3.710**	-0.251	-0.057	3.985**
	(0.857)	(0.657)	(0.753)	(0.924)	(0.806)	(1.183)	(0.680)	(0.569)	(0.891)
Squared: Av. Sunrise Time	-0.223**	-0.267**	-0.291**	-0.379**	-0.513**	-0.262**	0.007	-0.008	-0.305**
	(0.063)	(0.049)	(0.056)	(0.069)	(0.060)	(0.087)	(0.051)	(0.042)	(0.067)
Marginal Ef.	0.190**	0.104**	-0.008	0.354**	0.257**	0.174**	-0.161**	-0.163**	-0.158**
	(0.020)	(0.017)	(0.017)	(0.020)	(0.022)	(0.026)	(0.017)	(0.017)	(0.024)
N	26891	26891	26891	13511	13511	13511	13380	13380	13380
Adj. R2	0.16	0.46	0.79	0.26	0.41	0.74	0.64	0.71	0.81
Controls		✓	✓		✓	✓		✓	✓
State FX			✓			✓			✓

Regressions as in Table 3 but with quadratic term. Marginal effects estimated at means of respective sample.

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

Table 6: Main results by five latitude bands

	(1)	(2)	(3)
NORTH (1)	0.217**	0.179**	0.178**
	(0.026)	(0.027)	(0.038)
N	5418	5418	5418
Adj. R2	0.62	0.67	0.79
(2)	0.373**	0.282**	0.194**
	(0.027)	(0.033)	(0.039)
N	5438	5438	5438
Adj. R2	0.38	0.49	0.65
(3)	-0.011	-0.039	0.010
	(0.029)	(0.023)	(0.019)
N	5263	5263	5263
Adj. R2	0.68	0.76	0.87
(4)	-0.242**	-0.195**	-0.101**
	(0.023)	(0.024)	(0.031)
N	5394	5394	5394
Adj. R2	0.70	0.76	0.86
SOUTH (5)	-0.154**	-0.167**	-0.222**
	(0.023)	(0.021)	(0.042)
N	5378	5378	5378
Adj. R2	0.51	0.64	0.69
Controls		✓	✓
State FX			✓

Standard errors in parentheses & clustered at county level.

* $p < 0.05$, ** $p < 0.01$

Table 7: Main results robustness: Utilities serving at most 10 counties or at most 1 county

	All latitudes			North			South		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A:									
Av. Sunrise Time	0.177**	0.088**	0.003	0.327**	0.220**	0.191**	-0.172**	-0.184**	-0.134**
	(0.024)	(0.021)	(0.023)	(0.029)	(0.030)	(0.037)	(0.020)	(0.021)	(0.032)
N	23179	23179	23179	11688	11688	11688	11491	11491	11491
Adj. R2	0.13	0.38	0.65	0.21	0.33	0.60	0.49	0.59	0.67
Panel B:									
Av. Sunrise Time	0.069*	0.014	0.087*	0.152**	0.091	0.190**	-0.201**	-0.204**	-0.094
	(0.034)	(0.035)	(0.043)	(0.039)	(0.047)	(0.059)	(0.033)	(0.034)	(0.063)
N	9498	9498	9498	5618	5618	5618	3880	3880	3880
Adj. R2	0.05	0.29	0.59	0.11	0.20	0.49	0.39	0.51	0.64
Controls		✓	✓		✓	✓		✓	✓
State FX			✓			✓			✓

Regressions as in Table 3. Panel A uses only utilities that serve at most ten counties for the calculation of county level residential electricity consumption to minimise measurement error. Panel B uses only utilities that serve exactly one county. Here county level residential electricity consumption can be exactly calculated, at the cost of loosing 65% of counties.

* $p < 0.05$, ** $p < 0.01$

Figures

Figure 1: Length of the solar day, sunrise to sunset

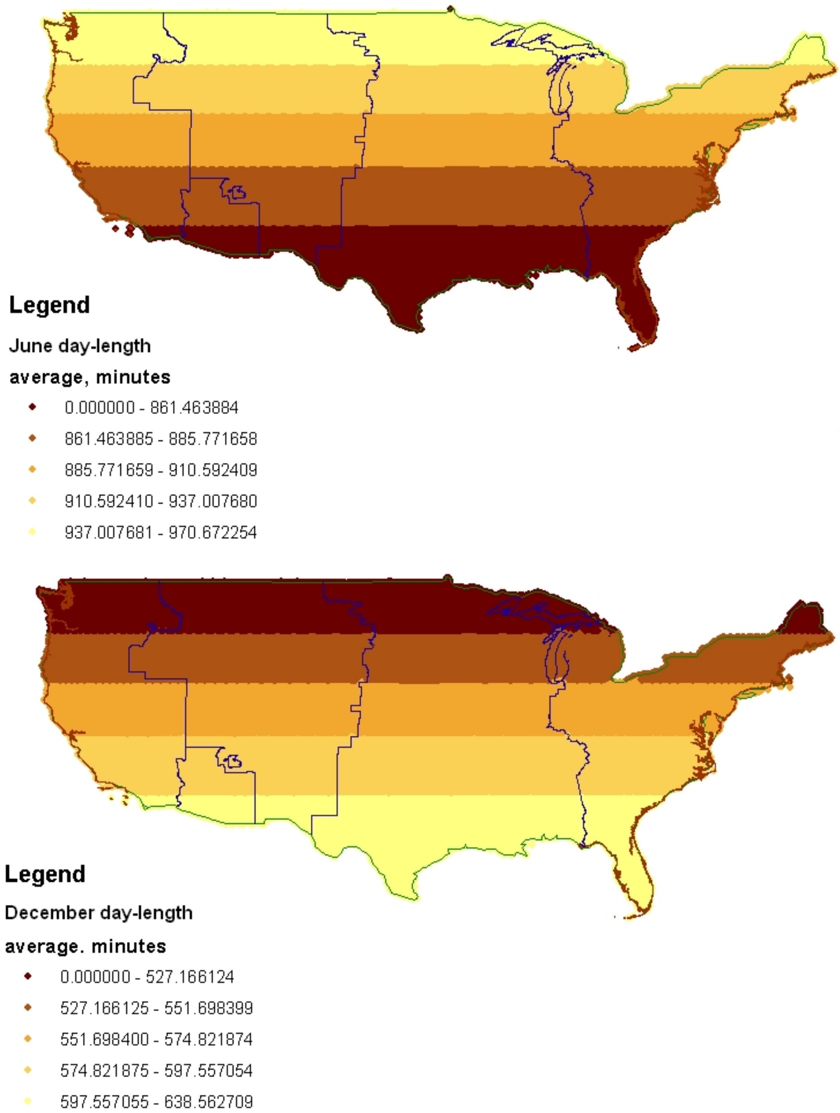


Figure 2: Local standard time of sunrise, June, December and Annual Average

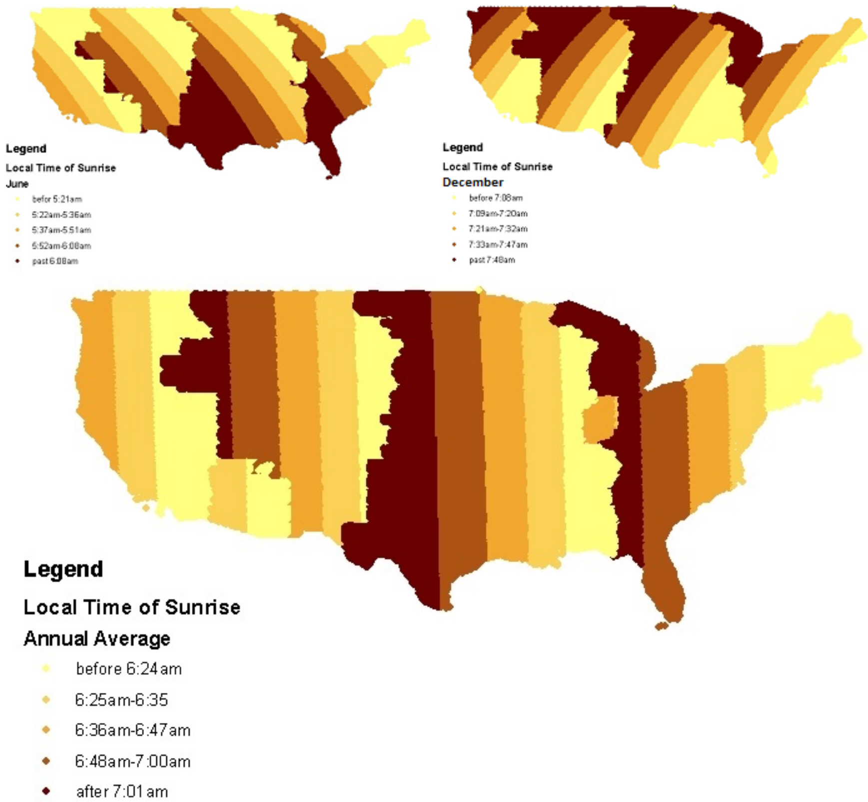


Figure 3: Model: some intuition first

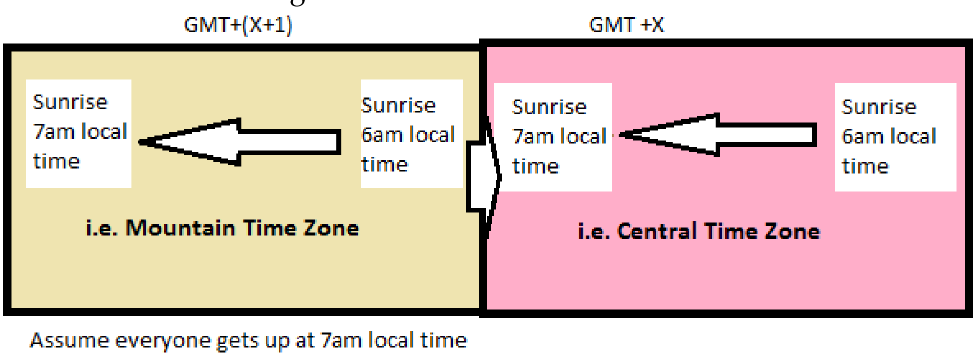


Figure 4: Boundary counties to inland time-zones, excluding Arizona

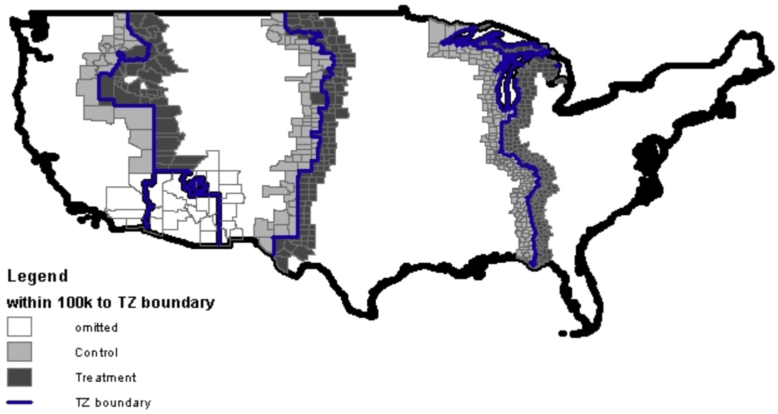


Figure 5: South: later daylight reduced demand for cooling

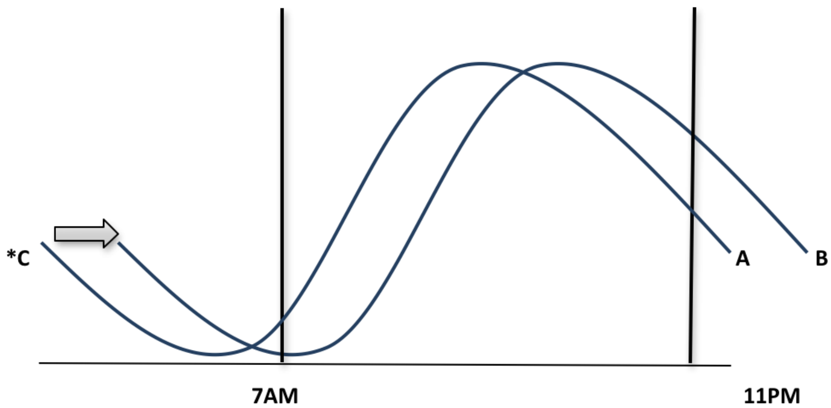
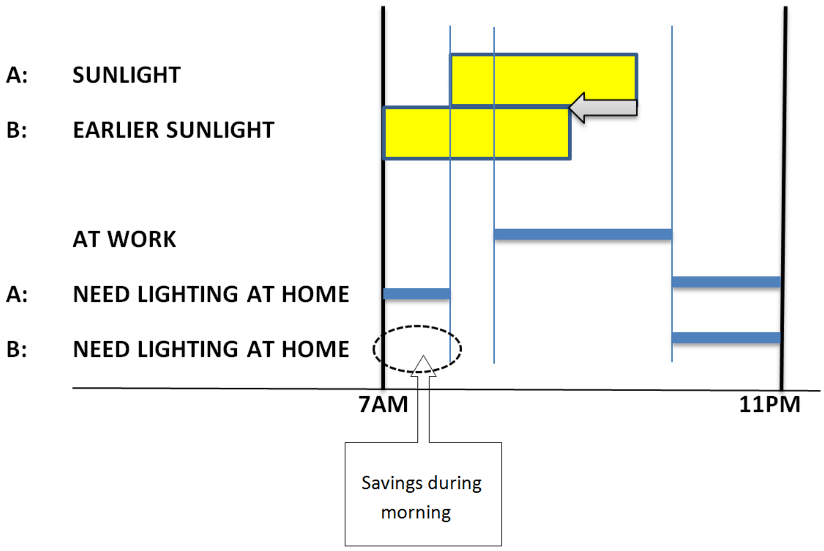


Figure 6: North: earlier daylight reduced demand for lighting



Appendix

Table A.1: County-level control variables

	All		Pacific		Mountain		Central		Eastern	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Population	154321.86	404043.91	398943.26	1052533.16	140465.16	357415.93	104236.65	308626.45	163492.12	275505.79
NORTH (1)	113523.52	202639.97	175691.37	287549.72	44446.81	59877.23	83667.49	155654.64	141252.39	217335.84
(2)	220006.11	430467.83	96042.12	95941.16	168278.36	226491.84	153891.30	572117.97	260886.44	383647.83
(3)	112297.43	211054.63	310562.46	436385.75	100505.19	164698.27	80403.91	147613.91	98185.43	167459.81
(4)	108584.05	205455.41	682318.49	598020.16	95939.09	129144.21	64438.49	108424.12	102943.84	140589.65
SOUTH (5)	201019.32	678989.10	3003335.89	3787174.65	437193.40	877075.18	132460.25	342584.65	157678.16	263005.51
Land Area	955.81	1416.78	2907.60	3259.36	3020.42	2766.38	746.50	431.65	555.86	397.72
NORTH (1)	1265.98	1198.67	1952.46	1369.84	2520.74	1776.43	870.95	677.37	921.92	823.13
(2)	816.15	1241.60	4536.92	3625.07	2051.05	2010.02	611.88	236.87	536.22	262.82
(3)	710.28	1112.66	1935.24	3004.44	1964.69	1296.16	622.13	221.83	400.46	170.10
(4)	1028.91	2058.50	6364.90	5504.57	5074.34	4384.97	676.57	263.97	482.48	198.11
SOUTH (5)	977.34	1108.59	3766.93	1679.38	4783.30	2630.24	846.86	451.52	624.50	362.13
Median Age	36.50	3.68	36.14	4.60	34.70	4.84	36.23	3.55	37.05	3.33
NORTH (1)	37.16	3.77	36.78	4.16	35.54	5.14	37.18	3.56	37.94	2.94
(2)	36.72	3.26	36.56	5.36	32.70	4.80	36.87	3.43	37.09	2.45
(3)	36.75	3.44	36.54	4.88	36.10	4.04	36.64	3.64	36.93	2.91
(4)	36.36	3.38	33.37	4.08	34.70	5.21	36.49	3.10	36.67	3.18
SOUTH (5)	35.62	4.33	33.86	4.38	34.35	3.56	34.99	3.54	36.99	5.29
Education	71.12	10.02	77.72	7.11	77.93	9.14	69.96	9.92	70.18	9.84
NORTH (1)	77.63	5.71	79.61	5.77	79.14	6.56	76.98	5.79	76.78	4.82
(2)	77.11	5.73	77.08	4.15	83.80	6.51	78.27	4.75	75.92	5.54
(3)	71.09	10.48	78.36	8.02	80.59	8.69	72.60	8.53	67.81	10.60
(4)	64.25	9.32	73.07	6.92	71.35	9.12	64.18	8.89	62.84	9.20
SOUTH (5)	65.99	9.39	70.10	11.37	69.18	8.26	65.10	9.24	67.01	9.53
Poverty Rate	20.00	7.99	20.63	7.67	20.89	9.47	20.32	8.17	19.50	7.62
NORTH (1)	16.23	5.76	17.96	4.79	19.53	7.16	13.72	5.25	17.28	5.04
(2)	15.36	5.92	21.97	7.98	13.77	5.31	14.13	4.40	15.62	6.08
(3)	19.15	7.79	20.37	8.46	18.68	9.04	18.19	6.02	19.57	8.40
(4)	23.02	6.88	25.73	7.88	29.04	9.27	23.34	6.71	21.87	6.26
SOUTH (5)	25.98	7.78	30.80	10.74	29.63	7.24	25.75	7.78	25.72	7.55
Industry Spec.	0.26	0.10	0.21	0.07	0.24	0.10	0.26	0.10	0.26	0.10
NORTH (1)	0.24	0.08	0.21	0.06	0.25	0.11	0.27	0.09	0.23	0.06
(2)	0.25	0.09	0.24	0.08	0.22	0.09	0.25	0.09	0.25	0.09
(3)	0.26	0.09	0.21	0.09	0.25	0.10	0.25	0.09	0.27	0.10
(4)	0.28	0.11	0.19	0.05	0.26	0.08	0.29	0.11	0.29	0.11
SOUTH (5)	0.25	0.10	0.18	0.07	0.22	0.09	0.25	0.10	0.26	0.10
Employment	35392.16	134444.38	99248.83	348241.04	19937.03	96567.02	22758.57	103083.08	45243.56	115045.41
NORTH (1)	24541.91	77751.64	42996.32	123072.34	6252.29	17752.56	19842.29	65956.20	39816.05	90817.44
(2)	56504.21	164213.71	21294.05	38019.53	29758.29	83415.78	29359.00	163178.63	88056.00	179921.12
(3)	25684.37	77950.56	86175.28	186269.90	11763.48	36436.79	18359.23	58189.35	25482.55	67429.96
(4)	26550.03	74033.12	205743.09	224925.70	16219.75	42429.73	15380.98	46266.32	31553.63	74851.73
SOUTH (5)	43670.77	212213.57	1078392.30	1370528.48	91445.76	299237.52	28996.59	125634.13	34969.90	92032.99

Notes: Number of counties: 2979, 170 in Pacific, 305 in Mountain, 1375 in Central and 1129 in Eastern time zone. Variable descriptions: From ICPSR 2896 Historical, Demographic, Economic, and Social Data, DS81: 2000 County Data Book (County and State): Population in 2001 (July 1), Land area in square miles, Median age in 2000, Education: Educational attainment, high school graduate or higher (1990), Poverty Rate: Persons below poverty level, persons under 18 years of age (percent). From County Business Pattern, averages for 2001 to 2009: Industry specialisation: main two-digit employer divided over total industry employment. Employment: total employment. The Census 2001 county-level population information is used as analytic weight.

Table A.2: Residential electricity consumption in MWh for time zone boundary counties

	All		Pacific		Mountain		Central		Eastern	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Electricity Cons.	12.06	2.70	12.16	1.71	10.90	2.10	11.41	2.80	12.67	2.65
NORTH (1)	9.57	2.40	12.85	1.10	12.29	1.40	8.82	1.26	7.32	0.81
(2)	10.97	1.77	11.41	2.15	10.72	1.67	10.03	1.42	11.52	1.66
(3)	13.36	1.86	10.52	1.23	8.39	1.03	12.84	1.70	14.11	0.99
(4)	13.90	2.04	.	.	9.38	1.68	14.17	2.34	14.16	1.27
SOUTH (5)	13.37	1.88	.	.	9.40	1.53	13.22	1.90	14.04	0.89
N	5508		369		1062		1746		2331	

As in Table 1 but only for the 612 countries at time zone boundary, see Figure 4

Table A.3: Cooling and Heating Degree Days for time zone boundary counties

	All		Pacific		Mountain		Central		Eastern	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Cooling Degree Days	4.25	1.46	2.32	0.79	3.68	1.16	4.24	1.41	4.59	1.40
NORTH (1)	2.45	0.61	1.96	0.64	2.92	0.77	2.60	0.46	2.19	0.35
(2)	3.63	0.59	2.64	0.47	3.58	0.33	3.77	0.57	3.71	0.48
(3)	4.80	0.47	3.32	0.90	4.22	0.78	5.00	0.00	4.86	0.27
(4)	4.87	0.50	.	.	4.44	0.77	5.03	0.26	4.81	0.54
SOUTH (5)	6.39	0.79	.	.	5.10	1.08	6.38	0.59	6.59	0.63
Heating Degree Days	5.79	1.86	7.47	0.95	6.63	1.59	6.02	1.95	5.31	1.74
NORTH (1)	8.00	0.66	7.63	1.05	7.75	0.81	8.21	0.45	8.03	0.37
(2)	6.95	0.48	7.44	0.49	7.22	0.44	7.04	0.54	6.79	0.37
(3)	5.42	0.55	6.78	0.91	6.33	0.52	5.30	0.43	5.31	0.37
(4)	4.58	0.56	.	.	4.98	0.82	4.46	0.46	4.62	0.57
SOUTH (5)	2.99	0.73	.	.	4.34	0.94	3.07	0.50	2.74	0.55
N	612		41		118		194		259	

Notes: As in Table 2 only for countries at time zone boundary, see Figure 4

Table A.4: Control variables for TZ-boundary counties

	All		Pacific		Mountain		Central		Eastern	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Population	103227.90	348927.73	42341.31	31397.32	42286.01	63554.73	169484.72	576696.51	77594.61	121466.15
NORTH (1)	80259.78	137996.17	41859.62	34066.57	57447.82	84393.50	118281.03	175999.61	58290.39	123415.66
(2)	239094.06	769162.94	39202.68	18969.32	16441.96	12936.75	577024.92	1277085.36	78473.83	66122.23
(3)	55963.05	99783.66	50465.81	41154.64	10548.25	6270.95	39435.36	41977.82	66127.96	119289.80
(4)	87868.25	142556.07	.	.	22826.96	14752.99	65444.29	63399.40	106581.05	175357.77
SOUTH (5)	63721.16	60508.07	.	.	44515.26	22005.27	60253.90	56677.97	68454.02	66122.81
Land Area	933.96	1415.71	3729.93	3652.10	2357.25	1693.68	751.61	727.03	482.21	230.76
NORTH (1)	1246.06	1158.29	2187.18	1394.31	1862.25	1335.86	986.97	1060.17	763.64	350.84
(2)	1162.20	2395.18	7131.23	5405.09	1830.25	743.13	607.20	348.95	494.87	161.47
(3)	650.69	1037.53	4145.51	2695.31	2165.86	1499.24	505.54	234.39	369.79	113.58
(4)	585.56	557.63	.	.	2270.68	1367.36	577.33	303.72	438.19	165.90
SOUTH (5)	960.31	1336.96	.	.	4314.80	2077.28	921.99	795.69	461.56	196.25
Median Age	36.19	3.51	34.50	5.78	35.44	4.51	36.42	3.17	36.36	3.12
NORTH (1)	37.69	4.26	37.18	5.35	35.39	5.23	37.97	3.16	38.97	3.86
(2)	35.17	3.21	30.72	3.14	39.31	2.71	34.63	3.00	35.87	2.54
(3)	35.97	3.12	29.79	4.77	37.13	3.04	36.58	3.51	36.05	2.36
(4)	36.36	2.76	.	.	33.16	3.84	36.17	2.30	36.76	2.71
SOUTH (5)	34.94	2.93	.	.	34.19	2.08	35.51	2.68	34.77	3.15
Education	69.73	10.58	79.17	5.44	73.53	8.52	70.83	10.34	67.26	10.60
NORTH (1)	76.38	6.00	79.29	5.33	76.24	7.78	76.86	5.56	74.28	4.99
(2)	77.05	5.46	76.60	5.22	79.21	2.68	79.48	5.35	75.42	5.24
(3)	68.37	9.97	83.54	4.04	73.41	5.43	67.93	8.03	67.19	10.33
(4)	60.68	10.12	.	.	67.42	7.98	61.85	10.35	59.41	9.94
SOUTH (5)	64.15	9.25	.	.	66.91	8.79	63.30	7.92	64.16	9.97
Poverty Rate	19.64	7.87	18.57	5.09	23.39	8.45	17.62	7.69	20.44	7.81
NORTH (1)	17.45	7.07	20.53	3.93	21.42	8.78	13.29	6.35	19.52	4.68
(2)	13.73	4.96	14.08	6.03	16.22	2.64	12.31	5.58	14.36	4.41
(3)	19.06	6.75	18.41	2.24	25.22	7.84	19.29	5.09	18.57	7.26
(4)	22.87	7.23	.	.	30.59	7.67	20.93	5.53	23.29	7.58
SOUTH (5)	26.28	7.20	.	.	26.77	4.56	26.87	5.72	25.90	8.19
Industry Spec.	0.28	0.11	0.23	0.08	0.26	0.13	0.27	0.11	0.29	0.11
NORTH (1)	0.26	0.09	0.21	0.06	0.26	0.14	0.28	0.09	0.26	0.06
(2)	0.28	0.12	0.27	0.10	0.28	0.13	0.21	0.09	0.33	0.12
(3)	0.28	0.10	0.24	0.09	0.29	0.12	0.27	0.10	0.28	0.10
(4)	0.31	0.13	.	.	0.29	0.10	0.32	0.12	0.32	0.13
SOUTH (5)	0.27	0.12	.	.	0.22	0.10	0.28	0.13	0.28	0.11
Employment	44083.09	163082.07	14156.20	13908.27	15702.72	33562.79	73552.36	258944.71	33209.86	81970.77
NORTH (1)	35094.93	72830.12	14011.99	15067.77	24463.73	44997.95	54703.08	90349.13	23666.13	69109.54
(2)	102329.37	343172.89	12484.94	8593.60	4703.72	4331.23	254755.36	562018.94	29559.33	33253.86
(3)	23084.82	56961.35	17985.76	16075.42	2314.91	1592.94	16326.52	26548.00	27588.37	67913.69
(4)	41783.34	108000.56	.	.	4771.37	3866.34	24217.27	31510.23	55187.80	135544.08
SOUTH (5)	21113.23	25777.76	.	.	11615.34	6395.06	20562.06	28371.24	22865.18	25961.55

Notes: Number of counties within 100km of inland boundary: 612, 41 in Pacific, 118 in Mountain, 194 in Central and 259 in Eastern time zone. Variable descriptions as in Table A.1.

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