



An Assessment of the Relationship Between Daylight Saving Time, Disruptions in Sleep Patterns and Dwelling Fires

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Received: 25 July 2019/Accepted: 13 April 2020

Abstract. Residential fires pose threats to living environments, generating costs to health and property. Understanding the roles of human behavior and social organization in determining fire occurrence is important for developing strategies to manage fire risk. This paper tests the impact of daylight saving time (DST) transitions on dwelling fire occurrence. DST transitions affect sleep patterns, impairing human cognitive and motor performance, potentially influencing the incidence of dwelling fires. Employing a regression discontinuity design with time as the running variable and using data from over 260,000 primary dwelling fires that took place in the U.K. over 8 years we do not find evidence suggesting that DST transitions impact on dwelling fire occurrence. For both the start of DST and end of DST transitions, estimated effects is quantitatively small and statistically insignificant. Results suggest that disruptions in sleep patterns induced by DST are not a driver of dwelling fires in the U.K.

Keywords: Dwelling fires, Sleep disruptions, Regression discontinuity, Daylight saving time

1. Introduction

Residential fires threaten living environments impacting on human welfare through injury, property and amenity loss. The majority of fire-related injuries in many countries around the world is due to residential fires [29, 30], while experiencing fire has severe medium and long term psychological effects [31, 32, 35]. Policies and social organization norms that are seemingly unrelated to fire safety can affect behavior and inadvertently influence residential fire occurrence. Understanding the links between policy, social organization, behavior and fire occurrence is important for assessing risk and developing robust fire safety strategies.

This paper examines whether elements of energy policy affect fire occurrence, focusing on the impact of daylight saving time (DST) transitions. This allows to explore the response of fire occurrence to aspects of behavior for which data are typically unavailable. In particular, examining the impact of DST transitions

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allows to comment on the relationship between disruptions in sleep patterns and residential fire occurrence. Individuals allocate time between work and leisure activities, and coordinate around clock time [20]. Changes in clock time driven by energy policy influence behavior by upsetting patterns of time distribution. Entering DST in Spring costs on average between 40 min and 60 min of sleep and leads to medium term disruption of sleep patterns that can last for up to 2 weeks¹ [4, 21, 51]. DST-induced disruptions in sleep patterns affect circadian rhythms [21, 34], increase accidents [4, 52] and impact health [57]. Exploring whether a link exists between residential fire occurrence, DST and sleep can assist in designing fire safety policies and information campaigns especially as sleep deprivation is becoming increasingly prevalent in contemporary societies [7, 59].

To assess the role of DST transitions and comment on the impact of sleep pattern disruption on dwelling fires, U.K. data recording all fire incidents from 2010 to 2018 are used. We employ a Regression Discontinuity Design with time as the running variable to compare fires on the days just before, against the days just after DST transitions [23, 41]. Should DST transitions impact fire occurrence, we would expect to observe a change in dwelling fires immediately following the start of DST in Spring, while a similar pattern should not be expected for the end of DST in Autumn when sleep duration is unaffected.

The paper contributes to the literature on the determinants of residential fire risk [22, 29, 30, 58]. To the best of our knowledge, this is the first paper to employ a quasi-experimental approach, assessing the causal effect of disturbances on the temporal organization of individual and social activity on dwelling fire occurrence, and to explicitly explore the role of the sleep mechanism. The paper further adds to the growing literature investigating the impact of DST on human behavior [4, 15, 26, 36, 39, 45, 52].

A small literature investigates the determinants of dwelling fire risk [12]. Most studies exploit spatial variation at the regional or neighborhood level to examine socio-demographic and economic correlates of residential fire risk [29, 30, 58], and characterize vulnerable populations [43, 55, 62, 63]. Jennings [30] highlights that socioeconomic deprivation is positively correlated with vulnerability to fire incidents. Hastie and Searle [22] look at the determinants of fire risk in the UK Midlands region and find that individual and area-wide socioeconomic characteristics including the proportion of single person households and local unemployment rates are significantly correlated with the incidence of accidental residential fires. Similarly, Duncanson, Woodward, and Reid [17] use cross-sectional data from New Zealand to explore the role of socioeconomic conditions on domestic fire incidents finding a positive correlation between fire occurrence and economic deprivation levels. Chhetri et al. [10] show that socioeconomic disadvantage approximated by unemployment rates and single parent families among others, contribute to increased fire rates in South East Queensland, Australia. Guldåker and Hallin [19] find that the incidence of intentional fires in Malmö, Sweden is positively correlated with social stress factors including the prevalence of unemployment, and overcrowding in living arrangements. It merits mentioning that the

¹ Contrary to the start of DST, exiting DST has no influence on time allocated to sleep [4, 51].

relationships presented in the aforementioned studies do not have causal interpretation due to the presence of unobserved confounders affecting both socioeconomic deprivation and fire occurrence.

Fewer studies examine the role of individual behaviors in inducing fire incidents. Ballard et al. [3] and Ducic and Ghezzi [16] for example, discuss the role of smoking in causing fire incidents. Xiong et al. [63] explore the significance of the human factor as a driver to residential fires conducting detailed interviews with people who survived accidental residential fires, concluding that over 40% were caused by human unsafe behaviors including leaving cooking unattended or placing combustible material close to heat sources. Furthermore, Xiong et al. [62] find that the likelihood of injury in fire is significantly correlated with being asleep. A strand of research explores mechanisms for interrupting sleep as means of reducing the risk of injury in fire. Bruck [8] and Thomas and Bruck [54] present comparisons of smoke alarm signals, assessing the probability that people are woken by the alarm.

The paper proceeds as follows: The next section discusses the relationship between DST transitions and sleep disruptions and summarizes the some of the relevant literature. Section 3 describes the data and presents the empirical approach. Section 4 presents the results, while Sect. 5 concludes.

2. Daylight Saving Time and Sleep

Daylight saving time was first introduced in the early twentieth century and is still in use in about 70 countries around the world aiming to reduce energy consumption by making better use of available sunlight. Since 2002, DST in the EU begins on the last Sunday of March when clocks move forward by 1 h. DST ends on the last Sunday of October when clock time moves back by 1 h, returning to Standard Time. The effectiveness of the policy as an energy saving mechanism is disputed. Evidence suggests that DST's impact on energy use is limited and location-dependent [11, 36, 38, 50, 60]. Given the mixed evidence regarding the policy's energy saving potential, EU members will phase out transitions and permanently switch to Standard or Summer time by 2022.

Multiple complementary theories have been proposed for the exact function of sleep, including energy conservation [6], tissue restoration [1] and memory consolidation [13] among others [27, 42]. Irrespective of the exact mechanism, sleep has important implications for human functioning and activity. Sleep improves performance in perceptual and categorization tasks [27, 44, 53]. On the other hand, lack of sleep impairs human performance [48], disrupts daytime functioning [61], upsets cognitive and motor skills [49], induces mood disturbances [14], impacts communication skills [25], and increases workplace accidents [4, 37].

DST affects human behavior through its influence on sleep duration and sleep patterns. Barnes and Wagner [4] use data from the American Time Use Survey (ATUS) and show that self-reported sleep duration decreases by approximately 40 min following start of DST in Spring but find no comparable effect from the end of DST. Sexton and Beatty [51] also use ATUS data to compare time spent sleep-

ing, at home and away from home in the days before and after a DST transition. They find that following the Spring transition into DST people sleep less spending additional time at home while the effects can be detected for at least a week. Lahti et al. [40] using diary data find that sleep duration is reduced by approximately 60 min while sleep efficiency suffers. While the quantitative impact of the transition in terms of minutes of sleep lost may appear small [45], sharp changes in clock time affect circadian rhythms and disrupt sleep patterns with longer term effects² [34].

Disruptions in sleep patterns due to DST impair human performance, impacting on behavior and activity. Kamstra et al. [33] argue that sleep imbalances following DST transitions lead to lower stock market performance while Nofsinger and Shank [47] show that reduced sleep quality impacts financial decision making, as agents become more susceptible to present bias and have greater discount rates. Kountouris and Remoundou [39] find that transitions lead to lower self-reported life satisfaction and worse mood, using data from the German Socioeconomic Panel. Toro et al. [57] find that myocardial infarction increases in the aftermath of DST. Importantly for the present paper, evidence suggests that a relationship exists between sleep and accident occurrence. Barnes and Wagner [4] show that workplace accidents increase following the start of DST, when sleep duration decreases by approximately 40 min, but do not find a comparable effect following the end of DST when sleep duration is unchanged. They conclude that the sleep mechanism is an important causal determinant of workplace accidents. Sleepiness and drowsiness are leading causes of traffic accidents attributed to human error [37]. Following Timoth and Folkard [56] who first noted a link between DST and traffic accidents in the UK, a growing literature examines the relationship between traffic accidents and DST transitions, assessing sleep disruptions and changes in light availability as the primary causal mechanisms [2, 46, 52].

DST transitions do not always have a detrimental effect on observed measures of human performance. Herber et al. [24] for example examine the impact of DST on cognitive performance using data from assessments of over 22,000 students in European countries. They find a quantitatively minimal and statistically insignificant impact from transitions. This suggests that while DST might impact human sleep patterns, the disturbance may not be large enough to lead to noticeable effects.

3. Data and Empirical Approach

3.1. Data

Data used in this paper come from the U.K. Home Office-collected, incident level dataset.³ The dataset includes information on all incidents attended by Fire and Rescue services in England from April 2010 to April 2018. Available information includes the type of incident categorized in (a) Primary Fires, (b) Secondary Fires,

² Harrison [21] provides an extensive review of the relevant literature.

³ Data are available at <https://www.gov.uk/government/statistical-data-sets/fire-statistics-incident-level-datasets>.

(c) False alarms and (d) Non-fire Incidents, the date of the incident and the responding Fire and Rescue service. Primary fires satisfy at least one of the following conditions: (a) The fire occurred in a building, vehicle or outdoor structure, (b) The fire involved fatalities, casualties or rescues, (c) The fire was attended by 5 or more pumping appliances. The analysis focuses exclusively on Primary Fires that occurred in dwellings.⁴

3.2. Empirical Approach

To assess the impact of DST on residential fires we employ a regression discontinuity design [28, 41]. In the potential outcomes framework following the notation of Imbens and Lemieux [28], let D_i denote a binary treatment with $D_i = 1$ if unit i is assigned to the treatment and $D_i = 0$ if not. Also let $Y_i(1)$ denote the outcome with exposure to the treatment and $Y_i(0)$ the outcome without exposure. The observed outcome Y_i can be written as:

$$Y_i = (1 - D_i) \times Y_i(0) + D_i \times Y_i(1) = \begin{cases} Y_i(0) & \text{if } D_i = 0 \\ Y_i(1) & \text{if } D_i = 1 \end{cases} \quad (1)$$

The fundamental problem when evaluating the treatment's impact, is that outcomes $Y_i(1)$ and $Y_i(0)$ are never simultaneously observed for i . In other words the difference $Y_i(1) - Y_i(0)$ is unobserved. Regression Discontinuity Designs take advantage of deterministic rules in the treatment allocation to estimate the treatment's average effect, comparing outcomes between units that were just exposed and just not exposed to the treatment. In a sharp regression discontinuity design, assignment to the treatment is a deterministic function of a forcing (or running) variable X :

$$D_i = \mathbf{I}\{X_i \geq c\} \quad (2)$$

where \mathbf{I} is an indicator function and c the threshold over which unit i receives the treatment. The discontinuity in the conditional expectation of the outcome at the threshold given X is interpreted as the average causal effect of the treatment at the threshold:

$$\tau = \lim_{x \uparrow c} E[Y_i | X_i = x] - \lim_{x \downarrow c} E[Y_i | X_i = x] \quad (3)$$

Inference relies on the continuity of expectation functions $E[Y_i(1)|X]$ and $E[Y_i(0)|X]$, allowing to use the average outcome in units just below the threshold as a counterfactual for the units just above the threshold. The average effect of the treatment, β_1 can be estimated in a single local linear regression,⁵ using observations within a bandwidth h to either side of the threshold:

⁴ Extending the analysis to include all building primary fires does not materially change the qualitatively or quantitatively as shown in Table 2 in the results

⁵ Gelman and Imbens [18] and Hausman and Rapson [23] argue against global polynomials of the running variable in regression discontinuity designs.

$$\min_{\alpha, \beta_1, \beta_2, \beta_3} \sum_{i=1}^N \mathbf{I}\{c - h \leq X_i \leq c + h\} \times (Y_i - \alpha - \beta_1 D_i + \beta_2 (X_i - c) - \beta_3 (X_i - c) D_i)^2 \times K\left(\frac{X_i - c}{h}\right) \quad (4)$$

where $K()$ is a kernel function that assigns different weights to observations depending on the distance from the threshold. In this paper, unit i represents a day-of-year, while i receives the treatment if it falls on or after the relevant DST date. To estimate the effect of DST, we use local linear regressions allowing different slopes to each side of the threshold and apply the two stage augmented local linear approach recommend by Hausman and Rapson [23]. In the first stage, we regress the natural logarithm of dwelling fires on year-specific and day-of-the-week dummy variables, and obtain the residuals. This way we remove the influence of day-of-week specific effects, account for the fact that DST transitions always take place on a Sunday and capture year-specific effects or policy changes that may systematically impact fire occurrence. In the second stage we regress the residualized natural logarithm of dwelling fires on the treatment indicator, the running variable and their interaction as described in Eq. (4). Specifically, the second-stage estimating equation is given by:

$$\ln F_{it} = \alpha + \beta_1 D_{it} + \beta_2 R_{it} + \beta_3 D_{it} \times R_{it} + \epsilon_{it} \quad (5)$$

where $\ln F_{it}$ is the residualized natural logarithm of the number of dwelling fires occurring on day-of-year i in year t . R_{it} is the forcing variable measuring days to and days following either the start of DST transition or the end of DST transition in days. The assignment variable is centered at zero, that is $R_{it} = 0$ on the DST entry and DST exit days. D_{it} is the treatment indicator, a binary variable equal to 1 if day i in year t falls in the relevant DST period and zero otherwise, that is $D_{it} = \mathbf{I}\{R_{it} \geq 0\}$. The coefficient of interest is β_1 capturing the impact of DST on dwelling fires. Estimates from global polynomials of the running variable are presented in later robustness tests. To choose the bandwidth h for the local linear regressions, we use the data driven approach minimizing the mean squared error proposed by Calonico et al. [9]. In later robustness tests, the analysis is repeated when extending and shrinking the bandwidth. We use a triangular kernel for the baseline specification to attach larger weight to observations near the threshold, but in later robustness tests repeat the analysis using uniform and Epanechnikov kernels [41].

The identifying assumption in regression discontinuity designs is that the expectation of the error term is smooth around the threshold or in other words, days to the left and to the right of the threshold are not systematically different. In the context of this paper, this implies that conditions determining daily dwelling fire occurrence do not change sharply at or around the date of a transition. There are valid reasons to expect this assumption to hold. Socio-demographic and economic conditions determining fire incidence change minimally and smoothly from day to day and are not expected to systematically jump on transitions. Furthermore, time

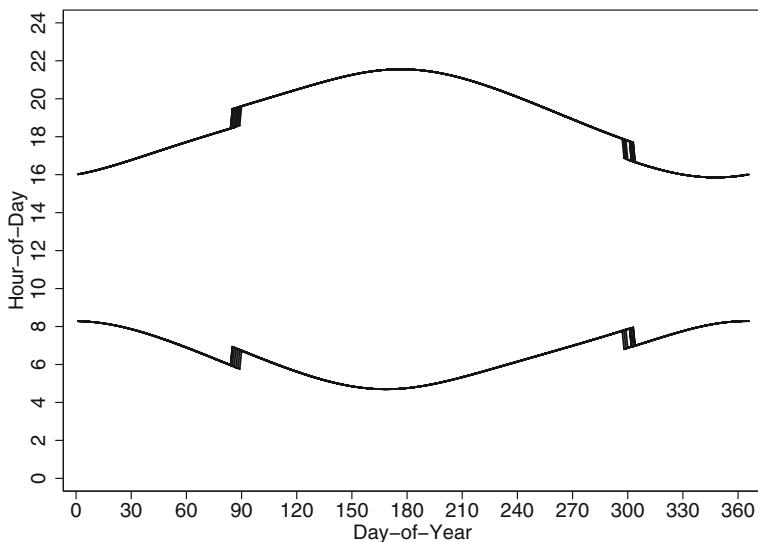
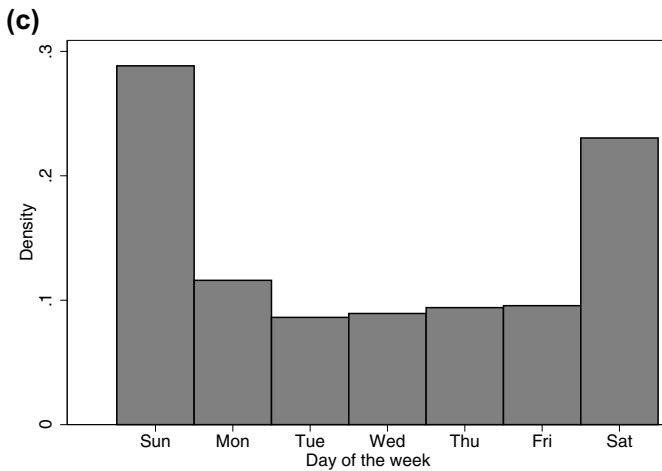
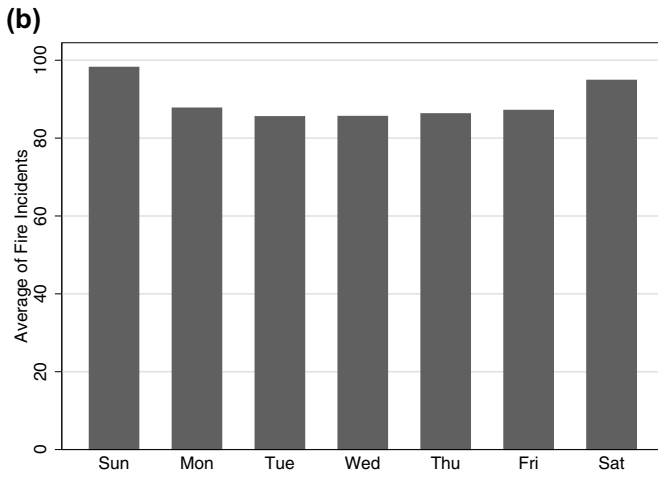
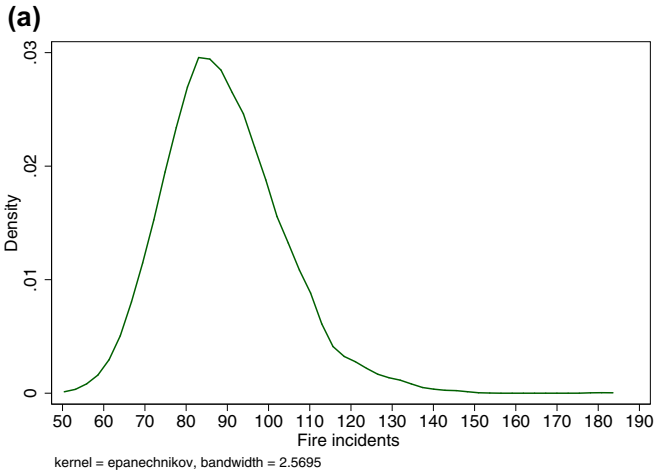


Figure 1. Sunrise and Sunset times at England’s geographic centroid for every day between 2010 and 2018.

varying fire determinants such as temperature are also distributed smoothly over time. In robustness tests we also employ a donut RDD approach [5], repeating the analysis when omitting ± 1 to ± 10 days around the transition threshold to account for unobserved confounders that may change discontinuously at the threshold. Similar approaches for estimating the impact of DST have been applied by Toro et al. [57], Doleac and Sanders [15] and Smith [52] among others.

Figure 1 illustrates the discontinuity motivating the empirical approach. The figure shows sunrise (bottom curve) and sunset (top curve) in local time for each day from 2010 to 2018. Sunrise and sunset times are smooth from 1 January until around the 90th day of the year when a jump is observed. The jump is due to the start of the DST period, when clocks move forward by 1 h, transferring sunrise and sunset in local time 1 h later. From that day onward sunrise and sunset times are smooth until the end of the DST period. As discussed earlier, the jump in local clock time occurring at the Spring transition disrupts sleep patterns, possibly affecting behavior in a way that may influence the number of dwelling fires. Comparing the number of incidents on the days just after the transition against incidents on the days just before the transition, provides an estimate of the immediate effect of DST transition on dwelling fires. If DST induced disruptions in sleep patterns contribute to the incidence of dwelling fires, a quantitatively and statistically significant increase in the number of incidents just after the Spring transition should be observed. Since exiting DST does not disrupt sleep, a significant change in fire occurrence at the second discontinuity is not expected.



◀Figure 2. Dwelling fires over time.**4. Results****4.1. Descriptive Results**

We begin by presenting some descriptive results illustrating the variation of fire occurrence in time. Figure 2a presents the distribution of dwelling fire incidents over the days in the sample. For the period investigated here 89 primary dwelling fire incidents were recorded on average per day (St.Dev. = 14.28), while the minimum and maximum number of incidents in a day is 53 and 181 respectively. Figure 2b shows the distribution of dwelling fires by day-of-week. Average fire incidence is markedly higher on Sundays and Saturdays. We test the equality of mean fire occurrence on Sundays against every other day of the week using t tests. The null of equality is rejected for all conventional significance levels in every case. When focusing on the days with the most fire incidents the results are striking: for the days with over 100 incidents, over 28% are Sundays and 23% Saturdays (Fig. 2c). The descriptive elements of the fire-time relationship suggest cyclicity in fire incidence with incidents peaking during weekends.

Table 1 presents estimates from a regression of fire occurrence on day-of-the week and year specific effects.⁶ Estimates confirm earlier findings. Relative to Sundays, fire incidents are around 14% lower on Tuesdays and Wednesdays and around 12% lower on Mondays and Fridays. Furthermore incidents appear to be decreasing over time. Compared to 2010, there were about 17% fewer incidents in 2013 to 2016 and around 18% fewer fires in 2017 and 2018.

Figure 3 illustrates the relationship between dwelling fire occurrence and time of the year in relation to the DST start and end dates. In both diagrams, the horizontal axis records 12 weeks leading and following DST transitions, while the vertical axis captures the average of fire incidents. Superimposed lines are local polynomial smoothers. A jump in average fire occurrence is observed on the week of DST entry (Fig. 3a) while fire occurrence gradually returns to its pre-transition level within about 5 weeks. A jump is also observed in fire occurrence on the week of exiting DST (Fig. 3b). However this is likely due to the seasonal increase in incidents due to Guy Fawkes Night an annual celebration that involves heavy use of fireworks and bonfires taking place on the 5th of November, that often falls in the week of the DST transition. Supporting this view, fire incidents immediately decrease to pre-transition levels within a week and appear to follow the previous trend.

4.2. Main Results

Figure 4 illustrates the relationship between residualized fires and the assignment variable in deviations from the DST entry date (Fig. 4a) and from the DST exit date (Fig. 4b) to assess the presence of a discontinuity at the threshold. In both panels the vertical axis measures dwelling fire occurrence after adjusting for day-

⁶ We thank an anonymous referee suggesting to present these results.

Table 1
Dwelling Fires, Days-of-Week and Years

	(1)
Monday	– 0.114*** (0.009)
Tuesday	– 0.139*** (0.009)
Wednesday	– 0.137*** (0.009)
Thursday	– 0.130*** (0.009)
Friday	– 0.120*** (0.009)
Saturday	– 0.037*** (0.009)
2011	– 0.040*** (0.011)
2012	– 0.088*** (0.011)
2013	– 0.115*** (0.011)
2014	– 0.166*** (0.011)
2015	– 0.163*** (0.011)
2016	– 0.168*** (0.011)
2017	– 0.189*** (0.011)
2018	– 0.176*** (0.018)
Observations	2922
R-squared	0.258

Depended variable is the natural logarithm of daily dwelling fire incidents. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

of-the-week and year-specific effects. In the case of DST exit we also account for the spike in incidents due to the Guy Fawkes night, controlling for a binary variable equal to 1 if i is the 5th of November. Dots represent the average number of incidents for each day prior to and following a DST transition while solid lines in both sides of the threshold are local linear polynomials estimated using a triangular kernel and a time window of 60 days. A small jump appears in the residualized count of incidents immediately after the start of DST. On the other hand there appears to be no influence on fire incidents from the end of DST in the Autumn.

Table 2 presents the estimated impact of the start and end of DST on dwelling fire incidents. Estimates are derived from Eq. 5, regressing residualized dwelling fires on the post-transition indicator D , the running variable and their interaction.

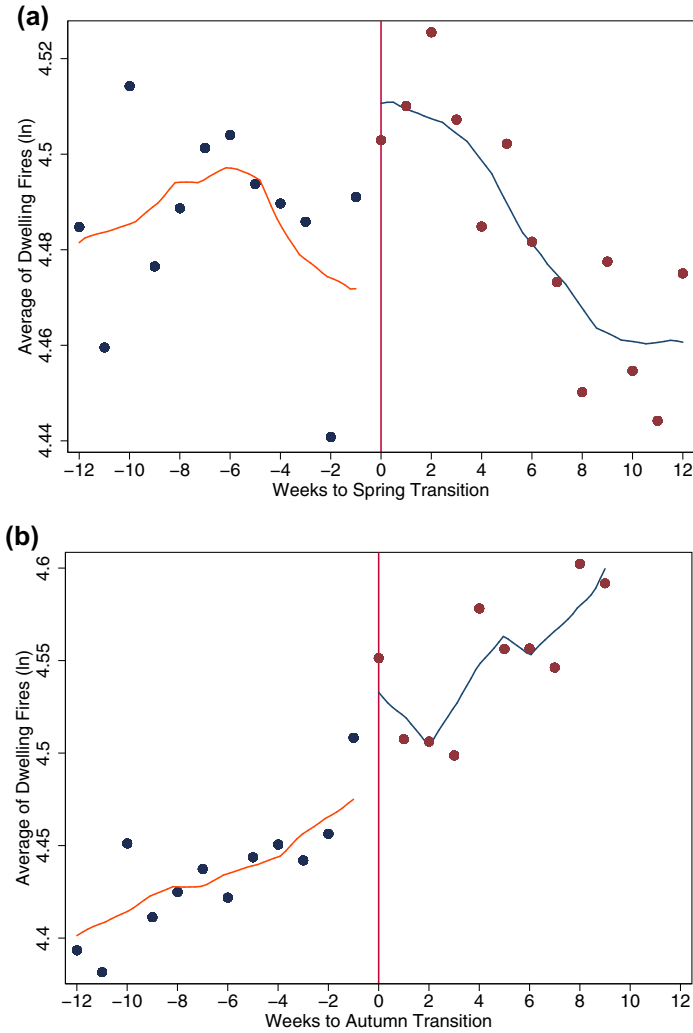


Figure 3. Average raw dwelling fire occurrence in the weeks around each transition.

The start of DST appears to increase incidents by about 3.1%, in accordance with visual evidence in Fig. 4. However the estimated effect is not statistically significant. As expected, the effect of the DST end transition is quantitatively very close to zero and statistically insignificant. Overall, despite the small increase in incidents on the weeks of DST transitions illustrated in Fig. 3, the RDD results suggest that disturbances in sleep patterns do not induce a noticeable change in fire occurrence. Columns 2 and 4 of Table 2 present the estimated impact of the start and end of DST respectively when extending the analysis on all building fire inci-

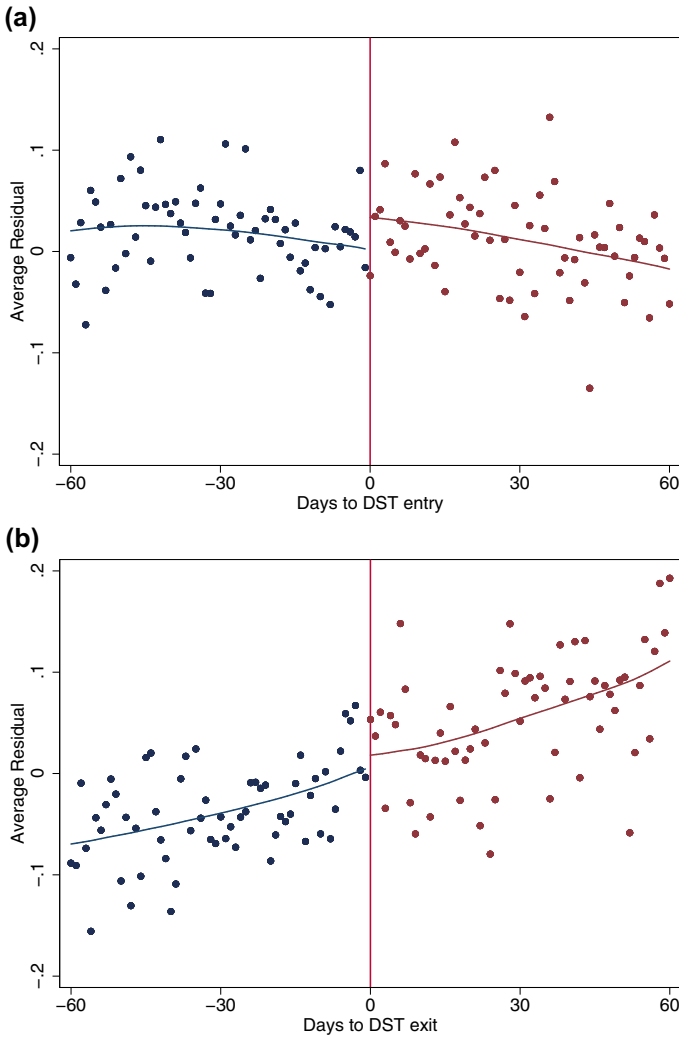


Figure 4. Dwelling fires in days around the start and end of DST transitions.

dents. As in the case of dwelling fires, there appears to be no evidence that DST transitions significantly affect fire occurrence.

4.3. Robustness Tests

The baseline estimates in Table 2 appear to contradict the hypothesis that sleep disruptions impact on the incidence of dwelling fires. Before concluding that this is indeed the case, we assess the results sensitivity to modeling assumptions applying a series of robustness tests.

Table 2
Building Fires Around the DST Entry and Exit Transitions

	DST start		DST end	
	(1) Dwelling fires	(2) All building fires	(3) Dwelling fires	(4) All building fires
<i>D</i>	0.031 (0.019)	0.2 (0.2)	0.001 (0.022)	0.014 (0.02)
Bandwidth	48	40	41	47
Observations	779	635	664	744

The table presents the estimated impact of DST transitions derived from Eq. 6. Robust standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

We begin by testing the result's sensitivity to observations near the DST thresholds. To this end, we apply a Donut-Hole RDD approach [5]. Specifically, we repeat the analysis estimating local linear regressions when omitting systematically 1 to 10 days on each side of the respective DST transition threshold. The results along with 95% confidence intervals are illustrated in Fig. 5. Estimates for both the start and end of DST transitions are similar in terms of magnitude and statistical significance as the baseline estimates reported in Table 2, suggesting that results are not driven by sorting behavior or by unobserved confounders that are discontinuous around the threshold. For both DST-entry and DST-exit the estimated effect is stable in terms of magnitude, but consistently statistically insignificant.

Table 3 collects the results of various robustness tests for the DST entry transition. We begin by testing whether the results are sensitive to the size of the bandwidth used to estimate the local linear regressions. Columns 1, 2 and 3 report estimates of the impact of DST transitions on fire incidents when using bandwidths equal to $0.5\times$, $0.75\times$ and $2\times$, the bandwidth used in the baseline results. The estimated effect is very close to zero and statistically insignificant when restricting observations to 24 days on each side of the threshold (column 1). Doubling the bandwidth (column 3) and allowing separate bandwidths on each side of the threshold (column 4) leads to estimates that quantitatively are almost identical to those reported in Table 2, but this time statistically significant. Columns 5 and 6 test the result's stability to the choice of different standard error estimators. Specifically, we allow errors terms to be correlated within days-of-year and weeks-of-year, and report standard errors clustered at the day-of-year and week-of-year levels. The estimated impact of the DST entry transition is statistically significant in the first case but not the second. Finally columns 7 and 8 report estimates from local linear regressions when using a uniform and an Epanechnikov kernel respectively. While the magnitude of the estimates for the Spring transition is comparable to the one derived using a triangular kernel, estimates are statistically significant when applying the uniform kernel.

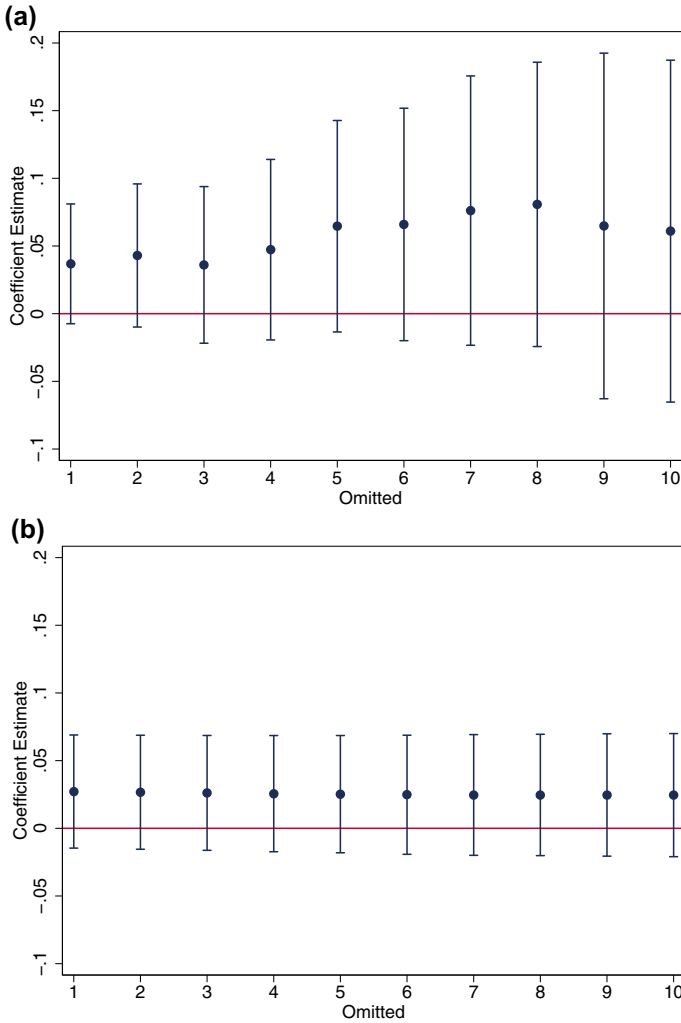


Figure 5. Estimates omitting observations close to the threshold.

Table 4 presents similar robustness tests for the DST exit transition. In all cases, estimates are very close to zero and statistically insignificant.

As a final way to assess confidence in the result, we run a series of placebo tests, repeating the analysis when centering the transition date in days $t - n$ where t is the actual date of the DST entry or DST exit transition. Specifically, $n \in [48, 317]$ for DST entry transition and $n \in [41, 324]$ for DST exit. We exclude observations that lie within the original bandwidth used in the initial analysis⁷ to

⁷ Original bandwidths were 48 days for the Spring transition and 41 days for the Autumn transition models.

Table 3
Robustness Tests for DST Entry

	(1)	(2)	(3)	(4)
<i>D</i>	0.003 (0.028)	0.025 (0.23)	0.030** (0.014)	0.033* (0.02)
Bandwidth	24	36	97	39 , 71
Observations	395	587	1563	891
	(5)	(6)	(7)	(8)
<i>D</i>	0.031** (0.016)	0.031 (0.026)	0.039** (0.020)	0.033 (0.020)
Bandwidth	48	48	43	46
Observations	779	779	699	747

The table presents results from a series of robustness tests: Column 1 uses bandwidth $0.5h$. Column 2 uses bandwidth $0.75h$ Column 3 uses bandwidth $2h$ Column 4 uses different bandwidths to the left and right of the threshold Column 5 reports standard errors clustered at the day-of-year level. Column 6 reports standard errors clustered at the week of the year level. Column 7 reports results based on uniform kernel. Column 8 reports results based on Epanechnikov kernel. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$

Table 4
Robustness Tests for DST Exit

	(1)	(2)	(3)	(4)
<i>D</i>	0.013 (0.033)	0.015 (0.026)	0.023 (0.015)	0.038 (0.024)
Bandwidth	20	31	83	53 , 26
Observations	328	604	1336	640
	(5)	(6)	(7)	(8)
<i>D</i>	0.001 (0.025)	0.001 (0.026)	0.013 (0.021)	0.007 (0.021)
Bandwidth	41	41	37	43
Observations	664	664	600	696

The table presents results from a series of robustness tests: Column 1 uses bandwidth $0.5h$. Column 2 uses bandwidth $0.75h$ Column 3 uses bandwidth $2h$ Column 4 uses different bandwidths to the left and right of the threshold Column 5 reports standard errors clustered at the day-of-year level. Column 6 reports standard errors clustered at the week of the year level. Column 7 reports results based on uniform kernel. Column 8 reports results based on Epanechnikov kernel. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$

avoid contaminating placebo estimates with the true effect. The distributions of placebo discontinuity estimates for the start and end of DST thresholds are shown in Fig. 6, along with the true estimate marked by a vertical line. The majority of placebo estimates is concentrated around zero. About 17% of placebo estimates

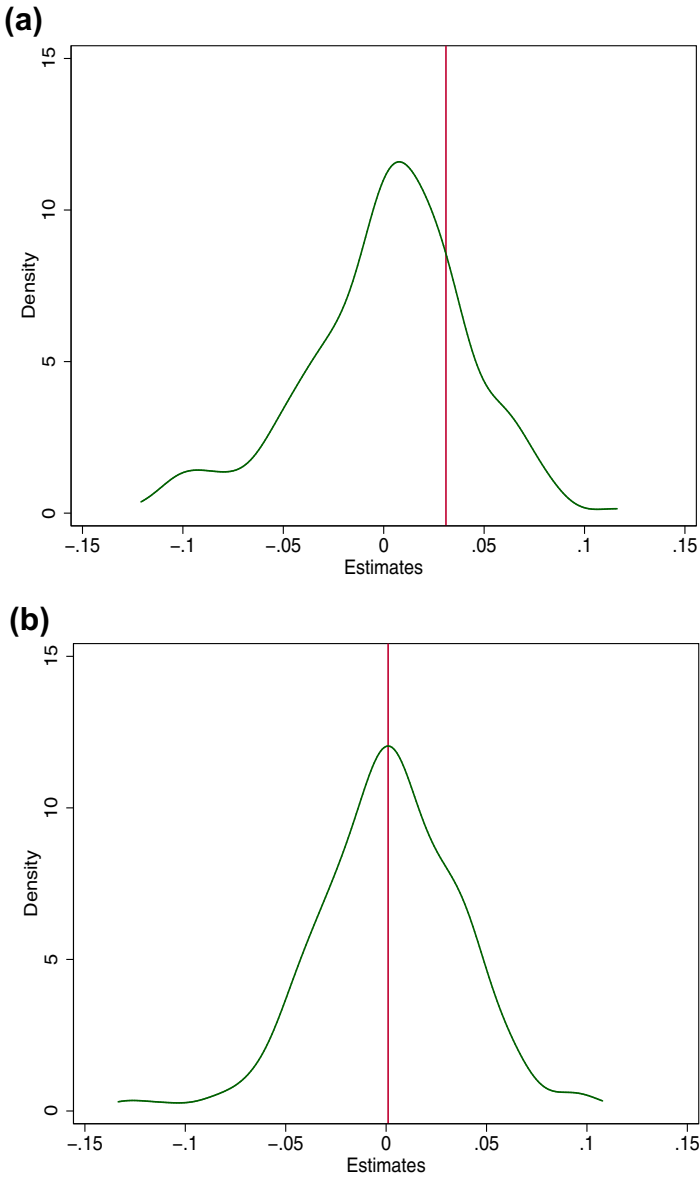


Figure 6. Distributions of start and end of DST placebo estimates.

are larger than the true start-of-DST transition estimate. Similarly, about 50% of placebo estimates are larger than the end-of-DST transition estimate. We also repeat the analysis with triangular and Epanechnikov smoothing kernels and find comparable results.

Table 5
Global Polynomials

	(1) Quadratic	(2) Cubic	(3) Quartic	(4) Quintic
<i>Panel A: DST start transition</i>				
<i>D</i>	0.038*** (0.014)	0.026 (0.017)	0.022 (0.022)	0.033 (0.025)
AIC	1493	1494	1494	1500
Observations	2399	2399	2399	2399
<i>Panel B: DST end transition</i>				
<i>D</i>	- 0.206*** (0.047)	- 0.240 (0.154)	- 0.284 (0.474)	3.181** (1.54)
AIC	1491	1493	1494	1501
Observations	2399	2399	2399	2399

The table presents estimates from regressions accounting for global polynomial of the assignment variable. Standard errors clustered at the day-of-year level in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

We further report estimates from global polynomials of the running variable in Table 5 for both the DST start and end transitions. Specifically estimates come from the following equation:

$$\ln F_{it} = \alpha_i + \gamma_1 D_{it} + f(R_{it}) + D_{it} \times f(R_{it}) + u_{it} \tag{6}$$

where $f(R_{it})$ is either a quadratic, cubic, quartic or quintic polynomial of the running variable R_{it} , using observations from ± 150 days from each of transitions. The preferred quadratic specification that minimizes the Akaike Information Criterion suggests that the impact of the start of DST transition is nearly identical to that estimated with the local linear approach. Specifically, the transition increases residential fires by approximately 3.8%. Nevertheless estimates of the transition’s immediate impact are unstable as both the magnitude and the statistical significance of the effect are sensitive to the degree of the polynomial and as suggested by Gelman and Imbens [18] does not inspire confidence to the result. Estimates of the impact of DST exit are highly unstable. The preferred specification suggests that incidents decrease by 20% following the transition. Nevertheless, as before estimates are highly dependent on the degree of the polynomial selected.

5. Discussion and Concluding Remarks

Residential fires can lead to destructive immediate and long term consequences generating costs to property, physical and mental health. Despite technological advances and public awareness of fire risk, the human factor remains an important driver of fire incidence. Researchers acknowledge human influence on fire occurrence and have explored in detail the sociodemographic correlates of fire risk [29]. Fewer studies examine how specific behaviors can impact on fire occurrence. This paper, extends the literature by assessing the impact of disruptions in sleep

patterns on dwelling fire occurrence. To this end, we apply a quasi-experimental approach leveraging the disruptions in sleep patterns introduced by DST transitions. Overall, evidence suggests that reducing the duration of sleep by 40 to 60 min and disrupting sleep patterns does not lead to increase in dwelling fire incidents. A series of tests performed to test the stability of the result point to the same direction. Importantly, estimates at the start of DST transition turn statistically significant only when expanding the time window used for the local linear regressions, giving more weight to observations that lie far from the transition threshold. On the other hand, examining fire behavior closer to the threshold by shrinking the bandwidth does not change the main result. Reassuringly, a series of placebo tests centering the running variable on “fake” transition days finds that around 17% of placebo effects exceed the real effect. The implication is that there is no evidence to support that DST transitions are in any way exceptional events for fire occurrence.

While the result is robust, we are careful do not to overemphasize it. Disruptions in sleep induced by DST are brief and temporary in nature. It is not implausible that sleep deprivation lasting longer than 1 h would impact on human performance sufficiently as to increase dwelling fire incidents. Furthermore, the result is contingent on the conditions prevailing in the UK for the years under investigation. While the relationship between sleep and performance is a human feature, the impact of sleep disruptions on fire occurrence will depend on institutions or policies, that may be region or country specific. Showing conclusively that a relationship between dwelling fires and sleep disruptions does not exist would require studies exploring the link in different institutional setups, under different fire prevention policies.

Finally, prior research has shown the negative effect of DST transitions on various domains of human activity [2, 4, 15]. The present paper suggests that DST does not appear to have significant impact on the occurrence of dwelling fires. In this sense the paper is compatible with findings by Herber et al. [24] and Neeraj and Arkadipta [46] who do not find an impact from DST in student school performance and traffic accidents respectively.

Acknowledgements

I am grateful to Kyriaki Remoundou and two anonymous Reviewers for useful comments and suggestions. Any remaining errors are mine.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

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