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Spring forward, don't fall back: The effect of daylight saving time on road safety

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Christian Bünnings
Valentin Schiele

Spring Forward, Don't Fall Back – The Effect of Daylight Saving Time on Road Safety

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Christian Bünnings and Valentin Schiele

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Christian Bünnings and Valentin Schiele[1]

Spring Forward, Don't Fall Back – The Effect of Daylight Saving Time on Road Safety

Abstract

In this paper, we analyze the effect of light conditions on road accidents and estimate the long run consequences of different time regimes for road safety. Identification is based on variation in light conditions induced by differences in sunrise and sunset times across space and time. We find that darkness causes annual costs of £790 million. By setting daylight saving time year-round and, hence, shifting more daylight to the evening, 10 percent of these costs could be saved. Thus, focusing solely on the short run costs related to the transition itself underestimates the total costs of the current time regime.

JEL Classification: R41, Q48

Keywords: Road accidents; light conditions; daylight saving time

September 2018

1 Christian Bünnings, FOM and RWI; Valentin Schiele, Paderborn University. *– We thank Daniel Kamhöfer, Irene Palnau, Hendrik Schmitz, Harald Tauchmann, Matthias Westphal and Ansgar Wübker for valuable comments. Moreover, we are grateful for comments at the Quantitative Economics Days in Soest, the annual conference of the German Health Economics Association in Hamburg, the European Health Economics Association conference in Maastricht and the European Conference on Data Analysis in Paderborn. This study uses road accident data from the Stats19 database gathered by the UK Department for Transport. Data access to weather data from the MET Office was provided by the Center for Environmental Data Analysis (CEDA).* *– All correspondence to: Valentin Schiele, Paderborn University, Warburger Str. 100, 33098 Paderborn, Germany, e-mail: valentin.schiele@uni-paderborn.de*

1 Introduction

Daylight Saving Time (DST), also summer time, refers to the practice of moving clocks forward by one hour from standard winter time in spring and backward by one hour to winter time in fall. It was first introduced in Germany followed by Great Britain, France and the US during World War I, initially as an effort to conserve energy by reducing electricity consumption, particularly for electric lighting through shifting daylight from morning to evening hours. Currently, around 70 countries (e.g. Europe and large parts of the US and Canada) covering about one quarter of the world's population adopt DST regimes, yet, concerns about the usefulness of DST raise. In February 2018, the European Parliament voted for a resolution to urge the European Commission to evaluate comprehensively the current DST regime (European Parliament, 2018). Virtually at the same time – in March 2018 – Florida's legislature voted to keep the state on DST throughout the year (Florida House of Representatives, 2018). The so called "Sunshine Protection Act" is supposed to become effective from July 2018 on, however, effectiveness is conditional on the authorization by the US Congress. Although both initiatives are non-binding, they mirror the rising concerns about whether the harms of changing the clocks twice a year potentially outweigh the intended benefits of this policy regulation.

Recent literature provides empirical evidence that DST does not have the originally intended effect on energy conservation. To the contrary, DST may even increase total energy consumption, since energy savings in lighting are at least offset by increased energy use in other areas such as heating or air conditioning (Kellogg and Wolff, 2008; Momani et al., 2009; Krarti and Hajiah, 2011; Kotchen and Grant, 2011; Sexton and Beatty, 2014).[1] In addition, several studies indicate that the transition in and out of DST causes disruptions in the circadian rhythm and adversely affects the duration and quality of sleep (Lahti et al., 2006; Kantermann et al., 2007), which in turn may have unintended negative side effects in various (economic) dimensions other than energy saving. These negative short term effects range from lower general well-being

[1] See Aries and Newsham (2008) for a literature review covering earlier studies on the relationship between DST and lighting energy usage.

(Kountouris and Remoundou, 2014) and life satisfaction (Kuehnle and Wunder, 2016), decreases in stock market returns (Kamstra et al., 2000) and students' performance (Gaski and Sagarin, 2011) to higher risk of work injuries (Barnes and Wagner, 2009; Lahti et al., 2011), acute myocardial infarction (Janszky and Ljung, 2008; Jiddou et al., 2013; Toro et al., 2015), suicides (Berk et al., 2008) and fatal road accidents (Varughese and Allen, 2001; Sullivan and Flannagan, 2002; Sood and Ghosh, 2007; Smith, 2016).[2]

While this literature provides evidence in favour of abolishing the yearly ritual of changing the clocks twice, at least from a short term perspective, it is less clear for which time regime – DST or standard winter time – a society eventually should opt for. From an economists point of view, this decision should be based on the long term costs and benefits of establishing one of these time regimes instead of the other. One area in which permanent costs and benefits might arise is road safety. This is mainly because choosing one time regime instead of the other affects the distribution of natural light across hours of the day. Since traffic density also differs by time of the day, shifting light from the morning hours to the evening hours or the other way round might have consequences for annual road accident counts, if light levels affect road safety. It is the aim of this paper to empirically assess to which extent this is indeed the case and how different time regimes affect road safety.

To estimate the effect of darkness on accident counts we make use of large, administrative data from England, Scotland and Wales covering all accidents on public roads that resulted in a personal injury and were reported to the police. Our identification strategy exploits arguably exogenous variation in darkness stemming from three sources of variation in sunrise and sunset times: day-by-day variation for a given region and hour; east-west variation for a given day of the year and hour; and north-south variation for a given day of the year and hour. The resulting estimates are used to simulate the number of fatal, serious and slight accidents under three different time regimes: the current regime with standard time during winter and DST during summer versus setting the clocks permanently either to DST or to standard winter time.

[2]There are also studies finding no effect of the transition into DST on stock market returns (Gregory-Allen et al., 2010), students' performance (Herber et al., 2017), myocardial infarction (Sandhu et al., 2014), hospital admissions (Jin and Ziebarth, 2015) and fatal accidents Lahti et al. (2010).

Our contribution to the literature is twofold. First, we extend the literature on the effects of DST on road safety by looking at the long-run consequences for accident counts of different time regimes. This allows us to assess whether year-round DST or all-year standard winter time should be implemented, at least from a road safety perspective. Most part of the related literature on the effect of DST on traffic accidents exploits the abrupt transition from standard winter time to DST in spring and vice versa in fall (e.g. Smith, 2016). This approach allows for credible identification of the effects of the transition into and out of DST under plausible assumptions, however, the resulting estimates cannot easily be used to assess the effects of DST over the entire year, as they are valid only locally (i.e. around the dates of transition into/ out of DST). There are only a few early papers that investigate the long-run consequences of time regime choice for road safety (e.g. Ferguson et al., 1995; Coate and Markowitz, 2004).[3] Yet, as these paper essentially compare accident counts during the morning / evening hours across weeks, strong assumptions have to be imposed to give their estimation results a causal interpretation.[4] Second, exploiting information about all individuals involved in each accidents, we shed some light on potential mechanisms through which darkness might affect road safety. Given that light levels do not only affect vision but might also influence concentration and fatigue due to adjustments of the circadian rhythm, it is unclear whether measures that aim at increasing visibility such as more road lighting can be effective in reducing road casualties.

We find that darkness increases accident counts by around 7 percent per hour, which translates into annual costs of £790 million caused by darkness. As the estimated effects are larger for fatal and serious accidents than for slight accidents, our results indicate that light conditions do not only increase accident risk but also accident severity. Simulations based on these estimates suggest that shifting light from the morning to the evening by setting the clocks permanently to DST could save lives and prevent injuries. Compared to an all-year standard winter time regime, setting the clocks to DST during the entire year could avoid around 25 fatal accident, 100 accidents with at least one se-

[3] For a broader overview about the previous literature see Carey and Sarma (2017).

[4] These studies assume that gradual changes in accident counts in the course of the year are only the result of gradual changes in the number of light hours and not influenced by other factors, such as road conditions, traffic composition or the number of road users.

riously injured casualties and 350 accidents with at least one slightly injured casualties or at least £80 million per year across England, Scotland and Wales. This indicates that existing literature on the effects of the transition itself underestimates the total costs of the current time regime. Our heterogeneity analysis indicates that the positive effects of darkness on accident counts are mainly due to an increased risk of poor night-vision among older drivers.

The remainder of the paper is structured as follows. Section 2 describes the data and the empirical approach. In Section 3 we present our main results as well as the results from heterogeneity and sensitivity analyses. Section 4 concludes and discusses policy implications.

2 Empirical Framework

2.1 Data and Measurement

Our accident data comes from the stats19 data base (Department for Transport, 2017b). It covers all accidents on public roads in England, Scotland and Wales that resulted in a personal injury and were reported to the police between 1996 and 2016. The data is collected by the police using a nationally standardised form for the collection of data on each road accident, on each casualty, on the vehicles involved in the accident as well as on drivers and passengers[5]. These accident reports are digitized and made available to the public in an anonymized form.[6]

There are three properties making the stats19 data especially suitable to study the effects of ambient light condition on road safety. First, it provides detailed information on the level of individual accidents. For each accident we do not only have information on the location and the exact date and time of the accident, but also on the type of accident, the number of slightly, seriously and fatally injured casualties and the age

[5] Although the local police forces are not obliged to use the standardised form to collect the relevant data, a great majority of forces use the precise form or a minor variation (Department for Transport, 2013).

[6] `https://data.gov.uk/dataset/road-accidents-safety-data`

of all drivers. Thus, we can assign each accident to a geographic region and are able to distinguish between certain types of accidents, e.g. we can distinguish car accidents from accidents involving pedestrians. Second, the coverage of the stats19 data is exceptionally large. As our identification strategy is based on variation in sunrise and sunset time across latitude, longitude and day of the year, we are reliant on data covering a sufficiently large area and time span. Our sample comprises information on more than 3.9 million accidents from all across England, Scotland and Wales between 1996 and 2016. Finally, the data can be considered to be highly reliable. According to our sample, a police officer attended the scene of accident to obtain the details for the report in almost 80 percent of all accidents. The information for another 20 percent of accidents were gathered in questionings at the police station while the details about the accidents were obtained using a self-completion form only in less than 0.2 percent of all accidents.

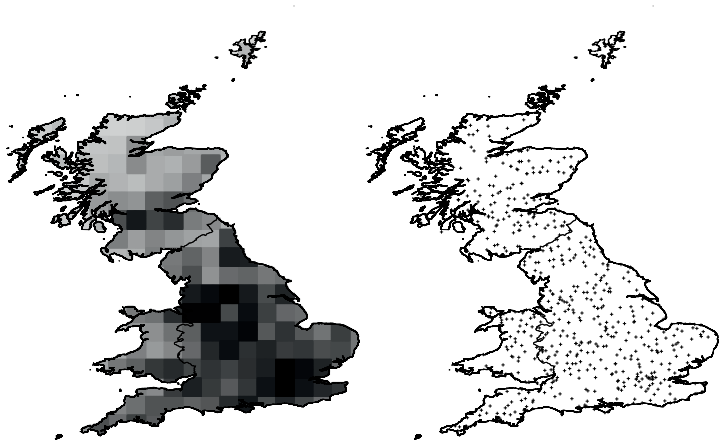
The individual level data is aggregated in order to yield hourly accident counts for a panel of 265 regions. We use a grid references system based on longitude and latitude to define regions. This system divides Great Britain into 265 regions, each of them spanning an area of the size 0.5° longitude $\times$ 0.5° latitude.[7] Using information about the type and severity of the accident as well as the age of the drivers,[8] we distinguish between the following accident categories: all accidents, accidents involving pedestrians, accidents involving drivers above the age of 45, accidents involving only drivers younger than 45, accidents with only slightly injured casualties, accidents with seriously injured casualties, and fatal accidents. The left panel of Figure 1 illustrates the grid reference approach and shows how accidents are distributed across regions.

As one might worry that changes in light intensity are systematically related to changes in weather conditions, we amend the accident data with information about weather conditions at site. Hourly weather data comes from the Met Office's MIDAS database

[7] 0.5° longitude corresponds to approximately 36 kilometres in the very south of GB and 28 kilometres in the very north; 0.5° latitude corresponds to approximately 55.5 kilometres. With respect to the grid size there is a trade-off between spatial precision and computational feasibility. Increasing spatial precision, for instance, by a factor of four (0.25° longitude $\times$ 0.25° latitude), quadruples the number of observations and increases the computational burden by a multiple of four.

[8] The term driver includes all active road users, i.e. car drivers, pedestrians, cyclists etc. but no passengers.

Figure 1: Distribution of accidents and weather stations across GB



Note: Own calculations and illustration based on stats19 and MIDAS data. The left part of the figure shows grid based regions and the distribution of accidents during the year 2016 across these regions. Darker shading indicates more accidents. The right part of the figure shows the distribution of weather stations across GB.

and includes information on wind speed, precipitation and temperature. In order to make the weather data compatible with the accident data, we first calculate simple averages of all stations within each region and hour for all weather variables. These regional averages are then used to generate three variables with four (wind speed), two (precipitation) and six (temperature) categories. Furthermore, we include a dummy variable to capture icy road conditions (i.e. positive precipitation and temperature below 2°C). As there are regions without operating weather stations during all or some time periods, the sample clearly decreases in size when we include weather information (see the right panel of Figure 1 for an overview about the distribution of relevant weather stations across Great Britain). In the following, we thus present results for both samples, the sample covering all observations from all regions during the whole observation period as well as the sample covering only those observations for which weather data is available.

Although the stats19 data does provide some information about lighting conditions at accident site, we cannot use it to derive a measure for darkness, since the raw data naturally provides such information only for regions (and hours) with at least one accident. Thus, if we would decide to make use of the information about lighting con-

ditions, we had to discard a large share of potentially informative observations (i.e. observations with a zero accident count) and had to run our estimations on the truncated sample. Instead, we treat a region-hour as a dark/light hour based on information about the position of the sun relative to the horizon in this region and at this date and time. For each region and date, we first calculate the times when the sun's position is six degree below the horizon as seen from an observer who is located in the centre of the region. This happens twice a day, once in the morning before sunrise and once in the evening after sunset and marks the beginning or ending, respectively, of civil twilight. For a detailed description of the procedure used here to calculate the position of the sun based on longitude, latitude, date and time see Cornwall et al. (2015). During civil twilight, no ray of sunlight touches the ground. Yet, higher air layers are still directly illuminated by the sun and diffract a relevant part of the sunlight to the ground. This indirect lighting during civil twilight is sufficient for the human eye to clearly distinguish objects. We thus make use of a definition of darkness that is based on the onset and offset of civil twilight rather than on sunrise and sunset. Similar definition of darkness have been used in the related literature (Sullivan and Flannagan, 2002) but also became part of UK law. The Road Vehicles Lighting Regulations 1984, for example, also refers to the beginning and ending of civil twilight when it defines the *daytime hours* as the time between half an hour before sunrise and half an hour after sunset and requires drivers to keep lamps lit during the *hours of darkness* (Department for Transport, 1984).

Based on the exact information about the beginning and ending of twilight at the centre of region i on day d of year t, we are then able to define our main treatment variable *dark*:

$$dark_{ihdt} = \begin{cases} 1 & \text{if } h < hour(b_{itd}) \text{ or } h > hour(e_{itd}) \\ min(b_{itd})/60 & \text{if } h = hour(b_{itd}) \\ (60 - min(e_{itd}))/60 & \text{if } h = hour(e_{itd}) \\ 0 & \text{if } hour(e_{itd}) < h > hour(b_{itd}) \end{cases}$$

where $hour(b_{itd})$ denotes the hour of day when civil twilight begins in the morning and $hour(e_{itd})$ denotes the hour of day when civil twilight ends in the evening in region i on day d of year t. Correspondingly, $min(b_{itd})$ and $min(e_{itd})$ denote the minute of civil twilight transition in the morning and evening, respectively. Thus, $dark_{ihdt}$ gives the fraction of the hour that is dark: It takes on the value 1 if the hour of observation is before the hour of transition from nautical twilight (dark) into civil twilight (light) in the morning or after the hour of transition from civil twilight into nautical twilight in the evening and the value 0 if the hour of observation is after the hour of transition into civil twilight in the morning and before the hour of transition out of civil twilight in the evening. If the hour of observation is instead the same as the hour of transition from or into civil twilight, $dark_{ihdt}$ can take on some value between 0 and 1. The exact value depends on the exact time of the transition. If the transition into (out of) darkness is in the beginning of the hour of observation, then $dark_{ihdt}$ will be close to one (zero). If the transition into (out of) darkness is, instead, in the end of the hour of observation, then $dark_{ihdt}$ will be close to zero (one).

Descriptive statistics for the outcome variable, the measure of darkness and selected controls are shown in Table 1.

2.2 Identification and Estimation

The basic intuition of our main empirical strategy is to make use of variation in darkness induced by variation in sunrise and sunset times across time and space to estimate the effect of darkness on road safety and then to simulate road safety under alternative time regimes. In order to be able to put the results of our main analysis into perspective, we follow the related literature and also present results based on a Regression Discontinuity Design (RDD). The RDD exploits the discrete change from standard winter time to DST in spring and vice versa in autumn and has been used (e.g. Smith, 2016) to directly estimate the effect of DST on road safety. The intuition behind this approach is that one might expect to see a sharp increase (decrease) in the number of accidents

Table 1: Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max
Dependent variables:				
All accidents	0.081	0.390	0	20
Fatal accidents	0.001	0.033	0	3
Serious accidents	0.011	0.112	0	6
Slight accidents	0.069	0.350	0	19
Accidents with age of oldest driver ≤ 25	0.009	0.097	0	5
Accidents with $25 <$ age of oldest driver ≤ 45	0.029	0.199	0	11
Accidents with $45 <$ age of oldest driver ≤ 65	0.023	0.167	0	11
Accidents with $65 <$ age of oldest driver	0.007	0.085	0	4
Pedestrian accidents	0.014	0.130	0	8
Pedestrian accident & age of oldest driver ≤ 45	0.007	0.092	0	6
Pedestrian accident & age of oldest driver > 45	0.004	0.063	0	4
Darkness:				
Dark proportion of the hour	0.427	0.480	0	1
Weather:				
Temperature ($^\circ C$) < 0	0.034	0.180	0	1
$0 \leq$ temperature ($^\circ C$) < 5	0.167	0.373	0	1
$5 \leq$ temperature ($^\circ C$) < 10	0.322	0.467	0	1
$10 \leq$ temperature ($^\circ C$) < 15	0.314	0.464	0	1
$15 \leq$ temperature ($^\circ C$) < 20	0.138	0.345	0	1
$20 \leq$ temperature ($^\circ C$)	0.026	0.159	0	1
Wind speed (knots) < 5	0.226	0.418	0	1
$5 \leq$ wind speed (knots) < 10	0.361	0.480	0	1
$10 \leq$ wind speed (knots) < 20	0.343	0.475	0	1
$20 \leq$ wind speed (knots)	0.070	0.256	0	1
No precipitation	0.827	0.378	0	1
Positive precipitation	0.173	0.378	0	1
No snow/ice	0.990	0.098	0	1
Snow or ice	0.010	0.098	0	1

Note: Own calculations based on the stats19 and MIDAS data.

around the date of DST transition if DST affects road safety. Specifically, we estimate regressions based on Equation (1):

$$\ln accidents_{dt} = f(days_{dt}) + \pi post_{dt} + f(post_{dt} \times days_{dt}) + \eta_{dt} \tag{1}$$

where $accidents_{dt}$ is the total number of accidents (of a certain type and net of day of the week and year fixed effects)[9] at day d in year t, $days_{dt}$ is the running variable and denotes the number of days until DST transition (either in spring or in autumn), $post_{dt}$ is a dummy equal to one for days after DST transition and η_{dt} an error term.

[9]To get rid of differences in accident counts by day of the week and year, we follow Smith (2016) and use the residuals from a regression of (logged) daily accident counts on day of the week and year fixed effects as dependent variable.

The interaction between *post* and *days* is included to allow for different slopes at both sides of the cut-off. The parameter of interest in this setting is π and gives the effect of the transition into or out of DST on accident counts. To account for the fact that the length of the day is 23 instead of 24 hours on the day of DST transition in spring, we follow Smith (2016) and count accidents during the hour 3 in the morning twice. Correspondingly, we drop half of the accidents during the hour 2 on the day of DST transition in autumn. To further increase comparability of daily accident counts, we drop holidays[10] from the estimation sample.

The assumption required for π being consistently estimated is that in the absence of DST transition, *ln accidents* would change continuously in *days* around the transition date. If this assumption holds, comparing accident counts just before with accident counts just after the cut-off date yields a reasonable estimate of the short-run effect of DST on road safety. Note that this assumption is likely to hold, if people cannot manipulate treatment – as in this setting where the whole country is treated – and if there are no other rules that might affect the outcome differently at both sides of the cut-off. To our knowledge there are no other discontinuities around the DST transition dates that might have an effect on road safety. To determine the number of days to be used at both sides of the cut-off, we make use of mean squared error optimal bandwidth selectors (see Calonico et al., 2017).

While the RDD provides causal estimates of the effect of DST *transition* on road safety under plausible assumptions and thus can be used to assess the costs of DST *transition*, its use is rather limited when it comes to the main goal of this paper, i.e. assessing the costs of alternative time regimes throughout the entire year. This is because the RDD estimates are valid only very locally, namely just a few days around the date of transition into and out of DST and cannot be used easily to extrapolate the number of accidents under DST far away from the transition date, e.g. in January. Our main approach, which aims at assessing the long-run consequences of different time regimes, is therefore to estimate the effect of darkness on accident counts and then – using these

[10] January 1, Easter holidays (Good Friday until Easter Monday), Early May and Spring Bank Holidays as well as Christmas Holidays (December 25 and December 26).

estimates – to simulate the number of accidents under the different time regimes. This approach uses variation in darkness and accident counts throughout the entire year and thus is more suitable to assess the relative costs of establishing one time regime instead of the other.

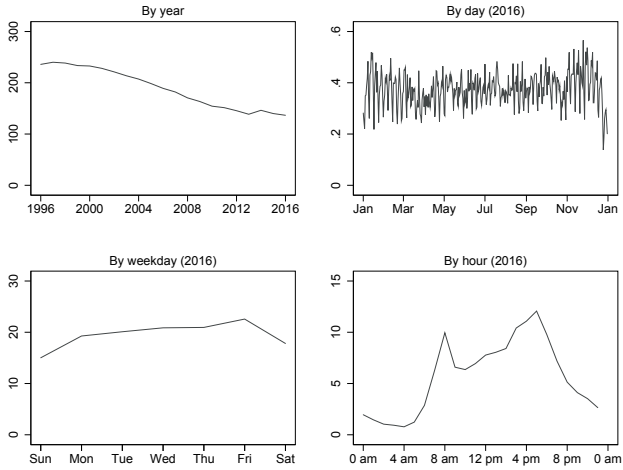
To identify the effect of darkness on accident counts we estimate regressions based on the following equation:

$$accidents_{ihdt} = f(\beta dark_{ihdt} + X'_{ihdt}\gamma + \alpha_i + \rho_h + \delta_d + \lambda_t + \varepsilon_{ihdt}) \tag{2}$$

where $accidents_{ihdt}$ denotes the number of accidents (of a certain type) in region i during hour h on day d of year t, $dark_{ihdt}$ is the dark share in hour h in region i on day d of year t (see above), α_i are region, ρ_h hour of the day, δ_d day of the year, and λ_t year fixed effects. Finally, X_{ihdt} includes weather variables and indicator variables for the day of week and ε_{ihdt} is an error term.

The parameter β is the parameter of interest and gives the causal effect of darkness on hourly accident counts. To estimate β consistently the necessary assumptions have to hold, most importantly, *dark* has to be conditionally exogenous. We argue that there are good reasons to assume that *dark* is exogenous conditional on the fixed effects and the weather controls included in X. First, by including hour of the day fixed effects (ρ_h) we account for the fact that both darkness as well as accidents are distributed unevenly across hours. Darkness concentrates on some hours during night when people are at home and road traffic and thus accident counts are quite low (see Figure 2), while daylight concentrates on hours when people go about their daily tasks and streets are rather crowded. Second, by including day of the year fixed effects (δ_d) we avoid bias due to correlated changes in road and light conditions in the course of the year. While most hours are dark and road conditions can be hazardous due to snow, ice and fog during winter, the opposite is true for the summer months. Third, to capture that differences in the number of accidents might be related to differences in the share of dark hours between regions (i.e. northern vs. southern regions), we include region

Figure 2: Distribution of accidents by year, day, hour and day of week

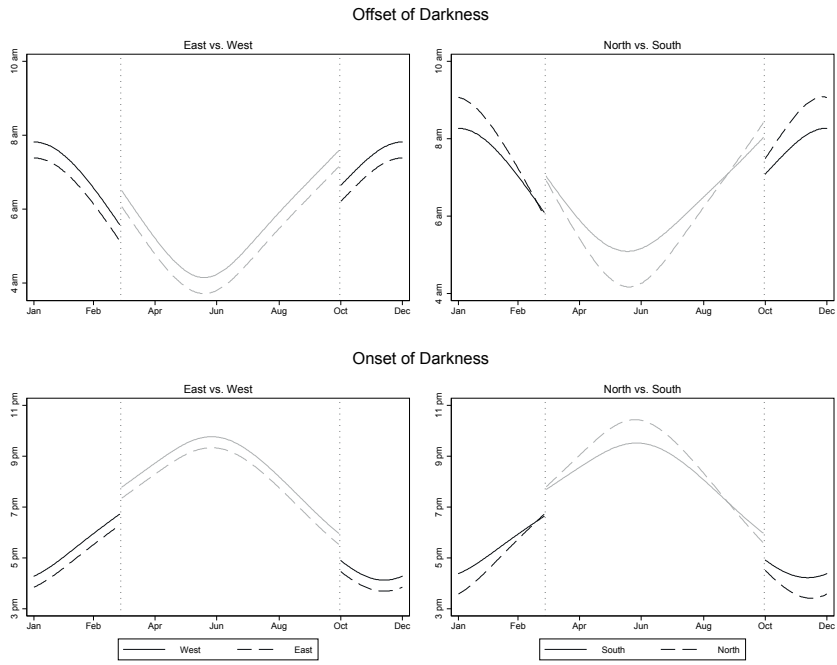


Note: Own calculations and illustration based on stats19 data. The figure shows the total number of accidents in thousands by year (upper left), the total number of accidents in thousands during the year 2016 by day of the year (upper right), day of the week (lower left) and hour (lower right).

fixed effects (α_i). Finally, as changes in light conditions might be directly related to changes in weather conditions, we also estimate variations of equation 2 where we control for weather conditions at accident site.

The variation in *dark* that is not captured by one of the fixed effects is used to identify β. It comes, as will be shown in the following figures, from variation in the offset and onset of darkness across time and space. The first figure, Figure 3, shows the timing of transition from darkness to daylight in the morning (upper two panels) and from daylight to darkness in the evening (lower two panels) over the course of the year. In the left two panels we distinguish between two places on the same line of latitude: one in the very east of Great Britain (dashed line) and one in the very west (solid line). Similarly, in the right panels we differentiate between two places on the same line of longitude: one in the very north (dashed line) and one in the very south (solid line). What can be seen immediately are three sources of variation in darkness: changes in the timing of onset and offset of darkness throughout the year and by longitude (east-west comparison) as well as latitude (north-south comparison).

Figure 3: Variation in Offset and Onset of Darkness

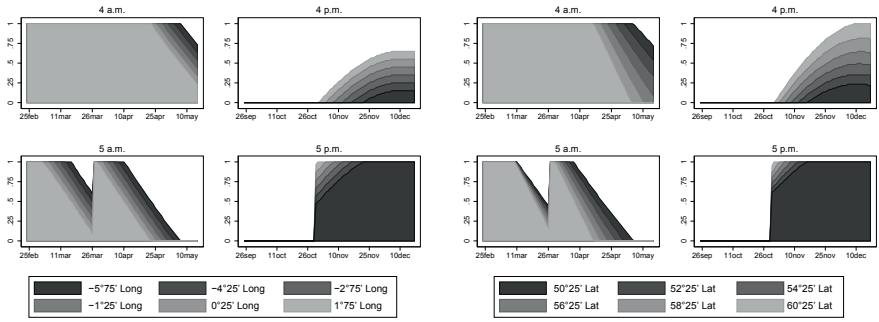


Note: Own calculations and illustration. The figure shows the timing of offset (upper panels) and onset (lower panels) of darkness at four different places in GB and over the course of the year. The panels on the left side differentiate between two places on the same line of latitude (52.25° latitude), a place in the very west (-5.25° longitude, solid line) and a place in the very east (1.25° longitude, dashed line) of the country. Correspondingly, the panels on the right side differentiate between two places on the same line of longitude (-4.25° longitude), a place in the very south (50.25° latitude, solid line) and a place in the very north (58.25° latitude, dashed line).

Figure 4 shows for selected hours of the day, days of the year and regions how this variation in the timing of onset and offset of darkness translates into variation in darkness. The shaded areas in each panel give the proportion of the respective hour that is dark. The hour five in the morning, for example, is completely dark until the end of February. Then, however, the dark proportion of this hours starts to decrease such that by March, 25 at least 40 percent of this hour is light all across Great Britain. As all clocks are then set one hour ahead due to daylight saving time transition[11], the dark proportion of hour five jumps back to 100 percent but then decreases again. By the beginning of May it is light during the whole hour all across Britain. Similar variation in darkness across time can be found for other hours of the day but at different days

[11]Note that our estimates are not sensitive to the exclusion of observations from two weeks after daylight saving time transition and thus do not reflect effects of daylight saving time *transition*.

Figure 4: Variation in Darkness used for Identification



(a) East vs. West (b) North vs. South

Note: Own calculations and illustration. The figure shows the dark proportion of an hour by day of the year and for selected hours and places. The four panels on the left side differentiate between six places on the same line of latitude but on different lines of longitude (the darker the colour the more in the west), the four panels on the right differentiate between 6 places on the same line of longitude but different lines of latitude (the darker the colour the more in the south).

of the year, e.g. during October, November and December for the hour four in the afternoon.

Aside from variation in darkness for a given hour and region across day of the year there is also variation in darkness for a given hour and day of the year across regions. As can be seen in the left part of Figure 4, the dark proportion of an hour is 0-50 percentage points higher in the morning in regions of the very west of Great Britain compared to regions (on the same line of latitude) in the very east. The opposite is true for hours in the evening. The left panel of the graph shows that the dark proportion of an hour varies also by latitude. The hour four in the morning, as an example, is completely light in the very south but still dark in the very north on May, 1. The hour four in the afternoon, on the other hand, is completely dark in the very north of Great Britain on December, 10 while the dark proportion of this hour is only 25 percent in the very south. By isolating these three parts of variation in darkness to estimate β and additionally controlling for weather conditions, we are confident to give our estimation results a causal interpretation.

Equation 2 is estimated using a Negative Binomial (Negbin) model, as our outcome variables are count variables with a large proportion of zeros and show signs of overdispersion. In order to avoid the well known incidental parameter bias problem, we es-

timate the Negbin fixed effects models by including full sets of dummies for regions, hours, days of the years and years. Although there is no formal proof available that this approach rules out inconsistencies due to the incidental parameter bias problem, simulations by Allison and Waterman (2002) and Greene (2004) suggest that the bias should be small even if the number of time periods is small (Cameron and Trivedi, 2015). Given that the number of time periods is rather high in our application, the incidental parameter bias problem should not pose a thread here, anyway. Nevertheless, we also estimated OLS regressions. Since the OLS results are similar to the Negbin results, but less precisely estimated, we focus in the following on the Negbin results and present OLS estimates in the appendix.

3 Results

3.1 Main Results

Before turning to the results of our main analysis, we show the results from the replication part of our analysis in Table 2. The corresponding graphical representation to the RD estimates can be found in Figure A1 in the Appendix. The first two columns of Table 2 report the estimates for the spring transition, while column three and four show the results for the fall transition. We do not find clear evidence that the transition into or out of DST increases accident counts. Only the RD estimates and graphs for fatal accidents suggest that DST transition adversely affects road safety. According to the point estimates entering DST increases the number of fatal accidents by 8-9 percent. While both estimates are of considerable size and in line with the results of Smith (2016), who finds that entering DST increases the number of fatal crashes in the US by around 6 percent, only one of them is significantly differently from zero. The results for the other accident types as well as the results for the total number of accidents rather point to small or zero effects of DST transition on road safety.

As already pointed out in Section 2.2, the RD estimates are of limited use when it comes to the estimation of the costs of different time regimes, as they can provide valid

Table 2: RD Estimates of DST Transition

	Spring Transition		Fall Transition	
Bandwidth selector	one	two	one	two
ln #all accidents	-0.011	-0.019	0.032*	0.016
	(0.018)	(0.015)	(0.018)	(0.018)
Obs.	591	945	651	630
ln # slight accidents	-0.033	-0.007	0.038**	0.010
	(0.021)	(0.015)	(0.019)	(0.019)
Obs.	480	987	609	609
ln # serious accidents	0.025	0.013	0.023	0.029
	(0.026)	(0.021)	(0.023)	(0.023)
Obs.	717	1179	735	777
ln # fatal accidents	0.090*	0.080	0.048	0.064
	(0.050)	(0.051)	(0.047)	(0.049)
Obs.	1544	1523	1356	1251

Notes: Each estimate gives the effect of DST transition on the number of accidents of the respective category and comes from a separate regression based on Equation 1. Bandwidth selectors are either a common mean squared error (MSE)-optimal bandwidth selector (denoted by one) or two different MSE-optimal bandwidth selectors below and above the cut-off (denoted by two). Robust standard errors are in parentheses. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

estimates only around the cut-off dates. Thus, we now turn to the main results and come back to the RD estimates when discussing our main results in Section 4.

Table 3 shows the baseline results of our main analysis. The first column gives the estimated coefficients of darkness on the total number of accidents and the number of accidents by accident severity for all regions. Columns 2 and 3 present the estimates for the same outcomes but the sample including only observations for which weather information is available. While column 2 gives the estimates from the regression including the standard controls, column 3 shows the results for our preferred specification in which we additionally control for weather conditions at accident site.

The results from our preferred specification, shown in column 3, suggest that darkness increases the total number of accidents for a given hour by 7.5 percent. As the effect of darkness is larger for the number of fatal (+31.9 percent) and serious (+11.8 percent) than for the number of slight accidents (+6.6 percent), darkness does not only seem to affect accident frequency considerably but also to increase accident severity. The corre-

Table 3: Main Results – Negbin

	All regions		Regions with weather data		Regions with weather data	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Weather controls	no		no		yes	
Dark						
# all accidents	0.068***	(0.006)	0.069***	(0.007)	0.075***	(0.007)
# slight accidents	0.058***	(0.006)	0.060***	(0.007)	0.066***	(0.008)
# serious accidents	0.103***	(0.007)	0.106***	(0.008)	0.118***	(0.008)
# fatal accidents	0.332***	(0.019)	0.309***	(0.022)	0.319***	(0.022)
Obs.	48,758,265		20,410,657		20,410,657	

Notes: Each estimate gives the effect of darkness on the number of accidents of the respective category and comes from a separate regression. All regressions include region, year, day-of-the-year, day-of-the-week, and hour fixed effects. Standard errors clustered at region level. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

sponding estimates derived from OLS regressions, though somewhat smaller and less precisely estimated, point in the very same direction and are shown in the Appendix (Table A1).

Our results are robust to the inclusion of weather controls. There are no relevant differences, neither with respect to size nor to statistical significance, between the estimates presented in columns 2 and 3. For both specifications and all outcomes we find relatively large negative and significant effects of darkness. This finding also holds when we use the entire sample (column 1), i.e. also observations for which weather information is not available.

Using simulations based on the Negbin results for all regions, we can now address two questions. First, how many accidents per year have been caused by darkness in England, Scotland and Wales under the current regime with Greenwich Mean Time (GMT) during winter and DST during summer? This number shows how many accidents could potentially be avoided if darkness-related accidents could be brought to zero. The second, related question is, whether having more light in the evening than in the morning can help to bring down accident counts, i.e. whether setting the clocks permanently to DST can prevent at least some accidents that would happen under an

Table 4: Annual Accident Counts by Time Regime

	Observed	GMT/DST	All hours light	GMT	DST
Slight	160,009	160,088	157,967	160,280	159,934
Serious	26,423	26,424	25,683	26,485	26,379
Fatal	2,529	2,529	2,254	2,545	2,519
Total	188,961	189,041	185,904	189,310	188,832

Notes: The table shows the average predicted number of accidents due to darkness by time regime. The first column (*Observed*) gives the observed number of accidents by accident severity, the second column (*GMT/DST*) gives the predicted number of accidents under the Status Quo (standard time during winter and daylight saving time during summer), the third column (*All hours light*) gives the predicted number of accidents in the hypothetical situation that all hours were light, the fourth column (*GMT*) gives the predicted number of accidents when the clocks were set to standard time during the entire year, and column five (*DST*) when the clocks were set to daylight saving time during the entire year.

all-year GMT regime. Using back-of-the-envelope calculations based on the predicted accident counts and the following average accident cost for 2016 as provided by the Department for Transport (2017a), we can broadly assess the social costs: £24,911 for a slight accident; £237,527 for a serious accident; £2,053,814 for a fatal accident. As these estimates are quite low compared to estimates used in the related literature,[12] our results for the social costs rather represent lower bounds of the true costs.

The first two columns of Table 4 show the observed and predicted number of accidents by accident class for the status quo with GMT during winter and DST during summer. In column 3 we report the predicted accident counts for the hypothetical situation in which none of the hours is dark. The difference in predicted accidents between this hypothetical situation and the status quo shows that according to our results darkness has caused 275 fatal, 741 serious and 2,121 slight accidents per year or annual total costs of £793 million. Thus, measures that can reduce accidents due to darkness (almost) to zero can have a positive net value only if the costs to implement these measures do not exceed around £800 million per year.

The remaining results of the simulation shown in columns 4 and 5 address the question whether setting the clocks permanently to DST instead of setting them to GMT for the whole year can save lives and prevent injuries. Indeed, our results provide some

[12] Smith (2016), for example, assumes average social costs of $4-$10 million per casualty.

evidence supporting this view. We estimate that there are 26 less fatal, 106 less serious and 346 less slight accidents under an all-year DST than under an all-year GMT regime. This implies annual cost savings of around £80 million, or 10 percent of total road accidents costs caused by darkness, under the all-year DST regime compared to the GMT regime. Although this seems to be not too much, one has to bear in mind that these £80 million are only due to the long term effects of DST on road safety, i.e. are the consequence of shifting light from the quiet morning hours to the rather busy afternoon hours. Abolishing the yearly transition into and out of DST has the potential to prevent additional road casualties that are due to low concentration and fatigue following the clock change.

3.2 Mechanisms

While the simulation reveals that establishing DST as the standard time throughout the year could prevent a considerable number of road casualties, the general mechanisms of the effect of darkness on accident counts are unknown. Although we cannot disentangle these mechanisms unambiguously with the data at hand, we exploit some features of the data to provide suggestive evidence in favour of one or the other channel. Theoretically, there are at least three potential channels through which ambient light condition might affect road safety. First, darkness might influence vision and thus the ability to recognize other road users early enough to prevent a collision. Second, natural light conditions influence the circadian rhythm. Thus, darkness might increase accident risk by increasing fatigue and reducing concentration. Third, people might expect driving to be more dangerous during darkness than during daylight. Consequently, they avoid driving during darkness, especially if they consider themselves as insecure drivers, which in turn might reduce accident counts during darkness.[13] As we find *positive* effects of darkness on accident counts, we can rule out that such behavioural responses are the main channel through which the effect operates.

[13]Note, that this does not imply any kind of selection that renders our results inconsistent, but would be a mechanism and thus a part of the effect.

Depending on the underlying mechanism, politicians might want to establish different measures to avoid at least some of the accidents that are due to poor light conditions. If, for example, darkness decreases road safety due to reduced vision of each and every driver during night, an option to reduce accidents might be to increase road lighting. However, it might also be that the risk of poor night vision is not the same for everybody but starts to increase at the age of 45, as the medical literature suggests (Darius et al., 2018). In case that this is the main driver of the effect, a more cost-efficient way to reduce road casualties might then be to identify drivers with impaired night vision, e.g. by establishing compulsory night vision screenings for older drivers. If, instead, the main driver of the effect is an increase in fatigue and poor concentration during darkness, neither an expensive expansion of road lighting nor visions screenings would help to reduce road casualties.

We cannot provide direct evidence for any of the mechanisms proposed above, as we neither have information about the vision of road users nor about their physical and mental constitution. However, we can use the information about the type of accident and characteristics of the drivers involved in the accident to see whether one of the mechanism is likely to be more important than others. Our approach is the following: First, we estimate the effect of darkness on the number of accidents involving pedestrians to see whether the result differs from our baseline result for all accidents. In a second step, we estimate the effect of darkness on accident counts, but this time differentiate by the age of the oldest driver involved in the accident. Finally, we run an interaction-like regression, i.e. we run separate regression for the number of pedestrian accidents by age groups. The intuition behind this approach is the following: If vision is a relevant mechanism, one would expect that darkness has a larger effect i. on the number of pedestrian accidents, as especially small and unlit objects are difficult to spot during night, and ii. on the number of accidents involving older drivers, as the risk of poor night vision increases in age. We would not expect different effect sizes neither by the type nor by the age of the road users involved in an accident, if adjustments of the circadian clock are the main mechanism.

Table 5: Effect Heterogeneity

	Coef.	(S.E.)
# all accidents	0.075***	(0.007)
# accidents involving pedestrians	0.123***	(0.015)
# accidents by age of oldest driver		
$0 <$age≤ 25	-0.040***	(0.011)
$25 <$age≤ 45	0.007	(0.010)
$45 <$age≤ 65	0.149***	(0.007)
$65 <$age	0.206***	(0.017)
# accidents involving pedestrians & age of oldest driver < 45	0.035**	(0.016)
# accidents involving pedestrians & age of oldest driver > 45	0.253***	(0.016)
Obs.	20,410,657	

Notes: Each estimate gives the effect of darkness on the number of accidents of the respective category and comes from a separate regression. All regressions include region, year, day-of-the-year, day-of-the-week, and hour fixed effects as well as weather controls. Standard errors clustered at region level. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

The results of this analysis (Table 5) suggest that reduced vision during darkness is indeed an important mechanism. We find that darkness increases the number of pedestrian accidents for a given hour on average by 12.3 percent. This relatively large positive effect is clearly larger that the baseline effect of 7.5 percent for all types of accidents. Furthermore, we find small negative or zero effects for accidents involving only young drivers, but large positive and significant effects for accidents involving drivers between 45 and 65 (14.9 percent) as well as drivers above the age of 65 (20.6 percent), indicating that reduced night vision among older drivers might be the key mechanism. This interpretation is supported by further results showing that the effect on pedestrian accidents is mainly driven by accidents that feature both "risk types" older drivers and pedestrians. For such accidents we find even larger effects of around 25.3 percent while the effect size for accidents also involving pedestrian but only younger drivers is quite small.

3.3 Sensitivity Analyses

The basic intuition behind our empirical approach is to capture the endogenous part of variation in darkness and accident counts by a set of fixed effects so that the remaining,

arguably exogenous part of variation can be used for estimation of β. Specifically, as shown in Section 2.2, we have used three sources of variation in darkness to estimate the effect of darkness on accident counts so far: day-by-day variation for a given region and hour; east-west variation for a given day of the year and hour; and finally, north-south variation for a given day of the year and hour. While there are no obvious reasons why this approach should produce inconsistent results – at least after controlling for weather conditions at accident site – one might nevertheless worry that one or several of these parts of variation are endogenous. To address this concern, we show the results of a sensitivity analysis where we eliminate one (two) source(s) of the variation and use the remaining two (one) source(s) to estimate the effect of darkness. The idea behind this approach to compare the resulting estimates to each other and the baseline results. If they do not differ too much from each other, we can be more confident that it is really darkness that drives our results.

In order to exclude one source of variation, we did not aggregate in cells as in the baseline specification, but either in vertical or in horizontal strips of width 0.5° longitude or latitude, respectively.[14] The resulting data provides information about the number of accidents (of the respective type), the mean proportion of the hour that is dark as well as about weather conditions for each hour and every strip (either along the lines of longitude or along the lines of latitude).

For the specification in which we eliminate day-by-day as well as east-west variation in darkness, we sum both the number of accidents and the treatment variable *dark* by region and day. By doing so we create a new treatment variable which gives the number of hours that are dark during the respective day in the respective region.[15] Thus, the interpretation of the estimates in this specification differs slightly from the interpretation of the other estimates.

[14] An alternative way to separate the different sources of variation, would be to include interactions between day of the year and hour (capturing day-by-day variation), day of the year, hour and longitude (capturing east-west variation), and day of the year, hour and latitude (capturing north-south variation). This approach, however, requires estimation of a huge number of coefficients and thus is impracticable in our application.

[15] Note that for some regions weather information is not available for all hours of the day. As we only sum over hours of a region if weather information is available for all hours of a day, the number of observations in column 4 is smaller than 1/24 of the original sample size.

Table 6: Sensitivity Analysis

	(I)	(II)	(III)	(IV)
Dark	0.075***	0.076***	0.080***	0.036***
	(0.007)	(0.009)	(0.010)	(0.011)
Variation				
Day-by-day	yes	yes	yes	no
East-west	yes	yes	no	no
North-south	yes	no	yes	yes
Obs.	20,410,657	3,346,100	3,840,831	794,818

Notes: All regressions include region, year, day-of-the-year, day-of-the-week, and hour fixed effects as well as weather controls. Clustered standard errors (at region level) in parentheses. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

Table 6 gives the results of this sensitivity analysis. Column (I) repeats the baseline results from Table 3 where we use all three sources of variation. The results for the specification where we only use day-by-day and east-west variation but exclude north-south variation are shown in column (II). The results for the specification where we only use day-by-day and north-south variation are given in column (III). Finally, column (IV) shows the estimates for the specification where we exclude both east-west and day-by-day variation in darkness and accident counts and only rely on north-south variation to estimate the effect of darkness on road safety.

We find that the results are quite robust to the different aggregation approaches and do not substantively change if the sources of variation in darkness that are used to estimate β change. The point estimates are all positive, highly significant and vary between 3.6 and 8 percent.

A potential problem with the aggregations schemes along lines of latitude or longitude is that eastern regions (e.g. the region between 0.5° and 0.0° longitude) are on average located more in the south and northern regions (e.g. the region between 56.0° and 56.5° latitude) are on average located more in the east. Thus, if we aggregate all regions along lines of latitude or longitude we cannot perfectly separate north-south variation in darkness from east-west variation and vice versa. To check whether this is a problem we also estimate regressions where we follow the same aggregation ap-

proach but restrict the sample to regions between 50.75° and 52.75° latitude (when using east-west variation) and -3.75° and -2.25° longitude (when using north-south variation). The results of this auxiliary regressions are shown in Table A2 in the Appendix and are similar to the results for the entire sample.

4 Conclusion

In a time when the political debate about the usefulness of DST flares up again, a thorough knowledge of all potential costs and benefits associated to the alternative time regimes is essential for policy makers who consider to abolish the biannual clock change. The aim of this paper was to assess the costs and benefits related to road safety of two alternative time regimes: an all-year standard time and an all-year DST regime. Since the choice of the time regime affects the distribution of light and darkness throughout the day, it has been hypothesized that establishing an all-year DST regime could prevent road casualties as this would shift light from the morning hours to the afternoon hours when streets are crowded and accident risk is high. To provide credible estimates of the number of accidents and the associated costs under the alternative time regimes, we estimated how darkness affects accident counts using arguably exogenous variation in darkness in a first step. The resulting estimates were then used in a second step to simulate the number of accidents under the two time regimes.

We find that darkness considerably affects road safety. Our results show that darkness increases accident counts for a given hour on average by around 7 percent. This implies that darkness causes more than 250 fatal, 700 serious and 2,100 slight accidents per year or total annual costs of at least £790 million in England, Scotland and Wales. Comparing the simulated accident counts under the different time regimes, our results suggest that road safety is indeed somewhat higher under an all-year DST than under an all-year standard time. According to our estimates, establishing DST throughout the year could prevent around 25 fatal, 100 serious and 350 slight accidents or social costs of at least £80 million per year compared to a situation with all-year standard

time.[16] These numbers result only from shifting daylight from the morning hours to the evening hours and do not include the number of prevented accidents that are due to the abolishment of the transitions, especially the spring transition. The latter has been reported to be quite substantial, at least for fatal accidents, with an increase of 6 percent for the US (Smith, 2016) and 9 percent for GB.

To put the effect size into perspective, we apply the same back-of-the-envelope calculation as Smith (2016).[17] Assuming that the estimated effect of the transition into DST on fatal accidents persists for six days – until the circadian rhythm has adjusted after the clock change – one would expect that abolishing the clock change would prevent around 3 fatal accidents each year. Compared to the estimated annual saving potential due to changes in light conditions (around 25 fatal accidents), the absolute number of prevented accidents due to disruptions of the circadian rhythm seems rather low, indicating that – other than hypothesized by Smith (2016) – the distribution of natural light across hours of the day still seems to matter for road safety. This interpretation is also consistent with the results from the heterogeneity analysis, where we found that the effect of darkness on accident counts most likely operates through a reduction in vision during darkness. Consequently, by simply focusing on the (spring) clock change, one runs the risk of significantly underestimating the total costs of the current time regime.

Against the ongoing debate about which time regime should be implemented, our results suggest that politicians should opt for an all-year DST regime if they decide to abolish the biannual clock change. This is in line with results from previous research that emphasizes the benefits of having more light during afternoon and evening hours and thus support the call for an all-year DST regime. Given that there is evidence that having more light during afternoon and evening hours, increase physical activity (Wolff and Makino, 2012) and reduce crime (Doleac and Sanders, 2015), the benefits of

[16] We assume no long term adjustments of the society to the new time regime, such as permanent changes in business hours or schooltime.

[17] To calculate the number of fatal accidents that are due to the clock change in spring, we multiply the estimated coefficient of the spring transition (0.09) with the average number of fatal accidents per day on Sundays and weekdays in March and April (6.2) and the number of days (6). We look at fatal accidents only, since costs due to fatal accidents constitute the largest part of total costs. In addition, the estimated coefficients of the remaining accident categories are rather small and broadly not statistically significant.

establishing DST throughout the entire year most likely outweigh potential disadvantages. Finally, adverse effects in various dimensions, such as well-being and health, caused by the biannual transitions could be avoided.

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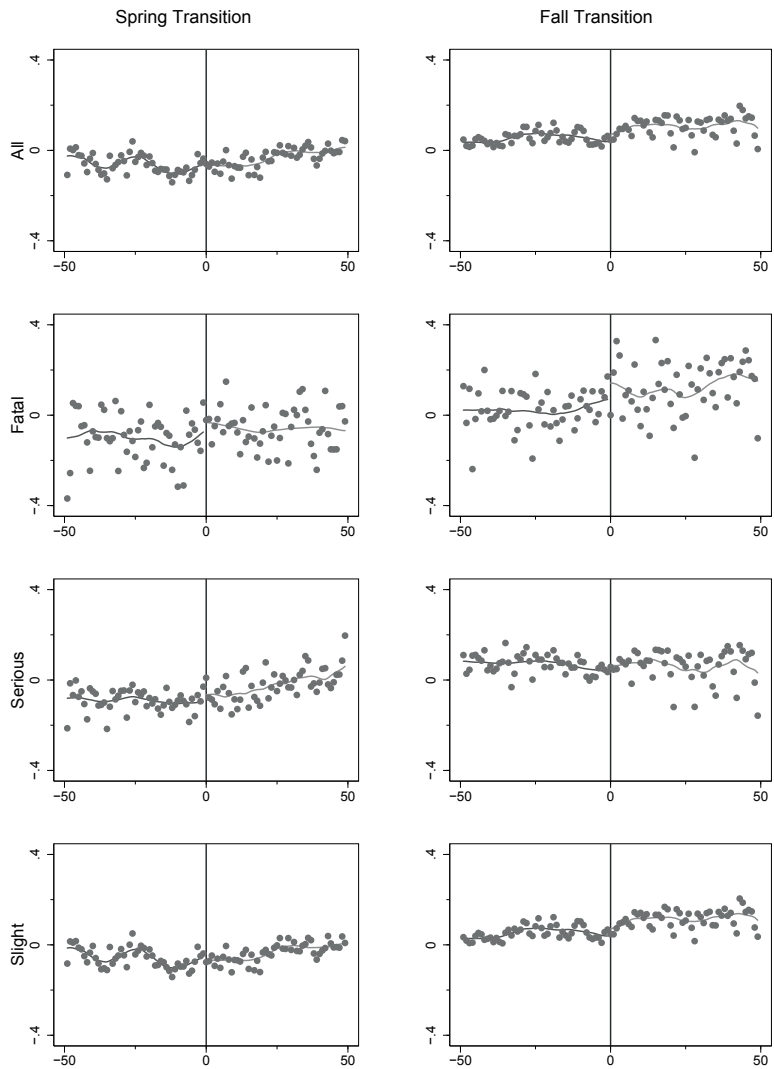
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Appendix

Figure A1: Residual Plots



Note: Own calculations and illustration based on stats19 data. The residuals come from a regression of $ln(accidentcounts)$ – either all (first row), fatal (second row), serious (third row), or slight (last row) – on year and day of week fixed effects. Each point gives the mean of all residuals at the respective date, where the date is defined relative to the spring (left part of the graph) or fall transition (right part). Fitted lines are based on locally weighted regressions.

Table A1: Baseline Results – OLS

	All regions		Regions with weather data		Regions with weather data	
	Coef. (S.E.)	Coef./$\overline{y}$	Coef. (S.E.)	Coef./$\overline{y}$	Coef. (S.E.)	Coef./$\overline{y}$
Weather controls	no		no		yes	
Dark						
# all accidents	0.0005 (0.0011)	0.0001	.0077** (0.0031)	0.0478	0.0073** (0.0032)	0.0458
# slight accidents	-0.0006 (0.0010)	-0.0090	0.0047* (0.0026)	0.0347	0.0044* (0.0027)	0.0324
# serious accidents	0.0008*** (0.0002)	0.0725	0.0023*** (0.0005)	0.1035	0.0023*** (0.0005)	0.1039
# fatal accidents	0.0003*** (0.0000)	0.3153	0.0006*** (0.0001)	0.3162	0.0006*** (0.0001)	0.3165
Obs.	48,758,265		20,410,657		20,410,657	

Notes: Each estimate gives the effect of darkness on the number of accidents of the respective category and comes from a separate negative binomial regression. All regressions include region, year, day-of-the-year, day-of-the-week, and hour fixed effects. Standard errors clustered at region level. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.

Table A2: Sensitivity Analysis – Restricted Sample

	(I)	(II)
Dark	0.100*** (0.007)	0.063*** (0.013)
Variation		
Day-by-day	yes	yes
East-west	yes	no
North-south	no	yes
Obs.	2,618,121	3,095,024

Notes: All regressions include region, year, day-of-the-year, day-of-the-week, and hour fixed effects as well as weather controls. Clustered standard errors (at region level) in parentheses. Significance levels: * p<0.1; ** p<0.05; *** p<0.01.