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A causal analysis of daylight savings and road casualties in Great Britain

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Abstract

Objectives: To determine whether daylight savings time (DST) transitions in the Spring and Autumn have a causal effect on road traffic casualties in Great Britain. We undertake aggregate and disaggregate spatial and temporal analyses to test the commonly referenced sleep and light hypotheses.
Design: The study takes the form of a natural experiment in which the DST transitions are interventions to be evaluated. Two outcomes are tested: (i) the total number of casualties of all severities (ii) the number of fatalities.
Data: Data are obtained from the UK Department for Transport STATS19 database. Over a period of 14 years between 2005 and 2018, 311,766 casualties of all severities and 5,429 fatalities occurred 3 weeks either side of the Spring DST transition and 367,291 casualties of all severities and 6,650 fatalities occurred 3 weeks either side of the Autumn DST transition.
Primary outcome measure: A regression discontinuity design method (RDD) is applied. The presence of a causal effect is determined via the degree of statistical significance and magnitude of the average treatment effect.
Results: DST transitions have had only a minor positive impact on road casualties and fatalities. The majority of significant average treatment effects are negative (70 out of 72 models), indicating that there tends to be fewer casualties following the transitions. Overall, we estimate that there are 0.25-0.36 fewer fatalities and 3.3-3.9 fewer total casualties on average per year at both the Spring and Autumn DST transitions combined.
Conclusions: The results indicate minor reductions in the number of fatalities following the DST transitions, and thus our analysis does not support the most recent UK parliamentary estimate that there would be 30 fewer fatalities in Great Britain if DST were to be abolished. Furthermore, the results do not provide conclusive support for either the sleep or light hypotheses.

Keywords: Road safety, Daylight savings time, Sleep, Visibility, Regression discontinuity design

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Strengths and limitations of this study

Strengths:

- We adopt a causal regression discontinuity design method to generate robust estimates of the impact of DST transitions on road traffic casualties and fatalities in Great Britain.
- We undertake both aggregate and disaggregate spatial and temporal analyses to investigate the impacts of sleep and light disruptions at the transitions.
- We account for potential confounding through the inclusion of seasonal variables at the level of year, day of week, and time of day, and treat heteroskedasticity and autocorrelation to account for unobserved confounders.

Limitations:

- Limitations include potential under-reporting of casualties in the Department for Transport STATS19 database, sparse data leading to estimation difficulties in the northernmost regions of Scotland, and the presence of potential additional unobserved confounders that could lead to biased estimates.

1. Introduction

Since its introduction, the implementation of daylight savings time (DST) has been a contentious issue which has regained attention in recent times. In response to a public consultation held in 2018, the European Parliament in 2019 adopted a position to support the elimination of daylight savings in the European Union (EU), with plans for implementation in 2021 [1, 2]. The United Kingdom (UK) initiated an inquiry to analyse the impact of the EU change to "understand what factors should inform [the UK's] approach" [3]. The UK also previously debated and ultimately rejected changes to daylight savings in the Daylight Saving Bill 2010-11, which proposed to shift UK time forward by one hour throughout the year to align with Central European Time (CET) [4]. A key argument in the elimination or alteration of daylight savings time is the impact that clock changes have on road safety. In both the academic literature and government parliamentary debates, two issues are highlighted as having an impact on road safety levels: (i) changes in daylight hours could impact alertness due to the required chronobiologic adjustments to the human circadian rhythm [1, 5, 6] - herein referred to as the 'sleep hypothesis', and (ii) changing of daylight hours could result in detrimental changes to visibility [7, 8, 4, 3] - herein referred to as the 'light hypothesis'.

Evidence on the impact of DST transitions on road traffic casualties is currently inconclusive. In the 2010-2011 Daylight Saving Bill, it was argued that there would be 80 fewer fatalities on UK roads if the UK switched to CET [4]. In the more recent UK report on the proposed EU changes, it was stated that abolishing time changes and adopting a permanent move to UK Summer Time could result in 30 fewer fatalities [3]. However, it is unclear how these figures were generated and whether robust causal statistical analysis methods were adopted. In the academic literature, there is mixed consensus regarding the impact of DST transitions. Increases in road casualties are reported for studies undertaken in the US by Smith [9] and in New Zealand by Robb and Barnes [10], while reductions in casualties in the US are reported by Coate and Markowitz [11] and Crawley [12]. Lindenberger et al. [13] reports no significant impacts in their analysis of accidents in Germany.

The aim of this paper is to estimate the causal effect of DST transitions on the number of road traffic casualties and fatalities in Great Britain. This paper contributes to the literature from several perspectives. First, the majority of studies adopt non-casual techniques to quantify the impact of DST transitions, including comparisons of descriptive statistics, linear regression based on ordinary least squares, and quasi-Poisson regression [13, 10, 11, 14, 15]. Two studies by Carey and Sarma [7] and Uttley and Fotios [16] adopt a casual regression discontinuity design (RDD) method similar to ours, however, the studies focus on road casualties in the USA and pedestrian casualties in the UK, respectively. We therefore contribute to the literature by adopting a casual RDD method to analyse road traffic accidents in Great Britain, which, to our knowledge, has not been previously undertaken. Second, use of the RDD method with time as the forcing variable requires stringent specification tests to be undertaken to ensure that the models are free from potential confounding factors that can lead to biased estimates. In the literature on RDD methods applied to DST analyses, these specification tests are not typically performed. In our analysis, we follow the recommendations made in Hausman and Rapson [17] to test for model robustness. Finally, evidence for the sleep and light hypotheses is limited, with only two known non-causal studies in the UK and US indicating an increase in casualties during darker periods at DST transitions [14, 15]. Therefore, in addition to a pooled analysis of Great Britain as a whole, we also undertake disaggregate spatial and temporal analyses to test the sleep and light hypotheses.

2. Methods

2.1. Patient and public involvement statement

Please note that no patients nor members of the public were involved in this study.

2.2. Study area and data

The STATS19 database produced by the Department for Transport is used to obtain records of road traffic accidents that resulted in personal injury in Great Britain between 2005 and 2018 [18]. Casualties are defined as personal injuries of any severity as a result of an accident. As specified in [19], a single accident can be associated with more than one casualty. In this analysis, we focus on total casualties (all severities combined) and fatal casualties.

Three week windows on either side of the DST transitions in Spring and Autumn are extracted from the total accident data set. Three weeks is chosen to provide enough data for the optimised local bandwidth to be calculated during the RDD modelling. Through data cleaning, less than 0.02% of records have been removed as a result of missing observations, as well as records over Bank Holidays. The descriptive statistics of the casualties for all of Great Britain over the three week windows either side of the transitions are summarised in Table 1. As shown in the table, there are increases in the number of casualties and fatalities after both transitions when considering 3 week windows before and after the transitions.

Table 1: Descriptive statistics of casualties, aggregated over Great Britain over ± 3 week windows from DST transition dates

	Spring		Autumn	
Casualty severity	Before DST	After DST	Before DST	After DST
Total casualties	153107	158659	175796	191495
Fatal casualties	2517	2912	3211	3439

To investigate whether the DST transitions have different regional effects across Great Britain, National Ordnance Survey data are used to divide Great Britain into distinct bands based on latitude and longitude [20]. Using the Ordinance Survey Grid Reference (OSGR) variable within STATS19, each accident and casualty is assigned a Northings band and an Eastings band.

2.3. Regression discontinuity design framework

DST is a policy enacted for the entire population of Great Britain and the treatment assignment is deterministic, i.e., there is no ambiguity in treated vs untreated observations. Therefore, the DST treatment imposed at the Spring and Autumn transitions is considered as a sharp discontinuity. Further information on RDD frameworks is presented in Imbens and Lemieux [21] and Lee and Lemieux [22].

In this analysis, we use spatio-temporal units where i refers to a given local area zone within Great Britain, t refers to a given time period, where each day is segmented into 5 time periods, and z refers to year. The assignment of the treatment, i.e. the imposition of the daylight savings transition, is solely dependent on the value of the forcing variable, time T, as follows:

$$W_{itz}\begin{cases}1 \text{ if } T_t \geq c \\ 0 \text{ if } T_t < c\end{cases} \qquad (1)$$

where c is the treatment threshold, which is defined as the DST transition date, and W_{itz} is the binary treatment in the sharp RDD. In the Spring transition, the treatment is the imposition of Summer Time, while in the Autumn transition, the treatment is the return to GMT. Observations recorded between 00:00 and 01:00 in March and between 00:00 and 02:00 in October on the day of the transition are designated as non-treated in line with when the transition occurs. Over the analysis time period of 2005 to 2018, the transition dates for Spring range from 25 to 31 March and those for Autumn range from 25 to 31 October.

The observation of a discontinuity in the average treatment effect either side of the treatment threshold is evidence of a causal effect of the treatment [21, 22]. The average treatment effect for a sharp discontinuity τ_{SRD} in time is defined as:

$$\tau_{SRD} = E\left[Y_{itz}(1) - Y_{itz}(0) \,\middle|\, T_t = c\right] = \lim_{t \downarrow c} E[Y_{itz}|T_t = t] - \lim_{t \uparrow c} E[Y_{itz}|T_t = t] \qquad (2)$$

where $Y_{itz}(1)$ indicates the potential outcome when treatment is received and $Y_{itz}(0)$ indicates the potential outcome when treatment is not received. The second equality holds assuming continuity of expectations in T i.e. $E[Y_{itz}(0) \mid T_t = c] = \lim_{t \uparrow c} E[Y_{itz}(0) \mid T_t = t] = \lim_{t \uparrow c} E[Y_{itz} \mid T_t = t]$ [21].

Since the forcing variable is time, we follow the recommendations in Hausman and Rapson [17] to address potential specification issues. To ensure that there are enough observations in the vicinity of the treatment threshold, we segment daily data into 5 time periods, and the data are aggregated at a local area zone level which also provides cross-sectional variance at each time point. By segmenting the data to increase the number of observations close to the treatment threshold, we avoid the need to include observations further away from the threshold which can introduce bias from unobserved confounding variables. We account for potential bias from known confounding variables correlated with time through the inclusion of covariates representing potential seasonal variation in casualties. The covariates are year, day of the week, and the time period associated with each observation. Since the daylight savings transitions are universally applied at fixed transition dates, we do not anticipate issues arising from manipulation of treatment status. Further specification tests are undertaken to ensure validity of the design and these are discussed in section 2.4.

The data sets are arranged in a pseudo-panel form with indexes of local area zone and time period per year. The response variable is the sum of the number of casualties per local area zone and time period per year; in cases where no casualties are observed, a value of 0 is designated. For each of the Spring and Autumn transitions, two base regressions are undertaken as follows: (i) the total number of casualties of all severities, and (ii) the total number of fatalities. The two base regressions are run for three scenarios: (i) for Great Britain overall, (ii) for each Northing band in each time period, and (iii) for each Easting band in each time period. The general equation for the aggregate model of Great Britain is given in equation 3. The regional and time of day analyses enable the investigation of the sleep and light hypotheses. It should be noted that in the disaggregate models, the time of day covariate in equation 3 is not included as the models are pre-segmented by time of day. All modelling has been undertaken using R statistical analysis software.

$$Y_{itz} = \alpha + \tau_{SRD} W_{itz} + \theta_1 K_{itz}(t) + \theta_2 K_{itz,post}(t) + \beta_1 X_{1z} + \beta_2 X_{2t} + \beta_3 X_{3t} + \varepsilon_{itz} \quad (3)$$

where Y_{itz} is the total number of casualties per local area zone i per time period t per year z, W_{itz} is the treatment assignment indicator as previously defined, τ_{SRD} is the average treatment effect of interest, $K_{itz}(t)$ represents the average long term trend across the entire bandwidth i.e. $K_{itz}(t) = t$, and $K_{itz,post}(t)$ is the time trend after the intervention where $K_{itz,post}(t) = 0, t < c$ and $K_{itz,post}(t) = t - c + 1, t \geq c$. The categorical variables X_{1z}, X_{2t}, X_{3t} condition for year, day of the week, and time period, respectively. Year takes a value from 1 – 14 corresponding to the years 2005 – 2018. As coded in the STATS19 database, the day of the week takes a value 1 – 7 with 1 corresponding to Sunday and 7 corresponding to Saturday. The time of the day takes values as follows: Twilight = 1, AM Peak = 2, Inter Peak = 3, PM Peak = 4, Night = 5. The peak time periods follow the standards adopted by the Department for Transport: AM Peak (07:00 – 09:59), Inter Peak (10:00 – 15:59) and PM Peak (16:00 – 18:59) [18]. Two additional time-bins are added to complete a 24-hour period: Twilight (0:00 – 06:59) and Night (19:00 – 23:59). α and ε_{itz} are the model constant and model random error term, respectively, where $\varepsilon_{itz} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$.

It should be noted that the inclusion of group-specific fixed effects for local area zone was trialled to account for potential time-invariant cross-sectional differences. However, using the Bayesian Information Criterion (BIC) as an indicator of model performance, we found that a majority of models performed better with no local area zone effects compared to those with local area effects, and so these effects are not included in the final model form.

2.4. Specification tests

As recommended by Hausman and Rapson [17], we perform the following specification tests:

- The optimal bandwidth for the RDD models is first calculated using a data-driven optimal bandwidth selection process via the 'rdrobust' package in the R statistical analysis software [23, 24]. We adopt a local linear specification for the forcing variable of time. Specification checks are performed by varying the bandwidth within the vicinity of the optimal bandwidth, and verifying that the average treatment effect remains consistent.

- Specification checks are performed for the polynomial order of the forcing variable of time, and the BIC is used to judge model performance. Polynomials of up to degree 4 are tested, and we verify that the local linear specification performs best in line with the bandwidth selection procedure.

- The Bruesch-Godfrey test [25, 26] is performed to test for autocorrelation of the error term for a lag value up to 10 (2 days). If autocorrelation is present, it is treated using Newey-West standard errors [27], which are heteroskedasticity and autocorrelation consistent (HAC).

- The Bruesch-Pagan test [28] is performed to test for heteroskedasticity. If heteroskedasticity is present with no error term autocorrelation, it is treated with heteroskedasticity consistent (HC3) errors [29].

  Note: Autoregression of the dependent variable is not considered in this analysis, since the majority of casualties per local area zone do not occur in consecutive time periods.

3. Results

The results for the aggregate Spring and Autumn RDD models are presented in Table 2. The results for the disaggregate spatial and temporal RDD analyses are presented in Tables 3 and 4. All results tables summarise cases where the RDD models have passed all specification tests as described in section 2.4, and the average treatment effect at the DST transition is significant at a minimum significance level of $\alpha = 0.1$ ($\geq 90\%$). A map of the corresponding Northing and Eastings bands is given in Figure 1.

Table 2: Aggregate models of Great Britain - RDD results summary

Transition	Location	Casualty type	BW	n	τ_{SRD}	% Change

Spring	Aggregate Great Britain	All casualties	32	173888	-0.075 (0.009)***	0.003%

Notes: Significance notation: p-values 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Standard errors in parentheses.
BW refers to bandwidth in time period units, τ_{SRD} refers to the sharp RDD average treatment effect due to DST transition.

Table 3: Spring transition - disaggregate spatial and temporal models RDD results summary

			All Casualties				Fatalities				
Location	Band	Time period	BW	n	τ_{SRD}	% Change	BW	Time period	n	τ_{SRD}	% Change
Aggregate		1	22	27145	-0.110 (0.024)***	-0.12%	40	1	12744	-0.067 (0.022)**	-0.70%
		3	62	65208	-0.157 (0.033)***	-0.01%					
		4	38	43472	-0.059 (0.020)**	-0.01%					
		5	46	48906	-0.130 (0.025)***	-0.03%					
Northing band	1,000-2,000	1	28	9925	-0.095 (0.034)**	-0.28%					
		3	36	15992	-0.162 (0.042)***	-0.06%					
		4	38	16008	-0.067 (0.029)*	-0.04%					
		5	48	17991	-0.146 (0.041)***	-0.08%					
	2,000-3,000	1	36	9758	-0.117 (0.069) .	-0.45%	50	1	3312	-0.134 (0.072) .	-3.07%
		3	74	19698	-0.137 (0.047)**	-0.06%					
	3,000-4,000	1	34	8365	-0.075 (0.035)*	-0.33%	44	1	2648	-0.046 (0.021)*	-2.58%
		3	64	14496	-0.167 (0.063)**	-0.07%					
		5	52	13233	-0.086 (0.042)*	-0.09%					
	4,000-5,000						54	1	1414	-0.049 (0.028) .	-4.89%
	5,000-6,000	3	42	2872	-0.209 (0.118) .	-0.53%					
	6,000-7,000	1	34	2135	-0.154 (0.082) .	-3.31%					
Easting band	2,000-3,000	3	72	8974	-0.108 (0.063) .	-0.10%					
		5	52	7029	-0.099 (0.051) .	-0.24%					
	3,000-4,000	1	28	8370	-0.148 (0.056)**	-0.64%	62	1	4510	-0.139 (0.055)*	-2.89%
		3	50	16930	-0.090 (0.050) .	-0.04%	56	3	6432	0.023 (0.013) .	0.59%
	4,000-5,000	1	30	11814	-0.069 (0.030)*	-0.18%					
		3	74	28000	-0.171 (0.049)***	-0.04%					
		5	50	20000	-0.083 (0.038)*	-0.05%					
	5,000-6,000	1	28	8530	-0.104 (0.039)**	-0.34%					
		3	70	24066	-0.090 (0.037)*	-0.02%					
		4	26	8565	-0.110 (0.045)*	-0.10%					
		5	44	15453	-0.149 (0.045)***	-0.09%					

Notes: Significance notation: p-values 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Standard errors in parentheses. BW refers to bandwidth in time period units, τ_{SRD} refers to the sharp RDD average treatment effect due to DST transition.

Table 4: Autumn transition - disaggregate spatial and temporal models RDD results summary

			All Casualties				Fatalities				
Location	Band	Time period	BW	n	τ_{SRD}	% Change	BW	Time period	n	τ_{SRD}	% Change
Aggregate		1	18	16197	-0.096 (0.019)***	-0.13%	38	1	13671	-0.030 (0.012)*	-0.40%
		2	22	21612	-0.028 (0.016) .	-0.02%					
		3	72	75642	-0.101 (0.028)***	-0.01%					
		4	34	37821	-0.077 (0.024)**	-0.01%					
		5	32	37821	-0.231 (0.030)***	-0.04%	60	5	24936	-0.035 (0.016)*	-0.17%
Northing band	0-1,000	1	38	2534	-0.153 (0.058)**	-2.38%					
		2	42	3104	0.058 (0.030) .	0.42%					
		5	64	5044	-0.156 (0.062)*	-0.56%					
	1,000-2,000	1	24	10015	-0.158 (0.036)***	-0.35%	40	1	4888	-0.052 (0.017)**	-1.45%
		4	30	12048	-0.129 (0.036)***	-0.09%					
							64	5	7904	-0.083 (0.043) .	-1.12%
	2,000-3,000	1	32	9695	-0.112 (0.035)**	-0.39%					
		5	48	12708	-0.190 (0.058)**	-0.17%					
	3,000-4,000	1	26	6010	-0.152 (0.045)***	-0.74%					
		4	40	9576	-0.118 (0.042)**	-0.11%					
		5	50	11950	-0.247 (0.055)***	-0.21%					
	4,000-5,000	5	50	6850	-0.315 (0.096)**	-0.38%					
	5,000-6,000	2	48	3440	-0.076 (0.031)*	-0.41%					
	7,000-8,000	5	70	1470	-0.094 (0.045)*	-1.84%					
	8,000-9,000	1	56	583	-0.280 (0.097)**	-11.53%					
		5	66	793	-0.362 (0.128)**	-5.69%					
Easting band	1,000-2,000	1	64	1092	-0.072 (0.036)*	-3.34%					
	2,000-3,000						78	3	3210	-0.056 (0.021)**	-3.00%
		4	54	7018	-0.091 (0.043)*	-0.15%					
		5	50	6280	-0.268 (0.076)***	-0.55%					
	3,000-4,000	1	26	8195	-0.136 (0.040)***	-0.46%	42	1	4905	-0.038 (0.021) .	-1.17%
		2	20	6644	-0.047 (0.025) .	-0.15%					
		4	34	11641	-0.080 (0.041) .	-0.06%					

			All Casualties				Fatalities				
Location	Band	Time period	BW	n	τ_{SRD}	% Change	BW	Time period	n	τ_{SRD}	% Change
		5	44	14985	-0.222 (0.050)***	-0.14%					
	4,000-5,000	1	26	9825	-0.129 (0.032)***	-0.36%					
	4,000-5,000	5	44	17874	-0.252 (0.057)***	-0.12%					
	5,000-6,000	1	22	8525	-0.187 (0.037)***	-0.46%	44	1	4491	-0.042 (0.014)**	-1.71%
		4	34	12033	-0.127 (0.039)**	-0.07%					
		5	48	15408	-0.279 (0.056)***	-0.14%					
	6,000-7,000	5	42	2394	-0.191 (0.086)*	-1.04%					

Notes: Significance notation: p-values 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Standard errors in parentheses. BW refers to bandwidth in time period units, τ_{SRD} refers to the sharp RDD average treatment effect due to DST transition.

3.1. Spring transition

As shown in the tables, the majority of models with significant average treatment effects show a reduction in the number of casualties at the Spring transition. For the whole of Great Britain, approximately 0.075 (-0.003%) fewer total casualties are observed on average per year. The time of day models further indicate reductions in total casualties ranging from 0.06 to 0.16 fewer casualties per year across all time periods except the morning peak (in percentages, -0.01% to -0.12%). In terms of fatalities in isolation, there are 0.07 (-0.7%) fewer fatalities observed in the twilight period.

Latitudinal analysis

In the disaggregate models of Northing bands, there are significant reductions in total casualties in 6 out of 12 bands. The reductions range from approximately 0.07 to 0.21 fewer total casualties (-0.04% to -3.31%) per year in all time periods except the morning peak. In terms of fatalities, there are 0.05 to 0.13 fewer fatalities per year (-2.58% to -4.89%) in the twilight time period in consecutive bands 2000-5000.

Longitudinal analysis

In the disaggregate models of Easting bands, there are significant effects in 4 out of 7 bands. There are approximately 0.07 to 0.17 fewer total casualties (-0.02% to -0.64%) in all time periods except the morning peak. For the fatality models, in band 3000-4000, there is a significant reduction of 0.14 fatalities (-2.89%) in the twilight time period, and a 0.02 increase in fatalities (0.59%) in the inter-peak time period.

3.2. Autumn transition

As with the Spring transition, in the Autumn transition, the majority of models with significant average treatment effects report a reduction in casualties. Considering Great Britain as a whole, there are no significant effects. However, when splitting by time of day, there are reductions in total casualties in every time period ranging from 0.01 to 0.23 fewer total casualties on average per year (-0.01% to -0.13%). In terms of fatalities, there are 0.03 fewer fatalities (-0.40%) in the twilight time period and 0.04 fewer fatalities (-0.17%) in the night time period.

Latitudinal analysis

In the disaggregate models of Northing bands, there are significant effects in 8 out of 12 bands. All significant effects are negative with the exception of band 0-1000, where there is an increase of 0.06 in the total number of casualties (0.42%) in the AM peak. The remaining negative effects range from a 0.08 to 0.36 reduction in the total number of casualties (-0.09% to -11.53%), and all signficant effects are observed across all time periods except the interpeak. For fatalities, in band 1000-2000, there are 0.05 fewer fatalities (-1.45%) in the twilight time period and 0.08 fewer fatalities (-1.12%) in the night time period.

Longitudinal analysis

In the disaggregate models of Easting bands, 6 out of 7 bands report significant effects in the total number of casualties. All significant effects are negative and they are observed in all time periods except the inter-peak. The effects range from 0.05 to 0.28 fewer total casualties (-0.06% to -3.34%). For the fatality models, in band 5000-6000, there are 0.04 fewer fatalities (-1.71%) in the twilight time period. There are additional reductions in fatalities in band 2000-3000 in the inter-peak, where there are 0.06 fewer fatalities (-3.00%), and in band 3000-4000 in the twilight time period, where there are 0.04 fewer fatalities (-1.17%).

4. Discussion

4.1. Pooled analysis of Great Britain

When Great Britain is viewed as a whole regionally and without time segmentation, there is a statistically significant casual effect indicating a very minor reduction of 0.075 (0.003%) in the total number of casualties at the Spring DST transition. The average treatment effect in all other pooled analyses are insignificant at a minimum significance level of ≥ 90%.

When segmenting the data, there are further geographical zones and time periods with statistically significant average treatment effects. Our analyses therefore indicate that it is important to investigate the impacts of DST transitions at disaggregate spatial and temporal levels, as well as analysing the aggregate effects.

4.2. Morning time periods - sleep and light hypotheses

At the Spring transition, clocks are moved forward one hour and this can result in a loss of sleep in the morning. Therefore, in the time of day models, we would expect to see an increase in casualties in the twilight and morning time periods. In terms of the regional effects, the sun rises later in the west and north. As such, those in the west and north of Great Britain would experience darker mornings than those in the east and south, and so more casualties would be expected in the west and north.

For the aggregate analysis of Great Britain, the time of day models show minor reductions in both total casualties and fatalities in the twilight period (from midnight to 7am) and no effect in the AM peak (7-10am), in opposition to the sleep hypothesis. For the Northing and Easting time of day models, the results again do not support the sleep hypothesis; in every significant twilight and AM peak model, there is a reduction in the number of total casualties and fatalities. In terms of regional differences, we do not observe a systematic pattern showing progressively more casualties in the west and north in morning time periods as per the light hypothesis.

In the Autumn transition, clocks are moved back one hour and this can lead to more sleep in the morning. Regionally, the west and north of Great Britain would again experience darker mornings than the east and south. Therefore, fewer casualties would be expected in the twilight and morning time periods, however, this effect could be minimised in the west and north as the darker mornings could offset the later wake up times, resulting in minimal overall sleep changes.

In the west and north regions, we would therefore expect to see minimal effects at the DST transition.

In the aggregate time of day models for Great Britain, the results support the sleep hypothesis as there are reductions in casualties during the twilight and AM peak periods. For the Northing and Easting time of day models, the sleep hypothesis is again supported with reductions in the twilight and AM peak periods, though with one exception. In the AM peak period in Northing band 0-1000, there is a minor increase in the total number of casualties, in opposition to the sleep hypothesis. In terms of regional differences, there is minimal support for a systematic pattern that shows progressively fewer casualties towards the east and south in morning time periods as per the light hypothesis.

4.3. Evening time periods - light hypothesis

At the Spring transition, there is a more light in the evenings and so we would expect to see a reduction in casualties. In terms of regional effects, the east and south become darker than the west and north in the evenings, and so we would expect fewer casualties in the west and north. In the aggregate models of Great Britain, we observe a minor reduction in the PM peak (4-7pm) and night time periods (7pm-midnight) in line with the light hypothesis. In the Northing and Easting time of day models, the light hypothesis is again supported in the PM peak and night time periods with reductions in casualties. However, for regional differences, there is minimal support for a systematic pattern that shows progressively fewer casualties towards the west and north in evening time periods.

At the Autumn transition, there is a reduction in light in the evenings and so an increase in casualties is expected. The east and south again become darker than the west and north in the evenings, and so fewer casualties are expected in the west and north. In the aggregate models of Great Britain, the light hypothesis is not supported in the PM peak and night time periods, as minor reductions in casualties are observed. In the Northing and Easting time of day models, the light hypothesis is again unsupported as reductions in casualties are observed in the PM peak and night time periods. Furthermore, we do not observe a systematic pattern that shows progressively fewer casualties towards the west and north in evening time periods.

4.4. Magnitude of impacts at DST transitions

In the Daylight Savings Bill 2010-2011, it was estimated that there would be 80 fewer fatalities if the UK followed CET time [4]. A more recent report on EU DST changes states that there would be 30 fewer fatalities as a result of eliminating DST transitions altogether [3].

Overall, our analysis suggests that DST transitions have a minor positive impact rather than a detrimental impact on road traffic casualties and fatalities. For total casualties, 59 out of 387 models have significant average treatment effects, while for fatalities 13 out of 189 models have significant effects. The majority of significant models (70 out of 72 models) report a negative effect, indicating a reduction in the number of casualties at the DST transitions.

If we sum the significant average treatment effects for fatalities in the regional time of day models, we can obtain estimates of the effect on the total number of fatalities per year in Great Britain for the Spring and Autumn transitions combined. Two estimates are generated: one for Easting band segmentation and one for Northing band segmentation. For the Eastings bands there are in total 0.25 fewer fatalities across Great Britain, while for the Northings bands there are in total 0.36 fewer fatalities across Great Britain per year for the Spring and Autumn transitions combined. Our analysis therefore reports minor reductions in fatalities at the DST transitions, rather than increases in fatalities as estimated in House of Lords [3] and Bennett [4].

Similarly, for the total number of casualties of all severities, we find that there are 3.3 fewer total casualties reported in the Eastings band analysis and 3.8 fewer total casualties per year in the Northings band analysis across Great Britain for the Spring and Autumn transitions combined. Therefore, the results for casualties of all severities also question the estimated reduction in fatalities only as per House of Lords [3] and Bennett [4].

4.5. Limitations

One limitation of the RDD methodology is that is applicable to ex-post analyses and not suitable for making ex-ante predictions. Therefore, the results reflect the impact of DST transitions on road safety over the study period of 2005-2018, and it is difficult to generalise the results to predict the impact of potential DST changes in the future. However, we have no compelling reason to believe that the average treatment effect will change significantly over time.

The data from the Department for Transport STATS19 database may also pose potential limitations, as the data are compiled from police reports. As a result, there could be potential under-reporting of casualties. One previous study estimated that the number of accidents classified as Serious could be under-reported by a factor of two [30]. Another data-related limitation is the sparse data in the northernmost regions of Scotland. Due to the limited number of observations, the RDD models reported high standard errors of the average treatment effect estimator and low statistical significance in these regions, and in some cases, estimates were not able to be computed. As such, in future work, either alternate data sources or alternate statistical analysis techniques for small sample data are recommended.

Finally, it should be noted that we aimed to condition for potential bias in traffic volumes through the inclusion of seasonal year, day of week, and time of day variables along with treatment of heteroskedasticity and autocorrelation of the error term to account for potential unobserved confounders. However, there may be additional unobserved factors that we have not accounted for which may lead to potentially biased estimates.

5. Conclusion

In this paper, we find that DST transitions have only a minor positive impact on road casualties and fatalities. For total casualties, 59 out of 387 models have significant average treatment effects, while for fatalities 13 out of 189 models have significant effects. The majority of models with a significant average treatment effect (70 out of 72 models) report a negative effect, indicating a reduction in the number of casualties at the DST transitions.

Considering Great Britain as a whole, we find a significant effect indicating a minor 0.003% reduction in the total number of casualties in the Spring transition into DST. The average treatment effects in all other aggregate models are insignificant at a minimum significance level of ≥ 90%. When segmenting the data spatially and temporally, there are more models with statistically significant average treatment effects. This highlights the importance of investigating the impacts of DST transitions at a disaggregate level.

The disaggregate spatial and temporal models do not provide clear support or rejection of the sleep and light hypotheses at the transitions. At the Autumn transition, the temporal analyses indicate support for the sleep hypothesis as there are fewer casualties in the morning time periods, and in the Spring transition, the temporal analyses indicate support for the light hypothesis as there are fewer casualties in the evening time periods. For the remaining transitions, there is minimal support for the sleep and light hypotheses in both the temporal and regional analyses. In cases where the hypotheses are not supported, other factors such as driver behaviour and other socio-economic characteristics may be the main cause of the observed estimated changes.

In terms of policy impacts, the Daylight Savings Bill 2010-2011 estimates that 80 lives would be saved per year from transitioning to CET [4] and the report on EU DST changes estimates 30 lives saved per year as a result of abolishing DST altogether [3]. Our results question these figures and indicate that there are 0.25 - 0.36 fewer road fatalities on average per year at both the Spring and Autumn DST transitions combined, and 3.3 - 3.9 fewer total casualties of all severities on average per year at Spring and Autumn transitions combined. The light hypothesis is the main driver for the Daylight Savings Bill, while both the sleep and light hypotheses are put forward in the recent report on abolishing DST altogether in the EU. However, as mentioned, we do not find definitive evidence to support the sleep and light hypotheses.

A number of areas for future work are recommended. In some cases, modelling was prohibited due to a lack of data in the north of Great Britain, and therefore it is suggested that alternate data sources or alternate statistical analysis techniques for small sample data are employed to ascertain the impact of DST transitions in these regions. In regions where the sleep and light hypotheses did not hold, further research to investigate the impact of other potentially influential socio-demographic factors could be undertaken. In this analysis, we considered all casualties across all socio-demographic groups. Further analyses could be undertaken to provide a more disaggregate characterisation of the impact of DST transitions, for example, segmenting casualties by age could assist in testing whether DST transitions impact children walking to school as hypothesised in the Daylight Saving Bill 2010-11.

Author contribution statement

The corresponding author attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

Author CRediT statement

Conceptualisation: DJ Graham; Data curation: R Sood; Methodology: DJ Graham, R Singh, R Sood; Formal analysis: R Singh, R Sood; Writing-original draft: R Singh, R Sood, DJ Graham; Writing-review and editing: R Singh, DJ Graham, R Sood; Supervision: DJ Graham; Funding acquisition: DJ Graham.

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None declared.

Ethics approval statement
Ethics approval is not applicable as no human nor animal participants were involved in the study.

Data sharing statement
The data used in this study are available open-source from the Department for Transport at the following URL: https://www.gov.uk/government/collections/road-accidents-and-safety-statistics.

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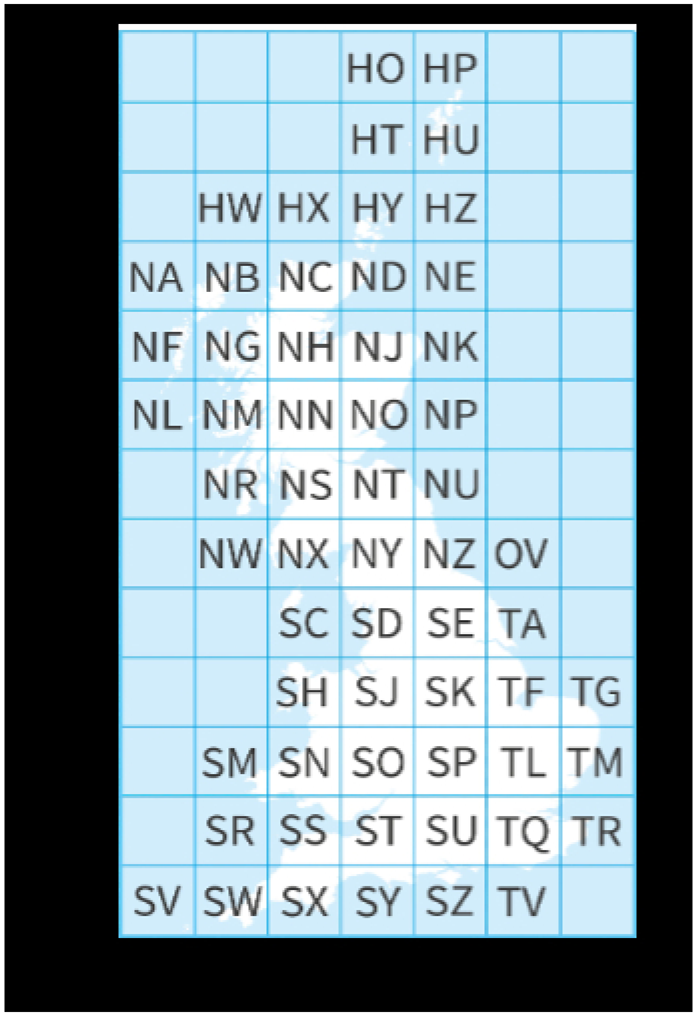

Figure 1: Definition of Northing and Eastings bands in Great Britain (adapted from Ordnance Survey [20], not to scale).

91x133mm (96 x 96 DPI)

STROBE Statement—checklist of items that should be included in reports of observational studies

	Item No	Recommendation	Page No
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	1
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	1
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	2-3
Objectives	3	State specific objectives, including any prespecified hypotheses	3
Methods			
Study design	4	Present key elements of study design early in the paper	3-6
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	3-4
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up *Case-control study*—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls *Cross-sectional study*—Give the eligibility criteria, and the sources and methods of selection of participants	NA
		(*b*) *Cohort study*—For matched studies, give matching criteria and number of exposed and unexposed *Case-control study*—For matched studies, give matching criteria and the number of controls per case	NA
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	5
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	*3-6*
Bias	9	Describe any efforts to address potential sources of bias	5-6
Study size	10	Explain how the study size was arrived at	3,4,6
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	5
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	4-6
		(*b*) Describe any methods used to examine subgroups and interactions	5
		(*c*) Explain how missing data were addressed	5
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed *Case-control study*—If applicable, explain how matching of cases and controls was addressed *Cross-sectional study*—If applicable, describe analytical methods taking account of sampling strategy	NA
		(*e*) Describe any sensitivity analyses	6

Continued on next page

Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	NA
		(b) Give reasons for non-participation at each stage	NA
		(c) Consider use of a flow diagram	NA
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	NA
		(b) Indicate number of participants with missing data for each variable of interest	NA
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	NA
		Note: No human/animal participants were involved but a summary of descriptive statistics on casualties is given	4
Outcome data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	NA
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	NA
		Cross-sectional study—Report numbers of outcome events or summary measures	NA
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	6-9
		(*b*) Report category boundaries when continuous variables were categorized	5
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	NA
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	NA
Discussion			
Key results	18	Summarise key results with reference to study objectives	10-13
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	13
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	11-13
Generalisability	21	Discuss the generalisability (external validity) of the study results	13
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	15

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in cohort and cross-sectional studies.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

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A causal regression discontinuity design analysis of road traffic casualties in Great Britain at daylight savings time transitions

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A causal regression discontinuity design analysis of road traffic casualties in Great Britain at daylight savings time transitions

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Abstract

Objectives: To determine whether daylight savings time (DST) transitions in the Spring and Autumn have a causal effect on road traffic casualties in Great Britain. We undertake aggregate and disaggregate spatial and temporal analyses to test the commonly referenced sleep and light hypotheses.
Design: The study takes the form of a natural experiment in which the DST transitions are interventions to be evaluated. Two outcomes are tested: (i) the total number of casualties of all severities (ii) the number of fatalities.
Data: Data are obtained from the UK Department for Transport STATS19 database. Over a period of 14 years between 2005 and 2018, 311,766 total casualties and 5,429 fatalities occurred 3 weeks either side of the Spring DST transition and 367,291 total casualties and 6,650 fatalities occurred 3 weeks either side of the Autumn DST transition.
Primary outcome measure: A regression discontinuity design method (RDD) is applied. The presence of a causal effect is determined via the degree of statistical significance and magnitude of the average treatment effect.
Results: All significant average treatment effects are negative (54 significant models out of 287 estimated), indicating that there are fewer casualties following the transitions. Overall, bootstrapped summary statistics indicate a reduction of 0.75 in the number of fatalities (95% CI: -1.61, -0.04) and a reduction of 4.73 in the number of total casualties (95% CI: -6.08, -3.27) on average per year at both the Spring and Autumn DST transitions combined.
Conclusions: The results indicate minor reductions in the number of fatalities following the DST transitions, and thus our analysis does not support the most recent UK parliamentary estimate that there would be 30 fewer fatalities in Great Britain if DST were to be abolished. Furthermore, the results do not provide conclusive support for either the sleep or light hypotheses.

Keywords: Road safety, Daylight savings time, Sleep, Visibility, Regression discontinuity design

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Strengths and limitations of this study

- We adopt a causal regression discontinuity design method to generate robust estimates of the impact of DST transitions on road traffic casualties and fatalities in Great Britain.
- We undertake both aggregate and disaggregate spatial and temporal analyses to investigate the impacts of sleep and light disruptions at the transitions.
- We account for potential confounding through the inclusion of seasonal variables at the level of year, day of week, and time of day, and treat heteroskedasticity and autocorrelation to account for unobserved confounders.
- Limitations include potential under-reporting of casualties in the Department for Transport STATS19 database, sparse data leading to estimation difficulties in the northernmost regions of Scotland, and the presence of potential additional unobserved confounders that could lead to biased estimates.

1. Introduction

Since its introduction, the implementation of daylight savings time (DST) has been a contentious issue which has regained attention in recent times. In response to a public consultation held in 2018, the European Parliament in 2019 adopted a position to support the elimination of daylight savings in the European Union (EU), with plans for implementation in 2021 [1, 2]. The United Kingdom (UK) initiated an inquiry to analyse the impact of the EU change to "understand what factors should inform [the UK's] approach" [3]. The UK also previously debated and ultimately rejected changes to daylight savings in the Daylight Saving Bill 2010-11, which proposed to shift UK time forward by one hour throughout the year to align with Central European Time (CET) [4]. A key argument in the elimination or alteration of daylight savings time is the impact that clock changes have on road safety. In both the academic literature and government parliamentary debates, two issues are highlighted as having an impact on road safety levels: (i) changes in daylight hours could impact alertness due to the required chronobiologic adjustments to the human circadian rhythm [1, 5, 6] - herein referred to as the 'sleep hypothesis', and (ii) changing of daylight hours could result in detrimental changes to visibility [7, 8, 4, 3] - herein referred to as the 'light hypothesis'.

Evidence on the impact of DST transitions on road traffic casualties is currently inconclusive. In the 2010-2011 Daylight Saving Bill, it was argued that there would be 80 fewer fatalities on UK roads if the UK switched to CET [4]. In the more recent UK report on the proposed EU changes, it was stated that abolishing time changes and adopting a permanent move to UK Summer Time could result in 30 fewer fatalities [3]. However, it is unclear how these figures were generated and whether robust causal statistical analysis methods were adopted. In the academic literature, there is mixed consensus regarding the impact of DST transitions. Increases in road casualties are reported for studies undertaken in the US by Smith [9] and in New Zealand by Robb and Barnes [10], while reductions in casualties in the US are reported by Coate and Markowitz [11] and Crawley [12]. Lindenberger et al. [13] reports no significant impacts in their analysis of road casualties in Germany.

The aim of this paper is to estimate the causal effect of DST transitions on the number of road traffic casualties and fatalities in Great Britain. This paper contributes to the literature from several perspectives. First, the majority of studies adopt non-causal techniques to quantify the impact of DST transitions, including comparisons of descriptive statistics, linear regression based on ordinary least squares, and quasi-Poisson regression [10, 11, 13, 14, 15]. Two studies by Carey and Sarma [7] and Uttley and Fotios [16] adopt a causal regression discontinuity design (RDD) method similar to ours, however, the studies focus on road casualties in the USA and pedestrian casualties in the UK, respectively. We therefore contribute to the literature by adopting a causal RDD method to analyse road traffic casualties in Great Britain, which, to our knowledge, has not been previously undertaken. Second, use of the RDD method with time as the forcing variable requires stringent specification tests to be undertaken to ensure that the models are free from potential confounding factors that can lead to biased estimates. In the literature on RDD methods applied to DST analyses, these specification tests are not typically performed. In our analysis, we follow the recommendations made in Hausman and Rapson [17] to test for model robustness. Finally, there are a number of studies in the UK and US indicating both causal and non-causal relationships between light levels and casualties at DST transitions [14,15,16,18,19], however, we are not aware of causal studies testing the sleep hypothesis at DST transitions. Therefore, in addition to a pooled analysis of Great Britain as a whole, we also undertake disaggregate spatial and temporal analyses to test the sleep and light hypotheses.

2. Methods

2.1. Study area and data

The STATS19 database produced by the Department for Transport is used to obtain records of road traffic accidents that resulted in personal injury in Great Britain between 2005 and 2018 [dataset][20]. Casualties are defined as personal injuries of any severity as a result of an accident event. As specified in [21], a single accident event can be associated with more than one casualty. In this analysis, we focus on total casualties (all severities combined) and fatal casualties.

Three week windows on either side of the DST transitions in Spring and Autumn are extracted from the total accident data set. Three weeks is chosen to provide enough data for the optimised local bandwidth to be calculated for each scenario as part of the RDD modelling. It should be noted that after calculation of the optimal bandwidth, the window around the DST transitions is likely to be much shorter than three weeks; further details on the optimal bandwidth calculations are given in Section 2.2. Through data cleaning, less than 0.02% of records have been removed as a result of missing observations in the fields representing latitude and longitude and accident event timestamps as well as records over Bank Holidays as these observations could potentially represent abnormal out-of-season traffic levels which could confound the baseline time trends before and after the DST transitions. The number of casualties and fatalities for all of Great Britain over three week windows either side of the transitions are summarised in Table 1. As shown in the table, there are increases in the number of casualties and fatalities after both transitions when considering 3 week windows before and after the transitions.

Table 1: Number of casualties, aggregated over Great Britain over ± 3 week windows from DST transition dates

Casualty severity	Spring		Autumn	
	Before DST	After DST	Before DST	After DST
Total casualties	153107	158659	175796	191495
Fatal casualties	2517	2912	3211	3439

To investigate whether the DST transitions have different regional effects across Great Britain, National Ordnance Survey data are used to divide Great Britain into distinct bands based on latitude and longitude [22]. Using the Ordnance Survey Grid Reference (OSGR) variable within STATS19, each accident event and associated casualties are assigned a Northings band and an Eastings band.

2.2. Regression discontinuity design framework

DST is a policy enacted for the entire population of Great Britain and the treatment assignment is deterministic, i.e., there is no ambiguity in treated vs untreated observations. Therefore, the DST treatment imposed at the Spring and Autumn transitions is considered as a sharp discontinuity. Further information on RDD frameworks is presented in Imbens and Lemieux [23] and Lee and Lemieux [24].

In this analysis, we use spatio-temporal units where i refers to a given local area zone within Great Britain, t refers to a given time period, where each day is segmented into 5 time periods, and z refers to year. The assignment of the treatment, i.e. the imposition of the daylight savings transition, is solely dependent on the value of the forcing variable, time T, as follows:

$$W_{itz}\begin{cases}1 \text{ if } T_t \geq c\\ 0 \text{ if } T_t < c\end{cases} \qquad (1)$$

where c is the treatment threshold, which is defined as the DST transition date, and W_{itz} is the binary treatment in the sharp RDD. In the Spring transition, the treatment is the imposition of Summer Time, while in the Autumn transition, the treatment is the return to GMT. Observations recorded between 00:00 and 01:00 in March and between 00:00 and 02:00 in October on the day of the transition are designated as non-treated in line with when the transition occurs. Over the analysis time period of 2005 to 2018, the transition dates for Spring range from 25 to 31 March and those for Autumn range from 25 to 31 October.

The observation of a discontinuity in the average treatment effect either side of the treatment threshold is evidence of a causal effect of the treatment [23, 24]. The average treatment effect for a sharp discontinuity τ_{SRD} in time is defined as:

$$\tau_{SRD} = E[Y_{itz}(1) - Y_{itz}(0) \mid T_t = c] = \lim_{t\downarrow c} E[Y_{itz}|T_t = t] - \lim_{t\uparrow c} E[Y_{itz}|T_t = t] \qquad (2)$$

where $Y_{itz}(1)$ indicates the potential outcome when treatment is received and $Y_{itz}(0)$ indicates the potential outcome when treatment is not received. The second equality holds assuming continuity of expectations in T i.e. $E[Y_{itz}(0) \mid T_t = c] = \lim_{t \uparrow c} E[Y_{itz}(0) \mid T_t = t] = \lim_{t \uparrow c} E[Y_{itz} \mid T_t = t]$ [23].

Since the forcing variable is time, we follow the recommendations in Hausman and Rapson [17] to address potential specification issues. To ensure that there are enough observations in the vicinity of the treatment threshold, we segment daily data into 5 time periods, and the data are aggregated at a local area zone level which also provides cross-sectional variance at each time point. By segmenting the data to increase the number of observations close to the treatment threshold, we avoid the need to include observations further away from the threshold which can introduce bias from unobserved confounding variables. We account for potential bias from known confounding variables correlated with time through the inclusion of covariates representing potential seasonal variation in casualties. The covariates are year, day of the week, and the time period associated with each observation. Since the daylight savings transitions are universally applied at fixed transition dates, we do not anticipate issues arising from manipulation of treatment status. Further specification tests are undertaken to ensure validity of the design and these are discussed in section 2.3.

The data sets are arranged in a pseudo-panel form with indexes of local area zone and time period per year. The response variable is the sum of the number of casualties per local area zone and time period per year; in cases where no casualties are observed, a value of 0 is designated. For each of the Spring and Autumn transitions, two base regressions are undertaken as follows: (i) the total number of casualties of all severities, and (ii) the total number of fatalities. The two base regressions are run for three scenarios: (i) for Great Britain overall, (ii) for each Northing band in each time period, and (iii) for each Easting band in each time period. We adopt a local linear specification for the forcing variable of time. The bandwidth for the models is specified according to the conventional method of minimising the mean squared error (MSE) of the average treatment effect [25, 26, 27]. This selection procedure selects the shortest (i.e. local) bandwidth in the vicinity of the treatment threshold subject to the minimisation of the MSE, thus ensuring that the key assumption of random treatment is upheld. The optimal bandwidth selection process is considered superior to nominating an arbitrary bandwidth as was common in the earliest implementations of RDD as it is objective and data-driven rather than subjective [25]. The 'rdrobust' package in the R statistical analysis software is used for the optimal bandwidth calculation [27, 28].

The general equation for the aggregate model of Great Britain is given in equation 3. The regional and time of day analyses enable the investigation of the sleep and light hypotheses. It should be noted that in the disaggregate models, the time of day covariate in equation 3 is not included as the models are pre-segmented by time of day. All modelling has been undertaken using R statistical analysis software.

$$Y_{itz} = \alpha + \tau_{SRD} W_{itz} + \theta_1 K_{itz}(t) + \theta_2 K_{itz,post}(t) + \beta_1 X_{1z} + \beta_2 X_{2t} + \beta_3 X_{3t} + \varepsilon_{itz} \quad (3)$$

where Y_{itz} is the total number of casualties per local area zone i per time period t per year z, W_{itz} is the treatment assignment indicator as previously defined, τ_{SRD} is the average treatment effect of interest, $K_{itz}(t)$ represents the average long term trend across the entire bandwidth i.e. $K_{itz}(t) = t$, and $K_{itz,post}(t)$ is the time trend after the intervention where $K_{itz,post}(t) = 0, t < c$ and $K_{itz,post}(t) = t - c + 1, t \geq c$. The categorical variables X_{1z}, X_{2t}, X_{3t} condition for year, day of the week, and time period, respectively. Year takes a value from 1 – 14 corresponding to the years 2005 – 2018. As coded in the STATS19 database, the day of the week takes a value 1 – 7 with 1 corresponding to Sunday and 7 corresponding to Saturday. The time of the day takes values as follows: Overnight = 1, AM Peak = 2, Inter Peak = 3, PM Peak = 4, Night = 5. The peak time periods follow the standards adopted by the Department for Transport: AM Peak (07:00 – 09:59), Inter Peak (10:00 – 15:59) and PM Peak (16:00 – 18:59) [18]. Two additional time-bins are added to complete a 24-hour period: Overnight (0:00 – 06:59) and Night (19:00 – 23:59). α and ε_{itz} are the model constant and model random error term, respectively, where $\varepsilon_{itz} \sim \mathcal{N}(0,\sigma_{\varepsilon}^{2})$.

It should be noted that the inclusion of group-specific fixed effects for local area zone was trialled to account for potential time-invariant cross-sectional differences. However, using the Bayesian Information Criterion (BIC) as an indicator of model performance, we found that a majority of models performed better with no local area zone effects compared to those with local area effects, and so these effects are not included in the final model form.

2.3. Specification tests

As recommended by Hausman and Rapson [17], we perform the following specification tests:

- Specification checks are performed for the bandwidth by varying the bandwidth within the vicinity of the optimal bandwidth and verifying that the magnitude and significance of average treatment effect remains consistent.

- Specification checks are performed for the polynomial order of the forcing variable of time. The BIC is used to judge model performance. Polynomials of up to degree 4 are tested, and we verify that the local linear specification performs best in line with the bandwidth selection procedure.

- The Breusch-Godfrey test [29, 30] is performed to test for autocorrelation of the error term for a lag value up to 10 (2 days). If autocorrelation is present, it is treated using Newey-West standard errors [31], which are heteroskedasticity and autocorrelation consistent (HAC).

- The Breusch-Pagan test [32] is performed to test for heteroskedasticity. If heteroskedasticity is present with no error term autocorrelation, it is treated with heteroskedasticity consistent (HC3) errors [33].

- We perform placebo tests as per the recommendations in [23] to verify the model specification. We partition the original data for each model at the DST cutoff to obtain two smaller data sets. We then calculate a placebo cutoff which is equivalent to the mean value of the running variable in each dataset. We perform two placebo tests for each original model by undertaking the RDD analysis for the placebo cutoffs before the DST cutoff and after the DST cutoff. The original models pass the placebo test if both placebo models yield an insignificant average treatment effect.

Note: Autoregression of the dependent variable is not considered in this analysis, since the majority of casualties per local area zone do not occur in consecutive time periods.

The R code for the generation of the RDD models and all specification tests is provided as a Supplementary file.

2.4. Patient and public involvement statement

Please note that no patients nor members of the public were involved in this study.

3. Results

The results for the aggregate Spring and Autumn RDD models are presented in Table 2. The results for the disaggregate spatial and temporal RDD analyses are presented in Tables 3 and 4. All results tables summarise cases where the RDD models have passed all specification tests as described in section 2.3, and the average treatment effect at the DST transition is significant at a minimum significance level of $\alpha = 0.05$ ($\geq 95\%$). A map of the corresponding Northing and Eastings bands is given in Figure 1. As shown in the figure, higher band numbers represent more northern and more eastern locations.

Table 2: Aggregate models of Great Britain - RDD results summary

Transition	Location	Casualty type	BW	n	Y_{before}	Y_{after}	τ_{SRD}	% Change
Spring	Aggregate Great Britain	All casualties	32	173888	32133	27842	-0.075 (0.009)***	0.003%
		Fatalities	Not significant					
Autumn	Aggregate Great Britain	All casualties	Not significant					
		Fatalities	Not significant					

Notes: Significance notation: p-values 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Standard errors in parentheses.
BW refers to bandwidth in time period units, τ_{SRD} refers to the sharp RDD average treatment effect due to DST transition.
n is the total number of observations, Y_{before} and Y_{after} refer to the total number of casualties or fatalities before and after the cutoff, respectively

Table 3: Spring transition - disaggregate spatial and temporal models RDD results summary

			All Casualties						Fatal					
Location	**Band**	**Time period**	**BW**	***n***	Y_{before}	Y_{after}	τ_{SRD}	**% Change**	**BW**	***n***	Y_{before}	Y_{after}	τ_{SRD}	**% Change**
Aggregate		1	22	27145	1260	1507	-0.110 (0.024)***	-0.12%	40	12744	133	81	-0.067 (0.022)**	-0.70%
		4	38	43472	6565	6597	-0.059 (0.020)**	-0.01%						
		5	46	48906	6918	4456	-0.130 (0.025)***	-0.03%						
Northing band	1,000-2,000	1	28	9925	474	591	-0.095 (0.034)**	-0.28%						
		3	36	15992	3880	3623	-0.162 (0.042)***	-0.06%						
		4	38	16008	2350	2343	-0.067 (0.029)*	-0.04%						
		5	48	17991	2606	1610	-0.146 (0.041)***	-0.08%						
	2,000-3,000	3	74	19698	3182	3346	-0.137 (0.047)**	-0.06%						
	3,000-4,000	1	34	8365	315	340	-0.075 (0.035)*	-0.33%	44	2648	25	19	-0.046 (0.021)*	-2.58%
		3	64	14496	3197	3044	-0.167 (0.063)**	-0.07%						
		5	52	13233	1342	1073	-0.086 (0.042)*	-0.09%						
Easting band	3,000-4,000	1	28	8370	324	311	-0.148 (0.056)**	-0.64%	62	4510	67	34	-0.139 (0.055)*	-2.89%
	4,000-5,000	1	30	11814	522	479	-0.069 (0.030)*	-0.18%						
		3	74	28000	6172	6235	-0.171 (0.049)***	-0.04%						
		5	50	20000	2244	1874	-0.083 (0.038)*	-0.05%						
	5,000-6,000	1	28	8530	428	559	-0.104 (0.039)**	-0.34%						
		3	70	24066	5588	5651	-0.090 (0.037)*	-0.02%						
		4	26	8565	1479	848	-0.110 (0.045)*	-0.10%						
		5	44	15453	2235	1388	-0.149 (0.045)***	-0.09%						

Notes: Significance notation: p-values 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Standard errors in parentheses. BW refers to bandwidth in time period units, *n* is the total number of observations, τ_{SRD} refers to the sharp RDD average treatment effect due to DST transition, Y_{before} and Y_{after} refer to the total number of casualties or fatalities before and after the cutoff, respectively, and time periods are as follows: 1-.Overnight, 2-AM Peak, 3-Inter-peak, 4-PM Peak, 5-Night.

Table 4: Autumn transition - disaggregate spatial and temporal models RDD results summary

			All Casualties						Fatal					
Location	**Band**	**Time period**	**BW**	***n***	Y_{before}	Y_{after}	τ_{SRD}	**% Change**	**BW**	***n***	Y_{before}	Y_{after}	τ_{SRD}	**% Change**
Aggregate		1	18	16197	1035	1043	-0.096 (0.019)***	-0.13%	38	13671	104	97	-0.030 (0.012)*	-0.40%
		3	72	75642	20645	20684	-0.101 (0.028)***	-0.01%						
		4	34	37821	7728	5448	-0.077 (0.024)**	-0.01%						
		5	32	37821	7449	3851	-0.231 (0.030)***	-0.04%	60	24936	285	282	-0.035 (0.016)*	-0.17%
Northing band	0-1,000	1	38	2534	90	53	-0.153 (0.058)**	-2.38%						
		5	64	5044	389	297	-0.156 (0.062)*	-0.56%						
	1,000-2,000	1	24	10015	630	572	-0.158 (0.036)***	-0.35%	40	4888	50	19	-0.052 (0.017)**	-1.45%
		4	30	12048	1993	1837	-0.129 (0.036)***	-0.09%						
	2,000-3,000	1	32	9695	408	353	-0.112 (0.035)**	-0.39%						
		5	48	12708	1534	891	-0.190 (0.058)**	-0.17%						
	3,000-4,000	1	26	6010	289	265	-0.152 (0.045)***	-0.74%						
		4	40	9576	1475	1540	-0.118 (0.042)**	-0.11%						
	5,000-6,000	2	48	3440	261	309	-0.076 (0.031)*	-0.41%						
	7,000-8,000	5	70	1470	66	69	-0.094 (0.045)*	-1.84%						
	8,000-9,000	1	56	583	34	27	-0.280 (0.097)**	-11.53%						
		5	66	793	89	51	-0.362 (0.128)**	-5.69%						
Easting band	1,000-2,000	1	64	1092	30	20	-0.072 (0.036)*	-3.34%						
	2,000-3,000	3							78	3210	26	37	-0.056 (0.021)**	-3.00%
		4	54	7018	853	678	-0.091 (0.043)*	-0.15%						
	3,000-4,000	1	26	8195	411	352	-0.136 (0.040)***	-0.46%						
		5	44	14985	2189	1351	-0.222 (0.050)***	-0.14%						
	4,000-5,000	1	26	9825	498	473	-0.129 (0.032)***	-0.36%						
		5	44	17874	2840	1663	-0.252 (0.057)***	-0.12%						
	5,000-6,000	1	22	8525	566	534	-0.187 (0.037)***	-0.46%	44	4491	34	12	-0.042 (0.014)**	-1.71%
		4	34	12033	2397	1532	-0.127 (0.039)**	-0.07%						
		5	48	15408	2853	1807	-0.279 (0.056)***	-0.14%						
	6,000-7,000	5	42	2394	257	106	-0.191 (0.086)*	-1.04%						

Notes: Significance notation: p-values 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Standard errors in parentheses. BW refers to bandwidth in time period units, n is the total number of observations, τ_{SRD} refers to the sharp RDD average treatment effect due to DST transition, Y_{before} and Y_{after} refer to the total number of casualties or fatalities before and after the cutoff, respectively, and time periods are as follows: 1-.Overnight, 2-AM Peak, 3-Inter-peak, 4-PM Peak, 5-Night.

3.1. Spring transition

As shown in the tables, all models with significant average treatment effects show a reduction in the number of casualties at the Spring transition. For the whole of Great Britain, approximately 0.075 (-0.003%) fewer total casualties are observed on average per year. The time of day models further indicate reductions in total casualties ranging from 0.06 to 0.13 fewer casualties per year across the overnight, PM peak, and night periods (in percentages, -0.01% to -0.03%). In terms of fatalities in isolation, there are 0.07 (-0.7%) fewer fatalities observed in the overnight period.

Latitudinal analysis

In the disaggregate models of Northing bands, there are significant reductions in total casualties in 3 out of 12 bands. The reductions range from approximately 0.07 to 0.17 fewer total casualties (-0.04% to -0.45%) per year in all time periods except the morning peak. In terms of fatalities, there are 0.05 fewer fatalities per year (-2.58%) in the overnight time period in band 3000-4000.

Longitudinal analysis

In the disaggregate models of Easting bands, there are significant effects in 3 out of 7 bands. There are approximately 0.07 to 0.17 fewer total casualties (-0.02% to -0.64%) observed in all time periods except the morning peak. For the fatality models, in band 3000-4000, there is a significant reduction of 0.14 fatalities (-2.89%) in the overnight time period.

3.2. Autumn transition

As with the Spring transition, in the Autumn transition, all models with significant average treatment effects report a reduction in casualties. Considering Great Britain as a whole, there are no significant effects. However, when splitting by time of day, there are reductions in total casualties in every time period except the morning peak ranging from 0.08 to 0.23 fewer total casualties on average per year (-0.01% to -0.13%). In terms of fatalities, there are 0.03 fewer fatalities (-0.40%) in the overnight time period and 0.04 fewer fatalities (-0.17%) in the night time period.

Latitudinal analysis

In the disaggregate models of Northing bands, there are significant effects in 7 out of 12 bands. The effects range from a 0.08 to 0.36 reduction in the total number of casualties (-0.09% to -11.53%), and all significant effects are observed across all time periods except the inter-peak. For fatalities, in band 1000-2000, there are 0.05 fewer fatalities (-1.45%) in the overnight time period.

Longitudinal analysis

In the disaggregate models of Easting bands, 6 out of 7 bands report significant effects in the total number of casualties. All significant effects are negative and they are observed in all time periods except the inter-peak. The effects range from 0.07 to 0.28 fewer total casualties (-0.07% to -3.34%). For the fatality models, in band 2000-3000, there are 0.06 fewer fatalities (-3.00%) in the inter-peak, and in band 5000-6000, there are 0.04 fewer fatalities (-1.71%) in the overnight time period.

4. Discussion

4.1. Pooled analysis of Great Britain

When Great Britain is viewed as a whole regionally and without time segmentation, there is a statistically significant causal effect indicating a very minor reduction of 0.075 (0.003%) in the total number of casualties at the Spring DST transition. The average treatment effects in all other pooled analyses are insignificant at a minimum significance level of ≥ 95%.

When segmenting the data, there are further geographical zones and time periods with statistically significant average treatment effects. Our analyses therefore indicate that it is important to investigate the impacts of DST transitions at disaggregate spatial and temporal levels, as well as analysing the aggregate effects.

4.2. Spring transition

At the Spring transition, clocks are moved forward one hour, resulting in an hour less sleep. The reduction in sleep could have an impact on road casualties throughout the day. In the morning, civil twilight sunrise times change from approximately 5-5:30am to 6-6:30am across Britain. There is an hour less sleep and mornings are darker by an hour before 6-6:30am. These conditions could result in a compounding effect of the sleep and light hypotheses, likely resulting in an increase in casualties. However, for all models with significant effects in the associated overnight period (from 12am-7am), there is a reduction in total casualties and fatalities, in opposition to the sleep and light hypotheses.

In terms of regional effects, in the most western locations of Great Britain, the sun rises approximately 23 minutes later than the most eastern locations. As the civil twilight sunrise times coincide with the beginning of the morning peak in traffic, there could be a possibility of more casualties in the darker western locations compared to the east. Furthermore, sunrise at the most southern locations occurs approximately 20 minutes after the most northern locations, and so there could be a possibility of more casualties in the south relative to the north. For the Northing and Easting time of day models, we do not observe a systematic pattern showing progressively more casualties in the west and south, thus we cannot provide conclusive support for the regional light hypothesis.

At the Spring transition, civil daylight occurs throughout the AM peak (7-10am), inter-peak (10am-4pm), and PM peak (4pm-7pm), and so the light hypothesis is not applicable in these time periods. The sleep hypothesis is applicable, and sleepiness could manifest throughout the day, leading to potential increases in casualties. However, all models with significant effects in these time periods indicate reductions in total casualties, in opposition to the sleep hypothesis.

In the evening, civil twilight sunset times change from approximately 7-7:30pm to 8-8:30pm across Great Britain. There is an hour less sleep throughout the day, but evenings are lighter by an hour in the off-peak travel time after 7-7.30pm, therefore resulting in a potential conflict of the sleep and light hypotheses. In all significant models in the associated night time period (7pm-12am), there is a reduction in the total number of casualties. This result aligns with the light hypothesis but at the same time opposes the sleep hypothesis, however, it is not possible to disentangle the effects. In terms of regional effects of the light hypothesis, the most western locations experience sunset approximately 23 minutes after the most eastern locations, so there may be potential for increased casualties in the east compared to the west due to the light hypothesis, however, the results do not support this. There is minimal difference (approximately 10 minutes) between sunset times in the north and south, and so we do not anticipate substantial differences between these locations. In the analysis of northing bands, there are only two models with significant effects in the night time period which show similar reductions in total casualties, however, this does not provide substantial systematic evidence of support for the regional light hypothesis.

4.3. Autumn transition

At the Autumn transition, clocks are moved back one hour, and this can lead to an hour more sleep. The increase in sleep could have an impact on road casualties throughout the day. In the morning, civil twilight sunrise times change from approximately 7-7:30am to 6-6:30am across Great Britain. There is an hour more sleep and mornings are lighter by an hour before the morning peak travel time, therefore compounding the sleep and light hypotheses and resulting in the most appropriate conditions for a reduction in casualties. For all models with significant effects in the associated overnight and AM peak periods, there are reductions in total casualties and fatalities. These results therefore support the compounded impact of the sleep and light hypotheses, though it is not possible to disentangle the individual impacts of the two hypotheses. In terms of regional impacts, the most eastern locations experience civil twilight sunrise approximately 23 minutes before the most western locations, and so eastern locations are expected to report greater reductions in casualties. Furthermore, the most southern locations experience sunrise approximately 21 minutes before the most northern locations and so southern locations are expected to report greater reductions in casualties. However, the results show minimal support for a systematic pattern that progressively shows a greater reduction in casualties towards the east and south in the overnight and AM periods, thus we cannot conclude conclusive support for the regional light hypothesis.

At the Autumn transition, civil daylight occurs throughout the inter-peak period (10-4pm), and so there are no anticipated effects from the light hypothesis. However, the sleep hypothesis could apply, as there is an extra hour of sleep gained throughout the day, potentially leading to a reduction in casualties. Indeed, for all models with significant effects in the inter-peak, there are reductions in total casualties and fatalities, thus supporting the sleep hypothesis.

In the evenings, civil sunset times change from approximately 6-6:30pm to 5-5:30pm across Great Britain. There is an hour more sleep throughout the day but evenings are darker by an hour during the PM peak of traffic. In this situation, there is a potential conflict between the sleep and light hypotheses. All models with significant effects in the PM peak period (4-7pm) report reductions in total casualties and fatalities. Therefore, the results support the sleep hypothesis but oppose the light hypothesis, however, it is not possible to disentangle the impacts of the two. In terms of regional effects, sunset in the most eastern locations occurs approximately 24 minutes before sunset in the most western locations, and so we can expect more casualties in the east. Sunset in the most northern locations occurs approximately 13 minutes before sunset in the most southern locations. Though it is difficult to ascertain whether it is feasible to expect regional differences, it could be plausible to anticipate more casualties in the north. However, the northing and easting band models do not provide support for a systematic pattern that progressively shows a greater increase in casualties towards the east and north in the night period, thus the results do not support the regional light hypothesis.

4.4. Magnitude of impacts at DST transitions

In the Daylight Savings Bill 2010-2011, it was estimated that there would be 80 fewer fatalities if the UK followed CET time [4]. A more recent report on EU DST changes states that there would be 30 fewer fatalities as a result of eliminating DST transitions altogether [3].

Overall, our analysis suggests that DST transitions have a minor positive impact rather than a detrimental impact on road traffic casualties and fatalities. All statistically significant models (54 models) report a negative average treatment effect, indicating a reduction in the number of casualties at the DST transitions. Over the 13 northings bands, 7 eastings bands, and aggregate models, we attempted to generate a total of 212 models for total casualties and fatalities, respectively. However, due to sparse data in several bands, a number of models were not able to be estimated; 167 were able to be estimated for total casualties and 120 were able to be estimated for fatalities. Of these, 46 out of 167 estimated models of total casualties have significant average treatment effects, and 8 out of 120 estimated models of fatalities have significant average treatment effects. A potential explanation for why there are fewer fatality models with a significant average treatment effect could be that there are relatively lower numbers of fatalities occurring either side of the DST threshold. Furthermore, we acknowledge that the models with insignificant average treatment effects indicate absence of evidence of a change in casualties/fatalities at the DST threshold rather than evidence of absence of a change in casualties/fatalities at the DST threshold.

We calculate the combined impact of the Spring and Autumn transitions on road casualties, and we generate associated 95% bootstrap confidence intervals using 10,000 iterations as per the bias corrected and accelerated (BCa) bootstrap method [34, 35]. The statistic of interest that we bootstrap is calculated in two steps: (1) We sum all average treatment effects in the regional time of day models over the Spring and Autumn transitions combined. Two estimates are generated: one for Easting band segmentation and one for Northing band segmentation. (2) We calculate the mean of the Easting and Northing band values, and this is taken as the estimated combined number of casualties over the Spring and Autumn transitions. We perform this procedure for fatalities and total casualties separately.

The bootstrapped values indicate a mean reduction of 0.75 in the number of fatalities on average per year with a 95% confidence interval ranging from -1.61 to -0.04 (reduction in fatalities). Our analysis therefore reports minor reductions in fatalities at the DST transitions, rather than an increase of 30-80 fatalities as estimated in House of Lords [3] and Bennett [4].

Similarly, for the total number of casualties of all severities, a mean reduction of 4.73 in the number of total casualties is estimated on average per year with a 95% confidence interval ranging from -6.08 to -3.27 (reduction in the total number of casualties). Therefore, the results for casualties of all severities also question the predictions of DST effects reported in House of Lords [3] and Bennett [4].

4.5. Limitations

One limitation of the RDD methodology is that is applicable to ex-post analyses and not suitable for making ex-ante predictions. Therefore, the results reflect the impact of DST transitions on road safety over the study period of 2005-2018, and it is difficult to generalise the results to predict the impact of potential DST changes in the future. However, we have no compelling reason to believe that the average treatment effect will change significantly over time.

The data from the Department for Transport STATS19 database may also pose potential limitations, as the data are compiled from police reports. As a result, there could be potential under-reporting of casualties. One previous study estimated that the number of casualties classified as Serious could be under-reported by a factor of two [36]. Another data-related limitation is the sparse data in the northernmost regions of Scotland. Due to the limited number of observations, the RDD models reported high standard errors of the average treatment effect estimator and low statistical significance in these regions, and in some cases, estimates were not able to be computed. As such, in future work, either alternate data sources or alternate statistical analysis techniques for small sample data are recommended.

In the interpretation of the results in Section 4.2 and 4.3, we identified instances of where the sleep and light hypotheses were in conflict, and it was not possible to disentangle and quantify the separate impacts of the two hypotheses on road casualties. We therefore recommend future work to investigate how to disentangle the two effects, with a potential solution involving gathering disaggregate data on sleeping patterns and conditioning for this in the models.

Finally, it should be noted that we have addressed potential sources of bias by conditioning out exogeneous changes in traffic volumes which cannot be attributed to the DST transitions through the inclusion of seasonal year, day of week, and time of day variables along with treatment of heteroskedasticity and autocorrelation of the error term to account for potential unobserved confounders. However, there may be additional unobserved factors that we have not accounted for which may lead to potentially biased estimates. For example, we were not able to obtain a data set that identifies every school holiday in each local area zone nor were we able to obtain weather data at a time period level in each local area zone from 2005-2018. We acknowledge that this could lead to potentially biased values of the average treatment effect. However, we would also like to highlight that the bandwidths for each model are narrow around the cutoffs (the mean bandwidth across all models is 4.3 days either side of the transition), and the narrow windows would minimise the degree of systematic impacts from school holidays and weather effects.

5. Conclusion

In this paper, we find that DST transitions have only a minor positive impact on road casualties and fatalities. For total casualties, 46 out of 167 models have significant average treatment effects, while for fatalities 8 out of 120 models have significant effects. All models with a significant average treatment effect (54 models) report a negative effect, indicating a reduction in the number of casualties at the DST transitions.

Considering Great Britain as a whole, we find a significant effect indicating a minor 0.003% reduction in the total number of casualties in the Spring transition into DST. The average treatment effects in all other aggregate models are insignificant at a minimum significance level of ≥ 95%. When segmenting the data spatially and temporally, there are more models with statistically significant average treatment effects. This highlights the importance of investigating the impacts of DST transitions at a disaggregate level.

The disaggregate spatial and temporal models do not provide clear support or rejection of the sleep and light hypotheses at the transitions. At the Autumn transition, the temporal analyses indicate support for the compounded effect of the sleep and light hypotheses in the overnight and AM peak periods as well as support for the sleep hypothesis in the inter-peak period. For the remaining transitions, there is minimal support for the sleep and light hypotheses in both the temporal and regional analyses and in some cases, it is difficult to disentangle potential conflicts between the sleep and light hypotheses. In cases where the hypotheses are not supported, other factors such as driver behaviour and other socio-economic characteristics may be the main cause of the observed estimated changes.

In terms of policy impacts, the Daylight Savings Bill 2010-2011 estimates that 80 lives would be saved per year from transitioning to CET [4] and the report on EU DST changes estimates 30 lives saved per year as a result of abolishing DST altogether [3]. Our results question these figures. We apply a bias corrected and accelerated bootstrap with 10,000 iterations to estimate the total number of fatalities and casualties on average per year over the Spring and Autumn transitions combined. The bootstrapped values indicate a mean reduction of 0.75 in the number of fatalities (95% CI: -1.61, -0.04) and a mean reduction of 4.73 in the number of total casualties (95% CI: -6.08, -3.27) on average per year at both the Spring and Autumn DST transitions combined. The light hypothesis is the main driver for the Daylight Savings Bill, while both the sleep and light hypotheses are put forward in the recent report on abolishing DST altogether in the EU. However, as mentioned, we do not find definitive evidence to support the sleep and light hypotheses.

A number of areas for future work are recommended. In some cases, modelling was prohibited due to a lack of data in the north of Great Britain, and therefore it is suggested that alternate data sources or alternate statistical analysis techniques for small sample data are employed to ascertain the impact of DST transitions in these regions. We also recommend further work to disentangle the impacts of the sleep and light hypotheses in cases where the two are in conflict. In regions where the sleep and light hypotheses did not hold, further research to investigate the impact of other potentially influential socio-demographic factors could be undertaken. In this analysis, we considered all casualties across all socio-demographic groups. Further analyses could be undertaken to provide a more disaggregate characterisation of the impact of DST transitions, for example, segmenting casualties by age could assist in testing whether DST transitions impact children walking to school as hypothesised in the Daylight Saving Bill 2010-11.

Author contribution statement

The corresponding author attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

Author CRediT statement

Conceptualisation: DJ Graham; Data curation: R Sood; Methodology: DJ Graham, R Singh, R Sood; Formal analysis: R Singh, R Sood; Writing-original draft: R Singh, R Sood, DJ Graham; Writing-review and editing: R Singh, DJ Graham, R Sood; Supervision: DJ Graham; Funding acquisition: DJ Graham.

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Competing interests statement

None declared.

Ethics approval statement

Ethics approval is not applicable as no human nor animal participants were involved in the study.

Data availability statement

The data used in this study are available open-source from the Department for Transport at the following URL: https://www.gov.uk/government/collections/road-accidents-and-safety-statistics.

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Figure 1 notes

Values on the x-axis refer to Eastings bands, and values on the y-axis refer to Northings bands. The two letters in each grid square refer to specific locations on the UK National Grid; the exact naming of each square can be found at Ordnance Survey [22].

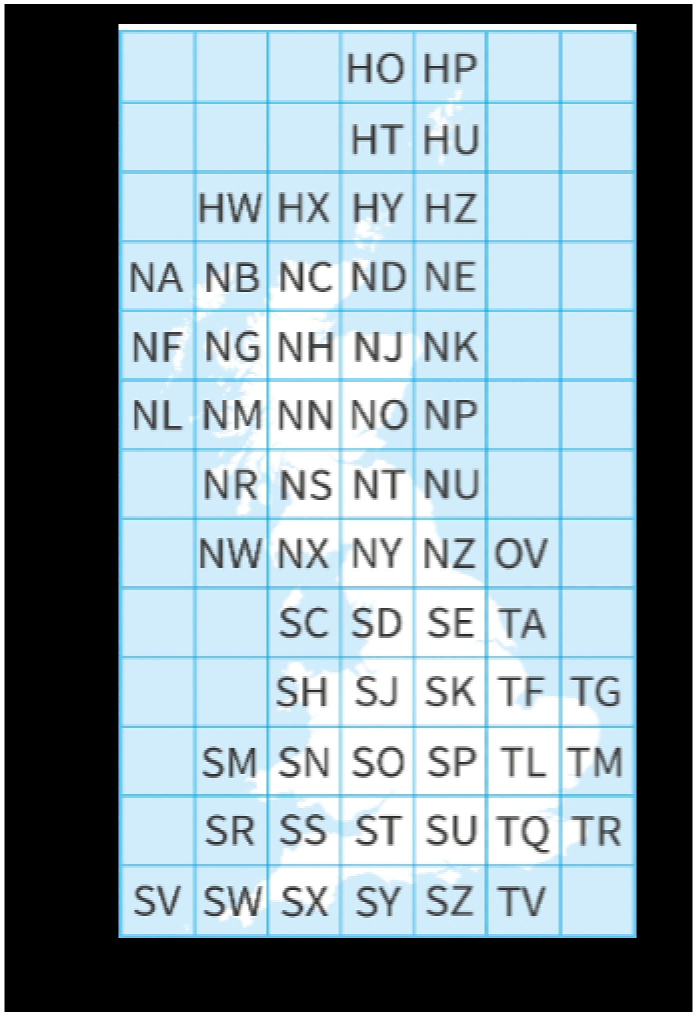

Figure 1: Definition of Northing and Eastings bands in Great Britain (adapted from Ordnance Survey [20], not to scale).

91x133mm (96 x 96 DPI)

```
#Script for RDD in time modelling for time period DST models, with specification checks on:
  #Autocorrelation of error term up to lag 10, Newey-West errors applied if present
  #Heteroskedasticity, HC3 errors applied if present
  #Specification checks of polynomial order of forcing variable (i.e. time); BIC is used to judge performance though other indicators also output
  #Specification checks by varying bandwidth for linear models

#attach packages
library(data.table)
library(DescTools)
library(rdrobust)
library(sandwich)
library(lmtest)

#set working directory
setwd("~/Documents/DST")

#Define sequences of data sets
  #The STATS19 data have been segmented into separate files representing 7 easting and 13 northing bands and 1 aggregate data set (21 files in total)
  #Datasets are named with same text prefix "data_", different numerical suffix "i"
  #We define the sequence of datasets as seq_i, which refers to the 21 segmented datasets described above
  #We define seq_t as the sequence of time periods ranging from 1 to 5
  #The functions will iterate through all sequences and output results tables with all models' results
seq_i<-c(1:21)
seq_t<-c(1:5)

#Define functions:
  #inputparams function calculates optimal bandwidth from rdrobust package; outputs from this are used in subsequent polynomial and bandwidth trials
  #rdd_calcs_poly function performs RDD with optimal bandwidth, and trials different polynomials for time
  #rdd_calcs_bw function trials RDD with different bandwidths for linear in time form

inputparams<-function(i,t){

  #compute bandwidth
  data_model<-data
```

```
  cols<-c("dow", "year")
  data_model<-data_model[, (cols):=lapply(.SD, as.factor), .SDcols=cols]
  tryCatch(
    expr = bw<-rdbwselect(y=data_model$tot_casualties, x=data_model$time_variable_tp,
                          covs=cbind(data_model$year,data_model$dow)),
    error = function(e) NULL
  )
  if(exists("bw")==TRUE){
    bw_exists=1
    bwl=ceiling(bw$bws[[1]])
    bwr=ceiling(bw$bws[[2]])
    #tabulate
    resultsline<-data.table(i,t,bwl,bwr,nrow(data_model),bw_exists)
    names(resultsline)<-c("model_no","tp","bw_mainl","bw_mainr","n","bw_exists")
  } else if (exists("bw")==FALSE){
    resultsline<-data.table(i,t,0,0,0,0)
    names(resultsline)<-c("model_no","tp","bw_mainl","bw_mainr","n","bw_exists")
  }
  return(resultsline)
}

rdd_calcs_poly<-function(i,t){
  #extract bandwidth info
  paras_i<-mod_paras[model_no==i & tp==t]
  bwl=paras_i$bw_mainl
  bwr=paras_i$bw_mainr
  bwexists=paras_i$bw_exists
  if (bwexists==1){
    #prepare data: need wt, kt and ktpost variables (cutoff is when time_variable_tp=0)
    data_model<-data[time_variable_tp>=-bwl & time_variable_tp<=bwr]
    data_model<-data_model[time_variable_tp>=0, wt:=1]
    data_model<-data_model[time_variable_tp<0, wt:=0]
    mintp=-1*min(data_model$time_variable_tp)
    interventiontp=mintp+1
    data_model<-data_model[time_variable_tp<0,kt:=(interventiontp)+time_variable_tp]
    data_model<-data_model[time_variable_tp>=0,kt:=mintp+time_variable_tp]
    data_model<-data_model[time_variable_tp<0, ktpost:=0]
```

```
    data_model<-data_model[time_variable_tp>=0, ktpost:=kt-interventiontp+1]

    cols<-c("dow", "year")
    data_model<-data_model[, (cols):=lapply(.SD, as.factor), .SDcols=cols]

    rdd_polytrial<-function(j){

      tryCatch(
        expr=lm_rdd<-lm(tot_casualties ~ wt + poly(kt, degree=j) + poly(ktpost, degree=j) + dow + year, 
data=data_model),
        error=function(e) NULL
      )
      if(exists("lm_rdd")==TRUE){
        #Breusch Godfrey autocorrelation test up to lag 10
        for (l in c(1:10)){
          tryCatch(
            expr = assign(paste0("bgtest_",l), value=BreuschGodfreyTest(lm_rdd, order = l, order.by = data_model$kt, 
type = "Chisq", data = data_model)),
            error = function(e) NULL
          )
          tryCatch(
            expr = assign(paste0("lag_",l), value=eval(parse(text=paste0("bgtest_",l,"$p.value")))),
            error = function(e) NULL
          )
          tryCatch(
            expr = assign(paste0("b",l),value=eval(parse(text=paste0("data.table(as.numeric(lag_",l,"),",l,")")))),
            error = function(e) NULL
          )
        }
        tryCatch(
          expr = bgtab<-rbind(b1,b2,b3,b4,b5,b6,b7,b8,b9,b10),
          error = function(e) NULL
        )
        if (exists("bgtab")==FALSE){
          lag_val=0
        } else if (exists("bgtab")==TRUE){
          bgtab_select<-bgtab[V1<=0.1]
```

```
      if (nrow(bgtab_select)>=1){
        lag_val=max(bgtab_select$V2)
      } else if (lag_1>0.1){
        lag_val=0
      }
    }
    #Bruesch Pagan heteroskedasticity test
    bp_pval=bptest(lm_rdd)$p.value
    if (is.na(bp_pval)){
      bp_pval=100
    }
    #adjust errors if needed to account for autocorrelation or heteroskedasticity
    if (lag_val>0){
      nw_vcov <- NeweyWest(lm_rdd, order.by = data_model$kt, data=data_model, lag = lag_val, prewhite = F,
adjust = T)
      lmsum<-as.matrix(coeftest(lm_rdd, vcov = nw_vcov))
      lm_sum<-lmsum[2,]
    } else if (lag_val==0 & bp_pval<=0.1){
      hc_vcov <- vcovHC(lm_rdd)
      lmsum<-as.matrix(coeftest(lm_rdd, vcov = hc_vcov))
      lm_sum<-lmsum[2,]
    } else if (lag_val==0 & bp_pval>0.1){
      lmsum<-as.matrix(summary(lm_rdd)$coefficients)
      lm_sum<-lmsum[2,]
    }

    data_model_l<-data_model[time_variable_tp<0]
    data_model_r<-data_model[time_variable_tp>=0]
    totcas_l=sum(data_model_l$tot_casualties)
    totcas_r=sum(data_model_r$tot_casualties)
    n_year=length(unique(data_model$year))

    resultsline<-
data.table(i,t,j,lm_sum[[1]],lm_sum[[2]],lm_sum[[4]],nrow(data_model),nrow(data_model_l),nrow(data_model_r),
                                as.numeric(bwl), as.numeric(bwr),as.numeric(lag_val),as.numeric(bp_pval),
                                summary(lm_rdd)$r.squared, summary(lm_rdd)$adj.r.squared, BIC(lm_rdd),
AIC(lm_rdd),totcas_l,totcas_r,n_year)
```

```
        names(resultsline)<-c("model_no","tp","poly_deg","coef","se", "pval",
"n_tot","n_left","n_right","bw_l","bw_r","lag","bp_pval",
                      "rsq","adj_rsq","bic","aic","totcas_l","totcas_r","n_year")
        return(resultsline)
      }}
    #run for polynomials order 1 to 4
    results_table<-c()
    for (j in 1:4){
      calcs<-rdd_polytrial(j)
      results_table<-rbind(calcs,results_table)
    }
    return(results_table)
  }}

rdd_calcs_bw<-function(i,t){
  #extract bandwidth info
  paras_i<-mod_paras[model_no==i & tp==t]
  bwl=paras_i$bw_mainl
  bwr=paras_i$bw_mainr
  bwexists=paras_i$bw_exists

  if (bwexists==1){
    rdd_bwtrial<-function(j){

      #prepare data: need wt, kt and ktpost variables (cutoff is when time_variable_tp=0)
      data_model<-data[time_variable_tp>=-(bwl+j) & time_variable_tp<=(bwr+j)]
      data_model<-data_model[time_variable_tp>=0, wt:=1]
      data_model<-data_model[time_variable_tp<0, wt:=0]
      mintp=-1*min(data_model$time_variable_tp)
      interventiontp=mintp+1
      data_model<-data_model[time_variable_tp<0,kt:=(interventiontp)+time_variable_tp]
      data_model<-data_model[time_variable_tp>=0,kt:=mintp+time_variable_tp]
      data_model<-data_model[time_variable_tp<0, ktpost:=0]
      data_model<-data_model[time_variable_tp>=0, ktpost:=kt-interventiontp+1]

      cols<-c("dow", "year")
      data_model<-data_model[, (cols):=lapply(.SD, as.factor), .SDcols=cols]
```

```
    tryCatch(
      expr=lm_rdd<-lm_rdd<-lm(tot_casualties ~ wt + poly(kt, degree=1) + poly(ktpost, degree=1)  + year + dow, 
data=data_model),
      error=function(e) NULL
    )
    if(exists("lm_rdd")==TRUE){
      #Breusch Godfrey autocorrelation test up to lag 10
      for (l in c(1:10)){
        tryCatch(
          expr = assign(paste0("bgtest_",l), value=BreuschGodfreyTest(lm_rdd, order = l, order.by = data_model$kt, 
type = "Chisq", data = data_model)),
          error = function(e) NULL
        )
        tryCatch(
          expr = assign(paste0("lag_",l), value=eval(parse(text=paste0("bgtest_",l,"$p.value")))),
          error = function(e) NULL
        )
        tryCatch(
          expr = assign(paste0("b",l),value=eval(parse(text=paste0("data.table(as.numeric(lag_",l,"),",l,")")))),
          error = function(e) NULL
        )
      }
      tryCatch(
        expr = bgtab<-rbind(b1,b2,b3,b4,b5,b6,b7,b8,b9,b10),
        error = function(e) NULL
      )
      if (exists("bgtab")==FALSE){
        lag_val=0
      } else if (exists("bgtab")==TRUE){
        bgtab_select<-bgtab[V1<=0.1]
        if (nrow(bgtab_select)>=1){
          lag_val=max(bgtab_select$V2)
        } else if (lag_1>0.1){
          lag_val=0
        }
      }
```

```
    #Bruesch Pagan heteroskedasticity test
    bp_pval=bptest(lm_rdd)$p.value
    if (is.na(bp_pval)){
      bp_pval=100
    }
    #adjust errors if needed to account for autocorrelation or heteroskedasticity
    if (lag_val>0){
      nw_vcov <- NeweyWest(lm_rdd, order.by = data_model$kt, data=data_model, lag = lag_val, prewhite = F,
adjust = T)
      lmsum<-as.matrix(coeftest(lm_rdd, vcov = nw_vcov))
      lm_sum<-lmsum[2,]
    } else if (lag_val==0 & bp_pval<=0.1){
      hc_vcov <- vcovHC(lm_rdd)
      lmsum<-as.matrix(coeftest(lm_rdd, vcov = hc_vcov))
      lm_sum<-lmsum[2,]
    } else if (lag_val==0 & bp_pval>0.1){
      lmsum<-as.matrix(summary(lm_rdd)$coefficients)
      lm_sum<-lmsum[2,]
    }

    data_model_l<-data_model[time_variable_tp<0]
    data_model_r<-data_model[time_variable_tp>=0]
    totcas_l=sum(data_model_l$tot_casualties)
    totcas_r=sum(data_model_r$tot_casualties)
    n_year=length(unique(data_model$year))

    resultsline<-
data.table(i,t,j,lm_sum[[1]],lm_sum[[2]],lm_sum[[4]],nrow(data_model),nrow(data_model_l),nrow(data_model_r),
                                as.numeric(bwl+j),as.numeric(bwr+j),as.numeric(lag_val),as.numeric(bp_pval),
                                summary(lm_rdd)$r.squared, summary(lm_rdd)$adj.r.squared, BIC(lm_rdd),
AIC(lm_rdd),totcas_l,totcas_r,n_year)
    names(resultsline)<-c("model_no","tp","bw_adjust","coef","se", "pval",
"n_tot","n_left","n_right","bw_l","bw_r","lag","bp_pval",
                               "rsq","adj_rsq","bic","aic","totcas_l","totcas_r","n_year")
    return(resultsline)
   }}
```

```
    #run for different bandwiths as follows:
    seq_bw<-c(1,0,-1)
    results_table<-c()
    for (j in seq_bw){
      calcs<-rdd_bwtrial(j)
      results_table<-rbind(calcs,results_table)
    }
    return(results_table)
  }}


#Run functions and save output as csv files
param_table<-c()
for (i in seq_i){
  for (t in seq_t){
    data_raw<-eval(parse(text=paste0("data_",i)))
    data<-data_raw[tp==t]
    param_table<-rbind(param_table,inputparams(i,t))
    }}
write.csv(param_table, file="model_params.csv", row.names=FALSE)

poly_table<-c()
for (i in seq_i){
  for (t in seq_t){
    data_raw<-eval(parse(text=paste0("data_",i)))
    data<-data_raw[tp==t]
    mod_paras<-fread("model_params.csv")
    poly_table<-rbind(poly_table,rdd_calcs_poly(i,t))
  }}
write.csv(poly_table, file="results_polytrial.csv", row.names=FALSE)

bw_table<-c()
for (i in seq_i){
  for (t in seq_t){
    data_raw<-eval(parse(text=paste0("data_",i)))
    data<-data_raw[tp==t]
    mod_paras<-fread("model_params.csv")
```

```
    bw_table<-rbind(bw_table,rdd_calcs_bw(i,t))
}}
write.csv(bw_table, file="results_bwtrial.csv", row.names=FALSE)

################################################################################
#Script for placebo tests as per Guido W. Imbens and Thomas Lemieux. Regression discontinuity designs: A guide to practice. Journal of Econometrics, 142:615–635, 2008.
#We use the same bandwidth as per the associated original models in file "model_params.csv" as generated in script "rdd_models.R"

#attach packages
library(data.table)
library(DescTools)
library(rdrobust)
library(sandwich)
library(lmtest)

#set working directory
setwd("~/Documents/DST")

#Define sequences of data sets
#The STATS19 data have been segmented into separate files representing 7 easting and 13 northing bands and 1 aggregate data set (21 files in total)
#Datasets are named with same text prefix "data_", different numerical suffix "i"
#We define the sequence of datasets as seq_i, which refers to the 21 segmented datasets described above
#We define seq_q so that we can split each data set into pre- ("left") and post- ("right") DST for 2 placebo tests per original model
#We define seq_t as the sequence of time periods ranging from 1 to 5
#The functions will iterate through all sequences and output results tables with all models' results
seq_i<-c(1:21)
seq_q<-c("left","right")
seq_t<-c(1:5)

#Define functions:
#rdd_calcs_poly function performs RDD with optimal bandwidth, and trials different polynomials for time
#rdd_calcs_bw function trials RDD with different bandwidths for linear in time form
```

```
rdd_calcs_poly<-function(i,q,t){
  #extract bandwidth info
  paras_iq<-mod_paras[model_no==i & tp==t]
  bwl=paras_iq$bw_mainl
  bwr=paras_iq$bw_mainr
  bwexists=paras_iq$bw_exists

  if (bwexists==1){
    #prepare data: need wt, kt and ktpost variables
    data_model<-data[time_variable_tp>=cut-bwl & time_variable_tp<cut+bwr]
    data_model<-data_model[time_variable_tp>=cut, wt:=1]
    data_model<-data_model[time_variable_tp<cut, wt:=0]
    mintp=min(data_model$time_variable_tp)
    interventiontp=abs(mintp)+1
    data_model<-data_model[,kt:=interventiontp+time_variable_tp]
    data_model<-data_model[wt==0, ktpost:=0]
    maxkt_wt0=max(data_model[wt==0]$kt)
    data_model<-data_model[wt==1, ktpost:=kt-maxkt_wt0]

    cols<-c("dow", "year")
    data_model<-data_model[, (cols):=lapply(.SD, as.factor), .SDcols=cols]

    rdd_polytrial<-function(j){

      tryCatch(
        expr=lm_rdd<-lm(tot_casualties ~ wt + poly(kt, degree=j) + poly(ktpost, degree=j)  + dow + year,
data=data_model),
        error=function(e) NULL
      )
      if(exists("lm_rdd")==TRUE){
        #Breusch Godfrey autocorrelation test up to lag 10
        for (l in c(1:10)){
          tryCatch(
            expr = assign(paste0("bgtest_",l), value=BreuschGodfreyTest(lm_rdd, order = l, order.by = data_model$kt,
type = "Chisq", data = data_model)),
            error = function(e) NULL
          )
```

```
     tryCatch(
      expr = assign(paste0("lag_",l), value=eval(parse(text=paste0("bgtest_",l,"$p.value")))),
      error = function(e) NULL
     )
     tryCatch(
      expr = assign(paste0("b",l),value=eval(parse(text=paste0("data.table(as.numeric(lag_",l,"),",l,")")))),
      error = function(e) NULL
     )
    }
    tryCatch(
     expr = bgtab<-rbind(b1,b2,b3,b4,b5,b6,b7,b8,b9,b10),
     error = function(e) NULL
    )
    if (exists("bgtab")==FALSE){
     lag_val=0
    } else if (exists("bgtab")==TRUE){
     bgtab_select<-bgtab[V1<=0.1]
     if (nrow(bgtab_select)>=1){
      lag_val=max(bgtab_select$V2)
     } else if (lag_1>0.1){
      lag_val=0
     }
    }
    #Bruesch Pagan heteroskedasticity test
    bp_pval=bptest(lm_rdd)$p.value
    if (is.na(bp_pval)){
     bp_pval=100
    }
    #adjust errors if needed to account for autocorrelation or heteroskedasticity
    if (lag_val>0){
     nw_vcov <- NeweyWest(lm_rdd, order.by = data_model$kt, data=data_model, lag = lag_val, prewhite = F,
adjust = T)
     lmsum<-as.matrix(coeftest(lm_rdd, vcov = nw_vcov))
     lm_sum<-lmsum[2,]
    } else if (lag_val==0 & bp_pval<=0.1){
     hc_vcov <- vcovHC(lm_rdd)
     lmsum<-as.matrix(coeftest(lm_rdd, vcov = hc_vcov))
```

```
          lm_sum<-lmsum[2,]
        } else if (lag_val==0 & bp_pval>0.1){
          lmsum<-as.matrix(summary(lm_rdd)$coefficients)
          lm_sum<-lmsum[2,]
        }

        data_model_l<-data_model[wt==0]
        data_model_r<-data_model[wt==1]

        resultsline<-
data.table(i,q,t,j,lm_sum[[1]],lm_sum[[2]],lm_sum[[4]],nrow(data_model),nrow(data_model_l),nrow(data_model_r),
                                as.numeric(bwl),as.numeric(bwr),as.numeric(lag_val),as.numeric(bp_pval),
                                summary(lm_rdd)$r.squared, summary(lm_rdd)$adj.r.squared, BIC(lm_rdd), AIC(lm_rdd))
        names(resultsline)<-c("model_no","data","tp","poly_deg","coef","se", "pval",
"n_tot","n_left","n_right","bw_l","bw_r","lag","bp_pval",
                               "rsq","adj_rsq","bic","aic")
        return(resultsline)
      }}
    #run for polynomials order 1 to 4
    results_table<-c()
    for (j in 1:4){
      calcs<-rdd_polytrial(j)
      results_table<-rbind(calcs,results_table)
    }
    return(results_table)
  }}

rdd_calcs_bw<-function(i,q,t){
  #extract bandwidth info
  paras_iq<-mod_paras[model_no==i & tp==t]
  bwl=paras_iq$bw_mainl
  bwr=paras_iq$bw_mainr
  bwexists=paras_iq$bw_exists

  if (bwexists==1){
    rdd_bwtrial<-function(j){
```

```
    #prepare data: need wt, kt and ktpost variables
    newcut=cut+j
    data_model<-data[time_variable_tp>=newcut-bwl & time_variable_tp<newcut+bwr]
    data_model<-data_model[time_variable_tp>=newcut, wt:=1]
    data_model<-data_model[time_variable_tp<newcut, wt:=0]
    mintp=min(data_model$time_variable_tp)
    interventiontp=abs(mintp)+1
    data_model<-data_model[,kt:=interventiontp+time_variable_tp]
    data_model<-data_model[wt==0, ktpost:=0]
    maxkt_wt0=max(data_model[wt==0]$kt)
    data_model<-data_model[wt==1, ktpost:=kt-maxkt_wt0]

    cols<-c("dow", "year")
    data_model<-data_model[, (cols):=lapply(.SD, as.factor), .SDcols=cols]

    tryCatch(
      expr=lm_rdd<-lm_rdd<-lm(tot_casualties ~ wt + poly(kt, degree=1) + poly(ktpost, degree=1) + dow + year,
data=data_model),
      error=function(e) NULL
    )
    if(exists("lm_rdd")==TRUE){
      #Breusch Godfrey autocorrelation test up to lag 10
      for (l in c(1:10)){
        tryCatch(
          expr = assign(paste0("bgtest_",l), value=BreuschGodfreyTest(lm_rdd, order = l, order.by = data_model$kt,
type = "Chisq", data = data_model)),
          error = function(e) NULL
        )
        tryCatch(
          expr = assign(paste0("lag_",l), value=eval(parse(text=paste0("bgtest_",l,"$p.value")))),
          error = function(e) NULL
        )
        tryCatch(
          expr = assign(paste0("b",l),value=eval(parse(text=paste0("data.table(as.numeric(lag_",l,"),",l,")")))),
          error = function(e) NULL
        )
      }
```

```
tryCatch(
  expr = bgtab<-rbind(b1,b2,b3,b4,b5,b6,b7,b8,b9,b10),
  error = function(e) NULL
)
if (exists("bgtab")==FALSE){
  lag_val=0
} else if (exists("bgtab")==TRUE){
  bgtab_select<-bgtab[V1<=0.1]
  if (nrow(bgtab_select)>=1){
    lag_val=max(bgtab_select$V2)
  } else if (lag_1>0.1){
    lag_val=0
  }
}
#Bruesch Pagan heteroskedasticity test
bp_pval=bptest(lm_rdd)$p.value
if (is.na(bp_pval)){
  bp_pval=100
}
#adjust errors if needed to account for autocorrelation or heteroskedasticity
if (lag_val>0){
  nw_vcov <- NeweyWest(lm_rdd, order.by = data_model$kt, data=data_model, lag = lag_val, prewhite = F,
adjust = T)
  lmsum<-as.matrix(coeftest(lm_rdd, vcov = nw_vcov))
  lm_sum<-lmsum[2,]
} else if (lag_val==0 & bp_pval<=0.1){
  hc_vcov <- vcovHC(lm_rdd)
  lmsum<-as.matrix(coeftest(lm_rdd, vcov = hc_vcov))
  lm_sum<-lmsum[2,]
} else if (lag_val==0 & bp_pval>0.1){
  lmsum<-as.matrix(summary(lm_rdd)$coefficients)
  lm_sum<-lmsum[2,]
}

data_model_l<-data_model[wt==0]
data_model_r<-data_model[wt==1]
```

```
          resultsline<-
data.table(i,q,t,j,lm_sum[[1]],lm_sum[[2]],lm_sum[[4]],nrow(data_model),nrow(data_model_l),nrow(data_model_r),
                                as.numeric(bwl+j),as.numeric(bwr+j),as.numeric(lag_val),as.numeric(bp_pval),
                                summary(lm_rdd)$r.squared, summary(lm_rdd)$adj.r.squared, BIC(lm_rdd), AIC(lm_rdd))
          names(resultsline)<-c("model_no","data","tp","bw_adjust","coef","se", "pval",
"n_tot","n_left","n_right","bw_l","bw_r","lag","bp_pval",
                              "rsq","adj_rsq","bic","aic")
          return(resultsline)
        }}

    #run for different bandwiths as follows:
    seq_bw<-c(1,0,-1)
    results_table<-c()
    for (j in seq_bw){
      calcs<-rdd_bwtrial(j)
      results_table<-rbind(calcs,results_table)
    }
    return(results_table)
  }}


#Run functions and save output as csv files
poly_table<-c()
for (i in seq_i){
  for (q in seq_q){
    for (t in seq_t){
      data_raw<-eval(parse(text=paste0("data_",i)))
      data_tp<-data_raw[tp==t]
      if (q=="left"){
        data<-data_tp[time_variable_tp<0]
        cut=round(mean(data$time_variable_tp))
      } else if (q=="right"){
        data<-data_tp[time_variable_tp>=0]
        cut=round(mean(data$time_variable_tp))
      }
      mod_paras<-fread("model_params.csv")
      poly_table<-rbind(poly_table,rdd_calcs_poly(i,q,t))
```

```
    }}}
write.csv(poly_table, file="results_placebo_polytrial.csv", row.names=FALSE)

bw_table<-c()
for (i in seq_i){
  for (q in seq_q){
    for (t in seq_t){
      data_raw<-eval(parse(text=paste0("data_",i)))
      data_tp<-data_raw[tp==t]
      if (q=="left"){
        data<-data_tp[time_variable_tp<0]
        cut=round(mean(data$time_variable_tp))
      } else if (q=="right"){
        data<-data_tp[time_variable_tp>=0]
        cut=round(mean(data$time_variable_tp))
      }
      mod_paras<-fread("model_params.csv")
      bw_table<-rbind(bw_table,rdd_calcs_bw(i,t))
    }}}
write.csv(bw_table, file="results_placebo_bwtrial.csv", row.names=FALSE)
```

STROBE Statement—checklist of items that should be included in reports of observational studies

	Item No	Recommendation	Page No
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	1
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	1
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	2-3
Objectives	3	State specific objectives, including any prespecified hypotheses	3
Methods			
Study design	4	Present key elements of study design early in the paper	3-6
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	3-4
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up *Case-control study*—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls *Cross-sectional study*—Give the eligibility criteria, and the sources and methods of selection of participants	NA
		(*b*) *Cohort study*—For matched studies, give matching criteria and number of exposed and unexposed *Case-control study*—For matched studies, give matching criteria and the number of controls per case	NA
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	5-6
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	*3-6*
Bias	9	Describe any efforts to address potential sources of bias	5-6
Study size	10	Explain how the study size was arrived at	3-6
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	5-6
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	4-6
		(*b*) Describe any methods used to examine subgroups and interactions	5-6
		(*c*) Explain how missing data were addressed	5
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed *Case-control study*—If applicable, explain how matching of cases and controls was addressed *Cross-sectional study*—If applicable, describe analytical methods taking account of sampling strategy	NA
		(*e*) Describe any sensitivity analyses	6

Continued on next page

Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	NA
		(b) Give reasons for non-participation at each stage	NA
		(c) Consider use of a flow diagram	NA
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	NA
		(b) Indicate number of participants with missing data for each variable of interest	NA
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	NA
		Note: No human/animal participants were involved but a summary of descriptive statistics on casualties is given	4
Outcome data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	NA
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	NA
		Cross-sectional study—Report numbers of outcome events or summary measures	NA
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	6-9
		(*b*) Report category boundaries when continuous variables were categorized	5-6
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	NA
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	NA
Discussion			
Key results	18	Summarise key results with reference to study objectives	11-15
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	15
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	12-15
Generalisability	21	Discuss the generalisability (external validity) of the study results	15
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	17

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in cohort and cross-sectional studies.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

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Road traffic casualties in Great Britain at daylight savings time transitions: a causal regression discontinuity design analysis

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Road traffic casualties in Great Britain at daylight savings time transitions: a causal regression discontinuity design analysis

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Abstract

Objectives: To determine whether daylight savings time (DST) transitions have an effect on road traffic casualties in Great Britain using causal regression discontinuity design analysis. We undertake aggregate and disaggregate spatial and temporal analyses to test the commonly referenced sleep and light hypotheses.
Design: The study takes the form of a natural experiment in which the DST transitions are interventions to be evaluated. Two outcomes are tested: (i) the total number of casualties of all severities (ii) the number of fatalities.
Data: Data are obtained from the UK Department for Transport STATS19 database. Over a period of 14 years between 2005 and 2018, 311,766 total casualties and 5,429 fatalities occurred 3 weeks either side of the Spring DST transition and 367,291 total casualties and 6,650 fatalities occurred 3 weeks either side of the Autumn DST transition.
Primary outcome measure: A regression discontinuity design method (RDD) is applied. The presence of a causal effect is determined via the degree of statistical significance and magnitude of the average treatment effect.
Results: All significant average treatment effects are negative (54 significant models out of 287 estimated), indicating that there are fewer casualties following the transitions. Overall, bootstrapped summary statistics indicate a reduction of 0.75 in the number of fatalities (95% CI: -1.61, -0.04) and a reduction of 4.73 in the number of total casualties (95% CI: -6.08, -3.27) on average per year at both the Spring and Autumn DST transitions combined.
Conclusions: The results indicate minor reductions in the number of fatalities following the DST transitions, and thus our analysis does not support the most recent UK parliamentary estimate that there would be 30 fewer fatalities in Great Britain if DST were to be abolished. Furthermore, the results do not provide conclusive support for either the sleep or light hypotheses.

Keywords: Road safety, Daylight savings time, Sleep, Visibility, Regression discontinuity design

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Strengths and limitations of this study

- We adopt a causal regression discontinuity design method to generate robust estimates of the impact of DST transitions on road traffic casualties and fatalities in Great Britain.
- We undertake both aggregate and disaggregate spatial and temporal analyses to investigate the impacts of sleep and light disruptions at the transitions.
- We account for potential confounding through the inclusion of seasonal variables at the level of year, day of week, and time of day, and treat heteroskedasticity and autocorrelation to account for unobserved confounders.
- Limitations include potential under-reporting of casualties in the Department for Transport STATS19 database, sparse data leading to estimation difficulties in the northernmost regions of Scotland, and the presence of potential additional unobserved confounders that could lead to biased estimates.

1. Introduction

Since its introduction, the implementation of daylight savings time (DST) has been a contentious issue which has regained attention in recent times. In response to a public consultation held in 2018, the European Parliament in 2019 adopted a position to support the elimination of daylight savings in the European Union (EU), with plans for implementation in 2021 [1, 2]. The United Kingdom (UK) initiated an inquiry to analyse the impact of the EU change to "understand what factors should inform [the UK's] approach" [3]. The UK also previously debated and ultimately rejected changes to daylight savings in the Daylight Saving Bill 2010-11, which proposed to shift UK time forward by one hour throughout the year to align with Central European Time (CET) [4]. A key argument in the elimination or alteration of daylight savings time is the impact that clock changes have on road safety. In both the academic literature and government parliamentary debates, two issues are highlighted as having an impact on road safety levels: (i) changes in daylight hours could impact alertness due to the required chronobiologic adjustments to the human circadian rhythm [1, 5, 6] - herein referred to as the 'sleep hypothesis', and (ii) changing of daylight hours could result in detrimental changes to visibility [7, 8, 4, 3] - herein referred to as the 'light hypothesis'.

Evidence on the impact of DST transitions on road traffic casualties is currently inconclusive. In the 2010-2011 Daylight Saving Bill, it was argued that there would be 80 fewer fatalities on UK roads if the UK switched to CET [4]. In the more recent UK report on the proposed EU changes, it was stated that abolishing time changes and adopting a permanent move to UK Summer Time could result in 30 fewer fatalities [3]. However, it is unclear how these figures were generated and whether robust causal statistical analysis methods were adopted. In the academic literature, there is mixed consensus regarding the impact of DST transitions. Increases in road casualties are reported for studies undertaken in the US by Smith [9] and in New Zealand by Robb and Barnes [10], while reductions in casualties in the US are reported by Coate and Markowitz [11] and Crawley [12]. Lindenberger et al. [13] reports no significant impacts in their analysis of road casualties in Germany.

The aim of this paper is to estimate the causal effect of DST transitions on the number of road traffic casualties and fatalities in Great Britain. This paper contributes to the literature from several perspectives. First, the majority of studies adopt non-causal techniques to quantify the impact of DST transitions, including comparisons of descriptive statistics, linear regression based on ordinary least squares, and quasi-Poisson regression [10, 11, 13, 14, 15]. Two studies by Carey and Sarma [7] and Uttley and Fotios [16] adopt a causal regression discontinuity design (RDD) method similar to ours, however, the studies focus on road casualties in the USA and pedestrian casualties in the UK, respectively. We therefore contribute to the literature by adopting a causal RDD method to analyse road traffic casualties in Great Britain, which, to our knowledge, has not been previously undertaken. Second, use of the RDD method with time as the forcing variable requires stringent specification tests to be undertaken to ensure that the models are free from potential confounding factors that can lead to biased estimates. In the literature on RDD methods applied to DST analyses, these specification tests are not typically performed. In our analysis, we follow the recommendations made in Hausman and Rapson [17] to test for model robustness. Finally, there are a number of studies in the UK and US indicating both causal and non-causal relationships between light levels and casualties at DST transitions [14,15,16,18,19], however, we are not aware of causal studies testing the sleep hypothesis at DST transitions. Therefore, in addition to a pooled analysis of Great Britain as a whole, we also undertake disaggregate spatial and temporal analyses to test the sleep and light hypotheses.

2. Methods

2.1. Study area and data

The STATS19 database produced by the Department for Transport is used to obtain records of road traffic accidents that resulted in personal injury in Great Britain between 2005 and 2018 [dataset][20]. Casualties are defined as personal injuries of any severity as a result of an accident event. As specified in [21], a single accident event can be associated with more than one casualty. In this analysis, we focus on total casualties (all severities combined) and fatal casualties.

Three week windows on either side of the DST transitions in Spring and Autumn are extracted from the total accident data set. Three weeks is chosen to provide enough data for the optimised local bandwidth to be calculated for each scenario as part of the RDD modelling. It should be noted that after calculation of the optimal bandwidth, the window around the DST transitions is likely to be much shorter than three weeks; further details on the optimal bandwidth calculations are given in Section 2.2. Through data cleaning, less than 0.02% of records have been removed as a result of missing observations in the fields representing latitude and longitude and accident event timestamps as well as records over Bank Holidays as these observations could potentially represent abnormal out-of-season traffic levels which could confound the baseline time trends before and after the DST transitions. The number of casualties and fatalities for all of Great Britain over three week windows either side of the transitions are summarised in Table 1. As shown in the table, there are increases in the number of casualties and fatalities after both transitions when considering 3 week windows before and after the transitions. Again, it should be noted that this study considers the impact on casualties in the immediate vicinity of the transition dates, and so the 3 week windows will shrink considerably after calculation of the optimal bandwidth around the transition dates for each model. Therefore, the general trend for the aggregate 3 week windows showing more casualties after the transitions may not be applicable at shorter bandwidths.

Table 1: Number of casualties, aggregated over Great Britain over ± 3 week windows from DST transition dates

Casualty severity	Spring		Autumn	
	Before DST	After DST	Before DST	After DST
Total casualties	153107	158659	175796	191495
Fatal casualties	2517	2912	3211	3439

To investigate whether the DST transitions have different regional effects across Great Britain, National Ordnance Survey data are used to divide Great Britain into distinct bands based on latitude and longitude [22]. Using the Ordnance Survey Grid Reference (OSGR) variable within STATS19, each accident event and associated casualties are assigned a Northings band and an Eastings band.

2.2. Regression discontinuity design framework

DST is a policy enacted for the entire population of Great Britain and the treatment assignment is deterministic, i.e., there is no ambiguity in treated vs untreated observations. Therefore, the DST treatment imposed at the Spring and Autumn transitions is considered as a sharp discontinuity. Further information on RDD frameworks is presented in Imbens and Lemieux [23] and Lee and Lemieux [24].

In this analysis, we use spatio-temporal units where i refers to a given local area zone within Great Britain, t refers to a given time period, where each day is segmented into 5 time periods, and z refers to year. The assignment of the treatment, i.e. the imposition of the daylight savings transition, is solely dependent on the value of the forcing variable, time T, as follows:

$$W_{itz}\begin{cases} 1 \text{ if } T_t \geq c \\ 0 \text{ if } T_t < c \end{cases} \qquad (1)$$

where c is the treatment threshold, which is defined as the DST transition date, and W_{itz} is the binary treatment in the sharp RDD. In the Spring transition, the treatment is the imposition of Summer Time, while in the Autumn transition, the treatment is the return to GMT. Observations recorded between 00:00 and 01:00 in March and between 00:00 and 02:00 in October on the day of the transition are designated as non-treated in line with when the transition occurs. Over the analysis time period of 2005 to 2018, the transition dates for Spring range from 25 to 31 March and those for Autumn range from 25 to 31 October.

The observation of a discontinuity in the average treatment effect either side of the treatment threshold is evidence of a causal effect of the treatment [23, 24]. The average treatment effect for a sharp discontinuity τ_{SRD} in time is defined as:

$$\tau_{SRD} = E[Y_{itz}(1) - Y_{itz}(0) \mid T_t = c] = \lim_{t \downarrow c} E[Y_{itz} | T_t = t] - \lim_{t \uparrow c} E[Y_{itz} | T_t = t] \qquad (2)$$

where $Y_{itz}(1)$ indicates the potential outcome when treatment is received and $Y_{itz}(0)$ indicates the potential outcome when treatment is not received. The second equality holds assuming continuity of expectations in T i.e. $E[Y_{itz}(0) \mid T_t = c] = \lim_{t \uparrow c} E[Y_{itz}(0) \mid T_t = t] = \lim_{t \uparrow c} E[Y_{itz} \mid T_t = t]$ [23].

Since the forcing variable is time, we follow the recommendations in Hausman and Rapson [17] to address potential specification issues. To ensure that there are enough observations in the vicinity of the treatment threshold, we segment daily data into 5 time periods, and the data are aggregated at a local area zone level which also provides cross-sectional variance at each time point. By segmenting the data to increase the number of observations close to the treatment threshold, we avoid the need to include observations further away from the threshold which can introduce bias from unobserved confounding variables. We account for potential bias from known confounding variables correlated with time through the inclusion of covariates representing potential seasonal variation in casualties. The covariates are year, day of the week, and the time period associated with each observation. Since the daylight savings transitions are universally applied at fixed transition dates, we do not anticipate issues arising from manipulation of treatment status. Further specification tests are undertaken to ensure validity of the design and these are discussed in section 2.3.

The data sets are arranged in a pseudo-panel form with indexes of local area zone and time period per year. The response variable is the sum of the number of casualties per local area zone and time period per year; in cases where no casualties are observed, a value of 0 is designated. For each of the Spring and Autumn transitions, two base regressions are undertaken as follows: (i) the total number of casualties of all severities, and (ii) the total number of fatalities. The two base regressions are run for three scenarios: (i) for Great Britain overall, (ii) for each Northing band in each time period, and (iii) for each Easting band in each time period. We adopt a local linear specification for the forcing variable of time. The bandwidth for the models is specified according to the conventional method of minimising the mean squared error (MSE) of the average treatment effect [25, 26, 27]. This selection procedure selects the shortest (i.e. local) bandwidth in the vicinity of the treatment threshold subject to the minimisation of the MSE, thus ensuring that the key assumption of random treatment is upheld. The optimal bandwidth selection process is considered superior to nominating an arbitrary bandwidth as was common in the earliest implementations of RDD as it is objective and data-driven rather than subjective [25]. The 'rdrobust' package in the R statistical analysis software is used for the optimal bandwidth calculation [27, 28].

The general equation for the aggregate model of Great Britain is given in equation 3. The regional and time of day analyses enable the investigation of the sleep and light hypotheses. It should be noted that in the disaggregate models, the time of day covariate in equation 3 is not included as the models are pre-segmented by time of day. All modelling has been undertaken using R statistical analysis software.

$$Y_{itz} = \alpha + \tau_{SRD} W_{itz} + \theta_1 K_{itz}(t) + \theta_2 K_{itz,post}(t) + \beta_1 X_{1z} + \beta_2 X_{2t} + \beta_3 X_{3t} + \varepsilon_{itz} \quad (3)$$

where Y_{itz} is the total number of casualties per local area zone i per time period t per year z, W_{itz} is the treatment assignment indicator as previously defined, τ_{SRD} is the average treatment effect of interest, $K_{itz}(t)$ represents the average long term trend across the entire bandwidth i.e.

$K_{itz}(t) = t$, and $K_{itz,post}(t)$ is the time trend after the intervention where $K_{itz,post}(t) = 0, t < c$ and $K_{itz,post}(t) = t - c + 1, t \geq c$. The categorical variables X_{1z}, X_{2t}, X_{3t} condition for year, day of the week, and time period, respectively. Year takes a value from 1 – 14 corresponding to the years 2005 – 2018. As coded in the STATS19 database, the day of the week takes a value 1 – 7 with 1 corresponding to Sunday and 7 corresponding to Saturday. The time of the day takes values as follows: Overnight = 1, AM Peak = 2, Inter Peak = 3, PM Peak = 4, Night = 5. The peak time periods follow the standards adopted by the Department for Transport: AM Peak (07:00 – 09:59), Inter Peak (10:00 – 15:59) and PM Peak (16:00 – 18:59) [18]. Two additional time-bins are added to complete a 24-hour period: Overnight (0:00 – 06:59) and Night (19:00 – 23:59). α and ε_{itz} are the model constant and model random error term, respectively, where $\varepsilon_{itz} \sim \mathcal{N}(0,\sigma_\varepsilon^2)$.

It should be noted that the inclusion of group-specific fixed effects for local area zone was trialled to account for potential time-invariant cross-sectional differences. However, using the Bayesian Information Criterion (BIC) as an indicator of model performance, we found that a majority of models performed better with no local area zone effects compared to those with local area effects, and so these effects are not included in the final model form.

2.3. Specification tests

As recommended by Hausman and Rapson [17], we perform the following specification tests:

- Specification checks are performed for the bandwidth by varying the bandwidth within the vicinity of the optimal bandwidth and verifying that the magnitude and significance of average treatment effect remains consistent.

- Specification checks are performed for the polynomial order of the forcing variable of time. The BIC is used to judge model performance. Polynomials of up to degree 4 are tested, and we verify that the local linear specification performs best in line with the bandwidth selection procedure.

- The Breusch-Godfrey test [29, 30] is performed to test for autocorrelation of the error term for a lag value up to 10 (2 days). If autocorrelation is present, it is treated using Newey-West standard errors [31], which are heteroskedasticity and autocorrelation consistent (HAC).

- The Breusch-Pagan test [32] is performed to test for heteroskedasticity. If heteroskedasticity is present with no error term autocorrelation, it is treated with heteroskedasticity consistent (HC3) errors [33].

- We perform placebo tests as per the recommendations in [23] to verify the model specification. We partition the original data for each model at the DST cutoff to obtain two smaller data sets. We then calculate a placebo cutoff which is equivalent to the mean value of the running variable in each dataset. We perform two placebo tests for each original model by undertaking the RDD analysis for the placebo cutoffs before the DST cutoff and after the DST cutoff. The original models pass the placebo test if both placebo models yield an insignificant average treatment effect.

Note: Autoregression of the dependent variable is not considered in this analysis, since the majority of casualties per local area zone do not occur in consecutive time periods.

The R code for the generation of the RDD models and all specification tests is provided as a Supplementary file.

2.4. Patient and public involvement statement

Please note that no patients nor members of the public were involved in this study.

3. Results

The results for the aggregate Spring and Autumn RDD models are presented in Table 2. The results for the disaggregate spatial and temporal RDD analyses are presented in Tables 3 and 4. All results tables summarise cases where the RDD models have passed all specification tests as described in section 2.3, and the average treatment effect at the DST transition is significant at a minimum significance level of $\alpha = 0.05$ ($\geq$ 95%). A map of the corresponding Northing and Eastings bands is given in Figure 1. As shown in the figure, higher band numbers represent more northern and more eastern locations. For further information, we have additionally included plots for every significant model including the original observations and fitted values as a Supplementary file. We have generated two plots for each scenario: the first shows all data points including the extent of raw observations, and the second is zoomed in to highlight the time trends.

Table 2: Aggregate models of Great Britain - RDD results summary

Transition	Location	Casualty type	BW	n	Y_{before}	Y_{after}	τ_{SRD}	% Change
Spring	Aggregate Great Britain	All casualties	32	173888	32133	27842	-0.075 (0.009)***	0.003%
		Fatalities	Not significant					
Autumn	Aggregate Great Britain	All casualties	Not significant					
		Fatalities	Not significant					

Notes: Significance notation: p-values 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Standard errors in parentheses.
BW refers to bandwidth in time period units, τ_{SRD} refers to the sharp RDD average treatment effect due to DST transition.
n is the total number of observations, Y_{before} and Y_{after} refer to the total number of casualties or fatalities before and after the cutoff, respectively

Table 3: Spring transition - disaggregate spatial and temporal models RDD results summary

			All Casualties						Fatal					
Location	**Band**	**Time period**	**BW**	***n***	Y_{before}	Y_{after}	τ_{SRD}	**% Change**	**BW**	***n***	Y_{before}	Y_{after}	τ_{SRD}	**% Change**
Aggregate		1	22	27145	1260	1507	-0.110 (0.024)***	-0.12%	40	12744	133	81	-0.067 (0.022)**	-0.70%
		4	38	43472	6565	6597	-0.059 (0.020)**	-0.01%						
		5	46	48906	6918	4456	-0.130 (0.025)***	-0.03%						
Northing band	1,000-2,000	1	28	9925	474	591	-0.095 (0.034)**	-0.28%						
		3	36	15992	3880	3623	-0.162 (0.042)***	-0.06%						
		4	38	16008	2350	2343	-0.067 (0.029)*	-0.04%						
		5	48	17991	2606	1610	-0.146 (0.041)***	-0.08%						
	2,000-3,000	3	74	19698	3182	3346	-0.137 (0.047)**	-0.06%						
	3,000-4,000	1	34	8365	315	340	-0.075 (0.035)*	-0.33%	44	2648	25	19	-0.046 (0.021)*	-2.58%
		3	64	14496	3197	3044	-0.167 (0.063)**	-0.07%						
		5	52	13233	1342	1073	-0.086 (0.042)*	-0.09%						
Easting band	3,000-4,000	1	28	8370	324	311	-0.148 (0.056)**	-0.64%	62	4510	67	34	-0.139 (0.055)*	-2.89%
	4,000-5,000	1	30	11814	522	479	-0.069 (0.030)*	-0.18%						
		3	74	28000	6172	6235	-0.171 (0.049)***	-0.04%						
		5	50	20000	2244	1874	-0.083 (0.038)*	-0.05%						
	5,000-6,000	1	28	8530	428	559	-0.104 (0.039)**	-0.34%						
		3	70	24066	5588	5651	-0.090 (0.037)*	-0.02%						
		4	26	8565	1479	848	-0.110 (0.045)*	-0.10%						
		5	44	15453	2235	1388	-0.149 (0.045)***	-0.09%						

Notes: Significance notation: p-values 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Standard errors in parentheses. BW refers to bandwidth in time period units, *n* is the total number of observations, τ_{SRD} refers to the sharp RDD average treatment effect due to DST transition, Y_{before} and Y_{after} refer to the total number of casualties or fatalities before and after the cutoff, respectively, and time periods are as follows: 1-.Overnight, 2-AM Peak, 3-Inter-peak, 4-PM Peak, 5-Night.

Table 4: Autumn transition - disaggregate spatial and temporal models RDD results summary

			All Casualties						Fatal					
Location	**Band**	**Time period**	**BW**	***n***	Y_{before}	Y_{after}	τ_{SRD}	**% Change**	**BW**	***n***	Y_{before}	Y_{after}	τ_{SRD}	**% Change**
Aggregate		1	18	16197	1035	1043	-0.096 (0.019)***	-0.13%	38	13671	104	97	-0.030 (0.012)*	-0.40%
		3	72	75642	20645	20684	-0.101 (0.028)***	-0.01%						
		4	34	37821	7728	5448	-0.077 (0.024)**	-0.01%						
		5	32	37821	7449	3851	-0.231 (0.030)***	-0.04%	60	24936	285	282	-0.035 (0.016)*	-0.17%
Northing band	0-1,000	1	38	2534	90	53	-0.153 (0.058)**	-2.38%						
		5	64	5044	389	297	-0.156 (0.062)*	-0.56%						
	1,000-2,000	1	24	10015	630	572	-0.158 (0.036)***	-0.35%	40	4888	50	19	-0.052 (0.017)**	-1.45%
		4	30	12048	1993	1837	-0.129 (0.036)***	-0.09%						
	2,000-3,000	1	32	9695	408	353	-0.112 (0.035)**	-0.39%						
		5	48	12708	1534	891	-0.190 (0.058)**	-0.17%						
	3,000-4,000	1	26	6010	289	265	-0.152 (0.045)***	-0.74%						
		4	40	9576	1475	1540	-0.118 (0.042)**	-0.11%						
	5,000-6,000	2	48	3440	261	309	-0.076 (0.031)*	-0.41%						
	7,000-8,000	5	70	1470	66	69	-0.094 (0.045)*	-1.84%						
	8,000-9,000	1	56	583	34	27	-0.280 (0.097)**	-11.53%						
		5	66	793	89	51	-0.362 (0.128)**	-5.69%						
Easting band	1,000-2,000	1	64	1092	30	20	-0.072 (0.036)*	-3.34%						
	2,000-3,000	3							78	3210	26	37	-0.056 (0.021)**	-3.00%
		4	54	7018	853	678	-0.091 (0.043)*	-0.15%						
	3,000-4,000	1	26	8195	411	352	-0.136 (0.040)***	-0.46%						
		5	44	14985	2189	1351	-0.222 (0.050)***	-0.14%						
	4,000-5,000	1	26	9825	498	473	-0.129 (0.032)***	-0.36%						
		5	44	17874	2840	1663	-0.252 (0.057)***	-0.12%						
	5,000-6,000	1	22	8525	566	534	-0.187 (0.037)***	-0.46%	44	4491	34	12	-0.042 (0.014)**	-1.71%
		4	34	12033	2397	1532	-0.127 (0.039)**	-0.07%						
		5	48	15408	2853	1807	-0.279 (0.056)***	-0.14%						
	6,000-7,000	5	42	2394	257	106	-0.191 (0.086)*	-1.04%						

Notes: Significance notation: p-values 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Standard errors in parentheses. BW refers to bandwidth in time period units, n is the total number of observations, τ_{SRD} refers to the sharp RDD average treatment effect due to DST transition, Y_{before} and Y_{after} refer to the total number of casualties or fatalities before and after the cutoff, respectively, and time periods are as follows: 1-.Overnight, 2-AM Peak, 3-Inter-peak, 4-PM Peak, 5-Night.

3.1. Spring transition

As shown in the tables, all models with significant average treatment effects show a reduction in the number of casualties at the Spring transition. For the whole of Great Britain, approximately 0.075 (-0.003%) fewer total casualties are observed on average per year. The time of day models further indicate reductions in total casualties ranging from 0.06 to 0.13 fewer casualties per year across the overnight, PM peak, and night periods (in percentages, -0.01% to -0.03%). In terms of fatalities in isolation, there are 0.07 (-0.7%) fewer fatalities observed in the overnight period.

Latitudinal analysis

In the disaggregate models of Northing bands, there are significant reductions in total casualties in 3 out of 12 bands. The reductions range from approximately 0.07 to 0.17 fewer total casualties (-0.04% to -0.45%) per year in all time periods except the morning peak. In terms of fatalities, there are 0.05 fewer fatalities per year (-2.58%) in the overnight time period in band 3000-4000.

Longitudinal analysis

In the disaggregate models of Easting bands, there are significant effects in 3 out of 7 bands. There are approximately 0.07 to 0.17 fewer total casualties (-0.02% to -0.64%) observed in all time periods except the morning peak. For the fatality models, in band 3000-4000, there is a significant reduction of 0.14 fatalities (-2.89%) in the overnight time period.

3.2. Autumn transition

As with the Spring transition, in the Autumn transition, all models with significant average treatment effects report a reduction in casualties. Considering Great Britain as a whole, there are no significant effects. However, when splitting by time of day, there are reductions in total casualties in every time period except the morning peak ranging from 0.08 to 0.23 fewer total casualties on average per year (-0.01% to -0.13%). In terms of fatalities, there are 0.03 fewer fatalities (-0.40%) in the overnight time period and 0.04 fewer fatalities (-0.17%) in the night time period.

Latitudinal analysis

In the disaggregate models of Northing bands, there are significant effects in 7 out of 12 bands. The effects range from a 0.08 to 0.36 reduction in the total number of casualties (-0.09% to -11.53%), and all significant effects are observed across all time periods except the inter-peak. For fatalities, in band 1000-2000, there are 0.05 fewer fatalities (-1.45%) in the overnight time period.

Longitudinal analysis

In the disaggregate models of Easting bands, 6 out of 7 bands report significant effects in the total number of casualties. All significant effects are negative and they are observed in all time periods except the inter-peak. The effects range from 0.07 to 0.28 fewer total casualties (-0.07% to -3.34%). For the fatality models, in band 2000-3000, there are 0.06 fewer fatalities (-3.00%) in the inter-peak, and in band 5000-6000, there are 0.04 fewer fatalities (-1.71%) in the overnight time period.

4. Discussion

4.1. Pooled analysis of Great Britain

When Great Britain is viewed as a whole regionally and without time segmentation, there is a statistically significant causal effect indicating a very minor reduction of 0.075 (0.003%) in the total number of casualties at the Spring DST transition. The average treatment effects in all other pooled analyses are insignificant at a minimum significance level of ≥ 95%.

When segmenting the data, there are further geographical zones and time periods with statistically significant average treatment effects. Our analyses therefore indicate that it is important to investigate the impacts of DST transitions at disaggregate spatial and temporal levels, as well as analysing the aggregate effects.

4.2. Spring transition

At the Spring transition, clocks are moved forward one hour, resulting in an hour less sleep. The reduction in sleep could have an impact on road casualties throughout the day. In the morning, civil twilight sunrise times change from approximately 5-5:30am to 6-6:30am across Britain. There is an hour less sleep and mornings are darker by an hour before 6-6:30am. These conditions could result in a compounding effect of the sleep and light hypotheses, likely resulting in an increase in casualties. However, for all models with significant effects in the associated overnight period (from 12am-7am), there is a reduction in total casualties and fatalities, in opposition to the sleep and light hypotheses.

In terms of regional effects, in the most western locations of Great Britain, the sun rises approximately 23 minutes later than the most eastern locations. As the civil twilight sunrise times coincide with the beginning of the morning peak in traffic, there could be a possibility of more casualties in the darker western locations compared to the east. Furthermore, sunrise at the most southern locations occurs approximately 20 minutes after the most northern locations, and so there could be a possibility of more casualties in the south relative to the north. For the Northing and Easting time of day models, we do not observe a systematic pattern showing progressively more casualties in the west and south, thus we cannot provide conclusive support for the regional light hypothesis.

At the Spring transition, civil daylight occurs throughout the AM peak (7-10am), inter-peak (10am-4pm), and PM peak (4pm-7pm), and so the light hypothesis is not applicable in these time periods. The sleep hypothesis is applicable, and sleepiness could manifest throughout the day, leading to potential increases in casualties. However, all models with significant effects in these time periods indicate reductions in total casualties, in opposition to the sleep hypothesis.

In the evening, civil twilight sunset times change from approximately 7-7:30pm to 8-8:30pm across Great Britain. There is an hour less sleep throughout the day, but evenings are lighter by an hour in the off-peak travel time after 7-7.30pm, therefore resulting in a potential conflict of the sleep and light hypotheses. In all significant models in the associated night time period (7pm-12am), there is a reduction in the total number of casualties. This result aligns with the light hypothesis but at the same time opposes the sleep hypothesis, however, it is not possible to disentangle the effects. In terms of regional effects of the light hypothesis, the most western locations experience sunset approximately 23 minutes after the most eastern locations, so there may be potential for increased casualties in the east compared to the west due to the light hypothesis, however, the results do not support this. There is minimal difference (approximately 10 minutes) between sunset times in the north and south, and so we do not anticipate substantial differences between these locations. In the analysis of northing bands, there are only two models with significant effects in the night time period which show similar reductions in total casualties, however, this does not provide substantial systematic evidence of support for the regional light hypothesis.

4.3. Autumn transition

At the Autumn transition, clocks are moved back one hour, and this can lead to an hour more sleep. The increase in sleep could have an impact on road casualties throughout the day. In the morning, civil twilight sunrise times change from approximately 7-7:30am to 6-6:30am across Great Britain. There is an hour more sleep and mornings are lighter by an hour before the morning peak travel time, therefore compounding the sleep and light hypotheses and resulting in the most appropriate conditions for a reduction in casualties. For all models with significant effects in the associated overnight and AM peak periods, there are reductions in total casualties and fatalities. These results therefore support the compounded impact of the sleep and light hypotheses, though it is not possible to disentangle the individual impacts of the two hypotheses. In terms of regional impacts, the most eastern locations experience civil twilight sunrise approximately 23 minutes before the most western locations, and so eastern locations are expected to report greater reductions in casualties. Furthermore, the most southern locations experience sunrise approximately 21 minutes before the most northern locations and so southern locations are expected to report greater reductions in casualties. However, the results show minimal support for a systematic pattern that progressively shows a greater reduction in casualties towards the east and south in the overnight and AM periods, thus we cannot conclude conclusive support for the regional light hypothesis.

At the Autumn transition, civil daylight occurs throughout the inter-peak period (10-4pm), and so there are no anticipated effects from the light hypothesis. However, the sleep hypothesis could apply, as there is an extra hour of sleep gained throughout the day, potentially leading to a reduction in casualties. Indeed, for all models with significant effects in the inter-peak, there are reductions in total casualties and fatalities, thus supporting the sleep hypothesis.

In the evenings, civil sunset times change from approximately 6-6:30pm to 5-5:30pm across Great Britain. There is an hour more sleep throughout the day but evenings are darker by an hour during the PM peak of traffic. In this situation, there is a potential conflict between the sleep and light hypotheses. All models with significant effects in the PM peak period (4-7pm) report reductions in total casualties and fatalities. Therefore, the results support the sleep hypothesis but oppose the light hypothesis, however, it is not possible to disentangle the impacts of the two. In terms of regional effects, sunset in the most eastern locations occurs approximately 24 minutes before sunset in the most western locations, and so we can expect more casualties in the east. Sunset in the most northern locations occurs approximately 13 minutes before sunset in the most southern locations. Though it is difficult to ascertain whether it is feasible to expect regional differences, it could be plausible to anticipate more casualties in the north. However, the northing and easting band models do not provide support for a systematic pattern that progressively shows a greater increase in casualties towards the east and north in the night period, thus the results do not support the regional light hypothesis.

4.4. Magnitude of impacts at DST transitions

In the Daylight Savings Bill 2010-2011, it was estimated that there would be 80 fewer fatalities if the UK followed CET time [4]. A more recent report on EU DST changes states that there would be 30 fewer fatalities as a result of eliminating DST transitions altogether [3].

Overall, our analysis suggests that DST transitions have a minor positive impact rather than a detrimental impact on road traffic casualties and fatalities. All statistically significant models (54 models) report a negative average treatment effect, indicating a reduction in the number of casualties at the DST transitions. Over the 13 northings bands, 7 eastings bands, and aggregate models, we attempted to generate a total of 212 models for total casualties and fatalities, respectively. However, due to sparse data in several bands, a number of models were not able to be estimated; 167 were able to be estimated for total casualties and 120 were able to be estimated for fatalities. Of these, 46 out of 167 estimated models of total casualties have significant average treatment effects, and 8 out of 120 estimated models of fatalities have significant average treatment effects. A potential explanation for why there are fewer fatality models with a significant average treatment effect could be that there are relatively lower numbers of fatalities occurring either side of the DST threshold. Furthermore, we acknowledge that the models with insignificant average treatment effects indicate absence of evidence of a change in casualties/fatalities at the DST threshold rather than evidence of absence of a change in casualties/fatalities at the DST threshold.

We calculate the combined impact of the Spring and Autumn transitions on road casualties, and we generate associated 95% bootstrap confidence intervals using 10,000 iterations as per the bias corrected and accelerated (BCa) bootstrap method [34, 35]. The statistic of interest that we bootstrap is calculated in two steps: (1) We sum all average treatment effects in the regional time of day models over the Spring and Autumn transitions combined. Two estimates are generated: one for Easting band segmentation and one for Northing band segmentation. (2) We calculate the mean of the Easting and Northing band values, and this is taken as the estimated combined number of casualties over the Spring and Autumn transitions. We perform this procedure for fatalities and total casualties separately.

The bootstrapped values indicate a mean reduction of 0.75 in the number of fatalities on average per year with a 95% confidence interval ranging from -1.61 to -0.04 (reduction in fatalities). Our analysis therefore reports minor reductions in fatalities at the DST transitions, rather than an increase of 30-80 fatalities as estimated in House of Lords [3] and Bennett [4].

Similarly, for the total number of casualties of all severities, a mean reduction of 4.73 in the number of total casualties is estimated on average per year with a 95% confidence interval ranging from -6.08 to -3.27 (reduction in the total number of casualties). Therefore, the results for casualties of all severities also question the predictions of DST effects reported in House of Lords [3] and Bennett [4].

4.5. Limitations

One limitation of the RDD methodology is that is applicable to ex-post analyses and not suitable for making ex-ante predictions. Therefore, the results reflect the impact of DST transitions on road safety over the study period of 2005-2018, and it is difficult to generalise the results to predict the impact of potential DST changes in the future. However, we have no compelling reason to believe that the average treatment effect will change significantly over time.

The data from the Department for Transport STATS19 database may also pose potential limitations, as the data are compiled from police reports. As a result, there could be potential under-reporting of casualties. One previous study estimated that the number of casualties classified as Serious could be under-reported by a factor of two [36]. Another data-related limitation is the sparse data in the northernmost regions of Scotland. Due to the limited number of observations, the RDD models reported high standard errors of the average treatment effect estimator and low statistical significance in these regions, and in some cases, estimates were not able to be computed. As such, in future work, either alternate data sources or alternate statistical analysis techniques for small sample data are recommended.

In the interpretation of the results in Section 4.2 and 4.3, we identified instances of where the sleep and light hypotheses were in conflict, and it was not possible to disentangle and quantify the separate impacts of the two hypotheses on road casualties. We therefore recommend future work to investigate how to disentangle the two effects, with a potential solution involving gathering disaggregate data on sleeping patterns and conditioning for this in the models.

Finally, it should be noted that we have addressed potential sources of bias by conditioning out exogeneous changes in traffic volumes which cannot be attributed to the DST transitions through the inclusion of seasonal year, day of week, and time of day variables along with treatment of heteroskedasticity and autocorrelation of the error term to account for potential unobserved confounders. However, there may be additional unobserved factors that we have not accounted for which may lead to potentially biased estimates. For example, we were not able to obtain a data set that identifies every school holiday in each local area zone nor were we able to obtain weather data at a time period level in each local area zone from 2005-2018. We acknowledge that this could lead to potentially biased values of the average treatment effect. However, we would also like to highlight that the bandwidths for each model are narrow around the cutoffs (the mean bandwidth across all models is 4.3 days either side of the transition), and the narrow windows would minimise the degree of systematic impacts from school holidays and weather effects.

5. Conclusion

In this paper, we find that DST transitions have only a minor positive impact on road casualties and fatalities. For total casualties, 46 out of 167 models have significant average treatment effects, while for fatalities 8 out of 120 models have significant effects. All models with a significant average treatment effect (54 models) report a negative effect, indicating a reduction in the number of casualties at the DST transitions.

Considering Great Britain as a whole, we find a significant effect indicating a minor 0.003% reduction in the total number of casualties in the Spring transition into DST. The average treatment effects in all other aggregate models are insignificant at a minimum significance level of $\geq$ 95%. When segmenting the data spatially and temporally, there are more models with statistically significant average treatment effects. This highlights the importance of investigating the impacts of DST transitions at a disaggregate level.

The disaggregate spatial and temporal models do not provide clear support or rejection of the sleep and light hypotheses at the transitions. At the Autumn transition, the temporal analyses indicate support for the compounded effect of the sleep and light hypotheses in the overnight and AM peak periods as well as support for the sleep hypothesis in the inter-peak period. For the remaining transitions, there is minimal support for the sleep and light hypotheses in both the temporal and regional analyses and in some cases, it is difficult to disentangle potential conflicts between the sleep and light hypotheses. In cases where the hypotheses are not supported, other factors such as driver behaviour and other socio-economic characteristics may be the main cause of the observed estimated changes.

In terms of policy impacts, the Daylight Savings Bill 2010-2011 estimates that 80 lives would be saved per year from transitioning to CET [4] and the report on EU DST changes estimates 30 lives saved per year as a result of abolishing DST altogether [3]. Our results question these figures. We apply a bias corrected and accelerated bootstrap with 10,000 iterations to estimate the total number of fatalities and casualties on average per year over the Spring and Autumn transitions combined. The bootstrapped values indicate a mean reduction of 0.75 in the number of fatalities (95% CI: -1.61, -0.04) and a mean reduction of 4.73 in the number of total casualties (95% CI: -6.08, -3.27) on average per year at both the Spring and Autumn DST transitions combined. The light hypothesis is the main driver for the Daylight Savings Bill, while both the sleep and light hypotheses are put forward in the recent report on abolishing DST altogether in the EU. However, as mentioned, we do not find definitive evidence to support the sleep and light hypotheses.

A number of areas for future work are recommended. In some cases, modelling was prohibited due to a lack of data in the north of Great Britain, and therefore it is suggested that alternate data sources or alternate statistical analysis techniques for small sample data are employed to ascertain the impact of DST transitions in these regions. We also recommend further work to disentangle the impacts of the sleep and light hypotheses in cases where the two are in conflict. In regions where the sleep and light hypotheses did not hold, further research to investigate the impact of other potentially influential socio-demographic factors could be undertaken. In this analysis, we considered all casualties across all socio-demographic groups. Further analyses could be undertaken to provide a more disaggregate characterisation of the impact of DST transitions, for example, segmenting casualties by age could assist in testing whether DST transitions impact children walking to school as hypothesised in the Daylight Saving Bill 2010-11.

Author contribution statement

The corresponding author attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

Author CRediT statement

Conceptualisation: DJ Graham; Data curation: R Sood; Methodology: DJ Graham, R Singh, R Sood; Formal analysis: R Singh, R Sood; Writing-original draft: R Singh, R Sood, DJ Graham; Writing-review and editing: R Singh, DJ Graham, R Sood; Supervision: DJ Graham; Funding acquisition: DJ Graham.

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Competing interests statement

None declared.

Ethics approval statement

Ethics approval is not applicable as no human nor animal participants were involved in the study.

Data availability statement

The data used in this study are available open-source from the Department for Transport at the following URL: https://www.gov.uk/government/collections/road-accidents-and-safety-statistics.

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Figure 1 notes

Values on the x-axis refer to Eastings bands, and values on the y-axis refer to Northings bands. The two letters in each grid square refer to specific locations on the UK National Grid; the exact naming of each square can be found at Ordnance Survey [22].

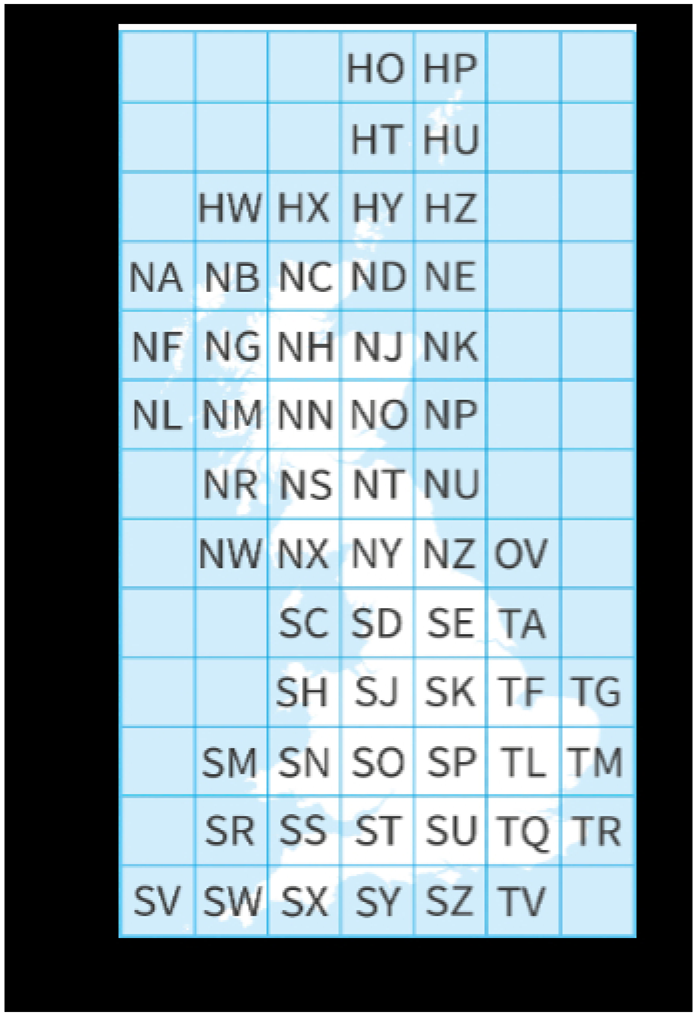

Figure 1: Definition of Northing and Eastings bands in Great Britain (adapted from Ordnance Survey [20], not to scale).

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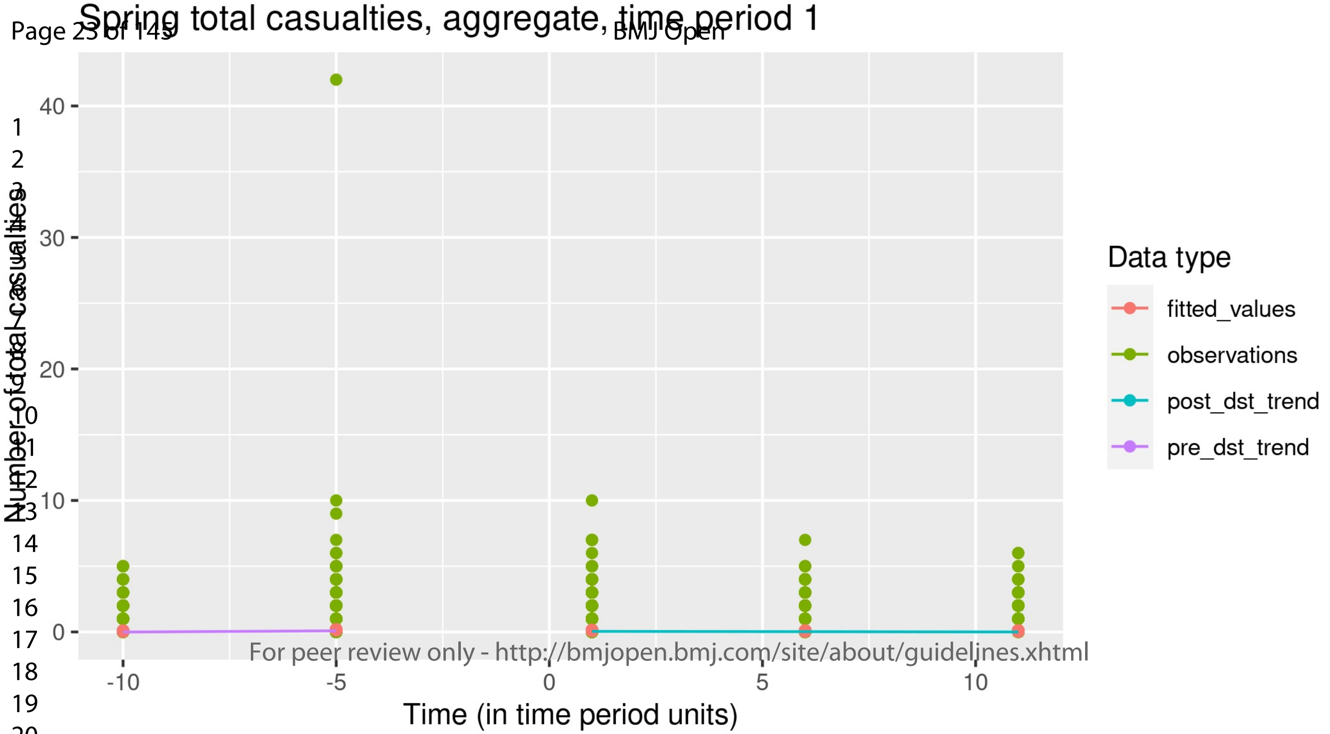
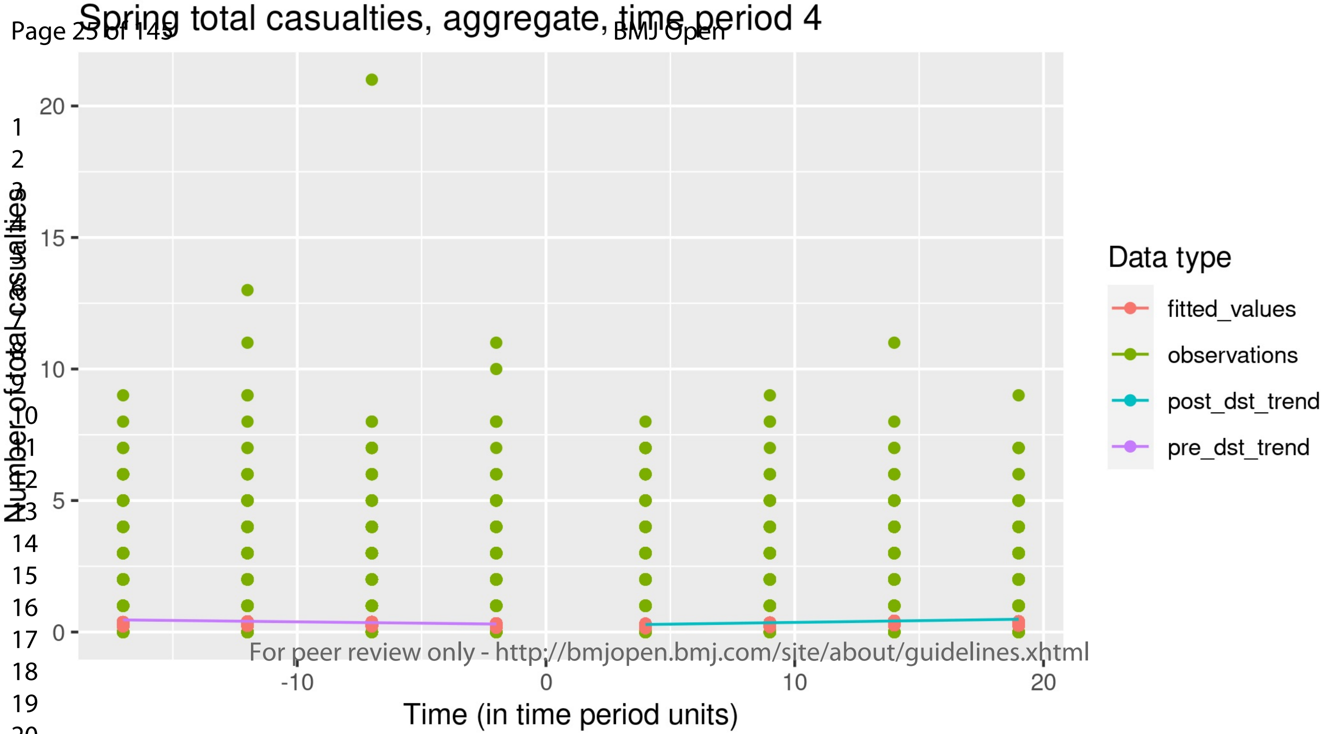

Spring total casualties, aggregate, time period 1
Number of total casualties
40
30
20
10
0
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Spring total casualties, aggregate, time period 1, zoomed in
Number of total casualties
2
0
-2
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend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Number of total casualties
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend
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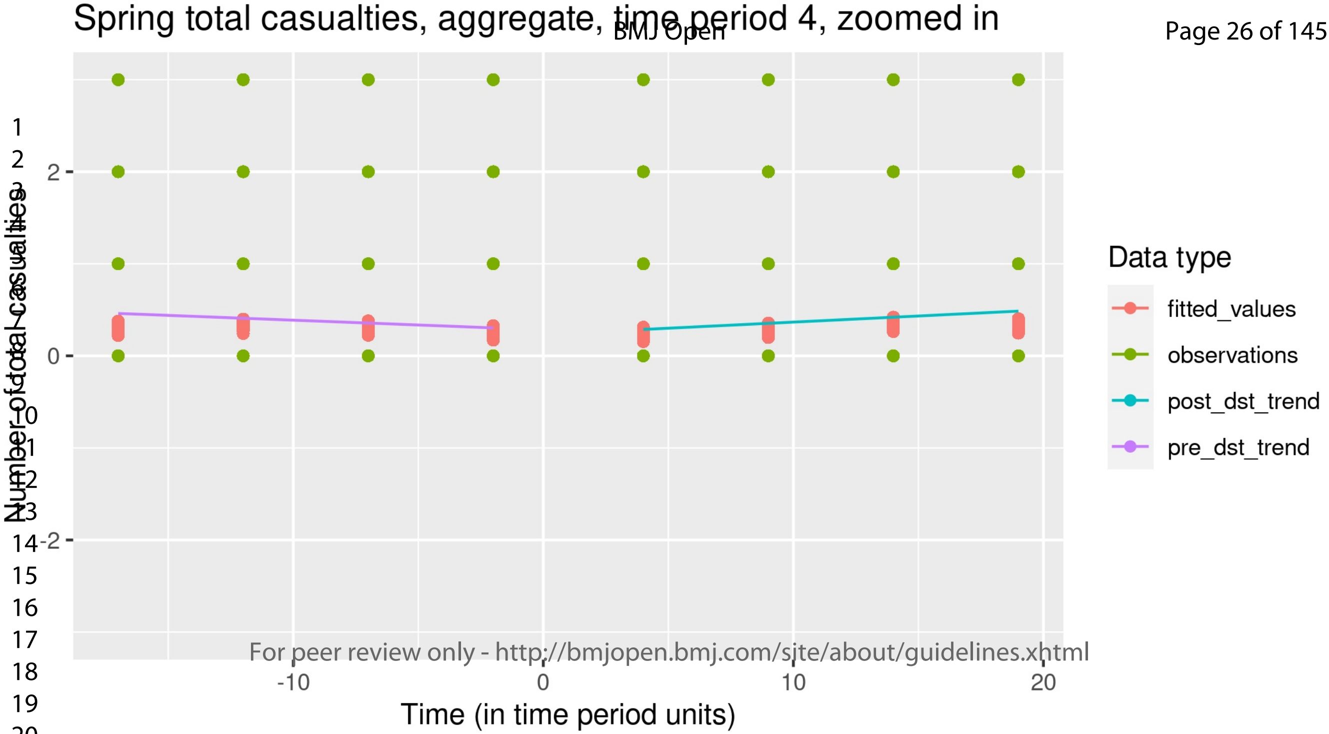
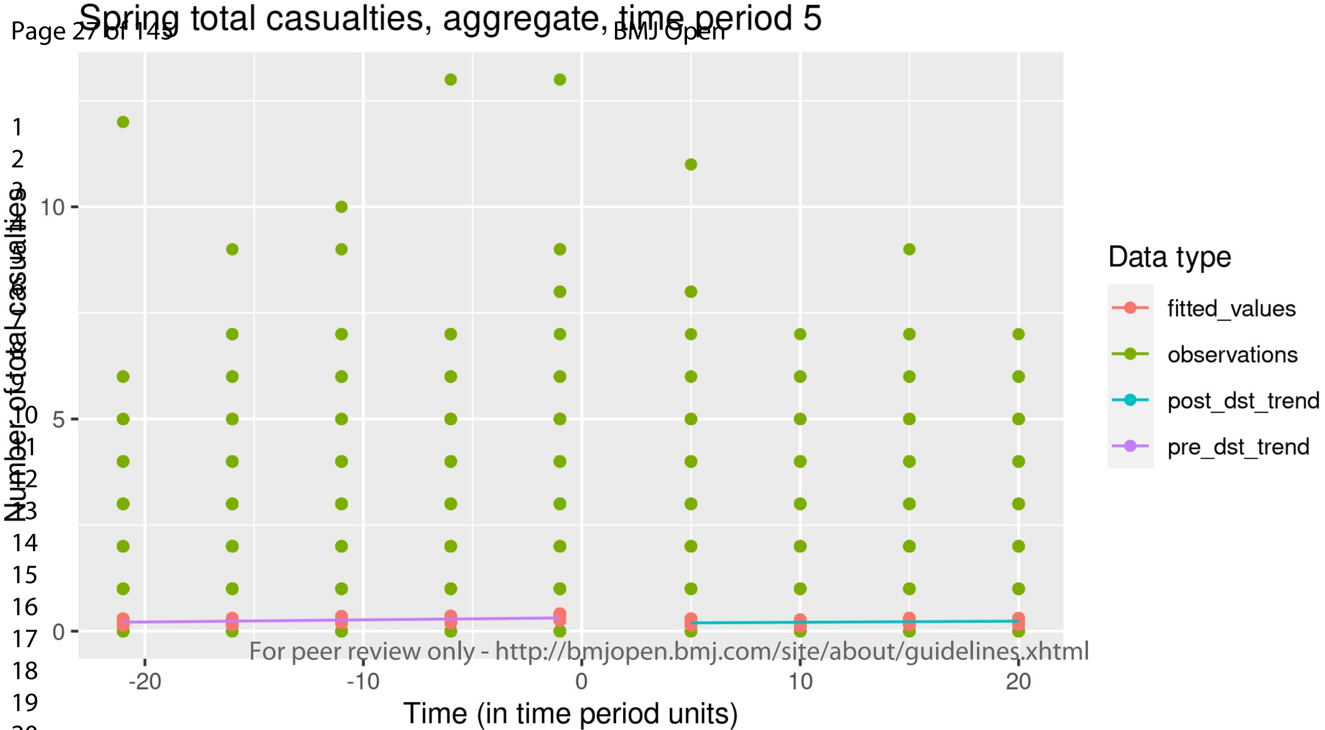
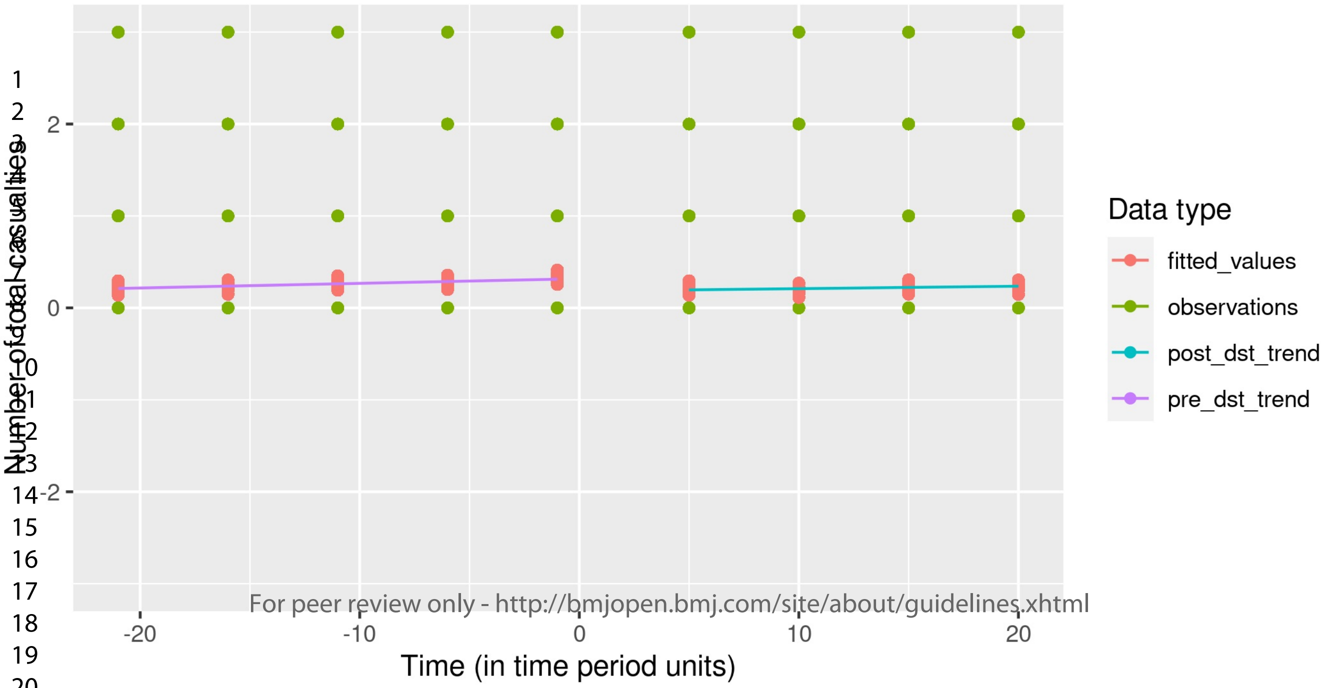
15
10
5
0
-10
0
10
20

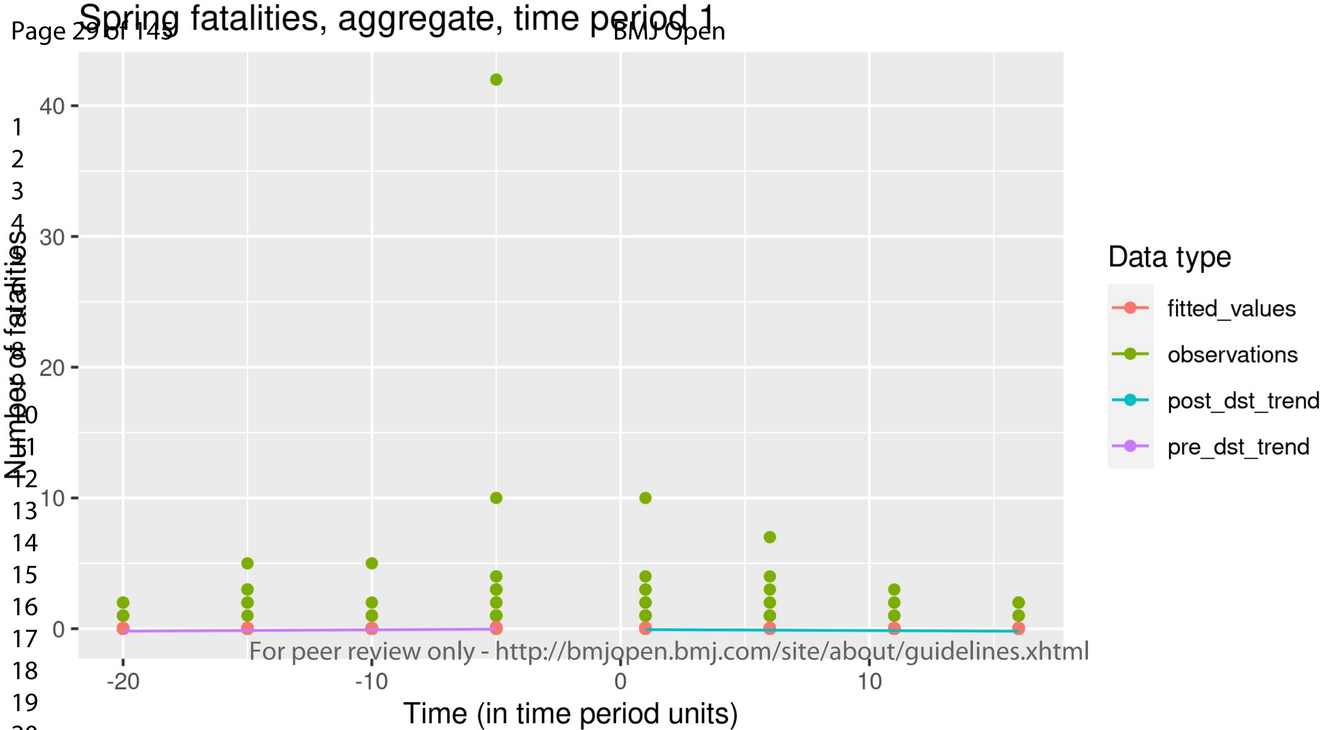

Spring total casualties, aggregate, time period 4, zoomed in
Number of total casualties
2
0
-2
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

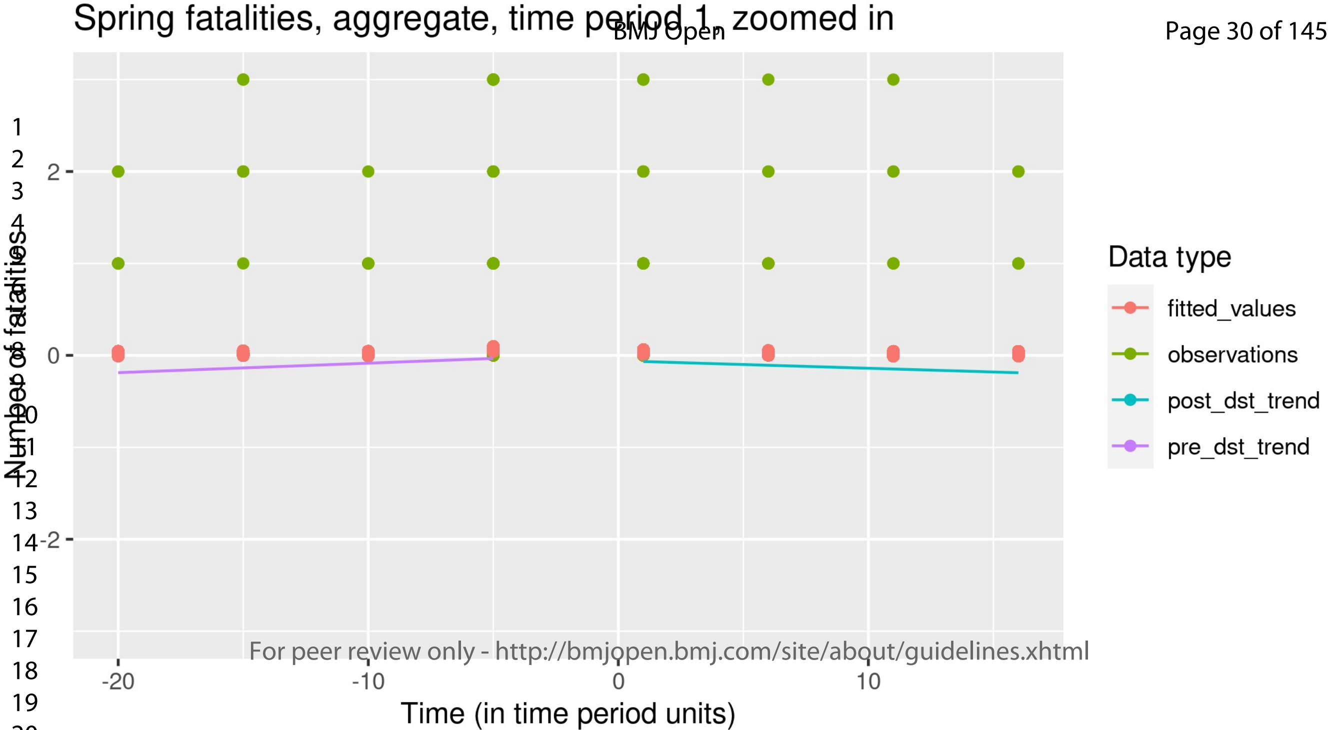


Spring total casualties, aggregate, time period 5
Number of total casualties
0
5
10
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

Spring total casualties, aggregate, time period 5, zoomed in




Spring fatalities, aggregate, time period 1
Number of fatalities
0
10
20
30
40
-20
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Spring fatalities, aggregate, time period 1, zoomed in
Number of fatalities
2
0
-2
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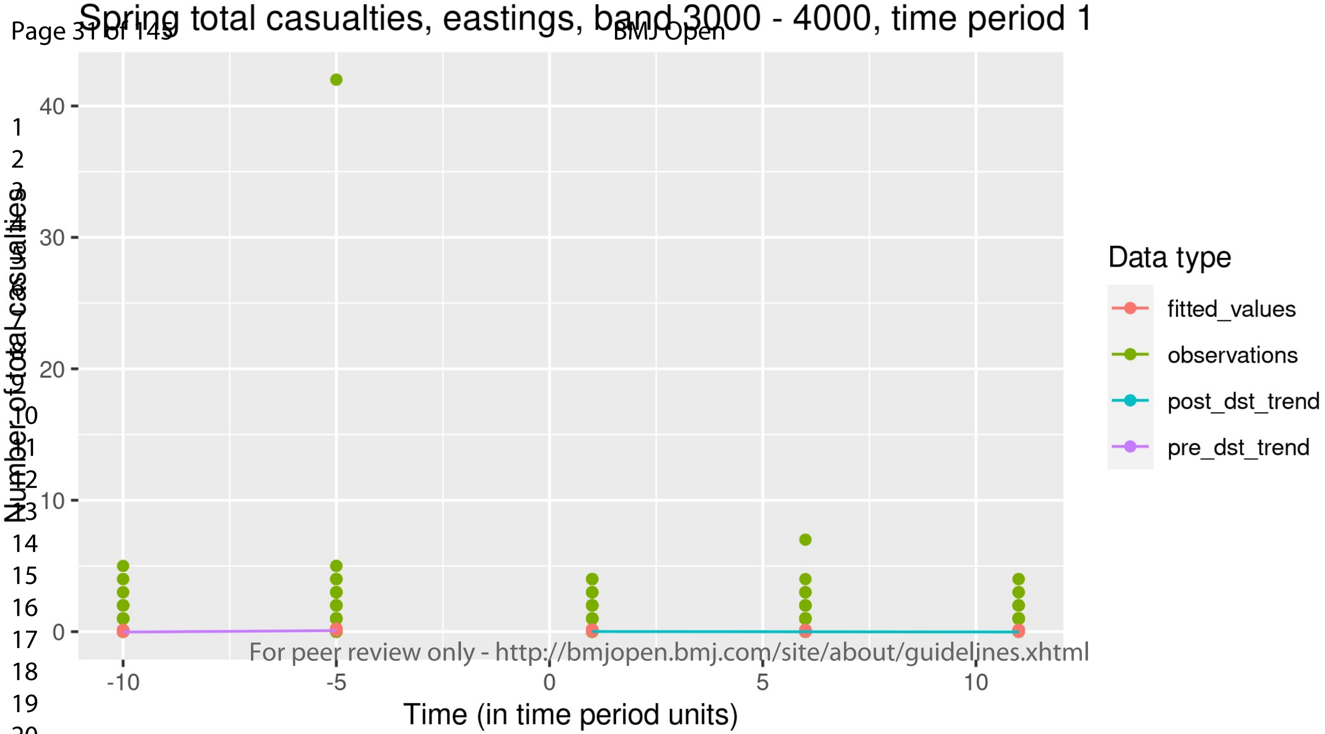
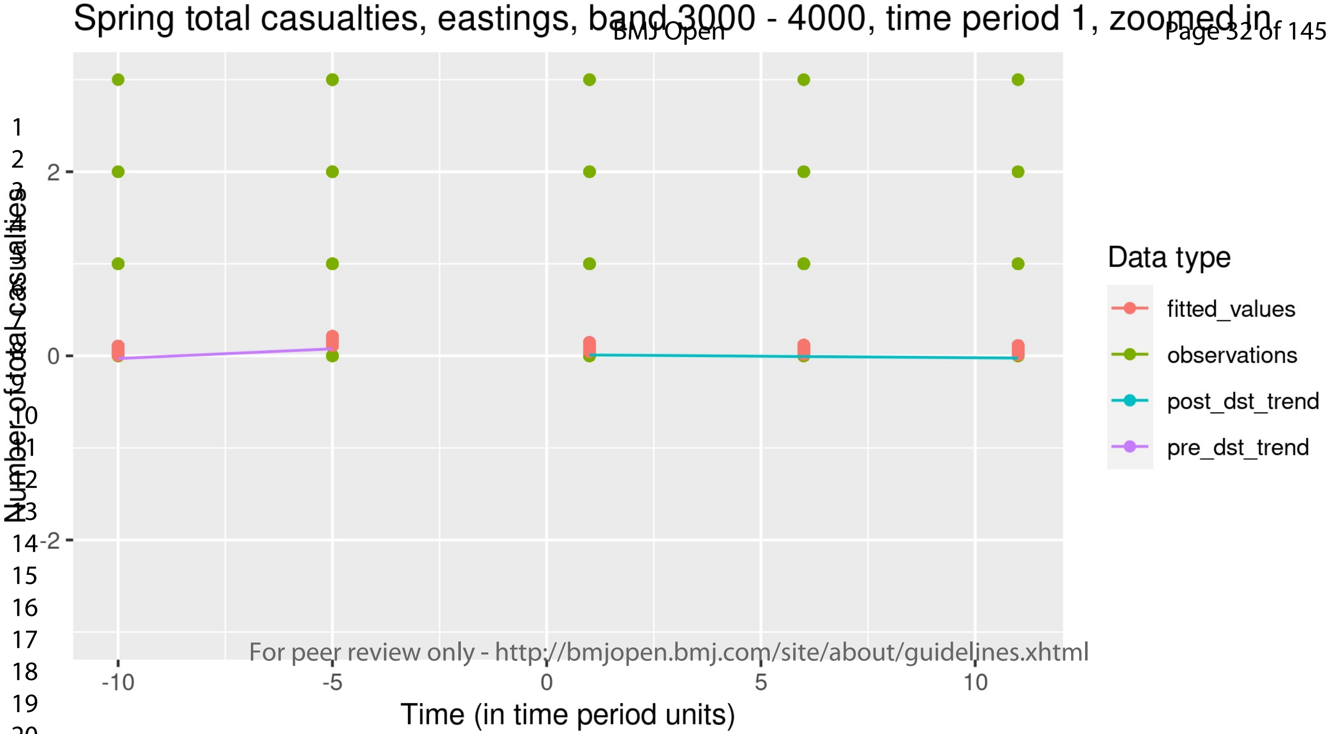
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Spring total casualties, eastings, band 3000 - 4000, time period 1
Number of total casualties
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend
40
30
20
10
0
-10
-5
0
5
10


Spring total casualties, eastings, band 3000 - 4000, time period 1, zoomed in
Number of total casualties
2
0
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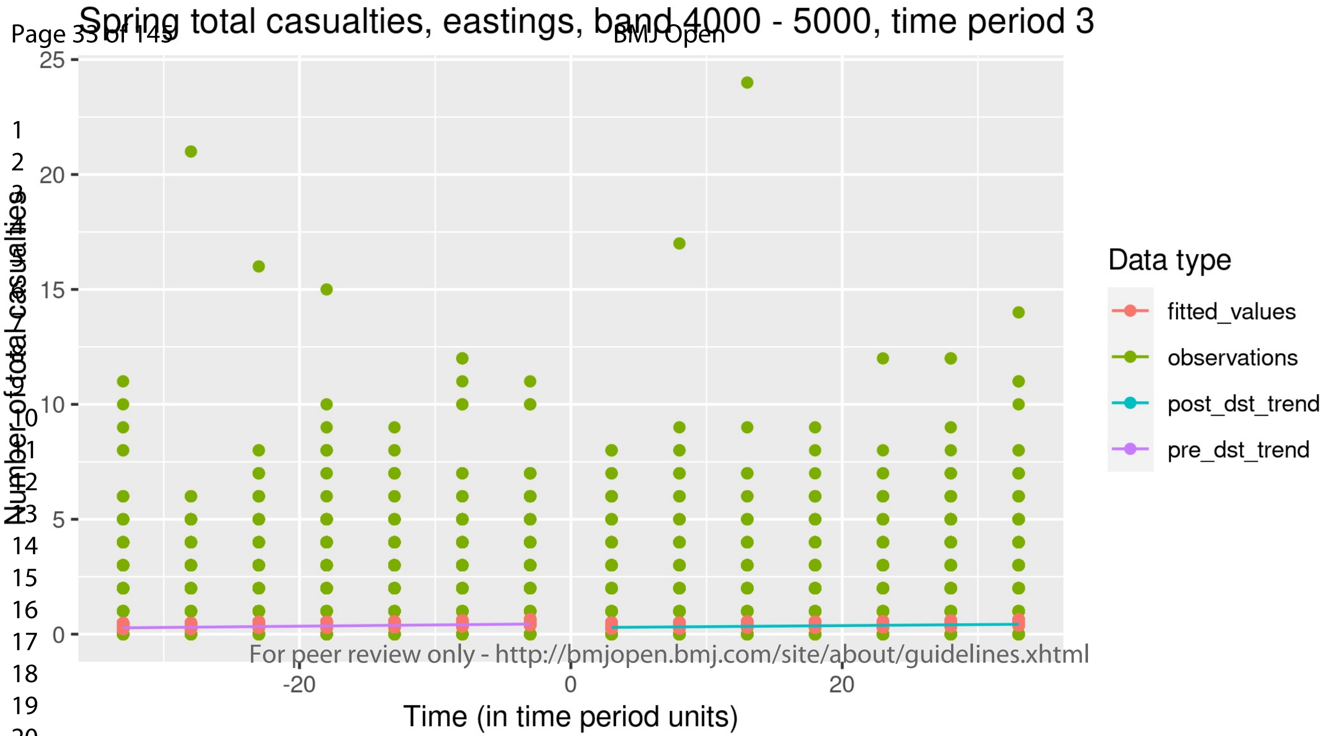
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend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Number of total casualties
Time (in time period units)
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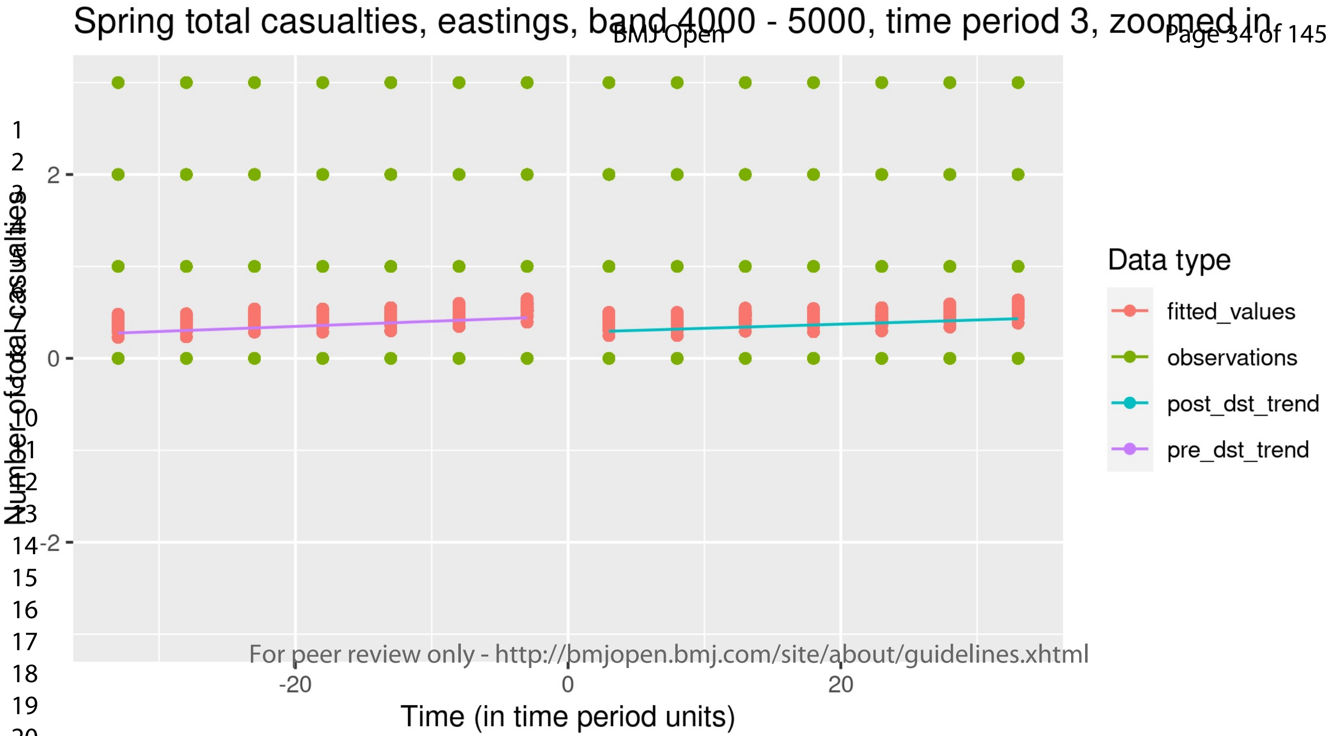
20
15
10
5
0
-20
0
20
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Spring total casualties, eastings, band 4000 - 5000, time period 3, zoomed in
Number of total casualties
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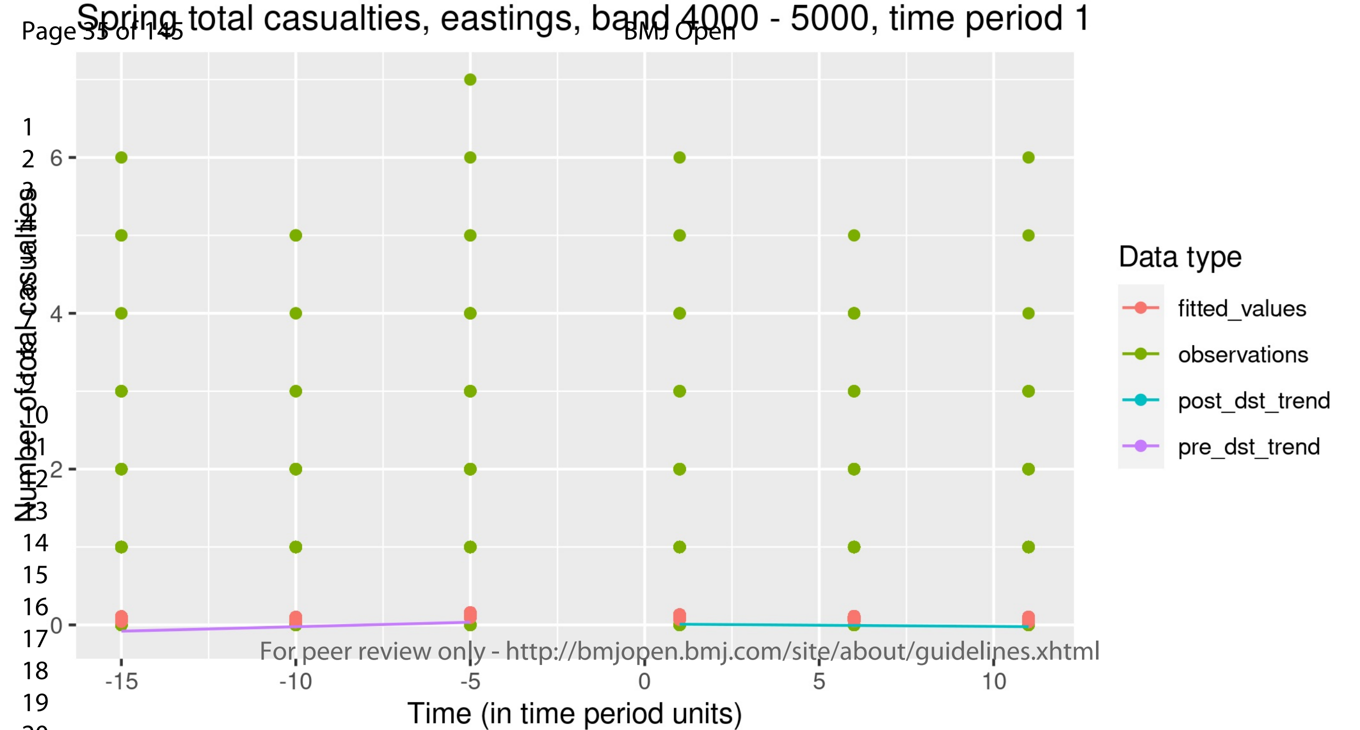
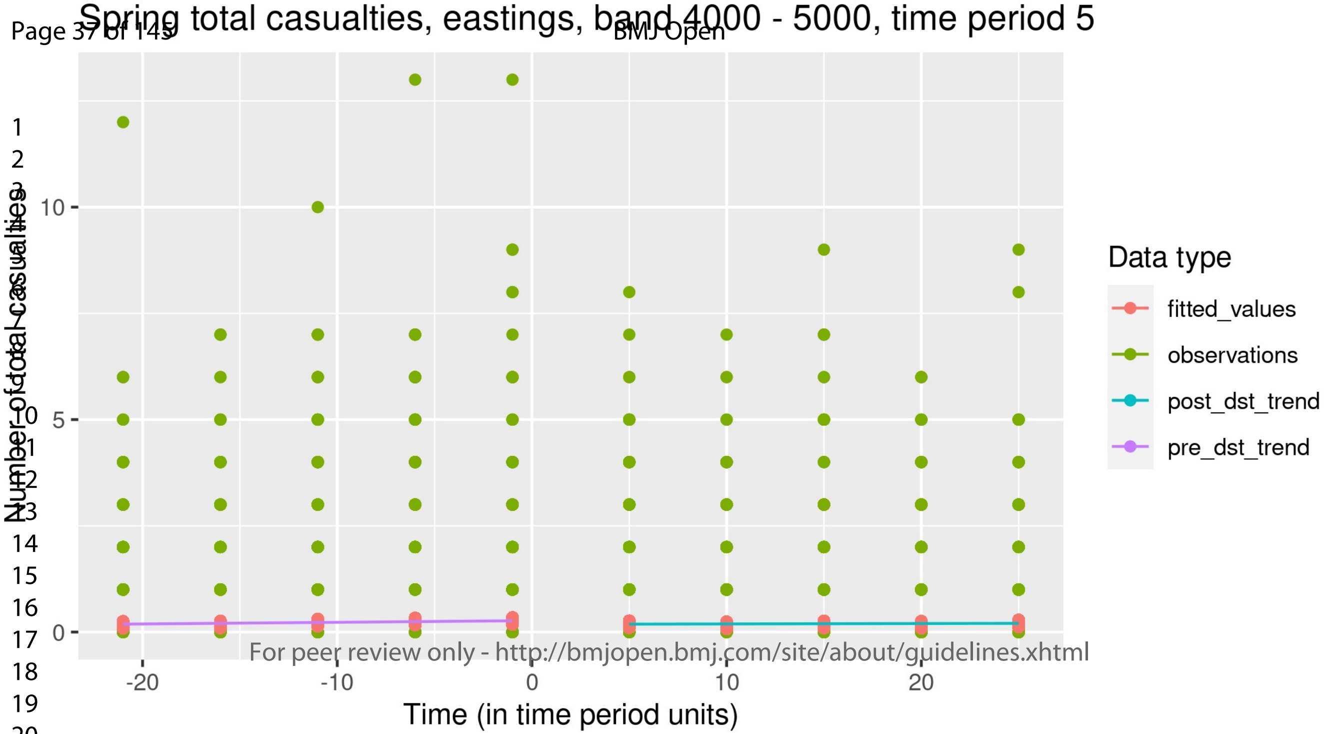
0
-2
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Spring total casualties, eastings, band 4000 - 5000, time period 1
Number of total casualties
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend
0
2
4
6
-15
-10
-5
0
5
10


Spring total casualties, eastings, band 4000 - 5000, time period 1, zoomed in
Number of total casualties
2
0
-2
-15
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend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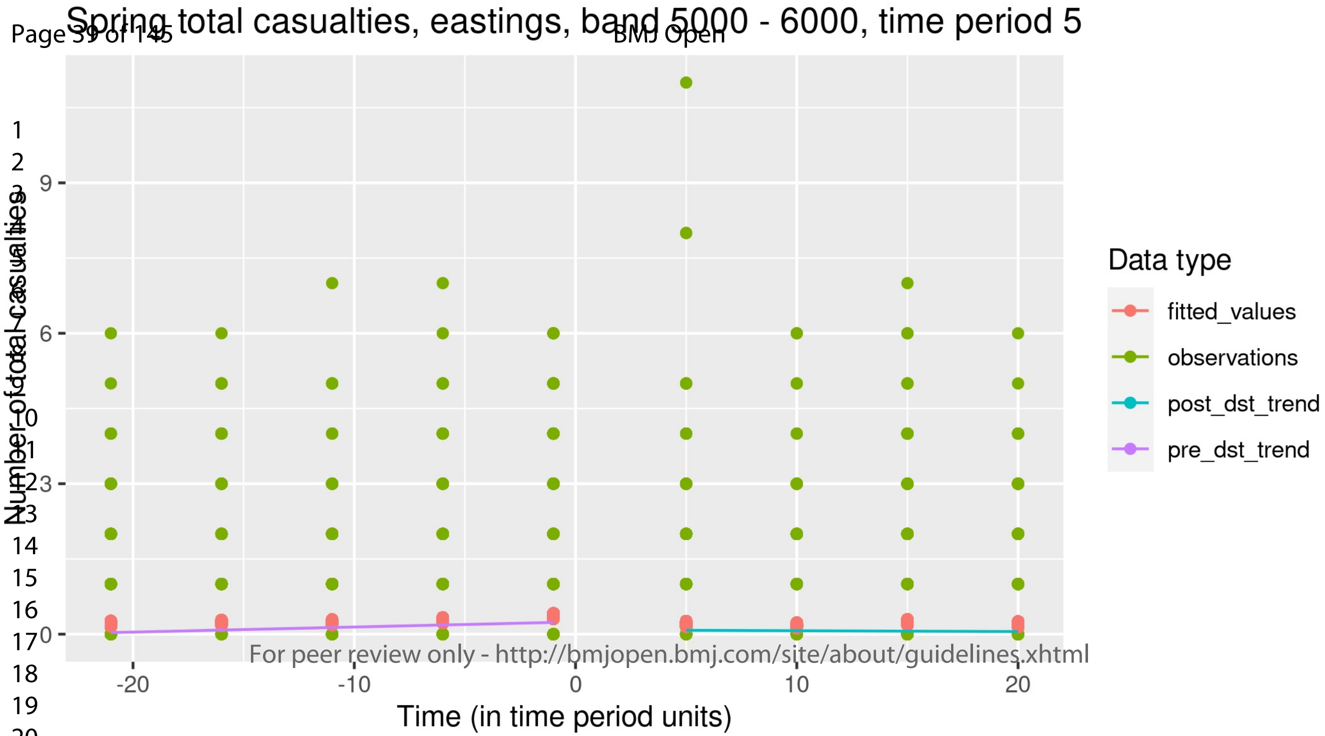
5
10
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Spring total casualties, eastings, band 4000 - 5000, time period 5, zoomed in
Number of total casualties
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend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Number of total casualties
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3
6
9
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

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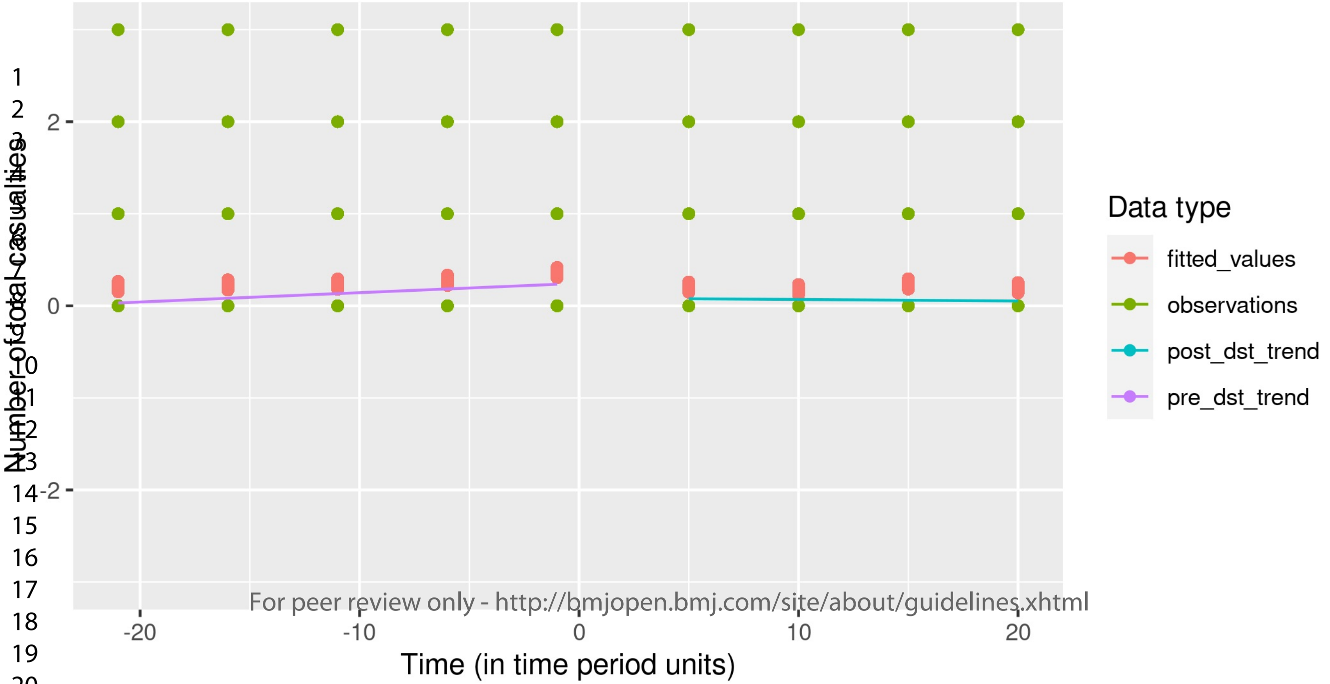

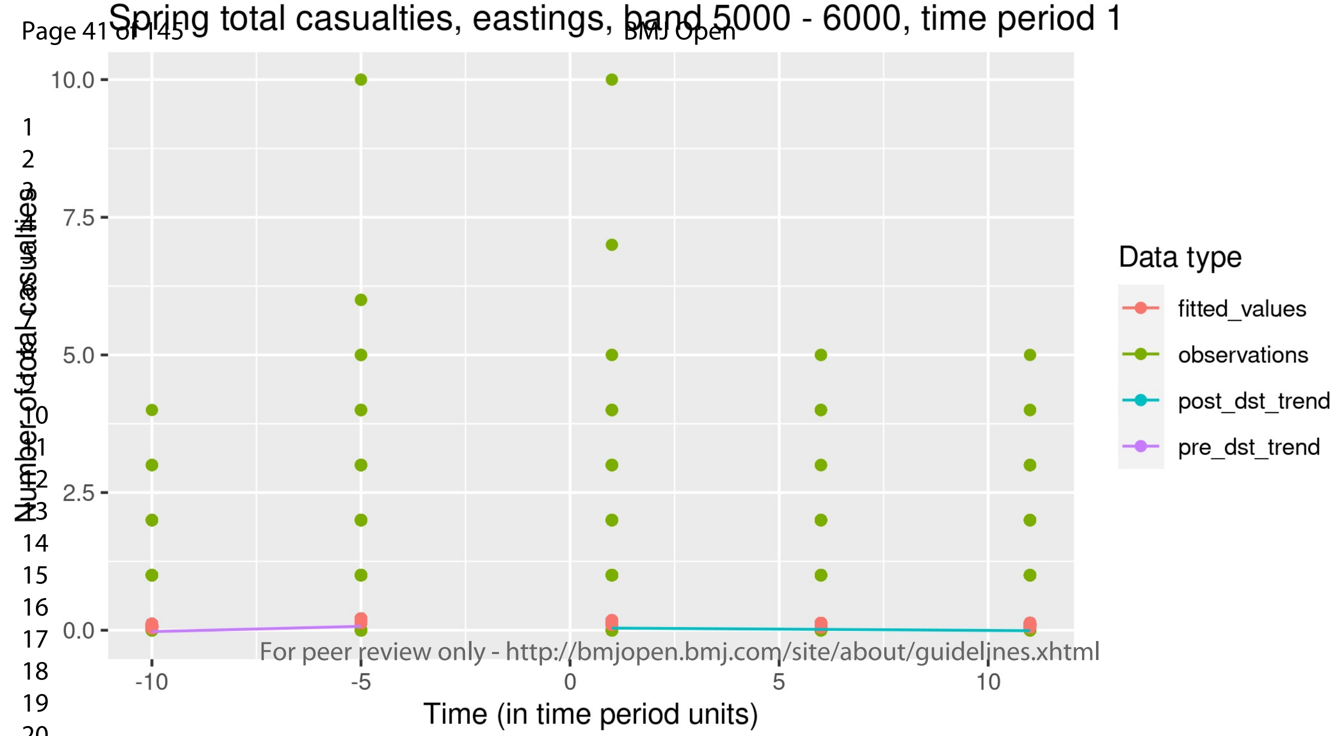
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5.0
2.5
0.0
-10
-5
0
5
10
Time (in time period units)
Data type
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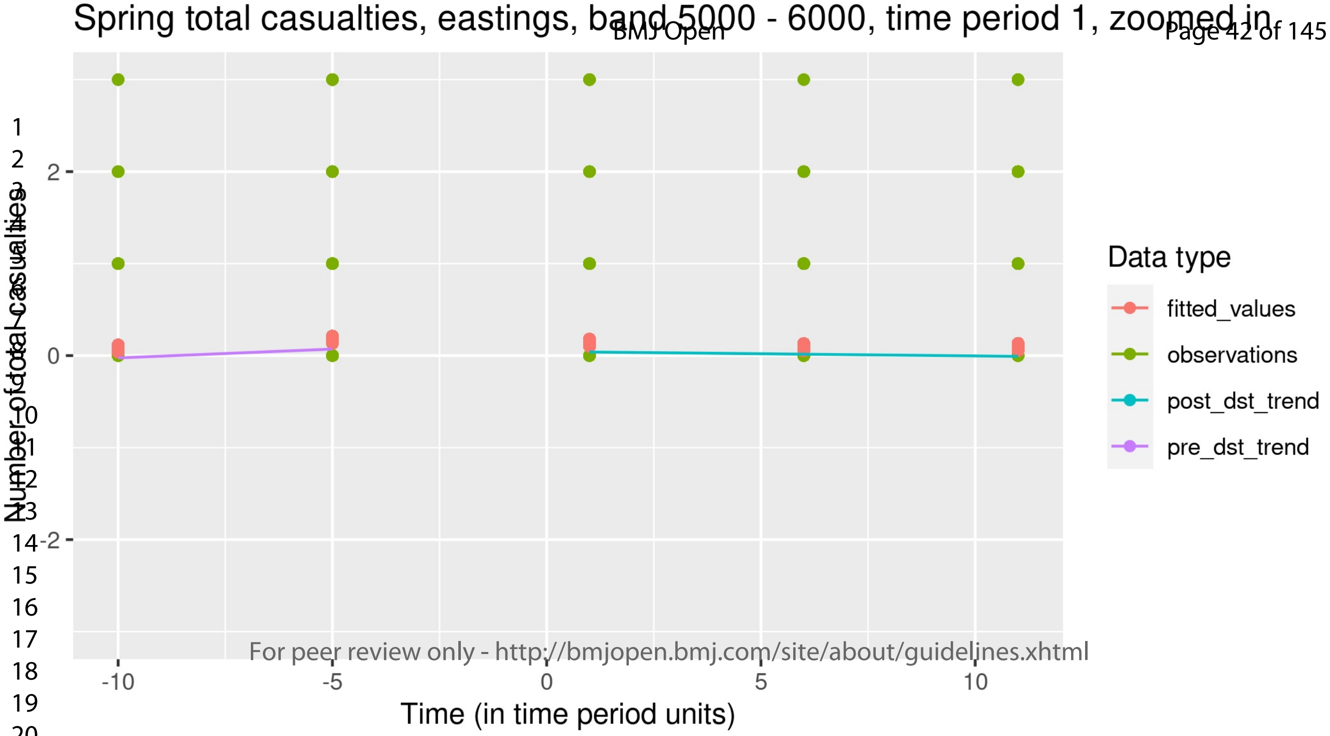
observations
post_dst_trend
pre_dst_trend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Number of total casualties
2
0
-2
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Time (in time period units)
Data type
fitted_values
observations
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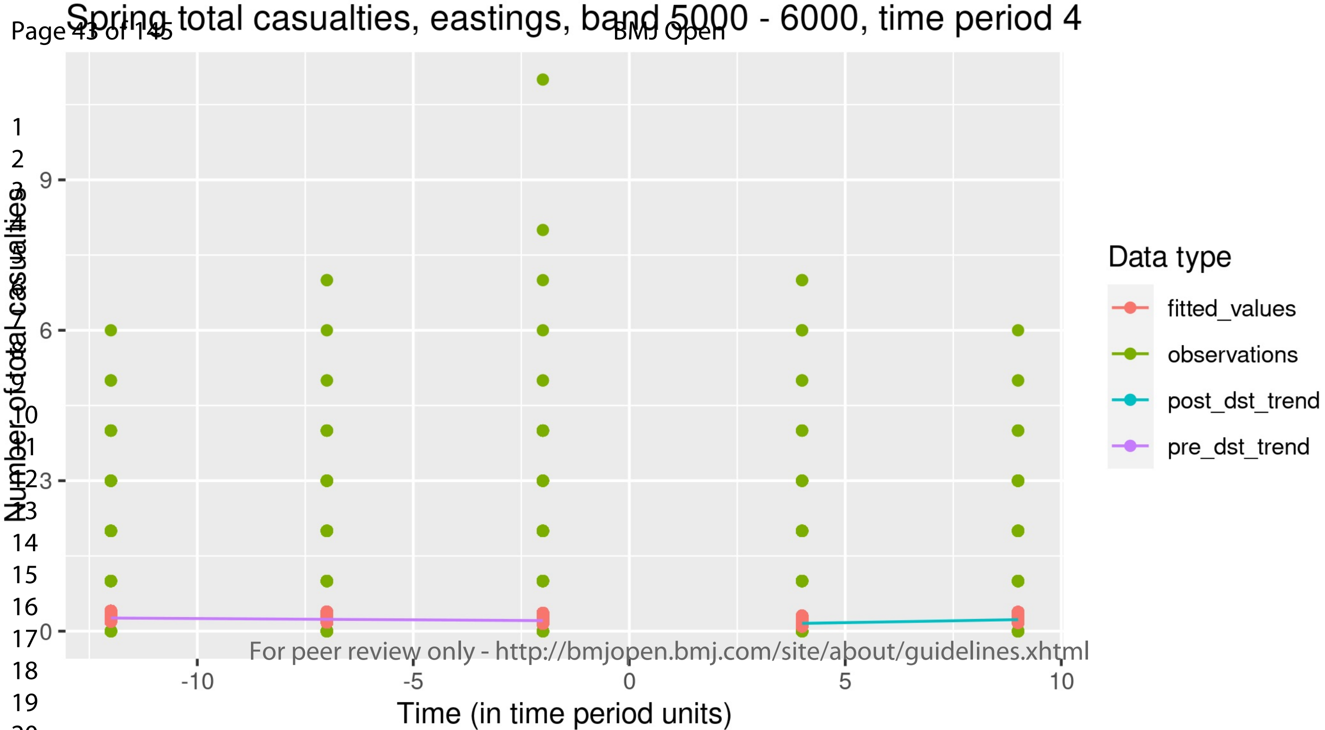
pre_dst_trend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6
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5
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Time (in time period units)
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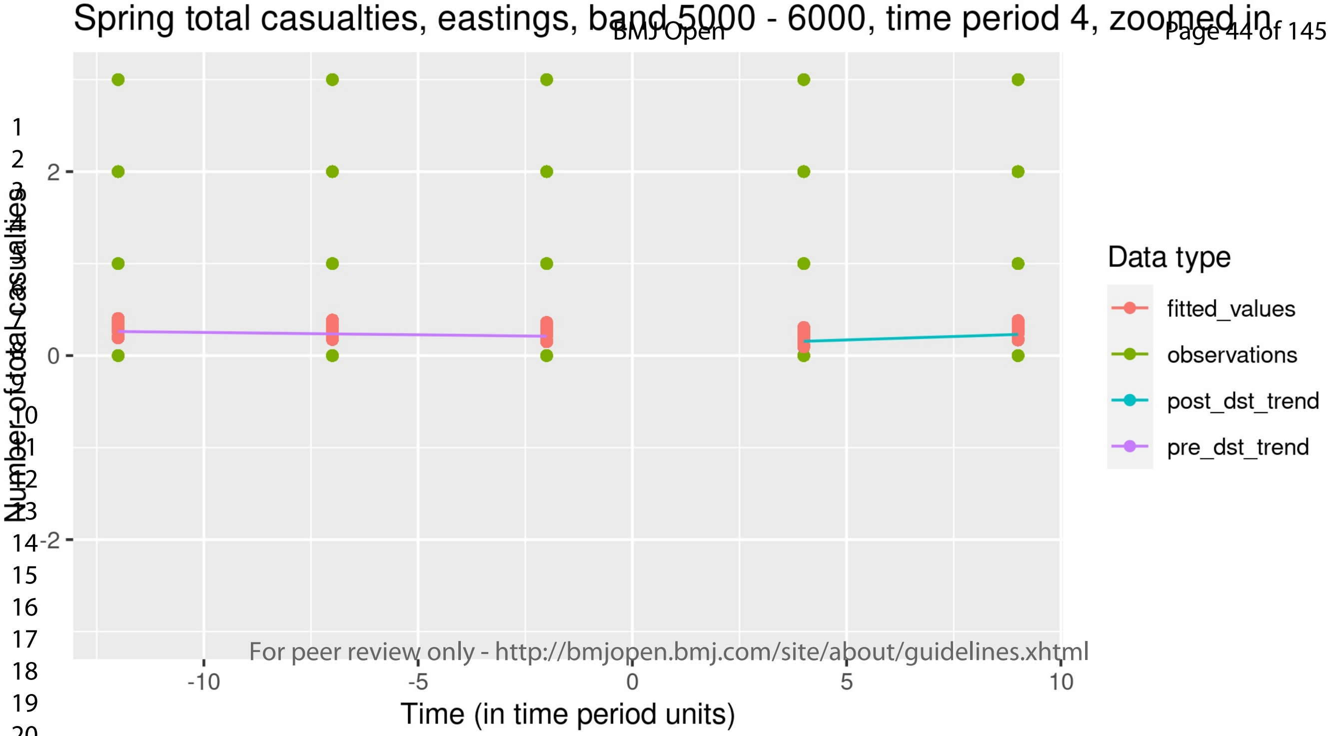
pre_dst_trend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Number of total casualties
2
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Time (in time period units)
Data type
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observations
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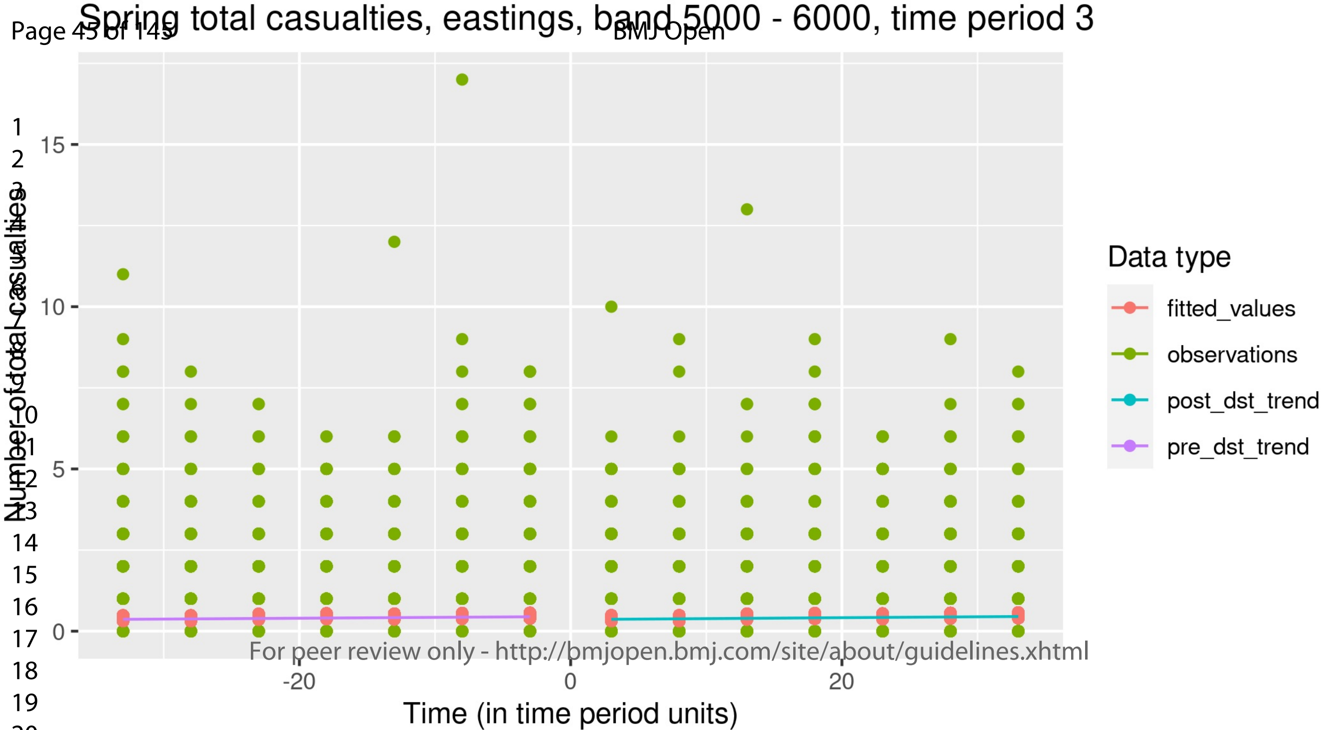
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Number of total casualties
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Time (in time period units)
Data type
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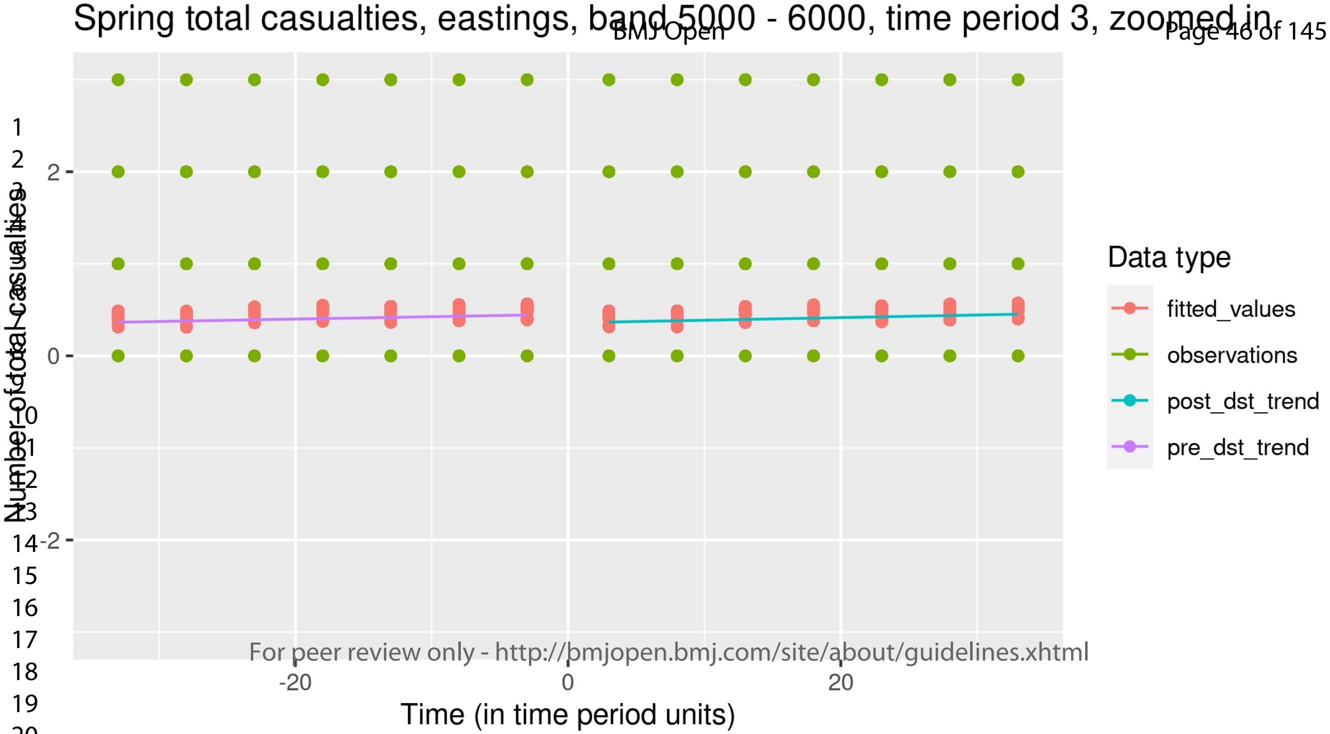
post_dst_trend
pre_dst_trend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Number of total casualties
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-2
-20
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Time (in time period units)
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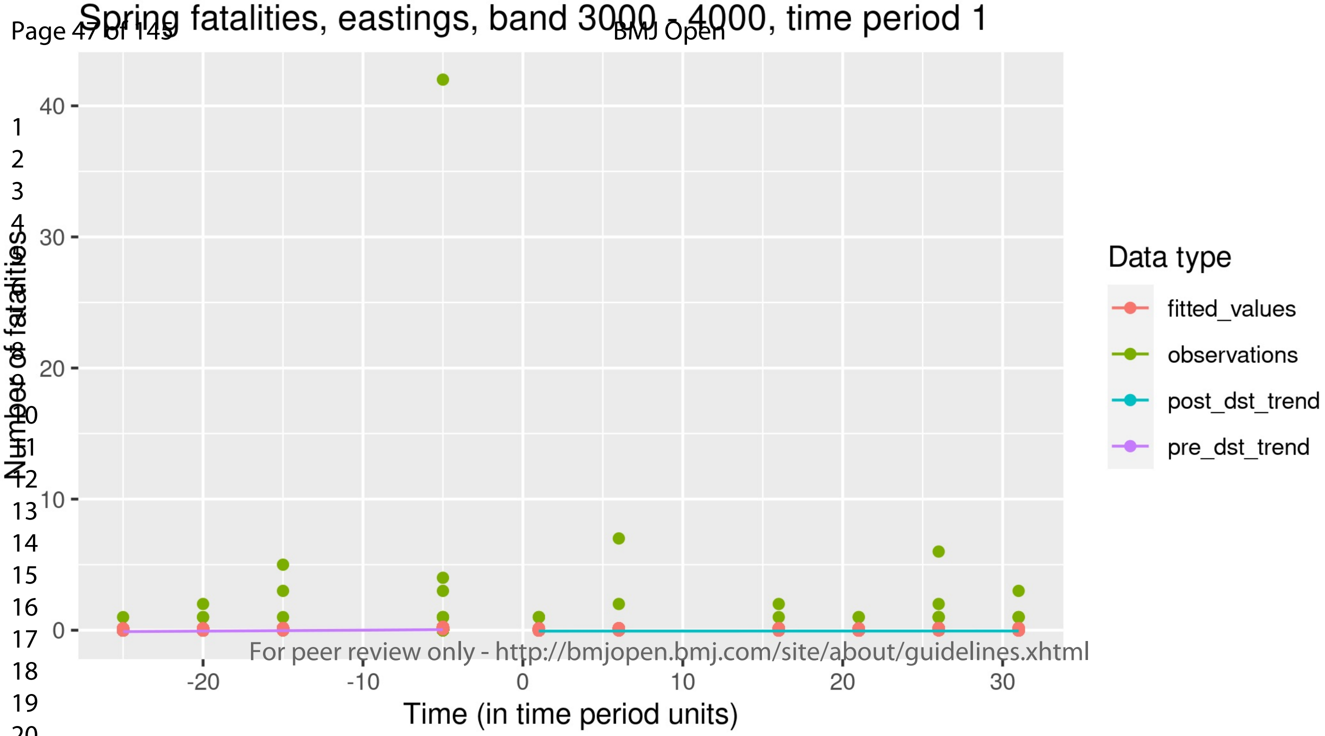
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Number of fatalities
40
30
20
10
0
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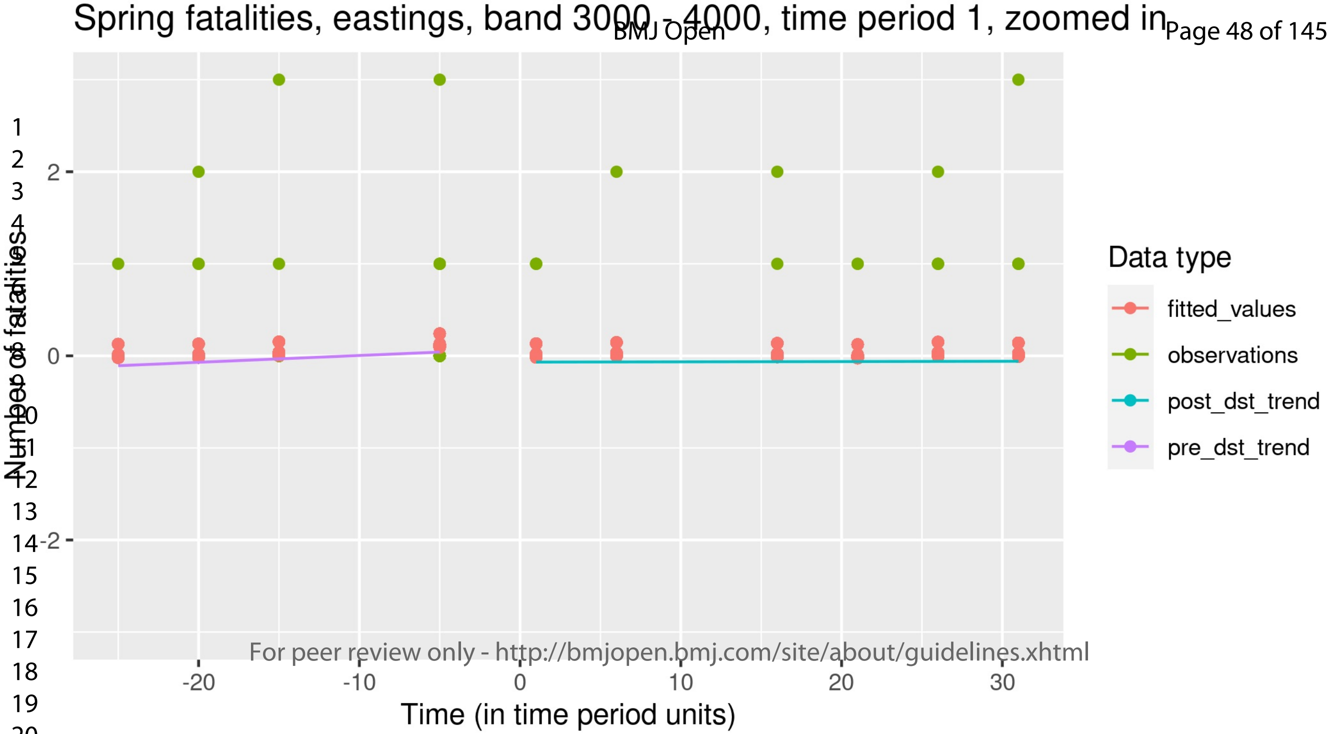
-10
0
10
20
30
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Spring fatalities, eastings, band 3000 - 4000, time period 1, zoomed in
Number of fatalities
2
0
-2
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10
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30
Time (in time period units)
Data type
fitted_values
observations
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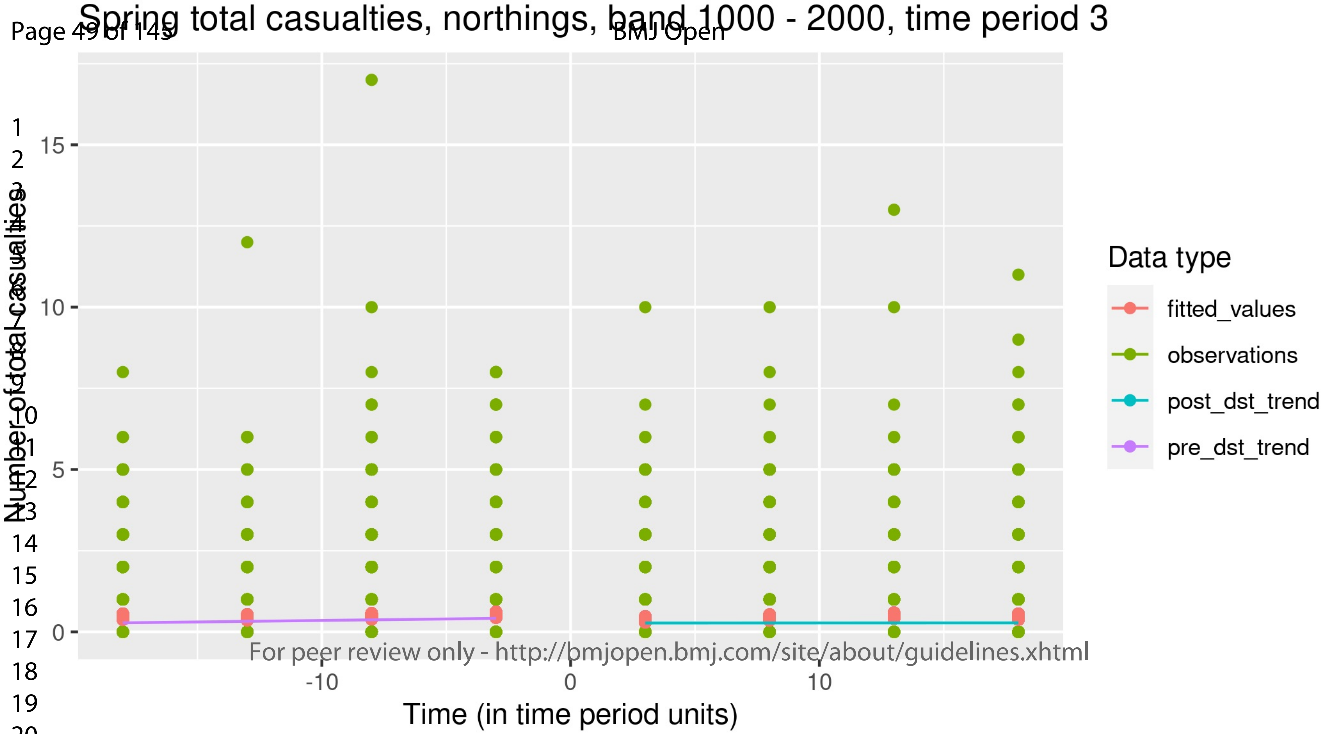
pre_dst_trend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Number of total casualties
Time (in time period units)
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Data type
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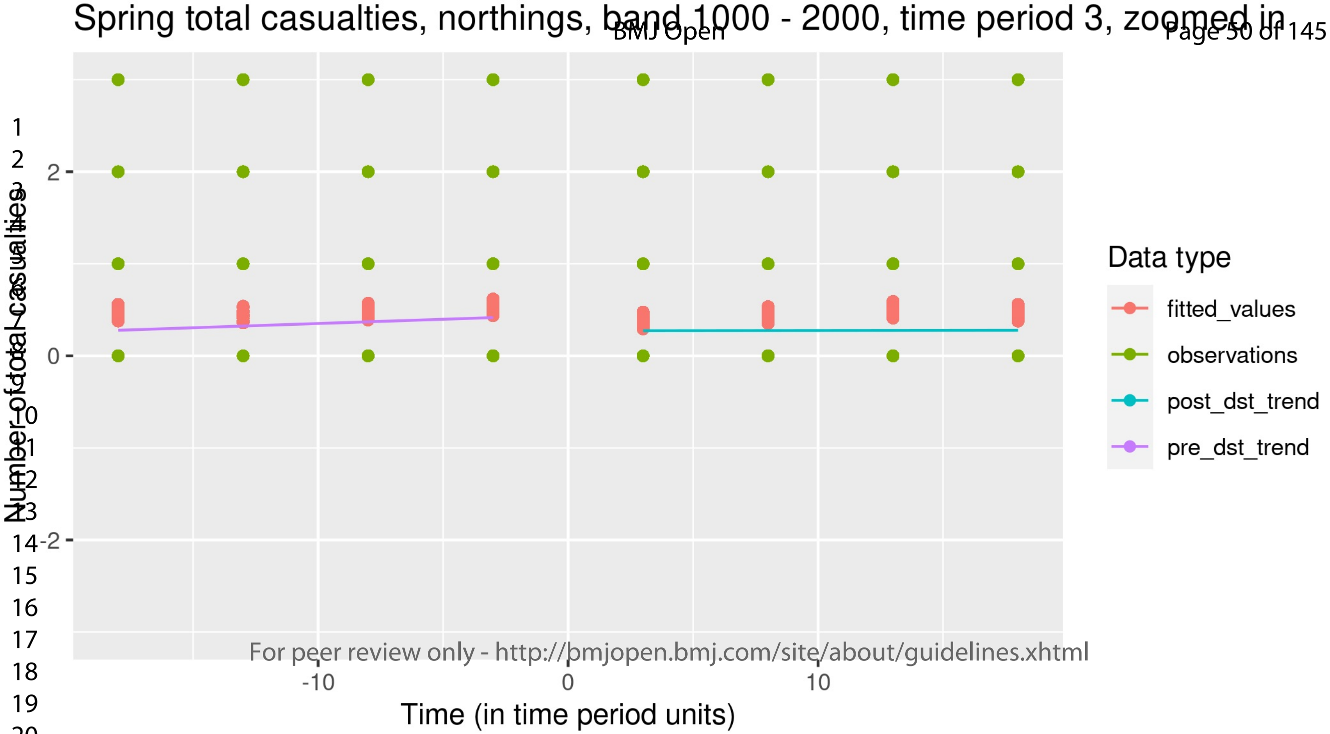
post_dst_trend
pre_dst_trend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Number of total casualties
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Time (in time period units)
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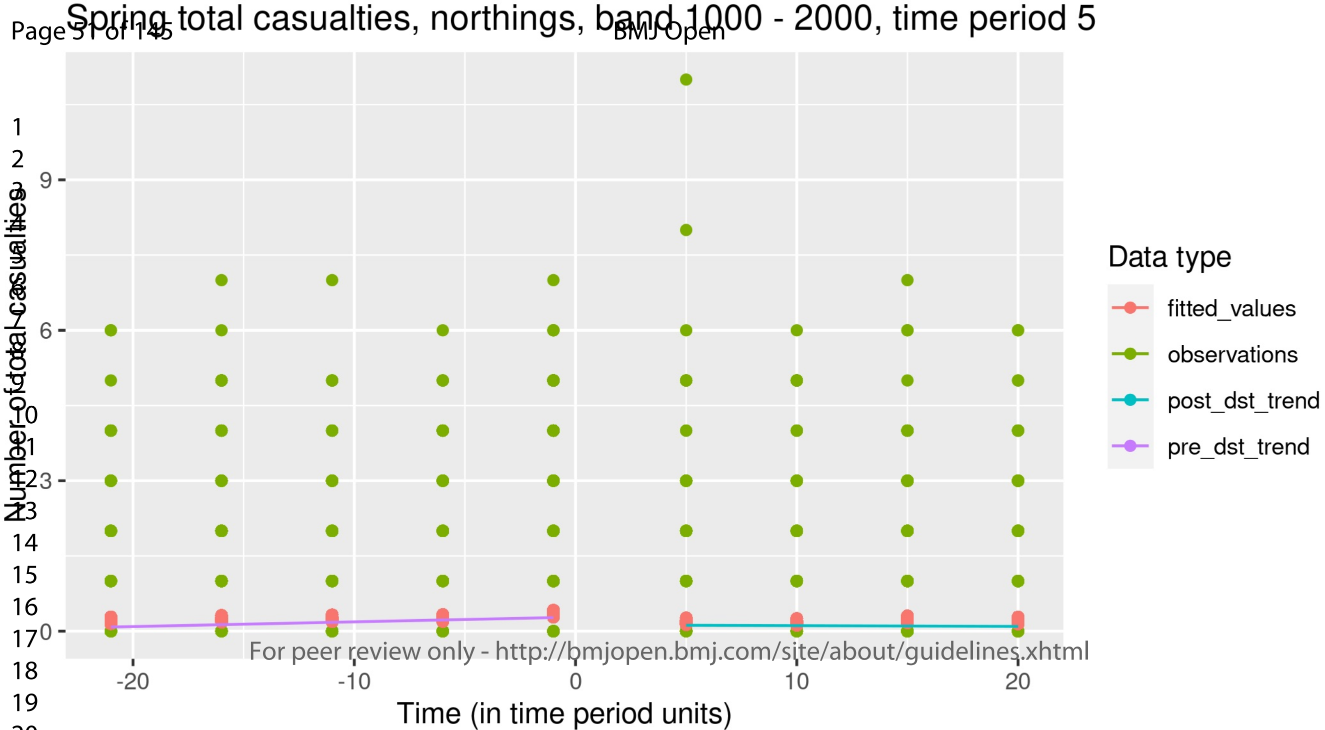
observations
post_dst_trend
pre_dst_trend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Number of total casualties
9
6
3
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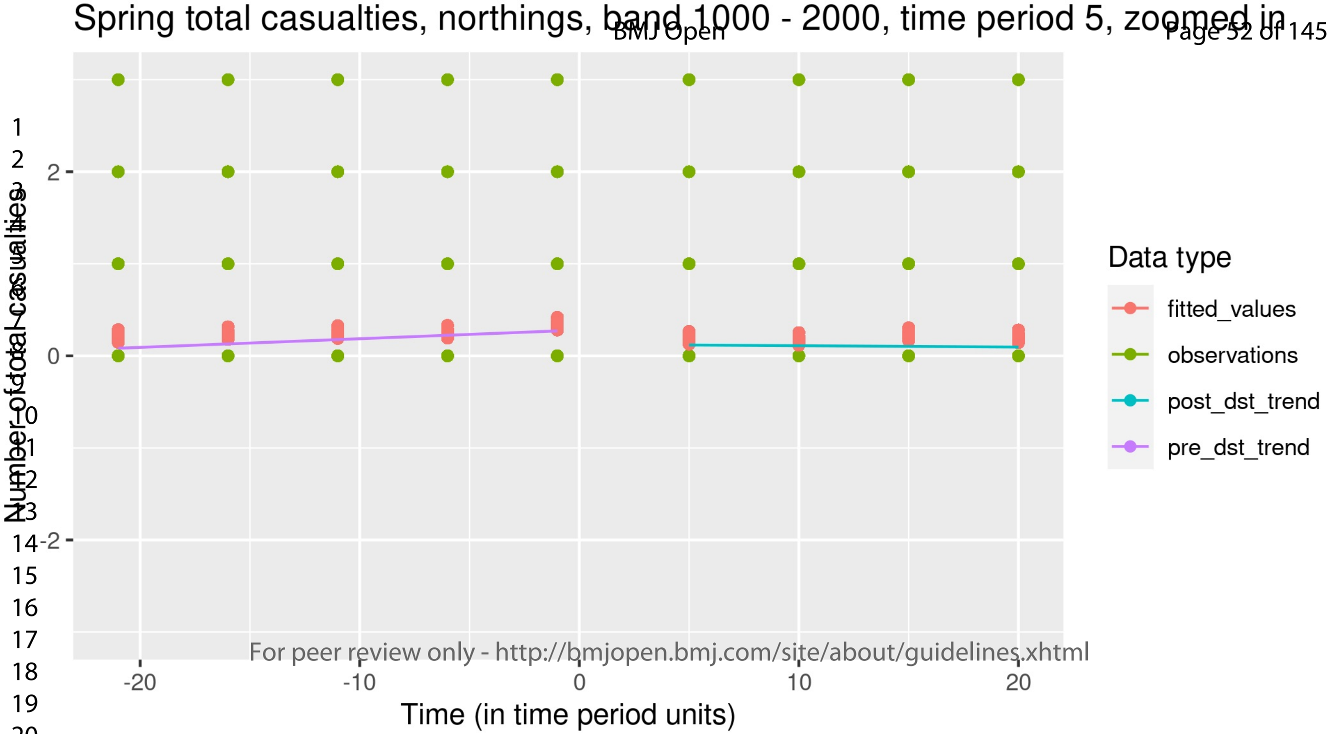
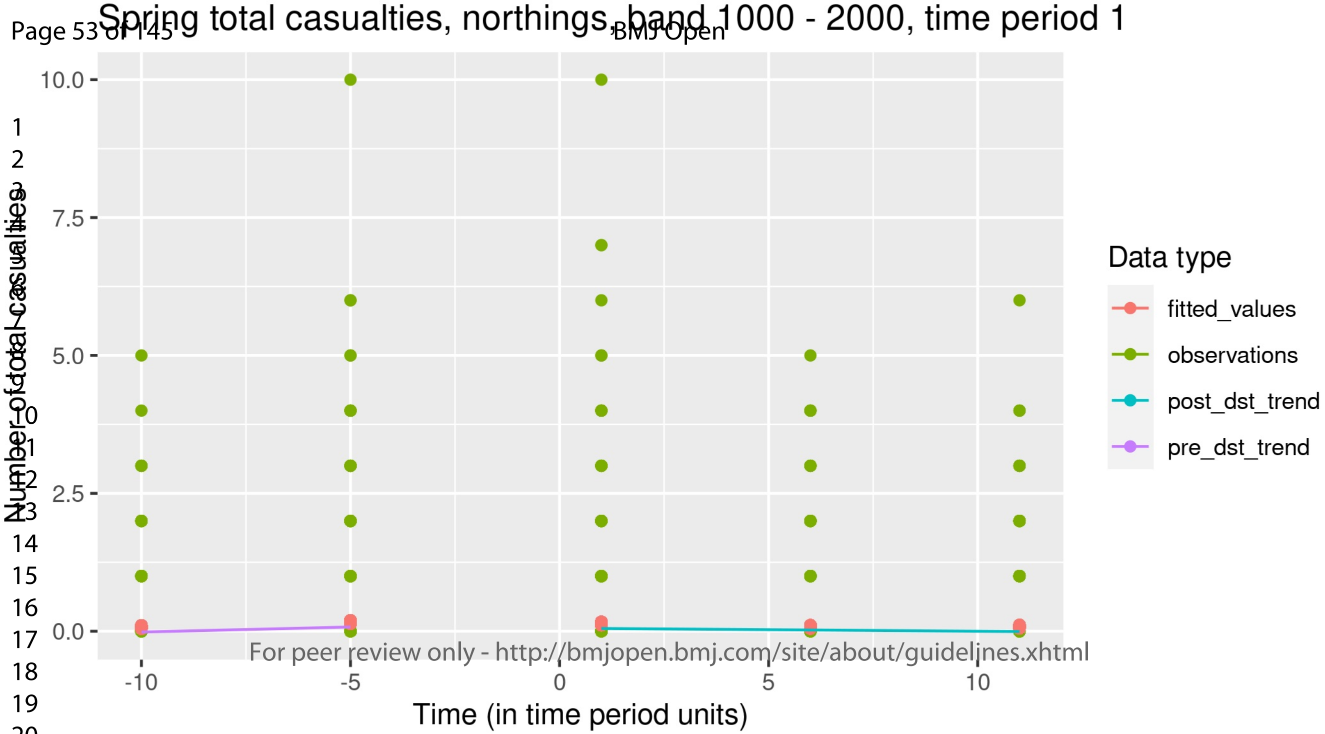
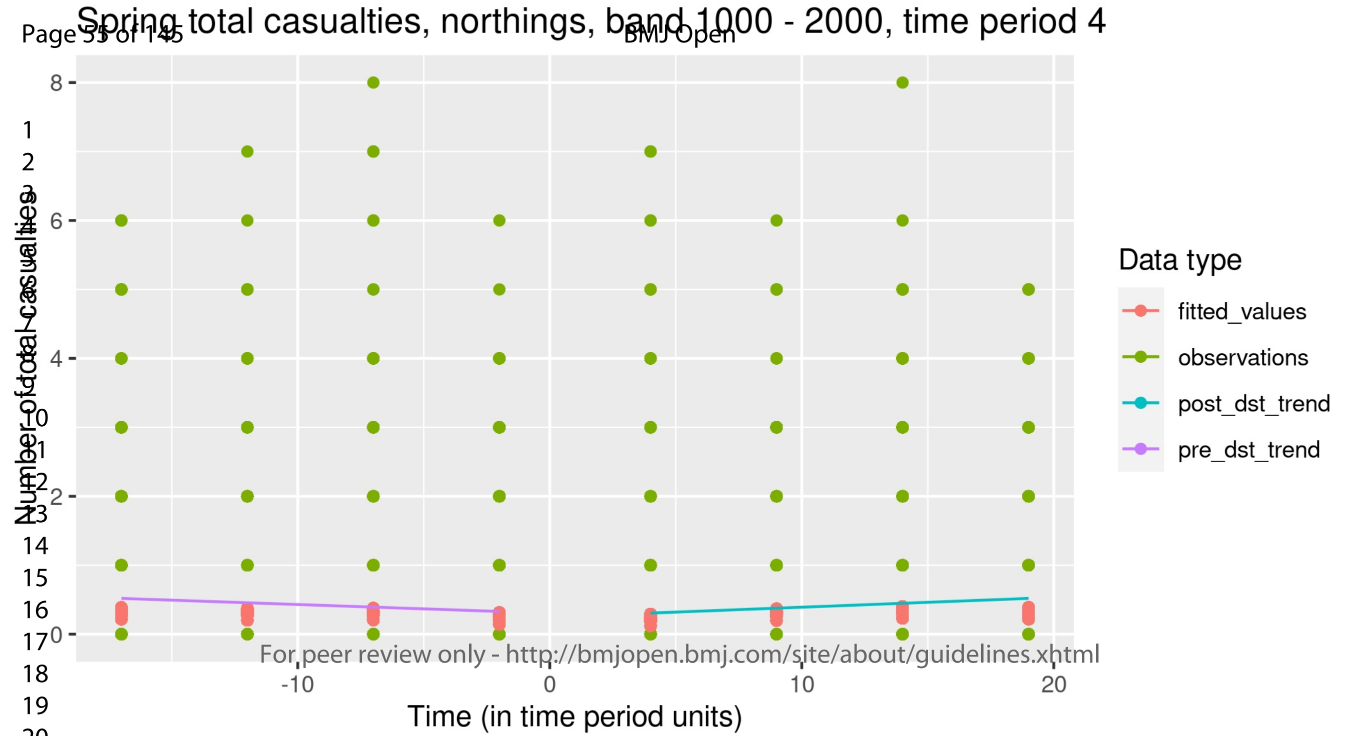
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

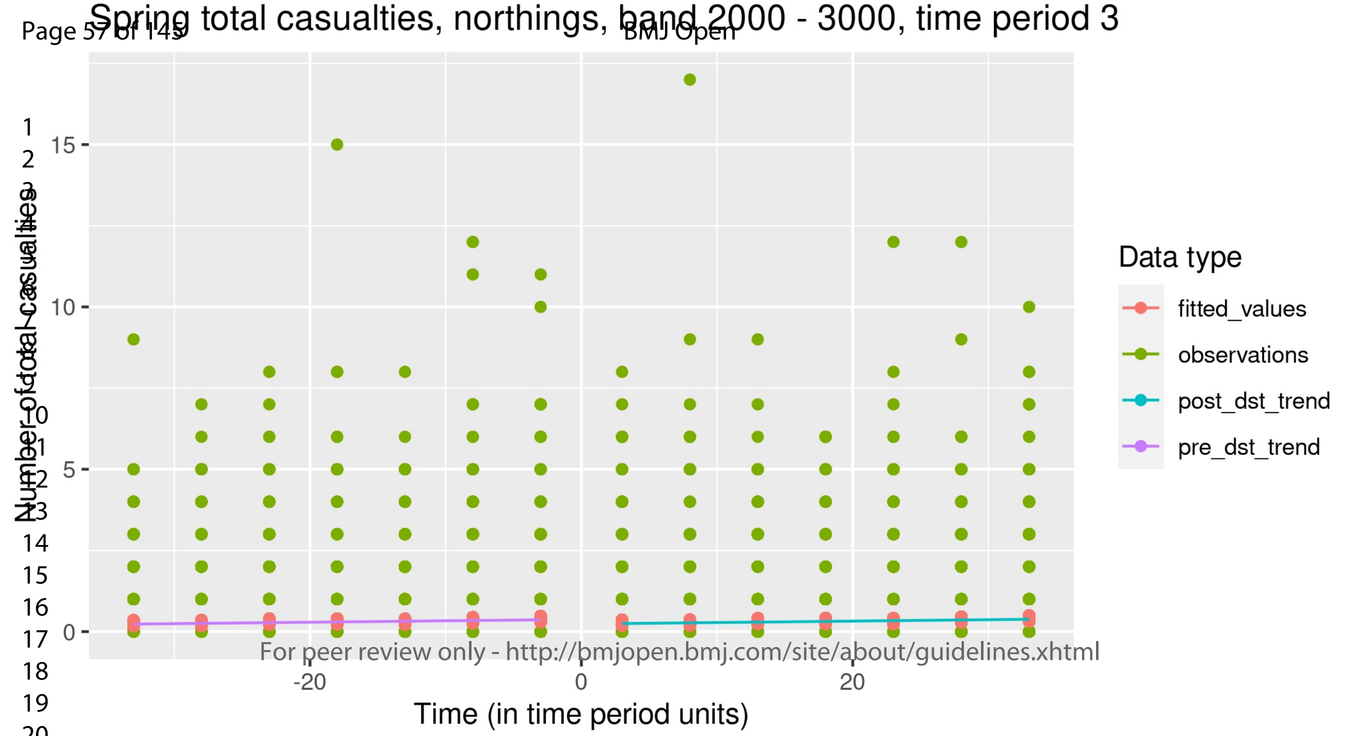

Spring total casualties, northings, band 1000 - 2000, time period 5, zoomed in
Number of total casualties
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Spring total casualties, northings, band 1000 - 2000, time period 1
Number of total casualties
10.0
7.5
5.0
2.5
0.0
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

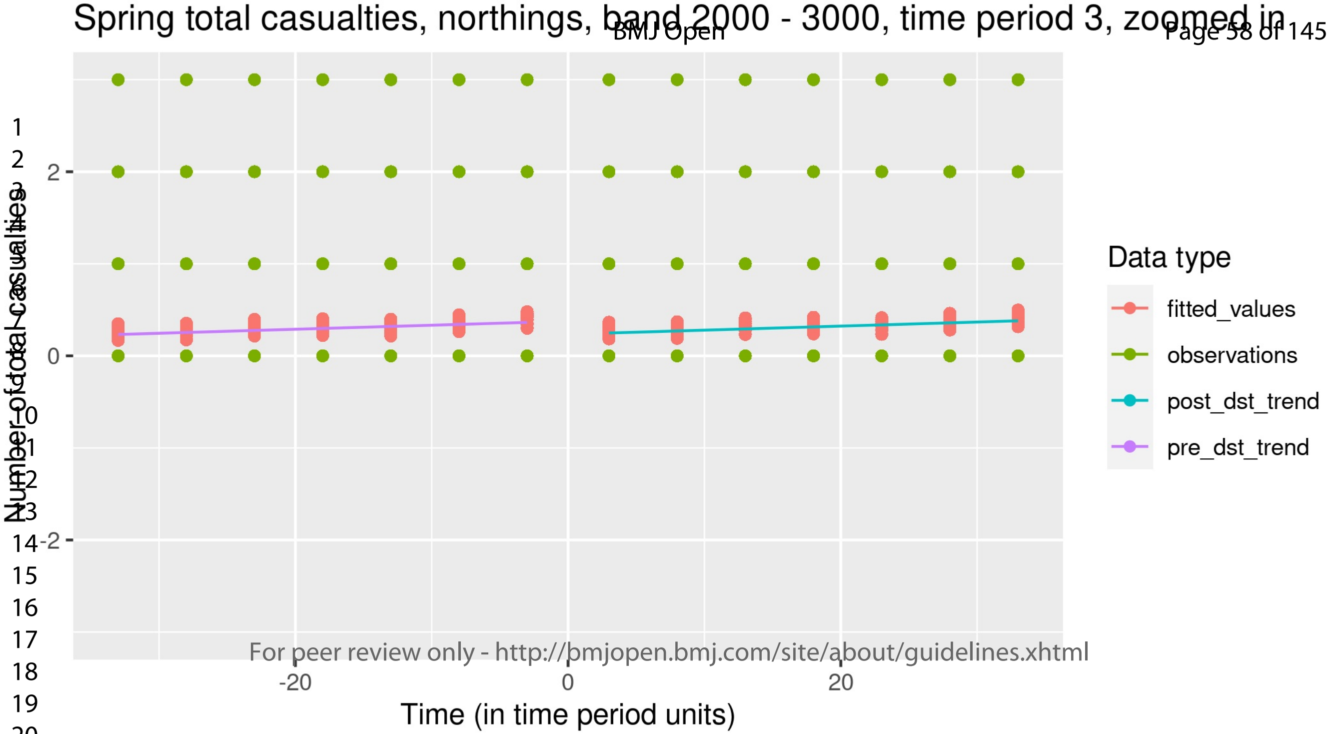

Spring total casualties, northings, band 1000 - 2000, time period 1, zoomed in
Number of total casualties
Time (in time period units)
2
0
-2
-10
-5
0
5
10
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

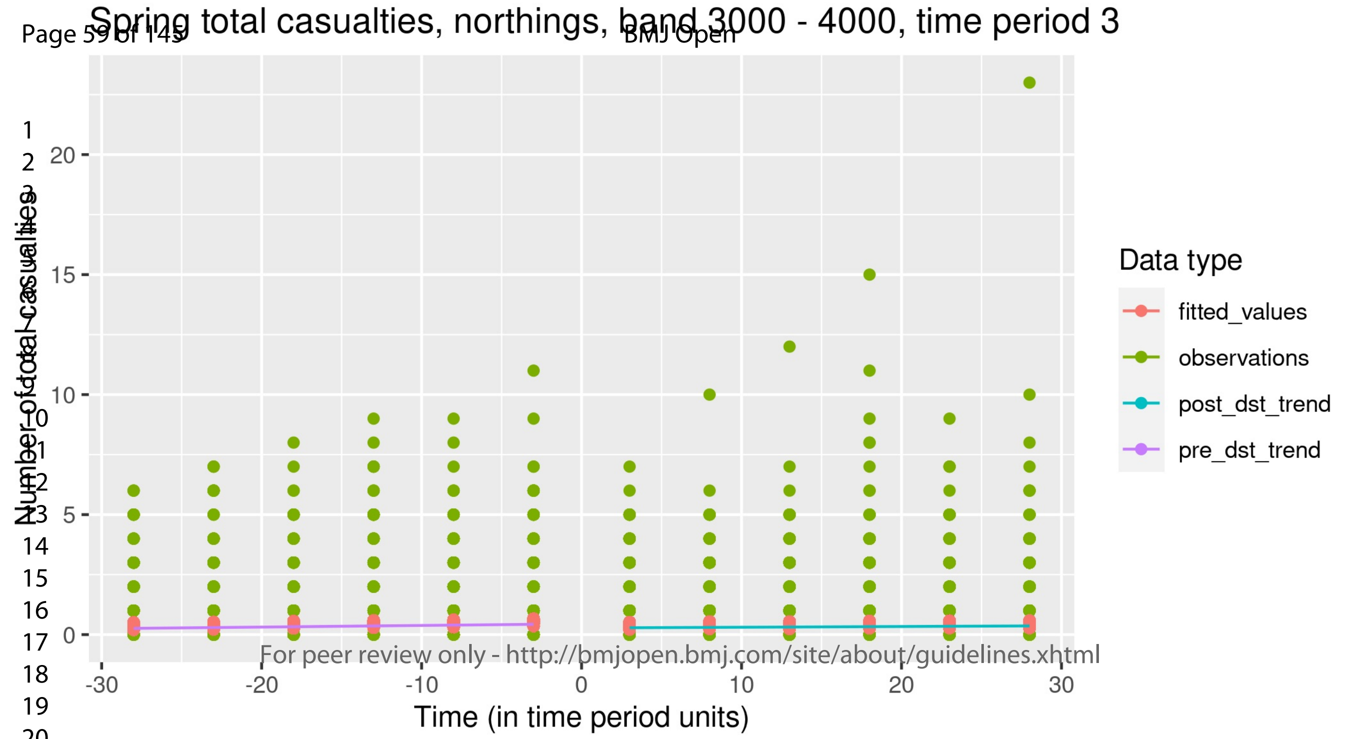

Spring total casualties, northings, band 1000 - 2000, time period 4
Number of total casualties
8
6
4
2
0
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

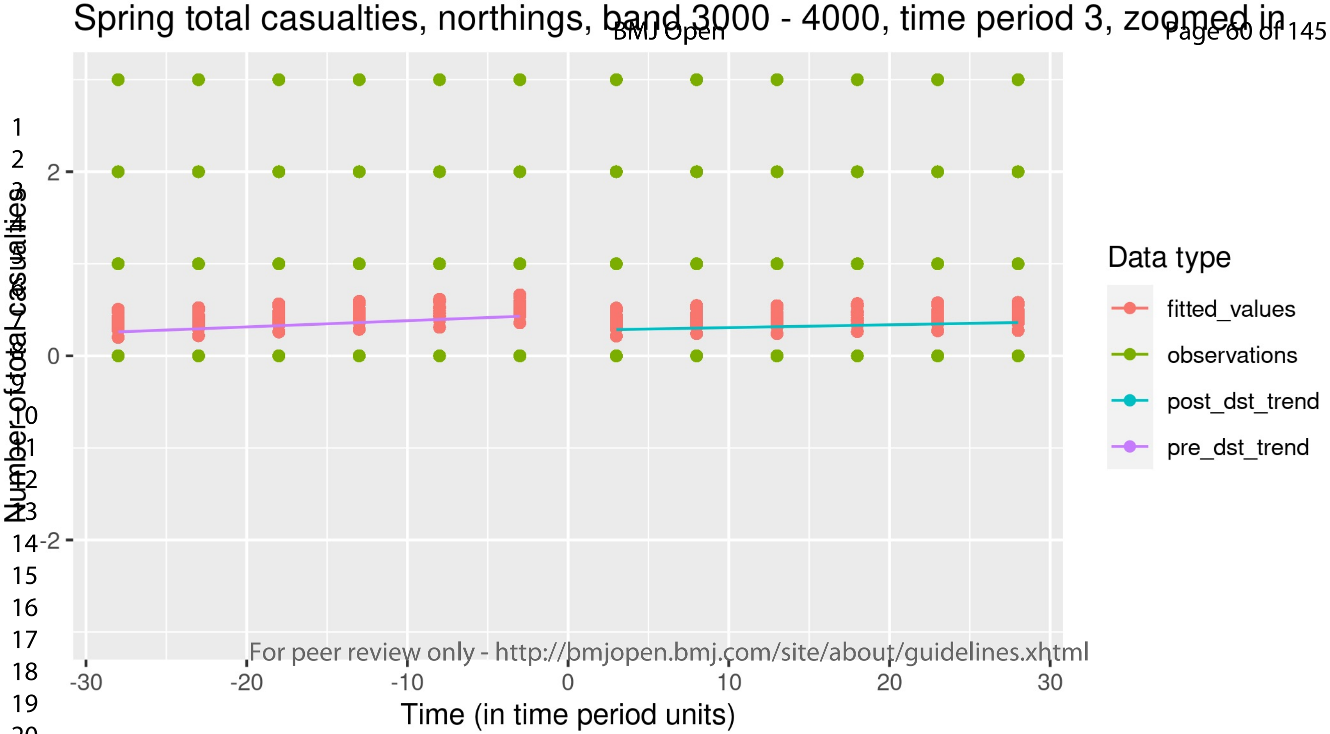

Spring total casualties, northings, band 1000 - 2000, time period 4, zoomed in
Number of total casualties
2
0
-2
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

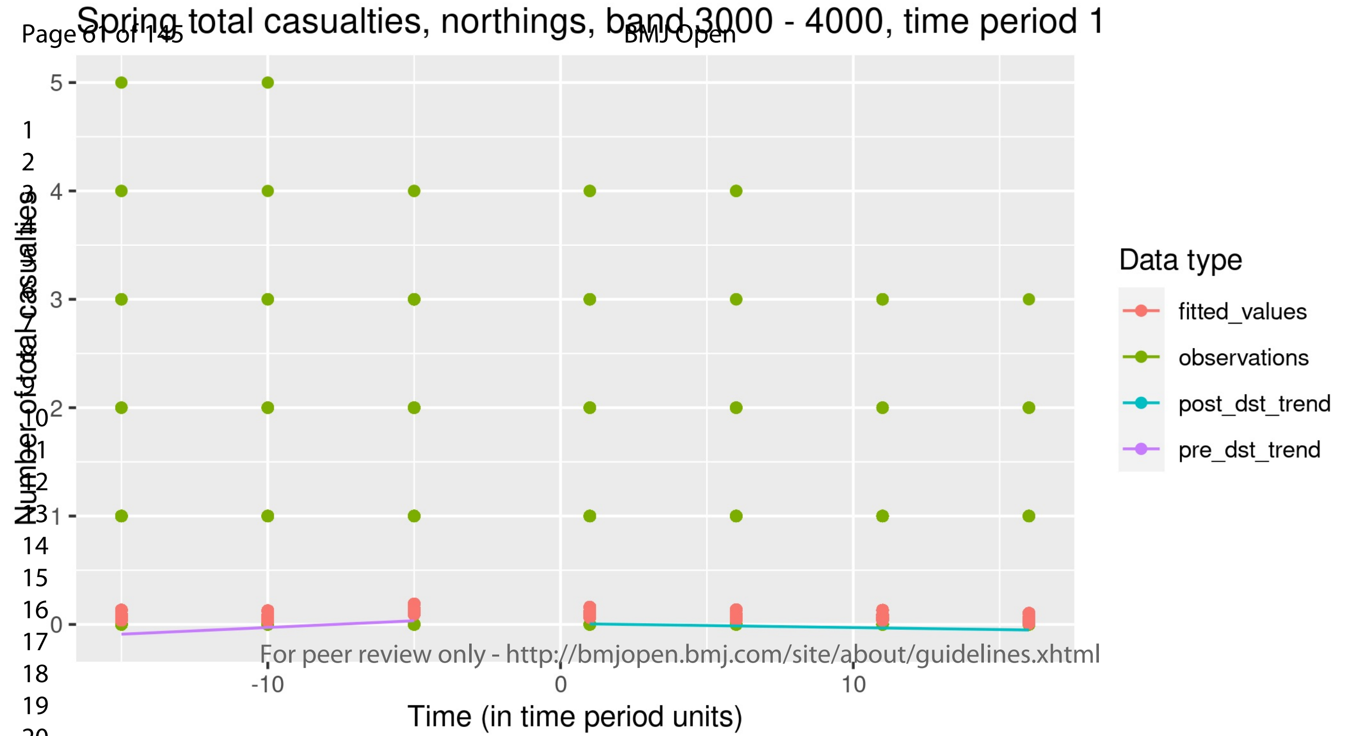


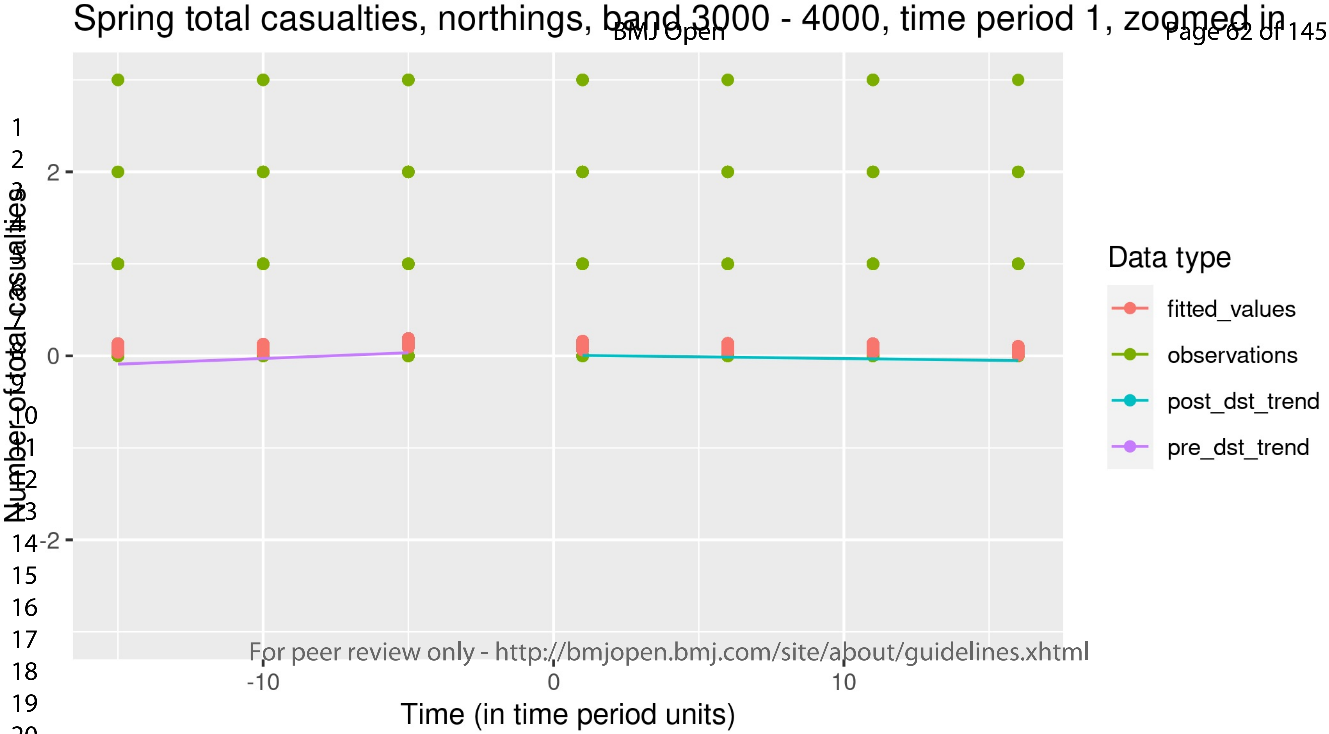
Spring total casualties, northings, band 2000 - 3000, time period 3
Number of total casualties
15
10
5
0
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

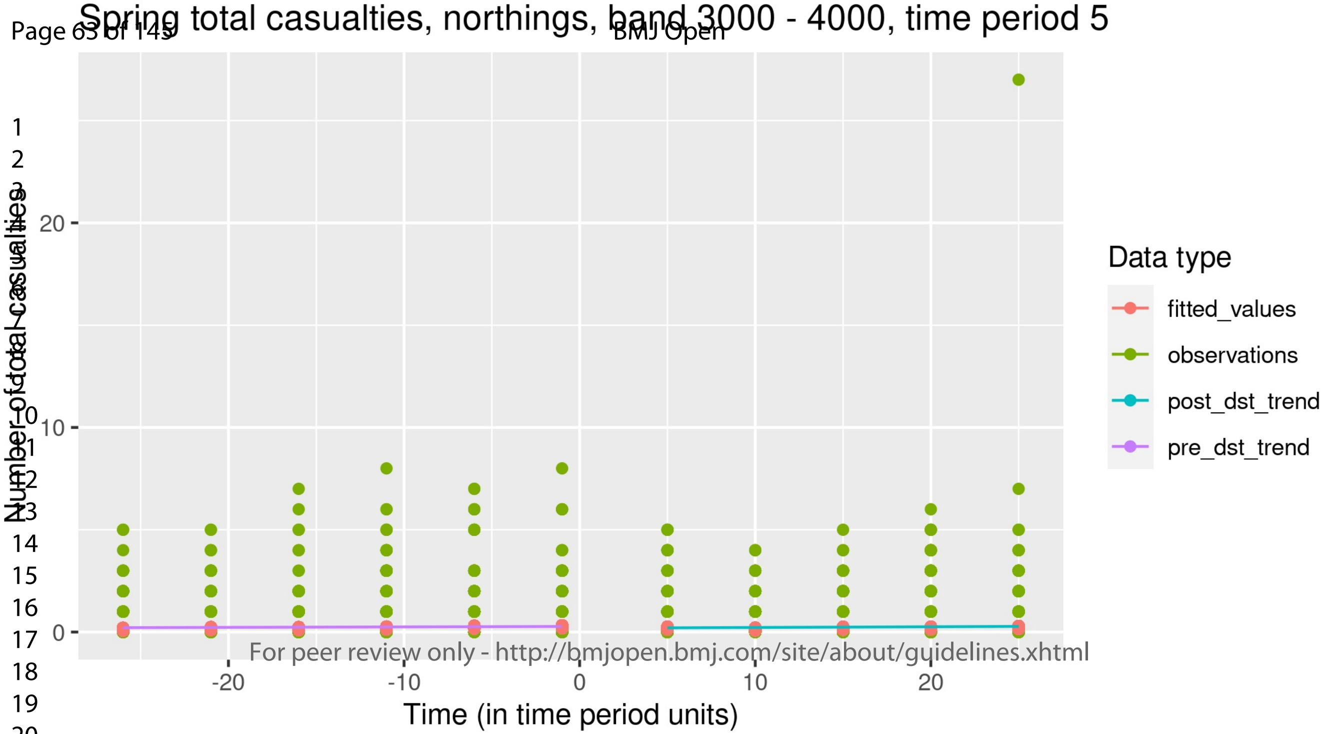

Spring total casualties, northings, band 2000 - 3000, time period 3, zoomed in
Number of total casualties
2
0
-2
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

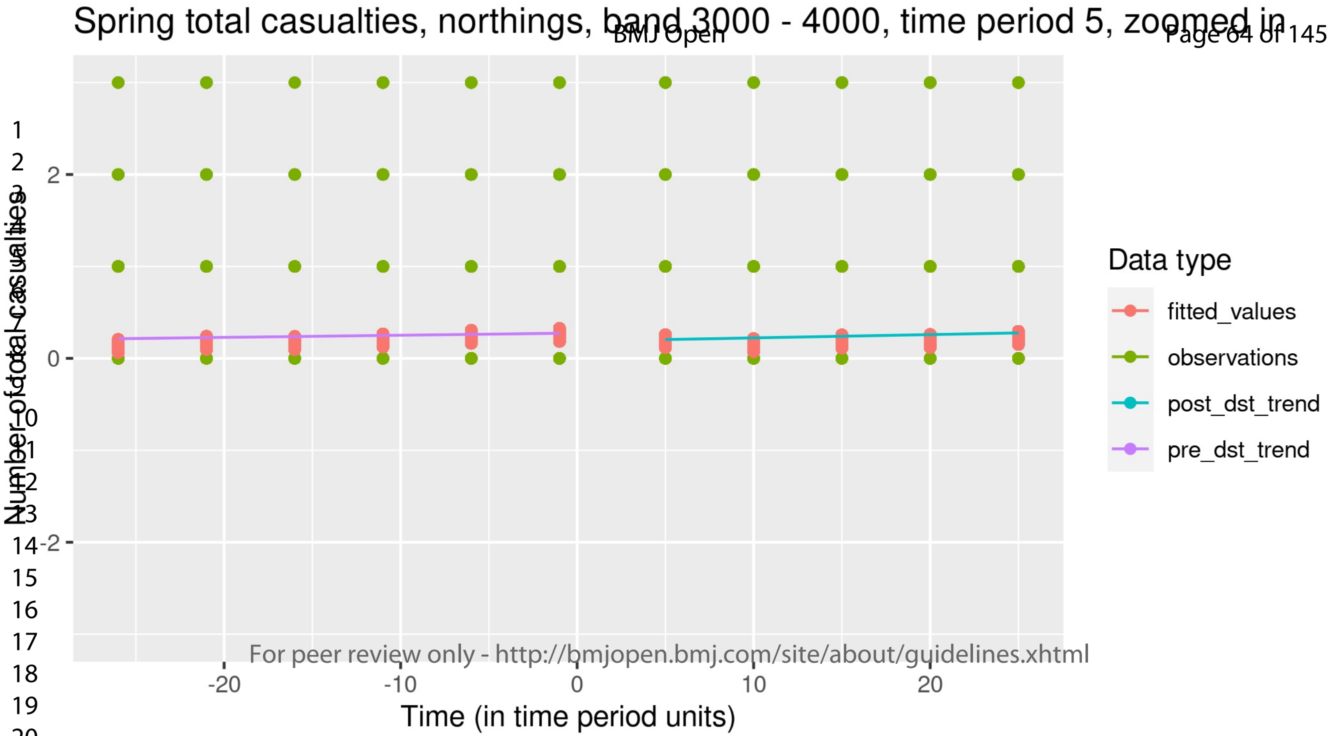

Spring total casualties, northings, band 3000 - 4000, time period 3
Number of total casualties
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

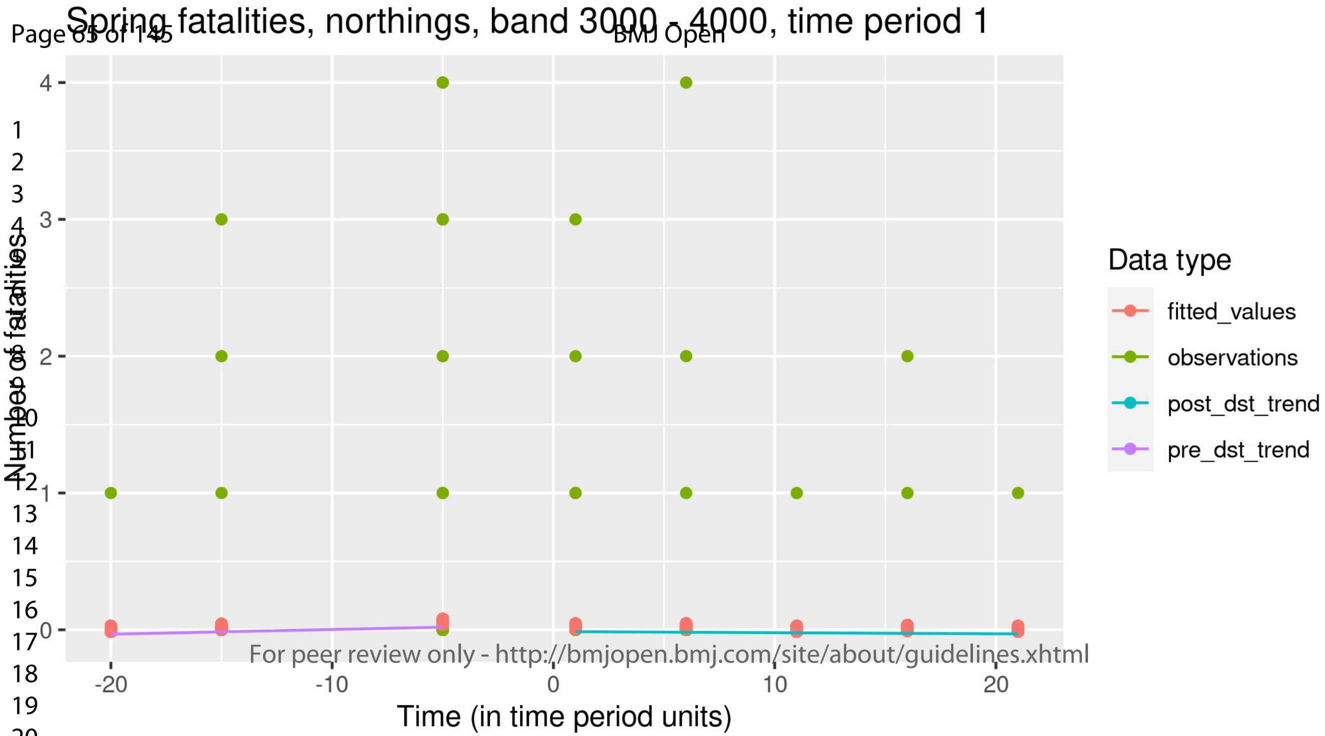

Spring total casualties, northings, band 3000 - 4000, time period 3, zoomed in
Number of total casualties
2
0
-2
-30
-20
-10
0
10
20
30
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

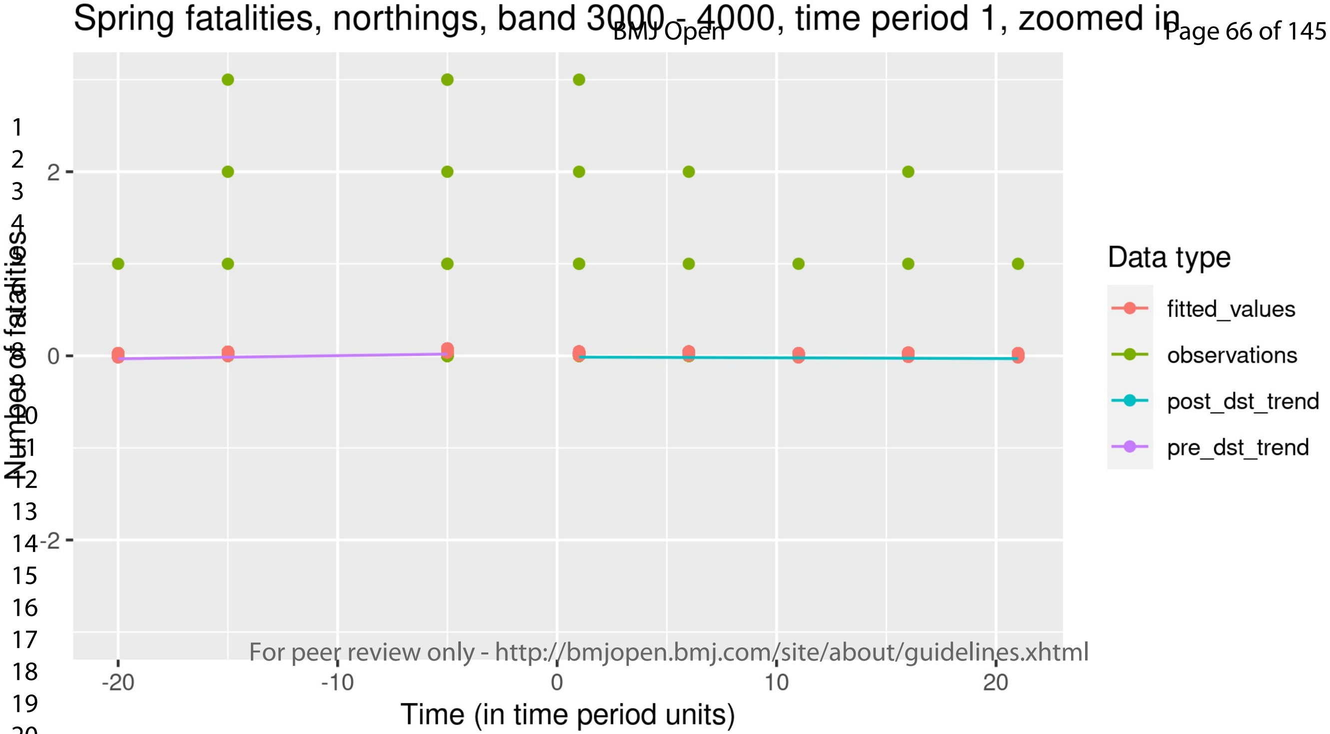

Spring total casualties, northings, band 3000 - 4000, time period 1
Number of total casualties
5
4
3
2
1
0
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

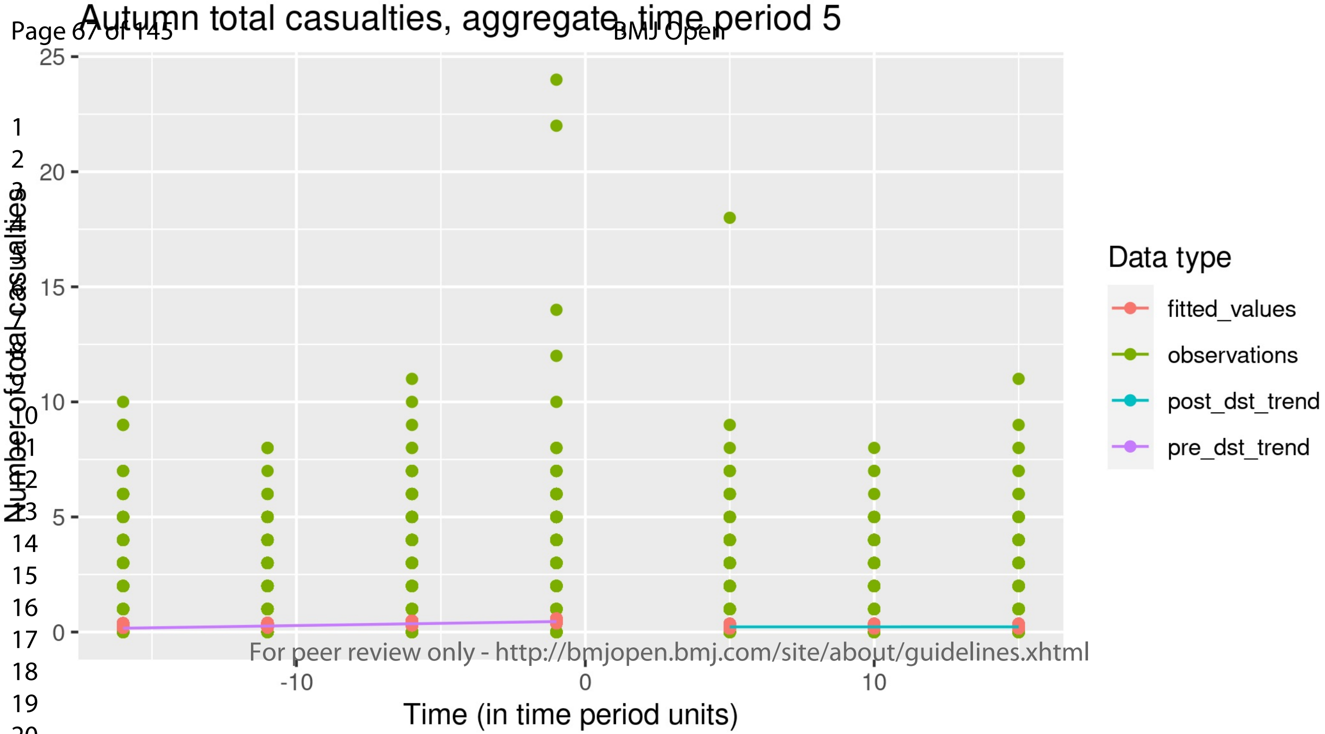

Spring total casualties, northings, band 3000 - 4000, time period 1, zoomed in
Number of total casualties
2
0
-2
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Spring total casualties, northings, band 3000 - 4000, time period 5
Number of total casualties
20
10
0
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

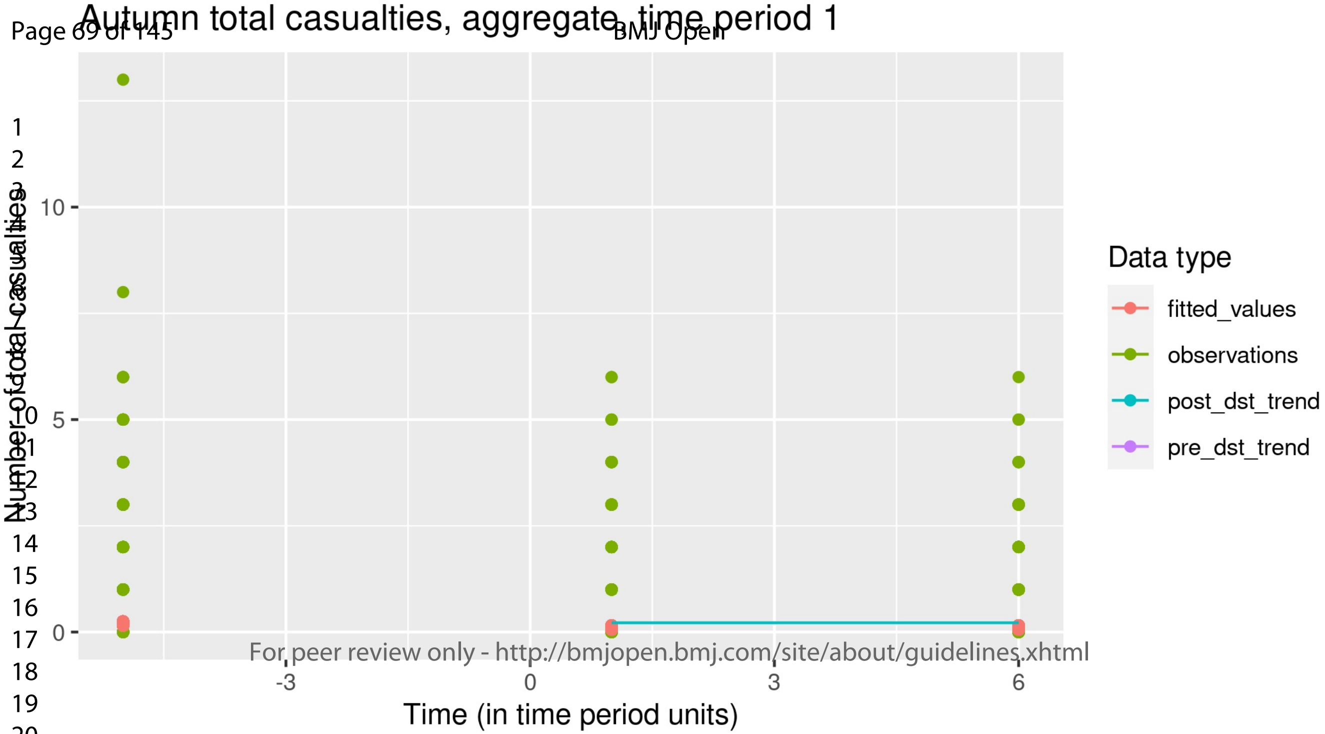

Spring total casualties, northings, band 3000 - 4000, time period 5, zoomed in
Number of total casualties
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

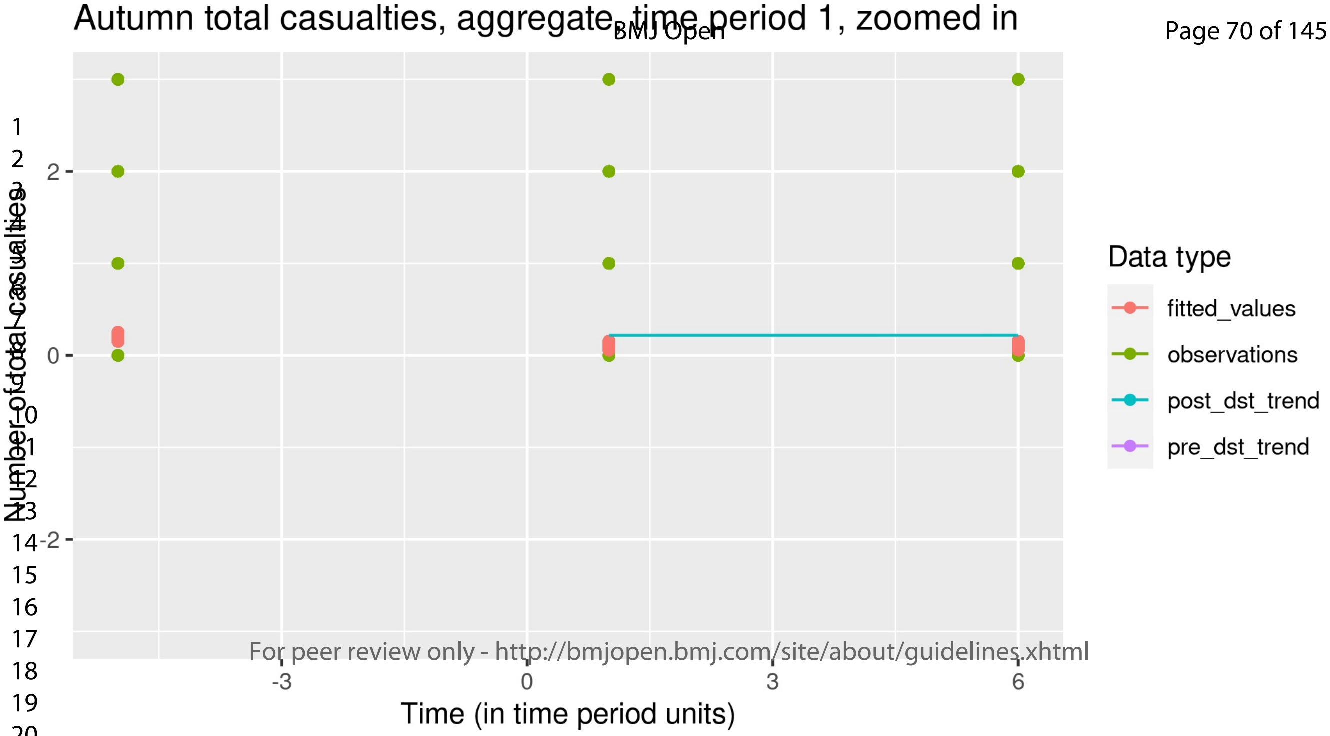

Spring fatalities, northings, band 3000 - 4000, time period 1
Number of fatalities
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend
0
1
2
3
4
-20
-10
0
10
20

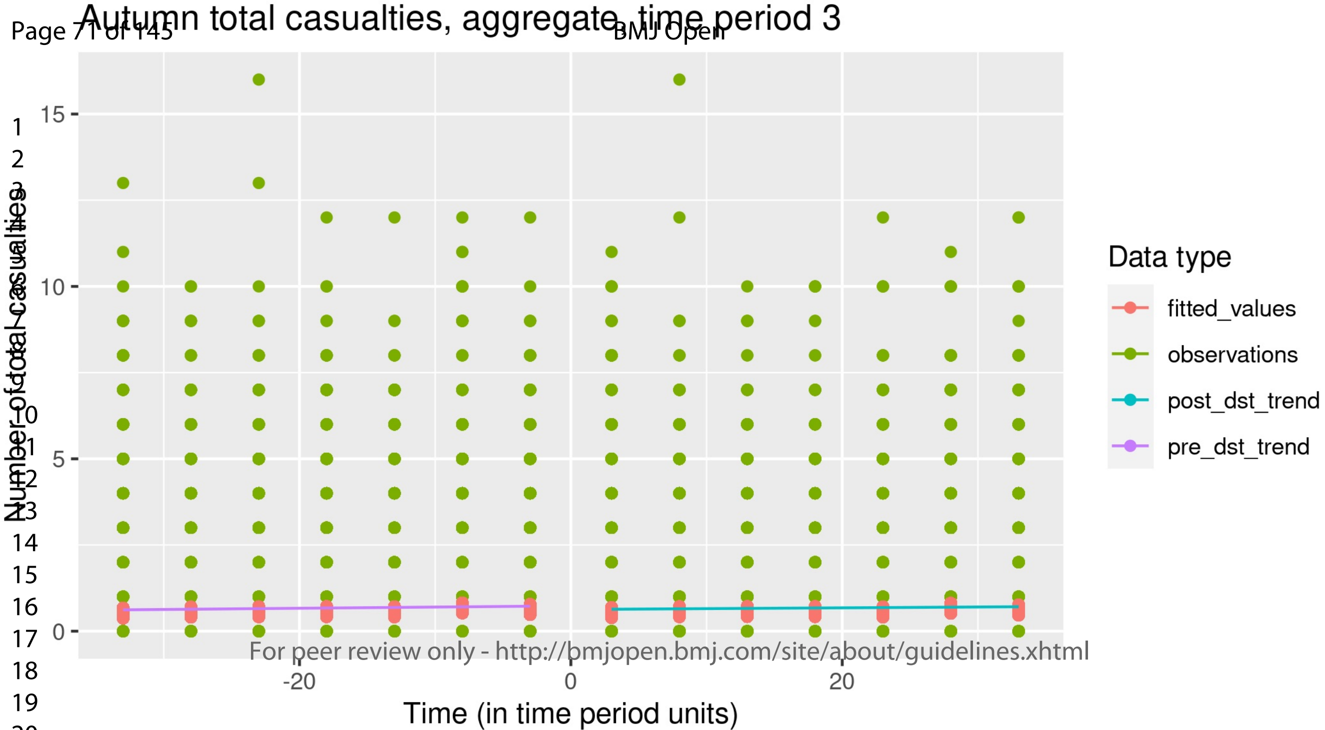

Spring fatalities, northings, band 3000 - 4000, time period 1, zoomed in
Number of fatalities
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Autumn total casualties, aggregate, time period 5
Number of total casualties
25
20
15
10
5
0
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

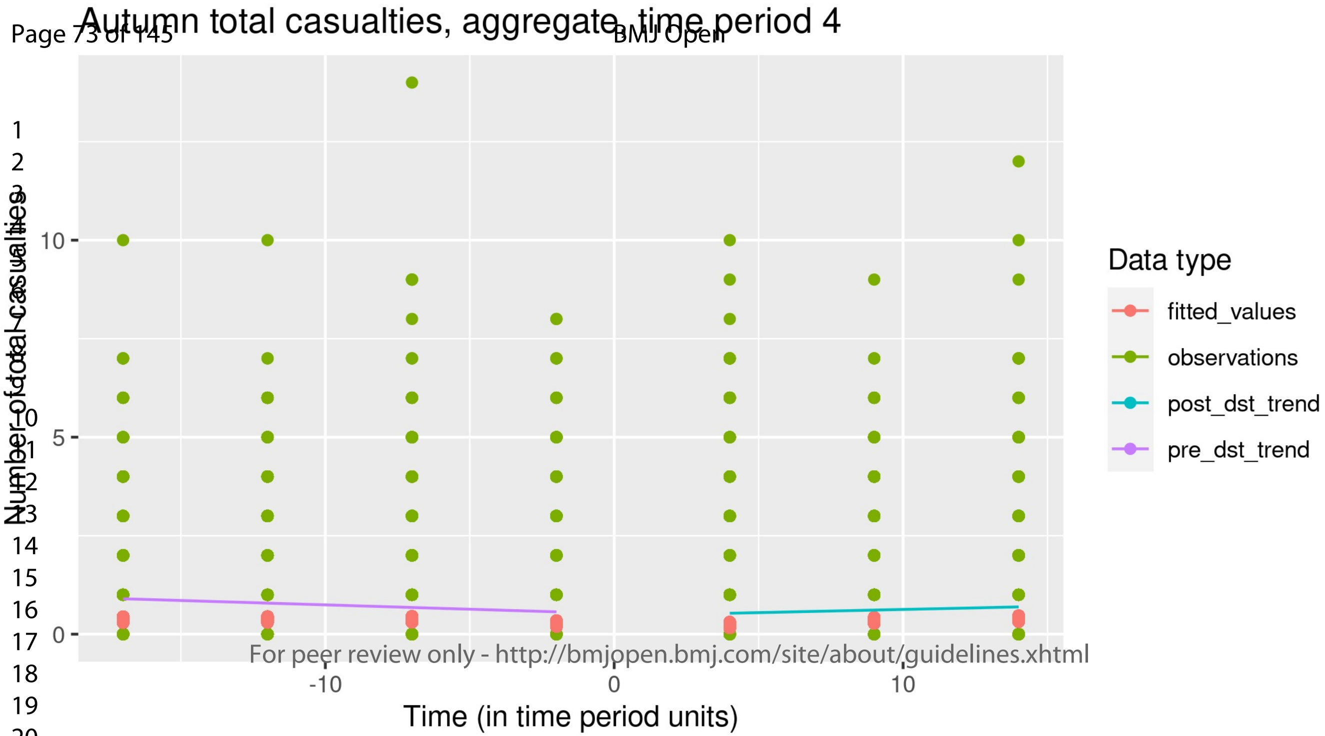

Autumn total casualties, aggregate, time period 5, zoomed in
Number of total casualties
2
0
-2
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

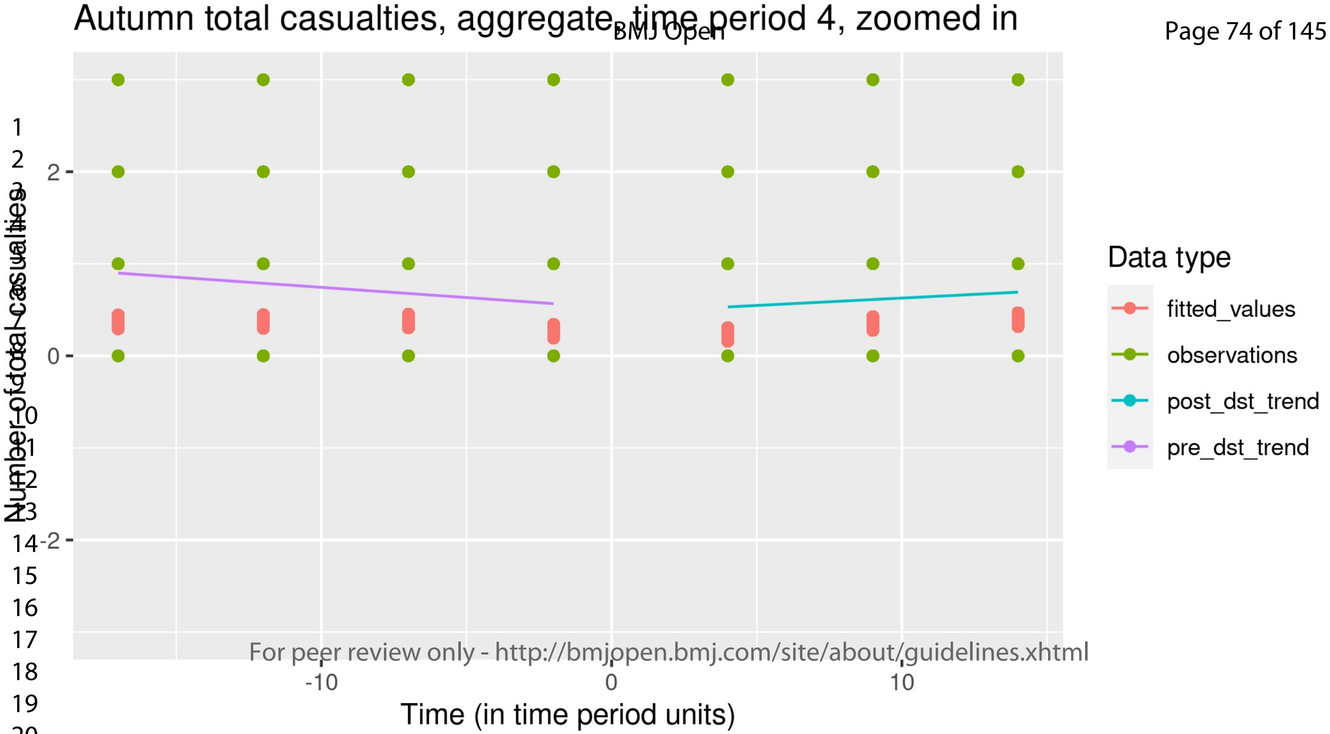

Autumn total casualties, aggregate, time period 1
Number of total casualties
10
5
0
-3
0
3
6
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

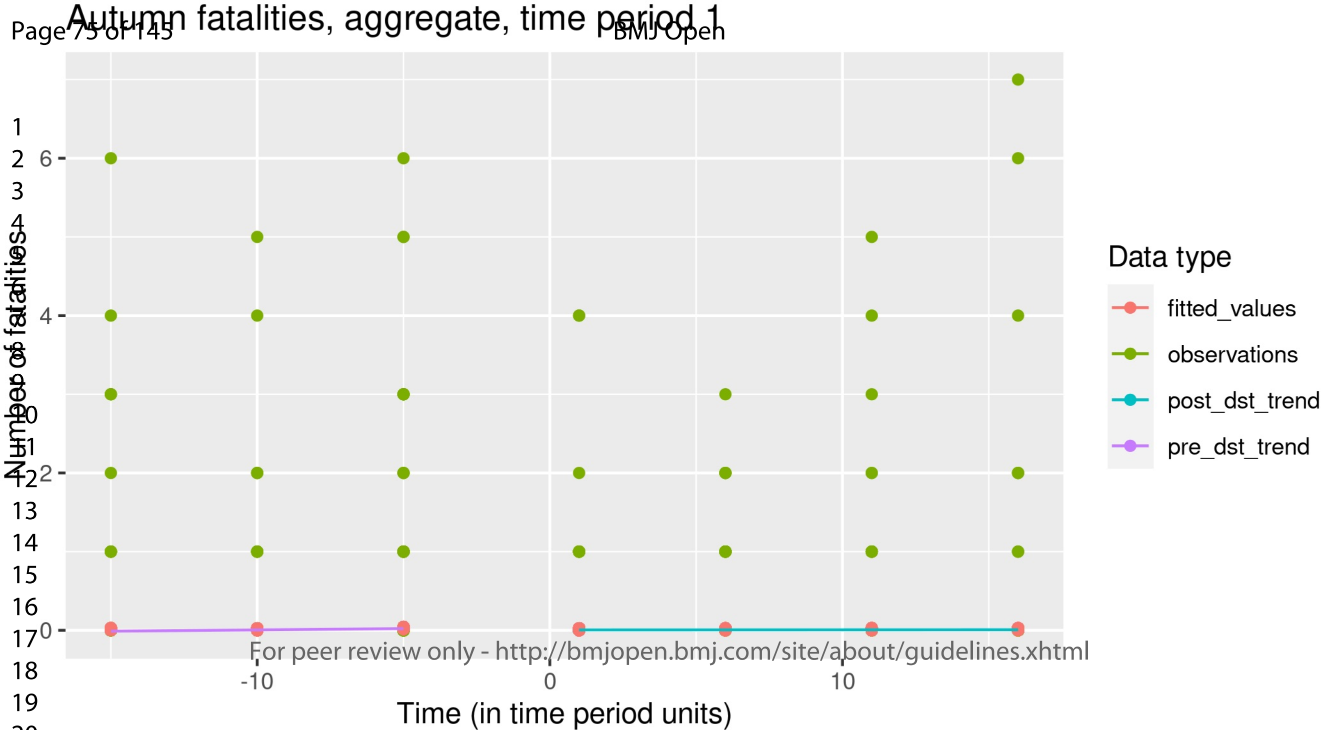

Autumn total casualties, aggregate, time period 1, zoomed in
Number of total casualties
2
0
-2
-3
0
3
6
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

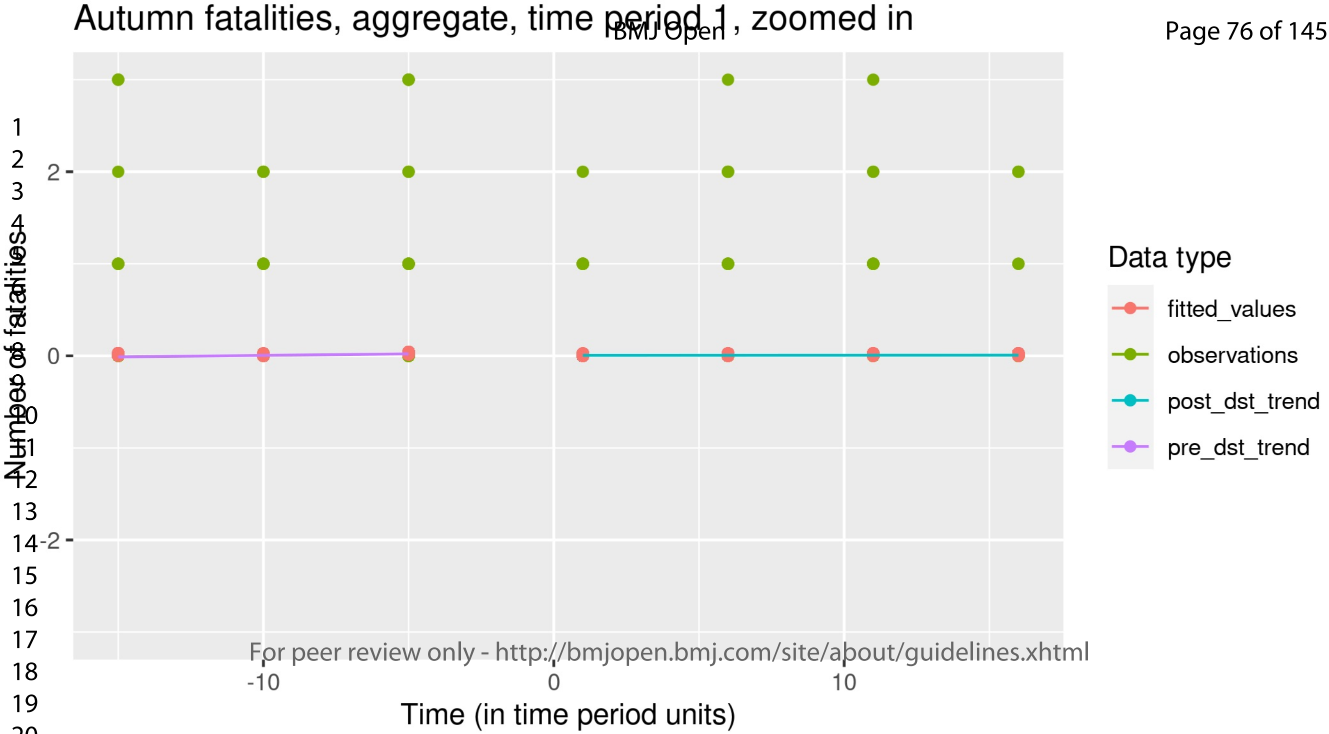

Autumn total casualties, aggregate, time period 3
Number of total casualties
15
10
5
0
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

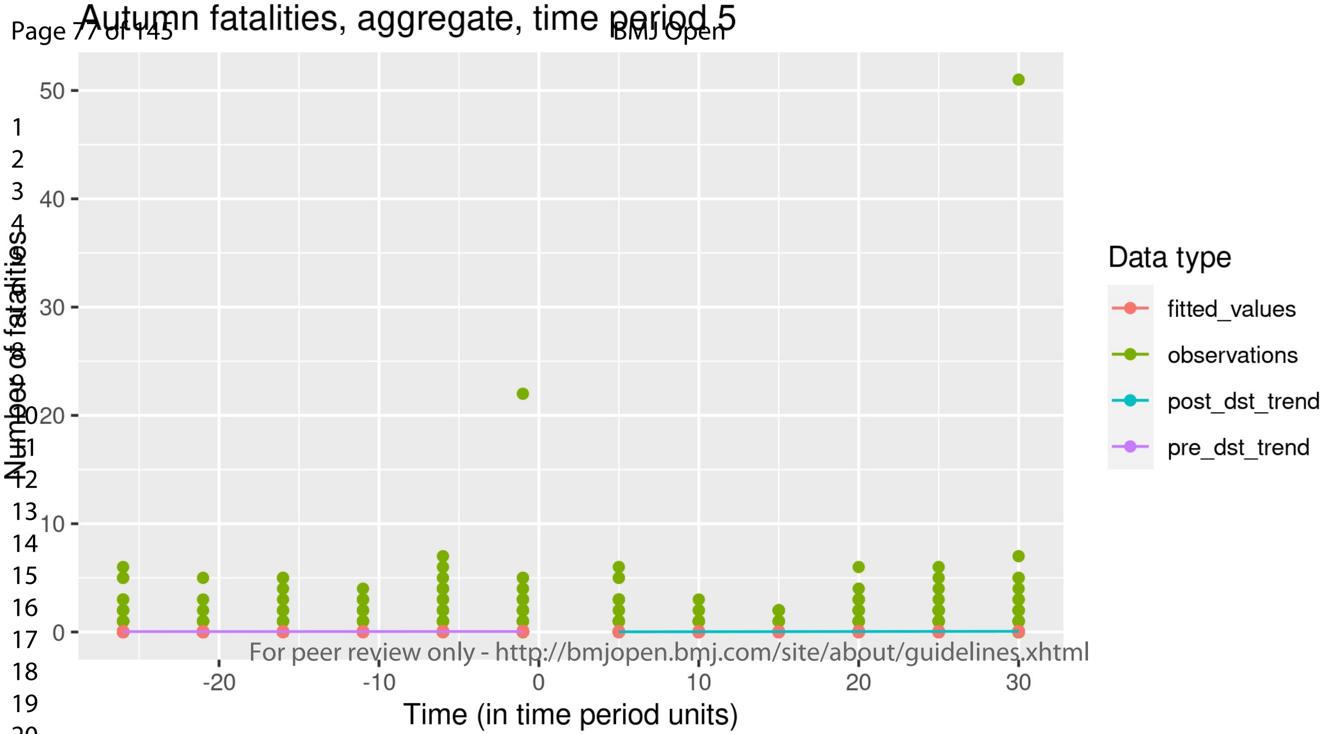

Autumn total casualties, aggregate, time period 3, zoomed in
Number of total casualties
2
0
-2
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

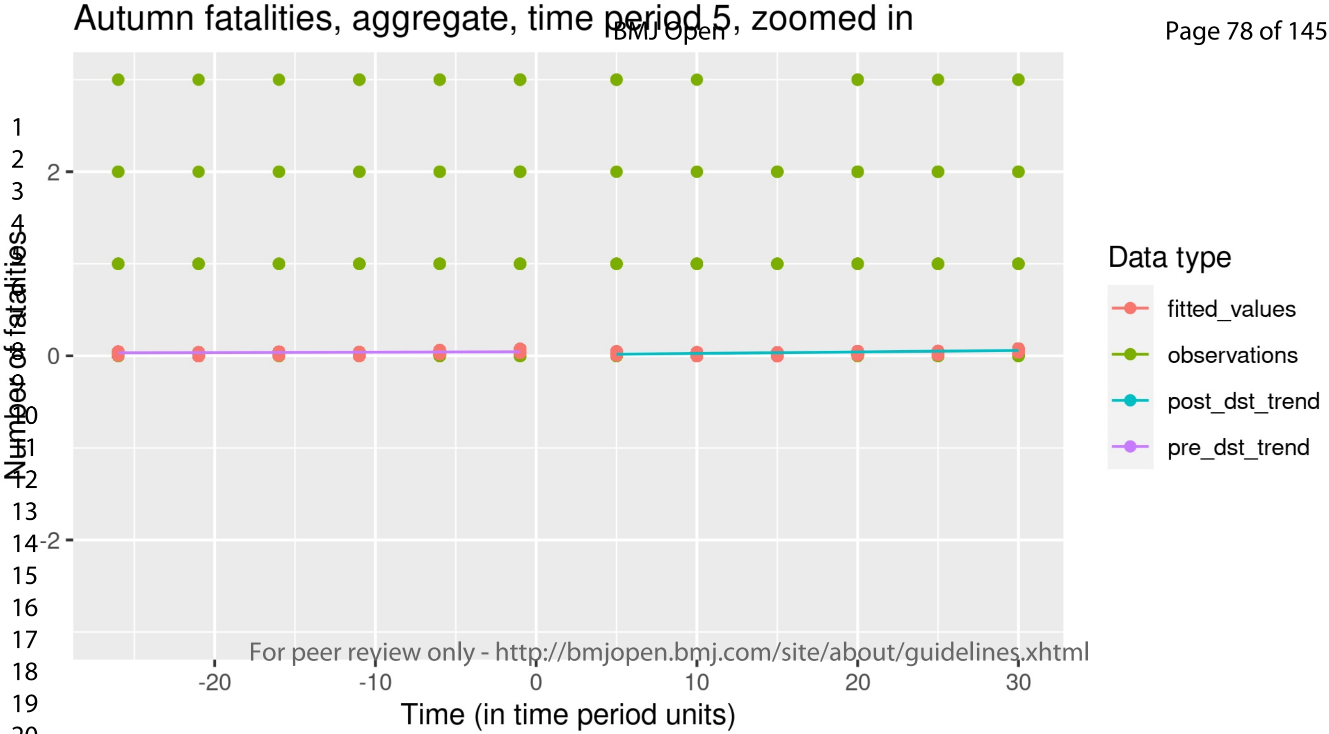

Autumn total casualties, aggregate, time period 4
Number of total casualties
10
5
0
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

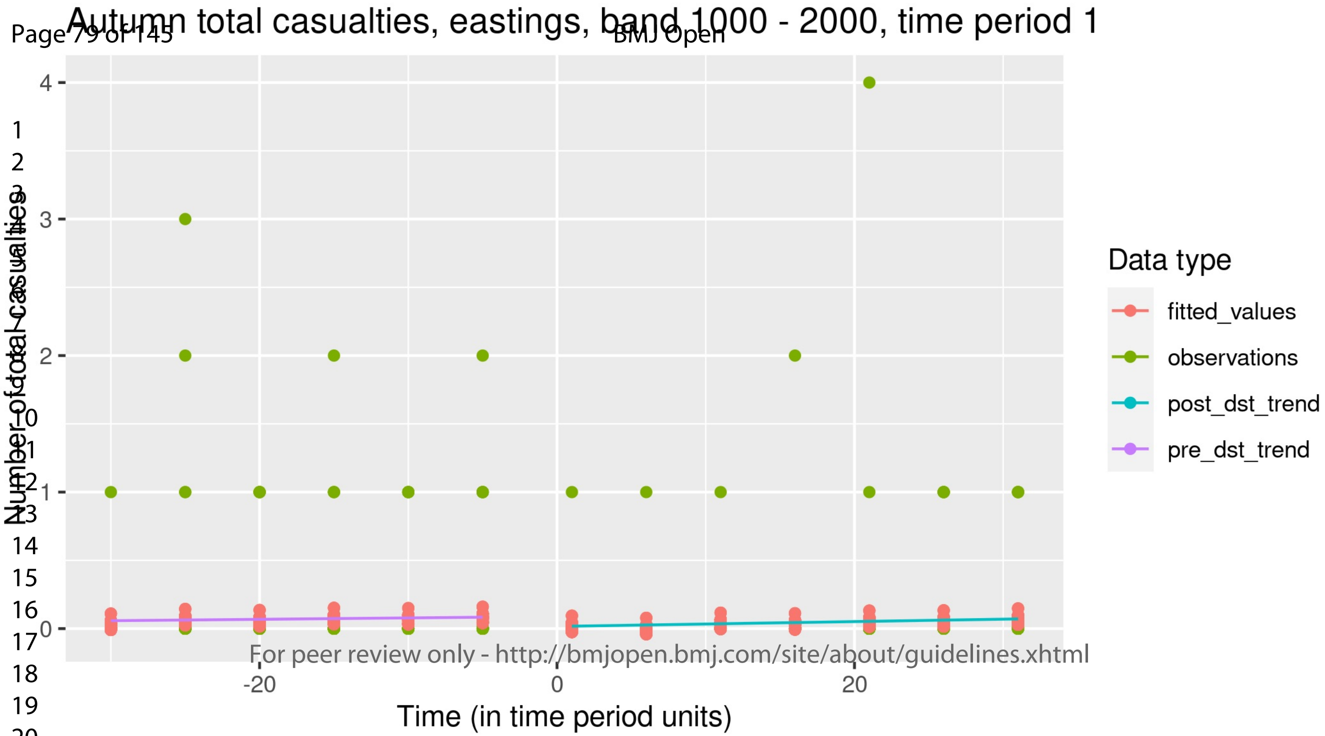

Autumn total casualties, aggregate, time period 4, zoomed in
Number of total casualties
2
0
-2
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

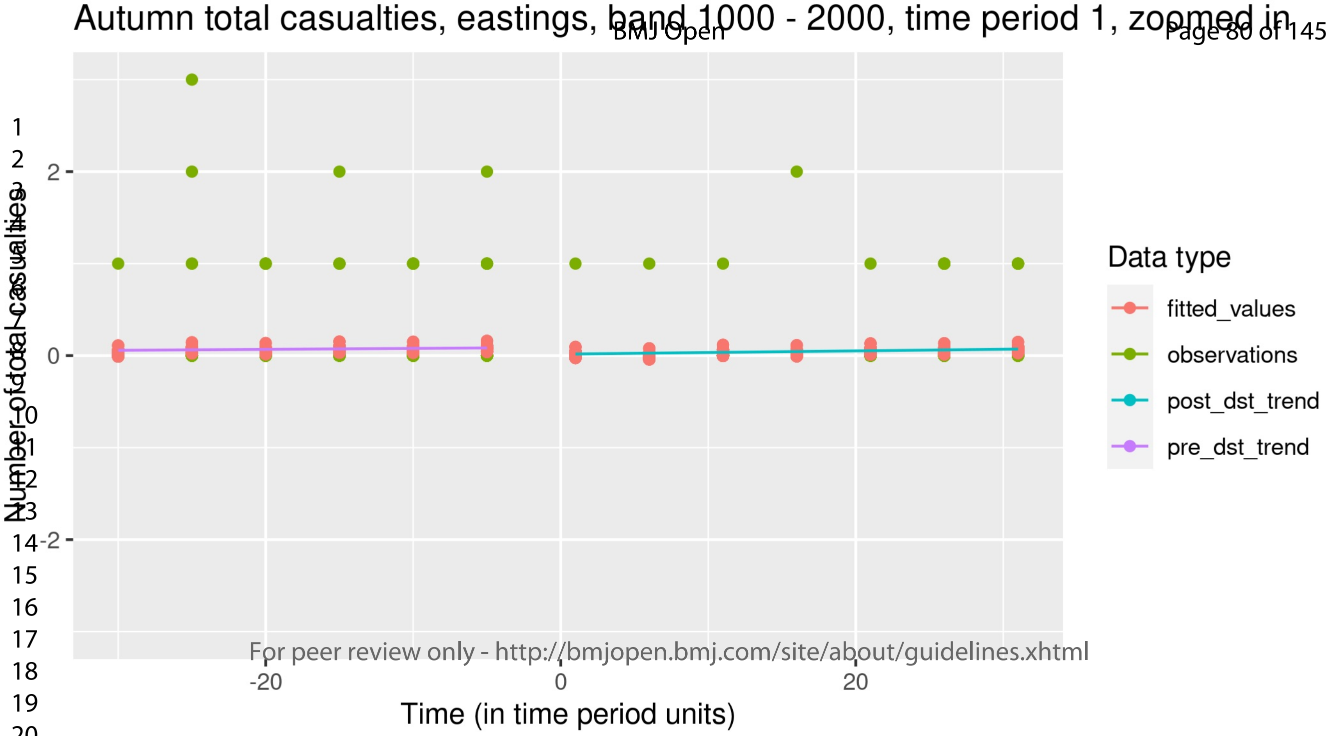

Autumn fatalities, aggregate, time period 1
Number of fatalities
0
2
4
6
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

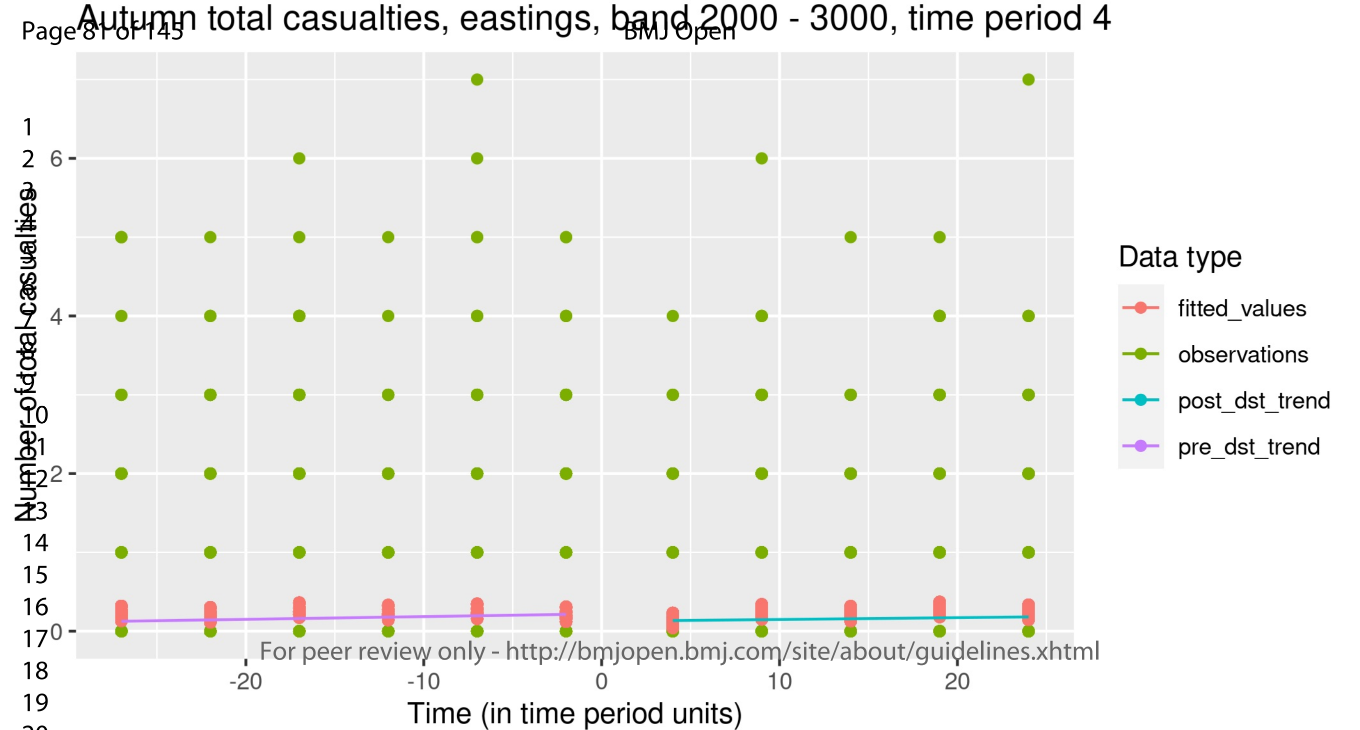

Autumn fatalities, aggregate, time period 1, zoomed in
Number of fatalities
2
0
-2
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Autumn fatalities, aggregate, time period 5
Number of fatalities
50
40
30
20
10
0
-20
-10
0
10
20
30
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

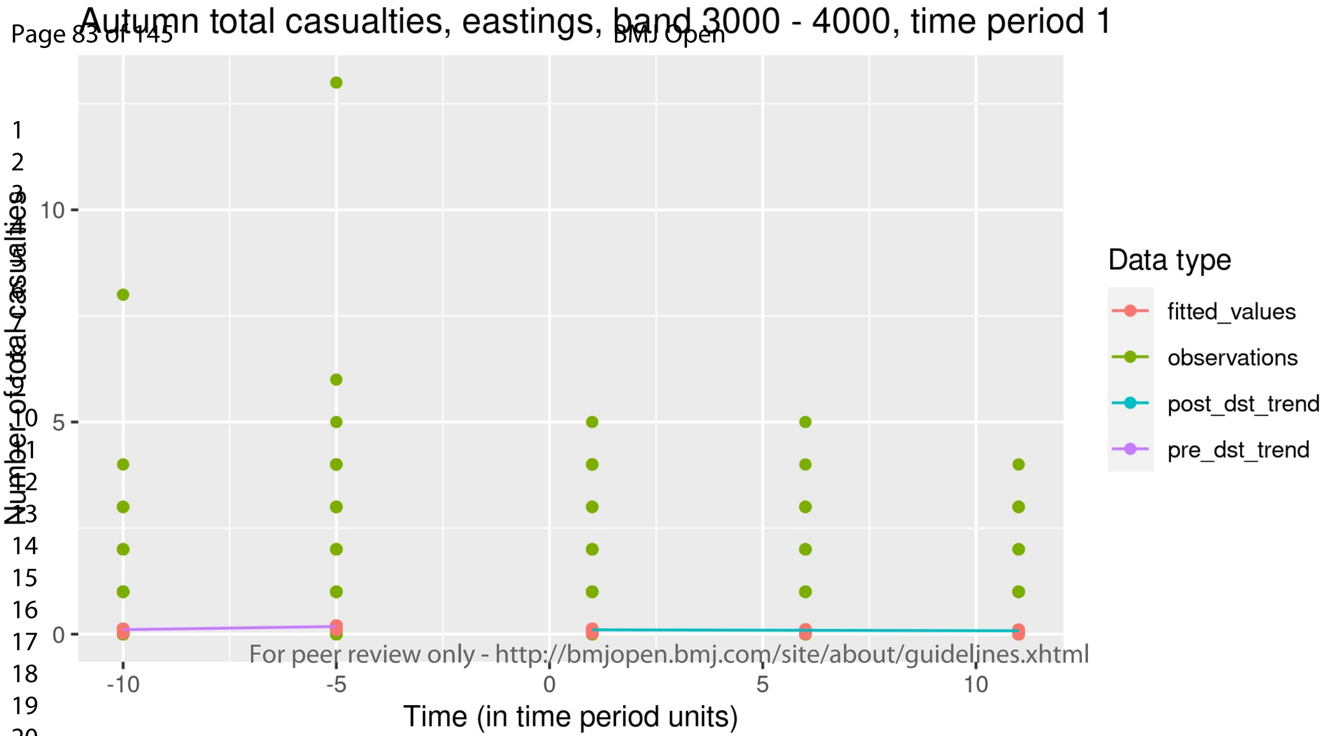

Autumn fatalities, aggregate, time period 5, zoomed in
Number of fatalities
2
0
-2
-20
-10
0
10
20
30
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

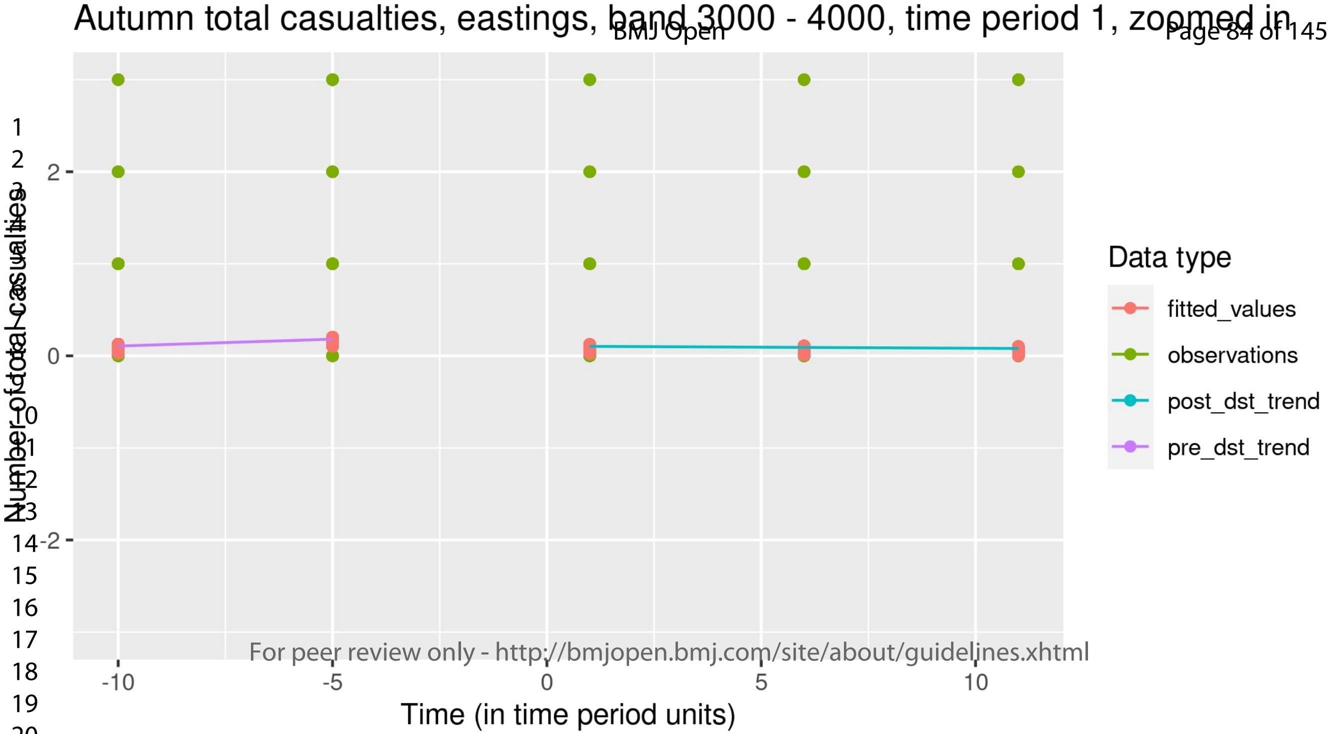

Autumn total casualties, eastings, band 1000 - 2000, time period 1
Number of total casualties
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend
4
3
2
1
0
-20
0
20

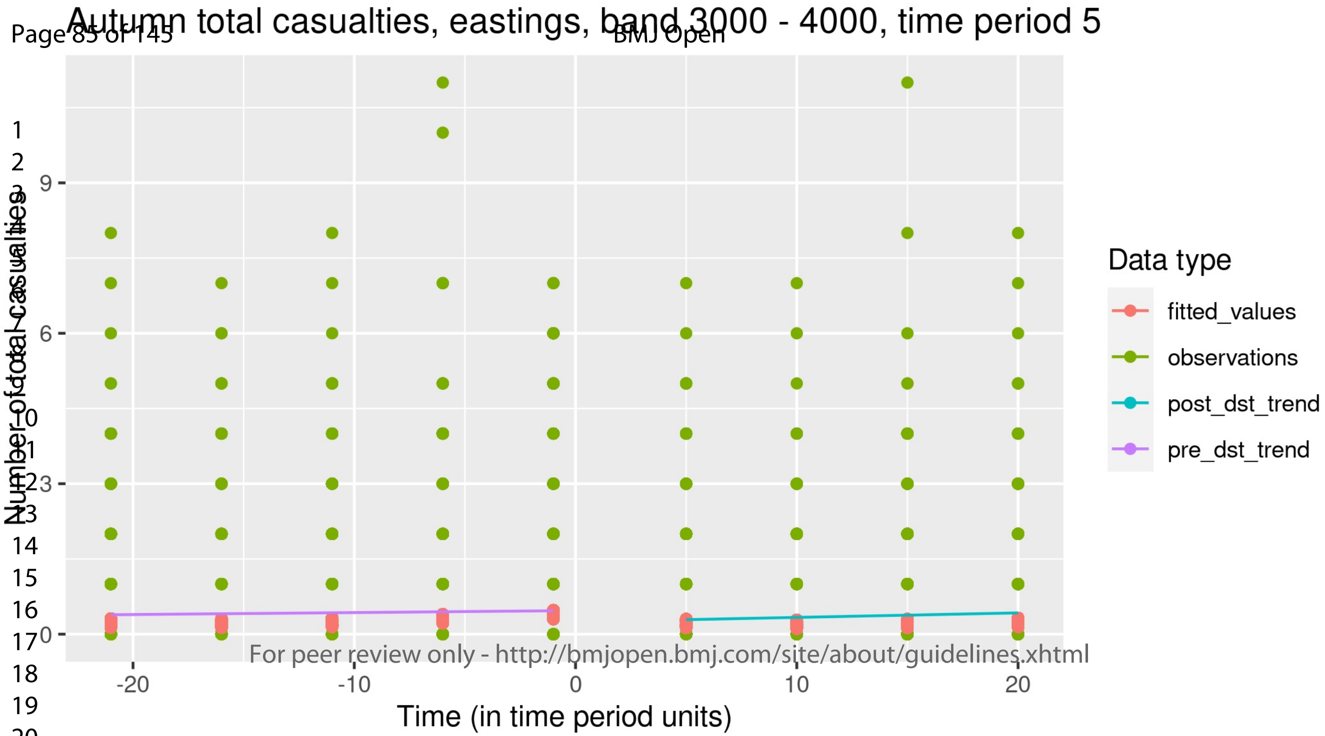

Autumn total casualties, eastings, band 1000 - 2000, time period 1, zoomed in
Number of total casualties
2
0
-2
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

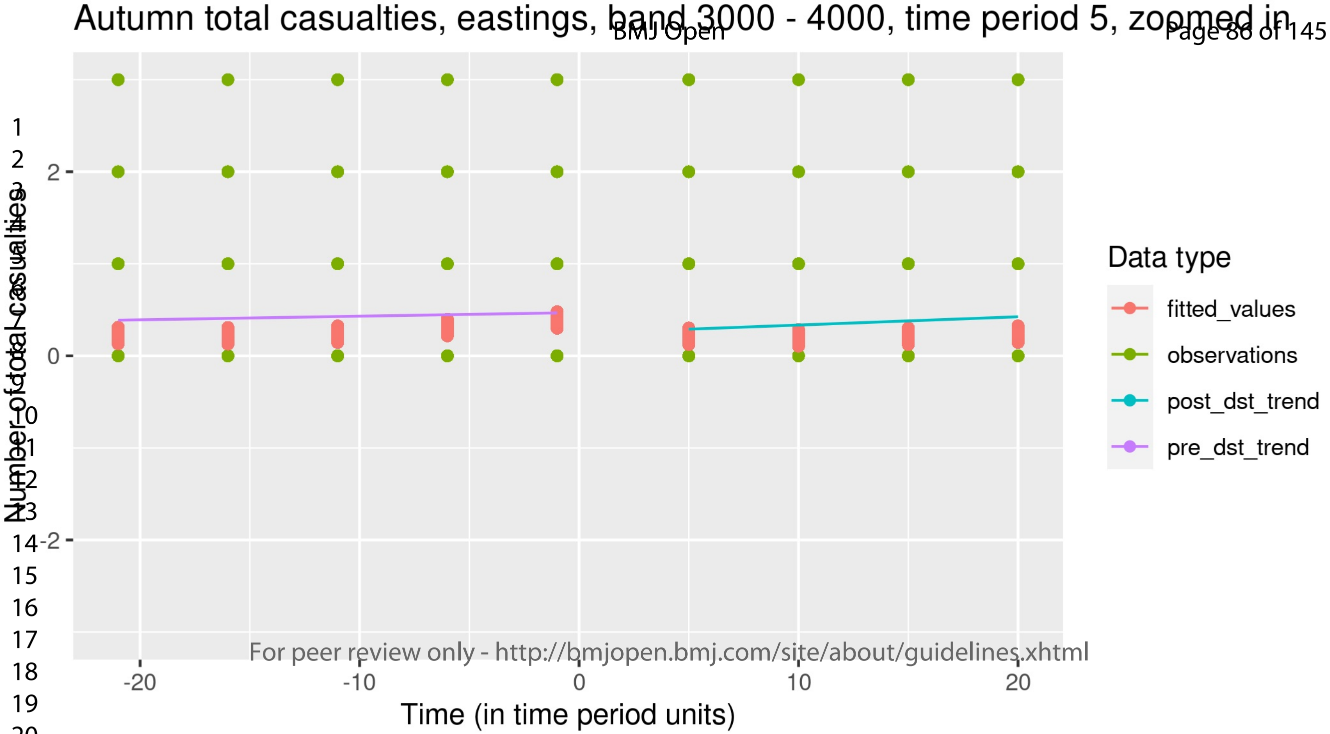

Autumn total casualties, eastings, band 2000 - 3000, time period 4
Number of total casualties
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend
0
2
4
6
-20
-10
0
10
20

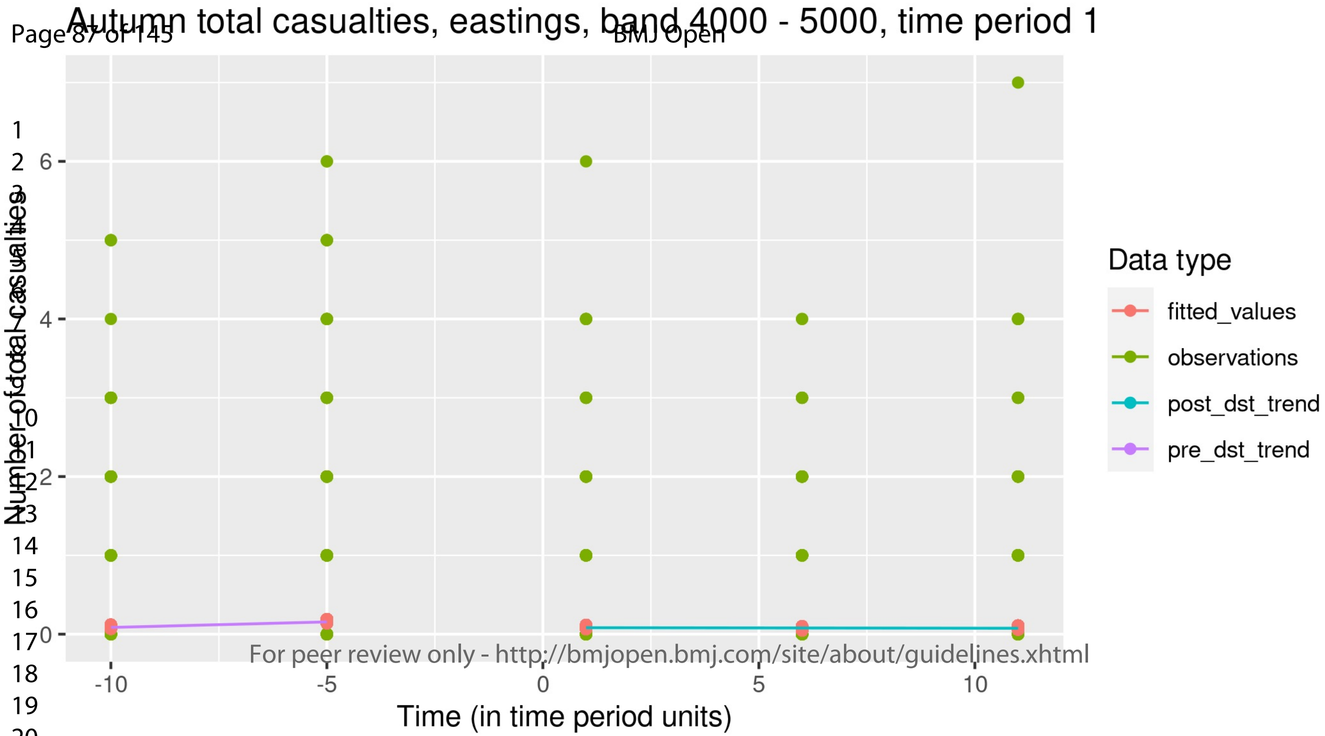

Autumn total casualties, eastings, band 2000 - 3000, time period 4, zoomed in
Number of total casualties
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

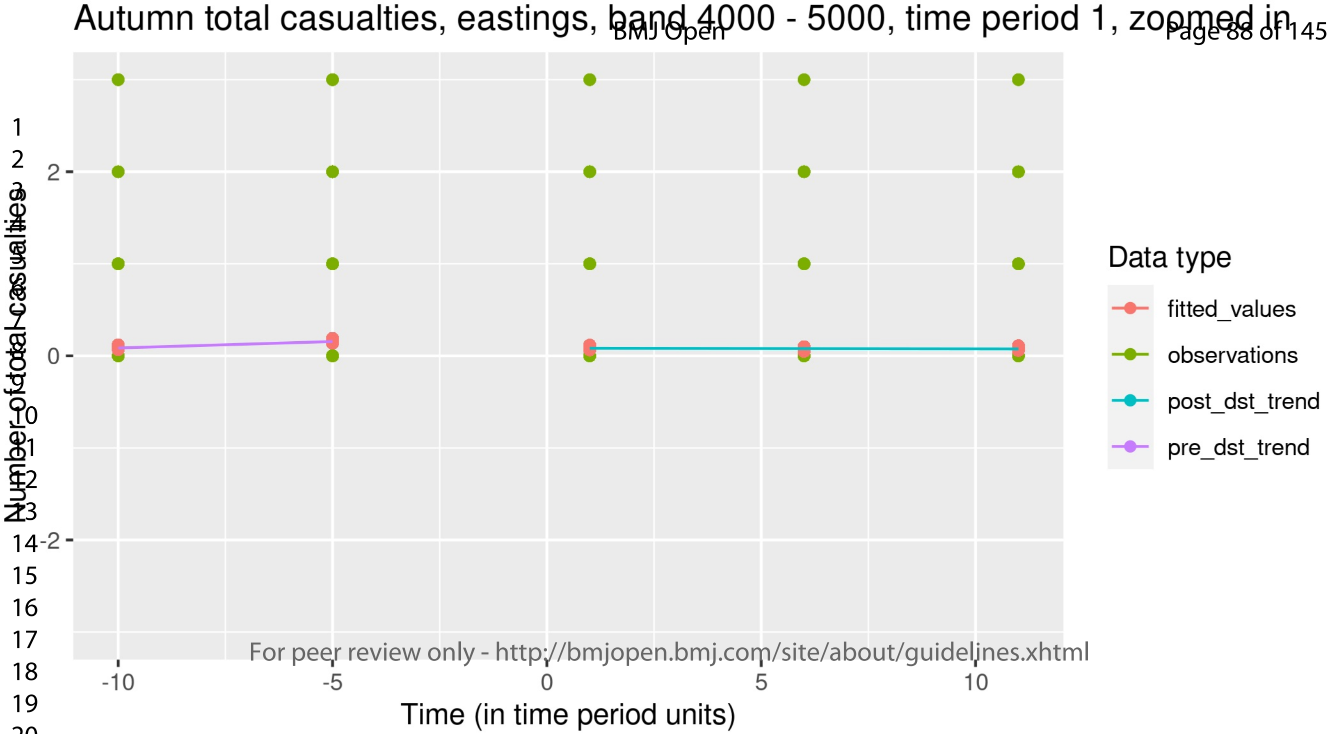

Autumn total casualties, eastings, band 3000 - 4000, time period 1
Number of total casualties
10
5
0
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

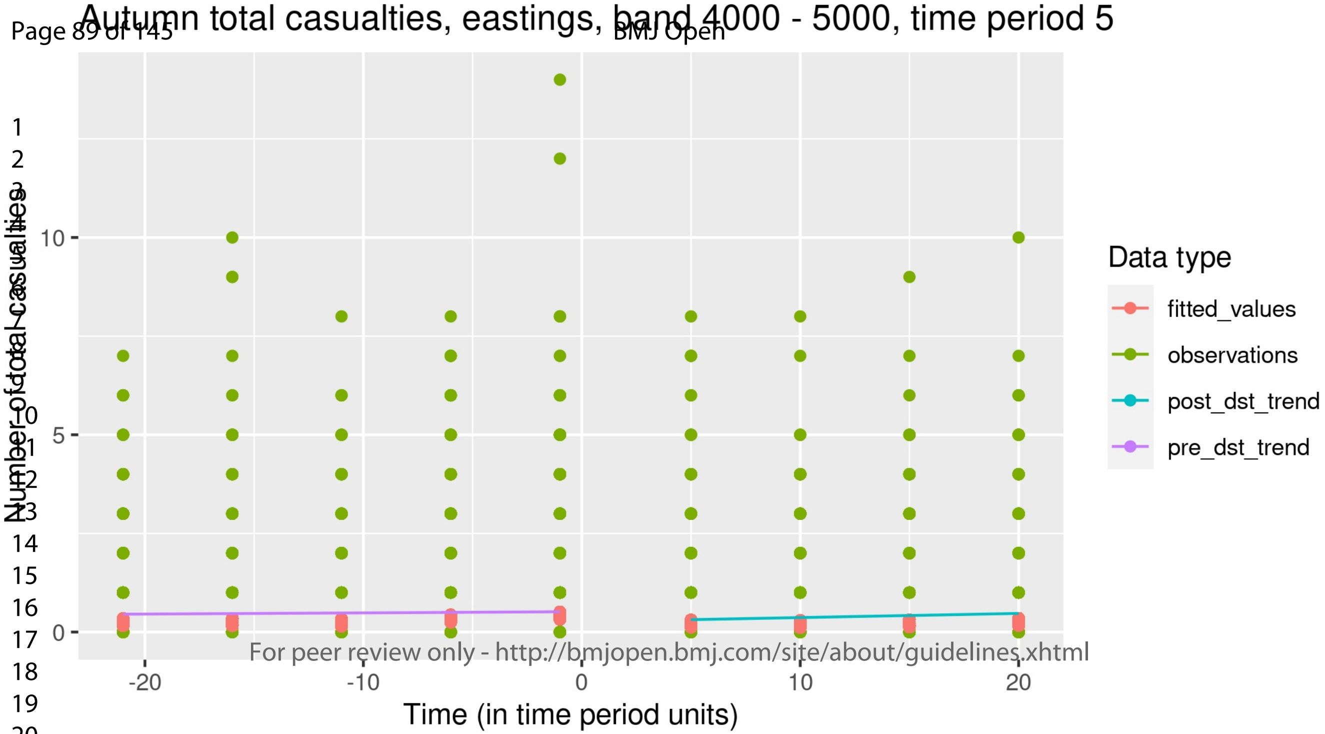

Autumn total casualties, eastings, band 3000 - 4000, time period 1, zoomed in
Number of total casualties
2
0
-2
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

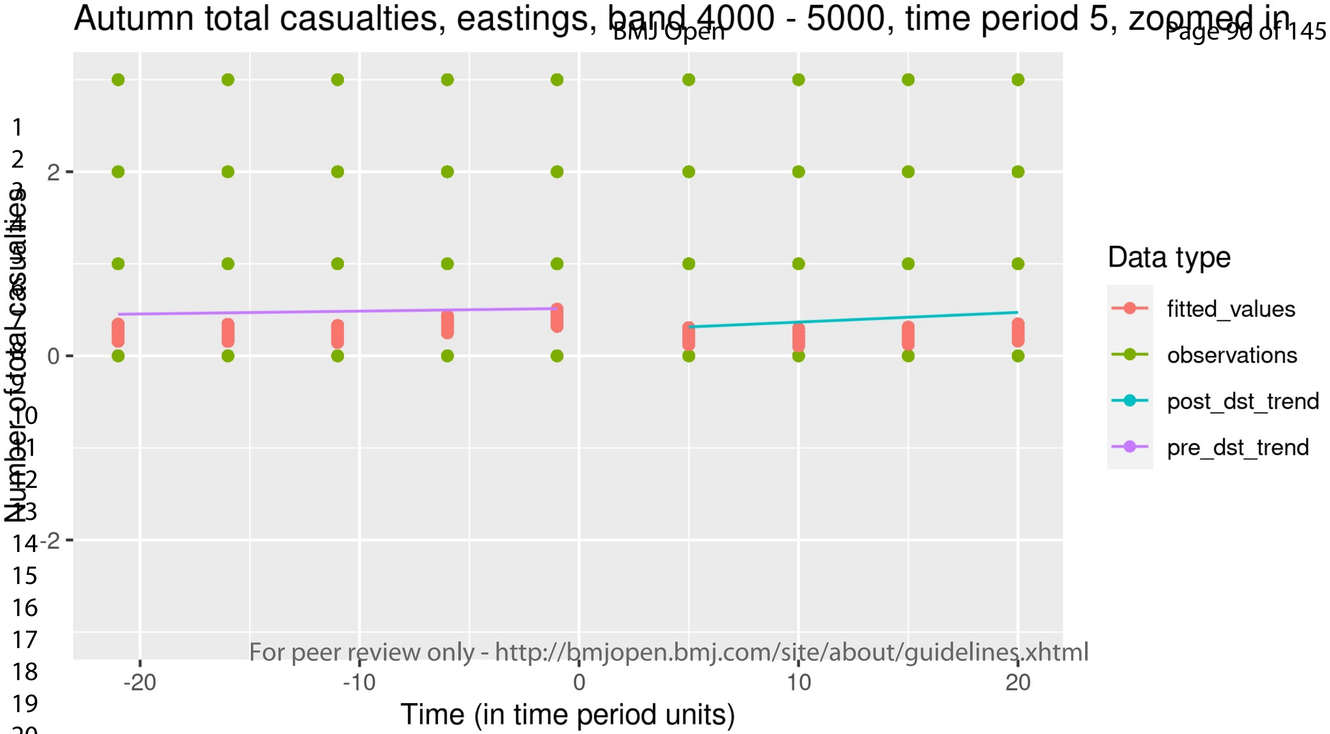

Autumn total casualties, eastings, band 3000 - 4000, time period 5
Number of total casualties
Time (in time period units)
0
3
6
9
-20
-10
0
10
20
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

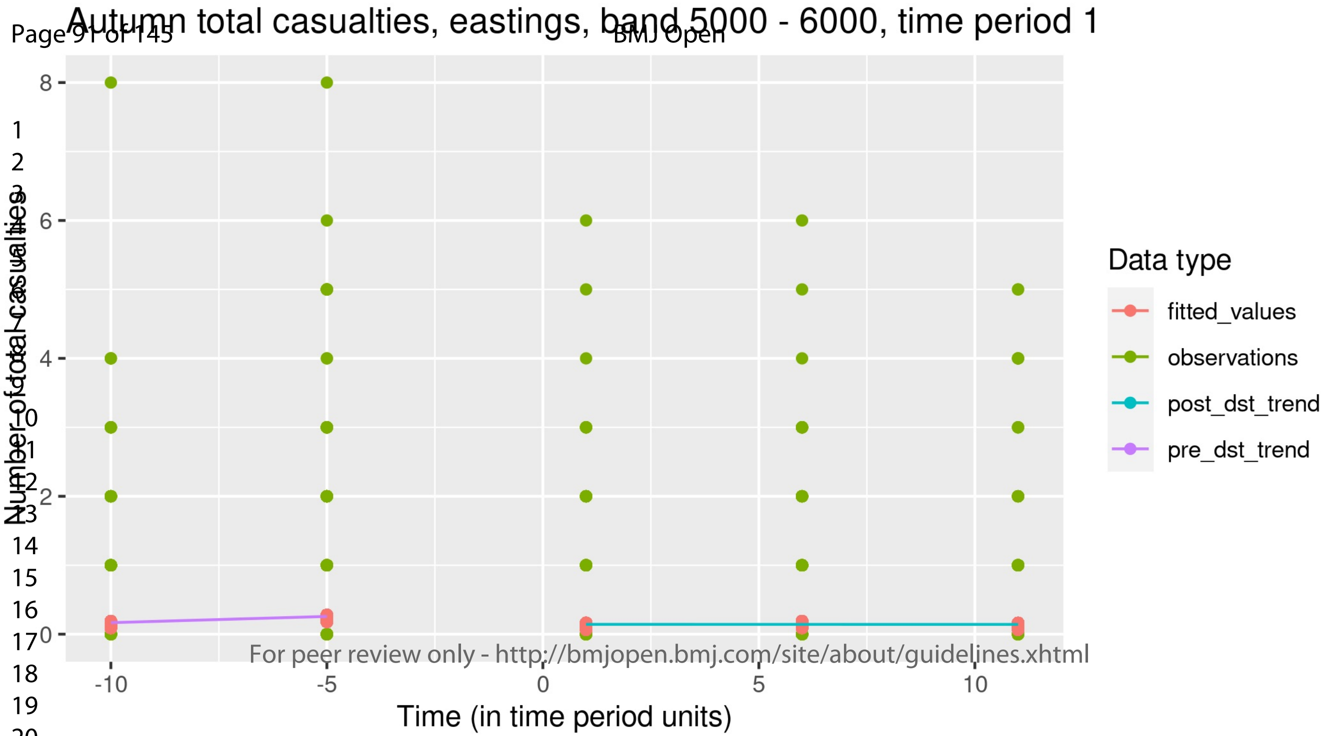

Autumn total casualties, eastings, band 3000 - 4000, time period 5, zoomed in
Number of total casualties
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

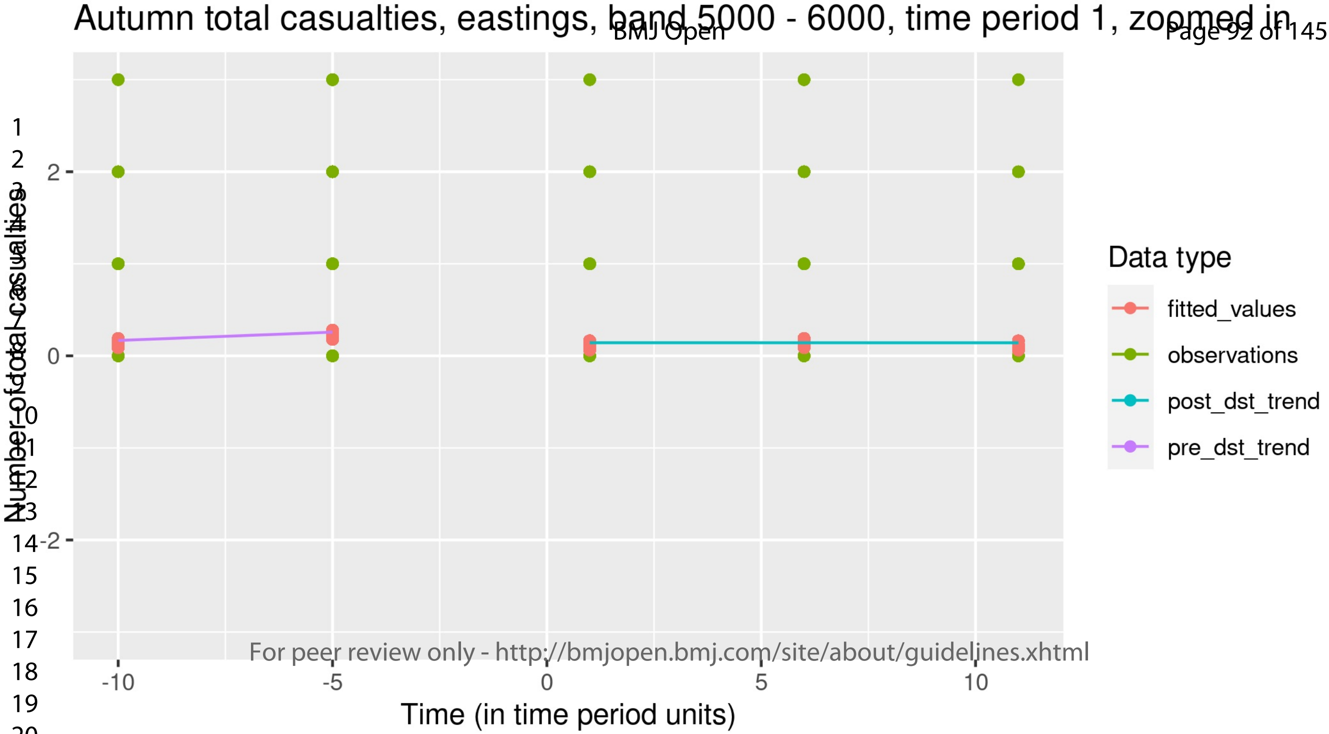

Autumn total casualties, eastings, band 4000 - 5000, time period 1
Number of total casualties
0
2
4
6
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

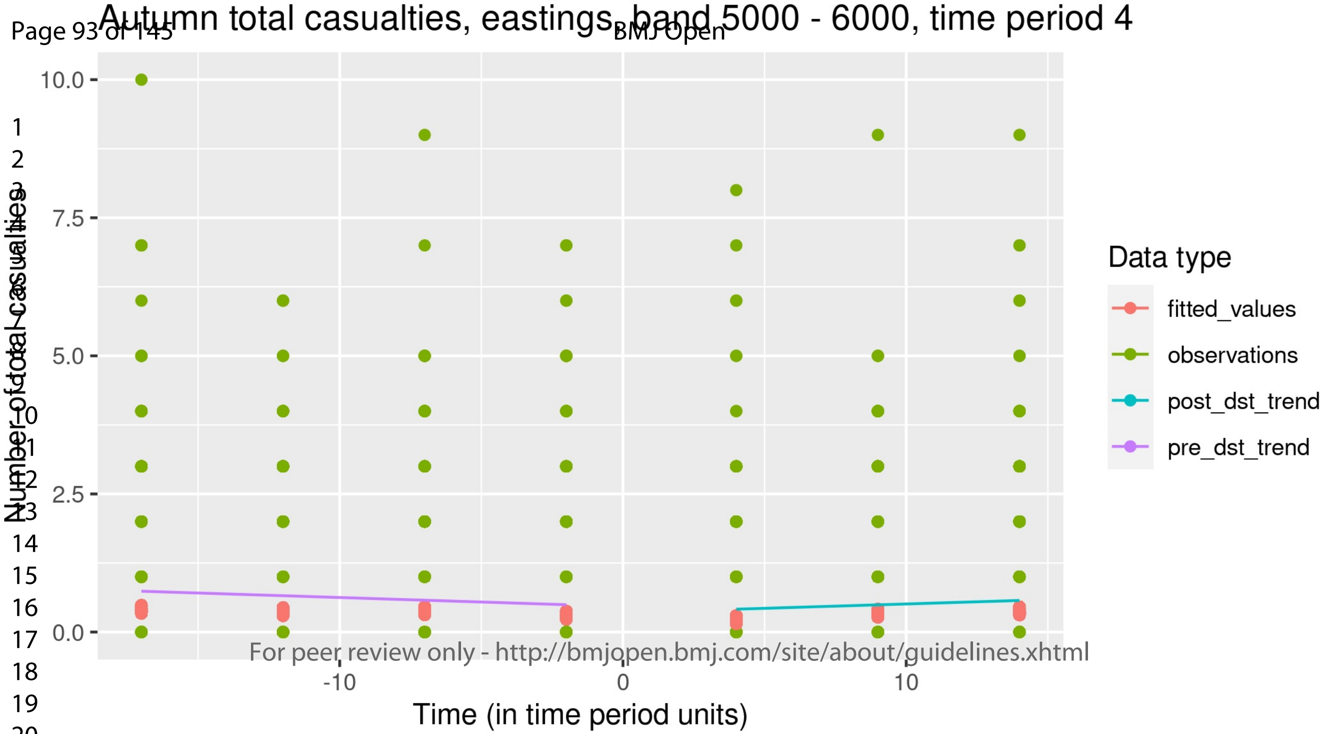

Autumn total casualties, eastings, band 4000 - 5000, time period 1, zoomed in
Number of total casualties
2
0
-2
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

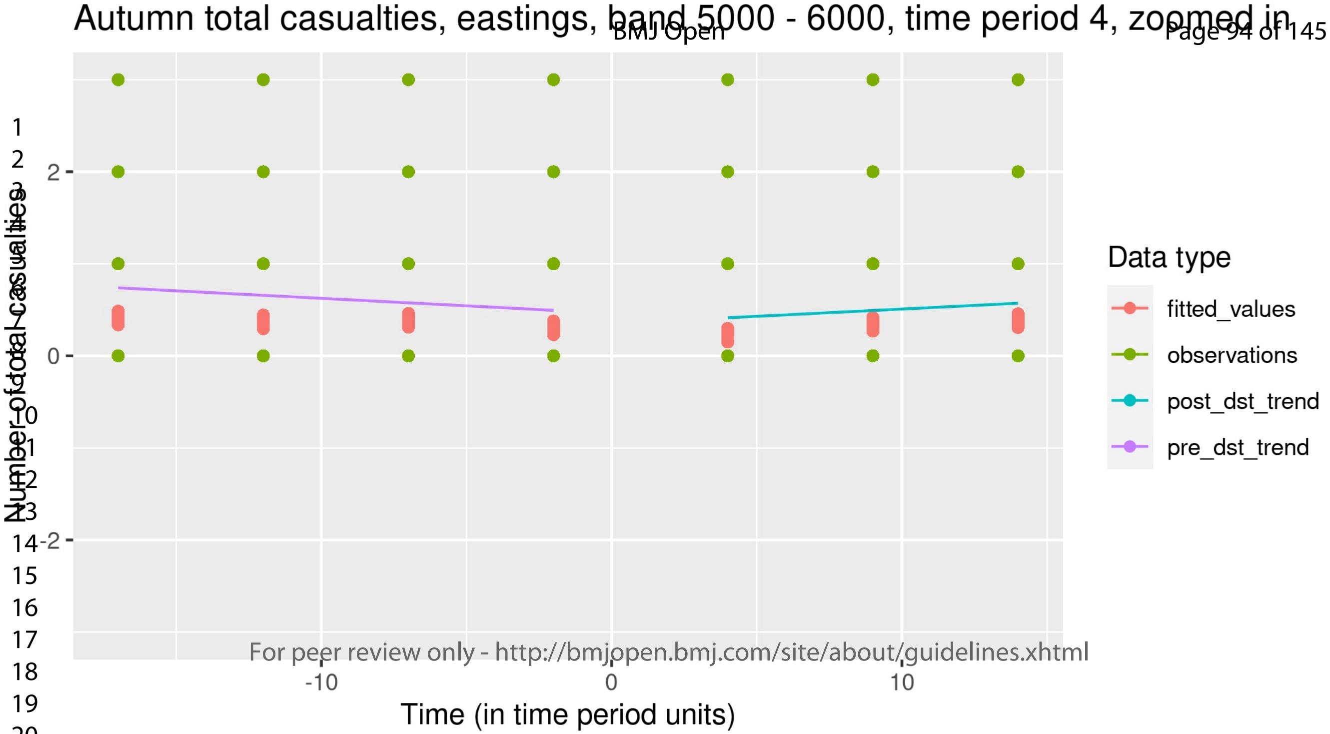

Autumn total casualties, eastings, band 4000 - 5000, time period 5
Number of total casualties
0
5
10
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

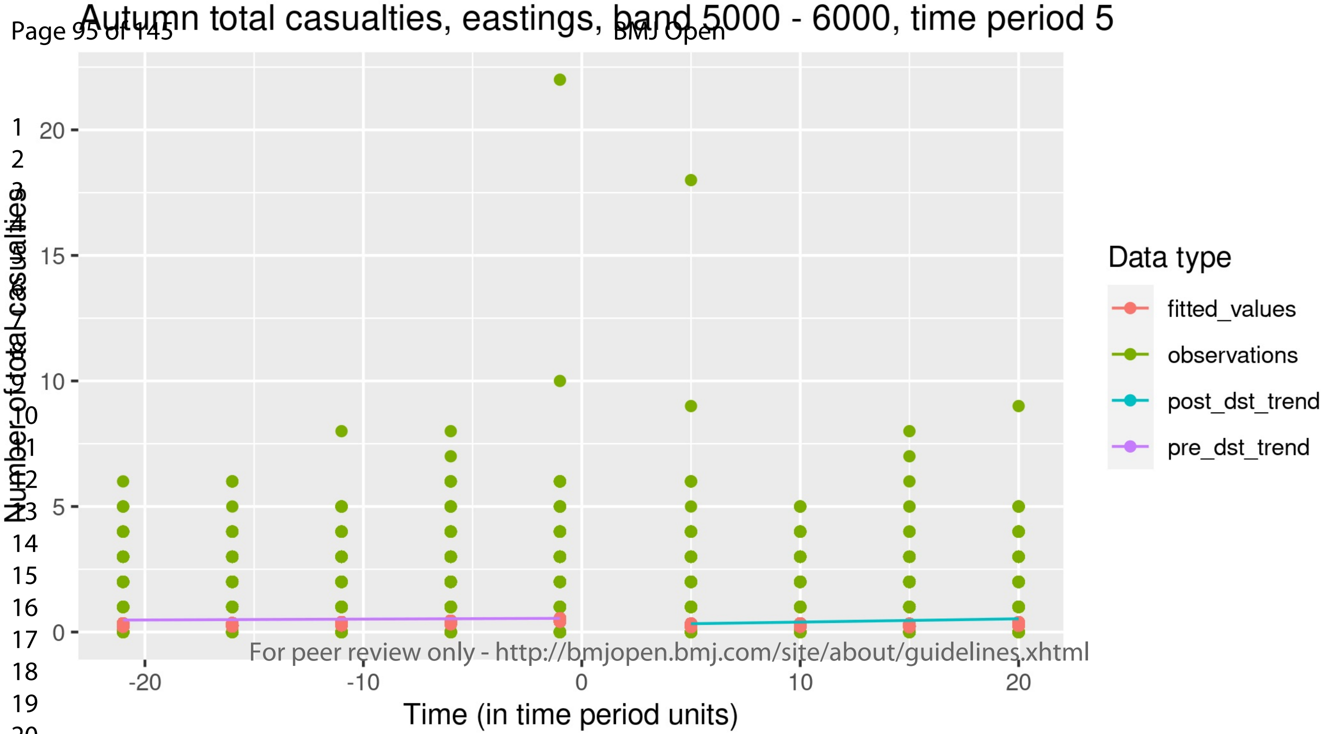

Autumn total casualties, eastings, band 4000 - 5000, time period 5, zoomed in
Number of total casualties
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

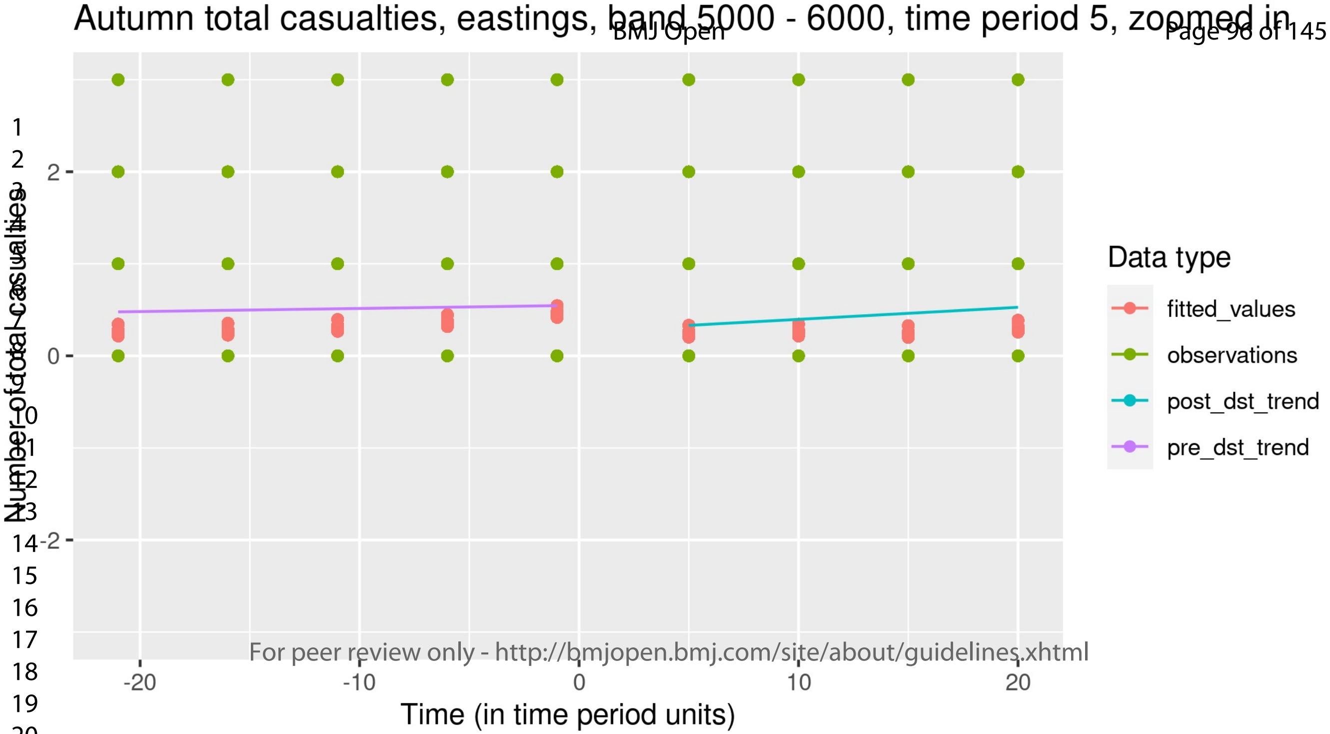

Autumn total casualties, eastings, band 5000 - 6000, time period 1
Number of total casualties
8
6
4
2
0
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

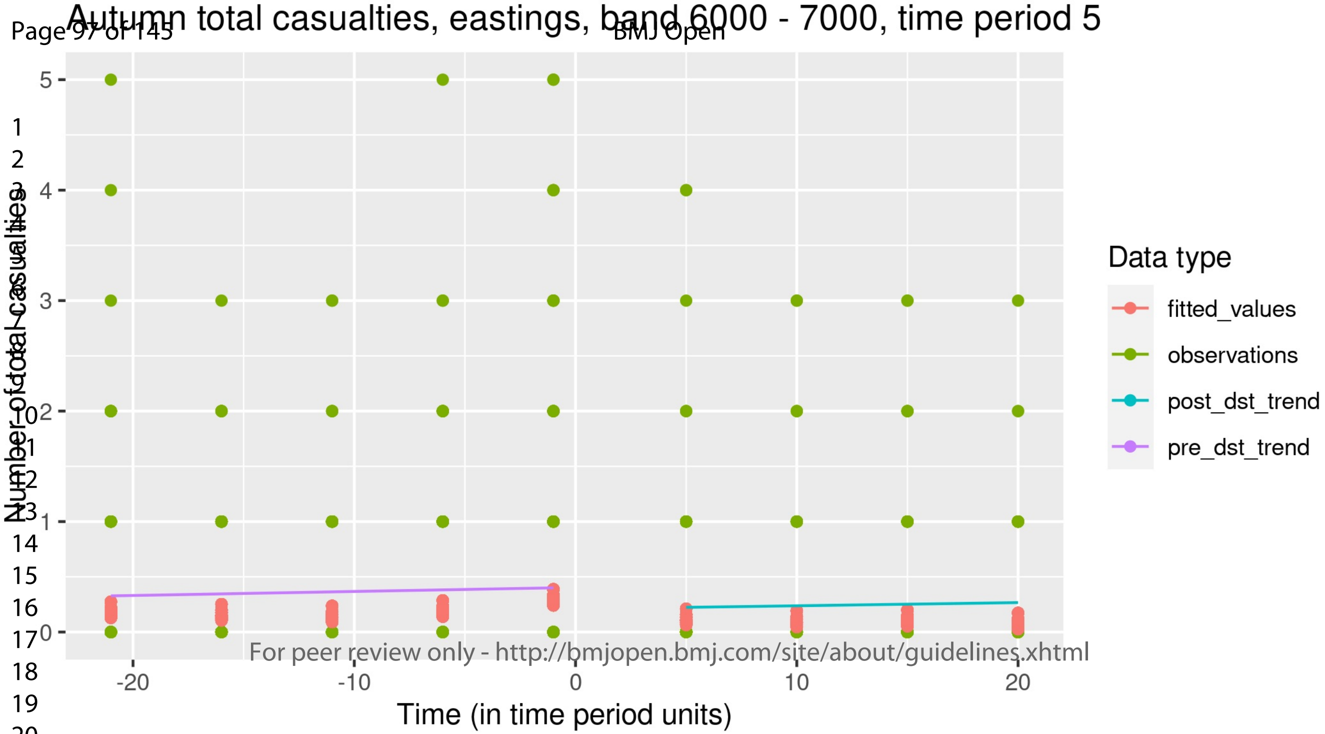

Autumn total casualties, eastings, band 5000 - 6000, time period 1, zoomed in
Number of total casualties
2
0
-2
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

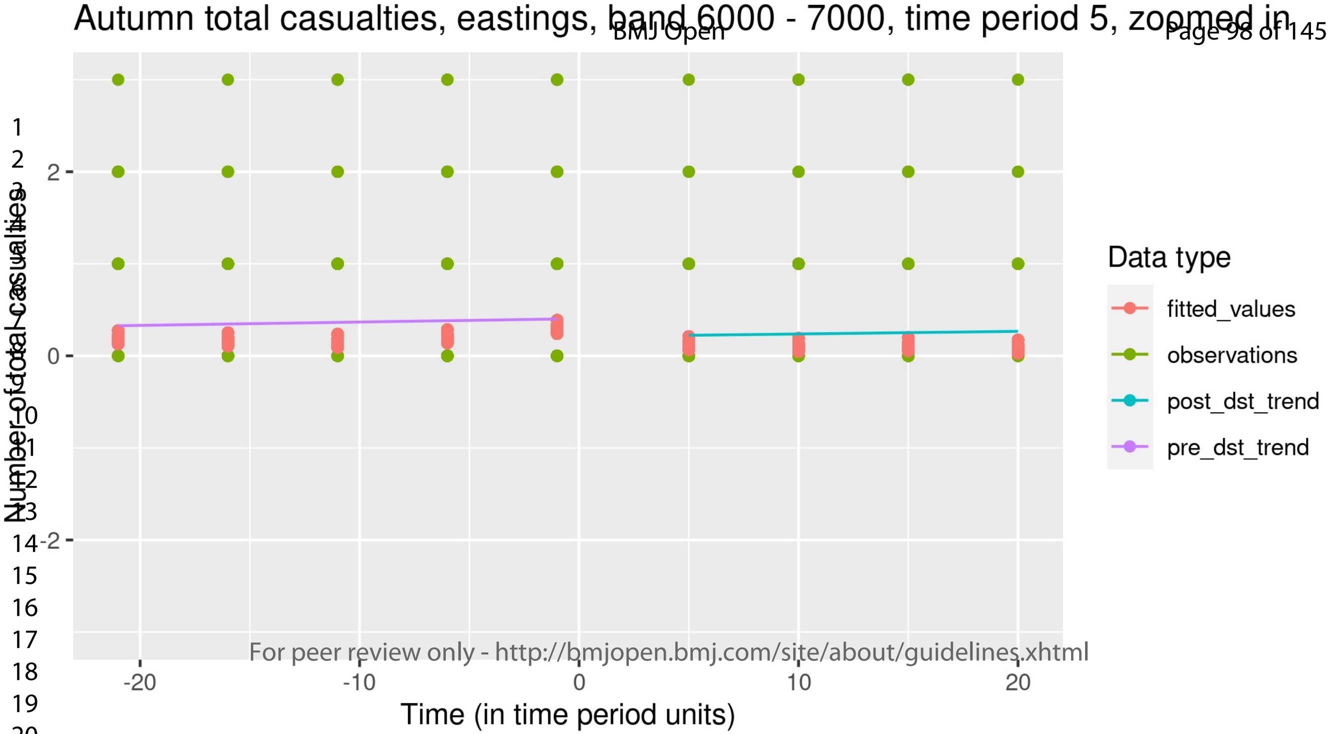

Autumn total casualties, eastings, band 5000 - 6000, time period 4
Number of total casualties
10.0
7.5
5.0
2.5
0.0
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

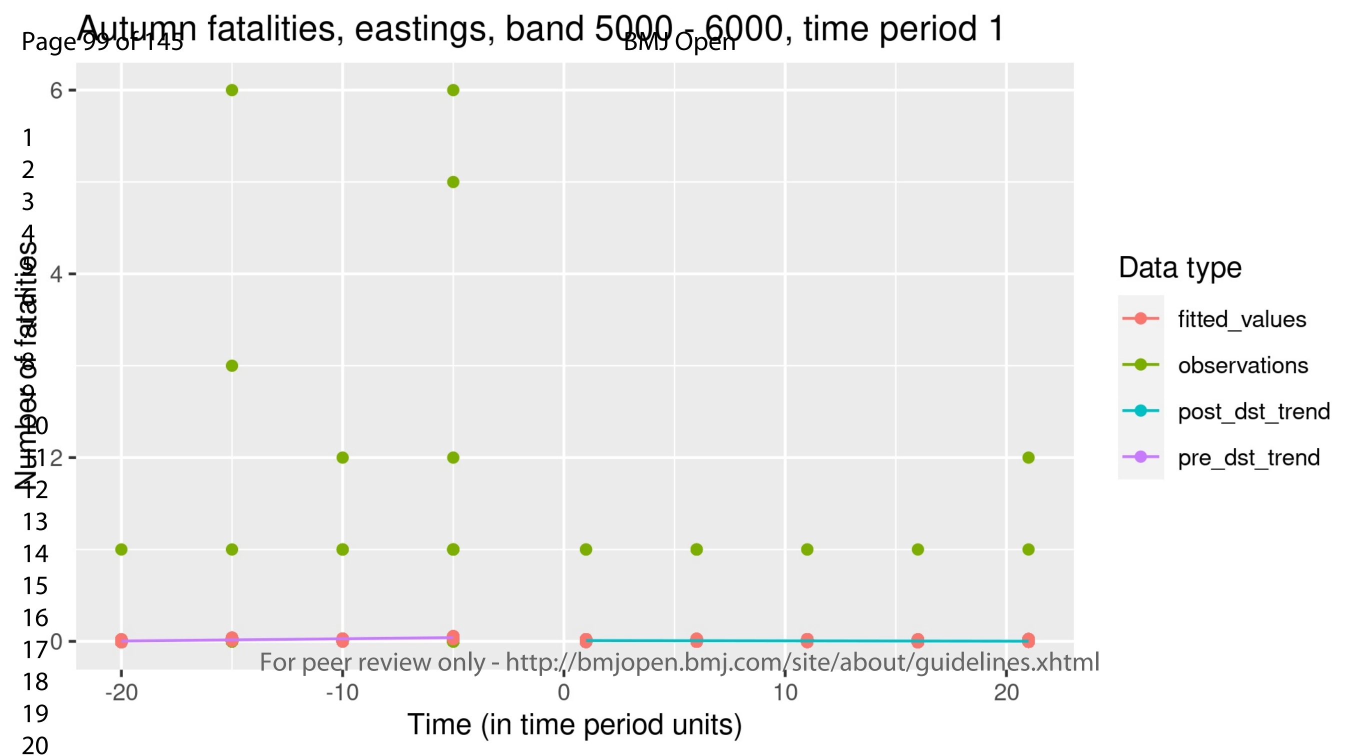

Autumn total casualties, eastings, band 5000 - 6000, time period 4, zoomed in
Number of total casualties
2
0
-2
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Autumn total casualties, eastings, band 5000 - 6000, time period 5
Number of total casualties
0
5
10
15
20
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

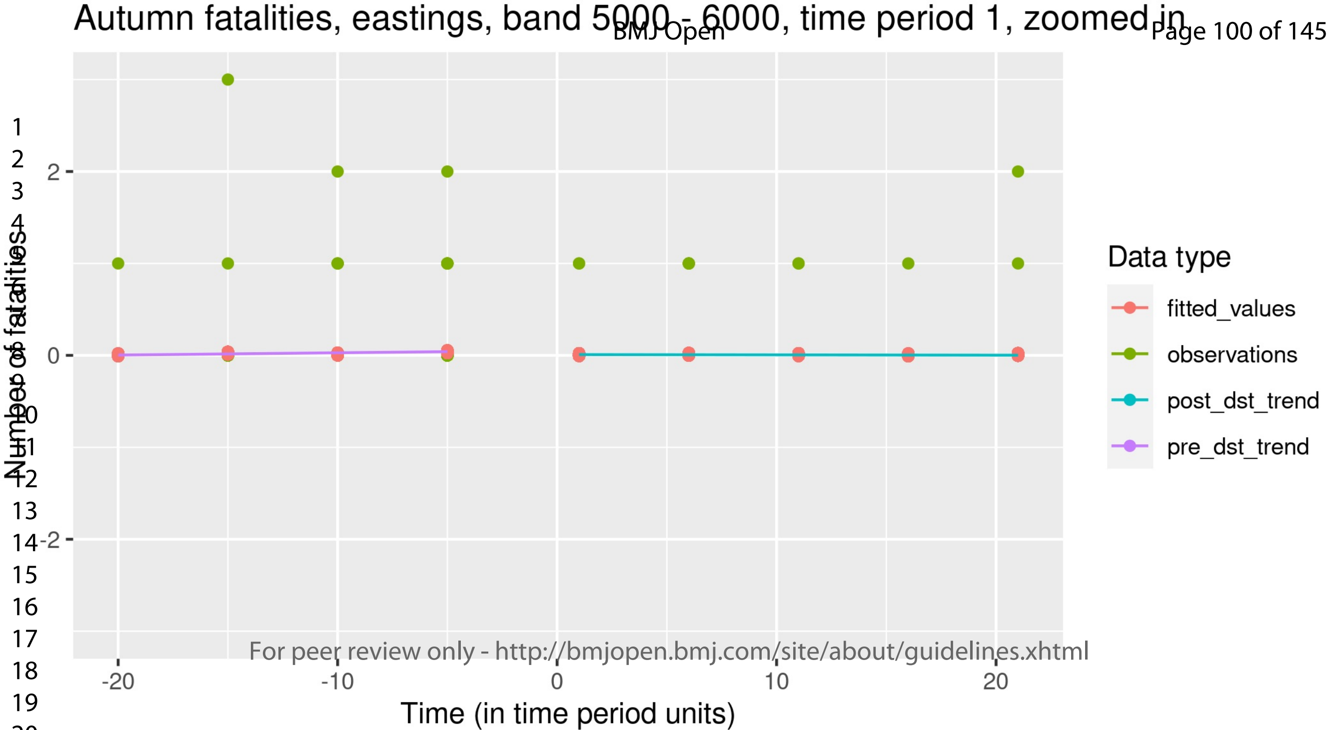

Autumn total casualties, eastings, band 5000 - 6000, time period 5, zoomed in
Number of total casualties
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

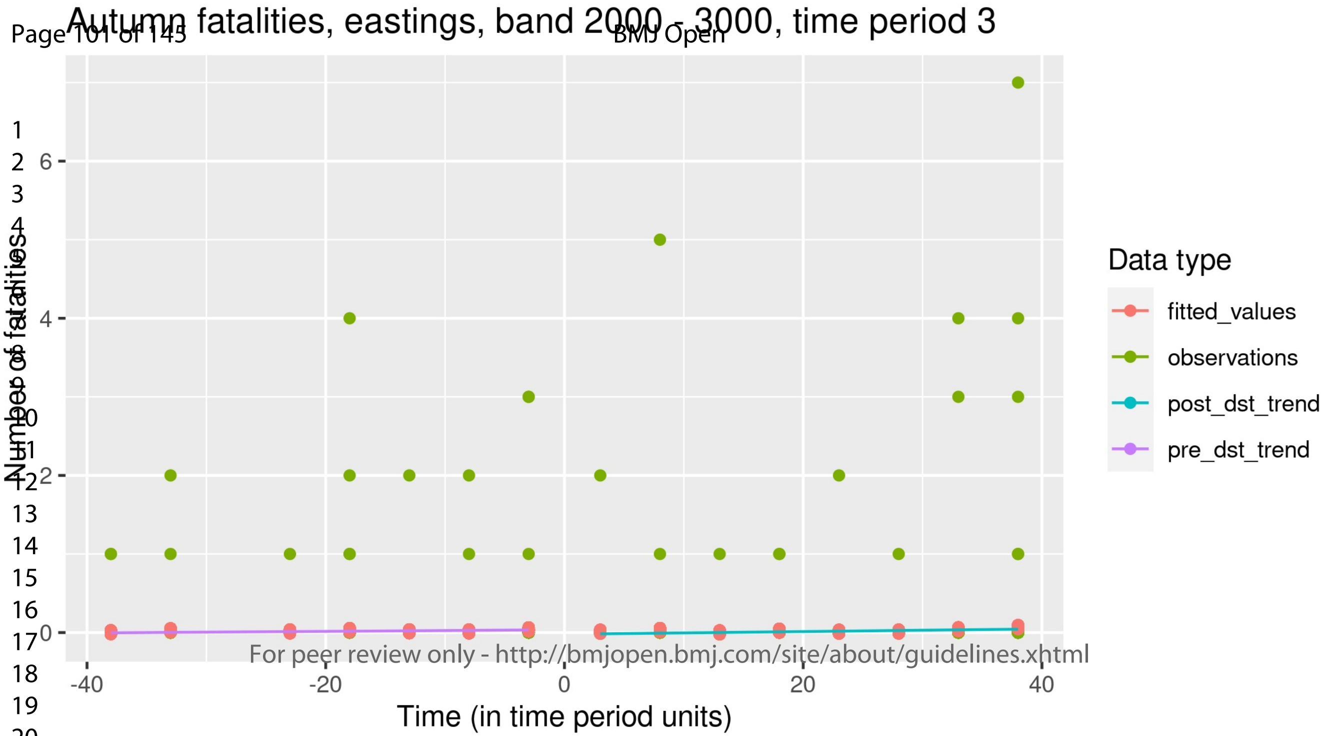

Autumn total casualties, eastings, band 6000 - 7000, time period 5
Number of total casualties
5
4
3
2
1
0
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

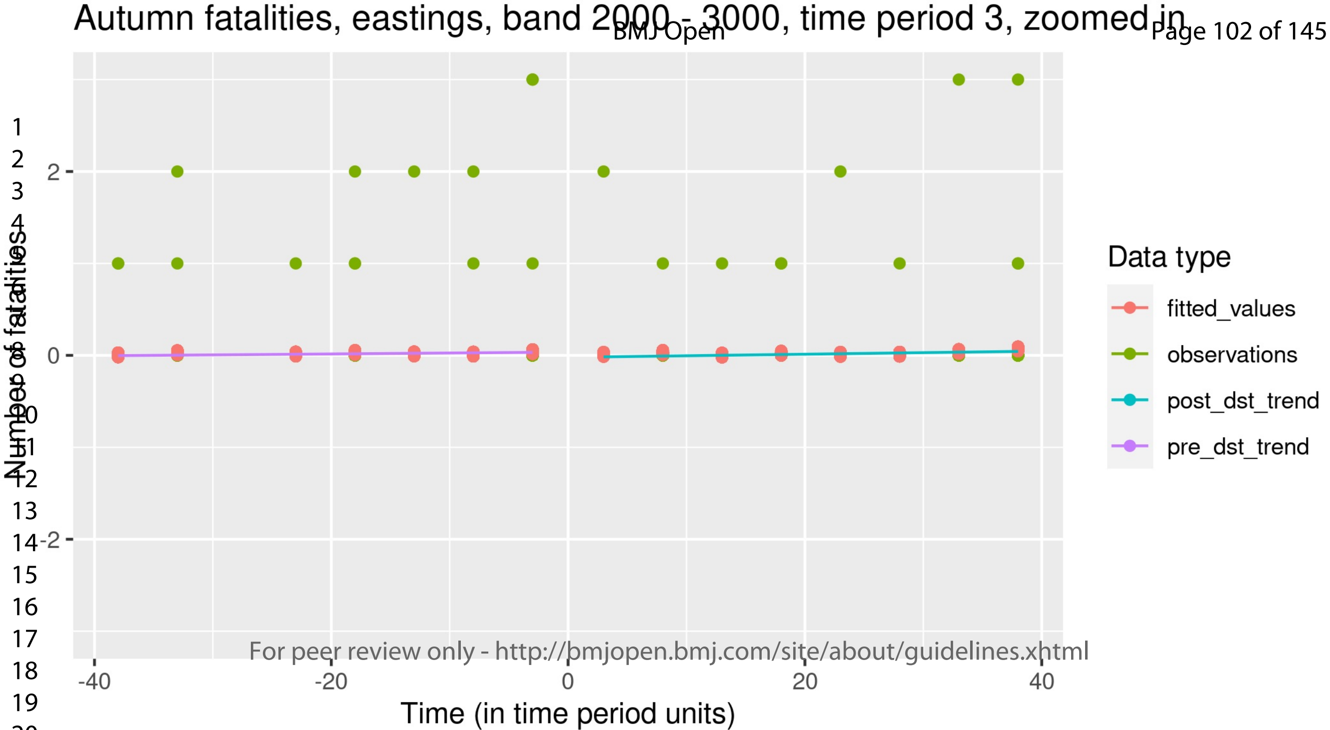

Autumn total casualties, eastings, band 6000 - 7000, time period 5, zoomed in
Number of total casualties
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

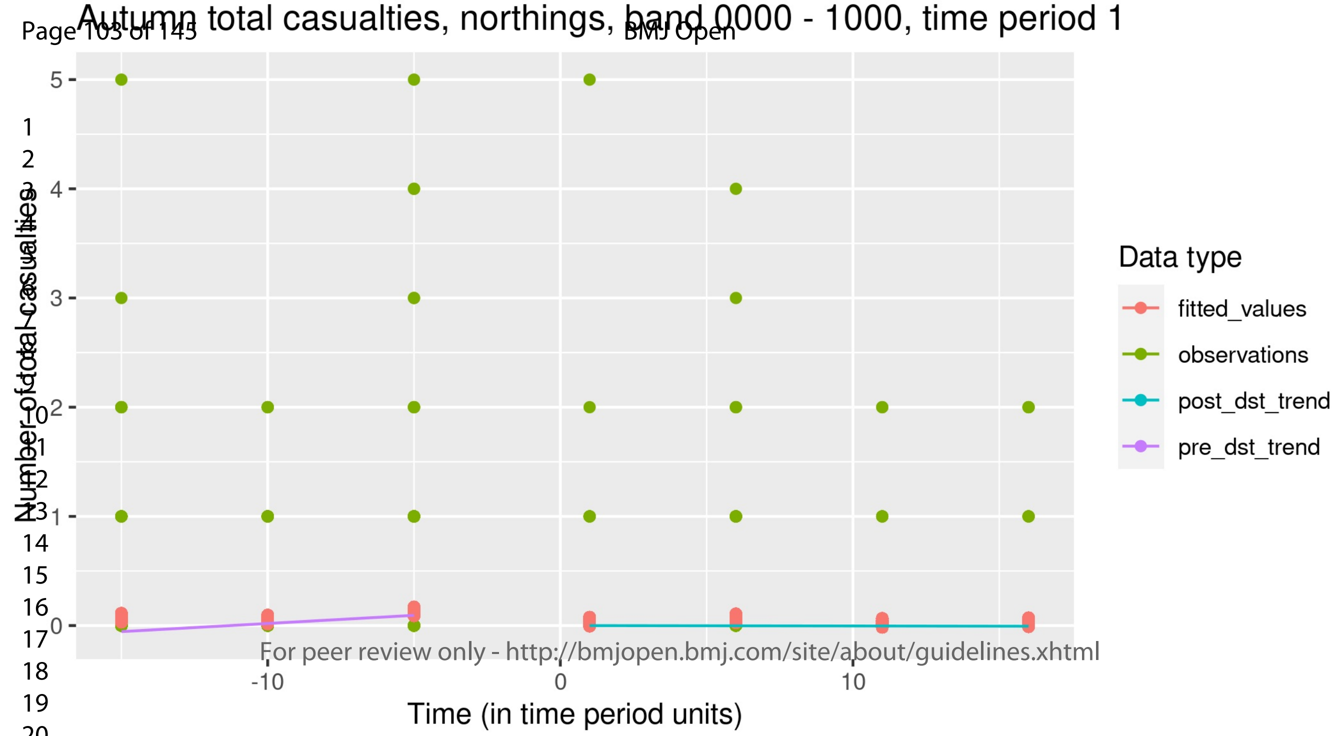


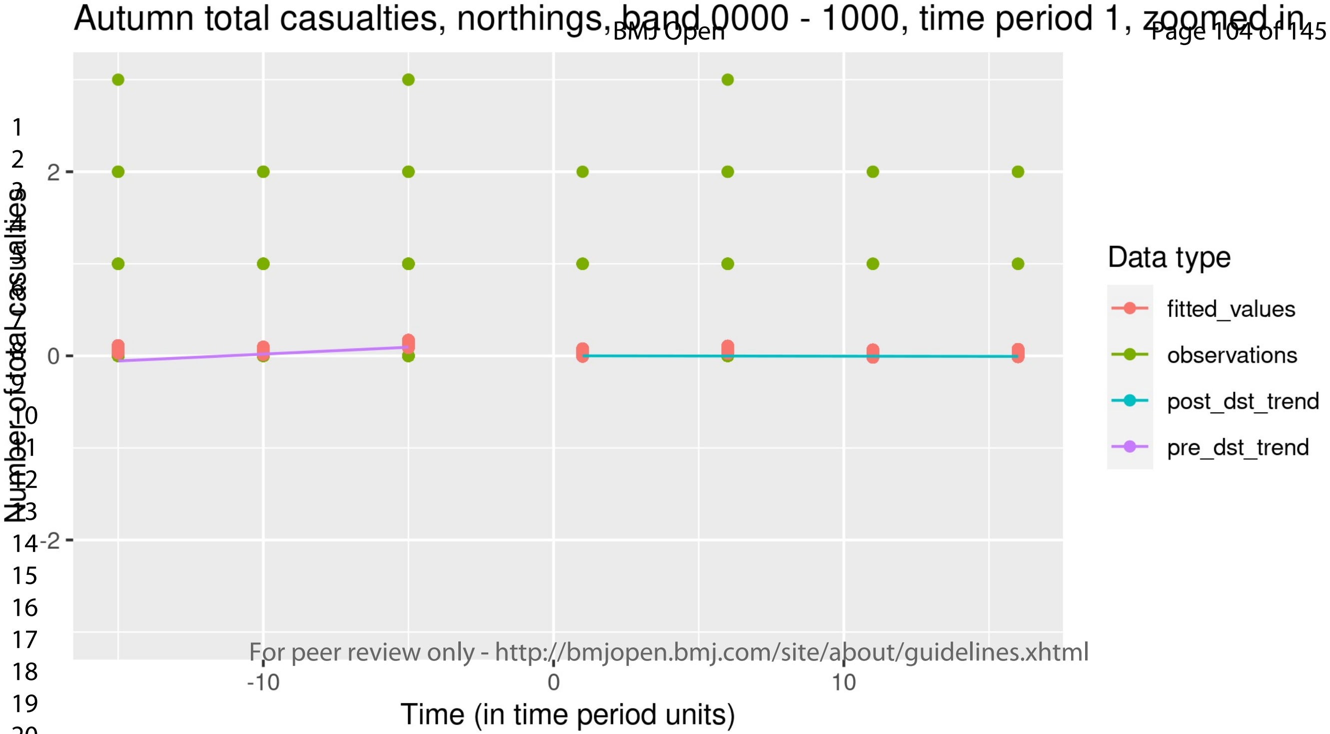
Autumn fatalities, eastings, band 5000 - 6000, time period 1
Number of fatalities
6
4
2
0
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

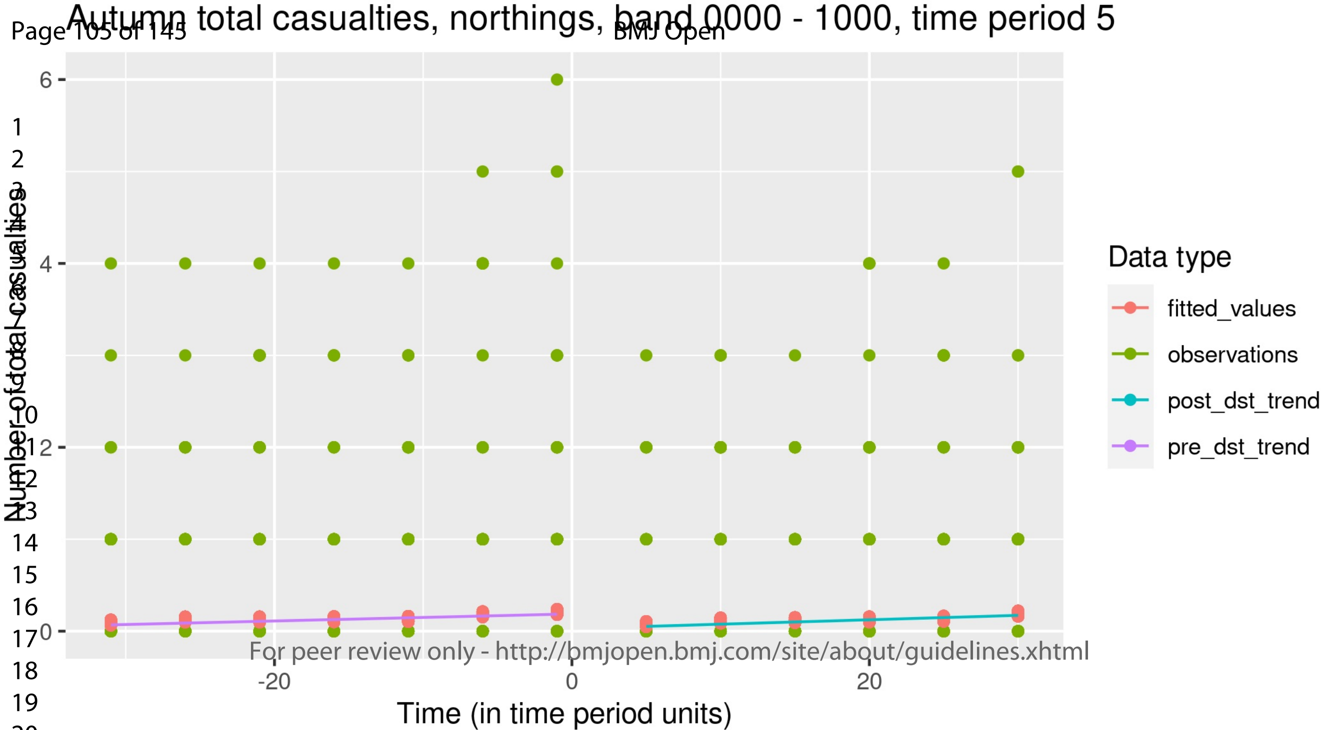

Autumn fatalities, eastings, band 5000 - 6000, time period 1, zoomed in
Number of fatalities
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

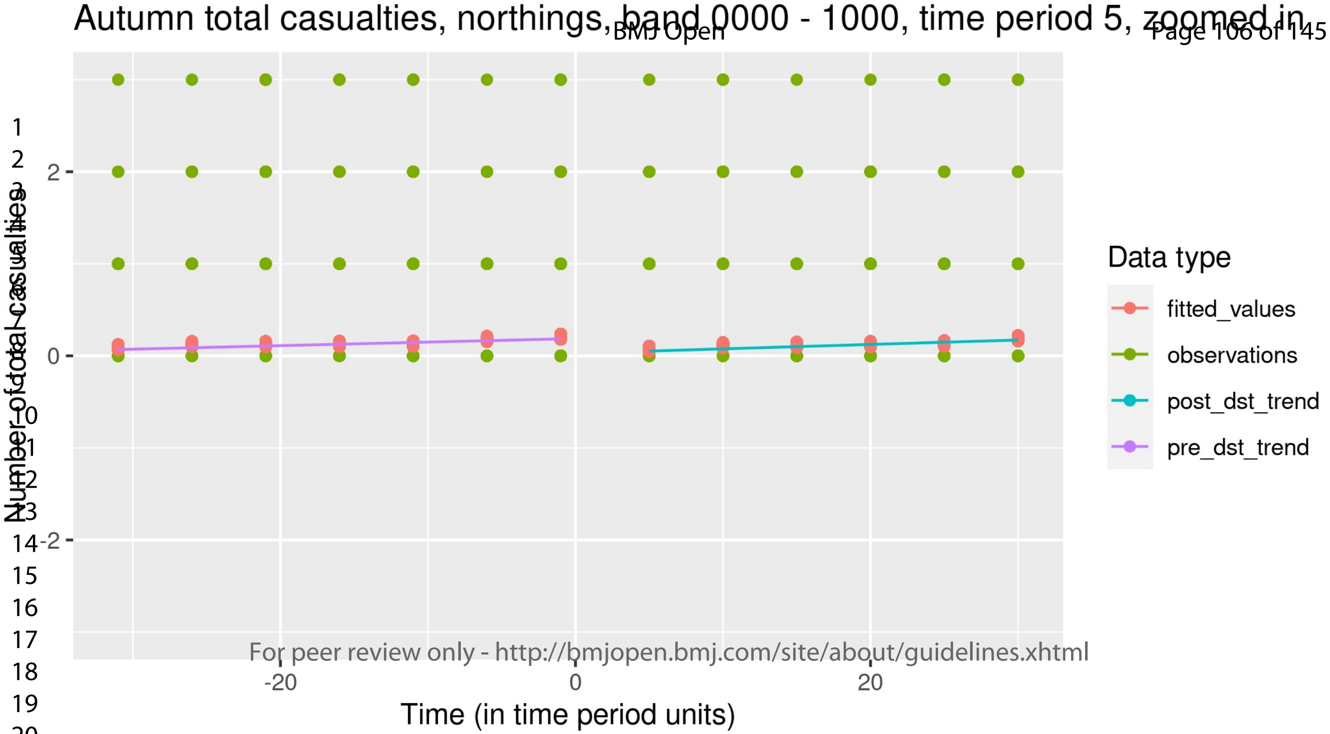

Autumn fatalities, eastings, band 2000 - 3000, time period 3
Number of fatalities
6
4
2
0
-40
-20
0
20
40
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

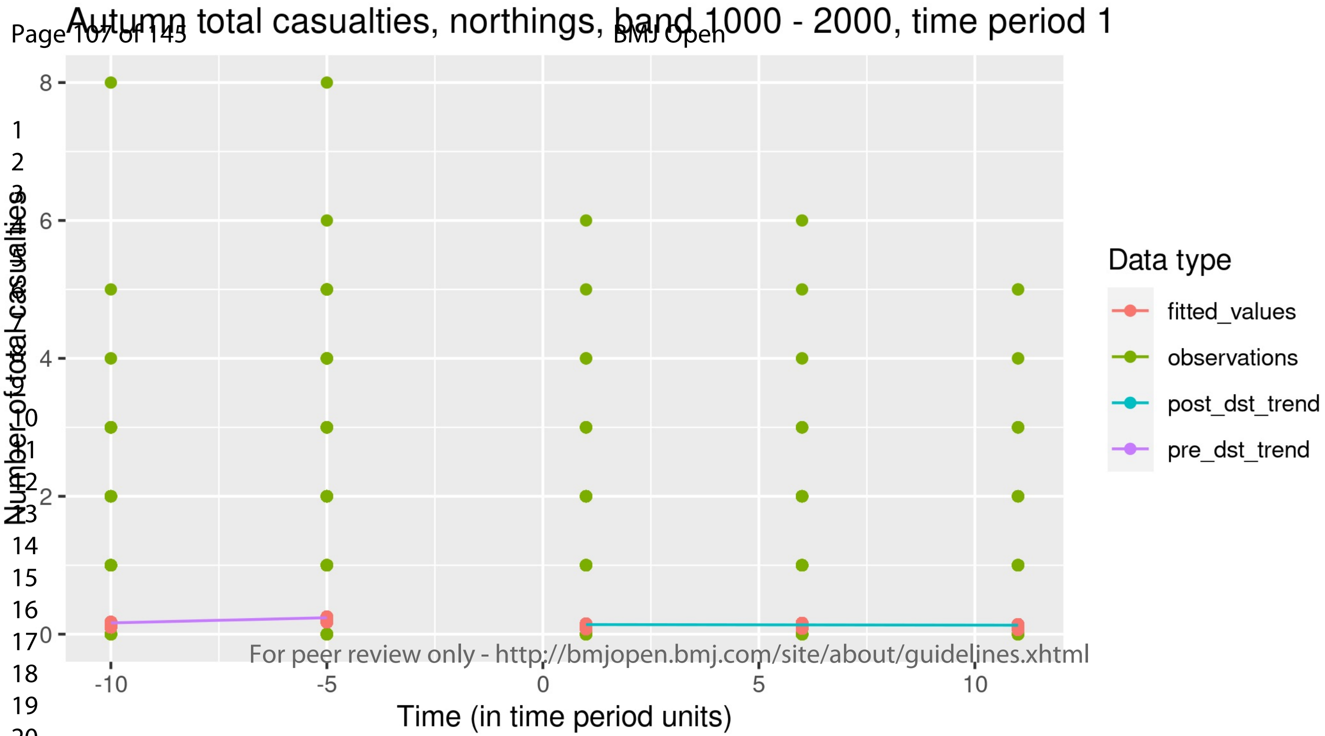

Autumn fatalities, eastings, band 2000 - 3000, time period 3, zoomed in
Number of fatalities
2
0
-2
-40
-20
0
20
40
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

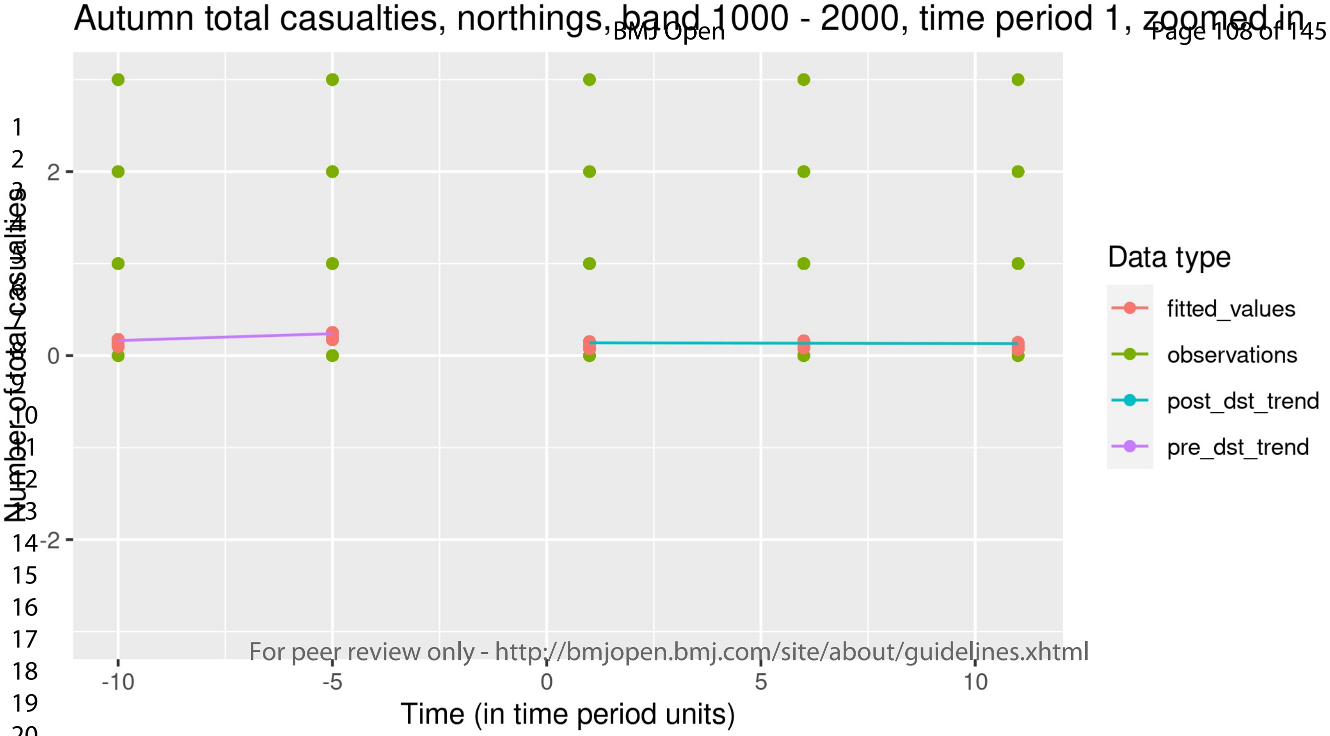

Autumn total casualties, northings, band 0000 - 1000, time period 1
Number of total casualties
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend
0
1
2
3
4
5
-10
0
10

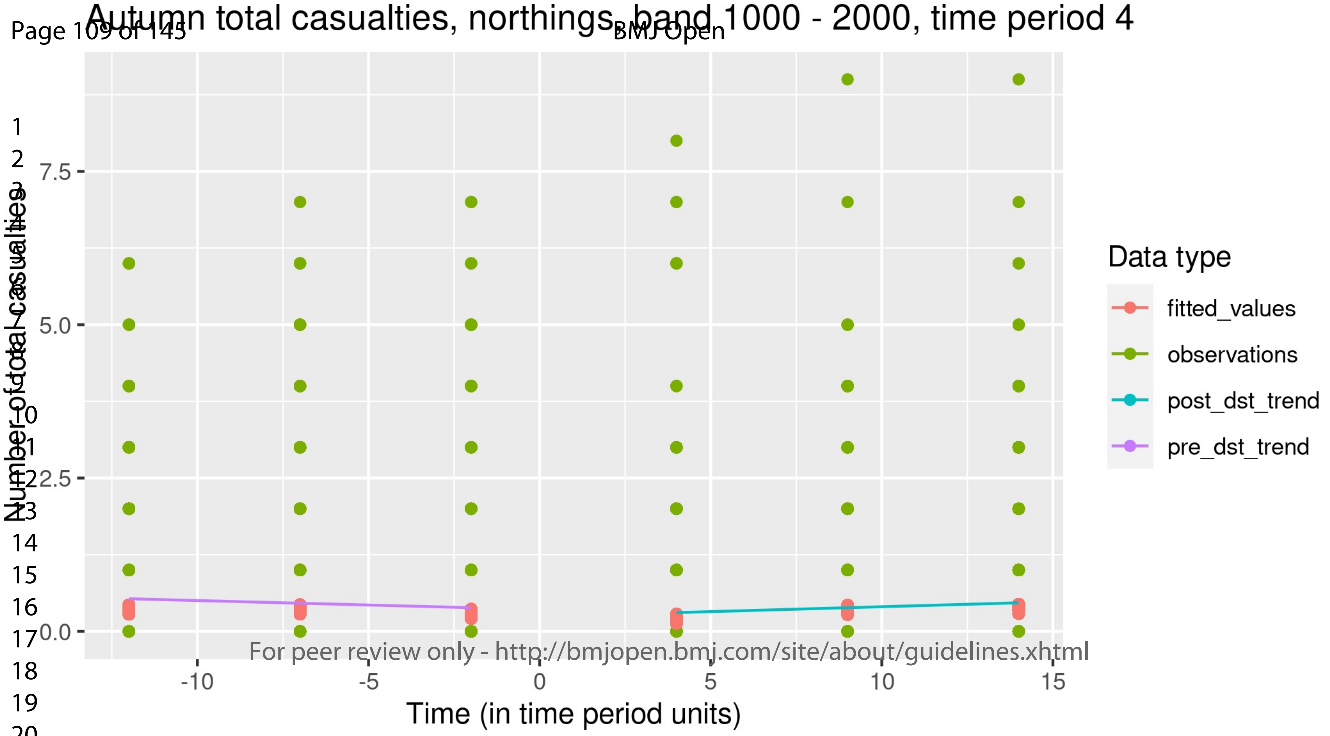

Autumn total casualties, northings, band 0000 - 1000, time period 1, zoomed in
Number of total casualties
2
0
-2
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Autumn total casualties, northings, band 0000 - 1000, time period 5
Number of total casualties
6
4
2
0
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

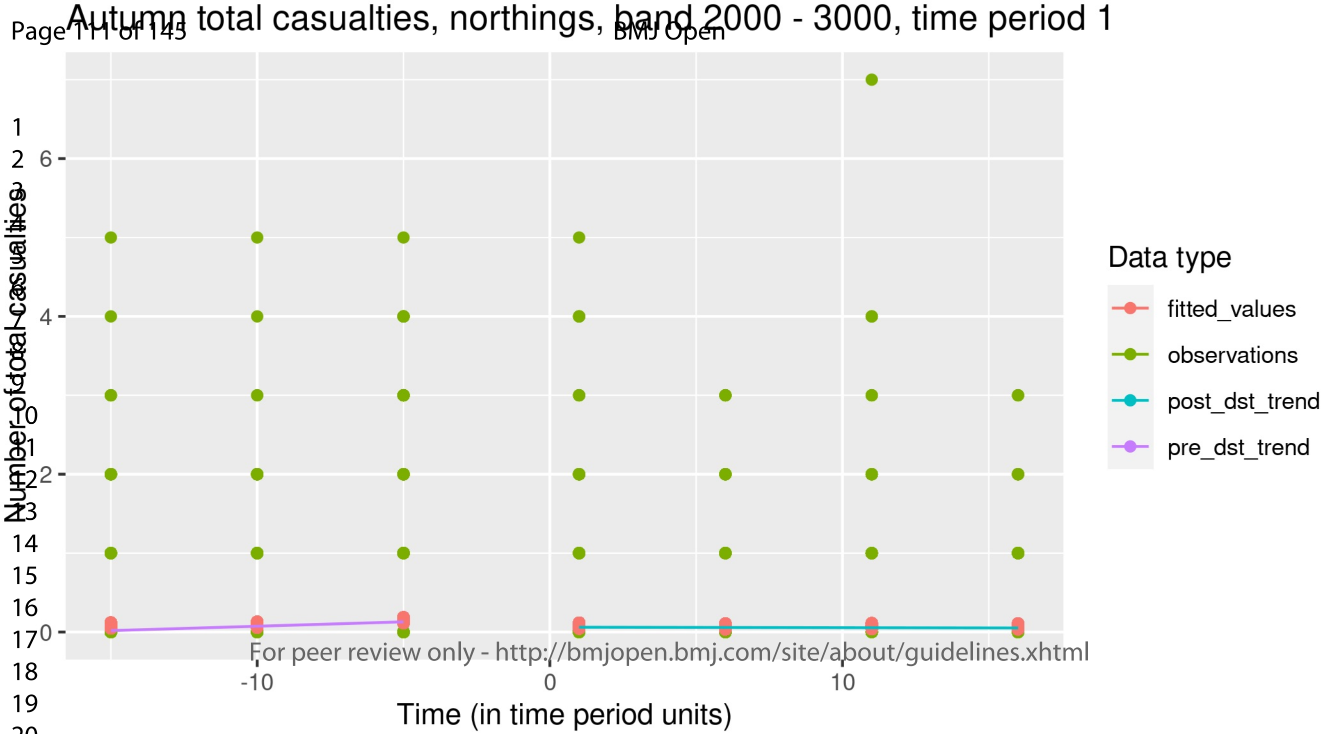

Autumn total casualties, northings, band 0000 - 1000, time period 5, zoomed in
Number of total casualties
2
0
-2
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

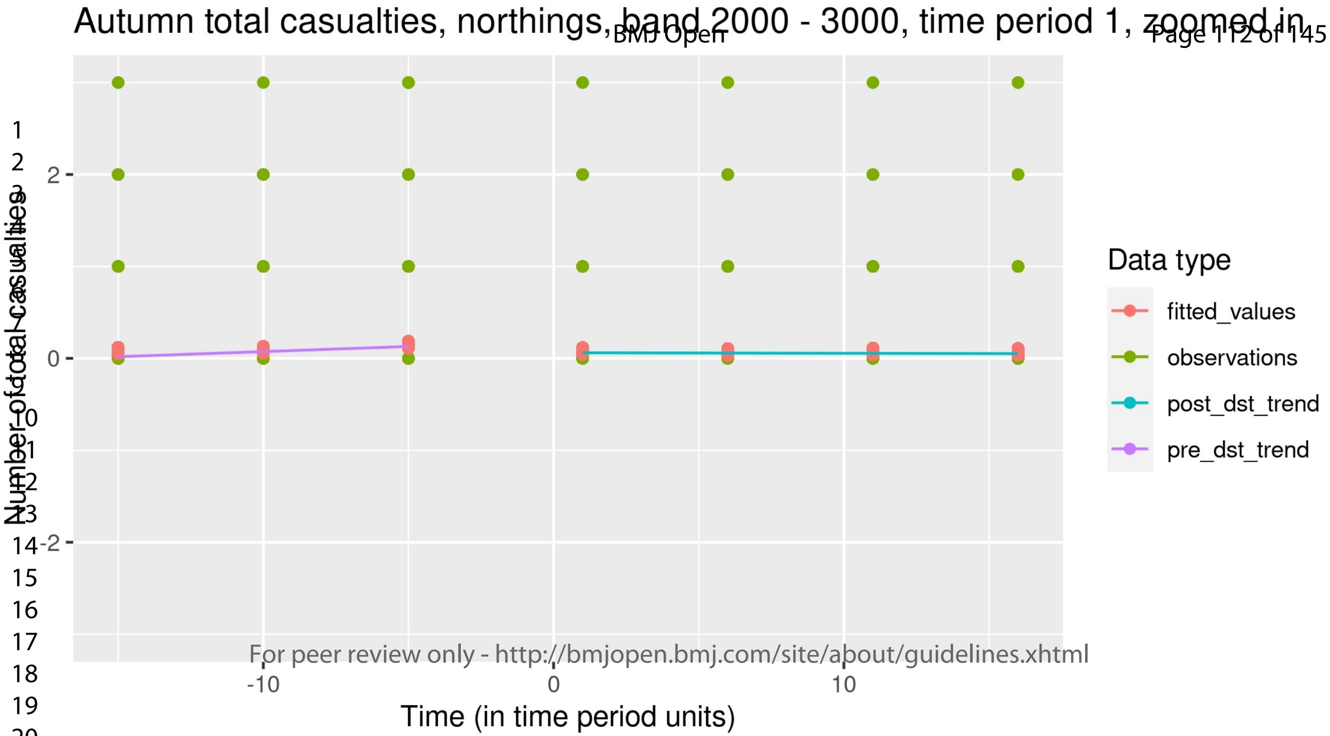

Autumn total casualties, northings, band 1000 - 2000, time period 1
Number of total casualties
8
6
4
2
0
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

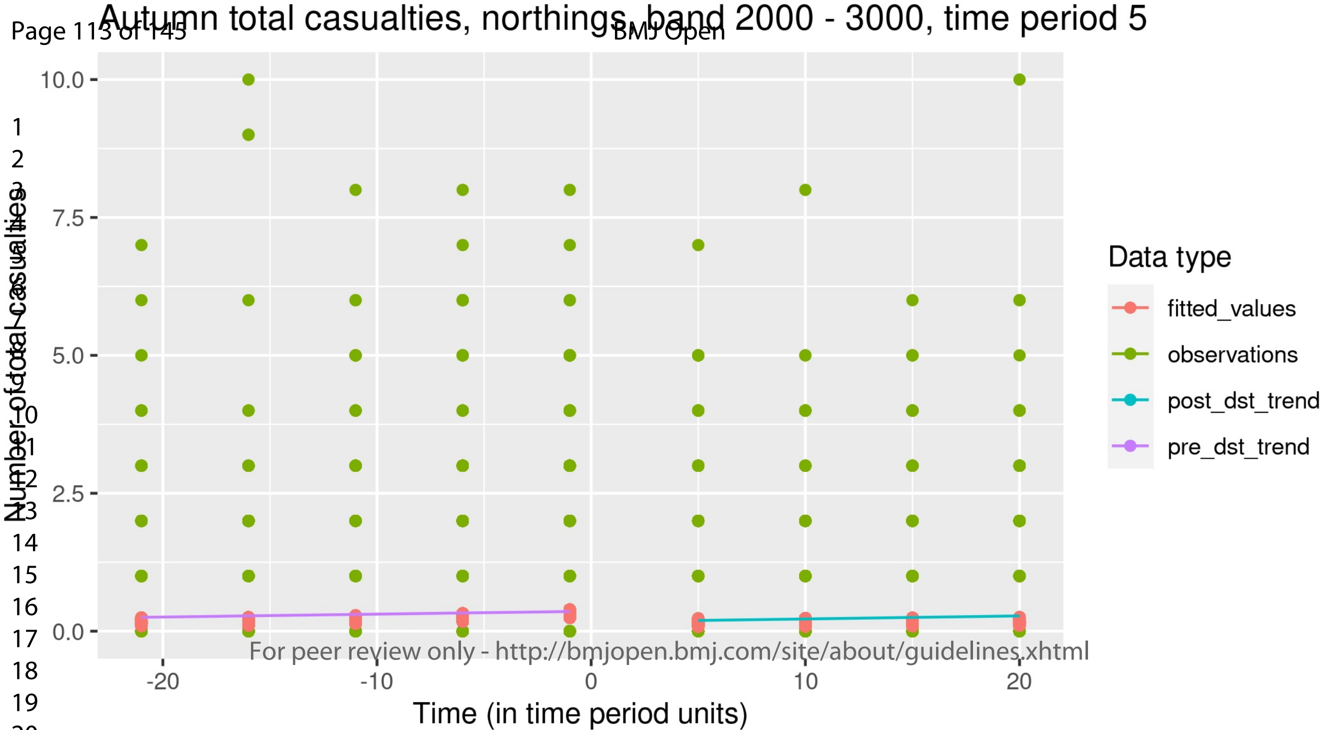

Autumn total casualties, northings, band 1000 - 2000, time period 1, zoomed in
Number of total casualties
2
0
-2
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

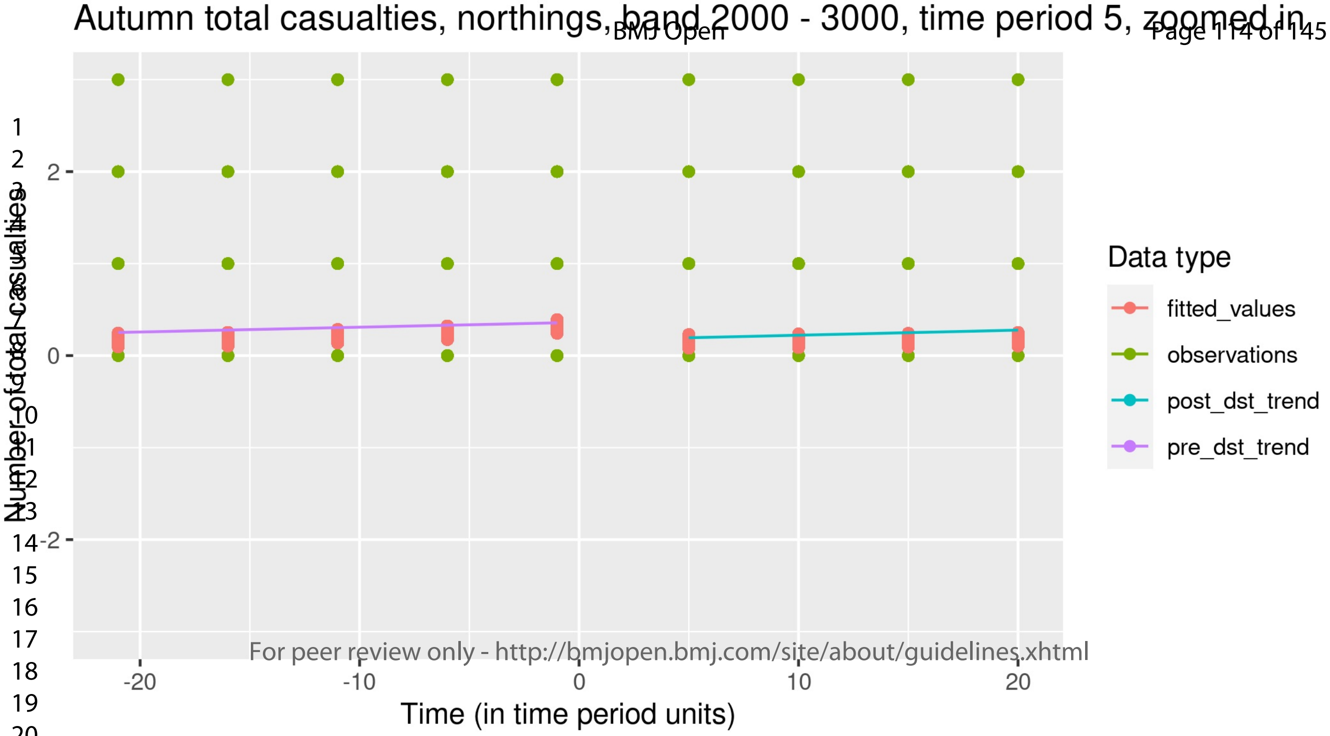

Autumn total casualties, northings, band 1000 - 2000, time period 4
Number of total casualties
7.5
5.0
2.5
0.0
-10
-5
0
5
10
15
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

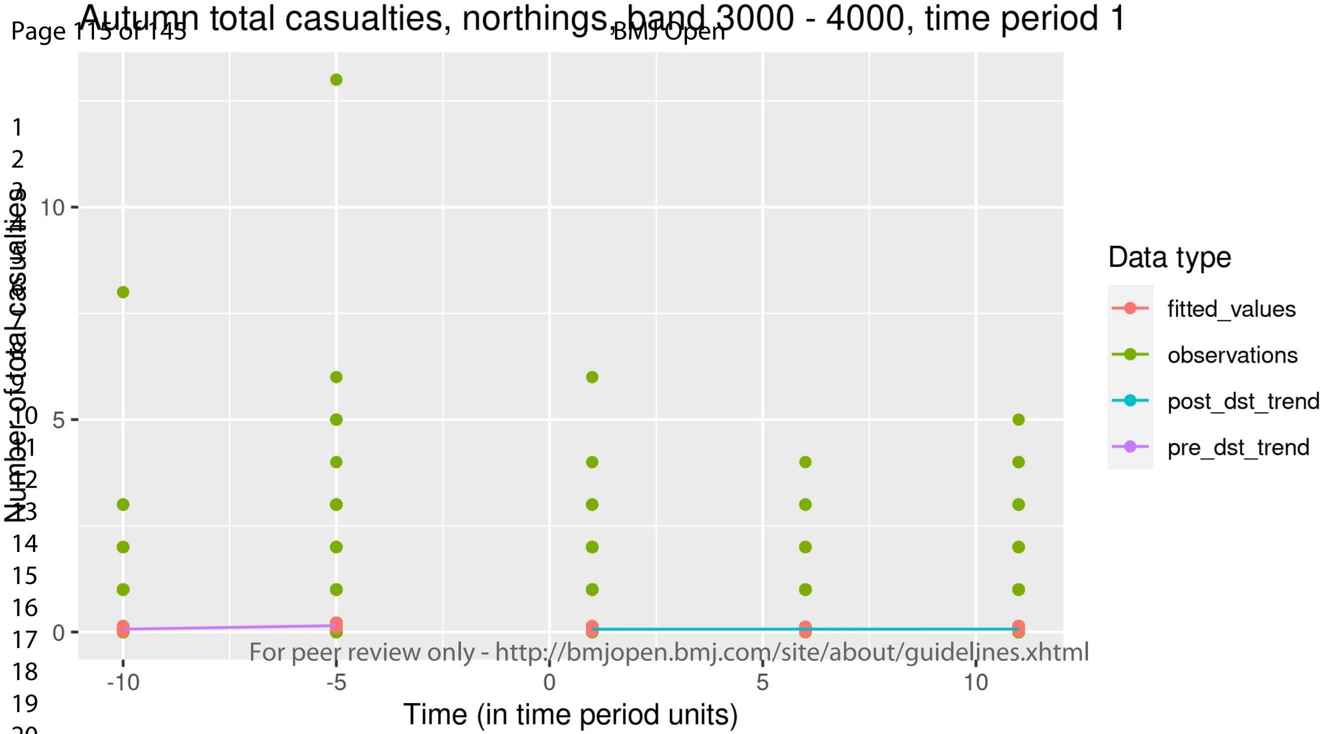

Autumn total casualties, northings, band 1000 - 2000, time period 4, zoomed in
Number of total casualties
2
0
-2
-10
-5
0
5
10
15
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

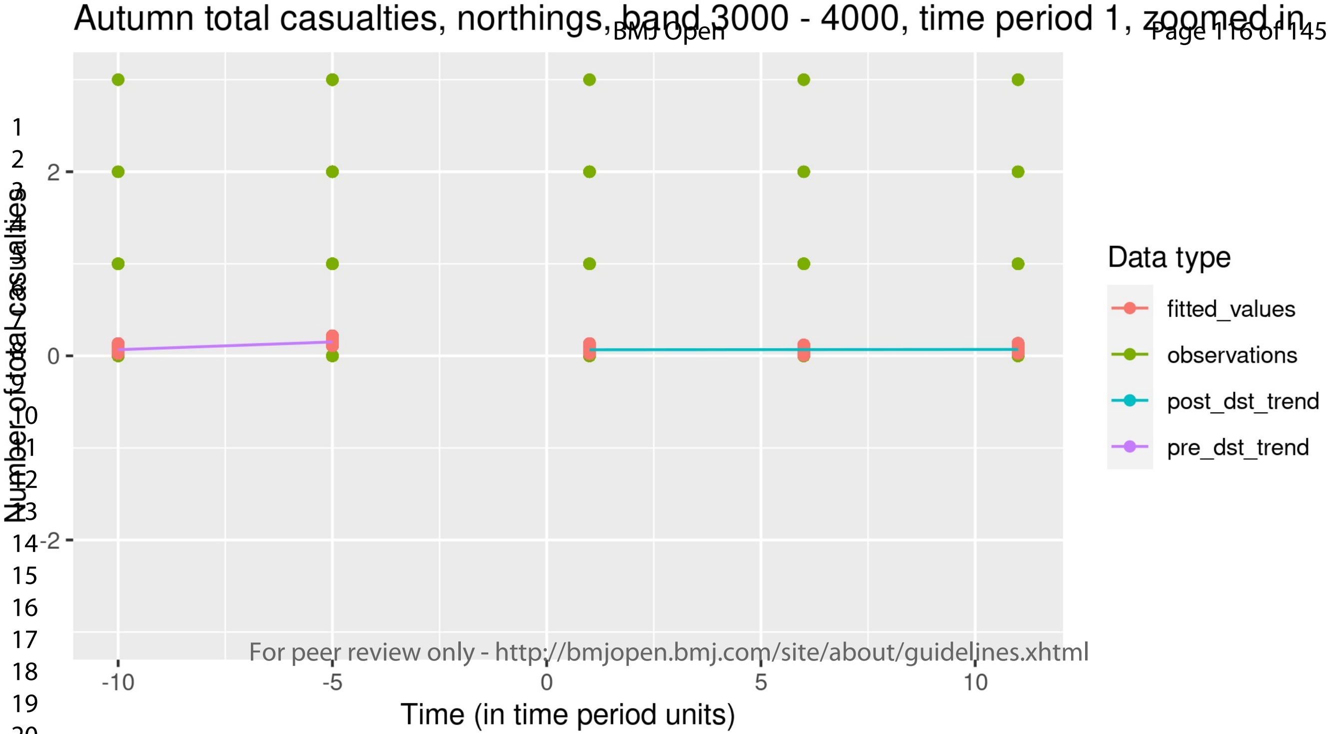

Autumn total casualties, northings, band 2000 - 3000, time period 1
Number of total casualties
6
4
2
0
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

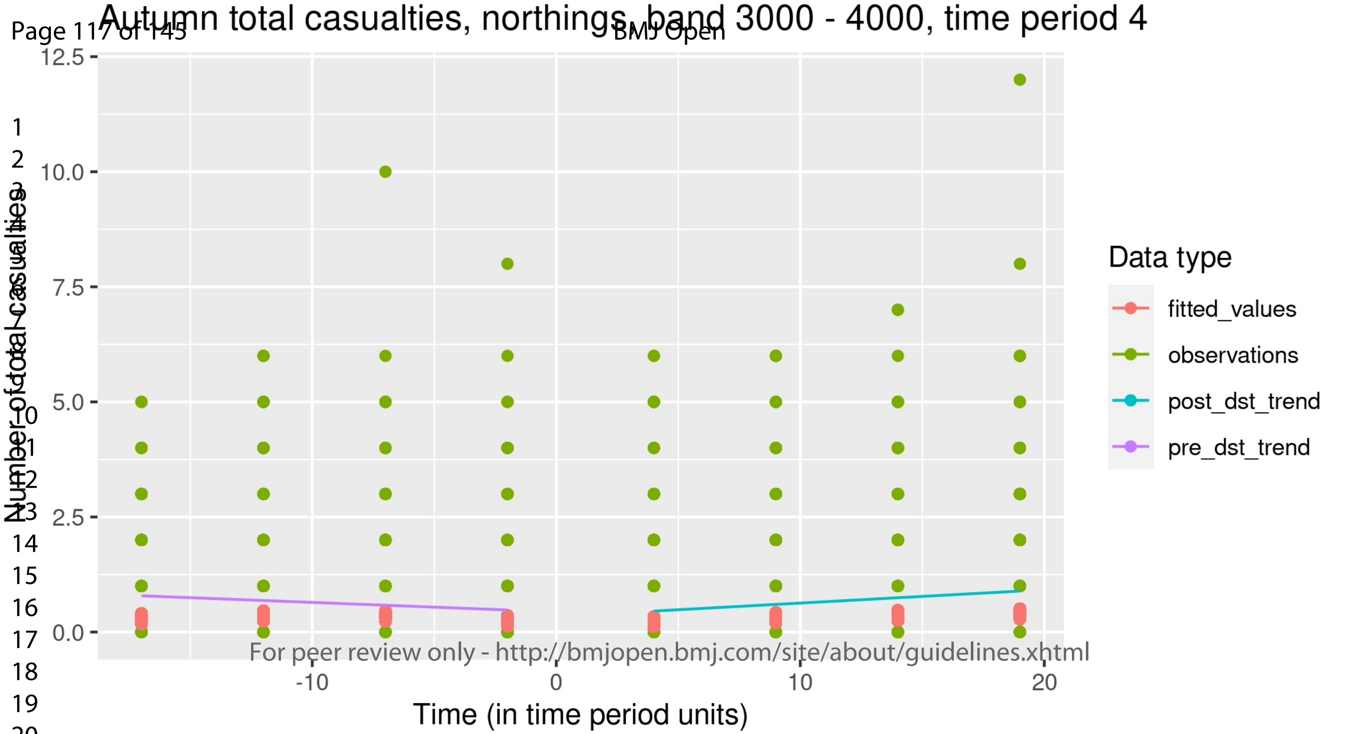

Autumn total casualties, northings, band 2000 - 3000, time period 1, zoomed in
Number of total casualties
2
0
-2
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

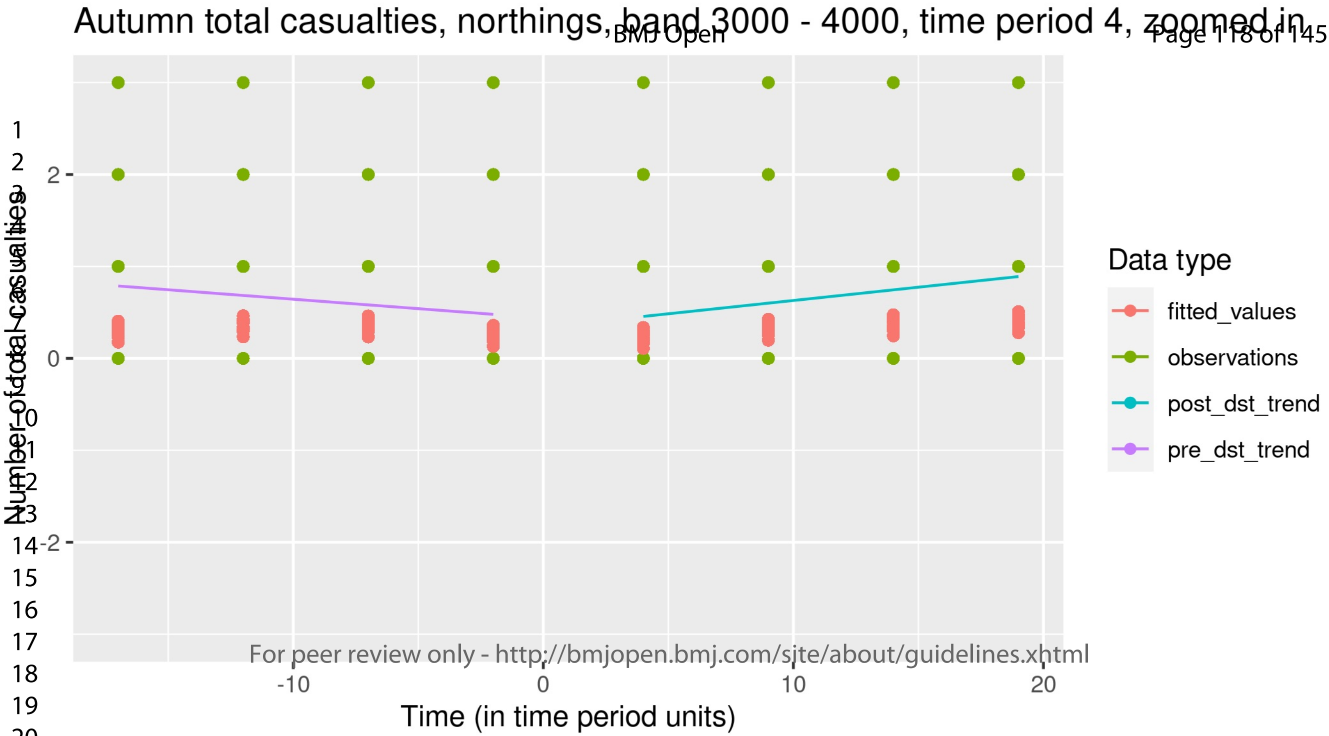

Autumn total casualties, northings, band 2000 - 3000, time period 5
Number of total casualties
10.0
7.5
5.0
2.5
0.0
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

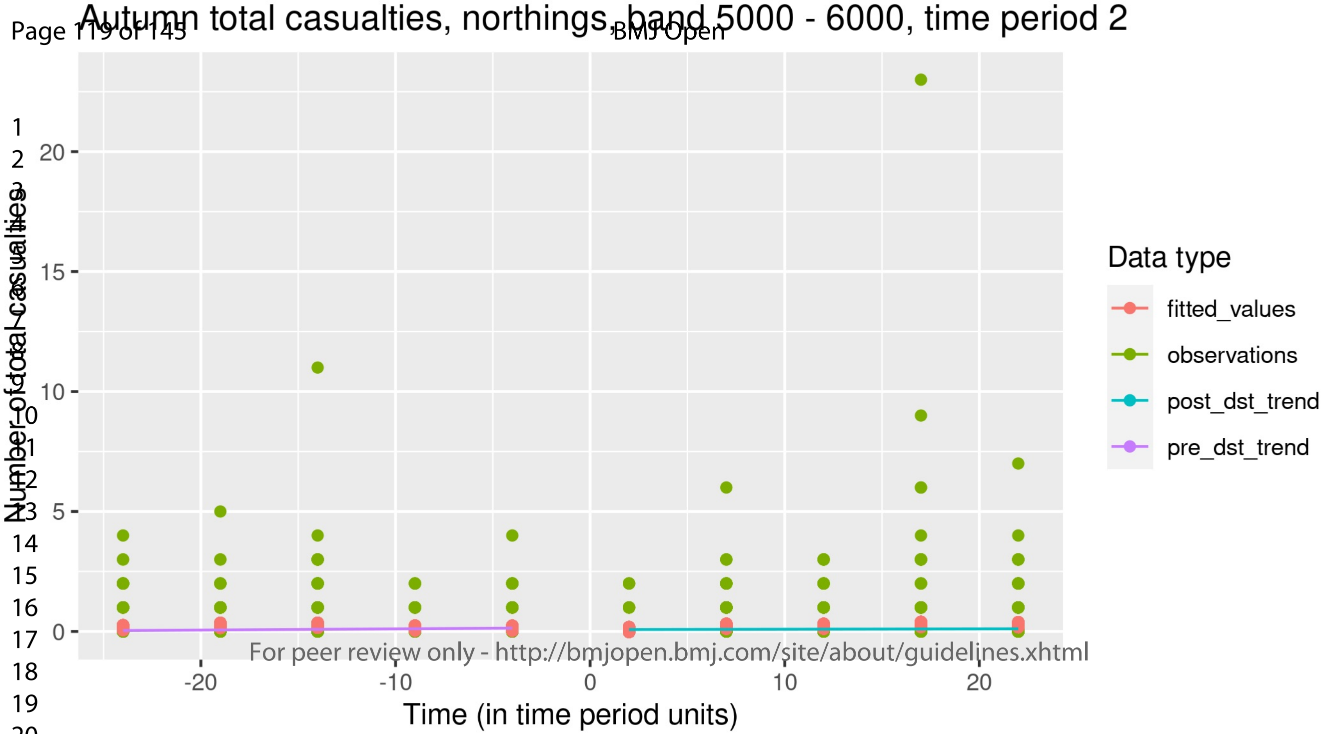

Autumn total casualties, northings, band 2000 - 3000, time period 5, zoomed in
Number of total casualties
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

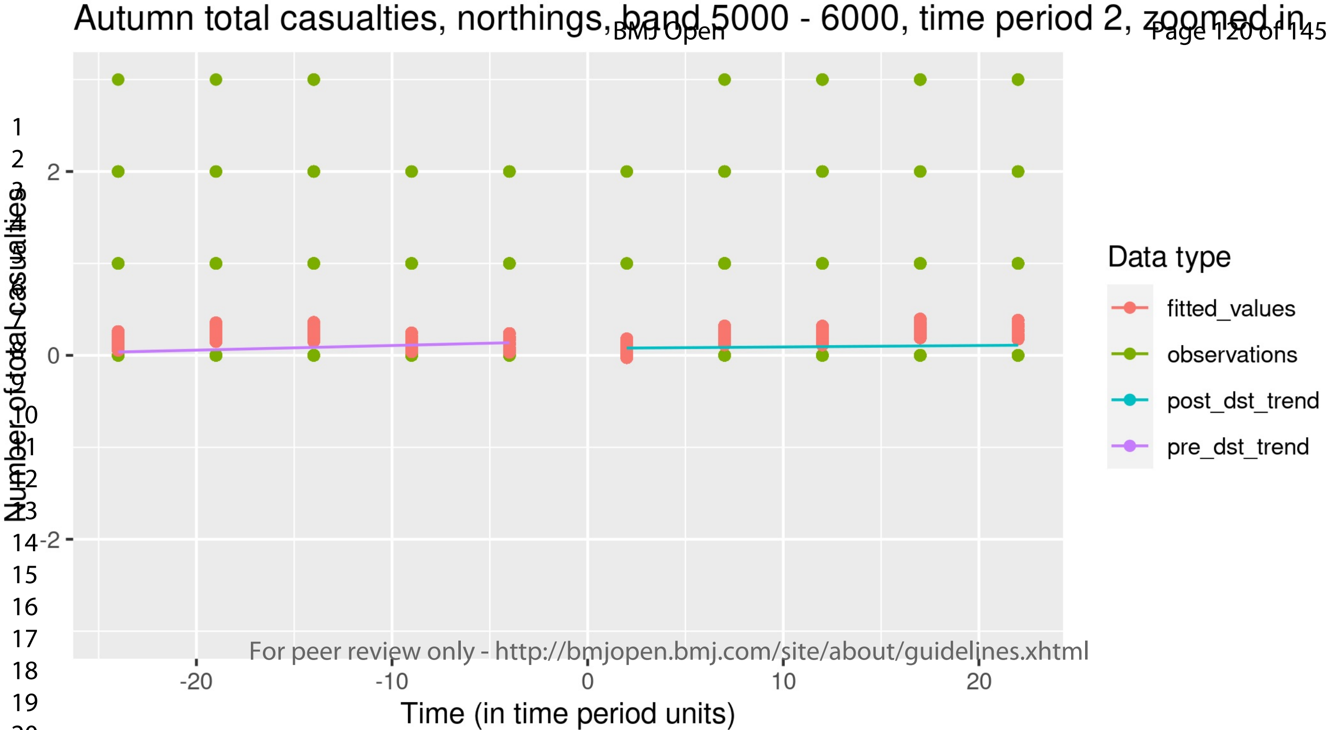

Autumn total casualties, northings, band 3000 - 4000, time period 1
Number of total casualties
10
5
0
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

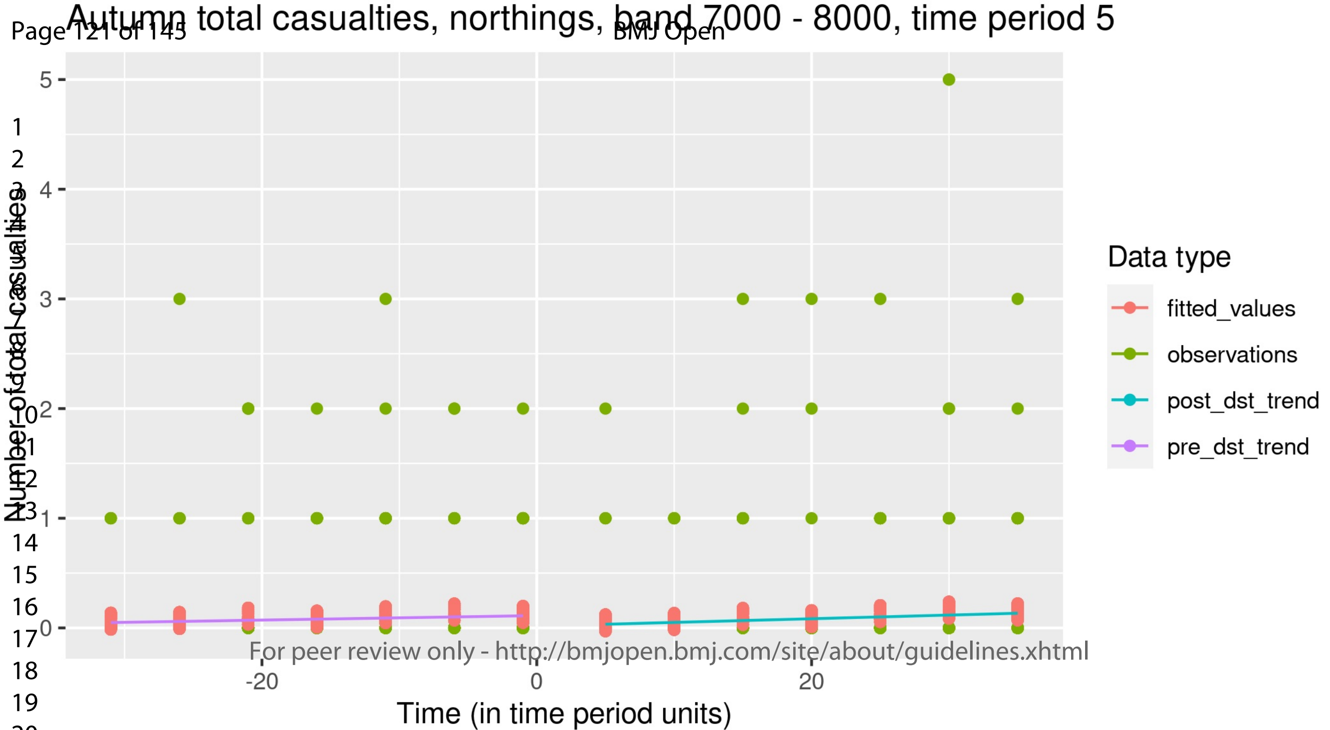

Autumn total casualties, northings, band 3000 - 4000, time period 1, zoomed in
Number of total casualties
2
0
-2
-10
-5
0
5
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

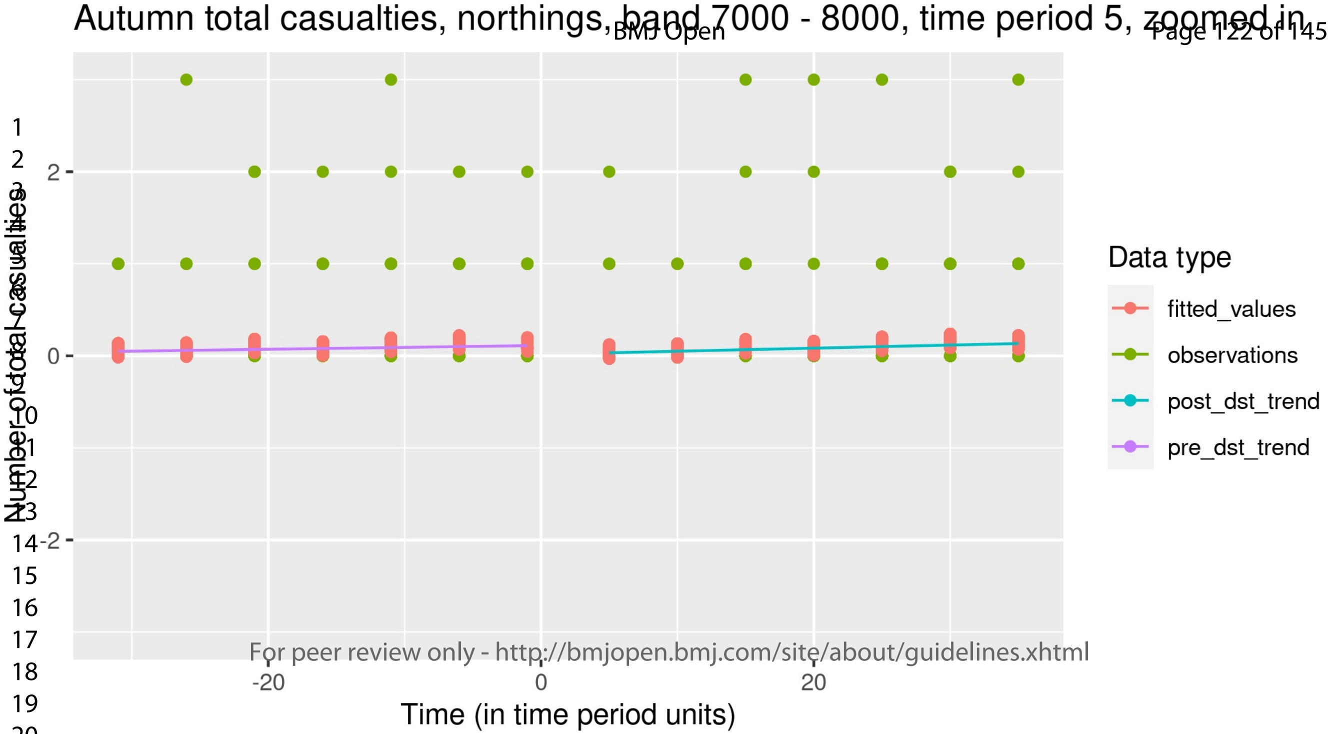

Autumn total casualties, northings, band 3000 - 4000, time period 4
Number of total casualties
12.5
10.0
7.5
5.0
2.5
0.0
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Autumn total casualties, northings, band 3000 - 4000, time period 4, zoomed in
Number of total casualties
2
0
-2
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

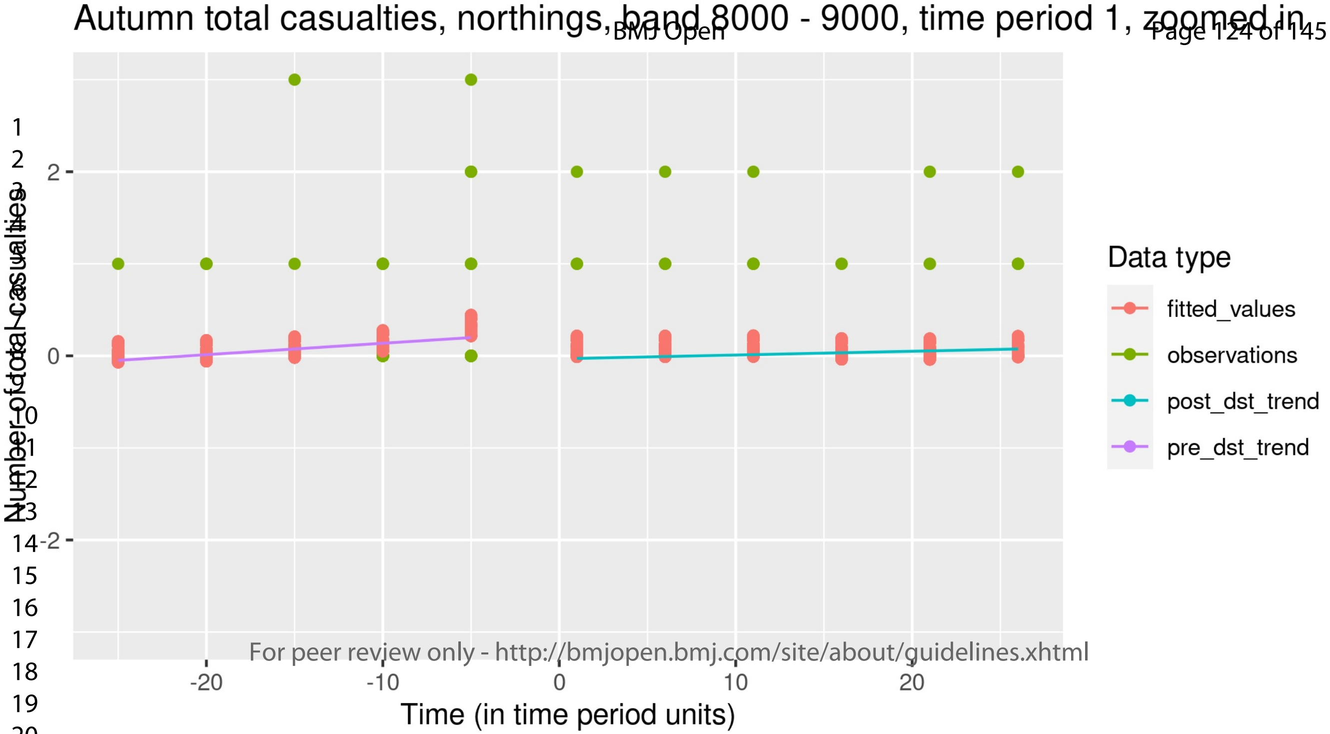

Autumn total casualties, northings, band 5000 - 6000, time period 2
Number of total casualties
0
5
10
15
20
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

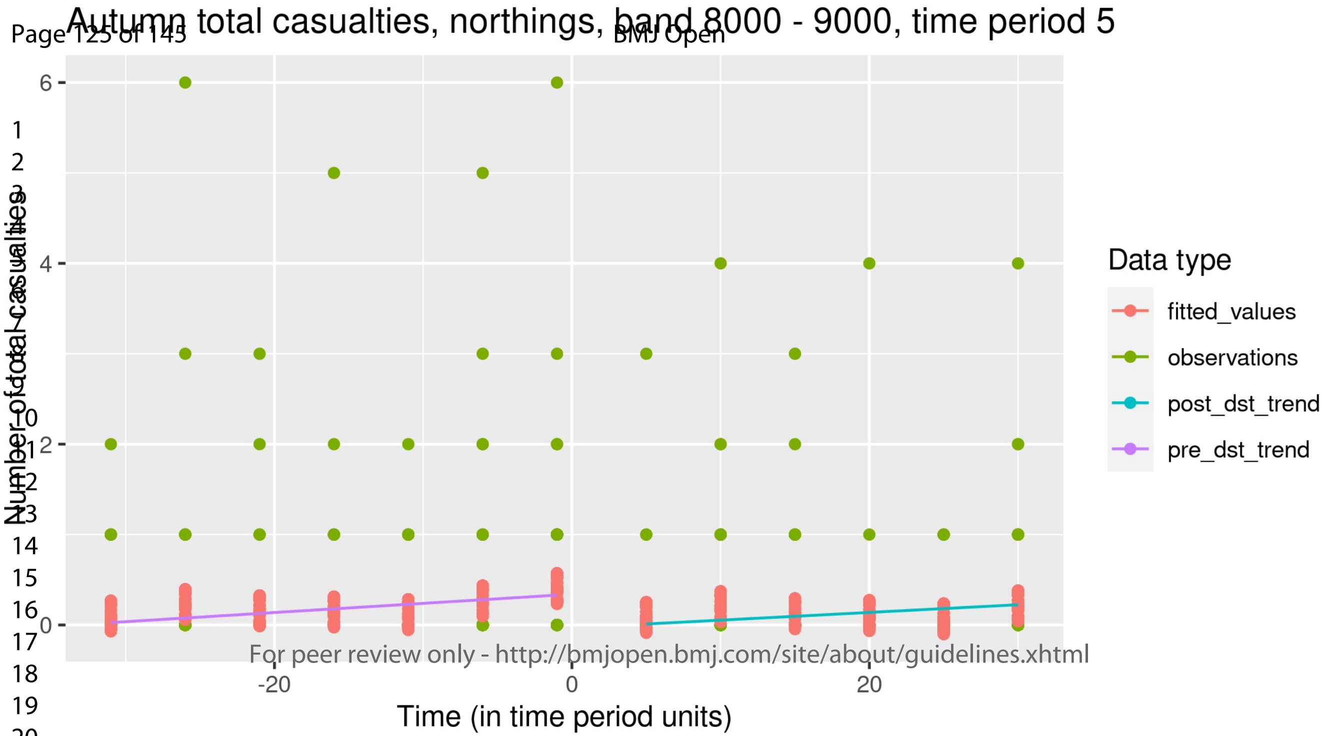

Autumn total casualties, northings, band 5000 - 6000, time period 2, zoomed in
Number of total casualties
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

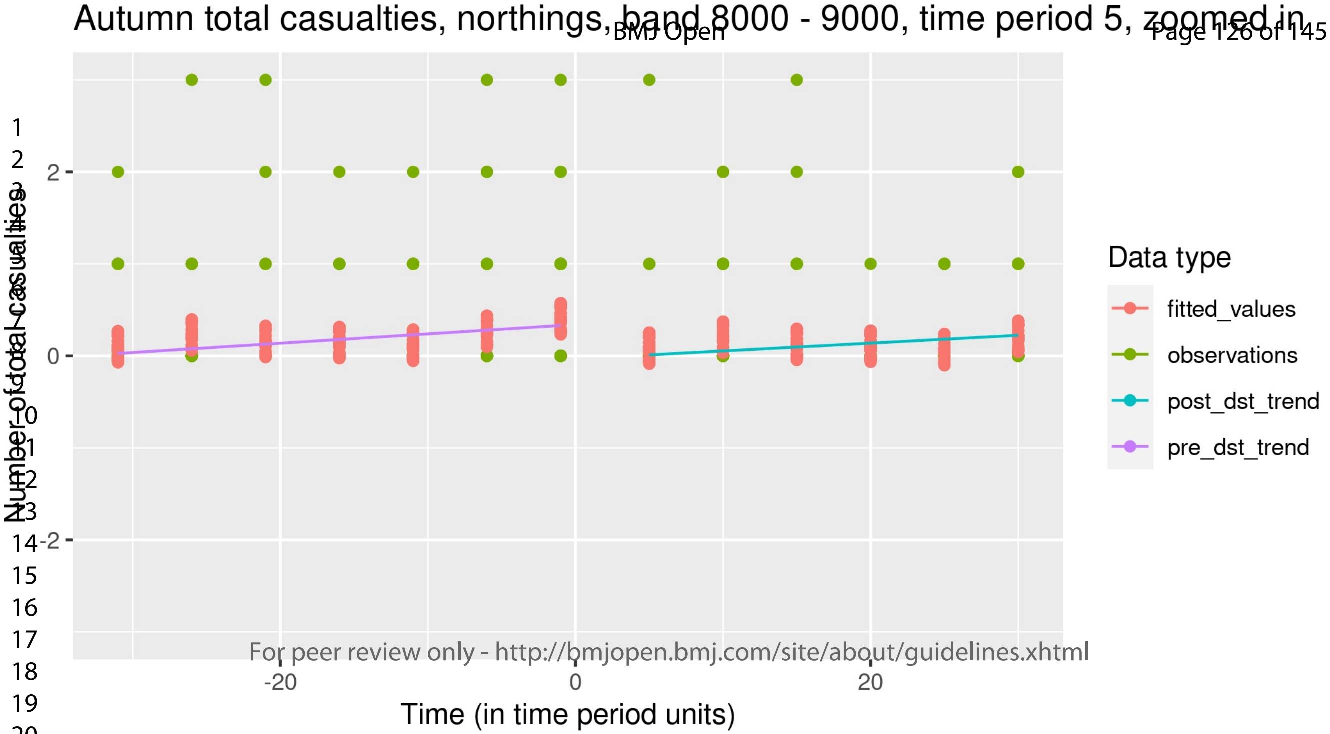

Autumn total casualties, northings, band 7000 - 8000, time period 5
Number of total casualties
5
4
3
2
1
0
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

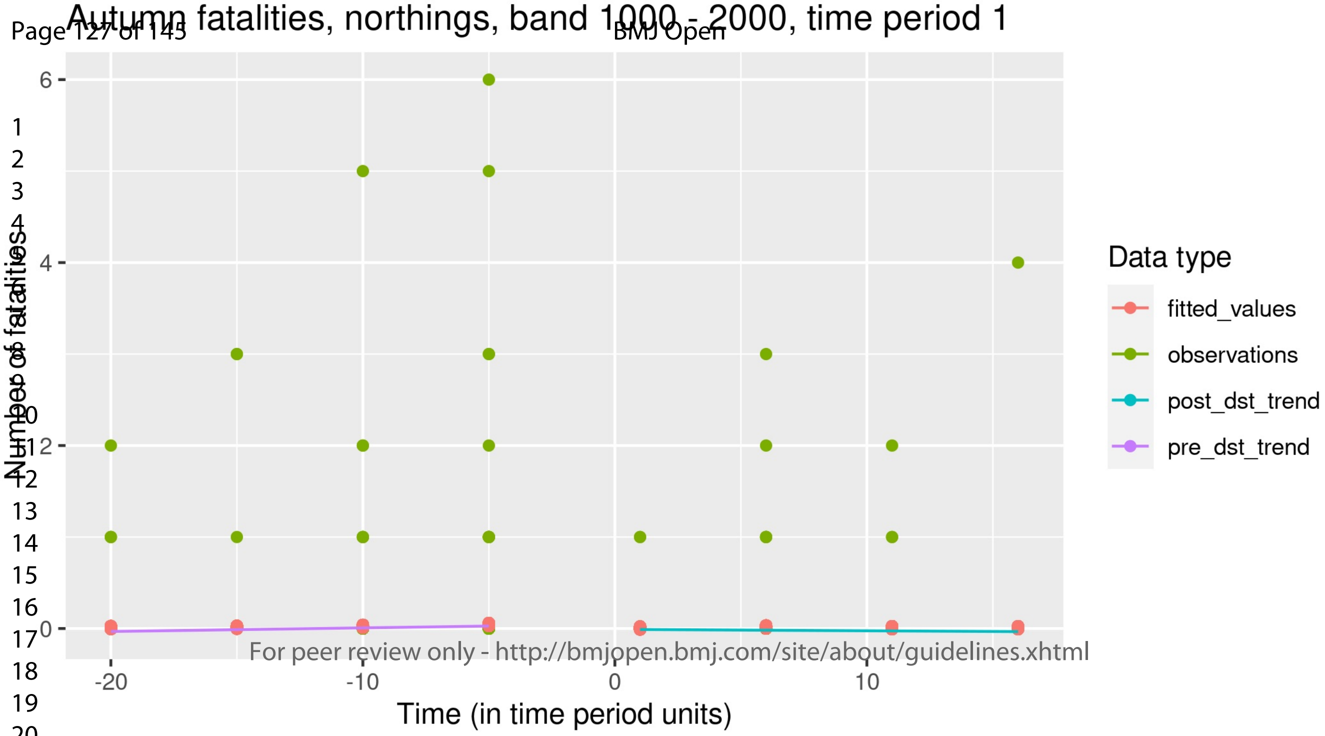

Autumn total casualties, northings, band 7000 - 8000, time period 5, zoomed in
Number of total casualties
2
0
-2
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

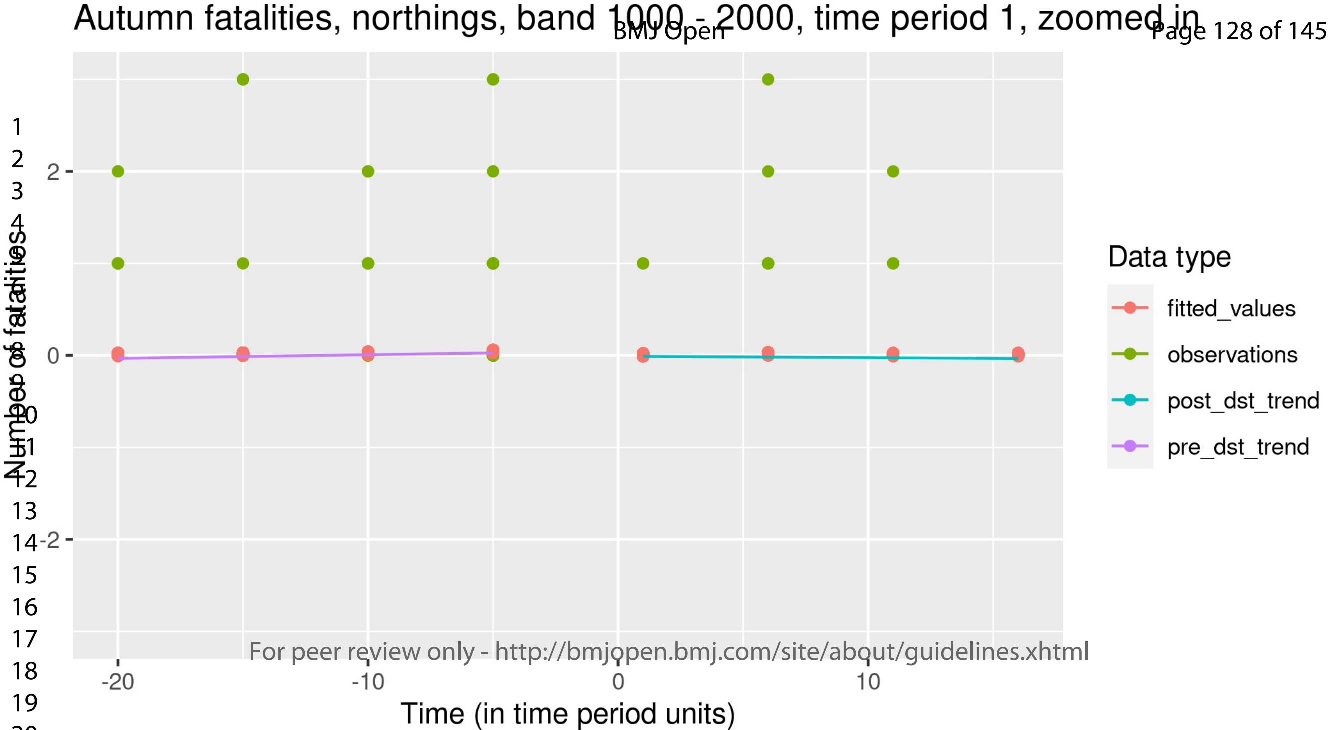

Autumn total casualties, northings, band 8000 - 9000, time period 1
Number of total casualties
4
3
2
1
0
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Autumn total casualties, northings, band 8000 - 9000, time period 1, zoomed in
Number of total casualties
2
0
-2
-20
-10
0
10
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Autumn total casualties, northings, band 8000 - 9000, time period 5
Number of total casualties
6
4
2
0
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Autumn total casualties, northings, band 8000 - 9000, time period 5, zoomed in
Number of total casualties
2
0
-2
-20
0
20
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Autumn fatalities, northings, band 1000 - 2000, time period 1
Number of fatalities
6
4
2
0
-20
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend


Autumn fatalities, northings, band 1000 - 2000, time period 1, zoomed in
Number of fatalities
2
0
-2
-20
-10
0
10
Time (in time period units)
Data type
fitted_values
observations
post_dst_trend
pre_dst_trend

```
#Script for RDD in time modelling for time period DST models, with specification checks on:
  #Autocorrelation of error term up to lag 10, Newey-West errors applied if present
  #Heteroskedasticity, HC3 errors applied if present
  #Specification checks of polynomial order of forcing variable (i.e. time); BIC is used to judge performance though other indicators also output
  #Specification checks by varying bandwidth for linear models

#attach packages
library(data.table)
library(DescTools)
library(rdrobust)
library(sandwich)
library(lmtest)

#set working directory
setwd("~/Documents/DST")

#Define sequences of data sets
  #The STATS19 data have been segmented into separate files representing 7 easting and 13 northing bands and 1 aggregate data set (21 files in total)
  #Datasets are named with same text prefix "data_", different numerical suffix "i"
  #We define the sequence of datasets as seq_i, which refers to the 21 segmented datasets described above
  #We define seq_t as the sequence of time periods ranging from 1 to 5
  #The functions will iterate through all sequences and output results tables with all models' results
seq_i<-c(1:21)
seq_t<-c(1:5)

#Define functions:
  #inputparams function calculates optimal bandwidth from rdrobust package; outputs from this are used in subsequent polynomial and bandwidth trials
  #rdd_calcs_poly function performs RDD with optimal bandwidth, and trials different polynomials for time
  #rdd_calcs_bw function trials RDD with different bandwidths for linear in time form

inputparams<-function(i,t){

  #compute bandwidth
  data_model<-data
```

```
  cols<-c("dow", "year")
  data_model<-data_model[, (cols):=lapply(.SD, as.factor), .SDcols=cols]
  tryCatch(
    expr = bw<-rdbwselect(y=data_model$tot_casualties, x=data_model$time_variable_tp,
                          covs=cbind(data_model$year,data_model$dow)),
    error = function(e) NULL
  )
  if(exists("bw")==TRUE){
    bw_exists=1
    bwl=ceiling(bw$bws[[1]])
    bwr=ceiling(bw$bws[[2]])
    #tabulate
    resultsline<-data.table(i,t,bwl,bwr,nrow(data_model),bw_exists)
    names(resultsline)<-c("model_no","tp","bw_mainl","bw_mainr","n","bw_exists")
  } else if (exists("bw")==FALSE){
    resultsline<-data.table(i,t,0,0,0,0)
    names(resultsline)<-c("model_no","tp","bw_mainl","bw_mainr","n","bw_exists")
  }
  return(resultsline)
}

rdd_calcs_poly<-function(i,t){
  #extract bandwidth info
  paras_i<-mod_paras[model_no==i & tp==t]
  bwl=paras_i$bw_mainl
  bwr=paras_i$bw_mainr
  bwexists=paras_i$bw_exists
  if (bwexists==1){
    #prepare data: need wt, kt and ktpost variables (cutoff is when time_variable_tp=0)
    data_model<-data[time_variable_tp>=-bwl & time_variable_tp<=bwr]
    data_model<-data_model[time_variable_tp>=0, wt:=1]
    data_model<-data_model[time_variable_tp<0, wt:=0]
    mintp=-1*min(data_model$time_variable_tp)
    interventiontp=mintp+1
    data_model<-data_model[time_variable_tp<0,kt:=(interventiontp)+time_variable_tp]
    data_model<-data_model[time_variable_tp>=0,kt:=mintp+time_variable_tp]
    data_model<-data_model[time_variable_tp<0, ktpost:=0]
```

```
    data_model<-data_model[time_variable_tp>=0, ktpost:=kt-interventiontp+1]

    cols<-c("dow", "year")
    data_model<-data_model[, (cols):=lapply(.SD, as.factor), .SDcols=cols]

    rdd_polytrial<-function(j){

      tryCatch(
        expr=lm_rdd<-lm(tot_casualties ~ wt + poly(kt, degree=j) + poly(ktpost, degree=j) + dow + year,
data=data_model),
        error=function(e) NULL
      )
      if(exists("lm_rdd")==TRUE){
        #Breusch Godfrey autocorrelation test up to lag 10
        for (l in c(1:10)){
          tryCatch(
            expr = assign(paste0("bgtest_",l), value=BreuschGodfreyTest(lm_rdd, order = l, order.by = data_model$kt,
type = "Chisq", data = data_model)),
            error = function(e) NULL
          )
          tryCatch(
            expr = assign(paste0("lag_",l), value=eval(parse(text=paste0("bgtest_",l,"$p.value")))),
            error = function(e) NULL
          )
          tryCatch(
            expr = assign(paste0("b",l),value=eval(parse(text=paste0("data.table(as.numeric(lag_",l,"),",l,")")))),
            error = function(e) NULL
          )
        }
        tryCatch(
          expr = bgtab<-rbind(b1,b2,b3,b4,b5,b6,b7,b8,b9,b10),
          error = function(e) NULL
        )
        if (exists("bgtab")==FALSE){
          lag_val=0
        } else if (exists("bgtab")==TRUE){
          bgtab_select<-bgtab[V1<=0.1]
```

```
          if (nrow(bgtab_select)>=1){
            lag_val=max(bgtab_select$V2)
          } else if (lag_1>0.1){
            lag_val=0
          }
        }
        #Bruesch Pagan heteroskedasticity test
        bp_pval=bptest(lm_rdd)$p.value
        if (is.na(bp_pval)){
          bp_pval=100
        }
        #adjust errors if needed to account for autocorrelation or heteroskedasticity
        if (lag_val>0){
          nw_vcov <- NeweyWest(lm_rdd, order.by = data_model$kt, data=data_model, lag = lag_val, prewhite = F,
adjust = T)
          lmsum<-as.matrix(coeftest(lm_rdd, vcov = nw_vcov))
          lm_sum<-lmsum[2,]
        } else if (lag_val==0 & bp_pval<=0.1){
          hc_vcov <- vcovHC(lm_rdd)
          lmsum<-as.matrix(coeftest(lm_rdd, vcov = hc_vcov))
          lm_sum<-lmsum[2,]
        } else if (lag_val==0 & bp_pval>0.1){
          lmsum<-as.matrix(summary(lm_rdd)$coefficients)
          lm_sum<-lmsum[2,]
        }

        data_model_l<-data_model[time_variable_tp<0]
        data_model_r<-data_model[time_variable_tp>=0]
        totcas_l=sum(data_model_l$tot_casualties)
        totcas_r=sum(data_model_r$tot_casualties)
        n_year=length(unique(data_model$year))

        resultsline<-
data.table(i,t,j,lm_sum[[1]],lm_sum[[2]],lm_sum[[4]],nrow(data_model),nrow(data_model_l),nrow(data_model_r),
                                as.numeric(bwl), as.numeric(bwr),as.numeric(lag_val),as.numeric(bp_pval),
                                summary(lm_rdd)$r.squared, summary(lm_rdd)$adj.r.squared, BIC(lm_rdd),
AIC(lm_rdd),totcas_l,totcas_r,n_year)
```

```
          names(resultsline)<-c("model_no","tp","poly_deg","coef","se", "pval",
  "n_tot","n_left","n_right","bw_l","bw_r","lag","bp_pval",
                            "rsq","adj_rsq","bic","aic","totcas_l","totcas_r","n_year")
          return(resultsline)
        }}
      #run for polynomials order 1 to 4
      results_table<-c()
      for (j in 1:4){
        calcs<-rdd_polytrial(j)
        results_table<-rbind(calcs,results_table)
      }
      return(results_table)
    }}

  rdd_calcs_bw<-function(i,t){
    #extract bandwidth info
    paras_i<-mod_paras[model_no==i & tp==t]
    bwl=paras_i$bw_mainl
    bwr=paras_i$bw_mainr
    bwexists=paras_i$bw_exists

    if (bwexists==1){
      rdd_bwtrial<-function(j){

        #prepare data: need wt, kt and ktpost variables (cutoff is when time_variable_tp=0)
        data_model<-data[time_variable_tp>=-(bwl+j) & time_variable_tp<=(bwr+j)]
        data_model<-data_model[time_variable_tp>=0, wt:=1]
        data_model<-data_model[time_variable_tp<0, wt:=0]
        mintp=-1*min(data_model$time_variable_tp)
        interventiontp=mintp+1
        data_model<-data_model[time_variable_tp<0,kt:=(interventiontp)+time_variable_tp]
        data_model<-data_model[time_variable_tp>=0,kt:=mintp+time_variable_tp]
        data_model<-data_model[time_variable_tp<0, ktpost:=0]
        data_model<-data_model[time_variable_tp>=0, ktpost:=kt-interventiontp+1]

        cols<-c("dow", "year")
        data_model<-data_model[, (cols):=lapply(.SD, as.factor), .SDcols=cols]
```

```
        tryCatch(
          expr=lm_rdd<-lm_rdd<-lm(tot_casualties ~ wt + poly(kt, degree=1) + poly(ktpost, degree=1)  + year + dow,
data=data_model),
          error=function(e) NULL
        )
        if(exists("lm_rdd")==TRUE){
          #Breusch Godfrey autocorrelation test up to lag 10
          for (l in c(1:10)){
            tryCatch(
              expr = assign(paste0("bgtest_",l), value=BreuschGodfreyTest(lm_rdd, order = l, order.by = data_model$kt,
type = "Chisq", data = data_model)),
              error = function(e) NULL
            )
            tryCatch(
              expr = assign(paste0("lag_",l), value=eval(parse(text=paste0("bgtest_",l,"$p.value")))),
              error = function(e) NULL
            )
            tryCatch(
              expr = assign(paste0("b",l),value=eval(parse(text=paste0("data.table(as.numeric(lag_",l,"),",l,")")))),
              error = function(e) NULL
            )
          }
          tryCatch(
            expr = bgtab<-rbind(b1,b2,b3,b4,b5,b6,b7,b8,b9,b10),
            error = function(e) NULL
          )
          if (exists("bgtab")==FALSE){
            lag_val=0
          } else if (exists("bgtab")==TRUE){
            bgtab_select<-bgtab[V1<=0.1]
            if (nrow(bgtab_select)>=1){
              lag_val=max(bgtab_select$V2)
            } else if (lag_1>0.1){
              lag_val=0
            }
          }
```

```
        #Bruesch Pagan heteroskedasticity test
        bp_pval=bptest(lm_rdd)$p.value
        if (is.na(bp_pval)){
          bp_pval=100
        }
        #adjust errors if needed to account for autocorrelation or heteroskedasticity
        if (lag_val>0){
          nw_vcov <- NeweyWest(lm_rdd, order.by = data_model$kt, data=data_model, lag = lag_val, prewhite = F,
adjust = T)
          lmsum<-as.matrix(coeftest(lm_rdd, vcov = nw_vcov))
          lm_sum<-lmsum[2,]
        } else if (lag_val==0 & bp_pval<=0.1){
          hc_vcov <- vcovHC(lm_rdd)
          lmsum<-as.matrix(coeftest(lm_rdd, vcov = hc_vcov))
          lm_sum<-lmsum[2,]
        } else if (lag_val==0 & bp_pval>0.1){
          lmsum<-as.matrix(summary(lm_rdd)$coefficients)
          lm_sum<-lmsum[2,]
        }

        data_model_l<-data_model[time_variable_tp<0]
        data_model_r<-data_model[time_variable_tp>=0]
        totcas_l=sum(data_model_l$tot_casualties)
        totcas_r=sum(data_model_r$tot_casualties)
        n_year=length(unique(data_model$year))

        resultsline<-
data.table(i,t,j,lm_sum[[1]],lm_sum[[2]],lm_sum[[4]],nrow(data_model),nrow(data_model_l),nrow(data_model_r),
                                as.numeric(bwl+j),as.numeric(bwr+j),as.numeric(lag_val),as.numeric(bp_pval),
                                summary(lm_rdd)$r.squared, summary(lm_rdd)$adj.r.squared, BIC(lm_rdd),
AIC(lm_rdd),totcas_l,totcas_r,n_year)
        names(resultsline)<-c("model_no","tp","bw_adjust","coef","se", "pval",
"n_tot","n_left","n_right","bw_l","bw_r","lag","bp_pval",
                              "rsq","adj_rsq","bic","aic","totcas_l","totcas_r","n_year")
        return(resultsline)
      }}
```

```
    #run for different bandwiths as follows:
    seq_bw<-c(1,0,-1)
    results_table<-c()
    for (j in seq_bw){
      calcs<-rdd_bwtrial(j)
      results_table<-rbind(calcs,results_table)
    }
    return(results_table)
  }}


#Run functions and save output as csv files
param_table<-c()
for (i in seq_i){
  for (t in seq_t){
    data_raw<-eval(parse(text=paste0("data_",i)))
    data<-data_raw[tp==t]
    param_table<-rbind(param_table,inputparams(i,t))
    }}
write.csv(param_table, file="model_params.csv", row.names=FALSE)

poly_table<-c()
for (i in seq_i){
  for (t in seq_t){
    data_raw<-eval(parse(text=paste0("data_",i)))
    data<-data_raw[tp==t]
    mod_paras<-fread("model_params.csv")
    poly_table<-rbind(poly_table,rdd_calcs_poly(i,t))
  }}
write.csv(poly_table, file="results_polytrial.csv", row.names=FALSE)

bw_table<-c()
for (i in seq_i){
  for (t in seq_t){
    data_raw<-eval(parse(text=paste0("data_",i)))
    data<-data_raw[tp==t]
    mod_paras<-fread("model_params.csv")
```

```
    bw_table<-rbind(bw_table,rdd_calcs_bw(i,t))
}}
write.csv(bw_table, file="results_bwtrial.csv", row.names=FALSE)

################################################################################
#Script for placebo tests as per Guido W. Imbens and Thomas Lemieux. Regression discontinuity designs: A guide to
practice. Journal of Econometrics, 142:615–635, 2008.
#We use the same bandwidth as per the associated original models in file "model_params.csv" as generated in script
"rdd_models.R"

#attach packages
library(data.table)
library(DescTools)
library(rdrobust)
library(sandwich)
library(lmtest)

#set working directory
setwd("~/Documents/DST")

#Define sequences of data sets
#The STATS19 data have been segmented into separate files representing 7 easting and 13 northing bands and 1
aggregate data set (21 files in total)
#Datasets are named with same text prefix "data_", different numerical suffix "i"
#We define the sequence of datasets as seq_i, which refers to the 21 segmented datasets described above
#We define seq_q so that we can split each data set into pre- ("left") and post- ("right") DST for 2 placebo tests
per original model
#We define seq_t as the sequence of time periods ranging from 1 to 5
#The functions will iterate through all sequences and output results tables with all models' results
seq_i<-c(1:21)
seq_q<-c("left","right")
seq_t<-c(1:5)

#Define functions:
#rdd_calcs_poly function performs RDD with optimal bandwidth, and trials different polynomials for time
#rdd_calcs_bw function trials RDD with different bandwidths for linear in time form
```

```
rdd_calcs_poly<-function(i,q,t){
  #extract bandwidth info
  paras_iq<-mod_paras[model_no==i & tp==t]
  bwl=paras_iq$bw_mainl
  bwr=paras_iq$bw_mainr
  bwexists=paras_iq$bw_exists

  if (bwexists==1){
    #prepare data: need wt, kt and ktpost variables
    data_model<-data[time_variable_tp>=cut-bwl & time_variable_tp<cut+bwr]
    data_model<-data_model[time_variable_tp>=cut, wt:=1]
    data_model<-data_model[time_variable_tp<cut, wt:=0]
    mintp=min(data_model$time_variable_tp)
    interventiontp=abs(mintp)+1
    data_model<-data_model[,kt:=interventiontp+time_variable_tp]
    data_model<-data_model[wt==0, ktpost:=0]
    maxkt_wt0=max(data_model[wt==0]$kt)
    data_model<-data_model[wt==1, ktpost:=kt-maxkt_wt0]

    cols<-c("dow", "year")
    data_model<-data_model[, (cols):=lapply(.SD, as.factor), .SDcols=cols]

    rdd_polytrial<-function(j){

      tryCatch(
        expr=lm_rdd<-lm(tot_casualties ~ wt + poly(kt, degree=j) + poly(ktpost, degree=j)  + dow + year,
data=data_model),
        error=function(e) NULL
      )
      if(exists("lm_rdd")==TRUE){
        #Breusch Godfrey autocorrelation test up to lag 10
        for (l in c(1:10)){
          tryCatch(
            expr = assign(paste0("bgtest_",l), value=BreuschGodfreyTest(lm_rdd, order = l, order.by = data_model$kt,
type = "Chisq", data = data_model)),
            error = function(e) NULL
          )
```

```
      tryCatch(
        expr = assign(paste0("lag_",l), value=eval(parse(text=paste0("bgtest_",l,"$p.value")))),
        error = function(e) NULL
      )
      tryCatch(
        expr = assign(paste0("b",l),value=eval(parse(text=paste0("data.table(as.numeric(lag_",l,"),",l,")")))),
        error = function(e) NULL
      )
    }
    tryCatch(
      expr = bgtab<-rbind(b1,b2,b3,b4,b5,b6,b7,b8,b9,b10),
      error = function(e) NULL
    )
    if (exists("bgtab")==FALSE){
      lag_val=0
    } else if (exists("bgtab")==TRUE){
      bgtab_select<-bgtab[V1<=0.1]
      if (nrow(bgtab_select)>=1){
        lag_val=max(bgtab_select$V2)
      } else if (lag_1>0.1){
        lag_val=0
      }
    }
    #Bruesch Pagan heteroskedasticity test
    bp_pval=bptest(lm_rdd)$p.value
    if (is.na(bp_pval)){
      bp_pval=100
    }
    #adjust errors if needed to account for autocorrelation or heteroskedasticity
    if (lag_val>0){
      nw_vcov <- NeweyWest(lm_rdd, order.by = data_model$kt, data=data_model, lag = lag_val, prewhite = F,
adjust = T)
      lmsum<-as.matrix(coeftest(lm_rdd, vcov = nw_vcov))
      lm_sum<-lmsum[2,]
    } else if (lag_val==0 & bp_pval<=0.1){
      hc_vcov <- vcovHC(lm_rdd)
      lmsum<-as.matrix(coeftest(lm_rdd, vcov = hc_vcov))
```

```
            lm_sum<-lmsum[2,]
          } else if (lag_val==0 & bp_pval>0.1){
            lmsum<-as.matrix(summary(lm_rdd)$coefficients)
            lm_sum<-lmsum[2,]
          }

          data_model_l<-data_model[wt==0]
          data_model_r<-data_model[wt==1]

          resultsline<-
  data.table(i,q,t,j,lm_sum[[1]],lm_sum[[2]],lm_sum[[4]],nrow(data_model),nrow(data_model_l),nrow(data_model_r),
                                  as.numeric(bwl),as.numeric(bwr),as.numeric(lag_val),as.numeric(bp_pval),
                                  summary(lm_rdd)$r.squared, summary(lm_rdd)$adj.r.squared, BIC(lm_rdd), AIC(lm_rdd))
          names(resultsline)<-c("model_no","data","tp","poly_deg","coef","se", "pval",
  "n_tot","n_left","n_right","bw_l","bw_r","lag","bp_pval",
                                 "rsq","adj_rsq","bic","aic")
          return(resultsline)
        }}
      #run for polynomials order 1 to 4
      results_table<-c()
      for (j in 1:4){
        calcs<-rdd_polytrial(j)
        results_table<-rbind(calcs,results_table)
      }
      return(results_table)
    }}

  rdd_calcs_bw<-function(i,q,t){
    #extract bandwidth info
    paras_iq<-mod_paras[model_no==i & tp==t]
    bwl=paras_iq$bw_mainl
    bwr=paras_iq$bw_mainr
    bwexists=paras_iq$bw_exists

    if (bwexists==1){
      rdd_bwtrial<-function(j){
```

```
#prepare data: need wt, kt and ktpost variables
newcut=cut+j
data_model<-data[time_variable_tp>=newcut-bwl & time_variable_tp<newcut+bwr]
data_model<-data_model[time_variable_tp>=newcut, wt:=1]
data_model<-data_model[time_variable_tp<newcut, wt:=0]
mintp=min(data_model$time_variable_tp)
interventiontp=abs(mintp)+1
data_model<-data_model[,kt:=interventiontp+time_variable_tp]
data_model<-data_model[wt==0, ktpost:=0]
maxkt_wt0=max(data_model[wt==0]$kt)
data_model<-data_model[wt==1, ktpost:=kt-maxkt_wt0]

cols<-c("dow", "year")
data_model<-data_model[, (cols):=lapply(.SD, as.factor), .SDcols=cols]

tryCatch(
  expr=lm_rdd<-lm_rdd<-lm(tot_casualties ~ wt + poly(kt, degree=1) + poly(ktpost, degree=1) + dow + year,
data=data_model),
  error=function(e) NULL
)
if(exists("lm_rdd")==TRUE){
  #Breusch Godfrey autocorrelation test up to lag 10
  for (l in c(1:10)){
    tryCatch(
      expr = assign(paste0("bgtest_",l), value=BreuschGodfreyTest(lm_rdd, order = l, order.by = data_model$kt,
type = "Chisq", data = data_model)),
      error = function(e) NULL
    )
    tryCatch(
      expr = assign(paste0("lag_",l), value=eval(parse(text=paste0("bgtest_",l,"$p.value")))),
      error = function(e) NULL
    )
    tryCatch(
      expr = assign(paste0("b",l),value=eval(parse(text=paste0("data.table(as.numeric(lag_",l,"),",l,")")))),
      error = function(e) NULL
    )
  }
```

```
tryCatch(
  expr = bgtab<-rbind(b1,b2,b3,b4,b5,b6,b7,b8,b9,b10),
  error = function(e) NULL
)
if (exists("bgtab")==FALSE){
  lag_val=0
} else if (exists("bgtab")==TRUE){
  bgtab_select<-bgtab[V1<=0.1]
  if (nrow(bgtab_select)>=1){
    lag_val=max(bgtab_select$V2)
  } else if (lag_1>0.1){
    lag_val=0
  }
}
#Bruesch Pagan heteroskedasticity test
bp_pval=bptest(lm_rdd)$p.value
if (is.na(bp_pval)){
  bp_pval=100
}
#adjust errors if needed to account for autocorrelation or heteroskedasticity
if (lag_val>0){
  nw_vcov <- NeweyWest(lm_rdd, order.by = data_model$kt, data=data_model, lag = lag_val, prewhite = F,
adjust = T)
  lmsum<-as.matrix(coeftest(lm_rdd, vcov = nw_vcov))
  lm_sum<-lmsum[2,]
} else if (lag_val==0 & bp_pval<=0.1){
  hc_vcov <- vcovHC(lm_rdd)
  lmsum<-as.matrix(coeftest(lm_rdd, vcov = hc_vcov))
  lm_sum<-lmsum[2,]
} else if (lag_val==0 & bp_pval>0.1){
  lmsum<-as.matrix(summary(lm_rdd)$coefficients)
  lm_sum<-lmsum[2,]
}

data_model_l<-data_model[wt==0]
data_model_r<-data_model[wt==1]
```

```
        resultsline<-
data.table(i,q,t,j,lm_sum[[1]],lm_sum[[2]],lm_sum[[4]],nrow(data_model),nrow(data_model_l),nrow(data_model_r),
                                as.numeric(bwl+j),as.numeric(bwr+j),as.numeric(lag_val),as.numeric(bp_pval),
                                summary(lm_rdd)$r.squared, summary(lm_rdd)$adj.r.squared, BIC(lm_rdd), AIC(lm_rdd))
        names(resultsline)<-c("model_no","data","tp","bw_adjust","coef","se", "pval",
"n_tot","n_left","n_right","bw_l","bw_r","lag","bp_pval",
                              "rsq","adj_rsq","bic","aic")
        return(resultsline)
      }}

    #run for different bandwiths as follows:
    seq_bw<-c(1,0,-1)
    results_table<-c()
    for (j in seq_bw){
      calcs<-rdd_bwtrial(j)
      results_table<-rbind(calcs,results_table)
    }
    return(results_table)
  }}


#Run functions and save output as csv files
poly_table<-c()
for (i in seq_i){
  for (q in seq_q){
    for (t in seq_t){
      data_raw<-eval(parse(text=paste0("data_",i)))
      data_tp<-data_raw[tp==t]
      if (q=="left"){
        data<-data_tp[time_variable_tp<0]
        cut=round(mean(data$time_variable_tp))
      } else if (q=="right"){
        data<-data_tp[time_variable_tp>=0]
        cut=round(mean(data$time_variable_tp))
      }
      mod_paras<-fread("model_params.csv")
      poly_table<-rbind(poly_table,rdd_calcs_poly(i,q,t))
```

```
    }}}
write.csv(poly_table, file="results_placebo_polytrial.csv", row.names=FALSE)

bw_table<-c()
for (i in seq_i){
  for (q in seq_q){
    for (t in seq_t){
      data_raw<-eval(parse(text=paste0("data_",i)))
      data_tp<-data_raw[tp==t]
      if (q=="left"){
        data<-data_tp[time_variable_tp<0]
        cut=round(mean(data$time_variable_tp))
      } else if (q=="right"){
        data<-data_tp[time_variable_tp>=0]
        cut=round(mean(data$time_variable_tp))
      }
      mod_paras<-fread("model_params.csv")
      bw_table<-rbind(bw_table,rdd_calcs_bw(i,t))
    }}}
write.csv(bw_table, file="results_placebo_bwtrial.csv", row.names=FALSE)
```

STROBE Statement—checklist of items that should be included in reports of observational studies

	Item No	Recommendation	Page No
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	1
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	1
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	2-3
Objectives	3	State specific objectives, including any prespecified hypotheses	3
Methods			
Study design	4	Present key elements of study design early in the paper	3-6
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	3-4
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up *Case-control study*—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls *Cross-sectional study*—Give the eligibility criteria, and the sources and methods of selection of participants	NA
		(*b*) *Cohort study*—For matched studies, give matching criteria and number of exposed and unexposed *Case-control study*—For matched studies, give matching criteria and the number of controls per case	NA
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	5-6
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	*3-6*
Bias	9	Describe any efforts to address potential sources of bias	5-6
Study size	10	Explain how the study size was arrived at	3-6
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	5-6
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	4-6
		(*b*) Describe any methods used to examine subgroups and interactions	5-6
		(*c*) Explain how missing data were addressed	5
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed *Case-control study*—If applicable, explain how matching of cases and controls was addressed *Cross-sectional study*—If applicable, describe analytical methods taking account of sampling strategy	NA
		(*e*) Describe any sensitivity analyses	6

Continued on next page

Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	NA
		(b) Give reasons for non-participation at each stage	NA
		(c) Consider use of a flow diagram	NA
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	NA
		(b) Indicate number of participants with missing data for each variable of interest	NA
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	NA
		Note: No human/animal participants were involved but a summary of descriptive statistics on casualties is given	4
Outcome data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	NA
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	NA
		Cross-sectional study—Report numbers of outcome events or summary measures	NA
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	6-9
		(*b*) Report category boundaries when continuous variables were categorized	5-6
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	NA
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	NA
Discussion			
Key results	18	Summarise key results with reference to study objectives	11-15
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	15
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	12-15
Generalisability	21	Discuss the generalisability (external validity) of the study results	15
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	17

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in cohort and cross-sectional studies.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.