A Survival Analysis with Random Parameter Approach for Assessing Temporal Instability in Treatment Effect (Extended Abstract)

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1. Introduction

Evaluation of the effect of safety-related countermeasures is among the most important tasks in road safety [1] and two of the most widely used methods to fulfill this task are probably the empirical Bayes (EB) and the full Bayesian (FB) methods. The implicit assumptions of these two methods are that the treatment effect is constant during the whole study period or each year after the countermeasure is implemented (i.e., the treatment effect is temporally stable during the whole after period or each year in the after period) [2-7]. However, as justified by Mannering [8], the assumption of temporal stability in treatment effect may not hold due to the potential changes in driver behaviors over time which are the basic and determining factors affecting the treatment effect.

Accordingly, assessing temporal instability in treatment effect at the year level may not be enough to capture the underlying change of treatment effect over time. This is especially the case when “countermeasures” that we are interested in may result in potentially fast-evolving changes to road safety, such as the COVID-19 pandemic. Also, from a methodological perspective, the requirement of converting individual or disaggregated crash events into aggregated crash frequency by the commonly used EB and FB methods may also hinders a flexible and comprehensive assessment of the potential temporal instability in treatment effect at more detailed temporal levels.

Therefore, in this study, we propose a new approach that can take advantage of the disaggregated nature of crashes and accommodate the assessment of temporal instability of treatment effect at different temporal levels. Specifically, we extend the survival analysis approach originally developed by Xie, et al. [9] and develop a survival analysis with random parameter approach that can account for the temporally unobserved heterogeneity in treatment effect. Also, we test the newly proposed approach to evaluate the impact of the ongoing COVID-19 pandemic on road safety in New York City (NYC). The results from this case study could also provide new insights in understanding the temporal safety effect of the pandemic.

2. Methodology

2.1. Modeling of Crash Time Interval

As discussed in Lord, et al. [10], the crash frequency obtained in a given time period is often assumed to follow a Poisson distribution and the time interval between each pair of consecutive crashes (we will refer to the time between each pair of consecutive crashes as crash time intervals) during the same time period follows an exponential distribution. Mathematically, the probability density function (PDF) of crash time interval T is thus

$$f(t \mid \lambda) = \lambda \exp(-\lambda t) \tag{1}$$

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2.2. Settings and Assumptions

This study proposes to divide the whole after period into several shorter time periods and estimate the treatment effect for each time period, as illustrated in Figure 1. The cutoff points of each time period should be based on the study objectives. The underlying assumption of this setting is that the treatment effect is constant within each time period but can be different from one time period to another. Additionally, due to the fact that it is often difficult to obtain detailed driver behavior data, we assume that the temporal instability in treatment effect is a result of unobserved factors and random parameter specification is used to account for this.

2.3. Censoring

Some crash time interval observations are censored in this setting because we could not know the actual time between a crash and its predecessor or successor due to the cutoff of the study period as summarized in Figure 1. To properly model the induced uncensored and censored observations, survival analysis, a branch of statistics with methods developed to handle censoring data, is employed in this study to model crash time intervals [9, 11].

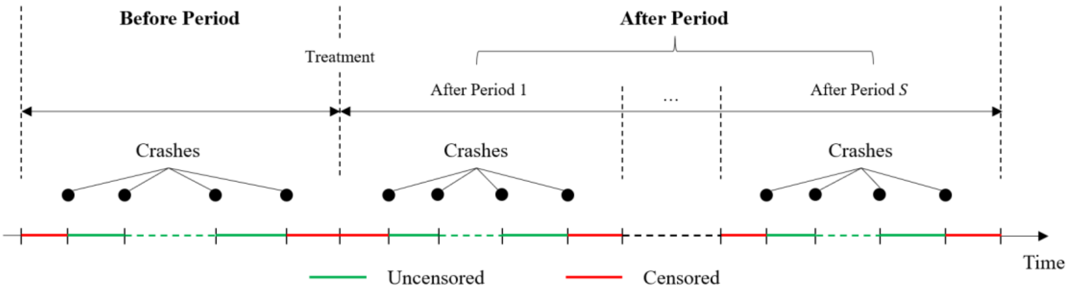

Figure 1. Before-after settings and indications of uncensored or censored observations for one site.

2.4. Model Formulation

A survival analysis with random parameter (SARP) model is proposed in this study to investigate the potential temporal instability in treatment effect. Briefly, the coefficient of binary treatment indicator is modeled as a random parameter to account for the potential temporal instability of treatment effect due to unobserved factors. Let λ_{ij} denote the crash hazard parameter for the j^{th} time interval ($j = 1,...,n_i$) at the i^{th} site ($i = 1,...,m$) where n_i is the total number of time intervals for the i^{th} site. The j^{th} time interval at the i^{th} site t_{ij} follows exponential distribution with the following PDF

$$f\left(t_{ij} \mid \lambda_{ij}\right) = \lambda_{ij} \exp\left(-\lambda_{ij} t_{ij}\right) \tag{2}$$

Suppose the whole after period is divided into S sub-time periods ($s = 1,...,S$). The crash hazard parameter can be specified as follows.

$$\log(\lambda_{ij}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{pij} + \beta_{T,s} \text{Treatment}_{ij} + \varepsilon_i \tag{3}$$

where, X_{pij} is the p^{th} longitudinal covariate ($p = 1,...,P$) for the j^{th} time interval at the i^{th} site. Treatment_{ij} is a binary variable that equals 0 if the j^{th} time interval of the i^{th} site is in the before period and 1 if the j^{th} time interval of the i^{th} site is in the after period. β_0 is the intercept and β_p is the coefficient corresponding to the p^{th} covariate. ε_i is a stochastic error term to account for the site-specific effect and overdispersion in crashes. $\exp\left(\varepsilon_i\right)$ is often assumed to follow Gamma distribution with mean 1 and variance α . $\beta_{T,s}$ is the treatment effect for the s^{th} time period and it is modeled as a random parameter as follows.

$$\begin{aligned} &\beta_{T,s} = \beta_T + \varphi_s, \forall \text{ the } j^{\text{th}} \text{ time interval at the } i^{\text{th}} \text{ site} \in \text{Time Period } s \\ &\varphi_s \sim \text{Gaussian}\left(0, \sigma^2\right) \end{aligned} \tag{4}$$

where, β_T is the mean treatment effect estimate across all the observations. φ_s is the time period-specific random term that quantifies the temporal heterogeneity in treatment effect across different time periods. By convention, φ_s is assumed to follow Gaussian distribution with mean 0 and variance σ^2. The CMF for the s^{th} time period is thus $\exp\left(\beta_{T,s}\right)$. Bayesian framework is adopted to estimate the model parameters as well as the treatment effect for each time period in this study and Deviance Information Criterion (DIC) is used to evaluate model performance and comparing competing models [12].

3. Analysis and Results

In this section, we conduct a case study that focuses on evaluating the impact of the COVID-19 lockdown on road safety to empirically test the proposed SARP method and aim to contribute to the transportation safety literature on unveiling the potential temporal changes of safety impact due to the COVID-19 lockdown. Specifically, we choose Manhattan, NYC as the study location and the beginning of the pandemic as the study time period since NYC was one of the epicenters in the U.S during that time. To reduce the infections of COVID-19 cases, the "New York State (NYS) on PAUSE"/stay-at-home executive order was placed into effect on 03/22/2020 by NY Governor Andrew Cuomo[2]. By applying the proposed SARP method, we hope to shed new light on the safety effect of this lockdown from the temporal perspective.

3.1. Data Preparation

Based on the data availability, approximately three months after the implementation of NYS lockdown policy (i.e., 03/22/2021 – 06/30/2021) is selected as the after period and approximately 15 months before the NYS lockdown is used as the before period (01/01/2019 – 03/21/2021). Mainly four datasets were processed to extract key variables used in this analysis, which are the NYPD collision dataset obtain from NYC Open Data Portal[3], yellow taxi trip dataset obtained from NYC Taxi and Limousine Commission[4], traffic speed dataset obtained from National Performance Management Research Data Set (NPMRDS)[5], and weather dataset obtained from Weather Underground[6]. Due to the obfuscation of taxi pick-ups and drop-off locations, neighborhoods tabulation area (NTA)[7] is selected as the spatial unit of analysis in this case study.

3.2. Model Development and Selection

Natural logarithm of the average number of taxi trips was used as the exposure for crash time interval. The speed before crash occurrences was converted into a binary variable that equals 1 if speed is greater than 25 MPH and 0 otherwise since 25 MPH is the citywide speed limit currently implemented in NYC [13]. To demonstrate the superiority of the proposed SARP method, the survival analysis (SA) approach that was originally proposed by Xie, et al. [9] and can estimate one average treatment effect in the after period is also tested as a comparison. The DIC values of the SA approach and the SARP approach are 13617.6 and 12046.0, respectively, which indicates that the SARP approach provides a better fit to the data than the SA approach. This implies the superiority of the proposed SARP approach in terms of accounting for the temporal instability in treatment effect.

4. Discussion

The results of the SARP model are summarized in Table 1. The logarithm of the average number of taxi trips is found to be positively associated with injury or fatal crashes and no injury crashes, respectively. This finding indicates that the surrogate exposure of crashes has an positive effect on crashes, which is consistent with a previous study [14]. The effects of speed limit violation are opposite between injury or fatal crashes and no injury crashes. The potential reason for the differences in the effect of speed violation is that speed violation may be a major risk factor that causes injury or fatal crashes but not for no injury crashes [15]. This speculation is similar to the observations made in several news reports that showed the connection between fatal or serious injury crashes and speeding due to the COVID lockdown [16]. The two weather-related covariates, namely temperature and

[2] https://www.governor.ny.gov/news/governor-cuomo-signs-new-york-state-pause-executive-order
[3] https://data.cityofnewyork.us/Public-Safety/Motor-Vehicle-Collisions-Crashes/h9gi-nx95
[4] https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page
[5] https://npmrds.ritis.org/analytics
[6] https://www.wunderground.com/
[7] https://www1.nyc.gov/site/planning/data-maps/open-data/dwn-nynta.page

precipitation, are both found to be positively associated with injury or fatal crashes and no injury crashes, respectively, which are relatively consistent with previous studies [17, 18].

The estimated CMFs of injury or fatal crashes are 0.428 ($e^{-0.848}$), 0.699 ($e^{-0.358}$), and 1.054 ($e^{0.053}$) for each month in the after period while the estimated CMFs of no injury crashes are 0.358 ($e^{-1.026}$), 0.385 ($e^{-0.954}$), and 0.437 ($e^{0.828}$) respectively. All the CMFs are statistically significant according to 95% BCI except the CMF of injury or fatal crashes for the third month. This finding suggests that comparing to the before period, no injury crashes decrease during all the three months after the implementation of NYS lockdown while injury or fatal crashes decrease during the first two months but are relatively similar to the before period during the third month. Besides, the estimated CMF of injury or fatal crashes for each month is larger than that of no injury crashes. A possible speculation for the larger decrease of no injury crashes is that the implementation of NYS lockdown leads to a significant reduction of traffic congestion on the road, which in turn leads to a larger decrease of no injury crashes that have shown be negatively correlated with traffic congestion [19]. In addition, for both crash severity levels, the estimated CMFs display an increasing trend after the largest decrease in the first month. This finding may imply that traffic safety conditions are gradually returning to normal as the time progresses during the first three months of the lockdown in NYC. The evidence of the temporal heterogeneous safety effect of the COVID lockdown may lead to gaining more detailed understanding of the safety effect of the lockdown and making future policies.

Table 1. Estimated parameters of the SARP method

	Injury or Fatal Crashes				**No Injury Crashes**			
	Mean	Std.Dev.	2.5% BCI	97.5% BCI	Mean	Std.Dev.	2.5% BCI	97.5% BCI
Intercept	-2.872	0.127	-3.126	-2.623	-1.216	0.100	-1.431	-1.015
Log(average number of taxi trips)	0.226	0.008	0.209	0.242	0.233	0.004	0.224	0.241
Average speed above 25 MPH	0.090	0.029	0.034	0.146	-0.136	0.016	-0.166	-0.104
Temperature ($^{\circ}F$)	0.006	0.001	0.005	0.007	0.003	<0.001	0.002	0.003
Precipitation (in)	0.357	0.367	-0.378	1.052	0.780	0.205	0.371	1.180
Treatment effect								
03/22/2021 - 04/22/2021	-0.848	0.103	-1.056	-0.652	-1.026	0.052	-1.130	-0.925
04/22/2021 - 05/22/2021	-0.358	0.079	-0.513	-0.205	-0.954	0.050	-1.051	-0.858
05/22/2021 - 06/30/2021	0.053	0.054	-0.055	0.158	-0.828	0.039	-0.905	-0.753
Dispersion	0.230	0.053	0.141	0.350	-	-	-	-

5. Conclusions

This study contributes to the existing transportation safety literature by proposing a survival analysis with random parameter (SARP) approach that that can flexibly assess the temporal instability in treatment effect at various temporal levels induced by unobserved factors. The proposed SARP method is applied to assess the temporal instability in safety effect during the first three months after the implementation of the COVID-19 lockdown policy in Manhattan, New York City. According to the Deviance Information Criterion values, the SARP method that can account for the monthly change of safety effect is superior to a previously proposed survival analysis before-after analysis approach (see Xie, et al. [9]) that can only estimate one average treatment effect over the whole study period. The temporally instable patterns of safety effect are found to be different for different crash severity levels and the estimated monthly crash modification factors display an increasing trend after the largest decrease in the first month after the lockdown, which implies that traffic safety conditions are gradually returning to normal and provides evidence on the existence of temporal instability in treatment effect at more detailed temporal levels. The proposed SARP method has the potential to be applied to assess the safety effect of smart city technologies (e.g., connected and autonomous vehicles) that may result in fast-evolving changes to road safety.

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