A Survival Analysis with Random Parameter Approach for Assessing Temporal Instability in Treatment Effect

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Collaborators

- This study was partially supported by C2SMART a Tier 1 USDOT University Transportation Center at NYU Tandon School of Engineering

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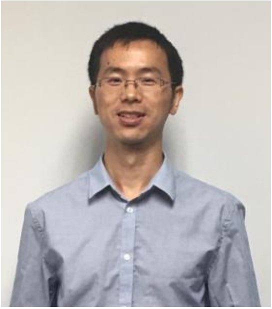

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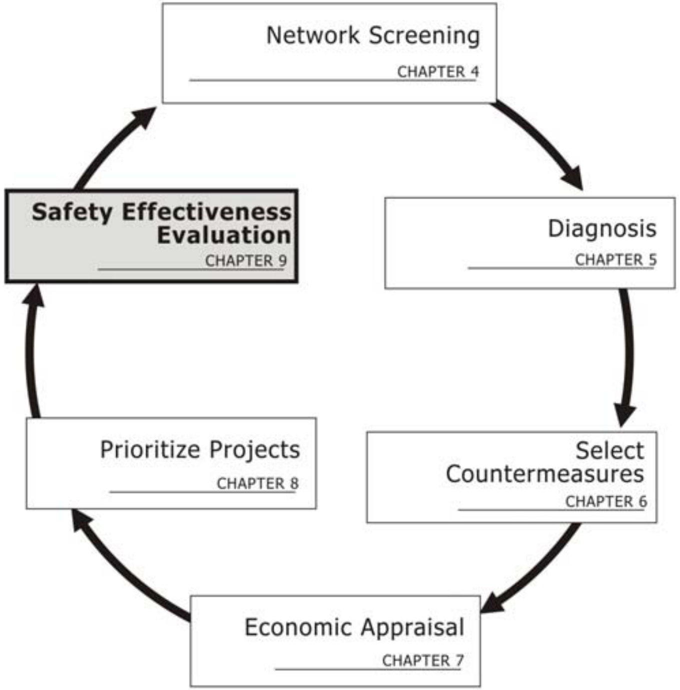
Before-After Safety Evaluation

- Evaluation of the effectiveness of safety-related countermeasures is an important step in road safety evaluation process

- Proper estimation of safety effectiveness can lead to better allocation of funds and revisions to existing policies



Roadway Safety Management Overview Process
(Exhibit 9-1 from Highway Safety Manual)

Motivation

Major Characteristics of Crashes

Individual Events

Relatively Rare

Common Practice in Before-After Analysis

Aggregate crashes to crash count over a time period (e.g., annual)

Implicit Assumption

Patterns of crashes is temporally stable

Does this assumption hold?

Motivation

Evidence of Temporal Instability

Empirical evidence supports the existence of temporal instability in crash data in safety literature (Malyshkina and Mannering 2009)

Speculation

Temporal instability may exist widely in crash data including before-after analysis (Mannering, 2018)

Reason: the potential changes in driver behavior over time (often unmeasurable)

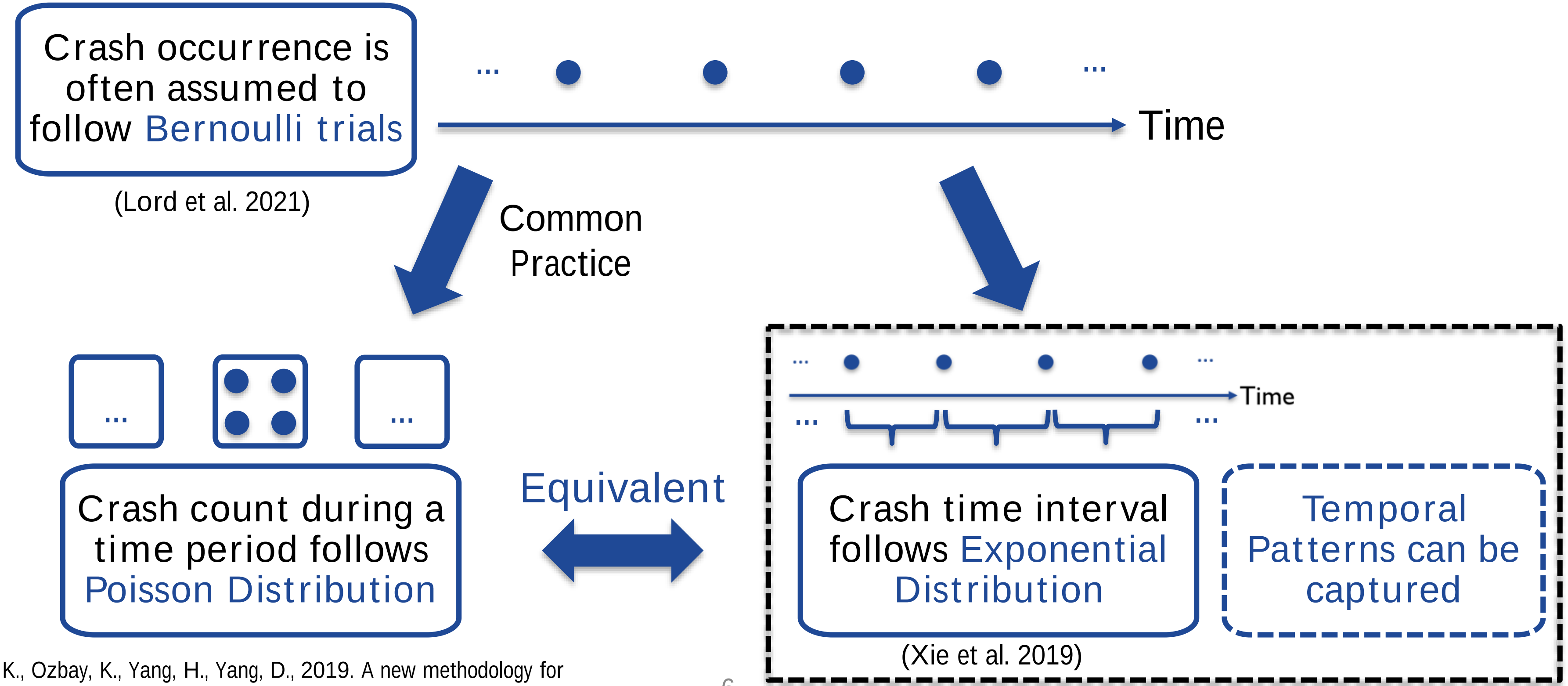
Limitations

By aggregating crashes, temporal patterns within the aggregation levels may lost

What should we do?

Malyshkina, N.V., Mannering, F.L., 2009. Markov switching multinomial logit model: An application to accident-injury severities. Accident Analysis & Prevention 41 (4), 829-838.
Mannering, F., 2018. Temporal instability and the analysis of highway accident data. Analytic Methods in Accident Research 17, 1-13.

Motivation

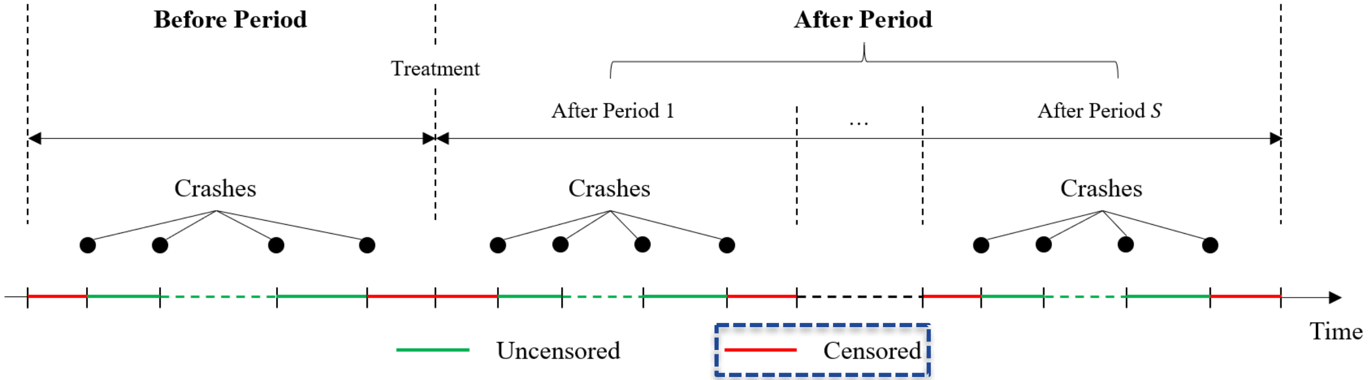


Xie, K., Ozbay, K., Yang, H., Yang, D., 2019. A new methodology for before–after safety assessment using survival analysis and longitudinal data. Risk analysis 39 (6), 1342-1357.

Methodology

- Settings

The actual values of these observations are greater than those shown in the figure but cannot be measured due to the cutoff of study horizon.



- Assumptions
  - After period is divided into several short time periods
  - The treatment effect of each time period is constant
  - Temporal instability in treatment effect is caused by unobserved factors that are difficult to collect, such as driver behavior and decision-making, i.e., there is unobserved heterogeneity in treatment effect with respect to time

Methodology – Survival Analysis with Random Parameter (SARP) Model

- Modeling crash time interval
  - Exponential distribution:
    - Probability density function: $f(t \mid \lambda) = \lambda \exp(-\lambda t)$
    - Cumulative density function: $F(t \mid \lambda) = \int_0^t f(t \mid \lambda)\, dt = 1 - \exp(-\lambda t)$
    - Survival function: $S(t \mid \lambda) = 1 - F(t \mid \lambda) = \exp(-\lambda t)$

To account for censored observations when constructing likelihood

- Modeling treatment effect

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

$$\beta_{T,s} = \beta_T + \varphi_s, \forall \text{ the } j^{\text{th}} \text{ time interval at the } i^{\text{th}} \text{ site} \in \text{Time Period } s$$

$$\varphi_s \sim \text{Gaussian}(0, \sigma^2)$$

The crash modification factor (CMF) for the s^{th} time period is $\exp(\beta_{T,s})$

- The proposed model is developed in the Bayesian framework using WinGUGS

X_{pij} : time-dependent exposure & risk factors

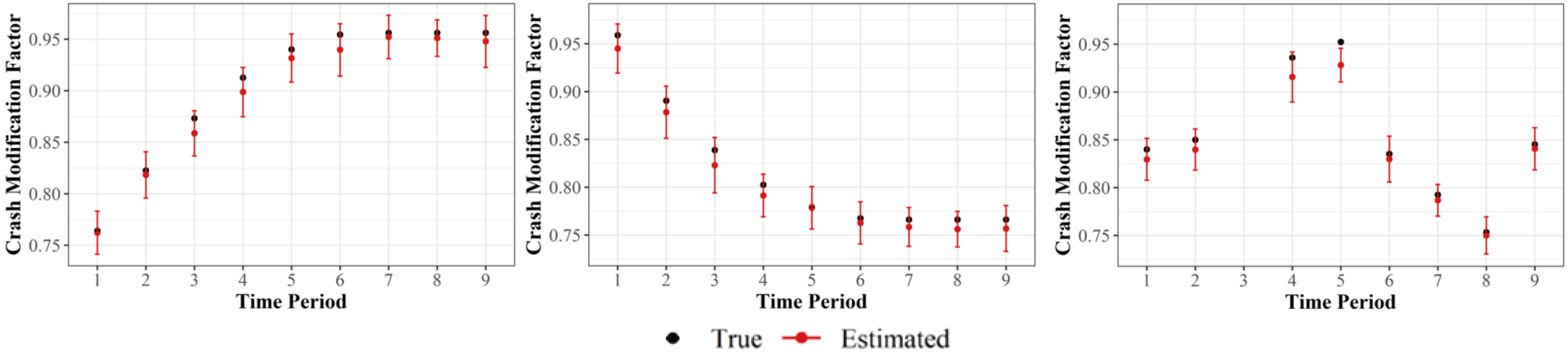
Treatment_{ij} : binary variable with 0 for before treatment and 1 for after treatment

ε_j : account for over-dispersion with $\exp(\varepsilon_i) \sim \text{Gamma}(1, \alpha)$

s : time period in the after period (month in the case study)

Statistical Validation

- Statistically simulated data with different types of hypothetical treatment effects is generated to validate the proposed SARP model
- Simulation results



- The estimated CMFs are very close to the true CMFs for all the three scenarios and all the time periods

Case Study: Safety Effect of COVID Lockdown

- Evaluate the safety effect at the beginning of the COVID lockdown in Manhattan, New York City
- Study period:
  - Before period: ~15 months before the NYS lockdown (01/01/2019 – 03/21/2020)
  - After period: ~ 3 months after the NYS lockdown (03/22/2020 – 06/30/2020)
  - After period is further divided into three time periods with the length of each time period equals approximately a month
    - 03/22/2020 - 04/22/2020, 04/23/2020 - 05/23/2020, and 05/24/2020 - 06/30/2020
- Data:
  - Police-reported crashes, number of taxi trips (pick-ups + drop-offs), speed from Inrix, and weather
- Neighborhoods tabulation area (NTA) is selected as the spatial unit of analysis

Results: Model Comparison

- SARP is compared with SA, i.e., survival analysis model with no random parameters (Xie et al. 2019).
- The SARP model performs better based on Deviance Information Criterion (DIC)

Model	DIC
Model 1. SA	13618
Model 2. SARP	12287

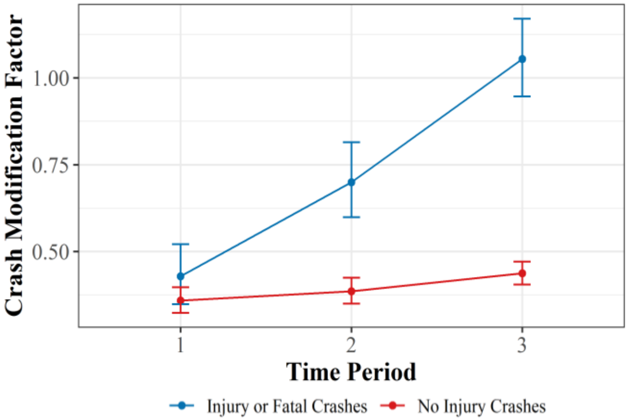
- This finding implies the need to account for temporal instability in treatment effect

Results: SARP Model

- Overall, the estimated coefficients are consistent with previous findings.

	Injury or Fatal Crashes		No Injury Crashes	
	Mean	95% BCI	Mean	2.5% BCI
Intercept	-2.872	(-3.126, -2.623)	-1.216	(-1.431, -1.015)
Log(average number of taxi trips)	0.226	(0.209, 0.242)	0.233	(0.224, 0.241)
Average speed above 25 MPH	0.090	(0.034, 0.146)	-0.136	(-0.166, -0.104)
Temperature (°F)	0.006	(0.005, 0.007)	0.003	(0.002, 0.003)
Precipitation (in)	0.357	(-0.378, 1.052)	0.780	(0.371, 1.180)
Dispersion	0.230	(0.141, 0.350)	-	-

- Estimated CMFs:



<u>Findings</u>:

- Increasing trends after the largest decrease in the first month after the lockdown.
- For injury or fatal crashes, the CMF may return to normal during the third month after initial NY lockdown

Conclusions & Potential Applications

- Conclusions:
  - A survival analysis with random parameter approach is developed to account for temporal instability in treatment effect for crash-based before-after analysis
  - The proposed approach is applied to investigate the safety effect of COVID-19 lockdown
  - The estimated CMFs show increasing trends after the largest decrease in the first month after the lockdown for both no injury crashes and injury or fatal crashes.
  - For injury or fatal crashes, the safety effect may return to normal during the third month after the initial lockdown in New York
- Potential Applications:
  - The proposed survival analysis approach can be applied to estimate safety impact of the implementation of various ITS technologies, such as connected and autonomous vehicles
  - The proposed survival analysis approach can be extended to analyze conflict risk events

Thank You!

Questions?

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