Impact of Sleep Time on Truck Driver Performance Over Long Driving Shift

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Background

- Truck crashes: major safety hazard for commercial truck drivers.
- Fatigue: major risk factor for long-haul truck drivers.
- Sleep: important factor affecting fatigue.
  - Drivers who slept less prior to trips would be more likely to involve in safety-critical events.
  - Breaks (including sleep) before driving are beneficial in reducing safety-critical events.
- Motivation
  - To evaluate the temporal profile of driving performance in a long shift.
  - To compare driving performance among drivers with

$$\text{sleep prior to a shift} \begin{cases} < 7 \text{ hours,} \\ 7\text{–}9 \text{ hours,} \\ > 9 \text{ hours.} \end{cases}$$

Data Collection

- Participants
  - 100 drivers from 4 for-hire trucking companies.
  - Followed up for around 4 weeks.
- Driving Data
  - Naturalistic data collection approach.
  - Truck fitted with unobtrusive data-collection equipment.
  - Data recorded from ignition-on to ignition-off at high frequency.

Figure: Photo: Five video camera images [2].

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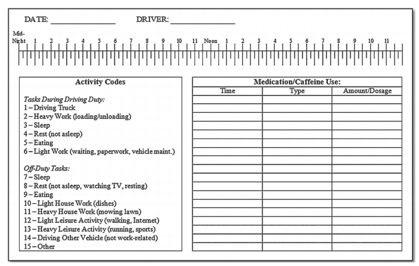
- Activity Data
  - Drivers self-reported using a daily activity registry.



DATE: ______________ DRIVER: ______________

Mid-Night 1 2 3 4 5 6 7 8 9 10 11 Noon 1 2 3 4 5 6 7 8 9 10 11

Activity Codes

Tasks During Driving Duty:
1 – Driving Truck
2 – Heavy Work (loading/unloading)
3 – Sleep
4 – Rest (not asleep)
5 – Eating
6 – Light Work (waiting, paperwork, vehicle maint.)

Off-Duty Tasks:
7 – Sleep
8 – Rest (not asleep, watching TV, resting)
9 – Eating
10 – Light House Work (dishes)
11 – Heavy House Work (mowing lawn)
12 – Light Leisure Activity (walking, Internet)
13 – Heavy Leisure Activity (running, sports)
14 – Driving Other Vehicle (not work-related)
15 – Other

Medication/Caffeine Use:

Time	Type	Amount/Dosage

Figure: A sample of the daily activity register [2].

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- Activity Data
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- Safety-Critical Events
  - Crash;
  - Near-crash;
  - Crash relevant conflict;
  - Unintentional lane deviation.

Data Processing

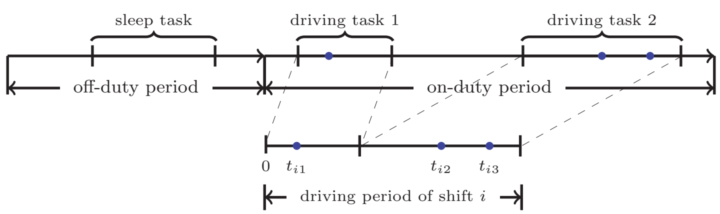


Figure: Illustration of data processing. Dots represent events, and t_{ij}, where $j = 1, 2, 3$, represents the driving time to event j in shift i.

1,880 shifts from 96 drivers contain valid sleep data.

- Off-duty sleep $<$ 7 hours: 388 (20.6%) shifts;
- Off-duty sleep in 7–9 hours: 1,095 (58.2%) shifts;
- Off-duty sleep $>$ 9 hours: 397 (21.1%) shifts.

Sleep Hours vs Driving Length

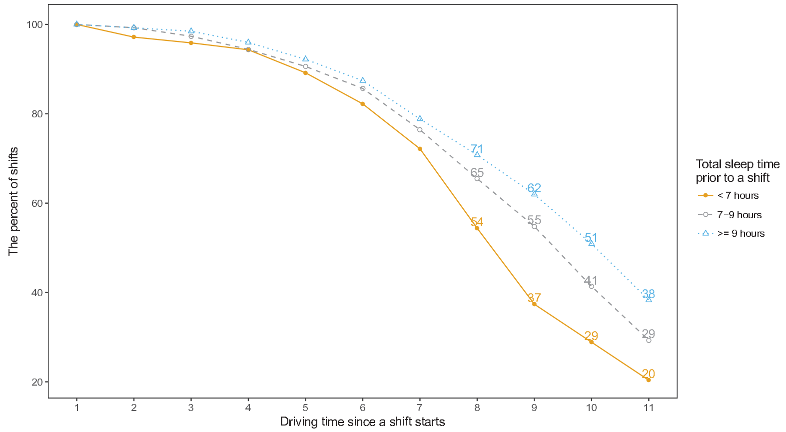


Figure: The percent of shifts driving into the 1st-11th driving hour by sleep time group.

Sleep Hours vs Breaks

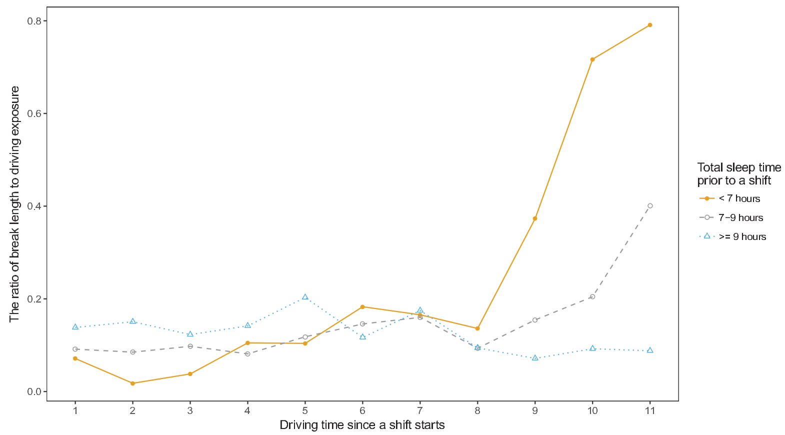
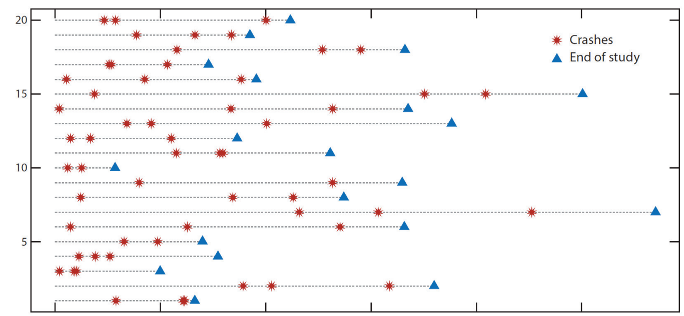


Figure: The ratio of break length (in hours) to driving exposure (in hours) in the 1st–11th driving hours by sleep time group. Exposure in the ith hour, where $i = 1, \ldots, 11$, is the total driving time for all shifts that occurred in the ith hour.

Overview

2 Time-Varying Coefficient Model for Recurrent Events



Notations

Consider a sample of I driving shifts. For $i = 1, \ldots, I$,

- Counting process $\{N_i(t), t \geq 0\}$
  - $N_i(t)$: the number of events occurred over $[0, t]$.
  - $\Delta N_i(t)$: the number of events occurred over $[t, t + \Delta t)$.
- Covariates
  - $\boldsymbol{x_i} = (x_{i1}, \ldots, x_{ip})'$ assumed to have constant coefficients.
  - $\boldsymbol{z_i} = (z_{i1}, \ldots, z_{iq})'$ assumed to have time-varying coefficients.
- Process history at time t, $H_i(t) = \{N_i(s), 0 \leq s < t, \boldsymbol{x_i}, \boldsymbol{z_i}\}$.
- Gamma frailty $u_i \sim \text{Ga}(\text{shape} = 1/\phi, \text{rate} = 1/\phi)$
  - $\text{E}(u_i) = 1$;
  - $\text{var}(u_i) = \phi$.

Model

- Conditional on u_i, the intensity function is defined as

$$\lambda_i(t|H_i(t), u_i) = \lim_{\Delta t \downarrow 0} \frac{P(\Delta N_i(t) = 1|H_i(t), u_i)}{\Delta t}.$$

- Assume $\{N_i(t), t \geq 0\}|\boldsymbol{x_i}, \boldsymbol{z_i}, u_i$ to be an independent Poisson process with conditional intensity function

$$\begin{aligned}\lambda_i(t|\boldsymbol{x_i}, \boldsymbol{z_i}, u_i) &= u_i \rho_i(t) \\ &= u_i \exp\{\boldsymbol{x_i'\alpha} + \beta_0(t) + z_{i1}\beta_1(t) + \cdots + z_{iq}\beta_q(t)\}.\end{aligned}$$

- Let $\mu_i(t) = \int_0^t \rho_i(s)\,\mathrm{d}s$. Marginal features of $\{N_i(t), t \geq 0\}$:
  - $\mathrm{E}[N_i(t)] = \mu_i(t)$.
  - $\mathrm{var}[N_i(t)] = \mu_i(t) + \phi\,\mu_i^2(t)$. $\Leftarrow$ extra-Poisson variation
  - $\mathrm{cov}[N_i(s_1, t_1), N_i(s_2, t_2)] = \phi\,\mu_i(s_1, t_1)\,\mu_i(s_2, t_2)$. $\Leftarrow$ association between counts over disjoint intervals

Model: Time-Varying Coefficients

Penalized B-splines [3] for smooth estimation of $\beta_l(t)$, where $l = 0, 1, \ldots, q$:

- Let $[t_{\min}, t_{\max}]$ be divided into k_l equal intervals by knots

$$t_{\min} = \zeta_{l0} < \zeta_{l1} < \cdots < \zeta_{l,k_l} = t_{\max}.$$

- The B-splines basis of degree v

$$\boldsymbol{B_l}(t) = \left(B_{l1}(t), \ldots, B_{l,K_l}(t)\right)', \text{ where } K_l = k_l + v.$$

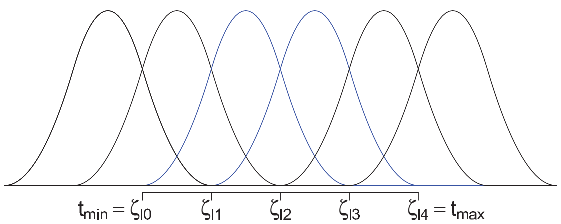


Figure: Illustration of the B-spline basis for $k_l = 4$ and $v = 2$.

Model: Mixed-Model Representation

Spline Parameters as Random Effects

Model

$$\lambda_i(t|\boldsymbol{x_i}, \boldsymbol{z_i}, u_i, \boldsymbol{\beta_l}) = u_i \exp\left\{\boldsymbol{x_i}'\boldsymbol{\alpha} + \boldsymbol{B_0}'(t)\boldsymbol{\beta_0} + \cdots + z_{iq}\boldsymbol{B_q}'(t)\boldsymbol{\beta_q}\right\},$$
$$u_i \sim \text{Ga}(1/\phi, 1/\phi), \quad \boldsymbol{\beta_l} \sim p(\boldsymbol{\beta_l}; \tau_l).$$

- Bayesian setting

$$\boldsymbol{D_l}\boldsymbol{\beta_l} = \begin{bmatrix} \Delta^r \beta_{l,r+1} \\ \vdots \\ \Delta^r \beta_{l,K_l} \end{bmatrix} \sim N\left(\boldsymbol{0}, \frac{1}{\tau_l}\boldsymbol{I}\right).$$

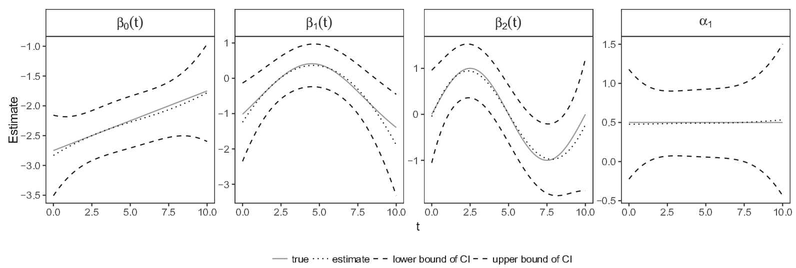
- Frequentist setting

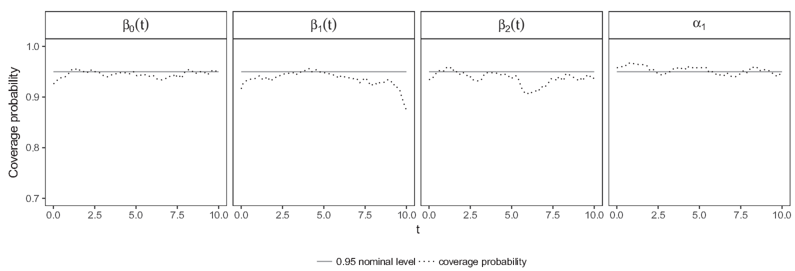
$$p(\boldsymbol{\beta_l}; \tau_l) \propto \tau_l^{(K_l - r)/2} \exp\left\{-\frac{1}{2}\tau_l\, \boldsymbol{\beta_l}'(\boldsymbol{D_l}'\boldsymbol{D_l})\boldsymbol{\beta_l}\right\}.$$

- Inverse variance τ_l ($\Leftrightarrow \lambda_l$) controls the amount of smoothness.

Simulation

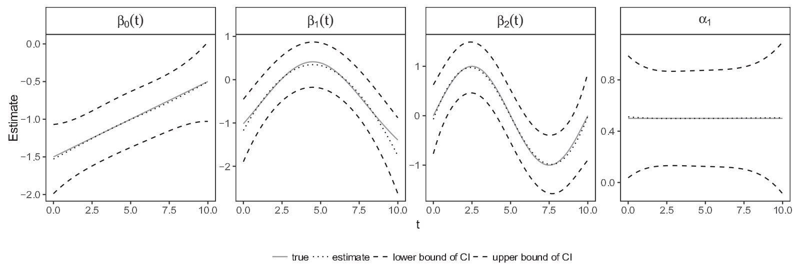
Low Curvature TVC, Low Event Rate

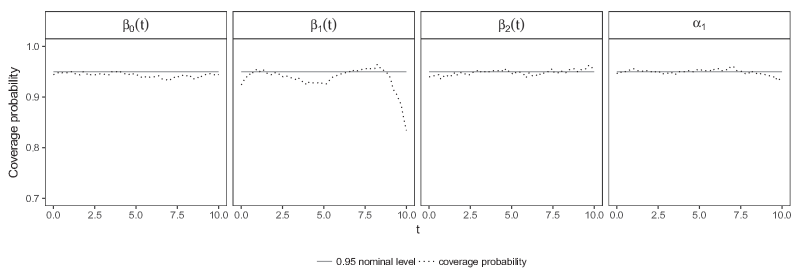




Simulation

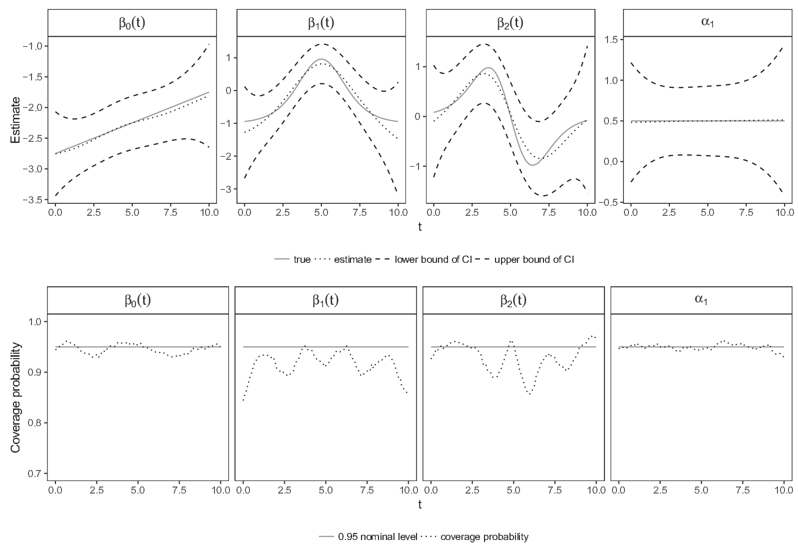
Low Curvature TVC, High Event Rate





Simulation

High Curvature TVC, Low Event Rate



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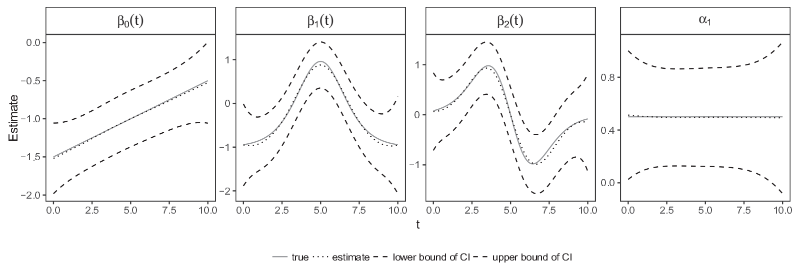
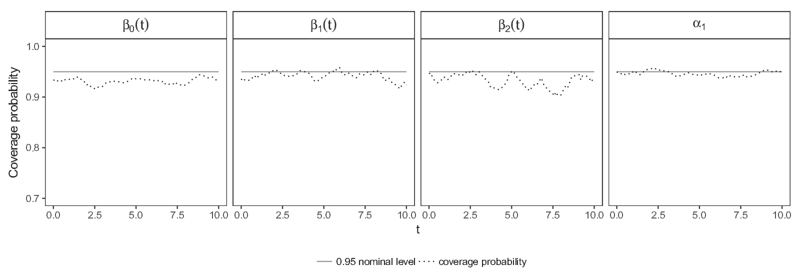
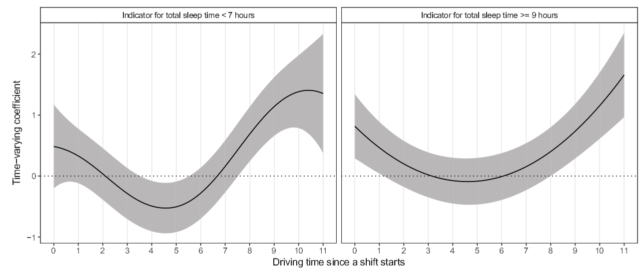
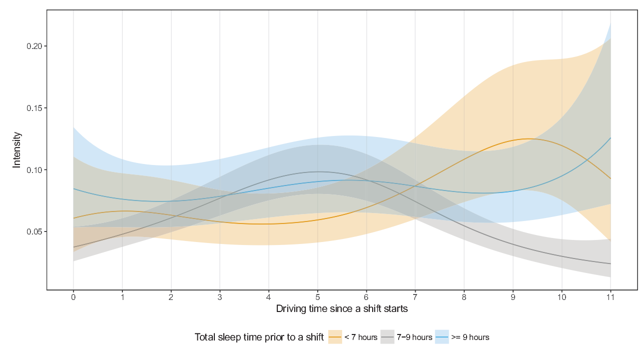





Indicator for total sleep time < 7 hours
Indicator for total sleep time >= 9 hours
Time−varying coefficient
2
1
0
−1
0 1 2 3 4 5 6 7 8 9 10 11
0 1 2 3 4 5 6 7 8 9 10 11
Driving time since a shift starts


Intensity
0.20
0.15
0.10
0.05
0 1 2 3 4 5 6 7 8 9 10 11
Driving time since a shift starts
Total sleep time prior to a shift
< 7 hours
7−9 hours
>= 9 hours

Conclusions

- The total sleeping time is directly related to the total driving time
- The total sleeping time is directly related to breaks while driving
- The total sleeping time will affect driving performance after 8 hours of driving
- There is a complicated interaction effect among total sleeping time, breaks, and driving performance over long trips.

Reference

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