Can we infer on behavioral impacts of public policy on accident severity outcomes?

A Swiss case study using historical disaggregate accident reports

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Outline

1. Context

2. Modeling Approach
   - Ordered logit
   - Latent variable

3. Dataset

4. Modeling Results

5. Conclusion
Outline

1. Context

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Traffic Accidents in Switzerland

From 1992 to 2017

- Approx. 1.8M reported crashes, 3.7M individuals involved.
- In total, 140k severely injured, 12’802 victims.
Via Sicura

Action program for road safety

• ”Reduce the number of fatalities and serious injuries on our roads.”
• 20 legislative measures, both preventive and repressive.
• Introduced step by step since January 2013.

<table>
<thead>
<tr>
<th>Preventive measures</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Prohibition for probationary license holders to supervise learners</td>
<td>01.2013</td>
</tr>
<tr>
<td>Minimum age for cyclists</td>
<td>01.2013</td>
</tr>
<tr>
<td>Minimum age for driving animal-powered vehicles</td>
<td>01.2013</td>
</tr>
<tr>
<td>Prohibition for certain groups to drive under the influence of alcohol</td>
<td>01.2014</td>
</tr>
<tr>
<td>Mandatory daytime running lights</td>
<td>01.2014</td>
</tr>
<tr>
<td>Additional training for offenders</td>
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<table>
<thead>
<tr>
<th>Repressive measures</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mandatory fitness-to-drive evaluation in case of serious offenses</td>
<td>01.2013</td>
</tr>
<tr>
<td>Longer license suspension and stiffer penalties for extreme offenders</td>
<td>01.2013</td>
</tr>
<tr>
<td>Confiscation of motor vehicles in case of ”unscrupulous” offenses</td>
<td>01.2013</td>
</tr>
<tr>
<td>Declaration of caused losses for public liability insurances</td>
<td>01.2013</td>
</tr>
<tr>
<td>Legal recourse from public liability insurers against drunk drivers</td>
<td>01.2013</td>
</tr>
<tr>
<td>Use of black box data recorders for speeding drivers</td>
<td>not yet</td>
</tr>
<tr>
<td>Alcohol ignition-locking systems for drunk drivers</td>
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</table>

<table>
<thead>
<tr>
<th>Other measures</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Support for cross-border criminal prosecutions</td>
<td>01.2013</td>
</tr>
<tr>
<td>Prohibition of traffic control warnings for public or commercial purposes</td>
<td>01.2013</td>
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</tbody>
</table>

...
Via Sicura

Action program for road safety

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Action program for road safety

- ”Reduce the number of fatalities and serious injuries on our roads.”
- 20 legislative measures, both **preventive** and **repressive**.
- Introduced step by step since January 2013.
How do we account for repressive measures in an injury severity model?

- Dissuasive effect on drivers’ behavior.
- In turn, taking less risks reduces crash severity!
- How do we model this?

Leverage the ICLV framework

- An ordered logit for individual injury severity is specified;
- We define a latent variable that represents the risky driving behavior;
- The impact of the Via Sicura on that behavior is captured.
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Model structure

Ordered logit

- explanatory variables
- injury propensity
- risk-taking behavior
- behavioral indicators
- reported injury level

Latent variable

disturbances
Ordered logit: structural equation

Ordered logit

explanatory variables

injury propensity

risk-taking behavior

behavioral indicators

reported injury level

Latent variable

disturbances

disturbances

disturbances

Ortelli, Bierlaire, de Lapparent

Public Policy & Accident Severity

21st STRC, 12–14 September 2021
Ordered logit: structural equation

Injury propensity \( y_n^* \)

\[
y_n^* = \sum_{k=1}^{K} \beta_k x_{nk} + \beta_z z_n^* + \epsilon_n = u_n + \epsilon_n
\]

- \( x_{nk} \) are the explanatory variables;
- \( \beta_k \) are the associated coefficients;
- \( z_n^* \) is the latent variable and \( \beta_z \) is its associated coefficient;
- \( \epsilon_n \sim \text{Logistic} (0, 1) \).
Ordered logit: measurement equation

Ordered logit

- explanatory variables
  - injury propensity
  - risk-taking behavior
  - behavioral indicators

- reported injury level

Latent variable

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Ordered logit: measurement equation

Reported level of injury $y_n$

\[
P_n(y_n = j) = P(\tau_{j-1} < y_n^* < \tau_j) = P(\tau_{j-1} < u_n + \varepsilon_n < \tau_j) = F(\tau_j - u_n) - F(\tau_{j-1} - u_n)
\]

- $j \in \{1, 2, 3, 4\}$;
- $\tau_1, \tau_2, \tau_3$ are thresholds to be estimated.
Ordered logit: measurement equation

Reported level of injury $y_n$

$$P_n(y_n = j) = P(\tau_{j-1} < y_n^* < \tau_j)$$

$$= P(\tau_{j-1} < u_n + \varepsilon_n < \tau_j) = F(\tau_j - u_n) - F(\tau_{j-1} - u_n)$$

- $j \in \{1, 2, 3, 4\}$;
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Latent variable: structural equation

Ordered logit

explanatory variables

risk-taking behavior

injury propensity

behavioral indicators

reported injury level

Latent variable
Latent variable: structural equation

Risk-taking behavior $z_n^*$

$$z_n^* = \gamma_0 + \sum_{\ell=1}^{L} \gamma_{\ell} x_{n\ell} + \omega_n$$

- $\gamma_0$ is an intercept;
- $x_{n\ell}$ are the explanatory variables;
- $\gamma_{\ell}$ are the associated coefficients;
- $\omega_n \sim \mathcal{N}(0, \sigma_\omega)$. 
Latent variable: measurement equation

Ordered logit

- Explanatory variables
- Injury propensity
- Reported injury level
- Risk-taking behavior
- Behavioral indicators

Disturbances

Latent variable: measurement equation

Continuous indicators $I_{in}^*$

$$I_{in}^* = \alpha_{i,0} + \alpha_{i,1} z_{in}^* + \nu_{in}$$

- $\alpha_{i,0}$ is an intercept;
- $\alpha_{i,1}$ measures the effect of the latent variable $z_{in}^*$;
- $\nu_{in} \sim \mathcal{N}(0, \sigma_i)$.

Discrete indicators $I_{in}$

$$
\begin{align*}
P(I_{in} = 0) &= P(I_{in}^* < \mu_i) = P(\alpha_{i,0} + \alpha_{i,1} z_{in}^* + \nu_{in} < \mu_i) = \Phi \left( \frac{\mu_i - \alpha_{i,0} - \alpha_{i,1} z_{in}^*}{\sigma_i} \right) \\
\end{align*}
$$

$$
\begin{align*}
P(I_{in} = 1) &= 1 - P(I_{in} = 0) = 1 - \Phi \left( \frac{\mu_i - \alpha_{i,0} - \alpha_{i,1} z_{in}^*}{\sigma_i} \right)
\end{align*}
$$

- $\mu_i$ are thresholds to be estimated.
Modeling Approach

Model structure

Ordered logit

explanatory variables

injury propensity

risk-taking behavior

behavioral indicators

reported injury level

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disturbances

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Dataset

Swiss Traffic Accidents (DWH-VU, FEDRO)

- **All traffic accidents** reported in Switzerland from 1992 to 2017.
- Derived from police reports.
- Variables at the accident, object and individuals levels.
- Injury severity reported on a 4-level scale:
  - 1 – no injury;
  - 2 – minor injury;
  - 3 – major injury;
  - 4 – fatal injury.
**Descriptive characteristics**

**Objects**

- Overall, almost 3M objects involved.
- 87.3% are cars and similar: 127k in 1992 down to 78k in 2017.
- The rest includes motorized two-wheelers, soft modes and pedestrians.
Descriptive characteristics

Objects

- Overall, almost 3M objects involved.
- 87.3% are cars and similar: 127k in 1992 down to 78k in 2017.
- The rest includes motorized two-wheelers, soft modes and pedestrians.
Dataset

Descriptive characteristics

Individuals

- Overall, 3.7M individuals involved.
- Approx. 81% are unhurt.
- Major and fatal injuries halved over the 26 years.

![Individuals: injury level, 1992–2017](image-url)
Descriptive characteristics

Individuals

- Overall, 3.7M individuals involved.
- Approx. 81% are unhurt.
- Major and fatal injuries halved over the 26 years.
Descriptive characteristics

Individuals

- Overall, 3.7M individuals involved.
- 62.7% are men (49.6% in the Swiss population).
- Women are more prone to suffer minor and major injuries.
Descriptive characteristics

Individuals

- Overall, 3.7M individuals involved.
- Young adults (18 – 35) are largely over-represented in the early years.
- Children and seniors are under-represented.
### Descriptive characteristics

#### Individuals

- Overall, 3.7M individuals involved.
- Young adults (18 – 35) are largely over-represented in the early years.
- Children and seniors are under-represented.
Main limitations

- Under-reporting of accidents without injuries.
- Precision and completeness of the data depend on accident severity.
- Precision and completeness of the data depend on the year.
- Only 831k complete observations!
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Model specification

Risk-taking behavior

• Explanatory variables:
  • Via Sicura;
  • Time of the accident (night);
  • Visibility conditions;
  • Road conditions;
  • Passengers’ age (child aboard);
  • Drivers’ gender.

• Indicators:
  • Driver’s substance consumption;
  • Driver’s protection;
  • Driver’s license.

Injury propensity

• Explanatory variables:
  • Accident type;
  • Speed limit;
  • Vehicle type;
  • Year of entry into service;
  • Seat belt use;
  • Gender and age, interacted.
### Estimation results: latent variable

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Rob. t-test</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_0$</td>
<td>54.4</td>
<td>68.5</td>
</tr>
<tr>
<td>$\gamma_{\text{via sicura}}$</td>
<td>$-71.0$</td>
<td>$-67.5$</td>
</tr>
<tr>
<td>$\gamma_{\text{late night}}$</td>
<td>96.0</td>
<td>68.2</td>
</tr>
<tr>
<td>$\gamma_{\text{bad visibility}}$</td>
<td>$-14.0$</td>
<td>$-40.9$</td>
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<tr>
<td>$\gamma_{\text{bad road}}$</td>
<td>$-9.01$</td>
<td>$-58.2$</td>
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<tr>
<td>$\gamma_{\text{child aboard}}$</td>
<td>$-30.5$</td>
<td>$-58.5$</td>
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<tr>
<td>$\gamma_{\text{female driver}}$</td>
<td>$-28.4$</td>
<td>$-68.9$</td>
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<td>$\sigma_\omega$</td>
<td>$-67.7$</td>
<td>$-68.8$</td>
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</tbody>
</table>
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<tr>
<th>Parameter</th>
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</thead>
<tbody>
<tr>
<td>$\alpha_{\text{substances},0}$</td>
<td>0</td>
<td>—</td>
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<tr>
<td>$\alpha_{\text{no-license},0}$</td>
<td>-2.20</td>
<td>-568</td>
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<tr>
<td>$\alpha_{\text{no-protec},0}$</td>
<td>-1.41</td>
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<tr>
<td>$\alpha_{\text{substances},1}$</td>
<td>1</td>
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<tr>
<td>$\alpha_{\text{no-license},1}$</td>
<td>0.00296</td>
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<td>$\alpha_{\text{no-protec},1}$</td>
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<tr>
<td>$\sigma_{\text{substances}}$</td>
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<tr>
<td>$\sigma_{\text{no-license}}$</td>
<td>1</td>
<td>—</td>
</tr>
<tr>
<td>$\sigma_{\text{no-protec}}$</td>
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<td>—</td>
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<tr>
<td>$\mu_{\text{substances}}$</td>
<td>95.9</td>
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<td>$\mu_{\text{no-license}}$</td>
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<tr>
<td>$\mu_{\text{no-protec}}$</td>
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## Estimation results: ordered logit

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<tr>
<th>Parameter</th>
<th>Value</th>
<th>Rob. t-test</th>
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<tbody>
<tr>
<td>$\beta_{\text{RISKY}}$</td>
<td>0.00293</td>
<td>42.5</td>
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<tr>
<td>$\beta_{\text{FRONTAL_COLLISION}}$</td>
<td>0.466</td>
<td>35.5</td>
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<tr>
<td>$\beta_{\text{WHILE_PARKING}}$</td>
<td>−1.81</td>
<td>−75.7</td>
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<tr>
<td>$\beta_{\text{PEDESTRIAN_INVOLVED}}$</td>
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<tr>
<td>$\beta_{\text{MAX_SPEED_TRAFFIC_NORM}}$</td>
<td>0.600</td>
<td>59.5</td>
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<tr>
<td>$\beta_{\text{MAX_SPEED_TRAFFIC_HIGH}}$</td>
<td>0.416</td>
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<td>$\beta_{\text{MAX_SPEED_TRAFFIC_UNK}}$</td>
<td>1.07</td>
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<tr>
<td>$\beta_{\text{TWO_WHEELER}}$</td>
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<tr>
<td>$\beta_{\text{SOFT_MODE}}$</td>
<td>1.96</td>
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<td>$\beta_{\text{PEDESTRIAN}}$</td>
<td>3.03</td>
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<td>$\beta_{\text{YEAR_ENTRY}}$</td>
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<td>$\tau_2$</td>
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<td>$\tau_3$</td>
<td>6.26</td>
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</table>
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Conclusion

Summary

- Inclusion of a behavioral construct in an injury-severity model.
- Appropriate way of capturing the dissuasive effect of repressive measures;
- The model is realistic and in line with the existing literature.

Future work

- Correlation at the vehicle and accident level.
- Additional behaviors: aggressive, distracted, or defensive driving.
- Increase sample size.
Can we infer on behavioral impacts of public policy on accident severity outcomes?

* A Swiss case study using historical disaggregate accident reports

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