



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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Public Policy & Accident Severity

Outline

- 1. Context
- 2. Modeling Approach
 - Ordered logit
 - Latent variable
- 3. Dataset
- 4. Modeling Results
- 5. Conclusion

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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.
- 230 victims in 2017.



Via Sicura

- "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.

Preventive measures	
Prohibition for probationary license holders to supervise learners Minimum age for cyclists Minimum age for driving animal-powered vehicles Prohibition for certain groups to drive under the influence of alcohol Mandatory daytime running lights Additional training for offenders	01.2013 01.2013 01.2013 01.2014 01.2014 not yet
Repressive measures	
Mandatory fitness-to-drive evaluation in case of serious offenses Longer license suspension and stiffer penalties for extreme offenders Confiscation of motor vehicles in case of "unscrupulous" offenses Declaration of caused losses for public liability insurances Legal recourse from public liability insurers against drunk drivers Use of black box data recorders for speeding drivers Alcohol ignition-locking systems for drunk drivers	01.2013 01.2013 01.2013 01.2013 01.2013 not yet not yet
Other measures	
Support for cross-border criminal prosecutions Prohibition of traffic control warnings for public or commercial purposes 	01.2013 01.2013

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Objective

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: structural equation



Ordered logit: structural equation

Injury propensity y_n^*

$$y_n^* = \sum_{k=1}^K \beta_k x_{nk} + \beta_z z_n^* + \varepsilon_n = u_n + \varepsilon_n$$

- x_{nk} are the explanatory variables;
- β_k are the associated coefficients;
- z_n^* is the latent variable and β_z is its associated coefficient;
- *ε_n* ~ Logistic (0, 1).

Ordered logit: measurement equation



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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• $j \in \{1, 2, 3, 4\};$

• τ_1 , τ_2 , τ_3 are thresholds to be estimated.



Latent variable: structural equation



Latent variable: structural equation

Risk-taking behavior z_n^*

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

- γ₀ is an intercept;
- $x_{n\ell}$ are the explanatory variables;
- γ_{ℓ} are the associated coefficients;
- $\omega_n \sim \mathcal{N}(0, \sigma_\omega).$

Latent variable: measurement equation



Latent variable: measurement equation

Continuous indicators I_{in}^*

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

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

Discrete indicators Iin

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

• μ_i are thresholds to be estimated.

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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.

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.



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- 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.



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



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Dataset

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

Parameter	Value	Rob. t-test
γ_0	54.4	68.5
$\gamma_$ via_sicura	-71.0	-67.5
$\gamma_$ late_night	96.0	68.2
$\gamma_{-}bad_{-}visibility$	-14.0	-40.9
γ_bad_road	-9.01	-58.2
γ_{-} child_aboard	-30.5	-58.5
γ_{-} female_driver	-28.4	-68.9
σ_{ω}	-67.7	-68.8

Estimation results: latent variable

Parameter	Value	Rob. t-test
$lpha_{substances,0}$ $lpha_{no_license,0}$ $lpha_{no_protec,0}$	0 -2.20 -1.41	
$lpha_{ ext{substances},1} \ lpha_{ ext{no_license},1} \ lpha_{ ext{no_protec},1}$	1 0.00296 0.00326	 36.9 58.6
$\sigma_{ m substances}$ $\sigma_{ m no_license}$ $\sigma_{ m no_protec}$	1 1 1	
$\mu_{ ext{substances}}$ $\mu_{ ext{no_license}}$ $\mu_{ ext{no_protec}}$	95.9 0.590 0.143	68.1 153 111

Estimation results: ordered logit

Parameter	Value	Rob. t-test
β_RISKY	0.00293	42.5
$\beta_{\rm FRONTAL_COLLISION}$	0.466	35.5
β_WHILE_PARKING	-1.81	-75.7
$\beta_{PEDESTRIAN_INVOLVED$	-0.948	-45.4
β_MAX_SPEED_TRAFFIC_NORM	0.600	59.5
$\beta_MAX_SPEED_TRAFFIC_HIGH$	0.416	38.8
$\beta_MAX_SPEED_TRAFFIC_UNK$	1.07	56.1
β_{-} TWO_WHEELER	1.82	117
β _SOFT_MODE	1.96	67.0
β_{-} PEDESTRIAN	3.03	82.6
$\beta_{}$ YEAR_ENTRY	-0.0692	-5.58
$\beta_{-}BELT$	-1.45	-115
$\beta_{-}FEMALE$	0.503	35.3
$\beta_{AGE_{FEMALE}}$	0.00455	18.6
$\beta_{-}AGE_{-}MALE$	0.000899	4.26
$\beta_{AGE_SQ_MALE}$	0.000108	11.0
$ au_1$	0.956	32.0
$ au_2$	3.38	377
$ au_3$	6.26	157

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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.





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