Risk estimation for different precrash factors in run-off road crashes in curves.

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Abstract The aim of this study was to estimate crash risk for precrash factors in run-off road crashes in curves by using a novel methodology for combining different types of available databases. When describing precrash situations, in-depth or statistical crash databases are frequently used. However, without exposure data, risk for crashes cannot be estimated. Exposure could be estimated from naturalistic driving study (NDS) data or national statistics, but each data source has its weakness with regard to details and representativeness.

Using one statistical crash database and one NDS dataset, a matched case-control methodology was applied to run-off road crashes in curves (n=367) and a set of controls consisting of curve driving events. Precrash factors were harmonised and the contribution to crash risk was estimated using a conditional logistic regression model. The results showed that the risk increased with longer travel times, slippery road conditions and driving late at night and a significantly lower crash risk was found for drivers travelling together with a passenger.

The methodology presented offers a new perspective on how available datasets can be used to estimate the contribution to crash risk for precrash factors on a more detailed level than was made in previous studies.

Keywords Case-control study, Precrash factors, Risk estimation, Run-off Road

I. INTRODUCTION

The interaction between the car, the driver and the traffic situation is complex and many questions on how different factors affect crash risk remain unanswered. It is clear that knowledge on the relative importance of precrash factors (here defined as identifiable states and/or behaviors that can influence a crash situation), is vital in order to be able to prioritize between countermeasures meant to reduce crash involvement.

To estimate how crash risk changes whether certain pre-crash factors are present or not, case- and exposure data is required. In other words, information on crashes and information on the driving circumstances for the corresponding population must be obtained. The challenge addressed by the present study is the fact that case- and exposure data rarely coexist in the same database. While statistical crash databases have a lot of information on the cases (crashes), they do not describe exposure. Other databases, in particular from Naturalistic Driving Studies (NDS), have lots of data on exposure, but generally not enough cases to study how crash risk is influenced by precrash factors.

There have been attempts to retrospectively collect exposure data in order to make risk estimates for certain crash databases [1-5] . While this approach does provide the opportunity to make detailed risk estimates, it is also clear that the resource demanding data acquisition limits the availability of exposure data. This means that these studies often are restricted to a geographical area, e.g. one part of a road, or to the study of only a few precrash factors.

The aim of the current study was to develop a methodology where available datasets can be used to estimate the contribution to crash risk for different precrash factors. To overcome the above mentioned difficulties, it is suggested to harmonize pre-crash information from already collected databases with case- and control data in an organized manner. Run-off road crashes which occur on curved road segments were selected for further analysis. In general, run-off road crashes represent a large proportion of the reported crashes, both in general and for severe injury crashes. In German official statistics, “leaving the carriageway” crashes represent 14% of all crashes with personal injury involving all kinds of road users but 30% of all fatalities and 23% seriously injured persons. [8]. In the US, 30 percent of all fatal crashes were single-vehicle crashes and 71 percent of these fatal single-vehicle crashes were run-off road crashes [9].

II. METHODS

Crash risk was estimated using a matched case-control method for two available crash- and NDS datasets. The datasets were matched and harmonized, and relative risk for different precrash factors was modeled, see Figure 1. With regard to differences in precrash factor characteristics in statistical crash databases from different countries [6], it is suggested to use cases and controls in databases from the same country. Also, car model and driver characteristics [4,7] might affect crash risk and should be considered. The two databases selected for this study both contain information on drivers in recent Volvo Car models in Sweden, and therefore met these basic requirements.

Figure 1. A schematic of the steps in the method.

Case Data (crashes)

Volvo Cars Traffic Accident Database (VCTAD) contains crashes involving Volvo passenger cars in Sweden where the repair cost exceeds a specified level. Inspectors from Volvia (If P&C Insurance), the company with which all new Volvo passenger cars are insured, identify the crashes. Volvo Cars crash investigation team collects data on precrash factors, the crash situation and on the car occupants for each case in the dataset. More information about the database is found in [10].

Crashes during 2002-2013 (car model years 1999-2014) were selected in VCTAD for the analysis. The crashes were classified based on the shape of the road at the scene, and a final sample of n=551 run off road crashes which occurred in curves were chosen as the crash population for this study.

Control Data (exposure)

Controls were selected from Volvo Cars EuroFOT Dataset (VCED) that comprises naturalistic driving data from 100 Volvo cars driven in real traffic during one year as part of the EuroFOT project [11]. In total, 195 car drivers are included in the database, which consists of 1.069.460 driven kilometers and 26.019 hours of data. Data was recorded continuously at 10Hz during the whole trips and included camera views (e.g., forward road view, rearward road view and driver view), onboard sensors, and CAN-bus signals. Information on precrash factors were available as signal data and as data based on video annotation. VCED is divided into *trips* defined from when the vehicle is started to when the vehicle is turned off.

To investigate the representativeness of VCED to the case data population, i.e. driving in Swedish traffic, VCED was compared to The Swedish national travel survey, RVU Sweden, [12]. RVU Sweden consists of national statistics for *main* trips, defined as trips starting and ending in a main destination, for all modes of transport on Swedish roadways. Main destinations in RVU Sweden were defined as places of residence or workplace. Thus a main trip can consist of several trips, such as a trip from the home to the store and then from the store and back home again. In VCED no classification of main trips exists, for the comparison main trips were defined as a collection of trips with less than one hour between stop and start times. The comparison of main trip duration and main trip length is shown in Table 1.

TABLE I
MAIN TRIP STATISTICS

Attribute	VCED	RVU
Main trip length	29.5 ± 0.3 km	36 ± 2 km
Main trip duration	48 ± 0.4 min	44 ± 2 min

A comparison of the main trip start time for weekends (Saturday-Sunday) and working days (Monday-Friday) is shown in Figure 2.

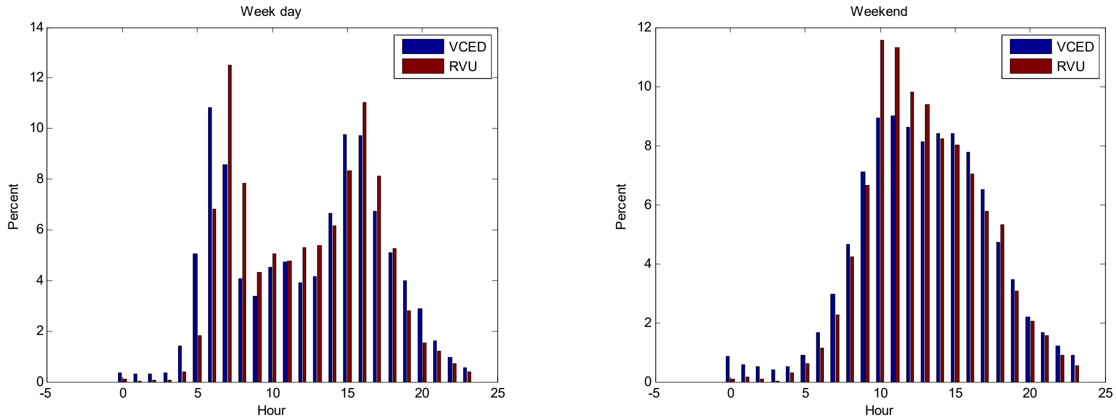

Figure 2. The distribution of main trip start time in VCED and RVU for week days (Monday-Friday) and weekends (Saturday-Sunday).

The starttime of main trips is similar across the hours of the day, with the main difference being at night, with more trips occurring at night in VCED. This may to some extent be explained by the fact that the number of trips with public transport and by bicycle are less frequent at night and more frequent during daytime. To further investigate this, the number of night trips from VCED was compared with the Official Statistics of Sweden [15], a study which included only motorvehicle traffic during nighttime. The proportion of vehicle traffic in the timespan between 22:00-05:59 is 5.65% in the Official Statistics of Sweden and 5.42% in VCED, which supports our hypothesis and thus makes our dataset representative in terms of traveltime of the day.

The crash population for this study was defined as run off road crashes in curves from VCTAD, and following this selection criteria, curve passages in VCED was chosen as exposure events. Curves were defined according to road design standards [17] based on speed limit and curvature radius. Curve events at a speeds below 20 km/h were not included in the study, due to the fact that at this speed curves are difficult to distinguish from low-speed maneuvers in driving data signals. In total, 3 071 140 curve events was identified in VCED.

Data matching

The crash population is derived from a sample of all drivers of recent Volvo cars in VCTAD and the drivers in the VCED database were chosen from a sample of drivers in the EuroFOT project. The databases are not assumed to be equal with regards to driver characteristics. To overcome this, a matching procedure was introduced. First, the trips were labeled by driver age and gender as presented in Table 2.

TABLE II
DRIVER GROUPS

Driver Group	Gender	Age
1	Male	18-25
2	Female	18-25
3	Male	26-35
4	Female	26-35
5	Male	36-45
6	Female	36-45
7	Male	46-55
8	Female	46-55
9	Male	56-65
10	Female	56-65

A comparison of the drivers in the case and the control population is presented in Figure 3. Clearly, older male drivers and younger female drivers are overrepresented in the control data compared to the case data population. Further, the controls were limited to a driving speed of above 20 km/h. The case data contains drivers older than 65 years while no exposure event was found with drivers older than 65. Hence, crashes at speeds between 1-20 km/h or with drivers older than 65 years were removed. After filtering, n=367 cases remained in the crash population. To handle the discrepancy in driver characteristics a 1:1 matched case-control methodology was applied. For each crash in VCTAD, a curve event for the same driver group was sampled from the identified

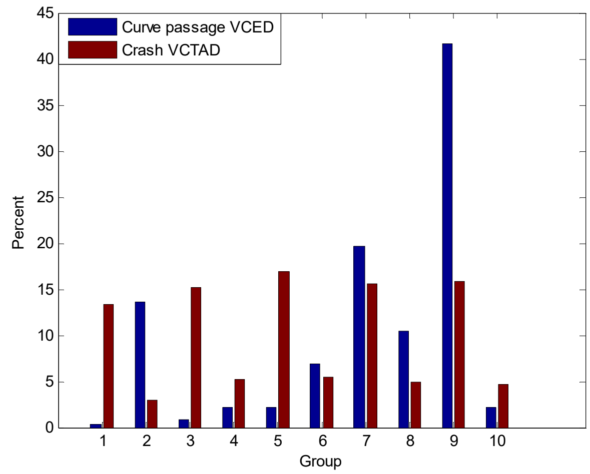

Figure 3. The distribution of driver group in VCED and VCTAD before data matching.

controls in VCED without replacement and added to the final combined dataset of both case and exposure data. For example, if the driver was from driver group 5 (male driver between age 36 and 45), one curve passage was chosen at random from the population of curve passages from driver group 5 in VCED and added to the final dataset. The selected curve passage was then removed from the selectable controls in the VCED database. The procedure was repeated until one control had been matched to every crash case. After matching, the dataset consisted of 367 crashes and 367 curve passages. The distribution of driver groups in the final dataset can be seen in Figure 4.

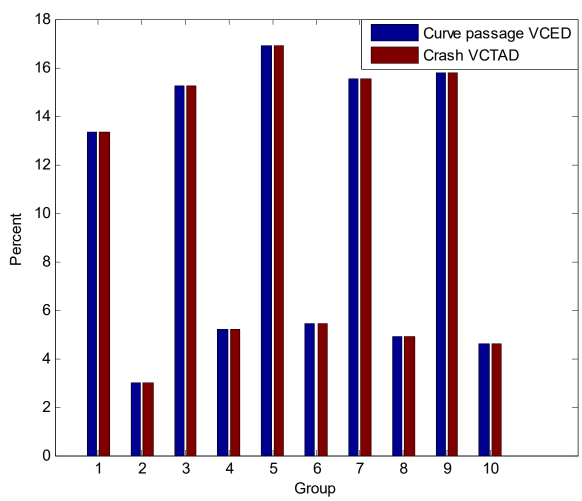

Figure 4. The distribution of driver group in VCED and VCTAD after data matching.

To estimate crash risk for specific precrash factors, information on them has to be present in both datasets and in same format. There were no possibilities of retrieving further case information in addition to what was collected at the crash investigation, so the information available in VCTAD formed the basis for the selection of precrash factors for further analysis. Corresponding variables were identified in the VCED dataset, either as signals or as annotations from video data. Table 3 lists variables used for the analysis, as well as the defined levels.

TABLE III

PRECRASH FACTORS

Variable	Source	Values
Number of occupants	Signal	1, 2, 3+
Time of day	Signal	02-04, 05-07, 08-10, 11-13, 14-16, 17-19, 20-22, 23-01
Weekday	Signal	Mon-Sunday
Month	Signal	Jan-Dec
Speed	Signal	21-40, 41-60, 61-80, 81-100, 100-120+ kmph
Temperature	Signal	<-5, -5 to 5, 5 to 15, 15+ °C
Travel time, planned	Signal	<0.5h, 0.5-1h, 1h+
Travel time, actual	Signal	<0.5h, 0.5-1h, 1h+
Weekend (Saturday, Sunday)	Signal	Yes, No
Weather	Annotation	Clear/Cloudy, Snow, Rain/Fog, Other/Unknown
Road condition	Annotation	Dry, Snow/Ice, Wet, Other/Unknown
Type of road	Annotation	Rural road, Highway, City Street, Other/Unknown
Distraction	Annotation	No, Phone, Passenger, Other
Road surface	Annotation	Asphalt, Other
Light conditions	Annotation	Daylight, Darkness, Dusk/Dawn

Risk estimation

A set of predictor variables, in this case the precrash factors, was assumed to be related to the outcome variable, Y, and therefore provide additional information for predicting Y. Realtive risk for each precrash factor was estimated by comparing the occurrence of the factor between the crash population and the reference population. For risk estimation, logistic regression analysis was applied. For the case with multinomial predictors, which are transformed to conditional binomial variables x_i, the risk of a crash can be stated as:

$$Y(x_1, x_2, \dots, x_n) = \beta_0 + x_1\beta_1 + x_2\beta_2 + \cdots + x_n\beta_n$$

A number of risk parameters $\beta_1, \beta_2, \dots \beta_n$ such that the likelihood (L) of the observed data is maximized in the model. The model parameters were found using a gradient descent method. Further, each precrash factor was evaluated by the explanatory value in the model by Akaikes information criterion (AIC) formulated as:

$$AIC = 2k - 2\ln(L)$$

where k is the number of precrash-factors included in the model. The AIC can be seen as a trade-off between the complexity and explanatory value of the model. The final model was chosen in a process where all possible models where evaluated. The final model was chosen as the model with the highest AIC for the observed data. The significance of the repective estimated risk parameters β_i was assessed by using the chi-square statistic and evaluating it against a chi-square (χ^2) distribution.

For the model with the highest AIC the estimated values of the risk parameters β_i are presented for the included precrashfactors. The risk parameters are relative risks showing the risk increase for a given precrash parameter, a value larger than 1 represents an increase in risk and a value smaller than 1 represents a decrease in risk.

III. RESULTS

Data from 367 run-off road crashes in curves matched to 367 references in terms of driving events in curves was investigated in the model including 15 precrashfactors. The estimated risk value for each precrash factor in the final model are presented in Table 2. Significance indicates a difference to the reference value for each precrash factor presented as the first value for each precrash factor.

Crash risk was lower when a passenger was present in the car, and remains lower when two or more passengers are present. For the precrash factor distraction, estimated risk was lower for the activities 'Telephone' and 'Passenger' while the category 'Other' showed a large increase in risk. Crash risk also increases with increased travel time. Driving for more than an hour increased risk by 4.7 times. A slightly lower risk when driving in the dark was noted, as well as a clear risk increase when driving during dusk and dawn.

The risk differs significantly over time of the day being lowest in the morning between 05 and 10 and hit a maximum between 23 and 04 o clock. Compared to crashes in Rural Roads, driving on 'Highway / Expressway' and 'Urban/Suburb streets' showed a lower crash risk. Road surface were mainly classified as 'Asphalt' and 'Other', where the latter consisted mostly of gravel roads and paving stone. The risk of crash involvement increased almost by a factor of 20 when driving on 'Other' road surfaces. 'Snow / Ice' posed the highest risk when investigating different road surface conditions, wet conditions increased the crash risk by a factor of 1.81. Precipitation in terms of snowfall contributed to a risk increase of 6.12 while rain increased the risk by 1.49.

TABLE IV
MEASURED PARAMETERS

Variable	Relative risk (exp(Beta))	Significance
Number of occupants: 1	1	NA
Number of occupants: 2	0.30	***
Number of occupants: 3+	0.29	**
Distraction: NoI	1	NA
Distraction: Phone	0.21	*
Distraction: Passenger	0.06	***
Distraction: Other	14.10	***
Travel time: <0.5h	1	NA
Travel time: 0.5-1h	3.60	***
Travel time: >1h	4.70	***
Light condition: Day light	1	NA
Light condition: Dark	0.9	
Light condition: Dusk/dawn	6.30	***
Time of day: 11-13	1	NA
Time of day: 14-16	0.65	
Time of day: 17-19	0.50	
Time of day: 20-22	0.72	
Time of day: 23-01	2.95	
Time of day: 02-04	1.64	
Time of day: 05-07	0.30	*
Time of day: 08-10	0.28	*
Road surface: Asphalt	1	NA
Road surface: Other	19.90	***

Road condition: Dry	1	NA
Road condition: Snow/ice	18.20	***
Road condition: Wet	1.81	.
Road condition: Other/Unknown	49.34	**
Type of road: Rural road	1	NA
Type of road: Highway/Expressway	0.68	
Type of road: Urban road	0.12	***
Type of road: Other/Unknown	3.64	.
Weather: Clear/cloudy	1	NA
Weather: Snowfall	6.12	*
Weather: Rain/fog	1.49	
Weather: Other/Unknown	3.39	

Table 4. The estimated risk parameters for the precrash factors in the final model. (Significance levels: * = less than 1%, ** = 1%, * = 5%, . = 10%.**

IV. Discussion

The aim of this study was to develop and apply a methodology for estimating how different precrash factors contribute to elevation or decrease in crash risk for run-off road crashes occuring in curves. The methodology was based on 1:1 matching of controls. A control dataset consisting of 3 071 140 curve events was used to represent baseline driving. It would be possible to match several curve passages against each crash, so called 1:n matching. With a larger sample of control the estimates of the coefficients β_i would be more precise, allowing for higher significance levels for the parameter estimates. An effect of this is that smaller effects could be estimated. In this study, each control sequence required manual annotation of factors which is time-consuming. Therefore a 1:1 matching scheme was applied. Variables used for matching will be risk-neutral in the consecutive analysis, therefore as few as possible factors should be used for matching. However using more factors in the matching procedure would allow for a more representative population of controls but with a narrower scope. In this application all the common precrashfactors between the databases VCED and VCTAD were used. In the datasets used there was a known difference in age and gender in the underlying populations, which motivated matching on these factors.

When looking at precrash factors associated with a relative increase or decrease in crash risk for run-off road crashes in curves, some results were expected while others were not. First, crash risk was elevated for drivers travelling alone as compared to when they had one or more passengers in the car. Many possible explanations can be though of, e.g. The effect of having a passenger might be resulting in more responsible driving, or, as suggested in a studies on elderly drivers [13-14], the passengers might be acting as co-drivers and hence improve safe driving performance. The underlying mechanism for this finding remains an interesting topic for further studies.

Somewhat unexpectedly, it was estimated that the distraction type “phone” was associated with lowered crash risk in run-off road crashes in curves. Previous reports on phone related distraction generally suggests that phone usage increases crash risk, depending on the type of useage, i.e talking or texting [15]. This might suggest that previous analysis have not been able to account for conflict situation and road geometry and their influence on phone usage in their studies. It might also be a question of how controls are selected. For example, one recent study that pointed toward increased risk associated with all phone usage selected their controls in a very particular way called “model” driving episodes, which required alert, attentive, and sober drivers [16]. In contrast, the controls in the present study were not selected based on driver performance, but rather represent normal driving variability, including various driver states in non-crash situations. Also, the fact that self-reported data on drivers distraction was used in this study, might contribute to this finding.

Traffic crashes are rather rare, and in order to get a sufficient sample to work with an aggregate of several years of crash data was used. The traffic environment is not static; vehicles, the road environment and other factors are constantly evolving. Using data aggregated over a time period of 10 years could mean that the factors causing crashes are not identical at the beginning and end of the time period of data collection. The aggregate dataset will by definition capture the mean of any effects that drift over time. The VCED data collection took place during 2008 and 2009, which is temporally around the center of the years of the crash population. The winter between these years was unusually cold in the area the data collection was carried out in, which could lead to underestimation of crash risk for cold and/or snowy road conditions.

In agreement with previous studies, driving at late night showed a relative elevation in crash risk. It would obviously have been interesting to study how details such as e.g. alcohol impairment and/or driver fatigue influence these results. However, the number of precrash factors that can be included in the analysis is by definition limited to what is known for both case-data (crashes) and exposure data.

The latter is however a general problem, and not a specific problem for the methodology proposed here. For example, while tyre status is simple to investigate on a crashed car, it is rarely ever collected over time in exposure studies. Another example is road road surface conditions. While crash databases give evidence for that friction loss often is correlated with run-off road crashes, friction are less often documented in NDS data. Despite this, for the case-data on crashes, the main limitation is still the presence and quality of precrash factor information that is available in crash databases. For future traffic safety data collection projects, this issue needs to be focused in order to better understand crash mechanisms. NDS-data on the other hand, while lacking in certain aspects such as continous measures of friction, often contains the information needed as exemplified in the present study. The number of precrashfactors that could influence crash risk is large, for crashes in curves road features such as curve radius and other road design features are of interest. A large number of datasets that could be used to set up the required exposure data have quite recently become available. Large amounts of relevant driving and context data has been collected in projects such as 100 cars study [17] and EuroFOT [11]. Another example is the recent SHRP2 project [18], which in addition to being the largest NDS to date also contains the largest number of crashes collected in a driving study to date. This forms an excellent opportunity to do risk estimations with relevant knowledge on both crash and exposure data for individual cases, given that issues such as potential bias in participant selection can be addressed. Another problem with the SHRP2 dataset is the same as for any crash data analysis; when splitting data in relevant subgroups of crashes, will there be enough data to represent the actual variety of precrash factors? Based on data from previous driving studies, different analyses were performed where “incidents” or “crash relevant events” were treated as crashes [19-22]. This gives a larger number of cases and hence the significance when modelling risk increases but on the other hand, the relationship between crashes and “incidents” are not established.

Given that the methodology proposed in this report is confirmed by further studies, great opportunities to future crash risk estimation projects are presented. The results show that it is indeed feasible to associate different available datasets in order to quantify the contribution of different precrash factors to an actual crash event.

V. CONCLUSIONS

The methodology developed in this study offers a new perspective on how available datasets can be leveraged to estimate the contribution to crash risk for different precrash factors on a more detailed level than in previous studies.

VI. ACKNOWLEDGEMENT

The research was made possible due to grant 2013-04680 from FFI. The authors would like to thank Olle Nerman at Mathematical Sciences - Chalmers University of Technology and University of Gothenburg for support during the project.

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ADDENDUM (20 January 2017)

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