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Comparing single vehicle and multivehicle fatal road crashes: A joint analysis of road conditions, time variables and driver characteristics

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ABSTRACT

The difference between single vehicle crashes and multivehicle crashes was investigated in a collection of fatal crashes from six European countries. Variables with respect to road conditions, time variables, and participant characteristics were studied separately at first and then jointly in a logistic multiple regression model allowing to weigh different accounts of single vehicle as opposed to multivehicle crash occurrence.

The most important variables to differentiate between single and multivehicle crashes were traffic flow, the presence of a junction and the presence of a physical division between carriageways. Heavy good vehicles and motorcycles were less likely to be involved in single vehicle crashes than cars. Moreover crashes of impaired drivers with more passengers were more likely to be single vehicle crashes than those of other drivers. Young drivers, rural roads, nights and weekends were all shown to have a higher proportion of single vehicle crashes but in the multivariate analysis these effects were demonstrated to be mediated by the road conditions named above.

1. Introduction

This study compares single vehicle (SV) and multivehicle (MV) fatal crashes sampled in six European countries (France, Finland, Germany, Italy, Netherlands and United Kingdom). The database used is based on retrospective studies integrating police reports and other sources like insurance and hospital documentation. The data can be considered as representative for the countries in which they have been collected and lie at an intermediate level between macroscopic crash data (like the national police data) and in-depth crash investigations. Variables that are not typically available in national crash statistics (most notably the traffic flow) can thus be used to further assess the nature of single vehicle (SV) vs. multivehicle (MV) crashes.

Single vehicle and multivehicle crashes are often separated in national statistics (e.g., Scheers and Casteels, 2008) as well as in crash prediction models (e.g., Geedipally and Lord, 2010; Qin et al., 2006), with the idea that the causation of these crashes are driven by different dynamics. Single vehicle crashes have been shown to differ from multivehicle crashes in a number of aspects, which relate to road conditions, time aspects, or driver characteristics.

With respect to *road conditions*, traffic flow appears to be an important factor differentiating between single vehicle (SV) and multivehicle (MV) crashes (Ivan et al., 1999; Qin et al., 2006; Geedipally and Lord, 2010) Moreover, higher proportions of single vehicle crashes have been reported for rural areas (Chen et al., 2009) and at road sections between junctions.

Single vehicle crashes are moreover likely to happen at night and during the weekends (Scheers and Casteels, 2008; Öström and Eriksson, 1993; Persaud and Mucsi, 1995), suggesting that *time of the accident* is also an important predictor.

With respect to *road user characteristics*, for young drivers crashes are more likely to be single vehicle crashes than for older ones (Lee and Abdel-Aty, 2008; Clarke et al., 2006; Öström and Eriksson, 1993). Öström and Eriksson found a whole range of differences between drivers who had been severely injured or killed in single vehicle (SV) crashes as opposed to those in multivehicle (MV) crashes: male and intoxicated drivers were found to be more likely involved in SV crashes. Moreover the drivers from SV crashes more often suffered from liver diseases (which are known to be associated with permanent alcohol abuse), did not wear a seatbelt, and had no driving license.

The observations made on the basis of the road conditions and time of the accident variable seem to illustrate one general principle: single vehicle crashes, rather than multivehicle ones, occur when vehicles are less likely to encounter each other, and when the error of one driver is less likely to involve another driver. This makes sense given the definition of single and multivehicle crashes (namely the number of vehicles involved). Often however, the single-vehicle crash category is used with the implicit

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assumption that any single-vehicle crash is a loss of control crash which involved only a single driver, and which is due to his errors. Matching with this assumption, the observations related to the road user characteristics sketch the picture of irresponsible drivers being overrepresented in single vehicle injury crashes (Clarke et al., 2006; Lee and Abdel-Aty, 2008; Öström and Eriksson, 1993; Scheers and Casteels, 2008).

Nevertheless, from the perspective of crash causation mechanisms, a categorization based on the number of vehicles could be inappropriate. For example, some single-vehicle crashes may result from interactions among several vehicles. A frequent case, on motorways, involves a driver who suddenly changes of lane and surprises another driver, who subsequently loses the control of his vehicle and hits the median. The driver who changed lanes generally remains unidentified, thus the crash is usually categorized as single-vehicle crash. Conversely, it happens that a driver, without any interaction with another vehicle or road user, loses the control of his vehicle, at a bend, for example, and hits a vehicle coming from the opposite direction. It will be categorized as multivehicle crash, whereas, from an etiological point of view, this case is not different from a crash which would occur with the same causal mechanisms, but in the absence of any vehicle coming from the opposite direction.

Often national crash statistics include the number of vehicles involved, but no information on causation. It would therefore be good to know whether single vehicle crashes could be considered a good proxy measure for crashes that were caused by the error of one single driver. The findings of different driver characteristics in single and multivehicle crashes (Clarke et al., 2006; Lee and Abdel-Aty, 2008; Öström and Eriksson, 1993) seem to suggest that the difference between these two categories does indeed have something to do with 'responsibility', which would mean that the examples for the opposite (MV that is caused by one driver losing control or SV accident that is caused by the interaction between two drivers) are the exception rather than the rule. Consequently it would be interesting to see the effects of driver characteristics confirmed in a multivariate analysis.

A multivariate analysis is necessary when different possible explanatory variables for a particular phenomenon are not independent from each other. In the present case, the characteristics of drivers involved in crashes, the road conditions and the time of the crash are most likely related. Young drivers drive more often at night, for example. And the fact that a crash on an emptier road at night is less likely to involve other drivers could also explain the fact that crashes with young drivers tend to be single vehicle crashes.

To understand better the relation between driver characteristics, road conditions, and time aspects to single vehicle crashes, it is thus utterly important to contrast them with multivehicles ones while *simultaneously* taking into account these different groups of factors. The objective of the present study is to weigh the contribution of these different types of factors in accounting for the single vs. multivehicle nature of fatal crashes. The variables related to each of these four factor groups were analysed jointly in a logistic multiple regression model.

2. Methodology

2.1. Data

The "Fatal Accident Investigation" (FAI) database was created in the SafetyNet project, as part of the 6th framework programme of the European Commission. Seven countries took part in the data collection (United Kingdom; France; Sweden; Finland; Germany; Italy; and the Netherlands), however, the data from Sweden had to be excluded from the analysis (see below). The FAI database was developed with retrospective investigation methods: information derived from the police documentation of fatal crash investigations in each country were complemented with information from hospital, insurance companies, and prosecution records (Reed and Morris, 2006). The data concern the crash itself (e.g.: the number, type and sequence of events, the type of infrastructure, etc.), as well as the vehicles (weight, width, length, age, the manoeuvre executed by the driver, and so on) and the road-users involved (level of impairment, familiarity with the road, etc.). All crashes occurred in 2003 and 2004. The total dataset contains 1296 fatal crash cases. The cases can be considered representative for the countries in which they have been collected, but not for the whole of Europe.

For privacy reasons, the 100 cases collected in Sweden did not contain information about the time of the crash. As this was a crucial variable in this study, all cases from Sweden had to be excluded from the study. Moreover, all crashes involving non-motorised road-users (122) have been excluded from the following analyses. Additionally, all crashes with missing data for one of the selected predictors (see Table 1) were also excluded (among them the 100 cases from Sweden) leaving 656 cases of which 244 were single vehicle crashes and 412 multivehicle crashes.

2.2. Analyses

First, a dichotomous dependent variable "single vehicle crash" was created. This variable takes a zero value for all crashes involving more than one vehicle[1] (MV crashes) and a one for all single-vehicle crashes (SV crashes).

All the predictors that have been considered for inclusion in the model are presented in Table 1. All analyses were logistic (stepwise) regression analyses. If more than one variable was tested, the stepwise function includes at first all variables and then removed them one by one until only those that have a significant effect remain in the model.

The results of all regression analyses are expressed in terms of exponential function of the beta coefficient for each variable, the *odds ratio* (OR). The odds is the probability of a SV crash divided by the probability of a MV crash. The odds-ratio is the odds for the current category divided by the odds for the reference category. As an example, an odds ratio (OR) of 2.35 for the variable <impairment> indicates that for a crash in which at least one driver was impaired the odds for this crash to be an SV one are 2.35 times higher than the odds for a crash in which none of the drivers was impaired to be an SV crash. The 95% confidence intervals CI+ and CI− are calculated by the following formulae.

$$\mathrm{CI} = \mathrm{Exp}(B \pm (1.96 \times \mathrm{SE}(B)))$$
$$\mathrm{OR} = \mathrm{Exp}(B)$$

The selection of predictors for the final model proceeded in three steps.

(1) Univariate tests were conducted to test whether each of these variables was in itself a significant predictor of single-vehicle crashes.
(2) Three separate models were fitted using road conditions, time variables, and participant characteristics as predictors respectively. For each of these models, the variables were entered on the basis of a stepwise procedure. This step allowed investigating which predictors *within* each of the three *clusters* significantly predict the single versus multivehicle nature of the crashes. For those variables that were not significant in this step, this means that they were related to one of the other predictors

[1] The number of vehicle in the MV crash category ranges from 1 to 5.

Table 1
Description of variables involved in logistic regression analysis.

Variable name	Explanation	Mean/proportion			SD	Missing
		Total	SV acc	MV acc	Total	
Dependent variable						
SingleVehicleCrash	1 = single vehicle crash, 0 = multivehicle crash	0.37			0.48	0
Road condition						
SLG50	1 = speedlimit greater 50, 0 = equal or smaller	0.71	0.66	0.78	0.46	9
SLG90	1 = speedlimit greater 90, 0 = equal or smaller	0.58	0.53	0.66	0.49	9
SLG70	1 = speedlimit greater 70, 0 = equal or smaller	0.36	0.29	0.5	0.48	9
SLG100	1 = speedlimit greater 100, 0 = equal or smaller	0.07	0.05	0.12	0.26	9
RuralArea	1 = rural, 0 = urban	0.71	0.68	0.77	0.45	1
CarrPhysDivided	1 = divided, 0 = undivided	0.12	0.08	0.2	0.33	0
Motorway	1 = motorway, 0 = other	0.08	0.05	0.13	0.27	0
TrafficFlowMedium	1 = traffic flow medium, 0 = other	0.43	0.49	0.34	0.5	193
TrafficFlowHigh	1 = traffic flow high, 0 = other	0.08	0.12	0.02	0.27	193
Junction	1 = junction, 0 = section between junctions	0.34	0.47	0.11	0.47	0
Time variables						
Light	1 = daylight, 0 = darkness, twilight, artificial light	0.42	0.35	0.54	0.49	7
Day	1 = 6:00–21:59; 0 = 22:00–5:59	0.73	0.8	0.61	0.44	100
Weekend	1 = Friday 22:00 to Sunday 22:59, 0 = other	0.45	0.41	0.5	0.5	100
WeekendNights	1 = Fri, Sat, Sun night; 0 = other					100
Participant characteristics						
PTWinvolved	1 = crash involved a powered two wheeler, 0 = other	0.29	0.36	0.17	0.45	0
HGVinvolved	1 = crash involved a heavy goods vehicle, 0 = other	0.22	0.32	0.05	0.42	0
AveNrOcc	Mean number of occupants in crash	1.65	1.49	1.93	0.99	0
pWomen	Percentage women among all occupants	0.2	0.21	0.17	0.26	49
pWomenDriver	Percentage women among drivers	0.12	0.13	0.1	0.26	50
AveDriverAge	Average age of all drivers in crash	38.85	40.4	36.23	13.33	0
Alcohol	1 = at least one driver suspected or proven under the influence of alcohol; 0 = no driver	0.16	0.1	0.25	0.36	53
Impairment	1 = at least one driver suspected or proven to be impaired by alcohol, drugs, or fatigue; 0 = no driver impaired	0.2	0.14	0.32	0.4	84

Note: Number of missing values is calculated on all accidents without vulnerable road users (N = 1174). Calculation of means and SD after exclusion of cases with missing values (N = 656).

and that their effect in step 1 was in fact mediated by that other predictor.

(3) In the last step, all predictors selected in step 2 were entered jointly into the model to test whether there were any correlations *between* variables from *different clusters* that made a variable redundant. Again, a stepwise procedure was used to select those that contributed over and above the other variables to the prediction of the single vs. multivehicle nature of the fatal crashes.

This three-step procedure was applied to investigate which variables had the strongest predictive power. Variables were removed from the analysis when another variable that was related explained the difference between single and multivehicle crashes more efficiently. The intermediate step served to keep an overview for those variables that were removed, which other variable it was that made the removed variable redundant.

3. Results

The results of all three analyses steps are summarized in Table 2.

3.1. Univariate tests

3.1.1. Road conditions

Roads with a higher speed limit have a larger chance for SV crashes than roads with a lower speed limit. All possible splits (speed limit equal or lower 50 vs. higher than 50; speed limit equal or lower 70 vs. higher than 70; 90; 100) show a significant difference in the proportion of SV crashes.

Furthermore, SV crashes as compared to MV ones, are more likely in rural areas, on roads where the carriage ways are physically divided (rather than those where they are just divided by painted lines) and on motorways. On roads with a high or medium traffic flow (as compared to roads with a low traffic flow), SV crashes are *less* likely.

3.1.2. Time variables

The analyses on time variables indicate that crashes are more likely to be single vehicle crashes at night than during the day, in the darkness or twilight as compared to day-light, at the weekend as compared to weekdays, and at weekend nights as compared to all other times (weekend-day, week-day, and week-night).

3.1.3. Participant characteristics

Within an analysis that is conducted at the crash level – as is the case with the present study, it is not trivial to include driver variables, because for the MV crashes this variable has to characterize several drivers. To analyse the driver (and occupant variables) together with other crash characteristic described in the sections above, these variables have been calculated at the crash level by taking the mean of continuous characteristics (e.g., age) and proportions of dichotomous characteristics (e.g., gender). In some cases we only differentiated between crashes in which a particular characteristic was present (e.g., crashes with at least one motorcyclist) or not.

While the use of averaging and proportions in case of multiple drivers might not be unproblematic, this method is chosen here, as it is impossible to identify a driver “at fault” in those crashes.

The results indicate that crashes with cars only are more likely to be single vehicle crashes than crashes involving either a heavy

Table 2
Results for stepwise logistic regression analyses.

	Univariate analysis				Groupwise analysis				Joint analysis				
	Sig.	Odds ratio	CI−	CI+	Sig.	Odds ratio	CI−	CI+	Sig.	Odds ratio	CI−	CI+	Effect size
Road condition													
SLG50	.002	1.79	1.24	2.58	ns								
SLG90	.000	2.45	1.76	3.41	.041	1.49	1.02	2.18	.010	1.76	1.14	2.7	1.76
SLG70	.001	1.71	1.23	2.37	ns								
SLG100	.035	2.9	1.59	5.27	ns								
RuralArea	.018	1.55	1.08	2.22	ns								
CarrPhysDivided	.000	2.98	1.85	4.81	.000	5.01	2.66	9.41	.000	6.73	3.29	13.76	6.73
Motorway	.000	3.01	1.66	5.46	ns								
TrafficFlowMedium	.000	0.43	0.31	0.6	.000	0.44	0.3	0.65	.009	0.57	0.37	0.87	1.76
TrafficFlowHigh	.000	0.08	0.03	0.24	.000	0.04	0.01	0.12	0	0.07	0.02	0.27	14.45
Junction	.000	0.14	0.09	0.21	.000	0.15	0.09	0.24	0	0.17	0.1	0.29	5.79
Time variables													
Light	.000	2.22	1.6	3.06	.017	1.62	1.09	2.4	ns				
Day	.000	0.39	0.27	0.56	.003	0.52	0.34	0.8	ns				
Newweekend	.030	1.42	1.04	1.96	.017	1.49	1.08	2.07	ns				
WeekendNights	.000	2.54	1.56	4.14	ns				ns				
Driver, occupant and vehicle characteristics													
PTWinvolved	.000	0.36	0.25	0.54	.000	0.34	0.22	0.52	.007	0.5	0.3	0.83	2
HGVinvolved	.000	0.12	0.07	0.21	.000	0.1	0.05	0.18	.000	0.09	0.04	0.18	11.19
AveNrOcc	.000	1.59	1.33	1.9	.001	1.42	1.17	1.74	.024	1.29	1.03	1.61	1.29
pWomen	.059	0.54	0.29	1.02	.000	0.19	0.09	0.41	ns				
pWomenDriver	.269	0.7	0.37	1.32									
AveDriverAge	.000	0.98	0.96	0.99	.005	0.98	0.97	0.99	ns				
Alcohol	.000	2.87	1.86	4.43	ns								
Impairment	.000	2.93	1.98	4.33	.000	2.5	1.6	3.88	.001	2.35	1.43	3.85	2.35

Note: No results indicates variable was not included in analysis because not significant in previous analysis. "ns" indicates variable was included but removed by stepwise procedure. Effect size = OR if OR > 0 and = 1/OR if OR < 1.

goods vehicle or a powered two wheeler. To analyse the presence of passengers in single and multivehicle crashes, the mean number of occupants per vehicle was calculated for each crash. This variable has an odds ratio significantly higher than 1 indicating that crashes in which vehicles carry many occupants are more likely to be single vehicle crashes, than those in which the vehicles carry few occupants.

The effect of those occupants' gender was investigated by calculating the proportion of females *among all vehicle occupants* in the crash (pWomen). This variable has an odds ratio significantly *lower* than 1, indicating that crashes with a high proportion of women among the occupants are less likely to be single vehicle crashes than those crashes with a low proportion (i.e. mostly male occupants).

We can summarize that crashes involving vehicles with many occupants, especially when they are male, seem to show a higher share of SV crashes. This is in line with a study investigating the crash causation of single vehicle crashes, where social pressure (via leaving small safety margins) is found to be an important factor (Sandin and Ljung, 2007).

The variable pWomenDriver indicates the proportion of females *among the drivers*. This variable was not significant in the present set of crash data. One possible reason is that the proportion of female drivers in this fatal-crash database is very low altogether (11%) leaving very little variation in this variable.

To analyse the role of driver age, the *mean* age of *all* drivers in the crash was analysed. There is a significant effect of mean driver age, indicating that crashes with a lower average age are more likely to be single vehicle crashes than those with a higher average age. This result agrees with the findings of many studies indicating that young people are overrepresented in SV crashes (e.g., Lee and Abdel-Aty, 2008; Clarke et al., 2006; Öström and Eriksson, 1993).

The results of the univariate tests indicated that most of the predictors in the "road conditions" and "daytime" groups are significantly associated with the SV vs. MV nature of the crashes. The participant characteristics also proved to be significant for the largest part but with the exception of the proportion of female drivers. Consequently, all variables, except <percentage of female drivers> (pWomen), were entered into the following analyses step.

3.2. Groupswise analyses

In the second analysis step, the variables of the same thematic cluster (road conditions, time variables, participant characteristics) are analysed jointly, but not together with the variables of the other thematic clusters. The results are presented in the middle block in Table 2.

3.2.1. Road conditions

When entering different splits between speed limits (SLG50, SLG70, SLG90, SLG100) jointly into the model the split between speed limits of 90 or below and those higher than 90 seemed the most effective one to predict single vehicle crashes. This means that although the proportion of single vehicle crashes tends to rise for higher speed limits, for the speed limits of 80 and 90 (rural roads in most countries) the proportion of multivehicle crashes is still higher than that of single vehicle crashes.

Whether the area is rural and whether the road is a motorway – both significant predictors of single vehicle crashes by themselves – are not significant anymore when grouped together with other road condition variables. Most notably the variables <junction> and <carriageway physically divided> seem to describe more efficiently the conflict potential of a road that determines the frequency of multivehicle crashes.

High and medium traffic flows are significantly associated with a lower proportion of single vehicle crashes. The odds ratio for this variable indicates that the proportion of single vehicle crashes for roads/times with medium traffic flow is less than half that of roads with a low traffic flow and for roads with a high traffic flow the chance that a crash involves only one vehicle is *more than 10 times smaller* than for roads with a low traffic flow. These effects (especially that of high vs. low traffic flow) are by far the strongest in the whole analysis.

3.2.2. Time variables

The results for the joint analysis of the variables characterising the time of the crash strongly resemble the individual tests. At night and in the weekends, the share of single vehicle crashes is higher. Although light condition is not a time variable, it was analysed together with the time variables, because of the obvious relation between *light* (daylight as opposed to all other light conditions like darkness or twilight) and *daytime*. The share of single vehicle crashes is higher in the darkness or twilight. Surprisingly, in the joint model, the effect of daylight proved to be independent of *daytime*. A substantial number of crashes occurred during the day, but in the absence of daylight (120), or at night hours, but in daylight conditions (20). Each variable has its own effect.

The only variable that did not become significant in the joint model for the time variables was *weekend nights*. This variable would be significant if there was an interaction between *weekend* and *daytime*, i.e. when the difference between day and night would be larger in the weekend than during the week. This was not the case and consequently the *weekend night* variable does not add any information over and above the separate effects of *weekend* and *daytime*.

3.2.3. Participant characteristics

Crashes involving a powered two-wheeler or a heavy goods vehicle are less often single vehicle crashes than those that involve cars only. Younger and impaired drivers have a higher share of single vehicle crashes. Cars with more passengers and especially with male passengers have a higher share of single vehicle crashes than those with fewer or no passengers or female passengers.

The results resemble very much the results of the univariate tests (see first column). The only variable that became non-significant in the joint analysis while being significant in the univariate analysis is "alcohol" (at least one of the drivers in a crash was under the influence of alcohol). This variable became non-significant when analysed together with the variable impairment (one or more drivers impaired by alcohol, drugs, or fatigue), because the second explains the difference between MV and SV crashes more efficiently.

It is important to note, that for all other variables there is little change in comparison to the univariate analyses. This is interesting because it indicates that – unlike <alcohol> and <impaired> – the other variables have effects on the SV–MV nature of the crashes that are more or less independent of each other.

3.3. Joint modelling of thematic groups

All variables that were significant in the groupwise analyses presented in Section 3.2 were entered into the final model to predict single vehicle as opposed to multivehicle crashes in one joint model. The results of this stepwise analysis are presented in the third column of Table 2.

The variables that remained significant in the joint model indicate that the chance of single vehicle crashes to happen increases as the traffic volume decreases. Moreover multivehicle crashes are more likely at junctions while single vehicle crashes have an increased chance to occur at road-sections between junctions. On roads with divided carriageways single vehicle crashes are overrepresented in comparison to multivehicle crashes. Heavy goods vehicles and powered two-wheelers are less likely to be involved in a single vehicle crash than car drivers. Cars in single vehicle crashes tend to carry more passengers as compared to those involved in multivehicle crashes. Fatal crashes involving impaired drivers have a greater tendency to be single vehicle crashes, as compared to fatal crashes involving only unimpaired drivers.

While these results seem to reflect more or less what was described in the previous sections, there are a few interesting differences. None of the time variables remains significant when analysed jointly with the road conditions. This means that their effect was mostly due to an indirect effect that is now better expressed by another variable. The effect of the time variables is related to that of traffic flow. At night and in the weekend the traffic flow is lighter than during weekdays. The joint analysis of these variables shows that the traffic density is more important for the explanation of SV crashes than other possible characteristics that might differ between weekdays on the one hand and nights or weekends on the other hand.

For the driver characteristics, it is important to note that while impairment is still significant (mean) age of driver is not. This suggests that unlike the impairment effect that seems to be independent of other effects, the age effect is at least for some part better explained via the road conditions. Younger drivers drive more often at night and in the weekend, when the roads are empty. The joint analysis indicates that among these related variables the traffic density is the most important one in differentiating between single and multivehicle effects.

In the leftmost column of Table 2, the effect size for each variable in the joint analysis is given. For variables with a positive effect this is simply the odds-ratio (OR), while for the variables with a negative effect, this is 1/OR. The effect sizes show that traffic flow is absolutely the most important variable to differentiate between single and multivehicle crashes. Involvement of a heavy goods vehicle is also extremely important and then there are two more variables that also stick out: junction and carriage way divided. This means that apart from the fact that heavy good vehicles seem to be very rarely involved in single vehicle crashes, the three most important variables to differentiate between single and multivehicle crashes are the variables that describe the conflict potential of a road.

4. Discussion

Single and multivehicle crashes differ on a large number of variables. These variables and their relation with each other have been systematically investigated using stepwise logistic regression analyses.

Conditions of the road, or more exactly the conflict potential of a road, have been found to be the most important predictors of whether a crash involves one or several vehicles. Multivehicle crashes take place on busy roads and junctions, while single vehicle crashes tend to take place on empty road-sections between junctions. Roads with physically divided carriageways see generally few crashes, and those that do happen have a higher proportion of single vehicle crashes than on other road types. This suggests that such physical divisions do in fact succeed in preventing drivers who make a mistake from involving other drivers in the crash (at least those drivers that go in the opposite direction).

The effect of these three variables, junction, traffic flow, and divided carriageway can be summarized under the principle that road conditions making it less likely that two vehicles encounter each other prevent the error of one driver involving another one and thus reduce the likelihood of multivehicle crashes as compared to single vehicle crashes.

Single vehicle crashes mostly involve cars. Motorbikes are less likely to be involved in single than in multivehicle crashes and heavy good vehicles are involved almost exclusively in multivehicle crashes. The cars in single vehicle crashes have more passengers on average and the drivers in single vehicle crashes tend to be impaired by alcohol, drugs, or fatigue more often than in multivehicle crashes.

Additional to these findings, the results presented here demonstrate the importance of modelling the difference between single and multivehicle crashes in a multivariate way. Earlier studies have attributed single vehicle crashes to rural areas (Wegman and Aarts, 2006; Scheers and Casteels, 2008), to young drivers (Öström and Eriksson, 1993), and to weekend nights (Öström and Eriksson, 1993; Scheers and Casteels, 2008). When each variable was analysed by itself, these results were generally replicated: single and multivehicle crashes do indeed differ on these variables. In a multivariate analysis, including traffic flow, junction, and divided carriageway, most of the driver characteristics were not significant anymore.

The more complete multivariate analyses therefore suggested, that the effects of rural area, weekends, nights, and age are mediated by other variables (in particular traffic flow, junction, and divided carriageway). This means the effect of rural areas is better explained by the absence of junctions and by the lighter traffic flow. The fact that single vehicle accidents are relatively more often observed in weekend nights and with young drivers is better explained by the fact that young drivers tend to drive at weekend nights more often than older ones and that those times the roads are more empty.

Other driver and occupant characteristics also mentioned by Öström and Eriksson (1993) like the *impairment of the driver* and the *number of passengers* proved to be significant predictors of single vehicle crashes even when correcting for road conditions. This is in agreement with an analysis of single vehicle accidents by Sandin and Ljung (2007), who name four different scenarios for single vehicle accidents: (1) vehicle drifting out of the lane; (2) unexpected reduction in road friction; (3) loss of control in curve; (4) excessive steering manoeuvres by alarmed drivers. The first scenario is strongly related to driver impairment (especially fatigue) and the third scenario is related to social pressure by passengers leading to high speed and small safety margins.

The results indicate that one has to be careful to identify single vehicle crashes with loss of control accidents which are entirely due to the error of one driver and multivehicle accidents as accidents that are due to the interaction between several drivers. Rather they should be seen as crashes that for some reason did not involve another driver. The strong effects of traffic flow and carriage way division suggest that the most important reason is simply that there was no other driver around or that other road users were shielded off. Driver characteristics play only a limited role in explaining the difference between single and multivehicle crashes.

It must be noted that the results presented here are based on fatal crashes only. Earlier reports of driver-effects (e.g., Öström and Eriksson, 1993), have however been based on fatal *and* non-fatal crashes. Further research is necessary, to investigate whether in non-fatal crashes the effect of some driver characteristics, like the age-effect, can also be brought back to road-condition factors.

5. Conclusion

A comparative analysis of single vehicle and multivehicle fatal crashes was conducted using a logistic regression method. The data were based on police reports rather than on national crash statistics and a variable that is not commonly found in macroscopic databases has proven to be extremely important in differentiating between single and multivehicle crashes. A low traffic flow is associated with a higher proportion of single vehicle crashes.

The multivariate analysis shows that, once this variable is taken into account, other variables that are usually found to be more strongly related to single vehicle crashes (age of driver, time of day, for example) are no more significant in the model.

Other road condition variables that influence the possibility of encounter of vehicles (divided carriageways, presence of junction), also bring significant contributions to the logistic model. Returning to the starting questions we can conclude that road conditions that limit the opportunities of encounter between vehicles, and prevent vehicles that are out of control to swerve into the path of other vehicles, are more important to understand the difference between single and multivehicle crashes than characteristics of the drivers involved.

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