P Periodica Polytechnica Transportation Engineering

43(3), pp. 129-137, 2015 DOI: 10.3311/PPtr.7520 Creative Commons Attribution ①

RESEARCH ARTICLE

Influence of Travelling Speed on the Risk of Injury Accident: a Matched Case-Control Study

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Received 12 May 2014; accepted after revision 03 November 2014

Abstract

This matched case-control study deals with the effect of the individual travelling speed on the risk of involvement in a road accident. The cases were cars involved in injury accidents dealt with within the framework of an in-depth accident investigation programme. The matched controls were cars passing the same road site as the crash-involved car, in the same conditions but without being involved in an accident. Only normal weather, daytime and free-flow conditions were considered. Overall, 52 cases and 817 controls were used. The speeds were obtained from kinematic reconstructions for the crash-involved cars, and using a laser speed gun for the controls. A significant positive relationship is found between the individual travelling speed and the risk of injury accident. Nevertheless, this study has limitations, due to the relatively small number of cases and to the data used (kinematic reconstructions always involve some degree of interpretation).

Keywords

Speed, road accident, in-depth accident investigation, casecontrol study, conditional logistic regression

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Influence of Travelling Speed on the Risk of Injury Accident

1 Introduction

The influence of the mean speed of road traffic on accident risk has been widely studied, mainly through before-and-after evaluations of modified or newly-implemented speed limits (see in particular the meta-analysis by Elvik, 2009, 2013a). Summarily, in these studies, the risk of road accident appears to vary as a power function of the mean speed of traffic: if the mean speed changes from V_1 to V_2 , then the risk varies by a factor of $(V_2 / V_1)^b$, where b is an exponent generally comprised between 1 and 4. This relationship is known as the power model or Nilsson model, in reference to the early contribution of this author in this field (Nilsson, 1982; Cameron and Elvik, 2010).

From a more psychosocial viewpoint, other authors (Fildes et al., 1991; Quimby et al., 1999) showed some correlations between the general level of crash frequency among drivers, obtained through their self-reported accident history, and their general speed behaviour as estimated from roadside speed measurements.

However, little is known on the influence of the individual speed of a driver, at a given time and place, on his/her risk of being involved in a road accident in these conditions. This is a different issue, and only a few studies have dealt with this subject. A well-established link between localised individual speed choices and accident risk would be useful, for example for driver education purposes, and therefore research efforts on this point are still needed. This paper presents a contribution on this subject, using a matched case-control method. It is based on a sample of 52 crash-involved vehicles (case vehicles), dealt with within the framework of an in-depth accident investigation programme, and 817 control vehicles, individually matched to these case vehicles and passing the same road sites in the same conditions.

2 Previous research

Till the 1990s, the rare studies that dealt with this subject used an unmatched case-control method: they globally compared the speeds – just before the accident – of a sample of crash-involved vehicles (case sample) with the speeds of a sample of vehicles not involved in accidents and travelling on the same road network (control sample) (Solomon, 1964; Cirillo, 1968; Harkey et al., 1990). The findings took the form of U-shaped relationships between speed and risk, showing an increased crash risk for higher than average speeds, as for lower than average speeds. The increased risk at lower speeds, however, could have been an artefact resulting from some important methodological flaws of these early studies, as suggested by other authors (Davis et al., 2006; Hauer, 2009). Firstly, the speeds of the crash-involved vehicles were generally obtained through police reports, where speeds are reported to the police by the drivers involved (Solomon, 1964; Cirillo, 1968; Harkey et al., 1990). As mentioned by Kloeden et al. (2001), this may lead to underestimate the speeds of crash-involved vehicles and to strongly bias the results. Secondly, none of these studies used control vehicles individually matched to each case vehicle. Thus, it was not possible to guarantee that crash-involved vehicles and control vehicles were travelling in comparable conditions. Detailed discussions of these early studies can be found in Kloeden et al. (2001) and Davis et al. (2006).

More recent research appears to be more robust (Moore et al., 1995; Kloeden et al., 1997, 2001, 2002; Davis et al., 2006). These studies used crash reconstruction techniques providing more reliable speed estimates for the crash-involved vehicles, and they were based on matched case-control methods. Several control vehicles were individually matched to each case vehicle (crash-involved vehicle): vehicles passing the same site, in the same direction and the same conditions as the case vehicle were selected and their speeds were measured by a laser speed gun. The studies reported by Moore et al. (1995) and Kloeden et al. (1997) dealt with injury accidents in the metropolitan area of Adelaide, South Australia. The same data were later reanalysed by Kloeden et al. (2002). Another study published by Kloeden et al. (2001) dealt with injury accidents occurred on rural roads in South Australia (with speed limits of 80 km/h or higher). More focussed analyses were published by Davis et al. (2006): they dealt with severe run-off-road accidents only, and were applied to a small sample of cases taken from Kloeden et al. (1997) and to a sample of fatal run-off-road crashes occurred in Minnesota.

None of these more recent studies showed evidence of an increased risk at lower speeds. All of them suggested a strong effect of travelling speed on accident risk. For example, Kloeden et al. (2001) found that, on rural roads, the relative risk for a given speed V (relatively to the mean speed V_m) can be modelled by an exponential-quadratic model:

$$RR = \exp(0.07039(V - V_m) + 0.0008617(V - V_m)^2), \quad (1)$$

for speeds ranging from -10 km/h to +30 km/h around the mean speed V_m . According to this model, for a speed increase of 10 km/h, for example, the risk would increase by a factor of 2.2.

Overall, apart from the results of Davis et al. (2006), which are focussed on a particular type of accident, sound findings on the relationship between localised individual driving speed and accident risk were mainly obtained in the context of South Australia. Therefore, further studies in this field are still needed, in order to analyse this relationship in other contexts.

3 Method

3.1 Data

We used a matched case-control study design, where controls are individually matched to each case. The cases were cars involved in traffic injury accidents dealt with within the framework of the in-depth accident study programme (IDAS programme) carried out by the French Institute of Science and Technology for Transport, Development and Networks (IFST-TAR) in the region of Salon de Provence (in the south of France), for years 2003 to 2012. For each case, the corresponding controls were other cars passing the same road site as the case, in the same conditions (same direction, same time of the day, etc.).

The IDAS programme is based on an "on-the-spot" method: just after the accident, the team of investigators (one psychologist and one technician) is informed through the alert system of the medical emergency service and immediately goes to the scene of the accident, where they proceed to a first collection of data. The psychologist interviews the drivers involved (and the other road users involved) - except, of course, if they are too severely injured or deceased - and witnesses when possible. Sometimes, the interview is not possible at the accident scene and takes place at the hospital. The interviewees are clearly informed that the data are collected only for research purposes, will be held confidential and anonymous, and will have no further implication for them. The technician gathers information on all the elements of the accident scene (final positions of the vehicles, presence of parked vehicles, obstacles and other objects, state of the road surface, marks such as skid or yaw marks, debris, vehicle deformations, meteorological and light conditions, etc.). Within a few days after the accident, the technician collects additional information on the accident site and the roads approaching this site, and the psychologist generally obtains a second interview with the people involved in the accident. Then, the investigators carry out a thorough analysis of the data that have been collated. In many cases (whenever possible), this analysis involves a kinematic reconstruction, which provides estimates of the speeds of the vehicles at different stages of the accident. The principles of the kinematic reconstruction method are briefly presented in appendix A. Further information on the methods used in the IDAS programme can be found in previous publications (Clabaux et al., 2012; Brenac et al., 2013).

It should be mentioned that kinematic reconstructions always involve some degree of interpretation of the data collected; thus, the reconstructed speeds may be subject to unknown errors, as already noted by other authors (Rosén et al., 2011). The sensitivity of the results to possible errors in these estimates of speed, for the crash-involved vehicles, will be examined in Subsection 4.2 and discussed in Section 5.

3.2 Selection of cases and controls

The selection of cases (crash-involved vehicles) was based on the following criteria:

- Vehicle type: only cars were considered.
- Driving situation: as in previous studies by Kloeden et al. (1997, 2001, 2002), cars involved in particular manoeuvres before the accident (such as overtaking, slowing or accelerating for turning or merging, starting from a Stop or Yield line, manoeuvring for parking, etc.) were excluded. Moreover, only cars traveling in free-flow traffic conditions before the accident were considered. These criteria were introduced in order that the obtained speedrisk relationship corresponds to the most simple and common driving situation, and that the control vehicles can be matched to the case vehicle without ambiguity.
- Light and weather conditions: cars involved in accidents occurred during the night-time or in wet weather or wet pavement conditions were excluded. These criteria were added for practical reasons. For accidents occurred in wet weather or wet pavement conditions, the measurement of the speeds of control vehicles cannot be made in conditions exactly comparable to the conditions prevailing at the time of the accident. Moreover, during the night hours, for some accident sites on minor roads, there are too few vehicles passing the site and thus it is not possible to obtain a sufficient number of control vehicles within a reasonable period, corresponding to the time of the accident.
- Sufficient information for kinematic reconstruction: the vehicles considered were only cars involved in accidents for which the data gathered by the IDAS investigators allowed them to carry out a kinematic reconstruction leading to an estimate of the speed of the car before the accident.

All these criteria (or equivalent ones) were used in the previous studies by Kloeden et al. (1997, 2001, 2002). However, these previous studies also used other selection criteria: These authors excluded vehicles with alcohol-impaired drivers, or for which the sleepiness or medical condition of the driver contributed to the accident. These latter criteria were not used in the present study, because they may lead to selection bias, since they cannot be applied to controls in the same way as to case vehicles (control vehicles are not stopped, and therefore it is not possible to exclude control vehicles with alcohol-impaired or sleepy drivers, for example).

Thus, 52 vehicles meeting this set of criteria were identified. In correspondence to each of these case vehicles, speed measurements were carried out for a set of matched control vehicles (about 16 control vehicles per case, on average), using a laser speed gun, within one or two weeks after the accident. These control vehicles were passing the same site in comparable conditions (same direction, type of day, time of the day) and met the same criteria as the corresponding case vehicle: car, no particular manoeuvre, free-flow traffic conditions, daytime, normal weather, dry pavement. Overall, 817 control vehicles were considered. Thus, the whole sample consists of 869 vehicles.

3.3 Statistical method and models

The outcome variable is the case-control variable Y, which takes the value 1 for the cases and 0 for the controls. This variable is considered as a Bernoulli variable with parameter p. This parameter can be viewed as the probability that a vehicle will be a case. The modelling aims to estimate the effect of the explanatory variable (the vehicle speed or a function of this speed) on this parameter p.

In the field of epidemiology, the usual and recommended method for such matched case-control studies is conditional logistic regression (Breslow and Day, 1980; Neuhaus and Jewel, 1990; Breslow, 1996). The standard method of logistic regression is not appropriate, due to the fact that the data are clustered: each case and the corresponding controls form a cluster or stratum. Conditional logistic regression (CLR) allows to estimate the effect of the explanatory variables independently from the cluster effects which are not estimated (they are considered as nuisance parameters and have no meaningful interpretation in case-control studies due to the retrospective sampling of the data). This method is based on the maximisation of the conditional likelihood (i.e. the likelihood conditional on the cluster sizes and the numbers of cases in the different clusters).

As mentioned by Agresti (2002), CLR cannot estimate between-cluster effects, but only within-cluster effects, and the results of CLR should be interpreted at the cluster level. From a practical point of view, as regards the present study, this means that the model obtained may be used to compare the effects of various speeds on accident risk, but only in the same conditions (same road site, type of day, time of the day, etc.).

Three types of model were tested: the power model (Nilsson, 1982; Elvik, 2013a), an exponential model which can be considered as a reasonable alternative to the power model, and an exponential-quadratic model in the form proposed by Kloeden et al. (2001, 2002).

Power model. Within the framework of conditional logistic regression, the power model can be expressed as follows:

$$\ln(\hat{p}_{ij}/(1-\hat{p}_{ij}) = \alpha_j + \beta \ln(V_{ij}),$$
(2)

where p_{ij} represents the modelled value of the parameter p_{ij} of the Bernoulli variable for the vehicle *i* of cluster *j*, $\ln(p_{ij} / (1 - p_{ij}))$ is the logit function of p_{ij} (or log-odds), a_j represents the cluster effect, β is the parameter representing the effect of speed (the exponent of the power model), and V_{ij} is the vehicle speed (velocity). By subtracting, from (2), the same equation applied to a reference speed V_0 , for the same cluster, the logodds-ratio can be obtained:

$$\ln\left(\frac{\hat{p}_{ij}/(1-\hat{p}_{ij})}{\hat{p}_0/(1-\hat{p}_0)}\right) = \beta \ln\left(\frac{V_{ij}}{V_0}\right).$$
 (3)

The exponential of this expression represents the odds-ratio (OR), which can be considered as an approximation of the relative risk. Therefore, we obtain

$$RR \approx OR = \left(V_{ij} / V_0 \right)^{\beta}, \qquad (4)$$

where *RR* represents the relative risk of being involved in an accident at a speed V_{ij} as compared to a speed V_0 , in the conditions prevailing within a same cluster (same road site, type of day, time of the day, etc.). This latter equation corresponds to the practical form of the power model. Conditional logistic regression makes it possible to estimate β independently from the a_i 's, which are not estimated.

Exponential model. The exponential model can be expressed in the following form:

$$\ln\left(\hat{p}_{ij}/(1-\hat{p}_{ij})\right) = \alpha_j + \gamma V_{ij}.$$
(5)

The parameter γ is also to be estimated by conditional logistic regression. By subtracting from (5) the same equation applied to a reference speed V_0 , the log-odds-ratio and the relative risk can be derived in the same way as above, leading to:

$$RR \approx OR = \exp(\gamma (V_{ij} - V_0)).$$
(6)

Exponential-quadratic model (of the Kloeden's type). This model expresses the log-odds as a function of the difference between the vehicle speed and the mean speed of the control vehicles in the cluster, $(V_{ii} - V_m)$, and not as a function of V_{ij} :

$$\ln(\hat{p}_{ij}/(1-\hat{p}_{ij})) = \alpha_{j} + \eta(V_{ij}-V_{m}) + \theta(V_{ij}-V_{m})^{2}, \qquad (7)$$

where a_j represents the cluster effect, and η and θ the model parameters to be estimated. By subtracting from (7) the same equation applied to the mean speed V_m , the log-odds-ratio and the relative risk can be derived, leading to:

$$RR \approx OR = \exp\left(\eta \left(V_{ij} - V_m\right) + \theta \left(V_{ij} - V_m\right)^2\right),\tag{8}$$

where *RR* represents the relative risk to be involved in an injury accident at a speed V_{ij} as compared to the mean speed V_m in the cluster, in the conditions prevailing in this cluster. The parameters η and θ can be estimated by conditional logistic regression. It can be easily shown that, if the quadratic term $\theta(V_{ij} - V_m)^2$ is removed from (7), this model becomes exactly equivalent to the exponential model described in (5) and (6).

4 Results

4.1 The models obtained

The results obtained, for the power model (PM), exponential model (EM), and exponential-quadratic model (EQM), are presented in Table 1. The three models appear as significantly better than the null model, as shown by the *p*-values obtained for the likelihood-ratio tests. However, for the exponential-quadratic

model, the parameter estimate of the quadratic term is not significantly different from zero (*z*-test: *p*-value = 0.2399). Moreover, applying a likelihood-ratio test to compare the EQM to its simplified form without the quadratic term leads to a *p*-value of 0.2488, which means that the quadratic term does not significantly improve the fit. These results suggest that the simple exponential model should be preferred to the exponential-quadratic model.

Among the three models, the exponential model corresponds to the minimum AIC (Akaike Information Criterion), which suggests that this model provides the best compromise between likelihood and complexity, and should be preferred to the others.

In practical terms, the exponential model would mean that the relative risk of involvement in an injury accident, at a driving speed V, as compared to a speed V_0 and in the same conditions, is equal to $\exp(0.0512(V - V_0))$, where V and V_0 are expressed in km/h. The power model obtained would mean that the relative risk of involvement in an injury accident, at a driving speed V, as compared to a speed V_0 and in the same conditions, is equal to $(V/V_0)^{3.41}$.

It would be difficult to give a strict physical interpretation of the exponent value obtained for the power model (3.41), due to the complexity of accident processes in the real world, and to their human component. However, this value appears to be roughly consistent with some physical aspects of car driving. The risk of injury accident can be viewed as a product $P_c \times P_{infle}$, where P_c is the probability of a collision and P_{injc} the probability of injury given that a collision has occurred. Assuming a probability of collision proportional to V² could make some sense, since important parameters of the safety of car driving, such as the braking distance and lateral acceleration in curves, are proportional to V^2 (even though other parameters, such as the distance driven during the reaction time of the driver, are simply proportional to V). Moreover, the probability of injury given that a collision has occurred depends on the kinetic energy, and therefore depends on V^2 . Thus, as regards the risk of injury accident, an exponent value in the range from 3 to 4 does not seem unreasonable.

In comparison, there is no clear way of interpreting the exponential model in relation with the physical processes involved in car driving.

The results presented in Table 1 should be interpreted at the cluster level, as mentioned in Subsection 3.3. This means that these models give the relative risk at a speed V as compared to a speed V_0 in the same conditions, corresponding to a same cluster. Moreover, the extrapolation of these results to speed values outside the range of speeds found in each cluster would be hazardous. On average, inside a cluster, the speeds range from $0.81 \times V_m$ to $1.23 \times V_m$, where V_m represents the mean speed of the control vehicles in the cluster.

In order to illustrate these results with an example, the relative risks for different speed values as compared to a reference speed of 80 km/h are presented in Table 2, for the exponential and power models.

 Table 1 Results obtained for the power model, exponential model,

 and exponential-quadratic model: parameter estimates, likelihood-ratio test,

 and Akaike Information Criterion (AIC)

Model	Parameter	Parameter estimate (and 95% CI)	Likelihood-ratio test	AIC
РМ	β	3.41 (1.07; 5.75)	PM <i>vs</i> null model <i>p</i> -value = 0.0030	277.9
EM	γ	0.0512 (0.0198; 0.0825)	EM <i>vs</i> null model <i>p</i> -value = 0.0015	276.6
EQM	$\eta \\ heta$	0.0375 (0.000100; 0.0742) 0.00119 (-0.000800; 0.00299)	EQM <i>vs</i> null model <i>p</i> -value = 0.0033	277.3

Table 2 An example: relative risks for different values of V (as compared to $V_0 = 80$ km/h) for the power model and exponential model

Speed (km/h)	Power model	Exponential model
65	0.49	0.46
70	0.63	0.60
75	0.80	0.77
<u>80</u>	1.00	<u>1.00</u>
85	1.23	1.29
90	1.49	1.67
95	1.80	2.16
100	2.14	2.78

4.2 Sensitivity to possible systematic errors in kinematic reconstruction

In case-control studies, some explanatory variables may be measured in different ways for cases and controls. In this situation, if a systematic error affects one group of data (the cases, for example) and not the other group (the controls), the results of the study can be substantially biased. In the present study, speeds were measured using a laser speed gun for the control vehicles, whereas, for the case vehicles, speeds were obtained through kinematic reconstruction. Although they are in large part based on material clues, kinematic reconstructions also depend on the expertise of the investigators and involve a degree of interpretation. Their results are therefore somewhat uncertain, and the possibility of a systematic error in kinematic reconstruction cannot be ruled out. In order to summarily examine the possible consequences of such errors on the results, models were fitted based on the hypothesis of a systematic underestimation (or overestimation) of speed in accident kinematic reconstructions. The findings of this analysis are summarized below:

(*i*) Hypothesis of systematic overestimation of speed in accident reconstruction. If the speeds of the case vehicles were systematically overestimated by 5%, the models would need to be corrected (by lowering the speed values for the case vehicles), which would lead to the following estimates: $\gamma = 0.0044$ (95% CI: -0.0282; 0.0373) for the exponential model, and $\beta = 0.245$ (-1.85; 2.34) for the power model.

(*ii*) Hypothesis of systematic underestimation of speed in accident reconstruction. Conversely, if the speeds of the case vehicles were systematically underestimated by 5%, the models would need to be corrected (by increasing the speed values for the case vehicles), which would lead to the following estimates: $\gamma = 0.0936$ (0.0611; 0.126) for the exponential model, and $\beta = 6.78$ (4.25; 9.31) for the power model.

Thus, overall, the results obtained appear to be highly sensitive to possible systematic errors affecting the reconstructed speeds. However, when interviewed about the possibility of such systematic errors in kinematic reconstructions, the IDAS investigators considered implausible a systematic overestimation of speeds, but did not completely exclude the possibility of a slight systematic underestimation (which could be due to certain approximations in reconstruction methods).

4.3 Models obtained for some subsamples

As already mentioned in Subsection 3.3., conditional logistic regression cannot estimate between-cluster effects. Although other methods such as random effects logistic regression can deal with clustered data and estimate some between-cluster effects, they are not appropriate for matched case control studies such as the present one, due to the retrospective sampling of the data (Agresti, 2002; Neuhaus and Jewell, 1990). Thus, the possible influence of various cluster characteristics, such as the urban or rural environment of the accident site, the level of severity of the accident, etc., cannot be integrated into the models.

Nevertheless, it is possible to restrict the modelling to some subsamples (rural accidents, urban accidents, slight injury accidents, severe or fatal injury accidents, etc.). The parameter estimates of the exponential model and power model applied to these subsamples are given in appendix B. These submodels, however, suffer from a lack of statistical power due to the limited sizes of the subsamples. Thus, although the results might suggest possible differential effects according to cluster characteristics, no firm conclusion can be drawn.

5 Discussion

In agreement with previous studies, the results presented in Section 4 suggest that, at a given time and place and in given conditions, the risk of involvement in an injury accident is positively and significantly correlated with the individual travelling speed of the vehicle, at least in normal weather, daytime, and free-flow conditions. No sign of an increased risk at lower speeds has been found. The exponential model (in which the relative risk depends on the difference between the speeds that are compared) appears to be slightly better than the power model (in which the relative risk depends on the ratio of speeds). According to the exponential model, in given conditions, a speed increase of 10 km/h would lead to an increase of about 67% in the risk of being involved in an injury accident. A speed decrease of 10 km/h would lead to a reduction of risk by about 40%.

This effect of speed, however, appears to be smaller than in the studies of Kloeden et al. (2001, 2002). A rough comparison can be made between the results found by Kloeden et al. (2001) for rural roads and the results obtained here, since in our data rural roads represent 40 clusters among the total of 52 clusters (see appendix B for more details). As mentioned in section 2, according to Kloeden et al. (2001), for a speed increase of 10 km/h, the risk would increase by a factor of 2.20, as compared to a factor of 1.67 according to our results (for the exponential model). It should be noted, however, that these authors removed from their sample of cases the crash-involved vehicles for which other major accident factors were present (alcohol-impaired driver, sleepiness, medical condition of the driver).

Comparisons could also be made with previous studies dealing with the effect of the *mean speed of traffic* on accident risk, but this would make less sense, since this effect is in fact an aggregated effect corresponding to the diversity of traffic situations (all times of the day, free-flow and congested traffic, etc.). In his meta-analysis of these studies, Elvik found that the average estimate of the exponent of the power model for injury accidents was 2.12 (Elvik, 2013a, p. 856), which is lower than the exponent found in the present study for the power model (3.41). But our results deal with the effect of the individual speed, in definite conditions: car, free-flow condition, no particular manoeuvre, daytime, normal weather.

Some limitations of the present study should also be considered. Firstly, although significant results were obtained, the parameter estimates are relatively imprecise, as indicated by their wide confidence intervals. A larger sample of crashinvolved vehicles would be needed to improve the precision of the estimates. Secondly, as shown in Subsection 4.2, the results seem to be highly sensitive to possible systematic errors in the estimation of the speeds of the crash-involved vehicles from kinematic reconstructions. This possibility cannot be completely excluded. Lastly, another source of bias could arise from the difference in the precision of speed data, between cases and controls, since the random error in the estimates of speed is certainly higher for the cases than for the controls, for which speeds are measured using a laser speed gun. Such a differential precision – less precision for the cases than for the controls – tends to result in some underestimation of the effect studied, in situations where the exposure variable (which, here, is the speed) is on average higher for the cases than for the controls (see for example Gregorio et al., 1985); this is the case for our data. Therefore, this differential precision could possibly lead to some underestimation of the effect of speed in our results.

The access to data routinely recorded by on-board electronic systems (such as the electronic control unit of Airbag systems) would make it possible to use more reliable estimates of speed for the crash-involved vehicles. In certain countries, these data can be accessed for research purposes, but in other countries, including France, this is not possible, probably for reasons related to the protection of personal data or to the protection of industrial property.

6 Conclusions

The results obtained in this study are consistent with the previous literature on the relationship between speed and risk of accident. More precisely, these results suggest that a small increase in the individual travelling speed leads to a large and significant increase in the risk of being involved in an injury accident, at least for cars, and for accidents occurring in normal weather, daytime and free-flow conditions. However, the results of this study should be considered with some caution. More robust findings would be obtained by using direct measures of the speeds of the crash-involved vehicles – based on data recorded by on-board systems – instead of kinematic reconstructions. Moreover, further research with larger samples would be needed in order to obtain more precise models.

From an applied perspective, models that quantify the effects of individual choices of speed on accident risk could be of some interest for driver education: drivers should be informed of the risks they take when driving at higher speeds. More generally, the convergent findings of international research - as regards the existence of a strong relationship between speed and accident risk - argue for the development of road safety strategies aiming to reduce the speed of automotive traffic. For example, the lowering of speed limits or stronger speed enforcement policies generally reduce the number of accidents (Carnis and Blais, 2013; Elvik, 2013b; Li et al., 2013; Soole et al., 2013; De Pauw, Daniels, Thierie et al., 2014; De Pauw, Daniels, Brijs et al. 2014). In France, large reductions in the numbers of injuries and fatalities were obtained through an automated speed enforcement policy (Carnis and Blais, 2013). This effectiveness is probably also related to the fact that in this country the penalty for exceeding the speed limit involves demerit points for the driver concerned, which may gradually lead to the revocation of the driving license. A consequence of such policies, however, is that an increasing number of drivers are excluded from driving. In France, for example, according to the statistics of the French Ministry of the Interior, the number of driving licenses revoked each year has increased by a factor of six due to the automated speed enforcement policy. Thus, in the long term, the social sustainability of such policies appears questionable. However, effective speed management strategies can also be based on other approaches, such as the treatment of road infrastructures (Mountain et al., 2005; Grundy et al., 2009; Jurewicz, 2009; Isebrands and Hallmark, 2012; Yannis et al., 2013). In the field of automotive technology, the introduction of speed adaptation systems or speed limiters in cars could

have positive effects on safety (Marchau et al., 2010). According to Hickman et al. (2012) speed limiters have resulted in reductions of the number of crashes for commercial vehicles.

Acknowledgements

The authors are grateful to the IDAS teams for their constant efforts in collecting and analysing in-depth accident data. Without them, this research would not have been possible.

Appendix A. Principles of the kinematic reconstruction method

The method used is based on a backward process. For the post-collision stage of the accident, the path and deceleration of the vehicles involved are estimated from their final positions and from the marks left during this stage. On this basis, the velocities of the vehicles just after the collision are calculated. The precollision velocities (just before the collision) are then calculated from the post-collision velocities and the energy dissipated during the collision, which is estimated from the deformations of the vehicles. This calculation is based on the laws of conservation of energy and momentum. Then, the pre-collision stage can be studied, using these pre-collision velocities and the marks (such as skid or yaw marks) left by the vehicles during this stage, in order to obtain estimates of the travelling speeds of the vehicles before the accident. For some accident cases, the vehicles involved do not leave marks before the impact (there may be various reasons for this: driver failing to see another road user; insufficient time for a braking manoeuvre before the impact; use of anti-lock braking systems - although in this latter case slight marks may sometimes be found; etc.). In this situation, the overall analysis of the data collected - including the in-depth interviews of the drivers - sometimes makes it possible to infer the travelling speed before the accident, but this is not always feasible. As regards the means used for kinematic reconstruction, the IDAS investigators do not use a fully integrated software tool. They rather use a software aid to calculation, developed in our laboratory (Lechner and Jourdan, 1994; Dubois-Lounis, 2012).

Appendix B. Parameter estimates obtained for some subsamples.

Since previous studies have suggested possible differences in speed-risk relationships between rural and urban roads (see, for example, the meta-analysis by Elvik, 2009), the two following subsamples were considered: clusters corresponding to rural road sites; clusters corresponding to urban road sites. The scientific literature also suggests that the effect of speed on accident risk may depend on the degree of severity of the accidents taken into account (Elvik, 2009). Therefore, the two following subsamples were also considered: clusters where the case vehicle is involved in a slight injury accident (no severe or fatal injury); clusters where the case vehicle is involved in a severe or fatal injury accident.
 Table 3 Exponential models obtained for some subsamples: parameter estimates,

 likelihood-ratio test (for each model as compared with the null model)

Subsample (Number of vehicles; number of cases)	Estimate of γ (and 95% CI)	p-Value of the LRT
Rural roads (688; 40)	0.0500 (0.0169; 0.0834)	0.0034
Urban roads (181; 12)	0.0608 (-0,0354; 0.1570)	0.2070 (NS)
Slight injury accidents (636; 39)	0.0416 (0.0040; 0.0788)	0.0291
Severe or fatal accidents (233; 13)	0.0735 (0.0159; 0.1310)	0.0128
Years 2003-2006 (351; 18)	0.0890 (0.0373; 0.1406)	0.0007
Years 2007-2012 (518; 34)	0.0284 (-0.0109; 0.0677)	0.1563 (NS)

Table 4 Power models obtained for some subsamples: parameter estimates,

 likelihood-ratio test (for each model as compared with the null model)

Subsample (Number of vehicles; number of cases)	Estimate of β (and 95% CI)	p-Value of the LRT
Rural roads (688; 40)	4.06 (1.32; 6.81)	0.0025
Urban roads (181; 12)	1.58 (-2.80; 5.97)	0.4713 (NS)
Slight injury accidents (636; 39)	2.96 (0.23; 5.68)	0.0261
Severe or fatal accidents (233; 13)	4.58 (0.09; 9.07)	0.0403
Years 2003-2006 (351; 18)	7.18 (2.93; 11.4)	0.0006
Years 2007-2012 (518; 34)	1.68 (-0.98; 4.33)	0.2001 (NS)

Moreover, two subsamples were considered according to the period: clusters corresponding to accidents occurred during the period 2003-2006; clusters corresponding to accidents occurred during the period 2007-2012. This was done in order to take into account the fact that the study period (2003-2012) was partially influenced by the French automated speed enforcement policy, implemented from 2003, which led to an overall and gradual decrease in traffic speeds by about 10 km/h; the observed driving speeds have nearly stabilised since 2007.

The parameter estimates of the models corresponding to these subsamples are presented in Table 3 (exponential model) and in Table 4 (power model). These tables also give the 95% confidence intervals of these estimates and the *p*-value of the

likelihood-ratio test (LRT) comparing each of these models with the null model. The letters NS stand for "not significant", for *p*-values higher than the threshold of 0.05. As can be seen from these tables, the 95% confidence intervals are wide, and they largely overlap. No firm conclusions can be drawn from these results as regards possible differences in model parameters between these subsamples. Larger samples would be needed to investigate this issue further.

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