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DETERMINANTS OF THE SEVERITY OF TRAFFIC ACCIDENTS IN LATVIA: AN ECONOMETRIC ANALYSIS

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The Determinants of the Severity of Traffic Accidents in Latvia:
An Econometric Analysis

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Abstract

The paper attempts to study the determinants of the severity of all registered traffic accidents in Latvia in year 2004 with application of the ordered probit model. Specific attention is devoted to drink-driving and its interaction with other determinants. A distinction between car accidents in Riga and in other regions of Latvia has been made. The results suggest that independently from the location of accidents, alcohol consumption, females, and passengers not drivers themselves are associated with higher probabilities of severe and lethal traffic accidents. Drunken drivers in particular have on average an eight times greater probability of getting into severe accidents and a thirteen times greater probability of incurring lethal accidents. It is also recognized that motorbikes are less safe, but heavy trucks and buses are safer than ordinary cars. With regard to location, differences are noticed only in external factors. Slopes, steep turns, weather conditions, surface or light conditions, except dark nights, have not been recognized to contribute to car accident severity in Riga. In Latvia, in turn, not only dark nights, but also steep turns and fog are associated with increased probability of severe and lethal accidents. It is believed that differences arise due to higher speed limits and lower traffic intensity in other regions of Latvia.

1 Introduction

Latvia is notorious as a country with extremely high rates of road traffic accidents. In fact, the rate of lethal traffic accidents involving children is the highest in Europe. A relatively huge number of severe accidents, if compared to other European countries, makes the topic of high importance to Latvian society. There were 48912 road accidents in Latvia in 2004, out of which 5081 were injury accidents of different severity (Road Traffic Safety Directorate, 2005). The issue of traffic fatalities has already long been widely discussed not only because of the increasing total number of traffic and fatal-injury accidents but also because all these road traffic accidents have created significant economic loss to the whole society amounting to 314.2 million euros in 2004. This sum incorporates not only the amount that was lost by insurance companies or property owners but also the administrative and indirect costs invested by the Latvian government in education, and the health care of fatally injured people.

Different actions have been taken to reduce the casualties and to improve the driving culture - penalties imposed have been stiffened and a penalty rating system has been introduced; however, as it appears, no improvements have been achieved so far. Quite the reverse, the situation is worsening even more – the number of the most severe (fatal) traffic accidents is increasing (Road Traffic Safety Directorate, 2005). Some experts blame the Latvian driving culture taught in driving schools, others explain it by the low quality of cars, or the low quality of road conditions. Moreover, the common belief exists that the most aggressive drivers, those that get into accidents most often, have common specific characteristics that determine their driving culture (Lama, personal interview, 2005).

It is clear that this field is full of controversies and no unanimous conclusions have been drawn so far. Moreover, the huge importance of the issue to Latvian society makes this topic an interesting area for research.

In this study, the issue of Latvian driving culture is narrowed down to quantitative analysis of the determinants of the severity of road accidents. Our particular interest was to identify any other factors, besides alcohol consumption, which might heavily affect the severity of traffic accidents. Therefore, the research question is as follows: Which factors determine the severity of traffic accidents in Latvia?

The analysis first attempts to identify the potential measurable as well as non-measurable determinants of the seriousness of road accidents, once they occur. Then, within the limits of the available database, several factors are tested and the effects of significant factors are quantified. Based on empirical data and a designed econometric model, it is possible to answer the questions, and to test the statistical significance of determinants of the severity of traffic accidents.

The analysis has both academic and practical importance. Academically, the research adds to the literature on road traffic accidents in Latvia and may serve as a basis for further research in this area. On the practical side, the severity of injuries sustained by drivers involved in crashes is of considerable interest to policy makers and safety specialists. This study could create guidelines to whose factors attention should most be paid in deciding what should be done or improved. Although analysis of traffic accidents is helpful for assessing risk factors and for designing governmental policies as road travel, no relevant research has been carried out by policymakers or Road Traffic Safety Directorates in the Baltics.

The structure of the work is as follows. First, the methodology of the research is presented. Then the literature review is introduced. The theoretical model of the thesis is added after the discussion; this section elaborates on the model and justifications it. This is followed by a dataset description, where all the available variables and their drawbacks are discussed. Econometric regressions are performed in the next part, and discussion of methods, initial expectations, and the findings of the research are presented shortly after. This leads to concluding remarks.

2 Methodology

The following paragraphs state the approach and the sequence taken in order to carry out the proposed research.

2.1 Methods indicated

For the purpose of identifying and hypothesizing the determinants of the severity of traffic accidents, three sources of information have been used:

1. *Database of registered car accidents in Latvia in year 2004 acquired from CSDD.*

In order to establish a basis for quantitative analysis, an interview with Aldis Lama, deputy of the head of the Statistics department at CSDD, was conducted (personal interview, 2005). During the meeting, the interviewee introduced the available dataset and the variables it includes. He also presented the general situation on traffic-related issues. Summary reports on statistical data on car accidents in Latvia and the electronic format of the available dataset were acquired as well.

2. *Expert interviews with the head of CSDD and the deputy head of the Statistics department at CSDD.*

In order to get a more elaborate insight into traffic-related issues, as well as to note the general expectations related to the severity of car accidents and to further hypothesize these expectations, two interviews were conducted. First, during the meeting with Aldis Lama a short interview was conducted (personal interview, 2005). He presented the general statistical indicators and his point of view about expected future trends. Second, Andris Lukstins, the head of CSDD, was interviewed (personal interview, 2005). This individual was chosen due to his experience in the field of research[1] and wide knowledge about the legal as well as social issues related to traffic accidents.

3. *Prior studies in the area of the particular research.*

The literature review was carried out to establish the general findings of prior research and to compare its consistency with the results in this work. The findings of prior research together with the information revealed during interviews are used for forming expectations. For a list of works studied, refer to the works cited list.

To test the significance of the hypothesized determinants and to quantify the effects of significant factors, the econometric software STATA was used.

2.2 Brief of Fieldwork

First, the hypothetical determinants of the severity of road accidents were identified, by studying the available sources of information. Then two expert interviews were arranged, in order to establish general beliefs about the issue of our analysis and to formulate expectations for the research. The search for prior studies was conducted in several publicly available libraries and databases, as well as through the Internet. In order to continue with the quantitative analysis, a database of registered car accidents in Latvia in year 2004 was acquired by arranging a meeting with representatives from CSDD. Furthermore, the observable determinants of accidents available in the database were regressed in order to test for the significance of the various factors that might influence the severity of traffic accidents. The expected determinants that are noticed

[1] Andris Lukstins has 14 years of experience working as a head of CSDD.

but not observable in the database are discussed as well, and potential bias in the quantitative research is described.

The initial predictions are that alcohol, weather, age, and season of the year are the main determinants; however, there are many more factors influencing the severity of traffic accidents, and finding these relevant factors is at the core of this research.

3 Literature Review

An extensive literature devoted to road traffic accident modeling was found during the study, and this review tries to give an insight into the most relevant research. In the most recent and sophisticated research of road traffic accidents, the Poisson and Negative Binomial are the most common model specifications. And logit-based models (*e.g.*, a log-linear specification) have been used to analyze injury severity across the classes. A variety of explanatory variables are typically available in accident records; however, the majority of models examine the effects of a few of such variables (*e.g.*, gender and age).

The first significant contribution in the area of research was done by Chipman (1992). He created an index incorporating both distance and travel time. Then he clustered the driver sample by age, gender, and region and compared the exposure-normalized accident and fatality rates. He discovered that the older the driver, the lower their speed, which results in less significant traffic accidents, *ceteris paribus*. Furthermore, he calculated that men spend only 30% more of their time driving 50% longer distances than women.

Doherty, using the Ontario Ministry of Transportation 1988 database, analyzed the situational risks of young drivers (1998). The author tried to estimate traffic accident rates by three risk factors: time of day, day of week, and the number of passengers. Results indicate that the traffic accident rates of 16–19 year-old drivers are significantly greater than those aged 20-24 and 25-59. Traffic accident involvement rates are even higher for 16–19 year-old drivers compared to 20–24 and 25–59 year-old drivers on weekends, at nighttime, and with passengers.

Shankar investigated the zero-inflated Poisson and the Negative Binomial models of Accident counts in Washington, D.C. (1997). Such specifications for the Accident-count may help in crash prediction, and the results suggest that there are many relations between geometric design of cars and crash rates.

By applying the Poisson, negative binomial, ordinary least squares, weighted least squares regression models, Gebers analyzed traffic accident-rate frequency (1998). He discovered that the driver accident involvement rate is positively correlated to the traffic accident, male gender, and youth. However, Gebers did not take into account the miles driven, which dramatically differ across gender and age.

Putting together the different databases, Ivan estimated the annual Traffic Accident rates as a function of the site and the traffic characteristics for single- and multi-vehicle accidents (1999). His research was based on a Poisson distribution. For single-vehicle accidents, he identified that the traffic conditions (e.g., weather) and the site characteristics (e.g., shoulder width and speed limit) were statistically significant, but the light conditions (e.g., day or night) were not. For multi-vehicle accidents, only the site characteristics were statistically significant in the final models.

Lourens found that there is no difference between men and women in terms of their accident involvement (1999). He identified that younger drivers have the highest traffic accident involvement rate per mile driven among all age groups.

Aljanahi also applied the Poisson model to discover the relationship between traffic speeds and accident rates under free-flow conditions in two different areas – Bahrain and the UK (1999). In Bahrain, he found statistical evidence for a strong relationship between speed and accident rate. In the UK, a strong relationship between accidents and variability of traffic speeds was found. His results suggest that the size of heavy vehicles is inversely associated with the accident rate, and the mean speed contributes to accident rates. What is more, he concluded that alcohol consumption violations have a positive effect on fatal accident rates. Rather interestingly, he also discovered that education level is irrelevant to accident involvement and that higher speeds go in hand with longer trips.

Dobson tried to examine the factors affecting driving behavior and accident rates in Australia (1999). Two groups of women were examined in the research (those aged 18-23 and those aged 45-50) and the negative binomial model was applied. He identified that younger women have a three times greater probability of getting into an accident than middle-aged women. Dobson associated riskier driving behavior among younger women with stress and habitual alcohol consumption. He also found that women born in non-English speaking countries had a greater probability of getting into accidents compared to those born in Australia.

These researches mainly deal with accident involvement and accident totals, while this study investigates accident severity. In such cases – where the dependent variable is a highly discrete value - different models should be used, such as the multinomial logit or ordered probit models. For example, by applying this method to 1994 and 1995 traffic accident data in Florida, Abdel-aty tried to find relationships between driver age and accident-related factors such as injury severity, average daily traffic, speed ratio, alcohol involvement, accident location, and collision types (1998). There were three levels of injury severity - no injury, injury and fatality. As a result, Abdel-aty identified that injury severity is positively correlated with younger age. Moreover, he discovered that middle-aged drivers have a greater probability of getting into traffic accidents, while older drivers are more likely to be involved in fatal traffic accidents.

Sachsida tried to identify whether a relationship exists between distraction and traffic accidents by applying the ordered probit model (2004). His findings were that the use of cell phones and cigarettes while driving negatively affect the probability of traffic accidents. He also found that males have a higher probability of getting into traffic accidents. What is more, he also detected a positive relationship between people with an average salary and the probability of getting into traffic accidents.

Ratnayake used the ordered probit model in order to analyze the factors leading to greater traffic accident severity in rural and urban highway accidents (2004). As the most contributory factors, the author named alcohol involvement, lack of seat belt use, excessive speed, and driver ejection. Additionally, curved and graded roads contribute to higher accident severity. Moreover, head-on, angle, and rear-ended traffic accident types are the cruelest. In rural areas, only single-vehicle accidents appeared to be statistically significant towards greater severity, while in urban areas, both single and two vehicle accidents are statistically significant.

However, the most relevant papers for this analysis are those of O’Donnell and Connor (1999) and Kockelman (2001). O’Donnell and Connor applied the ordered probit and the ordered logit models and then compared them, in order to analyze the probabilities of four levels of injury severity – no injury, slight injury, heavy injury, and fatal injury. They concluded that traffic accident severity rises with speed, vehicle age, occupant age (squared), female gender, blood alcohol levels over 0.08 per mille, non-use of a seatbelt, type of collision (e.g., head-on crashes), and use of a light-duty truck. They also discovered that the seating position of traffic accident victims was the most important (e.g., the left-rear seat of the vehicle is the most dangerous) and gender the least important.

Kockelman also applied the ordered probit model to assess the risk of different injury severities under all traffic accidents (2001). She, instead of examining the determinants of accident severity, tried to find the severity of traffic accidents for various vehicles in different types of collision. She concluded that pickups and sports cars are less safe than passenger cars in single-vehicle traffic accident conditions. Under two-vehicle traffic accidents, pickups and sports cars are safer for their drivers; however, at the same time these are less safe for the passengers of their collision partners. In addition, the author concludes that males and younger drivers, driving with new cars at low speed, get into less severe traffic accidents.

One of the latest studies on traffic accident severity was conducted by Xiaokun Wang and Kara M. Kockelman, where they use the ordered logit model to investigate the effect of vehicle, environmental, passenger, road descriptions on traffic accident occurrence (2005). The authors identified that the bigger the vehicle, the greater its crashworthiness and damage to others. Moreover, traffic accident injuries do not matter, if passenger vehicles weigh more than 1000 lbs. Besides, if all vehicles became light duty trucks, the fatalities would increase from 26% to 64 %. The authors also indicate the finding that males and young drivers at low speeds suffer less severe injuries.

As relates to similar studies in Latvia, CSDD every year publishes statistical reports covering general data on road traffic safety in Latvia, comparison to other countries, and the distributions of road traffic accidents by time, nature, and place (CSDD, 2006). However, as far as is known, no econometric analysis has been applied to their research.

The following analysis is considered to be the first attempt to apply an econometric model in determining road accident severity in Latvia and to comment on the major findings. The analysis will start by explaining the model to be applied, and afterwards, an empirical study and major findings are to be presented.

4 Theoretical Model

In order to carry out a thorough research, we chose to apply the ordered probit model for estimating the severity of car accidents. The following sections give a brief insight into the general model as well as justifying the chosen approach and discussion of alternatives.

4.1 Model Description

While most previous studies have attempted to study only characteristics of drivers in determining the severity of car accidents, it is of particular interest for us to control also other factors, such as weather and road conditions, vehicle type, and crash type. As already mentioned, Kara Maria Kockelman attempted to examine the risk of different injury levels sustained under various crash types (2001). The author used the ordered probit model to control for various vehicle and crash characteristics. In contrast to the chosen approach, we will attempt to study both driver-specific and crash-specific variables in explaining the severity of car accidents. The following paragraphs will describe the proposed model.

4.1.1 Application of Ordered Probit Model

Ordered response data arise when mutually exclusive qualitative categories do not have natural numerical values; however, they do have a natural order (Stock, Watson, 2003, 330). In application to our case, the dependent variable - severity of traffic accidents – has the following alternatives: unharmed; slightly injured; seriously injured; killed. While these categories are mutually exclusive and qualitative in nature, they do have natural ordering. It is clear that no injury has the lowest severity, while killed has the highest. Thus, driver injury severity was used as the ordered response to recognize the indexed nature of response variable in the ordered probit model.

When applying the general ordered probit model to the specific case of car accident severity analysis in Latvia, the following specification is used:

$$^{*}S_n = {}^{\wedge}\beta * x_n + \varepsilon_n$$

where:

$^{*}S_n$ is a latent and continuous measure of severity of car accident faced by driver *n*;

x_n is a vector of explanatory variables given in the data set;

β is a vector of parameters to be estimated;

ε_n is a random error term[2].

The observed injury severity variable S_n is determined in the following way:

$S_n = 0 \text{ if } {}^{*}S_n \in (-\infty; \mu_1];$

$S_n = 1 \text{ if } {}^{*}S_n \in (\mu_1; \mu_2];$

[2] Random error term is assumed to follow the standard normal distribution.

$S_n = 2 \text{ if } {}^*S_n \in (\mu_2; \mu_3];$

$S_n = 3 \text{ if } {}^*S_n \in (\mu_3; +\infty]$

where:

μ_i is an estimate of cut points (see figure 1).

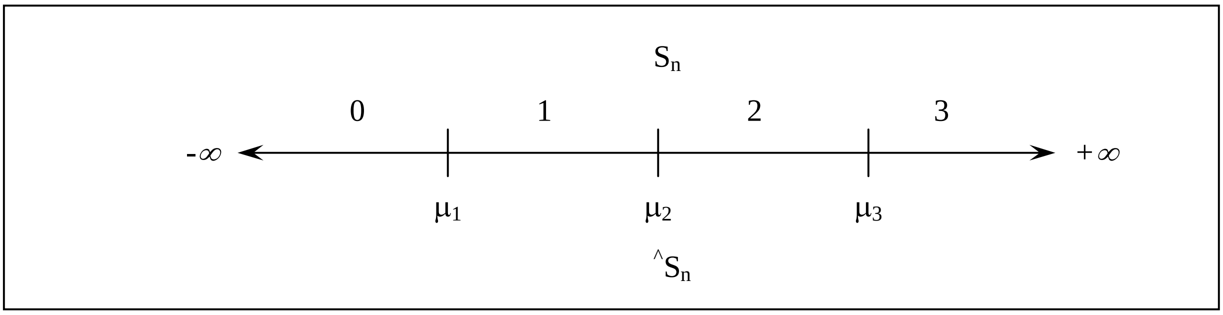

Figure 1: Relationship between latent injury severity variable ${}^*S_n$ and observed severity class S_n

One may further express the probabilities associated with the coded responses of an ordered probit model (see also figure 2):

$P_n(0) = P(S_n = 0) = P({}^*S_n \le \mu_1) = P({}^\wedge\beta{*}x_n + \varepsilon_n \le \mu_1) = P(\varepsilon_n \le \mu_1 - {}^\wedge\beta{*}x_n) = \phi(\mu_1 - {}^\wedge\beta{*}x_n)$

$P_n(1) = P(S_n = 1) = P(\mu_1 < {}^*S_n \le \mu_2) = P({}^\wedge\beta{*}x_n + \varepsilon_n \le \mu_2) - P({}^\wedge\beta{*}x_n + \varepsilon_n \le \mu_1) = P(\varepsilon_n \le \mu_2 - {}^\wedge\beta{*}x_n) - P(\varepsilon_n \le \mu_1 - {}^\wedge\beta{*}x_n) = \phi(\mu_2 - {}^\wedge\beta{*}x_n) - \phi(\mu_1 - {}^\wedge\beta{*}x_n)$

…

The probability function associated with the coded responses of an ordered probit model may thus be generalized as:

$P_n(k) = P(S_n = k) = P(\mu_k < {}^*S_n \le \mu_{k+1}) = \phi(\mu_{k+1} - {}^\wedge\beta{*}x_n) - \phi(\mu_k - {}^\wedge\beta{*}x_n)$

where:

n is an individual;

k is the severity alternative;

$\phi(\ldots)$ is the standard normal cumulative distribution function;

$P_n(k)$ is the probability that an individual n responds with severity alternative k.

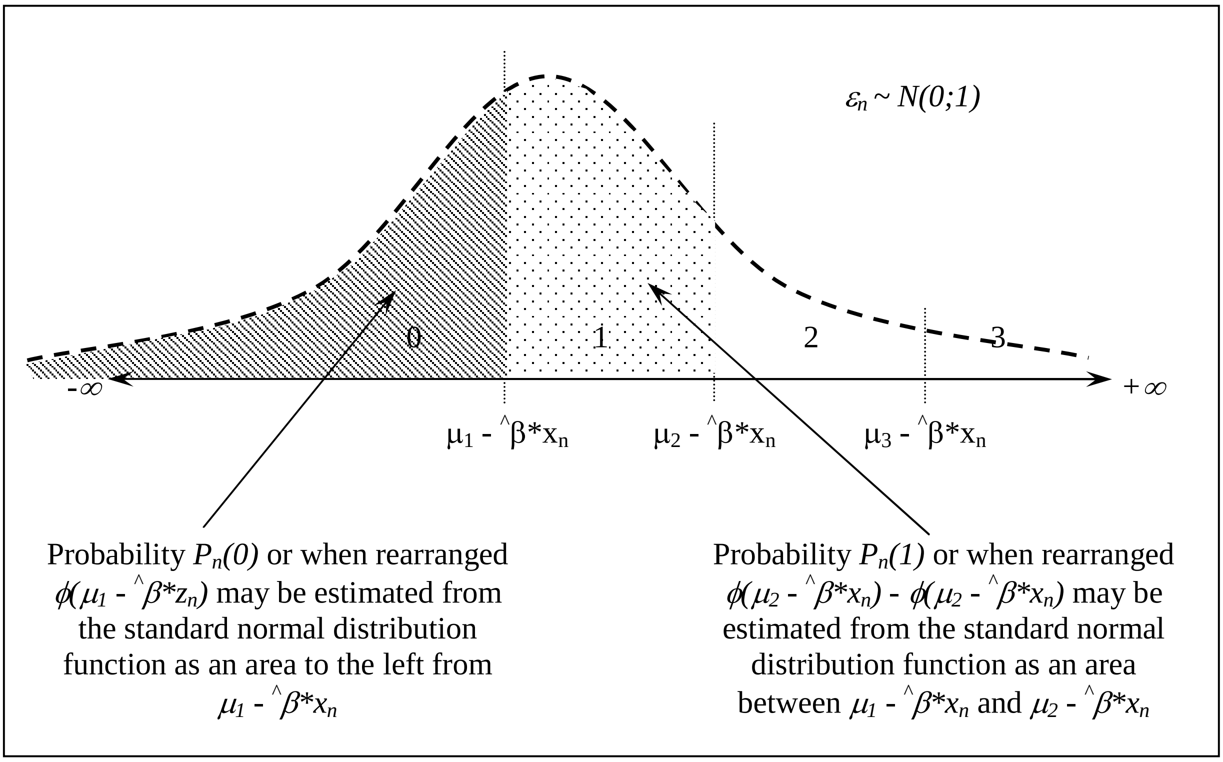

Figure 2: Probabilities associated with the coded responses of an ordered probit model

4.1.2 Interpretation of Coefficients

The diagram presented in the previous section has an important implication about interpretation of estimated coefficients. As the majority of car accidents appear to be without injuries, cut points are all positive (in other words, as the probability of no injury is high, the area to the left from the first cut point is large (>50%) meaning that the first cut point is positive (>0)). Furthermore, if estimated coefficient $^\wedge\beta$ is positive, then μ_1 - $^\wedge\beta * x_n$ is decreasing, and the estimated Z-value is decreasing as well. Consequently, it may be noticed that positive estimated coefficients $^\wedge\beta_n$ negatively affect Z-values and corresponding probabilities of no injury. Once the probability of no injury is decreasing, the other probabilities of more severe accidents are, in turn, increasing. To conclude the interpretation of coefficient signs, while positive estimated coefficient $^\wedge\beta$ negatively affects probability of no injury, it yields positive effect on more severe and lethal car crashes and *vice-versa*.

The very general interpretation of the parameter set β may be expressed as follows – due to the increasing nature of the dependent variable, positive estimated value indicates higher severity of car accident as the value of related variables increases and *vice-versa*. One must still notice that probit coefficients cannot be measured directly. The interpretation of ordinary probit coefficient attempts to estimate the effect of the independent variable on the Z scores of the dependent variable and not on the probability as such.

4.1.3 Modification of the Variables in the Dataset

As it appears people in the age group of 24 years are most often involved in car accidents, and both lower as well as higher age groups have a tendency of decreasing amount of crash rates, it seems reasonable to test the age variable by using the polynomial specifications. Expectedly, polynomial specifications should lead to a better fit of the final regression.

4.2 Model Justification

It is worth considering also whether the chosen approach to estimation of the severity of car accidents is the most desirable and whether there are no other alternative models that may fit better to the particular analysis.

Multinomial logit and probit models may serve as possible alternatives. The models use the maximum-likelihood estimation for the polytomous dependents. As the categories are formed of polytomous dependents that are interdependent, the multinomial logit model handles non-independence by estimating the outcomes simultaneously[3]. These models, however, do have significant drawbacks. First, the multinomial models neglect the natural order of data. Furthermore, the models require estimation of additional parameters, consequently decreasing the available degrees of freedom (Greene, 1995).

Ordered probit and logit models are in general also considered as superior to multinomial models when estimating the severity of car accidents by the majority of the researchers (Greene, 1995; Kockelman, 2001; Xiaodong and Kockelman, 2005; O’Donnell and Connor, 1999; Zhang, 2000).

5 Dataset Description

For the purpose of the analysis, a secondary database from CSDD is obtained (2005). It includes all 48 912 police-reported traffic accidents in 2004. The following section is the summary of the available information.

[3] When using dummy variables, one category is "left out" to serve as a baseline.

5.1 Data Available for Analysis

The database is quite extensive and divided into seven main sections (for summary statistics see also *Appendix 1: Summary Statistics*). First, information on the gender of the person involved, their age and severity of their injuries is provided. In addition it is registered whether a person is to be blamed for causing an accident and whether he/she has consumed alcohol. Roughly 20% of all accidents involve females. While in Riga only 1% of involved persons are registered as drunk, in other regions of Latvia approximately 5% of car accident participants are drunk, indicating that drink-driving is more of a problem in less traffic-intense regions, where road police controls are also likely to be less intensive. Also, while in Riga more than 95% of involved persons are unharmed, 5% with slight injuries, less than 0.03% with severe injuries and 0.1% killed, in other regions the corresponding probabilities are higher – 89%, 7%, 3% and 1%. From every hundred persons involved in car accidents in Latvia, one is killed. It is interesting also that in Riga more drivers are killed than severely injured.

Second, weather and light conditions are registered. Most common weather and light conditions are cloudy (42% of cases in Riga and 38% of cases in other regions of Latvia) and daylight (72% of cases in Riga and 69% of cases in other regions of Latvia). Other weather conditions are clear, sunny, fog, rain, and snow; other light conditions are twilight, darkness, street lighting.

Third, road architecture and condition is registered. The information on surface type (asphalt, concrete, crushed stone, gravel pavements, cobblestone, earth) and on surface condition (dry, wet, compressed snow, wet snow, ice-covered, slippery, covered with fresh asphalt, covered with non-slippery material) is provided. In other regions of Latvia the type of road (main road, first category road, second category road) is also notified. As it appears, most accidents in Riga and in other regions of Latvia are on asphalt (89% of cases in Riga and 82% of cases in other regions; intuitively this is due to the heaviest traffic being on roads covered with asphalt) and on dry and wet surface conditions (roughly 50% and 30% of all cases, correspondingly).

Next, the type of collision is notified. Roughly 66% of cases in Riga and only 41% of cases in Latvia are collisions with other cars. Besides two-car crashes, in Latvia a common crash type is also collision with an obstacle (25% of cases registered as collision with parked vehicles and 19% with other obstacles). Other options are rollovers, driving into ditches, collisions with pedestrians and cyclists.

Further, information on the status of the person involved is provided. While more than 90% of participants in both Latvia and Riga are drivers themselves, sometimes accidents also involve cyclists, pedestrians, and passengers.

Also the types of vehicles involved are registered in every single traffic accident. Not surprisingly, ordinary light cars are the most common vehicles in accidents (77% of cases). While trucks are also quite commonly involved in accidents, buses, motorcycles, trams and trolleys are significantly less involved.

Finally, additional dummy variables notifying specific periods of time (Easter, Christmas, New Year, Ligo night, ordinary Friday nights, ordinary Saturday nights) are included.

The database also allows exploring very detailed information, for instance, possible reason of accident (e.g., wrong choice of speed, disregarding distance, vehicle defect, inattentiveness of driver), and schema of accident (run off road in straight stretch, collision with parked vehicle or with obstacle, reverse movement, running in opposite line, collision with pedestrian after crash between vehicles). According to Andris Lukstins, such elaborate attention to these sections has to be conducted in order to identify the most common reasons for accidents and action needed to prevent them (placing traffic lights, sign, or pedestrian crossing) (personal interview, 2005). Still, these detailed cases are not studied in this paper due to the fact that it significantly reduces the number of observations and, consequently, also increases error terms.

5.2 Data Drawbacks

One must note that the available data is still subject to several drawbacks. First of all, the information is received from protocols prepared at the site of an accident. The protocol, in turn, is completed by a policeman. Consequently, the data is subject to the actions of a policeman, who theoretically can fail to complete the protocol correctly. Next, a person (or several people) involved in a car accident may also attempt to avoid police registration of car accidents. This is especially the case of small damage in urban areas, where individuals, in order to avoid time-consuming registration of accidents and fines for causing an accident, may come to a common agreement not to involve the police. This issue introduces bias in disinformation of car accidents with no injuries. What is more, differences may exist in driving behavior in urban and rural areas. In order to control for such differences, a distinction is made between car accidents registered in Riga and in other areas of Latvia to capture these differences. Still, one more bias is noticed in the dataset – the data available for research consists only of drivers who were actually involved in car accidents. This introduces the bias of avoiding drivers, that is, those who have not been involved in accidents. The final comment is about the variable notifying who is to blame for causing an accident. It is clear that sometimes this fact can not be easily recognized and the judgement may be arguable.

Although several drawbacks in the dataset are recognized, it is still believed that the available data contains very useful and truthful information for further analysis. In addition, it is assured by the Ministry of Transportation in Latvia that no better alternative dataset of registered car accidents in Latvia is available.

6 Empirical Analysis

The following section will attempt to apply ordered the probit model and to analyze which are the factors affecting the severity of car accidents. Due to very different traffic intensity and possible reasons behind the severity of car accidents in Riga as compared to other regions in Latvia, it was decided to split the available data in two distinct datasets – one capturing the factors affecting severity in Riga, and the other capturing the factors affecting severity in other regions of Latvia.

6.1 Personal Characteristics

At first, personal characteristics are to be studied. From the available datasets, it is possible to test for the effects of alcohol usage, aggressive and less skilled driving (captured by the variable concerning whether or not a driver has caused the accident), gender, and age.

6.1.1 Usage of Alcohol

It is generally believed that alcohol is the major reason behind the most severe accidents. This is also supported by previous studies. Aljanahi (1999) concluded that alcohol consumption violations have a positive effect on fatal accident rates. Dobson (1999) associated riskier driving behavior among young women with habitual alcohol consumption. Ratnayake (2004) and O' Donnell and Connor (1999) identified that an alcohol level over 0.08 per mille is one of the main factors that increases accident severity. Drivers under alcohol consumption have weak driving abilities, no feel for speed, and slow reaction, which all expectedly increase the severity, once an accident takes place. Also during both interviews conducted, alcohol was mentioned as the underlying reason behind the most severe accidents (Lukstins, personal interview, 2005; Lama, personal interview, 2005). It is thus believed that alcohol is a significant and positive determinant of the severity of traffic accidents.

In order to test for significance of alcohol, the dependent variable *severity* was regressed against *alcohol* as an independent dummy variable by applying the ordered probit model. When regressed, the estimated coefficient is positive and significant at 1% level of significance in both Riga's and Latvia's datasets. At this point, the estimated coefficient is biased due to correlation with other factors that may expectedly be significant determinants of *Severity* as well (e.g., *Friday_nights* and *Ligo* may, first, be significant determinants of *severity*, as during Friday nights and national holidays people tend to celebrate various events and to drive more aggressively, and, secondly, they may also be correlated with *alcohol* as during these periods alcohol consumption is the highest; similar reasoning may also apply to *light_cond_dark, fault*, etc.). In order to reduce bias, additional factors must be included.

6.1.2 Age

It may be considered whether the age of the driver affects his/her driving abilities and the severity of car accidents. Several studies have recognized the importance of age when examining causes of car accidents. Chipman (1992) as one of the first concluded that the older the driver is, the lower his speed is, which results in less significant traffic accidents. Lourens (1999) found that younger drivers have the highest traffic accident involvement rate per mile driven. Dobson (1999) recognized that young women have a three times greater probability of getting into an accident than middle-aged women. And also Abdel-aty (1998) supports the viewpoint that injury severity is positively correlated with younger age. These studies have attempted to use the linear specification and find a negative relation between age and severity. Consequently, the initial expectation is that older drivers are involved in less severe car accidents.

When studying drivers' age in Latvia, the variable *Age* indicates that an involved person's age is included in the regression. It appears that the linear specification appears to be significant at a 1% level of significance in both Latvia and Riga. However, when adding the quadratic specification with the variable *Age2* (squared variable *Age*), it not only makes the variables even more significant, but also substantially improves the R-squared, indicating better explanatory power. Consequently, quadratic specification is believed to be more informative when describing the effect of age on severity.

Regarding drink-driving, it is probable that some correlation exists between *Age* and *Alcohol*, implying a bias in the previously estimated coefficient on alcohol. The bias occurs once the following two conditions are fulfilled: first, the variable of interest (in this case *Alcohol*) correlates with the omitted variable (*Age* and *Age2*); second, the omitted variable is a significant determinant of the dependent variable. The coefficient on *Alcohol* changes only marginally, when *Age* and *Age2* are included, indicating that practically no correlation between age and drink-driving exists.

6.1.3 Gender Differences

A general perception about females as safe drivers is becoming increasingly popular. This belief is also supported by Gebers (1998) and Sachsida (2004) who have discovered a negative relation between female gender and traffic involvement. However, traffic accidents caused by women are considered to be more severe – according to recent study findings by O'Donnell and Connor (2000). While 32% of all legally registered drivers in Latvia are females, only in 19% of all car accidents are females found to be guilty of causing the accident. Although analysis of accident involvement should also be related to kilometers driven, the figures presented show that females are somewhat less involved in car accidents. With regard to previous research, it is expected that females are also involved in less severe accidents.

The effect is tested by including an additional dummy variable indicating whether a participant in an accident is a female. The coefficient on dummy variable *Female* is positive and significant at 1% level of significance. This holds in Riga as well as in all other regions of Latvia. This estimate contradicts previous studies. At this point, however, the estimate may be imprecise. It must first be controlled for additional factors that may introduce bias into estimates. Furthermore, while most studies focus on severity in accidents caused by females, this work attempts to analyze overall involvement in car accidents and consequent severity. If only females who have caused traffic accidents are studied, the results may differ substantially. The case is considered by including the additional variable *Fault* (a variable that indicates whether the person involved is found to be guilty of causing the accident) and by designing a regression with only those variables that are associated with drivers that caused car accidents (value on *Fault* equal 1). Still, the coefficient on *Female* changes only marginally and is still positive and significant at 1% level.

6.1.4 Fault Effects

The variable to be analyzed further is *Fault*. The dummy variable *Fault* may help to recognize whether drivers who are found to be guilty of accidents are also more likely to suffer from severe injuries. To our knowledge, no previous studies have attempted to study this effect. Still, an intuitive thought expressed by Lukstins is that those who drive most aggressively are also the ones to suffer from severe injuries (personal interview, 2005). Consequently, the expectation is that drivers to be found guilty are involved in more severe accidents and, consequently, the coefficient on *Fault* must be positive.

Once the variable is included, it appears to be significant even at 1% level of significance in both Latvia and Riga. Somewhat surprising and contrary to expectation, but, as it appears, the coefficient on *Fault* is negative.

It is worth noticing that after accounting for the *Fault* effect, the coefficient on *Alcohol* is increased substantially, indicating that both variables are correlated and in previous specifications the coefficient on *Alcohol* was biased downwards. Intuitively, the correlation seems very reasonable – the more alcohol a driver uses, the more likely it is that he/she will cause an accident. From statistical reasoning, the bias is explained as follows. As the coefficient value on *Alcohol* is increased after including the omitted variable *Fault*, this implies that in the early specification *Alcohol* has a negative correlation with the error term. Since *Fault* has a negative effect on the severity of accidents (that is, *Fault* reduces the probability of severe and lethal injuries), it is positively correlated with the error term. Therefore, in order for the error term to be negatively correlated with *Alcohol*, *Fault* must be positively correlated with *Alcohol*.

6.2 Weather and Light Conditions

It is possible to test the effects of the following light conditions: daylight, twilight, dark, and streetlight. In addition, the effects of the following weather conditions can be tested as well: dry, sunny, cloudy, fog, rain, and snow. The following section explores the effects of weather and light conditions on the severity of car accidents in detail.

6.2.1 Weather Conditions

It is intuitive that worse weather could be a stimulating factor for traffic accidents. And wintertime is perceived as the most risky, when driving is the most problematic. This is also statistically proved by Ivan (1999). The database has six different weather possibilities – clear, sunny, cloudy, foggy, rainy, snow. Dry weather conditions, considered to be the most favorable for driving safety, are to be used as a basis to identify the role of other weather conditions on the severity of traffic accidents. To study the effect of various weather conditions, dummy variables on other types of weather conditions (except the base condition “dry”) are included. It is intuitively expected that all other weather conditions, as compared to dry weather, must be associated with more severe car accidents, so that the coefficients must be positive.

When looking only at the Riga database, all weather conditions appear to be negative and statistically significant at 1% level. However, in Latvia the situation differs. The only variables that are statistically significant at 5% level are those indicating foggy and sunny weather conditions. The coefficient on sunny weather is negative and the one on foggy weather conditions is positive. These results may be due to picking up of other effects, and the conclusions are to be drawn only after a more elaborated regression is developed.

6.2.2 Light Conditions

When discussing light conditions, the intuitive impression is that darkness increases the probability of severe traffic accidents. Perhaps the same results should also be applied to twilight. Similar to weather conditions, dummy variables indicating every particular light condition are included and regressed with base variable daylight.

The ordered probit estimates suggest that the coefficient on darkness is statistically significant at 1% level in Riga as well as in Latvia, and positive. The coefficients on twilight and darkness with streetlights in Riga are insignificant. If looking at other regions in Latvia, the coefficients differ - twilight becomes significant and positive at 5% level. Having added new variables, the changes in z-values of the other variables are only marginal.

6.3 Road Architecture and Condition

The section covers road architecture and condition-related aspects. The available datasets allow controlling for the following factors: turn, slope, type of surface, condition of surface, and type of road.

6.3.1 Accidents on Turns and Slopes

It is of particular interest to explore how turned and sloped roads influence the severity of traffic accidents. It should intuitively be that steep turns on the roads increase the probability of an accident, for the following reason: steep turns reduce visibility and increase the probability of sideslip and, consequently, a driver is less likely to control his/her vehicle. This does not, however, imply that it automatically causes higher severity as well. The argument for car accident severity is not so straightforward. Still, in steep turns a vehicle is more likely to roll over or to run into a ditch, or any other dangerous obstacle that may increase severity. The reasoning for slopes is similar: driving up a slope reduces visibility and overtaking other cars becomes more dangerous, which theoretically may again increase the severity of car accidents. In support of this argument, Ratnayake (2004) has found out that curved and graded roads contribute to higher accident severity. Thus, the expectation is that turns and graded roads are positive determinants of severe accidents.

Two dummy variables *Turn* and *Slope* are included, indicating whether an accident occurs on steep turns and graded roads. The results somewhat differ between datasets – while both variables are strictly significant at 1% level of significance and positive in Latvia's dataset, the coefficient on *Slope* is negative in Riga and remains significant only if tested at 10% level of significance. The coefficient on *turn* is positive and more in line with initial predictions.

Only a marginal change in the factor *Alcohol* also indicates a weak correlation among the *Slope*, *Turn*, and *Alcohol* coefficients, which in a sense is very logical – there is no reason why road architecture should correlate with alcohol consumption.

6.3.2 Road Surface

At this point it is also logical to look at the surface of the road that may or may not affect severity. In the datasets, the following types of surfaces are considered: asphalt, concrete, crushed stone, gravel pavements, cobblestone, and earth. It may theoretically be that different road surfaces influence the ability to drive and, consequently, also accident severity. At this point it is unclear how exactly the surface can influence severity. From one side, the worse the road surface, the harder it is to steer the vehicle. From the other side, due to low quality of surface drivers tend to drive at lower speed and, consequently, reduce the probability of severe injuries.

When including these binary variables in regression (asphalt is used as base to compare with), it appears that the findings at this point more or less comply with the second expectation that it is less risky to drive on low quality surface at lower speed. Estimated coefficients on cobblestone, earth, and concrete are all significant and negative at 1% level of significance. The only coefficient that seems to bring a positive contribution to severity of accidents is gravel pavement. The mentioned signs of the coefficients are, however, valid only for Latvia overall. In Riga the situation is more uncertain. While the signs on the estimated coefficients are the same, only accident severity on cobblestone seems to be significantly lower as compared to asphalt, when tested at 1% level of significance. All the coefficients are, however, subject to bias, as it may be that actually it is not the surface itself, but the condition of the surface that matters in determining car accident severity. Furthermore, both factors may as well correlate with each other (e.g., asphalt roads are more likely to be repaired, cleared of snow, and maintained in better condition).

6.3.3 Surface Condition

To capture not only surface effects as such, surface condition factors as dummy variables are included in the regressions. Dry, wet, compressed snow, wet snow, ice, slippery, fresh asphalt, and covered with unslippery material are the possible alternatives. It is unclear up to this point how various road conditions could possibly affect accident severity, as it may be that a slippery surface (as compared to a dry surface) increases the severity of traffic accidents as steering becomes harder; however, a slippery surface may motivate drivers to drive more carefully, consequently reducing accident severity.

It appears that compressed snow and wet snow are the only variables significant at 1% level of significance for Latvia overall (the base case is dry road surface condition). A similar situation applies to Riga as well, except that also significant is the coefficient on the variable indicating a surface covered with ice[4]. The signs of coefficients, however, differ. In Latvia, the coefficient on wet snow is positive, while in Riga it is *vice-versa*.

After accounting for surface condition variables, surface type variables have neither changed considerably, nor have they lost or gained significance, indicating a weak correlation and no omitted variable bias from this perspective.

6.3.4 Type of Road

In addition to the above tested factors, it was decided to include binary variables indicating type of road. Though only applicable to the dataset for Latvia overall (in Riga roads are not classified according to their importance), the effects from road type may be helpful in assessing whether drivers tend to be involved in severe accidents on main roads, where driving speeds are higher, or on lower level roads (first category, second category, or other roads less important than second category roads) with worse steerability.

[4] When estimating road condition effects in Riga, the variable *road_cond_damaged* was dropped due to too little variation in cases.

As compared to main roads, the coefficients on first category roads, second category roads, and even lower category roads, are all significant at 1% level and positive. What is more, the coefficient on second category roads is higher in absolute values than the one on first category roads.

The only variable substantially changed from previous specification appears to be surface type gravel pavement, which was overestimated in early specifications and was subject to omitted variable bias. The bias was due to a high correlation between gravel pavement and second category roads (second category roads are very likely to be covered by a gravel pavement surface).

As there is no logical explanation why alcohol should be related to any type of road condition or architecture and, consequently, subject to any bias, the coefficient on *Alcohol* is changed only marginally after controlling for these variables.

6.4 Collision Type

Still, before concluding on the results, severity may be tested against collision type as well. The available options in datasets are the following: standard two-car collision, collision with rollover, collision with parked auto, collision with pedestrian, collision with bike, driving in ditch, and collision with other obstacle. Before controlling for collision types in empirical analysis, it must be noted that it is strongly believed that the most severe collisions are collisions with bikes and with pedestrians, which in a sense is logical – cyclists and pedestrians are more likely to suffer from a collision with a vehicle as they are involved in physical contact with the particular vehicle, while the driver is not involved in physical contact with the pedestrian or cyclist. For other types of collisions the effect is somewhat uncertain.

Once included in regressions, the results are similar in Riga as compared to other regions of Latvia. The estimated coefficients comply with the initial prediction and are both highly significant and large in absolute values. What is more, the effects of car accidents with rollover and driving into a ditch appear to be highly significant and positive as well, indicating increased severity. The only factor affecting severity negatively is collision with a parked vehicle.

In both regression specifications, after accounting for collision types, the coefficient on *alcohol* is significantly decreased, but still significant at 1% level of significance and positive. The findings suggest that in earlier specifications *Alcohol* was biased upwards due to a correlation with collision type binary variables. And that seems quite reasonable. If we consider collision type driving into a ditch, it is likely for a drink-driver to drive into a ditch or roll over a car, thus the positive correlation between *Alcohol* and *Collision_rollover,* and between *Alcohol* and *collision_ditch* is noticed. Furthermore, according to the regression coefficients, both *collision_rollover* and *collision_ditch* - are positive determinants of car accident severity. Consequently, *collision_rollover* and *collision_ditch* are omitted variables when determining the effect of *Alcohol* on *Severity*.

6.5 Status of Involved Person

The initial impression is that the status of a traffic participant highly impacts the severity of a traffic accident. Moreover, it is believed that pedestrians possess the highest risk of getting into the most severe accidents. Traffic participants such as passengers are considered to be involved in less severe traffic accidents than drivers of bikes or mopeds; however, still highly injurious.

In Riga as well as in other territories, driver is a basis for status of participant variable. Other drivers' status is included as dummy variables. When regressed, the analysis indicates that the variables on all other types of participants as compared to driver are almost two times greater in absolute value than the value on *Alcohol*, positive and statistically significant at 1% level.

6.6 Type of Vehicle

Before analyzing various types of vehicles, an attempt has been made to put down initial opinion on how different vehicles can be associated with the severity of traffic accidents. Several previous studies have found that heavier vehicles are associated with higher probabilities of severe traffic accidents (Xiaodong, Kockelman, 2005).

Car is used as the basis after including dummy variables on all other vehicle types. If the vehicle is a motorcycle, the probability of getting into a severe traffic accident is highly significant at 1% level in Riga as well as in other territory, while coefficients on heavy vehicles are negative. However, the coefficients on *Truck* and *Bus* are significant only at 5% level. The variables *Tractor* and *Tram* are insignificant. It must be noted that variables such as *Tram* and *Trolley* are not included in the database for other regions of Latvia due to the small variation of their results. Here, the *Truck* and *Tractor* variables reduce the severity of car accidents and are statistically significant at 1% level. However, *Bus* is identified as an insignificant item elsewhere in Latvia.

6.7 Time and Special Events

In addition to previously analyzed variables, another may be whether the time of an accident happening has some effect on severity. Intuitive prediction is that late night hours are associated with slower reaction times, less careful driving, and consequent more severe injuries. This prediction is also supported by Doherty's (1998) study indicating the increase of traffic accident rates on weekdays and at nighttime. The following sections cover some of these time-related aspects.

6.7.1 Celebrations

It is commonly discussed in Latvian society that the severity of car accidents increases extremely during public holidays, especially, during Ligo night. In order to test whether it is Ligo night as such that significantly contributes to the severity of car accidents, this was included in the final specification of the regression as well. In addition, binary variables indicating *Easter*, *New Year*, *Christmas*, and the *First school day* were included as well.

Once the coefficients on public holidays are estimated, it appears that none of them appear to be significant even at 10% level of significance in Riga. The effect of *Ligo* on *Severity* is negative if anything. Though public holidays tend to correlate with drink-driving, the variables, after accounting for all the other effects on the car accident severity, are not significant determinants of *Severity*. Consequently, there is also no omitted variable bias in early regression specification coming from public holidays.

In Latvia overall, however, the situation is more certain. *Ligo* becomes significant at 10% level of significance and positive. The difference may be explained by the fact that people tend to celebrate *Ligo* out of urban places. And, consequently, most severe driving accidents take place out of Riga. Significant is positive and significant at 5% level for *Christmas* as well.

6.7.2 Night Driving

To finalize the regression, binary variables indicating Friday nights and Saturday nights are added. However, the variables do not contain any valuable information on explaining car accident severity. Both are insignificant at 10% in Riga's dataset, and only *Friday_night* appears to be slightly positive and significant when tested in Latvia's dataset.

7 Findings

7.1 Findings and Possible Drawbacks

The results of the analysis conducted on the severity of car accidents in Latvia suggest that *Alcohol* appears to be a significant determinant of severity – a finding that is supported by many previous studies and is commonly perceived as a general truth. It is further estimated that on average drink-driving is associated with an eight times greater probability of incurring severe injuries and a 17 times greater probability of incurring lethal injuries (for more elaborated discussion see section 7.2). The estimate on *Alcohol* may still be subject to omitted variable bias, as there may also be other aspects that may correlate with alcohol and that can also be a significant determinant of a car accident. As an example, personal intellect could be mentioned, which is not so easy to estimate; IQ, however, could serve as a useful estimate. IQ could perhaps be negatively correlated with *Alcohol* and could also be a determinant of the severity of car accidents – a person with a higher IQ is more likely to drive safely, consequently, less severe car accidents are expected. By applying similar reasoning, net income, driving experience, and other similar variables could also be used to determine the pure effect on severity from alcohol consumption. At this point, however, the regression covering the analyzed characteristics is considered to be the best alternative available.

More uncertain discussion has been made on the gender effect as a determinant of the severity of car accidents. Also after controlling for other available factors, the coefficient on *female* remains highly significant and positive in both Latvia's and Riga's datasets. However, while this study explores the total *Female* involvement in car accidents, without regard to who caused the accident, other contradictory studies have attempted to study accidents caused by females. Still, if looking also purely at accidents caused by drivers, the coefficient on *Female* remains positive and significant in Latvia at a 2% level of significance and also in Riga at a 1% level of significance, indicating strong evidence behind the revealed statement that females do indeed contribute to car accident severity. Some experts associate this issue with the fact that women have slower reactions and do not possess wide knowledge of how to act in critical situations. The effect in an economic sense is not as serious as drink-driving – females are roughly two times more likely to suffer lethal injuries in car accidents and a slightly less than two times greater probability to suffer severe injuries.

Furthermore, age as a negative and significant factor of determining car accident severity is noticed by many previous researches. Still, not all of them have tested for quadratic specifications. While this study also found linear and negative relation, quadratic specification is proved to be better in explanatory power. Due to negative value on *Age* and positive value on *Age2*, it is concluded that while younger drivers are indeed involved in the most severe car accidents, for substantially older drivers the positive effect of *Age2* offsets the negative one of *Age* and above middle-age drivers are again associated with more severe accidents than middle-aged drivers. The lowest likelihood of severe and lethal accidents is for drivers around x age. The coefficient values on *age* and *age2*, however, are somewhat contradictory to what was found by Kockelman, who concluded that the effect of driver age appears to be significant only in one-vehicle crashes and not significant when accounting for all crashes (2001).

When analyzing the guilt of a driver, the results imply that actually more aggressive or less skilled drivers, who are guilty of causing accidents, are less likely to suffer from severe injuries than those involved by chance. This issue has not been studied by any prior works and is also quite surprising as the initial prediction was that aggressive drivers are the ones involved in the most severe accidents. The estimate, however, has a drawback in that not always is it possible to determine who is to be blamed for causing an accident. Also not always is aggressive driving the reason for causing an accident.

While during the analysis of empirical data most of the weather conditions as compared to dry conditions were found to be negative determinants of severity of traffic accidents, the variables lost their significance after controlling for other factors. Only fog remains a significant determinant in Latvia’s dataset and is positive, but rather small in absolute values. Fog raises the severity of accidents expectedly due to the fact that people do not realize the danger of fog and do not reduce their speed although the visibility of the road is affected.

Road conditions have also lost significance in determining the severity of traffic accidents. Still, steep turns in Latvia are found to be positive and significant determinants, while in Riga they are not. As to differences in datasets for Riga and for Latvia, the reason is clear – it is more likely that steep turns and slopes will cause severe accidents in Latvia as compared to Riga, because in Riga there are very few places where one can accelerate speed to a high level and steer through a turn. It is more likely that turns will be steered at lower speeds due to considerable speed limits and traffic density. The same reasoning applies to slope of the road.

From surface types it is found that in Latvia, interestingly enough, a surface covered with fresh asphalt is associated with more severe accidents. This is intuitively due to the fact that drivers are willing to accelerate to a high speed on a smooth surface, but they do not realize that fresh asphalt is also very slippery.

One finding that is exclusively valid only in other regions of Latvia is that roads of less importance (first and second category roads) are less safe as compared to main roads. This may be due to drivers' expectations that the police is less likely to control traffic on less important roads, and, consequently, drivers are more likely to drive aggressively.

The most important variables, when quantified, appear to be the participant's status-related aspects. It is hard to tell the underlying reason behind this, but one possibility is that there is considerable bias in datasets. It seems likely that passengers in a vehicle which is involved in a car accident are not likely to be registered by policemen, unless they have injuries. If this holds true, then there is a clear bias and the coefficients are, thus, overestimated. The issue can be clarified by studying in detail the protocol preparation process by policemen.

When different types of vehicles are analyzed, it appears that the findings by Xiaodong and Kockelman differ from those found in this study (2005). It is noticed in this study that trucks and buses are safer and do not worsen the severity of traffic accidents. Exactly the opposite is the case with motorcycles. The effect of a motorcycle as compared to an ordinary vehicle in explaining traffic accident severity appears to be positive and very large in absolute values. Motorcyclists are on average associated with a 33 times greater probability of suffering severe injuries and more than a hundred times greater probability of suffering lethal injuries.

7.2 Quantifying Effects

The following section attempts to quantify pure gender, drink-driving, surface type, age and other determinants' effects on the values of perceived probabilities of incurring no injuries, slight injuries, severe injuries, and fatal injuries. As a base case is considered an average age (38 years) male driver, who is driving in Latvia on standard road, surface and weather conditions.

Determinant	Probability of no injuries	Probability of slight injuries	Probability of severe injuries	Probability of lethal injuries
Base case	96,197%	3,559%	0,232%	0,013%
Additional factors:				

Alcohol	85,188%	12,957%	1,682%	0,173%
Female	95,388%	4,290%	0,304%	0,018%
Fresh asphalt	94,357%	5,210%	0,406%	0,027%
Turn	94,247%	5,308%	0,417%	0,028%
Age 18 years	96,079%	3,666%	0,242%	0,014%
Age 50 years	95,950%	3,782%	0,253%	0,015%
Motorcyclist	61,013%	29,642%	7,802%	1,543%
Fog	93,494%	5,973%	0,498%	0,035%

The first determinant to be analyzed is *alcohol*. Due to drink-driving the probability of lethal injuries increases from 0.013% to 0.173%, which is approximately thirteen times. The probability of severe injuries increases eight times, the probability of slight injuries grows almost four times; consequently, the probability of no injuries slightly decreases.

If the driver is female, the probability of having no injuries slightly decreases; thus, the probability of getting slight, severe, and lethal injuries rises by 30 %. This confirms the previously mentioned finding that women tend to be involved in traffic accidents associated with slightly greater severity.

Furthermore, a surface covered with fresh asphalt indicates similar patterns to the *female* variable. The probabilities of slight and severe injuries increase by 60% but the probability of lethal injuries doubles.

Furthermore, the effect of *turn* on *severity* is in absolute values similar to the results of *fresh asphalt*. However, all three types of injury levels (slight, severe, and lethal injuries) indicate around 10% higher increases than was the case under the variable *fresh asphalt*.

If a person is younger, namely 18 instead of 38 years, there is a 3% increase in slight injury probability, 4% in severe injury probability, and 7.6% in lethal injury probability. However, if the person is 50 years old, the probabilities change to slightly greater than when the person is 18 years old, around 6 to 15%. Both younger and older drivers are associated with higher probabilities of severe injuries, as illustrated by the quadratic specification used for controlling for age effects.

The next variable is the motorcyclist, meaning the person is a motorbike driver. This variable has the greatest influence on the change of probabilities for all types of injuries. For example, the probability of slight injury increases 8.3 times, the probability of severe injury increases 33.6 times, and finally the probability of lethal injury increases from 0. 013% to 1, 543%, around 119 times.

If the weather is foggy, it also increases the probability of injury – the probability of slight injury increases by 68%, the probability of severe injury double, and the probability of lethal injury almost triples.

8 Conclusions

This is the very first research in the field of car accident severity in Latvia. The approach taken in the research is focused on alcohol consumption and its interdependence with other factors of car accident severity. Although a similar approach is not taken by any other research and this is a new contribution to the previous literature, it is believed that this way of analysis helps to understand better the correlations among various factors that determine traffic accident severity. In addition, the work presents not only the findings of significant factors that determine car accident severity, but also deals with quantification of the pure effects of variables. Similar quantification of the probabilities of traffic accident severity is not provided in any of the previous research and, consequently, it may be considered as an innovation. The quantification added gives a better illustration on what is being measured and what is the relative importance of each of the significant factors determined.

A variety of different factors can play a role when car accidents occur. If looking specifically at the severity of traffic accidents, this work suggests that the type of collision, drink-driving, gender, vehicle type, weather conditions, light conditions, and road architecture are the major determinants. From the collision types, rollovers are particularly serious in contributing to the most severe traffic accidents. Next, females tend to drive less safely as compared to males, and motorcycles are the types of vehicles with the lowest safety, increasing the probability of lethal accidents by more than a hundred times. These findings in general comply with previous research in this area. This work, however, adds to the existing literature by noticing that drivers that are to blame for causing accidents are actually less likely to suffer from severe injuries as compared to those involved by chance. Also passengers are more endangered in car accidents than drivers themselves. The findings also support the view that steep turns are dangerous only in places with higher speed limits, as the effect of turns in Riga is insignificant, but in other regions of Latvia it does have a significant importance in determining accident severity. In contrast, the effects of Friday and Saturday nights, and special events, such as Ligo, New Year, and Christmas are rather negligible, after controlling for all driver characteristics, weather, road condition and architecture, vehicle type, and collision type. This in a way is very reasonable, as there is no reason why specific events as such should contribute to accident severity. Increases in traffic accidents during Ligo and Christmas are due to increased alcohol consumption and other driver character-related aspects, not due to some specific dates or period. Still, none of the previous research has looked at these factors.

A more practical model applicable to designing government policy can be derived by designing an additional regression that estimates the effect of the number of road police raids on the probability of preventing drink-driving. Once the estimate is found, it is possible to statistically quantify total government expenditure on road police that yields the highest surplus to society. This, however, is left for further research.

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Appendix 1: Summary Statistics

Summary statistics for Latvia:

Variable	Explanation	No of obs.	Mean	Standard deviation
Dependent Variable: Severity	**0 if a person involved in an accident is not harmed; 1 if a person involved in an accident is slightly injured; 2 if a person involved in an accident is severely injured; 3 if a person involved in an accident is killed**	**39168**	**.165849**	**.5149646**
severity_unharmed	1 if a person involved in an accident is not harmed; 0 otherwise	39168	.88671	.3169403
severity_slight_injuries	1 if a person involved in an accident is slightly injured; 0 otherwise	39168	.07156	.2577671
severity_severe_injuries	1 if a person involved in an accident is severely injured; 0 otherwise	39168	.03086	.1729596
severity_killed	1 if a person involved in an accident is killed; 0 otherwise	39168	.01085	.1036013
Alcohol	1 if a driver has consumed alcohol; 0 otherwise	39168	.04784	.2134413
Age	Age of a driver involved in an accident	37246	37.074	13.43199
Age2	Age of a driver involved in an accident squared	37246	1554.9	1126.982
Female	1 if a driver is female; 0 otherwise	38811	.20344	.4025677
Fault	1 if a driver has caused the accident; 0 otherwise	39168	.49499	.4999813
Condition_dry	1 if weather is dry; 0 otherwise	39168	.27473	.4463887
Condition_sunny	1 if weather is sunny; 0 otherwise	39168	.22298	.4162558
Condition_cloudy	1 if weather is cloudy; 0 otherwise	39168	.38186	.4858506
Condition_fog	1 if weather is fogy; 0 otherwise	39168	.00903	.094639
Condition_rain	1 if weather is rainy; 0 otherwise	39168	.06461	.2458556
Condition_snow	1 if weather is snowy; 0 otherwise	39168	.04429	.2057554
Light_cond_day	1 if daylight; 0 otherwise	39168	.69084	.4621513
Light_cond_twilight	1 if twilight; 0 otherwise	39168	.04687	.2113738
Light_cond_dark	1 if dark night; 0 otherwise	39168	.17006	.3756923
Light_cond_street_light	1 if street lights; 0 otherwise	39168	.02823	.1656523
Slope	1 if at the place of accident is slope of a road; 0 otherwise	37032	.15659	.3634227
Turn	1 if at the place of accident is steep turn; 0 otherwise	36383	.13253	.3390755
Surface_asphalt	1 if surface of road is asphalt; 0 otherwise	39168	.82919	.3763413
Surface_concrete	1 if surface of road is concrete; 0 otherwise	39168	.01072	.1029967
Surface_crash_stone	1 if surface of road is crash stone; 0 otherwise	39168	.00911	.0950355
Surface_gravel_pavement	1 if surface of road is gravel pavement; 0 otherwise	39168	.09512	.2933963
Surface_cobble_stone	1 if surface of road is cobble stone; 0 otherwise	39168	.02489	.1558003
Surface_ground	1 if surface of road is ground; 0 otherwise	39168	.01919	.1372269
Surface_cond_dry	1 if surface condition of road is dry; 0 otherwise	39168	.50372	.4999925
Surface_cond_wet	1 if surface condition of road is wet; 0 otherwise	39168	.26687	.4423327
Surface_cond__compr_snow	1 if surface condition of road is compressed snow; 0 otherwise	39168	.06283	.2426635
Surface_cond_wet_snow	1 if surface condition of road is wet snow; 0 otherwise	39168	.06262	.2422951
Surface_cond_ice	1 if surface condition of road is covered with ice; 0 otherwise	39168	.08815	.2835292
Surface_cond_slippery	1 if surface condition of road is slippery; 0 otherwise	39168	.00012	.0112979
Surface_cond_fresh	1 if surface condition of road is covered with fresh asphalt; 0 otherwise	39168	.00107	.0327289
Surface_cond_unslippery_mat	1 if surface condition of road is covered with unslippery material; 0 otherwise	39168	.00538	.0731995
Road_type_main	1 if road type is main road; 0 otherwise	39168	.15898	.3656638
Road_type_first	1 if road type is first category road; 0 otherwise	39168	.11542	.3195393
Road_type_second	1 if road type is second category road; 0 otherwise	39168	.06135	.2399763
Road_type_other	1 if road type is other; 0 otherwise	39168	.05267	.2233778
Colision_colision	1 if collision type is collision with a car; 0 otherwise	39168	.41454	.4926501
Colision_roll_over	1 if collision type is with rollover; 0 otherwise	39168	.03839	.1921592
Colision_parked_auto	1 if collision type is with a parked auto; 0 otherwise	39168	.25362	.4350912
Colision_obstacle	1 if collision type is with other obstacle; 0 otherwise	39168	.19296	.3946298
Colision_ditch	1 if collision type is driving in ditch; 0 otherwise	39168	.03275	.1780005
Colision_pedestrian	1 if collision type is collision with a pedestrian; 0 otherwise	39168	.04804	.2138734
Colision_bike	1 if collision type is collision with a bike; 0 otherwise	39168	.01383	.116819
Status_driver	1 if status of a person involved is driver; 0 otherwise	39168	.90709	.2903064
Status_passanger	1 if status of a person involved is passenger; 0 otherwise	39168	.04664	.2108805
Status_pedestrian	1 if status of a person involved is pedestrian; 0 otherwise	39168	.02553	.1577335
Status_cyclist	1 if status of a person involved is cyclist; 0 otherwise	39168	.01079	.1033599
Status_moped	1 if status of a person involved is mopedist; 0 otherwise	39168	.00293	.0541066
Truck_type_car	1 if truck type is a car; 0 otherwise	39168	.76679	.4228742
Truck_type_truck	1 if truck type is a truck; 0 otherwise	39168	.10197	.302614
Truck_type_bus	1 if truck type is a bus; 0 otherwise	39168	.02034	.1411903
Truck_type_motocycle	1 if truck type is a motorcycle; 0 otherwise	39168	.00566	.0750727
Truck_type_tractor	1 if truck type is a tractor; 0 otherwise	39168	.01682	.1286169

Truck_type_tram	1 if truck type is a tram; 0 otherwise	39168	.00163	.0403901
Truck_type_troley	1 if truck type is a trolley; 0 otherwise	39168	.00002	.0050528
Eastern	1 if an accident occurs during Eastern; 0 otherwise	39168	.00944	.0967341
New_year	1 if an accident occurs during New Year; 0 otherwise	39168	.00584	.0762402
Christmas	1 if an accident occurs during Christmas; 0 otherwise	39168	.00970	.09802
Ligo	1 if an accident occurs during Ligo; 0 otherwise	39168	.00229	.0478808
First_school_day	1 if an accident occurs during First school day; 0 otherwise	39168	.01034	.1011604
Friday_night	1 if an accident occurs during Friday night (12pm – 5am); 0 otherwise	39168	.01628	.1265855
Saturday_night	1 if an accident occurs during Saturday night (12pm – 5am); 0 otherwise	39168	.02639	.1603211

Summary statistics for Riga:

Variable	**Explanation**	**No of obs.**	**Mean**	**Standard deviation**
Dependent Variable: <u>Severity</u>	**0 if a person involved in an accident is not harmed; 1 if a person involved in an accident is slightly injured; 2 if a person involved in an accident is severely injured; 3 if a person involved in an accident is killed**	**49093**	**.054794**	**.2518814**
severity_unharmed	1 if a person involved in an accident is not harmed; 0 otherwise	49093	.949178	.2196361
severity_slight_injuries	1 if a person involved in an accident is slightly injured; 0 otherwise	49093	.048703	.2152496
severity_severe_injuries	1 if a person involved in an accident is severely injured; 0 otherwise	49093	.000264	.0162708
severity_killed	1 if a person involved in an accident is killed; 0 otherwise	49093	.001853	.0430143
Alcohol	1 if a driver has consumed alcohol; 0 otherwise	49094	.008188	.0901193
Age	Age of a driver involved in an accident	46235	38.1531	12.52629
Age2	Age of a driver involved in an accident squared	46235	1612.56	1080.474
Female	1 if a driver is female; 0 otherwise	48854	.202951	.4022009
Fault	1 if a driver has caused the accident; 0 otherwise	49094	.396219	.489116
Condition_dry	1 if weather is dry; 0 otherwise	49094	.228826	.4200815
Condition_sunny	1 if weather is sunny; 0 otherwise	49094	.223000	.4162631
Condition_cloudy	1 if weather is cloudy; 0 otherwise	49094	.417464	.4931459
Condition_fog	1 if weather is fogy; 0 otherwise	49094	.004134	.064171
Condition_rain	1 if weather is rainy; 0 otherwise	49094	.084002	.2773938
Condition_snow	1 if weather is snowy; 0 otherwise	49094	.032590	.1775642
Light_cond_day	1 if daylight; 0 otherwise	49094	.721473	.4482787
Light_cond_twilight	1 if twilight; 0 otherwise	49094	.034138	.1815869
Light_cond_dark	1 if dark night; 0 otherwise	49094	.116979	.3213993
Light_cond_street_light	1 if street lights; 0 otherwise	49094	.008229	.0903413
Slope	1 if at the place of accident is slope of a road; 0 otherwise	48371	.050009	.2179664
Turn	1 if at the place of accident is steep turn; 0 otherwise	45998	.048241	.2142779
Surface_asphalt	1 if surface of road is asphalt; 0 otherwise	49094	.893530	.3084404
Surface_concrete	1 if surface of road is concrete; 0 otherwise	49094	.008310	.0907838
Surface_crash_stone	1 if surface of road is crash stone; 0 otherwise	49094	.002464	.0495846
Surface_gravel_pavement	1 if surface of road is gravel pavement; 0 otherwise	49094	.002729	.0521734
Surface_cobble_stone	1 if surface of road is cobble stone; 0 otherwise	49094	.067401	.2507183
Surface_ground	1 if surface of road is ground; 0 otherwise	49094	.003788	.0614359
Surface_cond_dry	1 if surface condition of road is dry; 0 otherwise	49094	.510897	.4998863
Surface_cond_wet	1 if surface condition of road is wet; 0 otherwise	49094	.336619	.4725583
Surface_cond__compr_snow	1 if surface condition of road is compressed snow; 0 otherwise	49094	.024687	.155172
Surface_cond_wet_snow	1 if surface condition of road is wet snow; 0 otherwise	49094	.049476	.216863
Surface_cond_ice	1 if surface condition of road is covered with ice; 0 otherwise	49094	.053672	.2253727
Surface_cond_slippery	1 if surface condition of road is slippery; 0 otherwise	49094	.000142	.0119401
Surface_cond_fresh	1 if surface condition of road is covered with fresh asphalt; 0 otherwise	49094	.000244	.0156325
Surface_cond_unslippery_mat	1 if surface condition of road is covered with unslippery material; 0 otherwise	49094	.004216	.0647974
Road_type_main	1 if road type is main road; 0 otherwise	n/a	n/a	n/a
Road_type_first	1 if road type is first category road; 0 otherwise	n/a	n/a	n/a
Road_type_second	1 if road type is second category road; 0 otherwise	n/a	n/a	n/a
Road_type_other	1 if road type is other; 0 otherwise	n/a	n/a	n/a
Colision_colision	1 if collision type is collision with a car; 0 otherwise	49094	.658145	.4743359
Colision_roll_over	1 if collision type is with rollover; 0 otherwise	49094	.002077	.0455343
Colision_parked_auto	1 if collision type is with a parked auto; 0 otherwise	49094	.171772	.3771864
Colision_obstacle	1 if collision type is with other obstacle; 0 otherwise	49094	.119912	.3248629
Colision_ditch	1 if collision type is driving in ditch; 0 otherwise	49094	.001120	.0334525
Colision_pedestrian	1 if collision type is collision with a pedestrian; 0 otherwise	49094	.040004	.1959727
Colision_bike	1 if collision type is collision with a bike; 0 otherwise	49094	.005784	.0758385
Status_driver	1 if status of a person involved is driver; 0 otherwise	49094	.954841	.2076533
Status_passanger	1 if status of a person involved is passenger; 0 otherwise	49094	.016824	.1286162
Status_pedestrian	1 if status of a person involved is pedestrian; 0 otherwise	49094	.021591	.1453461

Status_cyclist	1 if status of a person involved is cyclist; 0 otherwise	49094	.004562	.067394
Status_moped	1 if status of a person involved is mopedist; 0 otherwise	49094	.001262	.035515
Truck_type_car	1 if truck type is a car; 0 otherwise	49094	.774493	.4179195
Truck_type_truck	1 if truck type is a truck; 0 otherwise	49094	.088137	.283497
Truck_type_bus	1 if truck type is a bus; 0 otherwise	49094	.037886	.1909237
Truck_type_motocycle	1 if truck type is a motorcycle; 0 otherwise	49094	.003055	.0551914
Truck_type_tractor	1 if truck type is a tractor; 0 otherwise	49094	.017048	.129455
Truck_type_tram	1 if truck type is a tram; 0 otherwise	49094	.006640	.081218
Truck_type_troley	1 if truck type is a trolley; 0 otherwise	49094	.010795	.1033406
Eastern	1 if an accident occurs during Eastern; 0 otherwise	49094	.004481	.0667923
New_year	1 if an accident occurs during New Year; 0 otherwise	49094	.002933	.0540796
Christmas	1 if an accident occurs during Christmas; 0 otherwise	49094	.006192	.0784473
Ligo	1 if an accident occurs during Ligo; 0 otherwise	49094	.002627	.0511934
First_school_day	1 if an accident occurs during First school day; 0 otherwise	49094	.006640	.081218
Friday_night	1 if an accident occurs during Friday night (12pm – 5am); 0 otherwise	49094	.010103	.100006
Saturday_night	1 if an accident occurs during Saturday night (12pm – 5am); 0 otherwise	49094	.012445	.1108642

Appendix 2: Regressions

Latvia:

	reg1	reg2	reg3	reg4	reg5	reg6	reg7	reg8
severity								
Alcohol	0,747** (0,299)	0,704** (0,029)	0,765** (0,302)	0.87** (0.03)	1.059** (0.03)	1,052** (0.032)	1.021** (0,032)	0.990** (0,0330
Age		-0,008** (0,001)	-0,101** (0,002)	-0.099** (0.002)	-0,10** (0.002)	-0,101** (0,003)	-0,102** (0,0025)	-0,100** (0,002)
Age2			0,001** (0.000)	0.001** (0.000)	0.001** (0,000)	0,001** (0.000)	0,001** (0,000)	0,001** (0,000)
Female				0.516** (0.019)	0,492** (0,019)	0.496** (0,0194)	0,502** (0,019)	0,5085** (0,020)
Fault					-0,409** (0,018)	-0,408** (0,019)	-0,399** (0,018)	-0,406** (0,019)
Condition_dry						base variable	base variable	base variable
Condition_sunny						-0.156** (0,0254)	-0,084** (0,026)	-0,074** (0,027)
Condition_cloudy						-0,033 (0,021)	-0,0335 (0,021)	-0,015 (0,022)
Condition_fog						0,293** (0,082)	0,222** (0.082)	0,212** (0,084)
Condition_rain						-0,066 (0.038)	-0,055 (0.038)	'-0,039 (0,039)
Condition_snow						-0.067 (0,046)	-0.0874 (0,046)	'-0,093* (0,048)
Light_cond_day							base variable	base variable
Light_cond_twilight							0,073 (0,041)	0,108** (0,042)
Light_cond_dark							0.293** (0,022)	0,34** (0,024)
Light_cond_street_light							-0,079 (0,056)	'-0,038 (0,056)
turn								0,385** (0,023)
slope								0,087** (0,024)
_cut1	1,262** (0,009)	-0,657** (0,047)	-0.657** (0.047)	-0.489** (0.047)	-0,679** (0,049)	-0,734** (0.05)	-0,655** (0,051)	'-0,541** (0,053)
_cut2	1,795** (0,012)	-0,082 (0,047)	-0.082 (0.0469)	0.1 (0.4774)	-0,077 (0,0488)	-0,131** (0,05)	-0,0489 (0,051)	0,082 (0,053)
_cut3	2,371** (0,019)	0,518** (0,049)	0,5182** (0,049)	0.704** (0.0499)	0,531** (0,051)	0,479** (0,052)	0,569** (0,053)	0,704** (0,055)
Pseudo R2	0.0207		0.0642	0.0845	0,0987	0,1004	0,1053	0,116

	reg 9	reg 10	reg 11	reg 12	reg 13	reg 14	reg 15	reg 16
severity								
Alcohol	0,977** (0,033)	1,206** (0,079)	0,941** (0,033)	0,844** (0,034)	0,773** (0,035)	0,732** (0,036)	0,731** (0,036)	0,729** (0,036)
Age	'-0,099** (0,002)	'-0,142** (0,003)	'-0,099** (0,002)	'-0,079** (0,002)	'-0,011** (0,003)	'-0,006* (0,003)	'-0,006* (0,003)	'-0,006* (0,003)
Age2	0,001** (0,000)	0,001** (0,000)	0,001** (0,000)	0,001** (0,000)	0,001** (0,000)	0,00** (0,000)	0,00** (0,000)	0,0002** (0,000)
Female	0,514** (0,020)	0,583** (0,023)	0,518** (0,020)	0,484** (0,021)	0,087** (0,025)	0,091** (0,025)	0,089** (0,025)	0,090** (0,025)
Fault	'-0,404** (0,019)	'-0,361** (0,023)	'-0,399** (0,019)	'-0,479** (0,021)	'0,056* (0,025)	'0,060* (0,025)	'0,060* (0,025)	'0,060* (0,025)
Condition_dry	base variable	base variable	base variable	base variable	base variable	base variable	base variable	base variable
Condition_sunny	'-0,067* (0,027)	'-0,125** (0,033)	'-0,068** (0,027)	'-0,087** (0,029)	'-0,076* (0,032)	'-0,087** (0,032)	'-0,089** (0,032)	'-0,086** (0,032)
Condition_cloudy	-0,010 (0,022)	-0,068* (0,029)	-0,014 (0,024)	-0,0069 (0,025)	-0,0044 (0,028)	-0,0037 (0,028)	-0,0036 (0,028)	-0,002 (0,028)
Condition_fog	0,218** (0,085)	'-0,988** (0,368)	0,184* (0,086)	0,253** (0,089)	0,253** (0,097)	0,270** (0,097)	0,260** (0,097)	0,260** (0,097)
Condition_rain	0,032 (0,039)	-0,021 (0,048)	0,060 (0,044)	-0,088 (0,047)	-0,094 (0,052)	-0,098 (0,052)	-0,099* (0,052)	-0,099* (0,052)
Condition_snow	-0,091 (0,048)	-0,045 (0,074)	-0,075 (0,054)	-0,060 (0,056)	-0,029 (0,062)	-0,034 (0,062)	-0,028 (0,062)	-0,022 (0,063)
Light_cond_day	base variable	base variable	base variable	base variable	base variable	base variable	base variable	base variable
Light_cond_twilight	0,105** (0,042)	0,078 (0,060)	0,068 (0,042)	-0,016 (0,045)	0,022 (0,048)	0,023 (0,049)	0,023 (0,049)	0,021 (0,049)
Light_cond_dark	0,335** (0,023)	0,429** (0,029)	0,312** (0,024)	0,225** (0,025)	0,156** (0,028)	0,158** (0,028)	0,158** (0,028)	0,147** (0,029)
Light_cond_street_light	0,011 (0,057)	0,078 (0,141)	0,077 (0,057)	0,054 (0,062)	0,007 (0,070)	-0,0049 (0,071)	-0,003 (0,071)	-0,011 (0,071)
turn	0,362** (0,024)	0,101* (0,049)	0,295** (0,024)	0,245** (0,025)	0,198** (0,027)	0,197** (0,028)	0,198** (0,028)	0,198** (0,028)
slope	0,076** (0,024)	-0,095 (0,054)	0,056* (0,024)	0,051* (0,025)	0,025 (0,027)	0,021 (0,027)	0,021 (0,028)	0,021 (0,028)
Surface_asphalt	base variable	base variable	base variable	base variable	base variable	base variable	base variable	base variable
Surface_concrete	0,609** (0,141)	-0,373* (0,157)	-0,548** (0,140)	-0,435** (0,155)	-0,403* (0,175)	-0,379* (0,176)	-0,383* (0,176)	-0,383* (0,176)
Surface_crash_stone	-0,159 (0,103)	-0,522 (0,344)	-0,266** (0,105)	-0,144 (0,112)	-0,209 (0,124)	-0,191 (0,125)	-0,189 (0,125)	-0,189 (0,125)
Surface_gravel_pavement	0,103** (0,028)	0,168 (0,192)	'-0,078* (0,033)	'-0,052 (0,035)	'-0,094 (0,038)	'-0,085* (0,039)	'-0,087* (0,039)	'-0,086* (0,039)
Surface_cobble_stone	-0,825** (0,107)	-0,207** (0,050)	-0,768** (0,108)	-0,633** (0,118)	-0,602** (0,137)	-0,618** (0,139)	-0,618** (0,139)	-0,616** (0,139)
Surface_ground	0,197** (0,075)	-0,518* (0,270)	-0,288** (0,078)	-0,143 (0,083)	-0,091 (0,087)	-0,115 (0,089)	-0,118 (0,089)	-0,117 (0,089)
Surface_cond_dry		base variable	base variable	base variable	base variable	base variable	base variable	base variable
Surface_cond_wet		-0,059 (0,028)	0,037 (0,025)	0,053* (0,027)	0,046 (0,029)	0,072* (0,03)	0,068* (0,030)	0,07* (0,030)
Surface_cond__compr_snow		-0,434** (0,094)	-0,340** (0,047)	-0,319** (0,0514)	-0,312** (0,057)	-0,275** (0,057)	-0,279** (0,057)	-0,277** (0,057)
Surface_cond_wet_snow		-0,279** (0,063)	0,121** (0,041)	0,063 (0,043)	-0,036 (0,048)	0,011 (0,049)	-0,011 (0,050)	-0,012 (0,050)
Surface_cond_ice		-0,215** (0,055)	-0,023 (0,034)	-0,053 (0,036)	-0,090* (0,040)	-0,050 (0,040)	-0,069 (0,041)	-0,065 (0,041)
Surface_cond_slippery		0,425 (0,609)	0,178 (0,777)	0,742 (0,840)	0,995 (0,770)	1,048 (0,765)	1,049 (0,765)	0,984 (0,777)
Surface_cond_fresh		1,066* (0,503)	0,112 (0,237)	-0,148 (0,247)	0,242 (0,253)	0,191 (0,259)	0,191 (0,259)	0,188 (0,260)
Surface_cond_unslippery_mat		0,035 (0,157)	0,337* (0,157)	-0,428** (0,165)	-0,262 (0,168)	-0,209 (0,169)	-0,211 (0,169)	-0,207 (0,169)
surf_cond_damaged			0,206 (0,199)	0,280 (0,201)	0,234 (0,217)	0,072 (0,230)	0,070 (0,230)	0,074 (0,230)

Road_type_main			base variable	base variable	base variable	base variable	base variable	base variable
Road_type_first			0,407** (0,025)	0,270** (0,027)	0,265** (0,029)	0,270** (0,029)	0,270** (0,029)	0,271** (0,029)
Road_type_second			0,453** (0,037)	0,483** (0,038)	0,279** (0,042)	0,259** (0,042)	0,260** (0,042)	0,260** (0,042)
Road_type_other			0,346** (0,041)	0,266** (0,043)	0,268** (0,046)	0,232** (0,047)	0,234** (0,047)	0,236** (0,047)
Colision_colision				base variable	base variable	base variable	base variable	base variable
Colision_roll_over				0,823** (0,037)	0,502** (0,039)	0,470** (0,040)	0,465** (0,040)	0,459** (0,040)
Colision_parked_auto				-0,942** (0,042)	-0,767** (0,046)	-0,754** (0,047)	-0,754** (0,047)	-0,756** (0,047)
Colision_obstacle				-0,080** (0,027)	-0,151** (0,03)	-0,138** (0,030)	-0,141** (0,030)	-0,143** (0,030)
Colision_ditch				0,455** (0,043)	0,212** (0,047)	0,217** (0,047)	0,221** (0,047)	0,219** (0,047)
Colision_pedestrian				0,956** (0,0327)	-0,382** (0,080)	-0,407** (0,081)	-0,410** (0,081)	-0,409** (0,081)
Colision_bike				0,811** (0,057)	0,184* (0,086)	0,168* (0,087)	0,168* (0,087)	0,168* (0,087)
Status_driver					base variable	base variable	base variable	base variable
Status_passanger					2,25** (0,036)	2,29** (0,036)	2,29** (0,036)	2,28** (0,036)
Status_pedestrian					2,699** (0,084)	2,752** (0,085)	2,757** (0,085)	2,757** (0,085)
Status_cyclist					1,686** (0,081)	1,733** (0,082)	1,730** (0,082)	1,730** (0,082)
Status_moped					1,685** (0,106)	1,740** (0,107)	1,741** (0,107)	1,741** (0,107)
Truck_type_car						base variable	base variable	base variable
Truck_type_truck						-0,250** (0,459)	-0,248** (0,459)	-0,249** (0,460)
Truck_type_bus						0,111 (0,075)	-0,130 (0,078)	-0,147 (0,079)
Truck_type_motocycle						1,497** (0,080)	1,497** (0,080)	1,494** (0,080)
Truck_type_tractor						-0,332** (0,122)	-0,328** (0,122)	-0,328** (0,122)
Eastern							-0,132 (0,110)	-0,142 (0,110)
New_year							0,140 (0,110)	0,999 (0,114)
Christmas							0,227* (0,094)	0,227* (0,094)
Ligo							0,178* (0,091)	0,180* (0,091)
First_school_day							-0,148 (0,248)	-0,142 (0,248)
Friday_night								0,129 (0,074)
Saturday_night								0,054 (0,060)
_cut1	'-0,541** (0,053)	'-0,996** (0,074)	-0,453** (0,054)	-0,175** (0,057)	1,551** (0,067)	1,675** (0,068)	1,674** (0,068)	1,680** (0,068)
_cut2	0,084 (0,053)	0,645** (0,08)	0,185* (0,0540	0,539** (0,0578)	2,569** (0,696)	2,714** (0,070)	2,714** (0,070)	2,720** (0,070)
_cut3	0,707** (0,055)	0,689** (0,081)	0,818** (0,056)	1,227** (0,060)	3,397** (0,073)	3,553** (0,074)	3,553** (0,074)	3,553** (0,074)
Pseudo R2	0.12	0,1734	0,1327	0,2117	0,3809	0,3927	0,3931	0,3932

Riga:

	reg1	reg2	reg3	reg4	reg5	reg6	reg7	reg8
severity								
Alcohol	0,801** (0,070)	0,791** (0,070)	0,882** (0,071)	1,002** (0,071)	1,174** (0,073)	1,156** (0,073)	1,169** (0,074)	1,121** (0,079)
Age		0,0028** (0,000)	-0,138** (0,003)	-0,138** (0,003)	-0,142** (0,003)	-0,142** (0,003)	-0,142** (0,003)	-0,143** (0,003)
Age2			0,001** (0,000)	0,001** (0,000)	0,001** (0,000)	0,001** (0,000)	0,001** (0,000)	0,001** (0,000)
Female				0,584** (0,021)	0,566** (0,022)	0,566** (0,022)	0,571** (0,022)	0,581** (0,023)
Fault					-0,349** (0,0228)	-0,349** (0,0221)	-0,361** (0,023)	-0,359** (0,023)
Condition_dry						base variable	base variable	base variable
Condition_sunny						-0,231** (0,030)	-0,156** (0,031)	-0,108** (0,033)
Condition_cloudy						-0,130** (0,025)	-0,142** (0,025)	-0,098** (0,027)
Condition_fog						-0,998** (0,352)	-1,087** (0,367)	-1,032** (0,370)
Condition_rain						-0,119** (0,041)	-0,115** (0,041)	-0,047** (0,042)
Condition_snow						-0,234** (0,066)	-0,297** (0,067)	-0,235** (0,068)
Light_cond_day							base variable	base variable
Light_cond_twilight							0,026 (0,059)	0,070 (0,060)
Light_cond_dark							0,415** (0,028)	0,408** (0,029)
Light_cond_street_light							0,044 (0,116)	0,040 (0,141)
turn								0,110* (0,049)
slope								-0,096 (0,054)
_cut1	1,648** (0,009)	1,737** (0,028)	-0,930** (0,065)	-0,758** (0,067)	-0,949** (0,068)	-1,069** (0,071)	-0,98** (0,071)	-0,965** (0,074)
_cut2	2,881** (0,031)	3,03** (0,043)	0,559** (0,070)	0,796** (0,072)	0,632** (0,073)	0,519** (0,075)	0,623** (0,076)	0,670** (0,080)
_cut3	2,924** (0,033)	3,070** (0,045)	0,601** (0,071)	0,838** (0,073)	0,674** (0,074)	0,560** (0,076)	0,665** (0,077)	0,714** (0,081)
Pseudo R2	0,0055	0,0064	0,108	0,1423	0,1546	0,1582	0,1683	0,1688

	reg9	reg10	reg11	reg12	reg13	reg14	reg15
severity							
Alcohol	1,121** (0,079)	1,206** (0,079)	1,101** (0,086)	0,928** (0,092)	0,926** (0,093)	0,924** (0,093)	0,916** (0,093)
Age	-0,143** (0,003)	'-0,142** (0,003)	'-0,119** (0,003)	'-0,039** (0,005)	'-0,036** (0,005)	'-0,036** (0,005)	'-0,036** (0,005)
Age2	0,001** (0,000)	0,001** (0,000)	0,001** (0,000)	0,000** (0,000)	0,000** (0,000)	0,000** (0,000)	0,0006** (0,000)
Female	0,584** (0,023)	0,583** (0,023)	0,583** (0,025)	0,202** (0,033)	0,221** (0,034)	0,223** (0,034)	0,224** (0,034)
Fault	-0,361** (0,023)	'-0,361** (0,023)	'-0,350** (0,026)	'-0,074* (0,031)	'-0,056 (0,031)	'-0,055 (0,031)	'-0,055 (0,031)
Condition_dry	base variable	base variable	base variable	base variable	base variable	base variable	base variable
Condition_sunny	-0,108** (0,033)	'-0,125** (0,033)	'-0,082* (0,036)	'0,008 (0,044)	'0,009 (0,045)	'0,008 (0,045)	'0,011 (0,045)
Condition_cloudy	-0,096** (0,027)	-0,068* (0,029)	-0,046 (0,032)	0,003 (0,039)	0,007 (0,040)	0,007 (0,040)	0,008 (0,040)
Condition_fog	-1,040** (0,371)	-0,988** (0,368)	-1,066* (0,465)	-1,004 (0,684)	-1,000 (0,698)	-1,116 (0,767)	-1,111 (0,767)
Condition_rain	-0,046 (0,042)	-0,021 (0,048)	0,002 (0,053)	0,024 (0,065)	0,022 (0,066)	0,024 (0,066)	0,024 (0,066)
Condition_snow	-0,228** (0,068)	-0,045 (0,074)	-0,073 (0,083)	-0,011 (0,099)	-0,004 (0,100)	-0,001 (0,100)	0,002 (0,100)
Light_cond_day	base variable	base variable	base variable	base variable	base variable	base variable	base variable
Light_cond_twilight	0,071 (0,060)	0,078 (0,060)	0,065 (0,067)	0,119 (0,080)	0,120 (0,081)	0,122 (0,081)	0,120 (0,081)
Light_cond_dark	0,406** (0,029)	0,429** (0,029)	0,379** (0,032)	0,297** (0,040)	0,297** (0,040)	0,293** (0,040)	0,282** (0,041)
Light_cond_street_light	0,038 (0,141)	0,078 (0,141)	0,166 (0,152)	0,108 (0,191)	0,125 (0,192)	0,119 (0,193)	0,109 (0,193)
turn	0,103* (0,049)	0,101* (0,049)	0,169** (0,521)	0,134* (0,061)	0,127* (0,062)	0,126* (0,062)	0,123* (0,063)
slope	-0,091 (0,054)	'-0,095 (0,054)	'-0,080 (0,058)	'-0,075 (0,071)	'-0,072 (0,072)	'-0,069 (0,072)	'-0,068 (0,072)
Surface_asphalt	base variable	base variable	base variable	base variable	base variable	base variable	base variable
Surface_concrete	-0,358* (0,156)	-0,373** (0,157)	-0,492** (0,184)	-0,520 (0,282)	-0,521 (0,285)	-0,521 (0,285)	-0,518 (0,285)
Surface_crash_stone	-0,537 (0,346)	-0,522 (0,344)	-0,544 (0,396)	-0,453 (0,547)	-0,461 (0,557)	-0,460 (0,558)	-0,461 (0,557)
Surface_gravel_pavement	'0,129 (0,190)	'0,168 (0,192)	'-0,203 (0,241)	'-0,165 (0,334)	'-0,154 (0,335)	'-0,154 (0,335)	'-0,146 (0,334)
Surface_cobble_stone	-0,202** (0,050)	-0,207** (0,050)	-0,225** (0,056)	-0,259** (0,072)	-0,264** (0,073)	-0,264** (0,073)	-0,268** (0,074)
Surface_ground	-0,543* (0,266)	-0,517* (0,270)	-0,570* (0,304)	-0,339 (0,374)	-0,450 (0,380)	-0,453 (0,380)	-0,447 (0,379)
Surface_cond_dry		base variable	base variable	base variable	base variable	base variable	base variable
Surface_cond_wet		-0,059* (0,028)	-0,040 (0,031)	-0,025 (0,038)	0,005 (0,038)	0,0045 (0,039)	0,006 (0,039)
Surface_cond__compr_snow		-0,434** (0,094)	-0,327** (0,107)	-0,112 (0,121)	-0,076 (0,122)	-0,075 (0,123)	-0,072 (0,123)
Surface_cond_wet_snow		-0,279** (0,062)	-0,248** (0,070)	-0,240** (0,088)	-0,195** (0,089)	-0,194** (0,089)	-0,188* (0,089)
Surface_cond_ice		-0,215** (0,055)	-0,141* (0,061)	-0,085* (0,073)	-0,036* (0,074)	-0,042* (0,074)	-0,036 (0,074)
Surface_cond_slippery		0,425 (0,609)	-0,065 (0,792)	0,486 (0,708)	0,686 (0,675)	0,688 (0,675)	0,696 (0,675)
Surface_cond_fresh		1,065* (0,503)	1,21* (0,507)	1,059 (0,572)	1,078 (0,572)	1,086 (0,573)	1,090 (0,574)
Surface_cond_unslippery_mat		0,035 (0,157)	0,025 (0,172)	0,272 (0,182)	0,321 (0,183)	0,324 (0,183)	0,325 (0,183)

Colision_colision			base variable	base variable	base variable	base variable	base variable
Colision_roll_over			1,884** (0,130)	1,372** (0,147)	1,018** (0,158)	1,014** (0,158)	1,011** (0,158)
Colision_parked_auto			-0,667** (0,062)	-0,640** (0,0747)	-0,637** (0,076)	-0,637** (0,076)	-0,640** (0,076)
Colision_obstacle			0,253** (0,356)	-0,113* (0,049)	-0,073 (0,050)	-0,072 (0,050)	-0,076 (0,050)
Colision_ditch			1,087** (0,209)	0,817** (0,243)	0,826** (0,244)	0,830** (0,244)	0,810** (0,245)
Colision_pedestrian			1,599** (0,035)	-0,278* (0,113)	-0,318** (0,116)	-0,315** (0,116)	-0,311** (0,116)
Colision_bike			1,536** (0,086)	0,632** (0,139)	0,653** (0,141)	0,655** (0,141)	0,656** (0,141)
Status_driver				base variable	base variable	base variable	base variable
Status_passanger				3,160** (0,064)	3,223** (0,066)	3,220** (0,066)	3,220** (0,066)
Status_pedestrian				3,734** (0,121)	3,806** (0,125)	3,804** (0,125)	3,799** (0,125)
Status_cyclist				1,954** (0,131)	1,982** (0,132)	1,982** (0,132)	1,984** (0,132)
Status_moped				2,171** (0,184)	2,239** (0,185)	2,251** (0,185)	2,251** (0,186)
Truck_type_car					base variable	base variable	base variable
Truck_type_truck					-0,164* (0,069)	-0,162* (0,069)	-0,161* (0,069)
Truck_type_bus					-0,200* (0,091)	-0,199* (0,091)	-0,197* (0,091)
Truck_type_motocycle					1,938** (0,115)	1,938** (0,115)	1,934** (0,115)
Truck_type_tractor					-0,270 (0,179)	-0,266 (0,179)	-0,264 (0,178)
Truck_type_tram					-0,131 (0,182)	-0,131 (0,181)	-0,130 (0,182)
Truck_type_troley					-0,325* (0,152)	-0,318* (0,152)	-0,316* (0,152)
Eastern						0,254 (0,183)	0,246 (0,184)
New_year						0,323 (0,216)	0,330 (0,215)
Christmas						-0,070 (0,203)	-0,080 (0,203)
Ligo						-0,148 (0,198)	-0,144 (0,197)
First_school_day						-0,658 (0,492)	-0,656 (0,492)
Friday_night							0,102 (0,133)
Saturday_night							0,153 (0,115)
_cut1	-0,974** (0,074)	-0,996** (0,074)	-0,357** (0,083)	1,445** (0,109)	1,565** (0,111)	1,563** (0,111)	1,570** (0,112)
_cut2	0,663** (0,080)	0,645** (0,080)	0,173* (0,09)	4,578** (0,122)	4,763** (0,126)	4,764** (0,126)	4,770** (0,126)
_cut3	0,707** (0,081)	0,689** (0,081)	1,787** (0,093)	4,627** (0,123)	4,814** (0,126)	4,815** (0,126)	4,822** (0,127)
Pseudo R2	0,1705	0,1734	0,3164	0,577	0,5916	0,592	0,5921