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FACULTY OF SOCIAL SCIENCES
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Daylight Saving Time and Traffic Safety: Evidence from the Czech Republic.

Master's thesis

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Declaration of Authorship

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Prague, February 26, 2021

Olga Mironova

Abstract

In this study we analyze the effect of DST on the traffic accidents in the short run period and the effect of darkness in the long run period. Applying Regression Discontinuity Design and Negative Binomial Regression Model we estimate that the impact of DST increases by 7% the number of total accidents in the short run period and the effect of darkness significantly increases all types of accidents in the long run period in the Czech Republic. The change to the all-year DST regime could decrease the number of all types of accidents.

Keywords	summer time, daylight saving time, traffic accidents, traffic safety
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Abstrakt

V této prace analyzujeme vliv střídání zimního a letního času, DST, na dopravní nehody v krátkém období a efekt tmy v dlouhodobém období. Použitím modelu regresní diskontinuity a negativního binomického regresního modelu odhadujeme, že dopad DST zvyšuje o 7 % počet celkových nehod v krátkodobém období a efekt temnoty významně zvyšuje všechny typy nehod v dlouhodobém období v České republice. Výsledek práce ukazuje, že letní čas během celého roku by mohl snížit počet všech typů nehod.

Klíčová slova	letní čas, dopravní nehody, dopravní bezpečnost
Název práce	Letní čas a Dopravní bezpečnost: Evidence z České Republiky.
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Acronyms

CET Central European Time

DST Daylight Saving Time

GMT Greenwich Mean Time

MLE Maximum Likelihood Estimator

MSE Mean Squared Error

NOAA National Oceanic and Atmospheric Administration

PRM Poisson Regression Model

RD Regression Discontinuity

RDD Regression Discontinuity Design

ST Standard Time

UTC Coordinated Universal Time

ADF Augmented Dickeyâ€“Fuller test

PP Phillips-Perron test

GLM Gineralized Linear Model

AIC Akaike Information Criterion

IRR Incidence rate ratio

Master’s Thesis Proposal

Author	Bc. Olga Mironova
Supervisor	PhDr. Zuzana Havránková, Ph.D.
Proposed topic	Daylight Saving Time and Traffic Safety: Evidence from the Czech Republic.

Motivation Many countries around the world use the Daily Saving Time (DST) in order to save energy and to improve the matching of daylight hours with the people’s activities. However, the recent research indicates that DST does not save energy and may even increase energy use (Kotchen and Grant, 2011). Since energy savings are no longer considered a sufficient rationale for the DST policy, the question is the validity of the policy. Researchers turning their attention towards its more imminent effects, especially the traffic incidence caused by the impact of DST. Recent literature review (Carey and Sarma, 2017) summarizes the existent evidence and points out to the possibility of positive outcomes of the current policy.

Transition into and out of DST changes time quickly, but short-term sleep deprivation or disruptions in the circadian rhythm persist up to five days after each time shift (Coren, 1996b), so the DST could increase the number of traffic accidents in the short run. The evidences on the short run impact of the shift to DST are contradictory. Several U.S. and Canada studies reported a significant increase of traffic incidents immediately after the shift to DST (Coren, 1996b, Varughese J, Allen R.P., 2001), other studies from Sweden (Lambe and Cummings, 2000) and Finland (Lahti et al, 2010) conducted that the shift to DST did not have measurable important effects on automobile crashes. Due to the sleep deprivation, the DST may increase the crash incidence in the short run in the morning in the first week, at the same time some studies conclude that DST reduces traffic crashes in the evening (Whittaker, 1996), thus the overall effect is ambivalent. The impact of DST on crashes is probably positive in the long run because the sleep deprivation is no longer valid argument and drivers have better visibility (Huang and Levinson, 2010). Some researchers report the significant crash saving effect (Fergusson et al., 1995, Sood and Ghosh, 2007).

The Czech Republic started to use summer time yearly since 1979 according to the next rule: the summer time was set in the last Sunday of March and ended in the last Sunday of September. Since 1996 according to the Directive 94/21/EC of the European Parliament, the summer time ends in the last Sunday of October. The recent debates around the DST prompted on the question whether the current policy in Europe still provides presumed benefits, some countries even suggest its abolishment. There are no studies about the DST and its impact on the traffic incidents in the Czech Republic therefore I want to find out what are the real effects here.

Hypotheses

Hypothesis #1: DST has no significant effect on traffic accidents in the short run.

Hypothesis #2: DST reduces traffic accidents and declines fatal crashes in the long run.

Hypothesis #3: DST reduces fatal pedestrian crashes in the short run during the morning and the dusk.

Methodology

1. I will study the number of traffic accidents the week before and the week after the DST shift from 2009 till 2017. Data will be compared from year to year. The number of traffic crashes will be analyzed using a Poisson regression model or negative binomial regression model because the count values are usually small. The proportion of personal injuries in all crashes will be modeled with logistic regression (Lahti et al, 2010, Coate and Markowitz, 2004).

2. I will examine weekly traffic accidents for 8 weeks before and 8 weeks after the shift to summer time and 8 weeks before and 8 weeks after the shift to fall time, so, I will get 16 weeks in DST and 16 weeks in standard time. After I will use linear regression.

3. I will study the number of traffic accidents with pedestrians the week before the shift to DST and the week after in the different time of day in 2016 and 2017. The number of traffic crashes will be analyzed using a Poisson regression model or negative binomial regression model.

Expected Contribution It will be the first study analyzing the impact of the DST to the Czech traffic accidents. I expect to obtain the effects of the transition into and out of DST in short-run and long-run period. These results can show if it is efficient to shift DST in terms of traffic accidents. Recent research indicates that DST does not save energy and may be DST has no effect on traffic accidents in the long-run and increase automobile crashes in the short-run due to disruptions in the circadian rhythm.

Outline

1. Motivation: according to many studies the evidence of the shift to DST on the traffic accidents is different. I will try to figure out the impact of the transition into and out of DST in Czech Republic.
2. Literature review: I will describe studies related to topics.
3. Data: I will explain how I will collect the data.
4. Methods: I will explain methodology.
5. Results: I will discuss my results.
6. Conclusion: I will summarize my results and their implications for the future.

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Author Supervisor

Chapter 1

Introduction

Many countries around the world use summertime arrangements to save energy and to improve the leisure activities by having longer daylight hours in the evening. However, the recent research indicates that Daylight Saving Time (DST) does not save energy (Kellogg & Wolff (2008)) and even increase energy use (Kotchen & Grant (2011)).

Kellogg & Wolff (2008) examined actual data from a natural experiment that took place in Australia in 2000. Typically, three of Australia's six states start DST in October but two of them began DST two months earlier than usual to accommodate the Sydney Olympics. Based on the difference-in-difference the framework estimated that the extension of DST in Australia did not reduce the overall electricity consumption but it did cause a substantial intraday shift in demand consistent with activity patterns.

Since energy savings are no longer considered a sufficient rationale for the DST policy, researches turning their attention towards its more imminent effects like road safety, crime, tourism, health and carbon emission.

There are two main categories of daylight saving time effects: domestic and trans-boundary. Summertime arrangements have positive impact on the tourism and leisure sector (Hillman (2008); Wolff & Makino (2012)). The effect on the agricultural sector is considered to be less than it was historically because the need for daylight was reduced due to modern agricultural techniques. There is no definite evidence of DST impact on cross-border business, trade and investment but EU governments believe that asynchronous arrangements would have a negative impact. The trans-boundary effects of DST are expected to be felt in the transport sector, especially in the air and rail services. It is also may be felt in the business and finance sectors for the firms which work across borders but it is difficult to detect. The costs of a shift in DST are significant for the software and IT-dependent economic sectors.[1]

The general concept of DST was suggested by Benjamin Franklin (1784) in a satirical essay. Europe had the first experience of daylight saving time during the First World War, when Germany, Austria-Hungary, the UK, France introduced summertime to reduce the fuel needed to produce electric power and to allow better of the daylight hours (Reincke *et al.* (1999)). After the end of the war, DST was abandoned by many countries. The DST got a wide extension during the 1970s. The main factors for the application of summertime were (Reincke *et al.* (1999)): energy savings due to the energy crisis of the 1970s, improving the matching of daylight hours with the people's activities, harmonization, and synchronization with neighboring countries.

The Czech Republic started to use summer time yearly since 1979 according to the next rule: the summer time was set in the last Sunday of March and ended in the last Sunday of September. Since 1996 according to the Directive 94/21/EC of the European Parliament, the summer time ends in the last Sunday of October. The transition of DST is characterized by the rule: to put clocks forward one hour in the spring and then change them back to the Standard Time in the autumn. According to this rule there is 1 "extra" hour during the summer in the evening.

This thesis will focus on the impact of DST on traffic incidents in the Czech Republic.

There are two primary mechanisms of DST impacts. First, under daylight saving time we observe darker mornings and lighter evenings time. This additional hour light in evenings can have major consequences, for example, it can reduce crime (Doleac & Sanders (2015)) and increase outdoor activity (Wolff & Makino (2012)). Second, circadian rhythm disruptions which change the quality and amount of sleep following the spring transition. These short-term disruptions can lead to different symptoms such as headache or loss of attention. Monk & Folkard (1976) estimated that measurable changes in pattern keep up to five days after each time transition.

Previous studies of the impact of DST on the traffic incidents investigated the ambient light mechanism (Ferguson *et al.* (1995)), sleep deprivation mechanism (Coren (1996)) and both of them (Sood & Ghosh (2007)).

[1] The application of summertime in Europe. A report to the European Commission Directorate - General for Mobility and Transport (DG MOVE), 2014. Available at https://ec.europa.eu/transport/sites/transport/files/facts-fundings/studies/doc/2014-09-19-the-application-of-summertime-in-europe.pdf.

To identify the overall impact of DST on the traffic incidents, I am planning on using detailed records of every incidents occurring in the Czech Republic from 2006 to 2019.

The thesis is structured as follows: Chapter 2 comprises the literature review on the effect of the transition into and out of daylight saving time on road safety. Chapter 3 introduces the hypothesis and describes the methodology. Chapter 4 introduces data and describes the models. Chapter 5 provides the results. Chapter 6 summarizes our findings.

Chapter 2

Literature review

This chapter presents a comprehensive review of the existing evidence of daylight saving time effects mainly focusing on the effects on vehicle motor crashes.

2.1 Previous studies

Recent literature review Carey & Sarma (2017) summarizes the existent evidence of daylight saving time effect. This review includes 24 studies from different countries, 17 studies were from the USA, 2 studies were based on DST in the UK. Other 5 studies were based on data from Canada, Finland, Sweden, Israel and Ireland. Most of the studies (71%) estimated the short run effects of DST using 1 or 2 weeks period before and after the transition into and out the DST. Half of the studies examined the long run effects of DST using the time range from 3 to 13 weeks around the DST shift. Only 5 studies investigated both short run and long run effects. Existing evidence of daylight saving time effect on road safety is focused on a sleep effect, ambient light and both of these mechanisms.

2.1.1 Studies focusing on the impact of a sleep disruption

Monk & Folkard (1976) and Monk & Alpin (1980) studied individual subjects before and after daylight saving time shift trying to find some evidence about significant disruptions in the sleep cycle, performance efficiency, and mood.

A small disruption in the cycle of sleep can lead to significant changes in sleep patterns for up to five days after both Spring and Autumn time shift (Monk & Folkard (1976)).

Using Canadian data for the years 1991 and 1992, Coren (1996) appraised the short run effect of the shift to and out DST on traffic incidents. He restricted data to the Monday preceding, the Monday immediately after and the Monday one week after the change for both spring and autumn time shifts. The author observed that the spring shift to daylight saving time increased the risk of road incidents of approximately 8% due to insufficient sleep. The autumn shift resulted in a decrease in traffic incidents of approximately 7%.

This estimation has been criticized by Vincent (1998). Using the extended Canadian data from 1984 to 1993 the author did not determine a significant effect of time change on traffic incidents.

The same results were observed by Lambe & Cummings (2000). The researches used the data of motor vehicle crashes from 1984 to 1995 that occurred in Sweden state roads to examine whether the DST transition has short run effects on the traffic incidents. Three Mondays in the spring and in autumn: the Monday preceding, the Monday immediately after DST shift and the Monday one week after the change was controlled for the analysis. The authors hypothesized that traffic crashes would be higher on Monday immediately after spring shift due to sleep cycle disturbances and less on Monday immediately after the autumn shift. The incidence rate ratio (1.04) for a Monday when drivers were expected to sleep one hour less compared with other Mondays was estimated using the negative binomial regression. In the spring shift, the crash rate ratio was 1.11 for Mondays after the DST change compared to other spring Mondays, for the autumn shift this ratio was 0.98. Based on the results Lambe & Cummings (2000) concluded that there are no measurable important immediate effects on motor vehicle crashes into and from daylight savings time shift.

Varughese & Allen (2001) received contradictory results. Using the United States data for 21 years from 1975 to 1995 period they investigated the impact of sleep loss and behavioral changes on fatal traffic crashes in the shift to daylight saving time. Comparing the mean number of incidents on the days at the time transition (Saturday, Sunday and Monday) to the average of the corresponding mean number of incidents on the matching day of the weeks before and weeks after the DST shift Varughese & Allen (2001) estimated a significant increase of the number of fatal crashes on Monday for the spring change to DST but there was no measurable change for fatal crashes on Sunday. For the autumn transition from DST, there was a significant increase in the number of fatal crashes for Sunday and a non-significant decrease on Monday.

Thus, the small effect of sleep loss was significant for the first working day after the spring DST shift. The behavioral effects decreasing the risk of incidents were observed neither Saturday nor Sunday data in the spring transition. The increase in Sunday incidents after the autumn shift supports Varughese & Allen (2001) the hypothesis of a behavioral adaptation. One 'extra' hour of sleep the next day may translate drivers into staying out longer and driving later with probable increasing sleepiness or more alcohol consumption.

Lahti *et al.* (2010) investigated the impact of DST shift on the number of road incidents one week before and one week after DST transitions using the data from Finnish Motor Insurers' Center the period from 1981 to 2006. They hypothesized that circadian rhythm disruption can lead to an increase in road accidents. According to the received results, there is no significant increase in number of traffic collisions. Additionally, it was found that the proportion of personal injuries was higher in spring, but it remained at the same level in autumn.

2.1.2 Studies focusing on the impact of ambient light

Ferguson *et al.* (1995) estimated the effect of light conditions on fatal motor vehicle crashes using the data from the USA in the 5-years from 1987 to 1991. They found that a change from daylight to twilight led to a 300% increase in fatal crashes for pedestrians, this effect was much smaller (about 15%) for vehicle occupants. They approximated that the extension of DST to the full calendar year would have reduced fatal pedestrian crashes by 727 and fatal vehicle occupants' crashes by 174. This policy would save for an average of about 180 fatal collisions per year. The authors explain that the continuation of daylight saving time throughout the year increases road safety because there is more traffic during the evening hours. The smaller effect for vehicle occupants is explained by the presence of vehicle headlights and taillights, which makes it more visible during periods of twilight and darkness. Despite the fact that linear models are not the best choice for modeling count data, authors have got the results that were expected, showing the inverse relationship between lighting conditions and the number of pedestrian and motor vehicle fatal crashes.

Using the data in the 11-years from 1983 to 1993 Whittaker (1996) investigated the effect of British summertime (BST) on vehicle and pedestrian incidents for short run period. He chose one week periods before and one week after the BST change with daily time intervals from 5 a.m. to 9 a. m. and 3 p.m. to 7 p.m. which corresponded with the hours around sunrise and sunset. The author estimated that there is a reduction in the total number of road incidents in both morning and evening periods in the spring. In the autumn there is a reduction in the morning (6.25%) but a 3.9% increase in numbers in the evening, mainly vehicle 5% and pedestrian 8% accidents. He observed that there is a reduction in the spring morning and evening periods for pedestrian crashes. The reduction in the darker morning is explained by the trend of diminishing walking as a method of getting to work or school. There is a reduction in the autumn morning period, but there is a significant (7.6%) increase in the evening period.

Broughton *et al.* (1999) in their study used the new statistical methods, based on solar altitudes, for analyzing the influence of daylight level and time changes on the traffic crashes. Using the official database for Great Britain (1969 - 1973) and the USA (1991 - 1995) for the analysis, they observed that twilight and darkness increase the risk of fatal crashes and serious injury in road incidents and retaining DST throughout the year would save lives. Authors confirmed previous findings that year-round DST could have prevented up to 833 pedestrian crashes and 140 motor vehicle crashes between 1987 and 1991 (in comparison to 727 and 174 in the research of Ferguson *et al.* (1995)).

Using the fatal crashes data from the United States between 1987 and 1997, Sullivan & Flannagan (2001), Sullivan & Flannagan (2002) investigated the pedestrian's risk in darkness and the influence of ambient light level on fatal pedestrian and motor vehicle crashes. Analyzing pedestrians and motor vehicle collisions, it was estimated 4.1 times as many pedestrian fatalities in darkness as in daylight, and 1.3 times as many motor vehicle collisions in darkness compared to the daylight. Dark effects were also found for incidents with parked vehicles and incidents with railway trains. Sullivan & Flannagan (2001) concluded that pedestrians are at greater risk in darkness and the situation is also deteriorating with traffic speed due to the driver's inability to successfully perform avoidance maneuvers successfully. Sullivan & Flannagan (2002) estimated that 78% of the fatal pedestrian crashes and 52% of the fatal non-pedestrians' crashes during the daylight saving time shift periods occurred in the dark. Accordingly, the fatal pedestrians' crashes were three to four times more likely in darkness than during the daylight.

The impact of ambient light was also confirmed by Coate & Markowitz (2004). They estimated the effects of daylight and DST using the 2-week periods in 1998 and 1999. They have also discovered that the effects of shifting an hour of daylight from the morning to the evening in the period of standard time would reduce fatal crashes involving pedestrians by 171 per year. It is 13% of all pedestrians' crashes in the morning hours from 5:00 to 10:00 and in the evening hours from 16:00 to 21:00. During the same periods of time, fatal crashes of the motor vehicle occupants would be reduced by 195 per year or by 3%. The smaller percentage change in a motor vehicle is explained by vehicle lights. These results are similar to the results which were obtained by Ferguson *et al.* (1995). Coate & Markowitz (2004) noticed that there are lower pedestrian fatalities and higher motor vehicle fatal crashes in rural areas. The mentioned effect is explained by the less supply of pedestrian activity in rural areas.

The safety effects of DST on collisions involving child pedestrians were investigated by Adams *et al.* (2005) using 15 years of police data between November 1988 and March 2003 from north-east England. Using sunrise and sunset tables in England, the light conditions were examined for each crash affecting a child. The results indicated that operating daylight saving time year-round would reduce the number of serious and fatal traffic crashes involving children. Based on these results, Adams *et al.* (2005) concluded that the transition to DST year-round would prevent around 7 serious or fatal accidents in the studied area. It is equivalent to a reduction of 0.5% per year.

Bünnings & Schiele (2018) investigated the data from England, Scotland and Wales from 1996 to 2016 and estimated that the darkness increases collisions number by around 7% per hour. As a result, the extension of daylight saving time year-round could prevent 25 fatal, 100 seriously injured and 350 slightly injured crashes per year.

2.1.3 Studies focusing on the impact of both ambient light and sleep disruption

Sood & Ghosh (2007) focused their research not only an ambient light but also a sleep disruption. The researches used 28 years of data of automobile crashes (1976 - 2003) from the United States to find the short run and long run effects of DST on automobile crashes. The analysis they have performed relies on a natural experiment resulting from a 1986 USA federal law. According to the low, all states switch to daylight saving time on the first Sunday of April starting from 1987. Sood & Ghosh (2007) included a set of control years with the absence of DST in the analysis to compare the accidents in the absence of DST. Using difference - to - difference estimator, they observed that DST has a significant saving effect in the long run. There is an 8-11% decline in collisions involving pedestrians, and a 6-10% decline in crashes in vehicular accidents after the spring shift to DST. Sood & Ghosh (2007) results are consistent with the previous studies. DST has a significant saving effect in pedestrian accidents, it saves lives for pedestrians and vehicle occupants by reducing the number of motor vehicle crashes. Sood & Ghosh (2007) did not find any significant effect on automobile crash incidents in the short run.

The most previous studies investigated the impact of DST looked only at the traffic incidents for the whole day, but they do not provide the understanding of the effects of daylight saving time on different periods of a day. Therefore, Huang & Levinson (2010) studied crashes in different periods of times of a day to test the hypothesis of their reasons. Also, they assumed that DST may change traffic flow patterns near sunrise and sunset, which can increase the number of crashes. Huang & Levinson (2010) evaluated a short run and long run effects of DST on daily vehicle collisions based on data in Minnesota from 2001 to 2007. They investigated weekly crashes during the sixteen weeks crossing the time change from standard time to DST in the spring and from DST to standard time in the autumn. The four periods of the day were categorized: 3 a.m. - 9 a.m., 9 a.m. - 3 p.m., 3 p.m. - 9 p.m., 9 p.m. - midnight. Using 2SLS model Huang & Levinson (2010) divided their results into three parts - traffic, crashes, and fatal crashes. They found that one 'extra' hour daylight in the afternoon in DST increases the number of vehicles on the road due to outdoor activities. According to their results, a 1% increase in traffic volume is associated with 2.2% more incidents, therefore the benefit of better visibility during dusk may be reduced an increase in traffic. Huang & Levinson (2010) did not find any measurable effect in the short run period. The overall effect of DST on fatal motor crashes specifies that the day in DST has about 0.008% fewer fatal crashes than the day in standard time.

By the Energy Policy Act of 2005, daylight saving time was extended in the United States by 1 month beginning in 2007. According to the legislation, four weeks were added to DST starting it on the second Sunday in March and ending on the first Sunday in November. This natural experiment, similar to the conduction in 1987 observed by Sood & Ghosh (2007), allowed Crawley (2012) to investigate the day of the month and seasonal effects. Crawley (2012) replicated Sood & Ghosh (2007) findings for the 1976 - 2003 time periods and studied crash data from 2004 to 2010. It was estimated that daylight saving time has significant fatal crash-saving effects in the long run due to higher evening visibility. Sleep disruption has no significant effect in the short run.

Smith (2016) obtained contradictory results. Shifting ambient light does not contribute to the increase in collisions and only reallocates the fatal crashes to additional morning accidents and fewer evening accidents during the DST. These effects are neutralized and Smith (2016) suggests that sleep deprivation is a reason for increase in fatal crashes in the spring transition. Using the United States data of the fatal crashes (2002-2011) he applied two identification strategies: regression discontinuity method for changes between Standard Time and DST and Day-of-Year Fixed Effects for dates that are included in DST in some years and Standard Time in other years. The data was adjusted in the following way: the 3-4 am hour was counted twice for the initial Sunday of the DST shift (the day is 23 hours long) and the crashes from 1-2 am were divided by two in the autumn shift (the day is 25 hours long). The holidays were omitted from the investigation. It also was discovered that the effect of DST rises the fatal crash risk 5-6.5% in the spring shift and there is no measurable impact in the autumn shift. To determine the reason for the collisions Smith (2016) applied four tests. In the first test and the second test, he isolated the light/sleep mechanism in the autumn/spring transition and determined the net impact. In the third test,the author examined the sleep impacted days (up to first two weeks of daylight saving time) with the other days of spring DST. In the final test, he studied crash factors of accidents provided by the investigating officer. According to these tests, ambient light does not have an impact on the increase in crashes.

2.2 Summary

Existing evidence of the impact of DST on vehicle crashes is contradictory. All previous studies can be divided into three groups. One set of studies focuses only on a sleep disruption comparing the counts of crashes on the Monday preceding, the Monday immediately after DST shift, and the Monday one week after the change (short run impact). These studies suggest either an increase in incidents (Coren (1996); Varughese & Allen (2001)) or no impact due to DST (Vincent (1998); Lambe & Cummings (2000); Lahti *et al.* (2010)).

The second set of studies focuses on the impact of ambient light mechanism. The researches estimate the effect of light conditions (Ferguson *et al.* (1995);

Coate & Markowitz (2004); Bünnings & Schiele (2018)) on traffic crashes and then simulate the effect of DST on the rest of the year. All the mentioned studies suggest a reduction in traffic crashes.

The third set of studies focuses on the impact of both ambient light and sleep disruption. The first research was performed by Sood & Ghosh (2007) where they have discovered that DST has no significant effect on automobile crash incidents in the short run, but it has a significant saving effect in the long run. Smith (2016) estimated that the transition into DST reduces fatal crashes and sleep disruption increases their risk in the spring.

Chapter 3

Methodology

This chapter describes the theoretical methodology used to examine the short run and long run effects of daylight saving time on traffic accidents.

3.1 Assumptions and Hypothesis

Following the discussion on the effect of transition into and out DST, we can divide our hypotheses for two periods of time - short run period and long run one and two mechanisms - ambient light and circadian rhythm disruption. The results from previous studies are contradictory therefore we cannot choose what would have a higher impact on motor vehicle crashes.

We suggest that Daylight saving time has no significant effect on traffic accidents in the short period and can reduce traffic accidents and decline fatal crashes in the long run period. These hypotheses may be explained by the suggestion that the ambient light and better visibility have higher effect than sleep disruption. As was mentioned in the Literature review the short term sleep deprivation or disruptions in the circadian rhythm keep up to five days. The light time of the day increases during the spring period and decreases in the autumn period.

In order to valuate our hypotheses two different approaches will be applied. The long run period will be estimated by Generalized Linear Model such as Poisson regression model or Negative Binomial regression model. The models will be selected based on overdispertion. The short run period will be estimated based on Regression Discontinuity Design.

The theoretical background of the menitoned approaches will be discussed in the following paragraphs.

3.2 Generalized Linear Models

Using the Linear Regression Model for count variables can lead to inefficient and biased estimates. Following Long (1997), Cameron & Trivedi (1998) the most suitable model for accident count data is the Poisson Regression Model which is a Generalized Linear Model. The probability of a count for this model is determined by Poisson distribution, the mean of the distribution is a function of the independent variables.

3.2.1 The Poisson Distribution

Let Y be a discrete random variable which indicates the number of the times that during an interval of time, the event has happened, Y has a Poisson distribution with intensity or rate parameter μ, μ >0 if

$$Pr(Y = y) = \frac{e^{-\mu} \cdot \mu^y}{y!} \qquad \text{for} \qquad y = 0, 1, 2, ...$$

The Poisson distribution has the following properties:

1. The variance is equal to the mean:

$$Var(Y) = E(Y) = \mu$$

2. Additivity:

   If $Y_i \sim P(\mu_i)$,i= $1, 2, ..$ are independent random variables and $\sum \mu_i < \infty$ then

$$\sum Y_i \sim P(\sum \mu_i)$$

3. The Poisson distribution approximates to a Normal distribution if the parameter μ increases.

The Poisson distribution can be obtained from a simple stochastic Poisson process, where the outcome is the number of times that the event has occurred. The events must be independent, it means that the probability that one event occurs does not affect the probability of another event occurring.

3.2.2 The Poisson Regression Model

The Poisson Regression Model is derived from the Poisson distribution by allowing the rate parameter μ to depend on regressors. The typical application of the Poisson Regression is to cross-sectional data which consists of n independent observations $(y_i, \mathbf{x}_i)$. The scalar dependent variable y_i is the number of events, $\mathbf{x}_i$ is the vector of linearly independent regressors. y_i has a Poisson distribution with a conditional mean, μ_i >0

The probability of a count y_i given $\boldsymbol{x_i}$ is

$$Pr(y_i|\boldsymbol{x_i}) = \frac{e^{-\mu_i} \cdot \mu_i^{y_i}}{y_i!}$$

The most common formulation for μ_i is the log-linear model.

$$\ln \mu_i = \boldsymbol{x_i}' \cdot \boldsymbol{\beta}$$

By the property of the Poisson $Var(y_i|\boldsymbol{x_i}) = E(y_i|\boldsymbol{x_i})$ that means that the variance is not a constant, therefore the regression is heteroscedastic.

$$\frac{\partial E(y_i|\boldsymbol{x_i})}{\partial \boldsymbol{x_i}} = \mu_i \beta$$

The maximum likelihood techniques is usually used for the estimation of the parameters of the Poisson Regression Model.

The likelihood function is

$$L(\beta|y, X) = \prod_{i=1}^{N} Pr(y_i|\mu_i) = \prod_{i=1}^{N} \frac{e^{-\mu_i} \cdot \mu_i^{y_i}}{y_i!}$$

Given independent observations, the log-likelihood function is

$$\ln L(\beta|y, X) = \sum_{i=1}^{N}(-\mu_i + y_i \boldsymbol{x_i}' \beta - \ln y_i!)$$

The Poisson MLE $\widehat{\beta_P}$ is the solution to the first order conditions. Differentiating with respect to β, we obtain the likelihood equations

$$\frac{\partial \ln L}{\partial \beta} = \sum_{i=1}^{N}(y_i - \mu_i)\boldsymbol{x_i} = 0$$

The Hessian is

$$\frac{\partial^2 \ln L}{\partial \beta \partial \beta^i} = -\sum_{i=1}^{n} \mu_i \boldsymbol{x_i} \boldsymbol{x_i}'$$

The Hessian is negative definite for all x and β. There is no analytical solution for $\hat{\beta}$. The standard computation algorithm for this model is Newton-

Raphson iterative method because it usually converges rapidly. At convergence, $\left[\sum_{i=1}^{n} \mu_i x_i x_i^{'}\right]^{-1}$ provides an estimator of the asymptotic covariance matrix for the parameter estimates.

Using maximum likelihood theory, we obtain

$$\hat{\beta}_P \overset{a}{\sim} N(\beta, V_{ML}[\hat{\beta}_P])$$

where

$$V_{ML}[\hat{\beta}_P] = \left[\sum_{i=1}^{n} \mu_i x_i x_i^{'}\right]^{-1}$$

Given the estimates, the prediction for observation i is $\hat{\mu}_i = exp(x_i^{'}\hat{\beta}_P)$

Following Cameron & Trivedi (1998), the Poisson MLE has the properties:

1. Consistency does not require the Poisson distribution for the dependent variable y. It requires the correct specification of the conditional mean.

2. Valid statistical inference using computed maximum likelihood standard errors and t statistics does not require the Poisson distribution for the dependent variable y. It requires the correct specification of the conditional mean and variance, in other words, equidispersion, the equality of conditional variance, and mean.

3. If the conditional mean is correctly specified, the valid statistical inference using appropriately modified maximum likelihood output is possible for data that are not equidispersed.

4. If data are not overdispersed, the more efficient estimators than Poisson MLE can be obtained.

The condition of the equidispersion in the Poisson model is analogous to homoscedasticity in the linear model. In practice, the Poisson regression model (PRM) rarely fits due to overdispersion, that is, the conditional variance is greater than the conditional mean. In this case, the estimates from the Poisson regression model are consistent but inefficient, standard errors are biased.

3.2.3 The Negative Binomial Regression Model

The assumed equidispersion is typically taken to be the disadvantage of the Poisson regression model. According to Long (1997),Greene (2002), we extend the model adding a parameter that allows the conditional variance of y_i to exceed the conditional mean. This model is the negative binomial regression model that is the most common one in terms of unobserved heterogeneity.

We generalize the Poisson model by replacing the mean μ_i with the random variable λ_i.

$$\lambda_i = exp(x_i\beta + \epsilon_i)$$

where the disturbance ϵ_i reflects either a random error as in the classical regression model that is assumed to be uncorrelated with x_i or the kind of cross-sectional heterogeneity.

$$\lambda_i = exp(x_i\beta)exp(\epsilon_i) = \mu_i u_i$$

$$\ln \lambda_i = \ln \mu_i + \ln u_i$$

According to Long (1997), the negative binomial regression model is not identified without the assumption about the mean and error term. The appropriate assumption is that the expected value of u_i is equal to 1.

$$E(u_i) = 1$$

This assumption implies that after adding the parameter the expected count is the same as it was for the Poisson regression model.

$$E(\lambda_i) = E(\mu_i u_i) = \mu_i E(u_i) = \mu_i$$

The distribution of observations y_i conditioned on x_i and u_i is still Poisson with conditional mean and variance λ_i:

$$Pr(y_i|x_i, u_i) = \frac{e^{-\lambda_i} \cdot \lambda_i^{y_i}}{y_i!} = \frac{e^{-\mu_i u_i} \cdot \mu_i u_i^{y_i}}{y_i!}$$

Since u_i is unknown we cannot compute $Pr(y_i|x_i, u_i)$. Instead of that we can compute the distribution of y_i given only x_i without conditioning on u_i. In this case we average $Pr(y_i|x_i, u_i)$ by the probability of each value of u_i.

$$Pr(y_i|x_i) = \int_0^\infty \frac{e^{-\mu_i u_i} \cdot (\mu_i u_i)^{y_i}}{y_i!} \cdot g(u_i) du_i$$

For solving the equation we have to specify the probability density function for u_i. According to Long (1997), Greene (2002), the most common assumption is that u_i has a gamma distribution with a parameter θ_i.

$$g(u_i) = \frac{\theta_i^{\theta_i}}{\Gamma(\theta_i)} \cdot \theta_i^{u_i - 1} \cdot e^{-\theta_i u_i}$$

where $\Gamma(\theta) = \int_0^\infty t^{\theta-1} e^{-t} dt$

3.2.4 Testing for overdispersion

The condition of the equidispersion in Poisson model is analogous to homoscedasticity in the linear model therefore a failure of the assumption of the equidispersion has similar qualitative effects to failure of the assumption of homoscedasticity in the linear regression model.

Data are overdispersed if the conditional variance is greater than the conditional mean. Comparing the sample mean and variance of the dependent count variable we can obtain an indication of the magnitude of overdispersion. The subsequent Poisson regression reduces the conditional variance of the dependent count variable. Following Cameron & Trivedi (1998), if the sample variance is more than twice the sample mean, then data are probably to be overdispersed even after the inclusion of regressors because, for example for cross-section data, regressors usually explain less than half the variation in the data.

The test based on regression approach, the conditional moment test, and Lagrange multiplier test are three statistical techniques for testing hypotheses. Following Greene (2002), the simple regression based procedure for testing the null hypothesis and alternative hypothesis

$$H_0 : Var[y_i] = E[y_i]$$

$$H_a : Var[y_i] = E[y_i] + \alpha g(E[y_i])$$

is carried out by regressing

$$z_i = \frac{(y_i - \widehat{\mu_i})^2 - y_i}{\sqrt{2} \cdot \widehat{\mu_i})^2},$$

where $\widehat{\mu_i}$ is the predicted value from the regression.

According to Greene (2002), the another regression based test for the overdispersion can be formulated around the alternative hypothesis:

$$H_0 : Var[y_i] = E[y_i]$$

$$H_a : Var[y_i] = E[y_i] + g(E[y_i])$$

It is a specific type of overdispersion because the variance $Var[y_i]$ is completely given by $E[y_i]$. $E[y_i]$ is equal to $exp(x_i\beta) = \mu_i$, thus the null hypothesis is $Var[y_i] = \mu_i$. This hypothesis can be tested by using the conditional moment test. The expected first derivatives and moments are the following:

$$E[\boldsymbol{x_i}(y_i - \mu_i)] = 0$$

$$E\left\{\boldsymbol{z_i}[(y_i - \mu_i)^2 - \mu_i]\right\} = 0$$

Let $e_i = y_i - \mu_i$ and $\boldsymbol{z_i} = \boldsymbol{x_i}$ without the constant term. According to Greene (2002), to perform the test we need to do the steps below:

- Compute the Poisson regression by maximum likelihood.
- Based on the maximum likelihood, to compute $\boldsymbol{r} = \sum_{i=1}^{n} \boldsymbol{z_i}[e_i^2 - \widehat{\mu_i}] = \sum_{i=1}^{n} \boldsymbol{z_i} v_i$
- Compute $\boldsymbol{M}^{'}\boldsymbol{M} = \sum_{i=1}^{n} \boldsymbol{z_i}\boldsymbol{z_i}^{i} v_i^2$, $\boldsymbol{D}^{'}\boldsymbol{D} = \sum_{i=1}^{n} \boldsymbol{x_i}\boldsymbol{x_i}^{i} e_i^2$ and $\boldsymbol{M}^{'}\boldsymbol{D} = \sum_{i=1}^{n} \boldsymbol{z_i}\boldsymbol{x_i}^{i} v_i e_i$
- Compute $\boldsymbol{S} = \boldsymbol{M}^{'}\boldsymbol{M} - \boldsymbol{M}^{'}\boldsymbol{D}(\boldsymbol{D}^{'}\boldsymbol{D})^{-1}\boldsymbol{D}^{'}\boldsymbol{M}$.
- $C = \boldsymbol{r}^{'}\boldsymbol{S}^{-1}\boldsymbol{r}$ is the chi-squared statistic with K degrees of freedom.

If an alternative distribution for which the Poisson model is obtained as a parametric restriction can be defined, the Lagrange multiplier statistic can be computed. The negative binomial model is a parametric restriction of the Poisson model therefore the Lagrange multiplier test can be computed. The LM statistic is

$$LM = \left[\frac{\sum_{i=1}^{n} \widehat{w_i}[(y_i - \widehat{\mu_i})^2 - y_i]}{\sqrt{2\sum_{i=1}^{n} \widehat{w_i}\mu_i^2}}\right]^2$$

, where weight $\widehat{w_i}$ depends on the assumed alternative distribution. It is equal to one for the Negative binomial regression model, hence, under this alternative, the LM statistic can be computed as:

$$LM = \frac{(\boldsymbol{e}'\boldsymbol{e} - n\overline{y})^2}{2\widehat{\mu}'\widehat{\mu}}$$

The Lagrange multiplier test statistic has the advantage that the only estimation of the Poisson model is needed to compute it. Under the hypothesis of the Poisson model, the limiting distribution of the LM statistic is chi-squared with one degree of freedom (Greene (2002)).

3.3 Regression Discontinuity Design

3.3.1 Overview of the Regression Discontinuity methodology

The Regression Discontinuity RD is one of the most credible non-experimental strategies for the analysis of the casual effects of the treatment on outcomes of interest.

RD was first introduced by Thistlethwaite and Campbell in 1960 as an alternative method for evaluating social programs and formalized by Hahn, Todd, and van der Klaauw in 2001. During the last decades, this approach has been used for such evaluation as the impact of unionization, anti-discrimination, social assistance programs, limits on unemployment insurance, etc (Jacob *et al.* (2012)). Now it is frequently used in Economics, Political Science, Education, Epidemiology, Criminology, and many other disciplines (Cattaneo *et al.* (2020)).

In the RD design, all elements have a score. The Regression Discontinuity analysis applies to the situations in which observations are selected for the treatment based on whether their value for the rating variable is above or below of known threshold or cutoff. The key feature of the analysis is that the probability of receiving the treatment changes sharply at the known threshold. The discontinuous change in this probability can be used for learning the local casual effect of the treatment on an outcome of interest. The elements with the scores below the cutoff can be used as a control group for elements with the scores above (Cattaneo *et al.* (2020)).

There are three fundamental features - a score, a threshold, and a treatment in the RD methodology which must exist and be well defined. The directly testable condition is that the probability of treatment assignment as a function of the score changes discontinuously at the threshold. The RD cannot be applied in practice to the real data without it.

There are two basic designs of the Regression Discontinuity: Sharp and Fuzzy. Following Cattaneo *et al.* (2020), the Sharp design has the following features:

- the score is continuously distributed and has only one dimension
- there is only one threshold (cutoff)
- all elements with the score equal to the threshold or greater than one receive the treatment, all elements with the score below the threshold receive the control condition. To summarize, all elements receive their assignment treatment or control condition.

The Fuzzy design is characterized by the fact that some elements from treatment group does not receive treatment and/or some elements from the control group receive treatment, in other words, the compliance is imperfect. According to Cattaneo *et al.* (2020), there are some different RD designs such as RD designs with multiple cutoffs, RD designs with multiple scores, geographic RD designs, and RD designs with discrete running variables.

The Regression Discontinuity is a non-experimental approach therefore it has to have plenty of conditions to provide the unbiased estimates of the impact. According to Jacob *et al.* (2012), the following conditions for the internal validity of RD approach are specified:

- the rating variable (score) cannot be caused by or influenced by the treatment.
- the threshold (cutoff) is exogenous, that should be determined independently of the rating variable. The assignment to the treatment group is based on the ratings (score) and the threshold (cutoff).
- only the treatment status is discontinuous in the analysis interval, in other words the observation on the one side of the cutoff should be treated the same as the observation on the other side of the cutoff.
- the functional form representing the relationship between the rating variable and the outcome should be continuous throughout the analysis interval absent the treatment. If there are other discontinuities in the analysis interval, the range of the data should be restricted: only the discontinuity that identifies the impact of interest should be included in the interval.

There are two main frameworks for RD analysis: one is based on continuity and another one is based on the local randomization assumptions. The first framework focuses on the smoothness of the regression functions. This mentioned framework is commonly applied in practice. The second framework is based on the premise that the treatment can be assigned randomly to the elements near the threshold. According to Cattaneo *et al.* (2020), the frameworks are distinguished by the formalization of the comparability. The comparability is designed as a continuity of the average potential outcomes close to the threshold in the continuity-based framework and it is designed as conditions that imitate a randomized experiment around the threshold in the local randomization framework.

3.3.2 The Sharp Regression Discontinuity Design

Based on Cattaneo *et al.* (2020) let assume that there are n elements indexed by $i = 1, 2, ..., n$. Each element has a rating variable(score) X_i and c is a known cutoff. Elements with $X_i >= c$ are assigned to the treatment condition and elements with $X_i < c$ are assigned to the control condition. The treatment assignment T_i is defined as $T_i = \mathbb{1}$ for $X_i >= c$. $\mathbb{1}(\cdot)$ is the function that indicates that the probability of treatment assignment as a function of the score changes discontinuously at the threshold.

Let assume that each element has two potential outcomes, $Y_i(1)$ and $Y_i(0)$ which correspond to the outcomes observed by treatment and control conditions respectively. The treatment effect is defined as the contrast between features of both potential outcomes, such as their means, variances, or quantiles. The outcomes are called potential because only one of them is observed. If element i receives the treatment, the outcome $Y_i(1)$ will be observed. Identically, if element i receives the control condition, the outcome $Y_i(0)$ will be observed. To summarize, the observed outcome is

$$Y_i = (1 - T_i) \cdot Y_i(0) + T_i \cdot Y_i(1) = \begin{cases} Y_i(0) & \text{if } X_i < c \\ Y_i(1) & \text{if } X_i >= c \end{cases} \tag{3.1}$$

The observed average outcome given the score is

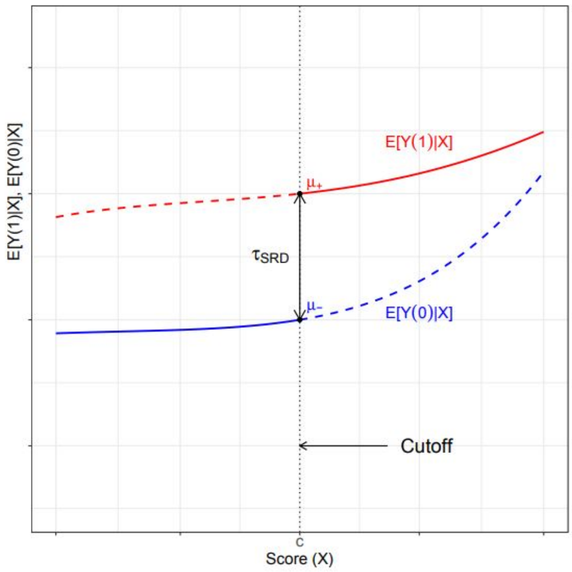
$$\mathbb{E}\left[Y_i \middle| X_i\right] = \begin{cases} \mathbb{E}\left[Y_i(0) \middle| X_i\right] & \text{if } X_i < c \\ \mathbb{E}\left[Y_i(1) \middle| X_i\right] & \text{if } X_i >= c \end{cases} \tag{3.2}$$

The average treatment effect $\mathbb{E}\left[Y_i(1)|\, X_i = x\right] - \mathbb{E}\left[Y_i(0)|\, X_i = x\right]$ is the vertical distance between two regression curves at the value of score. The distance cannot be directly estimated because both curves cannot be observed for the same value of x except the situation when the cutoff occurs, $x = c$.

The Sharp Regression Discontinuity treatment effect can be defined

$$\tau_{SRD} \equiv \mathbb{E}\left[Y_i(1) - Y_i(0)|\, X_i = c\right] \tag{3.3}$$

Figure 3.1: Regression Discontinuity treatment effect in the Sharp Regression Discontinuity design



Source: Cattaneo *et al.* (2020).A Practical Introduction to Regression Discontinuity Designs: Foundations.

According to the definition of the Sharp RD design, all elements with $X_i = c$ are treated, therefore τ_{SRD} can be interpreted an average treatment effect on the treated. Regression Discontinuity designs are based on the assumption of the comparability between elements with very similar values of the score on both sides of the cutoff (Cattaneo *et al.* (2020)). It was shown that if the regression functions as functions of x, $\mathbb{E}\left[Y_i(1)|\, X_i = x\right]$ and $\mathbb{E}\left[Y_i(0)|\, X_i = x\right]$, are continuous at $x = c$ then the equation below is valid for the Sharp RD design:

$$\mathbb{E}\left[Y_i(1) - Y_i(0)|\, X_i = c\right] = \lim_{x \downarrow c} \mathbb{E}\left[Y_i|\, X_i = x\right] - \lim_{x \uparrow c} \mathbb{E}\left[Y_i|\, X_i = x\right] \tag{3.4}$$

In other words, if the average potential outcomes are continuous functions of the score at c, the average treatment effect is equal to the difference between the limits of the average observed outcomes of both groups. The continuity near the cutoff c means that if the score x is getting closer to the cutoff c, the functions of the average potential outcome are getting closer to their value at the cutoff $\mathbb{E}\left[Y_i(\cdot)\middle|\, X_i = c\right]$. Take into account the continuity assumption, the Sharp RD effect can be estimated in a small neighborhood around the cutoff, focusing on the observation above and below. Based on the fact that the observations in the small neighborhood are very close to the cutoff, they will have very similar score values and due to the continuity, their average potential outcomes will also be similar. Thus, the observations just below the cutoff can be approximated by the average outcome of the elements just above the cutoff if they had received the control condition instead of the treatment (Cattaneo *et al.* (2020)).

3.3.3 The Continuity-Based Approach to Regression Discontinuity Analysis

The continuity-based RD approach uses methodological tools that directly rely on continuity assumptions and define τ_{SRD} as the parameter of interest. The estimation typically proceeds by polynomial methods to approximate the regression function $\mathbb{E}\left[Y_i\middle|\, X_i = x\right]$ independently on each side of the cutoff.

One of the basic features of the RD design is that there are no observations for which the score X_i is exactly equal to cutoff value c, therefore the local extrapolation is necessary in general. In order to estimate the average control response at the cut- off $\mathbb{E}\left[Y_i(0)\middle|\, X_i = c\right]$ and the average treatment response at the cutoff $\mathbb{E}\left[Y_i(1)\middle|\, X_i = c\right]$, the observations further away from the cutoff should be considered. As shown in Figure 3.1, the treatment effect in the Sharp RD design is a vertical distance between $\mathbb{E}\left[Y_i(1)\middle|\, X_i = x\right]$ and $\mathbb{E}\left[Y_i(0)\middle|\, X_i = x\right]$ which can be estimated by first approximating these unknown regression functions, and then computing the estimated treatment effect and/or the statistical inference procedure of interest (Cattaneo *et al.* (2020)).

Modern Regression Discontinuity empirical work applies local polynomial method as opposed to the early empirical approach where the idea of polynomial approximation globally (usually of fourth or fifth order polynomials) was applied. The modern local polynomial methods are focusing on the approximation of the regression functions near the cutoff and usually the linear or quadratic polynomials are used. The statistical properties of the local polynomial are controlled by the size of the neighborhood near the cutoff where the local polynomial is fit, separately for the treatment and control group. This approach uses observations from the interval $(c - h;\ c + h)$, where $h > 0$ is a bandwidth which defines the size of the neighborhood near the cutoff. The weighting scheme is usually applied to ensure that the weights for the observations which are closer to the cutoff c are higher than the weights for observations that are further away. The weights are defined by a kernel function $K(\cdot)$

According to Cattaneo *et al.* (2020), the local polynomial estimation is based on the following steps:

1. To choose a polynomial order p and a kernel function $K($Âů$)$.

2. To choose a bandwidth h.

3. For observations above the cutoff $(X_i >= c)$, to fit a weighted least squares regression of the outcome Y_i on a constant and $(X_i - c)$, $(X_i - c)^2$, ..., $(X_i - c)^p$ with weight $K\left(\frac{X_i - c}{h}\right)$ for each observation, where p is a chosen polynomial order. $\widehat{\mu_+}$ is the estimated intercept from the local weighted regression.

$$\mu_+ = [Y_i(1)|\, X_i = c]$$

$$\widehat{\mu_+}\text{: } \widehat{Y_i} = \widehat{\mu_+} + \widehat{\mu_{+,1}} \cdot (X_i - c) + \widehat{\mu_{+,2}} \cdot (X_i - c)^2 + ... + \widehat{\mu_{+,p}} \cdot (X_i - c)^p$$

4. For observations below the cutoff $(X_i < c)$, to fit a weighted least squares regression of the outcome Y_i on a constant and $(X_i - c)$, $(X_i - c)^2$, ..., $(X_i - c)^p$ with weight $K\left(\frac{X_i - c}{h}\right)$ for each observation, where p is a chosen polynomial order. $\widehat{\mu_-}$ is the estimated intercept from the local weighted regression.

$$\mu_- = [Y_i(0)|\, X_i = c]$$

$$\widehat{\mu_-}\text{: } \widehat{Y_i} = \widehat{\mu_-} + \widehat{\mu_{-,1}} \cdot (X_i - c) + \widehat{\mu_{-,2}} \cdot (X_i - c)^2 + ... + \widehat{\mu_{-,p}} \cdot (X_i - c)^p$$

5. To calculate the Sharp RD parameter $\tau_{SRD} = \widehat{\mu_+} - \widehat{\mu_-}$

To summarize the points above, there are three main ingredients should be chosen for the local polynomial estimation: kernel function $K(\cdot)$, bandwidth h and order of the polynomial p.

Based on Cattaneo *et al.* (2020), the kernel function $K(\cdot)$ is a function which assigns non-negative weights to each transformed observations $\frac{X_i - c}{h}$ based on the distance between the observation's score X_i and the cutoff c. There are three different types of kernel functions which can be used for estimation:

- Triangular kernel $K(u) = (1 - u)\mathbb{1}(u <= 1)$
- Uniform kernel $K(u) = \mathbb{1}(u <= 1)$
- Epanechnikov kernel $K(u) = (1 - u)^2\mathbb{1}(u <= 1)$

The triangular kernel function can lead to a point estimator with optimal properties but in practice, the estimation and inference results are not very sensitive to the choice of kernel.

The choice of the local polynomial order is based on various factors. The polynomial of order zero (a constant) can be unfitted at the boundary points. The increasing order of polynomial for a given bandwidth provides the more precise approximation but also increasing the variability of the treatment effect estimator. Moreover, it usually leads to the overfitting and unreliable results at the boundary. Thus, the local linear RD estimator is preferred.

The choice of the bandwidth h, that regulates the width of the neighborhood near the cutoff, has influence on the properties of the local polynomial estimation. The accuracy of the approximation can be improved by cutting the bandwidth. The smaller h will decrease a misspecification error (smoothing bias) but in the same time it leads to the increasing of the variance of the estimated coefficients because the number of observations to be used for the estimation is smaller. The larger h will decrease the variance but will result in more smoothing bias.

According to Cattaneo *et al.* (2020), the most popular approach for choosing the optimal bandwidth h is to minimize the mean squared error (MSE) of the local polynomial RD point estimator $\widehat{\tau_{SRD}}$, given the kernel function and a choice of polynomial order. The general form of the approximate MSE for the Regression Discontinuity treatment effect is

$$MSE(\widehat{\tau_{SRD}}) = Bias^2(\widehat{\tau_{SRD}}) + Variance(\widehat{\tau_{SRD}}) = h^{2(p+1)}\mathcal{B} + \frac{1}{nh}\mathcal{V}$$

,

where quantities $\mathcal{B}$ and $\mathcal{V}$ are the bias and variance of the RD point estimator $\widehat{\tau_{SRD}}$, not including the rates controlled by the sample size and bandwidth choice.

The general form of the bias is determined by the bandwidth h and quantities:

$$\mathcal{B} = \mathcal{B}_+ - \mathcal{B}_-$$

,

$$\mathcal{B}_+ \approx \mu_+^{p+1} B_+ \quad \text{and} \quad \mathcal{B}_- \approx \mu_-^{p+1} B_-$$

,

where the known constants B_+ and B_- are related to the kernel function, the derivatives below are related to the unknown regression function.

$$\mu_+^{p+1} = \lim_{x \downarrow c} \frac{d^{p+1}\mathbb{E}\left[Y_i(1) | X_i = x\right]}{dx^{p+1}}$$
$$\mu_-^{p+1} = \lim_{x \uparrow c} \frac{d^{p+1}\mathbb{E}\left[Y_i(0) | X_i = x\right]}{dx^{p+1}}$$

.

The variance depends on the sample size and involves the quantities:

$$\mathcal{V} = \mathcal{V}_- + \mathcal{V}_+$$

,

$$\mathcal{V}_- \approx \frac{\sigma_-^2}{f} V_- \quad \text{and} \quad \mathcal{V}_+ \approx \frac{\sigma_+^2}{f} V_+$$

,

where

$$\sigma_+^2 = \lim_{x \downarrow c} \mathbb{V}\left[Y_i(1) | X_i = x\right]$$

,

$$\sigma_-^2 = \lim_{x \uparrow c} \mathbb{V}\left[Y_i(0) | X_i = x\right]$$

capture the conditional variability of the outcome given the score at the cutoff for treatment and control units, f is the density of the score variable at the cutoff.

The bandwidth h that estimates the MSE approximation is equal to

$$\min_{h>0} \left(h^{2(p+1)} \mathcal{B}^2 + \frac{1}{nh} \mathcal{V} \right)$$

The MSE-optimal bandwidth is

$$h_{MSE} = \left(\frac{\mathcal{V}}{2(p+1)\mathcal{B}^2} \right)^{\frac{1}{2p+3}} \cdot n^{\frac{-1}{2p+3}}$$

The RD treatment effect $\tau_{SRD} = \mu_+ - \mu_-$ is the difference of two estimates thus two different bandwidths can be chosen considering an MSE approximation for each estimate separately (Cattaneo *et al.* (2020).

$$h_{MSE,-} = \left(\frac{\mathcal{V}_-}{2(p+1){\mathcal{B}_-}^2} \right)^{\frac{1}{2p+3}} \cdot n_-{}^{\frac{-1}{2p+3}}$$

$$h_{MSE,+} = \left(\frac{\mathcal{V}_+}{2(p+1){\mathcal{B}_+}^2} \right)^{\frac{1}{2p+3}} \cdot n_+{}^{\frac{-1}{2p+3}}$$

Given the choice of the polynomial order p and the kernel function $K(\cdot)$, the bandwidth h can be chosen. The common MSE-optimal bandwidth or two different MSE-optimal bandwidths leads to the RD point estimator $\widehat{\tau_{SRD}} = \widehat{\mu_-} - \widehat{\mu_+}$ which is consistent and MSE optimal.

Chapter 4

Empirical Framework

This chapter describes the data and models used for estimation.

4.1 Data Description

The main data for this research has been obtained from the Czech Traffic Police for the period from January 2006 to December 2019. The data contains detailed records of all traffic accidents for each region of the Czech Republic. During the 2006-2009 two important changes were made in the Czech Road Traffic law. Starting from 1.7.2006 the minimum damage below which the police should not be notified raised from 20000 CZK to 50000 CZK, starting from 1.1.2009 the minimum damage amount has been increased to 100000 CZK. All incidents involving affected people must be notified to police in any case.

Due to the fact since the method for data reporting has been changed, we cannot compare the data from year to year. Therefore the data for all traffic accidents will be studied starting from 1.1.2009.

Figure 4.1 presents the total number of accidents per year starting from 2006. The changes in the Czech Road Traffic law reduced the number of reported accidents significantly in 2009. All fatal traffic accidents must be reported to the police, therefore based on that condition, we can study the data for these types of accidents starting from 2006. Figure 4.2 presents the total amount of fatal road accidents over the years starting from 2006.

It is important to note that the police report of traffic crashes contains one record per crash with all details including the time of the accidents thus we can calculate the number of crashes per hour, day, and week. The Police did not know the accurate time for some of the crashes therefore the signs '25' for an hour and '60' for minutes were used in the report. The record with the sign '60' in the minutes was included to the defined hour, for example, the accident happened at '260' was calculated to 2-3 a.m. hour. The crashes with the unknown hour (the sign '25') were excluded from the dataset.

Figure 4.1: Total number of accidents per year

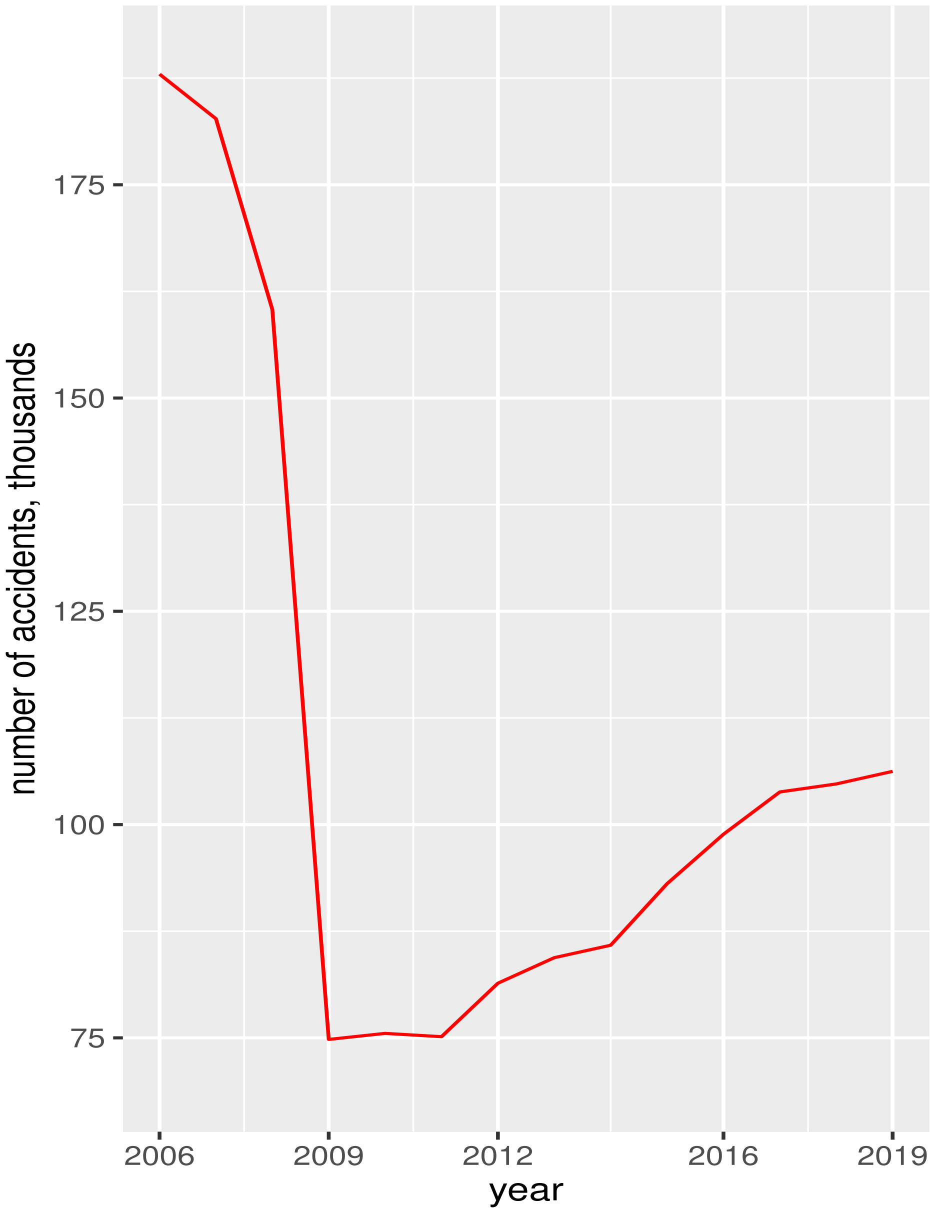
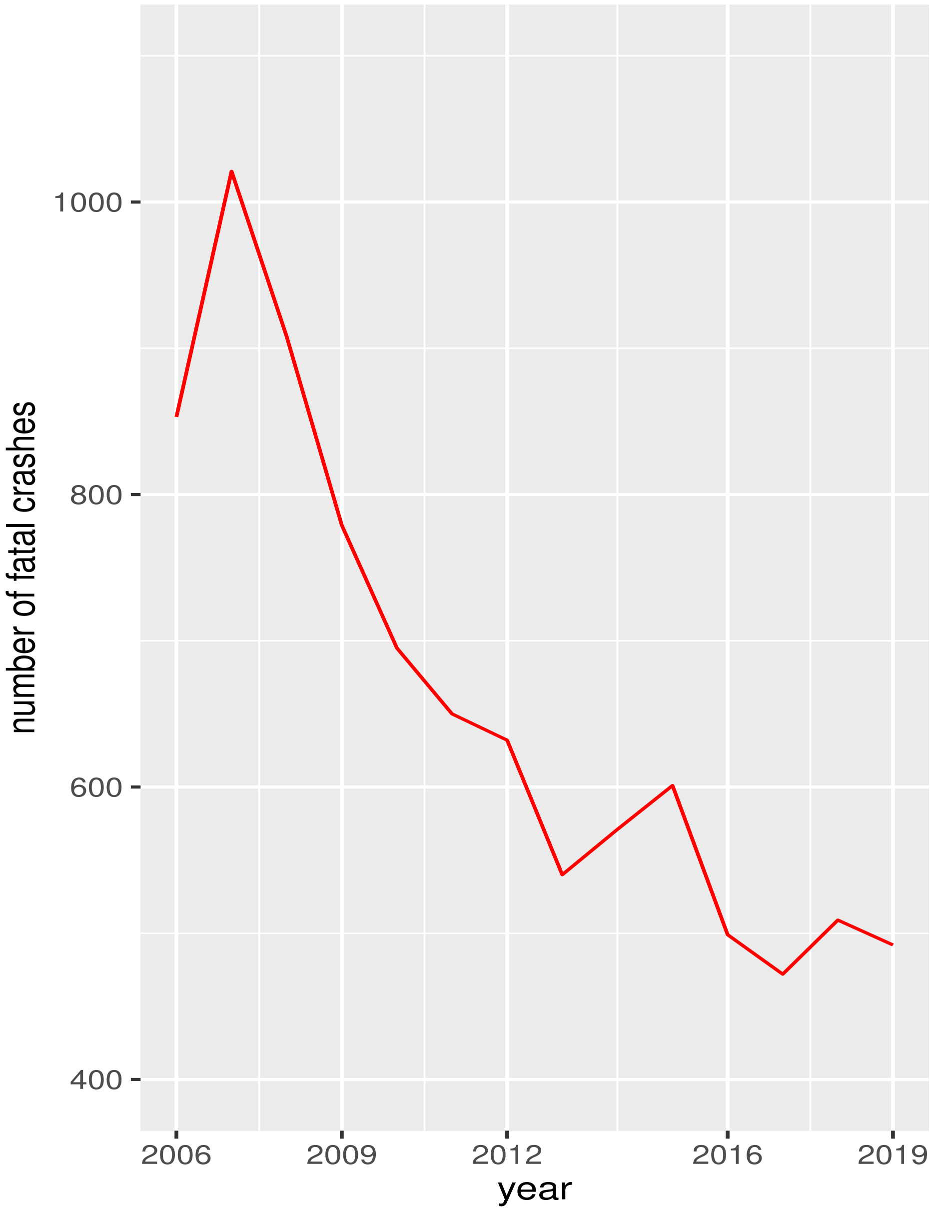


Figure 4.2: The number of fatal accidents per year



4.1.1 Explanatory variables constructed from the police report

Based on the report provided by the police the different dummy variables for non-aggregated dataset were constructed.

Using the type of an road accident the following variables were created:

- $Crash\_into\_solid\_obstacle$ is equal to one if the driver crashed a solid barrier and zero if otherwise.

Using the condition on the road surface and cause of the accident, the variables below were created:

- $Cause\_damaged\_road$ is equal to one if the cause of the accident was a bad road and zero if otherwise.
- $Cause\_car\_defect$ is equal to one if the cause of the accident was a technical failure of the car and zero if otherwise.
- $Good\_road\_surface$ is equal to one if the road surface is dry and clean and zero if it is wet, muddy, there is snow, ice, sand, oil spilled or other external conditions endangering the driver.

Using the data regarding the drug and alcohol influence from the police report the variable $Cause\_intoxication$ will be constructed.

- $Cause\_intoxication$ which is equal to one if the drugs or alcohol were involved and zero if otherwise.

The police report contains detailed information on the level of individual accidents. The number of slightly, seriously, and fatally injured casualties is provided for each accident. In order to receive the hourly accidents counts the data of individual accidents was aggregated. The following variables were obtained:

- *total accidents per hour*,
- *the number of slightly injured accidents per hour*,
- *the number of seriously injured accidents per hour*,
- *the number of fatal accidents per hour*,

The summary statistics for all type of accidents are presented in the Table 4.1. Taking into account the fact that the length of the day of the DST transition in the spring is 23 hours instead of 24 hours and the length of the day of the DST transition in the autumn is 25 hours the dataset was adjusted. Following Smith (2016) and Bünnings & Schiele (2018), the accidents between 3-4 a.m. in the spring were counted twice and added to the proxy hour 2-3 a.m. The half of accidents during 2 a.m. in the 25 hours day transition in the autumn was dropped because this hour occurred twice.

Table 4.1: Summary statistics of the different type of traffic accidents in the Czech Republic per year.

Year	Total number of accedents	Total number of fatal accidents	Total number of seriously injured accidents	Total number of slightly injured accidents
2006	187965	853	3568	18946
2007	182736	1021	3505	19877
2008	160375	908	3403	19372
2009	74815	779	3206	18830
2010	75522	695	2584	17240
2011	75137	650	2790	17971
2012	81403	632	2729	17975
2013	84398	540	2545	17993
2014	85859	571	2518	18761
2015	93067	601	2299	19389
2016	98864	499	2346	19262
2017	103825	472	2129	19334
2018	104764	509	2221	19884
2019	106240	492	1853	18753

4.1.2 Meteorological variables

The hourly meteorological data was downloaded from the National Oceanic and Atmospheric Administration National Oceanic and Atmospheric Administrations (NOAAs) website [1]. The data measured by the meteorological station Praha-Kbely was used for this study. The Czech Republic is not too wide geographically stretched, therefore we assume that the meteorological conditions are not much distinguished between different regions thus the meteorological data from the station Praha-Kbely can be used as an average meteorological data for the whole country. The data contains the observations of the air temperature, wind speed rate, sky condition observations, precipitations and much other information. All of the times in the weather dataset are recorded in UTC (Coordinated Universal Time) time zone. Coordinated Universal Time is equivalent to Greenwich Mean Time therefore the time was transformed to the CET time zone (Central European Time) which is one hour ahead of Greenwich Mean Time (GMT) during the winter period (starting from the last Sunday of October till the last Sunday of March) and two hours ahead of GMT during the

[1]NOAA National Centers for Environmental Information: Global Surface Hourly [station ID 11567099999]. https://gis.ncdc.noaa.gov/maps/ncei/cdo/hourly

summer period (starting from the last Sunday of March till the last Sunday of October).

In some cases, there was more than one element at the same observation time, therefore the duplicates were removed. The precipitation was often recorded for multiple hour periods instead of one hour. If the precipitation was missed for the previous hours, the aggregate value of precipitation was split. The missing values of the meteorological data were linearly interpolated.

Using the meteorological data and following Bünnings & Schiele (2018) and Huang & Levinson (2010) the dummy variables were constructed:

- $Temperature\_less\_zero$, which is equal to one if the air temperature is less than zero degrees Celsius and zero otherwise,
- $Temperature\_less\_five$, which is equal to one if the air temperature is more than zero degrees Celsius and less than five degrees Celsius and zero otherwise,
- $Temperature\_less\_ten$, which is equal to one if the air temperature is more than five degrees Celsius and less than ten degrees Celsius and zero otherwise,
- $Temperature\_less\_fifteen$ which is equal to one if the air temperature is more than ten degrees Celsius and less than fifteen degrees Celsius and zero otherwise,

Using the present weather observation from the meteorological data which describe the weather conditions at the time of the observation, the additional dummy variables fog, $mist$, $rain$, $drizzle$ and $snow$ were created. The mentioned variables are equal to one if the atmospheric condition was reported and zero otherwise.

4.1.3 Dark

The daylight length can have a significant impact on the road accidents therefore the variable relating to the light has to be constructed. Huang & Levinson (2010) in their research calculated the daylight length as the period of time in hours between the rising and setting of the sun. It is known that the darkness does not come immediately after sunset. There is a period of time before sunrise and after sunset in which the atmosphere is partially illuminated by the sun and the artificial light is not needed. Based on Sun's position astronomers define three stages of twilight - civil, nautical, and astronomical which follow each other[2].

Civil twilight occurs when the geometric center of the sun is six degrees below the horizon. Morning civil twilight (civil dawn) begins when the sun is six degrees below the horizon in the morning and ends at sunrise. Similarly, evening civil twilight (civil dusk) starts at sunset and ends when the sun is six degrees below the horizon in the evening. Civil twilight is the brightest form of twilight. In many cases, except such weather conditions as fog or other restrictions, the human eye is sufficient to distinguish the objects and artificial lighting is not needed.

Nautical twilight occurs in the morning and the evening when the geometric center of the sun is between six and twelve degrees below the horizon. During this period of time the horizon is still visible but the artificial lighting is needed for detailed outdoor activities.

Astronomical twilight occurs in the morning and the evening, when the geometric center of the sun is eighteen degrees below the horizon. During the astronomical twilight, the horizon is not visible, and most casual observers would consider the sky as fully dark.

Following the Bünnings & Schiele (2018) the variable *dark* based on the onset and offset of morning and evening twilight was constructed. Taking into account the fact that the Czech Republic is not too wide geographically stretched and has the same time on the whole territory, the geographical coordinates (longitude and latitude) of Praha-Kbely were used to obtain the information regarding the exact time of starting and ending of civil twilight on the day d for the year t. The exact time of the transition into (out of) civil twilight was calculated using the package 'Suncalc' in the software R.

$$dark_{hdt} = \begin{cases} 1 & \text{if } h < hour(b_{dt}) \text{ or } h > hour(e_{dt}) \\ min(b_{dt})/60 & \text{if } h = hour(b_{dt}) \\ (60 - min(e_{dt}))/60 & \text{if } h = hour(e_{dt}) \\ 0 & \text{if } h > hour(b_{dt}) \text{ and } h < hour(e_{dt}) \end{cases}$$

where

[2] https://www.weather.gov/fsd/twilight

- $hour(b_{dt})$ indicates the hour of day when civil twilight begins in the morning on day d for year t.
- $hour(e_{dt})$ indicates the hour of day when civil twilight ends in the evening on day d for year t.
- $min(b_{dt})$ indicates the minute of civil twilight transition in the morning.
- $min(e_{dt})$ indicates the minute of civil twilight transition in the evening.

The treatment variable $dark$ takes on the value zero if the hour of observation is after the hour of the transition when the civil twilight starts in the morning and before the hour of the transition when the civil twilight ends in the evening, in other words, when the amount of light is sufficient to distinguish the objects. It takes on the value one if the hour of the observation is before the the hour of the transition between nautical and civil twilight in the morning and after the hour of the transition between civil and nautical twilight in the evening. If the hour of observation is equal to the hour of transition from or into the civil twilight, the variable $dark_{hdt}$ is equal to the values between zero and one and indicates the fraction of the darkness. The exact value of $dark_{hdt}$ depends on the exact time (minutes) of the transition. If the transition into the darkness is at the beginning of the hour of observation then $dark_{hdt}$ will take the value closed to one and correspondingly, if the transition into the darkness is at the end of the hour of observation, then $dark_{hdt}$will take the value closed to zero. Accordingly, if the transition out of the darkness is at the beginning of the hour of observation, then $dark_{hdt}$ will take the value closed to zero and if the transition into the darkness is at the end of the hour of observation, then $dark_{hdt}$will take the value closed to one.

4.1.4 Daylight Saving Time

DST is a dummy variable that is equal to one if the observation belongs to the period of time when the daylight saving policy was implemented. The transition of DST is characterized by the rule: to put clocks forward one hour in the last Sunday of March and then change them back to the Standard Time in the last Sunday of October. The transition into (out of)DST takes place at 2 a.m. in the morning therefore the variable DST switches the value from zero to one (or one to zero) at 2 a.m. on the day of transition for the hourly dataset. The dates of transition the Daylight Saving Time are presented in Table A.1

4.1.5 Holidays

The number of traffic accidents can be changed during the National holidays at least because the traffic volume can be shifted. The dummy variable *holiday* was created to capture the potential effect on the accidents. The variable is equal to one if the day of observation is a national holiday and zero if otherwise.

The main aim of this study is to examine the impact of daylight saving time on traffic accidents in the short run and long run period. The short run period is mostly estimated by the amount of the accidents during the one week before and after transition (Lahti *et al.* (2010), Coren (1996)) or Mondays before, Mondays of and Mondays after the transition (Sood & Ghosh (2007), Crawley (2012)). The long run period is mostly estimated by the number of accidents during the range of 8 - 13 weeks. Following Huang & Levinson (2010) the subset of eight weeks before and after the DST transition will be used for long run period.

The descriptive statistics for the outcome variables and some of control variables for the subsample of eight weeks before and after the DST transition in spring period starting from 2009 are presented in Table 4.2. The descriptive statistics for the DST transition in the autumn period are presented in Table 4.3

4.2 Estimation

The Negative Binomial Regression Model will be used to obtain the effect of DST in the long-run period.

4.2.1 Generalized Linear Model

The one of the main assumptions which can have influences on the number of the traffic accidents is the light conditions therefore the effect of darkness on accidents counts will be investigated.

Following Bünnings & Schiele (2018), we estimate the regressions based on the following equations:

$$accidents_{hdwy} = f(\beta_0 + \beta_1 dark_{hdwy} + \alpha_h + \gamma_d + \delta_w + \lambda_y + \epsilon_{hdwy}) \qquad (4.1)$$

Table 4.2: Descriptive statistics of traffic incidents and fatal crashes for hourly data during the eight weeks before and after the spring DST transition for the period of time starting from 2009

Variable	*Mean*	*St.dev.*	*Min*	*Max*
Dependent variables				
All accidents	8.493	6.106	0	62
Fatal accidents	0.053	0.229	0	3
Serious accidents	0.244	0.532	0	8
Slight accidents	1.813	1.954	0	17
Crash into solid obstacle	1.855	1.751	0	24
Cause damaged road	0.038	0.200	0	3
Cause car defect	0.049	0.229	0	3
Cause intoxication	0.507	0.784	0	6
Darkness:				
Dark proportion of the hour	0.427	0.480	0	1
Weather:				
Temperature (°C) <0	0.162	0.369	0	1
0<Temperature (°C) < 5	0.236	0.425	0	1
5 <= Temperature (°C)<10	0.270	0.444	0	1
10 <= Temperature (°C)<15	0.200	0.400	0	1
Positive precipitation	0.086	0.281	0	1
Mist	0.105	0.307	0	1
Fog	0.005	0.073	0	1
Drizzle	0.003	0.055	0	1
Rain	0.070	0.255	0	1
Snow	0.027	0.161	0	1
Relative humidity	72.62	17.589	17	100
Sea level pressure (hectopascals)	1016	10.546	960	1047
DST	0.504	0.500	0	1
Holiday	0.030	0.170	0	1

Table 4.3: Descriptive statistics of traffic incidents and fatal crashes for hourly data during the eight weeks before and after the autumn DST transition for the period of time starting from 2009

Variable	*Mean*	*St.dev.*	*Min*	*Max*
Dependent variables				
All accidents	9.914	6.926	0	54
Fatal accidents	0.074	0.274	0	3
Serious accidents	0.274	0.563	0	5
Slight accidents	2.209	2.205	0	17
Crash into solid obstacle	2.157	1.878	0	19
Cause damaged road	0.032	0.191	0	6
Cause car defect	0.051	0.232	0	5
Cause intoxication	0.574	0.831	0	7
Good road surface	6.558	5.910	0	36
Darkness:				
Dark proportion of the hour	0.525	0.486	0	1
Weather:				
Temperature (°C) <0	0.102	0.302	0	1
0<Temperature (°C) < 5	0.217	0.413	0	1
5 <= Temperature (°C)<10	0.296	0.456	0	1
10 <= Temperature (°C)<15	0.231	0.421	0	1
Positive precipitation	0.091	0.287	0	1
Mist	0.151	0.358	0	1
Fog	0.038	0.192	0	1
Drizzle	0.009	0.093	0	1
Rain	0.087	0.282	0	1
Snow	0.019	0.136	0	1
Relative humidity	82.61	14.609	22	105
Sea level pressure (hectopascals)	1018	8.854	975	1041
DST	0.496	0.500	0	1
Holiday	0.032	0.179	0	1

Adding the weather and explanatory variables we estimate

$$
\begin{aligned}
accidents_{hdwy} = & f(\beta_0 + \beta_1 dark_{hdwy} + \beta_2 holiday_{dwy} + \\
& + \beta_3 TMP\_less\_0_{hdwy} + \beta_4 TMP\_less\_5_{hdwy} + \\
& + \beta_5 TMP\_less\_10_{hdwy} + \beta_6 TMP\_less\_15_{hdwy} + \\
& + \beta_7 mist_{hdwy} + \beta_8 fog_{hdwy} + \\
& + \beta_9 drizzle_{hdwy} + \beta_{10} rain_{hdwy} + \beta_{11} snow_{hdwy} + \\
& + \beta_{12} precipitation_{hdwy} + \beta_{13} RH_{hdwy} + \beta_{14} SLP_{hdwy} + \\
& + \beta_{15} cause\_intoxication_{hdwy} + \\
& + \beta_{16} cause\_damaged\_road_{hdwy} + \\
& + \beta_{17} cause\_car\_defect_{hdwy} + \\
& + \beta_{18} cause\_solid\_obstacle_{hdwy} + \\
& + \alpha_h + \gamma_d + \delta_w + \lambda_y + \epsilon_{hdwy})
\end{aligned}
\tag{4.2}
$$

where

- $accidents_{hdwy}$ is the number of the accidents of the certain type during the hour h, day of week d, week of year w and year y.
- $dark_{hdwy}$ is the dark share in hour h, day d, week w and year t.
- $holiday_{dwy}$ is a dummy variable which is equal to one if the day is a bank holiday and zero otherwise.
- $TMP\_less\_$ is a dummy variable which is equal to one if the temperature is less than indicated value and more the indicated value minus five.
- $mist_{hdwy}$, fog_{hdwy}, $drizzle_{hdwy}$, $rain_{hdwy}$, $snow_{hdwy}$ are dummy variables which are equal to one if the natural phenomena were indicated.
- $precipitation_{hdwy}$ is equal to one if the precipitation are positive.
- RH_{hdwy} is a relative humidity.
- SLP_{hdwy} is a sea level pressure.
- $cause\_intoxication_{hdwy}$ is a number of accidents caused by driver's intoxication.

- $cause\_damaged\_road_{hdwy}$ is a number of accidents caused by damaged road.
- $cause\_car\_defect_{hdwy}$ is a number of accidents caused by the defect of the car.
- $cause\_solid\_obstacle_{hdwy}$ is a number of accidents caused by the crash by solid obstacle
- α_h is a hour of the day.
- γ_d is a day of week.
- δ_w is a week of year.
- λ_y is a year.
- ϵ_{hdwy} is an error term.

The parameter β_1 is the parameter of interest which gives the impact of darkness on the number of the accidents during the hour. We assume that the variable *dark* is exogenous, the number of accidents and dark are unevenly distributed during the hour.

The Equations 4.1 and 4.2 were estimated for total accidents per hor, slightly injured accidents, seriously injured accidents and fatal accidents.

4.2.2 Regression Discontinuity Design

The Regression Discontinuity Design exploits the discrete change from Standard Time to Daylight Saving Time in spring and from DST to Standard Time in autumn (Smith (2016), Bünnings & Schiele (2018)). The approach is based on the intuition that if there is a significant impact of DST on traffic crashes, there should be a shock (sharp increase or decrease) in the number of accidents around the transition date. Measuring the discontinuity at the transition allows us to estimate the immediate impact of the DST policy. The general estimation equation is the following:

$$\begin{aligned}\ln accidents_{dy} = &\beta_0 + \beta_1 \cdot DST_{dy} + f(DaysToTran_{dy}) + \\ &+ f(DST_{dy} \times DaysToTran_{dy}) + \epsilon_{dy}\end{aligned} \tag{4.3}$$

where:

- $accidents_{dy}$ is the total number of different types of accidents at the day d and year y. Following Smith (2016) and Bünnings & Schiele (2018), the residuals from a regression of logged daily total numbers of accidents on day of the week and year fixed effects as dependent variables were used to avoid the persistent day-of-week effects and long-term time trends.
- DST_{dy} is a dummy variable which is equal to one for the day d in a year y after the DST transition.
- $DaysToTran_{dy}$ is the running variable which measures the time in days before and after DST transition (either in spring or in autumn). The variable is centered at the transition date in each year.
- ϵ_{dy} is an error term.
- β_1 is a coefficient of interest which gives the aggregate effect of the transition into or out of DST on accident counts.

The interaction $DST_{dy} \times DaysToTran_{dy}$ is included based on the fact that the treatment can impact not only the intercept, but also the slope of the regression line, the slope can vary at both sides of the cut-off (Jacob *et al.* (2012)).

It is required for β_1 to be consistently estimated, *ln accidents* and all other factors which can affect the accidents risk besides *DST* should be continuous at the transition date. If this assumptions holds, the Regression Discontinuity design will provide a consistent estimate of the short- run effect of DST on road safety. The numbers of days to be used at both sides of the cut-off, will be chosen by mean squared error optimal bandwidth selectors.

Based on the type of accidents, the following equations were estimated:

$$\begin{aligned}\ln(\text{total accidents})_{dy} =& \beta_0 + \beta_1 \cdot DST_{dy} + f(DaysToTran_{dy}) + \\ &+ f(DST_{dy} \times DaysToTran_{dy}) + \epsilon_{dy}\end{aligned} \tag{4.4}$$

$$\begin{aligned}\ln(\text{slightly injured accidents})_{dy} =& \beta_0 + \beta_1 \cdot DST_{dy} + f(DaysToTran_{dy}) + \\ &+ f(DST_{dy} \times DaysToTran_{dy}) + \epsilon_{dy}\end{aligned} \tag{4.5}$$

Due to the fact that the number of fatal and seriously injured accidents was equal to zero for some of days, the two different types of the transformation were used: log-transformation with adding a small constant and square-root transformation.

$$\begin{aligned}\ln(\text{seriously injured accidents} + 0.45)_{dy} =& \beta_0 + \beta_1 \cdot DST_{dy} + f(DaysToTran_{dy}) + \\ &+ f(DST_{dy} \times DaysToTran_{dy}) + \epsilon_{dy}\end{aligned} \tag{4.6}$$

$$\begin{aligned}\ln(\text{fata accidents} + 0.45)_{dy} =& \beta_0 + \beta_1 \cdot DST_{dy} + f(DaysToTran_{dy}) + \\ &+ f(DST_{dy} \times DaysToTran_{dy}) + \epsilon_{dy}\end{aligned} \tag{4.7}$$

$$\begin{aligned}\text{sqrt}(\text{seriously injured accidents})_{dy} =& \beta_0 + \beta_1 \cdot DST_{dy} + f(DaysToTran_{dy}) + \\ &+ f(DST_{dy} \times DaysToTran_{dy}) + \epsilon_{dy}\end{aligned} \tag{4.8}$$

$$\begin{aligned}\text{sqrt}(\text{fatal accidents})_{dy} =& \beta_0 + \beta_1 \cdot DST_{dy} + f(DaysToTran_{dy}) + \\ &+ f(DST_{dy} \times DaysToTran_{dy}) + \epsilon_{dy}\end{aligned} \tag{4.9}$$

The Regression Discontinuity Design provides casual estimates of the effect of DST transition on the road accidents. The estimates is valid very locally, just a few days from and after the day of the transition (short-run period).

Chapter 5

Results

In this section we confirm the validation on statistical assumptions, interpret the models estimates and discuss the obtained results.

5.1 Validation of assumptions

5.1.1 Stationarity

The stationary is an important statistical assumption in the analysis of time series. The mean, variance and autocorrelation structure are stable over time for the stationary time series process.

We have tested the stationarity of the series including into the model specifications using the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron test (PP).

The Augmented Dickey-Fuller test (ADF) tests the null hypothesis that a unit root is present in a time series sample (data series are not stationary). The alternative hypothesis is that the data is stationary. To confirm the results, we did the Phillips-Perron test (PP) which is an alternative to ADF and it is robust to the unspecified autocorrelation and heteroscedasticity. The null hypothesis of PP test is the same as ADF test. The p-value is less than 0.01 for all series, so we can reject the null hypothesis that data are not stationary and accept the alternative hypothesis that data are stationary. The results of both tests are present in the table A.2.

5.1.2 Heteroscedasticity

The homoscedasticity assumption means that the variance of structural error cannot depend on any of the explanatory variables (Wooldridge (2013)). This assumption is a key assumption for OLS regression. Generalized linear models (GLM) like Poisson regression or Negative binomial regression do not fulfill it because there is no assumption of constant variance. We consider that the variance is equal to the mean for the Poisson regression model and the variance is greater than the mean for the Negative binomial regression model. The overdispersion / underdispersion should be checked in GLM. Heteroscedasticity in Poisson or the Negative binomial model can mean that the level of overdispersion / underdispersion depends on another parameter.

5.1.3 Autocorrelation

Autocorrelation (serial correlation) is a characteristic of data which shows the degree of similarity between the values of the same variables across time. We have tested the serial correlation of residuals using Durbin-Watson test. The test uses the null hypothesis that there is no correlation between residuals and the alternative hypothesis that the residuals are autocorrelated. We did not obtain the $p-value$ less than 0.05 therefore we can consider that our models do not have the serial correlation.

5.1.4 Overdispersion

Overdispersion in count models describes the observation that the variation is larger than the mean. Different distributions are used in order to fix the overdispersion issue. The possible solutions are the Quasi-Poisson model or the Negative binomial regression model.

The simple test of overdispersion is the following :

$$H_0 : Var[y_i] = E[y_i]$$

$$H_a : Var[y_i] = E[y_i] + \alpha g(E[y_i])$$

If the $p-value$ is less than 0.05 we reject the hypothesis of equidispersion.

5.2 Generalized Linear Models

To estimate the impact of DST in the long-run period, the eight weeks from both sides of the spring and autumn transition were chosen. Due to the fact that we have a count data, we have to check what type of generalized linear model will be appropriate for the model evaluation. All the data have been divided by two periods, spring and autumn, and five types of accidents: number of fatal accidents per hour, number of seriously injured accidents per hour, number of slightly injured accidents per hour and number of total accidents per hour.

Due to the fact that fatal crashes should be always reported to the police, we operate with all available observations during 2006-2019 years. Other types of accidents are tested starting from the 2009 year.

To find the impact of the variable $dark$, we have tested the two types of regression models, the simple model without weather variables and the model with the weather and constructed explanatory variables. We have estimated every model using the Poisson regression model, the Quasi-Poisson regression model and the Negative binomial regression model. Due to the fact that our dataset contains a lot of zeros in the response variables we have checked the Zero-inflated regression model but this model was not well fitted to our data. The model with the smallest Akaike information criterion AIC was considered as the best-fitted model. The full results of the estimated models for the spring and autumn periods are present in Appendix.

The descriptive statistics of dependent variables in the spring and autumn periods are present in Table 5.1 and Table 5.2.

Table 5.1: Descriptive statistics for number of accidents in the spring period

Variable	*Min*	*1st Q.*	*Median*	*Mean*	*3rd Q.*	*Max*	*St. Dev.*	*Var*
# fatal	0.00	0.00	0.00	0.061	0.00	4.00	0.249	0.062
# serious	0.00	0.00	0.00	0.244	0.00	8.00	0.532	0.283
# slightly	0.00	0.00	1.00	1.813	3.00	17.00	1.954	3.818
# total	0.00	4.00	7.00	8.493	12.00	62.00	6.106	37.29

5.2.1 Regression results in the spring period

The densities of the fatal, seriously injured, slightly injured and total accidents in the spring period are illustrated in the Figures 5.1 - 5.4.

Table 5.2: Descriptive statistics of number of accidents in autumn period.

Variable	*Min*	*1st Q.*	*Median*	*Mean*	*3rd Q.*	*Max*	*St. Dev.*	*Var*
# fatal	0.00	0.00	0.00	0.083	0.00	3.00	0.292	0.085
# serious	0.00	0.00	0.00	0.274	0.00	5.00	0.563	0.317
# slightly	0.00	0.00	2.00	2.209	3.00	17.00	2.206	4.864
# total	0.00	4.00	9.00	9.914	15.00	54.00	6.927	47.98

The results of our main analysis are presented in the Table 5.3. The first column gives the results of the model without the weather variables. The second column provides us the outcome of the model with additional weather and explanatory variables. The model with the weather variables presents the results with the preferred specification. The results of the estimation of the variable dark are significant with the large negative effect for both models, the number of the observations is the same therefore we can suggest that results are robust to the adding of the weather and explanatory variables.

The effect of darkness increases the number of fatal accidents for a given hour by 61.6 percent, the number of the seriously injured accidents by 31 percent, the slightly injured accidents by 15.6 percent. According to the obtained results, the darkness not only increases the number of crashes but also increases their severity. The total number of traffic accidents per hour is increased by 20.3 percent. The obtained results have the similar behavior of the *dark* variable with the results obtained by Bünnings & Schiele (2018).

Following Bünnings & Schiele (2018) we estimate how many accidents have been caused by darkness for our dataset under the current regime GMT/DST, under the hypothetical situation when the all hours are light, under the all-year GMT regime and under the all-year DST regime. In order to find the number of predicted accidents under the all-year DST and GMT regime, we determine sunrise and sunset times for this situation. We add one hour to the sunrise and sunset time under the GMT regime to obtain the all-year DST and accordingly subtract one hour from the sunrise and sunset time under the DST regime to get all-year GMT time. After deriving the new time for sunrise and sunset, we adjust the variable *dark* and then predict the number of accidents using the estimation results of our model.

The Table 5.4 presents the total accident counts by different time regime. The column *Observed* gives the observed number of accidents, the second col-

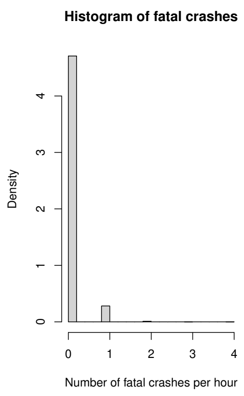


Figure 5.1: The density of fatal accidents.

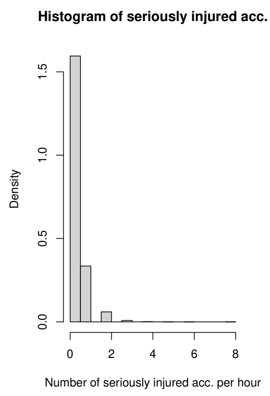


Figure 5.2: The density of seriously injured accidents.

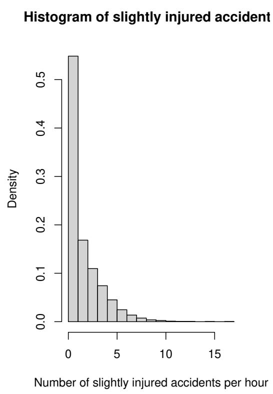


Figure 5.3: The density of slightly injured accidents.

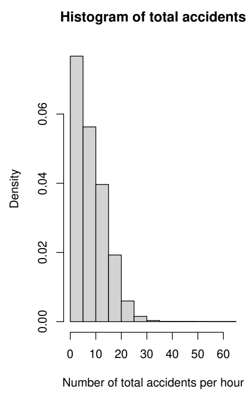


Figure 5.4: The density of total accidents.

umn *GMT/DST* presents the predicted number of accidents under the current regime with spring and autumn time transition, the third column *All hours light* presents the predicted number of accidents in the hypothetical situation when all hours are light, the column *GMT* presents the predicted number of accidents under all-year GMT regime and column *DST* under all-year DST regime.

The difference between predicted values and hypothetical situations when all hours are light gives the effect of the darkness. According to our results, 282 of fatal, 331 seriously injured, 1250 slightly injured and 10049 total traffic accidents have been caused by darkness in the period of 8 weeks from both side of the spring time transition during the 2006-2019 years for fatal accidents and

2009-2019 for the other types of accidents. Moreover, there are 13 less fatal accidents, 21 less serious injured accidents, 54 less slightly injured accidents and 546 less total accidents under all-year DST regime than under all-year GMT regime.

Table 5.3: The estimation of the darkness in the spring period.

		Model without weather variables			Model with weather variables		
		Coef.	*S.E.*	*IRR*	*Coef.*	*S.E.*	*IRR*
dark							
	# fatal	0.448***	(0.069)	1.565	0.482***	(0.117)	1.616
	# serious	0.207***	(0.069)	1.230	0.270***	(0.069)	1.310
	# slight	0.099***	(0.029)	1.104	0.145***	(0.027)	1.156
	# total	0.165***	(0.015)	1.179	0.184***	(0.014)	1.203
Obs.	*fatal*	37,968			37,968		
Obs.	*others*	29,832			29,832		

Table 5.4: Total accident counts by different Time Regime, spring period.

	Observed	*GMT/DST*	*All hours light*	*GMT*	*DST*
Fatal with weather	2308	2308	2026	2320	2307
Serious with weather	7275	7278	6947	7301	7280
Slight with weather	54074	54164	52914	54236	54182
Total with weather	253367	253871	243822	253871	253325

5.2.2 Regression results in the autumn period

The densities of the fatal, seriously injured, slightly injured and total accidents in the autumn period are illustrated on the Figures 5.5 - 5.8.

The results of the estimation of the dark variable in the autumn period are presented in the Table 5.5. The same as in the spring period, the results of the estimation are significant with the large negative effect for both models, without weather variables and including the weather variables.

The effect of darkness increases the number of fatal accidents for a given hour by 88.5 percent, the number of the seriously injured accidents by 37.1 percent, the slightly injured accidents by 23.2 percent. According to the obtained

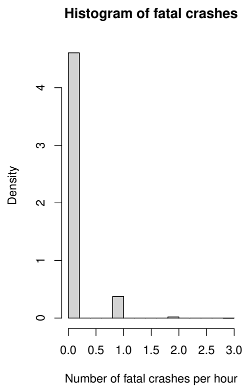


Figure 5.5: The density of fatal accidents.

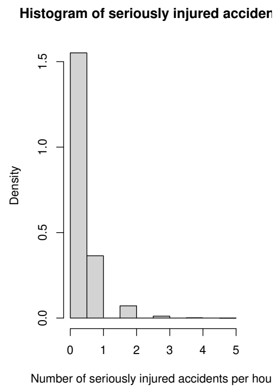


Figure 5.6: The density of seriously injured accidents.

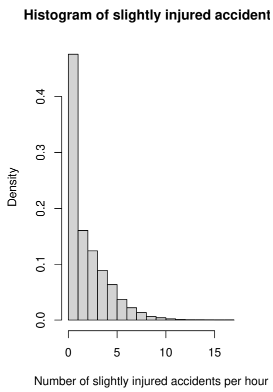


Figure 5.7: The density of slightly injured accidents.

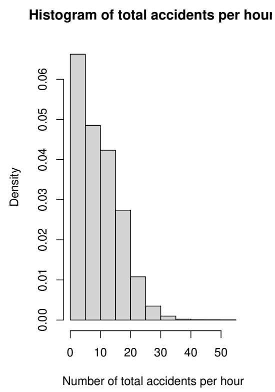


Figure 5.8: The density of total accidents.

results, the darkness not only increases the number of crashes but also increases their severity. The total number of traffic accidents per hour is increased by 32.6 percent. We can notice that the negative impact of darkness is larger in the autumn period when the length of the day becoming smaller.

In order to estimate the impact of darkness and compare it with the different time regimes in the autumn period we implement the same simulation as in the spring period.

The Table 5.6 presents the total accident counts by different time regime. Based on obtained results, 689 of fatal, 707 of seriously injured, 3600 of slightly injured and 24839 of total traffic accidents have been caused by darkness in the period of 8 weeks from both side of the time transition during the 2006-2019

Table 5.5: The estimation of the darkness in the autumn period.

		Model without weather variables			Model with weather variables		
		Coef.	*S.E.*	*IRR*	*Coef.*	*S.E.*	*IRR*
dark							
	# fatal	0.611***	(0.096)	1.843	0.634***	(0.097)	1.885
	# serious	0.298***	(0.060)	1.347	0.316***	(0.060)	1.371
	# slight	0.182***	(0.024)	1.200	0.209***	(0.023)	1.232
	# total	0.283***	(0.024)	1.327	0.282***	(0.013)	1.326
Obs.	*fatal*	37,968			37,968		
Obs.	*others*	29,832			29,832		

years for fatal accidents and 2009-2019 for the other types of accidents. We estimate that there are 21 less fatal accidents, 48 less serious injured accidents, 169 less slightly injured accidents and 1202 less total accidents under all-year DST regime than under all-year GMT regime.

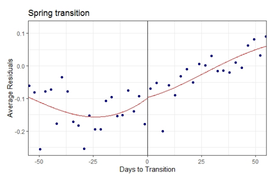
Table 5.6: Total accident counts by different Time Regime, autumn period.

	Observed	*GMT/DST*	*All hours light*	*GMT*	*DST*
Fatal with weather	3158	3158	2469	3168	3147
Serious with weather	8182	8184	7477	8210	8162
Slight with weather	65890	65973	62373	66082	65913
Total with weather	295748	295703	270864	296426	295224

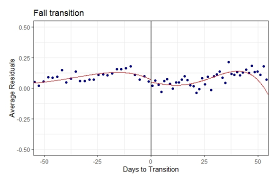
5.3 Regression Discontinuity Results

Based on the assumption that the Regression Discontinuity estimates are valid very locally, the dataset was reduced to 90 days from the both side of the transition date.

The Figure 5.9 illustrates the estimation impact of DST on the total accidents in the Czech Republic starting from 2009. The average residuals from a regression of logged daily total numbers of accidents on day of the week and year fixed effects as dependent variables are plotted centered by the transition date in the spring and the fall period. If DST has an impact on the number of total accidents there should be a shock right at the transition date. The spring transition is associated with 7.1% increase in the total accidents. The estimation results are provided in the Table 5.7 for the transition from the ST to the DST in the spring period, where the time is forwarded for one hour ahead and the day has only 23 hours. The Table A.3 illustrates the results for the fall transition, when the hour is forwarded back and the transition date contains 25 hours.



((a)) Spring transition



((b)) Fall transition

Figure 5.9: Residuals plot of the total number of accidents.

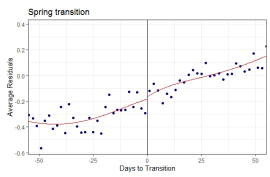
The average residuals generated by the regression of logged daily accident counts on day of the week and year fixed effects as dependent variable.

The first-order polynomial and two different types of kernel functions were used for the estimation. According to Cattaneo *et al.* (2020) the triangular kernel function is preferred but in the same time, the estimation and inference results are not very sensitive to the choice of kernel. The uniform kernel function is widespread in the practice therefore the two functions were used to compare the results. Also the two different types were used for the bandwidth selection. The MSE option one imposes the same bandwidth h on the both side of the cutoff. The MSE option two is the optimal bandwidth selector that can be different on the each side of the cutoff.

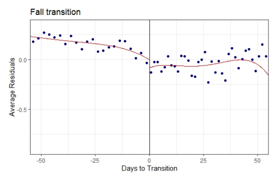
Taking into account that the number of fatal and seriously injured accidents were equal to zero for some observations, the log-transformation with adding of the small constant and square-root transformation were used instead of log-transformation. Comparing the results on the Figure A.3 and Figure A.4 there is no significant changes for seriously injured accidents and fatal accidents, which results are presented in the Figure A.1 and the Figure A.2. Despite the fact that the rules for the registering the road accidents were change in the beginning of 2009, we assume that the fatal crashes have to be reported in any case therefore the fatal crashes were estimated starting from 2006.

Based on the results provided in Table A.3 there is no clear evidence that the transition out of the DST increases the number of all types of accidents, all estimates are not significant. Looking at the Table 5.7 which represents the results from the spring transition, there are two significant estimations at the significance level 5%, thus the spring transition into DST is associated with a 7.1% increase in the total accidents and 12.4% increase in slightly injured accidents. Other choices of kernel function and bandwidth selection are not significant for the number of slightly injured accidents, the impact of the DST transition is also not visible on Figure 5.10 therefore this estimation could be obtained due to inconsistency or the random error.

Figure 5.10: Residuals plot of the slightly injured number of accidents.



((a)) Spring Transition.



((b)) Fall Transition.

The average residuals generated by the regression of logged daily accident counts on day of the week and year fixed effects as dependent variable

Taking into account that the real dataset was adjusted by adding a proxy hour and due to the fact that the estimator for the total number of the accidents during the spring time transition is also significant at 10% level for triangular kernel function and MSE option two, following Smith (2016), the two different adjustment of the dataset were made. Instead of counting two times the number of accidents at 3-4 a.m., the total number of accidents at the transition date was multiplied by 24/23. The results for this adjustment is present in the Table 5.8 and on the Figure 5.11. The second adjustment is to throw out the transition date. The result are in the Table 5.9 and on the Figure 5.12. The same logic was implemented for slightly injured accidents. The result of 24/23 adjustment is present in the Table A.4 and on the Figure A.5, due to insignificance we cannot consider the result of this estimation. The result of drop out the date of the transition is present in the Table A.5 and on the Figure A.6. We obtained the significant impact of DST based on the estimation for the 24/23 adjustment model. We will not consider this result because it can be due to the presence of the random error in the dataset.

Figure 5.11: Residuals plot of the total number of accidents with the adjustment 24/23 at the transition date.

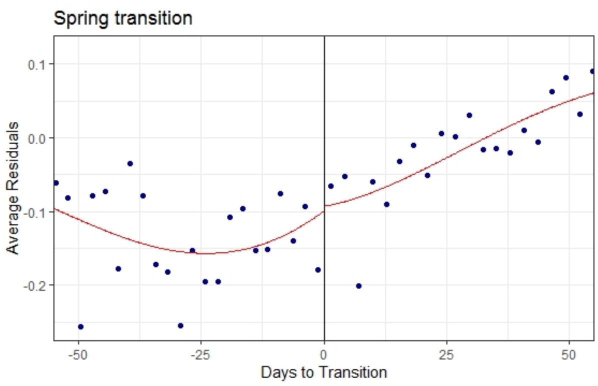
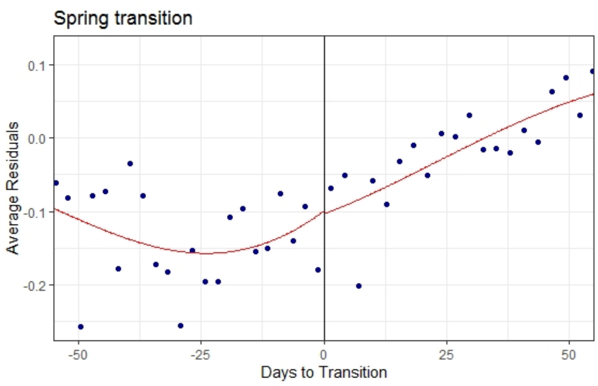


Figure 5.12: Residuals plot of the total number of accidents without the accidents at the transition date.



Taking into account that impact of DST in the spring transition was significant for three different adjustments of the dataset, we can make an assumption that the transition to the DST can increase the number of total accidents per day in the short-run period.

Table 5.7: Regression Discontinuity estimates of DST transition.

	Spring Transition			
Bandwidth selector	one		two	
Kernel	Uniform	Triangular	Uniform	Triangular
ln all accidents	0.028	0.071	0.016	0.059
st. error	0.028	0.036	0.026	0.034
Obs.	451	363	539	551
p-value	0.329	0.047**	0.542	0.079*
ln slightly injured accidents	0.052	0.124	0.059	0.066
st. error	0.054	0.063	0.051	0.058
Obs.	363	341	440	550
p-value	0.342	0.048**	0.244	0.252
ln seriously injured accidents	0.058	0.052	0.057	0.048
st. error	0.094	0.096	0.095	0.094
Obs.	583	715	572	759
p-value	0.536	0.587	0.548	0.609
ln fatal accidents	-0.173	-0.168	-0.169	-0.174
st. error	0.158	0.142	0.137	0.136
Obs.	350	518	476	588
p-value	0.274	0.237	0.215	0.203
sqrt seriously injured accidents	0.086	0.081	0.086	0.071
st. error	0.110	0.113	0.110	0.109
Obs.	561	693	581	737
p-value	0.432	0.473	0.432	0.512
sqrt fatal accidents	-0.143	-0.143	-0.143	-0.150
st. error	0.134	0.121	0.116	0.117
Obs.	350	518	476	588
p-value	0.286	0.237	0.218	0.197

Table 5.8: Regression Discontinuity estimates of DST transition for the total number of accidents, 24/23 adjustment.

	Spring Transition			
Bandwidth selector	one		two	
Kernel	Uniform	Triangular	Uniform	Triangular
ln all accidents	0.030	0.075	0.020	0.065
st. error	0.028	0.036	0.027	0.034
Obs.	451	363	517	429
p-value	0.282	0.036**	0.459	0.056**

Table 5.9: Regression Discontinuity estimates of DST transition for the total number of accidents without the accidents at the transition date.

	Spring Transition			
Bandwidth selector	one		two	
Kernel	Uniform	Triangular	Uniform	Triangular
ln all accidents	0.023	0.073	0.015	0.051
st. error	0.031	0.039	0.027	0.034
Obs.	418	352	528	551
p-value	0.465	0.060*	0.568	0.133

Chapter 6

Conclusion

Many countries use the Daily Saving Time (DST) in order to save energy and to improve the matching of daylight hours with the people's activities. The continuous debates regarding the efficiency of DST policy lead to the further investigation and contradictory results in this field.

This thesis aimed to determine the effect of DST policy on traffic safety in the Czech Republic and contribute to the existing literature on this topic. All previous studies can be divided into three groups. One group focuses only on sleep disruption, the second group focuses on the impact of ambient light and the third group focuses on the impact of both, sleep disruption, and ambient light. Following the discussion on the effect of transition into and out of DST, we divided our hypotheses for two periods of time - short run period and long run period. The effect of DST policy in the short run period was estimated by the Regression Discontinuity Design. The approach was based on the intuition that if there is a significant impact of DST there should be a shock around the transition date. The long run period was estimated by the Poisson regression model and the Negative Binomial regression model. In the long run period, we estimated how darkness affects the number of traffic accidents and then the estimates were used to simulate the impact of darkness under the different time regimes.

We find that the transition from standard time to DST can increase the total number of accidents per day by 7.1 percent in the short run period. We find that darkness has a significant impact on traffic safety in the long run period. We notice that the negative impact of darkness is larger in the autumn period than the length of day is small. The darkness caused 282 fatal, 331 seriously injured, 1250 slightly injured and 10049 total traffic accidents in the period 8 weeks from both sides of spring transition during 2009-2019. The change to the all-year DST regime could decrease the number of crashes by 13 for fatal accidents, by 21 for seriously injured accidents, by 54 for slightly injured accidents and by 546 for total accidents during 2009-2019 (2006 - 2019 for fatal crashes).

The number of accidents caused by darkness in the autumn period is almost three times higher than in the spring period and equal to 689 fatal, 707 seriously injured, 3600 slightly injured and 24839 total traffic accidents. We estimate that there are 21 fewer fatal accidents, 48 fewer serious injured accidents, 169 fewer slightly injured accidents and 1202 fewer total accidents under all-year DST regime than under all-year GMT regime in the period 8 weeks from both sides of autumn transition during 2009-2019 (2006 - 2019 for fatal crashes).

The findings of this study can be used in further researches and the results can be compared. The estimated model might be improved by including such explanatory variables as a volume of road traffic, price of gasoline. The future researcher might consider the full dataset without limitation to the spring and autumn period.

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Appendix A

Title of Appendix A

A.1 Supplementary tables

Table A.1: Dates of Daylight Saving Time in the Czech Republic

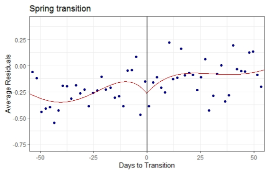
$Year$	$Spring(DSTbegins)$	$Autumn(DSTends)$
2006	26/03	29/10
2007	25/03	28/10
2008	30/03	26/10
2009	29/03	25/10
2010	28/03	31/10
2011	27/03	30/10
2012	25/03	28/10
2013	31/03	27/10
2014	30/03	26/10
2015	29/03	25/10
2016	27/03	30/10
2017	26/03	29/10
2018	25/03	28/10
2019	31/03	27/10

Table A.2: Stationarity assumption. Result of Augmented Dickey-Fuller test and Philips-Perron test test.

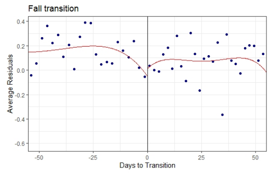
	Augmented Dickey-Fuller test		Phillips-Perron test	
Variable	*Dickey-Fuller*	*p-value*	*Dickey-Fuller Z(alpha)*	*p-value*
Number of fatal accidents	-31.762	0.01	-38190	0.01
Number of seriously injured accidents	-26.257	0.01	-36702	0.01
Number of slightly injured accidents	-24.396	0.01	-18992	0.01
Number of total accidents	-16.489	0.01	-5374.9	0.01
Pedestrian crashes	-24.799	0.01	-23133	0.01
Dark	-4.5954	0.01	-2688.7	0.01
Relative Humidity	-20.225	0.01	-1771.2	0.01
Sea Level Pressure	-12.64	0.01	-313.63	0.01
Precipitation	-27.907	0.01	-26044	0.01
cause intoxication	-23.19	0.01	-35664	0.01
cause car defect	-28.42	0.01	-29385	0.01
cause damaged road	-30.63	0.01	-30020	0.01

A.2 RDD

Figure A.1: Residuals plot of the fatal accidents, log transformation.



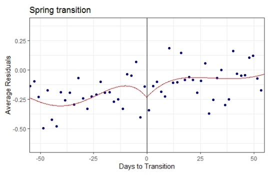
((a)) Spring Transition.



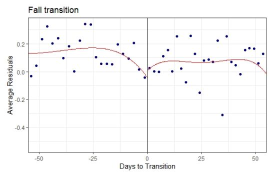
((b)) Fall Transition.

The average residuals generated by the regression of logged daily accident counts with a small constant on day of the week and year fixed effects as dependent variable

Figure A.2: Residuals plot for the fatal accidents, square-root transformation.



((a)) Spring Transition.



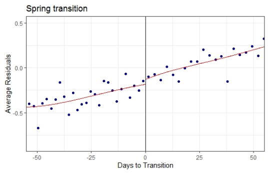
((b)) Fall Transition.

The average residuals generated by the regression of square-root transformation of daily accident counts on day of the week and year fixed effects as dependent variable

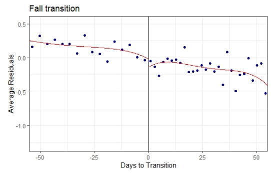
Table A.3: Regression Discontinuity estimates of DST transition in the autumn period.

	Fall Transition			
Bandwidth selector	one		two	
Kernel	Uniform	Triangular	Uniform	Triangular
ln all accidents	-0.008	-0.022	-0.025	-0.024
st. error	0.049	0.052	0.045	0.050
Obs.	253	297	275	319
p-value	0.871	0.669	0.582	0.631
ln slightly injured accidents	-0.047	-0.065	-0.059	-0.064
st. error	0.070	0.075	0.066	0.070
Obs.	253	299	275	330
p-value	0.505	0.387	0.370	0.355
ln seriously injured accidents	-0.003	-0.028	-0.109	-0.097
st. error	0.121	0.116	0.096	0.094
Obs.	231	319	320	440
p-value	0.977	0.807	0.256	0.304
ln fatal accidents	0.017	0.046	-0.029	-0.012
st. error	0.152	0.146	0.137	0.127
Obs.	406	518	476	700
p-value	0.909	0.752	0.833	0.925
sqrt seriously injured accidents	-0.066	-0.019	-0.186	-0.126
st. error	0.137	0.140	0.117	0.114
Obs.	275	319	352	451
p-value	0.632	0.894	0.112	0.269
sqrt fatal accidents	0.009	0.035	-0.028	-0.012
st. error	0.132	0.127	0.119	0.110
Obs.	406	518	476	700
p-value	0.946	0.780	0.814	0.914

Figure A.3: Residuals plot of the seriously injured accidents, log transformation.



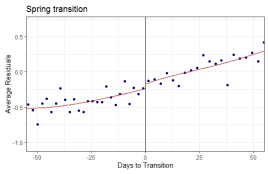
((a)) Spring Transition.



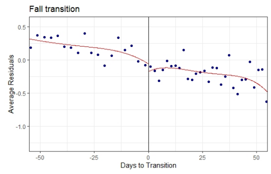
((b)) Fall Transition.

The average residuals generated by the regression of logged daily accident counts with a small constant on day of the week and year fixed effects as dependent variable

Figure A.4: Residuals plot for the seriously injured accidents, square-root transformation.



((a)) Spring Transition.



((b)) Fall Transition.

The average residuals generated by the regression of square-root transformation of daily accident counts on day of the week and year fixed effects as dependent variable

Table A.4: Regression Discontinuity estimates of DST transition for slightly injured accidents, 24/23 adjustment.

	Spring Transition			
Bandwidth selector	one		two	
Kernel	Uniform	Triangular	Uniform	Triangular
ln slightly injured accidents	-1.363	-2.211	-2.073	-2.678
st. error	0.109	0.173	0.070	0.080
Obs.	121	99	220	198
p-value	0.317	0.153	0.407	0.369

Table A.5: Regression Discontinuity estimates of DST transition for the slightly injured accidents without the accidents at the transition date.

	Spring Transition			
Bandwidth selector	one		two	
Kernel	Uniform	Triangular	Uniform	Triangular
ln slightly injured accidents	0.062	0.122	0.058	0.055
st. error	0.057	0.069	0.057	0.061
Obs.	374	330	385	473
p-value	0.283	0.076*	0.309	0.369

Figure A.5: Residuals plot of the slightly injured accidents with the adjustment 24/23 at the transition date.

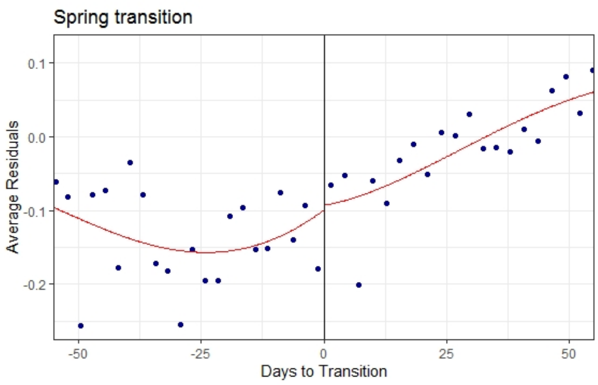
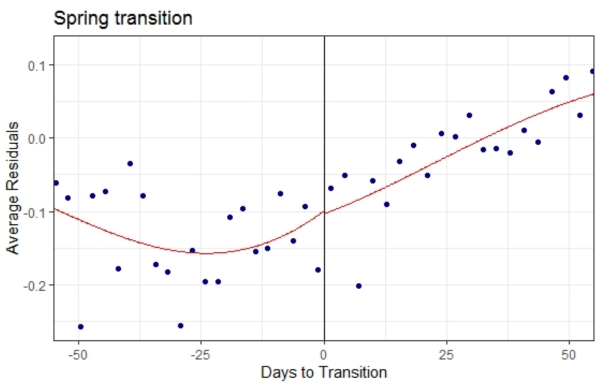


Figure A.6: Residuals plot of the slightly injured accidents without the accidents at the transition date.



A.3 The results of GLM for fatal crashes

Table A.6: The results of regression models for fatal accidents without weather variables in the spring period.

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.448***	0.448***	0.448***
	(0.114)	(0.114)	(0.115)
hour01	0.134	0.134	0.133
	(0.196)	(0.196)	(0.196)
hour02	0.007	0.007	0.007
	(0.202)	(0.202)	(0.202)
hour03	0.033	0.033	0.033
	(0.200)	(0.200)	(0.200)
hour04	0.069	0.069	0.069
	(0.200)	(0.200)	(0.200)
hour05	0.665***	0.665***	0.664***
	(0.186)	(0.186)	(0.187)
hour06	1.176***	1.176***	1.177***
	(0.195)	(0.195)	(0.196)
hour07	1.066***	1.066***	1.067***
	(0.211)	(0.211)	(0.211)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour08	1.141***	1.141***	1.141***
	(0.209)	(0.209)	(0.209)
hour09	1.089***	1.089***	1.089***
	(0.210)	(0.210)	(0.211)
hour10	1.229***	1.229***	1.229***
	(0.207)	(0.207)	(0.207)
hour11	1.067***	1.067***	1.067***
	(0.211)	(0.211)	(0.211)
hour12	1.110***	1.110***	1.110***
	(0.210)	(0.210)	(0.210)
hour13	1.446***	1.446***	1.447***
	(0.202)	(0.202)	(0.203)
hour14	1.619***	1.619***	1.619***
	(0.199)	(0.200)	(0.200)
hour15	1.580***	1.580***	1.580***
	(0.200)	(0.200)	(0.201)
hour16	1.431***	1.431***	1.431***
	(0.203)	(0.203)	(0.203)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour17	1.473***	1.473***	1.472***
	(0.199)	(0.199)	(0.200)
hour18	1.320***	1.320***	1.319***
	(0.183)	(0.183)	(0.184)
hour19	1.151***	1.151***	1.151***
	(0.178)	(0.178)	(0.178)
hour20	0.766***	0.766***	0.765***
	(0.182)	(0.182)	(0.182)
hour21	0.589***	0.589***	0.589***
	(0.179)	(0.179)	(0.179)
hour22	0.465**	0.465**	0.465**
	(0.182)	(0.182)	(0.183)
hour23	0.235	0.235	0.235
	(0.191)	(0.191)	(0.191)
day1	0.032	0.032	0.032
	(0.080)	(0.080)	(0.080)
day2	0.067	0.067	0.067
	(0.079)	(0.079)	(0.079)
day3	−0.114	−0.114	−0.114

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.083)	(0.083)	(0.083)
day4	0.057	0.057	0.057
	(0.079)	(0.079)	(0.079)
day5	0.177**	0.177**	0.177**
	(0.077)	(0.077)	(0.077)
day6	0.252***	0.252***	0.253***
	(0.075)	(0.075)	(0.076)
week6	0.080	0.080	0.080
	(0.150)	(0.151)	(0.151)
week7	−0.086	−0.086	−0.086
	(0.155)	(0.155)	(0.156)
week8	0.093	0.093	0.093
	(0.151)	(0.151)	(0.151)
week9	0.088	0.088	0.088
	(0.151)	(0.152)	(0.152)
week10	0.152	0.152	0.153
	(0.150)	(0.150)	(0.151)
week11	0.124	0.124	0.124
	(0.152)	(0.152)	(0.152)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week12	0.290**	0.290*	0.291*
	(0.148)	(0.148)	(0.148)
week13	0.137	0.137	0.138
	(0.152)	(0.152)	(0.153)
week14	0.308**	0.308**	0.308**
	(0.149)	(0.149)	(0.150)
week15	0.459***	0.459***	0.459***
	(0.147)	(0.147)	(0.147)
week16	0.401***	0.401***	0.401***
	(0.148)	(0.148)	(0.149)
week17	0.337**	0.337**	0.337**
	(0.150)	(0.150)	(0.150)
week18	0.343**	0.343**	0.343**
	(0.150)	(0.150)	(0.151)
week19	0.400***	0.400***	0.400***
	(0.149)	(0.150)	(0.150)
week20	0.478***	0.478***	0.478***
	(0.148)	(0.148)	(0.149)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week21	0.355**	0.355**	0.355**
	(0.168)	(0.168)	(0.169)
year2007	0.083	0.083	0.083
	(0.090)	(0.090)	(0.090)
year2008	0.011	0.011	0.011
	(0.091)	(0.091)	(0.092)
year2009	−0.203**	−0.203**	−0.204**
	(0.096)	(0.096)	(0.097)
year2010	−0.532***	−0.532***	−0.532***
	(0.106)	(0.106)	(0.107)
year2011	−0.379***	−0.379***	−0.379***
	(0.101)	(0.101)	(0.102)
year2012	−0.415***	−0.415***	−0.415***
	(0.103)	(0.103)	(0.103)
year2013	−0.537***	−0.537***	−0.537***
	(0.106)	(0.106)	(0.107)
year2014	−0.528***	−0.528***	−0.528***
	(0.106)	(0.106)	(0.106)
year2015	−0.526***	−0.526***	−0.526***

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	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.106)	(0.106)	(0.106)
year2016	−0.591***	−0.591***	−0.591***
	(0.108)	(0.108)	(0.109)
year2017	−0.794***	−0.794***	−0.794***
	(0.116)	(0.116)	(0.116)
year2018	−0.721***	−0.721***	−0.721***
	(0.113)	(0.113)	(0.113)
year2019	−0.658***	−0.658***	−0.658***
	(0.111)	(0.111)	(0.111)
Constant	−3.869***	−3.869***	−3.870***
	(0.243)	(0.243)	(0.243)
Observations	37,968	37,968	37,968
Log Likelihood	−8,565.546		−8,566.238
θ			12.093 (15.953)
Akaike Inf. Crit.	17,251.090		17,252.480
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.7: IRR of the best-fitted regression model for the fatal accidents without weather variables in the spring period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	-3.869	0.170	0	0.021
dark	0.448	0.069	0	1.565
hour01	0.134	0.162	0.409	1.143
hour02	0.007	0.167	0.965	1.007
hour03	0.033	0.186	0.860	1.033
hour04	0.069	0.165	0.676	1.072
hour05	0.665	0.138	0	1.944
hour06	1.176	0.142	0	3.243
hour07	1.066	0.143	0	2.905
hour08	1.141	0.145	0	3.130
hour09	1.089	0.144	0	2.970
hour10	1.229	0.144	0	3.417
hour11	1.067	0.144	0	2.906
hour12	1.110	0.143	0	3.034
hour13	1.446	0.142	0	4.248
hour14	1.619	0.141	0	5.046
hour15	1.580	0.141	0	4.855
hour16	1.431	0.142	0	4.184
hour17	1.473	0.142	0	4.360
hour18	1.320	0.134	0	3.742
hour19	1.151	0.134	0	3.161
hour20	0.766	0.137	0	2.151
hour21	0.589	0.139	0	1.803
hour22	0.465	0.143	0.001	1.592
hour23	0.235	0.157	0.133	1.265
day1	0.032	0.048	0.501	1.033
day2	0.067	0.048	0.166	1.069
day3	-0.114	0.047	0.016	0.892
day4	0.057	0.047	0.229	1.059
day5	0.177	0.046	0	1.193

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	Estimate	Robust SE	Pr(>|z|)	IRR
day6	0.252	0.048	0	1.287
week6	0.080	0.097	0.409	1.083
week7	-0.086	0.096	0.370	0.918
week8	0.093	0.097	0.339	1.098
week9	0.088	0.097	0.364	1.092
week10	0.152	0.095	0.107	1.165
week11	0.124	0.095	0.192	1.132
week12	0.290	0.094	0.002	1.337
week13	0.137	0.094	0.146	1.147
week14	0.308	0.094	0.001	1.361
week15	0.459	0.094	0	1.582
week16	0.401	0.093	0	1.493
week17	0.337	0.092	0	1.401
week18	0.343	0.093	0	1.409
week19	0.400	0.092	0	1.492
week20	0.478	0.092	0	1.613
week21	0.355	0.096	0	1.426
year2007	0.083	0.054	0.126	1.086
year2008	0.011	0.052	0.831	1.011
year2009	-0.203	0.053	0	0.816
year2010	-0.532	0.054	0	0.588
year2011	-0.379	0.053	0	0.684
year2012	-0.415	0.055	0	0.661
year2013	-0.537	0.054	0	0.585
year2014	-0.528	0.057	0	0.590
year2015	-0.526	0.056	0	0.591
year2016	-0.591	0.058	0	0.554
year2017	-0.794	0.170	0	0.452
year2018	-0.721	0.069	0	0.486
year2019	-0.658	0.162	0	0.518

Table A.8: The results of the regression models for fatal accidents with weather and explanatory variables in the spring period.

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.482***	0.482***	0.482***
	(0.115)	(0.114)	(0.115)
holiday1	0.063	0.063	0.062
	(0.123)	(0.122)	(0.124)
TMP_less_zero1	−0.470***	−0.470***	−0.470***
	(0.116)	(0.115)	(0.116)
TMP_less_five1	−0.465***	−0.465***	−0.465***
	(0.094)	(0.094)	(0.095)
TMP_less_ten1	−0.384***	−0.384***	−0.384***
	(0.078)	(0.077)	(0.078)
TMP_less_fifteen1	−0.320***	−0.320***	−0.321***
	(0.070)	(0.069)	(0.070)
mist1	−0.097	−0.097	−0.097
	(0.081)	(0.080)	(0.081)
fog1	−0.195	−0.195	−0.195
	(0.307)	(0.304)	(0.307)
drizzle1	0.295	0.295	0.295

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	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.358)	(0.354)	(0.358)
rain1	0.159	0.159	0.159
	(0.102)	(0.101)	(0.102)
snow1	−0.115	−0.115	−0.115
	(0.152)	(0.151)	(0.152)
precipitation1	−0.070	−0.070	−0.070
	(0.097)	(0.096)	(0.097)
crash_into_solid_obstacle	0.089***	0.089***	0.089***
	(0.010)	(0.010)	(0.010)
cause_intoxication	0.135***	0.135***	0.135***
	(0.023)	(0.023)	(0.023)
cause_damaged_road	−0.049	−0.049	−0.049
	(0.079)	(0.079)	(0.079)
cause_car_defect	−0.142*	−0.142*	−0.141*
	(0.074)	(0.073)	(0.074)
hour01	0.165	0.165	0.165
	(0.196)	(0.194)	(0.196)
hour02	0.059	0.059	0.059
	(0.202)	(0.200)	(0.202)

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	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour03	0.098	0.098	0.098
	(0.200)	(0.198)	(0.200)
hour04	0.160	0.160	0.160
	(0.201)	(0.199)	(0.201)
hour05	0.719***	0.719***	0.719***
	(0.186)	(0.185)	(0.187)
hour06	1.201***	1.201***	1.201***
	(0.196)	(0.194)	(0.196)
hour07	1.070***	1.070***	1.070***
	(0.213)	(0.211)	(0.214)
hour08	1.154***	1.154***	1.155***
	(0.211)	(0.209)	(0.212)
hour09	1.089***	1.089***	1.090***
	(0.212)	(0.210)	(0.212)
hour10	1.187***	1.187***	1.187***
	(0.209)	(0.207)	(0.209)
hour11	0.996***	0.996***	0.996***
	(0.212)	(0.210)	(0.213)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour12	1.026***	1.026***	1.027***
	(0.211)	(0.209)	(0.211)
hour13	1.317***	1.317***	1.317***
	(0.204)	(0.202)	(0.204)
hour14	1.445***	1.445***	1.445***
	(0.201)	(0.199)	(0.202)
hour15	1.399***	1.399***	1.399***
	(0.202)	(0.200)	(0.202)
hour16	1.232***	1.232***	1.232***
	(0.204)	(0.202)	(0.205)
hour17	1.291***	1.291***	1.291***
	(0.200)	(0.199)	(0.201)
hour18	1.159***	1.159***	1.159***
	(0.185)	(0.183)	(0.185)
hour19	1.003***	1.003***	1.003***
	(0.179)	(0.177)	(0.179)
hour20	0.664***	0.664***	0.664***
	(0.182)	(0.180)	(0.182)
hour21	0.488***	0.488***	0.488***

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	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.180)	(0.178)	(0.180)
hour22	0.401**	0.401**	0.401**
	(0.182)	(0.181)	(0.183)
hour23	0.189	0.189	0.189
	(0.191)	(0.189)	(0.191)
day1	0.035	0.035	0.035
	(0.081)	(0.080)	(0.081)
day2	0.087	0.087	0.087
	(0.080)	(0.079)	(0.080)
day3	−0.086	−0.086	−0.086
	(0.083)	(0.083)	(0.084)
day4	0.066	0.066	0.067
	(0.080)	(0.079)	(0.080)
day5	0.147*	0.147*	0.148*
	(0.077)	(0.076)	(0.077)
day6	0.194**	0.194***	0.194**
	(0.076)	(0.075)	(0.076)
week6	0.009	0.009	0.009
	(0.152)	(0.150)	(0.152)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week7	−0.126	−0.126	−0.126
	(0.156)	(0.155)	(0.156)
week8	0.052	0.052	0.052
	(0.153)	(0.151)	(0.153)
week9	0.035	0.035	0.036
	(0.154)	(0.153)	(0.155)
week10	0.086	0.086	0.086
	(0.154)	(0.152)	(0.154)
week11	0.044	0.044	0.044
	(0.156)	(0.154)	(0.156)
week12	0.193	0.193	0.193
	(0.153)	(0.151)	(0.153)
week13	0.009	0.009	0.010
	(0.160)	(0.158)	(0.160)
week14	0.155	0.155	0.155
	(0.158)	(0.157)	(0.158)
week15	0.265*	0.265*	0.265*
	(0.158)	(0.156)	(0.158)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week16	0.182	0.182	0.182
	(0.160)	(0.159)	(0.160)
week17	0.053	0.053	0.053
	(0.165)	(0.163)	(0.165)
week18	0.054	0.054	0.054
	(0.166)	(0.164)	(0.166)
week19	0.074	0.074	0.075
	(0.168)	(0.167)	(0.168)
week20	0.131	0.131	0.131
	(0.165)	(0.164)	(0.165)
week21	−0.021	−0.021	−0.021
	(0.184)	(0.183)	(0.185)
year2007	0.084	0.084	0.084
	(0.093)	(0.092)	(0.093)
year2008	0.062	0.062	0.062
	(0.094)	(0.093)	(0.094)
year2009	−0.092	−0.092	−0.092
	(0.100)	(0.099)	(0.100)
year2010	−0.354***	−0.354***	−0.354***

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.109)	(0.108)	(0.109)
year2011	−0.250**	−0.250**	−0.250**
	(0.104)	(0.103)	(0.105)
year2012	−0.298***	−0.298***	−0.298***
	(0.105)	(0.104)	(0.105)
year2013	−0.380***	−0.380***	−0.380***
	(0.108)	(0.107)	(0.108)
year2014	−0.412***	−0.412***	−0.412***
	(0.110)	(0.109)	(0.110)
year2015	−0.366***	−0.366***	−0.366***
	(0.109)	(0.108)	(0.109)
year2016	−0.451***	−0.451***	−0.451***
	(0.112)	(0.111)	(0.112)
year2017	−0.667***	−0.667***	−0.667***
	(0.119)	(0.118)	(0.119)
year2018	−0.655***	−0.655***	−0.655***
	(0.116)	(0.115)	(0.116)
year2019	−0.562***	−0.562***	−0.562***
	(0.114)	(0.113)	(0.114)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
Constant	-3.682^{***}	-3.682^{***}	-3.683^{***}
	(0.266)	(0.264)	(0.267)
Observations	37,968	37,968	37,968
Log Likelihood	−8,481.533		−8,482.478
θ			29.610 (90.126)
Akaike Inf. Crit.	17,113.070		17,114.960
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.9: IRR of the best-fitted regression model for the fatal accidents with weather and explanatory variables in the spring period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	-3.682	0.266	0	-97.484
dark	0.482	0.117	0	61.914
holiday1	0.063	0.122	0.606	6.500
TMP_less_zero1	-0.470	0.117	0	-37.518
TMP_less_five1	-0.465	0.095	0	-37.162
TMP_less_ten1	-0.384	0.080	0	-31.898
TMP_less_fifteen1	-0.320	0.070	0	-27.416
mist1	-0.097	0.080	0.224	-9.255
fog1	-0.195	0.328	0.553	-17.695
drizzle1	0.295	0.345	0.392	34.344
rain1	0.159	0.099	0.110	17.203

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
snow1	-0.115	0.153	0.452	-10.837
precipitation1	-0.070	0.092	0.448	-6.758
crash_into_solid_obstacle	0.089	0.010	0	9.347
cause_intoxication	0.135	0.023	0	14.458
cause_damaged_road	-0.049	0.077	0.530	-4.741
cause_car_defect	-0.142	0.074	0.054	-13.196
hour01	0.165	0.194	0.395	17.981
hour02	0.059	0.202	0.771	6.074
hour03	0.098	0.197	0.617	10.327
hour04	0.160	0.199	0.421	17.352
hour05	0.719	0.183	0	105.188
hour06	1.201	0.194	0	232.276
hour07	1.070	0.211	0	191.417
hour08	1.154	0.211	0	217.140
hour09	1.089	0.210	0	197.272
hour10	1.187	0.207	0	227.881
hour11	0.996	0.211	0	170.637
hour12	1.026	0.212	0	179.042
hour13	1.317	0.202	0	273.282
hour14	1.445	0.200	0	324.028
hour15	1.399	0.201	0	304.991
hour16	1.232	0.203	0	242.821
hour17	1.291	0.201	0	263.634
hour18	1.159	0.185	0	218.730
hour19	1.003	0.176	0	172.625
hour20	0.664	0.181	0	94.273
hour21	0.488	0.181	0.007	62.901
hour22	0.401	0.180	0.026	49.334
hour23	0.189	0.189	0.317	20.855
day1	0.035	0.080	0.661	3.590
day2	0.087	0.079	0.274	9.092
day3	-0.086	0.085	0.308	-8.259
day4	0.066	0.080	0.405	6.871

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
day5	0.147	0.078	0.058	15.881
day6	0.194	0.076	0.011	21.380
week6	0.009	0.152	0.955	0.871
week7	-0.126	0.156	0.420	-11.823
week8	0.052	0.154	0.737	5.303
week9	0.035	0.153	0.817	3.608
week10	0.086	0.154	0.577	8.951
week11	0.044	0.157	0.779	4.502
week12	0.193	0.154	0.210	21.239
week13	0.009	0.161	0.953	0.953
week14	0.155	0.158	0.328	16.747
week15	0.265	0.158	0.095	30.310
week16	0.182	0.161	0.259	19.939
week17	0.053	0.166	0.752	5.393
week18	0.054	0.165	0.744	5.555
week19	0.074	0.171	0.665	7.696
week20	0.131	0.165	0.430	13.943
week21	-0.021	0.185	0.909	-2.103
year2007	0.084	0.096	0.382	8.747
year2008	0.062	0.097	0.522	6.414
year2009	-0.092	0.102	0.367	-8.795
year2010	-0.354	0.109	0.001	-29.806
year2011	-0.250	0.105	0.018	-22.114
year2012	-0.298	0.106	0.005	-25.802
year2013	-0.380	0.110	0.001	-31.603
year2014	-0.412	0.112	0	-33.752
year2015	-0.366	0.114	0.001	-30.644
year2016	-0.451	0.115	0	-36.274
year2017	-0.667	0.119	0	-48.650
year2018	-0.655	0.116	0	-48.049
year2019	-0.562	0.116	0	-42.985

Table A.10: The results of regression model for fatal accidents without weather variables in the autumn period.

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.611***	0.611***	0.611***
	(0.097)	(0.098)	(0.098)
hour01	−0.000	−0.000	−0.00004
	(0.174)	(0.175)	(0.174)
hour02	−0.047	−0.047	−0.046
	(0.176)	(0.177)	(0.176)
hour03	−0.201	−0.201	−0.201
	(0.183)	(0.184)	(0.184)
hour04	−0.015	−0.015	−0.015
	(0.175)	(0.175)	(0.175)
hour05	0.808***	0.808***	0.808***
	(0.148)	(0.149)	(0.148)
hour06	1.380***	1.380***	1.380***
	(0.145)	(0.145)	(0.145)
hour07	1.290***	1.290***	1.290***
	(0.177)	(0.177)	(0.177)
hour08	1.175***	1.175***	1.175***

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.182)	(0.183)	(0.183)
hour09	1.242***	1.242***	1.242***
	(0.181)	(0.181)	(0.181)
hour10	1.274***	1.274***	1.274***
	(0.180)	(0.181)	(0.180)
hour11	1.274***	1.274***	1.274***
	(0.180)	(0.181)	(0.180)
hour12	1.363***	1.363***	1.363***
	(0.178)	(0.179)	(0.178)
hour13	1.540***	1.540***	1.540***
	(0.175)	(0.175)	(0.175)
hour14	1.620***	1.620***	1.620***
	(0.174)	(0.174)	(0.174)
hour15	1.569***	1.569***	1.569***
	(0.174)	(0.175)	(0.175)
hour16	1.725***	1.725***	1.724***
	(0.166)	(0.167)	(0.166)
hour17	1.538***	1.538***	1.538***
	(0.146)	(0.147)	(0.147)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour18	1.327***	1.327***	1.327***
	(0.147)	(0.148)	(0.147)
hour19	0.931***	0.931***	0.931***
	(0.149)	(0.149)	(0.149)
hour20	0.803***	0.803***	0.803***
	(0.148)	(0.149)	(0.148)
hour21	0.343**	0.343**	0.343**
	(0.161)	(0.161)	(0.161)
hour22	0.425***	0.425***	0.425***
	(0.158)	(0.159)	(0.158)
hour23	0.114	0.114	0.114
	(0.169)	(0.170)	(0.169)
day1	0.073	0.073	0.073
	(0.068)	(0.068)	(0.068)
day2	0.023	0.023	0.023
	(0.069)	(0.069)	(0.069)
day3	0.098	0.098	0.098
	(0.068)	(0.068)	(0.068)

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	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
day4	0.050	0.050	0.050
	(0.069)	(0.069)	(0.069)
day5	0.191***	0.191***	0.191***
	(0.066)	(0.066)	(0.066)
day6	0.205***	0.205***	0.205***
	(0.066)	(0.066)	(0.066)
week36	0.095	0.095	0.095
	(0.257)	(0.258)	(0.258)
week37	0.304	0.304	0.304
	(0.254)	(0.255)	(0.254)
week38	0.209	0.209	0.209
	(0.255)	(0.255)	(0.255)
week39	0.157	0.157	0.157
	(0.255)	(0.256)	(0.255)
week40	0.234	0.234	0.234
	(0.254)	(0.255)	(0.255)
week41	0.123	0.123	0.123
	(0.255)	(0.256)	(0.256)
week42	0.092	0.092	0.092

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.256)	(0.256)	(0.256)
week43	−0.002	−0.002	−0.002
	(0.257)	(0.257)	(0.257)
week44	0.061	0.061	0.061
	(0.256)	(0.257)	(0.256)
week45	−0.029	−0.029	−0.029
	(0.257)	(0.258)	(0.257)
week46	0.015	0.015	0.016
	(0.257)	(0.257)	(0.257)
week47	−0.007	−0.007	−0.007
	(0.257)	(0.258)	(0.257)
week48	0.013	0.013	0.013
	(0.257)	(0.257)	(0.257)
week49	−0.014	−0.014	−0.014
	(0.257)	(0.258)	(0.257)
week50	0.003	0.003	0.003
	(0.257)	(0.258)	(0.257)
week51	−0.055	−0.055	−0.055
	(0.258)	(0.259)	(0.258)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week52	−0.378	−0.378	−0.377
	(0.317)	(0.318)	(0.317)
year2007	0.062	0.062	0.062
	(0.078)	(0.078)	(0.078)
year2008	−0.061	−0.061	−0.061
	(0.080)	(0.081)	(0.081)
year2009	−0.191**	−0.191**	−0.191**
	(0.083)	(0.084)	(0.084)
year2010	−0.239***	−0.239***	−0.239***
	(0.085)	(0.085)	(0.085)
year2011	−0.420***	−0.420***	−0.420***
	(0.089)	(0.089)	(0.089)
year2012	−0.408***	−0.408***	−0.408***
	(0.089)	(0.089)	(0.089)
year2013	−0.599***	−0.599***	−0.599***
	(0.094)	(0.094)	(0.094)
year2014	−0.484***	−0.484***	−0.484***
	(0.091)	(0.091)	(0.091)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
year2015	−0.405***	−0.405***	−0.405***
	(0.089)	(0.089)	(0.089)
year2016	−0.612***	−0.612***	−0.613***
	(0.095)	(0.095)	(0.095)
year2017	−0.684***	−0.684***	−0.684***
	(0.097)	(0.097)	(0.097)
year2018	−0.586***	−0.586***	−0.586***
	(0.094)	(0.094)	(0.094)
year2019	−0.656***	−0.656***	−0.656***
	(0.096)	(0.096)	(0.096)
Constant	−3.610***	−3.610***	−3.610***
	(0.292)	(0.293)	(0.292)
Observations	37,968	37,968	37,968
Log Likelihood	−10,748.050		−10,749.000
θ			39.737 (125.932)
Akaike Inf. Crit.	21,618.100		21,620.000
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.11: IRR of the best-fitted regression model for the fatal accidents without weather variables in the autumn period.

	Estimate	Robust SE	Pr(>|z|)	exp
(Intercept)	-3.610	0.294	0	0.027
dark	0.611	0.096	0	1.843
hour01	0	0.173	1	1
hour02	-0.047	0.178	0.794	0.955
hour03	-0.201	0.185	0.278	0.818
hour04	-0.015	0.172	0.929	0.985
hour05	0.808	0.147	0	2.243
hour06	1.380	0.144	0	3.974
hour07	1.290	0.175	0	3.634
hour08	1.175	0.181	0	3.239
hour09	1.242	0.179	0	3.463
hour10	1.274	0.179	0	3.574
hour11	1.274	0.180	0	3.574
hour12	1.363	0.176	0	3.909
hour13	1.540	0.172	0	4.663
hour14	1.620	0.172	0	5.054
hour15	1.569	0.173	0	4.803
hour16	1.725	0.164	0	5.610
hour17	1.538	0.145	0	4.654
hour18	1.327	0.147	0	3.770
hour19	0.931	0.148	0	2.537
hour20	0.803	0.148	0	2.232
hour21	0.343	0.161	0.033	1.409
hour22	0.425	0.157	0.007	1.530
hour23	0.114	0.170	0.501	1.121
day1	0.073	0.068	0.281	1.076
day2	0.023	0.069	0.741	1.023
day3	0.098	0.068	0.149	1.103
day4	0.050	0.069	0.473	1.051
day5	0.191	0.067	0.004	1.210

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	Estimate	Robust SE	Pr(>|z|)	exp
day6	0.205	0.067	0.002	1.228
week36	0.095	0.264	0.720	1.099
week37	0.304	0.261	0.244	1.355
week38	0.209	0.261	0.424	1.233
week39	0.157	0.262	0.548	1.170
week40	0.234	0.261	0.370	1.263
week41	0.123	0.262	0.639	1.131
week42	0.092	0.263	0.726	1.097
week43	-0.002	0.263	0.993	0.998
week44	0.061	0.263	0.817	1.063
week45	-0.029	0.263	0.912	0.971
week46	0.015	0.263	0.953	1.015
week47	-0.007	0.264	0.979	0.993
week48	0.013	0.263	0.961	1.013
week49	-0.014	0.265	0.957	0.986
week50	0.003	0.263	0.992	1.003
week51	-0.055	0.265	0.836	0.947
week52	-0.378	0.327	0.248	0.685
year2007	0.062	0.078	0.428	1.064
year2008	-0.061	0.081	0.451	0.941
year2009	-0.191	0.084	0.023	0.826
year2010	-0.239	0.085	0.005	0.787
year2011	-0.420	0.089	0	0.657
year2012	-0.408	0.089	0	0.665
year2013	-0.599	0.094	0	0.550
year2014	-0.484	0.091	0	0.616
year2015	-0.405	0.089	0	0.667
year2016	-0.612	0.095	0	0.542
year2017	-0.684	0.096	0	0.505
year2018	-0.586	0.094	0	0.557
year2019	-0.656	0.097	0	0.519

Table A.12: The results of the regression models for the fatal accidents with weather and explanatory variables in the autumn period.

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.634***	0.634***	0.634***
	(0.098)	(0.098)	(0.098)
holiday1	−0.180	−0.180	−0.180
	(0.119)	(0.118)	(0.119)
TMP_less_zero1	−0.460***	−0.460***	−0.460***
	(0.112)	(0.112)	(0.112)
TMP_less_five1	−0.313***	−0.313***	−0.313***
	(0.088)	(0.088)	(0.088)
TMP_less_ten1	−0.262***	−0.262***	−0.262***
	(0.074)	(0.074)	(0.074)
TMP_less_fifteen1	−0.178***	−0.178***	−0.178***
	(0.062)	(0.062)	(0.062)
mist1	−0.022	−0.022	−0.022
	(0.055)	(0.054)	(0.055)
fog1	0.107	0.107	0.107
	(0.101)	(0.101)	(0.101)
drizzle1	−0.255	−0.255	−0.255

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	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.229)	(0.227)	(0.229)
rain1	−0.009	−0.009	−0.009
	(0.087)	(0.086)	(0.087)
snow1	−0.204	−0.204	−0.204
	(0.160)	(0.159)	(0.160)
precipitation1	0.046	0.046	0.046
	(0.082)	(0.081)	(0.082)
crash_into_solid_obstacle	0.080***	0.080***	0.080***
	(0.009)	(0.008)	(0.009)
cause_intoxication	0.126***	0.126***	0.126***
	(0.019)	(0.019)	(0.019)
cause_damaged_road	0.028	0.028	0.028
	(0.070)	(0.070)	(0.070)
cause_car_defect	0.082	0.082	0.082
	(0.057)	(0.057)	(0.057)
hour01	0.030	0.030	0.030
	(0.174)	(0.173)	(0.174)
hour02	−0.002	−0.002	−0.002
	(0.176)	(0.175)	(0.176)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour03	−0.122	−0.122	−0.122
	(0.184)	(0.183)	(0.184)
hour04	0.069	0.069	0.069
	(0.175)	(0.174)	(0.175)
hour05	0.845***	0.845***	0.845***
	(0.149)	(0.148)	(0.149)
hour06	1.354***	1.354***	1.354***
	(0.146)	(0.145)	(0.146)
hour07	1.253***	1.253***	1.253***
	(0.178)	(0.178)	(0.179)
hour08	1.135***	1.135***	1.135***
	(0.184)	(0.183)	(0.184)
hour09	1.191***	1.191***	1.191***
	(0.183)	(0.182)	(0.183)
hour10	1.204***	1.204***	1.204***
	(0.181)	(0.181)	(0.182)
hour11	1.196***	1.196***	1.196***
	(0.181)	(0.180)	(0.181)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour12	1.285***	1.285***	1.285***
	(0.179)	(0.178)	(0.179)
hour13	1.420***	1.420***	1.420***
	(0.176)	(0.175)	(0.176)
hour14	1.451***	1.451***	1.451***
	(0.175)	(0.174)	(0.175)
hour15	1.402***	1.402***	1.402***
	(0.175)	(0.174)	(0.175)
hour16	1.569***	1.569***	1.569***
	(0.167)	(0.166)	(0.167)
hour17	1.372***	1.372***	1.372***
	(0.147)	(0.147)	(0.147)
hour18	1.207***	1.207***	1.207***
	(0.148)	(0.147)	(0.148)
hour19	0.816***	0.816***	0.816***
	(0.149)	(0.149)	(0.149)
hour20	0.712***	0.712***	0.712***
	(0.149)	(0.148)	(0.149)
hour21	0.267*	0.267*	0.267*

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson* *link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.161)	(0.160)	(0.161)
hour22	0.378**	0.378**	0.378**
	(0.158)	(0.158)	(0.158)
hour23	0.083	0.083	0.083
	(0.169)	(0.168)	(0.169)
day1	0.065	0.065	0.065
	(0.069)	(0.069)	(0.069)
day2	0.045	0.045	0.045
	(0.070)	(0.069)	(0.070)
day3	0.113*	0.113*	0.113*
	(0.069)	(0.068)	(0.069)
day4	0.048	0.048	0.048
	(0.069)	(0.069)	(0.069)
day5	0.142**	0.142**	0.142**
	(0.067)	(0.067)	(0.067)
day6	0.143**	0.143**	0.143**
	(0.066)	(0.066)	(0.066)
week36	0.117	0.117	0.118
	(0.257)	(0.256)	(0.257)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week37	0.326	0.326	0.326
	(0.254)	(0.253)	(0.254)
week38	0.270	0.270	0.270
	(0.255)	(0.254)	(0.255)
week39	0.259	0.259	0.259
	(0.257)	(0.255)	(0.257)
week40	0.348	0.348	0.348
	(0.256)	(0.254)	(0.256)
week41	0.249	0.249	0.249
	(0.258)	(0.256)	(0.258)
week42	0.240	0.240	0.240
	(0.259)	(0.258)	(0.259)
week43	0.163	0.163	0.163
	(0.261)	(0.259)	(0.261)
week44	0.291	0.291	0.291
	(0.262)	(0.260)	(0.262)
week45	0.173	0.173	0.173
	(0.262)	(0.260)	(0.262)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week46	0.255	0.255	0.255
	(0.262)	(0.261)	(0.262)
week47	0.228	0.228	0.228
	(0.263)	(0.262)	(0.263)
week48	0.262	0.262	0.262
	(0.265)	(0.263)	(0.265)
week49	0.236	0.236	0.236
	(0.264)	(0.263)	(0.265)
week50	0.257	0.257	0.257
	(0.265)	(0.264)	(0.265)
week51	0.195	0.195	0.195
	(0.267)	(0.266)	(0.267)
week52	0.022	0.022	0.022
	(0.327)	(0.326)	(0.327)
year2007	0.083	0.083	0.083
	(0.080)	(0.080)	(0.080)
year2008	−0.009	−0.009	−0.009
	(0.082)	(0.081)	(0.082)
year2009	−0.045	−0.045	−0.045

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.085)	(0.085)	(0.085)
year2010	−0.042	−0.042	−0.042
	(0.088)	(0.087)	(0.088)
year2011	−0.291***	−0.291***	−0.291***
	(0.090)	(0.090)	(0.090)
year2012	−0.264***	−0.264***	−0.264***
	(0.090)	(0.090)	(0.090)
year2013	−0.452***	−0.452***	−0.452***
	(0.095)	(0.095)	(0.095)
year2014	−0.360***	−0.360***	−0.360***
	(0.092)	(0.091)	(0.092)
year2015	−0.286***	−0.286***	−0.286***
	(0.090)	(0.089)	(0.090)
year2016	−0.480***	−0.480***	−0.480***
	(0.096)	(0.095)	(0.096)
year2017	−0.566***	−0.566***	−0.566***
	(0.098)	(0.097)	(0.098)
year2018	−0.499***	−0.499***	−0.500***
	(0.094)	(0.094)	(0.094)

Continued on next page

	Dependent variable:		
	fatal_crashes		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
year2019	−0.555***	−0.555***	−0.555***
	(0.097)	(0.096)	(0.097)
Constant	−3.885***	−3.885***	−3.885***
	(0.293)	(0.292)	(0.293)
Observations	37,968	37,968	37,968
Log Likelihood	−10,659.170		−10,660.180
θ			339.095 (1,215.512)
Akaike Inf. Crit.	21,470.350		21,472.370
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.13: IRR of the best-fitted regression model for the fatal accidents with weather and explanatory variables in the autumn period.

	Estimate	Robust SE	Pr(>|z|)	exp
(Intercept)	-3.885	0.294	0	-97.946
dark	0.634	0.097	0	88.468
holiday1	-0.180	0.128	0.159	-16.434
TMP_less_zero1	-0.460	0.112	0	-36.899
TMP_less_five1	-0.313	0.087	0	-26.907
TMP_less_ten1	-0.262	0.073	0	-23.048
TMP_less_fifteen1	-0.178	0.062	0.004	-16.294
mist1	-0.022	0.053	0.687	-2.131

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	exp
fog1	0.107	0.103	0.298	11.288
drizzle1	-0.255	0.223	0.253	-22.473
rain1	-0.009	0.082	0.913	-0.894
snow1	-0.204	0.157	0.192	-18.475
precipitation1	0.046	0.078	0.557	4.679
crash_into_solid_obstacle	0.080	0.008	0	8.304
cause_intoxication	0.126	0.019	0	13.376
cause_damaged_road	0.028	0.068	0.680	2.824
cause_car_defect	0.082	0.058	0.155	8.529
hour01	0.030	0.172	0.863	3.003
hour02	-0.002	0.177	0.990	-0.220
hour03	-0.122	0.185	0.509	-11.465
hour04	0.069	0.172	0.687	7.176
hour05	0.845	0.147	0	132.686
hour06	1.354	0.144	0	287.409
hour07	1.253	0.177	0	250.192
hour08	1.135	0.183	0	211.168
hour09	1.191	0.181	0	229.009
hour10	1.204	0.180	0	233.486
hour11	1.196	0.181	0	230.683
hour12	1.285	0.177	0	261.535
hour13	1.420	0.173	0	313.915
hour14	1.451	0.174	0	326.851
hour15	1.402	0.173	0	306.341
hour16	1.569	0.165	0	380.023
hour17	1.372	0.146	0	294.442
hour18	1.207	0.147	0	234.473
hour19	0.816	0.148	0	126.235
hour20	0.712	0.147	0	103.854
hour21	0.267	0.161	0.096	30.657
hour22	0.378	0.157	0.016	45.889
hour23	0.083	0.169	0.624	8.649
day1	0.065	0.068	0.344	6.692

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	exp
day2	0.045	0.070	0.523	4.565
day3	0.113	0.068	0.098	11.931
day4	0.048	0.070	0.488	4.954
day5	0.142	0.067	0.034	15.238
day6	0.143	0.067	0.033	15.426
week36	0.117	0.264	0.656	12.468
week37	0.326	0.260	0.210	38.557
week38	0.270	0.261	0.301	31.022
week39	0.259	0.262	0.323	29.592
week40	0.348	0.261	0.183	41.610
week41	0.249	0.264	0.344	28.295
week42	0.240	0.265	0.364	27.178
week43	0.163	0.266	0.539	17.749
week44	0.291	0.268	0.278	33.723
week45	0.173	0.267	0.516	18.938
week46	0.255	0.268	0.341	29.007
week47	0.228	0.269	0.398	25.573
week48	0.262	0.270	0.332	30.008
week49	0.236	0.271	0.383	26.672
week50	0.257	0.271	0.342	29.355
week51	0.195	0.273	0.476	21.483
week52	0.022	0.340	0.949	2.190
year2007	0.083	0.080	0.300	8.694
year2008	-0.009	0.081	0.916	-0.856
year2009	-0.045	0.086	0.603	-4.354
year2010	-0.042	0.088	0.631	-4.151
year2011	-0.291	0.090	0.001	-25.233
year2012	-0.264	0.091	0.004	-23.189
year2013	-0.452	0.095	0	-36.351
year2014	-0.360	0.092	0	-30.236
year2015	-0.286	0.089	0.001	-24.893
year2016	-0.480	0.096	0	-38.094
year2017	-0.566	0.098	0	-43.208

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	exp
year2018	-0.499	0.095	0	-39.316
year2019	-0.555	0.098	0	-42.617

A.4 The results of GLM for seriously injured accidents

Table A.14: The results of regression models for seriously injured accidents without weather variables in the spring period.

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.207***	0.207***	0.207***
	(0.067)	(0.069)	(0.069)
hour01	0.092	0.092	0.093
	(0.162)	(0.166)	(0.163)
hour02	0.008	0.008	0.009
	(0.166)	(0.170)	(0.166)
hour03	−0.469**	−0.469**	−0.469**
	(0.188)	(0.193)	(0.189)
hour04	0.108	0.108	0.109
	(0.162)	(0.166)	(0.163)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour05	1.287***	1.287***	1.288***
	(0.137)	(0.140)	(0.138)
hour06	1.631***	1.631***	1.635***
	(0.142)	(0.145)	(0.143)
hour07	1.912***	1.912***	1.915***
	(0.144)	(0.148)	(0.146)
hour08	1.794***	1.794***	1.795***
	(0.145)	(0.149)	(0.147)
hour09	1.765***	1.765***	1.766***
	(0.145)	(0.149)	(0.147)
hour10	1.816***	1.816***	1.817***
	(0.145)	(0.148)	(0.146)
hour11	1.848***	1.848***	1.850***
	(0.144)	(0.148)	(0.146)
hour12	1.915***	1.915***	1.917***
	(0.144)	(0.148)	(0.146)
hour13	2.058***	2.058***	2.059***
	(0.143)	(0.146)	(0.144)
hour14	2.260***	2.260***	2.261***

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.141)	(0.145)	(0.143)
hour15	2.235***	2.235***	2.235***
	(0.141)	(0.145)	(0.143)
hour16	2.233***	2.233***	2.232***
	(0.141)	(0.145)	(0.143)
hour17	2.161***	2.161***	2.160***
	(0.141)	(0.144)	(0.143)
hour18	2.009***	2.009***	2.009***
	(0.135)	(0.138)	(0.136)
hour19	1.647***	1.647***	1.647***
	(0.135)	(0.138)	(0.136)
hour20	1.175***	1.175***	1.175***
	(0.138)	(0.142)	(0.139)
hour21	0.918***	0.918***	0.919***
	(0.139)	(0.142)	(0.140)
hour22	0.727***	0.727***	0.727***
	(0.143)	(0.146)	(0.144)
hour23	0.354**	0.354**	0.354**
	(0.153)	(0.157)	(0.154)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
day1	0.174***	0.174***	0.176***
	(0.045)	(0.047)	(0.047)
day2	0.158***	0.158***	0.159***
	(0.046)	(0.047)	(0.047)
day3	0.170***	0.170***	0.171***
	(0.045)	(0.046)	(0.046)
day4	0.132***	0.132***	0.133***
	(0.046)	(0.047)	(0.047)
day5	0.307***	0.307***	0.310***
	(0.044)	(0.045)	(0.045)
day6	0.183***	0.183***	0.186***
	(0.045)	(0.046)	(0.046)
week6	0.133	0.133	0.134
	(0.096)	(0.099)	(0.098)
week7	0.189**	0.189*	0.190*
	(0.096)	(0.098)	(0.097)
week8	0.168*	0.168*	0.169*
	(0.096)	(0.098)	(0.098)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
week9	0.090	0.090	0.091
	(0.097)	(0.100)	(0.099)
week10	0.265***	0.265***	0.267***
	(0.095)	(0.097)	(0.097)
week11	0.243**	0.243**	0.244**
	(0.095)	(0.098)	(0.097)
week12	0.347***	0.347***	0.348***
	(0.094)	(0.097)	(0.096)
week13	0.464***	0.464***	0.463***
	(0.093)	(0.096)	(0.095)
week14	0.479***	0.479***	0.477***
	(0.093)	(0.096)	(0.095)
week15	0.512***	0.512***	0.512***
	(0.093)	(0.095)	(0.095)
week16	0.566***	0.566***	0.565***
	(0.093)	(0.095)	(0.094)
week17	0.699***	0.699***	0.699***
	(0.091)	(0.094)	(0.093)
week18	0.651***	0.651***	0.651***

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.092)	(0.094)	(0.094)
week19	0.705***	0.705***	0.702***
	(0.092)	(0.094)	(0.094)
week20	0.716***	0.716***	0.718***
	(0.092)	(0.094)	(0.094)
week21	0.883***	0.883***	0.882***
	(0.097)	(0.099)	(0.099)
year2010	−0.240***	−0.240***	−0.238***
	(0.051)	(0.052)	(0.052)
year2011	−0.158***	−0.158***	−0.156***
	(0.050)	(0.051)	(0.051)
year2012	−0.185***	−0.185***	−0.185***
	(0.050)	(0.051)	(0.052)
year2013	−0.369***	−0.369***	−0.367***
	(0.052)	(0.054)	(0.054)
year2014	−0.242***	−0.242***	−0.240***
	(0.050)	(0.052)	(0.052)
year2015	−0.417***	−0.417***	−0.416***
	(0.053)	(0.055)	(0.055)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
year2016	-0.326^{***}	-0.326^{***}	-0.325^{***}
	(0.052)	(0.053)	(0.053)
year2017	-0.446^{***}	-0.446^{***}	-0.444^{***}
	(0.054)	(0.056)	(0.056)
year2018	-0.385^{***}	-0.385^{***}	-0.384^{***}
	(0.053)	(0.055)	(0.055)
year2019	-0.532^{***}	-0.532^{***}	-0.531^{***}
	(0.055)	(0.056)	(0.056)
Constant	-3.362^{***}	-3.362^{***}	-3.366^{***}
	(0.167)	(0.172)	(0.170)
Observations	29,832	29,832	29,832
Log Likelihood	−16,907.080		−16,892.900
θ			6.230^{***} (1.239)
Akaike Inf. Crit.	33,928.170		33,899.810
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.15: IRR of the best-fitted regression model for the seriously injured accidents without weather variables in the spring period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	-3.366	0.170	0	0.035
dark	0.207	0.069	0.003	1.230
hour01	0.093	0.162	0.567	1.097
hour02	0.009	0.167	0.958	1.009
hour03	-0.469	0.186	0.012	0.626
hour04	0.109	0.165	0.511	1.115
hour05	1.288	0.138	0	3.627
hour06	1.635	0.142	0	5.127
hour07	1.915	0.143	0	6.789
hour08	1.795	0.145	0	6.022
hour09	1.766	0.144	0	5.849
hour10	1.817	0.144	0	6.153
hour11	1.850	0.144	0	6.359
hour12	1.917	0.143	0	6.797
hour13	2.059	0.142	0	7.839
hour14	2.261	0.141	0	9.597
hour15	2.235	0.141	0	9.351
hour16	2.232	0.142	0	9.321
hour17	2.160	0.142	0	8.674
hour18	2.009	0.134	0	7.455
hour19	1.647	0.134	0	5.194
hour20	1.175	0.137	0	3.237
hour21	0.919	0.139	0	2.506
hour22	0.727	0.143	0	2.070
hour23	0.354	0.157	0.024	1.424
day1	0.176	0.048	0	1.192
day2	0.159	0.048	0.001	1.172
day3	0.171	0.047	0	1.187
day4	0.133	0.047	0.005	1.143
day5	0.310	0.046	0	1.363

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
day6	0.186	0.048	0	1.204
week6	0.134	0.097	0.168	1.143
week7	0.190	0.096	0.047	1.209
week8	0.169	0.097	0.082	1.184
week9	0.091	0.097	0.349	1.095
week10	0.267	0.095	0.005	1.306
week11	0.244	0.095	0.010	1.277
week12	0.348	0.094	0	1.416
week13	0.463	0.094	0	1.590
week14	0.477	0.094	0	1.611
week15	0.512	0.094	0	1.669
week16	0.565	0.093	0	1.759
week17	0.699	0.092	0	2.011
week18	0.651	0.093	0	1.918
week19	0.702	0.092	0	2.018
week20	0.718	0.092	0	2.050
week21	0.882	0.096	0	2.415
year2010	-0.238	0.054	0	0.788
year2011	-0.156	0.052	0.003	0.856
year2012	-0.185	0.053	0	0.831
year2013	-0.367	0.054	0	0.693
year2014	-0.240	0.053	0	0.787
year2015	-0.416	0.055	0	0.660
year2016	-0.325	0.054	0	0.722
year2017	-0.444	0.057	0	0.642
year2018	-0.384	0.056	0	0.681
year2019	-0.531	0.058	0	0.588

Table A.16: The results of the regression models for seriously injured accidents with weather and explanatory variables in the spring period.

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.268***	0.268***	0.270***
	(0.068)	(0.068)	(0.068)
holiday1	0.083	0.083	0.083
	(0.064)	(0.064)	(0.066)
TMP_less_zero1	−0.739***	−0.739***	−0.741***
	(0.066)	(0.066)	(0.067)
TMP_less_five1	−0.693***	−0.693***	−0.694***
	(0.053)	(0.053)	(0.054)
TMP_less_ten1	−0.610***	−0.610***	−0.610***
	(0.042)	(0.042)	(0.043)
TMP_less_fifteen1	−0.310***	−0.310***	−0.310***
	(0.036)	(0.036)	(0.037)
mist1	0.014	0.014	0.013
	(0.045)	(0.045)	(0.045)
fog1	−0.051	−0.051	−0.054
	(0.189)	(0.189)	(0.191)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
drizzle1	0.041	0.041	0.040
	(0.238)	(0.238)	(0.241)
rain1	0.028	0.028	0.030
	(0.063)	(0.063)	(0.064)
snow1	0.082	0.082	0.081
	(0.086)	(0.086)	(0.087)
precipitation1	−0.071	−0.071	−0.072
	(0.057)	(0.057)	(0.058)
crash_into_solid_obstacle	0.088***	0.088***	0.089***
	(0.006)	(0.006)	(0.006)
cause_intoxication	0.163***	0.163***	0.165***
	(0.014)	(0.014)	(0.014)
cause_damaged_road	−0.032	−0.032	−0.031
	(0.053)	(0.053)	(0.054)
cause_car_defect	−0.003	−0.003	−0.003
	(0.044)	(0.044)	(0.045)
hour01	0.129	0.129	0.130
	(0.162)	(0.162)	(0.162)
hour02	0.070	0.070	0.072

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.166)	(0.166)	(0.166)
hour03	−0.358*	−0.358*	−0.357*
	(0.188)	(0.188)	(0.189)
hour04	0.237	0.237	0.238
	(0.162)	(0.162)	(0.163)
hour05	1.399***	1.399***	1.401***
	(0.137)	(0.137)	(0.137)
hour06	1.721***	1.721***	1.724***
	(0.142)	(0.142)	(0.143)
hour07	1.970***	1.970***	1.973***
	(0.145)	(0.145)	(0.146)
hour08	1.831***	1.831***	1.834***
	(0.146)	(0.146)	(0.147)
hour09	1.762***	1.762***	1.766***
	(0.146)	(0.146)	(0.147)
hour10	1.756***	1.756***	1.759***
	(0.146)	(0.146)	(0.147)
hour11	1.738***	1.738***	1.741***
	(0.145)	(0.145)	(0.146)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour12	1.784***	1.784***	1.788***
	(0.145)	(0.145)	(0.146)
hour13	1.876***	1.876***	1.879***
	(0.144)	(0.144)	(0.145)
hour14	2.033***	2.033***	2.036***
	(0.142)	(0.142)	(0.143)
hour15	1.987***	1.987***	1.989***
	(0.142)	(0.142)	(0.143)
hour16	1.981***	1.981***	1.982***
	(0.142)	(0.142)	(0.143)
hour17	1.934***	1.934***	1.935***
	(0.142)	(0.142)	(0.143)
hour18	1.789***	1.789***	1.790***
	(0.136)	(0.136)	(0.137)
hour19	1.454***	1.454***	1.455***
	(0.135)	(0.135)	(0.136)
hour20	1.043***	1.043***	1.044***
	(0.138)	(0.138)	(0.139)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour21	0.793***	0.793***	0.794***
	(0.139)	(0.139)	(0.140)
hour22	0.647***	0.647***	0.647***
	(0.143)	(0.143)	(0.143)
hour23	0.301**	0.301**	0.301**
	(0.153)	(0.153)	(0.153)
day1	0.168***	0.168***	0.172***
	(0.046)	(0.046)	(0.047)
day2	0.144***	0.144***	0.148***
	(0.046)	(0.046)	(0.047)
day3	0.171***	0.171***	0.173***
	(0.046)	(0.046)	(0.046)
day4	0.114**	0.114**	0.117**
	(0.046)	(0.046)	(0.047)
day5	0.251***	0.251***	0.255***
	(0.044)	(0.044)	(0.045)
day6	0.122***	0.122***	0.124***
	(0.045)	(0.045)	(0.046)
week6	0.112	0.112	0.111

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.097)	(0.097)	(0.098)
week7	0.145	0.145	0.146
	(0.096)	(0.096)	(0.097)
week8	0.136	0.136	0.136
	(0.097)	(0.097)	(0.098)
week9	0.088	0.088	0.088
	(0.099)	(0.099)	(0.100)
week10	0.222**	0.222**	0.222**
	(0.097)	(0.097)	(0.098)
week11	0.151	0.151	0.151
	(0.099)	(0.099)	(0.100)
week12	0.199**	0.199**	0.199**
	(0.098)	(0.098)	(0.099)
week13	0.276***	0.276***	0.275***
	(0.098)	(0.098)	(0.099)
week14	0.207**	0.207**	0.207**
	(0.099)	(0.099)	(0.100)
week15	0.222**	0.222**	0.222**
	(0.100)	(0.100)	(0.101)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week16	0.233**	0.233**	0.233**
	(0.100)	(0.100)	(0.101)
week17	0.283***	0.283***	0.283***
	(0.100)	(0.100)	(0.101)
week18	0.220**	0.220**	0.219**
	(0.101)	(0.101)	(0.103)
week19	0.200*	0.200*	0.199*
	(0.102)	(0.102)	(0.103)
week20	0.252**	0.252**	0.253**
	(0.101)	(0.101)	(0.102)
week21	0.312***	0.312***	0.311***
	(0.107)	(0.107)	(0.108)
year2010	−0.157***	−0.157***	−0.156***
	(0.051)	(0.051)	(0.052)
year2011	−0.155***	−0.155***	−0.154***
	(0.050)	(0.050)	(0.051)
year2012	−0.182***	−0.182***	−0.182***
	(0.050)	(0.050)	(0.051)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
year2013	-0.319^{***}	-0.319^{***}	-0.318^{***}
	(0.053)	(0.053)	(0.054)
year2014	-0.253^{***}	-0.253^{***}	-0.252^{***}
	(0.051)	(0.051)	(0.052)
year2015	-0.357^{***}	-0.357^{***}	-0.355^{***}
	(0.054)	(0.054)	(0.055)
year2016	-0.282^{***}	-0.282^{***}	-0.282^{***}
	(0.052)	(0.052)	(0.053)
year2017	-0.425^{***}	-0.425^{***}	-0.424^{***}
	(0.055)	(0.055)	(0.055)
year2018	-0.453^{***}	-0.453^{***}	-0.453^{***}
	(0.054)	(0.054)	(0.055)
year2019	-0.545^{***}	-0.545^{***}	-0.544^{***}
	(0.056)	(0.056)	(0.056)
Constant	-2.864^{***}	-2.864^{***}	-2.872^{***}
	(0.177)	(0.177)	(0.178)
Observations	29,832	29,832	29,832
Log Likelihood	−16,579.450		−16,575.990
θ			12.251^{***} (4.312)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
Akaike Inf. Crit.	33,302.900		33,295.980
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.17: IRR of the best-fitted regression model for the seriously injured accidents with weather and explanatory variables in the spring period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	-2.872	0.176	0	0.057
dark	0.270	0.069	0	1.310
holiday1	0.083	0.065	0.201	1.086
TMP_less_zero1	-0.741	0.067	0	0.477
TMP_less_five1	-0.694	0.053	0	0.500
TMP_less_ten1	-0.610	0.042	0	0.543
TMP_less_fifteen1	-0.310	0.036	0	0.733
mist1	0.013	0.044	0.760	1.013
fog1	-0.054	0.188	0.775	0.948
drizzle1	0.040	0.234	0.866	1.040
rain1	0.030	0.063	0.640	1.030
snow1	0.081	0.089	0.363	1.084
precipitation1	-0.072	0.058	0.212	0.931
crash_into_solid_obstacle	0.089	0.007	0	1.093
cause_intoxication	0.165	0.015	0	1.179
cause_damaged_road	-0.031	0.053	0.553	0.969
cause_car_defect	-0.003	0.044	0.938	0.997
hour01	0.130	0.160	0.415	1.139

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
hour02	0.072	0.166	0.666	1.074
hour03	-0.357	0.184	0.053	0.700
hour04	0.238	0.164	0.146	1.269
hour05	1.401	0.135	0	4.059
hour06	1.724	0.139	0	5.608
hour07	1.973	0.143	0	7.195
hour08	1.834	0.144	0	6.261
hour09	1.766	0.144	0	5.850
hour10	1.759	0.143	0	5.807
hour11	1.741	0.143	0	5.705
hour12	1.788	0.142	0	5.976
hour13	1.879	0.141	0	6.547
hour14	2.036	0.140	0	7.662
hour15	1.989	0.140	0	7.311
hour16	1.982	0.141	0	7.256
hour17	1.935	0.141	0	6.925
hour18	1.790	0.134	0	5.989
hour19	1.455	0.133	0	4.285
hour20	1.044	0.136	0	2.840
hour21	0.794	0.138	0	2.212
hour22	0.647	0.142	0	1.909
hour23	0.301	0.155	0.052	1.352
day1	0.172	0.047	0	1.187
day2	0.148	0.048	0.002	1.159
day3	0.173	0.046	0	1.189
day4	0.117	0.047	0.012	1.124
day5	0.255	0.045	0	1.291
day6	0.124	0.047	0.009	1.132
week6	0.111	0.097	0.251	1.118
week7	0.146	0.096	0.129	1.157
week8	0.136	0.098	0.166	1.145
week9	0.088	0.099	0.374	1.092
week10	0.222	0.097	0.022	1.249

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
week11	0.151	0.099	0.126	1.163
week12	0.199	0.099	0.043	1.221
week13	0.275	0.100	0.006	1.317
week14	0.207	0.101	0.041	1.230
week15	0.222	0.101	0.028	1.249
week16	0.233	0.101	0.022	1.262
week17	0.283	0.101	0.005	1.328
week18	0.219	0.102	0.032	1.245
week19	0.199	0.103	0.053	1.220
week20	0.253	0.103	0.014	1.288
week21	0.311	0.106	0.003	1.365
year2010	-0.156	0.054	0.004	0.856
year2011	-0.154	0.052	0.003	0.858
year2012	-0.182	0.052	0	0.833
year2013	-0.318	0.054	0	0.728
year2014	-0.252	0.053	0	0.777
year2015	-0.355	0.056	0	0.701
year2016	-0.282	0.054	0	0.754
year2017	-0.424	0.057	0	0.655
year2018	-0.453	0.056	0	0.636
year2019	-0.544	0.058	0	0.580

Table A.18: The results of regression model for seriously injured accidents without weather variables in the autumn period.

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.300***	0.300***	0.298***
	(0.058)	(0.059)	(0.059)
hour01	−0.023	−0.023	−0.023
	(0.152)	(0.155)	(0.152)
hour02	−0.047	−0.047	−0.047
	(0.153)	(0.156)	(0.153)
hour03	−0.400**	−0.400**	−0.400**
	(0.168)	(0.172)	(0.169)
hour04	−0.108	−0.108	−0.108
	(0.155)	(0.159)	(0.155)
hour05	1.165***	1.165***	1.165***
	(0.122)	(0.125)	(0.123)
hour06	1.736***	1.736***	1.734***
	(0.119)	(0.122)	(0.120)
hour07	1.984***	1.984***	1.982***
	(0.129)	(0.132)	(0.130)
hour08	1.585***	1.585***	1.583***

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.134)	(0.137)	(0.135)
hour09	1.799***	1.799***	1.797***
	(0.131)	(0.135)	(0.132)
hour10	1.789***	1.789***	1.786***
	(0.131)	(0.135)	(0.133)
hour11	1.816***	1.816***	1.814***
	(0.131)	(0.134)	(0.132)
hour12	1.744***	1.744***	1.742***
	(0.132)	(0.135)	(0.133)
hour13	2.047***	2.047***	2.044***
	(0.129)	(0.132)	(0.130)
hour14	2.278***	2.278***	2.275***
	(0.128)	(0.131)	(0.129)
hour15	2.239***	2.239***	2.237***
	(0.128)	(0.131)	(0.129)
hour16	2.355***	2.355***	2.354***
	(0.125)	(0.128)	(0.126)
hour17	2.244***	2.244***	2.243***
	(0.117)	(0.120)	(0.118)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour18	1.874***	1.874***	1.872***
	(0.119)	(0.122)	(0.120)
hour19	1.514***	1.514***	1.513***
	(0.119)	(0.122)	(0.120)
hour20	0.984***	0.984***	0.983***
	(0.125)	(0.128)	(0.126)
hour21	0.764***	0.764***	0.765***
	(0.129)	(0.132)	(0.130)
hour22	0.450***	0.450***	0.449***
	(0.136)	(0.140)	(0.137)
hour23	0.318**	0.318**	0.317**
	(0.140)	(0.143)	(0.141)
day1	0.155***	0.155***	0.153***
	(0.043)	(0.044)	(0.043)
day2	0.160***	0.160***	0.159***
	(0.043)	(0.044)	(0.043)
day3	0.109**	0.109**	0.107**
	(0.043)	(0.044)	(0.044)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
day4	0.177***	0.177***	0.176***
	(0.043)	(0.044)	(0.043)
day5	0.303***	0.303***	0.302***
	(0.041)	(0.043)	(0.042)
day6	0.177***	0.177***	0.179***
	(0.043)	(0.044)	(0.043)
week36	−0.185	−0.185	−0.185
	(0.117)	(0.119)	(0.119)
week37	−0.055	−0.055	−0.057
	(0.115)	(0.117)	(0.117)
week38	−0.153	−0.153	−0.154
	(0.115)	(0.118)	(0.118)
week39	−0.186	−0.186	−0.188
	(0.116)	(0.118)	(0.118)
week40	−0.221*	−0.221*	−0.223*
	(0.116)	(0.119)	(0.118)
week41	−0.296**	−0.296**	−0.298**
	(0.116)	(0.119)	(0.119)
week42	−0.208*	−0.208*	−0.208*

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.116)	(0.119)	(0.118)
week43	−0.399***	−0.399***	−0.400***
	(0.117)	(0.120)	(0.120)
week44	−0.492***	−0.492***	−0.494***
	(0.118)	(0.121)	(0.121)
week45	−0.485***	−0.485***	−0.485***
	(0.118)	(0.121)	(0.121)
week46	−0.501***	−0.501***	−0.502***
	(0.119)	(0.121)	(0.121)
week47	−0.558***	−0.558***	−0.560***
	(0.119)	(0.122)	(0.122)
week48	−0.527***	−0.527***	−0.527***
	(0.119)	(0.122)	(0.121)
week49	−0.586***	−0.586***	−0.587***
	(0.120)	(0.123)	(0.122)
week50	−0.600***	−0.600***	−0.601***
	(0.120)	(0.123)	(0.122)
week51	−0.635***	−0.635***	−0.636***
	(0.121)	(0.124)	(0.124)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week52	−1.178***	−1.178***	−1.178***
	(0.181)	(0.186)	(0.184)
year2010	−0.231***	−0.231***	−0.232***
	(0.048)	(0.049)	(0.048)
year2011	−0.156***	−0.156***	−0.157***
	(0.046)	(0.048)	(0.047)
year2012	−0.229***	−0.229***	−0.230***
	(0.047)	(0.048)	(0.048)
year2013	−0.227***	−0.227***	−0.230***
	(0.047)	(0.048)	(0.048)
year2014	−0.312***	−0.312***	−0.313***
	(0.048)	(0.049)	(0.049)
year2015	−0.426***	−0.426***	−0.428***
	(0.050)	(0.051)	(0.050)
year2016	−0.398***	−0.398***	−0.399***
	(0.050)	(0.051)	(0.051)
year2017	−0.497***	−0.497***	−0.497***
	(0.051)	(0.052)	(0.052)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
year2018	−0.426***	−0.426***	−0.428***
	(0.050)	(0.051)	(0.051)
year2019	−0.660***	−0.660***	−0.662***
	(0.054)	(0.055)	(0.054)
Constant	−2.428***	−2.428***	−2.422***
	(0.161)	(0.165)	(0.163)
Observations	29,832	29,832	29,832
Log Likelihood	−18,050.390		−18,045.430
θ			11.272*** (3.440)
Akaike Inf. Crit.	36,216.770		36,206.850
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.19: IRR of the best-fitted regression model for the seriously injured accidents without weather variables in the autumn period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	-2.422	0.167	0	0.089
dark	0.298	0.060	0	1.347
hour01	-0.023	0.156	0.881	0.977
hour02	-0.047	0.158	0.768	0.954
hour03	-0.400	0.177	0.024	0.670
hour04	-0.108	0.157	0.493	0.898

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
hour05	1.165	0.126	0	3.206
hour06	1.734	0.124	0	5.661
hour07	1.982	0.133	0	7.257
hour08	1.583	0.137	0	4.868
hour09	1.797	0.136	0	6.032
hour10	1.786	0.136	0	5.968
hour11	1.814	0.135	0	6.135
hour12	1.742	0.136	0	5.711
hour13	2.044	0.133	0	7.724
hour14	2.275	0.131	0	9.731
hour15	2.237	0.133	0	9.364
hour16	2.354	0.130	0	10.530
hour17	2.243	0.122	0	9.421
hour18	1.872	0.122	0	6.503
hour19	1.513	0.123	0	4.540
hour20	0.983	0.128	0	2.671
hour21	0.765	0.133	0	2.148
hour22	0.449	0.142	0.002	1.567
hour23	0.317	0.145	0.029	1.373
day1	0.153	0.044	0	1.166
day2	0.159	0.044	0	1.173
day3	0.107	0.045	0.017	1.113
day4	0.176	0.043	0	1.192
day5	0.302	0.042	0	1.353
day6	0.179	0.044	0	1.196
week36	-0.185	0.117	0.114	0.831
week37	-0.057	0.115	0.619	0.944
week38	-0.154	0.115	0.182	0.857
week39	-0.188	0.116	0.104	0.829
week40	-0.223	0.116	0.054	0.800
week41	-0.298	0.116	0.010	0.742
week42	-0.208	0.116	0.074	0.812
week43	-0.400	0.117	0.001	0.670

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
week44	-0.494	0.119	0	0.610
week45	-0.485	0.119	0	0.616
week46	-0.502	0.118	0	0.605
week47	-0.560	0.119	0	0.571
week48	-0.527	0.120	0	0.590
week49	-0.587	0.121	0	0.556
week50	-0.601	0.121	0	0.548
week51	-0.636	0.120	0	0.529
week52	-1.178	0.181	0	0.308
year2010	-0.232	0.049	0	0.793
year2011	-0.157	0.048	0.001	0.855
year2012	-0.230	0.048	0	0.794
year2013	-0.230	0.048	0	0.795
year2014	-0.313	0.050	0	0.731
year2015	-0.428	0.051	0	0.652
year2016	-0.399	0.052	0	0.671
year2017	-0.497	0.052	0	0.608
year2018	-0.428	0.052	0	0.652
year2019	-0.662	0.055	0	0.516

Table A.20: The results of the regression models for the seriously injured accidents with weather and explanatory variables in the autumn period.

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.317***	0.317***	0.316***
	(0.058)	(0.059)	(0.059)
holiday1	−0.143*	−0.143*	−0.144*
	(0.074)	(0.075)	(0.075)
TMP_less_zero1	−0.418***	−0.418***	−0.418***
	(0.071)	(0.071)	(0.072)
TMP_less_five1	−0.329***	−0.329***	−0.329***
	(0.054)	(0.054)	(0.055)
TMP_less_ten1	−0.251***	−0.251***	−0.250***
	(0.045)	(0.045)	(0.045)
TMP_less_fifteen1	−0.233***	−0.233***	−0.233***
	(0.037)	(0.037)	(0.037)
mist1	−0.032	−0.032	−0.032
	(0.035)	(0.035)	(0.035)
fog1	0.069	0.069	0.070
	(0.066)	(0.067)	(0.067)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
drizzle1	−0.232*	−0.232*	−0.234*
	(0.133)	(0.133)	(0.134)
rain1	0.071	0.071	0.071
	(0.056)	(0.056)	(0.056)
snow1	−0.040	−0.040	−0.042
	(0.097)	(0.097)	(0.098)
precipitation1	0.096*	0.096*	0.095*
	(0.056)	(0.056)	(0.056)
crash_into_solid_obstacle	0.061***	0.061***	0.061***
	(0.006)	(0.006)	(0.006)
cause_intoxication	0.157***	0.157***	0.158***
	(0.013)	(0.013)	(0.013)
cause_damaged_road	0.041	0.041	0.041
	(0.048)	(0.049)	(0.049)
cause_car_defect	0.061	0.061	0.061
	(0.040)	(0.040)	(0.040)
hour01	0.002	0.002	0.001
	(0.152)	(0.152)	(0.152)
hour02	−0.002	−0.002	−0.002

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.153)	(0.153)	(0.153)
hour03	−0.320*	−0.320*	−0.320*
	(0.168)	(0.169)	(0.169)
hour04	−0.036	−0.036	−0.035
	(0.155)	(0.156)	(0.155)
hour05	1.205***	1.205***	1.206***
	(0.122)	(0.123)	(0.123)
hour06	1.736***	1.736***	1.735***
	(0.119)	(0.120)	(0.120)
hour07	1.972***	1.972***	1.970***
	(0.129)	(0.130)	(0.130)
hour08	1.573***	1.573***	1.571***
	(0.135)	(0.135)	(0.135)
hour09	1.775***	1.775***	1.773***
	(0.132)	(0.133)	(0.133)
hour10	1.740***	1.740***	1.739***
	(0.132)	(0.133)	(0.133)
hour11	1.755***	1.755***	1.753***
	(0.132)	(0.132)	(0.132)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
hour12	1.672***	1.672***	1.671***
	(0.132)	(0.133)	(0.133)
hour13	1.945***	1.945***	1.943***
	(0.130)	(0.130)	(0.130)
hour14	2.128***	2.128***	2.127***
	(0.128)	(0.129)	(0.129)
hour15	2.089***	2.089***	2.086***
	(0.128)	(0.129)	(0.129)
hour16	2.202***	2.202***	2.202***
	(0.125)	(0.126)	(0.126)
hour17	2.083***	2.083***	2.082***
	(0.118)	(0.119)	(0.119)
hour18	1.751***	1.751***	1.750***
	(0.119)	(0.120)	(0.120)
hour19	1.403***	1.403***	1.402***
	(0.119)	(0.120)	(0.120)
hour20	0.886***	0.886***	0.886***
	(0.125)	(0.126)	(0.126)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour21	0.687***	0.687***	0.687***
	(0.129)	(0.130)	(0.130)
hour22	0.396***	0.396***	0.396***
	(0.136)	(0.137)	(0.137)
hour23	0.282**	0.282**	0.281**
	(0.140)	(0.141)	(0.141)
day1	0.151***	0.151***	0.150***
	(0.043)	(0.043)	(0.043)
day2	0.184***	0.184***	0.184***
	(0.043)	(0.043)	(0.043)
day3	0.115***	0.115***	0.115***
	(0.044)	(0.044)	(0.044)
day4	0.181***	0.181***	0.180***
	(0.043)	(0.043)	(0.043)
day5	0.276***	0.276***	0.277***
	(0.042)	(0.042)	(0.042)
day6	0.126***	0.126***	0.127***
	(0.043)	(0.043)	(0.043)
week36	−0.158	−0.158	−0.157

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.117)	(0.117)	(0.118)
week37	−0.053	−0.053	−0.053
	(0.115)	(0.115)	(0.116)
week38	−0.092	−0.092	−0.091
	(0.116)	(0.116)	(0.117)
week39	−0.080	−0.080	−0.079
	(0.117)	(0.117)	(0.118)
week40	−0.102	−0.102	−0.102
	(0.117)	(0.117)	(0.118)
week41	−0.188	−0.188	−0.188
	(0.118)	(0.119)	(0.120)
week42	−0.070	−0.070	−0.069
	(0.118)	(0.119)	(0.120)
week43	−0.206*	−0.206*	−0.206*
	(0.121)	(0.121)	(0.122)
week44	−0.244**	−0.244**	−0.245**
	(0.123)	(0.123)	(0.125)
week45	−0.267**	−0.267**	−0.266**
	(0.122)	(0.122)	(0.124)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
week46	−0.244**	−0.244**	−0.243*
	(0.123)	(0.124)	(0.125)
week47	−0.313**	−0.313**	−0.314**
	(0.124)	(0.125)	(0.126)
week48	−0.260**	−0.260**	−0.259**
	(0.126)	(0.126)	(0.127)
week49	−0.322**	−0.322**	−0.322**
	(0.126)	(0.127)	(0.128)
week50	−0.344***	−0.344***	−0.344***
	(0.127)	(0.127)	(0.128)
week51	−0.393***	−0.393***	−0.392***
	(0.129)	(0.129)	(0.130)
week52	−0.859***	−0.859***	−0.857***
	(0.188)	(0.189)	(0.190)
year2010	−0.188***	−0.188***	−0.189***
	(0.048)	(0.048)	(0.049)
year2011	−0.159***	−0.159***	−0.160***
	(0.047)	(0.047)	(0.047)

Continued on next page

	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
year2012	−0.219***	−0.219***	−0.220***
	(0.047)	(0.048)	(0.048)
year2013	−0.204***	−0.204***	−0.205***
	(0.047)	(0.048)	(0.048)
year2014	−0.312***	−0.312***	−0.313***
	(0.049)	(0.049)	(0.049)
year2015	−0.436***	−0.436***	−0.437***
	(0.050)	(0.050)	(0.050)
year2016	−0.396***	−0.396***	−0.397***
	(0.050)	(0.051)	(0.051)
year2017	−0.505***	−0.505***	−0.506***
	(0.052)	(0.052)	(0.052)
year2018	−0.466***	−0.466***	−0.468***
	(0.051)	(0.051)	(0.051)
year2019	−0.692***	−0.692***	−0.693***
	(0.054)	(0.054)	(0.055)
Constant	−2.563***	−2.563***	−2.563***
	(0.161)	(0.162)	(0.163)

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	Dependent variable:		
	seriously_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
Observations	29,832	29,832	29,832
Log Likelihood	−17,853.690		−17,852.260
θ			18.181** (8.522)
Akaike Inf. Crit.	35,853.370		35,850.520
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.21: IRR of the best-fitted regression model for the seriously injured accidents with weather and explanatory variables in the autumn period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	-2.563	0.165	0	0.077
dark	0.316	0.060	0	1.371
holiday1	-0.144	0.072	0.044	0.866
TMP_less_zero1	-0.418	0.072	0	0.658
TMP_less_five1	-0.329	0.054	0	0.719
TMP_less_ten1	-0.250	0.044	0	0.779
TMP_less_fifteen1	-0.233	0.037	0	0.792
mist1	-0.032	0.035	0.366	0.969
fog1	0.070	0.067	0.297	1.072
drizzle1	-0.234	0.126	0.064	0.791
rain1	0.071	0.057	0.208	1.074
snow1	-0.042	0.101	0.681	0.959
precipitation1	0.095	0.057	0.096	1.100
crash_into_solid_obstacle	0.061	0.006	0	1.063
cause_intoxication	0.158	0.013	0	1.171

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	Estimate	Robust SE	Pr(>|z|)	IRR
cause_damaged_road	0.041	0.049	0.404	1.042
cause_car_defect	0.061	0.041	0.135	1.063
hour01	0.001	0.154	0.993	1.001
hour02	-0.002	0.157	0.989	0.998
hour03	-0.320	0.175	0.068	0.726
hour04	-0.035	0.156	0.823	0.966
hour05	1.206	0.126	0	3.339
hour06	1.735	0.123	0	5.668
hour07	1.970	0.132	0	7.170
hour08	1.571	0.137	0	4.811
hour09	1.773	0.135	0	5.891
hour10	1.739	0.136	0	5.691
hour11	1.753	0.135	0	5.775
hour12	1.671	0.135	0	5.317
hour13	1.943	0.133	0	6.979
hour14	2.127	0.131	0	8.388
hour15	2.086	0.132	0	8.057
hour16	2.202	0.129	0	9.041
hour17	2.082	0.122	0	8.022
hour18	1.750	0.122	0	5.755
hour19	1.402	0.122	0	4.062
hour20	0.886	0.127	0	2.425
hour21	0.687	0.133	0	1.988
hour22	0.396	0.140	0.005	1.485
hour23	0.281	0.144	0.051	1.324
day1	0.150	0.044	0.001	1.162
day2	0.184	0.044	0	1.202
day3	0.115	0.045	0.011	1.121
day4	0.180	0.043	0	1.198
day5	0.277	0.042	0	1.319
day6	0.127	0.044	0.004	1.135
week36	-0.157	0.116	0.174	0.855
week37	-0.053	0.114	0.642	0.949

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	Estimate	Robust SE	Pr(>|z|)	IRR
week38	-0.091	0.114	0.423	0.913
week39	-0.079	0.115	0.489	0.924
week40	-0.102	0.115	0.375	0.903
week41	-0.188	0.116	0.107	0.829
week42	-0.069	0.117	0.554	0.933
week43	-0.206	0.119	0.082	0.813
week44	-0.245	0.121	0.044	0.783
week45	-0.266	0.120	0.027	0.767
week46	-0.243	0.121	0.044	0.784
week47	-0.314	0.122	0.010	0.731
week48	-0.259	0.125	0.038	0.772
week49	-0.322	0.126	0.010	0.725
week50	-0.344	0.126	0.006	0.709
week51	-0.392	0.126	0.002	0.676
week52	-0.857	0.186	0	0.424
year2010	-0.189	0.049	0	0.828
year2011	-0.160	0.047	0.001	0.852
year2012	-0.220	0.048	0	0.802
year2013	-0.205	0.048	0	0.814
year2014	-0.313	0.050	0	0.731
year2015	-0.437	0.051	0	0.646
year2016	-0.397	0.052	0	0.672
year2017	-0.506	0.052	0	0.603
year2018	-0.468	0.052	0	0.626
year2019	-0.693	0.055	0	0.500

A.5 The results of GLM for slightly injured accidents

Table A.22: The results of regression models for slightly injured accidents without weather variables in the spring period.

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
dark	0.102***	0.102***	0.099***
	(0.026)	(0.029)	(0.028)
hour01	−0.145**	−0.145**	−0.144**
	(0.064)	(0.072)	(0.065)
hour02	−0.246***	−0.246***	−0.246***
	(0.065)	(0.074)	(0.067)
hour03	−0.281***	−0.281***	−0.281***
	(0.066)	(0.075)	(0.067)
hour04	−0.002	−0.002	−0.001
	(0.061)	(0.070)	(0.063)
hour05	1.121***	1.121***	1.119***
	(0.051)	(0.058)	(0.053)
hour06	1.541***	1.541***	1.537***
	(0.053)	(0.060)	(0.055)
hour07	1.917***	1.917***	1.913***
	(0.053)	(0.060)	(0.056)
hour08	1.733***	1.733***	1.730***

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.054)	(0.061)	(0.057)
hour09	1.739***	1.739***	1.733***
	(0.054)	(0.061)	(0.057)
hour10	1.768***	1.768***	1.763***
	(0.054)	(0.061)	(0.057)
hour11	1.786***	1.786***	1.781***
	(0.054)	(0.061)	(0.057)
hour12	1.814***	1.814***	1.807***
	(0.054)	(0.061)	(0.057)
hour13	2.013***	2.013***	2.006***
	(0.053)	(0.060)	(0.056)
hour14	2.254***	2.254***	2.244***
	(0.052)	(0.059)	(0.056)
hour15	2.272***	2.272***	2.262***
	(0.052)	(0.059)	(0.056)
hour16	2.195***	2.195***	2.183***
	(0.053)	(0.060)	(0.056)
hour17	2.041***	2.041***	2.031***
	(0.052)	(0.059)	(0.055)

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	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour18	1.871***	1.871***	1.866***
	(0.050)	(0.057)	(0.053)
hour19	1.444***	1.444***	1.439***
	(0.051)	(0.057)	(0.053)
hour20	1.049***	1.049***	1.044***
	(0.052)	(0.058)	(0.054)
hour21	0.812***	0.812***	0.810***
	(0.052)	(0.059)	(0.054)
hour22	0.618***	0.618***	0.615***
	(0.054)	(0.061)	(0.055)
hour23	0.164***	0.164**	0.161***
	(0.059)	(0.067)	(0.060)
day1	0.341***	0.341***	0.328***
	(0.017)	(0.019)	(0.019)
day2	0.265***	0.265***	0.253***
	(0.017)	(0.019)	(0.019)
day3	0.283***	0.283***	0.271***
	(0.017)	(0.019)	(0.019)

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
day4	0.305***	0.305***	0.294***
	(0.017)	(0.019)	(0.019)
day5	0.441***	0.441***	0.431***
	(0.016)	(0.019)	(0.018)
day6	0.195***	0.195***	0.204***
	(0.017)	(0.020)	(0.019)
week6	0.010	0.010	0.009
	(0.033)	(0.037)	(0.036)
week7	0.072**	0.072*	0.071**
	(0.033)	(0.037)	(0.036)
week8	0.034	0.034	0.036
	(0.033)	(0.037)	(0.036)
week9	−0.036	−0.036	−0.038
	(0.033)	(0.038)	(0.037)
week10	0.068**	0.068*	0.065*
	(0.033)	(0.037)	(0.036)
week11	0.120***	0.120***	0.120***
	(0.033)	(0.037)	(0.036)
week12	0.198***	0.198***	0.196***

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.032)	(0.037)	(0.036)
week13	0.240***	0.240***	0.234***
	(0.032)	(0.036)	(0.036)
week14	0.248***	0.248***	0.241***
	(0.032)	(0.036)	(0.036)
week15	0.290***	0.290***	0.283***
	(0.032)	(0.036)	(0.036)
week16	0.401***	0.401***	0.391***
	(0.032)	(0.036)	(0.035)
week17	0.440***	0.440***	0.428***
	(0.032)	(0.036)	(0.035)
week18	0.385***	0.385***	0.380***
	(0.032)	(0.036)	(0.036)
week19	0.456***	0.456***	0.446***
	(0.032)	(0.036)	(0.035)
week20	0.467***	0.467***	0.459***
	(0.032)	(0.036)	(0.035)
week21	0.572***	0.572***	0.567***
	(0.034)	(0.039)	(0.038)

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
year2010	-0.135^{***}	-0.135^{***}	-0.139^{***}
	(0.020)	(0.023)	(0.023)
year2011	-0.078^{***}	-0.078^{***}	-0.085^{***}
	(0.020)	(0.023)	(0.023)
year2012	-0.090^{***}	-0.090^{***}	-0.098^{***}
	(0.020)	(0.023)	(0.023)
year2013	-0.123^{***}	-0.123^{***}	-0.130^{***}
	(0.020)	(0.023)	(0.023)
year2014	-0.025	-0.025	-0.032
	(0.020)	(0.022)	(0.022)
year2015	-0.040^{**}	-0.040^{*}	-0.050^{**}
	(0.020)	(0.022)	(0.023)
year2016	-0.047^{**}	-0.047^{**}	-0.056^{**}
	(0.020)	(0.023)	(0.023)
year2017	-0.028	-0.028	-0.038^{*}
	(0.020)	(0.022)	(0.023)
year2018	0.037^{*}	0.037^{*}	0.025
	(0.020)	(0.022)	(0.022)

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
year2019	−0.052***	−0.052**	−0.063***
	(0.020)	(0.022)	(0.023)
Constant	−1.412***	−1.412***	−1.386***
	(0.061)	(0.069)	(0.065)
Observations	29,832	29,832	29,832
Log Likelihood	−46,691.430		−46,346.520
θ			8.749*** (0.409)
Akaike Inf. Crit.	93,496.860		92,807.040
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.23: IRR of the best-fitted regression model for the slightly injured accidents without weather variables in the spring period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	-1.386	0.070	0	0.250
dark	0.099	0.029	0.001	1.104
hour01	-0.144	0.070	0.039	0.866
hour02	-0.246	0.072	0.001	0.782
hour03	-0.281	0.073	0	0.755
hour04	-0.001	0.067	0.984	0.999
hour05	1.119	0.057	0	3.061
hour06	1.537	0.060	0	4.651
hour07	1.913	0.060	0	6.776

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
hour08	1.730	0.060	0	5.643
hour09	1.733	0.059	0	5.656
hour10	1.763	0.059	0	5.830
hour11	1.781	0.059	0	5.935
hour12	1.807	0.059	0	6.092
hour13	2.006	0.058	0	7.432
hour14	2.244	0.058	0	9.430
hour15	2.262	0.058	0	9.602
hour16	2.183	0.058	0	8.874
hour17	2.031	0.058	0	7.620
hour18	1.866	0.055	0	6.462
hour19	1.439	0.055	0	4.215
hour20	1.044	0.056	0	2.841
hour21	0.810	0.056	0	2.248
hour22	0.615	0.059	0	1.849
hour23	0.161	0.063	0.011	1.174
day1	0.328	0.019	0	1.388
day2	0.253	0.020	0	1.288
day3	0.271	0.020	0	1.312
day4	0.294	0.020	0	1.342
day5	0.431	0.019	0	1.539
day6	0.204	0.020	0	1.226
week6	0.009	0.040	0.816	1.009
week7	0.071	0.040	0.074	1.074
week8	0.036	0.039	0.355	1.037
week9	-0.038	0.039	0.327	0.963
week10	0.065	0.039	0.097	1.067
week11	0.120	0.039	0.002	1.127
week12	0.196	0.038	0	1.216
week13	0.234	0.038	0	1.263
week14	0.241	0.038	0	1.272
week15	0.283	0.037	0	1.327
week16	0.391	0.037	0	1.478

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
week17	0.428	0.037	0	1.534
week18	0.380	0.038	0	1.463
week19	0.446	0.037	0	1.562
week20	0.459	0.037	0	1.583
week21	0.567	0.040	0	1.762
year2010	-0.139	0.023	0	0.870
year2011	-0.085	0.023	0	0.918
year2012	-0.098	0.023	0	0.907
year2013	-0.130	0.023	0	0.878
year2014	-0.032	0.022	0.148	0.968
year2015	-0.050	0.023	0.027	0.951
year2016	-0.056	0.022	0.013	0.946
year2017	-0.038	0.023	0.097	0.963
year2018	0.025	0.023	0.268	1.025
year2019	-0.063	0.022	0.005	0.939

Table A.24: The results of the regression models for slightly injured accidents with weather and explanatory variables in the spring period.

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.142***	0.142***	0.145***
	(0.026)	(0.027)	(0.027)
holiday1	−0.198***	−0.198***	−0.200***
	(0.026)	(0.027)	(0.028)

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
TMP_less_zero1	−0.370***	−0.370***	−0.372***
	(0.024)	(0.024)	(0.025)
TMP_less_five1	−0.384***	−0.384***	−0.385***
	(0.019)	(0.020)	(0.020)
TMP_less_ten1	−0.394***	−0.394***	−0.393***
	(0.016)	(0.016)	(0.017)
TMP_less_fifteen1	−0.235***	−0.235***	−0.235***
	(0.014)	(0.014)	(0.014)
mist1	−0.013	−0.013	−0.013
	(0.016)	(0.017)	(0.017)
fog1	−0.132*	−0.132*	−0.131*
	(0.070)	(0.072)	(0.073)
drizzle1	−0.010	−0.010	−0.010
	(0.086)	(0.089)	(0.090)
rain1	0.024	0.024	0.026
	(0.022)	(0.023)	(0.023)
snow1	0.063**	0.063**	0.055*
	(0.030)	(0.031)	(0.032)

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
precipitation1	0.058***	0.058***	0.057***
	(0.020)	(0.020)	(0.021)
crash_into_solid_obstacle	0.095***	0.095***	0.097***
	(0.002)	(0.002)	(0.002)
cause_intoxication	0.183***	0.183***	0.191***
	(0.005)	(0.005)	(0.006)
cause_damaged_road	0.012	0.012	0.011
	(0.019)	(0.019)	(0.020)
cause_car_defect	0.060***	0.060***	0.063***
	(0.015)	(0.016)	(0.016)
hour01	−0.117*	−0.117*	−0.116*
	(0.064)	(0.065)	(0.064)
hour02	−0.202***	−0.202***	−0.200***
	(0.066)	(0.067)	(0.066)
hour03	−0.200***	−0.200***	−0.197***
	(0.066)	(0.068)	(0.067)
hour04	0.091	0.091	0.095
	(0.061)	(0.063)	(0.062)
hour05	1.173***	1.173***	1.176***

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.051)	(0.053)	(0.052)
hour06	1.548***	1.548***	1.550***
	(0.053)	(0.054)	(0.054)
hour07	1.889***	1.889***	1.890***
	(0.054)	(0.055)	(0.055)
hour08	1.704***	1.704***	1.708***
	(0.054)	(0.056)	(0.056)
hour09	1.692***	1.692***	1.699***
	(0.054)	(0.056)	(0.055)
hour10	1.691***	1.691***	1.699***
	(0.054)	(0.056)	(0.055)
hour11	1.677***	1.677***	1.684***
	(0.054)	(0.056)	(0.055)
hour12	1.700***	1.700***	1.706***
	(0.054)	(0.055)	(0.055)
hour13	1.856***	1.856***	1.863***
	(0.053)	(0.055)	(0.055)
hour14	2.052***	2.052***	2.058***
	(0.053)	(0.054)	(0.054)

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	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour15	2.056***	2.056***	2.062***
	(0.053)	(0.054)	(0.054)
hour16	1.977***	1.977***	1.979***
	(0.053)	(0.054)	(0.054)
hour17	1.845***	1.845***	1.848***
	(0.053)	(0.054)	(0.054)
hour18	1.682***	1.682***	1.686***
	(0.051)	(0.052)	(0.052)
hour19	1.276***	1.276***	1.277***
	(0.051)	(0.052)	(0.052)
hour20	0.936***	0.936***	0.936***
	(0.052)	(0.053)	(0.053)
hour21	0.702***	0.702***	0.702***
	(0.052)	(0.054)	(0.053)
hour22	0.542***	0.542***	0.541***
	(0.054)	(0.055)	(0.055)
hour23	0.112*	0.112*	0.111*
	(0.059)	(0.061)	(0.060)

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	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
day1	0.326***	0.326***	0.326***
	(0.017)	(0.018)	(0.018)
day2	0.238***	0.238***	0.239***
	(0.017)	(0.018)	(0.018)
day3	0.260***	0.260***	0.260***
	(0.017)	(0.018)	(0.018)
day4	0.274***	0.274***	0.273***
	(0.017)	(0.018)	(0.018)
day5	0.381***	0.381***	0.380***
	(0.017)	(0.017)	(0.017)
day6	0.120***	0.120***	0.122***
	(0.017)	(0.018)	(0.018)
week6	0.014	0.014	0.013
	(0.033)	(0.034)	(0.035)
week7	0.039	0.039	0.037
	(0.033)	(0.034)	(0.034)
week8	0.037	0.037	0.037
	(0.033)	(0.034)	(0.035)
week9	0.024	0.024	0.024

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.034)	(0.035)	(0.035)
week10	0.092***	0.092***	0.090**
	(0.034)	(0.035)	(0.035)
week11	0.123***	0.123***	0.124***
	(0.034)	(0.035)	(0.035)
week12	0.172***	0.172***	0.172***
	(0.034)	(0.035)	(0.035)
week13	0.212***	0.212***	0.212***
	(0.034)	(0.035)	(0.036)
week14	0.187***	0.187***	0.188***
	(0.034)	(0.035)	(0.036)
week15	0.211***	0.211***	0.212***
	(0.035)	(0.036)	(0.036)
week16	0.279***	0.279***	0.279***
	(0.034)	(0.035)	(0.036)
week17	0.264***	0.264***	0.264***
	(0.035)	(0.036)	(0.036)
week18	0.239***	0.239***	0.240***
	(0.035)	(0.036)	(0.037)

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	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
week19	0.256^{***}	0.256^{***}	0.258^{***}
	(0.035)	(0.036)	(0.037)
week20	0.238^{***}	0.238^{***}	0.239^{***}
	(0.035)	(0.036)	(0.037)
week21	0.276^{***}	0.276^{***}	0.279^{***}
	(0.038)	(0.039)	(0.040)
year2010	-0.077^{***}	-0.077^{***}	-0.077^{***}
	(0.020)	(0.021)	(0.022)
year2011	-0.073^{***}	-0.073^{***}	-0.075^{***}
	(0.020)	(0.021)	(0.021)
year2012	-0.099^{***}	-0.099^{***}	-0.102^{***}
	(0.020)	(0.021)	(0.021)
year2013	-0.130^{***}	-0.130^{***}	-0.132^{***}
	(0.021)	(0.021)	(0.022)
year2014	-0.021	-0.021	-0.022
	(0.020)	(0.020)	(0.021)
year2015	-0.014	-0.014	-0.016
	(0.020)	(0.021)	(0.021)

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	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
year2016	−0.023	−0.023	−0.024
	(0.020)	(0.021)	(0.021)
year2017	−0.017	−0.017	−0.019
	(0.020)	(0.021)	(0.021)
year2018	−0.030	−0.030	−0.033
	(0.020)	(0.020)	(0.021)
year2019	−0.067***	−0.067***	−0.069***
	(0.020)	(0.021)	(0.021)
Constant	−1.252***	−1.252***	−1.265***
	(0.065)	(0.066)	(0.067)
Observations	29,832	29,832	29,832
Log Likelihood	−44,394.650		−44,333.240
θ			23.145*** (2.253)
Akaike Inf. Crit.	88,933.300		88,810.470
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.25: IRR of the best-fitted regression model for the slightly injured accidents with weather and explanatory variables in the spring period.

	Estimate	Robust SE	Pr(>|z|)	exp
(Intercept)	-1.265	0.068	0	0.282
dark	0.145	0.027	0	1.156
holiday1	-0.200	0.028	0	0.819
TMP_less_zero1	-0.372	0.025	0	0.690
TMP_less_five1	-0.385	0.020	0	0.681
TMP_less_ten1	-0.393	0.016	0	0.675
TMP_less_fifteen1	-0.235	0.014	0	0.790
mist1	-0.013	0.017	0.455	0.987
fog1	-0.131	0.084	0.116	0.877
drizzle1	-0.010	0.093	0.915	0.990
rain1	0.026	0.024	0.285	1.026
snow1	0.055	0.032	0.088	1.057
precipitation1	0.057	0.022	0.008	1.059
crash_into_solid_obstacle	0.097	0.002	0	1.102
cause_intoxication	0.191	0.006	0	1.210
cause_damaged_road	0.011	0.020	0.562	1.011
cause_car_defect	0.063	0.016	0	1.065
hour01	-0.116	0.065	0.073	0.891
hour02	-0.200	0.066	0.003	0.818
hour03	-0.197	0.068	0.004	0.821
hour04	0.095	0.062	0.125	1.100
hour05	1.176	0.053	0	3.242
hour06	1.550	0.055	0	4.714
hour07	1.890	0.056	0	6.618
hour08	1.708	0.056	0	5.518
hour09	1.699	0.056	0	5.466
hour10	1.699	0.055	0	5.466
hour11	1.684	0.055	0	5.386
hour12	1.706	0.055	0	5.508
hour13	1.863	0.055	0	6.445

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	Estimate	Robust SE	Pr(>|z|)	exp
hour14	2.058	0.054	0	7.828
hour15	2.062	0.054	0	7.865
hour16	1.979	0.054	0	7.233
hour17	1.848	0.054	0	6.347
hour18	1.686	0.052	0	5.396
hour19	1.277	0.052	0	3.586
hour20	0.936	0.052	0	2.549
hour21	0.702	0.052	0	2.018
hour22	0.541	0.054	0	1.717
hour23	0.111	0.059	0.060	1.117
day1	0.326	0.018	0	1.386
day2	0.239	0.018	0	1.270
day3	0.260	0.018	0	1.297
day4	0.273	0.018	0	1.314
day5	0.380	0.017	0	1.463
day6	0.122	0.019	0	1.130
week6	0.013	0.037	0.715	1.013
week7	0.037	0.036	0.300	1.038
week8	0.037	0.036	0.301	1.038
week9	0.024	0.037	0.510	1.024
week10	0.090	0.037	0.015	1.094
week11	0.124	0.037	0.001	1.132
week12	0.172	0.037	0	1.188
week13	0.212	0.037	0	1.236
week14	0.188	0.038	0	1.207
week15	0.212	0.038	0	1.236
week16	0.279	0.037	0	1.322
week17	0.264	0.038	0	1.302
week18	0.240	0.038	0	1.271
week19	0.258	0.039	0	1.294
week20	0.239	0.038	0	1.270
week21	0.279	0.041	0	1.322
year2010	-0.077	0.022	0	0.926

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	Estimate	Robust SE	Pr(>|z|)	exp
year2011	-0.075	0.021	0	0.928
year2012	-0.102	0.021	0	0.903
year2013	-0.132	0.021	0	0.876
year2014	-0.022	0.021	0.308	0.979
year2015	-0.016	0.021	0.442	0.984
year2016	-0.024	0.021	0.264	0.976
year2017	-0.019	0.021	0.382	0.981
year2018	-0.033	0.021	0.111	0.967
year2019	-0.069	0.021	0.001	0.933

Table A.26: The results of regression model for slightly injured accidents without weather variables in the autumn period.

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.197***	0.197***	0.182***
	(0.021)	(0.024)	(0.024)
hour01	−0.249***	−0.249***	−0.250***
	(0.060)	(0.067)	(0.061)
hour02	−0.237***	−0.237***	−0.238***
	(0.059)	(0.067)	(0.061)
hour03	−0.411***	−0.411***	−0.412***
	(0.062)	(0.071)	(0.064)

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour04	−0.058	−0.058	−0.059
	(0.057)	(0.064)	(0.058)
hour05	1.236***	1.236***	1.230***
	(0.045)	(0.051)	(0.046)
hour06	1.694***	1.694***	1.679***
	(0.044)	(0.050)	(0.046)
hour07	2.041***	2.041***	2.016***
	(0.047)	(0.053)	(0.050)
hour08	1.823***	1.823***	1.802***
	(0.048)	(0.054)	(0.051)
hour09	1.875***	1.875***	1.857***
	(0.048)	(0.054)	(0.051)
hour10	1.900***	1.900***	1.881***
	(0.048)	(0.054)	(0.051)
hour11	1.857***	1.857***	1.839***
	(0.048)	(0.054)	(0.051)
hour12	1.905***	1.905***	1.887***
	(0.048)	(0.054)	(0.051)
hour13	2.083***	2.083***	2.065***

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.047)	(0.054)	(0.050)
hour14	2.274***	2.274***	2.253***
	(0.047)	(0.053)	(0.050)
hour15	2.312***	2.312***	2.288***
	(0.047)	(0.053)	(0.050)
hour16	2.310***	2.310***	2.293***
	(0.046)	(0.052)	(0.049)
hour17	2.151***	2.151***	2.139***
	(0.043)	(0.049)	(0.045)
hour18	1.845***	1.845***	1.835***
	(0.044)	(0.050)	(0.046)
hour19	1.438***	1.438***	1.432***
	(0.044)	(0.050)	(0.046)
hour20	1.017***	1.017***	1.014***
	(0.046)	(0.052)	(0.048)
hour21	0.695***	0.695***	0.691***
	(0.048)	(0.055)	(0.050)
hour22	0.563***	0.563***	0.560***
	(0.049)	(0.056)	(0.051)

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
hour23	0.207***	0.207***	0.203***
	(0.053)	(0.060)	(0.054)
day1	0.343***	0.343***	0.331***
	(0.015)	(0.017)	(0.017)
day2	0.242***	0.242***	0.230***
	(0.016)	(0.018)	(0.017)
day3	0.302***	0.302***	0.289***
	(0.015)	(0.017)	(0.017)
day4	0.333***	0.333***	0.321***
	(0.015)	(0.017)	(0.017)
day5	0.426***	0.426***	0.417***
	(0.015)	(0.017)	(0.017)
day6	0.148***	0.148***	0.157***
	(0.016)	(0.018)	(0.018)
week36	−0.072	−0.072	−0.077
	(0.045)	(0.051)	(0.051)
week37	−0.011	−0.011	−0.015
	(0.044)	(0.050)	(0.051)

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week38	-0.077^{*}	-0.077	-0.082
	(0.044)	(0.050)	(0.051)
week39	-0.116^{***}	-0.116^{**}	-0.118^{**}
	(0.044)	(0.050)	(0.051)
week40	-0.136^{***}	-0.136^{***}	-0.142^{***}
	(0.045)	(0.050)	(0.051)
week41	-0.125^{***}	-0.125^{**}	-0.128^{**}
	(0.044)	(0.050)	(0.051)
week42	-0.141^{***}	-0.141^{***}	-0.141^{***}
	(0.045)	(0.050)	(0.051)
week43	-0.241^{***}	-0.241^{***}	-0.240^{***}
	(0.045)	(0.051)	(0.051)
week44	-0.357^{***}	-0.357^{***}	-0.355^{***}
	(0.045)	(0.051)	(0.051)
week45	-0.366^{***}	-0.366^{***}	-0.366^{***}
	(0.045)	(0.051)	(0.051)
week46	-0.321^{***}	-0.321^{***}	-0.317^{***}
	(0.045)	(0.051)	(0.051)
week47	-0.356^{***}	-0.356^{***}	-0.354^{***}

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.045)	(0.051)	(0.052)
week48	−0.356***	−0.356***	−0.353***
	(0.045)	(0.051)	(0.052)
week49	−0.308***	−0.308***	−0.303***
	(0.045)	(0.051)	(0.051)
week50	−0.277***	−0.277***	−0.271***
	(0.045)	(0.051)	(0.051)
week51	−0.248***	−0.248***	−0.245***
	(0.045)	(0.051)	(0.052)
week52	−0.591***	−0.591***	−0.578***
	(0.061)	(0.069)	(0.067)
year2010	−0.103***	−0.103***	−0.102***
	(0.019)	(0.021)	(0.021)
year2011	−0.015	−0.015	−0.016
	(0.018)	(0.021)	(0.021)
year2012	−0.053***	−0.053**	−0.054***
	(0.018)	(0.021)	(0.021)
year2013	−0.040**	−0.040*	−0.041**
	(0.018)	(0.021)	(0.021)

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
year2014	−0.035*	−0.035*	−0.035*
	(0.018)	(0.021)	(0.021)
year2015	0.060***	0.060***	0.059***
	(0.018)	(0.020)	(0.020)
year2016	−0.009	−0.009	−0.012
	(0.018)	(0.021)	(0.021)
year2017	0.024	0.024	0.020
	(0.018)	(0.020)	(0.020)
year2018	0.037**	0.037*	0.034*
	(0.018)	(0.020)	(0.020)
year2019	−0.024	−0.024	−0.029
	(0.018)	(0.021)	(0.021)
Constant	−0.888***	−0.888***	−0.860***
	(0.061)	(0.069)	(0.067)
Observations	29,832	29,832	29,832
Log Likelihood	−50,048.210		−49,722.090
θ			10.871*** (0.515)
Akaike Inf. Crit.	100,212.400		99,560.180

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.27: IRR of the best-fitted regression model for the slightly injured accidents without weather variables in the autumn period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	-0.860	0.069	0	0.423
dark	0.182	0.024	0	1.200
hour01	-0.250	0.068	0	0.779
hour02	-0.238	0.067	0	0.788
hour03	-0.412	0.070	0	0.662
hour04	-0.059	0.062	0.336	0.942
hour05	1.230	0.050	0	3.422
hour06	1.679	0.051	0	5.362
hour07	2.016	0.054	0	7.505
hour08	1.802	0.054	0	6.064
hour09	1.857	0.054	0	6.402
hour10	1.881	0.054	0	6.561
hour11	1.839	0.054	0	6.293
hour12	1.887	0.054	0	6.596
hour13	2.065	0.053	0	7.886
hour14	2.253	0.053	0	9.518
hour15	2.288	0.053	0	9.854
hour16	2.293	0.052	0	9.903
hour17	2.139	0.049	0	8.492
hour18	1.835	0.049	0	6.264
hour19	1.432	0.049	0	4.185

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
hour20	1.014	0.051	0	2.756
hour21	0.691	0.053	0	1.996
hour22	0.560	0.054	0	1.751
hour23	0.203	0.059	0.001	1.225
day1	0.331	0.018	0	1.392
day2	0.230	0.018	0	1.258
day3	0.289	0.018	0	1.335
day4	0.321	0.018	0	1.379
day5	0.417	0.017	0	1.518
day6	0.157	0.019	0	1.170
week36	-0.077	0.048	0.111	0.926
week37	-0.015	0.048	0.756	0.985
week38	-0.082	0.048	0.090	0.921
week39	-0.118	0.049	0.015	0.888
week40	-0.142	0.049	0.004	0.868
week41	-0.128	0.049	0.008	0.880
week42	-0.141	0.049	0.004	0.869
week43	-0.240	0.049	0	0.787
week44	-0.355	0.050	0	0.701
week45	-0.366	0.049	0	0.694
week46	-0.317	0.049	0	0.728
week47	-0.354	0.050	0	0.702
week48	-0.353	0.050	0	0.703
week49	-0.303	0.049	0	0.738
week50	-0.271	0.049	0	0.762
week51	-0.245	0.050	0	0.783
week52	-0.578	0.069	0	0.561
year2010	-0.102	0.021	0	0.903
year2011	-0.016	0.021	0.426	0.984
year2012	-0.054	0.021	0.008	0.947
year2013	-0.041	0.020	0.043	0.960
year2014	-0.035	0.020	0.080	0.965
year2015	0.059	0.020	0.004	1.060

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	Estimate	Robust SE	Pr(>|z|)	IRR
year2016	-0.012	0.021	0.561	0.988
year2017	0.020	0.021	0.333	1.021
year2018	0.034	0.020	0.097	1.035
year2019	-0.029	0.021	0.162	0.972

Table A.28: The results of the regression models for the slightly injured accidents with weather and explanatory variables in the autumn period.

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.214***	0.214***	0.209***
	(0.021)	(0.022)	(0.023)
holiday1	−0.296***	−0.296***	−0.294***
	(0.028)	(0.029)	(0.029)
TMP_less_zero1	−0.334***	−0.334***	−0.335***
	(0.025)	(0.026)	(0.026)
TMP_less_five1	−0.278***	−0.278***	−0.279***
	(0.019)	(0.020)	(0.021)
TMP_less_ten1	−0.267***	−0.267***	−0.267***
	(0.016)	(0.017)	(0.017)
TMP_less_fifteen1	−0.198***	−0.198***	−0.197***

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	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.013)	(0.014)	(0.014)
mist1	−0.038***	−0.038***	−0.037***
	(0.012)	(0.013)	(0.013)
fog1	0.042*	0.042*	0.043*
	(0.023)	(0.024)	(0.025)
drizzle1	0.003	0.003	0.002
	(0.041)	(0.043)	(0.044)
rain1	0.079***	0.079***	0.078***
	(0.019)	(0.020)	(0.020)
snow1	0.056*	0.056*	0.055
	(0.032)	(0.034)	(0.034)
precipitation1	0.068***	0.068***	0.067***
	(0.019)	(0.020)	(0.020)
crash_into_solid_obstacle	0.078***	0.078***	0.081***
	(0.002)	(0.002)	(0.002)
cause_intoxication	0.155***	0.155***	0.162***
	(0.005)	(0.005)	(0.005)
cause_damaged_road	0.009	0.009	0.010
	(0.017)	(0.018)	(0.019)

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	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
cause_car_defect	0.031**	0.031**	0.033**
	(0.014)	(0.015)	(0.015)
hour01	−0.221***	−0.221***	−0.220***
	(0.060)	(0.063)	(0.060)
hour02	−0.192***	−0.192***	−0.191***
	(0.059)	(0.062)	(0.060)
hour03	−0.328***	−0.328***	−0.324***
	(0.062)	(0.066)	(0.063)
hour04	0.015	0.015	0.018
	(0.057)	(0.059)	(0.057)
hour05	1.259***	1.259***	1.259***
	(0.045)	(0.047)	(0.046)
hour06	1.664***	1.664***	1.657***
	(0.044)	(0.046)	(0.045)
hour07	1.987***	1.987***	1.977***
	(0.047)	(0.050)	(0.049)
hour08	1.765***	1.765***	1.758***
	(0.048)	(0.051)	(0.050)

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	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
hour09	1.809***	1.809***	1.805***
	(0.048)	(0.051)	(0.050)
hour10	1.814***	1.814***	1.810***
	(0.048)	(0.050)	(0.050)
hour11	1.764***	1.764***	1.760***
	(0.048)	(0.051)	(0.050)
hour12	1.805***	1.805***	1.800***
	(0.048)	(0.050)	(0.050)
hour13	1.950***	1.950***	1.946***
	(0.047)	(0.050)	(0.049)
hour14	2.090***	2.090***	2.084***
	(0.047)	(0.049)	(0.049)
hour15	2.133***	2.133***	2.125***
	(0.047)	(0.049)	(0.049)
hour16	2.132***	2.132***	2.129***
	(0.046)	(0.048)	(0.048)
hour17	1.968***	1.968***	1.965***
	(0.044)	(0.046)	(0.045)
hour18	1.703***	1.703***	1.700***

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	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.044)	(0.046)	(0.045)
hour19	1.318***	1.318***	1.315***
	(0.044)	(0.047)	(0.045)
hour20	0.905***	0.905***	0.905***
	(0.046)	(0.048)	(0.047)
hour21	0.608***	0.608***	0.606***
	(0.048)	(0.051)	(0.049)
hour22	0.497***	0.497***	0.495***
	(0.049)	(0.052)	(0.050)
hour23	0.163***	0.163***	0.160***
	(0.053)	(0.056)	(0.054)
day1	0.324***	0.324***	0.322***
	(0.015)	(0.016)	(0.016)
day2	0.251***	0.251***	0.250***
	(0.016)	(0.016)	(0.017)
day3	0.292***	0.292***	0.291***
	(0.016)	(0.016)	(0.016)
day4	0.320***	0.320***	0.318***
	(0.015)	(0.016)	(0.016)

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
day5	0.388***	0.388***	0.386***
	(0.015)	(0.016)	(0.016)
day6	0.090***	0.090***	0.094***
	(0.016)	(0.017)	(0.017)
week36	−0.039	−0.039	−0.039
	(0.045)	(0.047)	(0.048)
week37	−0.003	−0.003	−0.002
	(0.044)	(0.046)	(0.048)
week38	−0.008	−0.008	−0.010
	(0.044)	(0.047)	(0.048)
week39	0.013	0.013	0.013
	(0.045)	(0.047)	(0.048)
week40	−0.015	−0.015	−0.016
	(0.045)	(0.047)	(0.048)
week41	−0.014	−0.014	−0.014
	(0.045)	(0.047)	(0.048)
week42	−0.014	−0.014	−0.013
	(0.045)	(0.048)	(0.049)

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
week43	−0.045	−0.045	−0.045
	(0.046)	(0.048)	(0.049)
week44	−0.089*	−0.089*	−0.089*
	(0.047)	(0.049)	(0.050)
week45	−0.135***	−0.135***	−0.136***
	(0.046)	(0.049)	(0.050)
week46	−0.060	−0.060	−0.059
	(0.047)	(0.049)	(0.050)
week47	−0.120**	−0.120**	−0.120**
	(0.047)	(0.049)	(0.050)
week48	−0.130***	−0.130***	−0.129**
	(0.048)	(0.050)	(0.051)
week49	−0.092*	−0.092*	−0.091*
	(0.048)	(0.050)	(0.051)
week50	−0.067	−0.067	−0.067
	(0.048)	(0.050)	(0.051)
week51	−0.066	−0.066	−0.067
	(0.048)	(0.050)	(0.051)
week52	−0.274***	−0.274***	−0.264***

Continued on next page

	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.063)	(0.066)	(0.067)
year2010	−0.071***	−0.071***	−0.071***
	(0.019)	(0.020)	(0.020)
year2011	−0.017	−0.017	−0.018
	(0.018)	(0.019)	(0.020)
year2012	−0.052***	−0.052***	−0.053***
	(0.019)	(0.019)	(0.020)
year2013	−0.021	−0.021	−0.021
	(0.018)	(0.019)	(0.020)
year2014	−0.038**	−0.038*	−0.037*
	(0.018)	(0.019)	(0.020)
year2015	0.047***	0.047**	0.047**
	(0.018)	(0.019)	(0.019)
year2016	−0.012	−0.012	−0.014
	(0.018)	(0.019)	(0.020)
year2017	0.002	0.002	−0.001
	(0.018)	(0.019)	(0.020)
year2018	−0.014	−0.014	−0.017
	(0.018)	(0.019)	(0.020)

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	Dependent variable:		
	slightly_injured_accidents		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
year2019	-0.057^{***}	-0.057^{***}	-0.059^{***}
	(0.018)	(0.019)	(0.020)
Constant	-1.032^{***}	-1.032^{***}	-1.036^{***}
	(0.061)	(0.064)	(0.064)
Observations	29,832	29,832	29,832
Log Likelihood	−48,115.050		−48,021.140
θ			21.957^{***} (1.761)
Akaike Inf. Crit.	96,376.100		96,188.290
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.29: IRR of the best-fitted regression model for the slightly injured accidents with weather and explanatory variables in the autumn period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	-1.036	0.065	0	0.355
dark	0.209	0.023	0	1.232
holiday1	-0.294	0.031	0	0.745
TMP_less_zero1	-0.335	0.026	0	0.715
TMP_less_five1	-0.279	0.020	0	0.756
TMP_less_ten1	-0.267	0.017	0	0.766
TMP_less_fifteen1	-0.197	0.014	0	0.821
mist1	-0.037	0.013	0.004	0.964

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
fog1	0.043	0.025	0.083	1.044
drizzle1	0.002	0.044	0.963	1.002
rain1	0.078	0.021	0	1.081
snow1	0.055	0.036	0.124	1.056
precipitation1	0.067	0.021	0.001	1.069
crash_into_solid_obstacle	0.081	0.002	0	1.084
cause_intoxication	0.162	0.005	0	1.175
cause_damaged_road	0.010	0.018	0.587	1.010
cause_car_defect	0.033	0.015	0.033	1.033
hour01	-0.220	0.063	0	0.802
hour02	-0.191	0.062	0.002	0.826
hour03	-0.324	0.066	0	0.723
hour04	0.018	0.058	0.760	1.018
hour05	1.259	0.047	0	3.522
hour06	1.657	0.047	0	5.243
hour07	1.977	0.051	0	7.218
hour08	1.758	0.051	0	5.800
hour09	1.805	0.051	0	6.078
hour10	1.810	0.050	0	6.111
hour11	1.760	0.050	0	5.814
hour12	1.800	0.050	0	6.052
hour13	1.946	0.050	0	6.998
hour14	2.084	0.050	0	8.039
hour15	2.125	0.050	0	8.375
hour16	2.129	0.049	0	8.404
hour17	1.965	0.046	0	7.133
hour18	1.700	0.046	0	5.476
hour19	1.315	0.046	0	3.725
hour20	0.905	0.047	0	2.471
hour21	0.606	0.049	0	1.833
hour22	0.495	0.050	0	1.641
hour23	0.160	0.054	0.003	1.174
day1	0.322	0.017	0	1.380

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
day2	0.250	0.017	0	1.284
day3	0.291	0.017	0	1.338
day4	0.318	0.017	0	1.375
day5	0.386	0.016	0	1.471
day6	0.094	0.018	0	1.099
week36	-0.039	0.047	0.403	0.961
week37	-0.002	0.047	0.966	0.998
week38	-0.010	0.047	0.830	0.990
week39	0.013	0.047	0.781	1.013
week40	-0.016	0.047	0.730	0.984
week41	-0.014	0.048	0.762	0.986
week42	-0.013	0.048	0.788	0.987
week43	-0.045	0.048	0.352	0.956
week44	-0.089	0.050	0.073	0.915
week45	-0.136	0.049	0.006	0.873
week46	-0.059	0.049	0.228	0.942
week47	-0.120	0.050	0.016	0.887
week48	-0.129	0.050	0.010	0.879
week49	-0.091	0.050	0.071	0.913
week50	-0.067	0.050	0.184	0.936
week51	-0.067	0.051	0.187	0.935
week52	-0.264	0.068	0	0.768
year2010	-0.071	0.020	0	0.932
year2011	-0.018	0.020	0.352	0.982
year2012	-0.053	0.020	0.007	0.948
year2013	-0.021	0.020	0.285	0.979
year2014	-0.037	0.019	0.054	0.963
year2015	0.047	0.019	0.015	1.048
year2016	-0.014	0.020	0.477	0.986
year2017	-0.001	0.020	0.944	0.999
year2018	-0.017	0.019	0.374	0.983
year2019	-0.059	0.020	0.003	0.943

A.6 The results of GLM for total accidents

Table A.30: The results of regression models for total accidents without weather variables in the spring period.

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
dark	0.159***	0.159***	0.165***
	(0.011)	(0.016)	(0.015)
hour01	−0.146***	−0.146***	−0.144***
	(0.024)	(0.033)	(0.027)
hour02	−0.234***	−0.234***	−0.233***
	(0.025)	(0.034)	(0.028)
hour03	−0.281***	−0.281***	−0.281***
	(0.025)	(0.034)	(0.028)
hour04	−0.031	−0.031	−0.038
	(0.024)	(0.032)	(0.026)
hour05	0.784***	0.784***	0.767***
	(0.021)	(0.028)	(0.024)
hour06	1.145***	1.145***	1.128***
	(0.021)	(0.029)	(0.026)
hour07	1.493***	1.493***	1.476***
	(0.022)	(0.030)	(0.027)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour08	1.533***	1.533***	1.517***
	(0.022)	(0.030)	(0.027)
hour09	1.545***	1.545***	1.533***
	(0.022)	(0.030)	(0.027)
hour10	1.558***	1.558***	1.549***
	(0.022)	(0.030)	(0.027)
hour11	1.526***	1.526***	1.517***
	(0.022)	(0.030)	(0.027)
hour12	1.485***	1.485***	1.475***
	(0.022)	(0.030)	(0.027)
hour13	1.557***	1.557***	1.548***
	(0.022)	(0.030)	(0.027)
hour14	1.721***	1.721***	1.710***
	(0.021)	(0.029)	(0.027)
hour15	1.733***	1.733***	1.723***
	(0.021)	(0.029)	(0.027)
hour16	1.661***	1.661***	1.653***
	(0.022)	(0.029)	(0.027)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour17	1.550***	1.550***	1.546***
	(0.021)	(0.029)	(0.026)
hour18	1.429***	1.429***	1.430***
	(0.020)	(0.027)	(0.024)
hour19	1.120***	1.120***	1.120***
	(0.020)	(0.027)	(0.024)
hour20	0.953***	0.953***	0.950***
	(0.020)	(0.027)	(0.024)
hour21	0.778***	0.778***	0.767***
	(0.020)	(0.027)	(0.023)
hour22	0.520***	0.520***	0.506***
	(0.021)	(0.029)	(0.024)
hour23	0.236***	0.236***	0.225***
	(0.022)	(0.030)	(0.025)
day1	0.453***	0.453***	0.398***
	(0.008)	(0.011)	(0.011)
day2	0.432***	0.432***	0.378***
	(0.008)	(0.011)	(0.011)
day3	0.457***	0.457***	0.401***

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.008)	(0.011)	(0.010)
day4	0.465***	0.465***	0.414***
	(0.008)	(0.011)	(0.010)
day5	0.526***	0.526***	0.480***
	(0.008)	(0.011)	(0.010)
day6	0.187***	0.187***	0.188***
	(0.008)	(0.012)	(0.011)
week6	−0.021	−0.021	−0.015
	(0.014)	(0.019)	(0.019)
week7	0.031**	0.031*	0.032*
	(0.014)	(0.019)	(0.019)
week8	−0.035**	−0.035*	−0.025
	(0.014)	(0.019)	(0.019)
week9	−0.122***	−0.122***	−0.121***
	(0.014)	(0.019)	(0.019)
week10	−0.031**	−0.031	−0.024
	(0.014)	(0.019)	(0.019)
week11	−0.029**	−0.029	−0.020
	(0.014)	(0.019)	(0.019)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week12	0.017	0.017	0.024
	(0.014)	(0.019)	(0.019)
week13	0.036***	0.036*	0.042**
	(0.014)	(0.019)	(0.019)
week14	0.010	0.010	0.016
	(0.014)	(0.019)	(0.019)
week15	0.056***	0.056***	0.070***
	(0.014)	(0.019)	(0.019)
week16	0.131***	0.131***	0.146***
	(0.014)	(0.019)	(0.019)
week17	0.151***	0.151***	0.171***
	(0.014)	(0.019)	(0.019)
week18	0.128***	0.128***	0.163***
	(0.014)	(0.019)	(0.019)
week19	0.155***	0.155***	0.184***
	(0.014)	(0.019)	(0.019)
week20	0.202***	0.202***	0.231***
	(0.014)	(0.019)	(0.019)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
week21	0.220***	0.220***	0.245***
	(0.015)	(0.021)	(0.021)
year2010	0.016	0.016	0.004
	(0.010)	(0.014)	(0.013)
year2011	−0.025**	−0.025*	−0.033**
	(0.010)	(0.014)	(0.013)
year2012	0.089***	0.089***	0.077***
	(0.010)	(0.014)	(0.013)
year2013	0.135***	0.135***	0.125***
	(0.010)	(0.013)	(0.013)
year2014	0.123***	0.123***	0.115***
	(0.010)	(0.013)	(0.013)
year2015	0.209***	0.209***	0.199***
	(0.010)	(0.013)	(0.013)
year2016	0.264***	0.264***	0.258***
	(0.010)	(0.013)	(0.013)
year2017	0.307***	0.307***	0.299***
	(0.009)	(0.013)	(0.013)
year2018	0.331***	0.331***	0.321***

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.009)	(0.013)	(0.013)
year2019	0.367***	0.367***	0.367***
	(0.009)	(0.013)	(0.013)
Constant	0.324***	0.324***	0.364***
	(0.025)	(0.035)	(0.032)
Observations	29,832	29,832	29,832
Log Likelihood	−81,498.860		−78,853.010
θ			11.529*** (0.243)
Akaike Inf. Crit.	163,111.700		157,820.000
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.31: IRR of the best-fitted regression model for the total accidents without weather variables in the spring period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	0.364	0.036	0	1.439
dark	0.165	0.015	0	1.179
hour01	-0.144	0.034	0	0.866
hour02	-0.233	0.035	0	0.792
hour03	-0.281	0.034	0	0.755
hour04	-0.038	0.031	0.215	0.963
hour05	0.767	0.028	0	2.154

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
hour06	1.128	0.030	0	3.088
hour07	1.476	0.031	0	4.373
hour08	1.517	0.031	0	4.559
hour09	1.533	0.030	0	4.630
hour10	1.549	0.029	0	4.708
hour11	1.517	0.029	0	4.559
hour12	1.475	0.029	0	4.372
hour13	1.548	0.029	0	4.703
hour14	1.710	0.029	0	5.531
hour15	1.723	0.029	0	5.599
hour16	1.653	0.029	0	5.220
hour17	1.546	0.029	0	4.691
hour18	1.430	0.027	0	4.178
hour19	1.120	0.027	0	3.066
hour20	0.950	0.027	0	2.586
hour21	0.767	0.028	0	2.153
hour22	0.506	0.027	0	1.659
hour23	0.225	0.029	0	1.253
day1	0.398	0.012	0	1.489
day2	0.378	0.012	0	1.460
day3	0.401	0.012	0	1.494
day4	0.414	0.011	0	1.513
day5	0.480	0.011	0	1.616
day6	0.188	0.013	0	1.207
week6	-0.015	0.021	0.469	0.985
week7	0.032	0.022	0.152	1.032
week8	-0.025	0.021	0.225	0.975
week9	-0.121	0.021	0	0.886
week10	-0.024	0.021	0.254	0.976
week11	-0.020	0.021	0.337	0.980
week12	0.024	0.020	0.249	1.024
week13	0.042	0.021	0.043	1.043
week14	0.016	0.020	0.434	1.016

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
week15	0.070	0.020	0.001	1.073
week16	0.146	0.020	0	1.158
week17	0.171	0.020	0	1.186
week18	0.163	0.021	0	1.177
week19	0.184	0.021	0	1.202
week20	0.231	0.020	0	1.260
week21	0.245	0.023	0	1.277
year2010	0.004	0.014	0.765	1.004
year2011	-0.033	0.013	0.014	0.968
year2012	0.077	0.014	0	1.080
year2013	0.125	0.014	0	1.134
year2014	0.115	0.013	0	1.122
year2015	0.199	0.013	0	1.220
year2016	0.258	0.013	0	1.294
year2017	0.299	0.013	0	1.349
year2018	0.321	0.013	0	1.378
year2019	0.367	0.013	0	1.443

Table A.32: The results of the regression models for total accidents with weather and explanatory variables in the spring period.

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
dark	0.178***	0.178***	0.184***
	(0.012)	(0.015)	(0.014)
holiday1	−0.404***	−0.404***	−0.375***

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.014)	(0.017)	(0.016)
TMP_less_zero1	−0.053***	−0.053***	−0.013
	(0.014)	(0.018)	(0.014)
TMP_less_five1	−0.128***	−0.128***	−0.084***
	(0.013)	(0.016)	(0.012)
TMP_less_ten1	−0.144***	−0.144***	−0.098***
	(0.011)	(0.014)	(0.010)
TMP_less_fifteen1	−0.097***	−0.097***	−0.056***
	(0.010)	(0.013)	(0.009)
TMP_less_twenty1	−0.043***	−0.043***	
	(0.010)	(0.013)	
mist1	0.006	0.006	0.013
	(0.008)	(0.010)	(0.009)
fog1	0.023	0.023	0.025
	(0.030)	(0.038)	(0.037)
drizzle1	0.069*	0.069	0.101**
	(0.038)	(0.048)	(0.047)
rain1	0.048***	0.048***	0.047***
	(0.010)	(0.013)	(0.013)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
snow1	0.355***	0.355***	0.359***
	(0.013)	(0.016)	(0.017)
precipitation1	0.133***	0.133***	0.123***
	(0.009)	(0.012)	(0.012)
RH	−0.001***	−0.001**	−0.001***
	(0.0002)	(0.0002)	(0.0002)
SLP	−0.001***	−0.001***	−0.001***
	(0.0002)	(0.0003)	(0.0003)
cause_intoxication	0.153***	0.153***	0.173***
	(0.003)	(0.003)	(0.003)
cause_damaged_road	0.140***	0.140***	0.150***
	(0.008)	(0.011)	(0.011)
cause_car_defect	0.110***	0.110***	0.120***
	(0.007)	(0.009)	(0.010)
hour01	−0.138***	−0.138***	−0.135***
	(0.024)	(0.031)	(0.026)
hour02	−0.221***	−0.221***	−0.219***
	(0.025)	(0.031)	(0.027)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
hour03	-0.251^{***}	-0.251^{***}	-0.246^{***}
	(0.025)	(0.032)	(0.027)
hour04	0.004	0.004	0.009
	(0.024)	(0.030)	(0.026)
hour05	0.813^{***}	0.813^{***}	0.813^{***}
	(0.021)	(0.026)	(0.023)
hour06	1.178^{***}	1.178^{***}	1.176^{***}
	(0.021)	(0.027)	(0.025)
hour07	1.530^{***}	1.530^{***}	1.525^{***}
	(0.022)	(0.028)	(0.026)
hour08	1.573^{***}	1.573^{***}	1.571^{***}
	(0.022)	(0.028)	(0.025)
hour09	1.580^{***}	1.580^{***}	1.583^{***}
	(0.022)	(0.028)	(0.025)
hour10	1.589^{***}	1.589^{***}	1.597^{***}
	(0.022)	(0.028)	(0.025)
hour11	1.538^{***}	1.538^{***}	1.547^{***}
	(0.022)	(0.028)	(0.025)
hour12	1.497^{***}	1.497^{***}	1.505^{***}

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.022)	(0.028)	(0.026)
hour13	1.554***	1.554***	1.565***
	(0.022)	(0.028)	(0.025)
hour14	1.701***	1.701***	1.709***
	(0.022)	(0.027)	(0.025)
hour15	1.701***	1.701***	1.711***
	(0.022)	(0.027)	(0.025)
hour16	1.624***	1.624***	1.632***
	(0.022)	(0.027)	(0.025)
hour17	1.501***	1.501***	1.512***
	(0.022)	(0.027)	(0.025)
hour18	1.375***	1.375***	1.388***
	(0.020)	(0.026)	(0.023)
hour19	1.065***	1.065***	1.074***
	(0.020)	(0.026)	(0.023)
hour20	0.916***	0.916***	0.921***
	(0.020)	(0.025)	(0.023)
hour21	0.740***	0.740***	0.737***
	(0.020)	(0.025)	(0.022)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
hour22	0.491***	0.491***	0.485***
	(0.021)	(0.026)	(0.023)
hour23	0.216***	0.216***	0.210***
	(0.022)	(0.028)	(0.024)
day1	0.484***	0.484***	0.451***
	(0.008)	(0.010)	(0.010)
day2	0.449***	0.449***	0.419***
	(0.008)	(0.010)	(0.010)
day3	0.474***	0.474***	0.444***
	(0.008)	(0.010)	(0.010)
day4	0.476***	0.476***	0.447***
	(0.008)	(0.010)	(0.010)
day5	0.530***	0.530***	0.502***
	(0.008)	(0.010)	(0.010)
day6	0.145***	0.145***	0.141***
	(0.008)	(0.011)	(0.010)
week6	0.024*	0.024	0.028
	(0.014)	(0.018)	(0.018)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
week7	0.047***	0.047***	0.042**
	(0.014)	(0.018)	(0.017)
week8	−0.008	−0.008	−0.002
	(0.014)	(0.018)	(0.018)
week9	−0.057***	−0.057***	−0.054***
	(0.014)	(0.018)	(0.018)
week10	0.035**	0.035*	0.035*
	(0.014)	(0.018)	(0.018)
week11	0.030**	0.030	0.036*
	(0.015)	(0.018)	(0.018)
week12	0.063***	0.063***	0.068***
	(0.015)	(0.018)	(0.018)
week13	0.108***	0.108***	0.110***
	(0.015)	(0.019)	(0.019)
week14	0.083***	0.083***	0.087***
	(0.015)	(0.019)	(0.019)
week15	0.112***	0.112***	0.121***
	(0.015)	(0.019)	(0.019)
week16	0.172***	0.172***	0.184***

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.015)	(0.019)	(0.019)
week17	0.167***	0.167***	0.187***
	(0.015)	(0.019)	(0.019)
week18	0.197***	0.197***	0.224***
	(0.015)	(0.019)	(0.019)
week19	0.217***	0.217***	0.244***
	(0.016)	(0.020)	(0.020)
week20	0.210***	0.210***	0.238***
	(0.015)	(0.019)	(0.019)
week21	0.206***	0.206***	0.234***
	(0.017)	(0.022)	(0.022)
year2010	0.041***	0.041***	0.033***
	(0.010)	(0.013)	(0.013)
year2011	−0.003	−0.003	−0.005
	(0.010)	(0.013)	(0.013)
year2012	0.119***	0.119***	0.113***
	(0.010)	(0.013)	(0.012)
year2013	0.135***	0.135***	0.129***
	(0.010)	(0.013)	(0.012)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
year2014	0.174***	0.174***	0.169***
	(0.010)	(0.013)	(0.012)
year2015	0.252***	0.252***	0.246***
	(0.010)	(0.012)	(0.012)
year2016	0.319***	0.319***	0.319***
	(0.010)	(0.012)	(0.012)
year2017	0.360***	0.360***	0.359***
	(0.010)	(0.012)	(0.012)
year2018	0.356***	0.356***	0.353***
	(0.010)	(0.012)	(0.012)
year2019	0.426***	0.426***	0.431***
	(0.010)	(0.012)	(0.012)
Constant	0.819***	0.819***	0.954***
	(0.214)	(0.270)	(0.271)
Observations	29,832	29,832	29,832
Log Likelihood	−77,991.910		−76,623.600
θ			17.372*** (0.456)
Akaike Inf. Crit.	156,131.800		153,393.200

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.33: IRR of the best-fitted regression model for the total accidents with weather and explanatory variables in the spring period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	0.954	0.275	0.001	2.595
dark	0.184	0.014	0	1.203
holiday1	-0.375	0.021	0	0.687
TMP_less_zero1	-0.013	0.015	0.379	0.987
TMP_less_five1	-0.084	0.012	0	0.920
TMP_less_ten1	-0.098	0.010	0	0.906
TMP_less_fifteen1	-0.056	0.008	0	0.945
mist1	0.013	0.010	0.188	1.013
fog1	0.025	0.042	0.555	1.025
drizzle1	0.101	0.052	0.055	1.106
rain1	0.047	0.014	0.001	1.049
snow1	0.359	0.022	0	1.432
precipitation1	0.123	0.013	0	1.131
RH	-0.001	0	0.005	0.999
SLP	-0.001	0	0.001	0.999
cause_intoxication	0.173	0.003	0	1.189
cause_damaged_road	0.150	0.010	0	1.162
cause_car_defect	0.120	0.008	0	1.128
hour01	-0.135	0.032	0	0.873
hour02	-0.219	0.032	0	0.804
hour03	-0.246	0.032	0	0.782

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
hour04	0.009	0.029	0.770	1.009
hour05	0.813	0.026	0	2.254
hour06	1.176	0.028	0	3.241
hour07	1.525	0.029	0	4.597
hour08	1.571	0.028	0	4.813
hour09	1.583	0.028	0	4.868
hour10	1.597	0.028	0	4.938
hour11	1.547	0.027	0	4.697
hour12	1.505	0.027	0	4.505
hour13	1.565	0.027	0	4.784
hour14	1.709	0.027	0	5.522
hour15	1.711	0.027	0	5.533
hour16	1.632	0.028	0	5.115
hour17	1.512	0.027	0	4.538
hour18	1.388	0.026	0	4.007
hour19	1.074	0.025	0	2.928
hour20	0.921	0.026	0	2.511
hour21	0.737	0.026	0	2.091
hour22	0.485	0.026	0	1.624
hour23	0.210	0.027	0	1.233
day1	0.451	0.011	0	1.570
day2	0.419	0.011	0	1.520
day3	0.444	0.011	0	1.558
day4	0.447	0.011	0	1.564
day5	0.502	0.011	0	1.651
day6	0.141	0.012	0	1.151
week6	0.028	0.019	0.156	1.028
week7	0.042	0.020	0.032	1.043
week8	-0.002	0.019	0.899	0.998
week9	-0.054	0.019	0.005	0.947
week10	0.035	0.020	0.075	1.036
week11	0.036	0.020	0.069	1.036
week12	0.068	0.020	0.001	1.070

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	Estimate	Robust SE	Pr(>|z|)	IRR
week13	0.110	0.020	0	1.116
week14	0.087	0.020	0	1.091
week15	0.121	0.020	0	1.128
week16	0.184	0.020	0	1.202
week17	0.187	0.020	0	1.205
week18	0.224	0.021	0	1.251
week19	0.244	0.021	0	1.276
week20	0.238	0.020	0	1.268
week21	0.234	0.023	0	1.264
year2010	0.033	0.013	0.009	1.034
year2011	-0.005	0.012	0.704	0.995
year2012	0.113	0.013	0	1.120
year2013	0.129	0.013	0	1.138
year2014	0.169	0.012	0	1.184
year2015	0.246	0.012	0	1.279
year2016	0.319	0.012	0	1.376
year2017	0.359	0.012	0	1.432
year2018	0.353	0.012	0	1.424
year2019	0.431	0.012	0	1.538

Table A.34: The results of regression model for total accidents without weather variables in the autumn period.

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.303***	0.303***	0.283***
	(0.010)	(0.014)	(0.014)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour01	−0.140***	−0.140***	−0.140***
	(0.024)	(0.032)	(0.026)
hour02	−0.223***	−0.223***	−0.224***
	(0.024)	(0.032)	(0.026)
hour03	−0.292***	−0.292***	−0.296***
	(0.025)	(0.033)	(0.027)
hour04	−0.041*	−0.041	−0.048*
	(0.023)	(0.031)	(0.025)
hour05	0.824***	0.824***	0.804***
	(0.019)	(0.026)	(0.022)
hour06	1.398***	1.398***	1.362***
	(0.018)	(0.025)	(0.022)
hour07	1.758***	1.758***	1.707***
	(0.020)	(0.027)	(0.025)
hour08	1.713***	1.713***	1.669***
	(0.021)	(0.028)	(0.025)
hour09	1.751***	1.751***	1.713***
	(0.021)	(0.028)	(0.025)

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour10	1.772***	1.772***	1.736***
	(0.021)	(0.028)	(0.025)
hour11	1.730***	1.730***	1.695***
	(0.021)	(0.028)	(0.025)
hour12	1.694***	1.694***	1.658***
	(0.021)	(0.028)	(0.025)
hour13	1.779***	1.779***	1.745***
	(0.021)	(0.028)	(0.025)
hour14	1.901***	1.901***	1.865***
	(0.020)	(0.027)	(0.025)
hour15	1.917***	1.917***	1.880***
	(0.020)	(0.027)	(0.025)
hour16	1.966***	1.966***	1.932***
	(0.020)	(0.027)	(0.024)
hour17	1.823***	1.823***	1.800***
	(0.018)	(0.024)	(0.022)
hour18	1.567***	1.567***	1.550***
	(0.018)	(0.025)	(0.022)
hour19	1.297***	1.297***	1.287***

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.018)	(0.025)	(0.021)
hour20	0.980***	0.980***	0.971***
	(0.019)	(0.025)	(0.022)
hour21	0.704***	0.704***	0.696***
	(0.020)	(0.026)	(0.022)
hour22	0.532***	0.532***	0.520***
	(0.020)	(0.027)	(0.023)
hour23	0.264***	0.264***	0.254***
	(0.021)	(0.029)	(0.024)
day1	0.424***	0.424***	0.376***
	(0.007)	(0.010)	(0.010)
day2	0.357***	0.357***	0.313***
	(0.007)	(0.010)	(0.010)
day3	0.404***	0.404***	0.356***
	(0.007)	(0.010)	(0.010)
day4	0.421***	0.421***	0.378***
	(0.007)	(0.010)	(0.010)
day5	0.471***	0.471***	0.435***
	(0.007)	(0.010)	(0.010)

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
day6	0.169***	0.169***	0.181***
	(0.008)	(0.010)	(0.010)
week36	−0.067***	−0.067**	−0.079**
	(0.024)	(0.032)	(0.031)
week37	−0.007	−0.007	−0.019
	(0.023)	(0.032)	(0.031)
week38	−0.025	−0.025	−0.033
	(0.023)	(0.032)	(0.031)
week39	−0.045*	−0.045	−0.049
	(0.023)	(0.032)	(0.031)
week40	−0.027	−0.027	−0.039
	(0.023)	(0.032)	(0.031)
week41	0.020	0.020	0.011
	(0.023)	(0.031)	(0.031)
week42	0.009	0.009	0.004
	(0.023)	(0.032)	(0.031)
week43	−0.048**	−0.048	−0.054*
	(0.023)	(0.032)	(0.031)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
week44	−0.124***	−0.124***	−0.132***
	(0.024)	(0.032)	(0.031)
week45	−0.141***	−0.141***	−0.151***
	(0.024)	(0.032)	(0.031)
week46	−0.115***	−0.115***	−0.119***
	(0.024)	(0.032)	(0.031)
week47	−0.140***	−0.140***	−0.149***
	(0.024)	(0.032)	(0.031)
week48	−0.074***	−0.074**	−0.079**
	(0.024)	(0.032)	(0.031)
week49	−0.073***	−0.073**	−0.077**
	(0.024)	(0.032)	(0.031)
week50	−0.051**	−0.051	−0.058*
	(0.023)	(0.032)	(0.031)
week51	−0.023	−0.023	−0.023
	(0.024)	(0.032)	(0.031)
week52	−0.276***	−0.276***	−0.275***
	(0.030)	(0.040)	(0.038)
year2010	−0.013	−0.013	−0.008

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.009)	(0.013)	(0.012)
year2011	0.023**	0.023*	0.023*
	(0.009)	(0.013)	(0.012)
year2012	0.073***	0.073***	0.077***
	(0.009)	(0.012)	(0.012)
year2013	0.101***	0.101***	0.104***
	(0.009)	(0.012)	(0.012)
year2014	0.116***	0.116***	0.116***
	(0.009)	(0.012)	(0.012)
year2015	0.197***	0.197***	0.196***
	(0.009)	(0.012)	(0.012)
year2016	0.237***	0.237***	0.238***
	(0.009)	(0.012)	(0.012)
year2017	0.292***	0.292***	0.295***
	(0.009)	(0.012)	(0.012)
year2018	0.297***	0.297***	0.297***
	(0.009)	(0.012)	(0.012)
year2019	0.275***	0.275***	0.281***
	(0.009)	(0.012)	(0.012)

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
Constant	0.415***	0.415***	0.486***
	(0.029)	(0.039)	(0.037)
Observations	29,832	29,832	29,832
Log Likelihood	−83,370.180		−81,037.410
θ			14.341*** (0.314)
Akaike Inf. Crit.	166,856.400		162,190.800
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.35: IRR of the best-fitted regression model for the total without weather variables in the autumn period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	0.486	0.069	0	1.626
dark	0.283	0.024	0	1.327
hour01	-0.140	0.068	0.039	0.869
hour02	-0.224	0.067	0.001	0.799
hour03	-0.296	0.070	0	0.744
hour04	-0.048	0.062	0.440	0.953
hour05	0.804	0.050	0	2.235
hour06	1.362	0.051	0	3.903
hour07	1.707	0.054	0	5.514
hour08	1.669	0.054	0	5.308
hour09	1.713	0.054	0	5.543

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	Estimate	Robust SE	Pr(>|z|)	IRR
hour10	1.736	0.054	0	5.676
hour11	1.695	0.054	0	5.447
hour12	1.658	0.054	0	5.251
hour13	1.745	0.053	0	5.726
hour14	1.865	0.053	0	6.453
hour15	1.880	0.053	0	6.555
hour16	1.932	0.052	0	6.902
hour17	1.800	0.049	0	6.047
hour18	1.550	0.049	0	4.711
hour19	1.287	0.049	0	3.621
hour20	0.971	0.051	0	2.642
hour21	0.696	0.053	0	2.005
hour22	0.520	0.054	0	1.683
hour23	0.254	0.059	0	1.289
day1	0.376	0.018	0	1.457
day2	0.313	0.018	0	1.367
day3	0.356	0.018	0	1.428
day4	0.378	0.018	0	1.459
day5	0.435	0.017	0	1.545
day6	0.181	0.019	0	1.198
week36	-0.079	0.048	0.101	0.924
week37	-0.019	0.048	0.697	0.981
week38	-0.033	0.048	0.491	0.967
week39	-0.049	0.049	0.318	0.953
week40	-0.039	0.049	0.425	0.962
week41	0.011	0.049	0.817	1.011
week42	0.004	0.049	0.928	1.004
week43	-0.054	0.049	0.265	0.947
week44	-0.132	0.050	0.008	0.876
week45	-0.151	0.049	0.002	0.860
week46	-0.119	0.049	0.016	0.888
week47	-0.149	0.050	0.003	0.862
week48	-0.079	0.050	0.115	0.924

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	Estimate	Robust SE	Pr(>|z|)	IRR
week49	-0.077	0.049	0.118	0.926
week50	-0.058	0.049	0.241	0.944
week51	-0.023	0.050	0.650	0.978
week52	-0.275	0.069	0	0.760
year2010	-0.008	0.021	0.689	0.992
year2011	0.023	0.021	0.257	1.024
year2012	0.077	0.021	0	1.080
year2013	0.104	0.020	0	1.109
year2014	0.116	0.020	0	1.123
year2015	0.196	0.020	0	1.217
year2016	0.238	0.021	0	1.268
year2017	0.295	0.021	0	1.344
year2018	0.297	0.020	0	1.346
year2019	0.281	0.021	0	1.325

Table A.36: The results of the regression models for the total accidents with weather and explanatory variables in the autumn period.

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative binomial*
	(1)	(2)	(3)
dark	0.295***	0.295***	0.282***
	(0.010)	(0.013)	(0.013)
holiday1	−0.341***	−0.341***	−0.324***
	(0.013)	(0.017)	(0.016)
TMP_less_zero1	0.017	0.017	0.069***

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.015)	(0.019)	(0.015)
TMP_less_five1	−0.054***	−0.054***	−0.002
	(0.013)	(0.017)	(0.012)
TMP_less_ten1	−0.080***	−0.080***	−0.029***
	(0.012)	(0.015)	(0.010)
TMP_less_fifteen1	−0.059***	−0.059***	−0.010
	(0.011)	(0.013)	(0.008)
TMP_less_twenty1	−0.055***	−0.055***	
	(0.010)	(0.013)	
mist1	−0.042***	−0.042***	−0.038***
	(0.006)	(0.008)	(0.007)
fog1	−0.014	−0.014	−0.008
	(0.011)	(0.014)	(0.013)
drizzle1	0.040**	0.040*	0.045*
	(0.019)	(0.024)	(0.024)
rain1	0.095***	0.095***	0.093***
	(0.009)	(0.011)	(0.011)
snow1	0.212***	0.212***	0.217***
	(0.014)	(0.018)	(0.018)

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
precipitation1	0.114***	0.114***	0.115***
	(0.009)	(0.011)	(0.011)
RH	0.0003	0.0003	
	(0.0002)	(0.0003)	
SLP	−0.002***	−0.002***	−0.002***
	(0.0002)	(0.0003)	(0.0003)
cause_intoxication	0.129***	0.129***	0.149***
	(0.002)	(0.003)	(0.003)
cause_damaged_road	0.103***	0.103***	0.114***
	(0.008)	(0.010)	(0.011)
cause_car_defect	0.102***	0.102***	0.111***
	(0.007)	(0.008)	(0.009)
hour01	−0.129***	−0.129***	−0.127***
	(0.024)	(0.029)	(0.025)
hour02	−0.208***	−0.208***	−0.205***
	(0.024)	(0.030)	(0.026)
hour03	−0.256***	−0.256***	−0.250***
	(0.025)	(0.031)	(0.026)

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
hour04	−0.007	−0.007	−0.002
	(0.023)	(0.029)	(0.025)
hour05	0.852***	0.852***	0.848***
	(0.019)	(0.024)	(0.021)
hour06	1.414***	1.414***	1.399***
	(0.019)	(0.023)	(0.021)
hour07	1.767***	1.767***	1.741***
	(0.020)	(0.026)	(0.024)
hour08	1.725***	1.725***	1.705***
	(0.021)	(0.026)	(0.024)
hour09	1.774***	1.774***	1.759***
	(0.021)	(0.026)	(0.024)
hour10	1.790***	1.790***	1.778***
	(0.021)	(0.026)	(0.024)
hour11	1.749***	1.749***	1.738***
	(0.021)	(0.026)	(0.024)
hour12	1.711***	1.711***	1.699***
	(0.021)	(0.026)	(0.024)
hour13	1.784***	1.784***	1.773***

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
	(0.021)	(0.026)	(0.024)
hour14	1.892***	1.892***	1.880***
	(0.020)	(0.026)	(0.024)
hour15	1.897***	1.897***	1.883***
	(0.020)	(0.026)	(0.024)
hour16	1.926***	1.926***	1.915***
	(0.020)	(0.025)	(0.023)
hour17	1.773***	1.773***	1.766***
	(0.018)	(0.023)	(0.021)
hour18	1.528***	1.528***	1.524***
	(0.018)	(0.023)	(0.021)
hour19	1.258***	1.258***	1.255***
	(0.018)	(0.023)	(0.020)
hour20	0.947***	0.947***	0.947***
	(0.019)	(0.024)	(0.021)
hour21	0.678***	0.678***	0.676***
	(0.020)	(0.025)	(0.022)
hour22	0.505***	0.505***	0.500***
	(0.020)	(0.025)	(0.022)

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
hour23	0.242***	0.242***	0.236***
	(0.021)	(0.027)	(0.023)
day1	0.439***	0.439***	0.413***
	(0.007)	(0.009)	(0.009)
day2	0.379***	0.379***	0.357***
	(0.007)	(0.009)	(0.009)
day3	0.414***	0.414***	0.389***
	(0.007)	(0.009)	(0.009)
day4	0.435***	0.435***	0.413***
	(0.007)	(0.009)	(0.009)
day5	0.472***	0.472***	0.450***
	(0.007)	(0.009)	(0.009)
day6	0.142***	0.142***	0.147***
	(0.008)	(0.010)	(0.009)
week36	−0.015	−0.015	−0.035
	(0.024)	(0.030)	(0.029)
week37	0.031	0.031	0.009
	(0.024)	(0.030)	(0.029)

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
week38	0.028	0.028	0.004
	(0.024)	(0.030)	(0.029)
week39	0.068***	0.068**	0.042
	(0.024)	(0.030)	(0.029)
week40	0.043*	0.043	0.015
	(0.024)	(0.030)	(0.029)
week41	0.072***	0.072**	0.046
	(0.024)	(0.030)	(0.029)
week42	0.060**	0.060**	0.034
	(0.024)	(0.030)	(0.029)
week43	0.041*	0.041	0.014
	(0.024)	(0.030)	(0.030)
week44	0.002	0.002	−0.031
	(0.025)	(0.031)	(0.030)
week45	−0.061**	−0.061**	−0.090***
	(0.024)	(0.031)	(0.030)
week46	−0.016	−0.016	−0.043
	(0.025)	(0.031)	(0.030)
week47	−0.065***	−0.065**	−0.092***

Continued on next page

	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson* *link = log*	*negative* *binomial*
	(1)	(2)	(3)
	(0.025)	(0.031)	(0.030)
week48	−0.023	−0.023	−0.049
	(0.025)	(0.031)	(0.030)
week49	−0.023	−0.023	−0.047
	(0.025)	(0.031)	(0.030)
week50	−0.021	−0.021	−0.048
	(0.025)	(0.031)	(0.030)
week51	−0.0005	−0.0005	−0.024
	(0.025)	(0.031)	(0.031)
week52	−0.109***	−0.109***	−0.135***
	(0.031)	(0.039)	(0.038)
year2010	−0.025***	−0.025**	−0.023**
	(0.010)	(0.012)	(0.012)
year2011	0.054***	0.054***	0.054***
	(0.009)	(0.012)	(0.012)
year2012	0.088***	0.088***	0.089***
	(0.009)	(0.012)	(0.011)
year2013	0.137***	0.137***	0.139***
	(0.009)	(0.012)	(0.011)

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
year2014	0.158***	0.158***	0.160***
	(0.009)	(0.012)	(0.011)
year2015	0.234***	0.234***	0.234***
	(0.009)	(0.011)	(0.011)
year2016	0.280***	0.280***	0.283***
	(0.009)	(0.011)	(0.011)
year2017	0.323***	0.323***	0.327***
	(0.009)	(0.011)	(0.011)
year2018	0.327***	0.327***	0.330***
	(0.009)	(0.011)	(0.011)
year2019	0.302***	0.302***	0.309***
	(0.009)	(0.011)	(0.011)
Constant	1.807***	1.807***	1.816***
	(0.242)	(0.303)	(0.306)
Observations	29,832	29,832	29,832
Log Likelihood	−80,201.990		−78,895.690
θ			20.730*** (0.550)
Akaike Inf. Crit.	160,554.000		157,937.400

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	Dependent variable:		
	total_accidents_per_hour		
	Poisson	*glm: quasipoisson link = log*	*negative binomial*
	(1)	(2)	(3)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.37: IRR of the best-fitted regression model for the total accidents with weather and explanatory variables in the autumn period.

	Estimate	Robust SE	Pr(>|z|)	IRR
(Intercept)	1.816	0.314	0	6.145
dark	0.282	0.013	0	1.326
holiday1	-0.324	0.018	0	0.723
TMP_less_zero1	0.069	0.015	0	1.072
TMP_less_five1	-0.002	0.012	0.838	0.998
TMP_less_ten1	-0.029	0.010	0.003	0.972
TMP_less_fifteen1	-0.010	0.008	0.203	0.990
mist1	-0.038	0.007	0	0.963
fog1	-0.008	0.014	0.586	0.992
drizzle1	0.045	0.025	0.067	1.046
rain1	0.093	0.012	0	1.097
snow1	0.217	0.021	0	1.242
precipitation1	0.115	0.012	0	1.121
SLP	-0.002	0	0	0.998
cause_intoxication	0.149	0.003	0	1.160
cause_damaged_road	0.114	0.009	0	1.120
cause_car_defect	0.111	0.008	0	1.117
hour01	-0.127	0.031	0	0.881
hour02	-0.205	0.032	0	0.815
hour03	-0.250	0.032	0	0.778
hour04	-0.002	0.028	0.946	0.998

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
hour05	0.848	0.025	0	2.335
hour06	1.399	0.026	0	4.051
hour07	1.741	0.028	0	5.701
hour08	1.705	0.027	0	5.502
hour09	1.759	0.027	0	5.807
hour10	1.778	0.026	0	5.916
hour11	1.738	0.026	0	5.685
hour12	1.699	0.026	0	5.469
hour13	1.773	0.026	0	5.887
hour14	1.880	0.026	0	6.551
hour15	1.883	0.026	0	6.572
hour16	1.915	0.026	0	6.786
hour17	1.766	0.024	0	5.849
hour18	1.524	0.024	0	4.592
hour19	1.255	0.024	0	3.509
hour20	0.947	0.024	0	2.578
hour21	0.676	0.024	0	1.965
hour22	0.500	0.025	0	1.649
hour23	0.236	0.026	0	1.267
day1	0.413	0.010	0	1.511
day2	0.357	0.010	0	1.429
day3	0.389	0.010	0	1.476
day4	0.413	0.010	0	1.511
day5	0.450	0.010	0	1.568
day6	0.147	0.011	0	1.158
week36	-0.035	0.029	0.227	0.965
week37	0.009	0.029	0.745	1.010
week38	0.004	0.029	0.901	1.004
week39	0.042	0.029	0.147	1.043
week40	0.015	0.029	0.616	1.015
week41	0.046	0.029	0.118	1.047
week42	0.034	0.030	0.247	1.035
week43	0.014	0.030	0.631	1.014

Continued on next page

	Estimate	Robust SE	Pr(>|z|)	IRR
week44	-0.031	0.030	0.305	0.970
week45	-0.090	0.030	0.003	0.914
week46	-0.043	0.030	0.159	0.958
week47	-0.092	0.031	0.003	0.912
week48	-0.049	0.031	0.115	0.953
week49	-0.047	0.031	0.127	0.954
week50	-0.048	0.031	0.117	0.953
week51	-0.024	0.031	0.444	0.977
week52	-0.135	0.041	0.001	0.874
year2010	-0.023	0.012	0.047	0.977
year2011	0.054	0.011	0	1.056
year2012	0.089	0.011	0	1.094
year2013	0.139	0.011	0	1.149
year2014	0.160	0.011	0	1.173
year2015	0.234	0.011	0	1.264
year2016	0.283	0.011	0	1.327
year2017	0.327	0.011	0	1.387
year2018	0.330	0.011	0	1.390
year2019	0.309	0.011	0	1.362