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The impact of the Covid-19 pandemic and other factors on road traffic safety in the Czech Republic

Bachelor's thesis

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Declaration of Authorship

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Abstract

This thesis focuses primarily on determining the potential effect of Covid-19 on road traffic safety in the Czech Republic, measured by the daily volume of traffic collisions. The additional incorporation of weather and seasonal factors contributes to the complexity and uniqueness of this work. Although it is possible to find relevant foreign literature on the relationship between the pandemic and traffic accidents, this phenomenon has not been widely studied in the Czech Republic.

The hypotheses were tested by applying the Ordinary Least Squares estimation on time series data. The frequency of traffic accidents significantly decreased with the presence of Covid-19 disease, especially during the state lockdown periods. A similar pattern was observed by the remaining analysed categories of collisions, except for those with alcohol and drugs detected by the offender, which were positively influenced by the pandemic. The wind is the only statistically insignificant weather variable in our analysis, and the state holidays all turn out to significantly affect the number of traffic accidents. Overall, the thesis contributes to the revelation of traffic trends during the Covid-19 disease and helps to predict the traffic safety situation in a possible future state of emergency of a similar kind.

JEL Classification	R41, I19, C51, D91
Keywords	Traffic accidents, traffic safety, drivers' behaviour, Covid-19, weather, seasonality
Title	The impact of the Covid-19 pandemic and other factors on road traffic safety in the Czech Republic

Abstrakt

Tato bakalářská práce se zabývá primárně potenciálním vlivem onemocnění Covid-19 na bezpečnost silniční dopravy v České republice, která je měřena pomocí denního množství dopravních nehod. Dodatečné zahrnutí sezónních vlivů a počasí přispívá ke komplexitě a jedinečnosti této práce. Přestože je relevantní zahraniční literatura, zabývající se vztahem mezi pandemií a dopravními nehodami, dostupná, toto téma ještě nebylo detailně studováno pro Českou republiku.

Hypotézy byly testovány aplikováním lineární metody nejmenších čtverců na data typu časová řada. Četnost dopravních nehod značně poklesla za přítomnosti onemocnění Covid-19, obzvláště během období lockdownů. Ostatní analyzované kategorie dopravních nehod zaznamenaly podobné výsledky, kromě nehod, kde byl viník pod vlivem alkoholu nebo drog, které byly pandemií pozitivně ovlivněny. Jediným indikátorem počasí, který nemá statisticky významný vliv na dopravní nehody je vítr a naopak státní svátky jejich denní počet značně ovlivňují. Celkově teze přispívá k odhalení trendů v dopravě během onemocnění Covid-19 a napomáhá k odhadu situace dopravní bezpečnosti za případného budoucího nouzového stavu podobného typu.

Klasifikace JEL	R41, I19, C51, D91
Klíčová slova	Dopravní nehody, dopravní bezpečnost, chování řidičů, Covid-19, počasí, sezónnost
Název práce	Vliv pandemie Covid-19 a dalších faktorů na bezpečnost silniční dopravy v České republice

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Acronyms

RTC Road traffic collision

NHTSA National Highway Traffic Safety Administration of the United States

ETSC European Transport Safety Council

VMT Vehicle miles travelled

PCR Police of the Czech Republic

CHMI Czech Hydrometeorological Institute

CTRC Czech Transport Research Centre

CMH Czech Ministry of Health

ADF Augmented Dickey-Fuller

PP Phillips-Perron

KPSS Kwiatkowski-Phillips-Schmidt-Shin

BG Breusch-Godfrey

DW Durbin-Watson

BP Breusch-Pagan

HAC Heteroscedasticity and autocorrelation consistent standard error estimator

HC Heteroscedasticity consistent standard error estimator

OLS Ordinary Least Squares

Chapter 1

Introduction

Transportation inherently belongs to life in the 21st century, interconnecting distant places on the globe. In recent decades, it has gained popularity due to globalisation and the quickly growing international trade, guaranteeing the distribution of essential items for all industries and consumers. Road transportation is a very coveted middle to short-distance travel method, contributing to land transport for the most part. It comprises both personal and freight transport, having the biggest advantage in the reachability and speed it provides compared to other kinds of transport. Moreover, technological innovation continuously stimulates the evolution of more efficient and less time-consuming road transport and other ways of travel. For these reasons, the road transport sector is an attractive industry worth analysing from both the current and future perspectives, considering the fact that it dominates both in the personal and cargo transportation of the Czech Republic (Michalová 2018).

Although all the road vehicles undoubtedly facilitate our everyday life in many aspects, their massive use has negative effects too. The huge issues are the emissions rapidly increasing the concentration of greenhouse gasses in the atmosphere, and last but not least, road traffic is generally proven to be the most dangerous form of travel. According to the World Health Organization (2022), approximately 1.3 million people die each year as a result of road traffic crashes and considerably more people suffer non-fatal injuries on different levels of seriousness. To the risky factors, increasing either the probability of the incidence of traffic collisions or their severity, belong speeding, driving under the influence of alcohol and drugs, nonuse of protective items such as seatbelts or helmets and vehicles in bad condition.

To be able to prevent the maximum possible traffic incidents from happening or at least minimise their consequences, an analyst work is necessary to identify the mentioned riskiest factors of road vehicle conveyance. This thesis will examine them based on the sample containing all traffic accidents on the Czech land for the last five years.

During that period, the infective viral disease named Covid-19 stroke and paralysed the whole society in all its activities. Even though the immediate health, economic and trading responses were estimated, in reality, the consequences of the pandemic were much broader, touching the majority of areas of human interest. Traffic is no exception because of its strong connection to meeting human needs and interests, some of which were restrained during the anti-Covid areal restrictions. Based on this assumption and the foreign literature reviewed in the next chapter, we believe in very interesting and robust results of the analysed effect of the pandemic on road traffic collisions in the Czech Republic.

Besides the Covid-19 disease, plenty of other determinants affect the safety of driving. The easily measurable and accessible ones, such as weather, seasonality and state holidays, will be included in the analysis to improve the accuracy of the econometric models and to reveal whether adding these variables into the models somehow changes the estimated effect of Covid-19. However, not all the factors can be quantified and stored in a variable. For instance, the physical and mental condition of drivers, their reactions, the circumstances and others certainly influence the incidence and severity of traffic accidents but cannot be inspected due to the lack of data.

The reviewed relevant academic sources coincide in the finding that the overall traffic volume significantly lowered during the lockdown periods of the Covid-19 pandemic. When it comes to the change in the daily numbers of road traffic collisions during the times with Covid-19 disease, the effect is not unequivocal among the literature. In some academic articles, the authors concluded that the decrease in the vehicle miles travelled led to a remarkable decline in the traffic accidents. Others suggest that the emptier roads tempted drivers to speeding and dangerous style of driving, resulting in higher share of road vehicle crashes. The purpose of this bachelor's thesis is, among other things, to identify such trend for the road traffic situation in the Czech Republic. However, the thesis mainly aims to determine the key factors affecting road traffic accidents in the Czech Republic and to compare the collision statistic before and during the pandemic.

In this bachelor's thesis, we will use three different data sources and run the

Ordinary Least Squares (OLS) regressions to obtain the desired results. They will be helpful to the institutions concerning traffic safety on the Czech roads, when planning and implementing various measures and improvements. Also, the empirical findings about the traffic situation during the Covid-19 pandemic will contribute to an effective and fast handling of any potential emergency situation of a similar kind.

The thesis is structured in the following manner: the second part of Chapter 1 provides the readers with a theoretical background, which is essential for proper understanding of the topic (Section 1.1). Chapter 2 follows with an overview of the contemporaneous academic literature covering the topic of general traffic patterns and traffic accidents, both before and during the Covid-19 pandemic. Chapter 3 is devoted to the description of the dataset, used for answering the research questions, and the data collection process. The employed methods of the econometric analysis are presented in Chapter 4 together with the verification of the models' assumptions. Chapter 5 introduces a set of hypotheses that are evaluated in Chapter 6, based on the results of the regressions. Chapter 7 summarises our findings and emphasises the contribution of this thesis.

1.1 Theoretical background

Firstly, in this section, we will define the fundamental terms that are necessary for a proper insight to the given topic (Subsection 1.1.1). Afterwards, the latest global patterns of car traffic, as a substantial part of transportation, will be depicted (Subsection 1.1.2).

1.1.1 Definitions

For the purpose of this thesis, we need to precisely define a traffic accident and divide them into several categories by severity. Since the definitions slightly differ across distinct literature, we use their verbal part from Transport Scotland (2014) and the time specification of the medical status from the original dataset from (Policie ČR n.d.).

Definition 1 (Traffic accident). Traffic accident means an event that occurs during the movement, and with the participation, of a vehicle on a road, in which people are killed or injured, vehicles, equipment or goods are damaged, or any other material damage is caused (Law Insider n.d.).

Categories of traffic accidents by severity:

Definition 2 (Fatal traffic accident). It is an accident in which at least one person is fatally injured and dies within 24 hours.

Definition 3 (Serious traffic accident). It is a traffic accident in which at least one person is seriously injured (see Definition 6), but no-one suffers a fatal injury.

Definition 4 (Non-serious traffic accident). It is one in which at least one person suffers slight injuries (see Definition 7), but no-one is seriously injured, or fatally injured.

Categories of injuries by severity:

Definition 5 (Fatal injury). Fatal injury is one which causes death in less than 24 hour after the accident.

Definition 6 (Serious injury). Serious injury is one which does not cause death less than 24 hours after the accident, and which is in one (or more) of the following categories:
(a) an injury for which a person is detained in hospital as an in-patient or
(b) any of the following injuries (whether or not the person is detained in hospital): fractures, concussion, internal injuries, crushings, severe cuts and lacerations, severe general shock requiring treatment or
(c) any injury causing death 24 or more hours after the accident.

Definition 7 (Non-serious injury). Non-serious injury is any injury which is neither fatal nor serious - for example, a sprain, bruise or cut which is not judged to be severe, or slight shock requiring roadside attention.

1.1.2 Recent trends in road traffic

Road transportation accounts for a significant share of world traffic and is one of the industries subject to quickly evolving technological innovations. While public transport and cars are, for many people, an everyday direct means of transportation, road freight transport ensures the mediation of crucial commodities to meet people's various needs. In the year 2000, 58 million motor vehicles were produced worldwide and ever since the number of cars has steadily increased until it reached 97 million in both 2017 and 2018. The years of economic crisis (2008 and 2009) and the present pandemic are the only exceptions to the almost linear trend when the production declined by around 15% (Placek 2022). As production and consumption of a product are highly influenced by each other, we can also observe an increase in "consumption"- in our case, a traffic volume - during the last pre-pandemic years relative to the beginning of the 21st century. Regarding passenger transportation, the ratio of the population using public transport and personal cars in the USA and Europe will be compared. A survey of 1600 American commuters to work or university, conducted by Statista in 2022, resulted in 86% of questioned using their own car, only 10% travelling by mass transportation (Richter 2022). Cars are dominant among Europeans too. Their share of use relative to public means of transport is smaller, though. It ranges from 57% of the total daily distance travelled in Romania to 81% in Slovenia. The highest percentage of shared transportation use inhabitants of Poland and Romania, both 30%. Huxley-Reicher (2022), in his article, analyzes the data from OECD and compares them to the US Bureau of Transportation Statistics, thus supporting the hypothesis that USA citizens generally drive more than Europeans, on average. According to his findings, the average person from the United States travelled by car 2.23 times more than the average citizen of Great Britain, 2.06 more than the average inhabitant of Germany and 1.98 times more than the average French driver. On top of that, the United States held the position of absolutely first within OECD countries in per-capita passenger miles travelled by car each year from 2011 until 2019. Generally, during the last two decades, the USA surpassed Europe, Mexico, Russia, Australia and other states in terms of both per-capita passenger miles travelled by motor vehicles and the frequency of travel by own means of transport.

Chapter 2

Literature review

The subject of Section 2.1 is the overview of foreign literature on international traffic volume during the pandemic of Covid-19 (Subsection 2.1.1), the impact of Covid-19 on road traffic collisions (Subsection 2.1.2), review of the most relevant foreign articles for the topic of this thesis (Subsection 2.1.3). Then there is the description of existing Czech academic publications and surveys on the subject of road collisions, traffic volume and drivers' behaviour during the pandemic in Section 2.2. The final paragraph summarizes the reviewed studies and presents the motivation of this thesis (Section 2.3).

2.1 Foreign literature

2.1.1 Background of international traffic volume during the pandemic

Throughout the time of the world pandemic of Covid-19, it was necessary to restrict or even suspend some of the people's everyday activities in order to prevent the population from spreading a respiratory illness with severe consequences. The levels of lockdowns in each country evolved accordingly to the current situation. If we focus on the USA between March 20th and May 15th 2020 (the early phase of the pandemic), the majority of member states issued a lockdown at the stage of staying at home, followed by a ban on gatherings and many other restrictions (Ballotpedia 2021). According to the Research of traffic safety during the Covid-19 public health emergency by the National Highway Traffic Safety Administration of the United States, more than 25% of the national population stayed home on any given day from March to December 2020. It is by around 6% more than on average in the year 2019 and the beginning of 2020 - the last months before the pandemic. Specifically, in April 2020, this number reached a peak of around 28% (Wagner *et al.* 2021). This finding implies that public and private transportation volume significantly lowered. Who support this phenomenon are Vanlaar *et al.* (2021) in their academic paper “The impact of COVID-19 on road safety in Canada and the United States”, stating that the average vehicle miles travelled by Americans in the period of the first half of 2020 were 16.6% under the value of the same period the previous year. In April 2020, which was a month of the most strict measures within this pandemic, the overall vehicle miles measured on all national roads and streets of the USA plummeted by 112 billion, corresponding to -39.8% compared to the same period of 2019 (U.S. Department of Transportation 2020). These reductions were attributed mainly to a high proportion of people working from home, limited motivation to travel and social distancing based on fear of getting the disease.

This bachelor’s thesis aims to analyze traffic accidents, safety and behaviour in the Czech Republic. Having discussed the American patterns and research on traffic reduction in the past few years, we will now focus on insight into this problem from the European point of view. Due to the explanation of general trends in transportation (Subsection 1.1.2 of Theoretical background), the Czech traffic scheme shows more similarities to the European one than, for instance, to American traffic trends. Therefore we will next examine and review topic-relevant European literature. The whole period of the Covid-19 pandemic resulted in a 55 to 80% decrease in vehicle mobility throughout different European countries. Although the varying periods of global research do not allow us to compare the statistics properly, we can estimate the results to get an approximate picture. A survey of toll road traffic revealed the biggest decline of 81% of Europe, depicted in France in April 2020 relative to January 2020 (Fitch Ratings 2021). We can approximately compare it to the value of the USA (-39.8%) from the previous paragraph, considering that the conclusions were drawn based on different years before the pandemic. Based on these pieces of information, we can assume that pandemic restrictions generally caused more reduction in road traffic in Europe than in the United States. Fewer cars on the roads simply imply an opportunity to increase speed, a change in traffic flow and a reduction of congestion (Yasin *et al.* 2021). Extension of theory review of congestion during the mentioned viral disease in selected European cities provides Dickson’s article. The author selected seven metropolitan areas from five European states to measure the traffic intensity during peak time. The data from traffic flows were collected at 8 am on April 8th, 2019, then compared to the same time of the day on April 6th, 2020 and illustrated via colours on a satellite map of cities. Based on Dickson's expertise, the traffic reduction percentages were as follows: 96.9% in Bordeaux, 96% in Madrid, 90.2% in London, 72.2% in Berlin, etc. (Dickson 2020).

All the academic literature mentioned above justifies significant changes in road traffic volume during the initial stage of pandemics. More specifically, the trend of reduced mobility and travel demand was present during that time. Consequently, there were empty lines and minimal congestion but also an increased opportunity for speeding. The mentioned trend also impacts the number of road traffic collisions Road traffic collision (RTC), yet not apparent if positive or negative and how big this effect is. The literature about traffic accidents during the pandemic will be reviewed in the next section.

Subsection 2.1.1 summarizes the view of foreign literature on traffic volume during the lockdown period of the pandemic and shows that it is consistent throughout the different sources. An overall trend of a significant decrease was revealed, although there were disparities in the downturn extent.

2.1.2 Covid-19 and road traffic collisions

Firstly in this paragraph, the general impact of the given disease on road traffic accidents will be described. After that, we will review the literature touching on the effect of Covid-19 on the distinct types of crashes, based on their seriousness.

Focusing on road traffic collisions, The National Academies of Sciences, Engineering and Medicine, US, presented an online webinar with an overview of statewide crashes in California during the first three months of Covid-19 disease. The result is a steady decrease from -18% in early March to -60% at the beginning of April 2020, relative to a five-year average of corresponding weeks in previous years (Carter *et al.* 2021). Furthermore, Brodeur *et al.* (2021) justify this pattern by examining the impacts of COVID-19 safer-at-home policies on collisions and pollution. Based on the Poisson count model and data from states worldwide, it was proven that a state order of measures decreased the incidence of collisions by 16%. Additionally, the paper's authors introduced the number of Covid-19 cases and deaths per 10,000 people, a set of other Covid-19 policies, and weather controls to the model. They drove conclusion that daily collisions were reduced by 20%. Not only are all those added variables statistically significant, and their added influence on car crashes amplified, but they also provide meaningful conclusions and a good motivation for our data analysis in this bachelor's thesis, as we will use very similar variables but for the Czech Republic. Besides the topic of interest of this thesis, Brodeur, Cook, & Wright found a positive side effect of pandemic measures - a reduction in pollution worldwide by 25%, which is certainly a direct consequence of lower traffic volume during the lockdown period.

In general, a rational worldwide effect of Covid-19 lockdown on the average daily volume of traffic and the road traffic collisions - a significant reduction - was observed. A similar trend revealed studies on car accidents resulting in minor or no injuries (Brodeur *et al.* 2021)(Qureshi *et al.* 2020). However, the international literature concerning severe RTCs and road fatalities is inconsistent in the results across countries. Brodeur *et al.* in the already mentioned research referred to the 18% increase in the most severe type of collisions during the state orders around the world (spring 2020), which is, to some extent, a surprising conclusion. What also supports the scheme of higher incidence of collisions during the lockdown, where serious or fatal injuries were present, is an article using traffic accident records in Missouri from January 1st, 2020, through May 15th, 2020 (March 23rd, considered the first day of mandatory lockdown whereas May 3rd the end) (Qureshi *et al.* 2020). On the other hand, in many regions, the rates of fatality and serious injury crashes dropped together with the number of traffic accidents of all kinds or stayed unchanged. National Center for Statistics and Analysis (2021) presented the total volume of fatalities by quarters of the year, showing a year-to-year decrease of 0.6% in Q2 2020 relative to Q2 2019. Contrary to the nearly sluggish number of accidents, the identical period revealed an increased fatality rate (per 100 million vehicle miles travelled) from 1.08 to 1.46. In addition, the National Safety Council of America observed by 14% more fatal collisions per miles driven in March 2020 than in the same month the year before, despite the 8% fall in total deaths in traffic (National Safety Council 2020). The disparity in serious traffic accident rates worldwide can be attributed to two main principles working against each other: a decrease in traffic volume and a tendency to behave riskier while driving. If the decrease in serious traffic collisions for a particular area was detected, the decreased volume effect was likely to be more dominant. Elsewhere, the risky behaviour as a consequence of free road lines, higher stress and worsened drivers' mental health during the pandemic prevailed and led to an increase in overall deaths on roads. We can say with certainty that when we exonerate the statistics from the traffic volume, the rates of fatalities increased almost everywhere.

Qureshi *et al.* (2020) also described road traffic accidents resulting in non-serious or no injuries as indirectly affected by lockdown policies because they naturally reflected the attenuated traffic. In contrast, fatal collisions and those with serious injuries have unclear causes and a set of factors which determines them. One possible explanation for serious collisions during the first lockdown is an increase in average speed, as there was almost no congestion (Doucette *et al.* 2021). The empirical study of Vicuna *et al.* (2020) supports the hypothesis of increased speed patterns of drivers in five areas of New York, using the weekly average speed of all cars going through a specific point in March and April of both 2019 and 2020. The results showed a clear gradual increase in speed in March 2020 compared to 2019. Especially from the third week of March 2020, it surged, even more, followed by the steady values during April 2020. The interesting fact is also the doubled number of speeding tickets during March relative to February 2020 issued in New York City.

Social distancing in the sense of a lockdown can harm people's well-being, mental health and physical condition. Inaccessible out-of-home activities, lack of social interactions and self-developing activities can cause boredom, depression, frustration and stress (Brooks *et al.* 2020). If a person faces any mental discomfort or mental health diagnosis, there is a high chance that it will also be negatively reflected in driving. Although these non-physical conditions are hard to measure, drivers with mental health problems have a higher risk of being involved in a car crash (Waller 1965). That can be a second possible reason explaining the increase in risky drivers' behaviour and serious car crashes during the pandemic.

Last but not least, a survey on alcohol and cannabis usage in Canada during the pandemic was conducted by Nanos Research. 25% of Canadians between 35 and 54 years old reported an increase in alcohol consumption in quarantine during the pandemic, and 6% of all Canadians showed an increased usage of cannabis (Canadian Centre on Substance Abuse & NANOS 2020). The usage of drugs and alcohol before and during the lockdown in five different cities in the USA was empirically tested by National Highway Traffic Safety Administration of the United States (NHTSA). The sample included 3000 drivers participating in motor vehicle accidents with severe and fatal injuries. By 28.3% of drivers, alcohol was present during the lockdown, which is 6.5% more than before Covid-19. Even higher increases showed Cannabinoids, which were detected by 32.7% of drivers during the stay-at-home period compared to 20.8% before the pandemic (Thomas *et al.* 2020). In conclusion, excessive speed, mental health issues, alcohol and substance use significantly influence drivers' behaviour, and they increase the chance of traffic collisions.

To sum up, this section, mostly referring to traffic collisions, suggests that the non-serious ones reflect the general trend of fewer car accidents during the Covid-19 lockdown. It is probably a direct consequence of the decreased traffic volume. Contrary to that, two possible explanations exist for the distinct impacts of the lockdown on car crashes that result in serious and fatal injuries. In some locations, the decreased traffic volume caused a decrease in the most severe collisions, as a part of all traffic collisions dropping as well. In other cases, the lower traffic volume during lockdown allowed drivers to speed and stunt drive. Together with the worsened mental health during movement restrictions, which led to an increase in alcohol and drug usage, these factors may have contributed to the increase in serious and fatal collisions.

2.1.3 Review of literature focused on a similar research topic to this thesis

This section will provide an overview of this thesis's most relevant academic work in terms of content, important variables and trends. The NHTSA of the United States examined collisions and traffic safety environments in the pandemic state in a set of reports. The summary of the second quarter of 2020 brings comparison of economic crises from history with the current economic downturn caused by the Covid-19 pandemic and their impact on road safety. The previous economically unstable periods usually reported lower crash fatalities, and less risky behaviour, as the unemployment rate increased and vehicle miles travelled Vehicle miles travelled (VMT) dropped. However, the current pandemic diverged from other economic crises by a significant rise in speeding and alcohol-impaired driving during the second quarter of 2020. It led to a change in the fatality rate from 1.1 per 100 million VMT in the first quarter of 2020 to 1.42 in the second quarter of the same year. Furthermore, lower usage of seat belts was revealed, which also contributed to the decrease in traffic safety (Wagner *et al.* 2020). During Q3 of 2020, the number of unbelted participants in car accidents started to return to normal. However, still slightly elevated with respect to the year 2019. According to the studies from trauma centres where people after serious traffic collisions are placed, more than 29%

of them had a sign of alcohol in their systems, and around 26% were positively tested for drugs between July and September 2020. The popularity of these substances while driving remained high during Q3 of 2020 (Wagner *et al.* 2021). Whereas the first calendar year of the pandemic showed a sharp decrease in VMT, followed by an increase in the average speed of vehicles, the first half of 2021 in the USA proved the opposite, as VMT rose again, but the speed almost stayed on the same level as in 2020. The authors of the report Continuation of Research on Traffic Safety During the COVID-19 Public Health Emergency: January - June 2021 revealed that the decrease in traffic volume might not be the only explanation for the higher tendency to speed (Berning *et al.* 2021).

Another essential source published by European Transport Safety Council collected data from 25 EU member countries on traffic collisions, volumes and speeding during April 2020. April was selected because the implementation dates of pandemic countermeasures differed throughout the European Union member states, but by that month, all countries involved in this study had their policies tackling the Covid-19 situation set. The authors collected data from each country's national traffic reports and summarized the results from the whole EU's perspective. By 18 out of 25 inspected countries, a decrease in the number of deaths from road collisions in April 2020 in comparison to the three years average from 2017 to 2019 was found. Such pattern is in line with the findings of the majority of the reviewed literature the rational expectations. On the other hand, the rest of the countries, such as Denmark, Germany, Czech Republic, Netherlands, Sweden and Slovakia, revealed almost no change or even an increase in the number of fatalities per same period. This opposite trend can be partially explained by the fact that in some countries, especially in the small ones, the road death numbers are statistically small as the monitored period is very short. Generally, when some numbers are lower, their disparity is lower as well, and they tend to fluctuate around some value. Thus the effect of decreased traffic volume during the lockdown on the fatalities may be minor or none, and other factors negatively influencing driving safety might prevail. According to the European Transport Safety Council European Transport Safety Council (ETSC), in the month of the most robust Covid-19 restrictions, 36% fewer people lost their lives on the roads of 25 European countries compared to the already mentioned reference period of April, previous years. The stringent restrictions on people's mobility in Italy contributed to the most significant downturn in road deaths among the selected countries of the EU (by more than 80%). This article also states that there is empirical evidence of the increased amount of vehicles exceeding the speed limit during reduced traffic volumes from 10% in France to 39% in Spain. However, no major change in average speed in Sweden was detected, supposedly due to less strict countermeasures compared to other countries of the EU. The final part of this article lists some recommendations for the EU as well as for individual member states, suggesting tools and methods for enhancing road safety, including pedestrians and cyclists, if some possible future restrictions similar to those during the first spring of Covid-19 were implemented (European Transport Safety Council 2020).

2.2 Czech literature

The local Czech repository of literature relevant to this thesis's topic is quite limited compared to the international one. It gives us an opportunity to properly examine the research questions without being influenced by the results of other almost identical studies. First of all, there is a master's thesis concerning the topic: The Impact of the COVID-19 Movement Restrictions on the Road Traffic in the Czech Republic during the State of Emergency, which may seem very similar to the topic of this thesis at first glance. Actually, that academic text focuses mostly on the effects of Covid-19-related health measures during spring 2020 on the traffic volume changes. That is not the fundamental effect of interest of our work, as we focus rather on traffic safety and car accidents during the whole period of Covid-19 disease. The author of the mentioned master's thesis uses a dataset from the Road and Motorway Directorate of the Czech Republic, comprising the hourly average speed and the number of vehicles passing through given two-thirds of road segments in the whole of Czechia. The conclusion was the following: traffic volumes decreased during the first three weeks of restrictions as expected, and the average speed increased by 21% weekly, which according to the author, supports the hypothesis of empty roads tempting to speeding and stunt driving. Also, evidence of obeyed restrictions during the first three weeks of a state of emergency and ensuing gradual return to the pre-pandemic state in terms of traffic frequency was presented. Besides the primary analysis, the thesis lists various side consequences, for example, changing patterns in meal deliveries, the ratio of brick and mortar shopping vs online shopping, risky drivers' behaviour and the possibility of traffic collisions (Simunek *et al.* 2021). This paper will expand and deeply analyse some of these mentioned trends.

Czech Transport Research Centre (CTRC) (Centrum Doprvního výzkumu) published a press report in which the influence of Covid-19 on traffic safety was discussed. The author initially describes the increased occurrence of alcohol and other substances in car crashes worldwide during the pandemic, presenting the year-to-year comparisons processed by the NHTSA article, which was already reviewed in the previous chapter. Followed by CTRC's own overview of car accident statistics in the Czech Republic, the detailed numerical information and basic interpretation of trends during 2019 and 2020 prevail in the article, rather than explanations of possible influencing factors and logic behind such results. It can be seen as a limitation of that publication, and it will be included in this thesis. The article also verified the world pattern for the Czech Republic, which identifies the drivers behaviour as riskier during the Covid-19 period, despite the decreased traffic volume. An interesting fact was revealed and contributed to the overall literature on this topic. The number of road traffic participants that refused to undergo tests on the presence of alcohol or narcotic drugs increased by 24.1% in 2020 relative to the average of 2017-2019 (Centrum dopravního výzkumu 2021). Such behaviour may point out to higher usage of these substances during the pandemic, especially behind the wheel. Detailed information and statistics about traffic collisions in the Czech Republic can be found on the website Accidents in the Czech Republic (Nehody v ČR) (cdv.cz), also administrated by the Czech Transport Research Centre. The site allows the public to use filters to reveal the statistics of their interest, selecting a year and month of accidents, area of collision, age of the person involved in the accident, causality and many more. Traffic collisions' causes, circumstances and consequences are sorted into multiple categories and represented by graphs or numbers (Centrum dopravního výzkumu n.d.). Based on the exactly same source of data to that used for the analysis in this thesis, we may take inspiration from a few charts while describing the dataset on traffic accidents. The following chapters of this bachelor's thesis, focusing on the data, will examine the topic to a similar depth as this web page. On top of that, an inspection of the impact of variables related to Covid-19 disease and weather on traffic safety will extend the topic of the mentioned literature source.

During the periods when the outburst of the respiratory disease was very strong, Czech media behaved accordingly, trying to describe the health situation as well as its consequences impinging on other fields. Among all, Czech online newspaper iDNES.cz informed in one article about the transport in 2020 that the most considerable decrease in car crashes was observed in motorways - around 78% of accidents in 2019. Contrary to that, the number of fatalities increased in the first year of Covid-19 in that road type, which supports the hypothesis that drivers were generally prone to the violation of the rules because of free road lines (iDNES.cz 2020). Another article says that the year 2021 is the second-lowest in the number of deaths on the Czech roads, after the previous year full of movement restrictions. The tiny fall in both minor and serious injuries showed a slightly opposite trend within the last two calendar years (Mahdalova 2022). However, the articles in media are not considered a reliable source for academic work, as they present speculations, thoughts, and interviews on up-to-date topics. Such hypotheses can be studied and tested and then compared to the initial assumptions suggested by the media. That is why those two non-academic sources were included in the literature overview.

2.3 Summary of the reviewed literature and contribution of this thesis

This paragraph briefly summarises the main outcomes from all the relevant sources mentioned in the "Literature review" section of this thesis. Only a handful of them build their analysis on econometric or other advanced methods, that take into consideration some influencing factors. It is therefore an opportunity to provide such analysis and present the most precise results possible.

The pandemic of Covid-19 as a whole, but especially the lockdown policies, strongly influenced movement around the globe, among other things. All the academic sources from previous paragraphs coincide with the statement that traffic volume significantly decreased due to implemented anti-Covid-19 measures. The vast majority of literature on this phenomenon is based on observations from the first lockdowns during spring 2020. However, there were more periods of restrictions later on to stop the spreading of the mentioned respiratory disease, different for each country. There is a gap in the literature analysing the traffic patterns during these later periods of the Covid-19 pandemic. It is, therefore, an excellent opportunity for this thesis to focus even on the further development of the pandemic measures treating the massive outbursts of the virus and their effect on traffic volume and safety.

Several reviewed academic articles suggest that the limitations of mobility and social interactions led to increased stress and frustration among the population, which consequently encouraged drivers to behave riskier on the roads. When reviewing literature about severe and fatal collisions, it is not unambiguous whether lockdown had a positive or negative effect on these. Two main distinct mechanisms can explain the impact of the Covid-19 on the number of road deaths. In some areas, the decline in vehicle miles travelled and the similar drivers' behaviour to the pre-pandemic times, which concerns safety, resulted in the decrease of fatal car accidents. In other words, the fatality rates per mile driven stayed relatively the same compared to the era before the pandemic. However, elsewhere the fatality rates per miles driven plummeted during the lockdown. In such countries, more dangerous driving habits, such as speeding and explosive stunt driving, might have outweighed the effect of decreased traffic volume. Consequently, the total number of fatal crashes did not fall as much as VMT or even increased during the pandemic. This thesis will analyse the safety of the Czech roads and identify the key driving factors of the results. Another research question will bear on the alcohol-impaired driving in the Czech Republic before and during the pandemic. The results will be subsequently compared to the information from reviewed academic papers.

This bachelor's thesis will contribute to the current literature on the same topic in many ways. It will provide a complex analysis of multiple independent variables and their influence on the dependent variables from different perspectives, including the safety of drivers' behaviour, the impact of Covid-19-related variables and weather indicators on car accidents. The findings of that analysis can serve as a basis for suggestions and future strategies for tackling traffic safety issues. Provided that some relationship between the strength of the Covid-19 pandemic and traffic will be found, this thesis can help predict any future evolution of the epidemiological situation in terms of traffic collisions. It may even enhance the estimation of the impacts of any possible future pandemics. The focus will be as well on the detection of essential traffic trends during the initial phase of this pandemic and their examination during the following lockdown periods, which is a unique perspective among the known literature. Overall, the situation of extraordinary measures within modern history will be analysed for the whole period of its most serious consequences.

Chapter 3

Data

The third chapter will be dedicated to a description of the dataset relative to the topic of this thesis. In the first section, we will inspect the sources of the data, their format, the process of collecting them and editing for further use (Section 3.1). After that, Section 3.2 will present the dependent variables, which will be used in the econometric models as a part of the analysis. The most exciting features of these variables will be depicted graphically. The independent variables and the reasons for selecting them are summarized in the last section (Section 3.3).

3.1 Data extraction and sources

The data analysis for this bachelor's thesis is based on an exploration of the relationships between variables from the topics of traffic accidents, weather and Covid-19 in the Czech Republic. Therefore, the final dataset, from which the conclusions will be driven, comprises data from three distinct internet sources that will be properly described in the following paragraphs. Overall, our dataset consists of 1825 observations collected daily for five years, starting at the beginning of the year 2017. We gathered 27 variables describing different phenomena, each on the state level, meaning that they all provide information about the Czech Republic in total.

3.1.1 Traffic collision data

The data on traffic accidents were provided by the Police of the Czech Republic (PCR) (Policie České republiky), in the open database accessible on their webpage in the section "Statistics of accidents" (Policie ČR n.d.). The database consists of records from individual traffic accidents in the Czech Republic, available for the 2007-2021 period. Each month, the newly reported traffic accidents per each of the Czech 14 districts are added to a file, which after the end of the year displays all information about accidents within that specific year and district. The detailed description of each accident is split into 64 categories, from which the following ones were selected for the analysis: **date of the accident, alcohol and drugs presence by the offender, consequences of the accident, type of the road and cause of the accident**. Based on this selection of categories, the main research question - traffic safety during the Covid-19 pandemic - can be studied. In order to compare the pre-pandemic state of accidents and the period when Covid-19 occurred, we only need the observations from the beginning of 2017 until the end of 2021.

The database was downloaded in the *.xlsx* (MS Excel) format separately for each year and district. After that, all the files were merged into one Excel workbook for simplicity and further adjustments. As every line of the Excel document represents one accident, the data had to be modified into the format of the daily number of accidents falling under the categories from the previous paragraph. All the variables of interest are categorical but assigned with numbers, which allows us to count and sum the accidents falling into respective categories. This was performed by the functions *COUNTIF* and *SUMIF*, resulting in the daily number of crashes fulfilling specific criteria. Based on the categories from the original dataset and the summary of accidents, we obtained 20 general crashes-related variables. Each of these variables is further divided into 14 variables, which provide the same information as their "superior" variable, just at the district level. On top of that, in each of the 20 cases, 14 "sub-variables" were summed together to create a total daily number of accidents fulfilling the given criteria (see the Table B.1).

3.1.2 Weather data

The second part of our dataset consists of weather information. The Czech Hydrometeorological Institute (CHMI) (Český hydrometeorologický ústav), similarly to PCR, offers a publicly available database on several weather variables, conditional on the terms of use (Český hydrometeorologický ústav n.d.). This database comprises daily, monthly or annual extensive climatological characteristics detected on 179 weather stations (559 weather stations monitor precipitation). During the time period 1961-2021, the individual *.xlsx* (Excel) files with daily data from weather stations within a given district of the Czech Republic and meteorological variable are available. Among the offered weather variables there is the average, minimum and maximum ambient (air) temperature, average relative air humidity, precipitation (rainfall), the average speed of wind and others. For the purposes of this thesis, **the average daily air temperature, wind and daily precipitation** were downloaded from the Excel files per each weather station. The data had to be organized and adjusted. Therefore we applied an *AVERAGE* function in Excel to all three variables, putting together all the weather stations for each district and obtaining the average daily precipitation, wind and temperature for the specified area.

The motivation behind choosing these variables for the analysis is the following: the results of studies that examined the relationship between rainfall intensity and traffic accidents are contradictory. The majority of them revealed a positive correlation (Caliendo *et al.* 2007), but some also presented a negative association (Christoforou *et al.* 2010). There is an intuition behind the tendency for road traffic to be influenced by extreme temperatures as well. The time-series analysis of the extreme temperature and number of traffic collisions in Catalonia, Spain, was performed by Basagana *et al.* (2015). They showed that the risk of crashes significantly increased by 2.9% during the heat wave days. Therefore, that relationship is about to be studied, too, in this thesis. Surprisingly, the wind speed had a significant negative impact on the number of road traffic collisions in Shantou city, China (Gao *et al.* 2016). It might be interesting to confirm a similar pattern for our sample or to prove the opposite. To summarize this paragraph, the aim of implementing those three meteorological factors into the econometric models is to reveal the relationship between them and the total number of traffic accidents within the Czech Republic .

Table 3.1: Correlation of weather variables with the total accidents

	Avg_Precipitation	Avg_Wind	Avg_Temperature
Acc_Total	0.133	−0.020	0.253

This table of correlation coefficients between each of the three weather variables and the main variable describing total traffic accidents was constructed to provide a first insight into the relationship between those variables. It can be observed, that average daily precipitation and temperature are slightly positively correlated with the Acc_Total variable, whereas the average daily wind intensity seems not to be correlated with it at all.

3.1.3 Covid-19 data

The dataset on Covid-19 indicators was taken from the website of the Czech Ministry of Health (CMH) (Ministerstvo zdravotnictví České republiky) (Ministerstvo zdravotnictví České repubiky n.d.), which publishes daily numbers of various pandemic-related variables in an open database. They are available for the whole Czech Republic, and a selection of them also carries information about the district values of these variables. The online database brings an overview of the development of the pandemics in time through indicators depicting infection, testing on the presence of the disease, deaths, recoveries, hospitalization and vaccination. We thoroughly considered which of them could reasonably influence traffic safety and, consequently, the collision rates. The following were selected for the analysis: **the number of newly detected cases of Covid-19 in total, the number of people who died of Covid-19, the total number of currently hospitalized with Covid-19 and the number of total tests on the presence of the virus performed**.

Apart from the extraction of the previous two datasets, this one was acquired using the *Python* script. With the *get requests* and *BeautifulSoup* library, we managed to scrape the tables from the URL, intending to obtain the necessary data effectively. After storing the data in *pandas DataFrames*, the function *.to_excel* was used to transfer the data to an Excel file. Dividing the total number of newly detected cases by the total number of tests performed, we created a new variable: **the percentage of positively tested people out of all tested**. It allows us to detect the actual amount of newly infected people free from the influence of the testing volume on Covid-19, unlike the variable **the newly detected Covid-19 cases**.

Lockdown data

We obtained additional information about the Covid-19 pandemic from the official webpage of the Czech government (Vláda ČR 2022): **the lockdown periods** within the Czech Republic. Although the implemented epidemiological restrictions were of many degrees of severity during the distinct periods of the pandemic, we decided to involve only the dates of the strictest lockdown in the analysis, when the free movement of people was restricted. The reason for such selection is the rational assumption that the number of vehicles on the roads decreased during lockdowns, which could have impacted the car collision statistics. Therefore, three dummy variables arose, called **Lockdown1**, **Lockdown2** and **Lockdown3** in the periods: 16.3.2020 - 24.4.2020, 22.10.2020 - 20.11.2020 and 1.3.2021 - 11.4.2021, respectively. Their purpose will be to reveal the effect of the change in people's everyday lives on the number of traffic accidents.

3.2 Dependent variables

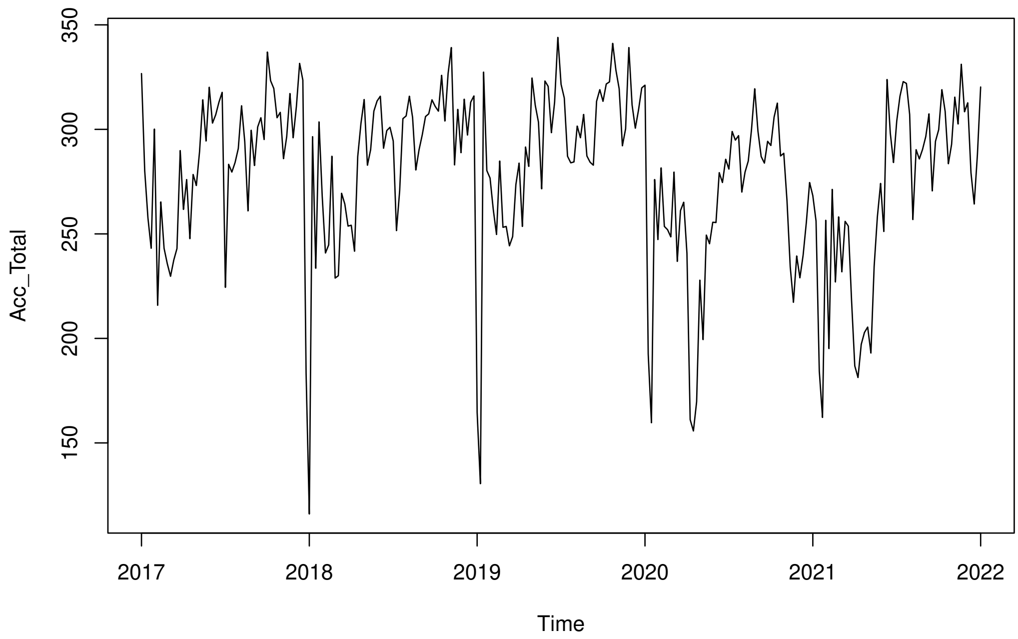
This part of the chapter that describes our data will focus on defining our dependent variables first (see the Table B.1 in Appendix B) and then on commenting on all categories of the regressand variables chosen for our models in more detail than in the previous paragraph. Graphical representations will be included as well to make the reader more familiar with the obtained values and the appearance of the whole dataset. Every mentioned variable presents its averaged values on the state level, already containing the information about the districts.

3.2.1 Total traffic accidents

The number of daily traffic accidents is a crucial variable for the whole thesis, allowing us to evaluate the safety of the Czech roads during previously specified time. The following dependent variables are just the specifications of the total accidents falling to some category. The number of crashes could not be found in the original dataset by PCR. Hence we acquired it from the daily records of all accidents, using the *COUNTIF* function conditional on the date and district. To obtain the total number of accidents per day, we added the values from every district.

The graph of monthly car accidents was constructed to visualize the development of that variable over time, depicting a slight change in its behaviour after the first incidence of Covid-19. It provides the first insight into these data and also a motivation for studying this field. We can point out that the maximum number of car accidents before the pandemic seems to occur during the late summer and autumn (the most accidents are in October each year). Contrary to that, the least road traffic collisions occur in February, when considering the regular years, which are not significantly influenced by other exogenous factors.

Figure 3.1: Daily statistics of total traffic accidents in the Czech Republic between the years 2017 and 2021



To approximate the effect of the pandemic on the number of total car accidents, we constructed a simple table of mean, minimum and maximum daily values for the whole period, period before and during the pandemic. We can observe the decrease in the daily mean of all traffic accidents by around 20 after the beginning of the Covid-19 pandemic (Table 3.3 and Table 3.4). It can be attributed to a decrease in traffic volume during the restrictive measures and to an overall change in the behaviour of society. A logical and expected finding, based on the evolution of the daily mean, is that both minimal and maximal observations lowered. What also decreased is the range between the minimum and the maximum number of daily collisions in the period of Covid-19 in the Czech Republic.

Table 3.2: Descriptive statistics of Total Accidents

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Total	1,826	279.450	65.239	76	548

Table 3.3: Descriptive statistics of Total Accidents before Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Total	1,155	287.177	63.365	116	548

Table 3.4: Descriptive statistics of Total Accidents during Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Total	671	266.149	66.312	76	466

3.2.2 Accidents with alcohol and drugs

The next two variables of our interest are the number of accidents where the offender was under the influence of alcohol or drugs. The overall usage of alcohol and other substances reflects the level of mental health and well-being of society to a certain point (Mäkelä *et al.* 2015). The results of the model, which will reveal the impact of lockdown, scale of pandemic severity and weather on the number of car collisions with alcohol and drugs involved, may be intriguing. However, the conclusions driven on the accidents with drugs may not precisely reflect the reality since there are very few or even no daily observations where the offender was positively tested on drugs.

The same pattern was shown using descriptive statistics before and during the pandemic. Although counting the mean, median and extreme values is not very reasonable, when having a small range of integers, we can still use the descriptive statistics to detect any structural break in our sample and eventually estimate its size. From the tables below, it is evident that both alcohol (Table 3.6 and Table 3.7) and drug-related traffic accidents (Table 3.9 and Table 3.10) were slightly more often during the years 2020-2021 than in the three years before, comparing the mean of daily collisions.

Table 3.5: Descriptive statistics of accidents with alcohol

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Alcohol	1,826	12.291	6.258	0	37

Table 3.6: Descriptive statistics of accidents with alcohol before Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Alcohol	1,155	12.194	6.341	0	37

Table 3.7: Descriptive statistics of accidents with alcohol during Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Alcohol	671	12.458	6.114	1	35

Table 3.8: Descriptive statistics of accidents with drugs

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Drugs	1,826	0.908	0.952	0	6

Table 3.9: Descriptive statistics of accidents with drugs before Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Drugs	1,155	0.848	0.929	0	6

Table 3.10: Descriptive statistics of accidents with drugs during Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Drugs	671	1.010	0.983	0	5

3.2.3 Severity of traffic accidents

Another phenomenon involved in our analysis of road accidents is the severity, divided into four categories, from no harm to travellers' health to the loss of human life. Based on them, we will be able to evaluate the patterns of drivers' responsibility and concentration while driving. The count of the accidents according to the specific category (**the number of accidents with no injury, with a non-serious injury, with a severe injury and fatalities**) and the number of people suffering from the specified type of injury (**the number of non-seriously injured passengers, seriously injured and dead people**) will be examined separately. It will allow us to determine whether there was a tendency to drive riskier during the pandemic and how many passengers were injured on average to what extent.

Similarly, as in the case of the other dependent variables, the *stargazer* function is used to present mainly the *mean, standard deviation, minimum* and *maximum* of our seven variables denoting the seriousness of the traffic collisions. The Table 3.11 provides information about the period 2017-2021, Table 3.12 and Table 3.13 enable comparison before and during the Covid period. The mean of daily accidents with no injury for the given 5-year period is 224, while only for the period of Covid-19 present in the Czech Republic, it is only 215. Generally, the means of daily accidents decreased by a relatively similar proportion, regardless of the severity. Only fatalities show a slightly lower difference between the before- and after-Covid mean values than the rest of the variables. The econometric models will reveal the more accurate dependencies, as there will be multiple explanatory factors.

Table 3.11: Descriptive statistics of accidents based on the degree of severity

Statistic	N	Mean	St. Dev.	Min	Max
Acc_No_Injury	1,826	224.400	53.216	72	440
Acc_Non_Serious_Injury	1,826	50.310	17.773	4	111
Acc_Serious_Injury	1,826	5.166	3.147	0	20
Fatality	1,826	1.280	1.150	0	8
Non_Seriously_Injured_People	1,826	63.172	22.497	4	146
Seriously_Injured_People	1,826	5.666	3.520	0	26
Dead_People_Acc	1,826	1.578	1.471	0	9

Table 3.12: Descriptive statistics of accidents based on the degree of severity before Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_No_Injury	1,155	229.634	52.205	92	440
Acc_Non_Serious_Injury	1,155	52.429	17.176	9	111
Acc_Serious_Injury	1,155	5.577	3.133	0	20
Fatality	1,155	1.335	1.184	0	8
Non_Seriously_Injured_People	1,155	66.517	21.865	12	146
Seriously_Injured_People	1,155	6.190	3.612	0	26
Dead_People_Acc	1,155	1.747	1.579	0	9

Table 3.13: Descriptive statistics of accidents based on the degree of severity during Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_No_Injury	671	215.390	53.771	72	373
Acc_Non_Serious_Injury	671	46.662	18.200	4	104
Acc_Serious_Injury	671	4.461	3.048	0	17
Fatality	671	1.185	1.084	0	5
Non_Seriously_Injured_People	671	57.414	22.422	4	126
Seriously_Injured_People	671	4.763	3.161	0	17
Dead_People_Acc	671	1.286	1.210	0	6

3.2.4 Causes of traffic accidents

The causes of the traffic accidents were narrowed from many sections of the original dataset to the five general categories. Those are **the daily numbers of crashes triggered by the not adjusted speed to the current surrounding conditions, risky overtaking, not giving the right way to other vehicles, technical issues of the vehicle and overall, the inappropriate style of driving**. By analyzing the impact of the independent variables (to be specified in the following sections) on this category of dependent variables, a solution preventing the given types of accidents can be suggested, provided that some significant relationship is found.

When looking at the table of descriptive statistics, we can clearly see that the minimum and maximum of the daily accidents caused by a technical problem of the vehicle did not change with the appearance of the studied respiratory disease, apart from the mean of the same variable, which decreased. A lower decline in the mean daily number of accidents between pre-pandemic time and during pandemic time is present to the accidents caused by not adjusted speed to current conditions, risky overtaking and to the overall inappropriate style of driving (by around 7.13%, 10.07% and 8.47% respectively), compared to the number of accidents caused by not giving right way or by a technical defect on the vehicle (decreased by 16,6% and 21,7% respectively). The accidents caused by a technical issue tend to reflect the decrease in the total traffic volume predominantly as any additional psychical factors influencing the driver's decision making are missing. Whereas the rest of the mentioned variables also depend on the mental and physical health condition of the driver. His current mood, attitude towards risky behaviour and many other factors may also be negatively influenced by the pandemic situation and thus incline to increase the risk of such road collisions.

Table 3.14: Descriptive statistics of accidents based on their causality

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Not_Adjusted_Speed	1,826	37.024	24.327	5	296
Acc_Risky_Overtaking	1,826	3.958	2.452	0	14
Acc_No_Right_Way	1,826	36.672	14.048	1	77
Acc_Technical_Issue	1,826	1.102	1.149	0	6
Acc_Inappropriate_Style	1,826	156.605	43.774	42	374

Table 3.15: Descriptive statistics of accidents based on their causality before Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Not_Adjusted_Speed	1,155	38.022	25.346	9	296
Acc_Risky_Overtaking	1,155	4.110	2.474	0	14
Acc_No_Right_Way	1,155	39.055	13.937	7	77
Acc_Technical_Issue	1,155	1.197	1.187	0	6
Acc_Inappropriate_Style	1,155	161.639	42.626	48	374

Table 3.16: Descriptive statistics of accidents based on their causality during Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Not_Adjusted_Speed	671	35.307	22.380	5	215
Acc_Risky_Overtaking	671	3.696	2.393	0	13
Acc_No_Right_Way	671	32.571	13.279	1	74
Acc_Technical_Issue	671	0.937	1.062	0	6
Acc_Inappropriate_Style	671	147.940	44.395	42	288

3.2.5 Location of traffic accidents

The last group of variables concerns the location of the accidents, meaning that we have four types of roads where traffic collisions may occur. These categories correspond to the British segmentation of road types into highways (motorways), A roads, B roads, C roads and local roads (East Riding of Yorkshire Council 2022), which was implemented on the Czech roads to avoid the misunderstanding in the translation to English. We constructed the following variables from these categories: **the number of accidents happening on highways, on A roads, B roads, C and local roads together**. Besides these four categories, we decided to add one more variable- **the number of accidents on crossings**, which behaves differently from the previous ones. In this context, the Police of the Czech Republic for the purposes of their database, defined the crossing as the monitored intersection of roads led by the traffic lights. Therefore, numerous daily cases of traffic accidents appear only in a few districts containing bigger cities. In the rest of the districts of the Czech Republic, there are hardly any observations of this phenomenon. This group of variables should provide a comparison of the safety of Czech roads, based on their types, during the distinct phases of the pandemic.

The summary tables below suggest several interesting findings. First of all, the lowest decrease in the mean of daily accidents among all the variables segmenting the traffic accidents based on their location, between the pre-pandemic and after-pandemic time, was found by the accidents on B roads (from the mean of 43.12 daily accidents until 1.3.2020 to the value of 42.59 after that date). Similarly, the number of car collisions happening on highways dropped slightly in the same period, suggesting that considering the substandard traffic volume, people were driving more dangerously. Even the variable describing the number of accidents on crossings, which has values only from several bigger cities, shows a significant fall in the daily mean of observations between both periods. The reason for a considerable decline in traffic flow in cities might be that the more urbanized area is, the fewer inhabitants need to travel to fulfil their daily necessities and work obligations. People working in bigger cities generally are more likely to be able to work from home, as metropolitan areas are naturally more services-oriented than the countryside. That may partially explain the downturn in traffic volume and the consequent decrease in the number of traffic collisions.

Table 3.17: Descriptive statistics of accidents based on the type of the road and location

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Highway	1,826	11.856	5.547	1	58
Acc_A_Road	1,826	38.745	10.699	6	85
Acc_B_Road	1,826	42.924	11.134	9	114
Acc_C_Local_Road	1,826	183.630	47.028	53	404
Acc_Crossing	1,826	6.689	3.437	0	20

Table 3.18: Descriptive statistics of accidents based on the type of the road and location before Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Highway	1,155	12.090	5.673	1	58
Acc_A_Road	1,155	40.007	10.738	10	85
Acc_B_Road	1,155	43.115	11.016	15	114
Acc_C_Local_Road	1,155	191.630	46.097	65	404
Acc_Crossing	1,155	7.269	3.455	0	20

Table 3.19: Descriptive statistics of accidents based on the type of the road and location during Covid

Statistic	N	Mean	St. Dev.	Min	Max
Acc_Highway	671	11.453	5.302	1	37
Acc_A_Road	671	36.572	10.281	6	72
Acc_B_Road	671	42.595	11.335	9	94
Acc_C_Local_Road	671	169.860	45.431	53	299
Acc_Crossing	671	5.690	3.169	0	19

3.3 Independent variables

In the following pages, we will conclude Chapter 3 by defining and describing the independent variables for our models and the reasons for choosing them as explanatory ones. They can be further selected into two main parts: Covid-19 related variables and weather-related ones. Similarly, as in the "Dependent variables" section (Section 3.2), each independent variable will be described and supported by a descriptive statistics table, presenting major trends.

3.3.1 Variables describing the Covid-19 development

The Covid-19 pandemic, with the attempts of the governments to slow down its spreading and minimize the negative consequences through the various measures, is believed to have a significant worldwide impact on the traffic volume (Fitch Ratings 2021). Since the probability of traffic accidents decreases with the lowered traffic intensity, we assume that indicators of the pandemic might have certain impact on the number of vehicle collisions. All the observations touching the Covid-19 topic begin after March 1st, 2020, which is officially the first day of the pandemic in the Czech Republic, since the first three people were positively tested on that disease. The further used descriptive statistics inform only about the period during Covid-19, since outside of that period, the values of all four variables indicating the situation of the pandemic are zero.

Newly detected cases

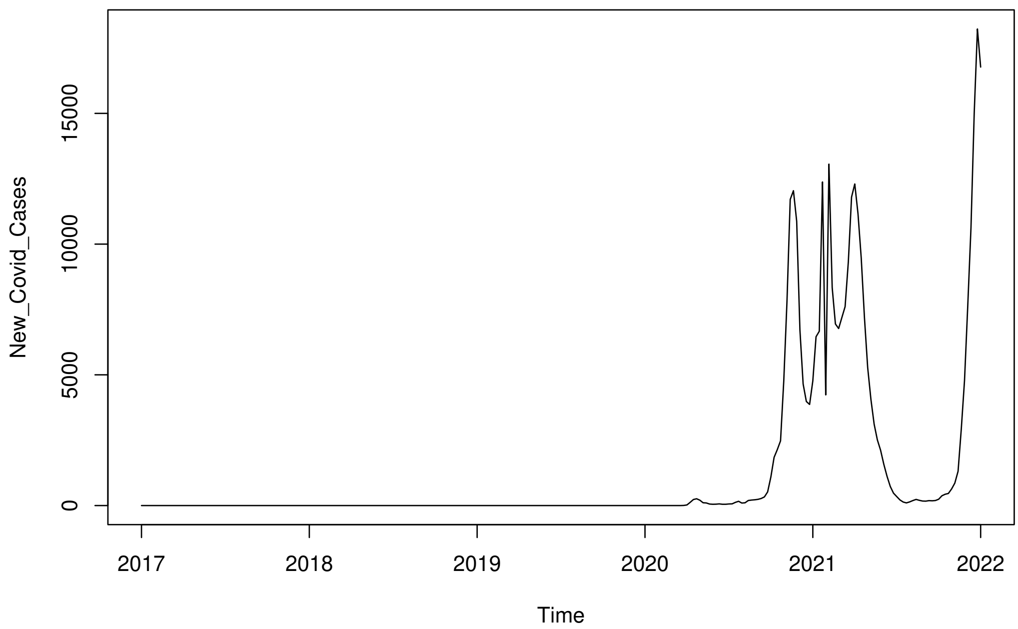
The number of newly detected cases of the disease Covid-19 is the first variable out of many, indicating the seriousness of the current stage of the pandemic, adding up the number of positive tests from both methods of detection: PCR and antigen. The intuition behind choosing this variable as an independent one in our models is that the higher the number of newly detected Covid-19 cases, the higher probability of the legislators to impose a lockdown or at least a higher possibility of the society being afraid of the infection. This could possibly lead to a lower traffic volume and thus to fewer car crashes. Such hypothesis will be tested in the econometric models.

It can be observed from the table below that the daily average of the newly detected cases of Covid-19 is 3 703 from March 2020 to the end of the year 2021. However, there is quite a vast range of 27 937 between the minimal and maximal value of the new Covid cases detected daily (Table 3.20) and the daily observations have a high variance and standard deviation across the seasons of the year, which can be observed in the Figure 3.2.

Table 3.20: Descriptive statistics of the number of newly detected Covid-19 cases

Statistic	N	Mean	St. Dev.	Min	Max
New_Covid_Cases	671	3,703.036	5,054.817	0	27,937

Figure 3.2: Evolution of the daily new Covid-19 cases



Deaths and hospitalized

A similar motivation is for the number of daily deaths caused by the mentioned illness and the number of people in hospitals because of Covid-19. While the mortality is given for each district and in total as well, the values of currently hospitalized people were available only at the state level. The purpose of these two explanatory variables in our models is to reveal their effect on the quantity of road traffic collisions, which is identical to the other two Covid-19 explanatory variables. However, the daily deaths and number of people in hospitals, as a clearer indicator of the seriousness of the pandemic situation, tend to influence the public's behaviour and mental state more than the amount of the positively tested on Covid-19. Also, the positive-cases-based variables might not accurately reflect the reality because of their dependency on the availability and the volume of testing.

We can observe the mean of the daily deaths because of Covid-19 and the number of total daily hospitalized people on that disease - 54 and 2025, respectively. The maximal daily number of people in a hospital with Covid at once was nearly 10 000, while the most Covid-related deaths were 261 in a single day.

Table 3.21: Descriptive statistics of the number of deaths on Covid-19

Statistic	N	Mean	St. Dev.	Min	Max
Dead_Covid	671	54.170	68.287	0	261

Table 3.22: Descriptive statistics of the number of currently hospitalized people with Covid-19

Statistic	N	Mean	St. Dev.	Min	Max
Hospitalized	671	2,504.718	2,923.596	0	9,551

From the graphs below, we can observe that both the deaths and hospitalisations connected to the Covid-19 disease evolve similarly in time, however their peak numbers were recorded in different periods. Whereas the highest daily number of people, who died on Covid was in autumn 2020, the most Covid-positive people lied in hospitals during the summer 2021 wave of the pandemic.

Figure 3.3: The daily numbers of deaths because of the Covid-19

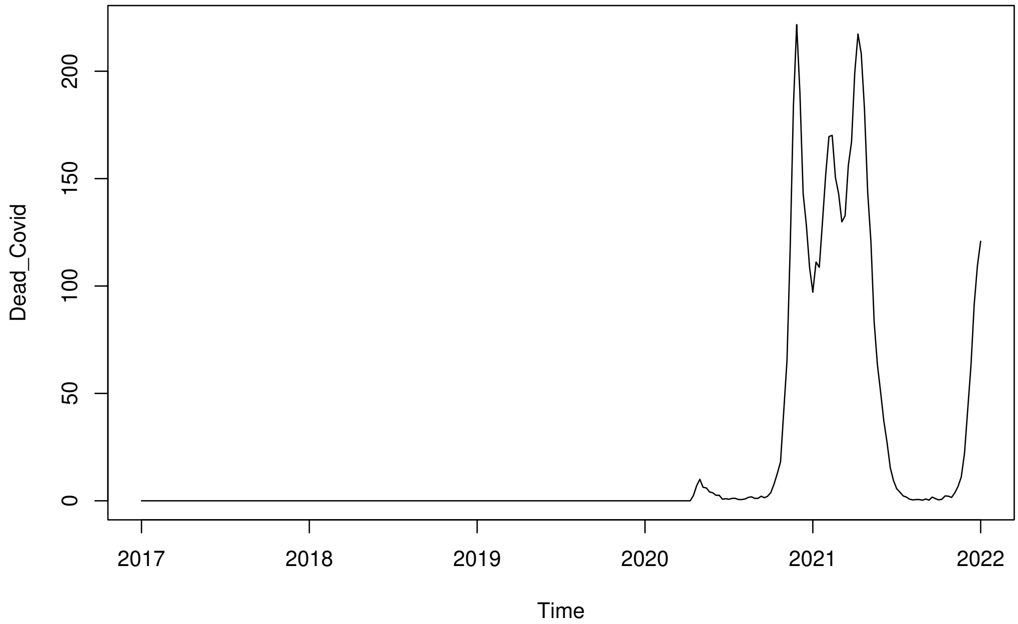
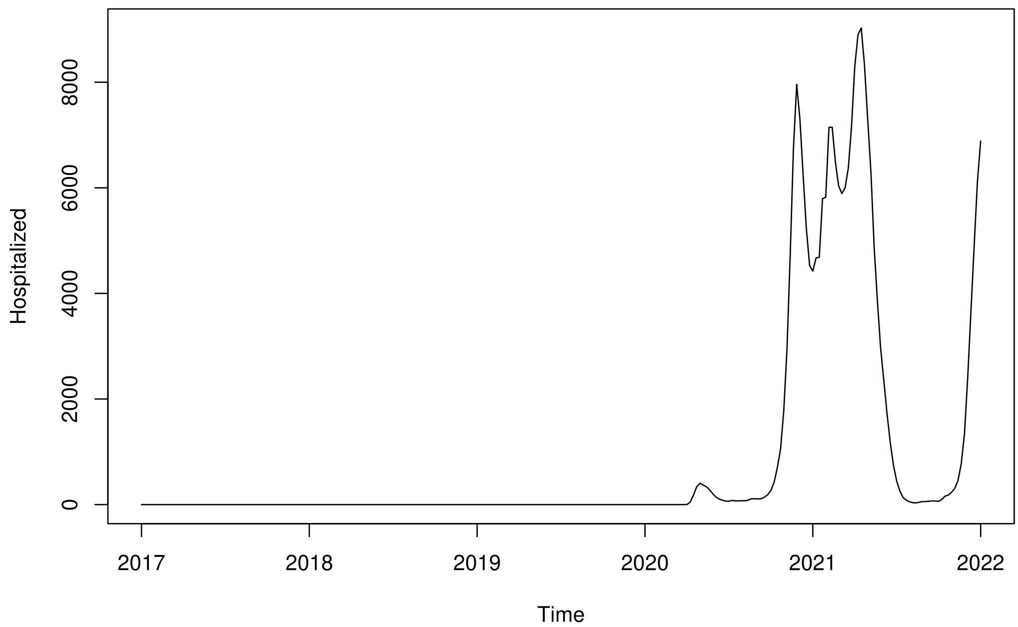


Figure 3.4: Daily amount of people in hospitals with Covid-19



Share of new cases from all tests

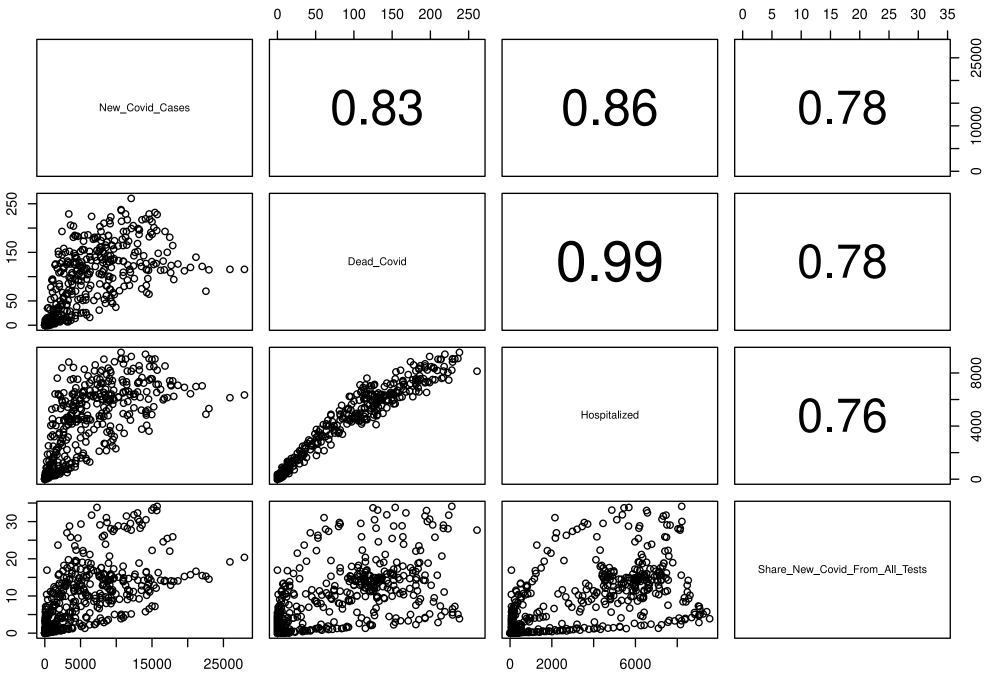
For the purpose of constructing a new variable indicating the percentage of the new Covid-19 cases from all the tests performed, we collected the information about the total volume of daily testing on the presence of the virus. The two obtained columns of values showed the number of PCR and antigen tests carried out each day since 1.06.2020 and 2.11.2020, respectively. The earlier values were not available because both testing methods were initiated with a delay compared to the first detected cases of Covid-19 in Czechia (1.3.2020). We created the new variable by dividing the total number of newly detected cases by the sum of both the number of PCR and antigen test volumes in MS Excel. Such variable should provide a more precise estimation of the real amount of new daily infections since the volume of testing fluctuates during the week and the season of the year.

The overview of the description statistics provides an insight into the dispersion of the Covid-19 incidence rate in time. The maximum percentage of the daily newly detected Covid-19 cases from all the tests performed a day is 34.1%. While the average daily share of newly detected Covid cases was 6.68%, the median value is less than half, which indicates that the data are skewed to the right. Meaning that at the beginning of the pandemic, the daily incidence rate of Covid-19 was generally much lower than during autumn 2020 and the year 2021.

Table 3.23: Descriptive statistics of the percentage of new cases of Covid-19 from all tests

Statistic	N	Mean	St. Dev.	Min	Max
Share_New_Covid_From_All_Tests	671	6.684	8.061	0.000	34.100

Figure 3.5: Correlogram of the Covid-19 indicators



From the correlogram 3.1, we can conclude that the four variables indicating the intensity of the pandemic are pairwise positively correlated. While the total number of deaths and the total amount of hospitalized people because of Covid-19 show almost a perfect linear relationship, the variables total new Covid-19 cases and the percentage of positive tests from all tests seem to be less correlated with each other. This phenomenon of a strong correlation between independent variables assumed to be used in the econometric models has to be treated. Otherwise, the regression might be very inaccurate. The methodology section will introduce the method to deal with this issue.

3.3.2 Weather variables

Out of all aspects of weather, the wind, precipitation and temperature have the highest potential to be at least moderately correlated with the traffic collisions. The descriptive statistics depict only the whole inspected five-year period, as there is no need to compare the differences between selected periods because weather variables are naturally very stationary.

Precipitation

Precipitation is the volume of rainfall in mm per 24 hours measured the following day at 7 a.m. The daily precipitation was extracted from around 750 weather stations across the country between 2017 and 2021. The data were averaged for each district and further for the whole country.

The average daily volume of rainfall for the whole republic is 1.895 millimetres for 2017-2021. However, this value does not carry much useful information since precipitation is more or less a random process, which can be predicted only a few days in advance. Also, it significantly differs across the reference area.

Table 3.24: Descriptive statistics of the average precipitation

Statistic	N	Mean	St. Dev.	Min	Max
Avg_Precipitation	1,826	1.895	3.060	0.000	25.336

Temperature

The temperature was recorded daily in degrees Celsius at 7 a.m., 2 p.m. and 9 p.m., and then averaged. Apart from the precipitation, the average temperature was measured in fewer weather stations - around 290. The low temperatures around and below zero might influence the number of traffic accidents the most, increasing the chance of ice accretion when vehicles tend to become uncontrollable. Reversely, we can assume that the very high, even tropical temperatures negatively affect drivers' attention. To reveal these effects, we will construct the dummy variables for the average temperatures below the 15th percentile - called **Low_Temperature** and above the 85th percentile - called **High_Temperature** of all observations of the variable: total average temperature. The 15th percentile means that 15% of observations of a specific variable are lying under this threshold, analogously to the 85th percentile. These percentiles were counted in Excel, resulting in the criteria below 0°C and above 18°C, respectively.

By looking at the table of basic statistics, describing the distribution of the observed values of the total average temperature, we can denote the mean for the whole selected five-year term being almost 9 degrees Celsius. The maximum daily value of the average temperature per the whole republic is 26.48 °C, and the minimum is -12.18 °C, which creates a range of nearly 40 degrees Celsius, throughout the year.

Table 3.25: Descriptive statistics of the average temperature

Statistic	N	Mean	St. Dev.	Min	Max
Avg_Temperature	1,826	8.896	7.810	−12.177	26.579

Wind

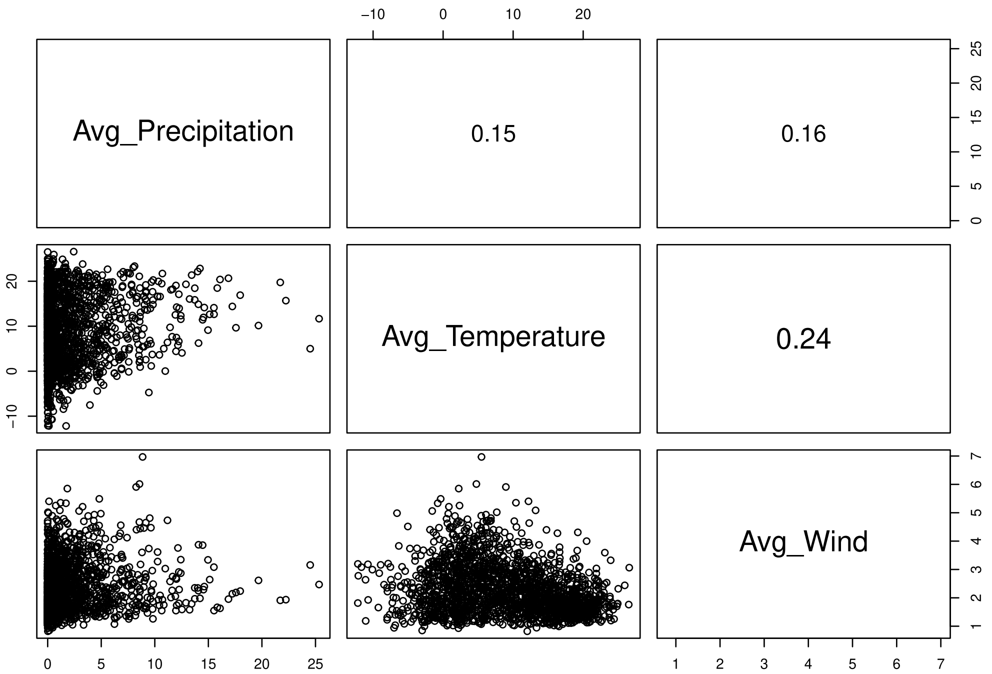
The last variable indicating the current weather situation is the wind. According to the analysis of the effect of weather conditions on road traffic collisions by Lio *et al.* (2019), wind speed significantly negatively affects the number of car accidents with severe injuries and deaths. It is one of the reasons for including that variable in our models and testing its effect and significance. Similarly to the temperature measurements, the wind was recorded three times a day in weather stations across the Czech Republic. Those three observations were averaged, providing one value in m/s per day. In addition, we will inspect if there is some effect of extreme wind on the number of daily accidents. To test that, a dummy variable, **Strong_Wind**, was created for 15% of the windiest days in our research period (2017-2021) in a similar way as the High_Temperature dummy.

The mean value of the daily average wind strength for the Czech Republic is 2.15 m/s, corresponding to 7.74 km/h. The maximum value of the average wind is 5 m/s, but the wind is very location-specific, and in the sudden gusts, it can reach much greater values.

Table 3.26: Descriptive statistics of the average strength of wind

Statistic	N	Mean	St. Dev.	Min	Max
Avg_Wind	1,826	2.284	0.865	0.822	6.968

Figure 3.6: Correlogram of the weather variables



A matrix of correlations between weather variables, suggesting no correlation.

Chapter 4

Methodology

The beginning of this section will characterize a general form of an OLS-based regression model with its assumptions Section 4.1, which will be used to reveal and explain the relationships between the variables mentioned in the previous chapter. Further paragraphs will describe the fundamental parts of the data analysis, concluding with verification of the validity of the implemented model's necessary assumptions.

4.1 Model form

The analysis of all variables of interest, subject to the topic of this thesis, is conducted in R using econometric methods. The results of our research will be obtained by regressing the dependent variable (described in Section 3.2), which is the number of traffic accidents, on the relevant independent variables (overviewed in Section 3.3). The general structure of the implemented ordinary least squares (OLS) regression models is the following:

$$Y_t = \beta_0 + \boldsymbol{\beta_1 X_t} + \boldsymbol{\beta_2 D_t} + \epsilon_t \tag{4.1}$$

Where:

- Y_t is the dependent variable
- β_0 is the intercept
- $\boldsymbol{\beta_1}$ is the transposed vector of coefficients, we are interested in
- $\boldsymbol{X_t}$ is the vector of independent variables
- $\boldsymbol{\beta_2}$ is the transposed vector of coefficients explaining the effect of dummy variables
- D_t is the vector of dummy variables
- ϵ_t are the disturbances (unobserved components of the model)

- t is the time

The OLS regressions for time series data have to fulfil these assumptions:

1. Linear model
2. Exogeneity
3. No perfect collinearity (or no multicollinearity)
4. Homoscedasticity
5. No serial correlation

Their validity will be described in the Section 4.3 of this chapter.

4.2 Functional form of the models

The fundamental functional form of this analysis is the linear model since our independent variables are mostly integers with a relatively small range of values or dummy variables. The first exception is the weather variables with decimal values, which would not provide meaningful outcomes being interpreted in percentages. The four Covid-19 indicators from CMH are the second exception, having quite a wide range of values. However, in the majority of the regressions, we focused only on the variable Share of newly detected Covid cases from all tests, which already carries its information in the percentages.

However, we decided to extend the analysis by adding the logarithmic transformations of the dependent variables in the selected models that are most relevant to the thesis topic. It allows us to estimate not only the change in traffic collisions in absolute terms but also to reveal the corresponding percentage change, which is helpful for comparing the effects on variables with a distinct range of values and for better insight. We faced an issue when implementing the logarithmic transformation of the accident variables with zero values in some observations. These variables had to be treated such that they do not input zero into the logarithm by adding a constant to each of them but not significantly altering the estimates of the regressions. Therefore a very small value of 0.0001 was added to each mentioned variable. Thus the coefficients can be further trusted.

4.3 Data analysis

Here we describe the methods used to analyze our dataset, consisting of 27 variables introduced in Chapter 3, 39 constructed dummy variables and 1825 observations of each day in the period 2017-2021. Having the daily observations of each variable, the data were organized into a time series format rather than a panel data structure. Otherwise, we would face a problem of having too many time periods (1825 days) against only 20 individuals (accident variables). Another reason for selecting the time-series format is that it allows us to determine the effect of explanatory variables on the total number of accidents - our main variable of interest for estimating the effects for the whole republic. If we decided to work with panel data for the districts, instead, these overall effects would not be possible to detect. Furthermore, the two of the variables explaining the Covid situation were only available at the state level. It would prevent us from including those in our models when using the panel structure. Another factor that contributed to the decision to arrange the data as time series for the whole Czech Republic was that if we divided the observations by districts, some of the variables with already very small range of values would not explain the desired effects adequately, as the models would have low adjusted R^2.

Our explained variable, the number of road traffic collisions, is divided into categories denoting the overall count of accidents, the usage of forbidden substances while driving, the severity, the causality and the location. Since each category shows several underlying options, we obtain the total number of 27 dependent variables. Because regression models of the described type cannot accept more than one explained variable at once, we will estimate the effect of independent variables on each dependent variable separately. Initially, we will inspect the effects of individual independent variables on the total number of car accidents. Afterwards, we will be able to compare the obtained explanatory variables' compound effects across the traffic accidents falling into each category. As a tool, we used RStudio based on the R program, which is suitable for solving econometric questions.

4.3.1 Stationarity

As a first step after loading the data, it is necessary to determine for the time series whether the data are stationary or not. Omitting that part of the analysis could lead to biased estimators and further to wrong interpretations of the results, and it may produce spurious results, provided that the data were non-stationary (Shrestha & Bhatta 2018). Stationarity means not to depend on time at which the series is observed. In other words, no trend is present (Hyndman & Athanasopoulos 2018). We started with the graphical visualization of each variable on time to check whether we could find out about stationarity just by looking at it. The variables describing the Covid-19 situation revealed much of an irregularity over time since the pandemic started in March 2020 in the Czech Republic, which is in the middle of the period relative to our analysis. Also, the Coronavirus pandemic had several waves over the examined period, reflected in our four variables indicating the severity of the pandemic. Therefore, we assumed those variables would be non-stationary over time.

In order to verify our estimate, we applied the Augmented Dickey-Fuller (ADF) test with the default one lag to all variables confirming non-stationarity by two of four mentioned Covid-19 variables. Those were the number of deaths of Covid and the number of hospitalized because of Covid-19 (not rejecting the null hypothesis of the unit root process being present even on 10% level of significance). The rest of the variables turned out to be very stationary, even at 1%. In fact, ADF tests may not be valid for variables with a structural break since they tend to be biased towards non-rejection of the unit root process, even though the individual subsamples may be stationary (Perron 1989). From the library *strucchange* in R, we used a *sctest* function to detect any structural change for those two variables indicated as non-stationary, separately, and breakpoints function to obtain dates of the revealed structural change. By both variables, at least one breakpoint was present. Based on these dates, we divided each series into subsamples according to the number of breakpoints and tested them individually using the ADF test again. Despite some of the subsamples turning out to be stationary, neither variable was found stationary in every subsample. Thus, the structural break was no longer important in the problem of stationarity.

Additionally, we used the Phillips-Perron (PP) test for all variables, which tests stationarity as well. Apart from the ADF test, it uses t statistics and the Newey-West procedure to correct the standard errors for autocorrelation in disturbances. The advantage of this test is that it is not required to choose an optimal level of lags, which might be challenging (Parker 2020). The test results confirmed the unit root process by those two Covid-19 variables, previously denoted as non-stationary, at all significance levels. Generally, the detection of stationarity is a complex task that requires using various testing methods, lots of decision making and is subject to the analyst's approach. Therefore, we decided to conduct one more test: the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, to confirm the non-stationarity of the two mentioned Covid-19 variables, with the null hypothesis of the inspected variable being stationary, which is the opposite of both the PP and the ADF tests. It turned out that both tested variables showed a lower p-value than 0.01, thus rejecting the null hypothesis of being level-stationary at all levels of significance. However, the number of deaths of Covid-19 was found to be trend-stationary, using the same method. The number of hospitalized on Covid-19 was not.

The problem of non-stationary data can generally be solved by several methods. The first option is to change the given non-stationary variable into stationary using one of the following methods: differencing or removing a trend or cycle component. However, there is a risk of losing some information carried by the variable when applying one of the mentioned procedures. Another possible solution is not to do anything about the detected non-stationarity and implement that variable into such model that can handle non-stationarity (Shrestha and Bhatta 2018). However, the differenced variables cannot be used in one model with non-differenced ones (the number of observations differs and the interpretation is difficult). As our dependent variables are all stationary, they cannot be regressed on non-stationary independent variables. The last option to treat the non-stationarity or avoid possible spurious relationships is to add a trend variable into the model (Long & Herrera 2020). Although our dependent variables are all stationary (previously detected by ADF tests), we tried to implement the trend variable in our models and observe the change in the significance of the variables. In the cases where the individual significances improve, we kept the trend variable. Otherwise, it was removed because it tends to explain part of the effect of other independent variables on the explained one and, therefore, would be more harmful than helpful in such regressions.

We decided to use the method of de-trending our two non-stationary variables to convert them into stationary ones. After that procedure, we verified if the new de-trended variables became stationary using the ADF and KPSS tests. One of them - the number of deaths on Covid, reported strongly significant stationarity, even on 1% significance level. The other variable describing the number of hospitalized people prevailed to be non-stationary (ADF p-value: 0.1587, KPSS p-value: 0.07358). Since it is not desirable to construct all models four times, each time for a different Covid-19 variable because of multicollinearity, we will use the number of hospitalized of Covid just as a supplementary one. Although the significance and the coefficient of such variable may not be accurate, we can use it as an approximation for the relationship between the society's perception of the pandemic seriousness and the number of traffic collisions.

4.3.2 Seasonality

Seasonality in time series regressions is usually treated by one of two possible methods. Either by seasonally adjusting the given variable or by using seasonal dummy variables based on the frequency of a seasonal pattern. The reason is to control for the differences between distinct periods. Since our data contain weather indicators, seasonality is also an issue of our analysis. We plotted the decomposed weather variables to reveal the seasonality pattern one by one. A solid annual pattern was shown by the Avg_Temperature variable, while the seasonality of Avg_Precipitation and Avg_Wind was moderate. Only the daily average temperature was seasonally adjusted in R, substracting its seasonal component. After constructing the models for both variants of the temperature variable (with the seasonal adjustment and without), we decided to use the seasonally adjusted one based on the improved fit of our models and more significant coefficients. By the rest of the weather variables, the seasonality effect is negligible.

To treat the possible seasonality of the dependent variables depicting the traffic accidents, we are going to add to the models a set of seasonal dummy variables. Some indicating the months of the year, and, to avoid multicollinearity, we create the extra models with dummies for each of the four seasons of the year. Moreover, the number of daily accidents may also vary during the week and holiday, as the traffic intensity changes during these periods. Therefore we decided to implement a days-of-the-week dummy and dummy variables for Easter, Christmas, New Year (on this day, drivers tend to behave differently) and other national holidays to reveal their impact on the traffic accidents and to increase the adjusted R^2 of the models. After constructing such models, we will compare the fit of the models and the statistical significance of the dummy variables and decide which model is the best for our purposes.

The seasonality of Covid-19 is hard to observe for quite a short period, and the evolution of Covid-19 is unpredictable at the same time. Therefore we will not implement any seasonality treatment for the pandemic indicators. However, the virus spreads faster in wet and cold conditions, implying that during summer, the number of newly detected Covid cases, the number of deaths and hospitalizations because of Covid are very low compared to the rest of the year. To estimate the difference between the periods of the low and high incidence of the disease and their impact on the number of daily accidents, we will construct an additional model with an interaction term of the Covid_19 variable and one of the seasonal dummies.

4.3.3 Linearity in parameters

For the valid estimators of the OLS regression, we need the dependent variable Y_t to be a linear function of the parameters β. This assumption is satisfied in all of our models, since the power of β coefficients is not higher than one.

4.3.4 Endogeneity

The OLS regression requires exogeneity of the independent variables to produce valid estimators. An endogenous variable is a variable depending on another explanatory variable or any of the unobserved variables as a component of the error term. In the opposite case, the variable is termed exogenous. Weather variables are generally considered very exogenous because they are hardly ever affected by other variables. Based on this assumption, we believe that all the weather variables used in our models are exogenous. The inspection of exogeneity of Covid-19 variables is slightly more complicated. We can find some variables that affect the indicators of the pandemic. Such as the weather indicators (the higher the temperature, the lower the spreading of the Covid-19) or the lockdown variables tend to have a mutual effect on each other with the pandemic indicators. Despite this fact, the number of traffic accidents of all kinds does not have any impact on the spreading of the disease, meaning that the dependent variable does not affect the variable suspected of endogeneity. In that case, endogeneity cannot be confirmed, and the OLS estimators can be trusted.

4.3.5 Multicollinearity

It is necessary to examine in the regression models whether the independent variables are correlated. If it is so, we can speak about multicollinearity being present between our explanatory variables, and it leads to reduced precision of the estimated coefficients, which weakens the statistical power of our models.

As we implemented variables continuous in time and also several dummy variables, deeper explaining the same phenomenon, there is a high probability of detecting the multicollinearity.

The relationships between our independent variables were explored using a custom *corstars* function for the detection of a correlation and its significance based on p-values in R. Expectedly, we found a positive correlation between the variables explaining the daily weather situation and the dummy variables derived from them. The only statistically insignificant correlation coefficient is between Avg_Wind and Low_Temperature, whereas the rest are very significant.

Table 4.1: Correlation table of daily weather variables and weather dummies

	Low_Temperature	High_Temperature	Strong_Wind
Avg_Temperature	-0.612^{****}	0.627^{****}	-0.198^{***}
Avg_Wind	-0.011	-0.206^{****}	0.758^{****}
Note:			*p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

The correlation coefficients between the Avg_Temperature and Low_Temperature, the Avg_Temperature and High_Temperature are -0.612 and 0.627, respectively. The correlation of 0.758 between the variable Avg_Wind and the Strong_wind dummy is even higher. To deal with the issue of the imprecise estimations of the OLS coefficients, which may arise from multicollinearity, we decided to construct two separate sets of models. One with the weather variables continuous in time and the other using just the dummy variables indicating the extreme weather conditions.

Generally, there is quite a high probability that the average daily temperature and the dummies describing the month of the year will be influenced by each other. In our case, the correlation coefficients revealed the highest values between July, August and Avg_Temperature, the lowest between January and Avg_Temperature, although none of them exceeded the value of 0.4 in absolute terms. Similarly, we have to verify whether the extreme weather dummy variables and the seasonal dummies are correlated or not. The highest correlation was observed between Low_Temperature and January, being 0.4. High_Temperature with July and August was also slightly positively correlated (0.36 and 0.34, respectively). Such values, though, indicate only a moderate correlation and thus can be neglected.

Table 4.2: Correlation table of average temperature, temperature dummies and monthly dummies

	Avg_Temperature	Low_Temperature	High_Temperature
January	−0.398****	0.407****	−0.130****
February	−0.315****	0.222****	−0.123****
March	−0.205****	0.031	−0.130****
April	−0.011	−0.103****	−0.122****
May	0.132****	−0.122****	−0.054*
June	0.353****	−0.120****	0.320****
July	0.373****	−0.122****	0.360****
August	0.368****	−0.122****	0.344****
September	0.170****	−0.120****	−0.083***
October	0.007	−0.122****	−0.130****
November	−0.181****	−0.016	−0.128****
December	−0.302****	0.191****	−0.130****

Note: *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

A significant correlation was found between the variables explaining the development of the pandemic in time and the dummy variables indicating the presence of a lockdown. The highest values were slightly above 0.5, occurring between the Covid-19 dummy (showing whether the pandemic of the Covid-19 was present in the Czech Republic) and our four Covid-19 variables explaining the strength of the pandemic. When we recall the period of the Covid-19 disease, it has been less than two years of the 5-year period of our expertise. Therefore the values of our four Covid-19 incidence variables show non-zero values only after the 1st March 2020. Since all dummy variables always have the only values of 0 and 1, it is very likely that the correlation coefficient will be biased, indicating a stronger relationship than there really is, between the Covid-19 dummy and the variables New_Covid_Cases, Dead_Covid, Hospitalized and Share_New_Covid_From_All_Tests. Therefore, we decided not to consider these correlations an issue which must be dealt with.

Table 4.3: Correlation table of the Covid-19 continuous variables and the Covid-19 dummy variables

	Cov_Cases	Dead_Covid	Hospitalized	Share_Cov
Covid_19	0.504****	0.534****	0.563****	0.551****
Lockdown_1	−0.050*	−0.044	−0.044	−0.063**
Lockdown_2	0.289****	0.426****	0.363****	0.505****
Lockdown_3	0.294****	0.491****	0.505****	0.083***
Bet_Lock_1_2	−0.022	−0.071**	−0.071**	0.210****
Bet_Lock_2_3	0.421****	0.575****	0.553****	0.516****
Aft_Lock_3	0.237****	0.084***	0.157****	0.061**

Note: *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001
The abbreviations may be consulted in Table B.1 and Table B.2

Furthermore, a slightly lower but still considerable positive correlation was detected within the dummy variables indicating the Covid-19 pandemic and the state of lockdown in the Czech Republic during that pandemic. The highest values occurred between the Covid_19 dummy and Between_lockdowns_1_2, Covid_19 and Between_lockdowns_2_3, Covid_19 and After_lockdown_3. Such results could be predicted in advance because the Covid_19 dummy shows values of 1 for the whole period of the pandemic. The longer the period of the lockdown dummies is, the higher the correlation of each of them with the Covid_19 dummy. The between lockdown periods are much longer than the lockdown ones, so the models including all of the pandemic-related dummy variables led to multicollinearity, resulting in the lost significance of between-lockdown variables. To avoid this issue, we removed the variable Covid_19 from all further models, as the lockdown dummies explain the whole period of the pandemic and the effect of the pre-pandemic time is explained by the intercept.

Table 4.4: Correlation table of the Covid-19 dummy variables

	Covid_19
Lockdown_1	0.196****
Lockdown_2	0.170****
Lockdown_3	0.201****
Between_lockdowns_1_2	0.434****
Between_lockdowns_2_3	0.316****
After_lockdown_3	0.539****

Note: *p<0.05; **p<0.01; ***p<0.001; ****p<0.0001

In Chapter 3 of this thesis, we have already inspected the relationship between the four Covid-19 variables indicating the strength of the pandemic (Figure 3.5). Resulting in the robust correlations between each other, we decided to choose only one of them as our main control variable for the expansion of the disease in society. The most significant and stationary one is the Share_New_Covid_From_All_Tests, based on the initial four models showing the individual effect of each Covid-19 variable on the number of traffic accidents. Therefore it was selected to represent the evolution of the pandemic in the majority of our models. As those four Covid-19 variables explain the same phenomenon, only using different methods of detection based on the distinct indicators, we assume that the respective coefficients will show a similar effect on each dependent variable in terms of the same sign and similar level of significance. This assumption will be tested using the three remaining Covid-19 variables as the alternatives to the main one in three additional models, with the primary dependent variable being the total amount of daily traffic accidents.

To summarize the models' construction, we initially created four trial models, each with one of these variables: New_Covid_Cases, Adj_Dead_Covid, Adj_Hospitalized and Share_New_Covid_From_All_Tests, to select our main control variable for the strength of the pandemic and to compare its effect with the effects of the rest of them on the principal dependent variable, being the Acc_Total. In the rest of the models of our analysis, only the main control variable Share_New_Covid_From_All_Tests remained to avoid the problem of multicollinearity. Finally, one model type, in terms of a combination of the explanatory variables with the best fit, was used to describe the dependent variables of each category.

4.3.6 Autocorrelation and Heteroscedasticity

Zero serial correlation, alternatively an autocorrelation, is a fundamental assumption of the time series analysis using OLS regressions, meaning that there is no relationship between the observations and the function of the time lags among them. To test for this property, we constructed the Breusch-Godfrey (BG) test within the *lmtest* package in R for all models of our analysis. It is designed to detect serial correlation for any specified number of lags, apart from the Durbin-Watson (DW) statistic, which only tests the presence of autocorrelation up to one lag. Our aim is to detect the presence of autocorrelation among the models' residuals. Therefore, it is equivalent to use either the DW test or the BG method with the default value of up to one time lag. The results revealed 48 models where autocorrelation was present on 5% level of significance and only 13 with the residuals independent of each other.

Furthermore, it was necessary to find out if the standard deviations of the estimated variable are constant over time, which would indicate homoscedasticity, or not. As mentioned in Section 4.1 of this chapter, homoscedasticity is required for the standard errors of the OLS estimation to be valid. The common method of detection is the Breusch-Pagan (BP) test based on chi-squared distribution, assuming homoscedasticity under the null hypothesis and heteroscedasticity as an alternative one. It was used to detect heteroscedasticity in our models as well, indicating that several models were homoscedastic at a standard 5% level of significance showing p-values higher than 0.05. These models also showed no serial correlation in the previous step, so they do not require any further treatment of the standard errors. Altogether, by the rest of them, we found heteroscedasticity, which has to be dealt with.

There are several options to treat the serial correlation in the models. The first one is to include the time lags of the dependent variable in the model. We constructed three lags of the dependent variable - Acc_Total, and estimated one of the models predicting that variable. Although all three lag variables were statistically significant, the following BG test still suggested autocorrelation in the model. Moreover, if the time lag variables are implemented in the model, they tend to explain part of the effect of the unobserved and explanatory variables. That may lead to an inaccurate interpretation of the model, as the coefficients next to the independent variables alter. To prevent this from happening, we decided to treat autocorrelation by using the Newey & West (1987) Heteroscedasticity and autocorrelation consistent standard error estimators (HACs), also suitable for coping with heteroscedasticity. They were used in 48 cases, obtaining both autocorrelation and heteroscedasticity robust standard errors, allowing us to interpret the correct significance of the estimators. Since none of the models was both autocorrelated and homoscedastic at the same time, the only issue left was to deal with the ten heteroscedastic models with no serial correlation present. Using the Heteroscedasticity consistent standard error estimators (HCs), we obtained the desired results of the correct significance of the respective coefficients (Hayes & Cai 2007).

In this chapter, all assumptions of the OLS regression models were verified, therefore we can proceed to the evaluation of the estimated effects.

Chapter 5

Hypotheses

Research question 1:
Does the Covid-19 pandemic have some impact on the amounts of traffic collisions?

HYPOTHESIS 1.1:
The number of total traffic accidents significantly decreased during the pandemic of Covid-19 relative to the pre-pandemic state and even more during the lockdown periods.

The periods of strong restrictions on people's movement and contact significantly negatively impacted the traffic volume. As stated in the Literature review chapter (Chapter 2), traffic volume decreased by between 70 and 96% in selected European cities during the early phase of the first lockdown in the spring of 2020 (Dickson 2020). It is believed that generally, the lower traffic density suggests fewer road traffic collisions. Altogether, the lockdowns during the pandemic of Covid-19 should have an indirect negative effect on traffic accidents. To support the first part of this hypothesis, people may have stayed at home more often than before the pandemic, even between the lockdown periods, due to the lack of "outside-of-home" activities, events and the persisting home offices. Such patterns in people's behaviour would lead to decreased traffic volume and thus fewer traffic accidents.

ALTERNATIVE HYPOTHESIS 1.1:
The number of RTCs significantly increased during the Covid-19 era compared to the period before the pandemic.

People around the globe were terrified of getting in touch with a Covid-19 positive person since the disease was deadly in many cases. It might have raised the popularity of private vehicles when avoiding the crowded public transportation means, and the raised traffic flow might have led to more frequent RTCs.

The real effects of the mentioned disease on traffic accidents in the Czech Republic will be revealed based on the regression outputs in the next chapter, confirming one or the other hypothesis.

HYPOTHESIS 1.2:
The indicators of the pandemic strength negatively influenced the collision rates, providing the incentive for a lockdown imposition.

A set of restrictions called “lockdown” is established by a government based on the evolution of an illness in the population. Its purpose is to reduce the spreading of the illness and to prevent the health system from collapsing (Atalan 2020). We believe that the higher values of the indicators of the Covid-19 pandemic, the bigger threat for society, therefore also the higher chance of the legislators imposing lockdown as a tool to prevent the disease from spreading. The reviewed literature suggests that the lockdown imposition has a significant negative impact on traffic volume and consequently on the number of traffic accidents. Therefore we predict the effect of the Covid-19 indicators on the total RTCs to be negative. That is, however, not the only explanation of the proposed relationship. During the period of a massive outburst of Covid-19, people are likely to alter their behaviour by spending more time at home, because of the fear of getting infected. It also implies the lower traffic on the roads and consequently less RTCs, even if no protective measures are imposed.

Research question 2:
Does the Covid-19 pandemic affect drivers’ behaviour and traffic safety?

HYPOTHESIS 2.1:
The number of traffic collisions where the offender was under the influence of alcohol or drugs significantly increased during the pandemic of Covid-19.

29% of respondents in an American survey reported an increase in alcohol usage during the Covid-19 pandemic (Capasso *et al.* 2021), and according to Rossow *et al.* (2021), the proportion of heavy drinkers in Norway increased significantly during that time. Cannabinoids and other forbidden substances were also overused during the pandemic (Thomas *et al.* 2020). These phenomena are mainly explained by the worsened mental health conditions of the population and inclination to depression and anxiety. It can be expected that the overall increase in alcohol usage will be reflected in the increased amount of drunk drivers and potentially in more alcohol-triggered traffic accidents.

HYPOTHESIS 2.2:
Road fatalities and severe traffic accidents significantly rose after the outbreak of Covid-19, especially during the stages of lockdown.

Certain academic sources suggest that the decreased traffic volume during lockdowns prompted drivers to increase speed and pay less attention to the emptier roads. It immediately led to more often severe RTCs and fatalities. (Brodeur *et al.* 2021) (Qureshi *et al.* 2020). However, different studies based on different samples prove the opposite. Yasin *et al.* (2021), in their study, revealed a significant decrease in the number of gravest crashes in 33 out of 42 countries, originating from the fall in traffic density and thus the lower exposure to critical situations while driving. The overall effect of the pandemic on the fatal and severe collisions can not be estimated beforehand and has to be examined, using the regression analysis.

ALTERNATIVE 2.2:
There was a drop or a similar level of traffic accidents with serious injuries and fatal consequences during the period of anti-virus measurements.

HYPOTHESIS 2.3:
RTCs resulting in minor or no injuries were less common during the pandemic relative to the pre-pandemic era.

As stated previously in the Literature review (Chapter 2), traffic accidents with lighter injuries tend to follow the general trend of decreased total road traffic collisions (Brodeur *et al.* 2021). This category of traffic collisions is likely to happen in the locations of the limited speed, e.g. crossings, and municipalities, where the lowered traffic volume during the pandemic was the most noticeable.

HYPOTHESIS 2.4:
The roads became more dangerous during the pandemic of Covid-19 and drivers' behaviour riskier.

This hypothesis will be tested using the variables describing the causality of the accidents. Namely, the number of RTCs caused by not adjusted speed to the surrounding conditions, risky overtaking, not giving the right way in driving and the unspecified inappropriate style of driving.

Research question 3:
Do the daily weather conditions influence the number of traffic accidents? How?

HYPOTHESIS 3.1:
Precipitation has a significant negative effect on traffic accidents.

Precipitation is often associated with a higher risk of traffic collisions, as the vehicle may become uncontrollable, and there is a threat of an unpleasant phenomenon called aquaplaning (Chen *et al.* 2010). The effect of precipitation is consistent and generally leads to increased accident frequency across multiple studies on this topic.

HYPOTHESIS 3.2:
Temperature positively affects the number of road traffic collisions, as well as the extremely low and high temperatures.

An empirical study by Theofilatos & Yannis (2014) suggests that the additional 1°C of the average temperature causes the RTCs to rise by 1-2%. In addition, hot weather is considered an essential factor, increasing stress, heart rate and a chance of heart disease and decreasing performance and concentration while driving. It naturally leads to an increased incidence of RTCs during the heatwave days (Nofal & Saeed 1997). The extremely low air temperatures show a similar effect on the traffic accidents as the heat conditions - an 11% increase in the risk of an accident as the average temperature drops by 1°C (Hou *et al.* 2022). Therefore we assume to find a similar relationship to the one defined in the hypothesis between the respective variables for the Czech Republic.

The wind is one of the weather variables inconsistent in its effects on the total accidents across multiple studies. It is very challenging to determine the hypothesis suggesting a certain relationship between the wind and traffic collisions. Nevertheless, the model outcomes will be inspected, providing precise results for the impact of wind on road safety.

Research question 4:
Does the season of the year, the national holiday and the weekday influence

the traffic collisions? How?

HYPOTHESIS 4.1:
The volume of motor vehicle collisions significantly varies during the week. The peak values were recorded on Fridays, while the least traffic accidents occurred on Sundays.

Several literature sources reviewing this topic coincide in the results of the RTC distribution over the week, providing the basis for our hypothesis (Andreescu & Frost 1998) (Keay & Simmonds 2005).

The seasonal effects on the number of traffic accidents significantly vary across the distinct locations of study. Such differences may be explained by the unique weather characteristics of the examined areas, according to Nofal & Saeed (1997). They found the peak number of RTCs during the summer months, supported by the fact that school breaks and employees' holidays cause the vehicle travel to increase, because of the pleasant weather and long daylight, among other things. Contrary to that, Sivak (2009) revealed in the study of US road crashes the highest numbers during October, followed by November and December. Considering the climate conditions of the Czech Republic, we are inclined to the theory that the most traffic accidents occurred during the summer season since this period brings quite a warm weather with heavy sunlight.

HYPOTHESIS 4.2:
The maximum of traffic accidents generally tend to occur during the summer months, the minimum values show the winter and spring seasons.

HYPOTHESIS 4.3:
New Year, Christmas, Easter and other national holidays have a significant impact on the total number of road traffic collisions, alcohol-impaired collisions and fatalities.

New Year is a specific day of the year in terms of the drivers' behaviour, following the Christmas celebration period. On this day, they are generally prone to drunk driving, risky speed and stunt driving more than during the Christmas season, during which traffic safety is slightly decreased compared to the rest of the year. Ponboon & Tanaboriboon (2005) evaluated these effects in their study, presenting the 147% increase in fatalities during the Christmas-

New Year time accompanied by the 98% increase in the accidents with injuries. Because these results may differ according to distinct locations and samples, we decided not to specify the sign of the effects in this hypothesis and test it and describe our results later in the model outcomes section.

Chapter 6

Results

The primary purpose of this chapter is to interpret the outcomes of our regressions and to provide answers to the previously defined hypotheses. The first Section 6.1 will discuss the structure of the models. Then, the models themselves will be described in Section 6.2 and Section 6.3. The overall empirical findings relative to the topic of this thesis will be summarised in the Conclusion (Chapter 7).

6.1 Models structure

The models are ordered by categories of the dependent variables, previously defined in Chapter 3. The first set of models with the dependent variable identifying the number of all traffic accidents in the Czech Republic is used to reveal the individual effects of our independent variables (Subsection 6.2.1 and Subsection 6.2.2). Afterwards, several models with different combinations of the explanatory variables and the same essential dependent variable were constructed to find the model with the best fit, providing the most accurate explanations for the hypotheses of this thesis. Such selection of independent variables was further used to indicate its effects firstly on the Acc_Total variable (Subsection 6.3.1) and then on every dependent variable, providing the opportunity to compare the results across the respective categories (Section 6.3).

Two sets of explanatory variables were used to show the robustness of the results and they offer an insight into the topic in more detail. Additionally, the "log-lin" models were included to provide the extension of the models for the more precise interpretation. These model extensions were placed in the Appendix A. For the comparison and better orientation and simplicity, we decided to insert multiple models into the tables based on the selection of included variables and the regressand category.

6.2 Outputs of auxiliary regressions

6.2.1 Covid-19 effect

Subsection 3.3.1 detected a significant correlation between certain Covid-related variables, therefore, such variables could not be used in the same model when comparing their effect on the dependent variable. We incorporated the days-of-the-week and monthly dummies as fixed independent variables to improve all the models in Subsection 6.2.1 and for a better comparison of the revealed effects.

Effects of Covid-19 dummy variables on total traffic accidents

The first four models of this thesis were constructed to reveal the net effects of the Covid-19 dummy variables on the main dependent variable - the total number of traffic accidents in the Czech Republic. Both linear models and the logarithmic transformations of the dependent variable were applied to estimate its absolute and relative change per unit absolute change of each explanatory variable.

From the regressions (1) and (2), we can see that the estimated coefficients in front of the Covid-19 variable are both negative and significant at 1% (level of significance). The total daily number of traffic accidents is estimated to have decreased by around 39 (column (1)), corresponding to approximately 16% (column (2)) during the period with Covid-19 disease present in the Czech Republic compared to the pre-pandemic period. Such finding is in line with the plentiful worldwide literature reporting a significant dowturn in traffic collisions during that period. The following models (3) and (4) inspect the relationship between the pandemic and the quantity of traffic collisions in more detail, distinguishing between several phases of the pandemic. Keeping other factors fixed, the most significant drop in the amounts of RTCs was observed during the first lockdown, estimated to decrease daily by 39% relative to the before pandemic state. Followed by the values of the lockdown in autumn 2020 and spring 2021, respectively, there is a clear trend of much fewer traffic accidents during the times of anti-virus measures than in the rest of the Covid-19 era. This trend is a consequence of the lowered traffic volume, directly stemming from the restricitons on public movement (Wagner *et al.* 2020) (Fitch Ratings 2021). Quite a surprising finding provided the negative coefficient in front of the After_Lockdown_3 variable, showing still prevailing effect of fewer RTCs against the years 2017-2019, despite reflecting the three quarters of the year after the last lockdown. One possible explanation for that might be the Covid-19 incidence rates and the number of newly detected Covid-19 cases significantly rising again during autumn 2021, according to the Figure 3.2, however, no lockdown was established. It might uncover people's responsibility in keeping the decreased mobility and minimal contacts because of fear of infection, despite the non-existing lockdown legislation.

The previous paragraph clearly supports the hypothesis 1.1 against the alternative in all its aspects.

Table 6.1: Regression outputs- individual effects of Covid-19 dummies

	Dependent variable:			
		log		log
		Acc_Total		
	HAC	*HAC*	*HAC*	*HAC*
	(1)	(2)	(3)	(4)
Covid_19	-38.70^{***}	-0.16^{***}		
	(4.02)	(0.02)		
Lockdown_1			-86.28^{***}	-0.39^{***}
			(7.46)	(0.04)
Lockdown_2			-82.91^{***}	-0.32^{***}
			(7.23)	(0.03)
Bet_Lock_1_2			-78.04^{***}	-0.35^{***}
			(7.82)	(0.04)
Bet_Lock_2_3			-23.60^{***}	-0.09^{***}
			(3.92)	(0.01)
Aft_Lock_3			-39.28^{***}	-0.16^{***}
			(6.71)	(0.03)
After_lockdown_3			-15.86^{***}	-0.06^{***}
			(4.98)	(0.02)
Monday	100.70^{***}	0.41^{***}	100.92^{***}	0.41^{***}
	(3.71)	(0.02)	(3.56)	(0.02)

Tuesday	86.87***	0.36***	87.15***	0.36***
	(3.64)	(0.02)	(3.51)	(0.01)
Wednesday	99.77***	0.41***	100.07***	0.41***
	(3.53)	(0.02)	(3.35)	(0.01)
Thursday	98.49***	0.40***	98.97***	0.41***
	(3.57)	(0.02)	(3.44)	(0.01)
Friday	117.28***	0.46***	117.75***	0.46***
	(3.74)	(0.02)	(3.59)	(0.01)
Saturday	27.62***	0.13***	27.83***	0.13***
	(3.10)	(0.01)	(2.99)	(0.01)
January	−4.42	−0.01	−2.04	0.004
	(7.72)	(0.03)	(7.67)	(0.03)
February	−18.59***	−0.05	−16.00**	−0.03
	(6.65)	(0.03)	(6.63)	(0.03)
March	−29.04***	−0.10***	−17.36**	−0.04
	(6.83)	(0.03)	(6.90)	(0.03)
April	1.50	0.02	11.35	0.07**
	(7.19)	(0.03)	(7.09)	(0.03)
May	25.98***	0.13***	21.44***	0.11***
	(6.70)	(0.03)	(6.82)	(0.03)
June	45.47***	0.20***	41.13***	0.18***
	(6.32)	(0.03)	(6.40)	(0.03)
July	17.93***	0.11***	13.79**	0.09***
	(6.58)	(0.03)	(6.66)	(0.03)
August	27.72***	0.14***	23.78***	0.12***
	(6.42)	(0.03)	(6.47)	(0.03)
September	40.80***	0.18***	37.07***	0.17***
	(6.56)	(0.03)	(6.66)	(0.03)
October	41.58***	0.18***	41.87***	0.18***
	(6.69)	(0.03)	(6.65)	(0.03)
November	21.98***	0.11***	27.59***	0.13***
	(6.60)	(0.03)	(6.58)	(0.03)
Time	0.02***	0.0001***	0.01**	0.0000***
	(0.004)	(0.0000)	(0.004)	(0.0000)
Constant	189.44***	5.21***	191.78***	5.22***
	(6.73)	(0.03)	(6.80)	(0.03)

Observations	1,826	1,826	1,826	1,826
Adjusted R^2	0.54	0.55	0.58	0.60
F Statistic	115.53***	118.07***	107.52***	114.98***
	(df = 19; 1806)		(df = 24; 1801)	

Note: *p<0.1; **p<0.05; ***p<0.01

The abbreviations may be consulted in Table B.1 and Table B.2

The relationship between the indicators of pandemic strength and total traffic collisions

Not only the decreased traffic flow during the lockdown explains the drop in RTCs. The indicators of the pandemic strength, such as the newly detected cases, deaths and hospitalizations on Covid, act as a threat to the public, contributing to the change in people's behaviour, also reflected in the attitude towards driving. The individual effects of such Covid-19 strength variables will be discussed in this section through four linear regression models with the same set of explanatory seasonal dummies, enabling precise comparison.

Every Covid-19 indicator variable is statistically very significant (p-value <0.01), and all four models show similar adjusted R-squared (around 0.55). The number of newly detected positive cases of Covid-19, denoted by the "Cov_Cases" variable in the model (1), indicates a little negative effect on the number of total RTCs, whereas, with an additional 1% increase in the share of new Covid-19 cases from the total tests, the RTCs are estimated to decrease by 2.14. The difference between these two variables is that apart from the Cov_Cases, the variable Share_Cov takes into account the daily variance in the volume of testing. It can be observed from the "Daily overview of the performed PCR and antigen tests" table at the official CMH website that the testing volume during the weekends was much lower than during the weekdays (Ministerstvo zdravotnictví České repubiky n.d.) Also, it differs across the phases of the pandemic. Therefore, we assume Share_Cov to be the most accurately estimating the true daily number of infected people by the virus and the best explanatory variable for the following regressions.

The motivation for constructing two separate models with the explanatory variables Adj_Dead_Covid and Adj_Hospitalized, respectively, is the following: the population tends to react more to the apparent serious bad news, in our case, the number of dead people and hospitalized because of the Covid-19 disease than to another news which brings some hope of not resulting in the worst scenario, both variables on the number of newly detected Covid-19 cases. The regression (3) in the table of model outputs suggests that per one additional death on Covid-19, the number of traffic collisions is estimated to decrease by 0.35, cetris paribus. It can be attributed to the higher public awareness of the deathly illness leading to a higher acceptance of the protective measures and thus providing fewer opportunities for the RTCs incidence. The coefficient in front of the Adj_Hospitalized variable, -0.01, suggests that the daily traffic accidents decrease by 0.01 per one additional hospitalized patient with Covid-19. It implies that society takes the information about Covid-19 mortality much more seriously than the number of hospitalized people with the same disease and that people adjust their behaviour accordingly.

The negative relationship between all the Covid-19 explanatory variables and the number of traffic accidents suggests that the stronger the pandemic is, indicated by those variables, the higher the probability of a lockdown being imposed to prevent Covid-19 from spreading. It leads to the decreased traffic volume and consequently the fewer RTCs. In addition, the high values of deaths and hospitalizations related to Covid-19 increase the population's awareness of the severity of that illness, leading to the better acceptance of the measures and the more responsible behaviour. The hypothesis 1.2 is supported by the results of the regressions and even theoretically extended and commented.

Table 6.2: Regression outputs - comparison of Covid-19 indicators

	Dependent variable:			
	Acc_Total			
	HAC	*HAC*	*HAC*	*HAC*
	(1)	(2)	(3)	(4)
Cov_Cases	-0.002^{***}			
	(0.0004)			
Share_Cov		-2.14^{***}		
		(0.22)		
Adj_Dead_Cov			-0.35^{***}	
			(0.03)	
Adj_Hosp				-0.01^{***}
				(0.001)
Monday	102.37^{***}	99.45^{***}	102.84^{***}	103.00^{***}
	(3.83)	(3.73)	(4.13)	(4.13)

Tuesday	89.71***	87.18***	89.04***	89.18***
	(3.77)	(3.65)	(4.09)	(4.08)
Wednesday	102.32***	100.09***	99.90***	100.08***
	(3.61)	(3.48)	(3.84)	(3.85)
Thursday	100.75***	98.72***	97.58***	97.67***
	(3.62)	(3.53)	(3.90)	(3.89)
Friday	119.48***	117.49***	116.23***	116.39***
	(3.84)	(3.76)	(4.09)	(4.07)
Saturday	28.66***	28.40***	27.46***	27.24***
	(3.23)	(3.13)	(3.50)	(3.49)
January	−8.10	−7.72	0.18	0.19
	(7.75)	(7.65)	(8.57)	(8.56)
February	−21.14***	−22.71***	−9.22	−8.93
	(6.75)	(6.62)	(7.46)	(7.47)
March	−38.42***	−43.25***	−25.90***	−24.96***
	(6.96)	(6.90)	(7.80)	(7.83)
April	−10.00	−14.02*	−1.15	1.06
	(7.49)	(7.40)	(8.18)	(8.13)
May	14.19**	10.42	17.77**	17.96**
	(6.94)	(6.77)	(7.53)	(7.54)
June	34.07***	31.63***	36.79***	35.43***
	(6.54)	(6.31)	(7.14)	(7.18)
July	7.27	4.90	7.44	7.15
	(6.78)	(6.55)	(7.39)	(7.40)
August	17.82***	15.46**	18.01**	17.75**
	(6.58)	(6.35)	(7.15)	(7.16)
September	32.29***	31.67***	31.80***	31.64***
	(6.79)	(6.56)	(7.46)	(7.48)
October	37.63***	41.44***	37.19***	36.60***
	(6.78)	(6.40)	(7.45)	(7.48)
November	22.61***	23.07***	26.46***	25.54***
	(6.83)	(6.50)	(7.38)	(7.37)
Time	−0.01***	−0.004**	−0.02***	−0.02***
	(0.002)	(0.002)	(0.003)	(0.003)
Constant	204.46***	206.71***	212.13***	211.84***
	(6.50)	(6.41)	(7.20)	(7.20)

Observations	1,826	1,826	1,462	1,462
Adjusted R^2	0.53	0.55	0.55	0.55
F Statistic	109.05***	116.28***	94.24***	94.62***
	(df = 19; 1806)		(df = 19; 1442)	

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted in Table B.1 and Table B.2

Selection of Covid-19 indicators and dummy variables for the final regressions

The following regression presents the best combination of the variables explaining the evolution and strength of the pandemic since all of them can not be involved in one model because of a significant correlation between some of them. When comparing the regressions in table 6.1, (3) and (4) have slightly higher adjusted R^2, explaining more of the variance of the dependent variable than the models (1) and (2). Moreover, Lockdown_1 to Aft_Lock_3 provide detailed information about the distinct pandemic periods rather than aggregating the whole Covid-19 era. Hence, we decided to use further the six variables discussing the stage of anti-Covid restrictions. As stated in the previous section, the share of new Covid cases from all performed tests variable is the most accurate one out of the four available in our dataset in estimating the number of Covid-19 positive people. It was used in the final regressions to obtain the most precise estimate of the effect of the pandemic intensity on the RTCs.

By adding the Share_Cov variable to the models (3) and (4) in table 6.1, we obtained the regressions below, where the adjusted R-squared improved to 0.7 and 0.71, respectively. Such set of Covid-19 variables provides a solid basis for the explanation of the impact of the pandemic on the traffic collisions by categories.

Table 6.3: Regression outputs - selected Covid-19 variables

	Dependent variable:	
	log Acc_Total	
	HAC	*HAC*
	(1)	(2)
Share_Cov	−1.14***	−0.005***

	(0.32)	(0.001)
Lockdown_1	-85.82^{***}	-0.39^{***}
	(7.48)	(0.04)
Lockdown_2	-56.16^{***}	-0.21^{***}
	(10.16)	(0.04)
Lockdown_3	-71.54^{***}	-0.33^{***}
	(8.02)	(0.04)
Bet_Lock_1_2	-15.76^{***}	-0.06^{***}
	(4.40)	(0.02)
Bet_Lock_2_3	-23.12^{***}	-0.10^{***}
	(7.38)	(0.03)
Aft_Lock_3	-12.06^{**}	-0.05^{**}
	(4.93)	(0.02)
Monday	100.30^{***}	0.41^{***}
	(3.56)	(0.01)
Tuesday	87.35^{***}	0.36^{***}
	(3.50)	(0.01)
Wednesday	100.27^{***}	0.41^{***}
	(3.32)	(0.01)
Thursday	99.02^{***}	0.41^{***}
	(3.41)	(0.01)
Friday	117.79^{***}	0.46^{***}
	(3.60)	(0.01)
Saturday	28.15^{***}	0.13^{***}
	(2.98)	(0.01)
January	-3.66	-0.003
	(7.67)	(0.03)
February	-18.40^{***}	-0.04
	(6.62)	(0.03)
March	-19.41^{***}	-0.05^{*}
	(6.93)	(0.03)
April	8.27	0.06^{**}
	(7.17)	(0.03)
May	17.04^{**}	0.09^{***}
	(6.95)	(0.03)
June	37.33^{***}	0.17^{***}
	(6.49)	(0.03)

July	10.10	0.07***
	(6.74)	(0.03)
August	20.17***	0.11***
	(6.54)	(0.03)
September	34.81***	0.16***
	(6.71)	(0.03)
October	42.88***	0.18***
	(6.60)	(0.03)
November	27.09***	0.13***
	(6.58)	(0.03)
Time	0.01**	0.0000***
	(0.004)	(0.0000)
Constant	193.92***	5.23***
	(6.83)	(0.03)
Observations	1,826	1,826
Adjusted R^2	0.70	0.71
F Statistic	132.74***	143.09***
		(df = 32; 1793)

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted
in Table B.1 and Table B.2

6.2.2 Weather and seasonal effects

All the regressions of this Subsection 6.2.2 contain the fixed set of previously selected Covid-19 variables. Similarly to the models in Subsection 6.2.1, this collection of variables is included to improve the adjusted R^2. The models differ only in weather and seasonal explanatory variables, allowing us to compare the individual effects of these pairwise correlated variables on the Acc_Total.

Weather effects on total traffic accidents

The average precipitation appears in both models of Table 6.4 since there is no derived dummy variable indicating the extreme rainfall in our dataset. The coefficients in front of this variable are significant (even at 1%) and positive in both regressions. It suggests that the total RTCs in the Czech Republic are estimated to increase (by around 2) with an extra millimetre of rainfall, keeping other factors fixed. This finding is in line with the hypothesis 3.1 and the majority of literature on this phenomenon (Sherretz & Farhar 1978) (Spasova & Dimitrov 2015). The elevated collisions during rain may be explained by the decreased road friction and lower visibility (Theofilatos & Yannis 2014).

The continuous average daily temperature, as well as the high-temperature dummy variable, are very statistically significant, apart from the Low_Temp not being significant at all. Both Adj_Avg_Temp and High_Temp have a positive impact on the number of total traffic accidents. Although the literature sources studying the relationship between traffic accidents and air temperature are not consistent in the results, Nofal & Saeed (1997) reports similar results to ours. According to his research, excessive exposure to heat is considered a hazard to personal health and to traffic safety, resulting in a significant increase in the frequency of collisions. The intense sunlight and radiance, often following the high temperatures, tend to decrease visibility and cause fatigue, which may contribute to the increased risk of RTCs. The hypothesis 3.2 is hereby accepted, except for the part explaining the effect of low temperatures on the total accidents. No conclusion can be driven from the non-significant coefficient by the High_Temp variable. However, we would estimate it to positively influence the dependent variable, according to the reviewed literature.

According to many academic papers, the average wind does not clearly impact the number of RTCs. Although Brijs *et al.* (2007) found a small but significant effect of maximum wind gust on the RTCs, being positive, the variable Str_Wind in our regression (2) suggests a negative but not significant effect. There is a possible clarification for no correlation found between those variables. Drivers might find windy weather dangerous, so they adjust their speed and behaviour accordingly, thus balancing the increased risk of an uncontrolled situation caused by the wind. That might be the case for interpreting the estimated coefficient by the Avg_Wind variable. Per increased wind speed by one m/s, the total traffic accidents are estimated to decrease by 3.09, cetris paribus, however this coefficient is significant only at 10%.

Table 6.4: Regression outputs - individual effects of weather variables

	Dependent variable:	
	Acc_Total	
	HAC	*HAC*
	(1)	(2)
Share_Cov	-1.04^{***}	-0.92^{**}
	(0.40)	(0.41)
Lockdown_1	-88.07^{***}	-93.65^{***}
	(9.19)	(9.82)
Lockdown_2	-29.38^{**}	-39.21^{***}
	(13.84)	(14.33)
Lockdown_3	-82.84^{***}	-94.04^{***}
	(8.19)	(9.83)
Bet_Lock_1_2	0.33	-10.85^{*}
	(4.89)	(6.07)
Bet_Lock_2_3	-30.89^{***}	-40.60^{***}
	(8.86)	(10.03)
Aft_Lock_3	9.01^{**}	-6.04
	(4.12)	(7.21)
Avg_Prec	2.37^{***}	2.14^{***}
	(0.49)	(0.50)
Adj_Avg_Temp	1.45^{***}	
	(0.44)	
Avg_Wind	-3.09^{*}	
	(1.83)	
Low_Temp		-4.22
		(5.18)
High_Temp		14.10^{***}
		(3.43)
Str_Wind		-5.17
		(4.62)
Time		0.01^{**}
		(0.01)
Constant	276.37^{***}	275.14^{***}
	(6.15)	(4.02)

Observations	1,826	1,826
Adjusted R^2	0.14	0.14
F Statistic	29.69***	25.57***
	(df = 10; 1815)	(df = 12; 1813)
Note:		*p<0.1; **p<0.05; ***p<0.01
		The abbreviations may be consulted in Table B.1 and Table B.2

Seasonal effects on total traffic accidents

The first two columns of Table 6.5 estimate the effect of days of the week on the total number of RTCs. While regression (1) distinguishes only between weekends and weekdays, model (2) uses the dummy variables from Monday to Saturday (omitting Sunday to avoid the dummy variable trap issue). According to (2), the day of the week with the most traffic accidents is estimated to be Friday, followed by Monday and Wednesday with the estimation of around a hundred collisions more than on Sunday. The RTCs are still more frequent on Tuesdays and Thursdays than on Sundays (the coefficients of 87.39 and 98.99, respectively). The model (1) indicates that during the weekends, the total number of traffic accidents is estimated to decrease significantly, which corresponds to the previous results of the model (2). The literature discussing the frequency of traffic collisions during the week varies in the results because of the differences in the sampling locations. The surveys on the RTCs in touristic and landscape areas match in the findings that significantly more accidents happen during the weekends and holidays than during the work days (Chung *et al.* 2005) (Yu & Abdel-Aty 2013). Our sample reflects both the landscape and the urbanised areas, similarly to the reviewed literature, based on which we formulated the hypothesis 4.1. in Chapter 5. This hypothesis about the distribution of RTCs during the week can be clearly supported by the outcomes of the regressions (1) and (2). Furthermore, the estimated effects of the days-of-the-week variables on the RTCs in the model (2) resembled the results of the study of Andreescu and Frost 1998, showing the almost equal amount of RTCs on Monday, Tuesday and Wednesday, the peak number on Fridays and the least Traffic accidents on Sunday.

National holidays and other festive seasons are expected to differ from the rest of the year in the drivers' behaviour. People are more likely to travel to visit their relatives, friends or simply stay outside of their homes. The majority of literature on this topic suggests that the number of RTCs during holidays is increased compared to non-holiday periods (Berning *et al.* 2021). Our model (3) presents the opposite effects. We can observe a significantly negative impact of Christmas, Easter and the other national holidays on the total traffic accidents. One source with similar results in the holiday statistics was found (Vandoros *et al.* 2014), but unfortunately, there was no explanation for such effect. Altogether, there is a gap in the literature suggesting a decrease in RTCs during holidays since this phenomenon seems unique. The clarification for that might be the decreased traffic volume on the date of the national holidays because people might arrive earlier to their final destination and extend their stay after the festive day. Also, minimum freight traffic occurs these days similarly to the weekends, which is a second possible explanation for the fewer traffic collisions. According to Levine *et al.* (1995), short holidays generate more daily traffic accidents than longer ones, primarily because of the lowered traffic volume during the long-lasting festivals. This hypothesis may explain the decreased amounts of RTCs during Christmas and Easter, considered as long holidays.

The New Year, however, is the only festive day connected to the significant increase in the RTCs, according to our analysis. The number of traffic accidents is estimated to rise by 191 during that day compared to the non-festive days. This phenomenon of elevated traffic accidents during January 1st can be explained by more frequent alcohol-impaired driving, as the New Year's celebrations are the season of majestic parties (Ponboon & Tanaboriboon 2005). The effect of such celebrations on the RTCs with the offender being under the influence of alcohol, drugs and on the severity of RTCs will be discussed in other sections. Overall, the part of hypothesis 4.3 stating that holidays significantly impact the total traffic collisions was accepted in this paragraph. Moreover, the models' outputs imply that RTCs are more often on the New Year but scarcer during Easter, Christmas, and the rest of the national holidays compared to the rest of the year.

The last two models of the Table 6.5 explore the distribution of total RTCs within the year. Although not all the monthly variables in our model (4) are statistically significant (because of the adjusted R-squared being only 0.19), the model (5) manages to summarise their effects in the quarterly variables, which are very statistically significant. Based on the results of our regressions, the month with the highest daily count of traffic accidents is October, followed by June and September. The minimum values show February and March. However, these conclusions are only approximate since we can not estimate the effect of the few statistically insignificant months. Accurate conclusions are driven by the model (5), suggesting that the highest number of RTCs occurs on autumn days and in winter, there are the least of them. Such findings are not in line with the proposed hypothesis 4.2. The literature reviewing the seasonality of RTCs provides very diverse outcomes, depending on the climate conditions of the studied location. To properly explain the reasons behind the observed effects, we had to find a study with the reference area showing similar weather characteristics to the Czech Republic. Sivak (2009) explores the monthly variation in the number of traffic collisions on U.S. roads. Such area can be taken as an approximately similar to the Czechia in the climatic conditions. The results of that study match with our findings in the distribution of RTCs throughout the year. The duration of darkness, consumption of alcohol, amount of leisure driving, and inclement weather are the main explanatory factors of such seasonal variation, according to Sivak. As the days are getting shorter in October - the month of the highest daily RTCs - and drivers are used to very long daylight from summer, they tend to underestimate the decreased visibility and thus contribute to the increased risk of RTCs. Alcohol consumption is positively correlated with the adverse weather occurring during the autumn months, which might explain the above-standard levels of the collisions. To conclude, the rainy, foggy weather and slippery roads also significantly contribute to the roads being more dangerous, as discussed in the previous section.

Table 6.5: Regression outputs - individual effects of seasonal variables

	Dependent variable:				
	Acc_Total				
	HAC	*HAC*	*HAC*	*HAC*	*HAC*
	(1)	(2)	(3)	(4)	(5)
Share_Cov	-0.85^{***}	-0.87^{***}	-1.14^{***}	-1.42^{***}	-1.53^{***}
	(0.31)	(0.29)	(0.38)	(0.45)	(0.43)
Lockdown_1	-101.54^{***}	-101.49^{***}	-94.41^{***}	-81.90^{***}	-95.22^{***}
	(8.18)	(8.07)	(9.80)	(9.76)	(9.67)
Lockdown_2	-44.31^{***}	-44.17^{***}	-33.22^{**}	-47.58^{***}	-47.77^{***}

	(10.91)	(9.86)	(13.22)	(14.89)	(14.34)
Lockdown_3	−99.13***	−98.93***	−94.12***	−69.46***	−78.24***
	(7.14)	(7.10)	(9.05)	(11.15)	(10.09)
Bet_Lock_1_2	−5.41	−5.14	−4.81	−13.98**	−9.60
	(4.61)	(4.47)	(5.80)	(6.36)	(6.33)
Bet_Lock_2_3	−44.77***	−44.36***	−42.74***	−20.50*	−18.61*
	(7.25)	(7.08)	(9.58)	(10.49)	(10.05)
Aft_Lock_3	−4.72	−4.55	−3.16	−10.37	−10.22
	(5.59)	(5.40)	(6.83)	(7.02)	(6.99)
Weekend	−86.88***				
	(2.25)				
Monday		100.42***			
		(3.90)			
Tuesday		87.39***			
		(3.86)			
Wednesday		100.20***			
		(3.63)			
Thursday		98.99***			
		(3.79)			
Friday		117.71***			
		(3.96)			
Saturday		28.17***			
		(3.37)			
Christmas			−133.32***		
			(6.20)		
Easter			−70.09***		
			(9.31)		
New_Year			191.22***		
			(12.92)		
Oth_Nat_Hol			−77.25***		
			(4.70)		
January				−2.91	
				(9.13)	
February				−18.72**	
				(8.21)	
March				−19.78**	
				(8.54)	

April				6.95	
				(8.85)	
May				16.36*	
				(8.51)	
June				36.67***	
				(8.17)	
July				9.60	
				(7.94)	
August				19.69**	
				(7.83)	
September				33.84***	
				(8.16)	
October				43.31***	
				(8.01)	
November				27.59***	
				(8.22)	
Spring					35.96***
					(4.53)
Summer					41.85***
					(4.29)
Autumn					57.09***
					(4.46)
Time	0.01**	0.01***	0.01**	0.01	0.01
	(0.004)	(0.004)	(0.01)	(0.01)	(0.01)
Constant	304.93***	204.05***	281.99***	270.32***	250.51***
	(3.02)	(3.82)	(3.61)	(7.91)	(4.86)
Observations	1,826	1,826	1,826	1,826	1,826
Adjusted R^2	0.49	0.51	0.22	0.19	0.21
F Statistic	192.14*** (df = 9; 1816)	138.38*** (df = 14; 1811)	42.97*** (df = 12; 1813)	23.91*** (df = 19; 1806)	44.99*** (df = 11; 1814)

Note: *p<0.1; **p<0.05; ***p<0.01

The abbreviations may be consulted in Table B.1 and Table B.2

Comparison of the models with different combinations of weather and seasonal effects

We constructed four regressions with different sets of independent variables depicting the seasonality and weather dependency of the total traffic collisions (Table 6.6). As can be observed, the coefficients slightly differ across the models since they are influenced by the other explanatory variables to a certain extent. However, the sign and the approximate scale of the effects, reviewed in Subsection 6.2.1 and earlier in Subsection 6.2.2, still hold.

All four models have a similar adjusted R^2 - around 0.6, which is relatively sufficient. The only differences are in the significance levels of certain explanatory variables. For illustration, model (4) explains the daily number of RTCs in March and August more precisely than model (2). On the other hand, regressions (3) and (4) estimate the daily number of traffic collisions after the third lockdown in spring 2021 with a lower level of significance than models (1) and (2). The effect of wind on the total number of RTCs is significant in neither of them, which supports the fact that the effect of wind on road traffic collisions is not evident.

Individual months explain the seasonality of RTCs in more detail than seasons of the year; the analogy holds for the days of the week and weekend dummy variables. The dummy variable Low_Temp was found statistically insignificant in Table 6.4 and might be insignificant in other models as well, although in models of Table 6.6 it is significant even at 1%. For that reason, we decided to focus on the continuous temperature variable in the following regressions. These findings contributed to the decision about the selection of the most accurate explanatory variables for the final models, being the structure of the model (4).

Table 6.6: Regression outputs - Covid-19 and comparison of seasonal variables

	Dependent variable:			
	Acc_Total			
	HAC	*HAC*	*HAC*	*HAC*
	(1)	(2)	(3)	(4)
Share_Cov	-1.36^{***}	-1.39^{***}	-1.33^{***}	-1.27^{***}
	(0.32)	(0.31)	(0.32)	(0.31)
Lockdown_1	-96.31^{***}	-86.58^{***}	-94.34^{***}	-82.12^{***}

	(8.24)	(7.78)	(7.75)	(7.57)
Lockdown_2	−51.67***	−49.31***	−53.97***	−52.47***
	(10.61)	(9.89)	(10.80)	(10.04)
Lockdown_3	−80.11***	−74.82***	−75.37***	−66.05***
	(7.42)	(8.48)	(7.35)	(8.09)
Bet_Lock_1_2	−13.68***	−15.72***	−12.49***	−14.64***
	(4.48)	(4.35)	(4.56)	(4.37)
Bet_Lock_2_3	−23.01***	−20.86***	−18.19**	−19.05***
	(7.02)	(7.24)	(7.17)	(7.33)
Aft_Lock_3	−14.16***	−13.06***	−10.18*	−8.82*
	(5.12)	(4.92)	(5.23)	(5.03)
Avg_Prec	2.52***	2.20***	2.48***	2.11***
	(0.37)	(0.35)	(0.37)	(0.35)
High_Temp	12.36***	14.72***		
	(2.55)	(2.47)		
Low_Temp	18.61***	19.81***		
	(4.07)	(4.41)		
Str_Wind	3.07	4.06		
	(3.25)	(3.30)		
Adj_Avg_Temp			0.84***	1.01***
			(0.29)	(0.28)
Avg_Wind			−0.78	−0.06
			(1.34)	(1.34)
Weekend	−87.30***		−86.94***	
	(1.97)		(1.99)	
Spring	41.60***		35.50***	
	(3.69)		(3.43)	
Summer	43.23***		40.10***	
	(3.76)		(3.40)	
Autumn	62.22***		57.06***	
	(3.40)		(3.36)	
Monday		100.06***		100.15***
		(3.50)		(3.50)
Tuesday		87.40***		87.22***
		(3.38)		(3.41)
Wednesday		100.64***		100.41***
		(3.22)		(3.28)

Thursday		99.50***		98.69***
		(3.32)		(3.37)
Friday		118.85***		117.72***
		(3.46)		(3.48)
Saturday		27.91***		27.95***
		(2.91)		(2.93)
January		−8.47		−2.99
		(7.37)		(7.67)
February		−19.47***		−18.87***
		(6.42)		(6.61)
March		−14.74**		−20.64***
		(6.91)		(6.92)
April		15.87**		8.08
		(7.34)		(7.17)
May		20.72***		13.94**
		(7.17)		(7.03)
June		33.75***		33.61***
		(6.92)		(6.60)
July		7.34		7.55
		(7.09)		(6.87)
August		16.99**		17.65***
		(6.92)		(6.65)
September		40.61***		33.02***
		(6.83)		(6.75)
October		49.98***		42.42***
		(6.74)		(6.62)
November		32.57***		27.57***
		(6.53)		(6.58)
Time	0.01**	0.01***	0.01*	0.01*
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	261.66***	181.35***	266.22***	183.29***
	(4.09)	(7.04)	(5.75)	(8.22)
Observations	1,826	1,826	1,826	1,826
Adjusted R^2	0.60	0.61	0.59	0.60
F Statistic	168.69***	97.56***	173.56***	97.59***
	(df = 16;	(df = 29;	(df = 15;	(df = 28;

	1809)	1796)	1810)	1797)

Note: *p<0.1; **p<0.05; ***p<0.01

The abbreviations may be consulted in Table B.1 and Table B.2

6.3 Outputs of final regressions

The consecutive econometric models reveal the desired effects of the selected explanatory variables on our dependent variables, based on which the conclusions of this thesis will be driven. These effects will be compared across the respective categories of traffic collisions.

6.3.1 Total traffic accidents

Table 6.7 displays the final two models explaining the total number of traffic accidents in the Czech Republic. Most of the relationships were already studied in the previous models, nevertheless, we will summarise them.

The total RTCs are estimated to decrease during the whole pandemic relatively to the pre-pandemic period. However, the most significant drop was during the spring lockdowns in 2020 and 2021 by around 37% and 29%, respectively. Such findings correspond to the trends in traffic flow, which is believed to be positively correlated with the RTCs (Retallack & Ostendorf 2019). Both the average precipitation and temperature have a positive impact on the RTCs, however, it is more moderate after including the seasonal dummy variables. The higher temperatures are usually impaired with intensive sunshine and the increased drivers' fatigue, causing deteriorated conditions for safe driving. Contrary to that, the lower the air temperatures, the higher the chance of a skid because of rime and snow layer on the road surface. Such weather conditions increase the number of RTCs. Overall, the effect of the warm weather seems to outweigh the increased risk of RTCs during the cold-weather season. The peak number of RTCs was detected on Fridays, followed by Mondays and Wednesdays. It is explained mainly by the regular ways to an occupation and the cargo transportation, occurring only during the work days. Weekends generally show less daily number of accidents than work days. More specifically, Sundays are the least risky days of the week regarding traffic collisions. According to the monthly dummy variables, January becomes significant after including the variables describing holidays. It is the third month with the lowest daily RTCs, after March and February, even though the New Year with 63% more accidents than on a non-holiday day, belongs to this month. The highest risk of an incidence of a traffic collision is in June and September, followed by the early autumn. It can be attributed to the nice weather during the warm season of the year, which entices drivers to set off and participate in outdoor activities more often, leading to increased traffic volume (Erenler & Gümüs 2019). At the same time, there might be an adverse effect of fewer RTCs during the summer holidays (July and August), as people use other means of transport to travel to their vacations. That is only a speculation since our coefficients in front of these moths are not statistically significant. During Christmas, Easter and the rest of the Czech national holidays, the RTCs decreased daily by 62%, 28% and 35%, respectively. These findings were described along with their causes in the table 6.5.

Table 6.7: Final regressions of total accidents

	Dependent variable:	
		log
	Acc_Total	
	HAC	*HAC*
	(1)	(2)
Share_Covid	-1.39^{***}	-0.01^{***}
	(0.27)	(0.001)
Lockdown_1	-79.85^{***}	-0.37^{***}
	(7.24)	(0.04)
Lockdown_2	-46.23^{***}	-0.18^{***}
	(7.87)	(0.03)
Lockdown_3	-61.59^{***}	-0.29^{***}
	(6.70)	(0.03)
Bet_Lock_1_2	-14.93^{***}	-0.05^{***}
	(3.75)	(0.01)
Bet_Lock_2_3	-17.78^{***}	-0.08^{***}
	(6.62)	(0.03)
Aft_Lock_3	-9.53^{**}	-0.04^{**}
	(4.27)	(0.02)
Avg_Prec	2.06^{***}	0.01^{***}
	(0.33)	(0.001)

Adj_Avg_Temp	0.86***	0.004***
	(0.26)	(0.001)
Avg_Wind	1.17	0.001
	(1.19)	(0.005)
Monday	101.20***	0.41***
	(2.99)	(0.01)
Tuesday	87.27***	0.36***
	(3.10)	(0.01)
Wednesday	100.01***	0.41***
	(2.86)	(0.01)
Thursday	98.76***	0.40***
	(3.11)	(0.01)
Friday	118.82***	0.47***
	(3.09)	(0.01)
Saturday	29.93***	0.14***
	(2.93)	(0.01)
January	−22.88***	−0.08***
	(6.55)	(0.03)
February	−31.95***	−0.11***
	(6.04)	(0.02)
March	−33.99***	−0.12***
	(6.25)	(0.03)
April	1.53	0.03
	(6.39)	(0.03)
May	7.09	0.04*
	(6.08)	(0.02)
June	21.36***	0.09***
	(6.00)	(0.02)
July	1.26	0.03
	(6.05)	(0.02)
August	5.64	0.04*
	(6.05)	(0.02)
September	24.11***	0.10***
	(6.08)	(0.02)
October	32.78***	0.13***
	(5.99)	(0.02)
November	17.55***	0.08***

	(5.97)	(0.02)
Christmas	-133.00^{***}	-0.62^{***}
	(14.96)	(0.07)
Easter	-60.37^{***}	-0.28^{***}
	(13.86)	(0.06)
New_Year	209.11^{***}	0.63^{***}
	(24.44)	(0.08)
Oth_Nat_Hol	-89.19^{***}	-0.35^{***}
	(8.38)	(0.04)
Time	0.01^{**}	0.0000^{***}
	(0.003)	(0.0000)
Constant	193.89^{***}	5.25^{***}
	(7.14)	(0.03)
Observations	1,826	1,826
Adjusted R^2	0.70	0.71
F Statistic	132.74^{***}	143.09^{***}
	(df = 32; 1793)	

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted in Table B.1 and Table B.2

6.3.2 Traffic accidents with alcohol and drugs

This section covers the traffic accidents predominantly caused by the usage of the substances forbidden while driving. Czech legislation prohibits the utilisation of addictive substances in connection with driving any vehicle and provides zero tolerance to alcohol in the blood system while driving (AION CS 2001).

The first two regressions characterise the occurrence of RTCs with alcohol involved. The models (3) and (4) in Table 6.8 explain the number of traffic accidents with the offender being under the influence of drugs. These models using the Acc_Drugs as the dependent variable are very poor in their adjusted R^2 and the significance of the explanatory variables. It is due to the very low variance of this variable as its values range from 0 to 6 (table 3.8). In that case, the independent variables can hardly explain the variation in the dependent variable over time because it is very little. To tackle this issue, we tried to remove the insignificant variables first, but the adjusted R-squared decreased even more. Therefore we decided to describe at least the statistically significant effects of the coefficients in both the models types, differing in the set of independent variables. The second-type supplemental models were placed in the Appendix A (Table A.1).

The regressions in Table 6.8 suggest that the alcohol-impaired traffic accidents significantly decrease with the additional percentage of positively tested people on Covid-19 (Share_Covid variable). The reason for that might be that the higher the Share_Covid indicator, the higher the chance of the imposition of restrictions on gatherings, including the social events and restaurants closely connected to alcohol consumption. Rodríguez-Pérez *et al.* (2020) in their study of dietary behaviours of Spanish inhabitants during the Covid-19 restrictions reported a decrease in their alcohol intake (by 57.3%), as there were less opportunities for binge drinking. Such finding also explains the decreased number of alcohol-impaired RTCs during the third lockdown in the Czech Republic, denoted by the negative coefficient significant at 5% (the rest of the lockdown variables are not statistically significant). Nothing can be concluded about the effect of the pandemic on the RTCs, where drugs were detected by the offender, except for one thing: after the release of the anti-Covid restrictions of the third lockdown, RTCs with drugs involved significantly rose to even higher numbers than before the pandemic. A similar phenomenon can be observed in the traffic accidents caused by alcohol. Rehm *et al.* (2020) suggest two approaches to alcohol and drugs consumption during the pandemic. Firstly, a short-term effect of the decreased physical and financial availability lowers the substance use during the lockdowns. The opposite long-term effect of the pandemic lies in distress and worsened mental health contributing to the elevated use of alcohol and drugs. Rehm's findings perfectly explain the outcomes of our regressions (1) to (4), assuming that the change in substance use is also reflected in driving.

The extended models in table A.1 summarise the overall effects of the Covid-19 pandemic on the Acc_Alcohol and Acc_drugs. The Covid-19 dummy variable becomes statistically significant in all four models and shows a positive effect on the RTCs caused by alcohol and drugs. Thomas *et al.* (2020) reached similar conclusions when analysing blood samples from patients in five trauma centres recovering from traffic collisions. A higher prevalence of alcohol, cannabinoids and opioids during the public health emergency was found by drivers compared to before.

Average daily precipitation seems to be increasing the number of alcohol- and drugs-related RTCs, according to Table A.1. A study of Redelmeier &

Manzoor (2019) presented a 19% increased risk of an alcohol-related traffic crash associated with adverse weather (rainy and snowy) compared with normal weather. According to this study, alcohol limits the ability to compensate for hazards because of decreased attention and reduced alertness. Average temperature and wind are significant only in the models explaining the traffic collisions with alcohol. An interesting observation was made about the effect of wind on the alcohol-impaired RTCs - the stronger the wind, the fewer such traffic collisions. A rational expectation would be that wind contributes to the risk factors leading to RTCs, but the literature suggests that the mentioned wind effect is very unpredictable.

Both Table 6.8 and Table A.1 indicate that the traffic accidents where alcohol was detected by the offender are estimated to increase during the New Year and other short national holidays. We can compare it with the holidays' effects on the total RTCs shown in Table 6.7 and conclude that the ratio of accidents with alcohol to the total number of RTCs increases during these festivals. Driving under the influence of alcohol results in double more fatal accidents than without, according to Boonserm & Wiwatwattana (2021), who studied the dataset of RTCs in Thailand during celebrations of the New Year. Such finding supports the elevated values of Acc_Alcohol in our regression, as the fatalities are one component of the overall RTCs. Unfortunately, these effects cannot be studied for the Acc_Drugs variable since the models' coefficients in front of the respective holiday variables are insignificant. However, the number of RTCs with drugs involved is estimated to decrease during the Christmas period. The possible explanation for it is that people spend time with their relatives or enjoy winter sports, not having time for thinking about their problems, which would otherwise mean that they tend to reach for a substance.

Ricci *et al.* (2008) examined the prevalence of alcohol and drugs in the urine of patients involved in road accidents and found out that the majority of cases occurred during weekends in contrast to the work days. Increased usage of alcohol and drugs during the weekends also presented the extended models (in table A.1) via the increased number of alcohol- and drugs-impaired RTCs. Weekends are generally a time of rest and social gatherings for the working population but also a perfect occasion for substance use.

The alcohol-caused traffic accidents are the most frequent during the summer months, which matches the outcomes of the study (Foster *et al.* 2015). The mentioned increase is attributed to the higher alcohol intake during that period rather than the increased traffic volume, according to Foster. Concerning the seasonality of the RTCs caused by drug use, the only explanatory model is the modified one in Table A.1. Although the coefficients by the variables Spring, Summer and Autumn present different levels of significance, autumn is considered the peak in the drugs-related accidents.

To summarise the findings of this section, hypothesis 2.1, covering the surge of RTCs related to alcohol and drugs, was supported by our models described in the previous paragraphs. However, the hypothesis suggesting the significant impact of all holidays on the alcohol-impaired traffic collisions was found only partially true. While Christmas and Easter do not show any significant effect, the New Year and the other national holidays are positively correlated with the Acc_Alcohol variable.

Table 6.8: Regression outputs - Acc_Alcohol and Acc_Drugs

	Dependent variable:			
	log Acc_Alcohol		log Acc_Drugs	
	HAC	*OLS*	*OLS*	*HC*
	(1)	(2)	(3)	(4)
Share_Covid	-0.08^{***}	-0.01	-0.01	-0.01
	(0.03)	(0.004)	(0.01)	(0.03)
Lockdown_1	-0.34	-0.01	-0.15	0.13
	(0.70)	(0.09)	(0.16)	(0.83)
Lockdown_2	0.13	0.04	0.40	1.48
	(0.95)	(0.14)	(0.25)	(1.20)
Lockdown_3	-1.08^{**}	-0.07	0.15	0.89
	(0.54)	(0.09)	(0.17)	(0.86)
Bet_Lock_1_2	1.03^{**}	0.09^{*}	0.11	0.44
	(0.42)	(0.05)	(0.09)	(0.46)
Bet_Lock_2_3	-0.08	0.03	0.17	0.37
	(0.57)	(0.08)	(0.15)	(0.72)
Aft_Lock_3	0.81^{***}	0.08^{**}	0.31^{***}	1.23^{***}
	(0.29)	(0.04)	(0.07)	(0.34)
Avg_Prec	0.05	0.01	0.03^{***}	0.11^{***}
	(0.03)	(0.004)	(0.01)	(0.03)
Adj_Avg_Temp	0.20^{***}	0.02^{***}	0.003	0.01
	(0.03)	(0.004)	(0.01)	(0.03)

Avg_Wind	−0.48***	−0.04***	−0.01	−0.05
	(0.12)	(0.02)	(0.03)	(0.14)
Christmas	−2.23	−0.20	−0.57**	−2.05
	(1.37)	(0.14)	(0.26)	(1.39)
Easter	1.31	0.17	−0.04	−1.01
	(1.05)	(0.12)	(0.22)	(1.23)
New_Year	21.43***	1.46***	0.09	0.69
	(3.37)	(0.24)	(0.43)	(2.58)
Oth_Nat_Hol	2.76***	0.24***	−0.14	−1.13
	(0.82)	(0.09)	(0.16)	(0.85)
Monday	−6.65***	−0.58***	−0.05	−0.21
	(0.36)	(0.05)	(0.08)	(0.41)
Tuesday	−7.57***	−0.72***	−0.18**	−0.67
	(0.34)	(0.05)	(0.08)	(0.42)
Wednesday	−6.46***	−0.54***	−0.06	−0.23
	(0.34)	(0.05)	(0.08)	(0.42)
Thursday	−6.41***	−0.57***	−0.08	−0.37
	(0.35)	(0.05)	(0.08)	(0.41)
Friday	−3.47***	−0.24***	−0.03	−0.0003
	(0.37)	(0.05)	(0.08)	(0.41)
Saturday	4.47***	0.26***	0.16*	0.92**
	(0.43)	(0.05)	(0.08)	(0.40)
January	−3.51***	−0.42***	−0.17	−0.38
	(0.49)	(0.06)	(0.11)	(0.57)
February	−3.13***	−0.32***	−0.11	0.12
	(0.48)	(0.06)	(0.11)	(0.57)
March	−2.78***	−0.38***	−0.19	−0.73
	(0.53)	(0.07)	(0.12)	(0.60)
April	−1.54***	−0.13*	−0.07	−0.04
	(0.51)	(0.07)	(0.12)	(0.61)
May	−0.78	−0.07	−0.09	−0.12
	(0.53)	(0.07)	(0.12)	(0.59)
June	2.27***	0.15**	−0.05	0.07
	(0.56)	(0.07)	(0.12)	(0.58)
July	2.26***	0.18***	0.03	0.10
	(0.53)	(0.07)	(0.12)	(0.59)
August	1.66***	0.12*	−0.18	−0.27

	(0.53)	(0.07)	(0.12)	(0.59)
September	0.38	0.02	−0.001	0.43
	(0.52)	(0.06)	(0.12)	(0.57)
October	−0.33	−0.06	−0.02	0.08
	(0.50)	(0.06)	(0.11)	(0.57)
November	−0.66	−0.06	−0.14	−0.15
	(0.49)	(0.06)	(0.11)	(0.57)
Constant	15.66***	2.69***	0.92***	−3.75***
	(0.61)	(0.08)	(0.14)	(0.68)
Observations	1,826	1,826	1,826	1,826
Adjusted R^2	0.60	0.38	0.03	0.02
F Statistic	91.03***	37.42***	2.68***	1.92***
		(df = 31; 1794)		

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted in Table B.1 and Table B.2

6.3.3 Traffic accidents by severity

In this section, we will reveal the factors that influence traffic safety reflected by the frequency of traffic accidents divided into categories based on their severity. We face a similar problem as with the Acc_Drugs variable - having a small range of values by fatalities and particularly by the accidents with a severe injury. Thus the models (3) and (4) of Table 6.9 with these dependent variables present very low model fits through their adjusted R^2 and R^2. Similarly to the Subsection 6.3.2, we described both model types and stored the extended ones in Table A.3 and Table A.4 of the Appendix A.

Unfortunately, almost no conclusions can be made about what has a significant influence on the fatalities incidence It is due to the small number of daily fatalities in the studied area and their little change over time. There are two possible implications of such findings. Either the model is not good enough to estimate the changes in the fatalities, or the fatality rates did not significantly change during the studied period. In our case, the model explains very little of the dependent variable variation around its mean, which can be observed from the R^2 and adjusted R^2. Since the Covid-19 dummy variables indicate no significant estimate of the effect of the pandemic on the fatality rates, the hypothesis 2.2 about the fatalities rising during the Covid-19 pandemic can be neither rejected nor accepted.

The non-fatal accidents significantly decreased during the period with Covid disease, which we can observe from Table A.3. These effects were amplified during the lockdown periods compared to the rest of the time when Covid-19 was spreading across the Czech Republic (Table 6.9 and Table A.2). Comparing the models with the logarithmic transformations of the dependent variables in Table A.2, we can observe the following pattern: the more serious the accidents are, the bigger the percentage drop in their numbers during every stage of the pandemic. All the present findings are in line with the results of a study of traffic accidents in Los Angeles and New York during the pandemic, suggesting that the distribution of accidents shifts towards "light" ones without injuries, leading to the overall decreased severity of RTCs (Lin *et al.* 2021). Altogether, the reduction of the traffic flow stemming from the mobility restrictions against Covid-19 resulted in fewer injuries on the roads, as the probability of having an accident is lower when there are fewer vehicles on the road. Thus the hypothesis 2.2 concerning the significant increase in the RTCs with severe injuries can be rejected.

Rainfall has the same positive effect on all traffic accidents regardless of their severity, which can be detected by observing Table 6.7 with total RTCs and Table A.4 with RTCs by severity. However, the average temperature seems to influence more the serious accidents than the "lighter" ones. If the average temperature rises by 1°C, the risk of a fatal accident increases by around 12%, whereas the risk of an accident with a minor injury increases only by 2%, keeping other factors fixed. Confalonieri *et al.* (2007) have shown in their study that drivers in hot environments tend to make more mistakes and suffer from fatigue, decreasing their concentration and leading to traffic injuries.

Regarding the seasonality, all categories of RTCs by severity match the holidays' effects on the total traffic accidents described in Subsection 6.3.1. The only holiday whose effect varies across the categories of the dependent variable is the New Year, suggesting that the fatalities significantly decrease during that day contrary to the traffic accidents with less severe or no injuries. This finding is contradictory to the results of many previous studies (Arnold & Cerrelli 1987). Such effect of fewer fatalities on January 1st may be biased due to the small sample (only five New Year days during the years from 2017 to 2021) and little range in these observations.

From the Table A.2, we can observe that the RTCs with minor, serious and no injuries reflect the total traffic accidents in the coefficients of the days-of-the-week dummies. However, the road fatalities show the opposite trend of having the peak numbers on Fridays and Saturdays. It is supported by the higher occurrence of alcohol and drugs behind the wheel during that time, often leading to worsened reactions and thus to more severe RTCs.

Traffic accidents with an injury are estimated to be the highest during the summer months, whereas the RTCs with no harm to human health tend to culminate during the autumn season, according to our models. Radun & Radun (2006) give an explanation for the peak in the serious accidents via the revelation of the momentary drowsiness mainly occurring during summer, which is one of the major causes of the grave accidents. The traffic collisions with no injury follow the trend of the total RTCs of the autumn months experiencing the highest values.

This section provides an explanation for the effects on the RTCs based on the degree of severity, suggesting the rejection of hypothesis 2.2 in favour of the alternative 2.2, that the accidents with severe injuries decreased during the Covid-19 pandemic and its lockdowns. However, the second part of this hypothesis about the fatalities significantly increased during that time could not be rejected or supported. Hypothesis 2.3 about the RTCs with minor health consequences having decreased significantly during the Covid-19 times is supported by the regressions.

Table 6.9: Regression outputs- severity of the accidents

	Dependent variable:			
	Acc_No_Inj	Acc_Non_Ser_Inj	Acc_Ser_Inj	Fatality
	HAC	*HAC*	*HAC*	*OLS*
	(1)	(2)	(3)	(4)
Share_Covid	-1.00^{***}	-0.37^{***}	-0.004	-0.01
	(0.22)	(0.09)	(0.02)	(0.01)
Lockdown_1	-68.81^{***}	-12.83^{***}	-1.61^{***}	-0.18
	(5.49)	(1.94)	(0.42)	(0.20)
Lockdown_2	-37.83^{***}	-10.12^{***}	-1.93^{***}	-0.31
	(6.34)	(2.66)	(0.57)	(0.30)
Lockdown_3	-53.08^{***}	-11.23^{***}	-1.49^{***}	-0.10
	(5.37)	(1.73)	(0.41)	(0.22)
Bet_Lock_1_2	-15.23^{***}	-1.75	-0.83^{***}	-0.27^{**}

	(3.09)	(1.07)	(0.29)	(0.13)
Bet_Lock_2_3	-14.67^{***}	-4.90^{***}	-1.33^{***}	-0.22
	(5.45)	(1.64)	(0.34)	(0.19)
Aft_Lock_3	-9.31^{***}	-3.32^{***}	-1.11^{***}	-0.18
	(3.46)	(0.81)	(0.22)	(0.14)
Avg_Prec	1.84^{***}	0.28^{***}	-0.04^{**}	0.002
	(0.26)	(0.11)	(0.02)	(0.01)
Adj_Avg_Temp	-0.42^{**}	1.05^{***}	0.18^{***}	0.03^{***}
	(0.21)	(0.08)	(0.02)	(0.01)
Avg_Wind	2.49^{***}	-1.23^{***}	-0.11	0.04
	(0.94)	(0.37)	(0.07)	(0.03)
Christmas	-111.79^{***}	-19.46^{***}	-1.91^{***}	-0.45
	(12.75)	(2.44)	(0.38)	(0.30)
Easter	-54.40^{***}	-5.86^{*}	-0.30	-0.09
	(11.00)	(3.21)	(0.66)	(0.27)
New_Year	177.15^{***}	29.64^{***}	3.12^{***}	-0.27
	(18.99)	(6.12)	(0.79)	(0.51)
Oth_Nat_Hol	-75.27^{***}	-13.50^{***}	-0.57	-0.13
	(6.89)	(1.82)	(0.48)	(0.19)
Monday	88.64^{***}	12.18^{***}	0.35	0.16^{*}
	(2.45)	(0.95)	(0.22)	(0.10)
Tuesday	76.71^{***}	10.07^{***}	0.44^{**}	-0.05
	(2.50)	(0.96)	(0.22)	(0.10)
Wednesday	86.65^{***}	12.72^{***}	0.62^{***}	-0.04
	(2.29)	(0.96)	(0.23)	(0.10)
Thursday	86.13^{***}	11.97^{***}	0.40^{*}	0.12
	(2.51)	(0.95)	(0.23)	(0.10)
Friday	99.55^{***}	18.20^{***}	1.06^{***}	0.17^{*}
	(2.45)	(0.98)	(0.22)	(0.10)
Saturday	22.45^{***}	7.11^{***}	0.61^{***}	0.26^{***}
	(2.35)	(0.96)	(0.23)	(0.10)
January	-14.87^{***}	-7.26^{***}	-0.40	-0.40^{***}
	(5.26)	(1.66)	(0.25)	(0.13)
February	-18.28^{***}	-12.64^{***}	-0.47^{*}	-0.47^{***}
	(4.85)	(1.55)	(0.27)	(0.14)
March	-22.90^{***}	-9.95^{***}	-0.12	-0.49^{***}
	(5.01)	(1.62)	(0.28)	(0.14)

April	−1.85	2.79*	1.95***	−0.19
	(5.11)	(1.69)	(0.30)	(0.14)
May	−0.06	6.44***	2.19***	−0.04
	(4.86)	(1.70)	(0.32)	(0.14)
June	−0.08	18.93***	4.04***	0.26*
	(4.82)	(1.67)	(0.34)	(0.14)
July	−15.10***	14.81***	2.79***	0.07
	(4.84)	(1.63)	(0.32)	(0.14)
August	−12.08**	15.55***	3.08***	0.37***
	(4.82)	(1.67)	(0.33)	(0.14)
September	8.17*	14.43***	2.69***	0.16
	(4.86)	(1.71)	(0.32)	(0.14)
October	23.00***	8.72***	1.64***	0.02
	(4.81)	(1.60)	(0.29)	(0.13)
November	17.02***	0.19	0.85***	0.01
	(4.75)	(1.61)	(0.27)	(0.14)
Time(1)	0.01***			
	(0.003)			
Time(4)				0.0001
				(0.0001)
Constant	158.11***	31.46***	2.29***	0.88***
	(5.70)	(1.94)	(0.35)	(0.17)
Observations	1,826	1,826	1,826	1,826
Adjusted R^2	0.71	0.61	0.31	0.06
F Statistic	137.67*** (df = 32; 1793)	91.84*** (df = 31; 1794)	26.88*** (df = 31; 1794)	4.60*** (df = 32; 1793)

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted in Table B.1 and Table B.2

6.3.4 Injuries by severity

The aim of this section is to examine the number of daily injuries resulting from traffic accidents. They are structured by severity into the same categories as the accidents reviewed in the previous Subsection 6.3.3 - non-seriously injured people, seriously injured people and dead people. These two categories of the dependent variables (traffic accidents and injuries by severity) both explain the same phenomenon, and we have already discussed one of them. Therefore a detailed analysis of the injuries caused by RTCs is not necessary since we believe in obtaining very similar results to the models in Subsection 6.3.3. Only the interesting and different outcomes of the number of injuries by severity are described in this part, using both the original and the modified structures of our models. As in the previous two sections, they provide an estimate of the overall effects of the pandemic and the seasons of the year.

When we compared the respective regressions of Subsection 6.3.3 and Subsection 6.3.4, the majority of them showed the analogous differences in the coefficients throughout the categories of injuries' severity. It means that the proportions between the number of injured people and the number of RTCs with such injuries stay relatively the same during the study period. The variables explaining the number of fatalities during the pandemic are mostly insignificant during Covid (Table A.2), but the variable: dead people in a traffic accident presents more significant Covid-19 indicators (Table A.5). During the first, second lockdown and all the periods without the strictest anti-Covid restrictions, the number of deaths on the roads significantly decreased (only the Lockdown_3 variable is not statistically significant). Moreover, it decreased the most compared to the other categories of injuries, which, assuming that the number of injured people and the RTCs with such injuries behave similarly, tends to support the observed trend of the more serious traffic accidents decreasing more than the lighter injuries. The variable Covid-19 summarising the effect of the pandemic became significant for the Dead_Pe_Acc (Table A.5) compared to the Fatalities (Table A.2), suggesting that the number of dead people as a consequence of RTCs decreased the most against the non-seriously and seriously injured people.

Table 6.10: Regression outputs - injured people by severity

	Dependent variable:		
	Non_Ser_Inj_Pe	Ser_Inj_Pe	Dead_Pe_Acc
	HAC	*HAC*	*HC*
	(1)	(2)	(3)
Share_Covid	-0.43^{***}	-0.003	-0.001
	(0.11)	(0.02)	(0.01)
Lockdown_1	-18.55^{***}	-1.38^{***}	-0.49^{**}

	(2.24)	(0.49)	(0.22)
Lockdown_2	−15.18***	−2.51***	−0.62
	(3.45)	(0.62)	(0.38)
Lockdown_3	−16.11***	−2.05***	−0.40*
	(2.15)	(0.40)	(0.23)
Bet_Lock_1_2	−4.11***	−1.15***	−0.73***
	(1.36)	(0.30)	(0.17)
Bet_Lock_2_3	−8.12***	−1.53***	−0.43**
	(2.21)	(0.36)	(0.21)
Aft_Lock_3	−6.52***	−1.52***	−0.61***
	(1.05)	(0.23)	(0.17)
Avg_Prec	0.55***	−0.03	0.01
	(0.14)	(0.03)	(0.01)
Adj_Avg_Temp	1.21***	0.19***	0.03***
	(0.10)	(0.02)	(0.01)
Avg_Wind	−1.41***	−0.13	0.005
	(0.49)	(0.08)	(0.04)
Christmas	−21.40***	−2.20***	−0.64**
	(3.76)	(0.42)	(0.30)
Easter	−8.39**	−0.36	−0.19
	(3.85)	(0.77)	(0.33)
New_Year	31.72***	3.77***	−0.43
	(7.95)	(0.76)	(0.61)
Oth_Nat_Hol	−15.39***	−0.44	−0.18
	(2.50)	(0.51)	(0.27)
Monday	11.32***	0.25	0.08
	(1.29)	(0.26)	(0.13)
Tuesday	8.00***	0.32	−0.15
	(1.31)	(0.25)	(0.12)
Wednesday	11.20***	0.42	−0.18
	(1.30)	(0.25)	(0.12)
Thursday	11.10***	0.24	0.01
	(1.28)	(0.25)	(0.13)
Friday	20.26***	1.04***	0.10
	(1.34)	(0.26)	(0.14)
Saturday	9.05***	0.65**	0.24*
	(1.36)	(0.26)	(0.13)

January	−10.32***	−0.49	−0.48***
	(2.19)	(0.31)	(0.14)
February	−16.63***	−0.54*	−0.53***
	(2.08)	(0.30)	(0.15)
March	−14.21***	−0.19	−0.44***
	(2.12)	(0.33)	(0.15)
April	1.40	1.98***	0.01
	(2.25)	(0.36)	(0.18)
May	5.55**	2.14***	0.21
	(2.23)	(0.36)	(0.18)
June	21.33***	4.32***	0.61***
	(2.20)	(0.38)	(0.18)
July	16.68***	3.32***	0.42**
	(2.12)	(0.37)	(0.18)
August	19.10***	3.39***	0.70***
	(2.20)	(0.36)	(0.19)
September	16.40***	2.80***	0.38**
	(2.24)	(0.36)	(0.19)
October	8.74***	1.85***	0.23
	(2.12)	(0.33)	(0.16)
November	−0.91	0.93***	0.22
	(2.10)	(0.31)	(0.18)
Time(3)			0.0001
			(0.0001)
Constant	44.74***	2.80***	1.27***
	(2.56)	(0.39)	(0.21)
Observations	1,826	1,826	1,826
Adjusted R^2	0.56	0.30	0.09
F Statistic	76.83*** (df = 31; 1794)	25.92*** (df = 31; 1794)	6.59*** (df = 32; 1793)

Note: *p<0.1; **p<0.05; ***p<0.01

The abbreviations may be consulted in Table B.1 and Table B.2

6.3.5 Traffic accidents by the location

In this section, we use the extended regressions with the logarithmic transformations of the dependent variables (Table A.9) to inspect their seasonality and compare the coefficients with the original regressions (Table A.8). In general, our five model types based on the location categories show the same sign in the majority of the explanatory variables, however, the intensity of the effects varies.

Czech Republic has a low proportion of motorways to the total road network (around 0.5%) compared to the other EU states, which is reflected, among other things, in the volume of traffic accidents by the road types (Nicodeme *et al.* 2012). The Table 3.17, with the descriptive statistics of the RTCs based on the type of road, reveals that the most RTCs occur on the C and local roads, followed by the B and A roads. The highway accidents contribute little to the total number of daily RTCs.

The traffic collisions significantly decreased on all the road types during the pandemic of Covid-19, except for the B roads, by which the between-lockdown dummy variables are not significant, causing the overall Covid-19 variable to be insignificant in this case. In the lockdown stages and after the third lockdown, the B roads seem to become slightly more dangerous compared to the rest of the road types when studying the incidence of the accidents. The traffic accidents at the road crossings are estimated to have decreased from all the road types by the biggest proportion during almost every stage of the pandemic. It can be explained by the more significant decrease in the traffic volume in the urban areas than on the rural roads because of the difference in the work-from-home availability since the crossings are located solely in the cities.

From the weather indicators, the precipitation has a small positive effect on all the RTCs regardless of their location, and particularly on the highways, the effect is stronger. The higher average speed of the vehicles on the highways compared to the other type of roads and the deep water film on the surface contributes to the risk of collision incidence through the loss of control over the vehicle (Jung *et al.* 2014). However, the average temperature does not appear to behave in a consistent way across the distinct locations of the accidents since two of the coefficients are not statistically significant, and the remaining show diverse effects. The Avg_Wind variable is significant in none of our regressions printed in the Table 6.11, Table A.8 and Table A.9. The only exception is the regression (2) of the table 6.11, where the additional m/s is estimated to increase the daily accidents on A roads by 0.67.

When we compare the number of total traffic accidents (Table 6.7) and the accidents in each of the studied locations during the Christmas holidays (Table A.8), we immediately find out that the recorded collisions gently shift from the C, local roads and crossings (representing the cities) to the higher-level roads such as highways, A- and B-roads. However, the number of RTCs significantly dropped on every road type during that period. The reason may be the more popular longer distance travel due to the often family visits and winter vacations compared to the non-holiday days, but the lower work-day traffic. Easter and other national holidays followed a similar pattern. Although we have already reviewed the effect of the New Year's celebrations on the traffic collisions statistics (in the Subsection 6.2.2), we can inspect it in more detail by distinguishing between the location of the RTCs concerning the road type. The biggest positive change experienced the accidents occurring on highways on January 1st - by more than 100% against the non-festive days. The models estimating the changes in Acc_Alcohol (Subsection 6.3.2) support this statement by suggesting that the alcohol-impaired RTC rates rose and alcohol with high speed are identified as factors elevating the chance of a traffic collision by Harrison & Fillmore (2011). They concluded that drivers under the influence of alcohol fail to effectively adopt compensatory strategies to avoid RTCs during a sudden dangerous event in comparison to the sober drivers.

On the weekends, the average daily RTCs decrease by the biggest proportion at the cities' crossings for similar reasons as during the holidays except for the New Year.

Regarding the monthly seasonality of the RTCs based on the road types, the significance level of the coefficients is very diverse across the regressions of Table A.8. While in regression (1), all the estimated effects of April to November can be trusted (p-values <0.01), regression (5) shows no statistical significance in the monthly dummy variables. To compare the seasonal effects of the accidents based on their locations, we examine Table A.9. The least RTCs occur during the winter season on all the road types, but the peak was observed during autumn on all the road types, excluding the highways, where the RTCs were the most common during the spring and summer season.

Table 6.11: Regression outputs - location of the accidents

	Dependent variable:				
	Acc_High	Acc_A	Acc_B	Acc_C_Loc	Acc_Cross

	HAC (1)	*HAC* (2)	*HAC* (3)	*HAC* (4)	*HAC* (5)
Share_Covid	-0.06^{*}	-0.23^{***}	-0.21^{***}	-0.84^{***}	-0.06^{***}
	(0.03)	(0.06)	(0.07)	(0.18)	(0.02)
Lockdown_1	-4.81^{***}	-10.57^{***}	-9.58^{***}	-57.37^{***}	-3.43^{***}
	(0.65)	(1.43)	(1.53)	(5.00)	(0.40)
Lockdown_2	-3.31^{***}	-5.37^{***}	-5.81^{***}	-35.77^{***}	-2.08^{***}
	(1.03)	(1.73)	(2.02)	(5.66)	(0.64)
Lockdown_3	-3.56^{***}	-11.95^{***}	-7.07^{***}	-40.54^{***}	-3.24^{***}
	(0.81)	(1.66)	(1.64)	(4.42)	(0.41)
Bet_Lock_1_2	-2.38^{***}	-3.45^{***}	-0.63	-13.11^{***}	-1.20^{***}
	(0.52)	(0.90)	(0.96)	(2.67)	(0.26)
Bet_Lock_2_3	-1.09	-1.95	-1.56	-15.79^{***}	-1.78^{***}
	(0.79)	(1.36)	(1.55)	(4.53)	(0.41)
Aft_Lock_3	-1.96^{***}	-3.70^{***}	-1.73	-7.10^{**}	-0.31
	(0.58)	(1.00)	(1.06)	(2.94)	(0.22)
Avg_Prec	0.58^{***}	0.41^{***}	0.34^{***}	0.72^{***}	0.08^{***}
	(0.05)	(0.08)	(0.09)	(0.20)	(0.02)
Adj_Avg_Temp	-0.09^{**}	0.03	0.14^{**}	0.73^{***}	-0.01
	(0.03)	(0.06)	(0.06)	(0.18)	(0.02)
Avg_Wind	0.13	0.67^{**}	0.39	-0.24	0.01
	(0.14)	(0.27)	(0.29)	(0.79)	(0.09)
Christmas	-3.14^{***}	-12.60^{***}	-18.00^{***}	-97.75^{***}	-4.38^{***}
	(1.04)	(2.61)	(2.93)	(10.59)	(0.59)
Easter	-1.36	-7.11^{***}	-6.41^{**}	-45.58^{***}	-1.89^{***}
	(1.14)	(2.04)	(2.75)	(10.09)	(0.61)
New_Year	16.91^{***}	12.81^{***}	13.66^{***}	164.90^{***}	2.37^{***}
	(4.42)	(4.63)	(3.78)	(18.39)	(0.86)
Oth_Nat_Hol	-3.03^{***}	-8.30^{***}	-7.70^{***}	-69.16^{***}	-2.60^{***}
	(0.61)	(1.63)	(1.42)	(6.38)	(0.46)
Monday	2.55^{***}	10.07^{***}	9.85^{***}	77.64^{***}	3.01^{***}
	(0.40)	(0.69)	(0.70)	(2.12)	(0.25)
Tuesday	2.35^{***}	6.93^{***}	8.15^{***}	68.83^{***}	2.89^{***}
	(0.43)	(0.72)	(0.77)	(2.05)	(0.24)
Wednesday	2.46^{***}	8.46^{***}	10.07^{***}	77.64^{***}	3.66^{***}
	(0.35)	(0.68)	(0.68)	(2.05)	(0.25)

Thursday	2.45***	8.97***	10.03***	76.14***	3.29***
	(0.39)	(0.70)	(0.73)	(2.17)	(0.24)
Friday	3.00***	12.79***	14.86***	87.08***	2.85***
	(0.38)	(0.69)	(0.76)	(2.15)	(0.24)
Saturday	0.42	2.87***	5.48***	21.02***	0.50**
	(0.37)	(0.68)	(0.70)	(2.01)	(0.21)
January	0.34	−5.40***	−4.34***	−14.79***	−0.92**
	(0.62)	(1.08)	(1.30)	(4.49)	(0.37)
February	−0.79	−5.91***	−8.80***	−17.70***	−1.10***
	(0.55)	(1.02)	(1.21)	(4.21)	(0.39)
March	0.29	−6.37***	−10.78***	−17.63***	−0.77**
	(0.55)	(1.09)	(1.26)	(4.34)	(0.38)
April	3.35***	−0.12	−3.61***	1.99	−0.13
	(0.59)	(1.13)	(1.27)	(4.47)	(0.40)
May	4.89***	2.01*	−2.28*	3.03	−0.86**
	(0.57)	(1.07)	(1.20)	(4.28)	(0.40)
June	3.78***	1.69	−0.51	16.29***	−0.92**
	(0.58)	(1.05)	(1.21)	(4.24)	(0.39)
July	3.37***	2.40**	−1.20	−3.34	−1.37***
	(0.53)	(1.11)	(1.24)	(4.25)	(0.38)
August	3.28***	4.26***	1.08	−2.95	−1.12***
	(0.59)	(1.06)	(1.27)	(4.21)	(0.40)
September	3.58***	5.89***	1.69	12.69***	−0.20
	(0.59)	(1.11)	(1.24)	(4.25)	(0.39)
October	3.88***	7.88***	3.89***	17.00***	0.34
	(0.55)	(1.03)	(1.28)	(4.17)	(0.39)
November	2.28***	3.24***	1.21	10.77***	0.28
	(0.54)	(1.07)	(1.23)	(4.18)	(0.38)
Time(1)	0.002***				
	(0.0004)				
Time(2)		0.002**			
		(0.001)			
Time(3)			0.003***		
			(0.001)		
Time(4)				−0.001	
				(0.002)	
Constant	6.49***	28.91***	32.64***	128.55***	5.52***

	(0.71)	(1.31)	(1.52)	(4.93)	(0.44)
Observations	1,826	1,826	1,826	1,826	1,826
Adjusted R^2	0.31	0.43	0.38	0.72	0.28
F Statistic	26.19*** (df = 32; 1793)	43.47*** (df = 32; 1793)	36.51*** (df = 32; 1793)	149.21*** (df = 32; 1793)	23.68*** (df = 31; 1794)

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted in Table B.1 and Table B.2

6.3.6 Causalities of traffic accidents

Risky overtaking, high speed, not giving the right way, technical issues and overall inappropriate style of driving are the leading causes of traffic accidents according to the Police of the Czech Republic. Both the previously mentioned sets of independent variables were used to identify the effects on the variables describing the RTCs' causality with higher precision.

From the coefficients, by the Share_Covid variable, we can see that if they are statistically significant (in the regressions (2), (3) and (5)), they indicate a negative relationship, meaning that the higher the Covid-19 incidence rate, the fewer the RTCs caused by the respective factors. It suggests that whenever there is some bad news strongly affecting people's lives, they tend to become aware of other, even non-related, risks and adjust their behaviour to minimise them. It is the explanation for the mentioned negative relationship, closely bearing on the decreased total RTCs with an additional unit of the Share_Covid.

Unfortunately, the regressions with the Not_Adjusted_Speed and Risky_Overtaking dependent variables are not statistically significant in the variables indicating the effects of the individual phases of the pandemic. Therefore, the better comparison provide the extended models (Table A.11 and Table A.12) with the Covid-19 variable being statistically significant at least at 5% for all five regressions. When we compare the logarithmic models of total traffic accidents (Table 6.1) and the models with causality variables during the Covid period (Table A.12), accidents where the offender exceeded the allowed speed or broke the traffic rules decreased by a lower proportion than the total number of RTCs. It means that the ratio of such causalities increased as the road lines seduced to speeding and law violation.

Contrary to that, the risky overtaking and technical issues as causality factors experienced a more significant drop than the total RTCs during the mentioned period. These phenomena can be justified by fewer occasions for overtaking because of the decreased traffic volume and the fewer occasional drivers on the road, who are more likely to have their vehicles in bad condition, respectively. By the regressions (3) and (5) of Table 6.12 and Table A.10, we can observe that the collisions caused by not giving the right way to other vehicles and by the inappropriate style of driving reflect the development of the total RTCs during the distinct phases of the pandemic. The effects of the pandemic indicators on the rest of the causality variables are impossible to detect due to the lack of statistical significance.

The effect of rainfall varies significantly across the types of accidents causality. While the not adjusted speed, not giving the right way and the overall inappropriate style of driving are estimated to increase with an additional millimetre of rainfall, the number of RTCs caused by risky overtaking significantly lowered during the rain. The Not_Adjusted_Speed and Avg_Precipitation are positively correlated because people tend to underestimate the increased risk of a skid on the wet road and do not modify the speed accordingly. The elevated number of cases of not giving the right way to other vehicles is connected to the lowered visibility conditions during the rain. Drivers are generally inclined to overestimating their abilities behind the wheel when raining and pay lower attention to the worsened adhesion of the tyres to the surface. On the other hand, the accidents caused by risky overtaking are estimated to decrease by around 0.06 per each additional millimetre of precipitation, ceteris paribus (Table A.11). The explanation might be the lowered visibility discouraging drivers from overtaking.

The only negative effect of the air temperature is on the RTCs caused by excessive speed (regression (1) of Table A.12 and Table 6.12). The models suggest that with 1°C decrease in the average ambient temperature, the accidents triggered by not adjusted speed to the surrounding conditions are estimated to rise by 2%. It is connected to the very low temperature bringing the black ice and a snow layer, which can be considered risk factors since the modified speed is necessary for a safe drive. Traffic accidents caused by risky overtaking and technical issues are predicted to increase the most from our causality regressions. The more common technical problems during warm weather can be attributed to the overheated motor. The factors influencing the collisions while overtaking may be the intensive sunshine decreasing visibility and heat exhaustion. These factors also contribute to the accidents caused by not giving the right way and by another inappropriate style of driving, which are estimated to increase by 1%, when the average temperature increases by one degree Celsius (Table A.12). Similarly to the previous models, the wind does not have any significant effect on the RTCs by causality.

The seasonality of the RTCs by causality reflects the temperature effect in the coefficients, as the temperature is positively correlated with the season of the year. The peak months in terms of the number of collisions due to non-adjusted speed to the surrounding conditions are December and January. However, the rest of the causalities used in our models culminate during the summer months.

Weekends play a very significant role in traffic accidents segmented by their causality. On those being a consequence of not adjusted speed, weekends, including Fridays, have a positive impact. It might be the occasional drivers who largely contribute to the Not_Adjusted_Speed accidents statistics. By the rest of the collision causalities in our analysis, the weekend numbers are lower than the work-days, and especially the Risky_Overtaking and Technical_Issue tend to decrease more during the weekends than No_Right_Way and Inappropriate_Style causes.

The regressions of this section provide the more specific results of the total traffic accidents. Therefore the estimated coefficients of all the explanatory variables, including the holiday dummies, resemble the coefficients in Table 6.7. Although some of the effects are insignificant, we can conclude that since accidents with Not_Adjusted_Speed and Risky_Overtaking are largely influenced by the decision-making and the mental state of the driver, the only significant holiday effect on these dependent variables is the New_Year. On this day, the drivers are more likely to be under the influence of alcohol or other substances (mentioned in Subsection 6.3.2), thus increasing the chances of speed- and overtaking-related collisions, as they tend to overestimate their driving skills and their concentration and reaction time fades out. Not giving the right way, technical issues and the inappropriate style of driving are negatively influenced by the holidays except for the New Year.

Table 6.12: Regression outputs - causality of accidents

	Dependent variable:				
	Not_Ad_Sp	Risk_Ovt	N_Ri_Way	Tech_Iss	Inap_Sty
	HAC	*HC*	*HAC*	*HC*	*HAC*
	(1)	(2)	(3)	(4)	(5)
Share_Covid	−0.01	−0.04**	−0.32***	0.01	−0.78***
	(0.16)	(0.01)	(0.06)	(0.01)	(0.16)
Lockdown_1	0.29	−0.48	−15.68***	−0.38**	−50.79***
	(1.96)	(0.38)	(1.51)	(0.15)	(4.37)
Lockdown_2	−3.17	0.32	−9.01***	−0.49*	−27.77***
	(4.50)	(0.52)	(1.82)	(0.27)	(4.90)
Lockdown_3	2.93	−0.92**	−11.26***	−0.23	−37.61***
	(3.35)	(0.41)	(1.44)	(0.19)	(3.67)
Bet_Lock_1_2	0.93	0.24	−3.51***	−0.31***	−11.61***
	(1.80)	(0.26)	(0.76)	(0.11)	(2.31)
Bet_Lock_2_3	4.49	0.56*	−4.50***	−0.46***	−13.46***
	(4.26)	(0.34)	(1.08)	(0.15)	(3.66)
Aft_Lock_3	1.52	0.27	−2.93***	−0.17**	−6.23**
	(2.21)	(0.26)	(0.59)	(0.08)	(2.53)
Avg_Prec	3.04***	−0.07***	−0.004	−0.02**	−0.15
	(0.24)	(0.02)	(0.07)	(0.01)	(0.15)
Adj_Avg_Temp	−0.89***	0.09***	0.35***	0.02**	1.40***
	(0.14)	(0.02)	(0.06)	(0.01)	(0.16)
Avg_Wind	1.68**	−0.13**	0.03	0.05	−1.50**
	(0.80)	(0.06)	(0.24)	(0.03)	(0.61)
Christmas	−10.02	−0.93*	−25.06***	−0.74***	−82.33***
	(6.14)	(0.49)	(2.68)	(0.15)	(8.39)
Easter	−0.09	−1.13**	−11.67***	−0.70***	−43.67***
	(2.50)	(0.50)	(2.82)	(0.21)	(8.92)
New_Year	4.12	0.88	−0.58	−0.18	201.27***
	(5.62)	(1.05)	(5.72)	(0.65)	(14.39)
Oth_Nat_Hol	−0.18	−1.08***	−18.74***	−0.73***	−62.92***
	(3.07)	(0.40)	(1.96)	(0.16)	(5.78)
Monday	−2.38	1.76***	19.71***	0.95***	74.02***
	(1.56)	(0.17)	(0.67)	(0.09)	(1.81)

Tuesday	−2.57	1.59***	19.69***	0.73***	62.45***
	(1.87)	(0.16)	(0.69)	(0.09)	(1.62)
Wednesday	−1.35	2.15***	22.67***	0.80***	70.62***
	(1.58)	(0.16)	(0.68)	(0.09)	(1.72)
Thursday	0.30	1.95***	22.64***	0.62***	67.05***
	(1.76)	(0.17)	(0.68)	(0.08)	(1.72)
Friday	4.92***	2.78***	23.14***	0.70***	79.66***
	(1.57)	(0.18)	(0.71)	(0.08)	(1.79)
Saturday	7.05***	0.70***	4.21***	0.18**	17.29***
	(1.72)	(0.16)	(0.60)	(0.08)	(1.65)
January	5.82	−0.41*	−7.18***	0.09	−15.53***
	(4.06)	(0.22)	(1.18)	(0.12)	(3.46)
February	−9.48***	−0.27	−7.75***	0.27**	−9.21***
	(3.38)	(0.22)	(1.20)	(0.13)	(3.41)
March	−22.10***	0.34	−5.61***	0.23*	−3.32
	(3.27)	(0.26)	(1.29)	(0.14)	(3.59)
April	−24.25***	1.38***	1.59	0.36**	14.84***
	(2.84)	(0.27)	(1.35)	(0.14)	(3.71)
May	−23.76***	0.93***	0.47	0.45***	16.50***
	(2.88)	(0.24)	(1.32)	(0.13)	(3.60)
June	−19.48***	1.61***	3.57***	0.62***	33.74***
	(2.94)	(0.26)	(1.31)	(0.14)	(3.52)
July	−18.60***	1.73***	−1.44	0.59***	17.92***
	(2.92)	(0.24)	(1.29)	(0.14)	(3.59)
August	−16.61***	1.97***	−0.82	0.41***	16.58***
	(2.98)	(0.27)	(1.30)	(0.14)	(3.52)
September	−12.04***	1.63***	4.65***	0.61***	26.65***
	(3.08)	(0.26)	(1.27)	(0.13)	(3.56)
October	−16.18***	1.63***	5.98***	0.25*	27.97***
	(2.94)	(0.25)	(1.28)	(0.13)	(3.48)
November	−12.17***	0.86***	3.17**	0.25**	15.18***
	(3.10)	(0.25)	(1.29)	(0.12)	(3.51)
Time(1)	−0.004**				
	(0.002)				
Time(2)		−0.001***			
		(0.0002)			
Time(5)					0.005***

					(0.002)
Constant	52.11***	1.58***	20.98***	0.06	87.63***
	(4.08)	(0.29)	(1.44)	(0.15)	(3.87)
Observations	1,826	1,826	1,826	1,826	1,826
Adjusted R^2	0.31	0.28	0.66	0.12	0.78
F Statistic	27.08*** (df = 32; 1793)	23.70*** (df = 32; 1793)	115.86*** (df = 31; 1794)	9.19*** (df = 31; 1794)	199.32*** (df = 32; 1793)

Note: *p<0.1; **p<0.05; ***p<0.01

The abbreviations may be consulted in Table B.1 and Table B.2

Chapter 7

Conclusion

Among the contemporary literature, this study is unique in examining the impact of Covid-19 and other factors such as weather, holidays and seasons of the year on the state-level road traffic crashes between the years 2017 and 2021. The research is done using the Ordinary Least Squares regressions on the time-series data. Information from four different sources form the dataset, based on which the conclusions concerning the density of traffic accidents, impaired driving, accidents by causality, location and severity are drawn. Our dataset also includes daily weather indicators extracted from the network of Czech weather stations and the information about the strength of the pandemic obtained from the statistic provided by the Czech Ministry of Health.

The main focus of this thesis is to test the hypothesis suggesting a significant downturn in traffic collisions during the Covid-19 period relative to the pre-pandemic state, which is amplified during the lockdowns. The results are in line with the hypothesis and provide information about the overall decrease in traffic accidents during the whole pandemic by 16%. The most significant reduction in collisions occurred during the first lockdown in March and April 2020, whereas the slightest change against the before-pandemic values was recorded after the third lockdown, showing the number of accidents still under the normal state. Although the lockdowns in autumn 2020 and spring 2021 were more serious in the number of newly detected Covid-positive people, deaths and hospitalisations on that disease than in the first lockdown, the traffic collisions decreased by a lower share. It implies that the repeated movement restrictions during the second and third lockdowns were less abided by the public than during the initial lockdown period. The significantly negative impact of the virus of Covid-19 on road traffic collisions is also supported by the indicators of the pandemic strength, creating the incentive for lockdown imposition through their extremely high values and reflecting the public perception of the Covid-19 threats. The only positive impact of the pandemic recorded the alcohol and drugs-related traffic collisions, as consumption of these substances generally increased in response to the worsened mental health condition of the population.

The rest of the research questions are constructed to inspect the topic of traffic safety from different perspectives. From the analysed weather variables, the precipitation and ambient temperature significantly influence vehicle crashes, in contrast to the wind, whose effect is mostly insignificant and inconsistent across the regressions. Both rainfall and extreme temperatures considerably higher the chance of a traffic incident. Specifically, the average daily temperature under 0°C belongs to the riskiest factors. Considering the causalities of traffic accidents included in our analysis, precipitation shows the strongest positive correlation with the accidents caused by excessive speed. Since the average rate of vehicles on the main corridors is much higher than on the local roads, the drivers on highways are at the greatest risk of being involved in an accident during the rain or the wet surface of all road types. In addition, drivers under the influence of some forbidden substance tend to manage critical situations with water on the road worse than others, based on the alcohol and drug-involved traffic accident regressions. This study showed that the effect of air temperature on traffic collisions is of various strength and sign among the accident types. However, we can clearly state that the heat weather conditions increase the threat of a traffic accident with severe consequences on human health.

Generally, weekends are less dangerous than the rest of the week in relation to the quantity of road traffic collisions. However, the consumption of alcohol and soft drugs is often connected to free time activities and social events, causing the road crashes with these substances detected in the blood system of the offenders to be significantly elevated on Fridays, Saturdays and Sundays compared to other workdays. On weekends, the cases of the overstepped speed limit as the main trigger of a vehicle incident are also more frequent with respect to the workday records. The remaining phenomena analysed in this thesis are negatively influenced by the weekends.

The seasonal effects on road traffic collisions significantly vary across the mentioned categories. Whereas the daily road crashes with an injury culminate in the summer months, the peak of the daily accidents with no harm to human health is in October and November. Relevant literature suggests that during the hot summer months, drivers are more likely to fall asleep behind the wheel, which usually has serious consequences. When it comes to the location of the accidents, the highway incidents seem to be evenly distributed from spring to autumn, contrary to the rural roads, on which the seasonality follows the total traffic accidents trend. The estimation is performed using both the monthly and quarterly dummy variables. However, the four seasons dummies provide lower-precision estimates of the desired effects than the monthly ones, we do not run into the problem of lack of statistical significance and the models can be better compared with each other.

The models showed that state holidays significantly influence road traffic collisions, but the size and sign of the effects differ for particular holidays. New Year is the only festive day in the year on which the total number of traffic collisions is elevated compared to the non-festive days. It is due to the areal celebrations of the upcoming year and the harmful use of substances during that period. The remaining state holiday dates present a significantly decreased volume of traffic collisions with respect to the rest of the year.

The thesis answered almost all of the research questions regarding safety on the Czech roads during the last five years, including the period of the Covid-19 pandemic and the pre-pandemic era. Although the fatal traffic collisions and collisions with the offender under the influence of drugs could not be adequately examined as they lack the coefficients' significance, the conclusions about the major issues were drawn based on the modified models. Since the daily numbers of these two collision types are only in units, the effects of the explanatory variables are hard to observe unless we use the longer-period dummy variables. The OLS regressions enabled not only to validate the hypotheses but also to reveal the patterns of the driver's behaviour, which were not expected in advance. We believe that the main contribution of this bachelor thesis is the inspection of the relationship between the pandemic of Covid-19 and the road traffic collision rates arising from the reduction in the traffic volume during the restrictive measures. The analysis of this topic distinguishes itself from the existing studies in applying selected econometric methods and the complexity of the explanatory factors, combining weather, seasonal, holiday and lockdown effects on traffic accidents. Furthermore, the other literature reviewing the traffic characteristic during the pandemic, if existing, analyses only the period of the first lockdown in spring 2020. This thesis extends the topic by also studying the following phases of the pandemic and thus getting the full picture of the evolution of traffic accidents during the period with Covid-19.

The absence of data on traffic density in the Czech Republic presents the main limitation of this academic paper. The observed effect of a reduced number of road traffic collisions could not be distributed among the changes in traffic volume and the drivers' habits using the OLS method. However, the majority of foreign literature sources coincide in the finding that road traffic generally experienced a significant downturn in its daily volume during the period of anti-Covid restrictions, which is trusted when drawing conclusions from the regressions. To estimate the mentioned effect on traffic collisions for our sample, a dataset collecting information about the number of vehicles going through selected road segments is essential. Since such database of the Czech Road and Motorway Directorate is only temporarily unavailable, it gives us the opportunity to extend this thesis in the future and to complete the analysis of traffic safety during the pandemic. Additionally, it would be interesting to find out if the revealed trends in road traffic from the studied period of Covid-19 prevail in the upcoming years or not. These are the propositions for future research.

The results of the analysis are not only helpful to institutions setting preventive measures against the incidence of traffic accidents but also serve as the predictor of the potential future waves of Covid-19 disease or any threatening pandemic regarding the changes in road traffic.

Overall, this bachelor thesis succeeded in shedding light on the influencing factors and their effects on road traffic collisions, especially on the changes in traffic patterns during the world pandemic of Covid-19.

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Appendix A

Additional OLS regression tables

Table A.1: Extended regression outputs - Acc_Alcohol and Acc_Drugs

	Dependent variable:			
	log			log
	Acc_Alcohol		Acc_Drugs	
	HAC	*HAC*	*HC*	*HC*
	(1)	(2)	(3)	(4)
Share_Covid	-0.10^{***}	-0.01^{***}	-0.01	-0.01
	(0.02)	(0.002)	(0.01)	(0.02)
Covid_19	0.63^{**}	0.06^{**}	0.17^{***}	0.70^{**}
	(0.28)	(0.03)	(0.06)	(0.28)
Avg_Prec	0.11^{***}	0.01^{***}	0.03^{***}	0.11^{***}
	(0.03)	(0.003)	(0.01)	(0.03)
Adj_Avg_Temp	0.21^{***}	0.02^{***}	0.002	0.01
	(0.03)	(0.003)	(0.01)	(0.03)
Avg_Wind	-0.61^{***}	-0.05^{***}	-0.02	-0.08
	(0.13)	(0.02)	(0.03)	(0.14)
Christmas	0.96	0.17	-0.37^{**}	-1.54
	(1.25)	(0.14)	(0.15)	(1.31)
Easter	0.32	0.11	-0.11	-1.18
	(1.17)	(0.09)	(0.23)	(1.17)
New_Year	20.74^{***}	1.40^{***}	0.09	0.65
	(3.46)	(0.18)	(0.43)	(2.54)
Oth_Nat_Hol	3.20^{***}	0.28^{***}	-0.10	-1.03

	(0.79)	(0.05)	(0.20)	(0.82)
Weekend	8.36***	0.66***	0.16***	0.75***
	(0.27)	(0.02)	(0.05)	(0.24)
Spring	2.59***	0.32***	0.13**	0.57*
	(0.30)	(0.05)	(0.06)	(0.34)
Summer	4.92***	0.51***	0.12*	0.46
	(0.31)	(0.05)	(0.07)	(0.34)
Autumn	3.04***	0.35***	0.18***	0.69**
	(0.29)	(0.05)	(0.06)	(0.32)
Constant	6.46***	1.78***	0.67***	−4.44***
	(0.46)	(0.09)	(0.10)	(0.52)
Observations	1,826	1,826	1,826	1,826
Adjusted R^2	0.51	0.32	0.02	0.02
F Statistic	148.67***	67.67***	4.43***	3.27***
		(df = 13; 1812)		

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted in Table B.1 and Table B.2

Table A.2: Regression outputs - log severity of the accidents

	Dependent variable:			
	log Acc_No_Inj	log Acc_Non_Ser_Inj	log Acc_Ser_Inj	log Fatality
	HAC	*HAC*	*HC*	*HC*
	(1)	(2)	(3)	(4)
Share_Covid	−0.005***	−0.01***	−0.02	−0.02
	(0.001)	(0.002)	(0.02)	(0.04)
Lockdown_1	−0.38***	−0.42***	−1.26**	−1.21
	(0.03)	(0.07)	(0.57)	(0.88)
Lockdown_2	−0.17***	−0.21***	−0.45	−1.70
	(0.03)	(0.07)	(0.63)	(1.25)
Lockdown_3	−0.29***	−0.38***	−1.25*	−0.49
	(0.03)	(0.06)	(0.64)	(0.90)
Bet_Lock_1_2	−0.07***	−0.01	0.09	−0.92*
	(0.01)	(0.02)	(0.19)	(0.51)

Bet_Lock_2_3	−0.08***	−0.13***	−0.50	−1.04
	(0.03)	(0.05)	(0.43)	(0.79)
Aft_Lock_3	−0.04***	−0.06***	0.05	−0.65
	(0.02)	(0.02)	(0.23)	(0.52)
Avg_Prec	0.01***	0.01***	−0.01	−0.01
	(0.001)	(0.002)	(0.01)	(0.03)
Adj_Avg_Temp	−0.002	0.02***	0.08***	0.12***
	(0.001)	(0.002)	(0.01)	(0.03)
Avg_Wind	0.01*	−0.03***	−0.01	0.17
	(0.004)	(0.01)	(0.06)	(0.13)
Christmas	−0.63***	−0.54***	−2.67**	−2.10
	(0.07)	(0.07)	(1.20)	(1.38)
Easter	−0.31***	−0.16	0.05	−0.003
	(0.06)	(0.10)	(0.63)	(1.16)
New_Year	0.63***	0.64***	1.58***	−3.47
	(0.08)	(0.11)	(0.44)	(2.12)
Oth_Nat_Hol	−0.37***	−0.27***	−0.37	−0.73
	(0.04)	(0.05)	(0.32)	(0.80)
Monday	0.44***	0.33***	0.53***	0.63*
	(0.01)	(0.02)	(0.17)	(0.38)
Tuesday	0.40***	0.28***	0.38**	−0.12
	(0.01)	(0.02)	(0.19)	(0.39)
Wednesday	0.44***	0.34***	0.48***	−0.05
	(0.01)	(0.02)	(0.18)	(0.39)
Thursday	0.44***	0.32***	0.53***	0.72*
	(0.01)	(0.02)	(0.17)	(0.38)
Friday	0.49***	0.44***	0.67***	0.80**
	(0.01)	(0.02)	(0.17)	(0.38)
Saturday	0.13***	0.19***	0.19	1.10***
	(0.01)	(0.03)	(0.21)	(0.37)
January	−0.06***	−0.17***	−0.50*	−1.43***
	(0.02)	(0.04)	(0.29)	(0.54)
February	−0.07***	−0.29***	−0.36	−1.61***
	(0.02)	(0.04)	(0.27)	(0.54)
March	−0.09***	−0.22***	−0.24	−1.40**
	(0.02)	(0.04)	(0.26)	(0.56)
April	0.01	0.10**	0.61**	−1.11*

	(0.02)	(0.04)	(0.24)	(0.58)
May	0.01	0.14***	0.60***	−0.18
	(0.02)	(0.04)	(0.21)	(0.54)
June	0.01	0.37***	0.97***	0.76
	(0.02)	(0.04)	(0.20)	(0.50)
July	−0.05**	0.31***	0.74***	0.25
	(0.02)	(0.04)	(0.22)	(0.53)
August	−0.04	0.32***	0.73***	1.07**
	(0.02)	(0.04)	(0.23)	(0.51)
September	0.05**	0.30***	0.74***	0.08
	(0.02)	(0.04)	(0.22)	(0.53)
October	0.11***	0.21***	0.52**	−0.06
	(0.02)	(0.04)	(0.24)	(0.51)
November	0.09***	0.02	0.43**	0.13
	(0.02)	(0.04)	(0.21)	(0.50)
Time(1)	0.0001***			
	(0.0000)			
Time(3)			−0.0003*	
			(0.0002)	
Time(4)				0.0005
				(0.0004)
Constant	5.04***	3.41***	0.12	−3.85***
	(0.03)	(0.05)	(0.32)	(0.67)
Observations	1,826	1,826	1,826	1,826
Adjusted R^2	0.72	0.63	0.16	0.05
F Statistic	150.90*** (df = 32; 1793)	99.41*** (df = 31; 1794)	11.84*** (df = 32; 1793)	4.10*** (df = 32; 1793)

Note: *p<0.1; **p<0.05; ***p<0.01

The abbreviations may be consulted in Table B.1 and Table B.2

Table A.3: Extended regression outputs- severity of the accidents

	Dependent variable:			
	Acc_No_Inj	Acc_Non_Ser_Inj	Acc_Ser_Inj	Fatality
	HAC	*HAC*	*HAC*	*HAC*
	(1)	(2)	(3)	(4)
Share_Covid	-1.14^{***}	-0.43^{***}	-0.02	-0.01^{*}
	(0.16)	(0.06)	(0.01)	(0.01)
Covid_19	-9.57^{***}	-4.44^{***}	-1.08^{***}	-0.09
	(1.95)	(0.79)	(0.18)	(0.07)
Avg_Prec	2.33^{***}	0.62^{***}	-0.001	0.01
	(0.28)	(0.12)	(0.02)	(0.01)
Adj_Avg_Temp	-0.43^{*}	1.01^{***}	0.18^{***}	0.03^{***}
	(0.23)	(0.09)	(0.02)	(0.01)
Avg_Wind	2.16^{**}	-1.82^{***}	-0.19^{**}	0.02
	(1.00)	(0.39)	(0.07)	(0.03)
Christmas	-83.71^{***}	-8.35^{***}	-1.50^{***}	-0.02
	(13.15)	(2.35)	(0.35)	(0.25)
Easter	-66.48^{***}	-12.58^{***}	-0.92	-0.17
	(11.50)	(3.17)	(0.67)	(0.24)
New_Year	185.33^{***}	32.86^{***}	3.10^{***}	-0.29
	(15.28)	(5.15)	(0.82)	(0.51)
Oth_Nat_Hol	-76.42^{***}	-11.96^{***}	-0.34	-0.14
	(6.71)	(1.83)	(0.49)	(0.20)
Weekend	-75.85^{***}	-9.36^{***}	-0.26^{*}	0.06
	(1.58)	(0.66)	(0.14)	(0.06)
Spring	17.05^{***}	17.02^{***}	2.60^{***}	0.32^{***}
	(2.44)	(0.91)	(0.19)	(0.08)
Summer	18.31^{***}	26.21^{***}	3.29^{***}	0.58^{***}
	(2.36)	(0.84)	(0.19)	(0.08)
Autumn	46.77^{***}	15.90^{***}	1.46^{***}	0.45^{***}
	(2.33)	(0.81)	(0.16)	(0.07)
Constant	228.80^{***}	35.13^{***}	2.66^{***}	0.63^{***}
	(3.77)	(1.30)	(0.27)	(0.12)
Observations	1,826	1,826	1,826	1,826
Adjusted R^2	0.65	0.51	0.25	0.05

F Statistic	263.65***	145.85***	48.12***	7.84***
		(df = 13; 1812)		

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted in Table B.1 and Table B.2

Table A.4: Extended regression outputs - log severity of the accidents

	Dependent variable:			
	log Acc_No_Inj	log Acc_Non_Ser_Inj	log Acc_Ser_Inj	log Fatality
	HAC	*HAC*	*HAC*	*HC*
	(1)	(2)	(3)	(4)
Share_Covid	−0.01***	−0.01***	−0.03*	−0.05**
	(0.001)	(0.002)	(0.01)	(0.02)
Covid_19	−0.05***	−0.11***	−0.46***	−0.16
	(0.01)	(0.02)	(0.12)	(0.27)
Avg_Prec	0.01***	0.01***	0.01	0.02
	(0.001)	(0.002)	(0.01)	(0.03)
Adj_Avg_Temp	−0.002	0.02***	0.08***	0.12***
	(0.001)	(0.002)	(0.01)	(0.03)
Avg_Wind	0.01	−0.04***	−0.03	0.08
	(0.005)	(0.01)	(0.06)	(0.13)
Christmas	−0.50***	−0.28***	−2.22**	−0.62
	(0.08)	(0.07)	(1.12)	(1.35)
Easter	−0.38***	−0.32***	−0.32	−0.52
	(0.07)	(0.10)	(0.53)	(1.10)
New_Year	0.66***	0.71***	1.53***	−3.64*
	(0.06)	(0.09)	(0.34)	(2.18)
Oth_Nat_Hol	−0.38***	−0.24***	−0.25	−0.72
	(0.04)	(0.05)	(0.31)	(0.80)
Weekend	−0.37***	−0.24***	−0.41***	0.17
	(0.01)	(0.02)	(0.11)	(0.22)
Spring	0.08***	0.39***	1.02***	0.75**
	(0.01)	(0.02)	(0.15)	(0.32)
Summer	0.10***	0.59***	1.32***	1.71***
	(0.01)	(0.02)	(0.15)	(0.32)

Autumn	0.22***	0.39***	0.93***	1.53***
	(0.01)	(0.02)	(0.15)	(0.30)
Constant	5.41***	3.52***	0.04	−4.42***
	(0.02)	(0.03)	(0.26)	(0.51)
Observations	1,826	1,826	1,826	1,826
Adjusted R^2	0.66	0.52	0.14	0.04
F Statistic	273.35***	155.05***	23.39***	6.39***
		(df = 13; 1812)		

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted in Table B.1 and Table B.2

Table A.5: Regression outputs - log injured people by severity

	Dependent variable:		
	log Non_Ser_Inj_Pe	log Ser_Inj_Pe	log Dead_Pe_Acc
	HAC	*HAC*	*HC*
	(1)	(2)	(3)
Share_Covid	−0.01***	−0.02	−0.01
	(0.002)	(0.02)	(0.04)
Lockdown_1	−0.48***	−1.18**	−1.77**
	(0.07)	(0.49)	(0.88)
Lockdown_2	−0.25***	−0.65	−2.20*
	(0.07)	(0.59)	(1.27)
Lockdown_3	−0.42***	−1.51***	−1.16
	(0.06)	(0.53)	(0.90)
Bet_Lock_1_2	−0.04*	−0.07	−1.57***
	(0.02)	(0.13)	(0.50)
Bet_Lock_2_3	−0.16***	−0.54	−1.50*
	(0.05)	(0.37)	(0.79)
Aft_Lock_3	−0.09***	−0.31***	−1.17**
	(0.02)	(0.12)	(0.51)
Avg_Prec	0.01***	−0.01	0.01
	(0.002)	(0.01)	(0.03)
Adj_Avg_Temp	0.02***	0.08***	0.09***

	(0.002)	(0.01)	(0.03)
Avg_Wind	−0.03***	0.01	0.01
	(0.01)	(0.05)	(0.13)
Christmas	−0.44***	−2.83**	−2.87**
	(0.09)	(1.12)	(1.40)
Easter	−0.17	−0.05	−0.27
	(0.10)	(0.59)	(1.17)
New_Year	0.56***	1.56***	−3.88*
	(0.11)	(0.35)	(2.14)
Oth_Nat_Hol	−0.24***	−0.29	−1.01
	(0.05)	(0.30)	(0.80)
Monday	0.25***	0.46***	0.50
	(0.03)	(0.16)	(0.37)
Tuesday	0.20***	0.27	−0.24
	(0.03)	(0.18)	(0.39)
Wednesday	0.26***	0.44***	−0.22
	(0.03)	(0.16)	(0.38)
Thursday	0.25***	0.43***	0.53
	(0.03)	(0.16)	(0.37)
Friday	0.39***	0.61***	0.54
	(0.03)	(0.16)	(0.37)
Saturday	0.18***	0.19	1.06***
	(0.03)	(0.19)	(0.35)
January	−0.19***	−0.43	−1.39***
	(0.04)	(0.27)	(0.53)
February	−0.30***	−0.33	−1.55***
	(0.04)	(0.26)	(0.53)
March	−0.26***	−0.16	−1.04*
	(0.04)	(0.23)	(0.55)
April	0.05	0.62***	−0.91
	(0.04)	(0.23)	(0.57)
May	0.09**	0.58***	0.22
	(0.04)	(0.21)	(0.51)
June	0.33***	0.99***	0.93*
	(0.04)	(0.20)	(0.48)
July	0.28***	0.81***	0.65
	(0.04)	(0.21)	(0.50)

August	0.30***	0.77***	1.14**
	(0.04)	(0.23)	(0.50)
September	0.27***	0.79***	0.16
	(0.04)	(0.20)	(0.51)
October	0.17***	0.53**	0.11
	(0.04)	(0.23)	(0.49)
November	0.001	0.40*	0.03
	(0.04)	(0.21)	(0.50)
Time(3)			0.0004
			(0.0004)
Constant	3.73***	0.09	−2.66***
	(0.05)	(0.29)	(0.66)
Observations	1,826	1,826	1,826
Adjusted R^2	0.59	0.16	0.06
F Statistic	84.15*** (df = 31; 1794)	12.32*** (df = 31; 1794)	4.81*** (df = 32; 1793)

Note: *p<0.1; **p<0.05; ***p<0.01

The abbreviations may be consulted in Table B.1 and Table B.2

Table A.6: Extended regression outputs - injured people by severity

	Dependent variable:		
	Non_Ser_Inj_Pe	Ser_Inj_Pe	Dead_Pe_Acc
	HAC	*HAC*	*HC*
	(1)	(2)	(3)
Share_Covid	−0.50***	−0.02	−0.002
	(0.16)	(0.06)	(0.01)
Covid_19	−7.80***	−1.40*	−0.49***
	(1.95)	(0.79)	(0.08)
Avg_Prec	0.96***	0.01	0.01
	(0.28)	(0.12)	(0.01)
Adj_Avg_Temp	1.16***	0.20**	0.04***
	(0.23)	(0.09)	(0.01)
Avg_Wind	−2.14**	−0.22	−0.02

	(1.00)	(0.39)	(0.04)
Christmas	−6.62	−1.76	−0.18
	(13.15)	(2.35)	(0.28)
Easter	−16.19	−0.89	−0.28
	(11.50)	(3.17)	(0.31)
New_Year	35.44**	3.72	−0.49
	(15.28)	(5.15)	(0.64)
Oth_Nat_Hol	−13.77**	−0.17	−0.16
	(6.71)	(1.83)	(0.27)
Weekend	−7.71***	−0.12	0.15**
	(1.58)	(0.66)	(0.07)
Spring	19.92***	2.65***	0.58***
	(2.44)	(0.91)	(0.10)
Summer	32.54***	3.64***	0.86***
	(2.36)	(0.84)	(0.10)
Autumn	19.42***	1.55*	0.61***
	(2.33)	(0.81)	(0.09)
Constant	44.43***	3.04**	0.91***
	(3.77)	(1.30)	(0.14)
Observations	1,826	1,826	1,826
Adjusted R^2	0.46	0.25	0.08
F Statistic	121.13***	47.07***	12.81***
		(df = 13; 1812)	

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted in Table B.1 and Table B.2

Table A.7: Extended regression outputs - log injured people by severity

	Dependent variable:		
	log Non_Ser_Inj_Pe	log Ser_Inj_Pe	log Dead_Pe_Acc
	HAC	*HAC*	*HC*
	(1)	(2)	(3)
Share_Covid	−0.01***	−0.03**	−0.04

	(0.002)	(0.01)	(0.02)
Covid_19	-0.14^{***}	-0.37^{***}	-0.78^{***}
	(0.02)	(0.10)	(0.26)
Avg_Prec	0.02^{***}	0.004	0.03
	(0.002)	(0.01)	(0.03)
Adj_Avg_Temp	0.02^{***}	0.08^{***}	0.10^{***}
	(0.002)	(0.01)	(0.03)
Avg_Wind	-0.04^{***}	-0.01	-0.07
	(0.01)	(0.05)	(0.13)
Christmas	-0.17^{*}	-2.45^{**}	-1.52
	(0.09)	(1.12)	(1.36)
Easter	-0.33^{***}	-0.33	-0.92
	(0.10)	(0.53)	(1.11)
New_Year	0.63^{***}	1.49^{***}	-4.12^{*}
	(0.09)	(0.33)	(2.22)
Oth_Nat_Hol	-0.21^{***}	-0.17	-0.90
	(0.05)	(0.31)	(0.81)
Weekend	-0.17^{***}	-0.34^{***}	0.32
	(0.02)	(0.10)	(0.21)
Spring	0.36^{***}	0.86^{***}	0.95^{***}
	(0.02)	(0.14)	(0.32)
Summer	0.58^{***}	1.21^{***}	1.73^{***}
	(0.02)	(0.14)	(0.32)
Autumn	0.38^{***}	0.81^{***}	1.40^{***}
	(0.02)	(0.14)	(0.30)
Constant	3.76^{***}	0.20	-3.35^{***}
	(0.03)	(0.25)	(0.51)
Observations	1,826	1,826	1,826
Adjusted R^2	0.47	0.14	0.05
F Statistic	127.65^{***}	22.97^{***}	8.02^{***}
		(df = 13; 1812)	

Note: *p<0.1; **p<0.05; ***p<0.01

The abbreviations may be consulted in Table B.1 and Table B.2

Table A.8: Regression outputs - log location of the accidents

	Dependent variable:				
	log Acc_High	log Acc_A	log Acc_B	log Acc_C_Loc	log Acc_Cross
	HAC	*HAC*	*HAC*	*HAC*	*HC*
	(1)	(2)	(3)	(4)	(5)
Share_Covid	-0.01^{*}	-0.01^{***}	-0.01^{***}	-0.01^{***}	-0.02^{**}
	(0.003)	(0.002)	(0.002)	(0.001)	(0.01)
Lockdown_1	-0.54^{***}	-0.39^{***}	-0.30^{***}	-0.39^{***}	-1.31^{***}
	(0.09)	(0.06)	(0.05)	(0.04)	(0.46)
Lockdown_2	-0.29^{***}	-0.12^{**}	-0.13^{**}	-0.22^{***}	-0.57^{*}
	(0.11)	(0.05)	(0.05)	(0.04)	(0.34)
Lockdown_3	-0.34^{***}	-0.48^{***}	-0.23^{***}	-0.27^{***}	-1.38^{***}
	(0.09)	(0.06)	(0.05)	(0.03)	(0.46)
Bet_Lock_1_2	-0.18^{***}	-0.08^{***}	-0.02	-0.07^{***}	-0.15^{**}
	(0.05)	(0.02)	(0.02)	(0.02)	(0.07)
Bet_Lock_2_3	-0.10	-0.06	-0.04	-0.11^{***}	-0.56^{**}
	(0.08)	(0.04)	(0.04)	(0.03)	(0.22)
Aft_Lock_3	-0.17^{***}	-0.10^{***}	-0.05^{**}	-0.04^{**}	-0.04
	(0.05)	(0.03)	(0.02)	(0.02)	(0.07)
Avg_Prec	0.04^{***}	0.01^{***}	0.01^{***}	0.004^{***}	0.02^{***}
	(0.003)	(0.002)	(0.002)	(0.001)	(0.01)
Adj_Avg_Temp	-0.01^{*}	0.002	0.005^{***}	0.004^{***}	0.01
	(0.003)	(0.002)	(0.002)	(0.001)	(0.01)
Avg_Wind	0.02	0.01^{*}	0.004	-0.004	0.01
	(0.01)	(0.01)	(0.01)	(0.005)	(0.03)
Christmas	-0.37^{**}	-0.41^{***}	-0.51^{***}	-0.72^{***}	-0.78^{***}
	(0.16)	(0.10)	(0.09)	(0.07)	(0.22)
Easter	-0.21^{*}	-0.24^{***}	-0.21^{**}	-0.31^{***}	-0.49
	(0.13)	(0.07)	(0.09)	(0.07)	(0.49)
New_Year	1.10^{***}	0.36^{***}	0.33^{***}	0.71^{***}	0.73^{***}
	(0.17)	(0.11)	(0.09)	(0.09)	(0.28)
Oth_Nat_Hol	-0.30^{***}	-0.23^{***}	-0.19^{***}	-0.43^{***}	-0.43^{***}
	(0.07)	(0.05)	(0.04)	(0.04)	(0.11)
Monday	0.31^{***}	0.30^{***}	0.26^{***}	0.48^{***}	0.88^{***}
	(0.04)	(0.02)	(0.02)	(0.01)	(0.13)

Tuesday	0.27***	0.22***	0.22***	0.44***	0.81***
	(0.04)	(0.02)	(0.02)	(0.01)	(0.14)
Wednesday	0.31***	0.26***	0.27***	0.49***	1.01***
	(0.04)	(0.02)	(0.02)	(0.01)	(0.13)
Thursday	0.29***	0.27***	0.27***	0.48***	0.91***
	(0.04)	(0.02)	(0.02)	(0.01)	(0.13)
Friday	0.35***	0.36***	0.37***	0.53***	0.85***
	(0.04)	(0.02)	(0.02)	(0.01)	(0.13)
Saturday	0.10**	0.09***	0.15***	0.16***	0.28*
	(0.04)	(0.02)	(0.02)	(0.01)	(0.15)
January	−0.002	−0.16***	−0.10***	−0.08***	−0.28
	(0.06)	(0.03)	(0.03)	(0.03)	(0.19)
February	−0.11*	−0.17***	−0.22***	−0.08***	−0.21
	(0.06)	(0.03)	(0.03)	(0.03)	(0.17)
March	0.04	−0.18***	−0.27***	−0.08***	−0.21
	(0.07)	(0.03)	(0.03)	(0.03)	(0.17)
April	0.37***	0.01	−0.06**	0.03	0.04
	(0.06)	(0.03)	(0.03)	(0.03)	(0.16)
May	0.50***	0.06*	−0.03	0.03	−0.13
	(0.06)	(0.03)	(0.03)	(0.03)	(0.11)
June	0.40***	0.05*	0.01	0.11***	−0.07
	(0.06)	(0.03)	(0.03)	(0.03)	(0.11)
July	0.39***	0.07**	−0.01	0.01	−0.19
	(0.06)	(0.03)	(0.03)	(0.03)	(0.13)
August	0.35***	0.11***	0.04	0.01	−0.10
	(0.06)	(0.03)	(0.03)	(0.03)	(0.11)
September	0.37***	0.15***	0.05*	0.09***	0.07
	(0.06)	(0.03)	(0.03)	(0.03)	(0.11)
October	0.41***	0.20***	0.10***	0.11***	0.16
	(0.06)	(0.03)	(0.03)	(0.03)	(0.10)
November	0.26***	0.08***	0.04	0.08***	0.13
	(0.06)	(0.03)	(0.03)	(0.03)	(0.11)
Time(1)	0.0001***				
	(0.0000)				
Time(2)		0.0001***			
		(0.0000)			
Time(3)			0.0001***		

			(0.0000)		
Time(4)				−0.0000	
				(0.0000)	
Constant	1.77***	3.33***	3.45***	4.82***	1.05***
	(0.08)	(0.04)	(0.04)	(0.03)	(0.19)
Observations	1,826	1,826	1,826	1,826	1,826
Adjusted R^2	0.31	0.46	0.43	0.73	0.16
F Statistic	26.31***	50.01***	44.47***	159.11***	12.59***
	(df = 32; 1793)	(df = 32; 1793)	(df = 32; 1793)	(df = 32; 1793)	(df = 31; 1794)
Note:	*p<0.1; **p<0.05; ***p<0.01				
	The abbreviations may be consulted in Table B.1 and Table B.2				

Table A.9: Extended regression outputs - log location of the accidents

	Dependent variable:				
	log Acc_High	log Acc_A	log Acc_B	log Acc_C_Loc	log Acc_Cross
	HAC	*HAC*	*HAC*	*HAC*	*HAC*
	(1)	(2)	(3)	(4)	(5)
Share_Covid	−0.01**	−0.01***	−0.004***	−0.01***	−0.02**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.01)
Covid_19	−0.08***	−0.09***	−0.01	−0.10***	−0.34***
	(0.03)	(0.02)	(0.01)	(0.01)	(0.08)
Avg_Prec	0.05***	0.01***	0.01***	0.01***	0.03***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.01)
Adj_Avg_Temp	−0.01	0.003*	0.004**	0.004***	0.01
	(0.003)	(0.002)	(0.002)	(0.001)	(0.01)
Avg_Wind	0.01	0.01	−0.002	−0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
Christmas	−0.25	−0.19**	−0.29***	−0.60***	−0.43**
	(0.16)	(0.10)	(0.09)	(0.08)	(0.19)
Easter	−0.34**	−0.33***	−0.29***	−0.40***	−0.79
	(0.13)	(0.09)	(0.09)	(0.07)	(0.50)
New_Year	1.18***	0.38***	0.42***	0.74***	0.72***

	(0.17)	(0.10)	(0.06)	(0.07)	(0.18)
Oth_Nat_Hol	−0.23***	−0.21***	−0.18***	−0.43***	−0.43***
	(0.07)	(0.05)	(0.04)	(0.04)	(0.10)
Weekend	−0.26***	−0.24***	−0.20***	−0.40***	−0.74***
	(0.03)	(0.01)	(0.01)	(0.01)	(0.08)
Spring	0.44***	0.18***	0.13***	0.13***	0.21**
	(0.03)	(0.02)	(0.02)	(0.01)	(0.10)
Summer	0.43***	0.29***	0.24***	0.16***	0.31***
	(0.03)	(0.02)	(0.02)	(0.01)	(0.09)
Autumn	0.39***	0.34***	0.28***	0.22***	0.51***
	(0.03)	(0.02)	(0.02)	(0.01)	(0.09)
Constant	2.09***	3.47***	3.59***	5.20***	1.65***
	(0.05)	(0.03)	(0.03)	(0.02)	(0.14)
Observations	1,826	1,826	1,826	1,826	1,826
Adjusted R^2	0.28	0.38	0.32	0.68	0.13
F Statistic	54.34***	85.51***	68.24***	293.25***	22.43***
			(df = 13; 1812)		

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted in Table B.1 and Table B.2

Table A.10: Regression outputs - log causality of accidents

	Dependent variable:				
	log Not_Ad_Sp	log Risk_Ovt	log N_Ri_Way	log Tech_Iss	log Inap_Sty
	HAC	*HAC*	*HAC*	*HC*	*HAC*
	(1)	(2)	(3)	(4)	(5)
Share_Covid	−0.003	−0.02	−0.01***	0.04	−0.01***
	(0.003)	(0.02)	(0.002)	(0.03)	(0.001)
Lockdown_1	−0.08	−0.50	−0.68***	−1.10	−0.40***
	(0.05)	(0.44)	(0.10)	(0.74)	(0.04)
Lockdown_2	−0.05	0.39	−0.26***	−2.69**	−0.20***
	(0.10)	(0.61)	(0.06)	(1.21)	(0.04)
Lockdown_3	0.02	−1.78***	−0.45***	−0.76	−0.30***
	(0.09)	(0.64)	(0.06)	(0.79)	(0.03)

Bet_Lock_1_2	0.0002	0.07	−0.09***	−1.25***	−0.07***
	(0.04)	(0.20)	(0.02)	(0.44)	(0.02)
Bet_Lock_2_3	0.12	−0.65	−0.16***	−2.53***	−0.12***
	(0.08)	(0.47)	(0.04)	(0.69)	(0.03)
Aft_Lock_3	−0.02	0.01	−0.07***	−0.73**	−0.04**
	(0.05)	(0.24)	(0.02)	(0.34)	(0.02)
Avg_Prec	0.06***	−0.03**	−0.001	−0.05	−0.001
	(0.004)	(0.01)	(0.002)	(0.04)	(0.001)
Adj_Avg_Temp	−0.02***	0.05***	0.01***	0.05	0.01***
	(0.003)	(0.02)	(0.002)	(0.03)	(0.001)
Avg_Wind	0.02	−0.20***	−0.01	0.08	−0.01**
	(0.01)	(0.07)	(0.01)	(0.13)	(0.005)
Christmas	−0.17	−1.35	−1.07***	−3.98***	−0.79***
	(0.13)	(1.04)	(0.10)	(0.80)	(0.07)
Easter	0.04	−1.41*	−0.39***	−3.83***	−0.36***
	(0.08)	(0.84)	(0.11)	(1.08)	(0.08)
New_Year	0.28***	1.17***	0.03	0.36	0.97***
	(0.10)	(0.39)	(0.19)	(3.25)	(0.09)
Oth_Nat_Hol	−0.02	−0.34	−0.61***	−3.10***	−0.45***
	(0.06)	(0.33)	(0.07)	(0.92)	(0.04)
Monday	−0.07**	1.15***	0.68***	3.72***	0.54***
	(0.03)	(0.23)	(0.03)	(0.37)	(0.01)
Tuesday	−0.11***	1.35***	0.69***	2.80***	0.48***
	(0.03)	(0.21)	(0.03)	(0.40)	(0.01)
Wednesday	−0.06*	1.55***	0.77***	3.19***	0.53***
	(0.03)	(0.20)	(0.03)	(0.39)	(0.01)
Thursday	−0.03	1.37***	0.76***	2.94***	0.51***
	(0.03)	(0.21)	(0.02)	(0.39)	(0.01)
Friday	0.12***	1.57***	0.77***	3.15***	0.58***
	(0.03)	(0.21)	(0.03)	(0.39)	(0.01)
Saturday	0.19***	0.48*	0.19***	0.85**	0.16***
	(0.03)	(0.25)	(0.03)	(0.40)	(0.02)
January	0.05	−0.28	−0.19***	0.38	−0.10***
	(0.06)	(0.34)	(0.04)	(0.54)	(0.03)
February	−0.24***	0.07	−0.20***	1.57***	−0.04
	(0.06)	(0.31)	(0.04)	(0.55)	(0.03)
March	−0.57***	0.03	−0.16***	0.97*	−0.003

	(0.06)	(0.36)	(0.04)	(0.57)	(0.03)
April	−0.57***	0.82***	0.10**	1.59***	0.12***
	(0.05)	(0.28)	(0.04)	(0.57)	(0.03)
May	−0.51***	0.53*	0.03	2.25***	0.12***
	(0.05)	(0.30)	(0.04)	(0.55)	(0.03)
June	−0.39***	0.81***	0.12***	2.57***	0.23***
	(0.05)	(0.29)	(0.04)	(0.57)	(0.03)
July	−0.38***	0.79***	−0.001	2.60***	0.15***
	(0.05)	(0.29)	(0.04)	(0.55)	(0.03)
August	−0.33***	0.72**	0.02	1.36**	0.14***
	(0.05)	(0.30)	(0.04)	(0.57)	(0.03)
September	−0.27***	0.72**	0.16***	2.64***	0.19***
	(0.05)	(0.29)	(0.04)	(0.54)	(0.03)
October	−0.32***	0.80***	0.18***	1.13**	0.21***
	(0.05)	(0.29)	(0.04)	(0.56)	(0.03)
November	−0.26***	0.22	0.10***	1.19**	0.12***
	(0.05)	(0.33)	(0.04)	(0.54)	(0.03)
Time(1)	−0.0001*				
	(0.0000)				
Time(2)		−0.0001			
		(0.0002)			
Time(5)					0.0000***
					(0.0000)
Constant	3.81***	−0.39	2.95***	−7.16***	4.49***
	(0.07)	(0.39)	(0.05)	(0.65)	(0.03)
Observations	1,826	1,826	1,826	1,826	1,826
Adjusted R^2	0.37	0.15	0.68	0.13	0.77
F Statistic	35.18*** (df = 32; 1793)	11.23*** (df = 32; 1793)	126.60*** (df = 31; 1794)	9.84*** (df = 31; 1794)	192.82*** (df = 32; 1793)

Note: *p<0.1; **p<0.05; ***p<0.01

The abbreviations may be consulted in Table B.1 and Table B.2

Table A.11: Extended regression outputs - causality of accidents

	Dependent variable:				
	Not_Ad_Sp	Risk_Ovt	N_Ri_Way	Tech_Iss	Inap_Sty
	HAC	*HAC*	*HAC*	*HC*	*HAC*
	(1)	(2)	(3)	(4)	(5)
Share_Covid	0.14	-0.02^{**}	-0.32^{***}	-0.004	-1.08^{***}
	(0.11)	(0.01)	(0.04)	(0.01)	(0.12)
Covid_19	-4.46^{***}	-0.33^{**}	-5.04^{***}	-0.23^{***}	-8.55^{***}
	(0.93)	(0.13)	(0.54)	(0.07)	(1.55)
Avg_Prec	3.03^{***}	-0.06^{***}	0.12^{*}	-0.01	0.42^{**}
	(0.26)	(0.02)	(0.07)	(0.01)	(0.17)
Adj_Avg_Temp	-1.09^{***}	0.09^{***}	0.34^{***}	0.02^{**}	1.48^{***}
	(0.15)	(0.02)	(0.06)	(0.01)	(0.18)
Avg_Wind	1.37^{*}	-0.15^{**}	0.08	0.04	-2.25^{***}
	(0.81)	(0.06)	(0.25)	(0.03)	(0.68)
Christmas	-3.73	-0.70	-16.65^{***}	-0.85^{***}	-64.96^{***}
	(5.85)	(0.43)	(2.64)	(0.13)	(8.53)
Easter	-0.36	-1.21^{***}	-15.06^{***}	-0.76^{***}	-55.65^{***}
	(2.29)	(0.43)	(2.73)	(0.19)	(8.67)
New_Year	15.73^{***}	0.72	-0.17	-0.19	200.61^{***}
	(4.44)	(0.70)	(5.62)	(0.61)	(11.75)
Oth_Nat_Hol	-2.47	-0.94^{**}	-19.23^{***}	-0.65^{***}	-61.36^{***}
	(2.85)	(0.37)	(1.95)	(0.16)	(5.62)
Weekend	3.69^{***}	-1.70^{***}	-19.35^{***}	-0.67^{***}	-61.73^{***}
	(1.07)	(0.10)	(0.41)	(0.05)	(1.17)
Spring	-15.37^{***}	1.46^{***}	8.83^{***}	0.28^{***}	29.46^{***}
	(1.56)	(0.14)	(0.61)	(0.08)	(1.77)
Summer	-9.89^{***}	2.12^{***}	9.51^{***}	0.43^{***}	36.17^{***}
	(1.63)	(0.16)	(0.62)	(0.08)	(1.67)
Autumn	-3.30^{*}	1.21^{***}	12.83^{***}	0.15^{**}	37.01^{***}
	(1.84)	(0.14)	(0.58)	(0.07)	(1.59)
Constant	45.36^{***}	3.10^{***}	34.31^{***}	0.96^{***}	147.25^{***}
	(2.74)	(0.22)	(0.99)	(0.12)	(2.68)
Observations	1,826	1,826	1,826	1,826	1,826
Adjusted R^2	0.24	0.24	0.63	0.11	0.72

F Statistic	44.48***	46.48***	241.58***	19.17***	355.58***
			(13; 1812)		

Note: *p<0.1; **p<0.05; ***p<0.01
The abbreviations may be consulted in Table B.1 and Table B.2

Table A.12: Extended regression outputs - log causality of accidents

	Dependent variable:				
	log Not_Ad_Sp	log Risk_Ovt	log N_Ri_Way	log Tech_Iss	log Inap_Sty
	HAC	*HAC*	*HAC*	*HC*	*HAC*
	(1)	(2)	(3)	(4)	(5)
Share_Covid	0.003	−0.03**	−0.01***	−0.03	−0.01***
	(0.002)	(0.01)	(0.002)	(0.02)	(0.001)
Covid_19	−0.11***	−0.27**	−0.17***	−0.75***	−0.06***
	(0.02)	(0.11)	(0.02)	(0.27)	(0.01)
Avg_Prec	0.07***	−0.02	0.004*	−0.03	0.003***
	(0.004)	(0.01)	(0.002)	(0.04)	(0.001)
Adj_Avg_Temp	−0.02***	0.05***	0.01***	0.06*	0.01***
	(0.003)	(0.02)	(0.002)	(0.03)	(0.001)
Avg_Wind	0.01	−0.20***	−0.005	0.03	−0.02***
	(0.01)	(0.07)	(0.01)	(0.13)	(0.01)
Christmas	0.02	−1.12	−0.83***	−4.65***	−0.68***
	(0.12)	(1.05)	(0.09)	(0.69)	(0.06)
Easter	0.01	−1.72*	−0.52***	−3.99***	−0.45***
	(0.07)	(0.89)	(0.11)	(0.97)	(0.08)
New_Year	0.51***	1.07***	0.05	0.07	0.96***
	(0.08)	(0.31)	(0.18)	(2.52)	(0.08)
Oth_Nat_Hol	−0.06	−0.23	−0.61***	−2.61***	−0.44***
	(0.06)	(0.34)	(0.07)	(0.87)	(0.04)
Weekend	0.12***	−1.15***	−0.64***	−2.72***	−0.45***
	(0.02)	(0.14)	(0.02)	(0.24)	(0.01)
Spring	−0.31***	0.96***	0.27***	1.11***	0.20***
	(0.03)	(0.15)	(0.02)	(0.32)	(0.01)
Summer	−0.15***	1.13***	0.32***	1.45***	0.26***
	(0.03)	(0.16)	(0.02)	(0.32)	(0.01)

Autumn	−0.02	0.78***	0.39***	0.55*	0.27***
	(0.03)	(0.17)	(0.02)	(0.31)	(0.01)
Constant	3.62***	0.62**	3.45***	−3.27***	4.95***
	(0.05)	(0.26)	(0.03)	(0.49)	(0.02)
Observations	1,826	1,826	1,826	1,826	1,826
Adjusted R^2	0.27	0.13	0.63	0.12	0.71
F Statistic	52.39***	22.35***	241.76***	19.27***	347.62***
			(13; 1812)		

Note: *p<0.1; **p<0.05; ***p<0.01

The abbreviations may be consulted in Table B.1 and Table B.2

Appendix B

Description and overview of variables

Table B.1: Overview of dependent variables

Dependent variables describing traffic accidents	
Variable name (Abbreviation)	Description
Acc_Total	Total number of all daily accidents in the Czech Republic
Acc_Alcohol	Total number of daily accidents, where alcohol was detected by the offender
Acc_Drugs	Total number of daily accidents, where an illegal substance other than alcohol was present by the offender
Acc_No_Injury (Acc_No_Inj)	Total number of daily accidents, where nobody was injured
Acc_Non_Serious_Injury (Acc_Non_Ser_Inj)	Total number of daily accidents, where the worst injury was a minor injury
Acc_Serious_Injury (Acc_Ser_Inj)	Total number of daily accidents, where the worst injury was a severe injury
Fatality	Total number of daily accidents, where at least one person died
Non_Seriously_Injured_People (Non_Ser_Inj_Pe)	Total daily number of people who suffered a minor injury in a traffic collision
Seriously_Injured_People (Ser_Inj_Pe)	Total daily number of people who suffered a severe injury in a traffic collision

Dead_People_Acc (Dead_Pe_Acc)	Total daily number of people who died during or as a consequence of a traffic accident
Acc_Highway (Acc_High)	Total daily number of accidents, which occurred on highways
Acc_A_Road (Acc_A)	Total daily number of accidents, which occurred on A roads
Acc_B_Road (Acc_B)	Total daily number of accidents, which occurred on B roads
Acc_C_Local_Road (Acc_C_Loc)	Total daily number of accidents, which occurred on C roads and local roads
Acc_Crossing (Acc_Cross)	Total daily number of accidents, which occurred on the monitored road intersections lead by traffic lights
Acc_Not_Adjusted_Speed (Not_Ad_Sp)	Total daily number of accidents, where the main cause of the accident was not properly adjusted speed to the current surrounding conditions
Acc_Risky_Overtaking (Risk_Ovt)	Total daily number of accidents, which were caused mainly by inappropriate overtaking
Acc_No_Right _Way (N_Ri_Way)	Total daily number of accidents, which were caused by the driver not giving right way to other drivers, when necessary
Acc_Technical_Issue (Tech_Iss)	Total daily number of accidents, which were caused by technical defect on the vehicle
Acc_Inappropriate_Style (Inap_Sty)	Total daily number of accidents, which were caused by other inappropriate style of driving or not paying attention

Table B.2: Overview of independent variables

Independent variables	
Variable name (Abbreviation)	Description
New_Covid _Cases (Cov_Cases)	Total number of daily newly detected Covid-19 cases in the Czech Republic
Dead_Covid	Total number of people, who died because of Covid-19 disease in the given day
Hospitalized	Total number of people, that where hospitalized with Covid-19 to a given date
Share_New_Covid_From-_All_Tests (Share_Cov)	The daily ratio of positive tests from the number of all tests on Covid-19
Covid_19	Dummy variable indicating the Covid-19 disease present in the Czech Republic (1 after 1.3.2020, 0 otherwise)
Lockdown_1	Dummy variable indicating the period of the first lockdown (i.e. 16.3.2020 - 24.4.2020)
Lockdown_2	Dummy variable indicating the period of the second lockdown (i.e. 22.10.2020 - 20.11.2020)
Lockdown_3	Dummy variable indicating the period of the third lockdown (i.e. 1.3.2021 - 11.4.2020)
Between_Lockdowns_1_2 (Bet_Lock_1_2)	Dummy variable indicating the period between the first and second lockdown in the Czech Republic
Between_Lockdowns_2_3 (Bet_Lock_2_3)	Dummy variable indicating the period between the second and third lockdown in the Czech Republic
After_Lockdown_3 (Aft_Lock_3)	Dummy variable indicating the period after the third lockdown in the Czech Republic

Avg_Precipitation (Avg_Prec)	Average daily volume of rainfall for the Czech Republic, measured in mm
Avg_Temperature ((Adj_) Avg_Temp)	(Seasonaly adjusted) average daily temperature for the whole Czech Republic in degrees Celsius
Low_Temperature (Low_Temp)	Dummy variable indicating the 15% of the coldest days in the year when the average daily temperature for the whole Czech Republic dropped under 0 degrees Celsius
High_Temperature (Low_Temp)	Dummy variable indicating the 15% of the warmest days in the year when the average daily temperature for the whole Czech Republic reached more than 18 degrees Celsius
Avg_Wind	Average daily speed of wind in the Czech Republic in m/s
Strong_Wind (Str_Wind)	Dummy variable indicating whether the average daily speed of wind in the Czech Republic exceeded 3.1 m/s corresponding to the 85th percentile
Easter	Dummy variable indicating the Easter period in the Czech Republic
Christmas	Dummy variable indicating the Christmas period in the Czech Republic
New_Year	Dummy variable indicating the January 1st - New Year
Other_National_Holidays (Oth_Nat_Hol)	Dummy variable indicating the other state holidays in the Czech Republic, except for Christmas, Easter and New Year
Days of the week variables	Dummy variables indicating the day of the week or weekend vs. workday
Months of the year	Dummy variables indicating the calendar months (January to December)
Seasons of the year	Dummy variables indicating the quarters of the year (spring to winter)