Master Thesis

University of Basel
Faculty of Business and Economics

Master of Science in Economics and Public Policy

The Less the Better? An Empirical Analysis of Vehicle Density and Accident Relationships

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Submitted:
June 7, 2024

Abstract

Accidents are a driver of costs related to traffic. While they have a direct impact on the people involved, the associated external costs reduce societal welfare. Research on the effect of different traffic conditions on total accidents and injury severity in Switzerland is rare. I am the first to use the reduction in traffic volume during the Covid-19 lockdown to analyse its effect on accidents and related injuries in Switzerland, using an extensive data set of all police reported accidents. I find an increase in the probability of being fatally injured in an accident during the lockdown period, with a decrease in probability of remaining unharmed. Higher speed is a known amplifier of injury severity and is associated to low traffic density. Analysing accidents in different traffic densities reveals an increased probability of dying in an accident occurring in a low density environment and higher probabilities of sustaining light injuries or remaining unharmed in high traffic density. Combining daily accident counts with daily traffic counts shows, that the relative rate of total accidents and unharmed casualties remains unchanged with increasing traffic volume. The relative rate of fatalities decreases, while the relative rates of severe and light injuries increases as traffic counts rise. Investigation of the impact of average speed in different categories throughout the day revealed no usable results and implies the need of further research on that topic.

Applying the results on two independent scenarios of possible mobility policies leads to expected daily savings of 15’895 - 42’076 CHF, but also potential emergence of additional daily costs of 8’501 CHF. This shows, that policies targeting mobility behavior can generate both additional costs and savings, depending on the segment of traffic they target. My results help policy makers to anticipate the effects of mobility policies and to adjust them accordingly.

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1 Introduction

Accidents are a daily part of traffic and with increasing mobility, on a regional and global level, the interest in contributing factors of both accident frequency as well as accident severity is rising. Accidents are multilayered events, including one to multiple vehicles and persons, each suffering different levels of damage or injuries. Different types and weights of vehicle pose diverse threats to damage on itself and other vehicles, as well as possible injury patterns on the own occupants or persons colliding with that vehicle. In addition, factors like speed, traffic density and volume have a large impact on accident results.
This Master Thesis examines the research question: What is the effect of traffic density and traffic volume on the relative rate of accidents and more importantly their impact on injury patterns resulting from accidents in Switzerland? Using the Swiss National Accident Register and combining it with traffic counts on Swiss highways and the results from the MOBIS and MobisCovid experiment, the goal is to exploit changes in traffic behavior and different traffic situations and their impact on the accidents. One of the major problems with traffic analyses, including accident research, is the heterogeneity of people's mobility behaviors. Gathering data on traffic is difficult, because the situation strongly varies between places and over time. And collecting information on all relevant factors is associated to immense effort. Most research is therefore based on datasets gathered by the researchers themselves at given segments or areas during a specific period, selectively collecting the information needed. With a recent emergence of comprehensive datasets based on individual smartphone tracking. Both methods are technically sophisticated and costly, which results in me not being able to collect data on traffic volume or speed for this work myself. The last survey on Swiss streets was performed by the Swiss bord for accident prevention and published in Niemann (2020). It was a pilot project and results showed, that average speeds are not exceeding the speed limits, except fro 30km/h regimes. Additionally, by reducing the individual speeds measured above the speed limit, Niemann (2020) states a possible reduction of 22 fatal and 337 severely injured accident casualties per year. Nevertheless, the automatic measuring systems are found to be imprecise due to errors in detection and periodical measurements were not started. The Swiss Federal Statistical Office collects daily counts on some major highway sections, which are only counts on a daily aggregation and do not include any information on speed or volume distribution over the days. As of my knowledge there are no official countrywide information on traffic volume besides the highways or on vehicle speeds at all. With my supervisor Prof. Dr. Beat Hintermann being part of the MOBIS and MobisCovid research group, I could access their extensive dataset of individual mobility tracking in Switzerland between fall 2019 and summer 2020.
Most research on this topic is based on within-day variation, which exploits different traffic conditions over the day and its impact on speed, density, injury patterns and accident frequency. The disadvantage of this approach is the necessity to compare different groups with each other. The driver characteristics, reason of trips, vehicles etc. are very heterogeneous over 24 hours. A professional driver delivering goods on a tight timetable during the night most likely shows a different driving behavior than a parent doing the weekly shopping before noon, maybe even having kids in the car. The first is assigned to a low density high speed period, while the latter falls into a period with more traffic density and assumably lower speeds. But what is the reason for a possible finding of relatively more accidents during the night? It could be due to higher speed, but also originate in reckless driving of the strained professional driver. Careful inclusion of control variables is mandatory for any within-day approach and it remains an artificial comparison. In addition to the within-day analysis, I therefore want to use the period of the Covid-19 lockdown in Switzerland in spring 2020, which brought a reduction of nearly

50% in traffic volume in Switzerland, and compare it to the same periods in the previous years. I believe that the lockdown, being a natural experiment affecting the whole country, comes with less variation in driver composition than the within-day approach. Which assumably makes it a superior model. Though, also the Lockdown had a large impact on the mobility behavior of Switzerland.

I am interested in two aspects of accidents. The number of accidents, which can be expressed in total or relative accidents. The total number of accidents is largely dependent on the number of vehicles on the road, thus I am more interested in the relative number of accidents. They show the number of accidents proportional to traffic volume and I want to analyse whether this relationship varies in different traffic conditions. The second aspect I analyse is the severity of injuries following an accident. The injury severity is influenced by multiple factors and I am assessing the effect of different traffic conditions on these outcomes. Based on the theory and literature reviewed in Section 2, I post two hypotheses about what I expect to have happened in Switzerland during the Covid-19 lockdown period and more general when comparing low versus high traffic volume situations:

1. A reduction of traffic volume leads to an increase in relative accident rates.
2. A reduction of traffic volume causes a shift in the crash injury pattern from light injuries towards more severe and fatal outcomes.

I built two different models to perform logit regression of the impact of varying traffic conditions on the probabilities of accident outcomes. First I used the individual accidents and calculated the change in probability of ending up in a specific injury category when comparing the Lockdown period in the Covid-19 year of 2020 with the previous years. I found an increased probability of being fatally injured during the Covid-19 lockdown, compared to the same time in 2019 and a slight decrease in the probability of remaining unharmed in an accident during this time. Second, I also estimated the change in probability of ending up in a specific injury category by different traffic densities at the time of accident. This measure of density is part of the accident data and was determined by the police when filing the accident report. Both models estimate the probability conditional on having an accident, because there is no detailed data on traffic volume that can be merged with the individual accidents, thus the dataset used for these calculations consists of accidents only. Based on a deviation from normal traffic density, I find a statistically significant increase of 130% in the probability of being fatally injured in low traffic density, while in high density the probabilities of light injury and remaining unharmed rise by 12.81% and 2.69% respectively. For all other categories I find a reduction in probability of ending up in them.

To be able to incorporate measures for traffic volume, I aggregated the accidents on daily counts and combined them with the daily traffic counts from Swiss highways. This is necessary to control for traffic volume variation, without which I could not isolate the effect on relative accident numbers. Polynomial OLS regression was conducted and I found a positive linear correlation between total accidents and traffic volume, indicating that the relative accidents are unchanged by the number of traffic on the road. Additionally, no correlation between traffic counts and fatal outcomes was found, but increasing effects on accidents with severely injured, lightly injured and unharmed persons. Including the traffic counts also allows to calculate scenarios of mobility policies targeting the number of vehicles on the road, in addition to policies aiming at reducing congestion. By that, this model gives valuable insights on accident related costs when traffic volume varies. Finally, I used data from the MOBIS and MobisCovid experiments, both tracking smartphones, calculating average speeds for 12 categories of time and speed regimes for each day. Analyzing the effect of increasing average speed on accident numbers produced mostly insignificant results, with few categories showing significant positive or negative effects.

An overview of the four models can be found in Table 1. It includes the outcome of interest and the variable used to explain the observed changes in the specific outcome(s). Further the main results are summarized in the last column.

Outcome of Interest	**Explanatory Variable**	**Results**
Probability of experiencing a specific injury	Covid-19 Lockdown (difference in traffic volume between spring 2019 and 2020)	+130% probability of fatal injury -1.54% probability of remaining unharmed *during the Lockdown in 2020, compared to 2019*
Probability of experiencing a specific injury	Traffic Density	Increased probability of fatal injury in low traffic density and of less severe injuries and unharmed during high traffic density conditions. Decrease in the probabilities of the other categories.
Accidents and injury categories as daily counts	Daily traffic counts from Swiss highways	No changes in the relative rate of accidents as well as unharmed casualties. Decrease of relative rate of fatal accidents. Increase of relative rate of severe and lightly injured. *All with regard to increasing traffic counts*
Accident counts in 12 categories per day	Daily average speed in 4 time and 3 speed regime categories	Heterogeneous results, largely varying between the categories with no clear expressiveness.

Table 1: Summary of the four models included in this thesis.

To analyse the effect of mobility policies, targeting congestion or individual car travelling over all, I imagined two scenarios. First, an increase in the price of travelling by car leads to a shift of transport mode away from the car and to a reduction of distance travelled by car, resulting in savings of accident costs of 15'895 - 42076 CHF per day. Second, individual pricing of produced external cost leads to changes in driving behavior and a reduction of congestion. This results in additional accident costs of daily 8'501 CHF due to more severe injuries, assumably caused by higher speed. The two scenarios are not directly comparable, but give an insight that we can expect both reductions and increases of accident related costs by mobility policies impacting traffic volume.

This Thesis is organized as followed. In Section 2 I compile existing theory and empirical results on the topic, Section 3 reviews previous work on the reactions of mobility behavior on the Covid-19 measures in Switzerland and Section 4 explains the methodology I apply. In Section 5 the used data is explained, Section 6 provides the results of the estimations and in Section 7 I apply the results in calculating Policy Implications. Finally, I discuss the results in Section 8 and a conclusion is provided in Section 9.
All calculations were performed using StataMP 16 on a MacBook Pro M1 2020. All figures and tables are created by the author with the data used in the specific model. Additional data used for particular figures is mentioned in the caption.

2 Theory and Existing Literature

2.1 Speed-Density Relationship

As with all compressible physical materials that need to pass through a confined space, increasing the volume we want to pass through inevitably increases the density of the material inside the confined space. The same accounts for traffic flowing on roads which build a confined space with capacity limits. But unlike a gas the increase in pressure does not accelerate traffic, it slows down and eventually comes to a full stop. Thus, we can not rely on basic physics to understand the mechanisms of dense traffic, even though concepts like friction, e.g. drivers do not want to bump in each other, and inhomogeneous speeds are likely explanations.
Since the beginning of the 20^{th} century researchers from different fields tried to understand and mathematically express the density of traffic and its impact on speed. Greenshields et al. (1935) were some of the first building up a model for the relationship of traffic density and speed in the style that is still used today. They also reinforced their theoretical work with an extensive field study by collecting data on roads. The model stated a linear negative relation of speed and density, saying that as density on roads increase the average speed will decline. Since then the negative relationship was never challenged. Nevertheless, the functional form of the relationship was largely debated over and still is up to this day. They also introduced the concept, that below a specific density the average speed does not increase anymore. This is called "free speed" and might either be defined through the shape of the road, e.g. curves slow down, or by speed limits. Greenshields et al. (1935) also invented the concept of traffic flow, which is number of vehicles per hour, and called it Density-Vehicles per hour without knowing that twenty years later Lighthill and Whitham (1955) would include this as traffic flow in their work. They challenged the assumption of linear relationship and explained, that the impact of one additional car, with regard to different density states, is not always the same. Therefore the slope of the function differs depending on which number of car the marginal car is in a specific segment, which leads to a nonlinear relationship. This is also based on work done by the Great Britain Road Research Laboratory. As mentioned above, Lighthill and Whitham (1955) use the flow density relationship which is conceptually similar, but has an increasing section at lower densities. This comes from the fact that flow equals vehicles per hour and at very low densities there are only few vehicles passing the section. As density raises the flow does so to until the "free speed" limit is reached, leading to a stagnation of flow increase. After passing another threshold of density the flow starts to decline since the whole column of cars gets slower. Multiple researchers propose different forms of the functional relationships between speed and traffic density and a comprehensive summary, including empirical testing can be found in Bramich et al. (2022). They conclude that the newest model developed by Sun et al. (2014) fits best on their extensive empirical data and propose to use this one as the current state of the art. The major superiority comes from applying a non-parametric smoothing function which approximates the empirical data closest.
Modern research on this topic highly focuses on exploiting large empirical datasets. Qu et al. (2015) re-estimate some of the aforementioned models with the weighted least squares method (WLSM), instead of the ordinary least squares method (OLS), which assigns a weight to the squared error of every observation that is smaller in denser areas and vice versa. This reduces the impact of dense areas on the slope of the regression line an allows for better fitting the model over the whole distribution of observations. Further, both Chiappone et al. (2016) and Wang et al. (2022) use large datasets from Italy and from Shanghai respectively, to calibrate and validate their models more sophisticated in order to make them capable to even simulate future traffic conditions.
With the possibility of exploiting large datasets arose a literature investigating confounding

factors that impact the speed-flow-density relationships. Ben-Edigbe (2010) found that adverse road conditions account for a 50% reduction of optimal speed. Heydecker and Addison (2011) analyze data from the United Kingdom and find, that conditional on varying speed limits it is not always density defining the current speed, but causality can also be inverted such that limited speed effects the degree of density. Loder et al. (2019) analyzed traffic network topologies with data from 41 major cities around the world and the impact of topology on speed, flow and density. Showing that topology accounts for 90% of critical point (boundary of free speed and crowded) variation and concluding that infrastructure investments have decreasing marginal returns on traffic volume capabilities. In line with that is the work of Zefreh and Török (2020) separating Budapest traffic in different traffic conditions by analyzing video footage. They emphasize that diverse traffic conditions also need diverse fundamental diagrams, i.e. speed-density and flow-density relationships, and that one over all relationship is too much of a simplification. Finally the impact of speed heterogeneity and rainfall on the fundamental diagram was investigated by Bai et al. (2021). Concluding that speed heterogeneity accounts for 18%-24% of free speed and mean speed variance. In addition rainfall intensity leads to a reduction in both free speed and mean speeds in all observed specifications. This research shows, that there are numerous confounding factors influencing the fundamental diagram and its depicted relationships. Therefore, it will be mandatory to control for as many of them as possible in my upcoming models and estimations.
Anyhow, the detailed form of the functional relationship of density and speed is not of importance for this Master Thesis. Decreasing density does increase average vehicle speed until a certain "free speed", about that the aforementioned agree on. Therefore, I will stay with the basic linear relationship invented by Greenshields et al. (1935) and depicted in Equation (1), for it will sufficiently explain the concept.

$$V = v_f(1 - \frac{k}{k_j}) \tag{1}$$

V is the average speed derived by the model, while v_f is the "free speed", k is the current traffic density and k_j its maximum value. Meaning that k/k_j is the current proportionate density. We see that when current density starts to rise, which will happen after a specific number of vehicles on the segment is exceeded, the average speed will start to decline.

2.2 Speed, Accident-Incidence and Injury Severity

Here I summarize literature investigating the relationship between speed and accidents, mainly number of accidents and their severity. The vast majority of researchers find a positive correlation between mean speed and relative accident frequency, as well as resulting severity of injuries. The concept of relative accident frequency is of big importance here, since the absolute accident frequency is largely dependent of the volume of traffic, i.e. cars on the road, which is again highly correlated with speed as discussed in the previous section. The most common approach is to calculate vehicle-miles travelled (or kilometers, also person-miles travelled are possible). This generates useful and credible measure of traffic volume which can be further exploited. As a second approach, researchers define a segment or area and count passing vehicles and accidents during the period of interest. This approach is inferior to the vehicle-miles, due to the fact that each count weights the same independent of trip length, while vehicle-miles also account for different trip lengths and therefore for the real time on the road. This disadvantage of the section counts can be attenuated by performing counts on several small segments and aggregating the results to a bigger geographical picture of traffic flows. Data based on counts has been used more often, since it is easier to gather compared to tracking individual peoples mobility. In earlier days, vehicle- or person-miles travelled were based on travel survey or extrapolated from traffic counting systems. Nevertheless, with the opportunity of modern smartphone tracking exact information on vehicle-miles travelled is on the advance. I will focus on publications after the year 2000 because there is plenty of recent literature to discuss this topic and older conclusions are often reviewed in those papers.

Taylor et al. (2000) investigated road data from the United Kingdom separating roads into several categories. They find that accidents increase with increasing speeds and that accident frequency rises over proportional with higher average speed. Positive correlation between speed and relative numbers of accidents, as well as good prediction of accidents with injured people by the power model is reported by Nilsson (2004). Adding, that fatal accidents are underestimated by this model. To calculate the relative numbers of accidents, he used person-kilometers travelled as well as vehicle-kilometers travelled. The power model, in this scenario, raises ratios of before/after speed with an exponent and results in a ratio of before/after accidents. An extensive explanation of the power model can be found at the beginning of Elvik et al. (2004) who report similar results and state that the relationship between speed and accidents is causal, with speed being a major risk factor for relative accident frequency and severity of injuries. They specifically control for traffic volume, by only including data in their model that origins from research which already included any measure of traffic volume itself. Aarts and Van Schagen (2006) provide a first summary of results and enforce the state of knowledge that increasing speed does increase both relative accident occurrence and injury severity. But road and traffic characteristics, including traffic density, as well as driver characteristics play a crucial role in the magnitude of this relationship. Further, not only average speed but also speed variance, meaning the heterogeneity of individual vehicle speeds, leads to a large increase in crash risks at all speed levels.

An interesting variation in travel speeds is analyzed by Ossiander and Cummings (2002) and 13 years later by Van Benthem (2015). In 1987 multiple states in the United States of America were allowed to increase the speed limits from 55 mph to 65 mph. While Ossiander and Cummings (2002) found more than a doubling of fatal accidents, but no increase in total accident counts after the increase of the speed limit using Poisson regression models. Van Benthem (2015) finds a 44.1% increase in fatal accidents, and a 13.2% to 23.5% increase in total accidents, while the average speed only increases by 3 to 4 mph after the 10 mph increase in speed limit. Based on an extensive combined private and social cost-benefit analysis, he concludes that 55 mph was the better speed limit with accident costs and pollutant linked health issues being the by far largest cost factors.

A deeper investigation of confounding factors is performed by Gargoum and El-Basyouny (2016). They used structural equation modelling which, by combining several analysis, allows multiple variables to influence the outcome directly or via mediators. Average speed was set to be a mediator specified by several road and traffic characteristics and was found to have a significant positive correlation with crash frequency. The factors traffic volume (after controlling for congestion effects) and segment length had significant effects not only on average speed but also directly on crash frequency. Posted Speed Limits only had an indirect effect on collision frequencies via average speed, while curvy roads only show a direct decrease in crash frequency and no significant effect mediated through average speed. These results are of big importance for my own work, because much of the mentioned confounders are available in the data at hand and must be controlled for. Similarly, Gitelman et al. (2017) used a negative binomial regression model to calculate the impact of travel speeds on the relative number of accidents. As expected, a positive correlation was found between average speed and accidents, controlling for the same factors as Gargoum and El-Basyouny (2016), including traffic volume. But contrary to them, Gitelman et al. (2017) find a negative effect of curves on the accident frequency. The latest publication on this topic yields no new knowledge. Higher speeds and

lower density both lead to an increase in the relative accident rate while controlling for vehicle density, with the relationship between speed and accidents showing an exponential like pattern Kriswardhana et al. (2023).
ITF (2018) and Elvik et al. (2019) both provide summaries of literature on this topic and agree on the fact, that mean speed has a strong positive correlation to the relative number of accidents and injury severity, mainly on severely injured and fatally injured casualties. This correlation remains after controlling for different road and driver related confounders, as well as environmental impacts. The power model persists to be very precise, complemented with the exponential model Elvik et al. (2004). Both summaries also include work with partly diverting results, as has been found with all research about traffic in the last century, but the main findings always remain the same.
One of the diverting papers is Quddus (2013), who found no statistically significant effect of mean speed on accident rates, but stated a consistent impact of speed variance on accident rates. Estimated with segment-based data from the region of London, including variable traffic volume and controlling for several road characteristics in the segments. This relationship has already been mentioned by Taylor et al. (2000) and later Aarts and Van Schagen (2006). Unfortunately there is no possibility to collect or construct this measurement from my data and thus, I can not include this in my calculations. A direct comparison between congestion and accidents for traffic around London was tested by Wang et al. (2009). They report no impact of congestion on accidents (relative accident rate compared to the vehicle flow) when controlling for other factors like traffic flow and road characteristics, which seem to explain all variation in accident rates. Summarizing different studies on the congestion accident relationship, Retallack and Ostendorf (2019) conclude that some of the diverging results originate from the difference in detail of the used data. Suggesting the use of high-quality traffic data including a spatial differentiation between rural and urban areas. In addition they highlight that the relationship alters when differentiating between first, accident rates being either positively linear or U-shaped (thus most accidents with low or high congestion based on the specific traffic flow) and second, fatal accidents showing an inverse U-shape with most fatalities at medium congestion levels.
From a medical and physical view, speed is clearly one of the main driver for increased injuries. Job and Brodie (2022) explain how the kinetic energy released into the body at an impact increases exponentially with the increase in speed. This was empirically tested by Doecke et al. (2020), confirming that increasing impact speed leads to a higher probability of serious injury. Publications like Daffner et al. (1988) or Weninger and Hertz (2007) made early statements that security measures like seat belts or airbags and the point of impact, i.e. front, side or rear-end, play a crucial role in injury pattern and therefore their severity. Speeding was found to be accountable for 18% of fatal and serious injury accidents in Australia by Doecke et al. (2021). Further, Anderson and Auffhammer (2014) analysed the impact of vehicle weight on the probability of being fatally injured during an accident. They find a large increase in the risk of fatal injury when being hit by a heavier car or even a light truck or SUV, while an increase in own vehicle weight correlates with a decrease in mortality. They suggest to incorporate these external costs of heavier vehicles in a gas tax or a weight varying mileage tax, with the latter being very challenging to implement due to the need of information on the exact vehicle-miles travelled.

2.3 Impact of Covid-19 Measures on Mobility Behavior

The majority of the aforementioned publications exploited the variation of traffic volume and its influence on speed and accidents during the day, this is called within-day variation. While some used the change of policies, mainly adapted speed limits, to investigate the related conse-

quences. In 2020 the Covid-19 pandemic brought large challenges for the whole world including massive lockdowns impacting every part of peoples lives, including their mobility behavior. It did not take long for researchers to publish first analysis of the impact of mobility change, i.e. reduction in traffic volume, on the average speed and accident patterns. The first results were plain statistical comparisons without accounting for any confounding effects. They found a decrease of traffic volume of slightly more than 50% combined with a decrease in accidents of around 75% in Spain Saladié et al. (2020) and around 50% in California, Shilling and Waetjen (2020), who also found an increase in average and maximum speed. Both publications look at total numbers and do not consider changes in number and severity of accidents relative to the change in mobility behavior. The National Highway Traffic Safety Administration of the United States of America published slightly different results, weighting the accidents with an inflation rate which contains the change in Vehicle Miles Travelled (VMT) and accidents from 2019, NHTS (2021), and found a relative increase in fatal accidents for the majority of analyses. Indicating that there was a shift from less to more serious injury accidents.
The methods rapidly improved and results using econometrical approaches were published. Doucette et al. (2021a) used an interrupted time series design, finding that the 43% decrease in VMT lead to an increase in crash rates mainly in single vehicle accidents (2.29 times) and fatal accidents (4.1 times), controlling for temperature and precipitation. In their following work, Doucette et al. (2021b), show that these results are consistent to further robustness checks and differentiation. Throughout the published research the decrease in traffic volume led to mixed effects on the relative occurrence of accidents. Adanu et al. (2021) and Inada et al. (2021) find a relative increase in crashes, though the latter only accounts for fatal crashes. Decreasing relative crash rates are reported by Lin et al. (2020), Brodeur et al. (2021), Hughes et al. (2023) and Patwary and Khattak (2023). Further, all of these find a shift in injury patterns from non-serious to severe injured and especially a large increase in fatal accidents.
Increases in dangerous driving behavior like reckless driving or drinking, Hughes et al. (2023), Patwary and Khattak (2023), omitting of seat belts, Adanu et al. (2021) and speeding are all positively correlated to crash rates and highly increase the probability of being involved in a fatal accident, Katrakazas et al. (2021),
Concluding this subsection, the available research finds mixed results of Covid-19 lockdown measurements on the relative number of accident occurrence. But very consistent results of a shift of accident severity towards more serious and fatal injuries. Additionally increases in dangerous behaviour during and around driving are seen which are highly correlated to the relative increase in fatal accidents. The results for accident severity are in line with the results from earlier work using within-day variation in traffic and speed. While contrary to previous work, the majority of the Covid-19 research finds a relative decrease in total accidents after the reduction in traffic volume and the subsequent increase in average speed.

This thesis is, to my knowledge, the first research investigating the impact of traffic density and traffic volume on relative occurrence of accidents and the distribution of related injury severity patterns in Switzerland. While there is international consensus on the negativity of the speed-density relationship, there is no unanimity in the results for the speed-accident relationship. Analysing not only within-day variation, but also the large change in mobility behavior during the Covid-19 lockdown, combined with the extensive data on accidents in Switzerland, leads to insights on accident mechanisms from different perspectives. By that my work contributes to the national understanding of accident influencing factors and adds to the international literature on this topic. The results are important in supporting policy makers to anticipate related effects and by that adjust policies accordingly.

3 Changes in Mobility Behavior during Covid-19 Measures in Switzerland

The Covid-19 pandemic affected our lives for multiple years and in several ways. The most radical impact was likely by the two lockdowns in the first year of the pandemic. In Switzerland the federal council decided to put the country into a national lockdown starting on March 16^{th} 2020. This measure included a strong recommendation to work from home if possible, closure of all commercial leisure activities, including restaurants and bars, as well as closure of all non-essential shops. Schools were closed and public gatherings of more than 5 persons were prohibited. Additionally, people were asked to limit their social contacts outside of their household to as few as possible. When infection rates decreased by the end of spring, the lockdown was terminated on May 11^{th} 2020, with some important businesses already allowed to reopen two weeks earlier. Public transport was never inflicted during the lockdown, however it experienced an enormous decrease in usage during this time, with low occupation rates continuing far longer than the Lockdown measures. This could have partly be intensified by the national mask mandate in public transport starting at June 6^{th} 2020. In fall 2020, Switzerland experienced another increase in infection rates largely exceeding the spring counts. This second wave was counteracted with a second lockdown starting on December 22 and lasting until January 17^{th} 2021. Preceding this lockdown was a period of two months with less stringent limitations on mainly gastronomical and cultural locations. As of May 2021 all restrictions were gradually removed. Besides the forced closure of specific shops and locations and the mask mandate all measures in Switzerland were urgent recommendations. Thus correctly there were only "soft" lockdowns in Switzerland. A comprehensive timeline of all events during the first year of the Covid-19 pandemic in Switzerland can be found in Hintermann et al. (2023). These measures led to a large change in daily lives which also affected peoples mobility behavior. Figure 1 shows the differences in mobility behavior compared to the reference period, which is defined by Google as the mean of the five weeks from January 3^{rd} - February 6^{th} 2020, and separated for different locations in Switzerland. The data was published by Google LLC, based on anonymized mobility data gathered from users of Google Maps, Google (2021). The available data contains the daily proportional difference from the reference period for every canton and whole Switzerland.

The enforced closure of nearly all retail shops and all commercial recreational locations led to a large decrease in people visiting those places. A less but still imminent reduction can be observed at the workplaces, which is related to the work from home recommendation. The reduction in grocery store and pharmacy visits show that even though these locations remained opened people adjusted their behavior and reduced their visits. The data for transit stations includes all stations of public transport, taxi stands and also highway rest stops. Thus it does no reveal much about the mode of transport people chose. But it shows that overall there was a massive reduction in mobility during the Lockdown period. The two right hand side graphs show where the people went instead. A large increase can be found at residential locations, being the place where people live and close around the house. A similar increase of around 20% can be found at parks during the second half of the lockdown. Parks here combine public gardens, national forests, camp grounds and so on, summarizing the outdoors on public land. These remained open or accessible during the lockdown and were only subject to the social distancing measures. Whether the decrease in the park visit frequency during the first couple of weeks of the lockdown was due to bad weather, or if the people were just reluctant to go out at the beginning of the pandemic remains unclear. Though I would opt for the latter, since according to the Swiss weather service spring 2020 was one of the warmest and sunniest in decades, MeteoSchweiz (2020). Since there is no direct comparison, I can not say anything

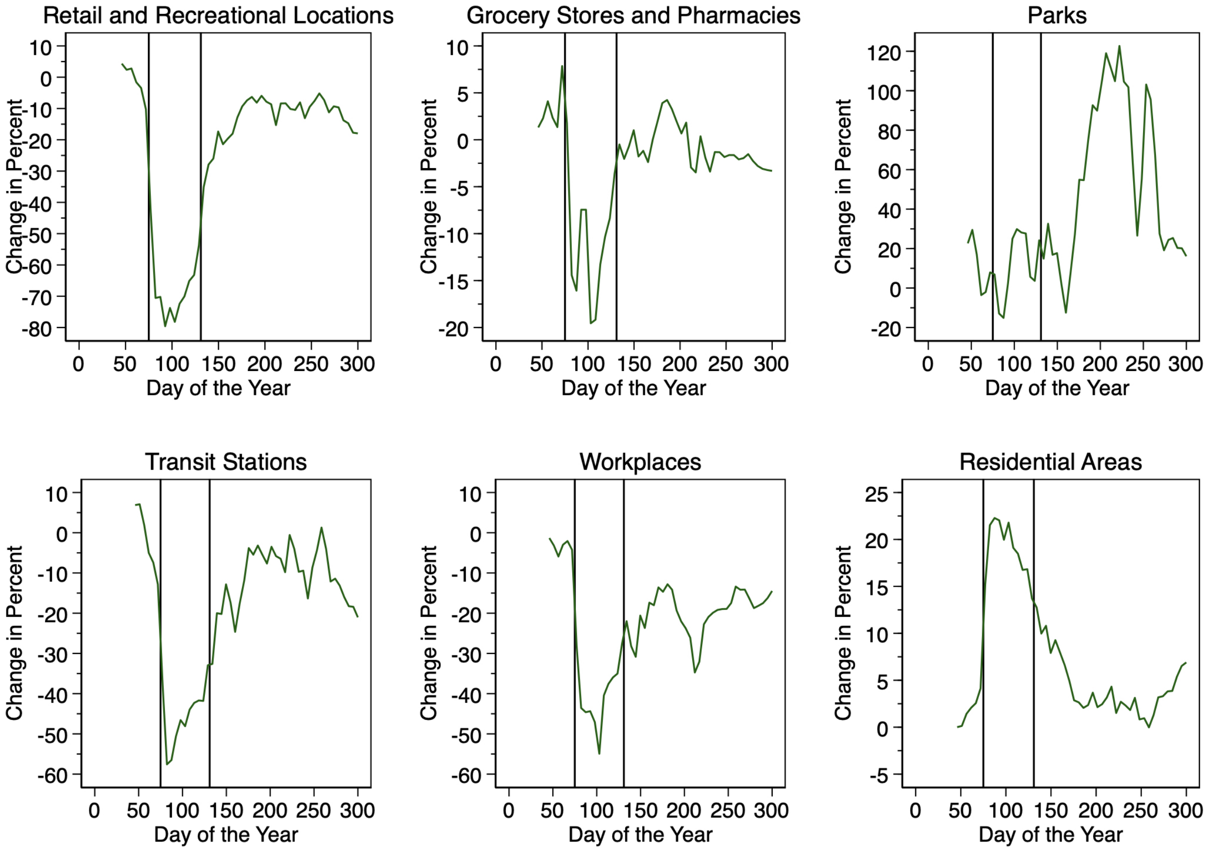

Figure 1: Proportional changes in mobility behavior separated by location compared to the reference period (mean of January 3^{rd} - February 6^{th} 2020). Vertical lines mark the beginning and end of the lockdown. Graphs constructed by author based on data from Google (2021).

about the large increase in park visits in the second half of the year. Nevertheless, the data is not adjusted for any seasonality which seems problematic for comparing outdoor activity behavior with a winter reference period, so the increase might as well be usual seasonal fluctuation. But there were also relaxations of additional security measures throughout summer which could have intensified the effect.

I now want to turn to the mobility behavior and more specifically the impact of the Covid-19 lockdown on traffic density on Swiss roads. Since mobility was one of the main targets of the counter Covid-19 measures, the impact of those on mobility was monitored over time. On behalf of different national and cantonal stakeholders, including the Swiss National COVID-19 Science Task Force, the research institute intervista AG published a report called Mobility-Monitoring COVID-19, intervista (2021). They used data from their "Footprints-Panel" which tracks participants smartphones since October 2018 and provides a large representative sample of the Swiss population. In the evaluation we see, that the average covered distances decline by more than 50%. When further separating into mode of transport they find a reduction of nearly 60% in the usage of cars or motorbikes and even an 80% reduction in public transport use. This shows, that the Covid-19 lockdown indeed reduced the mobility of Swiss people. Similarly, Molloy et al. (2021) using data from smartphone tracking, from the MOBIS and MobisCovid experiment, found a reduction of daily trips to nearly half and a massive reduction

of the activity space (measured in km^2) of more than 75%. When looking at average daily distances by car, they report a 50% reduction during the lockdown. Both studies state a fast return to normal behavior after the lockdown was cancelled. Of specific interest for this work are the results for average speed during the lockdown found by Molloy et al. (2021). They show an increase of up to 15km/h during some hours of the day, but with most of the observed speed increases in the range of 2-5km/h. These results are in line with what has been found in other studies on mobility behavior during Covid-19 lockdowns around the world, i.e. Hughes et al. (2023) & Katrakazas et al. (2021). This supports the theoretical approach, that the lockdown led to a decrease in traffic volume, which reduced traffic density followed by an increase in average speeds on Swiss roads.
The MOBIS and MobisCovid experiment were conducted in Switzerland from September 2019 until May 2020. The MOBIS experiment was designed to analyze people's behavior response on mobility policies. Study participants were tracked via their smartphones and their choice of route and transport modes were recorded. After an initial control phase, the participants were randomly separated into three groups, a control group and two treatment groups, either being provided with information on the produced external costs, or information and pricing of external costs on a budget of which they could keep the remainder. By that a large data set of people's mobility behavior and policy responses could be collected. MOBIS officially ended in January 2020, but some participants remained recording their activities. As the Covid-19 situation exacerbated in Switzerland, all participants were asked to start tracking again, to gather mobility information during the lockdown period. This created the MobisCovid dataset containing trips between March and May 2020. In their recent work, Hintermann et al. (2023) found e nearly 60% decrease in overall distance travelled during the first lockdown in spring 2020. When splitting this reduction into different modes of transport, they report a massive reduction of over 90% in public transport and a 50% decrease in car travel. This is particularly important for the upcoming work with traffic counts from Swiss highways explained in the next part. Traffic count data only contains vehicles passing by, thus a one dimensional measure. Traffic is instead a two dimensional system containing both the number of vehicles on the roads, but also the trip length which states how long each vehicle remained on the roads. The results from Hintermann et al. (2023) provide important insight on the change of distance travelled during the Lockdown and by that helps to justify the use of the travel counts as a measure for traffic volume.

Another source of traffic monitoring is provided by the Swiss Federal Roads Office (ASTRA). Which conducts daily automatic traffic counts on several major highway positions. From which the results are freely available for twelve counting stations over the years 2019 - 2022, ASTRA (2020). The available data contains daily counts for all twelve stations and the percental change compared to the previous year. I focus on the year 2020 and the comparison to 2019. The data also contains a differentiation between passenger cars, including coaches, and commercial trucks. I decided not to differentiate between those two categories and to show the total counts, since my interest lies in traffic counts as a number of volume. Even though the behavior from and around trucks on streets differs from a situation with only cars, trucks do provide their part on traffic density. Figure 2 shows the total counts for the years 2020, as well as 2019 in thousands of vehicles. We can clearly see a seasonal trend in the year 2019, which is also visible in the beginning and the end of 2020. During the lockdown, marked with the two vertical black lines, there is a massive decrease in vehicles passing the counting stations. To better understand the dimension of this reduction, the lower graph in Figure 2 shows the change in traffic volume in percents. The decrease in vehicle on highways also reaches up to 60%, which is in line with the results of Molloy et al. (2021), intervista (2021) and Hintermann et al. (2023). The minimum is reached at the beginning of April 2020, after which the number of vehicles gradually

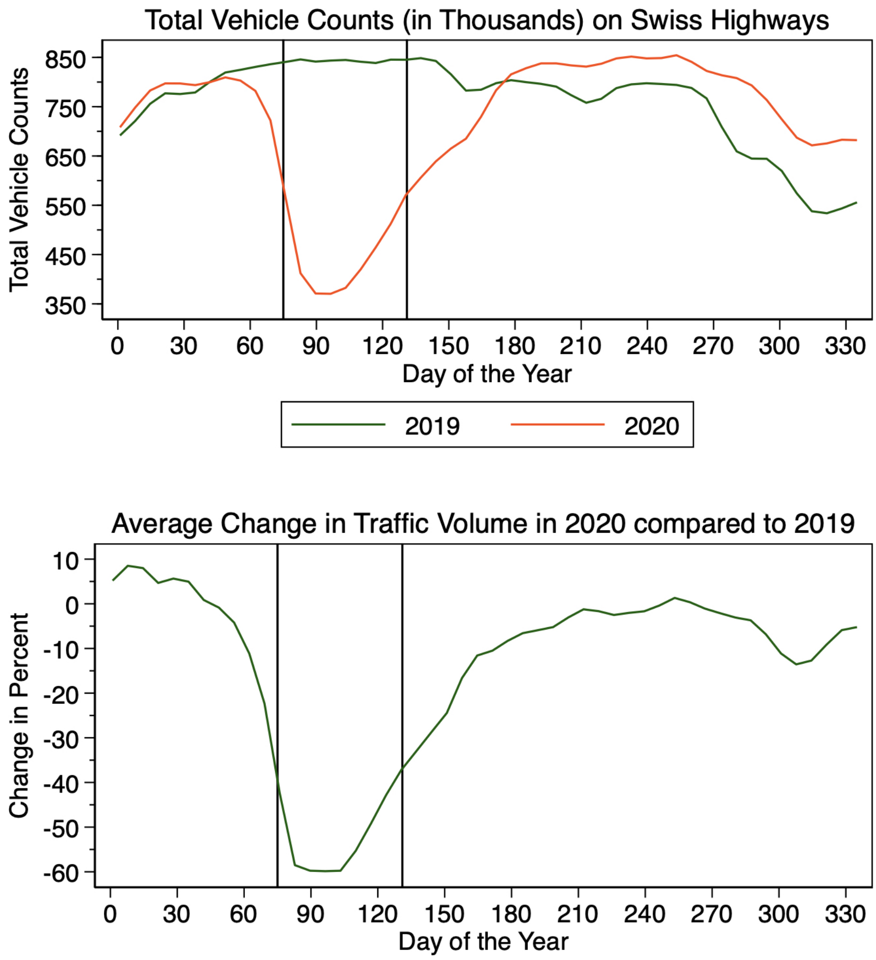

Figure 2: Top: Total vehicle counts (in thousands) on Swiss Highways in the years 2019 and 2020. Bottom: Proportional change in vehicle counts in 2020 compared to 2019. Vertical lines mark the beginning and end of the lockdown. Graphs constructed by author based on data from ASTRA (2020).

starts to increase again. Interestingly, we also see that people anticipated the beginning of the pandemic themselves and traffic volume decreased before the official lockdown. This has also been widely observed by other researchers.
In the second half of the year we see that the counts of the year 2019 lie below the counts of 2020, while the proportional change shows values between 0 and -10. This comes from the fact that there are some months with missing values for single stations. Which were replaced with the mean of the corresponding station. The daily proportional changes are provided by the ASTRA and only contain stations with available data for 2019 and 2020, thus they are based on less observations but are better suited to compare the two years. Also, there are no observations for the majority of days in December for which the month of December is not included in Figure 2 and all upcoming calculations.

Figure 3 shows the cumulative yearly hours of traffic jams on Swiss highways. The data is collected by the Swiss Federal Statistical Office (BFS) and publicly available on their homepage, BFS (2023b). The total hours are differentiated by the cause which is categorized to congestion, accidents, construction work or other. We can see that other is only a minimal share of all jam

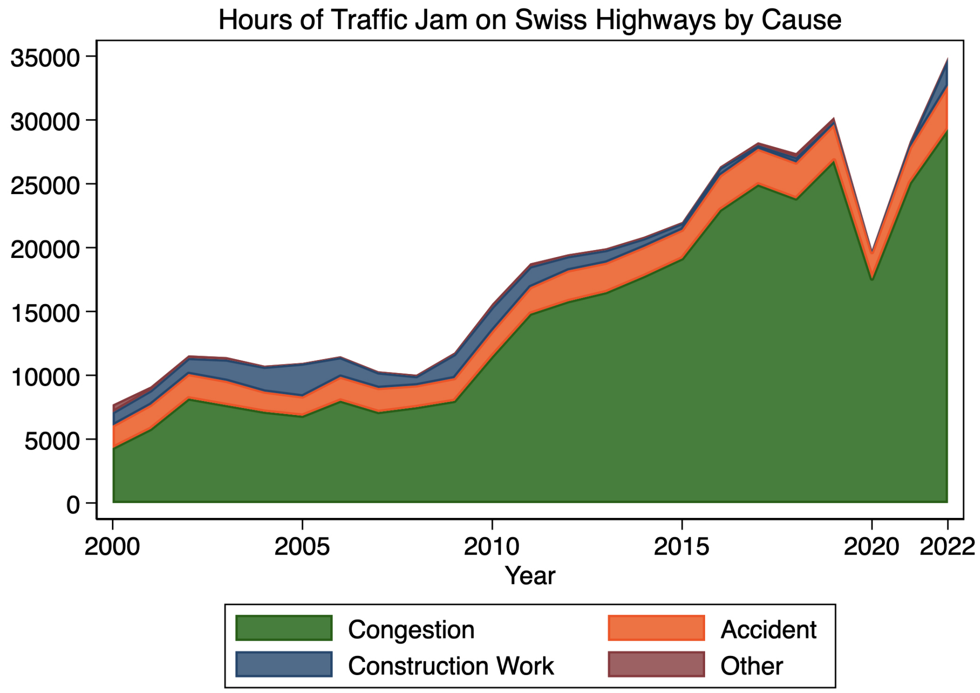

Figure 3: Hours of traffic jam on Swiss highways separated into cause of the jam. Graphs constructed by author based on data from BFS (2023b).

hours, while the share of construction work related jams is a bit higher followed by the jams due to accidents. The majority of all hours of jam comes from congestion, which we also see to massively increase over the years, while the amount of jam hours due to the other three reasons remain similar over the whole 22 years. The reduction of traffic jam hours in 2020 is quite obvious and accounts for an around 35% decrease of jammed hours when comparing 2020 with 2019.

Together, all this work paints a similar picture of the changes in mobility behavior during the Covid-19 lockdown in Switzerland in spring 2020. The traffic volume decreased by more than 50% with differences between transport modes. While the effects on other transport modes are very interesting, I only focus on car mobility in the upcoming work, since I only examine the effects on accidents with cars. The reduction in traffic jams depicted in Figure 3 together with the increased speeds found by Molloy et al. (2021) support the concept of a negative speed-density relationship. Further, the results of Hintermann et al. (2023) confirm a reduction in distance travelled by car during the lockdown of about 50%. This is important, for I want to use the daily traffic counts from Swiss highways as a proxy for traffic volume, which lacks the length dimension of trips. As we saw in Figure 2 the traffic counts decreased by nearly 60%, thus using them to also account for differences in distance travelled, includes a small overestimation of the reduction in trip lengths. Nevertheless, I decided to use the traffic counts as a credible measure for the variation in traffic volume.

4 Methodology

I want to estimate three different effects. The change in probability of ending up in a specific injury category conditional on having an accident, based on individual accidents. The effect on the relative accident rate and distribution of injury categories by changes in traffic volume on a daily bases. Further, the impact on accident numbers of changes in average speed. For that, three different estimation models are needed, suited to the effect of interest.

4.1 Accident Severity as a Function of Traffic Volume, Based on Lockdown Induced Traffic Reduction and Variation of Traffic Density During the Day

To estimate the probability of ending up in a specific injury category a logit model was chosen. For each injury category there is a binary variable which turns one when there is at least one casualty with according injuries. Having a binary dependent variable makes logit the most suitable regression model. It estimates the probability of suffering an injury of the specific severity, based on the explanatory and control variables. The estimation is performed separately for each injury category, since the injury severity should be independent of each other no ordinal rule shall be applied. The following equation shows the logit model used:

$$\mathrm{P}(\mathit{Injury\ Category}_{it} = 1|EX) = \mathrm{c} + \beta \cdot EX_{ei} + \gamma \cdot FE_{ft} + \delta \cdot CO_{ci} + \varepsilon_{it} \tag{2}$$

The dependent variable on the left hand side is the probability of the binary variable for the specific injury category being 1, thus accident i on day t has a casualty showing this injury pattern. On the right hand side there is the constant c and the error term ε_{it}. EX_{ei} is a vector of dummies e for the specific accident i building the explanatory part of the model, with β being the vector of estimated coefficients belonging to the dummies. For the Covid-19 lockdown approach the explanatory variable are dummies for the years 2015-2020, with 2020 being the characteristic of interest. Implementing a "treatment" variable differentiating between 2020 and the previous years and adding year fixed-effects (FE) was not possible in this context, because the year FE would collect the whole variation during the lockdown period in 2020. To estimate the effect of different traffic densities on injury severity, EX_{ei} consisted of binary variables for the three density levels available in the accident data.
To control for seasonal variation, I used f season fixed-effects (FE) *(day-of-week FE, month FE and holidays)* for the day t on which the accident occurred, which are included in the vector FE_{ft} and the corresponding vector of coefficients γ. The term CO_{ci} is a vector of control variables c for each accident i consisting of driver controls *(gender and age of the driver* and environmental controls *(speed limit, weather, light conditions, streetlights and road type)*, which are added for some specifications. These control variables are further explained in Subsection 5.3. δ is the vector of estimated coefficients belonging to the specific control variables.
Since the coefficients of a logit model are not directly interpretable, the results reported in Section 6 do not show the estimated coefficients β_e, but the marginal effect on P*(Injury Category$_{it}$=1|EX)* of dummy e turning to 1. The marginal effects were calculated using Stata's "margins dy/dx" function.

4.2 Daily Accident Counts and Injury Severity as a Function of Daily Traffic Counts

The estimation of the effect of traffic counts on the relative accident rate and the distribution of accident severity is based on count data consisting of daily aggregation of the accidents, their injury patterns an the specific traffic counts. Not all models are well suited to handle

count data, especially when the distribution of the observation is right skewed do to a high density of low observations, or even a majority of counts with the value of zero. This is the case for the more severe injury categories, especially for the fatal accidents, where most days in Switzerland do not show any fatal accident. In addition to performing an Ordinary Least Squares (OLS) regression, I targeted this problem by using Pseudo Poisson Maximum Likelihood (PPML) regression to estimate all count data based results, which is in line with Hintermann et al. (2023). PPML is well suited to deal with zero inflated count data and compared to classic Poisson regression, PPML needs no assumption about the distribution of the dependent variable, Correia et al. (2020), besides a correctly specified conditional mean of the dependent variable, Gourieroux et al. (1984). Compared to the ordinary least squares regression (OLS), PPML works consistently with heteroskedastic error terms, with which OLS has proven to estimate the parameters quite inconsistently, Santos and Tenreyro (2006).
The applied model followed the form of this equation:

$$Counts_t = \mathrm{c} + \beta_1 \cdot Traffic\ Counts_t + \beta_2 \cdot Traffic\ Counts^2{}_t + \gamma \cdot FE_{ft} + \varepsilon_t \tag{3}$$

Where $Counts_t$ are the counts of all accidents or a specific injury category on day t. *Traffic Counts* are the daily traffic counts from Swiss highways on day t. The β_1 coefficient is the estimated linear relationship between *Traffic Counts* and accident *Counts*. Since this relationship is unlikely to be linear, I defined a polynomial regression model by also including a quadratic term of traffic counts, with the corresponding coefficient β_2. Additionally a cubic function was estimated to allow for a sigmoid functional relationship. Since accidents depend on multiple influencing factors confounding with traffic volume, such a correlation is imaginable. The cubic term showed significance on the 10%-level for total accidents and lightly injured and remained insignificant for all other models. With the significant cubic coefficients only being a very small fraction of the linear and quadratic coefficients, I decided that the cubic model contains no additional information and refrained from including it.
When aggregating on a daily level, much of the information on individual drivers is lost, therefore I only include a vector FE_{ft} of f seasonal fixed-effects *(day-of-week FE, month FE and holidays)* on day t in this model. With γ being the vector of corresponding coefficients to it.
The model described by Equation 3 can either be estimated using OLS or PPML. To report the results, both estimated coefficients β_1 and β_2 were combined to show the marginal effect of a change in traffic counts on accidents.

4.3 Accident Counts as a Function of Average Speed in 12 Categories During the Day

The third model used does not differ substantially from the previous one. The explanatory variable changes to be average speed and the traffic counts become a control variable. In addition each day gets separated into 12 categories, four time and three speed categories, which allows finer investigation of accident occurrence differentiated by time and road specifics.

$$Counts_{ths} = \mathrm{c} + \beta_{is} \cdot Average\ Speed_{ths} + \gamma \cdot Controls_{ct} + \varepsilon_{ths} \tag{4}$$

Thus the dependent variable is accident *Counts* on day t during the time period h in the speed regime s. Based on data from the MOBIS and MobisCovid experiments, *Average Speed* is calculated for each category in every day. The vector of control variables c contains the FE from above and is extended by the daily traffic counts. I only used OLS to perform estimations based on this model.

5 Data

5.1 Swiss Accident Register

In Switzerland the Federal Roads Office (ASTRA) collects all data on vehicle accidents since 1992. After project description and a usage contract the ASTRA gave access to the full anonymized data set. It contains every accident from 1992 to 2022 in Switzerland, which sums up to 2'031'162 crashes. There is information on date, approximate time, count of people involved and the severity of their injuries. Further it has geographical information for every accident, as well as cause of the crash, weather, road and light conditions. One additional data-set incorporates information on all involved persons like age, gender, years of driving experience and usage of seat belts. While another data-set holds all specific information about the driver and the involved vehicles, like type of vehicle, power of the engine, number of places, weight, but also type of collision, results from alcohol and drug tests and reason of trip. A full record of all available data in the three different sets can be downloaded from the homepage of the Swiss Federal Roads Office, ASTRA (2019).

5.2 Data Cleaning and Preparation

These three data-sets were merged by the accident-ID number, which individually identifies every single accident. This resulted in many accidents being multiply listed, once for each person involved. Since I am interested in the number and severity of accidents and the driver related factors, I removed details of the passengers from the data set. Keeping only the count of passenger casualties in each injury category per accident. Next I cut the lower bound of the involved years to 2015, since traffic pattern as well as car security has changed much over the last decades and therefore, I do not expect any credible insight from accidents that occurred more than 9 years ago. Additionally, I restricted the data-set to only contain accidents with passenger cars. Motorbikes, any kind of trucks and coaches are deliberately excluded, because they offer different injury patterns compared to passenger cars, i.e. motorbikes offer less protection, while the weight of trucks and coaches is very destructive. Some accidents were included multiple times, once for each vehicle involved. This was solved by only keeping the accident perpetrator, resulting in 325'127 remaining accidents. An additional check for further duplicates revealed 35'589 exact duplicates of unknown origination, which were removed. Five accidents with missing accident time were deleted, because this could become problematic for the fourth analysis. Resulting in 289'533 accidents after preparing the basic data-set.

The following main analyses are restricted on four subsets. To investigate the variation due to the Covid-19 lockdown I use the data from the years 2015 until 2020. Where 2015 - 2019 build the control group against which I compare the observations from 2020. More importantly, the dataset for this analysis is further restricted to the time of year when there was the lockdown in 2020, thus from march 16^{th} until may 10^{th} of each year. For the second approach, exploiting the within-day variation, I use all observations from 2015 until 2022 deliberately excluding the full year 2020 due to its distorted mobility behavior. The third dataset uses all days for which traffic counts from Swiss highways are available, which is from January 1^{st} until December 1^{st} 2019 and from January 1^{st} until November 30^{th} 2020. With 2020 being a leap year, this results in 669 included days.

For the last model, estimating the relationship between average speed and accident occurrence, I used every day for which there is data from the 3 phases of the MOBIS experiment, as well as phase 4 which is the MobisCovid experiment. Together they span from September 2^{nd} 2019 until May 10^{th} 2020, thus ending at the same day as the first Covid-19 lockdown in Switzerland, containing 252 days. These days were further divided into four time categories and three speed limit categories, resulting in 3024 observations each containing average speed and number of accidents during that specific period and speed category. Since I perform single regressions on each category of time and speed limit, thus 12 calculations, each of it only contains one observation per days which lets us return to the 252 days.

Type of Variation	**Type of Observation**	**Period**	**N=**
Covid Variation	Individual Accidents	2015-2020 Lockdown Period only	30'485
Within Variation	Individual Accidents	2015-2022 (excluding 2020)	254'077
Traffic Counts	Daily Aggregation	2019-2020 (excluding December)	669
Average Speed (per category)	Daily Aggregation (per category)	2019-2020	Total: 3024 Each Model: 252

Table 2: Tabular presentation of the four datasets including specific number of observations.

5.3 Variable Preparation

For the upcoming calculations some additional variables were created.

- To restrict the number of different ages of the drivers, I built 8 age categories starting at < 25, next 25-35 and continuing with categories of 10 years up to the last being ≥ 85.
- Speedlimits were reduced to 4 categories: *30*, *50*, *80* and *120*.
- There are 3 light conditions: *day*, *night* and *twilight*
- 5 road types: *straight*, *curvy*, *intersection*, *roundabout* and *other*
- 5 different weathers: *sunny*, *clouded*, *rain*, *(snow, hail or freezing rain)* and *other*
- The times of the accidents were divided into 4 categories:
  - 06:30 - 08:30 "Morning Rush-Hour
  - 08:30 - 16:30 & 18:30 - 20:00 "Off-Peak Hours
  - 16:30 - 18:30 "Evening Rush-Hour
  - 20:00 . 06:30 "Night"
- Three categories for speed limits were created to assign different average speeds, derived from the MOBIS and MobisCovid data, with the accidents. The categories are $<$ *50km/h*, *50-80km/h* and $>$*80km/h* and all accidents were assigned according to the speed zone they took place. The average speed in these zones were calculated by assigning trips to the three zones as explained in Section 5.4.

Further and in addition to the two seasonal controls *Day of Week* Fixed-Effects and *Month* Fixed-Effects, I decided to also control for holidays because of the different traffic patterns during these days. Holidays in Switzerland are very heterogeneously distributed over the cantons, Holidays (2024). Besides the national holiday on the *First of August*, only *New Year*, *Ascension Day* and *Christmas* are stated as holidays in the whole country, while *Easter Sunday* and *Pentecost Sunday* are always Sundays. Numerous other holidays are known in Switzerland, some just celebrated in a handful of cantons, others in nearly the whole country. I decided to include all holidays which are acknowledged in at least 20 of the 26 cantons, which added *Good Friday*, *Easter Monday*, *Pentecost Monday* and *St. Stephen's Day* (26. December).

5.4 Average Speeds from MOBIS and MobisCovid

The main goal and procedure of data gathering of the MOBIS and MobisCovid experiment were already explained in Section 3, more detailed information on MOBIS can be found in Hintermann et al. (2024) and on MobisCovid in Hintermann et al. (2023). For the last model of this thesis I derived average speeds for multiple subcategories from the combined MOBIS and MobisCovid data. The goal is to estimate the impact on accidents by varying average speed during different time frames in three speed regimes. The four time categories are already explained in the previous Subsection, so are the three speed categories. While the accidents could be easily assigned to the speed regime they occurred in, the trips from the two MOBIS and MobisCovid experiments include multiple speed limits for each trip. I therefore relied on the categorization by Molloy et al. (2021), who assigned the trips into three categories according to their distance *<20km*, *20-50km* and *>50km*. The derived average speeds fit well in the three speed categories and I decided to use the trip length to assign the trips to the according speed regime. This involves the bold assumption, that trip length serves well enough to proxy the main speed regime a trip took place in. I can not further verify this assumption. But since I am interested in the variation of average speed in these 12 categories over each single day, the precision of the assignment is not that important, since all average speeds are derived by the same rule and are only compared against each other.
I trimmed the data for some unrealistic values. For that I removed average speeds >120km/h, duration of trip >10 hours or <12 minutes and trip lengths >500km. This resulted in 69'303 trips, which were then collapsed into the 12 categories for each of the 252 days. These categories where then merged with the accident dataset, also divided into the 252 times 12 categories. Due to some categories with 0 trips, the average speeds are only available for 2'923 of the theoretical 3024 categories. Table 3 shows the the average speeds per category over all 252 days, the denoted standard deviations indicate, that there is sufficient variation distributed over the days to specify the model.

Average Speed	<50 km/h	50-80 km/h	>80 km/h
Morning Rush-Hour	48.41	79.61	97.19
	(19.14)	(20.93)	(16.77)
Off-Peak Hours	42.04	80.59	94.33
	(21.51)	(22.53)	(18.94)
Evening Rush-Hour	43.49	77.09	94.39
	(19.99)	(21.19)	(17.41)
Night	49.94	86.43	99.10
	(21.37)	(20.19)	(18.97)

Table 3: Average speed in km/h for all 12 categories over the whole 252 days. Standard deviations in brackets.

6 Results

6.1 Descriptive Statistics

In this section I will show descriptive statistics of the four datasets for some selected variables. Tables with descriptives for all included variables can be found in the Appendix Tables A.1 & A.2.

	2015-2018 Mean	2019	2020	Total	change %
All Accidents	5'557	5'343	2'914	30'485	-45.46
	72.91	17.53	9.56		
Unharmed	5'287	5'077	2'724	28'947	-46.35
	95.13	95.02	93.48	94.95	
Light Injured	1'415	1'296	695	7'650	-46.37
	25.46	24.26	23.85	25.09	
Severly Injured	226	193	122	1'218	-36.79
	4.06	3.61	4.19	4	
Fatals	13	10	12	75	20.00
	0.24	0.19	0.41	0.25	
Traffic Density					
low	2'532	2'319	1'711	14'157	-26.22
	45.83	43.65	59.27	46.73	
normal	1'908	1'865	945	10'441	-49.33
	34.53	35.1	32.73	34.46	
high	1'085	1'129	231	5'700	-79.54
	19.64	21.25	8	18.81	
Speedlimit					
30	503	548	324	2'884	-40.88
	9.05	10.26	11.12	9.46	
50	2'864	2'641	1'446	15'544	-45.25
	51.54	49.43	49.62	50.99	
80	1'604	1'621	937	8'973	-42.20
	28.86	30.34	32.16	29.43	
120	586	533	207	3'084	-61.16
	10.55	9.98	7.1	10.12	
Female	1'823	1'813	949	10'055	-47.66
	33.58	34.49	33.43	33.73	
Reason of trip					
Commuting	1'175	1'093	608	6'402	-44.37
	21.15	20.46	20.86	21	
Holiday or Daytrip	172	148	35	870	-76.35
	3.09	2.77	1.2	2.85	
Leisure or Shopping	3'608	3'604	1'934	19'968	-46.34
	64.92	67.45	66.37	65.5	
Freight- or Worktrip	123	175	93	760	-46.86
	2.21	3.28	3.19	2.49	
others	480	323	244	2'485	-24.46
	8.63	6.05	8.37	8.15	

Table 4: Descriptive statistics of main variables for the Covid-19 lockdown variation. Numbers below the counts denote the shares of accidents having a casualty in the specific category. Except for the first row, where the percentage shares show the distribution over the three periods.

Table 4 displays descriptive statistics for single accidents exploiting the the Covid variation. Note that the first column shows the mean of the period 2015-2018 for better comparability with the other two years. The last column tells the change from 2019 to 2020 in percents. In the first row the numbers below the counts denote the shares of the accidents in each period. Dividing 72.91 by 4, which would be accurate in relation to the mean that is displayed for the counts, gives 18.23%. Thus the distribution of accidents over the periods is slightly weighted towards the earlier ones and not surprisingly there is a large decrease of accidents during the lockdown in 2020. Nevertheless, the decrease of 45.46% in all accidents comparing 2020 with 2019 is less than what has been stated for the traffic volume in Section 3. For the injury categories, the number below the counts denote the proportion of accidents showing at least one casualty in the specific category. As mentioned before, an accident can have multiple casualties in different categories, thus the shares exceed 100% when combined. For all following variables, the percentage shares show the distribution of the characteristics inside each period. By that we are able to see whether the distribution changes over the periods and if the composition of the sample varies. Looking at the injury categories, we see that the shares of accidents with unharmed and lightly injured persons stay nearly the same over the whole periods. Variations like that are normal when investigating accident data, since accident occurrence underlies stochastic rules. The two higher injury categories both show an increase in their share in 2020. While the numbers of severely injured is just reduced by 36.79%, which results in a higher share of it during the Covid period, the absolute number of fatal accidents even increases. This leads to an increase of fatal accidents by 20% from 2019 to 2020. Nevertheless, the number of fatal accidents is very small during each period and we look at only two more fatals in 2020. When comparing 2020 to the average of 2015-2018 it stands out, that the latter is even higher. Fatal accidents in Switzerland have been continuously decreasing in the last 50 years, from a yearly 1'694 dead in 1970 to below 300 since 2013. The yearly dead on Swiss roads from 2015 to 2018 were between 216 and 253, 2019 had the lowest number since the record with 187 fatalities. Which increased to 227 in 2020, decreased to 200 in 2021 and then rose again to 241 in 2022, BFS (2023a). We must keep this in mind, since 2019 being the year with the lowest fatality count on Swiss roads ever and also the baseline for the Covid-19 approach might bias the results upwards. Additionally as explained in Section 5.2, the yearly counts by BFS (2023a) include every person that died by an accident, while I reduce the accidents to a binary indicator for each injury category, thus multiple fatal casualties of one accident summarize to only one fatal accident in the two logit models.

The composition of traffic density over the three periods is shown next. We see that the share of accident in normal density does not change substantially over the years. But there is an increase in the share of accidents in low traffic density in 2020 together with a large decrease in the share of high traffic density accidents. This reinforces the findings discussed in Section 3 and my assumption, that the change in traffic volume also impacts the accident occurrence. Differentiating accidents by speed limits on the road where they occurred we see an increase in the shares for 30km/h and 80km/h over the years. No big change in the 50km/h category, but a decrease in the 120km/h category in 2020. This is in line with the findings of Molloy et al. (2021), who find a large drop in peoples mobility spaces during the Covid-19 lockdown, which might result in a reduced highway usage. The gender distribution of the drivers being included in an accident does not change over all three periods. We see that male drivers are accountable for two thirds of all accidents. This is interesting because the Swiss Microcensus of mobility behavior BFS and ARE (2023), covering the period of 2016 until 2021, finds an average daily distance by car of 24.2km for men and 17.4km for women. It shows that men are above the total average daily car distance of 20.8km and women are below, but it is no 2 to 1 proportion. There are two possible explanations for that, first men have a more reckless or riskier driving

behavior, or second, some of the accounted trips are not being taken alone and whenever there is a man and a woman taking a trip together the man is more likely to be the driver. Both are just hypotheses and can not be further analysed.
The last part of Table 4 looks at the distribution of accidents between different reasons of trips. Interestingly the share of commuting related trips did not shrink in 2020, even though this was the time of working from home. The changes in daily distances differentiated by reason of trip published by intervista (2021), show that while all distances fell during the Lockdown, leisure activities had a more than proportional reduction. Work and education related trips, as well as shopping trips just reduced by the "normal" approximately 50% with the distribution between them remaining nearly unchanged. This is also what can be seen here in the accident data, with a large decrease in accidents related to holiday or day trips. Since leisure and shopping trips are together in one category, it is difficult to say how behavior changed, but since the share does not alter much I would assume that shopping trips account for the majority of these accidents. Finally, the freight and work trips did not change much. Again there could be a possible shift from some reduced work trips to more freight journeys, since people tended to shop online during the lockdown. The category "other" combines multiple reasons of trip that are in the original data, all reacting heterogeneously on the lockdown and therefore this specification does not have a specific meaning. The further variables used for the single accident analysis are shown in the Appendix in Table A.1. We see an increase in accidents with young drivers, while older drivers are involved in less accidents. This might be due to the fact, that older people tend to be more affected by a Covid-19 infection and therefore practiced social distancing more conscientious. There is no major deviation between the periods for the light conditions under which the accidents happened, as well as for the usage of seat belts. But we see an increase in accidents in areas without streetlights. This, together with the increase in accidents in 80km/h speed limit rule, indicates a shift from accidents from urban to rural areas. There was an over proportional decrease in pedestrian involved, road crossing, rear-end, take-over and lane changing accidents, where especially the latter three are highly driven by traffic volume. There was an increase in accidents while entering or exiting the road, which we also see in accidents at intersections and roundabouts in the roadtype variable. Head-on accidents mostly happen on rural, non highway, roads and also show and increase, that is inline with the assumed shift towards accidents in these areas. Finally there is a very high increase in the share of skidding related and self-accidents. These types of accidents are intensified by low traffic volume, because there is less external restriction in the speed chosen by the driver. This can be seen in the slight increase in the share of speeding related accidents and even more in the large increase of 80% in the share of accidents related to relative speeding. In the differentiation for road types we see a reduction in the share of accidents on straight roads and an increase in curvy sections. This could also be an indicator of increased misjudgment of speed. Regarding the weather the spring 2020 was very beautiful with below average shares of accidents during bad weather. This is in line with the report of MeteoSchweiz (2020) and particularly the large increase in accident share during sunny weather stands out. This is one of the reasons, besides the above mentioned increased injury patterns, why I excluded motorbikes from the data, since motorbike trips are very weather dependent.

In Table 5 we see the descriptive statistics for all accidents differentiated by the traffic density at time of their occurrence. We see that the majority of accidents (45.36%) happened during low density and 35.45% occurred in normal density, while only 19.19% of accidents happened during high traffic density. This is in line with most findings from Section 2.2, which align low traffic volume with higher speeds and more accidents. More importantly, high but also normal traffic density conditions cover only a part of a whole days time, thus there is much more time covered by low traffic density and by that more opportunities for accidents to happen in this time. Similarly to Table 4 the percentages in the first column show the distribution of accidents over the three density levels, while for the injury categories there are again the proportions of accidents having a casualty in the specific category and for the rest of the table the percentages show the distribution of the different variable characteristics inside one density level.

	Traffic Density			
Variable	Low	Normal	High	Total
All Accidents	115'241	90'079	48'757	254'077
	45.36	35.45	19.19	
Unharmed	107'055	85'461	47'348	239'864
	92.9	94.87	97.11	94.41
Light Injured	22'103	25'664	15'709	63'476
	19.18	28.49	32.22	24.98
Severely Injured	4'299	4'661	1'753	10'713
	3.73	5.17	3.6	4.22
Fatals	409	233	67	709
	0.35	0.26	0.14	0.28
Female	35'794	31'627	16'360	83'781
	31.86	35.98	34.1	33.75
Speedlimit (km/h)				
30	17'993	5'464	953	24'310
	15.61	6.07	1.75	9.57
50	55'307	49'405	20'413	125'125
	47.99	54.85	41.87	49.25
80	34'906	26'624	15'806	77'336
	30.29	29.56	32.42	30.44
120	7'035	8'586	11'685	27'306
	6.1	9.53	23.97	10.75
Type of Accident				
Pedestrian or crossing	6'940	6'785	2'257	15'982
	6.02	7.53	4.63	6.29
rear-end, take-over or changing lane	11'816	25'670	31'602	69'088
	10.25	28.5	64.82	27.19
Enter or Exit road	13'337	19'966	7'252	40'555
	11.57	22.16	14.87	15.96
Head-on collision	4'391	3'228	719	8'338
	3.81	3.58	1.47	3.28
Skkiding or self-accident	50'933	23'729	4'994	79'656
	44.2	26.34	10.24	31.35
other	27'824	10'701	1'933	40'458
	24.14	11.88	3.96	15.92
Road Type				
Straight	48'817	41'352	33'347	123'516
	42.36	45.91	68.39	48.61
Curves	25'681	13'838	3'896	43'415
	22.28	15.36	7.99	17.09
Intersection	19'770	22'394	8'458	50'622
	17.16	24.86	17.35	19.92
Roundabout	3'317	5'547	2'004	10'868
	2.88	6.16	4.11	4.28
Other	17'656	6'948	1'052	25'656
	15.32	7.71	2.16	10.1

Table 5: Descriptive statistics of main variables differentiated into categories of traffic density. Numbers below counts denote shares analogous to Table 4.

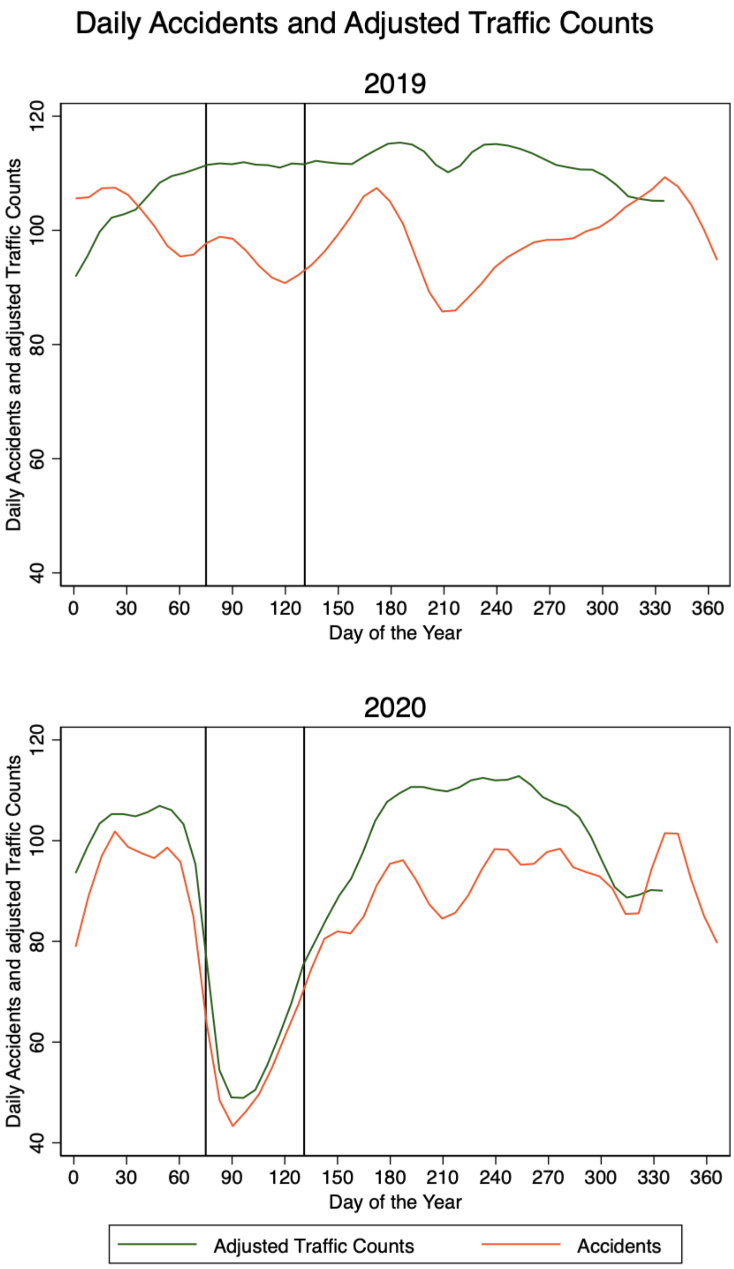

Figure 4: Daily accident counts and adjusted traffic counts for the years 2019 and 2020. The accident counts have been divided by 7572 to make them the same scale as the accident counts. Vertical lines mark the beginning and end of the Lockdown. Graphs constructed by Author with using ASTRA (2020) and accident register.

While the shares of accidents including unharmed or lightly injured persons increases as traffic density gets higher, the opposite is the case for fatal casualties. No relationship between severe injury and traffic density can be seen here in the raw comparison. There are again no changes in the shares of the gender of the driver. In the categories for speed limits we see, that in 30km/h regimes the accidents are prone to happen in low density times, while on express- and highways (120km/h regime) the majority of accidents occur when traffic is very dense. This can also bee seen in the type of accidents, where accident patterns associated to sticky traffic like rear-end collisions or lane changing related are most likely to happen in high traffic density. While others like hitting a pedestrian, most likely by overseeing them, colliding head-on or producing a self accident, which are often related to inadequate speed, are more frequent in low density environments. The road types show a similar pattern. Easy straight roads show the highest accident share in high density situations, thus many other object to collide with. While more difficult curvy roads seem to experience most accidents during low density times, presumably because people do not adjust speed according to the road. Intersections and roundabouts show an interesting distribution, both have the highest share in normal traffic density conditions. A possible explanation could be, that during low density there are few other vehicles to collide with and in high density times the speed is very low, so drivers have sufficient time to react. The full table including all variables can be consulted in the Appendix, Table A.2.

			Lockdown period only		
	2019	2020	2019	2020	change %
Vehicle Counts	833’365	716’488	844’314	431’920	-48.84
	(77’110)	(170’284)	(78’829)	(130’642)	
Total Accidents	98.51	84.6	95.41	52.04	-45.46
	(21.03)	(23.17)	(18.13)	(14.59)	
Unharmed	70.1	60.4	69.34	37.66	-45.69
	(15.74)	(16.83)	(12.69)	(10.69)	
Light Injured	24.3	20.37	22.46	12.04	-46.39
	(7.59)	(7.66)	(7.4)	(4.9)	
Severely Injured	3.91	3.53	3.43	2.13	-37.90
	(2.3)	(2.22)	(1.79)	(1.7)	
Fatals	0.207	0.293	0.179	0.214	19.55
	(0.457)	(0.545)	(0.386)	(0.456)	
N=	334	335	56	56	

Table 6: Descriptive statistics of accidents and injury categories, aggregated on days. The numbers on the left hand side show means on daily level for the years 2019 and 2020, excluding December for which no traffic counts are available. On the right hand side, only the days during the Lockdown period march 16^{th} until may 10^{th} are included. Values in parentheses show the standard deviation.

In Table 6 we see the means of total accident counts and separated into the injury categories. The data contains one aggregated observation for every day during the years 2019 and 2020, excluding December since there are no traffic counts for this month. In addition, on the right hand side there are the means of the same variables constricted on the lockdown period, i.e. march 16^{th} until may 10^{th}. The last column displays the change from 2019 to 2020 in percents during the lockdown period. On the left hand side we only see slightly lower means in 2020 for all variables but fatals, which shows that the Covid-19 measures did have a small impact on the whole year. Thus the large reduction in accidents and traffic counts during the lockdown, visible on the right hand side, was mostly compensated by the rest of the year. This indicates, that besides spring, the year 2020 did not diverge much from a usual traffic year. Again we see a smaller decrease of severe injuries compared to total accidents and also traffic counts and even an increase in fatal accidents. The positive 20% change in fatal accidents is comparable to the one in Table 4, and it is worth noting that the average during spring 2019 is much lower than the total average in 2019. Comparing the lockdown period in 2020 with the mean of the whole 2019, fatal accidents would only increase by 3.3%. Figure 4 shows the two first variables of Table 6 over the years 2019 and 2020. Note that the daily traffic counts have been divided by 7572 to make them the same scale as the accident counts for better comparability. 7572 is the result from dividing average traffic counts by average accident counts for the two years. In the upper portion of Figure 4 we see that in 2019 there was no obvious correlation between traffic volume and accidents and both have a similar amplitude. In Spring 2020 there is an obvious reaction to the Covid-19 lockdown and we see that traffic volume and accident counts behave very similar and show nearly parallel trends. The graph for 2020 also shows that by summer the two lines were about back to pre-Covid values and behavior.

6.2 The Effect of the Covid-19 Lockdown on the Probability of Sustaining a Specific Injury Severity

The first specification I estimated is the effect of the Covid-19 Lockdown change in mobility behavior on the probability of sustaining a specific injury severity when having an accident. As explained in Section 3, the lockdown led to a 55% decrease in traffic volume in Switzerland. Therefore, the estimated effects displayed in Table 7 show the overall change in probability comparing the period from march 16^{th} until may 10^{th} of the specific year against this period in 2019, which is the reference year.

We see that during the Covid-19 lockdown (year 2020), even though the overall traffic volume decreased by around 50%, the probability of suffering a fatal injury when having an accident increased by 0.25%, compared to the reference year 2019. With an a priori probability of only 0.19% of being fatally injured when having an accident, this results in an increase of 130% of

	(1)	(2)	(3)	(4)
VARIABLES	Fatals	Severely Injured	Lightly Injured	Unharmed
2015	0.0003	0.0045	0.0208**	-0.0052
	(0.0009)	(0.0038)	(0.0084)	(0.0043)
2016	-0.0005	0.00423	0.0037	0.0035
	(0.0009)	(0.0038)	(0.0082)	(0.0042)
2017	0.0012	0.0067*	0.0036	0.0066
	(0.0010)	(0.0038)	(0.0082)	(0.0041)
2018	0.0011	0.0010	0.0020	-0.0036
	(0.0010)	(0.0037)	(0.0082)	(0.0043)
2020	0.0025*	0.0026	-0.0109	-0.0146***
	(0.0014)	(0.0044)	(0.0097)	(0.0054)
Baseline 2019 (%)	0.19	3.61	24.26	95.02
Percental Change	130%	7.31%	-4.49%	-1.54%
Observations	27,288	29,783	29,783	29,783
Season FE	YES	YES	YES	YES
Driver Controls	YES	YES	YES	YES
Environment Controls	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Results for the effect of the Covid-19 lockdown change in mobility behavior on the probability of ending up in a specific injury category, conditional on having an accident, using the logit regression model. Displayed coefficients are marginal changes compared to the reference year of 2019.
Note: The baseline 2019 shows the proportion of accidents showing at least one person with the specific injury, since accidents can contain multiply casualties with different injury severity the shares combined exceed 100%.

the probability of dying when having an accident. Based on the literature reviewed in Section 2, the decrease in traffic volume should lead to a decrease in traffic density and therefore, based on the speed-density relationship to an increase in average speeds, which is one of the main drivers for higher injury severity and eventually fatal outcomes. No significant changes can be reported for the probability of suffering severe or light injuries, but the signs of the coefficients correlate with the expected shift from light to more severe injuries. As for the probability of remaining unharmed when involved in an accident, it is also reduced on a statistically significant level by 1.54%. While constructing the binary variables for the injury categories, I defined them to turn 1 if at least one person suffered from the according level of injury. The reduction of 1.54% in the probability of being unharmed can therefore be interpreted as 1.54% of accidents, in which someone got injured who was previously unharmed, compared to 2019. All control variables are included, since the coefficients proved to be robust to adding and leaving the fixed-effect and controls. The full tables of the whole model, including different specifications of controls are to be found in the Appendix Tables A.3 to A.6. Further, besides two coefficients the estimates for the previous years remain insignificant. This is an important fact, indicating that the reference year 2019 does not deviate substantially from other years.

6.3 The Effect of Varying Traffic Density on the Probability of Sustaining a Specific Injury Severity

In this subsection I present the results of my estimations on the effect of traffic density on the probability of suffering a specific injury, given being involved in an accident. This approach exploits varying traffic density over the period of a day, which is the within-day variation. The current density during the time of the accidents is defined by the police filing the accident report and by that, it includes subjectivity and is not the most precise measure. Nevertheless, given the scarce data on traffic volume or average speed, it offers a crude differentiation between

VARIABLES	(1) Fatals	(2) Severely Injured	(3) Lightly Injured	(4) Unharmed
Low Traffic Density	0.0011***	-0.0073***	-0.0522***	-0.0171***
	0.0003	-0.001	-0.002	-0.0012
Percental Change (Low)	41.15%	-14.20%	-18.32%	-1.80%
Baseline Normal Density (%)	0.26	5.17	28.49	94.87
Percental Change (High)	-50.38%	-22.44%	12.81%	2.69%
High Traffic Density	-0.0013***	-0.0116***	0.0365***	0.0255***
	-0.0002	-0.0011	0.0025	0.0011
Observations	247,989	247,989	247,989	247,989
Season FE	YES	YES	YES	YES
Driver Controls	YES	YES	YES	YES
Environment Controls	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Results for the effect of different traffic densities on the probability of ending up in a specific injury category, conditional on having an accident, using the Logit regression model. Displayed coefficients are marginal changes compared to the reference "Normal Traffic Density".

traffic conditions. As the reference I chose normal traffic density and the shown coefficients in Table 8 state the marginal change in each injury probability estimated for the specific traffic density. From theory and literature we know, that lower traffic density is associated with higher speed and vice versa. Note, that Table 8 shows the results of four different estimations, each calculating the probability of anybody involved in an accident experiencing the specific injury. Thus, the estimated results are completely independent from each other. In line with theory, I find that accidents in low traffic density show a higher probability of being fatally injured and less probabilities of being non-fatally injured that in normal traffic density. I am surprised about the decrease in the probability of being severely injured, because I would have expected this category to be also increasing with increasing speeds.
During high traffic density the opposite can be observed. There is a decrease in the probability of being fatally or severely injured in an accident, but an increase in suffering light injury or remaining unharmed. Again being in line with the assumption based on the speed-density relationship and lower average speed leading to less severe accident outcomes. As with the first model, I included all available fixed-effects and control variables in the estimation, since varying specification showed the results to be robust. The full tables with different controls are included in the Appendix Table A.7 to A.10.

Both models showed results according to the literature reviewed in Section 2, especially the relation between average speed and injury severity. Nevertheless, neither actual speed nor the traffic volume could be measured for the individual accidents. The underlying relationship between speed and density is proven by previous research, but density in this context is also just an assumption based on inaccurate information. I therefore want to continue with aggregating the accidents on a daily bases and combine this daily counts with more detailed measures of traffic volume in the following subsection.

6.4 The Effect of Traffic Volume on Daily Accident Counts and the Distribution of Injury Severity

Including the daily traffic counts from Swiss highways, collected by the Swiss Statistical Office, and estimating their impact on daily accidents and casualties gave the results shown in Table 9. The displayed effect is the marginal effect on the specific category of increasing traffic counts

VARIABLES	(1) All Accidents	(2) Fatals	(3) Severely Injured	(4) Lightly Injured	(5) Unharmed
Traffic Counts *(in 100'000)*	10.82***	-0.0331	0.594***	3.625***	10.41***
	(0.779)	(0.0251)	(0.112)	(0.311)	(0.739)
Constant	27.45***	-0.337	1.501	11.74***	25.77***
	(7.182)	(0.214)	(0.990)	(2.678)	(6.698)
Observations	669	669	669	669	669
R-squared	0.532	0.026	0.150	0.480	0.543
Season FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Results of the OLS regression of all accidents and the four injury categories on the daily traffic counts from Swiss highways. The results show the marginal effect of an increase in traffic counts by 100'000 on the number of accidents/casualties in the specific categories.

by 100'000. The used model is a polynomial OLS regression, thus as explained in Section 4, the explanatory variable is both included directly, as well as in a quadratic form and the shown marginal effect is calculated from both coefficients. I also included the seasonal fixed-effects *day-of-week*, *month* and *holidays*, to capture unobserved differences between the days besides traffic volume. Results from the estimations without seasonal fixed-effects can be found in the Appendix in the upper portion of Table A.11.

I found a highly significant linear relationship between traffic counts and all accidents, as well as accidents involving unharmed occupants. The similarity between accidents and unharmed was to be expected, since 94.2% of all accidents include at least one unharmed person. The marginal effect shows, that with an increase of 100'000 cars on Swiss highways, an increase of 10.82 accidents can be expected. To better understand and depict the quadratic term of the model, I predicted total accidents and differentiated by injury category based on the OLS estimation. The resulting graphs are displayed in Figure 5 and do not only show the slope of the relationship between traffic counts and accidents, but also the polynomial influence. Since all accidents and unharmed show virtually the same picture, the prediction of unharmed was omitted here and can be found in the Appendix in Figure A.1. A positive correlation between traffic counts and accidents was to be expected, since more vehicles posses more opportunities to have an accident. Based on the theory presented in Section 2, increasing traffic counts are assumed to result in a decrease in speed after a certain threshold. Thus, the nonlinear effect of the quadratic term shows us how the elasticity of the estimated correlation changes as counted vehicles increase. Table 9 shows no statistically significant relationship between traffic counts and accidents with at least one fatality. This is good news, since fatalities seem not to depend on vehicle counts. Having a look at the prediction in 5, shows the potential reason for this result. While we see an increase in predicted daily fatal accidents as traffic counts increase, there is a slow reduction of this correlation until it eventually reaches zero. This shows, that a potential decrease of speed due to high traffic volume, leads to a stagnation of a further increase of fatal accidents. For both categories, severely and lightly injured a positive correlation with traffic counts can be reported. While the effect on accidents with severely injured is rather small, only 0.6 more accidents of this category, an increase of traffic volume by 100'000 vehicles can be associated with an additional 3.6 accidents with lightly injured occupants. Both relationships show a convex pattern, when inspecting the graphs in Figure 5, thus increasing traffic volume and possibly lower speeds increases the positive correlation between them. While this increase in the slope is only small for severely injured, it rises quite a bit for the lightly injured. This means that the relative counts of these injuries increase. Interpreting this as a shift from fatal injury patterns towards severe and mostly light injury pattern lies at hand, especially since the relationship between overall accidents and traffic counts seems to be linear. Nevertheless, I can not state that so far. But besides fatal accidents, a statistically significant relationship between traffic counts and accidents as well as injury categories can be reported.

Working with count data, especially including many days with zero fatal accidents, OLS might no be the best suited method. I already explained the benefits of Pseudo Poisson Maximum Likelihood (PPML) estimation on this kind of data in Section 4. I estimated the exact same specifications as for Table 9 with PPML and found, that the results are virtually identical. These results are displayed in the lower portion of Table A.11, both with and without season FE. The only difference can be found in the estimation of the relationship between fatal accidents and traffic counts with a majority of zeros, which is exactly where OLS is known to be vulnerable. Here PPML perfomrs better, mainly to be seen in the non-negative constant and also a better prediction of fatal accidents. The predictions of all models as well as a plot of the original data is included in the Appendix for comparison, Figures A.1 & A.2. Here we also see, that PPML does not predict negative values for fatal accidents, which is one of OLS downsides that also occurs here. Due to its simplicity and as shown, still highly accurate estimations, I chose to report the OLS results.

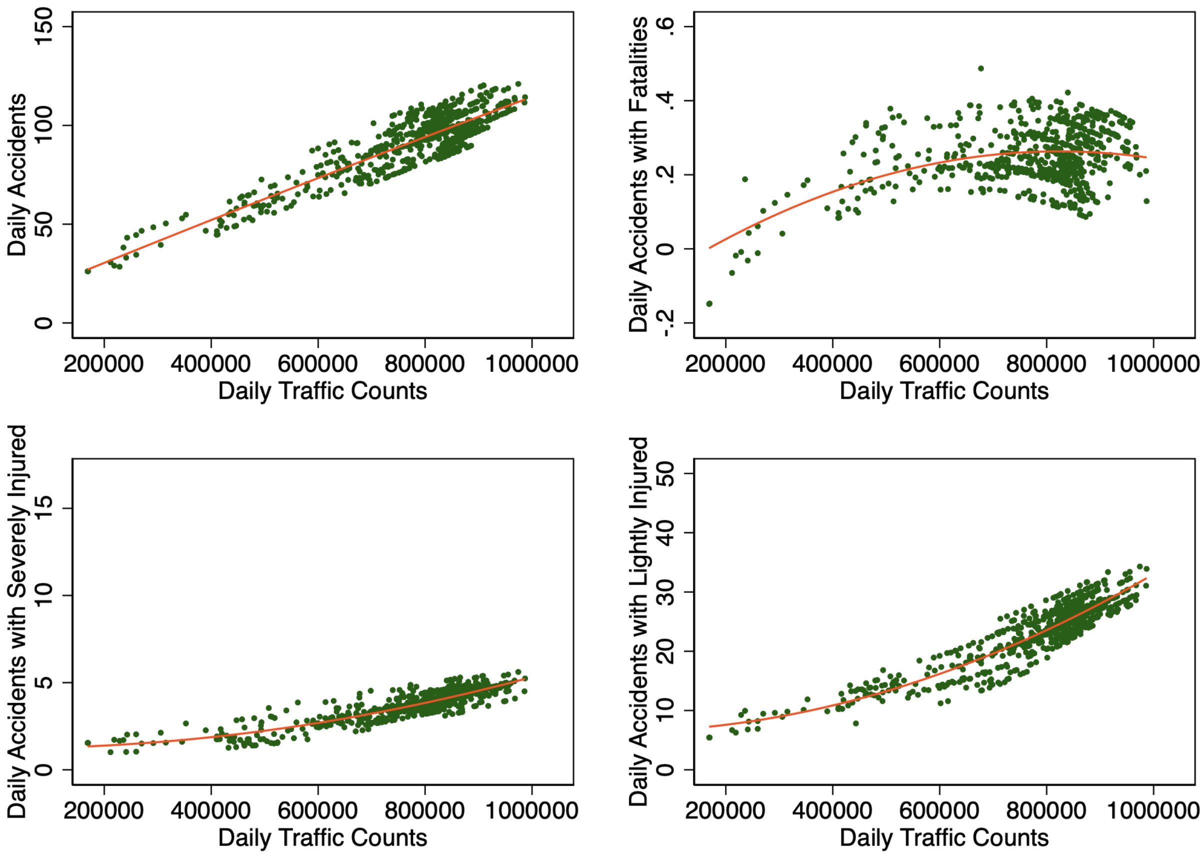

Figure 5: Prediction of all accidents and differentiated by injury category based on the OLS estimation.

6.5 The Effect of Speed on Accidents

For the last estimation, I used mobility Data from the MOBIS and MobisCovid experiments. The tracked trips were separated into four time and three speed zone categories, as explained in Section 5. For all 12 resulting categories an OLS regression was performed, estimating the effect of daily average speed on daily accident counts in each case. The base model only includes accident counts and average speed, which bears the problem of speed also collecting all variation in traffic volume and is only in the Appendix. Thus, this specification is more likely to capture the speed-density relationship with density being moderated by the number of accidents. To credibly defend that, we must rely on the assumption of linear correlation between accidents and traffic volume, which was estimated accordingly in the previous model. We see, that there is a statistically significant negative relationship between average speed and accident counts in some categories. Especially during the rush-hour periods, but also in 50km/h zones during the off-peak times. These are exactly the times at which we would expect an increase in average speed with decreasing traffic volume leading to less congestion. I therefore, trusting in the assumption made above, believe that the average speeds and accidents are confounded by traffic volume, which leads to an overestimation of the negative effect in this specification due to omitted variable bias. Nevertheless, I would value the results of that model as support for the negative speed-density relationship in Switzerland. In addition it is important to point out, that this specification finds a positive relationship between average speed and accidents during

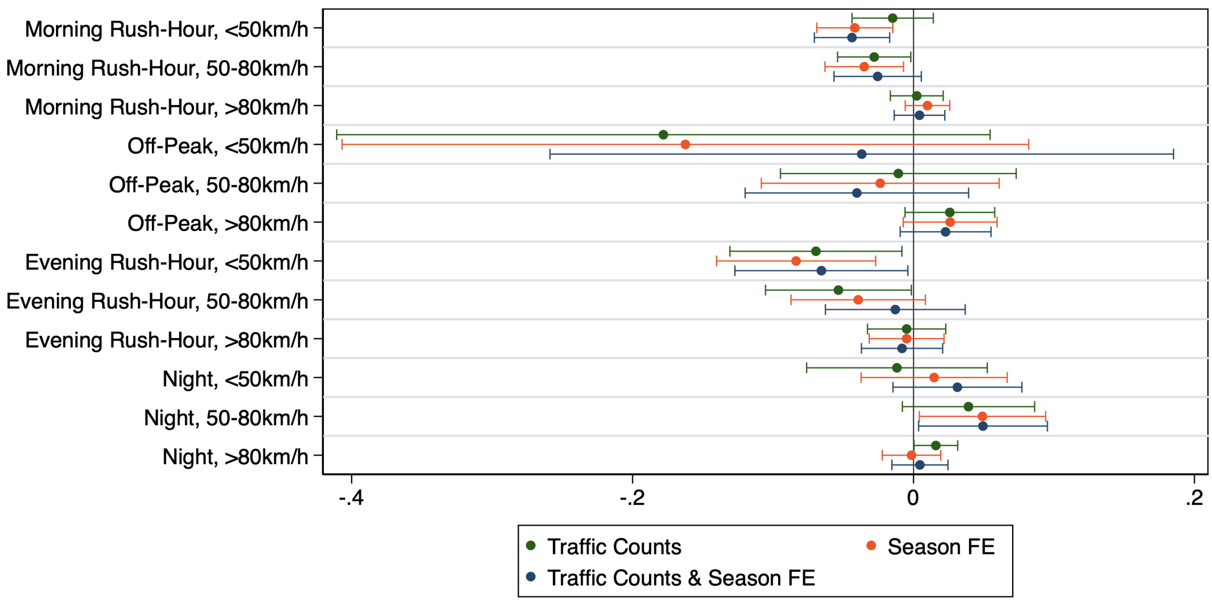

Figure 6: Estimated effects of average speed on daily accident counts, separated into the 12 categories. Bars represent the respective 95% confidence intervals. All calculations made using robust standard errors.

off-peak hours in the >80km/h speed zone. This includes expressways and highways and states, that on these streets, during a time period not prone to crowding, an increase in average speeds does have a positive effect on accident counts. Due to the fact, that besides this last coefficient none are a big support for the question asked here and including this model highly skews the figure due to one low outlier, this specification is only included in the Appendix, Figure A.3.

The resulting coefficients of the following specifications are depicted in Figure 6, with the accompanying 95% confidence interval. And they show the estimated change in accident numbers in that category by increasing the average speed by 1 km/h. To take daily changes in traffic volume out of the equation, I controlled for it in the green model. This absorbs much of the observed variation from the first specification, but helps to better isolate the effect of changes in average speed on accident counts. This step brought the estimated coefficients closer to zero, especially the previously highly significant ones. They remain statistically significant during the morning rush-hour in 80km/h zones, as well as during the evening rush-hour in 50km/h and 80km/h zones, but with far lower estimated effects. These are still the categories where congestion can be very well expected. An increase in speed could lead to a reduction in accidents, due to better flow of traffic and less variation of speed within vehicles. People might also be less impatient when traffic flows at higher speeds, and by that they drive more considerate. But there is also the possibility, that the daily traffic counts are not detailed enough to control for traffic volume differences inside the congestion prone categories. So the question remains open, whether I really find a negative correlation between average speeds and accident counts, or if this specification still captures part of the speed-density relationship. I found no way to further differentiate this with the data at hand, but if I had to decide, I would opt for the latter explanation of the results.
I repeated the model with two other specifications. First including the already known season fixed-effects and second by including the daily traffic counts and the season FE. Most importantly, the estimated effects for the morning rush-hour in the <50km/h regime became significant. With the traffic counts being collected on highways, they might not be the best

option to control for traffic volume in this regime. And by that, especially the day-of-week FE might much better control for changes in mobility behavior between weekdays and weekends, i.e. commuting and business related trips vs leisure trips. The aforementioned reasoning of less accidents with more fluent traffic, which equals higher average speed, is particularly credible in urban settings. Therefore the results in these two specifications could show a negative correlation between average speed and accident. But an influence of traffic volume on the accident numbers and therefore the results can not be ruled out completely.
Interesting results can also be found during the night in the 50-80km/h regime. Besides the green specification, all results show a statistically significant positive effect of average speed on the accident numbers in that category. Rural streets show the highest shares of accidents with fatal and severely injured persons. This is due to higher speed compared to urban streets and less security measures, i.e. crash barriers and direction separation, compared to highways. And rural streets show higher numbers of speeding and relative speeding (speed below speed limit, but believed to be to high for the road specifics or weather circumstances). Additionally, there is no congestion to be assumed during the night. By that, I believe to have credibly isolated a positive effect of average speed on accident numbers in this category. This is also in line with other research presented in Section 2.
Most results are statistically not significant. This is good news in the context of mobility policies, since most of them aim on reducing congestion and by that increase average speeds. Figure 6 shows, that except for the night 50-80km/h category, no significant increase in accidents and therefore accident related internal and external costs were found. With this category most likely not being prone to congestion and therefore no density related speed reductions. But for other categories, there remains the danger of possible relative increases in accidents (by increased speed) being absorbed by a simultaneous reduction in traffic volume which is not observed individually for each category. Therefore, further research with traffic volume like vehicle-kilometers travelled assigned to each category is needed for a deeper understanding of these effects. The full results displayed in table form with further specifics of each model can be found in the Appendix in Tables A.12 & A.13. In the previous model on traffic counts, polynomial regression showed do deliver more precise results. To check the robustness of the estimations on average speed in the 12 categories, I performed the same estimations using average speed and, if included, daily vehicle counts in a linear but also quadratic form. The results differ slightly, but not substantially and can be found in the Appendix in Figure A.4, showing the marginal effects of the linear and quadratic term combined by increasing average speed by 1 km/h on accidents. The most important difference is the disappearance of all statistical significance of the positive results during the night.

7 Policy Implications

In this Section I want to evaluate the impact of my results on accident costs in Switzerland, specifically changes in accident costs that can be expected by implementing mobility policies. For that I created two scenarios of policy induced changes in mobility behavior and their influence on accidents and accident related costs.
In Switzerland, the internal and external costs of accidents are being calculated by the Federal Office for Spatial Development (ARE). The latest available costs are from 2020 and were provided to my by ARE upon request. By the end of 2024 new cost calculations will be published, based on not only new numbers, but also with a completely new calculation scheme. The costs used for this work are based on the calculation scheme of 2010, which is extensively explained in ARE (2014). They consist of costs incurring at every accident, including damage to property, administrative costs, police cost and jurisdiction costs all internal and external, which I

combined to the *Damage to Property* costs visible in Table 10. Additionally, costs related to the severity of injury, including medical costs, production/labor downtime, replacement costs, administrative costs and immaterial costs, are available. The social costs are the direct or internal costs borne by individuals or firms, while the external costs are borne by the society. ARE knows two different views of external costs, first the view of the traffic carrier and second the view of the traffic user. The view of the traffic user assigns more costs, not borne by the accident causer, to society and therefore to be external compared to the traffic carriers view. I chose to use the traffic carriers view, since it is more general and the lower external costs in this view prevent an overestimation of the effects. Together these costs define the total costs for each injury category shown in Table 10. The shares denote the distribution of injury categories over all accidents. Note, that in contrast to the previous estimations I assigned the accidents to the most serious injury only. Following the same procedure as before, thus assigning an accident once to each injury occurring in this accident, would lead to an overestimation of costs due to multiple inclusion of one accident into the calculations, especially repeating inclusion of damage to property costs. With this method the costs of accidents are again rather underestimated, which is preferred over overestimation. Another source for underestimation is the exclusion of invalidity costs. As visible in the last row of Table 10 the costs of invalidity are much higher than the costs associated to severe injury. Nevertheless, in the accident data casualties suffering from lifelong invalidity are most likely labeled as severely injured and by that the assigned costs for severe injuries are certainly to low. Having no numbers on the share of invalidity related to the included accidents, I found no way to adjust the costs accordingly.

	Social Costs	External Costs	Damage to Property	Total Costs	Share in %
Unharmed	0	0	49’139	49’139	71.59
Lightly Injured	28’607	2’246	49’139	79’992	24.15
Severely Injured	808’801	45’198	49’139	903’138	3.99
Fatals	7’236’937	500’489	49’139	7’786’565	0.27
Invalidity	*3’409’906*	*870’053*	*49’139*	*4’329’098*	*unknown*

Table 10: Accident costs (in CHF) separated into injury catagories and type of cost calculated by the Swiss Federal Office for Spatial Development, ARE (2014), and shares of injury categories in 2019 & 2020 based on the accident data.

For the first scenario, I calculated the expected change in accident costs based on an increase in the price for driving a car. The total costs for each injury category were weighted with the share of each category to derive the average cost of one accident, which is 111’556 CHF.

In their most recent work, Hintermann et al. (2024) estimate price elasticities for different transport modes based on data from the MOBIS experiment. They find a reduction of 0.17% in the probability of taking the car for a trip when facing an increase of 1% in the price for car usage. Looking at travel time (-0.35%) or distance travelled (-0.45%) the estimated elasticity for car trips is even bigger. I underlay the assumption, that this reduction in probability of taking the car translates into the traffic counts used for the model shown in Subsection 6.4. Multiplying this reduction with the estimated effect of traffic counts on accident numbers, a reduction o 0.17% leads to 0.0184 less accidents per 100’000 vehicles counted on Swiss highways. This can be seen for all elasticities in the first multiplication depicted in Figure 7. As stated before,

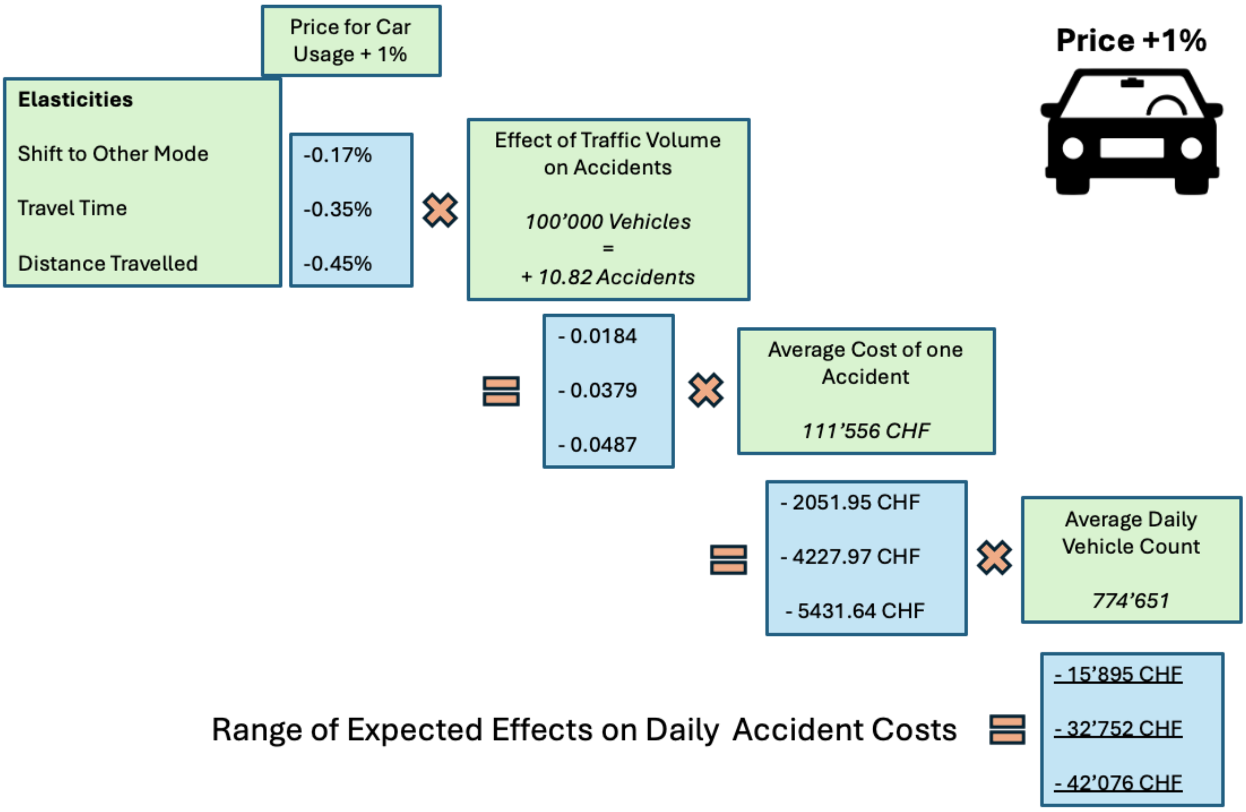

Figure 7: Path of calculations leading to the range of expected effects on daily accident costs based on a fictive scenario of a 1% increase in the cost of driving a car.

the traffic counts are not representative for actual numbers of vehicle counts on Swiss roads, but were shown to proxy changes in traffic volume quite reliable. Combining the reduction of 0.0184 accidents with the average cost of an accident (second step in Figure 7), this translates to savings of 2051.95 CHF. With a daily average of 774'651 vehicles counted over the whole period, this results in savings of 15'895 CHF daily. The above calculation only includes mode shifts, thus diverting from using the car to another transport mode or not taking the trip at all. Using the reported elasticity for reduced travel time of -0.35% and distance travelled of -0.45% from Hintermann et al. (2024), Figure 7 shows their effect on expected accident costs. Previously I explained how traffic volume is a two dimensional system and that not only the number of vehicles must be accounted for, but also the kilometers travelled and the time on the road system. Legitimizing the usage of the elasticity of distance and time travelled.
Together I conclude, that an increase of the price of travelling by car of 1%, via fuel tax or road pricing, results in an estimated daily savings of accident costs, internal and external combined, of 15'895 - 42'076 CHF.

The second scenario is based on people's responses to individual mobility pricing based on the generated external costs. I again base this calculations on results from Hintermann et al. (2024) derived from the MOBIS experiment. In the treatment period of the experiment, participants in the "pricing group" were assigned a virtual account with a starting budget adjusted to their mobility behavior in the observation period. For each trip they undertook, the external costs were deducted from that budget and participants knew that they could keep the remainder of the budget after the experiment. In addition, the participants of this group also received weekly information on their external costs per mode and how they could reduced them. Be-

sides other effects, they report a statistically significant reduction of 6.4% in congestion per km. This reduction is assigned to a change in route or departure time and an additional estimation for departure time shows a significant change to 5 minutes earlier in the morning. However, Hintermann et al. (2024) state that this result might be biased since it also captures possible mode shifts during this time. I focus on the reduction of congestion for this scenario and set the assumption, that the shift in mode is neglectable due to the measure of congestion per km. Knowing, that this might slightly bias my calculations upwards.
For this scenario I want to calculate the change in accident costs by the decrease of congestion by 6.4% as a reaction to individual mobility pricing. For that I rely on my estimations from the within-day estimation shown in Table 8. I calculated the average accident costs based on the distribution of injury categories in normal density, given by the shares denoted in Table 8, which is 94'322 CHF. By adding the estimated marginal effects of high traffic density to the shares of normal traffic density, I derived the distribution of injury categories in high traffic density and the corresponding average accident costs, 87'365 CHF. The different distribution of injury patterns in the two density environments can be seen in the top portion of Figure 8. The advantage of using the estimated differences in comparison to pure statistical differences lies in the exclusion of confounding effects. Note, that in this scenario I returned to account for casualties in each category they occurred and not only for the worst per accident. This is possible since I calculate the difference between the two states of traffic density, assuming that

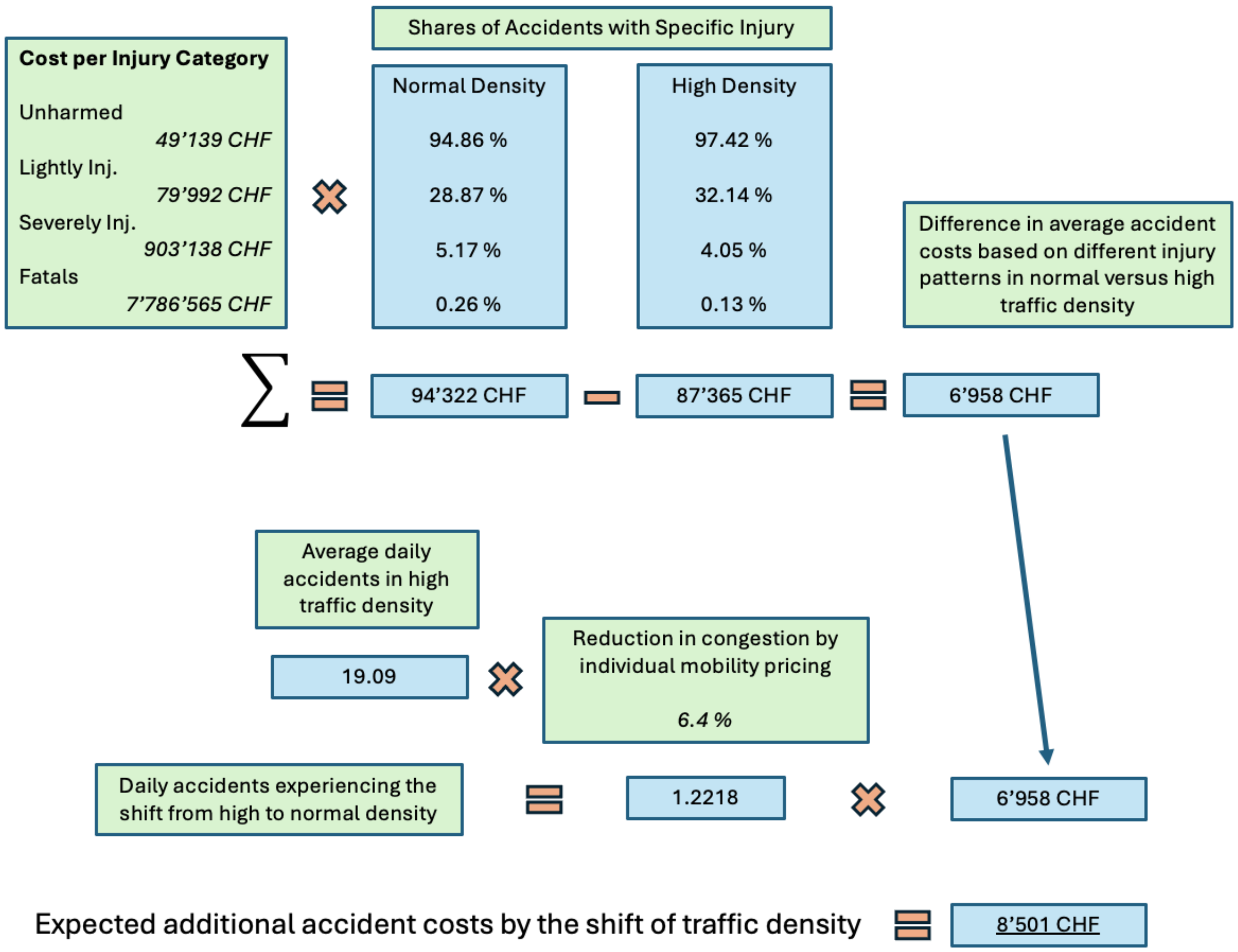

Figure 8: Path of calculations leading to the expected additional accident costs by shifting 6.4% of accidents occurring in high traffic density to a normal traffic density environment.

the number of accidents stays unchanged, thus damage to property wrongly included multiply for one accident gets equaled out. By that the depicted shares are the portion of accidents showing a casualty in each specific injury category and exceed 100% when being combined. The difference in costs arises from the higher shares of fatally and severely injured casualties in accidents happening in normal traffic density, that is most likely due to increased speed, and equals 6'958 CHF. The average daily count of accidents during high traffic density for the years 2015-2022 (excluding 2020), thus the years included in the within-day estimation, is 19.09. Multiplied by the reduction of 6.4% in congestion, this gives 1.2218 accidents per day experiencing a shift in traffic conditions and thus different injury patterns. Resulting in an increase of 8'501 CHF per day, when being combined with the difference in costs derived above, depicted in the lower portion of Figure 8.
In addition to the above mentioned changes in costs, reduced congestion also reduces the external costs related to traffic jams, i.e. prolonged fuel consumption, delays, increased emissions and noise. Which is of special interest when congestion arises as a result of an accident, thus it would have to be included in the accident costs. Both scenarios measure one reaction of accidents, number or severity, to a change in traffic volume while holding the other fixed. This is unrealistic but a necessary simplification to estimate some changes in accident costs by introducing a mobility policy. Creating a model able to calculate combined results of these two effects would be very interesting, but also worth a thesis for itself.
I conclude this Section with reporting both savings and additional costs of accidents by introducing mobility policies which increase the price, at least partially, of driving. In my two scenarios I find higher savings than costs, but comparing the two seems unfair since I do not know whether the individual externality pricing used in the second scenario lies somewhere even close to the 1% price increase used for the first scenario.

8 Discussion

In the first part of this work, I estimated the impact of different traffic conditions on the probability of experiencing a specific injury pattern when having an accident. By using the decrease in traffic volume of up to 60% during the Covid-19 Lockdown as an exogenous effect, I found an increase of 130% in the probability of being fatally injured and a reduction of 1.54% in the probability of remaining unharmed in an accident. Both categories severely and lightly injured showed no statistically significant differences. With the underlying assumption of less traffic volume leading to higher speed, based on the speed-density relationship discussed in Section 2, these results are in line with previous research stating a shift towards more severe injury patterns with increasing vehicle speeds.
Investigating the impact of changes in traffic density at the time of the accident, as reported by the police, provides comparable results. Accidents during low traffic density show a 41.15% higher probability of fatal injury compared to accidents in normal traffic density, while all other injury categories show a reduction of probability between 1.80-18.32%. Again, lower traffic density comes with higher speed which bears more energy to be transformed in the body at a crash. In high traffic density the probabilities of fatal or severe injury are 50.38% and 22.44% lower respectively, while the probability of light injury (12.81%) and remaining unharmed (2.69%) increase. This shows that speed has an imminent influence on injury patterns and how much severe and fatal injuries can be reduced by lower speed. Therefore, my results show that the probability of dying in an accident is highest in low traffic density, the probability of being severely injured is highest in normal traffic density and for both, lightly injured and unharmed, the probabilities are highest in high traffic density conditions. This is particularly interesting, since free speed conditions bring many benefits like no delays, less emissions and noise but are

obviously associated with more severe injury patterns. Which, with accident costs substantially rising with the severity of the injury, see Table 10, brings drastic welfare reduction.
Including the daily traffic counts from Swiss highways allowed to also analyse the effect of traffic volume on total accidents. It showed that an increase of 100'000 vehicles is associated with an additional 10.82 accidents. No significant correlation between traffic counts and fatal injuries was found, but on all other categories traffic counts have a statistically significant positive effect. Performing polynomial regression and further analyzing the shape of the estimated correlation showed, that all accidents, as well as accidents with unharmed persons are linearly correlated to traffic counts. This is exactly what Wang et al. (2009) found in their reserach on London data. Fatal accidents show a concave correlation to traffic counts, thus the marginal effect of additional vehicles counted tapers off. Contrarily, severe and light injury associated accidents show a convex correlation to traffic counts and increase over proportional as traffic counts rise. Thus, the relative accident rate remains unchanged for total accidents and unharmed, declines for fatal accidents and increases for accidents with severely or lightly injured casualties. The form of relationship found for the different injury categories approximately reflects the shapes described by Retallack and Ostendorf (2019), discussed in Subsection 2.2. More important is the insight we gained on the relationship between traffic volume and total accidents. The fact, that it is linear is good news for potential mobility policies. They can focus on effects on traffic distribution and total traffic volume, knowing that this will have an impact on accident occurrence based on the number of vehicles en route, but without worrying about disproportional reactions of accident numbers.
The last model uncovered different effects, with most of the estimated coefficients being insignificant. The results for the uncontrolled specification bear a high possibility of omitted variable bias, but by that and using accidents as a proxy for traffic volume, show an imprecise measure of the speed-density relationship in Switzerland. Especially during the off-peak and evening rush-hour periods. Controlling for daily traffic counts and later for seasonal FE reduces the observed effects, but the significant ones still remain negative. According to literature on this topic, we would assume a positive effect of speed on accident numbers. But with higher speed being associated to lower traffic density, it might as well be the case, that the effects of increased accidents by higher speed and reduced accidents by lower vehicle numbers on the streets just cancel each other out. Thus, further research on isolating these two effects is recommended. Nevertheless, the results of speed having no impact on relative accident numbers is in line with the linear relationship between traffic counts and accidents I found in the previous model. I found significant positive effects of speed on the accident numbers during the off-peak hours in the >80km/h and during night in the 50-80km/h regime with some specifications. These categories are most likely not prone to congestion, so that I state to have credibly isolated the speed-accident relationship here, which coincides with the majority of the literature on this topic.
Based on my calculations of possible policy implications, I estimate a reduction of accident related daily costs of 15'895-42'076 CHF to be expected from a 1% price increase of driving. This calculation includes both shift of transport mode and reduction of travel time and distance, but does not account for any changes in injury patterns resulting in different cost weights. The second calculation excludes mode shifts and accounts for changed injury probabilities. By holding the accident numbers fixed and changing the cost weights corresponding to the different injury distributions in varying traffic density, I find an increase of accident costs of 8'501 CHF per day when congestion decreases by 5%. Besides the included controls, there is no further differentiation between day of the week, holidays or also reason of trip or car occupancy. I also do not know in which relation the 1% increase in driving costs (first scenario) and the pricing of external costs in the second scenario have to each other. Thus, comparing these two

results is not possible and I can not make a final statement on expected consequences of any policy. Niemann (2020) also found potential for reduction in accidents and combining the two approaches could further support policy makers in their decisions.

Limitations I see are mainly based on the lack of sufficient data. The dataset on accidents contains all police reported accidents in Switzerland, but no information on all accidents which were handled without the police, i.e. by the insurances. In Europe, there is the *European Accident Statement* which is an international standard form to record accidents without damage to persons in absence of the police. Many accidents resulting in damage to property are solely handled by that and the insurances of the involved drivers negotiate the quilt and payments among each other. Thus, these accidents are missing. Including accidents where two vehicles slightly bump into or touch upon each other, which is more likely to happen on dense traffic environments. By that, the effect of traffic volume on total accidents might by underestimated by my models. Additionally, the variable of traffic density during the accident is a subjective evaluation of the filing police officer and consistency of this evaluation is not ensured.
The information on traffic volume is also limited, mostly because of the complexity of collecting extensive data on traffic behavior. The traffic counts from Swiss highways provide a useful workaround to include some daily variation of traffic volume in the models. But they lack detail, mainly in all regions besides the highways and especially on the distribution of the vehicles over the day. Being able to distinguish the counts, at least into the four time categories used in the last model, would increase the credibility of the results largely.
Another limitation is my reduction of casualties to maximum one per accident and injury category. I did this for the logit models, to be able to calculate the probability of an accident producing a casualty with the given injury category. For this model that approach seemed appropriate. For the count based third model, aggregating every person experiencing a specific injury on that day would have been superior. I realized the downside of this specification for that model to late to redo all calculations, but including all casualties would improve that model. Though besides unharmed, there are only few accidents with more than one person in a specific injury category.
Finally, there is imprecision with the speed data from the MOBIS and MobisCovid experiments. The derived average speeds for the 12 categories are a good start, but much more is possible. The assignment of the trips to speed regimes, based on their length seems to work approximately, but is highly experimental and very imprecise. Also each trip was attached to the time frame corresponding to the starting time, which is problematic for trips lasting multiple hours. Here I see a large problem with the calculations leading to the results of the fourth model. As mentioned above, the included effects are not well separated and will never be with the used approach. Overall, it seems like there was always one information missing, thus most interpretations strongly rely on assumptions based on existing literature.

To solve that, I propose to differentiate the trips into single sections, which can be assigned by their GPS tracks to categories like urban, suburban and rural or even speed regimes. This could also relax the problem of bottlenecks in the traffic system showing different traffic behavior than unrestricted roads discussed in Section 2, which is neglected in this work. Calculating average speeds based on the trip snippets, also allowing for more precise assignment of time, the average speed in the categories can be identified much better. Derivation of some measure of density in the categories might also be possible based on the MOBIS and MobisCovid data further improving the richness of the model. This was one of the ideas Prof. Hintermann and I had during the first meetings for this thesis. Unfortunately, we misunderstood each other for a while and meanwhile I followed different approaches. By the time we finally figured it out, the work was already in the final stages and it was to late to process all the data. I am sure, that including the available details contained in the data would largely improve my results and this would be the first direction of future research I see here. Additionally, separating the accidents into the corresponding injury categories could give advanced insight on the relationship of speed and injury patterns.

Sophisticated estimation of the speed-density relationship would be very useful for policy makers and efforts towards data gathering for that should be undertaken. This, together with behavioral research of peoples reaction to mobility policies would allow to make useful predictions of the consequences of such policies. Here is where I see the most extensive value and a need for future research. Understanding and maybe even being able to model the complex system of policies and their impact via multiple paths and mechanisms on the behavior of people, the direct and external costs they produce and their consequences on society and societal welfare would be very beneficial. This is very voluminous and as I stated before, only a solid calculation of changes in accident related costs based on one or two policies would fill one thesis by itself. I therefore hope, that many future researchers find an interest in this topic, since there are still many unknowns.

I would wish for more available data on that. Globally tracking smartphones becomes a source for extensive data on mobility behavior. A large project, maybe by the Swiss Federal Statistical Office, the Federal Roads Office or the Federal Office for Spatial Development, collecting data over a longer period and from a representative sample like in the microcensus of BFS and ARE (2023) would open uncountable options for further research.

9 Conclusion

In this thesis I wanted to analyse the impact of changes in traffic volume on the relative number and injury severity of accidents. The first hypothesis was: *"A reduction of traffic volume leads to an increase in relative accident rates.*, which could not be proved. I found a linear correlation between traffic counts and number of accidents, indicating no substantial changes in the relative accident rate. The second hypothesis was: *"A reduction of traffic volume causes a shift in the crash injury pattern from light injuries towards more severe and fatal outcomes."* and could be confirmed. The main driver is an increase in the share of fatal accidents with lower traffic volume, while I found higher shares of lightly injured and unharmed persons in high traffic density.

I can conclude that, with the data at hand, total accidents in Switzerland are mainly dependent on the volume of traffic en route and are not additionally increased or reduced by variations in speed. The severity of injuries experienced when having an accident on the other hand is largely driven by the speed of the vehicles, with higher speed leading to more fatal outcomes. Differentiation into subcategories of time during the day and speed regimes did not show more precise results. This is supposedly not an accurate finding, due to traffic counts availability being limited on daily level and very rough assignment of tracked trips into these categories. Which leads to a need in further research on that topic.

Calculation of two independent scenarios for policy implications show, that the reduction of accidents by an increase in the price of driving by 1% results in daily savings of accident costs of 15'895 - 42'076 CHF by shifting of transport mode or reduction of travelling distance. Individual pricing of external costs from driving reduced congestion by 5% and a possible shift in departure times. These changes in traffic density environment come with additional daily costs of 8'501 CHF due to more severe injuries. The two scenarios are not directly comparable, since the unit of impact is different, but shows that savings and additional costs associated with accidents can be expected by mobility policies.

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Appendix

Descriptive statistics of variables for the Covid-19 Lockdown variation.

	2015-2018 Mean	2019	2020	Total	change %
All Accidents	5'557	5'343	2'914	30'485	-45.46
	72.91	17.53	9.56		
Unharmed	5'287	5'077	2'724	28'947	-46.35
	95.13	95.02	93.48	94.95	
Light Injured	1'415	1'296	695	7'650	-46.37
	25.46	24.26	23.85	25.09	
Severly Injured	226	193	122	1'218	-36.79
	4.06	3.61	4.19	4	
Fatals	13	10	12	75	20.00
	0.24	0.19	0.41	0.25	
Speedlimit					
30	503	548	324	2'884	-40.88
	9.05	10.26	11.12	9.46	
50	2'864	2'641	1'446	15'544	-45.25
	51.54	49.43	49.62	50.99	
80	1'604	1'621	937	8'973	-42.20
	28.86	30.34	32.16	29.43	
120	586	533	207	3'084	-61.16
	10.55	9.98	7.1	10.12	
Traffic Density					
low	2'532	2'319	1'711	14'157	-26.22
	45.83	43.65	59.27	46.73	
normal	1'908	1'865	945	10'441	-49.33
	34.53	35.1	32.73	34.46	
high	1'085	1'129	231	5'700	-79.54
	19.64	21.25	8	18.81	
Streetlights					
ON	970	869	384	5'131	-55.81
	17.45	16.26	13.18	16'83	
Lightcondition					
Day	4'113	3'821	2'121	22'393	-44.49
	74.13	71.53	72.84	73.55	
Night	1'136	1'076	603	6'221	-43.96
	20.47	20.14	20.71	20.43	
Twilight	300	445	188	1'831	-57.75
	5.4	8.33	6.46	6.01	
Roadtype					
Straight	2'706	2'670	1'226	14'720	-54.08
	48.7	49.97	42.07	48.29	
Curves	843	766	563	4'699	-26.50
	15.16	14.34	19.32	15.41	
Intersection	1'180	1'066	643	6'429	-39.68
	21.23	19.95	22.07	21.09	
Roundabout	242	216	145	1'328	-32.87
	4.35	4.04	4.98	4.36	
Other	587	625	337	3'309	-46.08
	10.56	11.7	11.56	10.85	
Age					
<25	911	817	569	5'029	-30.35
	16.39	15.29	19.53	16.5	
25-34	1'965	1'009	554	5'821	-45.09
	19.16	18.88	19.01	19.09	
35-44	905	822	460	4'901	-44.04
	16.28	15.38	15.79	16.08	
45-54	900	864	455	4'920	-47.34
	16.2	16.17	15.61	16.14	
55-64	665	705	394	3'759	-44.11
	11.97	13.19	13.52	12.33	
65-74	471	474	169	2'538	-64.35
	8.47	8.87	6.25	8.33	
75-84	379	407	169	2'090	-58.48
	6.81	7.62	5.8	6.86	
>84	263	254	131	1'427	-48.43
	4.73	4.59	4.5	4.68	

	2015-2018 Mean	2019	2020	Total	change %
Female	1'823	1'813	949	10'055	-47.66
	33.58	34.49	33.43	33.73	
Holidays					
YES	259	219	105	1'358	-52.05
	4.65	4.1	3.6	4.45	
Reason of trip					
Commuting	1'175	1'093	608	6'402	-44.37
	21.15	20.46	20.86	21	
Holiday or Daytrip	172	148	35	870	-76.35
	3.09	2.77	1.2	2.85	
Leisure or Shopping	3'608	3'604	1'934	19'968	-46.34
	64.92	67.45	66.37	65.5	
Freight- or Worktrip	123	175	93	760	-46.86
	2.21	3.28	3.19	2.49	
others	480	323	244	2'485	-24.46
	8.63	6.05	8.37	8.15	
Type of Accident					
Pedestrian or crossing	334	319	118	1'772	-63.01
	6.01	5.97	4.03	5.81	
rear-end, take-over or changing lane	1'645	1'548	568	8'696	-63.31
	29.6	28.97	19.49	28.53	
Enter or Exit road	942	826	533	5'127	-35.47
	16.95	15.46	18.29	16.82	
Head-on collision	175	156	90	944	-42.31
	3.14	2.92	3.09	3.1	
Skkiding or self-accident	1'520	1'487	1'030	8'595	-30.73
	27.34	27.83	35.35	28.19	
other	942	1'007	575	5'351	-42.90
	16.96	18.85	19.73	17.55	
Weather					
sunny	3'492	3'352	2'278	19'596	-32.04
	62.83	62.74	78.17	64.28	
clouded	1'272	1'280	358	6'725	-72.03
	22.89	23.96	12.29	22.06	
rain	658	550	249	3'430	-54.73
	11.84	10.29	8.54	11.25	
snow, hail or freezing rain	91	119	4	486	-96.64
	1.63	2.23	0.14	1.59	
other	45	42	25	248	-40.48
	0.81	0.79	0.86	0.81	
Seatbelt					
YES	5'357	5'172	2'818	29'418	-45.51
	96.4	96.8	96.71	96.5	
Alcohol					
YES	408	383	271	2'286	-29.24
	7.34	7.17	9.3	7.5	
Speeding					
YES	12	11	8	67	-27.27
	0.22	0.21	0.27	0.22	
Relative Speeding					
YES	125	131	129	759	-1.53
	2.24	2.45	4.43	2.49	

Table A.1: Descriptive statistics of variables for the Covid-19 Lockdown variation. Numbers below the counts denote the shares of accidents in the specific category in percents for each year (vertical share comparison). Except for the first row, where the percental shares show the distribution over the three periods.

Descriptive statistics of main variables differentiated into categories of traffic density.

Variable	Low	Traffic Density Normal	High	Total
All Accidents	115'241	90'079	48'757	254'077
	45.36	35.45	19.19	
Unharmed	107'055	85'461	47'348	239'864
	92.9	94.87	97.11	94.41
Light Injured	22'103	25'664	15'709	63'476
	19.18	28.49	32.22	24.98
Severely Injured	4'299	4'661	1'753	10'713
	3.73	5.17	3.6	4.22
Fatals	409	233	67	709
	0.35	0.26	0.14	0.28
Speedlimit (km/h)				
30	17'993	5'464	953	24'310
	15.61	6.07	1.75	9.57
50	55'307	49'405	20'413	125'125
	47.99	54.85	41.87	49.25
80	34'906	26'624	15'806	77'336
	30.29	29.56	32.42	30.44
120	7'035	8'586	11'685	27'306
	6.1	9.53	23.97	10.75
Streetlights				
ON	33'028	14'594	9'265	56'887
	28.66	16.2	19	22.39
Light Condition				
Day	58'480	69'951	36'396	164'827
	50.86	77.7	74.69	64.96
Night	47'895	13'264	6'754	67'913
	41.65	14.73	13.9	26.76
Twilight	8'610	6'811	5'582	21'003
	7.49	7.57	11.45	8.28
Road Type				
Straight	48'817	41'352	33'347	123'516
	42.36	45.91	68.39	48.61
Curves	25'681	13'838	3'896	43'415
	22.28	15.36	7.99	17.09
Intersection	19'770	22'394	8'458	50'622
	17.16	24.86	17.35	19.92
Roundabout	3'317	5'547	2'004	10'868
	2.88	6.16	4.11	4.28
Other	17'656	6'948	1'052	25'656
	15.32	7.71	2.16	10.1
Age				
<25	21'849	12'747	7'831	42'427
	18.96	14.15	16.06	16.7
25-34	22'442	16'104	10'724	49'270
	19.47	17.88	21.99	19.39
35-44	17'639	14'042	8'577	40'258
	15.31	15.59	17.59	15.84
45-54	17'408	14'367	8'010	39'785
	15.11	15.95	16.43	15.66
55-64	13'263	11'822	5'849	30'934
	11.51	13.12	12	12.18
65-74	9'295	8'918	3'507	21'720
	8.07	9.9	7.19	8.55
75-84	7'531	7'315	2'555	17'401
	6.54	8.12	5.24	6.85
>84	5'814	4'764	1'704	12'282
	5.05	5.29	3.49	4.83

Variable	Low	Traffic Density Normal	High	Total
Female	35'794	31'627	16'360	83'781
	31.86	35.98	34.1	33.75
Holidays				
Yes	3'032	1'322	482	4'836
	2.63	1.47	0.99	1.9
Reason of trip				
Commuting	18'937	19'322	16'127	54'396
	16.43	21.46	33.08	21.41
Holiday or Daytrip	3'499	3'282	2'050	8'831
	3.04	3.64	4.2	3.48
Leisure or Shopping	80'179	57'846	26'372	164'397
	69.58	64.22	54.09	64.7
Freight- or Worktrip	2'703	2'450	1'471	6'624
	2.35	2.72	3.02	2.61
others	9'923	7'169	2'737	19'829
	8.61	7.96	5.61	7.8
Seatbelt				
Yes	110'140	87'727	47'950	245'817
	95.57	97.39	98.34	96.75
Type of Accident				
Pedestrian or crossing	6'940	6'785	2'257	15'982
	6.02	7.53	4.63	6.29
rear-end, take-over or changing lane	11'816	25'670	31'602	69'088
	10.25	28.5	64.82	27.19
Enter or Exit road	13'337	19'966	7'252	40'555
	11.57	22.16	14.87	15.96
Head-on collision	4'391	3'228	719	8'338
	3.81	3.58	1.47	3.28
Skkiding or self-accident	50'933	23'729	4'994	79'656
	44.2	26.34	10.24	31.35
other	27'824	10'701	1'933	40'458
	24.14	11.88	3.96	15.92
Weather				
sunny	63'290	53'177	28'501	144'968
	54.92	59.03	58.46	57.06
clouded	32'168	23'042	13'172	68'382
	27.91	25.58	27.02	26.91
rain	12'193	9'814	5'805	27'812
	10.58	10.89	11.91	10.95
snow, hail or freezing rain	6'186	3'546	1'035	10'767
	5.37	3.95	2.12	4.24
other	1'404	500	244	2'148
	1.22	0.56	0.5	0.85
Alcohol				
YES	14'413	3'888	1'104	19'820
	12.87	4.32	2.26	7.8
Speeding				
YES	366	189	36	591
	0.32	0.21	0.07	0.23
Relative Speeding				
YES	3'891	1'673	237	5'801
	3.38	1.86	0.49	2.28

Table A.2: Descriptive statistics of main variables differentiated into categories of traffic density. Numbers below the counts denote the proportional shares of accidents in the three density categories in percents.

VARIABLES	(1) Fatals	(2) Fatals	(3) Fatals	(4) Fatals
Jahr *(2019)*				
2015	0.000520	0.000568	0.000628	0.000351
	(0.000888)	(0.000895)	(0.000907)	(0.000940)
2016	-0.000432	-0.000451	-0.000419	-0.000462
	(0.000780)	(0.000775)	(0.000783)	(0.000856)
2017	0.000940	0.000969	0.00106	0.00122
	(0.000918)	(0.000919)	(0.000936)	(0.00103)
2018	0.00101	0.000977	0.00101	0.00118
	(0.000932)	(0.000924)	(0.000933)	(0.00103)
2020	0.00225*	0.00239*	0.00259*	0.00263*
	(0.00133)	(0.00136)	(0.00144)	(0.00149)
Holiday		0.00199**	0.00211**	0.00197*
		(0.00101)	(0.00103)	(0.00111)
Female			-0.00133*	-0.00107
			(0.000701)	(0.000757)
Age *(26-34)*				
<25			0.000870	0.000607
			(0.000900)	(0.000874)
35-44			–0.00126*	-0.00124*
			(0.000668)	(0.000695)
45-54			0.000838	0.00110
			(0.000942)	(0.00101)
55-64			0.000800	0.00120
			(0.00102)	(0.00112)
65-74			0.00189	0.00288*
			(0.00140)	(0.00171)
75-84			0.00480**	0.00699***
			(0.00193)	(0.00269)
>84			-0.000519	0.000114
			(0.00147)	(0.00211)
Weather *(sunny)*				
clouded				0.000570
				(0.000794)
rain				-0.000740
				(0.000873)
snow, hail or freezing rain, omitted				-
other, omitted				-
Speedlimit (km/h) *(50)*				
30				-0.000176
				(0.000736)
80				0.00339***
				(0.000885)
120				0.00195*
				(0.00112)
Light Condition *(Day)*				
Night				-0.00104
				(0.000755)
Twilight, omitted				-
Streetlights, omitted				-
Road Type *(Straight Road)*				
Curves				0.00380***
				(0.00121)
Intersection				-0.00129**
				(0.000598)
Roundabout, omitted				-
Others				-0.00104
				(0.000832)
Season FE		YES	YES	YES
Driver Controls			YES	YES
Environment Controls				YES
Observations	30,485	30,485	29,812	27,288

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Full results of the regression analysis explained Section 6.2 corresponding to Table 7. Categories in parentheses denote the reference category for the particular variable.

VARIABLES	(1) Severely Injured	(2) Severely Injured	(3) Severely Injured	(4) Severely Injured
Jahr *(2019)*				
2015	0.00472	0.00470	0.00538	0.00448
	(0.00370)	(0.00370)	(0.00374)	(0.00380)
2016	0.00490	0.00501	0.00532	0.00429
	(0.00369)	(0.00369)	(0.00373)	(0.00377)
2017	0.00675*	0.00672*	0.00723*	0.00671*
	(0.00371)	(0.00370)	(0.00373)	(0.00379)
2018	0.00158	0.00180	0.00211	0.00104
	(0.00361)	(0.00362)	(0.00365)	(0.00369)
2020	0.00574	0.00563	0.00645	0.00264
	(0.00450)	(0.00449)	(0.00459)	(0.00444)
Holiday		-0.00643	-0.00427	-0.00207
		(0.00589)	(0.00595)	(0.00592)
Female			0.00318	0.00195
			(0.00240)	(0.00241)
Age *(25-34)*				
<25			0.00336	0.00261
			(0.00352)	(0.00354)
35-44			0.00429	0.00398
			(0.00358)	(0.00362)
45-54			0.00554	0.00469
			(0.00361)	(0.00363)
55-64			0.00948**	0.00785*
			(0.00405)	(0.00401)
65-74			0.0232***	0.0209***
			(0.00516)	(0.00511)
75-84			0.0202***	0.0190***
			(0.00547)	(0.00553)
>84			0.0190**	0.0187**
			(0.00846)	(0.00859)
Weather *(sunny)*				
clouded				-0.00941***
				(0.00274)
rain				-0.0137***
				(0.00333)
snow, hail or freezing rain				-0.0176**
				(0.00782)
other				-0.0111
				(0.0162)
Speedlimit (km/h) *(50)*				
30				-0.0187***
				(0.00347)
80				0.00237
				(0.00291)
120				-0.0213***
				(0.00342)
Light Condition *(Day)*				
Night				-0.00829**
				(0.00347)
Twilight				-0.00200
				(0.00537)
Streetlights				-0.00793*
				(0.00470)
Road Type *(Straight Road)*				
Curves				0.0149***
				(0.00371)
Intersection				0.0174***
				(0.00321)
Roundabout				0.0194***
				(0.00613)
Others				-0.0180***
				(0.00282)
Season FE		YES	YES	YES
Driver Controls			YES	YES
Environment Controls				YES
Observations	30,485	30,485	29,812	29,783

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.4: Full results of the regression analysis explained Section 6.2 corresponding to Table 7. Categories in parentheses denote the reference category for the particular variable.

VARIABLES	(1) Lightly Injured	(2) Lightly Injured	(3) Lightly Injured	(4) Lightly Injured
Jahr *(2019)*				
2015	0.0277***	0.0273***	0.0265***	0.0208**
	(0.00841)	(0.00840)	(0.00848)	(0.00836)
2016	0.00825	0.00836	0.00869	0.00370
	(0.00826)	(0.00826)	(0.00835)	(0.00822)
2017	0.00748	0.00719	0.00831	0.00363
	(0.00821)	(0.00820)	(0.00828)	(0.00816)
2018	0.00514	0.00497	0.00539	0.00199
	(0.00825)	(0.00824)	(0.00831)	(0.00822)
2020	-0.00406	-0.00523	-0.00488	-0.0109
	(0.00983)	(0.00982)	(0.00993)	(0.00973)
Holiday		-0.0400***	-0.0393***	-0.0184
		(0.0131)	(0.0133)	(0.0130)
Female			0.0368***	0.0263***
			(0.00522)	(0.00516)
Age *(25-34)*				
<25			0.00803	0.0125
			(0.00847)	(0.00838)
35-44			-0.00399	-0.00517
			(0.00843)	(0.00823)
45-54			-0.0167**	-0.0204**
			(0.00834)	(0.00813)
55-64			0.00343	-0.00504
			(0.00915)	(0.00887)
65-74			-0.0179*	-0.0255**
			(0.0102)	(0.00995)
75-84			-0.0247**	-0.0254**
			(0.0108)	(0.0109)
>84			-0.00385	-0.000560
			(0.0168)	(0.0168)
Weather *(sunny)*				
clouded				-0.0343***
				(0.00600)
rain				-0.0196**
				(0.00801)
snow, hail or freezing rain				-0.00972
				(0.0205)
other				-0.0144
				(0.0366)
Speedlimit (km/h) *(50)*				
30				0.111***
				(0.00808)
80				0.000597
				(0.00612)
120				-0.0251***
				(0.00891)
Light Condition *(Day)*				
Night				-0.125***
				(0.00680)
Twilight				-0.0194*
				(0.0112)
Streetlights				-0.0106
				(0.0110)
Road Type *(Straight Road)*				
Curves				-0.00592
				(0.00755)
Intersection				0.0634***
				(0.00705)
Roundabout				0.0811***
				(0.0133)
Others				-0.175***
				(0.00619)
Season FE		YES	YES	YES
Driver Controls			YES	YES
Environment Controls				YES
Observations	30,485	30,485	29,812	29,783

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5: Full results of the regression analysis explained Section 6.2 corresponding to Table 7. Categories in parentheses denote the reference category for the particular variable.

VARIABLES	(1) Unharmed	(2) Unharmed	(3) Unharmed	(4) Unharmed
Jahr *(2019)*				
2015	-0.00559	-0.00553	-0.00620	-0.00522
	(0.00430)	(0.00430)	(0.00439)	(0.00429)
2016	0.00444	0.00466	0.00452	0.00345
	(0.00408)	(0.00407)	(0.00416)	(0.00415)
2017	0.00726*	0.00730*	0.00726*	0.00659
	(0.00400)	(0.00401)	(0.00409)	(0.00405)
2018	-0.00199	-0.00192	-0.00219	-0.00360
	(0.00421)	(0.00421)	(0.00429)	(0.00427)
2020	-0.0154***	-0.0156***	-0.0158***	-0.0146***
	(0.00546)	(0.00548)	(0.00558)	(0.00541)
Holiday		-0.00865	-0.00884	-0.00203
		(0.00572)	(0.00584)	(0.00575)
Female			-0.0127***	-0.0200***
			(0.00265)	(0.00264)
Age *(25-34)*				
<25			-0.0170***	-0.00966**
			(0.00460)	(0.00396)
35-44			0.00658	0.00273
			(0.00415)	(0.00390)
45-54			0.00738*	0.00158
			(0.00413)	(0.00396)
55-64			0.00739*	-0.00151
			(0.00444)	(0.00450)
65-74			0.00446	-0.0113*
			(0.00514)	(0.00577)
75-84			-0.00405	-0.0298***
			(0.00584)	(0.00724)
>84			-0.00559	-0.0308***
			(0.00907)	(0.0116)
Weather *(sunny)*				
clouded				0.00225
				(0.00309)
rain				-0.000436
				(0.00403)
snow, hail or freezing rain				-0.00346
				(0.00898)
other				-0.0130
				(0.0201)
Speedlimit (km/h) *(50)*				
30				0.00998***
				(0.00364)
80				-0.0335***
				(0.00334)
120				-0.0269***
				(0.00492)
Light Condition *(Day)*				
Night				-0.0174***
				(0.00377)
Twilight				-0.0199***
				(0.00594)
Streetlights				0.00285
				(0.00465)
Road Type *(Straight Road)*				
Curves				-0.0564***
				(0.00474)
Intersection				0.0154***
				(0.00296)
Roundabout				0.0208***
				(0.00477)
Others				0.0192***
				(0.00378)
Season FE		YES	YES	YES
Driver Controls			YES	YES
Environment Controls				YES
Observations	30,485	30,485	29,812	29,783

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.6: Full results of the regression analysis explained Section 6.2 corresponding to Table 7. Categories in parentheses denote the reference category for the particular variable.

VARIABLES	(1) Fatals	(2) Fatals	(3) Fatals	(4) Fatals
Traffic Density *(Normal)*				
Low Traffic Density	0.000962***	0.000879***	0.000897***	0.00107***
	(0.000244)	(0.000247)	(0.000251)	(0.000272)
High Traffic Density	-0.00121***	-0.00121***	-0.00117***	-0.00131***
	(0.000238)	(0.000242)	(0.000253)	(0.000244)
Holiday		0.00156***	0.00162***	0.00141**
		(0.000577)	(0.000589)	(0.000586)
Female			-0.00157***	-0.00125***
			(0.000265)	(0.000260)
Age *(25-34)*				
<25			0.000494	0.000183
			(0.000339)	(0.000298)
35-44			-0.000461	-0.000266
			(0.000317)	(0.000308)
45-54			-7.53e-05	0.000162
			(0.000333)	(0.000330)
55-64			4.03e-05	0.000380
			(0.000363)	(0.000369)
65-74			0.00161***	0.00228***
			(0.000494)	(0.000550)
75-84			0.00250***	0.00400***
			(0.000585)	(0.000739)
>84			0.00302***	0.00514***
			(0.000929)	(0.00124)
Weather *(sunny)*				
clouded				-0.000359
				(0.000264)
rain				-0.000787**
				(0.000336)
snow, hail or freezing rain				-0.00170***
				(0.000359)
other				0.00375*
				(0.00193)
Speedlimit (km/h) *(50)*				
30				-0.00127***
				(0.000201)
80				0.00280***
				(0.000314)
120				0.00142***
				(0.000434)
Light Condition *(Day)*				
Night				-0.000313
				(0.000309)
Twilight				-0.000596
				(0.000407)
Streetlights				0.000374
				(0.000477)
Road Type *(Straight Road)*				
Curves				0.00217***
				(0.000364)
Intersection				-0.000846***
				(0.000266)
Roundabout				-0.00214***
				(0.000285)
Others				-0.00122***
				(0.000314)
Season FE		YES	YES	YES
Driver Controls			YES	YES
Environment Controls				YES
Observations	254,077	254,077	248,246	247,989

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.7: Full results of the regression analysis based on the within-day variation explained Section 6.3 corresponding to Table 8. Categories in parentheses denote the reference category for the particular variable.

VARIABLES	(1) Severely Injured	(2) Severely Injured	(3) Severely Injured	(4) Severely Injured
Traffic Density *(Normal)*				
Low Traffic Density	-0.0144***	-0.0139***	-0.0134***	-0.00730***
	(0.000920)	(0.000927)	(0.000936)	(0.000997)
High Traffic Density	-0.0155***	-0.0157***	-0.0145***	-0.0112***
	(0.00112)	(0.00111)	(0.00113)	(0.00112)
Holiday		-0.00825**	-0.00711**	-0.00715**
		(0.00327)	(0.00331)	(0.00329)
Female			0.000442	0.000109
			(0.000849)	(0.000853)
Age *(25-34)*				
<25			0.00205	0.00105
			(0.00127)	(0.00125)
35-44			0.00229*	0.00224*
			(0.00128)	(0.00128)
45-54			0.00490***	0.00457***
			(0.00130)	(0.00130)
55-64			0.0106***	0.0103***
			(0.00146)	(0.00146)
65-74			0.0174***	0.0175***
			(0.00173)	(0.00176)
75-84			0.0161***	0.0169***
			(0.00187)	(0.00193)
>84			0.0131***	0.0150***
			(0.00279)	(0.00291)
Weather *(sunny)*				
clouded				-0.00704***
				(0.000960)
rain				-0.00593***
				(0.00130)
snow, hail or freezing rain				-0.0211***
				(0.00172)
other				0.00518
				(0.00595)
Speedlimit (km/h) *(50)*				
30				-0.0187***
				(0.00124)
80				0.00457***
				(0.00105)
120				-0.0189***
				(0.00126)
Light Condition *(Day)*				
Night				-0.00602***
				(0.00123)
Twilight				0.000455
				(0.00171)
Streetlights				-0.00223
				(0.00164)
Road Type *(Straight Road)*				
Curves				0.0122***
				(0.00127)
Intersection				0.0160***
				(0.00118)
Roundabout				0.0109***
				(0.00205)
Others				-0.0224***
				(0.000999)
Season FE		YES	YES	YES
Driver Controls			YES	YES
Environment Controls				YES
Observations	254,077	254,077	248,246	247,989

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.8: Full results of the regression analysis based on the within-day variation explained Section 6.3 corresponding to Table 8. Categories in parentheses denote the reference category for the particular variable.

VARIABLES	(1) Lightly Injured	(2) Lightly Injured	(3) Lightly Injured	(4) Lightly Injured
Traffic Density *(Normal)*				
Low Traffic Density	-0.0899***	-0.0860***	-0.0879***	-0.0492***
	(0.00187)	(0.00189)	(0.00191)	(0.00202)
High Traffic Density	0.0392***	0.0364***	0.0366***	0.0387***
	(0.00257)	(0.00256)	(0.00260)	(0.00252)
Holiday		-0.0145**	-0.0138**	-0.00957
		(0.00662)	(0.00669)	(0.00654)
Female			0.0343***	0.0303***
			(0.00177)	(0.00176)
Age *(25-34)*				
<25			0.0161***	0.0151***
			(0.00287)	(0.00284)
35-44			-0.00645**	-0.00806***
			(0.00284)	(0.00280)
45-54			-0.00777***	-0.0105***
			(0.00284)	(0.00280)
55-64			-0.00187	-0.00546*
			(0.00308)	(0.00303)
65-74			-0.0112***	-0.0127***
			(0.00343)	(0.00342)
75-84			-0.0187***	-0.0180***
			(0.00368)	(0.00373)
>84			-0.0210***	-0.0164***
			(0.00552)	(0.00565)
Weather *(sunny)*				
clouded				-0.0121***
				(0.00204)
rain				-0.00375
				(0.00281)
snow, hail or freezing rain				-0.0178***
				(0.00459)
other				0.0135
				(0.0115)
Speedlimit (km/h) *(50)*				
30				-0.0871***
				(0.00303)
80				-0.0222***
				(0.00213)
120				-0.0527***
				(0.00293)
Light Condition *(Day)*				
Night				-0.0484***
				(0.00262)
Twilight				0.0124***
				(0.00352)
Streetlights				-0.0179***
				(0.00332)
Road Type *(Straight Road)*				
Curves				0.000903
				(0.00254)
Intersection				0.0655***
				(0.00247)
Roundabout				0.0881***
				(0.00463)
Others				-0.154***
				(0.00228)
Season FE		YES	YES	YES
Driver Controls			YES	YES
Environment Controls				YES
Observations	254,077	254,077	248,246	247,989

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.9: Full results of the regression analysis based on the within-day variation explained Section 6.3 corresponding to Table 8. Categories in parentheses denote the reference category for the particular variable.

VARIABLES	(1) Unharmed	(2) Unharmed	(3) Unharmed	(4) Unharmed
Traffic Density *(Normal)*				
Low Traffic Density	0.103***	0.0990***	0.100***	0.0557***
	(0.00199)	(0.00200)	(0.00203)	(0.00213)
High Traffic Density	-0.0225***	-0.0196***	-0.0213***	-0.0267***
	(0.00267)	(0.00266)	(0.00270)	(0.00262)
Holiday		0.0198***	0.0181**	0.0142**
		(0.00695)	(0.00702)	(0.00682)
Female			-0.0336***	-0.0296***
			(0.00188)	(0.00186)
Age *(25-34)*				
<25			-0.0186***	-0.0161***
			(0.00301)	(0.00295)
35-44			0.00468	0.00614**
			(0.00298)	(0.00294)
45-54			0.00308	0.00594**
			(0.00300)	(0.00294)
55-64			-0.00863***	-0.00507
			(0.00325)	(0.00319)
65-74			-0.00777**	-0.00687*
			(0.00365)	(0.00364)
75-84			0.000120	-0.00238
			(0.00394)	(0.00398)
>84			0.00455	-0.00305
			(0.00591)	(0.00607)
Weather *(sunny)*				
clouded				0.0195***
				(0.00215)
rain				0.0106***
				(0.00296)
snow, hail or freezing rain				0.0411***
				(0.00472)
other				-0.0236**
				(0.0119)
Speedlimit (km/h) *(50)*				
30				0.107***
				(0.00316)
80				0.0153***
				(0.00225)
120				0.0679***
				(0.00310)
Light Condition *(Day)*				
Night				0.0529***
				(0.00278)
Twilight				-0.0126***
				(0.00369)
Streetlights				0.0201***
				(0.00351)
Road Type *(Straight Road)*				
Curves				-0.0161***
				(0.00269)
Intersection				-0.0821***
				(0.00258)
Roundabout				-0.0985***
				(0.00480)
Others				0.177***
				(0.00245)
Season FE		YES	YES	YES
Driver Controls			YES	YES
Environment Controls				YES
Observations	254,077	254,077	248,246	247,989

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.10: Full results of the regression analysis based on the within-day variation explained Section 6.3 corresponding to Table 8. Categories in parentheses denote the reference category for the particular variable.

Estimated Effect of Daily Traffic Counts on Accidents and Injury Categories using OLS Regression

VARIABLES	(1) All Accidents	(2) All Accidents	(3) Fatals	(4) Fatals	(5) Severely Injured	(6) Severely Injured	(7) Lightly Injured	(8) Lightly Injured	(9) Unharmed	(10) Unharmed
Traffic Counts *(in 100'000)*	10.29***	10.82***	0.00560	-0.0331	0.637***	0.594***	4.094***	3.625***	10.01***	10.41***
	(0.691)	(0.779)	(0.0192)	(0.0251)	(0.0866)	(0.112)	(0.256)	(0.311)	(0.646)	(0.739)
Constant	7.813	27.45***	-0.154	-0.337	1.251*	1.501	6.429***	11.74***	7.240	25.77***
	(6.647)	(7.182)	(0.171)	(0.214)	(0.720)	(0.990)	(2.301)	(2.678)	(6.196)	(6.698)
Season FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Observations	669	669	669	669	669	669	669	669	669	669
R-squared	0.425	0.532	0.005	0.026	0.117	0.150	0.399	0.480	0.437	0.543

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Estimated Effect of Daily Traffic Counts on Accidents and Injury Categories using PPML Regression

VARIABLES	(1) All Accidents	(2) All Accidents	(3) Fatals	(4) Fatals	(5) Severely Injured	(6) Severely Injured	(7) Lightly Injured	(8) Lightly Injured	(9) Unharmed	(10) Unharmed
Traffic Counts *(in 100'000)*	9.875***	10.48***	0.000743	-0.0499**	0.648***	0.655***	4.147***	3.604***	9.624***	10.03***
	(0.789)	(0.950)	(0.0209)	(0.0242)	(0.101)	(0.153)	(0.307)	(0.396)	(0.740)	(0.902)
Constant	19.24***	23.33***	0.0192***	0.0057***	0.920	1.280	4.686***	6.178***	17.73***	21.61***
	(2.505)	(2.940)	(0.0284)	(0.0109)	(0.313)	(0.494)	(0.884)	(1.259)	(2.310)	(2.730)
Season FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Observations	669	669	669	669	669	669	669	669	669	669

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.11: Results of the OLS and PPML regression of all accidents and the four injury categories on the daily traffic counts on Swiss highways. The results show the marginal effect of an increase in traffic count by 100'000, which is included linearly and quadratic in the model.
Note the exclusion of all seasonal fixed-effect in the first specification for each category.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Morning Rush-Hour			Off-Peak			Evening Rush-Hour			Night		
VARIABLES	<50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h
Average Speed	-0.0169	-0.0674***	0.00371	-0.815***	-0.0568	0.0373**	-0.197***	-0.130***	-0.00912	-0.0256	0.0536**	0.00817
	(0.0234)	(0.0154)	(0.00983)	(0.132)	(0.0489)	(0.0172)	(0.0363)	(0.0268)	(0.0131)	(0.0328)	(0.0242)	(0.00798)
Constant	5.703***	9.312***	2.008**	63.63***	16.04***	0.599	18.37***	15.47***	3.328***	11.22***	2.365	1.901**
	(1.216)	(1.337)	(0.982)	(5.635)	(3.926)	(1.609)	(1.758)	(2.183)	(1.267)	(1.673)	(2.076)	(0.824)
Observations	216	199	108	252	251	210	248	247	163	239	249	152
R-squared	0.003	0.074	0.001	0.143	0.004	0.017	0.088	0.082	0.004	0.002	0.017	0.004
Season FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Morning Rush-Hour			Off-Peak			Evening Rush-Hour			Night		
VARIABLES	<50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h
Average Speed	-0.0148	-0.0280**	0.00234	-0.178	-0.0108	0.0259	-0.0695**	-0.0535**	-0.00488	-0.0118	0.0392	0.0159**
	(0.0147)	(0.0132)	(0.00946)	(0.118)	(0.0426)	(0.0162)	(0.0311)	(0.0263)	(0.0141)	(0.0326)	(0.0239)	(0.00786)
Daily Traffic Counts	0.945***	0.486***	0.322**	3.730***	1.309***	0.703***	1.315***	0.677***	0.248***	0.737***	0.539***	0.0206
(in 100'000)	(0.0823)	(0.0788)	(0.129)	(0.265)	(0.126)	(0.0823)	(0.108)	(0.0793)	(0.0528)	(0.148)	(0.0999)	(0.0850)
Constant	-1.504**	2.195	-0.612	9.302	2.864	-3.517**	3.075*	4.452*	0.928	4.973**	-0.330	1.046
	(0.756)	(1.439)	(1.516)	(6.283)	(3.705)	(1.591)	(1.695)	(2.305)	(1.525)	(2.217)	(1.922)	(1.061)
Observations	191	172	91	222	221	181	218	217	135	209	219	129
R-squared	0.260	0.162	0.023	0.506	0.252	0.184	0.313	0.228	0.070	0.082	0.112	0.019
Season FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.12: Results of the OLS estimation of accidents on average speed in the 12 categories explained in Subsection 6.5.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Morning Rush-Hour			Off-Peak			Evening Rush-Hour			Night		
VARIABLES	<50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h
Average Speed	-0.0418***	-0.0351**	0.00997	-0.162	-0.0237	0.0261	-0.0836***	-0.0394	-0.00489	0.0147	0.0491**	-0.00141
	(0.0137)	(0.0142)	(0.00798)	(0.124)	(0.0430)	(0.0169)	(0.0288)	(0.0243)	(0.0135)	(0.0264)	(0.0228)	(0.0105)
Constant	0.901	2.630*	-1.742*	19.09***	12.80***	-1.154	13.56***	6.978***	1.677	10.18***	-0.509	2.753**
	(0.932)	(1.556)	(1.003)	(6.560)	(3.456)	(1.661)	(1.839)	(2.058)	(1.165)	(1.555)	(2.063)	(1.199)
Observations	216	199	108	252	251	210	248	247	163	239	249	152
R-squared	0.398	0.377	0.220	0.495	0.299	0.287	0.453	0.374	0.202	0.497	0.250	0.158
Season FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Morning Rush-Hour			Off-Peak			Evening Rush-Hour			Night		
VARIABLES <50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h	<50km/h	50-80km/h	>80km/h	
Average Speed	-0.0438***	-0.0255	0.00428	-0.0368	-0.0403	0.0228	-0.0656**	-0.0129	-0.00815	0.0313	0.0495**	0.00457
	(0.0136)	(0.0157)	(0.00905)	(0.113)	(0.0403)	(0.0164)	(0.0312)	(0.0252)	(0.0146)	(0.0233)	(0.0232)	(0.0101)
Daily Traffic Counts	0.516**	-0.0627	0.277	4.320***	1.387***	0.644***	0.674**	0.202	-0.103	1.330***	0.743***	0.202
(in 100'000)	(0.203)	(0.153)	(0.510)	(0.518)	(0.223)	(0.202)	(0.273)	(0.167)	(0.153)	(0.320)	(0.191)	(0.179)
Constant	-1.500	2.653	-1.677	0.923	2.889	-2.816	8.381**	4.452*	6.070***	6.885***	5.587**	0.132
	(1.472)	(2.105)	(3.224)	(7.427)	(3.827)	(2.265)	(3.265)	(2.587)	(2.183)	(2.437)	(2.228)	(1.415)
Observations	191	172	91	222	221	181	218	217	135	209	219	129
R-squared	0.432	0.369	0.230	0.600	0.359	0.315	0.455	0.410	0.235	0.551	0.302	0.200
Season FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.13: Results of the OLS estimation of accidents on average speed in the 12 categories explained in Subsection 6.5.

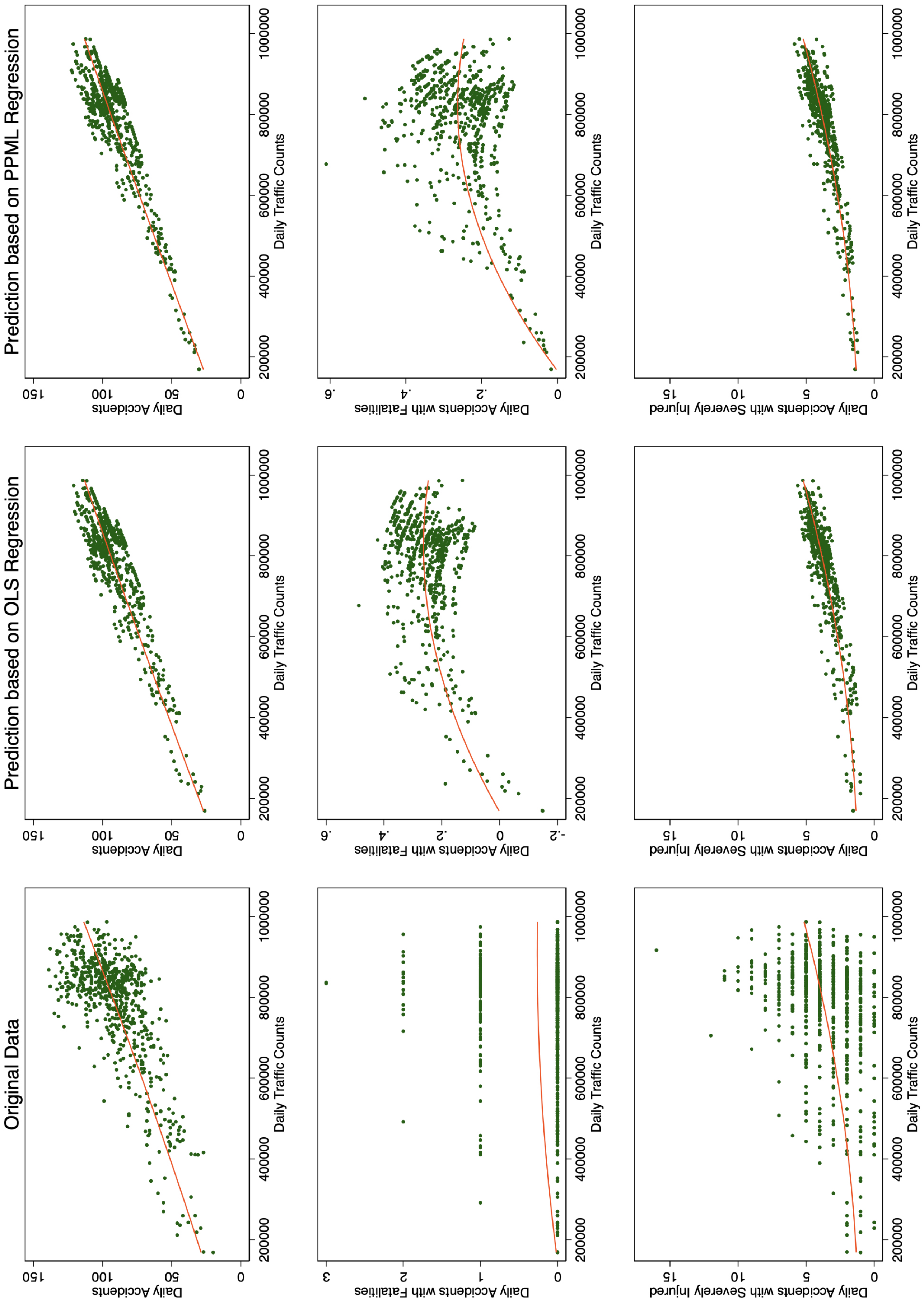

Figure A.1: DESCRIPTION

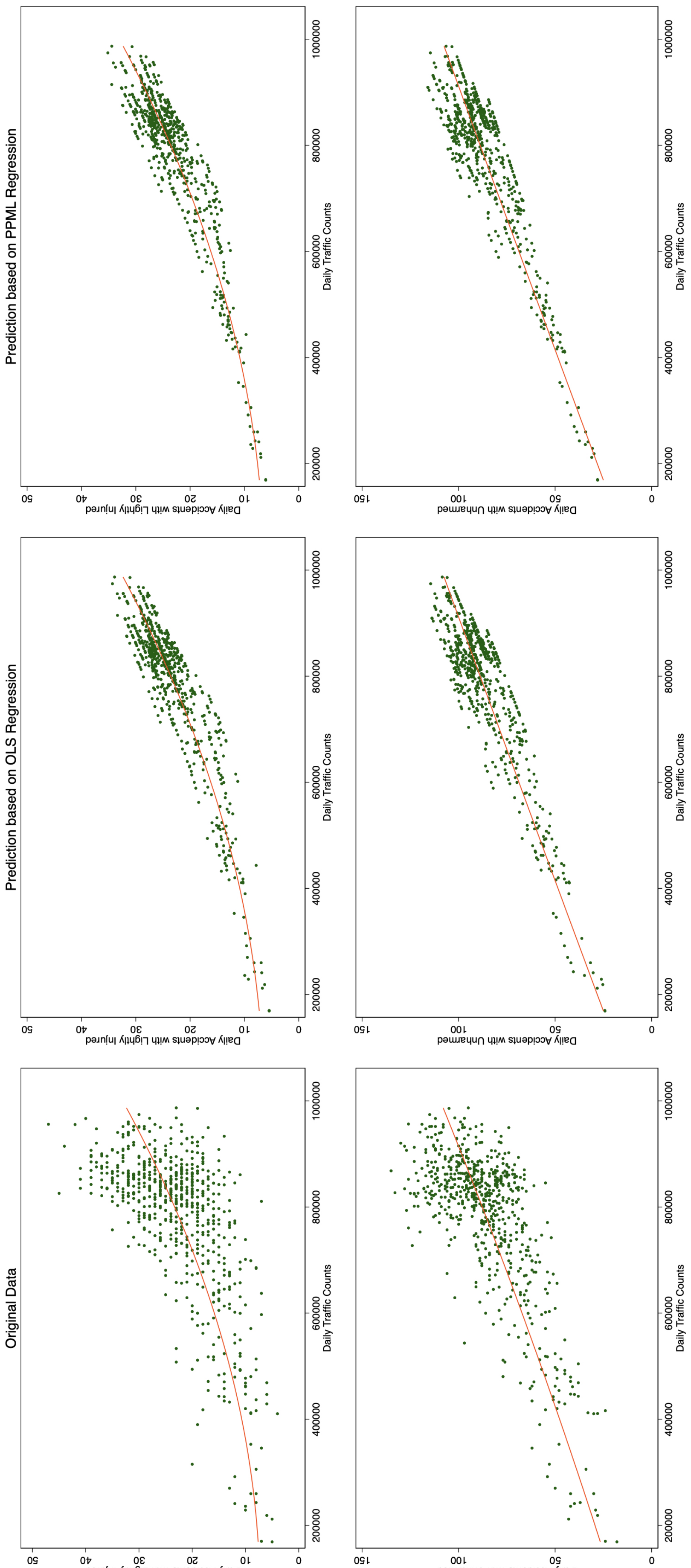

Figure A.2: DESCRIPTION

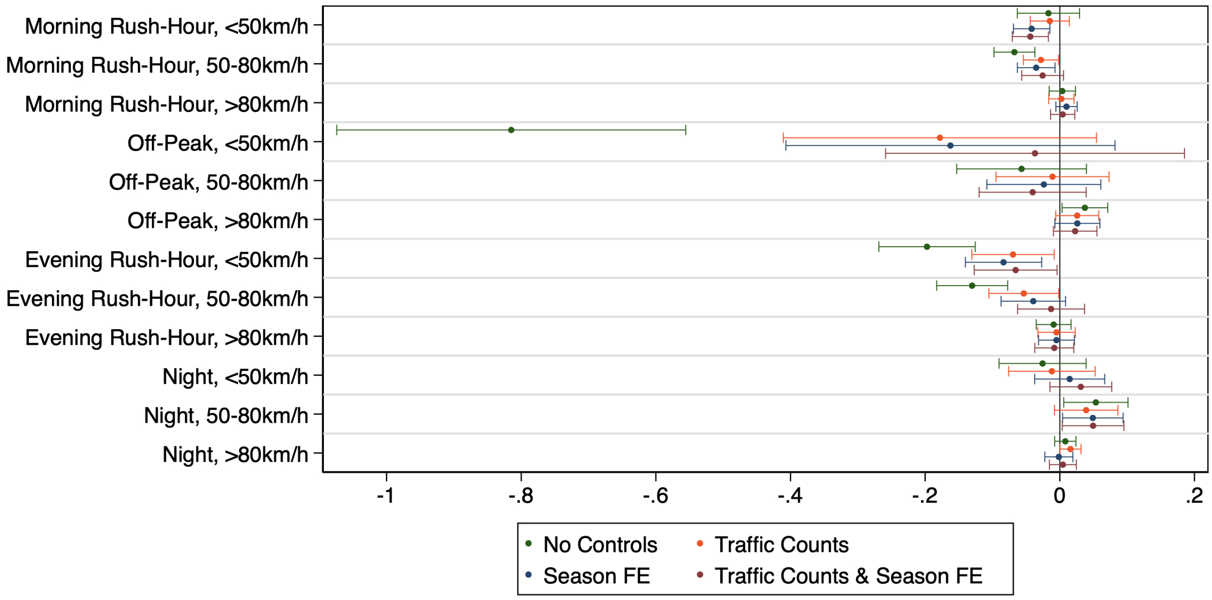

Figure A.3: Estimated effects of average speed on daily accident counts, separated into the 12 categories. Bars represent the respective 95% confidence intervals.

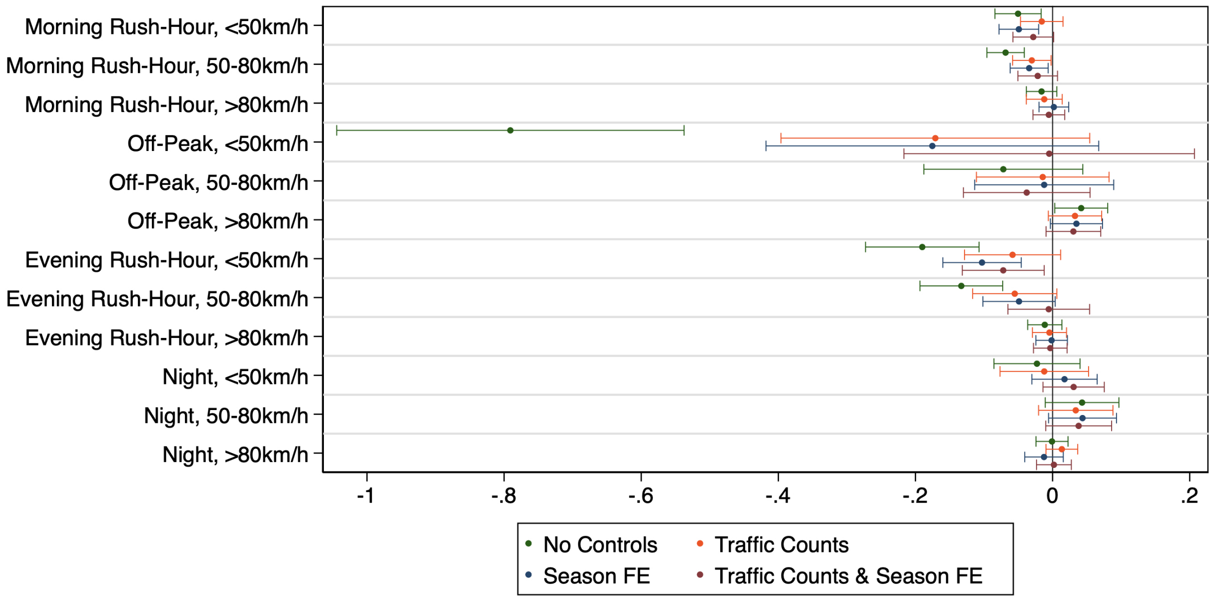

Figure A.4: Estimated marginal effects of average speed on daily accident counts, separated into the 12 categories. Bars represent the respective 95% confidence intervals. Including speed, and where applied also traffic counts, not only linear but additionally also in a squared form.