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The relationship between the traffic flow from commercial vehicles and road safety: a case study of the M8 motorway

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ABSTRACT

Road accidents are one of the greatest externalities of the contemporary transport networks. In the meantime, freight transportation is rising swiftly in all around the world, as the ever-growing trends in e-commerce generate the need for businesses of more immediate goods' distribution and shorter delivery cycles. In addition, both the number of fatalities and the road freight lifted by trucks in the roads of Scotland have seen a rise during the past years. This thesis intends to shed light to the relationship between the traffic flow from commercial trucks and accidents on motorways. This has been achieved by examining the association between the AADF from commercial vehicles with both accident frequency and accident severity, using two appropriate statistical models, namely Negative Binomial and Binomial logistic models respectively. Empirical data were collected from the M8 motorway for the years 2014-2017. The findings of this thesis reveal that the AADF from commercial vehicles has little or no statistically significant relationship with the accidents' occurrence, in terms of both accident frequency and severity. An accident which occurs between 12:00am-5:59am is found to be more likely fatal/severe than when occurring at any other time, a fact that could possibly be linked to the preference of freight operators and retailers towards choosing more night-time freight trips and off-hours deliveries. Limitations on delivery times and establishment of resting areas on roadways can contribute in enhancing road safety.

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CHAPTER 1 INTRODUCTION

1.1 Background

During the past decades, the demand for road transportation is constantly growing following a swift pace. Specifically, the road traffic volume has risen dramatically, reflecting the increase in economic activities, population and car ownership (Department for Transport, 2008). Statistical releases from the Department for Transport reveal that, in 2016, 252.6 billion vehicle miles were travelled on UK roads, whereas this figure was just above 30 billion in 1950 (Department of Transport, 2017). Out of this number, the 21% was driven on UK motorways, a proportion that has increased by 10% in the past ten years, while in 1960 it was just at 0.6% (Department of Transport, 2017).

Meanwhile, the ever-growing trends in e-commerce are having a huge influence on the urban environment and consequently on the transport network (Rutter *et al.*, 2017). Online retailing is constantly developing and consumers are increasingly selecting companies that offer faster delivery services (Lin, Wu and Chang, 2011). As e-commerce providers acknowledge that it is essential to stay competitive, the need for more immediate goods' distribution and shorter delivery cycles is emerging. This demand is fundamentally modifying the urban logistics and, therefore, affecting the road network; as electronic commerce expands, companies require more warehouses and truck fleet (Rutter *et al.*, 2017). These storage centres can be found more and more often in urban zones and necessitate access to motorways in order to adjust to higher daily truck traffic (Rutter *et al.*, 2017). In 2010, the UK presented the largest online retailing market globally, as measured by the value purchased per individual (Shahriari, Shahriari and Gheiji, 2015) and the same year 67% of the freight was carried by road (Transport Scotland, 2013). Moreover, in 2016, 184 million tonnes of road freight were lifted in Scotland (increase by 8,5% in a ten-year period), with trucks being the most preferable mode for freight mobility, compared to previous years that coastwise shipping was the most ubiquitous means of merchandise distribution (Transport Scotland, 2016b). According to Chopra and Meindl (2013), the transport sector is one of the most important links in the supply chain, along with the manufacturers and customers. In the United States, the truck is the leading mode of products' distribution, carrying more than 67% of the goods by weight (U.S. Department of Transportation, 2014). The suppliers' preference for using commercial vehicles derives mainly from the fact that they are a comparatively fast and very flexible means of travel that can deliver products to customers who are located even in regions that are hard to approach (Chopra and Meindl, 2013). The same time, heavy trucks are entangled in 11% of all road fatalities in the United States (Bezwada, 2010).

Despite the beneficial effects in mobility of both goods and travellers that derive from the above-mentioned growths in demand, both road users and the society experience several daily costs. These can be internal costs (e.g. vehicle expenses, traffic accident costs, etc) and external costs such as transportation infrastructure, environmental damage, delays arising from traffic congestion as well as fatalities and injuries as consequences from road accidents (Litman, 1999). This study is concerned with two critical elements of transportation systems and their potential relationship; road accidents and trucking.

Road accidents are a great, if not the greatest, externality of the contemporary transport networks. The constant increase in the number of road accidents following the growth in population and car ownership has made them one of the most critical matters on a global scale (World Health Organization, 2015). Road crashes are known to be one of the leading causes of death while at the same time they are one of the primary causes of serious and permanent injuries (World Health Organisation, 2015). Every year, millions of people are involved in road accidents, with thousands of them ending killed or suffering from long-term health problems and different types of disabilities. According to the World Health Organisation, 1.25 million fatalities from road crashes occur every year worldwide, while 1,732 road deaths were noted in the UK in 2015 (Department of Transport, 2015; World Health Organization, 2015). It is worth noted that the number of fatalities in the roads of Scotland has witnessed an increase of 14% from 2015 to 2016 (Transport Scotland, 2016a), however, no empirical studies have been undertaken in order to examine the potential link of this increase with the rise in the road freight lifted in Scotland. In addition, the average number of heavy goods vehicles involved in accidents of all levels of severity for these years was 355 vehicles (Transport Scotland, 2016a).

The problem of road crashes is particularly important when considering the socio-economic costs that they impose. Economic cost is defined as the cost of road accidents that can be valued in money (such as loss of future productive hours, compensatory damages, hospital care costs), while the social cost is defined as the non-financial cost of the accidents (e.g. psychological or demographic repercussions) (European Transport Safety Council, 2007).

Therefore, enhancing road safety is of vital importance for all societies as road accidents are an everyday-life nightmare of citizens. The numbers and statistics reveal the magnitude of the problem on a global level. In addition to this, the ever-growing truck activities can provide opportunities but also potential threats for road users. This thesis intends to gain insight into the association between road safety and trucking flow.

1.2 Problem Statement and Objectives

As mentioned above, road accidents threaten the prosperity and quality of people's lives and, as such, their mitigation is considered to be highly significant. In the meantime, the rapid rise in e-retailing has brought many challenges in the urban environment and transport systems; companies are adjusting to the demand for faster deliveries by relocating distribution centres nearer to urban zones for faster access to motorways (Rutter *et al.*, 2017). Moreover, the need for more commercial fleet is emerging as businesses choose to carry freight by road with heavy goods vehicles over other means of freight movement (i.e. rail, water and air) (Transport Scotland, 2016b).

Even though trucks comprise a relatively small share of the total traffic volume, their influence on their surrounding traffic is very important and becomes especially prominent during congested situations (Fwa, Ang and Goh, 1996; Sarvi, 2013; Moridpour, Mazloumi and Mesbah, 2015). Commercial vehicles impose physical and psychological burdens on the other drivers, as a consequence of their physical attributes (e.g. length, height) and their operational features (e.g. manoeuvre, breaking distance) (Al-Kaisy, 2006; Sarvi, 2013; Moridpour, Mazloumi and Mesbah, 2015).

Generally, heavier and larger vehicles have been positively associated with their own driver's safety, however, it has been acknowledged that they pose a great danger for the overall road safety (Gayer, 2004; White, 2004; Bezwada and Dissanayake, 2009; Bezwada, 2010; Li, 2012; Anderson and Auffhammer, 2014; Muehlenbachs, Staubli and Chu, 2017). Previous studies show that vehicle's weight plays an important role in the risk of being involved in a fatal accident (Anderson and Auffhammer, 2014), though no clear link has been established between trucking and road safety. Apart from that, the driver fatigue is considered as one of the major reasons behind commercial vehicle accidents globally (Lupova, 2006).

Freight transportation is rising swiftly in all around the world (Sarvi, 2013). The increasing demand in road freight movement is also acknowledged to be a major contributor to congestion, especially on highways, and can emerge from a variety of factors such as the lack of space for trucks (U.S. Department of Transportation, 2008). The aforementioned indications of implications on other drivers' behaviour and traffic stream emerging from the presence of trucks indicate that the relationship between the commercial flow and accidents' occurrence needs to be examined.

The issues described above give rise to the following objectives that formulate the aim of this study:

- To present various factors affecting traffic accidents
- To identify an appropriate statistical model based on previous studies
- To investigate if the Annual Average Daily Flow from commercial vehicles on motorways is associated with serious accidents
- To investigate the relationship between the Annual Average Daily Flow from commercial vehicles and the accidents' occurrence on motorways
- To provide policy makers and transport planners with a better understanding of the effects of commercial trucks on motorways' road safety and therefore to contribute to the mitigation of future road crashes.

The above-mentioned objectives are formed by two research questions; i) What is the relationship between the Annual Average Daily Flow from commercial vehicles and the accidents frequency on motorways? ii) In case of a road accident, what is the association between the Annual Average Daily Flow from commercial vehicles and the accident's severity?

The aims of this thesis will be accomplished by utilising road-section based data acquired from the M8 motorway in Scotland. The primary reason for selecting the M8 motorway as the case study is that it not only is the busiest motorway in Scotland but with a traffic flow up to 180,000 vehicles/day, it is also recognised as one of the busiest motorways in Europe (Glasgow Motorway Archive, 2017). Running to 61 miles (or 97km) in length, the route links the two biggest cities of the country; Edinburgh and Glashow while serving other important areas (e.g. Paisley, Greenock). A rare feature of M8 compared to UK motorways is that it serves in a direct way and passes through an extensive urban zone. Moreover, the M8 contains one of the busiest river crossings in Europe at the Kingston Bridge, a root cause behind its very high congestion levels (Glasgow Motorway Archive, 2017). Generally, these characteristics make M8 an efficient case study, where sufficient observations and a clear pattern are possible to be drawn. According to Transport Scotland, a total of 325 motorway sections comprising both directions are identified on the M8. Focusing on individual motorway sections is an accurate method for observing the effects of commercial flow on accidents' occurrence. The detailed methods used to achieve the aim of this thesis will be presented in Chapter 3.

1.3 Clarifications of terms

The terms "motorway section", "Annual Average Daily Flow" and "commercial vehicles" and will be frequently mentioned throughout this study, therefore it is necessary to define them.

The "motorway sections" are created as the stretch of road is too large to be considered as one section. According to the Highways Agency (2006), they choose to split sections where there is a change in lane numbers, major junctions, slip roads etc. This allows the route to be broken up into more manageable segments which help with surveys, inspections, road works and other practical tasks. The total length of the M8 motorway accounts for 61 miles and for the purposes of this thesis a total of 325 motorway sections was used.

"Annual Average Daily Flow" or AADF is defined as the average number of vehicles that will pass from a road section on an average day of the year and are presented as 'vehicles per day' (Department for Transport, no date). Hence, the Annual Average Daily Flow from commercial vehicles demonstrates the number of commercial vehicles that will drive on a specific section of the motorway on an average day of the year. The commercial vehicle flow is measured in one direction.

"Commercial vehicles" (CVs) are defined by the Highways Agency (2006) as the heavy vehicles that carry goods (HGVs) and are over 3.5 tonnes gross vehicle weight but are not public service vehicles (i.e. buses and coaches). A typical percentage of commercial vehicles within the AADF on motorways is 11% (Highways Agency, 2006). The types and classes of commercial vehicles can be seen in Figure 1.

Figure 1. Types and classes of commercial vehicles (CVs) (Highways Agency, 2006)

Commercial vehicle (cv)	cv class*
	2-axle rigid
	3-axle rigid
	3-axle articulated
	4-axle rigid
	4-axle articulated
	5-axle articulated
	6 (or more) -axle articulated

* Classed by axles in contact with the road

1.4 Structure of the Thesis

The remainder of this thesis is organized as follows: Chapter 2 provides a summary of the literature on the factors affecting road safety and reviews the statistical background in accident frequency and severity modelling. Chapter 3 provides a description of the data that were used and discusses the methodology which was followed behind the applied statistical models. This is followed by Chapter 4, which presents the results and main findings from the statistical analysis and suggests potential policy implementations with the aim of enhancing road safety. Finally, Chapter 5 completes this thesis with a summary and discussion of the contribution to knowledge, limitations of the research and directions for further research.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

The investigation of the association between various aspects of road accidents (e.g. frequency, rate, severity) and traffic characteristics seems to have started more than 50 fifty years ago. Since then, car accidents have been commonly discussed and analysed, however, their relationship with trucking clearly lack examination. The literature on truck vehicles is mainly concentrated around the economic effects originated from the presence of heavy vehicles in a transport network (e.g. Li, 2012; Jacobsen, 2013; Anderson and Auffhammer, 2014; Bento, Gillingham and Roth, 2017). Although the safety risks of commercial vehicles have been subject of considerable research, the majority of the studies have focused on finding indicators of truck crash rates, for example, safety management policies, driver and company features (Muehlenbachs, Staubli and Chu, 2017).

Moreover, in order to understand effectually the link between trucking and road accidents when conducting a statistical analysis, it is crucial to examine and control for other confounding variables that can affect road safety. Numerous studies have been carried out that are concerned with the factors affecting traffic safety with the majority of them focusing on traffic characteristics, road infrastructure, vehicles, drivers' behaviour and weather conditions (e.g. Carson and Mannering, 2001; Chang and Xiang, 2003; Golob and Recker, 2003; Noland and Oh, 2004; Shinar and Compton, 2004).

The rest of this literature review is split into 2 sections. Section 2.2 provides a summary of the literature on the factors affecting road safety. This is followed by Section 2.3, which presents a review of existent road accident analyses concerning accidents frequency and severity along with the main findings. A discussion of the statistical models applied in past studies is also provided in this section.

2.2 Factors affecting road safety

During the past decades, several researchers have conducted studies seeking to determine the elements that influence road safety, as road accidents are one of the most important problems on a global scale. Considering that road crashes are known to be one of the leading causes of death and at the same time one of the primary causes of serious and permanent injuries, their elimination is recognised as one of the top priorities for societies (World Health Organisation, 2015). Despite the wide diversity among the factors that are associated with accidents' occurrence and frequency, they generally refer to three main categories namely traffic characteristics; road geometrics and infrastructure; demographics, environmental conditions and driver behaviour. An overview of the literature related to these factors is provided below.

2.2.1 Traffic characteristics

Very significant attempts have been made to investigate how car accidents are connected to traffic characteristics (e.g. speed, V/C ratio) and significant progress has been made so far. Several of these factors will also be discussed in Section 2.3.

The investigation of the effects of speed on road safety has been the aim of extensive research in transport studies. Generally, most studies demonstrate a positive linear link between travel speeds and accidents (e.g. Solomon, 1964; Taylor, Lynam and Baruya, 2000; Taylor, Baruya and Kennedy, 2002; Jung et al., 2014; Gitelman, Doveh and Bekhor, 2017). For instance, Taylor, Lynam and Baruya (2000) conducted a road and driver-based research and their outcome was that increased speed was linked to higher accident frequency. Although this theory is mostly accepted, some studies arrive at a controversial conclusion. For example, in his investigation of the speed-accident association on different roadway types in Europe, Baruya (1998) developed a Poisson model with datasets acquired from 4 countries. His results demonstrated that the mean speed is negatively related to the accident frequency, something that can be justified by the impact of the road geometrics. A recent study by Roshandel *et al.* (2015) also reports that higher average speeds are related to lower accident likelihood, in particular with an odds ratio of 4.8%.

Solomon (1964) seems to be the first to present that variations in speed induce higher accident frequency than the mean speed. The study undertaken by Zheng *et al.* (2010) about how traffic oscillations affect accident incidences confirms this theory; a one unit rise in the standard deviation of the speed was found to raise the odds ratio of a crash by almost 8%. On the contrary, Kockelman and Ma (2007) did not find any shreds of evidence of an association between speed variation and crash occurrence on freeways.

Golob and Recker (2003) undertook a nonlinear multivariate statistical analysis to investigate the link among accidents, traffic flow, environment and lighting situations. After they controlled for the two last-mentioned elements, they found indications that traffic volume had a greater impact on the crashes severity than the speed, as more rear-end crashes were observed under the presence of heavy congestion and stop and go driving.

The traffic characteristic that will be considered in this thesis is the Annual Average Daily Flow for each road section. The speed limit will not be considered in this study, as it is found to be relatively the same across the motorway M8, with minor fluctuations from 40 to 70 mph.

2.2.2 Road geometrics and infrastructure

It is often alleged that improved road infrastructure could act as a mitigating factor to road accidents. Findings from several studies encourage this belief. Road geometric characteristics can include the radius of curve, lanes’ number and width, gradient, roadway section’s length and other features.

Shankar *et al.* (1996) reported that higher horizontal curvature per km raises the probability of having no injuries in an accident. The degree of curve has been generally recognised as a protective factor by many researchers (e.g. Milton and Mannering, 1998; Haynes *et al.*, 2008). In their study, Noland and Oh (2004) dealt with how roadway infrastructure and geometric changes affect road fatalities. As they concluded, more and wider lanes induce more crashes and fatalities, in contrast to wider outside shoulders that contribute to a reduction of accidents.

Moreover, rutting in pavement (i.e. longitudinal permanent distortion of the road surface) is recognised as a contributing factor to crash occurrence as it can reduce vehicle control (Cenek *et al.*, 2014; Nair Baskara *et al.*, 2016). Start *et al.* (1998) quantify that accidents rise as the rut depth gets deeper than 7.6mm. Anastasopoulos *et al.* (2012) found that lower rut depth reduces crash rates by using a random-parameter approach. Chan's *et al.* (2010) findings revealed that accidents frequency grows significantly by the rut depth during night-time and under rainy weather circumstances, as water can also be collected in the ruts imposing a risk hazard of aquaplaning (Cenek *et al.*, 2014). In addition, the surface texture depth is known to affect skid resistance, thus road safety; higher skid resistance minimises the skidding, therefore, enhances traffic safety (Cenek *et al.*, 2014). On the other hand, lower skid resistance induces higher accident risk especially on wet pavements because of inadequate development of friction (Cenek *et al.*, 2014).

In this thesis, the road geometrical characteristics that will be considered are the rut depth (frequently used to assess the safety and structural characteristics of the pavement surface condition (Highways Agency, 2006)) and the texture depth (used as an indication of potential loss of skid resistance (Highways Agency, 2006)). Due to data unavailability, no further characteristics could be taken into account.

2.2.3 Demographics, environmental conditions and driver behaviour

Road accidents are directly related to the human factor and the environmental conditions since they have an impact on drivers' behaviour. Additionally, elements like population and employment correspond to development and activities that can expose drivers to potential collisions.

Chang and Xiang (2003) revealed that snowy weather causes less severe crashes, whereas, on the other hand, Theofilatos (2017) found that weather parameters are not significantly affecting accident likelihood and severity. Jung *et al.* (2014) investigated the factors that contribute to higher accident frequency and severity under rainfall. Among other variables, the AADF and the pavement surface material change were identified to cause a rise in the probability of a car accident during rainy conditions, whereas, surprisingly, this probability was observed to decline as the average daily precipitation increased. Moreover, the GIS analysis of Perrels *et al.* (2015) illustrated that adverse weather conditions may increase the crash occurrences by 20% or more. Generally, the wet street surface is known to increase the risk of aquaplaning, while icy and snowy surface increase the accident hazard due to skidding (Ihs and Magnusson, 2000).

Noland and Quddus (2004) examined how road casualties in England are linked to area-wide factors (e.g. land use, demographics, roadway category). Their NB models consisted of these factors and the level of injury in casualties (fatal, severe, slight). Some of their main findings were that in urban areas a smaller number of fatalities tends to occur, whereas more casualties are developed in deprived areas. On the other, Kim *et al.* (2006) report that urban environments provide poorer road safety as well as that population, work and economic activities induce more accidents. A research undertaken by Li (2014) showed that regions with improved roadway systems' connection appear to have a greater number of casualties, as the roads are more accessible by pedestrians and cars.

Shinar and Compton (2004) conducted an observational study of aggressive by car users' behaviour. One of their main observations was that a greater number of aggressive behaviours occurred during peak times than off-peak times implying, therefore, a strong linear connection between congestion and such behaviours. This association might consequently have impacts on road safety. In addition to this, the driver fatigue is considered as one of the major reasons behind commercial vehicle accidents globally (Lupova, 2006). Previous studies have proved that sleepy driving raises the risk of being involved in an accident by 4 to 6 times (Klauer *et al.*, 2006). This risk factor of the driver's tiredness will be taken into account by considering the time when the accident occurred.

The NB model employed by Abdel-Aty and Radwan (2000) to inspect crash frequency and involvement accounted for the driver's demographic features (i.e. sex, age) and revealed that women tend to be more frequently involved in road accidents under congested conditions, whereas men experience more crashes while speeding. Older drivers or victims are also connected to more severe injuries (O'Donnell and Connor, 1996; Abdel-Aty, 2003). The seat belt use is positively associated with road safety (Noland, 2003).

While this thesis seeks to determine the relationship between commercial vehicles' flow and road accidents (in terms of both accident frequency and severity) by employing two statistical models, various of the above-mentioned contributing factors will be taken into consideration and controlled for. Nevertheless, some of these influential factors will not be included in the modelling process, mainly due to data unavailability and inaccessibility. The risk factors being considered in this study comprise AADF; time of the accident; motorway section length; rut and texture depth; weather conditions (fair; rainy/snowy); and surface conditions (dry; wet/ icy).

2.3 Statistical Background

2.3.1 Accident frequency

The General Linear Models (GLMs), like Poisson and Negative Binomial models, have been extensively applied in preceding accident frequency analyses (e.g. Miaou, 1994; Shankar, Mannering and Barfield, 1995; Baruya, 1998; Noland and Quddus, 2005; Jung *et al.*, 2014).

Although with GLMs it might be complex to account for heteroskedasticity and autocorrelation, the nonnegative and discrete structure of the accident data makes this a widely used estimation method. Negative Binomial regression is a generalised Poisson regression (based on the Poisson-gamma distribution) which is highly efficient in modelling count variables (non-negative integer data) like the number of accidents. NB models are also suitable to use in the presence of over-dispersion in accident data (Miaou, 1994; Shankar, Mannering and Barfield, 1995; Noland and Quddus, 2005), that is when the conditional variance of the outcome is greater than the conditional mean of the outcome.

Jovanis and Chang's (1986) study reported that Poisson distribution is recognised as a better approach than the typical linear regression and they managed to link higher accident frequency with increased miles travelled. Later on, Shankar, Mannering and Barfield (1995) undertook a study of the accidents' frequency on highways employing a Negative Binomial which consisted of road geometric (e.g. horizontal alignment) and environmental (e.g. monthly rainy days) variables. They used an equal-length road segment method and collected accident data on a monthly basis. Although important conclusions were drawn regarding the effects of weather conditions and geometrics on car crashes, the commercial vehicles' traffic flow was not taken into account.

Persaud and Dzbik (1993) carried out a research using GLMs with data at a micro (accidents per unit length/hour) and macro (accidents per unit length/year) level in order to predict crashes on freeways. Their study indicated that accidents were observed in higher frequencies on roads with congestion than on roads without when the traffic volume was similar. In identical results concluded Shefer and Rietveld (1997), who proposed that traffic congestion reduces mobility and prevents the development of high speed, having consequently a positive impact on road safety. Lower average speeds are less likely to provoke fatal accidents, whereas, on the other hand, more interactions induce higher accident frequency

(Shefer and Rietveld, 1997). Nonetheless, their analysis was undermined since they made use of simulated data to test their model, thus further research with empirical evidence is required.

In a similar study in Denmark, Greibe (2002) made use of generalised linear Poisson models attempting to anticipate the number of accidents on urban roads. The Annual Average Daily Traffic (AADT) was also found to be the most influential explanatory variable in accidents frequency. Another study which provided evidence of a relationship among congestion and accidents frequency, rate and severity on freeway sections and arterials is the one undertaken by Chang and Xiang (2003). The authors developed multivariate models through Poisson and NB regressions and managed to show that higher levels of traffic congestion, more lanes and intersections bring about a rise in crash frequency on both examined locations.

Wang *et al.* (2009) examined the relationship between the occurrence of accidents and congestion doing a spatial analysis for the M25 highway. While they controlled for pertinent factors such as the number of lanes, the flow, etc, their results demonstrated that traffic congestion has little or no impact on the occurrence of crashes in their case study. However, in a later examination, Wang (2010) studied the same motorway and employed a Negative Binomial and Bayesian spatial model to investigate the same issues. His model revealed that congestion shows a positive association between the incidence of fatal or severe injury crashes. Nevertheless, in of these studies was examined the impact of trucking flow on the accidents' occurrence.

Moreover, Abdel-Aty and Radwan (2000) employed the NB regression to inspect crash frequency and involvement. Their modelling results presented that among other variables the AADT, segment's length, type of roadway, number of lanes and horizontal curve were significant on crash occurrence. In addition to this, the model showed that for accidents with only one involved vehicle, the accident rate was maximum when the volume/capacity ratio was relatively low. This outcome does not completely match the examination of Lord, Manar and Vizioli (2005), who demonstrated that when the volume/capacity ratio increased, the fatal and one-vehicle crashes reduced at one moment and the crash rates had a U-shaped pattern. Nevertheless, the authors suggested that further research is needed with more accurate datasets. The connection between crash rates, congestion and the lanes' number was also explored by Kononov *et al.* (2008) on three American freeways using safety performance functions. Their research results proved that a rise in the AADT induces a rise in crash rates, though their approach counted only for the number of lanes and the AADT without controlling for other factors, such as weather conditions. Again, no examination was undertaken about the impact of truck vehicles' presence on the road.

More recently, a case-control study with data acquired from a loop detector was undertaken by Zheng *et al.* (2010) to study how traffic oscillations affect accident incidences. As revealed by their logistic regression models, a one unit rise in the standard deviation of the velocity rises the odds ratio of a crash by almost 8%. Following this study, Zheng became further concerned with the accident occurrence likelihood and its link with traffic conditions. In his next analysis, he utilised a series of logit models and a multi-resolution structure. Thus, he revealed that under congested situations, the accident occurrence likelihood is about 6 times of the one in a free state (Zheng, 2012). He also found that speed is significantly affecting crash occurrence likelihood, which was found to decrease when the former increased. This result appeared to be at variance with previous studies, but as he supported stop and go driving is connected to reduced mean speeds. On the other hand, Dias *et al.* (2009) conducted a study about the impacts of congestion on accidents and found out that crash incidences are positively associated with traffic density levels, which represent congestion. In particular, in a pre-accident period, he found that the probability of the roadway segment being congested fluctuates from 60% to 87%, reflecting that when a crash happens the road section will most likely be congested.

Generally, the results of most of the research demonstrate that there is a pattern between higher levels of AADF and increased accident frequency, though no studies were found to investigate the effect of the Annual Average Daily Flow from commercial vehicles. From the above-mentioned studies, it can be seen that Poisson and Negative Binomial models are recognised as the stronger approaches for accident modelling (Jovanis and Chang, 1986; Miaou, 1994; Shankar, Mannering and Barfield, 1995; Abdel-Aty and Radwan, 2000; Greibe, 2002).

2.3.2 Accident severity

In the existent literature, accident severity has been extensively examined as a function of contributing factors, as for instance driver characteristics, roadway geometrics, automobile condition and weather phenomena. The most considerable attempts that have addressed these relationships along with their primary findings are presented below.

The severity rate of a crash is usually determined by the degree of injury of the most severely hurt passenger (Chang and Mannering, 1999). Typically it is categorised as 'fatal', 'severe', 'slight' and 'non-injury' (or solely property damage) (Hutchinson, 1986; Wang, 2010). Therefore, accident severity is a categorical variable (usually ordered) and as it is argued by many researchers, the most appropriate approach in modelling it is the multinomial logistic regression (Shankar and Mannering, 1996; Chang and Mannering, 1999; Carson and Mannering, 2001). Apart from this method, accident severity has also been examined as a binary variable by many researchers with the indicators 1, 0 representing fatal and non-fatal incidents (Pitt *et al.*, 1990; Farmer, Braver and Mitter, 1997; Al-ghamdi, 2002). For example, Al-Ghamdi (2002) applied this technique and the two most statistically significant variables that would explain the severity level in his model were found to be the location and the accident's cause. Pitt *et al.* (1990) also represented severity with binary values (severe and non-severe) to consider the impacts of different factors, like age, sex, velocity on its relative risk.

The arbitrary ordered nature of accident severity as a variable makes the ordered response models (ORMs) an extensively accepted technique in its modelling. The most frequently employed regression models in this category are the ordered logit and ordered probit model, that can be found in several analyses for accident severity (e.g. O'Donnell and Connor, 1996; Abdel-Aty, 2003; Chang and Xiang, 2003; Lee and Abdel-Aty, 2005; Quddus, Wang and Ison, 2010). In particular, O'Donnell and Connor (1996) predicted the level of car accident injury considering characteristics of road users. As indicated by his modelling results, the probability of getting a severe or fatal injury slightly increases when the victim's age and automobile speed increase. Seating spot, car type and presence of alcohol in blood were also found to influence the level of injury.

A number of studies have explored the traffic flow-severity relationship but without considering the presence of heavy vehicles. One of these was undertaken by Martin (2002), who investigated the association of hourly traffic flow, severity levels and accident rates. Using data acquired from French motorways, he found indications that light traffic induces greater crash rates, particularly on 3-lane highways. In addition to this, the author observed that when considering for severity, night-time and less congested traffic volume were causing more serious accidents. Thus, Martin concluded that lower traffic flow was an issue for both crash rates and severity, although no clear conclusion could be drawn. These inferences are in line with the findings of Zhou and Sisiopiku (1997), who reported that the accident rates were connected to V/C ratio with a U-shape pattern, meaning that greater rates were noticed when traffic flow was very low or very high.

Golob, Recker and Pavlis (2008) observed that crash severity appears to be rather constant when changing from free flow to congestion. However, they recognised that under congested conditions the severity declines significantly at the moment that all lanes have approximately the same traffic flow. Besides, the researchers perceived that under unsteady situations, rear end accidents present a higher likelihood of occurrence, an observation that confirmed the study of Lee, Abdel-Aty and Hsia (2006). The research undertaken by Chang and Xiang (2003) presented an analogous outcome, since they found out that accident severity on both freeway segments and arterials has a tendency to be lower in the presence of higher congestion levels. Using ordered probit models they also reported that snowy weather causes less severe crashes, in contrast to alcohol and intersection points which bring about graver accidents.

Abdel-Aty (2003) analysed the factors that can cause differentiations in the injury severity degree of drivers at multiple locations. His ordered probit modelling results for road segments, intersections and toll locations in Florida illustrated that age, sex, speed, car type and seatbelt usage were significant on the examined matter. A few years later, Lee and Abdel-Aty (2005) employed the same modelling approach to investigate the probability of vehicle-pedestrian collisions at junctions. Their findings showed that the roadway geometrics, environmental and traffic circumstances as well as the demographic characteristics of the involved people were significant on the accident severity and frequency.

Finally, a considerable number of studies have investigated the impact of vehicle weight on accidents severity (Gayer, 2004; White, 2004; Li, 2012; Anderson and Auffhammer, 2014), however, these examinations concern private vehicles that are mostly light trucks. A relevant research was conducted by Anderson and Auffhammer (2014) who used three different methods and demonstrated that when controlling for the own-car heaviness, the risk of being involved in a fatal crash, when hit by a vehicle that weighs 1000 pounds more, is increasing by 40% to 50%.

All things considered, the statistical models that will be used for the purposes of this thesis are the Negative Binomial logistic and Binomial logistic for the accident frequency and severity analysis respectively.

CHAPTER 3 METHODOLOGY

3.1 Introduction

The intention of this thesis is to identify the relationship between the Annual Average Daily Flow from commercial trucks and road accidents on motorways. The road accidents are appraised in two aspects: accident *frequency* (i.e. the number of accidents on each motorway section); and accident *severity* (i.e. the level of severity of a crash incident when it occurs). Hence, for this two-sided examination two different models will be employed based on the statistical background provided in the literature review: a Negative Binomial logit model will be used to determine the association between the AADF from CVs and crash frequency; a Binomial logit model will be built in order to investigate the relationship between the AADF from CVs and the level of severity of the accident when it occurs, which was examined as a binary variable as described in the following sections.

This chapter provides a description of the data that were used and discusses the methodology which was followed behind the applied statistical models.

3.2 Data description

Empirical data have been acquired to examine the effects of the AADF from commercial vehicles on the road safety on the M8 motorway. According to Transport Scotland, a total of 325 motorway sections comprising both directions are identified on the M8.

The data used for the purposes of this thesis (accident, traffic and road characteristics) was derived from Transport Scotland. Transport Scotland holds information about road accidents which involve an injury and is provided to them by Police Scotland, excluding accidents between Junction 6 and 8. The accident data were obtained for the period 01/01/2014 to 25/12/2017 and, among other figures, contained information regarding the road segment where the accident occurred, casualties, involved vehicles, the severity level (slight/ serious/ fatal), the time of the accident, as well as the weather (raining; fine; with/ without high winds) and surface conditions (wet/ damp; dry; icy). The accident data were integrated with the traffic and road characteristics datasets, as each accident was assigned to the particular motorway section where it occurred. As detailed in the next sections, the time of the crash, the weather and road surface condition figures were included in the accident severity statistical model as explanatory variables. In fact, the time when the accident occurred was contained in the accident severity model in order to account for the effect of the rush hours (e.g. morning and evening peak hours) and the driver fatigue (which is mainly increased during the night shift) on the level of severity. A potential increase in the severity level during night-time could be associated with the preference of freight operators and retailers towards choosing more night-time freight trips and off-hours deliveries in order to ensure more effective movement of goods and on-time distribution (Department for Transport, 2014).

In addition, Transport Scotland holds information regarding the traffic and road condition for major motorways in the country. Specifically, the traffic data are recorded continually from a network of Automatic Traffic Counters (ATCs), which are magnetic induction loops in the road surface that collect traffic counts on a daily basis for a specific count point on a road section. ATCs also record important physical attributes of passing vehicles which are utilized to categorise traffic by type (e.g. commercial vehicles, motorcycles). After a series of calculations conducted by Transport Scotland including considering for expansion factors, road section length and other figures, the AADF for each roadway section is obtained. The road condition characteristics for road sections on the M8 which were used as explanatory variables in the statistical model for the investigation of the relationship HGVs' traffic flow and accident frequency comprise the rut depth and texture depth. Both figures can be used to identify road sections with deteriorating surface conditions, which is recognised as a confounding factor in road safety (Highways Agency, 2008). In particular, the texture depth can signify a possible loss of skid resistance or another type of surface failure, such as fretting.

The rut depth can be used to appraise road safety and assess the pavement surface condition. Both values are collected over 10m lengths from the start point to the end point of each road section on an annual basis. In order to import them as independent variables in the accident frequency model, the rut and texture depths were aggregated over the total length of each motorway section. Finally, it is worth mentioning that due to road condition data unavailability for some segments, the number of motorway sections was reduced to 286 compared to the initial 325.

At this point, it is important to clarify that the accident frequency and accident severity model consisted of different explanatory variables. This fact derives from the temporal scale of the variables. In other words, the time, weather and surface condition referred to the exact moment when the accident occurred, thus can be used to explain the level of severity of each specific incident. On the other hand, the rut and texture depths are calculated annually and refer to road sections for a long period of time, therefore, can be a useful implement for explaining accident frequency on a motorway section.

The details of the accident frequency and severity statistical models that were employed in this thesis, as well as the descriptive statistics of the variables included, are described in the remainder of this chapter.

3.3 Accident frequency model

As discussed in Chapter 2, the Poisson and Negative Binomial (NB) models are recognised as highly efficient approaches in modelling count dependant variables, such as the number of road accidents (Jovanis and Chang, 1986; Miaou, 1994; Shankar, Mannering and Barfield, 1995; Baruya, 1998; Abdel-Aty and Radwan, 2000; Greibe, 2002; Noland and Quddus, 2005). Hence, the Poisson model that was initially built for the accident frequency analysis has the following structure:

$$Pr(y_i/\lambda) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} \text{ , } y = 0, 1, 2, \ldots \tag{1}$$

where,

y is the observed number of accidents that occurred on a motorway section i;

λ is the expected number of occurrences (i.e. accidents) on a motorway section i in the examined period (in other words, the mean of y).

Nevertheless, the Poisson distribution requires the restrictive assumption that the mean of the outcome equals its variance. This assumption is usually violated when working with crash data mainly because of its nature. The rate at which incidents take place during a period of observations may be inconstant, resulting to various deviations in the variance of Y and the mean and, hence, overdispersion (Noland and Quddus, 2005; Li, 2014). Since this assumption was tested in this case and the findings demonstrated that the variance is substantially greater than the mean (see Appendix), an NB regression was applied to overcome this obstacle and model the relationship between the AADF from CVs and the accidents frequency. Specifically, assuming that the accidents frequency is a function of traffic flows and road condition factors, the equation (1) can be written as follows:

$$y_i \sim \textit{Negative Binomial}\ (\textit{mean} = \exp\ (\alpha + \beta_{CV/d}\, X_{CV/di} + \beta_{AADF}\, X_{AADFi} + \beta^{T}_{RC}\, X_{RCi}),$$
$$\textit{overdispersion} = w), \quad \text{for } i = 1, 2, \ldots, n \tag{2}$$

where,

a is the intercept;

$X_{CV/di}$ is the AADF from commercial vehicles on a motorway section i divided by the section's length;

X_{AADFi} is the AADF from all vehicles on a motorway section i divided by the section's length;

X_{RCi} is the vector of the road condition characteristics (i.e. rut depth and texture depth) which are divided by the section's length;

w is the parameter representing overdispersion.

After the car accidents were assigned to the M8 motorway segment where they occurred, the number of accidents on each roadway section for the time period of interest is aggregated. As such, the count of crashes (i.e. accident frequency) per motorway section is acquired. The rut and texture depths were aggregated over the total length of each motorway section, as they are collected over 10m lengths from the start point to the end point of each road section. Additionally, all the predictor variables that were included in the Negative Binomial model (i.e. AADF from CVs, AADF, rut, texture) were standardised by length in order to consider the fact that longer motorway sections are more likely to present a higher accidents' occurrence (Abdel-Aty and Radwan, 2000; Wang, 2010). The standardisation was achieved by diving the values by the length of each corresponding motorway section. Finally, a panel dataset containing 286 observations for the motorway sections during a 4-year period (2014-2017) was obtained. The descriptive statistics of the variables included in the accidents frequency NB model are demonstrated in Table 1.

Table 1. Descriptive statistics of the variables for the accident frequency model

Variable	Mean	Standard deviation	Min	Max
Number of accidents per section	2.30	3.48	0	31
Traffic characteristics				
AADF from CVs (CVs/day)	3,138.46	2,690.73	46	16,921
AADF (veh/day)	23,520.42	18,693.12	1,241	74,999
Road condition characteristics				
Rut depth (mm)	5.73	2.01	1.87	16.25
Texture depth (mm)	0.93	0.27	0.32	1.72
Road section length (m)	803.56	879.92	27	4,940
Sample size 286				

As demonstrated in Table 1, the mean AADF from CVs and the mean AADF are 3,138 CVs/day and 23,520 vehicles/day respectively, while they present large fluctuations. In addition, the mean texture depth is 0.93mm presenting small variations, whereas the mean rut depth is equal to 5.73mm with a maximum value of 16.25mm. The motorway section length fluctuated from 27m to almost 5km, with a mean value of 803m. The mean number of accidents per road section is 2.3, fluctuating from 0 to 31. Most roadway sections present zero or very few crashes. This situation is demonstrated in Figure 2. It is worth noting that a zero-inflated Negative Binomial regression usually works better in modelling overdispersed count data that has an excess of zero counts (Miaou, 1994). However, due to data limitation (unavailability of the Instrumental variable that is required for the application of the zero-inflated model), this model could not be employed for the purpose of this thesis.

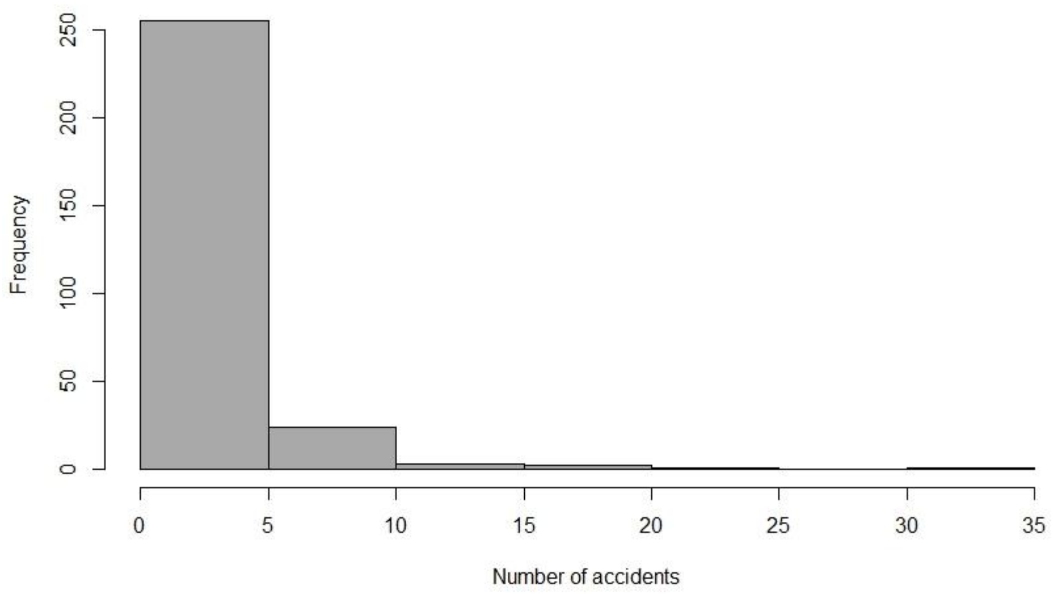

Figure 2. Histogram of the accident frequency on the M8

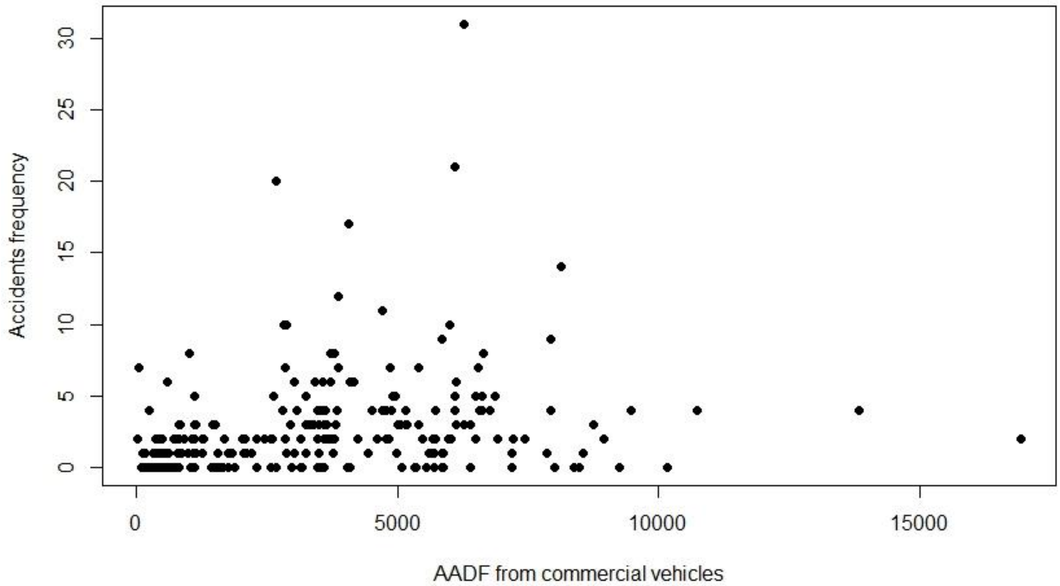

Figure 3. Accidents frequency and AADF from commercial vehicles

As can be seen from Figure 3, no clear pattern can be found between the accidents frequency and the Annual Average Daily Flow from commercial vehicles, thus a statistical model accounting for other confounding factors will be employed to fully explore the association between the two figures.

3.4 Accident severity model

As stated in Chapter 2, accident severity has been examined as a binary variable by many researchers due to its dichotomous structure, with the indicators 1, 0 representing fatal and non-fatal incidents (Pitt *et al.*, 1990; Farmer, Braver and Mitter, 1997; Al-ghamdi, 2002). The optimal approach for modelling a binary response variable, such as the accident fatality, is the Binomial logistic statistical model and will be applied in this study in order to investigate the relationship between the AADF from trucks and accident severity when a road accident occurs. During the years 2014-2017, a total of 686 car accidents were identified on the M8 motorway. Out of this number, a proportion of 93% (or 638 accidents) were slight accidents, just 40 were categorised as serious and only 8 crashes resulted in a fatality. Hence, due to the low frequency of both fatal and serious accidents during the examined period, the classification of the crashes severity was regrouped into two categories: slight; and severe or fatal. In this case, the accident severity was represented by 0 and 1 for slight and serious/fatal injuries respectively. Therefore, the logistic regression that was applied can be described by the following formula:

$$Pr(Y_i=1|X)= \frac{exp(a+ X_{CV/di}\beta+X_{AADFi}\beta+X_{weathi}\beta+X_{surfi}\beta+X_{timei}\beta)}{1+ exp\left(a+ X_{CV/di}\beta+X_{AADFi}\beta+X_{weathi}\beta+X_{surfi}\beta+X_{timei}\beta\right)} \qquad (3)$$

where,

$Pr(Y)$ is the probability of Y occurring given known values of the explanatory variables X;

Y is the binary response variable (i.e. severity) , $\begin{cases} 0, & slight\ accident \\ 1, & severe\ or\ fatal\ accident \end{cases}$

$X_{CV/d}$ is the AADF from commercial vehicles on a motorway section *i* divided by the section's length;

X_{AADF} is the AADF from all vehicles on a motorway section *i* divided by the section's length;

X_{weath} is the weather conditions when the accident occurred;

X_{surf} is the surface conditions when the accident occurred;

X_{time} is the time when the accident occurred;

β's are the regression constants;

α is the intercept.

The accident severity when a crash occurs was assumed to be a function of traffic characteristics (AADF and AADF from commercial vehicles), the time of the accidents, weather and road surface conditions. Specifically, the weather classifications that were initially included in the data were 'raining (with/without high winds)', 'fine (with/without high winds)' and 'snowing (with/without high winds)'. Since the wind parameter was not found to be confounding in the literature it was excluded from the model. Thus, the weather element was regrouped in two categories: "fine"; and "raining or snowing" and was examined as a binary explanatory variable represented by 1 and 0 respectively. In a parallel way, the road surface conditions were split into two categories, namely “dry” and “wet/damp or icy” and were also coded by 1 and 0 respectively. The hours when the crashes occurred were grouped in five categories: 12:00 am- 5:59 am (due to the preference of freight operators and retailers towards choosing more night-time freight trips and of-hours deliveries (Department for Transport, 2014) and the driver fatigue that is usually increased during this time); 6:00 am - 9:59 am (morning rush hours); 10:00 am- 15:59 pm; 16:00 pm- 19:59 pm (evening rush hours); and 20:00 pm- 23:59 pm. This dataset was then integrated into the dataset containing the traffic characteristics based on the road segment where the accident occurred. The AADF from commercial trucks and the AADF were standardised by the interaction term of length, as they also were in the accident frequency model. The standardisation was achieved by diving the values by the length of each corresponding motorway section. Finally, due to some missing values regarding the weather and the surface condition, a new dataset with 658 observations (compared to the initial number of 686 accidents) was obtained. The descriptive statistics of the variables included in the accidents severity model are presented in Table 2.

Table 2. Descriptive statistics of the variables for the accident severity model

Variable	Mean	Standard deviation	Min	Max
Accident severity*	0.07	0.25	0	1
Traffic characteristics				
AADF from CVs (CVs/day)	3,138.46	2,690.73	46	16,921
AADF (veh/day)	23,520.42	18,693.12	1,241	74,999
Other indicators				
Weather (fine=1)	75%			
Surface condition (dry=1)	57%			
Time of accident (hh:mm)				
12:00am – 5:59 am (night shift)	4.86%			
6:00am – 9:59am (morning peak)	22.64%			
10:00am – 15:59am	30.09%			
16:00am – 19:59am (evening peak)	33.59%			
20:00am – 23:59am	8.81%			
Road section length (m)	803.56	879.92	27	4,940
Sample size 658				

* 0= slight injury accident, 1= severe injury or fatal accident

From Table 2 it is observed that the mean value of the accident severity is 0.07, indicating that 93% of the crashes that occurred during the examined period are slight accidents. A small proportion of 4.86% of the accidents occurred between 12:00 am- 5:59 am (night shift), compared to a high percentage of 33.59% of the accidents which occurred during the evening peak hours (i.e. 16:00 pm- 19:59 pm). The mean values of the variables of interest at each accident severity level are demonstrated in Table 3.

Table 3. Means of variables of interest at each severity level

Accident Severity	AADF from CVs	AADF	Weather	Surface Conditions
Slight	4353.56	33417.16	0.76	0.57
Severe/ fatal	4417.60	34595.96	0.71	0.55

As shown above, the average AADF from commercial trucks is 4354.56 CVs/day in the case of slight accidents, however, the figure increases to 4417.6 CVs/day for the case of serious/ fatal accidents. This suggests that there might be a positive association between the flow from CVs and the severity of a crash when the incident occurs. A similar relationship can be observed for the AADF. The average weather and surface condition present an expected outcome: when the severity of the accident is slight, both values are closer to 1 (meaning closer to “fine” weather and “dry” surface).

This chapter has described the data to be employed in the subsequent chapter. It has also provided the summary statistics of the variables (e.g. AADF from commercial trucks, weather, surface condition, rut and texture depth) that were applied in the accidents frequency and severity models. The model results utilizing this data are analysed in the following chapter.

CHAPTER 4 RESULTS, DISCUSSION AND POLICY IMPLICATIONS

4.1 Introduction

This chapter presents the results and main findings of the statistical models intended to investigate the relationship between the AADF from CVs and road accidents. This relationship is appraised in two aspects: the effect of the AADF from CVs on accident *frequency* and on accident *severity*. As discussed in Chapters 2 and 3, the most efficient models for count dependent variables with a presence of overdispersion (i.e. accident frequency) and binary response variables (i.e. severity level) are the Negative Binomial logit and Binomial logit model respectively.

This chapter is organised as follows: the first section discusses the results and findings from the Negative Binomial logistic model that was employed to examine the accident frequency aspect. This is followed by the presentation of the results and findings from the Binomial logistic model that was applied in order to investigate the accident severity point of view. Finally, the policy implications and implementations that emerge from the two models' results are discussed in the last section of this chapter.

4.2 Accident frequency model results

A total of 286 motorway sections on the M8 were examined (excluding the sections with missing values). The motorway sections that did not have any accidents were also included in the model. For each motorway section, annual average daily traffic characteristic data (i.e. AADF from CVs and AADF) standardised by the section's length have been utilised. Additionally, road condition characteristics (i.e. rut and texture depth), that are collected over 10m lengths from the start point to the end point of each road section, have been aggregated over the total length of each motorway section, standardised by length and used as explanatory variables in the NB model. However, a limitation of this study is that some confounding factors that play an important role in the accidents' occurrence (e.g. degree of road curvature, width of lanes, gradient), as stated in the literature review, were not considered in the model due to data unavailability. Accident data (of all injury levels) for the 4-year period (2014-2017) were also obtained and assigned to the M8 motorway segment where they occurred. The dependant variable of the model (i.e. accident frequency) was acquired after aggregating the number of accidents on each roadway section for the years 2014-2017.

The results from the Negative Binomial regression for the accident frequency model are demonstrated in Table 4. The amount of multicollinearity in the regression analysis was tested using the variance inflation factor (VIF). The small VIF values suggest that the regression coefficients are not problematic. The test results can be seen in the Appendix. The impacts of the different explanatory variables in the model are discussed in the next sections.

Table 4. Results from the Negative Binomial regression for the accident frequency model

	Estimate	Std. Error	Pr(>|z|)
(Intercept)	1.224	0.117	0.000*
Traffic characteristics			
AADF from commercial vehicles (CVs/day)	0.026	0.024	0.273
AADF (vehicles/day)	0.010	0.003	0.001*
Road condition characteristics			
Rut depth (mm)	1.317	0.898	0.014**
Texture depth (mm)	4.814	0.803	0.202
Sample size	286		

*Significant at the 0.01 level; **Significant at the 0.05 level

4.2.1 Annual Average Daily Flow from commercial vehicles

As can be seen in Table 4, the independent variable of the main interest, that is the AADF from CVs, is found to be statistically insignificant. This means that it has little or no association with the accident frequency on a motorway section according to the data derived from the M8.

The reason behind the investigation of the above-mentioned relationship emerges from a series of indications that imply an existent linkage between the AADF from CVs and road safety. In the first place, the ever-growing trends in e-commerce are fundamentally modifying the urban logistics and affecting the road network, as companies require larger truck fleets and more warehouses with access to motorways in order to adjust to higher daily truck traffic (Rutter *et al.*, 2017). In addition to this, the number of fatalities in the roads of Scotland has witnessed an increase of 14% from 2015 to 2016 (Transport Scotland, 2016a), while the road freight lifted by trucks in Scotland has also increased by 8,5% in a ten-year period (Transport Scotland, 2016b). Nevertheless, no empirical studies have been undertaken in order to examine the potential link between these two rises. The M8 was selected as the case study primarily because it is the busiest motorway in Scotland (Glasgow Motorway Archive, 2017), thus it could be feasible to draw a clear pattern between the aforementioned relationship. However, no statistically significant association could be identified on the M8 motorway according to the data for the years 2014-2017.

4.2.2 Annual Average Daily Flow

On the contrary to the insignificance of the AADF from CVs, the AADF for all vehicles standardised by length is found to be a statistically significant variable in the model. As demonstrated in Table 4, the p-value is significant at the 0.01 level. The AADF factor is positively associated with the frequency of accidents as the coefficient is equal to 0.01. This means that for each additional unit (i.e. vehicle) in the Annual Average Daily Flow the difference in the log of the anticipated counts for the number of accidents on a motorway section is increasing by 0.01, when holding all the explanatory variables of the model (i.e. AADF from CVs; rut depth; and texture depth) constant. In other words, the change percentage in the number of accidents incident rate is a 1% increase for each additional unit increase in the AADF on a motorway section. This result suggests that roadways with higher levels of traffic volume impose a greater risk of being involved in a road accident.

The positive relationship between the traffic flow and the number of accidents seems a rather intuitive outcome, as increased AADF means more interactions between vehicles and subsequently higher possibilities of being involved in a crash. This result is consistent with many previous studies that were mentioned in Chapter 2 (e.g. Shefer and Rietveld, 1997; Abdel-Aty and Radwan, 2000; Greibe, 2002; Golob and Recker, 2003; Kononov *et al*., 2008; Dias *et al*., 2009; Wang, 2010). Based on the literature, the AADF was expected to develop this positive association, as it recognised as one of the main exposures to accident hazard.

4.2.3 Road condition characteristics

The road condition characteristics that were implemented in the accident frequency model are the rut and texture depth, two values that are frequently used to assess the structural characteristics of the road surface and to indicate a potential loss of skid resistance respectively (Highways Agency, 2006). Both figures have been aggregated over the total length of each motorway section (as they are collected over 10m lengths from the start point to the end point of each road section) and divided by the length of the corresponding section in order to be standardised by it.

As can be seen in Table 4, the texture depth is found to be statistically insignificant to the accident frequency on the M8. On the contrary, the result indicates that the rut depth is showing a strong positive association with the frequency of accidents. The variable presents a p-value significant at the 0.05 level and a positive coefficient that is equal to 1.317. This means that for each additional unit (i.e. mm) the difference in the log of the anticipated counts for the number of accidents on a motorway section is increasing by 1.317, when holding all the explanatory variables of the model (i.e. AADF from CVs; AADF; and texture depth) constant.

The above-mentioned outcome implies that road sections with greater longitudinal distortions of their surface induce higher accidents' occurrence. This conclusion is found to be in accord with a variety of previous research that is mentioned in Chapter 2 (e.g. Start *et al.*, 1998; Chan *et al.*, 2010; Anastasopoulos *et al.*, 2012; Cenek *et al.*, 2014; Nair Baskara *et al.*, 2016). Deep rut depth is recognised as a contributing factor to crash occurrence as it can reduce vehicle control (Cenek *et al.*, 2014, Nair Baskara *et al.*, 2016). Rutting in pavement can also retain water in the road surface which is a major cause of aquaplaning hazard (Cenek *et al.*, 2014) and, therefore, can trigger a higher accident frequency, especially under rainy weather conditions.

4.3 Accident severity model results

As discussed in Chapter 3, accident severity has been examined as a binary variable by many researchers due to its dichotomous structure (Pitt et al., 1990; Farmer, Braver and Mitter, 1997; Al-ghamdi, 2002). In the Binomial logistic statistical model that was employed in order to answer the second research question of this thesis (i.e. the association between the AADF from CVs and the accident's severity when the accident occurs), the accident severity was coded by 1 and 0, representing slight and serious/fatal injuries respectively. The accident severity was assumed to be a function of traffic characteristics (AADF and AADF from commercial vehicles; both standardised by the section's length), time of the accidents, weather parameters and road surface conditions. The weather and surface conditions were included in the model as dummy variables with 1 representing 'fine' and 'dry'. 'Rainy/snowy' weather and 'wet/damp/icy' surface were represented by 0. As reference categories in the model were considered the 'fine' weather conditions and the 'dry' surface conditions. The hours when the crashes occurred were grouped into five categories, as described in Chapter 3. During the years 2014-2017, a total of 686 car accidents were identified on the M8 motorway, however, the figure was reduced to 658 observations due to missing values.

The results from the Binomial logit regression for the accident severity model are demonstrated in Table 5. The amount of multicollinearity in the regression analysis was tested using the variance inflation factor (VIF). The small VIF values suggest that the regression coefficients are not problematic. The test results can be seen in the Appendix. The impacts of the different explanatory variables in the model are discussed in the next sections.

Table 5. Results from the Binomial logit regression for the accident severity model

	Estimate	Std. Error	Pr(>|z|)
(Intercept)	-1.108	0.497	0.026**
Traffic characteristics			
AADF from commercial vehicles (CVs/day)	-0.044	0.046	0.336
AADF (vehicles/day)	0.004	0.005	0.389
Weather conditions (fine = 1)	-0.297	0.490	0.545
Road surface conditions (dry = 1)	0.171	0.443	0.699
Time of the accident (reference= 12:00am - 5:59am)			
6:00am - 9:59am (morning peak)	-1.251	0.536	0.019**
10:00am - 15:59pm	-1.663	0.542	0.002*
16:00pm - 19:59pm (evening peak)	-1.688	0.533	0.001*
20:00pm - 23:59pm	-0.924	0.615	0.133
Sample size	658		

*Significant at the 0.01 level; **Significant at the 0.05 level

4.3.1 Traffic characteristics

From Table 5, it is clear that the independent variable of the main interest, that is the AADF from commercial vehicles, is found to be statistically insignificant. This means that it has little or no association with the severity of an accident when it occurs on a motorway section according to the data derived from the M8 for the years 2014-2017.

Previous studies indicate that the vehicle's weight plays an important role in the risk of being involved in a fatal accident (Anderson and Auffhammer, 2014). However, the case study of the M8 motorway did not reveal a statistically significant relationship between the traffic flow from commercial trucks and the level of accident severity, even though it has been acknowledged that they pose a great danger for the overall road safety (Gayer, 2004; White, 2004; Bezwada and Dissanayake, 2009; Bezwada, 2010; Li, 2012; Anderson and Auffhammer, 2014; Muehlenbachs, Staubli and Chu, 2017). The physical attributes (e.g. length, height) and the operational features (e.g. manoeuvre, breaking distance) of the commercial vehicles are also recognised to impose physical and psychological burdens on the other drivers (Al-Kaisy, 2006; Sarvi, 2013; Moridpour, Mazloumi and Mesbah, 2015). Despite the evidence suggesting that the presence of CVs can affect the level of accident severity, this hypothesis could not be supported by this study on the M8 motorway. This also implies that the increase in the number of fatalities in the roads of Scotland (Transport Scotland, 2016a) cannot be linked to the rise of road freight lifted by trucks in the same country (Transport Scotland, 2016b).

Moreover, as demonstrated in Table 5, the AADF flow standardised by the section's length was also found to be statistically insignificant at the 5% level. Previous studies have shown that the effect of the AADF on the level of an accident's severity is complicated. Some researchers report that lower traffic volume can cause more severe accidents (Martin, 2002), whereas others conclude that the accident severity is connected to the traffic volume with a U-shape pattern (Zhou and Sisiopiku, 1997). Another study showed that crash severity appears to be rather constant when changing from free traffic flow to congestion (Golob, Recker and Pavlis, 2008), implying that the AADF may not affect the severity level. The accident severity model that was employed in this thesis is consistent with the aforesaid study, as it made evident that the AADF has little or no relationship with the level of severity when a crash occurs on a section of the M8 motorway.

4.3.2 Weather and surface conditions

The weather the surface conditions that were included in the accident severity model for the moment when the accident occurred did not present statistically significant coefficients either, according to the results of Table 5.

The result regarding the insignificance of the weather condition is consistent with the study undertaken by Theofilatos (2017), who found that weather parameters are not significantly affecting the accident severity. On the other hand, other researchers report that the environmental phenomena are significant on the severity level (e.g. Lee and Abdel-Aty, 2005) and that snowy weather is associated with less severe accidents (Chang and Xiang, 2003). As for the road surface conditions, the wet street surface is known to increase the risk of aquaplaning and snowy surface to increase the accident hazard due to skidding (Ihs and Magnusson, 2000). However, no statistically significant evidence was drawn from the M8 case-study to indicate an association between damp or icy road surfaces and more serious crashes.

4.3.3 Time of the accident

As demonstrated in Table 5, the '20:00 pm- 23:59 pm' time group does not have a significant association at the 0.05 level of significance with the severity of accident when the incident occurs. Nevertheless, the remained time groups were statistically significant with negative coefficients. This means that when an accident occurs between 6:00 am- 9:59 am; 10:00 am- 15:59 pm; 16:00 pm- 19:59 pm it is less likely to be fatal or severe than slight, compared to occurring between 12:00 am- 5:59 am (that is the reference time category). Specifically, the log odds of an accident being fatal/severe decrease by 1.25 when occurring between 6:00 am- 9:59 am versus occurring between 12:00 am- 5:59 am. In the same way, the log odds of an accident being fatal/severe decrease by 1.66 when occurring between 10:00 am- 15:59 pm versus occurring between 12:00 am- 5:59 am. Finally, the log odds of an accident being fatal/severe decrease by 1.69 when occurring 16:00 pm- 19:59 pm compared to occurring between 12:00 am- 5:59 am.

The above-mentioned results imply that an accident which occurs between 12:00 am- 5:59 am is more likely to be fatal/severe than when occurring at any other time. This fact could be potentially linked to the preference of freight operators and retailers towards choosing more night-time freight trips and off-hours deliveries in order to ensure more effective movement of goods and on-time distribution (Department for Transport, 2014). In addition, the driver fatigue is acknowledged to increase during the night shift that mainly consists of the hours between 12:00 am- 5:59 am. The driver tiredness is considered one of the major reasons behind commercial vehicle accidents on a global level (Lupova, 2006). The findings of this study suggest that this factor is also associated with the level of severity when an accident occurs. A series of policy implications can emerge from this association and will be analysed in the following section.

4.4 Policy implications

Three parameters were found significant to the road safety in this thesis: the AADF; the rut depth on a motorway section; and the time when the accident occurred.

Since it has been shown that the AADF has a positive relationship with the number of accidents, it is important for transport policy makers to optimise the overall flow of traffic and inform the drivers adequately about increased traffic volumes. Many measures could be reinforced to improve and smooth the traffic flow. For instance, electronic variable message signs (VMS) can be displayed in real-time at some sites, making drivers more prepared for the increased traffic volume and the associated risk of accidents. VMS are already located at strategic points throughout the Scottish trunk road network and on many motorways throughout the UK, displaying traffic information/messages to make the road users aware about incidents on the network, their likely impacts and the appropriate action to take. According to Traffic

Scotland (2018), who manages Scotland's Intelligent Transport Systems (ITS), 30 electronic traffic signs are located on the M8. For example, Figure 4 shows an overhead gantry electronic warning sign on M8 Glasgow displaying a "Drive safely" message (Alamy, 2015). The results from this study acknowledge the advantage of VMS, as they not only smooth the traffic flow, but also enhance road safety and, as such, more warning signs could be introduced on major roads in the UK.

4. Overhead gantry electronic warning sign on M8 Glasgow (Alamy, 2015)

In addition to the VMS, the introduction of adaptive traffic signal systems (ATCS) as a part of advanced traffic management systems on the UK roads could contribute to a more efficient management of higher traffic volumes. In contrast with the traditional signal timing, with ATCS signal timing is adapted to the measured traffic in real time and is updated continually by receiving and processing data from strategically placed sensors. The findings of this thesis suggest that the implementation of such systems may improve road safety by smoothing the traffic flow, in addition to reducing traffic congestion and improving travel time reliability.

In regard to the asphalt rutting, the deformations of the road surface can hold water and cause aquaplaning and, therefore, trigger the chances of vehicular collisions. The result of this study confirms that rutting is a safety hazard, as it is shown that for each additional millimetre in the rut depth the difference in the log of the expected accident frequency increases by 1.3. The optimum way to eliminate the negative impacts of rutting on road safety is by preventing its formation with good construction practices. Moreover, it is crucial for transport agencies to conduct frequent surveys in order to identify and repair any existent pavement ruts. Warning messages about the presence of deep ruts on a road section could also be displayed on VMS so that road users can be alerted and prepared to adjust their driving performance in a potentially hazardous condition.

Finally, the findings of this thesis revealed that an accident which occurs between 12:00 am- 5:59 am is more likely to be fatal or severe than when occurring at any other time. As discussed in the previous Chapters, in order to stay competitive, businesses require operators to reach markets and delivery destinations quickly when traffic is not slow or congested. The efficient movement of goods can be achieved through more night-time freight trips and off-hours deliveries that are usually made between 12:00 am- 6:00 am. Nevertheless, as revealed in Table 5, the night shift trips are closely related to the level of the accident's severity. The driver tiredness may also play an important role in this association. Therefore, it is important for policy makers to set limitations on delivery times and establish more resting areas on all roadways. In addition to these measures, it is crucial that the drivers are informed and aware of the need to take regular rest breaks to prevent fatigue or to restore alertness. One break every two hours is an effective way to stay alerted (Société de l'assurance automobile du Québec, 2011). Especially for heavy vehicle operators, poor planning of schedules and routes, inadequate training, lack of flexibility for pick up hours as well as the lack of rest areas can be major causes of the driver fatigue. Thus, it is critical for drivers to attend fatigue management programs and comply with fatigue management methods so that their ability to operate a vehicle is not negatively affected. Recognizing and controlling the consequences of tiredness can prevent road crashes and save lives.

CHAPTER 5 CONCLUSIONS AND FURTHER RESEARCH

5.1 Summary and conclusions

Road accidents are one of the greatest externalities of the contemporary transport networks. In the meantime, freight transportation is rising swiftly in all around the world (Sarvi, 2013), as the ever-growing trends in e-commerce generate the need for businesses of more immediate goods' distribution and shorter delivery cycles, which can be accommodated by more commercial fleet (Rutter *et al.*, 2017). In addition to this, the number of fatalities in the roads of Scotland has witnessed an increase of 14% from 2015 to 2016 (Transport Scotland, 2016a), while the road freight lifted by trucks in Scotland has also increased by 8,5% in a ten-year period (Transport Scotland, 2016b). Nevertheless, no empirical studies have been undertaken in order to examine the potential link between these two rises. The several indications that the presence of trucks disturbs other drivers' behaviour and the traffic stream require the relationship between the commercial flow and accidents' occurrence to be examined. This thesis, therefore, intended to shed light on the relationship between the traffic flow from commercial trucks and accidents on motorways. This has been achieved by examining the effect of the AADF from CVs on both accident frequency and accident severity, using two appropriate statistical models. Empirical data were collected from the M8 motorway for the years 2014-2017 and provided by Transport Scotland.

This thesis firstly examined various factors affecting road accidents by conducting an in-depth literature review. These factors were related to traffic characteristics (e.g., traffic flow, speed and congestion), road geometry and infrastructure, demographic characteristics, driving behaviour, and environmental conditions. The factors that were considered in the statistical models in this study include the AADF; the time of the accident; the motorway section length; the rut and texture depth; the weather conditions; and the surface conditions. Other factors were not included in the models because of data unavailability.

In terms of statistical models, previous transport modelling approaches were considered and reviewed. The most widely used models for count dependent variables with a presence of overdispersion (i.e. accident frequency) and binary response variables (i.e. severity level) were found to be the Negative Binomial logit and Binomial logit model respectively and were employed in this study.

For the investigation of the relationship between the AADF from commercial trucks and the frequency of accidents, the model reveals that there is no statistically significant association between the AADF from CVs and the count of accidents on the M8 at the 0.05 level of significance. However, the effects of the other contributing factors that were taken into account were found to be consistent with previous studies; the AADF and the rut depth are positively linked with the accident frequency and have a negative impact on the road safety. Specifically, concerning the AADF, for each additional unit (i.e. vehicle) increase in the AADF on a motorway section, the change percentage in the number of accidents incident rate is a 1% increase. This result suggests that roadways with higher levels of traffic volume impose a greater risk of being involved in a road accident. As for the rut depth, a strong positive association with the frequency of accidents is observed; that for each additional unit (i.e. mm) the difference in the log of the anticipated counts for the number of accidents on a motorway section is increasing by 1.317, when holding all the explanatory variables of the model (i.e. AADF from CVs; AADF; and texture depth) constant.

As for the case of accident severity analysis, the AADF from CVs was found to be statistically insignificant to the level of severity at the 5% level of significance when an accident occurs. The weather and the surface conditions that were included in the accident severity model for the moment when the accident occurred did not present statistically significant coefficients either. Nevertheless, regarding the time when the accident occurred, all the time groups except 20:00 pm- 23:59 pm (that was found to be statistically insignificant) were statistically significant with negative coefficients. This means that when an accident occurs between 6:00 am- 9:59 am; 10:00 am- 15:59 pm; 16:00 pm- 19:59 pm it is less likely to be fatal or severe than slight, compared to occurring between 12:00 am- 5:59 am. In other words, an accident which occurs between 12:00 am- 5:59 am is more likely to be fatal/severe than when occurring at any other time.

Based on the results from the accident frequency and severity model, no firm conclusion can be drawn regarding the relationship between the traffic flow from commercial trucks and road accidents. However, the findings suggest that late-night deliveries can be associated with the level of severity when an accident occurs. This can be mitigated with the facilitation of policy makers by setting limitations on delivery times and introducing more resting areas on all roadways, as well as by providing adequate awareness about the drivers' tiredness. Optimising the overall flow of traffic and informing the drivers adequately about increased traffic volumes using VMS and ATCS would also be beneficial for the road safety.

5.2 Contribution to knowledge

Commercial trucks are acknowledged to be a major contributor to congestion (U.S. Department of Transportation, 2008) and congestion is positively associated with the frequency of fatal and serious injury accidents (Wang, 2010). The M8 is not only one of the most congested motorways in the UK, but also the busiest motorway in Scotland (Glasgow Motorway Archive, 2017), where the number of fatalities has witnessed an increase of 14% from 2015 to 2016 (Transport Scotland, 2016a). These indications required, therefore, the conduction of an empirical study in order to examine the potential link between the aforementioned elements. The AADF from CVs was found to have little or no statistically significant relationship with the accidents' occurrence (in terms of both accident frequency and severity).

However, as shown in Table 5, an accident which occurs between 12:00am - 5:59am is more likely to be fatal/severe than when occurring at any other time. This fact could be potentially linked to the preference of freight operators and retailers towards choosing more night-time freight trips and off-hours deliveries in order to ensure more effective movement of goods and on-time distribution (Department for Transport, 2014). A series of policy implementations including limitations on delivery times could be applied in order to mitigate the negative effects of off-hours deliveries on road safety.

5.3 Limitations and further research

In this research, there are several limitations that mainly concern the data and statistical models. These limitations are discussed below. Recommendations for further research are also provided at the end of this Chapter.

In terms of statistical models, there is a number of areas could be extended. Specifically, the accident frequency model suffers from the issue of excess of zero counts, as most roadway sections present zero or very few crashes. As discussed in Chapter 3, a zero-inflated Negative Binomial regression usually works better in modelling overdispersed count data that has an excess of zeros (Miaou, 1994). However, due to data limitation (unavailability of the Instrumental variable that is required for the application of the zero-inflated model), this model could not be employed for the purpose of this thesis. Therefore, further research can be conducted to employ a more efficient modelling approach regarding the examination of the relationship between accident frequency and AADF from CVs.

As for the data limitations, many confounding factors that play an important role in the accidents' occurrence (e.g. degree of road curvature, width of lanes, gradient) were not considered in this thesis due to data unavailability. Apart from that, the number of severe and especially fatal accidents on the M8 for the examined period was rather low and, as such, the two severity level categories were combined. It is crucial that further studies are conducted, considering a wider variety of contributing factors and a greater number of serious and fatal accidents, so that a clearer pattern for the relationship between the AADF and road accidents can be demonstrated.

Finally, as an extension of the study area, further research should investigate the effect of commercial flow on road safety considering not only motorways, but also other major roads that might have variations in the speed limit and different infrastructure characteristics. Further studies on major roads in the UK and other countries can offer further empirical evidence, which may eventually provide a conclusive statement on the above-mentioned relationship and widen the potential use of the findings from this thesis. Lastly, the impact of the commercial flow on junctions also needs to be carefully examined, as junctions are usually considered comparatively hazardous since this is where more vehicles interact, and accidents are more likely to occur (Noland and Quddus, 2005).

APPENDIX

Overdispersion of the data

The Poisson regression can rarely be applied to accident data as due to the nature of this data, overdispersion is usually present. The results from the overdispersion test revealed an overdispersion ratio of 4.37, reflecting the extra variation beyond what is predicted under the Poisson model.

Overdispersion test result

Overdispersion test result	
Overdispersion ratio	P-value
4.37	1

Multicollinearity of the independent variables

Multicollinearity can cause problems because it can increase the variance of the regression coefficients, making it difficult to assess the individual effect that each of the explanatory variables has on the response. The degree of inflation of the variance of a coefficient due to multicollinearity can be calculated by using the variance inflation factor (VIF). The VIF values from both models were lower than 5, suggesting that the regression coefficients are not problematic.

VIF values for the accident frequency model

Variable (standardised by length)	AADF from CVs	AADF	Rut	Texture
VIF	1.15	1.04	2.67	3.58

VIF values for the accident severity model

Variable	AADF from CVs (standardised by length)	AADF (standardised by length)	Weather conditions	Road surface conditions	Time group
VIF	2.43	2.29	1.99	1.23	1.04

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