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# **THE RELATIONSHIP BETWEEN TRAFFIC CONGESTION AND ROAD ACCIDENTS: AN ECONOMETRIC APPROACH USING GIS**

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By  
**Chao Wang**

A Doctoral Thesis

Submitted in partial fulfilment of the requirements  
for the award of  
Doctor of Philosophy of Loughborough University

February 2010

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## ABSTRACT

Both traffic congestion and road accidents impose a burden on society, and it is therefore important for transport policy makers to reduce their impact. An ideal scenario would be that traffic congestion and accidents are reduced simultaneously, however, this may not be possible since it has been speculated that increased traffic congestion may be beneficial in terms of road safety. This is based on the premise that there would be fewer fatal accidents and the accidents that occurred would tend to be less severe due to the low average speed when congestion is present. If this is confirmed then it poses a potential dilemma for transport policy makers: the benefit of reducing congestion might be off-set by more severe accidents. It is therefore important to fully understand the relationship between traffic congestion and road accidents while controlling for other factors affecting road traffic accidents.

The relationship between traffic congestion and road accidents appears to be an under researched area. Previous studies often lack a suitable congestion measurement and an appropriate econometric model using real-world data. This thesis aims to explore the relationship between traffic congestion and road accidents by using an econometric and GIS approach. The analysis is based on the data from the M25 motorway and its surrounding major roads for the period 2003-2007. A series of econometric models have been employed to investigate the effect of traffic congestion on both accident frequency (such as classical Negative Binomial and Bayesian spatial models) and accident severity (such as ordered logit and mixed logit models). The Bayesian spatial model and the mixed logit model are the best models estimated for accident frequency and accident severity analyses respectively. The model estimation results suggest that traffic congestion is positively associated with the frequency of fatal and serious injury accidents and negatively (i.e. inversely) associated with the severity of accidents that have occurred. Traffic congestion is found to have little impact on the frequency of slight injury accidents. Other contributing factors have also been controlled for and produced results consistent with previous studies. It is concluded that traffic congestion overall has a negative impact on road safety. This may be partially due to higher speed variance among vehicles within and between lanes and erratic driving behaviour in the presence of congestion.

The results indicate that mobility and safety can be improved simultaneously, and therefore there is significant additional benefit of reducing traffic congestion in terms of road safety. Several policy implications have been identified in order to optimise the traffic flow and improve driving behaviour, which would be beneficial to both congestion and accident reduction. This includes: reinforcing electronic warning signs and the Active Traffic Management, enforcing “average speed” on a stretch of a roadway and introducing minimum speed limits in the UK.

This thesis contributes to knowledge in terms of the relationship between traffic congestion and road accidents, showing that mobility and safety can be improved simultaneously. A new hypothesis is proposed that traffic congestion on major roads may increase the occurrence of serious injury accidents. This thesis also proposes a new map-matching technique so as to assign accidents to the correct road segments, and shows how a two-stage modelling process which combines both accident frequency and severity models can be used in site ranking with the objective of identifying hazardous accident hotspots for further safety examination and treatment.

**Key words:** *Traffic congestion, road accidents, GIS, M25 motorway, site ranking, accident hotspots, spatial econometrics, full Bayesian hierarchical models, ordered and nominal response models, two-stage mixed multivariate models*

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# CHAPTER 1 INTRODUCTION

## 1.1 Background

During the past few decades, there has been rapid growth of demand for road transport. In particular, road traffic volume has increased significantly during this period, which reflects increasing economic activity, population and car ownership. According to the UK Department for Transport (DfT, 2009a), traffic measured in vehicle kilometres was around 50 billion in 1950, and this figure increases to 400 billion in 1990, more than 450 billion in 2000 and over 500 billion by 2008.

This increase in road transport brings benefits to society in terms of mobility and accessibility, it also however has costs. The costs include not only the direct cost of providing transport services such as infrastructure, personnel, equipment costs but also the various indirect costs in terms of the impact on the environment, most notably noise and air pollution; travel delay due to traffic congestion; and the loss of life and property damage as a result of road accidents. This thesis focuses on two major aspects of road transport activities namely: traffic congestion and road accidents.

The growing traffic volume presents the problem of traffic congestion in modern society, since increased travel time caused by traffic congestion imposes costs to road users. For example, average “all day” traffic speed within central London decreased from 17.2 (km/h) in 1986 to 14.2 (km/h) at comparable times in 2002, the year before the Congestion Charging scheme was implemented in central London (Transport for London, 2003). On the UK major roads (motorways and A roads), thousands of hours of traffic delay were recorded per day (ranging from 8 to 567 thousand vehicle hours) in the year ending March 2009 (DfT, 2009a). In the US, it has been recently reported that the total direct economic cost of traffic congestion was about \$87.2 billion dollars (£54.6 billion) in the 439 urban areas in 2007; and the average cost per traveller during the peak period was \$757 (£474) in 2007 (Schrink and Lomax, 2009). The reported cost only includes direct costs, namely additional time and wasted fuel caused by congestion. Therefore, if indirect costs such as opportunity cost of increased travel time were included, the total cost of traffic congestion would be larger. The total cost of traffic congestion in the UK is also considerable – it has been estimated that the congestion cost could be as large as £15-20 billion per year in the UK (Grant-Muller

and Laird, 2006). In addition to economic costs, traffic congestion also has implications for the environment, quality of life and mobility. As such, reducing congestion has been one of the major objectives for transport policy makers in the UK (DfT, 2009a), and in recent years several measures have been proposed and implemented aiming to reduce traffic congestion such as the Congestion Charging scheme in London and the Active Traffic Management (ATM) on the M42 motorway.

The costs of road traffic accidents to individuals, property and society in general have been significant. For example, in the European Union, more than 40,000 people die and over one million are injured every year because of road accidents (CARE, 2008). According to the UK Department for Transport (DfT), there were a total of 224,640 road casualties in Great Britain for the year (12-month period) ending in the first quarter 2009, of which 2,490 were killed and 25,250 were seriously injured (DfT, 2009b). According to the International Road Traffic and Accident Database (IRTAD, 2005), the UK however is one of the safest countries in the world – with an average of 6.4 killed per 1 billion veh-km, which is low compared to other countries including most European countries, Japan and the US. There are still considerable costs associated with road accidents, including human costs (e.g. willingness to pay to avoid pain, grief and suffering); the direct economic costs of lost output; the medical costs associated with road accident injuries; costs of damage to vehicles and property; police costs and administrative costs of accident insurance (DfT, 2008). The total costs of road accidents were estimated to be around £19 billion in Great Britain in 2007 (DfT, 2008), and it has been estimated that economic costs of road traffic accidents for high income countries are about 2% of their Gross National Product (IRTAD, 2005). As such, improving road safety is often one of the primary aims of transport policy. The UK government has recently proposed a road safety strategy for 2010-2020, with the objective to reduce the number of killed or seriously injured road users by about 33% compared with the average for 2004 to 2008 by 2020 (DfT, 2009c). The number of road casualties, including killed or seriously injured (KSI), has decreased in recent years: according to a recent estimation (12-month period to March 2009), the number of KSI was 42% below the 1994–1998 average; and the slight injury rate was 37% below the 1994-1998 average (DfT, 2009b).

## 1.2 Problem statement and intention of this thesis

As discussed earlier, both traffic congestion and road accidents impose a burden on society, it is therefore important to reduce the impact of traffic congestion and accidents. An ideal solution would be to reduce them simultaneously. This may not be possible, however, since it is speculated that there may be an inverse relationship between traffic congestion and road fatalities (Shefer and Rietveld, 1997). Shefer and Rietveld (1997) suggested that in a less congested road network, the average speed of traffic would be normally high which is likely to result in more road fatalities; on the other hand, in a congested road network, traffic would be slower and may cause fewer fatalities. This increased traffic congestion may lead to more accidents due to increased traffic volume; however, those accidents may be less severe. This suggests that the total external cost of accidents may be less in a congested condition relative to an uncongested condition. As such, traffic congestion may improve road safety. However, traffic congestion reduces mobility which subsequently decreases economic productivity.

This poses a potential dilemma for transport policy makers: on the one hand it is desirable to reduce traffic congestion, but on the other hand this may lead to more severe road accidents, which may eventually increase the total costs associated with both congestion and accidents. In other words, the benefit of reducing congestion might be off-set by more severe accidents. It is, therefore, important to understand the relationship between traffic congestion and road accidents so that effective policy can be implemented to control both congestion and accidents.

The relationship between traffic congestion and road accidents would however appear to lack attention in the current literature and the studies that exist tend to employ a proxy for traffic congestion or lack an appropriate econometric model. For example, the studies by Shefer (1994) and Shefer and Rietveld (1997) were based on simulation to test their hypothesized model, as such support from empirical evidence is required. Very few studies have looked at real-world data to provide solid empirical evidence using advanced econometric models. There were some exceptions, such as those studies by Baruya (1998), Noland and Quddus (2005) and Kononov et al. (2008) who investigated the effects of traffic congestion on road accidents using real-world data and econometric models. Those studies, however, seem to use a weak proxy for traffic

congestion, such as the “proportion of vehicles slower than half the speed limit”, differences between spatial locations (e.g., Inner and Outer London), employment density and level of traffic flow. These proxies may not appropriately or truly represent levels of traffic congestion, and thus the results from econometric models may be biased. For instance, Noland and Quddus (2005) used an indicator variable for Inner London as a proxy for congestion, and no significant differences were found between Inner London and Outer London and they speculated that speed is generally low in both areas. This suggested that such proxies for congestion may not precisely represent levels of congestion, and therefore a more precise congestion measurement is required to more accurately represent congestion in an econometric model so as to provide more robust empirical evidence. Noland and Quddus (2005) suggested that instead of an area-wide based study, a road segment based study can be used to better capture the variation of traffic congestion.

In terms of econometric models, Poisson or Negative Binomial (NB) regression models have been used in previous studies (e.g., Baruya, 1998; Noland and Quddus, 2005) to establish a relationship between accident frequency and traffic congestion (and other factors that contribute to accident occurrence). NB models are Poisson based models (also known as Poisson-gamma models) and it has been argued that they are more suitable for count data (such as accident frequency) compared to the simple Poisson model. NB models have the advantage in that they can accommodate overdispersion in accident data. NB models, as with other traditional Poisson based models such as Poisson-lognormal models, however ignore the unmeasured spatially correlated effects among neighbouring spatial units. Accidents and their unmeasured contributing factors (such as weather conditions and road pavement roughness) are likely to be correlated among neighbouring spatial units. In other words, unmeasured factors such as weather conditions are likely to be similar between neighbouring sites. Traditional accident frequency models ignore such spatially correlated effects, which is a concern especially when the spatial unit is on a small scale, such as wards and road segments, as spatial dependence is envisaged to be larger in these cases (MacNab, 2004). Recent developments in spatial econometrics has enabled researchers to address the issues of unmeasured spatial correlation. Spatial econometrics were initially used in ecological analysis and then recently in road accident analysis (e.g., Ghosh et al., 1999; Miaou et al., 2003). In order to more accurately estimate the association between traffic

congestion and road accident frequency, more sophisticated models recently developed in safety research such as spatial econometrics need to be employed.

Besides the effect of traffic congestion on road accident frequency, it is also desirable to examine the effect of traffic congestion on road accident severity. The previous studies mentioned above (e.g. Baruya, 1998; Noland and Quddus, 2005) mainly focus on the effect of traffic congestion on accident frequency. Yet again, few studies have focused on the effect of traffic congestion on accident severity. While the relationship between traffic congestion and accident severity may seem straightforward: increased traffic congestion causes accidents to be less severe given the accidents occurred, due to lower speed in congested situations, whether this hypothesis is true needs to be examined. In addition, the effect of traffic congestion on accident severity also needs to be quantified.

This thesis seeks to investigate the relationship between traffic congestion and road accidents (frequency and severity) using a suitable congestion measurement and appropriate econometric models. This has been achieved using a road segment based analysis (instead of other spatial units such as areas) as congestion measurement at a road segment level is available. It examines whether traffic congestion has any positive or negative impact on road safety, which will assist the transport policy makers with transport and safety planning.

Since improving road safety is an important objective for transport policy makers, considerable development has to be made in all aspects of the road transport system which involves three main parties: roads (for which government, local authorities and roadway infrastructure engineers are responsible); vehicles (for which vehicle manufacturers and vehicle owners are responsible); and road users (for which drivers, passengers and pedestrians are responsible). An accident analysis therefore needs to take account of all risk factors related to these parties and their interactions. Various other factors that may affect road accidents also need to be evaluated and controlled for, such as traffic flow and road geometry such as horizontal curvature, gradient and number of lanes. Therefore to effectively improve road safety (in terms of both accident frequency and severity, see discussion below), it is necessary to fully understand what and how these factors affect road accidents. Once the risk factors are identified, government or transport policy makers can develop corresponding measures to improve

road safety. As such, this thesis examines the impact of traffic congestion on road accidents while controlling for various other factors that may affect road accidents.

There are also technique issues in analysing accidents, notably the method to match accidents to the correct road segments. Due to the error in location of both accident and roadway data, when the accident dataset is overlaid onto spatial road segment (centre-line) data, mismatches between them are often observed. A new technique has been proposed in this thesis to map accidents onto correct road segments on major roads, which ensures the accident count for each segment and data (e.g., traffic flow) for each individual accident are correct.

In addition to the relationship between traffic congestion and road accidents, policy implications for improving road safety using the results and findings will also be offered. An important application of the accident prediction models in road safety management – site ranking, which aims to identify hazardous accident hotspots, has been explored. Once accident hotspots are identified, further safety examination and remedial treatment can be performed on the hazardous locations in order to improve the safety of a road network. Previous research usually only use accident frequency models in site ranking. In this thesis an innovative method has been developed and illustrated as to how to combine both accident frequency and severity models in site ranking. This method is transferable and can be applied to other road networks.

### 1.3 Research aim and objectives

In light of the research problems described above, the aim of this thesis is to **explore the relationship between traffic congestion and road accidents**. This is formulated in the following objectives:

- To examine the various factors affecting road accidents.
- To identify appropriate econometric models and a suitable congestion measurement.
- To investigate and refine data so as to improve the quality of the analysis.
- To develop the association between traffic congestion and both accident frequency and accident severity.
- To analyse practical applications of the models developed in the previous objective and recommend safety policies for policy makers.

In this thesis, the aim and objectives will be achieved using the real-world road segment based data collected from the M25 motorway and its surrounding major roads in England. The details of the methods used to fulfil the objectives at different stages and the research design are discussed in Chapter 4 of this thesis.

## **1.4 Clarifications of the terms “traffic congestion”, “road accidents” and “safety” used in this thesis**

The terms “traffic congestion”, “road accidents” and “road safety” will be frequently used throughout this thesis. It is therefore necessary to clarify what these terms mean.

“Traffic congestion” has no clear definition and for different organisations this term has different meanings, such as “delays”, “a lot of traffic”, “slow moving traffic”, “not being able to drive smoothly” or “traffic jam” (DfT, 2005a). Complete standstill conditions are often described as “traffic jam” or “gridlock”. Traffic congestion on the UK major roads is defined by the DfT as the vehicle delay which is the difference between the actual travel time and the travel time at a reference speed (often free flow speed) (DfT, 2009a). Therefore traffic conditions were considered as “congested” if the vehicles were travelling below the free flow speed. This means congestion occurs when there are so many vehicles that traffic moves slower than the situation when no other vehicles were there. Based on this definition, there are many methods to measure traffic congestion, which are discussed in Chapter 4.

A road accident is defined by the DfT as “involves personal injury occurring on the public highway (including footways) in which at least one road vehicle or a vehicle in collision with a pedestrian is involved and which becomes known to the police within 30 days of its occurrence.” (DfT, 2008). The accident data used in this thesis was obtained from the UK STATS19 database and this database is also used by the DfT (DfT, 2008). According to the STATS19 database, cyclists, horse riders and animals (except ridden horse) involved in a vehicle collision is also included in the accident database, although there are few such cases on major roads (motorways and A roads)<sup>1</sup>.

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<sup>1</sup> Cyclists and horse riders represent 5% and 0.01% of all road causalities respectively; and animals (except ridden horse) represent 0.54% of carriageway hazards on motorways and A roads in the UK in 2007.

It should be noted that accidents resulting only in property damage are not included in the STATS19 database. Road accidents are also known as road traffic crashes or collisions in various literature (Ivan et al., 2000; El-Basyouny and Sayed, 2009a), although their definitions may not necessarily be the same as the DfT definition. For example, road traffic collisions are defined by Edmonton's Transportation Department as the "reportable on street collisions that do not occur on private property, include at least one motor vehicle, and result in injury, at least \$1,000 in property damage, or both" (El-Basyouny and Sayed, 2009a). It should be noted that the word "accident" implies that the incidents are *unintended*. Therefore *intended* road collisions or crashes, such as car crashes caused by terrorist attacks may not be considered as "road accidents". This aspect however is not clearly defined by the DfT.

In this thesis road accidents are investigated in two respects: accident *frequency* and accident *severity*. Accident frequency refers to the count of accidents at certain entities during certain periods of time; and accident severity refers to the level of severity of an accident given that the accident has occurred. There are three categories of accidents classified by their severity levels, namely fatal, serious and slight injury accidents. A fatal accident is defined as "an accident in which at least one person is killed"; and a serious injury accident is defined as an accident "in which at least one person is seriously injured<sup>2</sup> but no person (other than a confirmed suicide) is killed"; and a slight injury accident is defined as an accident "in which at least one person is slightly injured<sup>3</sup> but no person is killed or seriously injured" (DfT, 2008). It should be noted that an accident may involve several fatalities or injuries. For example, a fatal accident may involve two fatalities. It has been reported that on average a fatal accident involved 1.09 fatalities in 2007 (DfT, 2008). Therefore the *number of accidents* is not equivalent to the *number of casualties*. For accident frequency analysis, this thesis will focus on the effect of traffic congestion on the number of accidents.

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<sup>2</sup> Serious injury is "an injury for which a person is detained in hospital as an 'in-patient', or any of the following injuries, whether or not they are detained in hospital: fractures, concussion, internal injuries, crushings, burns (excluding friction burns), severe cuts, severe general shock requiring medical treatment and injuries causing death 30 or more days after the accident." (DfT, 2008)

<sup>3</sup> Slight injury is "an injury of a minor character such as a sprain (including neck whiplash injury), bruise or cut which are not judged to be severe, or slight shock requiring roadside attention. This definition includes injuries not requiring medical treatment." (DfT, 2008)

Safety is the quality or state of being safe; freedom from harm or danger. Therefore “road safety” aims to reduce the impact of road accidents. Since road accidents have two respects, namely accident frequency and severity, a road safety study needs to address both. For the former, road safety can be improved through preventing the accident occurring, i.e. to reduce accident frequency (given an exposure factor, e.g., vehicle kilometres or population during certain time periods). For instance, if increased average speed was found to increase the number of accidents, then relevant policies could be implemented to decrease average speed, which would result in less road accidents and improved road safety. As for accident severity, road safety can be improved through making the accident less severe given that the accident has occurred. For example, while cable median barriers would have little impact on accident frequency (as vehicles have already departed the travel lane when they encounter the barriers), this device however can significantly reduce accident severity, especially the head-on accidents on high speed rural roads (Oh et al., 2010). Therefore, an effective road safety scheme should consider and reduce both accident frequency and severity.

## 1.5 Outline of the thesis

This thesis is organised into ten chapters. This section provides an overview of each following chapters.

**Chapter 2** provides a literature review of the various factors affecting road accidents. The factors considered include traffic congestion and other factors related to traffic characteristics, road geometry and infrastructure, demographic characteristics, driving behaviour, land use and the environment.

**Chapter 3** reviews the range of econometric methods used in accident modelling. This includes a review of an accident analysis based on road segment and area-wide levels. This is followed by a review of econometric models used in modelling both accident frequency and accident severity. Based on the review, appropriate econometric models are identified. Practical applications of the econometric models, especially the method to identify hazardous accident hotspots (i.e. site ranking) are then discussed.

**Chapter 4** presents the methodology utilised in this thesis. A review of traffic congestion measurements in the literature is conducted in order to identify a suitable congestion measurement. This chapter also details a new method to assign accidents to

the correct road segments. Details of the econometric models used for both accident frequency and accident severity analyses are then presented. For accident frequency analysis, classical count outcome and full Bayesian spatial models are employed. For accident severity analysis, ordered and nominal response models are employed. Finally, the method used for site ranking, namely the two-stage modelling process is detailed.

**Chapter 5** explores and presents the data used in this thesis. The study area is the M25 motorway and its surrounding motorways and major A roads. The congestion measurements employed in the following chapters are presented. This is followed by a description of the data for both accident frequency and accident severity analyses. The validation of data is also detailed.

**Chapter 6** and **Chapter 7** present the results from accident frequency and accident severity models respectively. Various econometric models detailed in Chapter 4 are developed and tested using the real-world data from the M25 and surround. The effect of traffic congestion and various other factors on road accidents are explored.

Based on the results provided in Chapter 6 and Chapter 7, site ranking which aims to identify accident hotspots is explored and presented in **Chapter 8**. This is achieved by using a two-stage modelling process which combines both accident frequency and accident severity models.

**Chapter 9** discusses further the relationship between traffic congestion and road accidents, with respect to both accident frequency and accident severity based on the results from Chapter 6 and Chapter 7. The overall impact of traffic congestion on road safety is then discussed. Policy implications based on the findings are also detailed. Several potential policy implementations are proposed with the objective of improving road safety.

Finally, **Chapter 10** concludes this thesis with a brief summary and discussion of the contribution to knowledge, limitations of the research and directions for further research.

## **CHAPTER 2 LITERATURE REVIEW OF FACTORS AFFECTING ROAD ACCIDENTS**

### **2.1 Introduction**

As discussed in Chapter 1, in order to fully understand the relationship between traffic congestion and road accidents, it is necessary to control for other factors affecting road accidents in an econometric analysis. An econometric model would perform better in terms of both statistical fit and model inference if relevant contributing factors are included. As such, in addition to traffic congestion, other factors affecting road accidents need to be considered and examined. The objective of this chapter is therefore to provide a review of current literature relating to the various factors affecting road accidents. This would benefit the development and interpretation of an econometric model relating to traffic congestion and accidents.

As detailed in the following sections, many factors affecting road accidents have been identified and evaluated in the literature. While this chapter identifies these risk factors, it does not intend to take into account nor address all the factors in the analysis in the following chapters, but to focus on traffic congestion. This is an important but apparently less studied area of research and as such will form the basis of this thesis. Several other factors will be controlled for in the analysis, subject to data availability and econometric modelling requirements.

The rest of this chapter will review the various factors affecting road accidents in the literature, along with the intentions of whether and how this thesis will address these factors. It is then followed by the discussion of the research scope and factors to be investigated in this thesis.

### **2.2 An overview of factors affecting road accidents**

There is a broad range of factors affecting road accidents. These factors are usually related to traffic characteristics, road users, vehicles, roadway infrastructure and environment. Traffic characteristics such as traffic flow and speed might affect road accidents. As for road users, their behaviour, such as seat belt usage, alcohol consumption, age, passengers' impact on drivers (for instance, talking to drivers while

driving) might affect road safety; and different road users could expect different accident severity levels, for example, non-motorised transport (NMT) could be more vulnerable to accidents compared to motorised transport (MT) considering their different physical conditions. With regard to vehicle related factors, many vehicle designs play an important role in safety, such as airbags, electronic stability control, anti-lock braking systems (ABS) and low centre of gravity design so as to avoid rollover. In terms of the roadway system, the quality of infrastructure and road geometry design might also have certain effects on road safety. Other factors such as lighting and weather conditions can affect road safety through both the road user and roadway system. These factors are summarised and classified in Table 2.1:

**Table 2.1 Factors involved in a road accident**

| Category                                     | Factors   |
|--|---|
| Traffic characteristics                      | <ul style="list-style-type: none"> <li>• Speed</li> <li>• Density</li> <li>• Flow</li> <li>• Congestion</li> </ul>  |
| Road infrastructure and geometry, vehicle    | <ul style="list-style-type: none"> <li>• Street/road layout</li> <li>• Road geometry (e.g. number of lanes and road curvature)</li> <li>• Infrastructure quality</li> <li>• Vehicle design</li> </ul> |
| Demographic, driving behaviour, and land use | <ul style="list-style-type: none"> <li>• Age, gender, population and employment densities</li> <li>• Seat belt, helmet usage</li> <li>• Shopping/commercial activities; urban scale</li> </ul>        |
| Environment                                  | <ul style="list-style-type: none"> <li>• Lighting</li> <li>• Road surface conditions</li> <li>• Weather (e.g., rain, snow)</li> </ul>   |

There has been a long history of analysing accidents by exploring various contributing risk factors, and there is a body of research literature related to road accidents from a broad range of aspects using various approaches. Smeed (1949, 1972) estimated the number of road fatalities by considering the number of licensed motor vehicles and population, in which a simple formula<sup>4</sup> consisting of two covariates is examined: motor vehicles and population based on data from several countries, and concluded that the

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<sup>4</sup>  $D = 0.0003(NP^2)^{1/3}$ , where  $D$  is number of road fatalities;  $N$  is number of motor vehicles; and  $P$  is population. This formula was developed by examining data of 20 countries in 1938 (Smeed, 1949). The starting form of the formula is  $D = AN^\alpha P^\beta$  and the parameters  $A$ ,  $\alpha$ , and  $\beta$  were estimated by using the least squares method.

formula could give good estimates in many countries. This is an example of early work which attempts to estimate the number of accidents by using risk or exposure factors.

Thereafter there has been a large amount of research with respect to road safety, which investigates road accidents and its contributing factors from a wide range of aspects and approaches, namely economic, engineering and policy. As road accidents are a classic form of external cost, many economists are involved in road safety research (Peirson et al., 1998; Dickerson et al., 2000; Graham and Glaister, 2003). Improved infrastructure design and engineering work is also believed to play an important role in road safety (Navin et al., 2000; Pérez, 2006). Laws and legislation are also often used as tools to improve road safety, for instance, Bjørnskau and Elvik (1992) discussed the impact of laws and legislation on accidents by employing a game-theoretic model. Many researchers attempt to investigate accidents by establishing statistical relationships between risk factors and accidents. For example, Levine et al. (1995a) developed a spatial pattern of different types of motor vehicle accident distribution in Honolulu, from which they found that accidents fluctuate dramatically in different areas, thus the “blackspot” of accidents can be identified. They also examined the zonal generators – i.e. factors that generate trips, trying to explain the spatial pattern of accidents (Levine et al., 1995b). Temporal effects are also considered in both studies by looking at accidents in terms of the time of the day, weekdays and weekends.

Most previous research mentioned above tends to use a statistical or empirical approach. Few however have explained the basic mechanism of accident causation. A recent exception is Elvik (2006), who focused on the basic mechanism of accident causation and proposed general regularities that can explain the relationship between the risk factors and accidents, which are expressed by several “laws”: the universal law of learning; the law of rare events; the law of complexity; and the law of cognitive capacity. *The universal law of learning* states that the accident rate tends to decline as the number of kilometres travelled increases; *the law of rare events* implied that “rare events” such as environmental hazards would have more effect on accident rates than “regular events”; *the law of complexity* states that the more complex the traffic situation road users encounter, the higher the probability that accidents would happen; and *the law of cognitive capacity* implies that accidents are more likely to happen as cognitive capacity approaches its limits. Although these proposed laws need further empirical evidence in order to confirm, they are useful in explaining fundamental questions such

as why and how a factor affects road safety. Researchers often can establish statistical relationships between various risk factors and accidents but have difficulties in explaining the underlying mechanisms. These laws are useful in this aspect, and in turn, statistical findings can validate the laws. In addition to the type of work by Elvik (2006), another research effort is to develop a causal model to determine whether a factor was a *cause* of a road accident (Davis and Swenson, 2006). This type of analysis compares “what happened” to “what would have happened had the supposed cause been absent” (Davis and Swenson, 2006). Davis and Swenson (2006) applied these methods to freeway rear-end accidents, finding that, for example short following headways were probable causal factors for the rear-end accidents. It should be noted however that, this thesis is based on an *observational* analysis rather than a causal analysis. This is mainly because the various risk factors considered in this thesis are correlated, thus it is unlikely that one factor can be changed without changing other factors. For instance, traffic flow would also be changed if there was a change in traffic congestion. Therefore this thesis will focus on observational analyses using various econometric models which allow establishing associations between risk factors and road accidents.

In the following sections, previous work on major factors affecting road accidents are reviewed. These will form the basis of the econometric analysis of factors affecting road safety which are the focus of this thesis.

## 2.3 Traffic characteristics

Accidents occur when traffic moves, and it is obvious that if there was no traffic there would be no accidents. Therefore it is natural to investigate traffic characteristics to understand their impacts on accidents. Traffic characteristics can often be classified as follows: speed, density, flow and congestion. This section looks at how these characteristics affect road accidents.

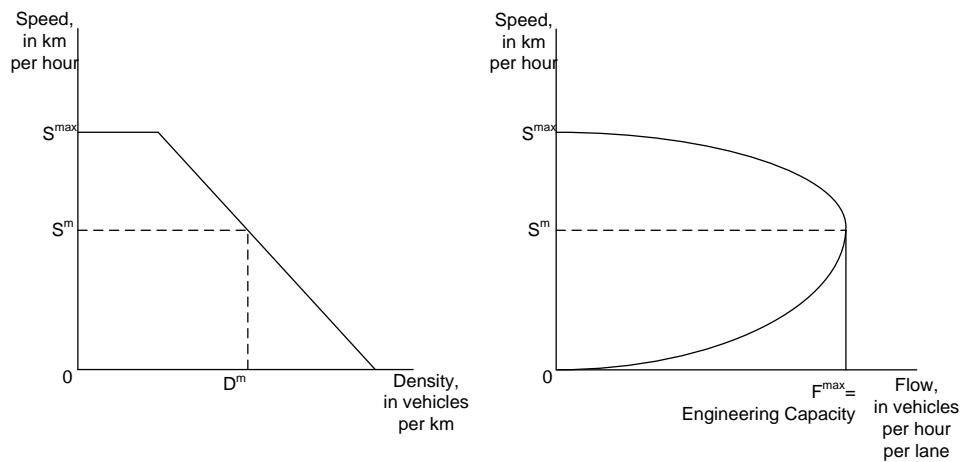
It is worth mentioning that speed, density, flow and congestion are inextricably linked to each other, so an understanding of one of them could provide useful knowledge on the other three. In addition, in previous studies while explaining phenomenon such as higher accident rates during night-time (Martin, 2002), all four factors are involved so it

is necessary to determine which is the key factor affecting accidents. The relationship between speed, density and flow can be expressed as follows:

$$q = k\bar{v}$$

where  $q$  is flow (vehicles per unit time);  $k$  is density (vehicles per length of road); and  $\bar{v}$  is mean speed (distance per unit time). As for traffic congestion it arises when traffic flow or density increases on the road with limited capacity until at some stage when delay occurs, which would in turn, speed decreases.

One can expect that speed would decrease as density increases. The speed-density and speed-flow relationships can be illustrated as in Figure 2.1.



2.1 (a)

2.1(b)

**Figure 2.1 Speed-density and speed-flow curves (source: Hau, 1992)**

Figure 2.1 (a) shows that when density increases, speed initially remains the same and then decreases. This is because during the initial period as density increases, there is not enough traffic on the road to cause congestion so vehicles are able to travel at their maximum speed. When density increases at the point that congestion occurs, the speed would then decrease. Figure 2.1 (b) shows that, as traffic enters the road the speed decreases (in the upper portion of the curve), and when the speed decreases to  $S^m$ , traffic flow reaches its maximum, which is referred to as the “Engineering Capacity”  $F^{max}$  (Hau, 1992). This means that during this period, as  $q = k\bar{v}$ , the density  $k$  increases more quickly than speed  $v$  decreases so the flow  $q$  increases, until  $F^{max}$ . If the traffic continues entering the road, the road becomes more congested and since during this period speed decreases more quickly than density increases, the flow decreases and the

speed-flow curve turns back on itself towards zero. The upper portion of this curve (i.e. speed higher than  $S^m$ ) is referred to as the “*normal flow*” situation; and the lower portion of this curve (i.e. speed lower than  $S^m$ ) is referred to as the “*forced flow*” situation (Button, 1993).

As mentioned above an understanding of one of the traffic characteristics is helpful to understand the other three factors. For example, if speed and number of accidents were positively correlated (i.e. higher speed is associated with more accidents) then according to Figure 2.1 (a) an inverse relationship between accidents and density may be expected. The following sections will review previous studies on the effects of speed, density, flow and congestion on road accidents.

### 2.3.1 Speed

Speed is an important factor affecting road accidents both in terms of accident occurrence and severity (Elvik et al., 2004). It seems reasonably safe to assume that increased speed would mean that the accidents that have occurred would be more severe, if other factors (e.g., environment and vehicle design) remain the same. This can be shown by both Newtonian physics and empirical data (e.g. O'Donnell and Connor, 1996; Shankar and Mannering, 1996; Kockelman and Kweon, 2002; Hauer, 2009). It is however less straightforward for the relationship between speed and the possibility of accidents occurring, which subsequently brings into the question the relationship between speed and the frequency of accidents (or accident rate).

There have been some studies that aim to explore the relationship between speed and the number of accidents, most of which suggest that increased speed is associated with more accidents or higher accident rates (Elvik et al., 2004; Taylor et al., 2002). Elvik et al. (2004) undertook an extensive evaluation on the effects of speed on accidents using the Power Model<sup>5</sup>. They concluded that there is a causal relationship between changes in speed and changes in road accidents, i.e., the number of accidents will go down if speed goes down and vice versa. The limitation of the study is that, such a relationship is derived mainly from before-and-after studies and only the Power Model is evaluated. As such, more evidence is needed to support this conclusion using various types of analysis (e.g. cross-sectional analysis) and statistical models. Taylor et al. (2002)

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<sup>5</sup> The Power Model is a model employing a set of power functions to estimate the effects of changes in speed on the number of accidents.

employed a cross-sectional analysis on 174 road segments from rural roads in England, and a positive relationship between accident frequency and average speed was found. This appeared to confirm the result of Elvik et al. (2004); however it seems that there are flaws in Taylor et al.'s study. Taylor et al. (2002) classified the sample into four different road groups based on a set of characteristics such as accident rate, mean speed, annual average daily traffic (AADT), junction density, bend density, access density and hilliness. Four dummy variables were created and included in the models to represent the road groups, and the variables used to classify road groups were also included in the model. This means that data such as average speed and AADT were used twice in the models. In addition, the Poisson regression model may be misspecified and a more sophisticated model such as a Negative Binomial model or a spatial econometric model may be better to model the accident frequency data. The econometric model specifications are discussed further in Chapter 3.

The positive relationship between speed and accidents that is advocated by the studies above are, however, questioned by some empirical evidence. For example, a study undertaken by Baruya (1998) employing a series of cross-sectional analyses found that, average speed is negatively associated with accident frequency. The author compared this result with previous studies which also found similar results, and concluded that this "interesting" result (i.e. the negative association) is due to other factors (e.g., geometric characteristics) rather than speed. Whether this is the case however needs to be confirmed by further studies, and it is possible that such an inverse relationship between speed and accidents may indeed exist, as the model results indicated. One limitation of Baruya (1998)'s study is that a simple Poisson model was used to investigate the relationship between the number of accidents and various contributing factors, while a better model specification such as a Negative Binomial (NB) model could be employed to better fit the accident data. Based on data from the Netherlands, Sweden and England, Taylor et al. (2000a) found that there is an inverse relationship between accident frequency and average speed on European rural roads. Similar to Baruya (1998), Taylor et al. (2000a) attributed this phenomenon to inadequate design standard features represented in the model. The model employed in their study is also a simple Poisson regression model, which again may be misspecified as discussed above. A recent study by Kockelman and Ma (2007) examined the freeway speed and speed variation preceding accidents in California while controlling for other factors such as

weather and lighting conditions. Their findings suggest that there was no evidence that speed condition influences accident occurrence. Again the authors avoided explaining this phenomenon but attributed the result to data aggregation and accident-time reporting errors. Clearly more empirical evidence is required to ascertain the relationship between speed and accident frequency.

In addition, it has been speculated that it is the dispersion of vehicle speeds (i.e. speed variance rather than speed itself) that affects the accident frequency (e.g. Lave, 1985). Lave (1985) found that fatality rate was strongly associated with speed variance rather than average speed, thus it was argued that speed variance caused safety problems instead of speed itself. There has also been research exploring the relationship between speed and accidents in which other variables have been used instead of mean speed such as the speed limit (e.g., Johansson, 1996; Aljanahi et al., 1999; Ossiander and Cummings, 2002). These studies are often based on either a disaggregate road-level speed or a highly aggregate county level speed. For example, Johansson (1996) looked at the reduced speed limits' impact on accidents based on the data in several Swedish counties from 1982 to 1991. It was found that the reduced speed limit can decrease the number of accidents involving minor injuries and vehicle damage. Shefer and Rietveld (1997) proposed a hypothesis that the rate of road fatalities is strongly related to traffic density, speed and congestion, which is supported by empirical evidence such that the fatality rate is lower during the morning period compared to the other times of the day. Their findings are not conclusive since it has not been possible to identify which factors (speed, density, or congestion) play a more important role in reducing fatalities during the morning peak period. This is due to the fact that these three factors are inter-related. Other factors, such as poor night time visibility also needs to be controlled for. Their study is partially confirmed by Ossiander and Cummings (2002) who examined the change of the freeway speed limit in Washington State using time series data and found that an increased speed limit was associated with a higher fatality rate. The spatial differences in road speeds among various spatial units however may affect road accidents. This was not evaluated by Ossiander and Cummings (2002). Aljanahi et al. (1999) found that the number of accidents would reduce if the speed limit could be lowered. In some cases, the relationship between mean speed and the accident rate is significant. Generally accidents are more serious at higher speeds. They also suggest that speed variance plays an important role. However their study did not differentiate

accidents by severity levels so it is unclear how speed would affect fatal, serious and slight injury accidents separately.

In this research, data for average speed and speed limit are available and their effects on road accidents are investigated. Average speed may however, be correlated with the level of traffic congestion which is the main interest of this thesis. If this is the case, then average speed needs to be excluded from an econometric model so as to avoid collinearity (see Chapter 6 sections 6.2 and 6.3; and Chapter 7 section 7.2 for more details on the correlations between various variables).

### **2.3.2 Traffic density**

The relationship between traffic density and accidents has been investigated less in the previous literature due to the issue of data availability. There have however been a few studies using other variables to represent density, for example volume capacity (V/C) ratio (Shefer, 1994; Ivan et al., 2000). Previous studies examining the effects of density or V/C ratio on accidents include: Zhou and Sisiopiku (1997); Ivan et al. (2000); and Lord et al., (2005a). Zhou and Sisiopiku (1997) examined the hourly accident rates and the V/C ratio and found that the relationship follows a U-shaped pattern and accidents involving injury and fatalities tend to decrease while the V/C ratio increases.

Ivan et al. (2000) investigated single and multi-vehicle highway accident rates and their relationship with traffic density while controlling for land use, time of day and lighting conditions. This was a road segment level study in which Poisson regression models were employed to analyse the data. Temporal effects were also controlled for. For single-vehicle accidents, they found a negative-exponential relationship with the density (volume/capacity ratio), meaning that the accident rate is the highest at low V/C ratio, but this is not fully consistent with the study by Lord et al. (2005a). With regards to the time of day effect, the author claimed that the morning peak period is the safest time. Lord et al. (2005a) conducted a freeway segment based analysis on the relationship between accident, density and the V/C ratio. In their study density is measured as vehicles per km per lane. It is found that both density and V/C ratio have an inverse relationship with the number of accidents. With V/C ratio increasing, fatal and single vehicle accidents deceased at some point, and accident rates followed a U-shaped relationship.

In this thesis, it is envisaged that traffic density may be highly correlated with other variables such as traffic flow. If this is the case, the correlated variables cannot be included in an econometric model simultaneously and so traffic density would be excluded from the model.

### **2.3.3 Traffic flow**

Many researchers have examined the relationship between traffic flow and accidents. This includes early seminal works undertaken by Belmont and Forbes (1953); Gwynn (1967); Ceder and Livneh (1982); Ceder (1982); and Turner and Thomas (1986). Belmont and Forbes (1953) developed a theory relating traffic volume and accident occurrences and found that the accident rate increases linearly with the hourly traffic flow for two-lane road sections during daylight. Gwynn (1967) later found that a U-shaped relationship exists between hourly traffic flow and accident rates on four-lane sections. The findings of Belmont and Forbes (1953) and Gwynn (1967) seem inconsistent, which may be due to the fact that different ranges of traffic flows and road designs were considered in the analyses. Ceder and Livneh (1982) looked at single and multi-vehicle accident rates and their associations with the hourly traffic flow by using power functions. They found that for different types of accidents, the relationships between accident rates and hourly traffic flow are different. For example, hourly traffic flow was found to be inversely related with accident rates for single-vehicle accidents in all cases; while in some cases hourly traffic flow was found to be positively related with accident rates for multi-vehicle accidents. Ceder (1982) further analysed the relationship between the accident rate and hourly flow under different flow conditions and found that the relationship between the total accident rate and hourly flow follows a U-shaped curve under free flow conditions while for the case of “congested” flow data the accident rate increases more sharply. This study implies the importance of investigating the impact of traffic flow on accident rates under different traffic flow conditions. It should be noted that in their study traffic flow is viewed as congested (i.e. the “congested flow”) when the percentage of multi-vehicle accidents is high (e.g., it was considered congested when 95% or more accidents were multi-vehicle accidents). This measurement for congestion may not be appropriate as it does not reflect the nature of congestion (i.e. delay). The study undertaken by Turner and Thomas (1986) also investigated the relationship between accidents and traffic flow in which several linear regression models were fitted. They observed that during the early morning when

traffic is light there are a high number and percentage of fatal and serious injury accidents.

A later study by Peirson et al. (1998) examined the accident risk by additional road use and how road users respond to it. In order to estimate the external cost caused by road accidents, the authors proposed that it is necessary to investigate the relationship between road accidents and traffic flow and found that the number of accidents increase while traffic flow increases proportionally. Work undertaken by Dickerson et al. (2000) investigated the accident external costs and also examined the relationship between road traffic accidents and traffic flow, so that the change in the external cost of accidents caused by the additional traffic flow could be estimated. Different road types and geographical areas were considered and they found that a strong negative accident externality was associated with high traffic flows. Lord et al. (2005a) explored accident-flow relationships by using predictive models for rural and urban freeway segments. They also found a positive relationship, but the accidents increase at a decreasing rate as flow increases.

Generally these studies suggested a positive relationship between traffic flow and number of accidents. Later studies looked at this issue in more detail by investigating hourly traffic flow and accident rates. For example, Martin (2002) investigated the relationship between accidents and traffic flow on French motorways, and found that accident rates are highest in light traffic compared to heavy traffic, especially on three-lane motorways. There is no significant difference between daytime and night-time accidents. If accident severity however was considered, night-time and light-traffic hourly accidents were much worse. Therefore, the author concluded that light traffic (low traffic flow) is a safety problem both in terms of accident rate and severity. As many things could affect road safety during night time however such as lighting, the conclusion is that the night time needs further study. Hiselius (2004), on the other hand, showed the importance of the consideration of types of traffic flows: the accident rate would be different depending on whether the traffic flow is homogeneous or not.

Apart from a post-processing statistical analysis, there are also some real-time analyses. For instance, Golob et al. (2004) demonstrated a strong relationship between traffic flow conditions and accidents with the objective of providing real-time assessment of the level of safety. Similar work undertaken by Golob and Recker (2003) demonstrated

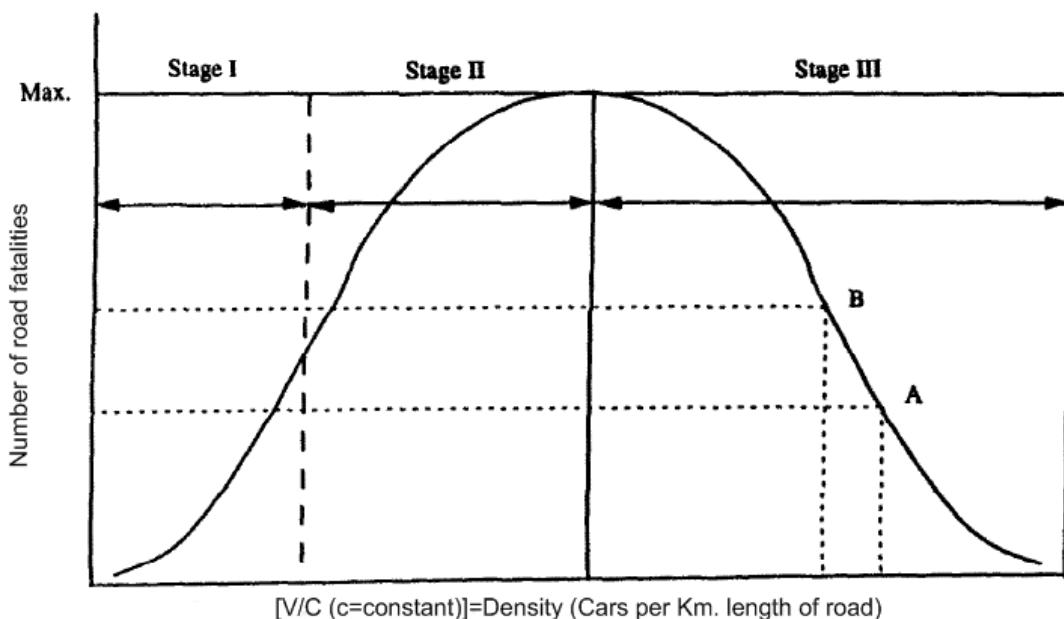
how accidents are related to traffic flow conditions just prior to the occurrence of each accident. It was shown that accident severity generally tracks the inverse of traffic volume.

In this thesis, traffic flow will be considered as one of the primary variables in the econometric models to be developed (see Chapters 6 and 7).

### 2.3.4 Traffic congestion

The effects of traffic characteristics such as speed, density and flow on road safety in current literature have been reviewed as above. The impact of traffic congestion, however, seems to be less studied in the literature.

Although the relationship between traffic congestion and road accidents is important, there would appear to be a dearth of literature, especially in terms of appropriate empirical and quantitative evidence. There is rarely a study on the effects of congestion on accident severity given an accident occurs. As for accident frequency (i.e. number of accidents), there is, however, analytical and empirical evidence. Shefer (1994) proposed the hypothesis that there is an inverse relationship between congestion and accidents, in which the author used volume over capacity ratio ( $V/C$ ), i.e. density as a proxy to measure the level of congestion. The relationship can be illustrated as follows:



**Figure 2.2 Hypothetical road fatalities-density function (Source: Shefer, 1994)**

As described in Figure 2.2, during the initial stage (Stage I), there are very few vehicles on a road so the number of fatalities is small. As density increases (i.e. number of

vehicles increases as capacity  $c$  is constant), the number of fatalities also increases. Meanwhile the vehicle speed decreases but could still be at a high level (relative to the speed limit) until at some point in Stage II. This portion is represented by a steep slope in Stage II (Figure 2.2). In the next portion of Stage II, as the slope is getting flatter, the number of fatalities increases but at a decreasing rate. The author explained that this is due to the effects of congestion. Then in Stage III, the number of fatalities starts to decrease. The author hypothesised that speed is positively related to the number of fatalities if other conditions hold the same. Therefore, if density continues to increase the vehicle speed would decrease due to congestion (because the road capacity  $c$  is constant), which will eventually reduce the number of fatalities as indicated in Stage III. This hypothesis could be true if we consider the two extreme examples which are represented by the far left and far right in Figure 2.2 respectively: there would be no casualties (fatalities) if there was no vehicle on the road at all or there were too many vehicles so it was extremely congested that speed is zero.

Shefer and Rietveld (1997) made a further investigation between congestion and road fatalities based on a similar approach to Shefer (1994). The authors suggested that the factors affecting highway fatalities are speed, speed differences and traffic composition. They proposed a model in which speed is considered as a function of density (density was used as a proxy for congestion); and hence accidents as a function of the combination of speed and density. The authors provided empirical evidence by comparing fatality rates throughout the day and found that during peak hours the fatality rate is obviously lower than at other times in the day. Due to the unavailability of data they examined the proposed model by using a simulated dataset rather than real-world data to describe the relationship between road fatalities and traffic density.

The drawbacks of these studies are that they used density as a simple proxy for congestion, which may not represent congestion characteristics properly. Congestion and traffic density are not equivalent and it is unclear how the congestion level evolves with respect to density. It was suggested that a V/C value greater than 0.77 is viewed as congested (Boarnet et al., 1998). It is likely that the increase in congestion is not proportional to the increase in density. Additionally, congestion is also related to speed and flow. Therefore congestion, speed, flow and density are thought to be inter-related to each other, but not equivalent, and congestion has its own definition meaning that a good measurement of congestion is needed. Moreover, in their studies only fatality was

analysed so the relationship between other types of accidents and congestion is unclear. More importantly, their hypothesis was not tested or examined with real-world data using an appropriate statistical analysis (e.g., spatial econometrics). The two studies also failed to control for other factors (e.g., road geometry) that affect road safety and in particular exposure factors (such as traffic volume) should be controlled for to examine the effect of traffic congestion on road accidents if an appropriate congestion measurement can be employed. Therefore their results might be biased and need further investigation.

As discussed above, the previous works on the relationship between traffic congestion and road safety lack empirical evidence that employed an appropriate econometric analysis. Some exceptions are studies undertaken by Hanbali and Fornal (1997), Baruya (1998), Noland and Quddus (2005) and Kononov et al. (2008). Hanbali and Fornal (1997) found that the implementation of adaptive traffic signal systems on intersections reduced both traffic congestion and accidents. It was argued that improvements in facility capacity (i.e. decreased traffic congestion) could reduce the “stop-and-go” driving related collisions. A before-and-after analysis of the implementation of the adaptive traffic signal systems was conducted and confirmed this hypothesis while controlling for exposure factors. Their study however did not differentiate severities of accidents thus the relationship between traffic congestion and severe injury accidents was unknown. In addition, since their study was based on data from intersections, the relationship between traffic congestion and road accidents on road segments needs to be analysed. By using a linear accident model on 63 road segments of A and B roads in the UK, Baruya (1998) found that the “degree of congestion” has negative effects on accident frequency. The study however did not differentiate accidents by their severity. Given that the proportion of slight injury accidents are very high (for example, see DfT, 2009b), the result may suggest that congestion has an inverse relationship with slight injury accidents, but it is unclear how congestion affects fatal/serious injury accidents. One limitation of Baruya’s study is the use of the simple Poisson model, where more sophisticated models such as a Negative Binomial (NB) model or a spatial econometric model should be employed to better fit the data. Another limitation is the use of “*proportion of vehicles slower than half the speed limit*” as a proxy for congestion, which may not appropriately reflect the actual amount of traffic delay.

Noland and Quddus (2005) investigate congestion and safety in London using an area-wide spatial analysis approach. London was divided into 15,366 spatial units, real-world data in each area were collected and analysed using NB models by controlling for other contributing factors. Accidents were disaggregated to 3 levels by severity (fatality, serious injury and slight injury). Congestion levels were measured using several proxy variables, including an indicator variable for Inner and Outer London (spatially), proximate employment and employment density. A series of NB models were used for analysing peak time (congested time period: 7:00 am–8:30 pm, weekdays) and off-peak time (uncongested time period: 8:30 pm–7:00 am, weekdays) accidents, so as to control for congestion temporally by comparing results from peak time and off-peak time periods. Their results are indeterminate and the proxy variables for congestion are generally statistically insignificant in their models, suggesting that there is little effect of traffic congestion on road safety. This may be due to the weakness of the proxies used for congestion, which is a major limitation of their study. London was divided into Inner London and Outer London, so congestion can be controlled spatially; but it was speculated that speeds are generally low in both areas, which means London is generally congested so there may not be enough variation of congestion between Inner London and Outer London. Additionally, as the authors suggested road infrastructure in these two areas are different (e.g., streets in inner London might be narrower and more curved) and this infrastructure difference in two areas may also affect accidents, so it is unclear which factor plays a more important role in explaining accident difference between the two areas: infrastructure or congestion. Therefore using Inner/Outer London as a proxy for congestion may not provide an accurate association between accidents and congestion. Thus, due to the weakness of the use of a proxy for congestion, their results are inconclusive. The authors suggested that because congestion can be highly localised and time-of-day specific, a more precise congestion measurement should be used to better understand the effects of congestion on safety. In terms of econometric methods, the NB models used in their study ignored the effect of spatial correlation, which is a limitation since their study is based on small areas and thus these areas are more likely to be correlated. In addition, as the authors suggested, their study was area-wide based, and as such evidence from road segment based analysis is needed. Finally, their study is based on urban conditions and as such results may be different on high speed roads (e.g., motorways).

A recent study by Kononov et al. (2008) investigated the relationship between traffic congestion and road accident rates on urban freeways using the data from California, Colorado and Texas. They found that total as well as fatal and injury accident rates increase with the increase in traffic congestion. Again, traffic congestion was measured using a proxy in their study, namely the annual average daily traffic (AADT). It was found that the accident rate increases faster when AADT reaches some “critical point” (e.g., 90,000 AADT on 6-lane freeways), which suggests that an increase in traffic congestion can deteriorate road safety. Similar to the studies using traffic density as a proxy for congestion, AADT may not accurately represent the level of traffic congestion, and therefore a more suitable congestion measurement is required. In addition, only AADT and the number of lanes were considered as risk factors in their study, therefore other factors affecting road accidents such as road geometry need to be controlled for.

There are other studies providing evidence from various aspects though not investigating congestion directly. For example, as discussed above Martin (2002) found that light traffic (i.e. less congested) is a safety problem both in terms of accident rate and severity. Shinar and Compton (2004) investigated accidents through drivers’ behaviour. They found that a linear relationship exists between congestion and frequency of aggressive behaviours which may subsequently affect road safety.

The exploration of the relationship between traffic congestion and road accidents is the aim of this thesis, and thus traffic congestion will be investigated and included in the econometric models.

## 2.4 Road geometry and infrastructure

One could expect that road infrastructure plays an important role in road safety, and improved infrastructure could in turn help to improve road safety.

Findings from several researchers support this hypothesis. Shankar et al. (1995) explored the effects of various roadway geometrics (e.g., horizontal and vertical alignments) on road accident frequency. Shankar et al. (1996) found that the increased number of horizontal curves per kilometre increase the possibility of possible injury relative to property damage only in an accident. A further study undertaken by Milton and Mannering (1998) observed the annual accident frequency on sections of principal

arterials in Washington State, and by using a Negative Binomial model, they found that short sections are less likely to experience accidents than longer sections; narrow lanes (less than 3.5 m) and sharp horizontal curves tend to decrease accident frequency in Eastern Washington. Other findings include “the smaller the tangent length before a horizontal curve the lower the accident frequency”. These findings confirm that road infrastructure designs do affect road safety. However, the authors did not consider spatial correlation – i.e. an accident on one road segment may be correlated to the one on the adjacent segment as they are sharing similar traffic, infrastructure or environment conditions.

Similar research was conducted by Noland and Oh (2004) and Haynes et al. (2007, 2008), who investigated the relevant factors at an aggregate area level. Noland and Oh (2004) analysed the county-level panel data from the State of Illinois in the US. Their results showed that an increase in the number of lanes and lane widths was associated with increased fatalities; and an increase in the outside shoulder width was found to be associated with reduced accidents. There are some studies focusing on the effects of road horizontal curvature. Haynes et al. (2007) studied road curvature and its association with traffic accidents at the district level (a census tract) in England and Wales. Their study developed a number of measures for road curvature and found that at the district level, road curvature is a protective factor meaning that more curved roads in an area result in less road accidents, which partially confirms the results by Milton and Mannering (1998). Similar research based on New Zealand data (Haynes et al., 2008) concluded that road curvature has an inverse relationship with fatal accidents in urban settings. Curvature was generally found to be a protective factor. This finding is generally in line with their previous study based on England and Wales data (Haynes et al., 2007), although the results are not completely consistent. This may be because these two countries have different land and demographic characteristics and the spatial units used are also different (district vs. territorial local authority). As stated, none of these studies considered spatial correlation among neighbouring road segments or areas, which could mislead the results. This suggests that more sophisticated models are needed in future studies.

Road infrastructure improvements (e.g., road upgrading and pavement) and roundabout design are also found to be beneficial for safety. Navin et al. (2000) suggested that not only better vehicle design, but improvements in road safety engineering can also reduce

the severity of whiplash injuries when accidents occur, and this could be done by enhanced signal visibility or through complex intersection geometric upgrades. Similarly, Pérez (2006) found that highway upgrading has a significant positive effect on road safety. Hels and Orozova-Bekkevold (2007) discussed roundabout design features on cyclist accident rates. Accident rates were modelled by various geometric features, age and traffic volume. They found some interesting results, for example, the older the roundabouts the higher the probability of accidents. De Brabander and Vereeck (2007) also investigated accidents at roundabouts and suggested that traffic lights can be more effective in protecting vulnerable road users than roundabouts by comparing safety situations between signalised intersections and non-signalised roundabouts at intersections. Thus signalisation is an important factor. Their research demonstrated how roundabout design can improve safety. Another recent study by Abdel-Aty and Wang (2006) investigated different types of intersections and found that the design of intersections has an impact on accidents. For example, intersections having 3-legs, with exclusive right-turn lanes on both roadways are associated with lower accident frequencies.

It is worth noting that, as argued by Noland (2003) and Noland and Oh (2004), it appears unclear as to the role of infrastructure improvement in road accident reduction (i.e. whether infrastructure improvement can effectively reduce accidents), as there may be “system-wide effects” or “black-spot migration”, i.e. improvement in infrastructure at one location may lead to increased risk on other parts of the road network. Therefore more research is needed on both the road segment level and area-wide (e.g., ward and county) level so as to verify the relationship between road infrastructure/geometry and road accidents.

In this thesis, several road geometry related factors will be investigated, such as radius of curvature, gradient and number of lanes.

## 2.5 Demographic, driving behaviour and land use

It is people who travel and are involved in accidents; therefore their activities should also be considered as a factor affecting accidents. In addition, factors such as population and employment reflect economic movement and activity, and as traffic volume, serve as a main exposure to potential accidents.

Researchers have investigated various demographic factors as risk factors in accidents. Several researchers have found that increased driver or victim age is associated with a more serious outcome in an accident (e.g., O'Donnell and Connor, 1996; Abdel-Aty, 2003). This is particularly true for those aged 60 or over (Zajac and Ivan, 2003; Eluru et al., 2008). It is also found that females were more likely to be involved in more severe accidents (Bédard et al., 2002; Kockelman and Kweon, 2002; Abdel-Aty, 2003). Females are apparently also worse off in terms of the number of accidents they encounter. For instance, Abdel-Aty and Radwan (2000) looked at the data from a principal arterial which was divided into 566 segments in Central Florida, and developed an accident prediction model (i.e. Negative Binomial model in this case) while controlling for other factors. They found that female drivers encounter more accidents than male drivers in heavy traffic volume, which is also the case for young and older drivers; but male drivers are more likely to be involved in traffic accidents while speeding. Using a similar approach, a study in France (Amoros et al., 2003) compared different counties by controlling for factors such as age, the proportion of single persons (i.e. who were not married) and the number of new driver licences to see whether socioeconomic characteristics can explain road casualties. Noland and Oh (2004) looked at the Illinois county-level data, including several demographic factors in their model, such as population, income per capita and age. Although they found that the inclusion of demographic variables does not change the results significantly, the demographic variables captured much of the unmeasured changes over time. Using English ward-based data, both Graham et al. (2005) and Graham and Stephens (2008) found that there is an association between area deprivation and child pedestrian casualties. Graham et al. (2005) found that increased deprivation is associated with a higher number of pedestrian casualties, and this impact of deprivation is larger for children than adults. The later study by Graham and Stephens (2008) confirms the earlier study (Graham et al., 2005) that a positive association generally exists between deprivation and child pedestrian casualties; however the impact of different domains of deprivation (e.g., income, health, education and crime) on child pedestrian casualties are subject to varying degrees and sometimes even in different directions.

Driving behaviour is complex. Researchers have investigated this by looking at alcohol consumption, helmet or seat belt usage. For example, a study in Australia (O'Donnell and Connor, 1996) found that higher blood alcohol level increases the possibility of a

severe accident. Similar findings were observed by Abdel-Aty (2003) who found that drunk drivers not wearing a seat belt are more likely to have severe accidents. Seat belt and helmet usage are expected to play an important role in road safety. Washington et al. (1999) compared fatal accidents between the southeastern and non-southeastern United States and concludes that regional differences exist due to, for example, differences in seat-belt usage and speed limits. Branas and Knudson (2001) looked at helmet laws on motorcycle rider death rates in the United States. By controlling other factors such as population density and temperature, they found that on average death rates in states with full helmet laws were lower than deaths rates in states without full helmet laws. Noland (2003) found that seat belt usage is beneficial to safety. Curtis et al. (2007) investigated the effect of seat belt on accidents by examining the seat belt law in New Hampshire in the US. More extensive research on the effect of seat belt use on safety can be seen in Kim and Kim (2003), who investigated belted and unbelted road users and the accident characteristics, with the purpose of better design enforcement and education programmes. The studies above generally indicate that seat belt and helmet usage are beneficial to road safety. Some studies however found that helmet usage tends to increase the possibility of fatality (e.g., Shankar and Mannerling, 1996). This could be due to the misspecification of the econometric model used in their study (i.e. a simple multinomial logit model). A more sophisticated model specification such as a mixed logit model may be used to better understand the effect of helmet usage.

As for other driving behaviour related factors, Jun et al. (2007) investigated the impact of driving behaviour on accident involvement using a GIS tool, and they found that accident-involved drivers are often associated with longer mileage travelled and higher speed. Kar and Datta (2008) developed an approach to identify areas with safety issues due to driving behavioural factors, so this could help policy makers to prioritise areas for safety improvement measures. In terms of drivers and driving style, aggressive driving can be identified and was investigated. For instance, as discussed in section 2.3.4, a strong linear association between traffic congestion and aggressive driving behaviour was found, and such aggressive driving behaviour imposes road safety concerns (Shinar and Compton, 2004).

With regard to land use, Noland and Quddus (2004) conducted a spatially disaggregate ward level analysis finding that urbanised areas have fewer casualties, and areas with higher employment or areas that are more deprived suffer more casualties, while

controlling for other exposure factors such as population and traffic flow. Kim et al. (2006) compared accidents on agricultural, conservation and urban areas, finding that most accidents occur in an urban environment, which appeared to suggest that urban areas are worse in road safety. This conclusion seems inconsistent with Noland and Quddus (2004). It should be noted that Kim et al. (2006) did not control for exposure factors (such as population and traffic volume) when looking at the relationship between land use and accidents, so accident rate in urban areas may not necessarily be higher than in agricultural and conservation areas. They also reported that land use variables were statistically insignificant if other factors (e.g., population and employment) were controlled for in a model, which means land use has little impact on accident frequency. They also found that population, employment and economic output are positively associated with frequency of accidents. A study conducted by Graham and Glaister (2003) found that urban scale, density and land-use mix affect pedestrian casualties. For instance, pedestrian casualties are lower in economic zones than those in residential zones (measured by population and employment). They used proxy variables namely proximate population and employment to take account of the impact of traffic flows. Priyantha Wedagama et al. (2006) looked at the relationship between non-motorised road traffic casualties and land-use; several types of road users, such as pedestrians and cyclists are investigated in relating to land use type (such as retail and commercial zone). A study by Noland (2003) investigated the use of medical facilities (e.g., hospitals in an area) in road safety improvement. Most of these studies mentioned above used a Negative Binomial model to investigate accident data either at a road segment level or at an area level. However, few of them take into account spatial correlation, which will be examined in this thesis by using spatial econometrics.

In this thesis, the factors identified in this section however are not investigated and included in the econometric models. This is mainly due to a lack of data, and in addition the analysis in this thesis is based on road segments (i.e. M25 and surround), and as such some demographic factors such as population and employment are not applicable in this situation.

## 2.6 Environment

Environment is another important category of risk factors that could affect roads, such as lighting conditions and weather. It is expected that the environmental factors would affect road safety by affecting drivers' behaviour, vehicle speed and breaking distance.

Previous early work undertaken by Ivey et al. (1981) examined the effect of rainfall on accident occurrences by looking at 68 highway segments in Texas, finding that wet weather accident rates are much higher in urban areas than in rural areas. Shankar et al. (1995) explored the effects of environmental factors on rural freeways, in which the impact of rainfall and snowfall on accidents are discussed. They found several environment related findings, for instance, increased average daily rainfall tends to increase rear-end accidents. A later study by Shankar et al. (1996) examined a series of environmental factors, finding that, for example, rain may increase the possibility of injury relative to property damage only (i.e. no injury) in a rear-end accident.

Later research further revealed the environmental effects on road safety. Golob and Recker (2003) studied accidents on freeways in Southern California to see how they are related to weather and ambient lighting conditions. As shown by Abdel-Aty (2003) and Eluru et al. (2008), darker periods often lead to higher accident severity. Plainis et al. (2006) investigated night-time accidents finding that low luminance contributes much to night-time fatalities, and increased stopping distances caused by longer reaction time might be the reason for this. Similar results can be found from the studies by Khorashadi et al. (2005) and Kim et al. (2007). A study in Pennsylvania (Aguero-Valverde and Jovanis, 2006) examined various factors affecting accidents including weather condition by including variables such as total precipitation, number of rainy days, total snow fall and number of days with snow. Only total precipitation was found to be statistically significant and positively associated with accidents in NB models; but this variable is insignificant in full Bayesian spatial models. The authors claimed that the spatial model is more suitable overall, meaning that total precipitation may have a limited impact on road accidents.

In this thesis, some environmental factors are investigated, including lighting and weather conditions, but only in the accident severity analysis (i.e. the effect of the factors on accident severity). The data for lighting and weather conditions (e.g., rainfall) at an aggregate road segment level are not available so they are not examined.

## 2.7 Conclusion

Improving road safety is often one of the important objectives for transport policy makers. In order to improve road safety effectively it is necessary to understand what and how factors affect road safety. This chapter has offered a broad review of current literature on various factors affecting road safety, including traffic characteristics (traffic speed, density, flow and congestion), road geometry and infrastructure (e.g., number of lanes and road curvature), demographic factors (e.g., age, gender and employment), driving behaviour, land use and environmental factors (e.g., lighting and weather conditions). It has been found that factors affecting road safety are numerous and many of these factors have been investigated from a range of perspectives (e.g., economic and engineering) using various methods.

Among these factors it has been found that an important factor – traffic congestion has been studied less in previous research, both in terms of its effect on accident frequency and severity. More empirical evidence using an appropriate econometric analysis with real-world data on traffic congestion is required, which is the basis of this thesis. One important limitation of previous research on the effect of traffic congestion on road accidents is that they often employed a weak proxy for congestion, which may not accurately represent the level of congestion spatially or temporally and thus possibly lead to a misleading result. Hence this thesis will employ a direct congestion measurement. Another limitation of previous studies is the use of simple Poisson or Negative Binomial models. There has been significant development in econometric methods in recent years and it is believed that use of more advanced econometric models (such as spatial econometrics to control for the spatial correlation) can improve the model performance and could offer better understanding of the relationship between congestion and accidents. This thesis will employ and compare various econometric models (including the classical and more sophisticated models) in cross-sectional or cross-sectional time-series settings to examine both accident frequency and severity.

While this thesis focuses on analysing the effect of congestion on road accidents using an econometric approach, several other factors affecting road accidents as identified in this chapter will also be controlled for. It may however not be possible to include all the factors in the models due mainly to a lack of data. Attention will be given so that the

models will not suffer from omitted variable bias. The risk factors considered in the econometric analysis in this thesis include:

- Traffic congestion
- Traffic flow
- Road geometry (i.e. radius of curvature, gradient, length of the segment and number of lanes)
- Speed limit
- Roadway classification (comparison between motorway and A road)
- Lighting condition\*
- Weather condition\*

Note the factors with \* are only considered in the accident severity analysis. Factors such as vehicle design, average speed, roadway infrastructure (e.g., pavement conditions), demographic factors (e.g., age and gender), driving behaviour (e.g., seat belt usage) and land use are not investigated in this thesis due to: (1) data for some factors not being available; (2) from the econometric modelling perspective, some factors need to be excluded (for example average speed is highly correlated with traffic congestion so average speed is excluded to avoid collinearity); and (3) some factors are not applicable to road segment based analysis which is employed in this thesis, such as population and employment.

Though not all risk factors are considered in the analysis, the econometric models employed in this thesis are able to take into account unobserved heterogeneity due to omitted variables in the models. For example, the spatial econometrics employed in this thesis can take into account unobserved similar traffic and roadway characteristics (e.g., pavement conditions) among neighbouring road segments. In addition, some indicator variables that are included in the models are able to capture the effects of unobserved factors, such as the year dummies which may capture the improvement of medical service over time; and the peak time indicator variable (in accident severity models) which may capture different driving behaviours between peak and off-peak time. Therefore, not all risk factors identified in this chapter are required to be included in the models. Indeed, if all risk factors can be measured and included (which is unlikely if not impossible as there are unknown factors that have not been identified), there may be no need to use a complex model as all factors have been controlled for. In other words,

the problem of imperfect information is a major motivation of developing and using a complex model.

The analysis in this thesis is based on road segment, since area-wide data (e.g., area-wide congestion measurement) is not available, so the “system-wide effects” mentioned above will not be examined. A literature review and discussion of econometric methods used to identify contributing factors in accidents will be provided in the next chapter.

# CHAPTER 3 ECONOMETRIC METHODS USED IN ACCIDENT MODELLING

## **3.1 Introduction**

As discussed in Chapter 2, there are a wide range of methods used in accident analysis to identify factors affecting road accidents. Such methods include both hypothetical and econometric approaches as well as empirical evidence. The primary focus of this thesis is to analyse accidents using econometric models, particularly models suitable for either cross-sectional or cross-sectional time-series datasets. Different types of entities (e.g., road segments, areas, junctions and other spatial units) can be considered while modelling road traffic accidents. Econometric models employed to analyse accident frequency are different from those used for analysing accident severity. On one hand, accident frequency models develop the relationship between contributing factors and accidents observed on a specific entity (such as road segments or English wards) over a specified time-period (such as one year). On the other hand, accident severity models usually develop the relationship between different levels of accident severity (e.g., fatal, serious and injury accident) and the characteristics of the accidents using information from individual accidents. Both accident frequency and severity models can be used to establish a relationship between accidents and contributing factors, and as such they can be referred to as “*accident prediction models*” which have a variety of applications aimed at reducing accident occurrences and their severity.

This chapter first looks at existing studies on accident modelling related to two commonly employed spatial levels, namely road segment and area-wide levels. It is then followed by a review of econometric models that are employed for modelling both accident frequency and severity. Practical applications of the accident prediction models are then reviewed and discussed.

## **3.2 Road segment level analysis**

A road segment level accident analysis looks at the relationship between counts of accidents associated with road segments and various features (risk factors in accidents) of those road segments. As discussed in Chapter 2, factors normally considered in a

road segment level analysis are road geometry of the segments (e.g., number of lanes, horizontal and vertical curves), traffic characteristics (e.g., traffic flow and speed) and road pavement conditions (i.e., roughness). This road segment level data can be collected and then analysed using an appropriate statistical model, such as a Poisson model or a Poisson-gamma (also known as a Negative Binomial) model.

Many studies on the development of accident models are based on a road segment level analysis (for example, see Ivey et al., 1981; Shankar et al., 1995; Milton and Mannering, 1998; Baruya, 1998; Abdel-Aty and Radwan, 2000; Ivan et al., 2000; Lord et al., 2005a; Li et al., 2007; Liu, 2008; Aguero-Valverde and Jovanis, 2008). Many of the studies have been undertaken on motorways (or highways) (e.g., Milton and Mannering, 1998; Ivan et al., 2000; Lord et al., 2005a; Li et al., 2007; Liu, 2008). Other types of roads studied include interstate roads (Shankar et al., 1995), state roads (SR 50 in Florida, see Abdel-Aty and Radwan, 2000) and A and B roads in the UK (Baruya, 1998). In order to obtain a series of observations for a cross-sectional study, a number of methods have been used to divide the whole road network into several sub road segments. There are mainly two methods in existing studies: use of fixed-length segments (i.e. equal length segment) and variable-length segments. The latter method mainly refers to using homogeneous sections with similar geometric characteristics, for example roads with the same shoulder width can be treated as one segment. Shankar et al. (1995) discussed the advantages and disadvantages of these two methods concluding that the fixed-length method is better. Researchers however tend not to follow the suggestion but use homogeneous segments in their studies (see Milton and Mannering, 1998; Abdel-Aty and Radwan, 2000; and Li et al., 2007). Lord et al. (2005a) and Liu (2008) also used variable-length segments. Liu (2008) divided the roads by junctions, local authority or urban/rural area boundaries, implying that segments may not be geometrically homogeneous. It is interesting to note that Ivan et al. (2000) used fixed-length road segments in which each of the segments is assumed to have “homogeneous cross-sectional features (lane and shoulder width)”. However, this assumption may not hold, especially for a long road or a sample consisting of several different roads.

There are some interesting findings in recent studies at the road segment level analysis. For example, Li et al. (2007) looked at intra-city motor vehicle accidents using a spatio-temporal model. Different directions of roadways (each roadway section has two parallel links in different directions) and road types were disaggregated. A risk map was

produced showing the hazardous road segments where safety improvements were required. They found the existence of “direction differentiation”, i.e. for many roadways the relative risks on different directions of the same road section are significantly different, and so directions need to be differentiated in a safety analysis. A study by Liu (2008) analysed road segment and junction based accident data and various models were used and compared. For the road segment based sample, the author concluded that the models which considered the effect of spatial dependence among neighbouring segments offered the best fit. Both studies (i.e. Li et al., 2007; Liu, 2008) however did not consider some important explanatory variables in their models such as road geometry.

In summary, accidents were analysed in many road segment based studies, most of which were conducted on motorways (or highways) and variable-length segments were used. From the previous studies, it can be seen that it is necessary to take into account direction differentiation of roadways while modelling road segment based accidents. In addition, it is essential that the effect of spatial correlation is considered.

### 3.3 Area-wide analysis

Unlike the road segment level analysis, an area-wide analysis divides a whole entity of interest (e.g., a country or a city) into a number of smaller areas, such as regions, counties, districts and wards. The fundamental idea is to develop a relationship between counts of accidents in these smaller areas and different characteristics (thought as contributing factors in accidents) of those areas. Area-wide contributing factors normally considered in such analyses include employment, population, traffic density, road network density, land-use characteristics and environment (e.g., Noland and Quddus, 2005). A number of studies indicate that area-based analysis has the advantage compared to road segment based analysis in that the area-wide analysis can take into account “system-wide effects” or “hotspot migration”<sup>6</sup> (Barker et al., 1999; Noland and Oh, 2004; Haynes et al., 2007).

Aggregate area-wide accident analyses were developed by researchers such as Barker et al. (1999) and Washington et al. (1999). Later examples include: Miaou et al. (2003);

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<sup>6</sup> “System-wide effects” or “hotspot migration” refer to the situation where actions to improve road safety at one site may result in increased risk elsewhere.

Amoros et al. (2003); Noland and Oh (2004); Noland and Quddus (2004); Noland and Quddus (2005); Aguero-Valverde and Jovanis (2006); Kim et al. (2006); Haynes et al. (2007); Haynes et al. (2008). It is interesting to note that different studies have used different levels of aggregation such as regions (Washington et al., 1999)<sup>7</sup>, counties (Miaou et al., 2003; Amoros et al., 2003; Noland and Oh, 2004; Aguero-Valverde and Jovanis, 2006), districts (Haynes et al., 2007; Jones et al., 2008), English wards (Graham and Glaister, 2003; Noland and Quddus, 2004; Graham et al., 2005); and enumeration districts which are much smaller than wards (Noland and Quddus, 2005). While analysing accident data in New Zealand, Haynes et al. (2008) used the territorial local authority (TLA) as a spatial unit which is equivalent to districts in England and Wales. Besides administrative units, Kim et al. (2006) used artificial spatial units, i.e. uniform grid cells (each cell being approximately 0.259 km<sup>2</sup>) for a study in Hawaii.

Some examples of later studies base on area-wide analysis include: Delmelle and Thill (2008), who investigated young and adult bicycle crashes in the City of Buffalo, NY, based on data at the “Census Tracts” level. The method used is stepwise ordinary least squares (OLS) regression analysis. Similarly a case study in Chicago undertaken by Thakuriah and Cottrill (2008) was also based on the “Census Tracts” level. They examined pedestrian accident data using a Poisson regression model. Kar and Datta (2008) studied driver behaviour trying to identify areas with safety issues due to driver behaviour. They calculated the Safety Performance Index (SPI)<sup>8</sup> to examine and rank counties in the State of Arizona. They however did not employ any accident prediction models.

Whether to analyse accidents directly or base on some spatial levels (e.g., road segment, regions, counties and wards) depends on the study design, nature and availability of the data. Usually an accident severity model is based on individual accident data; and an accident frequency model is based on data related to spatial levels so counts of accidents and contributing factors on the spatial units can be obtained. In this thesis, information on individual accidents (such as severity and contributing factors) will be

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<sup>7</sup> Washington et al. (1999) compared fatal crashes between southeastern and non-southeastern United States and concludes that regional difference exist due to, e.g. differences in seal-belt usage and speed limits.

<sup>8</sup> A SPI is a disutility function (of weighted crash frequency and the sum of crash rate composites) in which the area scoring the highest value has the worst safety performance.

employed for modelling accident severity; and for modelling accident frequency, road segment based analysis will be utilised. This is because area-wide direct measurements of traffic congestion (for example, delay per square km of area) are unavailable, though a number of proxies could be used such as area-wide average speed. In addition, it is necessary that counts of accidents at area-wide or road segment levels are obtained correctly. There are, however some difficulties in assigning accidents to appropriate areas, while accidents can be assigned to the correct road segments using the method described in Chapter 4. Regardless of the spatial levels, researchers tend to collect relevant data which is then analysed by an appropriate econometric model. The following section provides a review of the econometric models used in accident modelling.

### 3.4 Econometric models

As discussed, an econometric analysis of traffic accident data could be employed either at a road segment, area-wide or individual accident level. The selection of an appropriate econometric model primarily depends on the types of accident data available and the purpose of the study. There are mainly three types of data: time series data (e.g., number of annual accidents in England from 1950-2009), cross-sectional data (e.g., annual number of accidents across different districts in England in a particular year) and longitudinal/panel data which combines both cross-sectional and time-series data (also known as cross-sectional time-series data). Depending on the data characteristics, the data may be further categorised as continuous, count (e.g., number of accidents) or categorical (binary, ordinal or nominal, e.g., fatal, serious and slight injury accidents).

Different econometric models should be used to model different types of data. The literature suggests that a highly aggregate time series dataset can be analysed using an autoregressive integrated moving average (ARIMA) model (Quddus, 2008a), a cross-sectional count outcome dataset can be analysed using a Poisson based model and a panel count outcome dataset can be modelled using either a fixed- or random-effects Poisson based model. As for categorical outcome data, a logit or probit model and their extensions (e.g., multinomial logit and ordered probit model) may be appropriate. The primary focus of this thesis is to analyse either cross-sectional or panel data (count or categorical outcomes). Time-series accident data are not considered in this study as this

type of data is normally used to identify the impact of a specific safety policy on accidents (e.g., the impact of increasing speed limit on traffic casualties) rather than developing a relationship between accidents and their contributing factors.

### **3.4.1 Accident frequency models**

There is a long history of modelling the frequency of accidents depending on various explanatory variables in previous research. Early accident prediction models were based on a linear regression model as this model is relatively easy to understand and implement (e.g., Jovanis and Chang, 1986; Joshua and Garber, 1990; Miaou and Lum, 1993). It should be noted that this type of model is suitable for continuous data. However, the *number of accidents* is typically a count dataset which has a lot of unique properties such as randomness, discreteness and is non-negative. Therefore, researchers found that a linear regression model was unsuitable for dealing with accident count data (e.g., Jovanis and Chang, 1986; Zeeger et al., 1990; Miaou and Lum, 1993). Econometric models for count data had been developed a long time ago (early applications can be traced back to the 1890's. See Cameron and Trivedi, 1998) but have not been used in accident analysis until the 1980's and 1990's. Count data such as the number of accidents were then modelled by assuming a Poisson distribution (e.g., Joshua and Garber, 1990; Jones et al., 1991; Miaou et al., 1992; Miaou and Lum, 1993; Kulmala, 1994). As such, Poisson regression models were used to establish a statistical relationship between road accidents and various factors that contribute to accident occurrence. However, the Poisson regression model is not without limitations. One important constraint in the Poisson regression model is that the mean must be equal to the variance. If this assumption is invalid, the standard errors will be biased resulting in incorrect conclusions (Shankar et al., 1995). Accident data were found to be significantly overdispersed (i.e. the variance is much greater than the mean) by a number of researchers (e.g., Miaou, 1994; Shankar et al., 1995; Vogt and Bared, 1998). To address this problem of overdispersion, a Negative Binomial (NB, also known as Poisson-gamma) regression model was then proposed (e.g., Miaou, 1994; Shankar et al., 1995; Milton and Mannering, 1998; Abdel-Aty and Radwan, 2000; Lord, 2000; Ivan et al., 2000; Graham and Glaister, 2003; Noland and Quddus, 2005). There has been a significant development in the extension of NB models in the application of road accident research. This is discussed below.

The Poisson/Negative Binomial (NB) models have been extended in many ways to better explain the characteristics of accident data. For instance, the use of either the Poisson or NB models in the case of cross-sectional time-series data would be inappropriate as such models assume that observations are independent of each other. This is particularly a concern for the case of a panel dataset in which multiple observations are made for a single entity over time. To deal with panel data, either fixed- or random-effects Poisson/NB models have been proposed and used in accident analysis (e.g., Hausman et al., 1984; Shankar et al., 1998; Chin and Quddus, 2003a; Noland and Oh, 2004). Another extension of the NB model has been proposed to handle count data with excess zero observations. It was argued that if the data contains many zero observations, results from the Poisson or NB models would be biased (Shankar et al., 1997). In this case, researchers employed a dual-state (non-zero and zero accident observations) zero-inflated Poisson (ZIP) or zero-inflated NB (ZINB) models (Shankar et al., 1997; Chin and Quddus, 2003b; Graham and Stephens, 2008) to account for this. However, Lord et al. (2005b) pointed out that ZIP/ZINB has some theoretical issues while applying to accident data. By examining both empirical and simulated data, they confirmed that the assumption of the dual-state (i.e. inherently safe and unsafe) process in the case of accident data is not appropriate. They provided evidence which suggested that excess zero observations in the case of accidents mainly arise from low exposure (e.g., low traffic density) and the selection of spatial and temporal scales, for example, relatively smaller entities (such as individual junction or shorter road segment) and shorter time periods (e.g., monthly or weekly) would have low or zero accidents. Therefore, having excess zero-observations does not necessarily mean that the entities on which accidents are being counted are inherently safe. Therefore, although ZIP/ZINB models can provide a good statistical fit for data with excess zero-observations, they are misleading as they cannot characterise underlying accident processes. One solution the authors suggested is to use the Poisson/NB models with an unobserved heterogeneity effect term. Thereafter, Lord et al. (2007) made a further note on their previous paper (Lord et al., 2005b). They discussed the maximising statistical fit fallacy in statistics and the logic problems with the ZIP/ZINB models and confirmed their inappropriateness in terms of road safety modelling. However some studies neglected this warning and still used ZIP/ZINB models (e.g., Li et al., 2008).

Although the application of the NB model in accident research is rapidly becoming popular among safety researchers (see the descriptions and examples above), there are some constraints and limitations with this model. For instance, cross-sectional accident data are often collected with reference to location in space, and two problems arise when data have a locational dimension (LeSage, 1999):

- Spatial correlation exists among the observations, and
- Spatial heterogeneity occurs in the relationships that are modelled.

Traditional econometrics such as Poisson or NB models used in accident research have largely ignored the issue of spatial correlation that violates the traditional Gauss-Markov assumptions used in regression modelling (Song, 2004). Poisson or NB models assume observations are independent so the result might be biased.

Studies in other disciplines have developed methods using spatial econometrics to address the issue of unmeasured spatial correlation among neighbouring spatial units (e.g., Calyton et al., 1993). Such studies have primarily been based on a Bayesian framework in which conditional autoregressive (CAR) models are often employed to take into account spatial dependence among neighbouring spatial units; and temporal effects (for a panel dataset) can also be easily included under this framework. This method was initially used in ecological analysis and disease mapping (e.g., Clayton and Kaldor, 1987; Calyton et al., 1993; Xia et al., 1997; Knorr-held and Besag, 1998; Ghosh et al., 1999; Sun et al., 2000; Best el al., 2000; MacNab and Dean, 2001; Lagazio et al., 2001). The basic idea of disease mapping is to locate environmental hazard and groups of people and then allocate scarce resources, so it is useful to access environmental justice (Xia et al., 1997). There are similarities between disease mapping and road accidents as both are random count events and have a locational dimension. Therefore, there is the possibility that the method used in disease mapping could be applied to road accident research.

The use of spatial econometrics in ecological analysis and disease mapping has a long history. Clayton and Kaldor (1987) explained the necessity for map smoothing and proposed empirical Bayes models to produce a smoothed map. Clayton et al. (1993) explored the relationship between disease rates and their contributing factors. By analysing adjacent areas, they proposed a Bayesian hierarchical model which includes unstructured heterogeneity and clustering. Markov Chain Monte Carlo (MCMC)

simulation was then used to estimate the model. The authors discussed the confounding effects due to location such as migration. The authors also suggested keeping the clustering term for flexibility and other reasons such as location effects. Other disease mapping research undertaken by Xia et al. (1997) used hierarchical models for mapping Ohio lung cancer rates suggesting that Bayesian and empirical Bayes methods could analyse small-population areas accurately while allowing for complicated data structures and models. The authors claimed that empirical Bayes methods do not allow an assessment of uncertainty accurately and therefore they proposed a full Bayesian method to address this problem. Knorr-Held and Besag (1998) also used a Bayesian framework and included both spatial and temporal effects using the MCMC method for computation. Similar work was conducted by Ghosh et al. (1999) who defined the “neighbours” as within 30km of the central tract while controlling for spatial dependence among areas, meaning that they used a distance based neighbouring structure. As an alternative to the Bayesian approach, MacNab and Dean (2001) proposed generalised additive mixed models which have spatial and temporal features. Therefore, such “spatio-temporal” models that use autoregressive local smoothing across the spatial dimension and B-spline smoothing over the temporal dimension are developed. Time trend can be identified and classified as fixed or random terms in the models. Their models were estimated using a penalized quasi-likelihood (PQL) method; while the models could also be implemented under a Bayesian framework.

Unlike ecological analysis and disease mapping, the application of spatial econometrics in accident research is relatively new. It seems that Miaou et al. (2003) first used spatial econometrics to deal with spatial and temporal correlation in accident data. They reviewed methods used in existing studies on disease mapping and pointed out how such methods could be employed in accident research, especially area-wide accident modelling. They concluded that accidents and disease analysis share similar properties, suggesting that a “disease mapping” concept could be thought of as an equivalent to a “traffic crash mapping”. In their study, a Bayesian hierarchical model was advocated to analyse county-level accident data from Texas; and a conditional autoregressive (CAR) model was used to model spatial correlation in the Bayesian framework and MCMC methods were used to perform the computation. One limitation of their analysis was using a series of surrogate variables due to data unavailability. For example, the number of sharp horizontal curves in different counties was represented by the proportion of

crashes that occurred on sharp horizontal curves in each county. Later work undertaken by Song (2004) also discussed Bayesian spatial models and their application in accident analysis. The author provided an excellent review of the CAR models which were first introduced by Besag (1974) and has the capability of accounting for spatial correlation normally found in accident data. Song et al. (2006) further discussed multivariate spatial models in which different types of accidents (such as intersection accidents, driveway access accidents and non-intersection accidents) could be analysed simultaneously. The authors proposed that different types of crashes could be correlated to each other so modelling one particular crash type could be improved by borrowing information from other crash types. Based on the data of British Columbia, MacNab (2004) looked at Bayesian spatial and ecological regression models applied on a small-area accident analysis. The author used a regression spline<sup>9</sup> for modelling age effects finding that the age effect is moderately non-linear. In the study, a “neighbour” is defined by an area sharing a common border. This neighbouring structure (i.e. contiguity based) is often used in Bayesian disease mapping to model spatial correlation instead of using distance based neighbours. The author discussed a more general formulation of neighbours, including distance based neighbours.

A later study by Aguero-Valverde and Jovanis (2006) employed a spatial analysis of fatal and injury accidents in Pennsylvania using both spatial econometrics under a Bayesian framework and classical NB models using the maximum likelihood estimation (MLE) method. Compared with classical NB models, the author claimed that a Bayesian framework has the advantage of “its flexibility in structuring complicated models, inferential goals, and analysis”. The authors also developed a space-time model to allow for spatial-temporal interactions as the temporal trend in accident risk may be different for different spatial locations. Their results showed that the spatial model and non-spatial NB model can generally produce consistent results and spatial correlation does exist in accident data. Thus they concluded that a spatial model is better than a classical NB model due to the existence of spatial correlation. Another similar study by Quddus (2008b) compared several spatial models (such as the classical spatial model and Poisson based model under Bayesian framework) and traditional NB models using ward-level road accident data from London. It was found that the Bayesian spatial model is more appropriate in modelling accident data, especially for the case of smaller

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<sup>9</sup> A spline represents “a smooth curve of piecewise polynomial” (MacNab, 2004).

spatial units such as English wards used because the spatial correlation effect is likely to be larger in this condition.

Besides the area-wide based accident analysis mentioned above, spatial econometrics were also applied for analysing road segment level accident data in a few recent studies. For instance, Li et al. (2007) looked at intra-city motor vehicle accidents using a spatial-temporal model. A spatial-temporal analysis was conducted by comparing different risk maps at different time periods. They found the existence of direction differentiation, i.e. for different directions, 30% of the roadways have statistically significant different risk values. A recent study by Liu (2008) used various spatial models to analyse road segment based accident data, finding that the CAR model is the most appropriate model. Aguero-Valverde and Jovanis (2008) employed a similar spatial model (i.e. a Poisson based full Bayesian model) on rural two-lane segments in Pennsylvania, finding that spatial models show a significantly better fit than non-spatial models and a spatial model with the simplest neighbouring structure (i.e. the first-order neighbours in their study) is preferable. Similar studies include El-Basyouny and Sayed (2009b) who employed several spatial models to examine the effects of corridor variation; and Guo et al. (2009) who applied Bayesian spatial models in a safety analysis of corridor level signalised intersections in Florida.

It should be noted that in addition to the CAR model mentioned above, there are several other spatial models that can take into account the effects of spatial correlation, such as the spatial filter model and the simultaneous autoregressive (SAR) model (Griffith, 2005). The spatial filter model is involved with regressing a variable (e.g., accidents) on a set of synthetic variates representing distinct map patterns that accounts for spatial autocorrelation (Griffith, 2005). This approach (spatial filtering) was used in disease mapping (e.g., Johnson, 2004; Griffith, 2005), but it appears less common in road safety research. As for the SAR model, Quddus (2008b) compared this model (two types of SAR models were tested, and they were referred to as the spatial autoregressive model and spatial error model in the paper) with CAR model using London accident data, finding that the CAR model is more appropriate.

The previous studies mentioned above mainly used a *univariate* modelling approach, i.e. modelling count of different types of accidents separately. For example, Noland and Quddus (2005) disaggregated road casualties into three categories by their severity

levels – i.e. fatalities, serious injuries and slight injuries, and they applied accident frequency models on each category of road casualties separately, resulting in three independent univariate models. This approach has been adopted by most safety researchers mentioned above. Different than the univariate approach, some researchers explored the *multivariate* modelling approach which can analyse different types of accidents simultaneously (instead of separately). Several multivariate models have been employed such as multivariate spatial models (Song, 2004; Song et al., 2006), multivariate Poisson (MVP) models (Ma and Kockelman, 2006), and multivariate Poisson-lognormal (MVPLN) models (Ma et al., 2008; Aguero-Valverde and Jovanis, 2009; El-Basyouny and Sayed, 2009a). Compared to the univariate modelling approach, the multivariate models (i.e. MVP or MVPLN) are argued to be able to better model different types of accidents as multivariate models can take account of correlations between different types of accidents, or in other words to “borrow strength” from similar sources (Song et al., 2006).

The multivariate (MVP or MVPLN) models advocated by these researchers however have limitations. First, the multivariate models were argued to be superior since multivariate models can take account of correlations between different types of accidents. As shown by Frees (2004, pp. 222-223) however, while multivariate linear regression models can take into account correlations between different responses, the parameter estimation is *equivalent* to separately estimated univariate models. For count data models (i.e. Poisson based models), empirical evidence has also shown that coefficient estimations are very similar between multivariate and univariate models (e.g. Aguero-Valverde and Jovanis, 2009). In some cases parameters estimated from univariate models are even more precise than multivariate models (see El-Basyouny and Sayed, 2009a), as the standard errors of coefficients of explanatory variables are smaller in the univariate models. In other words, there seems little benefit in using multivariate models in terms of coefficient estimates. Indeed, as noted by Ma et al. (2008), the superiority of multivariate models compared to univariate models is not “theoretical” but rather “empirical”. Therefore the differences (in terms of coefficient estimations) between the two modelling approaches may merely be due to different model specifications. A recent study by Lan and Persaud (2010) also confirmed this: they compared several Poisson based models using both multivariate and univariate

approaches, finding that univariate models fit the data better and outperform the multivariate models, and thus univariate models were recommended.

Another limitation of the classic multivariate regression is that the same set of explanatory variables is required for each type of response (Frees, 2004, pp. 223). This is a concern as factors affecting one type of accidents may have no effect on the other. The multivariate (e.g., MVP or MVPLN) models are often justified in “borrowing strength” from similar sources. Accident data, however often suffers from an under-reporting problem, which is especially a concern for less serious accidents such as slight injury accidents. This means that the data qualities of different types of accidents are different, and thus different types of accidents may be more suitable to be modelled separately.

Importantly, the accident data (classified by severities) may not be suitable for the multivariate models discussed above (i.e. the MVP or MVPLN models). There are a wide range of multivariate modelling approaches, the use of which largely depends on the nature of the data. Accidents are, essentially *mutually exclusive* and *collectively exhaustive* events. To put it another way, an accident is in and can only be in one category of different severities (i.e. either fatal or serious or slight). Such data involving two types of discrete outcomes (i.e. count and discrete choice) can be modelled using a *mixed multivariate model* (Cameron and Trivedi, 1998, pp. 269-271). In contrast, the MVP or MVPLN models discussed above are suitable to model events that are not *mutually exclusive* and *collectively exhaustive*, such as several measures of healthcare services (e.g., number of prescribed and nonprescribed medicines taken). There are several approaches for estimating a mixed multivariate model, for instance a mixed multinomial (logit) Poisson model, or alternatively simply estimating the Poisson based models for each category of events independently. These two approaches are equivalent (see Cameron and Trivedi, 1998, pp. 269-271), and as such applying Poisson based models to different categories of accidents separately is essentially a multivariate modelling approach. Mixed multivariate models have been applied in econometric literature. For instance, Terza and Wilson (1990) proposed the mixed multinomial Poisson model and used this model in analysing frequency of different trip types (e.g., trips for work, shopping and social).

Another approach of estimating a mixed multivariate model is using a two-stage model, in which count data models (e.g., a Poisson regression) and discrete choice models (e.g., a multinomial logit regression) are estimated in two stages (Cameron and Trivedi, 1998, pp. 269-271). This approach is useful for predicting the number of different types of accidents, and the details of this approach will be discussed in section 3.4.3.

In this thesis, accident frequency models are primarily used for examining the effect of traffic congestion on road accident frequency, in which both classical count outcome models (such as Negative Binomial models) and spatial models under a full Bayesian framework will be employed. The accident data will be disaggregated into different categories by their severity levels, and each category of accident is modelled separately. This approach can also be seen as a mixed multivariate modelling approach. Accident frequency models will also be used jointly with accident severity models for site ranking. The accident severity model and site ranking will be discussed in the following sections.

### **3.4.2 Accident severity models**

Accident severity is often measured categorically, for instance, the severity level of an accident can be classified as fatal, serious injury, slight injury or no injury (property damage only). As such, econometric models that are suitable for categorical data, such as logistic and probit models, have been used to analyse accident severities. For modelling binary outcomes, such as “fatal” and “non-fatal” accidents, a binary logistic regression model is a natural choice for modelling such data and has been widely used in the road safety literature (e.g., Pitt et al., 1990; Shibata and Fukuda, 1994; Miles-Doan, 1996; Farmer et al., 1997; Toy and Hammitt, 2003). For example, Pitt et al. (1990) employed a logistic model to investigate the effects of various factors, such as age, gender and speed, on the relative risk of serious injuries (i.e. serious vs. non-serious injury).

Although it is possible to fit sequential binary logistic regression models for modelling accident data with multiple (three or more) outcomes of accident severity (see Shibata and Fukuda, 1994; Miles-Doan, 1996), more sophisticated models have been proposed and used in previous studies. Two types of such model were proposed: (1) ordered response models (ORM), such as ordered logit and probit; and (2) unordered nominal

response models, such as multinomial, nested and mixed logit models. Studies employing such models are discussed below.

Since the accident severity is ordered in nature (ranging from non-injury to fatality), it seems natural to choose discrete ordered response models for analysing accident severity data. The ordered response models (ORM) refer to ordered logit and probit models and their various extensions, such as a generalised ordered logit model. There is a body of previous studies employing an ordered response model in the accident severity analysis. For example, O'Donnell and Connor (1996) investigated how attributes of road users affect the accident severity using an ordered logit and probit model. The ordered probit model has been used by several researchers in recent works to examine the accident severity (e.g., Khattak et al., 1998; Duncan et al., 1998; Kockelman and Kweon, 2002; Quddus et al., 2002; Zajac and Ivan, 2003; Abdel-Aty, 2003; Lee and Abdel-Aty, 2005). Both ordered logit and probit models are essentially equivalent and according to O'Donnell and Connor (1996) and Abdel-Aty (2003), both these ordered models produce very similar results.

The ordered logit and probit models can be extended in many ways to address the restrictions arising from their underlying assumptions. One of the primary assumptions of ordered logit and probit models is that the error variances are the same for all observations. When this assumption is violated (i.e. heteroscedasticity) the parameter estimates are biased and the standard errors are incorrect (Yatchew and Griliches, 1985; Keele and Park, 2006). To correct this, Williams (2008) suggested employing a heterogeneous choice (also known as location-scale or heteroscedastic ordered) model which relaxes the assumption by explicitly specifying the determinants of heteroscedasticity. Another important assumption associated with ordered logit and probit models is that the relationship between each pair of outcome groups is the same. That is, for example, for the three categories of severity levels (slight injury, serious injury and fatality), the ordered model assumes that the slope coefficients for slight injury vs. serious injury plus fatality are equal to the slope coefficients for serious injury vs. fatality. This assumption in the literature is known as the *parallel regression assumption*, or for the ordered logit model as the *proportional odds assumption* (Long and Freese, 2006). This assumption is frequently violated and can lead to inappropriate or misleading model estimation results (Long and Freese, 2006; Fu, 1998). To relax the restrictive *parallel regression assumption* on slope coefficients, a *generalised ordered*

*logit model* can be used to model ordinal data (Fu, 1998). This model allows the coefficients to vary across different outcome groups. Similarly, a *partial proportional odds model* has been proposed (Peterson and Harrell, 1990; Lall et al., 2002; Williams, 2006) to constrain only a subset of coefficients across different outcome groups. This model (the *partial proportional odds model*) has been recently used to investigate the left-turn injury severity at intersections by Wang and Abdel-Aty (2008); and the effect of traffic congestion on accident severity by Quddus et al. (2010).

Recent developments in ordered response models include those works undertaken by Eluru and Bhat (2007) and Eluru et al. (2008). Eluru and Bhat (2007) employed a random coefficient (i.e. mixed) ordered logit model in order to allow randomness in the effects of explanatory variables due to unobserved factors. Eluru et al. (2008) then extended this work by using a mixed generalised ordered response (MGORL) model. In ordered logit/probit models the thresholds are fixed across accidents. The MGORL model, proposed by Eluru et al. (2008), relaxed this restriction by allowing thresholds to vary according to both observed and unobserved factors. The MGORL can accommodate heterogeneity in both explanatory variables and threshold values. However, no significant heterogeneity effects were found in their results suggesting that the MGORL model became a generalised ordered logit model.

Although the use of ordered response models (ORM) in analysing accident severity seems popular and sensible as accident severity is ordinal in nature, the use of such models can be criticised. As discussed by Kim et al. (2007) and Savolainen and Mannering (2007), two major problems raised with using ORMs are: first, traditional ORMs assume that the effects of a variable would either increase or decrease accident severity (i.e. in one direction). However it is highly possible that a variable may have a U-shaped effect on different categories of accident severity. In other words, a variable may simultaneously increase (or decrease) the possibility of high and low level severities. Following the example given by Washington et al. (2003) (also see Ulfarsson and Mannering, 2004; and Khorashadi et al., 2005), the deployment of airbags may cause slight injuries and reduce the likelihood of fatality, i.e. the airbag deployment can simultaneously decrease the possibility of having “no injury” and “fatality”, but only increases the possibility of “slight injury”. In addition, a variable may only have effects on a subset of severity levels, for example, only increase the likelihood of severity levels from “slight injury” to “serious injury” but does not increase “fatality”. Therefore

the constraint (either increase or decrease severity) imposed by traditional ordered response models would be inappropriate in such a case. The second issue associated with traditional ordered response models is related to the fact that accident data often suffers from the under-reporting problem, especially for lower severity categories, such as “no injury” and “slight injury”. The presence of under-reporting means that high level severity accidents such as “fatality” and “serious injury” are over presented in the data, which can lead to biased and inconsistent results using traditional ordered response models (Yamamoto et al., 2008).

While the first problem discussed above may be solved to a great extent by using a generalised ordered response model (GORM) which allows the coefficients to vary across different levels of severities, the second problem is more difficult to correct. Thus alternative methods such as an (unordered) nominal response model are proposed. A nominal response model, such as a multinomial logit (MNL) model does not recognise ordinality in the model structure. A MNL model however is more flexible in terms of the functional form as the independent variables are not assumed to be identical across all severities in the model. Therefore, a MNL model allows different severity categories to be associated with different sets of independent variables (Yamamoto et al., 2008). Another advantage of a MNL model is that it provides consistent coefficient estimates except constant terms when under-reporting occurs (Cosslett, 1981; Yamamoto et al., 2008). The MNL model has been employed to analyse accident severity in early studies (e.g., Shankar and Mannering, 1996; Carson and Mannering, 2001) and has more recently been used as a preferred model specification to ordered response models (Ulfarsson and Mannering, 2004; Khorashadi et al., 2005; Kim et al., 2007).

One potential problem of a MNL model is that this model assumes that the unobserved components (effects) associated with each accident severity category are independent, which is referred to as the *independence of irrelevant alternatives* (IIA) property (Long and Freese, 2006). If the IIA assumption is violated, i.e. different accident severity categories share unobserved effects, the model estimation results would be incorrect. To circumvent this limitation, a more generalised modelling approach has been used by assuming a homoscedastic generalised extreme value (GEV) distribution for unobserved effects (Train, 2003). One popular GEV formulation, the nested logit (NL) model has thus been used in some previous safety research (Shankar et al., 1996; Chang

and Mannerling, 1999; Lee and Mannerling, 2002; Abdel-Aty and Abdelwahab, 2004; Savolainen and Mannerling, 2007). The NL model groups severity outcomes with shared unobserved effects in a nest, for example “no injury” and “slight injury” could be grouped to form a low severity accident “nest”.

While the GEV models can take many different forms (MNL is also a special case of GEV, see Train, 2003), a more flexible approach has been proposed by adding a more general mixing distribution of error component in the model. This model, which is referred to as the mixed logit model, is enormously flexible and powerful. As showed by McFadden and Train (2000), any discrete choice model can be approximated to any degree of accuracy by a mixed logit model. Thus the mixed logit model can be used to accommodate complex patterns of correlation among accident severity outcomes and unobserved heterogeneity. The mixed logit model has been recently employed by Milton et al. (2008) to analyse highway accident severity in Washington State.

In this thesis, a series of ordered and nominal response models will be developed to analyse the effect of traffic congestion on road accident severity, such as a generalised ordered logit model and a mixed logit model. Accident severity models will also be used to estimate expected proportions of accidents at different severity levels on road segments.

### ***3.4.3 Practical applications of accident prediction models***

The results obtained from accident prediction models (frequency or severity) could be applied in different practical scenarios for improving road safety. Accident severity models, for instance, can be used to identify factors affecting accident severity; this is useful for developing countermeasures to reduce the severity of accidents. For example, accidents in dark periods were found to be more severe compared to accidents in daylight (Abdel-Aty, 2003; Eluru et al., 2008), thus lighting conditions can then be improved at night in order to reduce severity outcomes once accidents occur.

In terms of accident frequency models, an important application is to identify risk factors affecting road accident frequency, in other words, to evaluate the effectiveness of safety treatments implemented to roadway sites. There are two approaches of this application: (1) a cross-sectional or a panel data analysis in which risk factors can be taken as explanatory variables in the models; and (2) before-after studies in which

empirical or full Bayesian methods can be employed to assess the effect of a particular safety treatment (Park et al., 2009). As mentioned, this thesis is based on cross-sectional or panel data analysis, which is useful to identify risk factors affecting road safety; and this cross-sectional or panel data analysis has been used in previous studies (e.g. Milton and Mannerling, 1998; Noland and Quddus, 2005). On the other hand, the before-after studies are often employed to evaluate the change of safety performance between untreated sites (in the “before” periods) and treated sites (in the “after” periods). Empirical Bayes methods have been successfully employed in the before-after studies for a long time (e.g. Hauer, 1986; Persaud et al., 1997; Persaud and Lyon, 2007). The motivation of the use of the empirical Bayes (a model based method) instead of a simple naïve comparison between before and after periods is largely due to the regression-to-the-mean problem. In the empirical Bayes method, accident prediction models (i.e. Negative Binomial models) are calibrated to correctly estimate the “expected” accident frequency in the after period had the safety treatments not been applied, which eliminates the regression-to-the-mean effect.

The use of cross-sectional/panel data analysis or before-after analysis largely depends on the study design and the nature of the data. In before-after studies, risk factors (e.g., signalisation at junctions) are often already known, and information on the implementation of specific countermeasures for safety improvement (e.g., installation of traffic signals) is available, thus the effect of these countermeasures (or safety treatments) on the sites can be evaluated. In this thesis however, the relationship between traffic congestion and road accidents is unknown and there are no specific countermeasures related to traffic congestion. Therefore this thesis employs a cross-sectional or panel data analysis.

Whether a study is based on a cross-sectional/panel data analysis or a before-after analysis, accident prediction models are required to be accurately estimated in both types of study. Recent studies have shown that full Bayesian models are superior to conventional accident frequency models such as Negative Binomial models while using cross-sectional/panel datasets (see discussions in section 3.4.1); and empirical Bayes methods in before-after safety analysis (Park et al., 2009; Persaud et al., 2009). Therefore, accident frequency models using a full Bayesian approach as developed in this thesis are promising tools for safety policy makers or traffic engineers for

identifying risk factors or evaluating the effectiveness of safety treatment applied to roads or road users.

Another important application of accident prediction models is *site ranking*, which aims to identify hazardous sites or locations with underlying safety problems. Site ranking is also referred to as network screening (Persaud et al., 2009); and the sites with potential for safety treatments are also known as *sites with promise*, *accident blackspots* or *hotspots* in the literature (Hauer et al., 2004; Maher and Mountain, 1988; Elvik, 2007; Cheng and Washington, 2005; Huang et al., 2009). The terms “site ranking” and “accident hotspots” are used in the following chapters for consistency. Site ranking is essential in designing engineering programmes to improve safety of a road network. After identification of accident hotspots, necessary engineering improvements could be applied to the selected sites with limited highway funds. This improves road safety and ensures cost-effectiveness in resource allocation. There are several methods in site ranking, which can be mainly classified as the naïve ranking method and the model based ranking method. The naïve ranking method is a simple method which purely uses observed accident data, for example ranking sites in descending order of accident frequency or rate using observed accident data.

Although the naïve ranking method is relatively simple, it has serious limitations and the results obtained from the method can be seriously biased (Elvik, 2007). One major limitation of naïve ranking method is the regression-to-the-mean problem (Elvik, 2007; Persaud and Lyon, 2007). Since accidents are random events, observations of accidents for sites in short time periods may not reveal the true safety problems of sites. In other words, sites with high accident frequency or rate may merely be due to statistical variation rather than intrinsic safety problems. Previous studies show that there are substantial regression-to-the-mean effects in 3 years’ accident data (Persaud and Lyon, 2007) and the effects are fairly large even for 5 years’ accident data (Hauer and Persaud, 1983). Another limitation of the naïve method is that it is unable to examine the accident dispersion, since it may be useful to rank sites by excess of their “normal” expected number of accidents (Elvik, 2007; Huang et al., 2009). The naïve method cannot obtain the expected number of accidents by controlling for various heterogeneities.

To account for the limitations, mainly the regression-to-the-mean problem, many model based ranking methods have been proposed. Similar to before-after studies, the empirical Bayes approach has been successfully applied and considered to be more reliable than the naïve method (Cheng and Washington, 2005; Elvik, 2007). For example, using experimentally derived simulated data (therefore, accident hotspots are known a priori), Cheng and Washington (2005) found that empirical Bayes significantly outperforms the traditional naïve and confidence interval ranking techniques<sup>10</sup>. Similarly, Elvik (2007) reviewed the state-of-the-art site ranking methods, finding that the empirical Bayes is the most accurate method. As with the before-after studies, the empirical Bayes in site ranking also require calibrating an accident prediction model which is usually the Negative Binomial model.

Although empirical Bayes has been widely used in site ranking in the past few years, it is not without limitations. One criticism is that, unlike before-after studies in which accident prediction models can be obtained externally, site ranking studies may require all sites in a road network to be screened in the accident prediction models. Therefore in such situations the empirical Bayes method is allegedly using the data twice: once to estimate the accident prediction models; and once to estimate the posterior accident count based on the models and observed accident count (Huang et al., 2009). In addition, the accident prediction models used in empirical Bayes (i.e. Negative Binomial models) may be inadequate to account for all uncertainties associated with road accidents and their contributing factors, especially spatial correlation between sites (Persaud et al., 2009; Huang et al., 2009).

To overcome these limitations of empirical Bayes in site ranking, a full Bayesian approach has been proposed. Compared to empirical Bayes, the full Bayesian approach has the advantage of an integrated procedure to obtain estimated outcomes, the ability to take account of all uncertainties associated with parameter estimations and to accommodate complex structured heterogeneities (spatial or temporal) in accident data (see Miaou and Song, 2005; Huang et al., 2009). Miaou and Song (2005) investigated the full Bayesian ranking method, in which various ranking criteria have been

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<sup>10</sup> In the confidence interval ranking method, a site is identified as “unsafe” if the observed number of accidents on this site exceeds the observed average of counts of comparison (similar) sites at certain confidence level. See Cheng and Washington (2005) for details.

compared, such as ranking by posterior mean and posterior expected rank of the decision parameter. Generally the results from the two ranking criteria are very similar to each other, and they both significantly outperform the naïve ranking method. They also found that the inclusion of spatially correlated effects in the accident prediction models can significantly improve the performance of the model and thus the ranking results. Huang et al. (2009) conducted a comparison study between different ranking methods, including naïve, empirical Bayes and full Bayesian ranking methods, using intersection data from Singapore. It has been found that model based (i.e. empirical or full Bayesian) ranking methods perform significantly better than the naïve ranking method. The full Bayesian method outperformed the empirical Bayes, especially when complex model structures were used such as the hierarchical models. This further confirms that the full Bayesian is a promising ranking method compared to conventional naïve or empirical Bayes methods in identifying sites with potential safety problems for further engineering examination and treatment.

While the full Bayesian method has been shown to be an appropriate method in site ranking, two modelling approaches are present as discussed in the end of section 3.4.1: univariate and multivariate approaches. Safety researchers commonly employed a univariate modelling approach, i.e. to develop separate models for accidents at different severity levels (Elvik, 2007). Recently, some studies advocated the use of a multivariate approach in site ranking, such as the multivariate spatial model (Miaou and Song, 2005) and the multivariate Poisson-lognormal (MVPLN) models (Aguero-Valverde and Jovanis, 2009; El-Basyouny and Sayed, 2009a). Both Aguero-Valverde and Jovanis (2009) and El-Basyouny and Sayed (2009a) found that the standard deviations of the predicted accident frequency estimated from MVPLN models are lower than the univariate Poisson-lognormal models. This suggests that the MVPLN models are more precise in terms of accident prediction. As noted in section 3.4.1 however, the MVPLN models have certain limitations, and a two-stage mixed multivariate model may be appropriate for estimating expected accident frequency at each severity level. In the two-stage model, a count (accident frequency) model is used to predict the total number of events (accidents); and then a discrete choice (accident severity) model is used to “allocate” these events (accidents) into different categories (severities) (Cameron and Trivedi, 1998, pp. 269-271). While this modelling approach appears to be less used by safety researchers, it has been employed by Hausman et al. (1995) in modelling the

number of trips to alternative recreational sites, in which the model was referred to as a “combined discrete choice and count data model”.

The two-stage model has two distinctive advantages compared to the regular frequency models (such as the MVPLN models): (1) more detailed data associated with individual accidents can be incorporated into accident severity models to accurately estimate the proportions of accidents at different severity levels; (2) there are cases that some categories of accident severities, due to many zero or low accident counts at an aggregated road segment (or an area) level, cannot be analysed using accident frequency models (e.g., MVPLN) directly. This is particularly an issue for high severity level accidents (such as fatal accidents). This issue can be addressed using the accident severity models as there may be enough observations for each category of severities at a disaggregate individual accident level.

In this thesis, the illustration of site ranking using empirical data will be presented. A two-stage mixed multivariate model will be employed to estimate the expected numbers of accidents at different severity levels. The results will be presented in Chapter 8.

### 3.5 Conclusion

This chapter has demonstrated that various econometric methods have been used in existing accident studies. It has been shown that econometric methods are applied to modelling both accident frequency and severity. In this thesis the accident frequency analysis will be based on road segment level accident data; and the accident severity analysis will be based on individual accident data.

As discussed, different econometric models have been used depending on the nature of the data. It has been found that models used to develop a relationship between *frequency* of accidents and their contributing factors include: linear regression, Poisson, Negative Binomial (NB) models and their various extensions such as fixed- or random-effects NB models. Recently spatial models are becoming popular in accident analysis, in which models are often constructed under a full Bayesian framework and conditional autoregressive (CAR) models are employed to take into account spatial dependence among neighbouring spatial units. It was believed that spatial models provide a better statistical fit compared to classical count outcome models (such as NB models). Both classical count outcome models and Bayesian spatial models will be investigated and

applied to the accident data at different severity levels in this thesis. A summary of various accident frequency models, their key features and the researchers who utilised these models is presented in Table 3.1.

As for modelling accident *severity*, a model suitable for categorical data has commonly been used to establish a relationship between risk factors and the severity outcome of an accident, such as a logistic model, an ordered response model and an (unordered) nominal response model. The ordered response model includes ordered logit/probit models and their extensions such as a generalised ordered logit model; the nominal response model includes multinomial logit, nested logit and mixed logit models. As discussed in this chapter, an unordered nominal response model such as a mixed logit model may be preferred to an ordered response model. Both ordered and nominal response models will be tested in this thesis. A summary of various accident severity models, their key features and the researchers who utilised these models is presented in Table 3.2.

**Table 3.1 Summary of the accident frequency models reviewed in this chapter**

| <b>Models</b>   | <b>Key feature(s) of the model</b>  | <b>Examined and/or used by the following researchers</b>  |
|---|---|---|
| <b>Linear regression model</b>  | Suitable for continuous data  | Jovanis and Chang, 1986; Joshua and Garber, 1990; Miaou and Lum, 1993   |
| <b>Poisson model</b>  | Suitable for non-negative count data; the mean is equal to the variance   | Joshua and Garber, 1990; Jones et al., 1991; Miaou et al., 1992; Miaou and Lum, 1993; Kulmala, 1994   |
| <b>Negative Binomial (NB) model</b>   | Allow overdispersion in the data (i.e. mean and variance is not assumed to be equal)  | Miaou, 1994; Shankar et al, 1995; Milton and Mannerling, 1998; Abdel-Aty and Radwan, 2000; Lord, 2000, Ivan et al., 2000; Graham and Glaister, 2003; Noland and Quddus, 2005  |
| <b>Fixed- or random-effects Poisson/NB model</b>  | Suitable for panel data   | Hausman et al., 1984; Shankar et al., 1998; Chin and Quddus, 2003a; Noland and Oh, 2004   |
| <b>Zero-inflated Poisson (ZIP) or zero-inflated NB (ZINB) model</b>                                 | Suitable for data with excess zero observations; however, the assumption of dual-state (i.e. inherently safe and unsafe) process in the case of accident data is not appropriate                        | Shankar et al., 1997; Chin and Quddus, 2003b; Lord et al., 2005b; Lord et al., 2007; Graham and Stephens, 2008; Li et al., 2008   |
| <b>Spatial econometrics using the Bayesian approach</b>   | Can take into account spatial correlation in the data   | <i>Ecological analysis and disease mapping:</i> Clayton and Kaldor, 1987; Calyton et al., 1993; Xia et al., 1997; Knorr-held and Besag, 1998; Ghosh et al., 1999; Sun et al., 2000; Best et al., 2000; Lagazio et al., 2001<br><i>Accident analysis:</i> Miaou et al., 2003; Song, 2004; Song et al., 2006; MacNab, 2004; Aguero-Valverde and Jovanis, 2006; Li et al., 2007; Quddus, 2008b; Liu, 2008; Aguero-Valverde and Jovanis, 2008; El-Basyouny and Sayed, 2009b; Guo et al., 2009 |
| <b>Other spatial models such as spatial filter models; simultaneous autoregressive (SAR) models</b> | Can also take into account spatially correlated effects   | Johnson, 2004; Griffith, 2005; Quddus, 2008b  |
| <b>Multivariate count model</b>   | Able to model different categories of accidents simultaneously and take account of correlations between different types of accidents. The coefficient estimations are very similar to univariate models | Song, 2004; Song et al., 2006; Ma and Kockelman, 2006; Ma et al., 2008; Aguero-Valverde and Jovanis, 2009; El-Basyouny and Sayed, 2009a   |
| <b>Mixed multivariate model</b>   | Suitable for model frequency of events that are <i>mutually exclusive</i> and <i>collectively exhaustive</i> (e.g. accidents)   | Terza and Wilson, 1990; Hausman et al., 1995  |

**Table 3.2 Summary of the accident severity models reviewed in this chapter**

| <b>Models</b>  | <b>Key features(s) of the model</b>   | <b>Examined and/or used by the following researchers</b>  |
|--|---|---|
| <b>Binary logistic regression model</b>                    | Suitable for binary outcomes  | Pitt et al., 1990; Shibata and Fukuda, 1994; Miles-Doan, 1996; Farmer et al., 1997; Toy and Hammitt, 2003   |
| <b>Ordered logit/probit model</b>                          | Suitable for ordinal outcomes   | O'Donnell and Connor, 1996; Khattak et al., 1998; Duncan et al., 1998; Kockelman and Kweon, 2002; Quddus et al., 2002; Zajac and Ivan, 2003; Abdel-Aty, 2003; Lee and Abdel-Aty, 2005 |
| <b>Heterogeneous choice model</b>                          | Relaxes the assumption of the error variances are the same for all observations imposed by ordered logit/probit models  | Williams, 2008; Quddus et al., 2010   |
| <b>Generalised ordered logit model</b>                     | Relaxes the parallel regression assumption to allow the coefficients to vary across different outcome groups  | Fu, 1998; Quddus et al., 2010   |
| <b>Partial proportional odds model</b>                     | A subset (not all) of coefficients across different outcome groups are constrained to be the same   | Peterson and Harrell, 1990; Lall et al., 2002; Williams, 2006; Wang and Abdel-Aty, 2008; Quddus et al., 2010  |
| <b>Random coefficient (i.e. mixed) ordered logit model</b> | Allow randomness in the effects of explanatory variables due to unobserved factors  | Eluru and Bhat, 2007  |
| <b>Mixed generalised ordered response model</b>            | Thresholds are allowed to vary according to both observed and unobserved factors; the model can accommodate heterogeneity in both explanatory variables and threshold values                                  | Eluru et al., 2008  |
| <b>Multinomial logit (MNL) model</b>                       | Suitable for nominal outcomes. More flexible functional form and consistent coefficient estimates except constant terms when under-reporting occurred in the data (compared to ordered response models)       | Shankar and Mannering, 1996; Carson and Mannering, 2001; Ulfarsson and Mannering, 2004; Khorashadi et al., 2005; Kim et al., 2007   |
| <b>Nested logit model</b>                                  | Relaxes the assumption of independence of irrelevant alternatives (IIA) by MNL models   | Shankar et al., 1996; Chang and Mannering, 1999; Lee and Mannering, 2002; Abdel-Aty and Abdelwahab, 2004; Savolainen and Mannering, 2007  |
| <b>Mixed logit model</b>                                   | Can accommodate complex patterns of correlation among accident severity outcomes and unobserved heterogeneity; any discrete choice model can be approximated to any degree of accuracy by a mixed logit model | McFadden and Train, 2000; Milton et al., 2008   |

Finally, this chapter discussed the practical applications of the accident prediction models. Two most important applications in road safety management using accident prediction models are: (1) evaluation of the effectiveness of safety treatments implemented to roadway sites; and (2) site ranking to identify hazardous locations with underlying safety problems. For the former, it is useful to identify and evaluate risk factors in order to develop corresponding countermeasures to improve road safety. This could be achieved using a before-after analysis or a cross-sectional/panel data analysis which will be employed by this thesis. For the latter (i.e. site ranking), it is useful to identify accident hotspots for further safety treatments, which ensures cost-effectiveness in resource allocation for improving safety of a road network. The full Bayesian ranking method has been found to be the most reliable and therefore will be used in this thesis. The two-stage mixed multivariate model which combines both accident frequency and severity models, will be used to estimate expected numbers of accidents at different severity levels on road segments.

## CHAPTER 4 METHODOLOGY

### 4.1 Introduction

The aim of this thesis is to explore the relationship between traffic congestion and road accidents. “Accident” is evaluated in two aspects: accident *frequency* and accident *severity*. Accident *frequency* refers to the count of accidents on certain spatial units (e.g., road segments) during certain time periods (e.g., a year). Accident *severity* refers to the level of severity of an accident outcome (e.g., fatal, serious or slight) given that an accident has occurred. This thesis will therefore examine the effects of traffic congestion on the two aspects of accidents using two different types of analyses: a road segment level analysis which will explore the relationship between traffic congestion and road accident *frequency*; and an individual accident level analysis which will explore the relationship between traffic congestion and road accident *severity*.

In order to conduct the analyses, it is of importance to employ a suitable congestion measurement and to address the problem of mapping accidents to the correct road segment. The following section of this chapter will firstly present the research design for this thesis, which gives an overview of research stages and methods employed throughout this thesis. It is then followed by the discussion of the congestion measurement and the method used to assign accidents to the correct road segments. This is followed by the description of econometric models for modelling both accident frequency and accident severity. Finally site ranking, an important application of accident prediction models is detailed and a summary of this chapter is provided.

### 4.2 Research design

The aim of this thesis is to explore the relationship between traffic congestion and road accidents. To achieve this goal, several objectives have been outlined. Table 4.1 shows the objectives at different stages of this research, the methods used to fulfil the objectives and their corresponding chapters in this thesis.

**Table 4.1 Research map**

| <b>Objectives</b>  | <b>Methods</b>   | <b>Chapter(s)</b>  |
|--|--|--|
| To examine the various factors affecting road accidents.   | Literature review of various risk factors  | Chapter 2: Literature review   |
| To identify appropriate econometric models and a suitable congestion measurement.  | Review of econometric models and congestion measurements   | Chapters 3 and 4: Review of econometric models and congestion measurements. Chapter 4 also finalises the models and congestion measurements to be used in the thesis |
| To investigate and refine data to improve the quality of the analysis.   | Gather and analyse the data; aggregate the hourly raw data for accident frequency analysis; assign accidents to appropriate road segments; validate accident, traffic and road geometry data externally  | Chapter 4: Mapping accidents to the correct road segments;<br>Chapter 5: Preliminary and descriptive analysis of the data  |
| To develop the association between traffic congestion and both accident frequency and accident severity.                             | Investigate the association between congestion and accident frequency using classical count outcome models and Bayesian spatial models; and formulate the association between congestion and accident severity using ordered and nominal response models | Chapter 6: Results from the accident frequency analysis;<br>Chapter 7: Results from the accident severity analysis   |
| To analyse practical applications of the models developed in the previous objective and recommend safety policies for policy makers. | Identify accident hotspots using a site ranking and review the results and findings for potential policy implementations   | Chapter 8: Site ranking and other practical applications<br>Chapter 9: Discussion and policy implications  |
| Chapter 10: Conclusions and further research   |  |  |

Some of the objectives, as indicated in Table 4.1, have already been achieved in Chapters 2 and 3. The following sections will focus on the details of the methods to be employed in this thesis.

### 4.3 Congestion measurement

As discussed in Chapter 2, previous road safety studies often used a “proxy” for traffic congestion while developing a relationship between traffic congestion and road accidents. For example, Shefer and Rietveld (1997) used the volume capacity ratio to represent the congestion level. Noland and Quddus (2005) used employment density, inner/outer zones of London and peak/off-peak times of a day as a proxy for congestion. To fully understand the association between traffic congestion and road accidents, a suitable and direct congestion measurement needs to be utilised while

developing a statistical relationship between them. Literature on traffic congestion does actually provide some direct measurements of traffic congestion and this is detailed below.

### **4.3.1 Review of congestion measurements**

The UK Department for Transport (DfT) has introduced a series of measurements of traffic congestion (DfT, 2005a, *Appendix E*), in which traffic congestion is measured as:

- Time lost per unit travel
  - *U: driving time lost per mile*
  - *V: average time lost on a typical journey (e.g. on a 100-mile journey)*
  - *W: average time lost over a whole year (maybe also standardised on a “typical journey”)*
- Time spent in jams
  - *X: percentage of time spent in traffic jams*
  - *Y: amount of time spent in traffic jams*
- Risk of serious delays (Z: how predictable journeys are)

It is noticeable that DfT's measurements of traffic congestion are normally based on time lost (delay).

Taylor et al. (2000b) have documented some measurements of congestion:

- Congestion Index (CI)

$$CI = (T - T_0) / T_0$$

where  $T$  is the actual travel time and  $T_0$  is the free flow travel time.

- Proportion stopped time (PST)

$$PST = T_s / T$$

where  $T_s$  is stopped time, which is defined as the speed of a vehicle is zero or less than some threshold value.

- Acceleration Noise (AN)

$$AN^2 = \frac{1}{T_r} \sum_{i=1}^n \frac{\Delta v_i^2}{\Delta t_i}$$

where  $T_r$  is running time ( $T_r = T - T_s$ );

$\Delta t_i$  is the time interval taken for a speed change  $\Delta v_i$ .

It is also noticeable that Taylor et al. (2000b) suggests a similar concept to measuring congestion as the DfT, i.e. the time lost (delay). The first two parameters (i.e. CI and PST) are dimensionless meaning that they can be used to compare traffic congestion in different routes with different characteristics. The congestion measurements suggested by the DfT and Taylor et al. (2000b), especially the *driving time lost per mile* and the *congestion index* (CI) are conceptually simple and capable of accurately reflecting the nature of congestion (i.e. delay), and as such these congestion measurements would be appropriate to employ in a statistical model.

Other congestion measurements described in the literature include those studies by Boarnet et al. (1998) and Bremmer et al. (2004). Boarnet et al. (1998) employed capacity adequacy (CA)<sup>11</sup> to measure congestion at the roadway level and used a process to aggregate CA to the county level which is named ACCESS (weighted average by average daily travel). In their study, ACCESS was compared with another congestion measurement – Texas Transportation Institute (TTI) index<sup>12</sup>, which is a weighted average of vehicle miles travelled and lane miles of freeway. Generally ACCESS and the TTI's index can produce similar results, but there are differences, and in some cases the differences are large. This may be due to the different data used for ACCESS and the TTI's index as CA is a peak hour measurement and TTI's index is a daily average. Bremmer et al. (2004) discussed measuring traffic congestion from operational data such as vehicle counts and the length of time each vehicle occupies the induction loop. Real-time measurements are preferred in such an approach.

Some researchers differentiate congestion into two categories: recurrent and non-recurrent congestion (e.g., Skabardonis et al., 2003; Dowling et al., 2004). The former (i.e. recurrent congestion) is caused by fluctuations in demand and the latter (i.e. non-recurrent congestion) arises from incidents, breakdowns, bad weather and other random events. Skabardonis et al. (2003) calculated the delays and then estimated these two

<sup>11</sup>  $CA = \frac{\text{rated volume capacity}}{\text{volume during present design hour}} \times 100$

<sup>12</sup> TTI's congestion index =  $\frac{(FwyVMT/Ln-Mi) \times FwyVMT + (ArtVMT/Ln-Mi) \times ArtVMT}{13,000 \times FwyVMT + 5,000 \times ArtVMT}$

where *FwyVMT* is freeway daily vehicle miles travelled; *ArtVMT* is principal arterial daily vehicle miles travelled; *Ln-Mi* is lane-mile; 13,000 and 5,000 are estimates of capacity per lane-mile on freeways and principal arterials respectively.

types of congestion. It is suggested that non-recurrent congestion contributes 13-30% to the total congestion during peak periods, and incidents (e.g., accidents) account for most of the non-recurrent congestion delay. Similar to the DfT methods, they use delay to define and measure congestion. Dowling et al. (2004) developed a more complex and advanced method to estimate recurrent and non-recurrent traffic congestion: a Freeway Performance Measurement System (PeMS) method which estimates annual delay on a system-wide basis using data collected from loop detectors; and a non-PeMS method which also estimates annual delay using data such as geometric and demand data. Unlike a simple index for congestion (e.g., the congestion index suggested by Taylor et al., 2000b, which is expressed as a simple equation as shown above), the non-PeMS method is more complex as it is involved with a lot of procedures and computations<sup>13</sup>; and recurrent delay is estimated by calculating the road segment level travel time using a speed-flow relationship.

It can be concluded that most of the previous studies outlined above including the DfT (2005a) and Taylor et al. (2000b) measure traffic congestion based on delay. Thus it is natural to consider delay as an appropriate measurement of traffic congestion in the statistical models to analyse the relationship between congestion and accidents.

### **4.3.2 Congestion measurements used in this thesis**

Two simple and suitable congestion measurements are considered in this study: the *congestion index* and *total delay per length of road*. The main reason to employ these two congestion measurements are: (1) both of the measurements reflect and directly measure the nature of traffic congestion – delay; (2) data is available to allow for computing of the variables for congestion. In addition, these congestion measurements are simple in concept and relatively easy to understand and interpret. The two congestion measurements are described as below.

#### **4.3.2.1 Congestion index**

The congestion measurement detailed by Taylor et al. (2000b) is considered to estimate segment-level traffic congestion. This is known as the *congestion index* (CI):

$$CI = \frac{T - T_0}{T_0}, \quad T_0 \neq 0 \quad (4.1)$$

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<sup>13</sup> 11 steps and 19 equations were involved in this method.

where  $T$  is the actual travel time and  $T_0$  is the free flow travel time on a particular road segment for a vehicle. CI is dimensionless and independent of road segment length or road geometry, so it can be compared among different road segments. CI is a highly averaged congestion measurement; and the value of it is non-negative and the higher the CI value the higher the level of congestion. Vehicle delay and average travel time data are available from the UK Highways Agency. Free flow travel time is calculated by average vehicle travel time minus average vehicle delay (weighted by traffic flow).

#### 4.3.2.2 Total delay per length

*Total delay per length* is the other congestion measurement considered in this study. Instead of calculating average vehicle delay, this measurement sums traffic delay incurred on all vehicles travelling on a road segment during a certain period of time, then it is normalised by road segment length. This congestion measurement can be expressed as:

$$\text{Total delay per segment length} = \frac{\text{Total delay}}{\text{Segment length}} \quad (4.2)$$

This congestion measurement is used by the DfT, for instance the *driving time lost per mile* (DfT, 2005a).

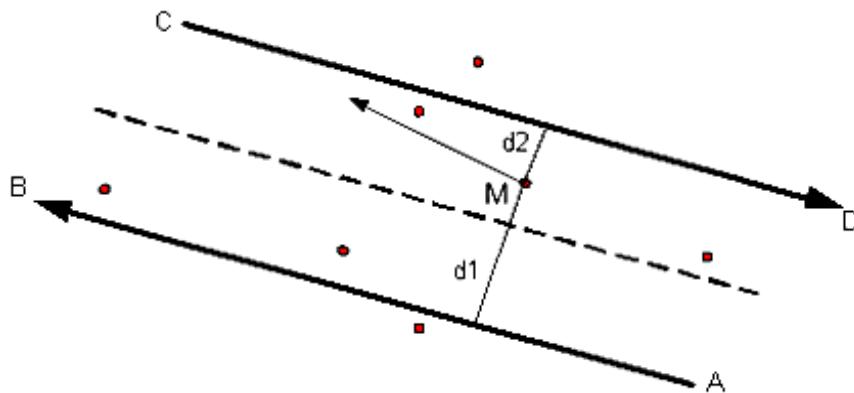
The two congestion measurements described in this chapter will be further compared and investigated using empirical data in Chapter 5.

## 4.4 Mapping accidents to the correct road segments

In the STATS19 national road accident database that is used in this thesis, accident data are provided with reference to a location measured as points, i.e. the easting and northing coordinates in the local British National Grid Coordinate system. While the accidents are overlaid onto spatial road segments (centre-line data), mismatches between them are observed. This is due to the error in both accident data and roadway segment data and the fact that accident data and spatial motorway network data are obtained from different sources. An appropriate method is needed for assigning accidents to the correct road segments. This is to ensure that the counts of accidents for each segment (for accident frequency analysis) and data (e.g., traffic flow and level of

congestion) for each individual accident (for accident severity analysis) are correct. Otherwise, the modelling results would be misleading. This method is discussed below.

Suppose there are mismatches between accidents and road network as shown in Figure 4.1.



**Figure 4.1 Accident location and motorway centre-line data**

In Figure 4.1, the dots show the locations where accidents occurred. Two solid lines (AB and CD) represent the centre-line of two carriageways of the motorway and the dotted line denotes the central barrier of the carriageways. If M refers to the location of an accident then a robust method is required to assign this accident correctly either to segment AB or segment CD. One can employ two variables from the available information: (1) the perpendicular distance from the accident point to the segment; and (2) the angular difference (assuming  $\Delta\theta$ ) between the direction of the vehicle just before the accident and the segment direction. The perpendicular distance and the segment direction can be obtained from the coordinates of the start and end nodes of a segment; and the direction of the vehicle just before the accident can be obtained from the accident database<sup>14</sup>. A segment is more likely to be the correct segment if the perpendicular distance is short and the angular difference is small. Therefore, a weighting score (WS) is developed based on these two factors:

$$WS_i = \frac{1}{d_i} + \cos(\Delta\theta_i), \quad d_i \neq 0 \quad (4.3)$$

where  $d_i$  is the perpendicular distance (in metres) from an accident point to a road segment,  $i$ , and  $\Delta\theta_i$  is the angular difference between the direction of an accident and

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<sup>14</sup> This direction information is available in the STATS19 database.

the direction of a segment  $i$  ( $0 - 180^\circ$ ). The minimum value of  $d_i$  is set to be 1 metre and the  $WS_i$  for a segment ranges from -1 to +2. If the WS for a segment is high then it is considered as the correct segment.

In this thesis, if  $WS_1$  was significantly greater than  $WS_2$  (i.e.  $(WS_1 - WS_2) > 0.3$ )<sup>15</sup> then the accident was assigned to segment 1, and *vice versa*. In the case where there was no significant difference between  $WS_1$  and  $WS_2$  (i.e.  $|WS_1 - WS_2| \leq 0.3$ ) then the accidents are assigned to the nearest road segment (i.e. more weight given to the perpendicular distance). There were about 2% such accidents in the data. In order to investigate the impact of randomly assigned accidents, a sensitivity analysis was conducted on the M25 motorway and no significant difference in the modelling results was found.

It should be noted that this map-matching technique is more suitable for major roads such as motorways, as major roads are relatively less curved and less complex compared to minor roads. For other roads, especially for the minor roads in dense urban areas, it may be more difficult to apply this technique, because the road network is more complex and there are many unclassified roads where accidents occurred.

## 4.5 Accident frequency models

A road segment level analysis has been adopted to explore the impact of traffic congestion on the *frequency* of road accidents. The number of accidents that occurred on certain road segments during certain periods of time are aggregated, and as such the count of accidents occurring on these road segments can be obtained. Econometric models suitable for count data can then be employed to examine the relationship between accident frequency and various contributing factors such as traffic flow and congestion. The details of the models to be used in this thesis are discussed in the following sections.

### 4.5.1 Classical count outcome models

The classical count outcome models refer to Poisson, Negative Binomial (NB) models and their various extensions estimated using the maximum likelihood estimation (MLE) method. The classical count outcome model has been widely used in the past among

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<sup>15</sup> 0.3 is equal to 10% of the range of WS. Other threshold values such as 0.15 and 0.45 (i.e. 5% and 15% of the range of WS respectively) for the difference between  $WS_1$  and  $WS_2$  have also been tested. The results are not significantly different.

safety researchers (e.g. Miaou and Lum, 1993; Shankar et al, 1995; Milton and Mannering, 1998; Shankar et al., 1998; Abdel-Aty and Radwan, 2000; Chin and Quddus, 2003a; Graham and Glaister, 2003; Noland and Quddus, 2005). The basic Poisson model structure in cross-sectional settings can be defined as follows:

$$Y_i \sim \text{Poisson}(\mu_i) \quad (4.4)$$

$$\log(\mu_i) = \alpha + \beta \mathbf{X}_i \quad (4.5)$$

where,

$Y_i$  is the observed number of accidents that occurred on road segment  $i$ ;

$\mu_i$  is the expected accident count at road segment  $i$ ;

$\alpha$  is the intercept;

$\mathbf{X}_i$  is the vector of explanatory variables for road segment  $i$ ;

$\beta$  is the vector of coefficients to be estimated;

The Poisson model has the restriction of mean equals to variance. This can be relaxed using NB models which allows for overdispersion. There are several different parameterisations of NB models (see Cameron and Trivedi, 1998). Using equation (4.4), (4.5) becomes  $\log(\mu_i) = \alpha + \beta \mathbf{X}_i + v_i$ , where  $v_i$  is an additional random term which captures the heterogeneity effects. For the NB model it is assumed that  $\exp(v_i)$  is independent across observations and follows a gamma distribution with mean 1 and variance  $1/\phi$ , i.e.  $\exp(v_i) \sim \text{Gamma}(\phi, \phi)$ . Note under this parameterisation a gamma distribution  $\theta \sim \text{Gamma}(a, b)$  is defined with mean  $E(\theta) = a/b$  and variance  $\text{Var}(\theta) = a/b^2$ .  $1/\phi$  is often referred to as the “overdispersion parameter”. The larger  $1/\phi$  is, the greater the overdispersion. The NB model reduces to the Poisson model if  $1/\phi = 0$ , therefore the Poisson model is a special case of an NB model. Since  $\exp(v_i)$  follows a gamma distribution, NB is a Poisson-gamma mixture and the NB model is also known as a Poisson-gamma model. The NB distribution has a closed form and can be expressed as follows (referred to as the NB2 model in Cameron and Trivedi, 1998):

$$\Pr(y_i | \mu_i) = \frac{\Gamma(y_i + \phi)}{y_i! \Gamma(\phi)} \left( \frac{\phi}{\mu_i + \phi} \right)^\phi \left( \frac{\mu_i}{\mu_i + \phi} \right)^{y_i} \quad (4.6)$$

Poisson/NB model can be estimated using the maximum likelihood estimation (MLE) method. An exposure factor can also be integrated into the model to estimate the accident rate given that the coefficient ( $\beta$ ) for the exposure variable is fixed to 1.

For longitudinal/panel data, a fixed- or random-effects term for location (i.e. road segments in this case) specific characteristics can be added to equation (4.5) so as to form a fixed- or random-effects model. For a Poisson model, the form of the model becomes:

$$Y_{it} \sim \text{Poisson}(\mu_{it}) \quad (4.7)$$

$$\log(\mu_{it}) = \alpha + \beta \mathbf{X}_{it} + \delta_i \quad (4.8)$$

where  $\delta_i$  is the parameter representing the location-specific effect. For fixed-effects models,  $\delta_i$  is assumed to be a fixed unknown parameter; and for random-effects models  $\delta_i$  is assumed to be a random variable. The other terms were previously defined.

Extensions to the NB model were employed to form a fixed- or random-effects NB model suitable for panel data (Hausman et al., 1984)<sup>16</sup>. In a fixed- or random-effects model,  $Y_{it}$  is assumed NB distributed with parameters  $\theta_i \lambda_{it}$  and  $k_i$ , where  $\theta_i$  is the location-specific effect,  $\lambda_{it} = \exp(\alpha + \beta \mathbf{X}_{it})$  and  $k_i$  is the Negative Binomial overdispersion parameter.  $Y_{it}$  thus has mean  $\theta_i \lambda_{it} / k_i$  and variance  $(\theta_i \lambda_{it} / k_i) \times (1 + \theta_i / k_i)$ . For a fixed-effects NB model, the location effect  $\theta_i$  is modelled as a fixed unknown parameter; and for a random-effects NB model, it is treated as a random variable with independently and identically distributed (*i.i.d.*) and  $(1 + \theta_i / k_i)^{-1}$  is assumed beta distributed with Beta( $a$ ,  $b$ ). One can employ a Hausman test (Hausman, 1978) to determine the appropriateness of using a fixed- or random-effects model. A Hausman test compares the difference between coefficients estimated from the random-effects model and coefficients estimated from the fixed-effects model. The null hypothesis is

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<sup>16</sup> It has however been reported that the conditional fixed effects NB model proposed by Hausman et al. (1984) and implemented in some statistical packages (such as Stata and LIMDEP) is not a true fixed-effect model (Allison and Waterman, 2002; Guimarães, 2008). In addition, such extensions to NB models in panel data settings do not always work and may not be necessary because the main arguments made to justify the use of an NB model in cross-sectional settings is its ability to control for unobserved heterogeneity; the panel data method already controls for heterogeneity so Poisson fixed- or random-effects models may be sufficient (Cameron and Trivedi, 1998).

that both the estimators are consistent, and the alternative hypothesis is that one of the estimators is inconsistent. If no difference between the two estimators is found (i.e. the difference is statistically insignificant), then both the estimators are consistent (null hypothesis not rejected) and thus one can use the random-effects model; otherwise (null hypothesis rejected) the fixed-effects model should be used.

#### **4.5.2 Spatial models using a full Bayesian hierarchical approach**

Spatial econometric models suitable for count data have been considered and investigated in this thesis. “Spatial models” refer to the models that can take account of spatial correlations, which in this thesis are estimated under a full Bayesian hierarchical framework with conditional autoregressive (CAR) models for spatial effects. This modelling framework is flexible and can accommodate various spatial and temporal heterogeneities (MacNab and Dean, 2001).

The Bayesian theorem features a learning process which updates the *prior* knowledge of the parameter values with the observed data, so as to obtain the *posterior* knowledge of the parameters (Congdon, 2001). Unlike the classical statistical methods (i.e. the frequentist inference), the parameters under Bayesian inference are represented by a probability distribution over all possible values that the parameters can take (Train, 2003). The Bayesian rule of updating the knowledge of parameter  $\theta$  based on observed sample  $Y$  can be expressed as follows:

$$K(\theta|Y) = \frac{L(Y|\theta)k(\theta)}{L(Y)}$$

where  $K(\theta|Y)$  denotes the posterior distribution of  $\theta$  given the data  $Y$ ;  $k(\theta)$  denotes the prior distribution of  $\theta$ ;  $L(Y|\theta)$  denotes the likelihood of the observed data  $Y$ , given the prior beliefs of  $\theta$ ; and  $L(Y)$  denotes the marginal likelihood of  $Y$ , marginal over  $\theta$ .

The Bayesian theorem indicates that the posterior distribution is proportional to the prior distribution times the likelihood of the observed data. It can be shown that the resulting estimator under Bayesian inference is asymptotically equivalent to the classical maximum likelihood estimator under certain conditions (e.g., when large sample size used) (Train, 2003). The mean of the posterior distribution of  $\theta$  can be seen

as the classical point estimate; and the standard deviation of the posterior distribution can be seen as the standard error of the estimate.

One important advantage of the Bayesian approach is that it does not require calculating and maximising the likelihood function (Train, 2003). For some complex models, such as the Poisson-lognormal model, the distribution is not in a closed form, and thus the model is difficult to be estimated using the classical maximum likelihood method. The Bayesian approach avoids the need to calculate the likelihood function by utilising a sampling based estimation method (Train, 2003). The sampling based method often used is Gibbs sampling which is often referred to as the Markov Chain Monte Carlo (MCMC) method (Congdon, 2001; Train, 2003). The Gibbs sampling was implemented in a software package WinBUGS (Spiegelhalter et al., 2003) and has been employed in this thesis. The Gibbs sampling allows one to draw values of one parameter given the values of other parameters at a time, instead of taking draws of all parameters simultaneously. After sufficient iterations, the process converges to provide draws from the joint density of all parameters.

Similar to classical count outcome models, Poisson based models have been considered and used for modelling accident frequency under the Bayesian framework. For cross-sectional data, the types of models include a Poisson-lognormal, a Poisson-gamma and a Poisson-lognormal with conditional autoregressive (CAR) priors. The base form of a Poisson based model can be expressed as follows:

$$Y_i \sim \text{Poisson}(\mu_i) \quad (4.9)$$

$$\log(\mu_i) = \alpha + \beta \mathbf{X}_i + v_i + u_i \quad (4.10)$$

in which  $v_i$  is the random term which captures the heterogeneity effects for road segment  $i$ ; and  $u_i$  is the random term which captures the spatially correlated effects for road segment  $i$ . All other terms were previously defined.

Models are estimated under a full hierarchical Bayesian framework by using a software package WinBUGS (Spiegelhalter et al., 2003). Models are differentiated by various specifications of the random terms (i.e.  $v_i$  and  $u_i$ ) and each specification creates a Poisson based model. This is described below:

**Poisson-lognormal model:** It is of interest to test the model (see equation 4.9) with only heterogeneity effects and therefore the spatially correlated effects term  $u_i$  is excluded, resulting in a Poisson-lognormal model. Model specification follows the recommendations used in the WinBUGS user manual (Spiegelhalter et al., 2003). A uniform prior distribution is assigned to  $\alpha$ ; highly non-informative normal priors are assigned to all  $\beta$ 's with zero mean and 100,000 variance<sup>17</sup>. Similar specifications for the prior distributions were suggested and used in the literature (e.g., Quddus, 2008b). The prior distribution for uncorrelated heterogeneity term  $v_i$  is a normal prior with  $N(0, \tau_v^2)$ , where  $\tau_v^2$  is the precision (1/variance) with a vague gamma prior  $Gamma(0.5, 0.0005)$  as suggested by Aguero-Valverde and Jovanis (2006).

**Poisson-gamma model:** Similar to the Poisson-lognormal model, the spatial correlation term ( $u_i$ ) can be excluded and the same prior distributions can be assigned to  $\alpha$  and  $\beta$ 's. The term,  $\exp(v_i)$ , is however assigned to a gamma prior i.e.,  $\exp(v_i) \sim Gamma(\phi, \phi)$ , where  $\phi$  is assigned to a non-vague hyper prior with  $Gamma(0.1, 1.0)$  as suggested by Lord and Miranda-Moreno (2008). Such a model is known as a Negative Binomial (NB) model.

**Poisson-lognormal CAR model:** This model accommodates both heterogeneity and spatially correlated effects (i.e.  $v_i$  and  $u_i$ ). The same priors are assigned to  $\alpha$ ,  $\beta$ 's and  $v_i$  as in the Poisson-lognormal model. The spatial correlation term  $u_i$  is modelled with a conditional autoregressive (CAR) model proposed by Besag (1974):

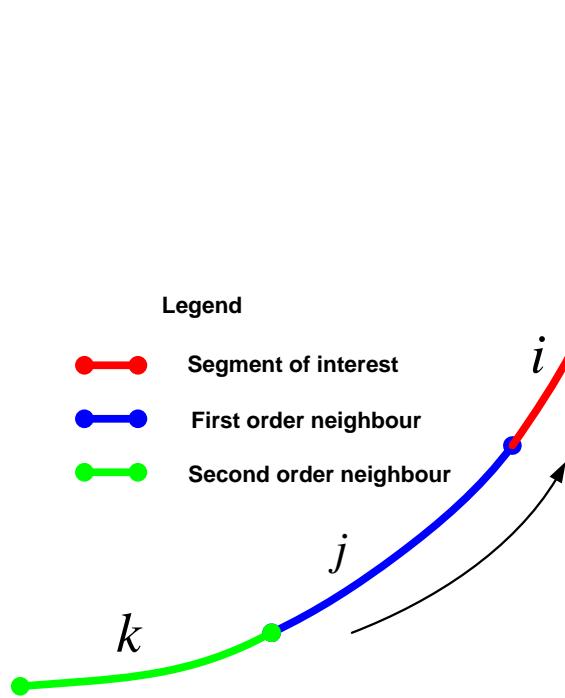
$$u_i | u_j, i \neq j \sim N\left(\frac{\sum_j u_j w_{ij}}{w_{i+}}, \frac{\tau_u^2}{w_{i+}}\right)$$

where  $w_{ij}$  denotes the weight between road segment  $i$  and  $j$ ;  $w_{i+} = \sum_j w_{ij}$ ; and  $\tau_u^2$  is a scale parameter assumed as a gamma prior  $Gamma(0.5, 0.0005)$ , as suggested and used by Aguero-Valverde and Jovanis (2006) and Quddus (2008b).

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<sup>17</sup> The large variance indicates that the priors are non-informative. This is used because there is no sufficient prior knowledge of the distribution.

There are several methods to define the weights ( $w_{ij}$ ) between road segments depending on the consideration of different neighbour structures. The weighting scheme could use contiguity based weights, for example,  $w_{ij} = 1$  if spatial unit  $i$  and  $j$  are adjacent (i.e. shared border and/or vertex) and  $w_{ij} = 0$  otherwise. Alternatively, distance based weights can be used, for example, the shorter the distance between  $i$  and  $j$ , the larger the weight ( $w_{ij}$ ). In this thesis contiguity based weights are employed because the analyses are based on road segments: unlike contiguous road segments, two parallel road segments (with opposite directions) are close to each other but they do not share similar traffic flow (the traffic conditions may be very different on two parallel road segments); and in addition, the distance between two road segments is usually measured by the distance between the central points of the segments, however the length of road segments varies (see the data in Chapter 5) so this measurement of distance between road segments is unreliable (i.e. two road segments may be close to each other but the central points can be far). For the contiguity based weighting scheme, two different neighbouring structures are considered as suggested by Aguero-Valverde and Jovanis (2008): first-order neighbours and second-order neighbours. First-order neighbours are defined as road segment  $j$  is directly connected to segment  $i$  and  $w_{ij} = 1$ ; second-order neighbours are defined as road segment  $j$  is connected to first-order neighbours of segment  $i$  and  $w_{ij} = 1/2$ .  $w_{ij} = 0$  if segment  $i$  and  $j$  are not neighbours to each other (first or second order). The first- and second-order neighbouring structures are illustrated in Figure 4.2.



**Figure 4.2 First- and second-order neighbouring structure**

The models described above are suitable for cross-sectional data. For panel data, additional fixed or random effect terms can be incorporated to accommodate temporal effects. Models expressed in (4.9) and (4.10) can be modified accordingly to form a panel data model:

$$Y_{it} \sim \text{Poisson}(\mu_{it}) \quad (4.11)$$

$$\log(\mu_{it}) = \alpha + \beta \mathbf{X}_{it} + \nu_i + u_i + \delta_t + e_{it} \quad (4.12)$$

where  $\delta_t$  is the term representing time effects (e.g., year-to-year effects);  $e_{it}$  is a random term for extra space-time interaction effects; and all other terms are previously defined.

As can be seen from (4.11) and (4.12) the modelling framework is similar to that presented in (4.9) and (4.10), but with additional terms included in the latter to control for time and extra space-time effects (i.e.  $\delta_t$  and  $e_{it}$ ). Therefore, the panel data model presented in (4.11) and (4.12) is a two-way fixed-/random-effects (location and time) model.

As with cross-sectional data models, panel data models are estimated under a full hierarchical Bayesian framework by using the software package WinBUGS

(Spiegelhalter et al., 2003). The same prior distributions are applied to the terms  $\alpha$ ,  $\beta$ 's,  $v_i$ , and  $u_i$  as in the cross-sectional data models.

For the specifications of the terms  $\delta_t$  and  $e_{it}$ , since the panel data used in this thesis has a large number of cross-sectional units (298 road segments) but relatively short time periods (2003-2007) (details are given in Chapter 5), two simple modelling structures for temporal effects ( $\delta_t$ ) can be considered: fixed-effects varying by  $t$ ; and random effects with first-order random walk – RW (1) – prior. For the fixed-time-effects model,  $\delta_1$  is set to be zero and  $\delta_2 - \delta_5$  is assigned highly non-informative normal priors with zero mean and 100,000 variance. Miaou et al. (2003) also used non-informative priors for the fixed time effects. For the random-effects model,  $\delta_t$  is assumed temporally correlated and assigned a RW (1) prior, which can be modelled using the CAR prior in WinBUGS (Lagazio et al., 2001; Thomas et al., 2004). Similar to the specification of the prior distribution of  $u_i$ , the weight between two consecutive time periods (e.g., 2003 and 2004) is set to be 1 otherwise 0. For the space-time interaction term  $e_{it}$ , Miaou et al. (2003) suggested the use of a vague normal prior  $N(0, \tau_v^2)$  where  $\tau_v^2 \sim \text{Gamma}(0.5, 0.0005)$  is assumed.

One limitation of WinBUGS software package is the limited ability to handle missing values associated with independent variables (Kynn, 2006). If there were missing values for some segments at time  $t$ , which forms an unbalanced panel dataset, it would be difficult to estimate the models using WinBUGS. One solution is to remove the segments with missing values from the data, which forms a balanced panel dataset that can be estimated using WinBUGS. The unbalanced panel data however can be analysed using classical count outcome models as described in section 4.5.1.

All models discussed in this section can be estimated using the Markov Chain Monte Carlo (MCMC) method under the full hierarchical Bayesian framework. The deviance information criterion (DIC), which can be thought as a generalisation of the Akaike information criterion (AIC), can be used to compare goodness-of-fit and complexity of different models estimated under a Bayesian framework (Spiegelhalter et al., 2002).

The DIC is defined as:

$$\text{DIC} = D(\bar{\theta}) + 2p_D = \bar{D} + p_D$$

where  $D(\bar{\theta})$  is the deviance evaluated at  $\bar{\theta}$ ;  $\bar{\theta}$  is the posterior means of the parameters of interest;  $p_D$  is the effective number of parameters in the model, measuring the complexity of the model; and  $\bar{D}$  is the posterior mean of the deviance statistic  $D(\theta)$  and  $\bar{D}$  can be taken as a Bayesian measure of fit. A model which can maximise fit with less model parameters (i.e. less complexity) is generally preferred (Lord et al., 2007). As with AIC, in terms of model fit and complexity, the lower the DIC the better the model (Spiegelhalter et al., 2002).

## 4.6 Accident severity models

Contrary to accident *frequency* models, accident *severity* models have normally been employed at an individual accident level to examine the effects of factors (e.g., traffic congestion) on the severity outcome, given that an accident has occurred. As discussed in Chapter 3, accident severity is often measured in categories, to be specific “slight injury”, “serious injury” and “fatal” in this thesis. Therefore, econometric models that are suitable for categorical data have been explored and tested. This includes the use of either ordered response models or unordered nominal response models (also known as discrete choice models in econometrics). The two modelling specifications are presented in the following sections.

### 4.6.1 Ordered response models

Since the severity outcome of an accident is ordinal in nature, it is natural to consider an ordered response model such as an ordered logit model. An ordered logit (OLOGIT) model and its extensions such as a generalised ordered logit model are considered and tested in this thesis. The OLOGIT model can be derived using a latent variable model (Long and Freese, 2006). Suppose, a latent variable  $y^*$  which measures the accident severity ranging from  $-\infty$  to  $+\infty$ :

$$y_i^* = \beta \mathbf{X}_i + \varepsilon_i \quad (4.13)$$

where  $\mathbf{X}_i$  is a vector of explanatory variables related to the accident;  $\beta$  is a vector of coefficients to be estimated; and  $\varepsilon_i$  is the error term which is assumed to be distributed logically. The observed accident severity  $y$  is coded as follows: 1 = slight injury accident; 2 = serious injury accident; and 3 = fatal accident. The severity level  $y$  is determined by the value of the latent variable  $y^*$  as follows:

$$y_i = \begin{cases} 1 (\text{slight}) & \text{if } -\infty \leq y_i^* < \tau_1 \\ 2 (\text{serious}) & \text{if } \tau_1 \leq y_i^* < \tau_2 \\ 3 (\text{fatal}) & \text{if } \tau_2 \leq y_i^* < +\infty \end{cases}$$

where  $\tau_j$  is the cut-point (threshold) to be estimated ( $j=1,2$ ). The probabilities of observing each accident severity outcome are (see O'Donnell and Connor, 1996; Abdel-Aty, 2003):

$$\Pr(y_i = 1) = \Pr(y_i^* < \tau_1) = \Pr(\varepsilon_i < \tau_1 - \beta \mathbf{X}_i) = F(\tau_1 - \beta \mathbf{X}_i) \quad (4.14)$$

$$\Pr(y_i = 2) = \Pr(\tau_1 \leq y_i^* < \tau_2) = \Pr(\tau_1 - \beta \mathbf{X}_i \leq \varepsilon_i < \tau_2 - \beta \mathbf{X}_i) = F(\tau_2 - \beta \mathbf{X}_i) - F(\tau_1 - \beta \mathbf{X}_i) \quad (4.15)$$

$$\Pr(y_i = 3) = \Pr(\tau_2 \leq y_i^*) = 1 - F(\tau_2 - \beta \mathbf{X}_i) \quad (4.16)$$

where  $F$  is the cumulative distribution function (cdf) for  $\varepsilon_i$  and assumed logistic with mean 0 and variance  $\pi^2/3$ . Thus  $F(\tau_j - \beta \mathbf{X}_i) = \frac{1}{1 + \exp(-\tau_j + \beta \mathbf{X}_i)}$ .

It can be shown that equations (4.15) – (4.16) are equivalent to one simple cumulative probability function:

$$\Pr(y_i \leq j) = F(\tau_j - \beta \mathbf{X}_i), \quad j=1,2 \quad (4.17)$$

Alternatively equation (4.17) can be re-written as:

$$\Pr(y_i > j) = \frac{\exp(\beta \mathbf{X}_i - \tau_j)}{1 + \exp(\beta \mathbf{X}_i - \tau_j)}, \quad j=1,2 \quad (4.18)$$

The OLOGIT model is represented by equation (4.18). This model, as discussed in Chapter 3, has two restrictions in that it assumes the residuals are homoscedastic and the relationship between each pair of outcome groups is the same (also known as *proportional odds assumption*. See discussions in Chapter 3 section 3.4.2). The violation of the assumptions would lead to misleading results (see for example, Yatchew and Griliches, 1985; Keele and Park, 2006; Long and Freese, 2006; Fu, 1998). To address the issue of heteroscedasticity, one solution is to use a heterogeneous choice model (HCM) which can be expressed as follows (Williams, 2008):

$$\Pr(y_i > j) = \frac{\exp\left(\frac{\beta \mathbf{X}_i - \tau_j}{\sigma_i}\right)}{1 + \exp\left(\frac{\beta \mathbf{X}_i - \tau_j}{\sigma_i}\right)}, \quad j=1,2 \quad (4.19)$$

where  $\sigma_i = \exp(\mathbf{Z}\gamma)$ .  $\mathbf{Z}$  is the vector of explanatory variables (dummy or continuous) which have different error variances;  $\gamma$  is the vector of coefficients associated with  $\mathbf{Z}$ .  $\mathbf{Z}$  and  $\mathbf{X}$  may include the same set (or a subset) of variables. When  $\mathbf{Z}$  is equal to 0,  $\sigma_i$  becomes 1 and the HCM reduces to a OLOGIT model.

As for the second restriction imposed by the proportional odds assumption, a generalised ordered logit (GOLOGIT) model can be employed to relax the assumption (Fu, 1998). The GOLOGIT model can be written as:

$$\Pr(y_i > j) = \frac{\exp(\beta_j \mathbf{X}_i - \tau_j)}{1 + \exp(\beta_j \mathbf{X}_i - \tau_j)}, \quad j=1,2 \quad (4.20)$$

Note the expression for GOLOIT in (4.20) is very similar to the expression for OLOGIT in (4.18). The only difference in GOLOGIT is that the  $\beta$ 's differ across different severity outcomes.

Considering the case when only a subset of the explanatory variables violate the proportional odds assumption, a partial proportional odds (PPO) model may be used, for which only a subset of coefficients are constrained to be the same across different severity outcomes (Williams, 2006). The PPO model can be written as:

$$\Pr(y_i > j) = \frac{\exp(\beta_1 \mathbf{X}_{1i} + \beta_{2j} \mathbf{X}_{2i} - \tau_j)}{1 + \exp(\beta_1 \mathbf{X}_{1i} + \beta_{2j} \mathbf{X}_{2i} - \tau_j)}, \quad j=1,2 \quad (4.21)$$

where the coefficients ( $\beta_1$ ) associated with  $\mathbf{X}_{1i}$  are constrained to be the same and coefficients ( $\beta_{2j}$ ) associated with  $\mathbf{X}_{2i}$  differ across different severity outcomes.

All the models described in this section can be estimated using the MLE method. HCM is estimated using a user written Stata program (-oglm-) developed by Williams (2008); GOLOGIT and PPO models are estimated using a user written Stata program (-gologit2-) which is also developed by Williams (2006).

As discussed in Chapter 3, ordered response models have two limitations which are related to the constraint on variable influences and under-reporting in accident data. This will lead to the use of alternative and more flexible unordered nominal response models which are described below.

#### **4.6.2 Nominal response models**

Compared to ordered response models, unordered nominal response models offer more flexibility in terms of the functional form and consistent coefficient estimates with under-reporting data (Kim et al., 2007; Savolainen and Mannering, 2007). As discussed in Chapter 3, two nominal response models are considered in this thesis: a standard multinomial logit (MNL) model and a mixed logit model.

For a dataset with three categories of accident severity outcomes (1=“slight injury”, 2=“serious injury” and 3=“fatal”), the MNL model can be written as (Long and Freese, 2006):

$$\log \Omega_{j|b} = \log \frac{\Pr(y_i = j)}{\Pr(y_i = b)} = \beta_{j|b} \mathbf{X}_i, \quad j=1,2,3 \quad (4.22)$$

where  $\Omega_{j|b}$  denotes the odds of an outcome  $j$  compared with outcome  $b$ ;  $b$  is the base outcome that other severity outcomes are compared with;  $\beta_{j|b}$  is a vector of injury-specific coefficients and  $\beta_{b|b}=0$ . Equation (4.22) can be shown as:

$$\Pr(y_i = j) = \frac{\exp(\beta_{j|b} \mathbf{X}_i)}{\sum_{m=1}^M \exp(\beta_{m|b} \mathbf{X}_i)}, \quad j=1,2,3 \quad (4.23)$$

The MNL model, as discussed in Chapter 3, assumes that the unobserved terms associated with each accident severity category are independent. This may not always be the case because some severity categories may share unobserved effects (for example, fatal and serious injury accidents may share effects that relate to higher severity accidents). To account for the unobserved correlated effects and additional unobserved heterogeneity (related to traffic, vehicle, driver and environment) between severity categories, a mixed logit model is then used. This mixed logit model is formed by integrating a standard MNL model over a “mixing distribution” of parameters (Train, 2003). The mixed logit model can be expressed as follows:

$$\Pr(y_i = j) = \int \frac{\exp(\beta_{j|b} \mathbf{X}_i)}{\sum_{m=1}^M \exp(\beta_{m|b} \mathbf{X}_i)} f(\beta) d\beta, \quad j=1,2,3 \quad (4.24)$$

where  $f(\beta)$  is a density function.

The mixed logit probability is then a weighted average with weights given by  $f(\beta)$ . Some parameters of the vector  $\beta$  may be fixed or randomly distributed. The standard MNL model is a special case of the mixed logit model when  $\beta$  are fixed parameters. For random parameters, the coefficients  $\beta$  are allowed to vary over different accidents and assumed randomly distributed. For example, a coefficient  $\beta_1$  can be specified to be random and normally distributed:  $\beta_1 \sim N(b, W)$  where  $b$  is the mean and  $W$  is the variance. Other distributions can also be specified, such as a lognormal distribution:  $\log \beta_1 \sim N(b, W)$ .

The MNL model can be easily estimated using the standard maximum likelihood method. The estimation for mixed logit models however is difficult as the probability function is involved with integration and hence not in a closed form. One solution is to use the maximum simulated likelihood (MSL) method in which Halton draws<sup>18</sup> can be used to achieve convergence more efficiently (Bhat, 2003; Train, 2003). MSL is also shown to be more efficient to achieve the same degree of accuracy than other estimation methods such as the classical Gauss Hermite quadrature or adaptive quadrature (Haan and Uhlendorff, 2006). In this thesis the mixed logit model is estimated using a user written Stata program (`-mixlogit-`) developed by Hole (2007). The Akaike information criterion (AIC) can be used to compare goodness-of-fit and complexity of different models estimated using the maximum likelihood method. The AIC is defined as:  $AIC = -2\log L + 2P$ , where  $L$  is the likelihood of the model and  $P$  is the number of parameters to be estimated in the model. As with the DIC, the lower the AIC the better the model (Spiegelhalter et al., 2002).

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<sup>18</sup> Halton draws use number theory to create a sequence of quasi-random numbers, which is generally more efficient to compute integrals compared to a purely random sequence (see Train, 2003; Long and Freese, 2006).

Accident frequency and severity models can be combined to form a two-stage mixed multivariate model, which can be used in identifying accident hotspots (i.e. site ranking). This is discussed in the following section.

## 4.7 Site ranking

As discussed in Chapter 3, a two-stage mixed multivariate model can be used in site ranking, aimed at identifying accident hotspots for further safety examination and remedial treatment. The procedure of a two-stage model is as follows: at the first stage, the total number of accidents at all severity levels on a road segment for a given year is estimated using an accident frequency model; then at the second stage, the proportions of accidents at different severity levels on a road segment for a given year is estimated using an accident severity model, which then ‘allocates’ the number of accidents to different severity levels. Finally, the number of accidents at different severity levels can be obtained. A similar two-stage modelling approach has been used by Hausman et al. (1995) to estimate the number of trips to alternative recreational sites, in which the model was referred to as a “combined discrete choice and count data model”.

The two-stage model which combines both accident frequency and severity models, as discussed in Chapter 3, has advantages compared to traditional accident frequency based models (e.g., Aguero-Valverde and Jovanis, 2009; El-Basyouny and Sayed, 2009a) in site ranking, because more detailed data on individual accidents can be employed to better predict the expected number of accidents at different severity levels. In the case of this thesis, as shown in the next chapter, only traffic and road characteristics data are available at the aggregate road segment level for accident frequency models. On the other hand, in addition to the traffic and road characteristics more detailed data are available at individual accident level for accident severity models, such as lighting and weather conditions, time when the accident occurred and number of vehicles in an accident. It is expected that the additional information in accident severity analysis would allow a better understanding of the severity outcome of an accident, and subsequently the distribution (proportion) of accidents at different severity levels on a given road segment.

Another important advantage of the two-stage model is that it is still possible to predict the expected number of accidents at different severity levels even when there are many

zero or low accident counts at an aggregated road segment (or area) level. In the case of this thesis, as shown in the next chapter, there are only 216 fatal accidents on the 298 road segment during 2003-2007, resulting in many zero (more than 85% cases) and low count of fatal accidents (per road segment per year). Therefore, it is not statistically feasible to use accident frequency models to directly predict the number of fatal accidents. Traditionally a researcher avoids this problem by combining two or several categories of accidents, for instance combining fatal accidents with injury accidents (e.g., El-Basyouny and Sayed, 2009a). This issue however can be addressed using the two-stage model, as there are enough cases of fatal accidents to develop an accident severity model which can predict the expected proportion of fatal accidents on a road segment.

The two-stage modelling approach to be used in each stage is detailed as follows:

At the first stage, the total number of accidents (all severity levels) is estimated using an accident frequency model. As discussed in Chapter 3, the full Bayesian approach is appropriate for this purpose (see Chapter 4 section 4.5.2 for the details of Bayesian models). A recent study has shown that the full Bayesian approach significantly outperforms the naïve and traditional empirical Bayes approach (Huang et al., 2009). The posterior estimates of counts of accidents could be easily obtained by monitoring the posterior mean of expected accident counts.

At the second stage, the expected proportions of accidents at different severity levels are obtained using the accident severity models. This can be achieved by aggregating the predicted probabilities for each severity category across all individual accidents on a road segment for a given year. Suppose there are a number of  $N$  accidents on a road segment, and  $P_{ij}$  is the predicted probability of accident  $i$  at severity level  $j$ , then the proportion of accidents for severity  $j$  on this road segment is:

$$\hat{S}(j) = \frac{1}{N} \sum_{i=1}^N P_{ij} \quad (4.25)$$

where  $\hat{S}(j)$  is the predicted proportion of accident for severity  $j$ .

The results from both the accident frequency and severity models can then be combined to estimate the number of accidents at each severity level.

After obtaining the expected number of accidents at each severity level, road segments can then be ranked by an appropriate decision parameter ( $\Theta$ ) for further engineering examination and treatment. The choice of decision parameter ( $\Theta$ ) depends on the context under which the rank is to be used, especially the range of safety treatments to be implemented (Miaou and Song, 2005). Therefore, inputs from decision makers can be useful, for their interests can be taken into consideration for ranking. Since accident data used in this thesis are classified into different categories according to their severity levels, monetary costs of accidents are used as an illustration. The decision parameter  $\Theta_i$  in this thesis is defined as the total accident cost per vehicle kilometre for road segment  $i$ :

$$\Theta_i = \frac{\sum_t \sum_j \text{cost}_j \hat{\mu}_{ijt}}{365 \times \text{length}_i \times \sum_t \text{AADT}_{it}} \quad (4.26)$$

where  $\text{cost}_j$  is the monetary cost of an accident at severity level  $j$ ;  $\hat{\mu}_{ijt}$  is the posterior mean of count of accidents at severity level  $j$  on road segment  $i$  at time (year)  $t$ , estimated from the two-stage model;  $\text{length}_i$  is the length of road segment  $i$ ;  $\text{AADT}_{it}$  is the annual average daily traffic on road segment  $i$  at time (year)  $t$ .

As for the monetary cost of an accident, it is expected that there are higher costs associated with higher severity level accidents. The Department for Transport's (DfT) measurement of accident cost is used in this thesis. According to the DfT (2008) the cost of an accident, or in other words the value of preventing an accident includes: the human costs (e.g., willingness to pay to avoid pain, grief and suffering); the direct economic costs of lost output; the medical costs associated with road accident injuries; costs of damage to vehicles and property; police costs; and administrative costs of accident insurance. The details of the reported valuation of accident costs at different severity levels for a given year are presented in Chapter 8.

The decision parameter ( $\Theta_i$ ) above provides a direct measurement of expected accident cost rate for the time period of interest. The ranking criteria are the posterior means of the expected accident cost rate ( $\Theta_i$ ) for road segments. In other words, a road segment with higher expected accident cost per vehicle kilometre is considered more hazardous, and thus is ranked higher as an accident hotspot for further safety treatment.

## 4.8 Summary

This chapter has provided a discussion of the methodology to be followed in this thesis, including the research design, the measurement of congestion, mapping accidents to the correct road segments, econometric methods for modelling accident frequency and severity. Site ranking, an important application of accident prediction models for identifying accident hotspots has also been presented.

Since previous studies often lack a suitable method to measure traffic congestion in safety research, this chapter has firstly reviewed various congestion measurements in the literature and has then identified the congestion index and total traffic delay per length as appropriate measurements of traffic congestion. Both measurements will be employed and tested in this thesis. This chapter has also developed a weighed matching technique to map accidents to the correct road segments, so the count of accidents over a specific time period for each road segment (for accident frequency analysis) and data (e.g., traffic flow and level of congestion) for each individual accident (for accident severity analysis) can be correctly obtained.

This chapter has also detailed the econometric models to be used in analysing accident frequency and severity. For modelling the frequency of accidents, a count outcome model (classical or full Bayesian hierarchical models) has been found to be more appropriate and has been described in detail. It is expected that Bayesian spatial models will provide more coherent estimation results than classical count outcome models. As for modelling the severity of accidents, econometric models suitable for categorical data, such as an ordered response model and unordered nominal response model have been considered.

Finally, this chapter has described the method used to identify accident hotspots (i.e. site ranking), in which a two-stage mixed multivariate model combining both accident frequency and severity models is employed.

In conclusion, the econometric models used in accident frequency analysis, accident severity analysis and site ranking are summarised in Table 4.2:

**Table 4.2 Econometric models used in this thesis**

| Type of analysis                   | Econometric models   | Comments  |
|------------------------------------|--|---|
| <b>Accident frequency analysis</b> | Fixed- or random-effects Negative Binomial models (classical count outcome models)   | For modelling panel count data                  |
|                                    | Poisson-lognormal, Poisson-gamma and Poisson-lognormal CAR models using full Bayesian hierarchical approach                    | For modelling cross-sectional count data        |
|                                    | Spatial models (Poisson-lognormal CAR models) with fixed or random-walk time effects using full Bayesian hierarchical approach | For modelling panel count data                  |
| <b>Accident severity analysis</b>  | Ordered response models: ordered logit, heterogeneous choice, generalised ordered logit and partial proportional odds models   | For modelling categorical data                  |
|                                    | Nominal response models: multinomial logit and mixed logit models  |   |
| <b>Site ranking</b>                | Two-stage mixed multivariate model   | Road segments are ranked by accident cost rates |

The econometric models described in this chapter will be used to analyse the data that is described in the next chapter (Chapter 5). The model estimation and site ranking results and discussion will be presented in the subsequent chapters.

## CHAPTER 5 DATA DESCRIPTION

### 5.1 Introduction

Empirical data have been collected to investigate the relationship between traffic congestion and road accidents. The roads chosen are the M25 motorway and its surrounding motorways and major A roads<sup>19</sup> connected to the M25 that fall within approximately 50km of the centre of London. The M25 motorway is an orbital motorway that encircles London, England. The primary reason for selecting the M25 and surround in this thesis is that the M25 is one of the busiest motorways in Europe, and as such it is expected that there would be large spatial and temporal variations in both traffic flows and the levels of congestion on the M25 and its surrounding roads, which allows a statistical association between accidents and congestion to be established. In addition, the M25 is long enough (188.3 km each direction) so that sufficient spatial observations can be obtained.

Traffic and road infrastructure data was obtained from the UK Highways Agency (HA). The HA collects hourly traffic characteristics and road infrastructure data for major motorways and A roads at the road segment level in the UK. A series of meetings were held with the HA, during which several presentations regarding this research were given and relevant data were requested. The data required were then identified by the staff at the HA and were stored on DVD discs. In addition, data were transferred through email and downloaded from the website of the Highways Agency's Traffic Information System (HATRIS) database (<http://www.hatris.co.uk/>). The data obtained include the hourly traffic characteristics data for road segments on the M25 and surround during the years 2003-2007, including average travel time, average travel speed, traffic flow and total vehicle delay. Road infrastructure data such as segment length, number of lanes, radius of curvature and gradient for each road segment have also been obtained. According to the Highways Agency, a total number of 298 road segments (a road segment starts or ends at a junction) comprising both directions are identified on the M25 and surround.

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<sup>19</sup> ‘A’ roads are classified as major roads in England

Accident data for the years 2003-2007 were derived from the STATS19 UK national road accident database. The STATS19 database contains three data files: accident, vehicle and casualty data. The three data files contain information regarding accidents, vehicles and casualties involved in an accident. There is a unique accident reference number in each data file and thus it is possible to integrate the accident data file with the vehicle or casualty data files. The vehicle data file contains information on the direction of the vehicles just before an accident, and this information can be used to match the accidents onto the correct road segments using the method described in Chapter 4. Only accidents recorded as occurring on the M25 motorway and surround are retained. Accidents coded as junction accidents (around 30% of total accidents within the study area) were also excluded from the analysis. This is because major road junctions are complicated in terms of road design (such as fly-overs and slip roads) compared to road segments and it is also difficult to obtain a single measure of traffic flow at fly-over and/or slip roads merging to and diverging from the main roads.

The details of the data used in this study, including the discussion of the two congestion measurements and descriptive statistics of the variables to be employed in both accident frequency and accident severity models are presented in the following sections. This is followed by the data validation and a summary of this chapter.

## 5.2 Congestion measurements

As stated, the aim of this thesis is to develop a relationship between traffic congestion and road accidents. Therefore, it is of importance to adopt a suitable measurement of congestion. There are two congestion measurements considered and used in this thesis as described in Chapter 4, i.e. the *congestion index* (CI) and *total delay per length* (per hour or per year). Both the congestion measurements require data on traffic delay (or “actual journey time” and “free flow journey time”) on a road segment. Traffic delay data have been obtained from the UK Highways Agency. According to the HA, traffic delay for a vehicle was calculated by subtracting the journey time at a reference speed (i.e. free flow speed) from the observed journey time (actual journey time). Only positive values of delay were kept. Details of the data on travel time, traffic delay and other traffic information (such as traffic flow) are documented and available from the website of the HATRIS database (<http://www.hatris.co.uk/>). The HATRIS database combines data from various sources, including:

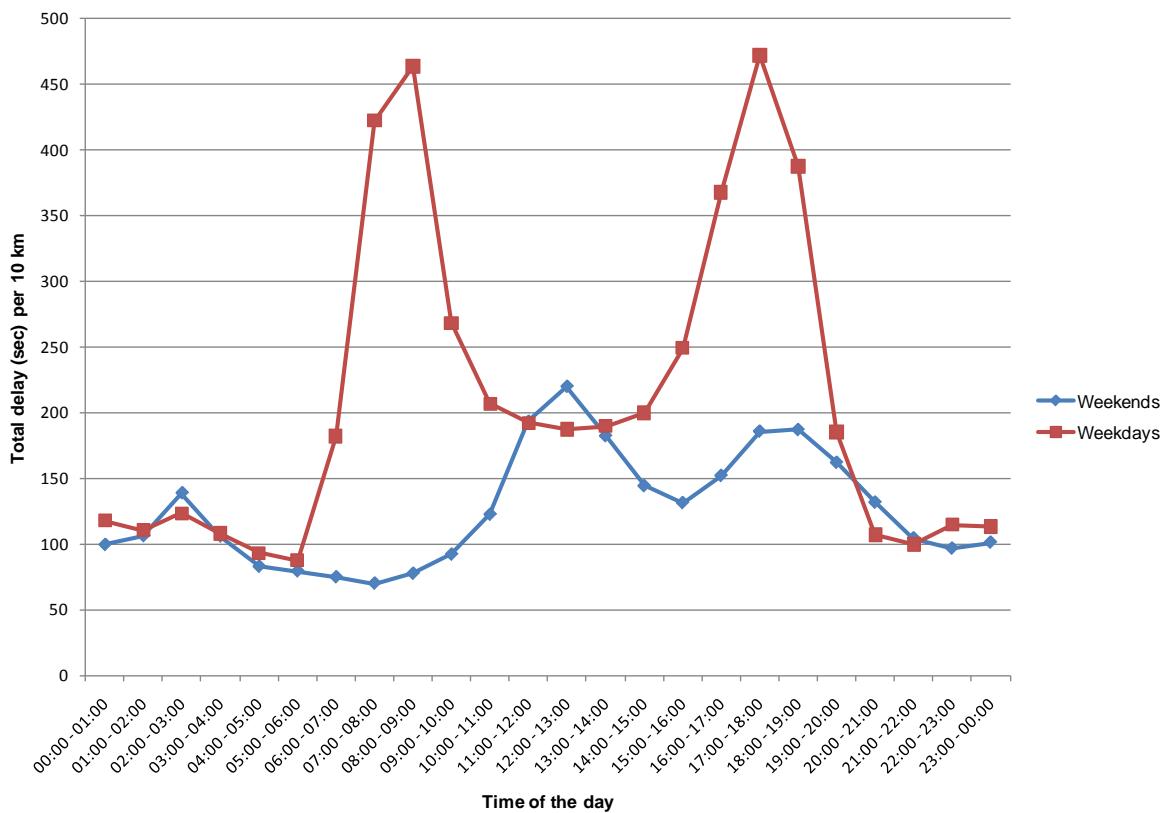
- The Highways Agency Motorway Incident Detection Automatic Signalling (MIDAS) inductive loops
- Trafficmaster Automatic Number Plate Recognition (ANPR) cameras
- National Traffic Control Centre (NTCC) ANPR cameras
- In-vehicle Global Positioning System (GPS) satellite navigation and traffic advice systems

The HATRIS database has also been used by the UK Department for Transport (DfT) for monitoring congestion levels and journey time reliability on a road network (DfT, 2007a and 2009a).

The two congestion measurements derived from the HATRIS database – the *congestion index* (CI) and *total delay per length*, are similar to each other as both are calculated as normalised traffic delay. The correlation coefficient between the two measurements (using annual data aggregated as a road segment level) is 0.71, suggesting a high correlation and similarity between the two measurements. This is not surprising as both of them directly measure traffic delay. The difference between the two measurements is: CI measures traffic delay averaged to a *single* vehicle (per free flow travel time); and *total delay per length* measures the traffic delay for *all* vehicles (per travel length). In other words, CI captures average delay (per vehicle); and *total delay per length* captures total delay, over a certain period of time.

Therefore, compared to *total delay per length*, CI is a highly averaged congestion measurement. This means CI is essentially measuring “average congestion” (per vehicle); and *total delay per length*, on the other hand, measures the “total congestion” imposed on all vehicles travelling on a road segment. According to Taylor et al. (2000b), CI is useful in comparing congestion between different road segments, thus it can be used in a road segment level *spatial* analysis for modelling accident frequency.

To illustrate how the level of traffic congestion evolves over a day on the M25 and surround, hourly total vehicle delay averaged over 10km at different time periods in a day (differentiated by weekdays and weekends) has been plotted and presented in Figure 5.1.



**Figure 5.1 Total vehicle delay (sec) per 10 km on the M25 and surround over a day in 2007**

Figure 5.1 shows that, as expected, the level of traffic congestion is higher in peak time periods and lower in off-peak time periods in a day. This suggests that *delay per 10 km* appears to be appropriate in a disaggregate individual accident level as congestion is time-of-day specific (hourly data are used in the accident severity analysis, see section 5.4 below). It is also noted that the peak time periods are different between weekdays and weekends. Generally, as expected the congestion level is lower in weekends than in weekdays.

The level of traffic congestion over a day (Figure 5.1) can be further compared to average hourly traffic flow and speed which are presented in Figure 5.2 and Figure 5.3:

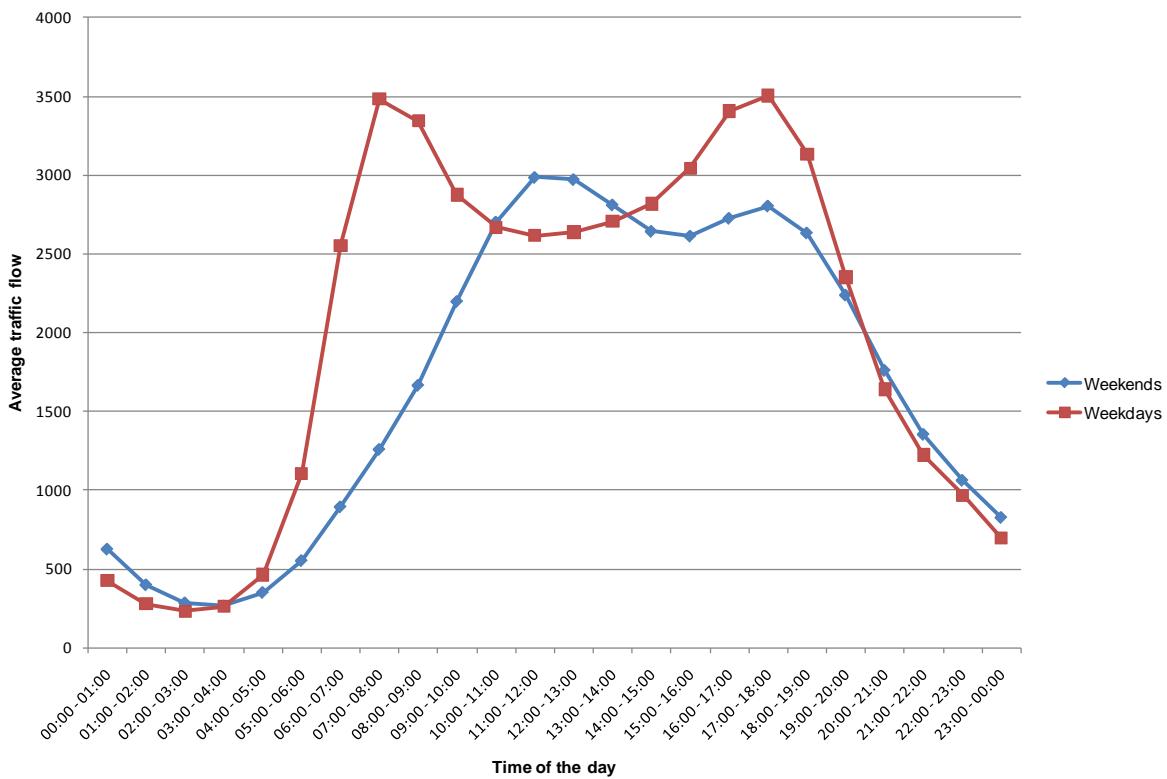


Figure 5.2 Average traffic flow on the M25 and surround over a day in 2007

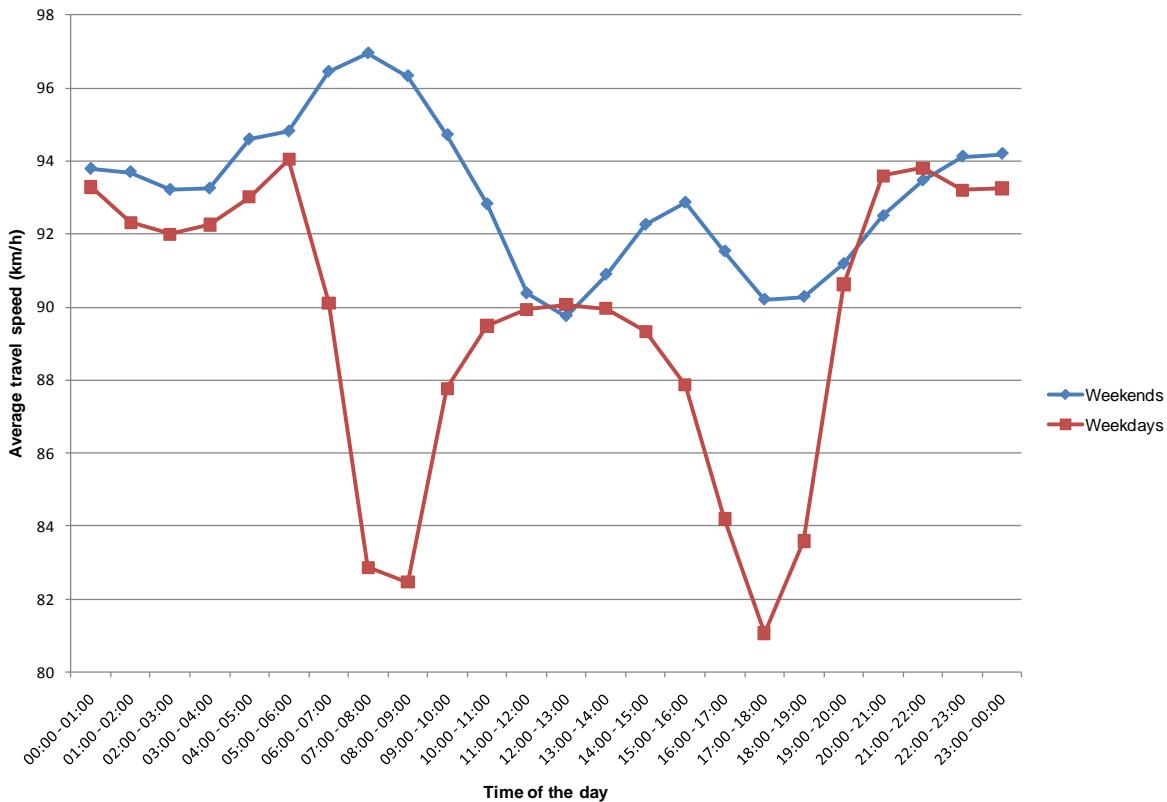
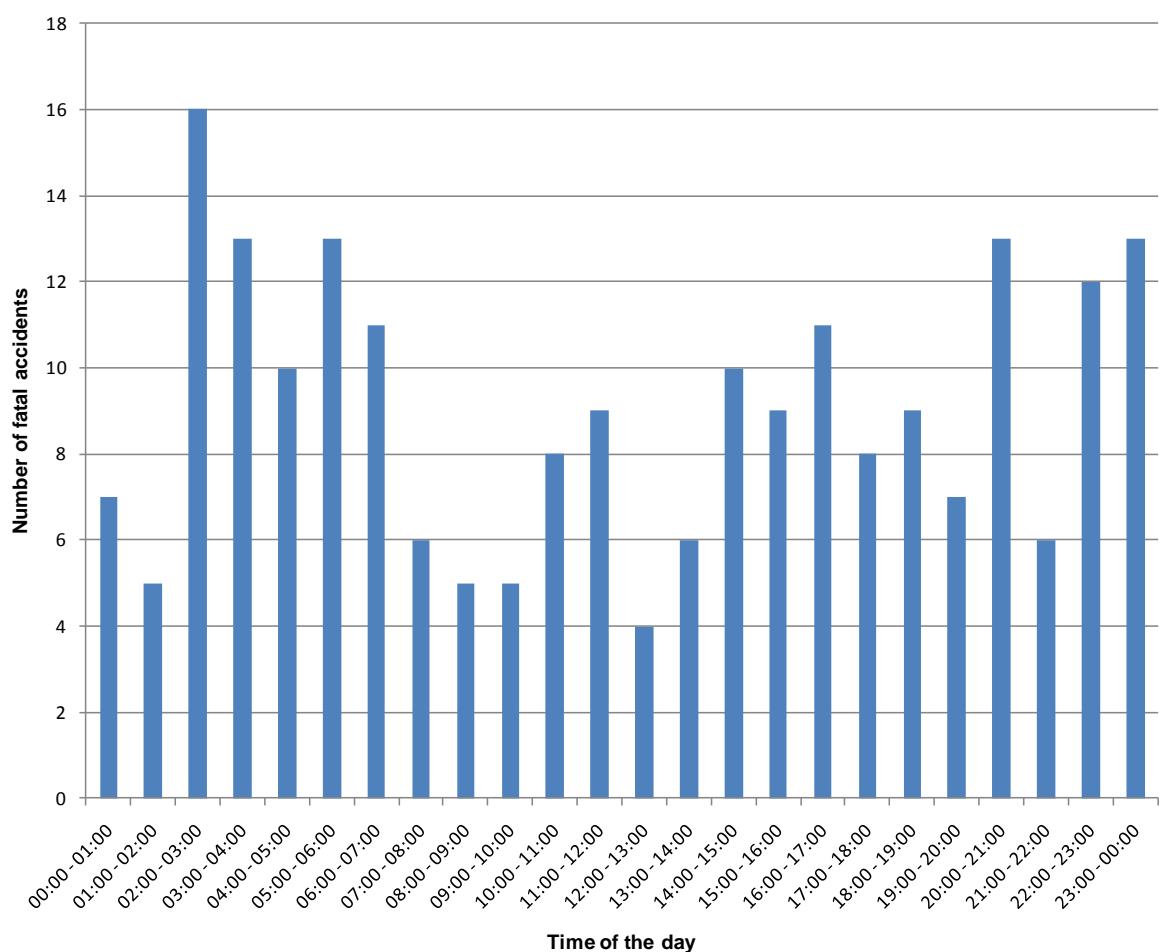


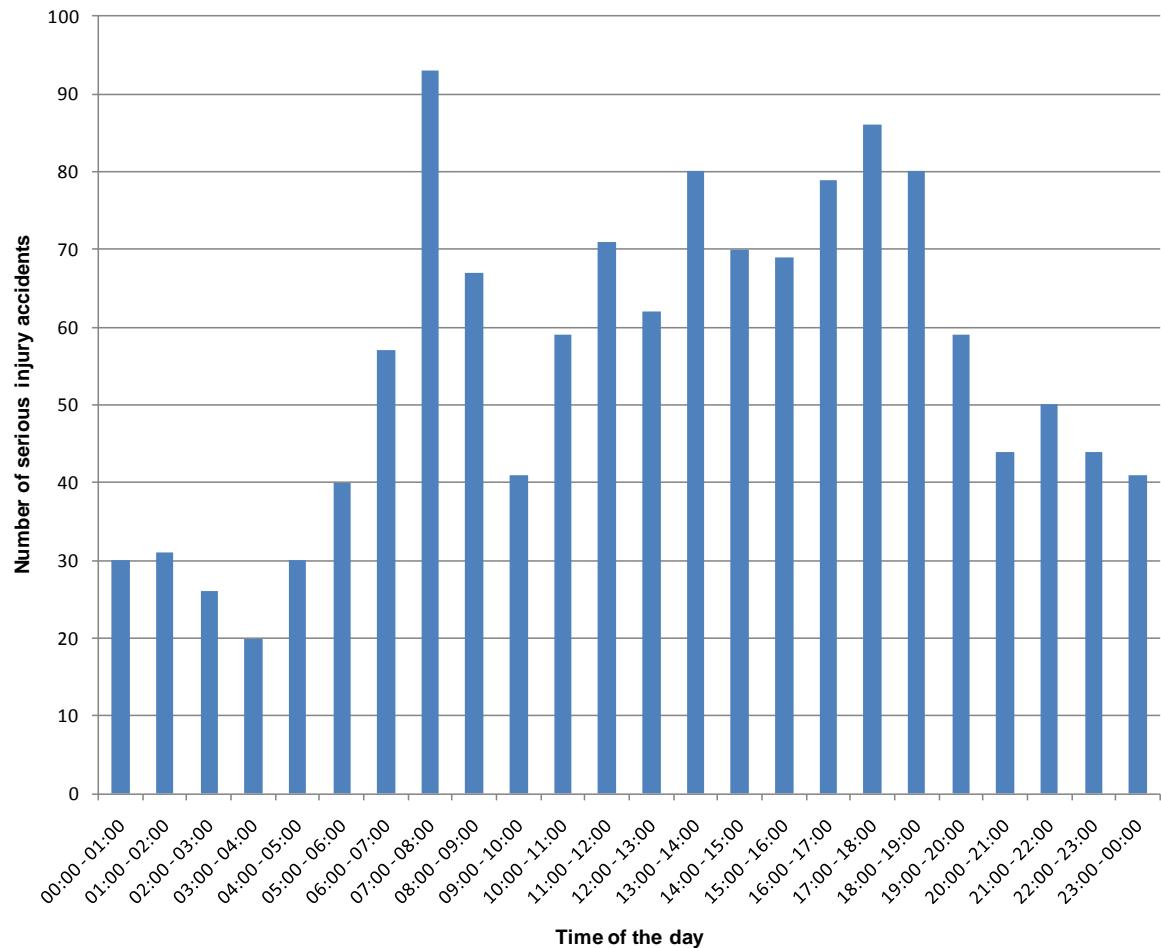
Figure 5.3 Average travel speed on the M25 and surround over a day in 2007

It is interesting to note from Figure 5.2 that traffic flow is consistently higher during 6:00am – 8:00pm in weekdays and 9:00am – 8:00pm in weekends, while the fluctuation in average speeds is much more obvious during the same time periods (Figure 5.3). Generally the average speed in Figure 5.3 shows an inverse pattern relative to the level of congestion shown in Figure 5.1, which indicates less delay occurs when speed is high, *vice versa*. This is expected as vehicles move more slowly when traffic is incurred more delay.

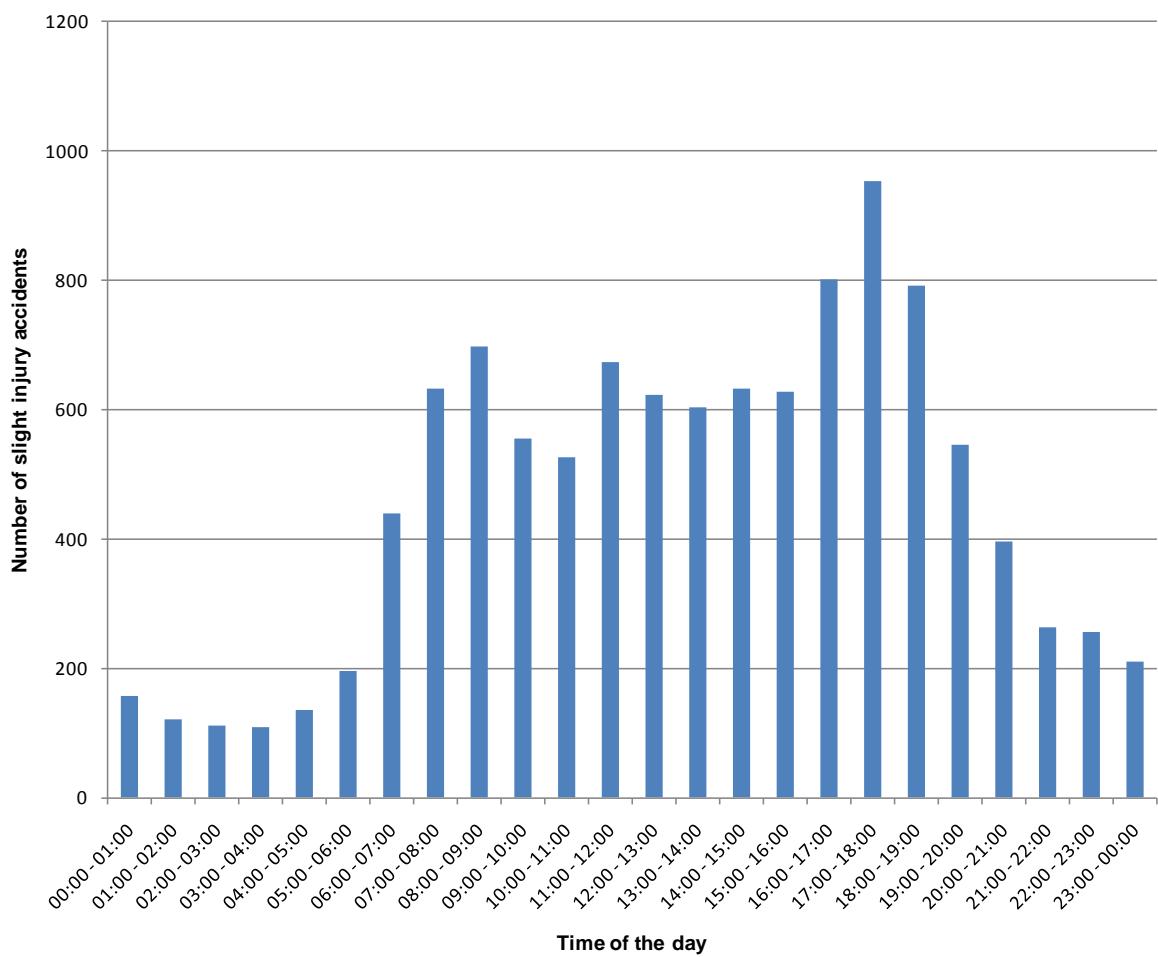
Similar to Figures 5.1-5.3, total number of accidents per hour on the M25 and surround over a day has been plotted in Figures 5.4-5.6. It can be seen that many fatal accidents occurred during off-peak night time when traffic is less congested. Serious injury accidents, however shows a similar trend to slight injury accidents that most accidents occurred during peak time periods.



**Figure 5.4 Total number of fatal accidents per hour on the M25 and surround over a day (2003-2007)**



**Figure 5.5 Total number of serious injury accidents per hour on the M25 and surround over a day (2003-2007)**



**Figure 5.6 Total number of slight injury accidents per hour on the M25 and surround over a day (2003-2007)**

As mentioned above, CI is useful in comparing traffic congestion between different road segments, and there is high correlation between CI and *total delay per length* based on annual data aggregated at a road segment level. Annual CI and *total delay per length* have been compared spatially across the road segments on the M25 and surround, in which they appear to be consistent to each other at a road segment level. The spatial distributions of annual CI and *total delay per length* on the M25 and surround are shown in Figures 5.7 and 5.8, which present a spatial variation in the two congestion measurements. London Heathrow Airport was also shown in the figures, since it is a major airport near to the M25 and as such it is expected that the airport would attract considerable traffic and the road segments near the airport may be more congested.

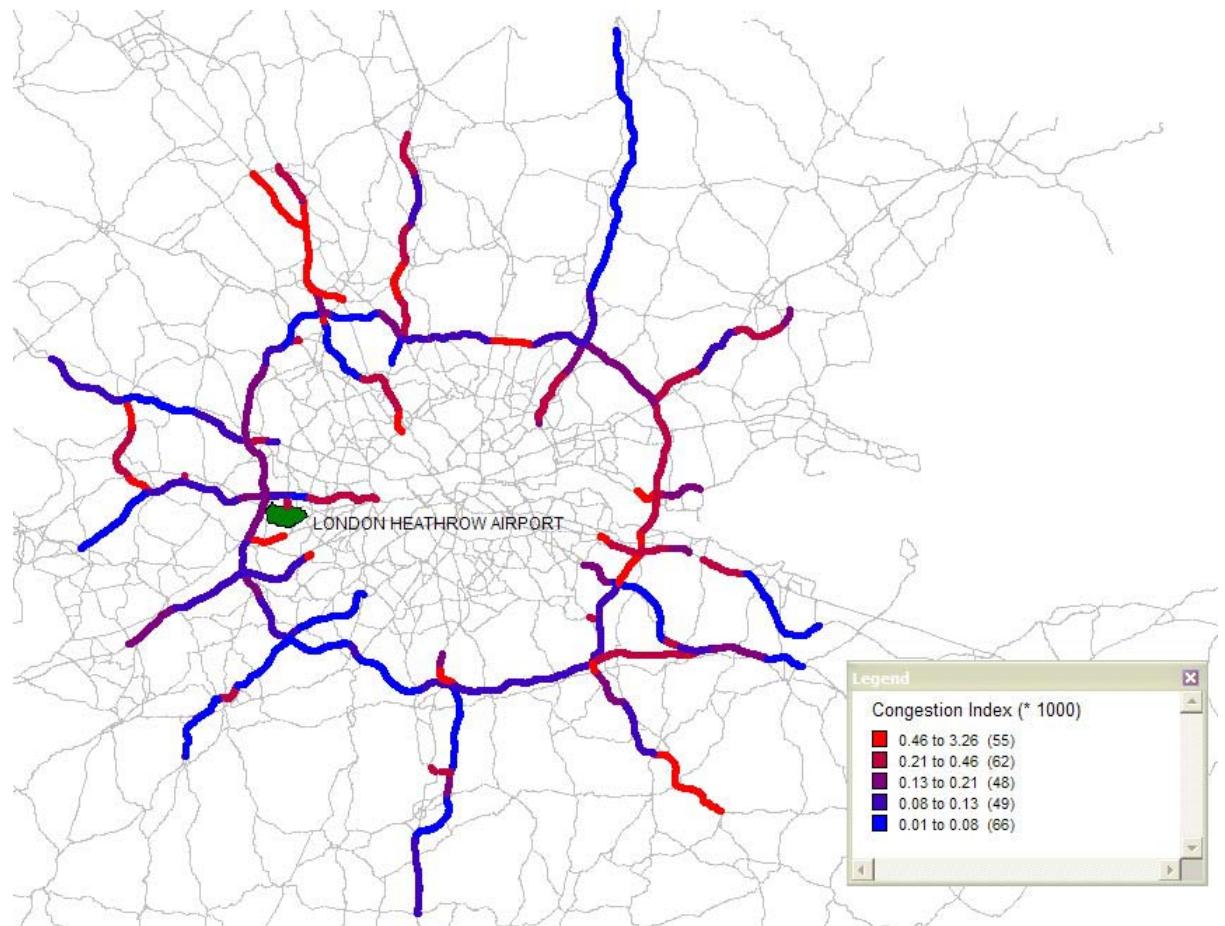
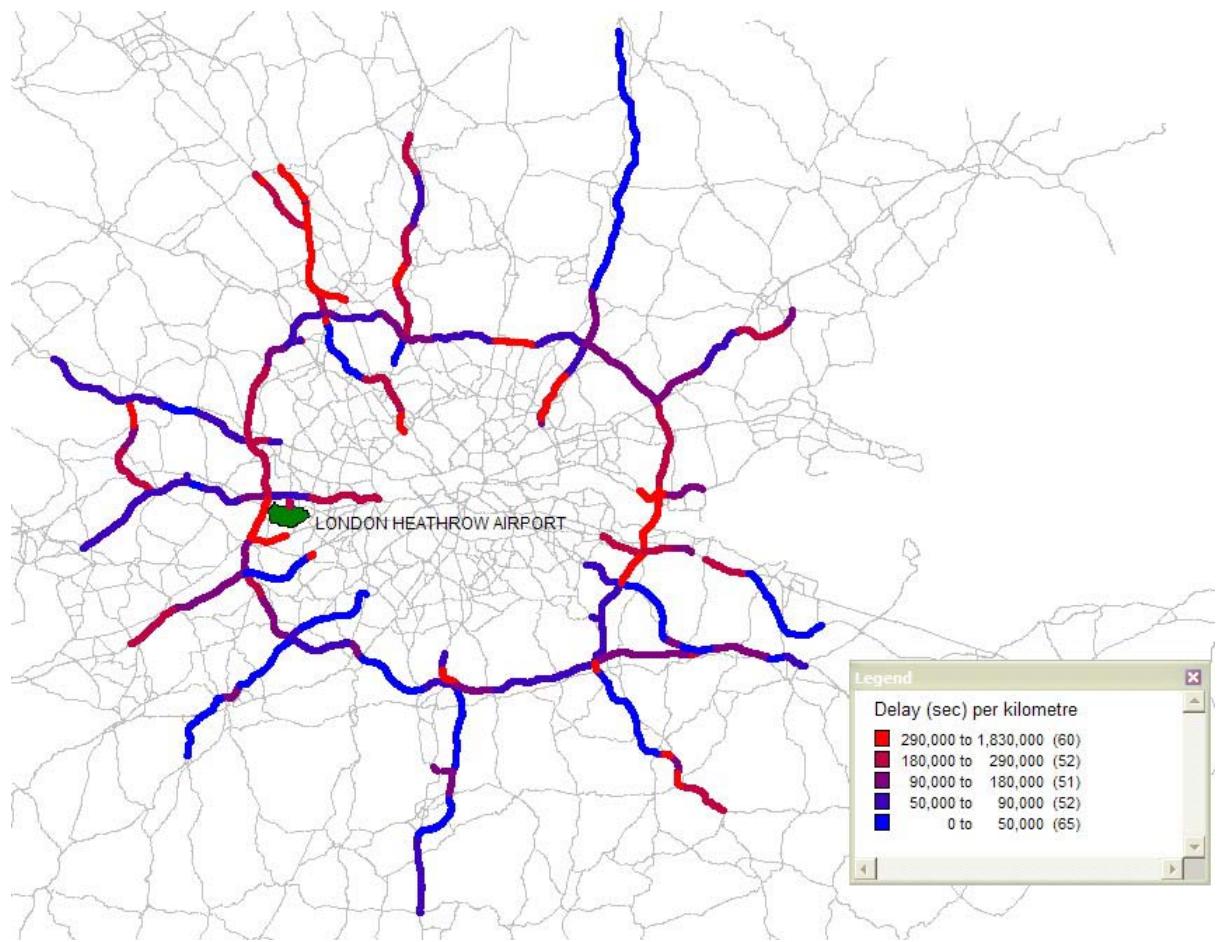


Figure 5.7 Spatial distribution of congestion index (CI) on the M25 and surround in 2007



**Figure 5.8 Spatial distribution of total delay (sec) per km on the M25 and surround in 2007**

It can be seen from Figures 5.7 and 5.8 that both the congestion measurements produce very similar spatial patterns of traffic congestion on the M25 and surround. For example, both figures indicate that the southern segments of the M25 have a low level of traffic congestion. Therefore, it appears that these two congestion measurements are reasonably consistent to each other in terms of spatial variations at a road segment level.

### 5.3 Data for analysing accident frequency

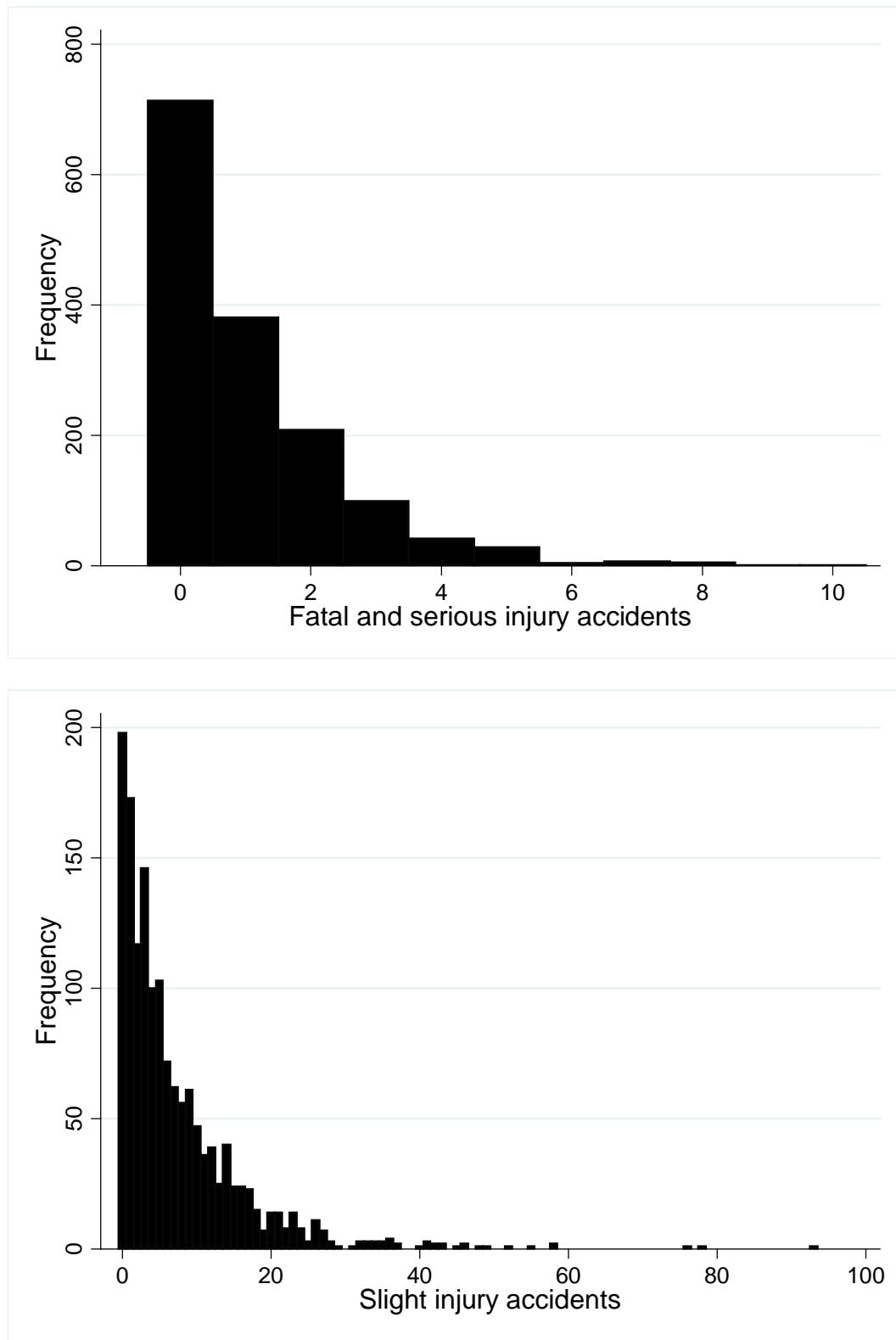
For the accident frequency analysis, using the map-matching technique described in Chapter 4 (section 4.4), all accidents have been assigned to the correct road segments. Counts of accidents (i.e. accident frequency) per segment per year were then obtained. Traffic characteristics data were aggregated at a road segment level (e.g., total traffic volume on a road segment in 2007), and eventually a panel dataset containing 298 cross-sectional observations for all road segments during 5 years' (2003-2007) period was created. Summary statistics of the accident, traffic characteristics and road

infrastructure data on the M25 motorway and surround for the accident frequency analysis are presented in Table 5.1:

**Table 5.1 Summary statistics of the variables for accident frequency analysis**

| Variable                                       | Obs   | Mean      | Standard Deviation | Min     | Max       |
|--|-------|-----------|--------------------|---------|-----------|
| <i>Accident</i>                                |       |           |                    |         |           |
| Fatal and serious injury accidents             | 1,391 | 1.071     | 1.418              | 0       | 10        |
| Slight injury accidents                        | 1,391 | 7.774     | 8.999              | 0       | 93        |
| <i>Traffic characteristics</i>                 |       |           |                    |         |           |
| Total delay (sec per km)                       | 1,391 | 197,279.7 | 242,742.9          | 622.865 | 1,900,374 |
| Congestion index (*1000)                       | 1,391 | 0.305     | 0.425              | 0.001   | 3.260     |
| Annual average daily traffic (AADT) (vehicles) | 1,391 | 45,675.48 | 20,667.55          | 5.918   | 98,394.83 |
| Average vehicle speed (km/h)                   | 1,391 | 84.918    | 14.757             | 33.663  | 118.134   |
| <i>Road segment characteristics</i>            |       |           |                    |         |           |
| Segment length (km)                            | 1,391 | 4.980     | 3.611              | 0.32    | 22.08     |
| Minimum radius (m)                             | 1,391 | 674.331   | 364.787            | 4.94    | 2,000     |
| Maximum gradient (%)                           | 1,391 | 3.175     | 1.337              | 0.6     | 8         |
| Number of lanes                                | 1,391 | 2.904     | 0.715              | 1       | 6         |
| Speed limit (km/h)                             | 1,391 | 109.628   | 7.997              | 64      | 112       |
| Motorway indicator                             | 1,391 | 0.689     | 0.463              | 0       | 1         |

The total number of observations is 1,391. Observations due to missing values for some road segments in certain years were excluded. This results in an unbalanced panel dataset which consists of repeated observations of a series of entities (e.g., road segments) over time (2003-2007), and as such the data are both cross-sectional and time-series. Due to the low frequency of fatal accidents, they have been combined with serious injury accidents. Therefore, there are two categories of accidents considered: fatal and serious injury accidents; and slight injury accidents. Average vehicle speed is weighted (by traffic flow) harmonic mean of hourly speed data. Minimum radius is the minimum value of radius for a road segment; and maximum gradient is the maximum value of gradient for a road segment (radius and gradient were measured around every 10 metres on a road section by the Highways Agency). Motorway indicator is a dummy variable with 1 representing motorway or A roads with motorway standard such as A1(M); and 0 representing other major A roads. Most road segments have very few or even zero accidents. This situation is shown by the histogram plots in Figure 5.9 (skewed to the right distribution).



**Figure 5.9 Histograms of road accidents on the M25 and surround (2003-2007)**

The spatial distributions of AADT and number of accidents in 2007 are shown in Figure 5.10 and Figure 5.11. It is noticeable from Figure 5.10 that the M25 has a higher traffic volume than other motorways and A roads. Comparing the level of congestion (Figure

5.7 and Figure 5.8) to the number of accidents (Figure 5.11), it is found that the southern segments of the M25 show a lower level of traffic congestion but a large number of accidents, suggesting that there may be an inverse relationship between traffic congestion and the number of accidents.

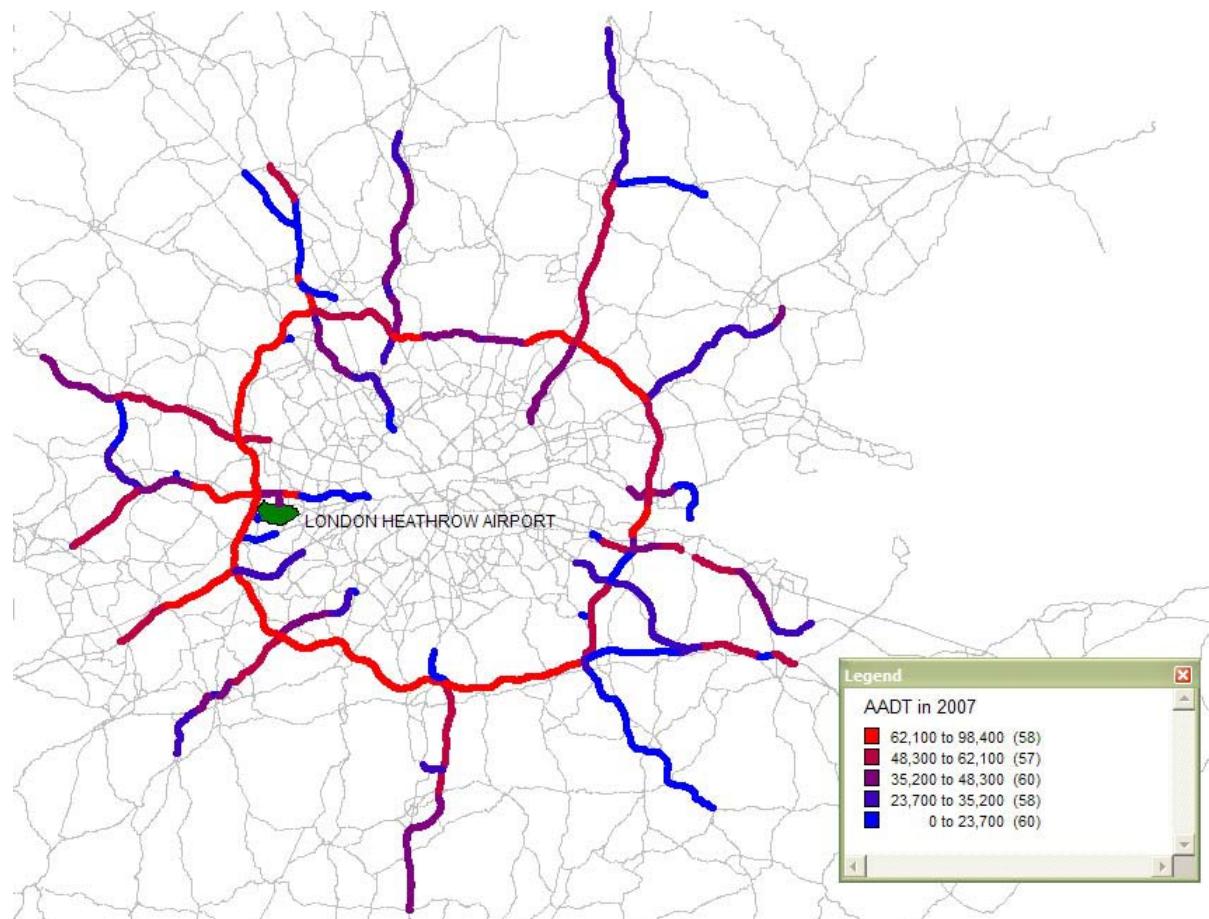
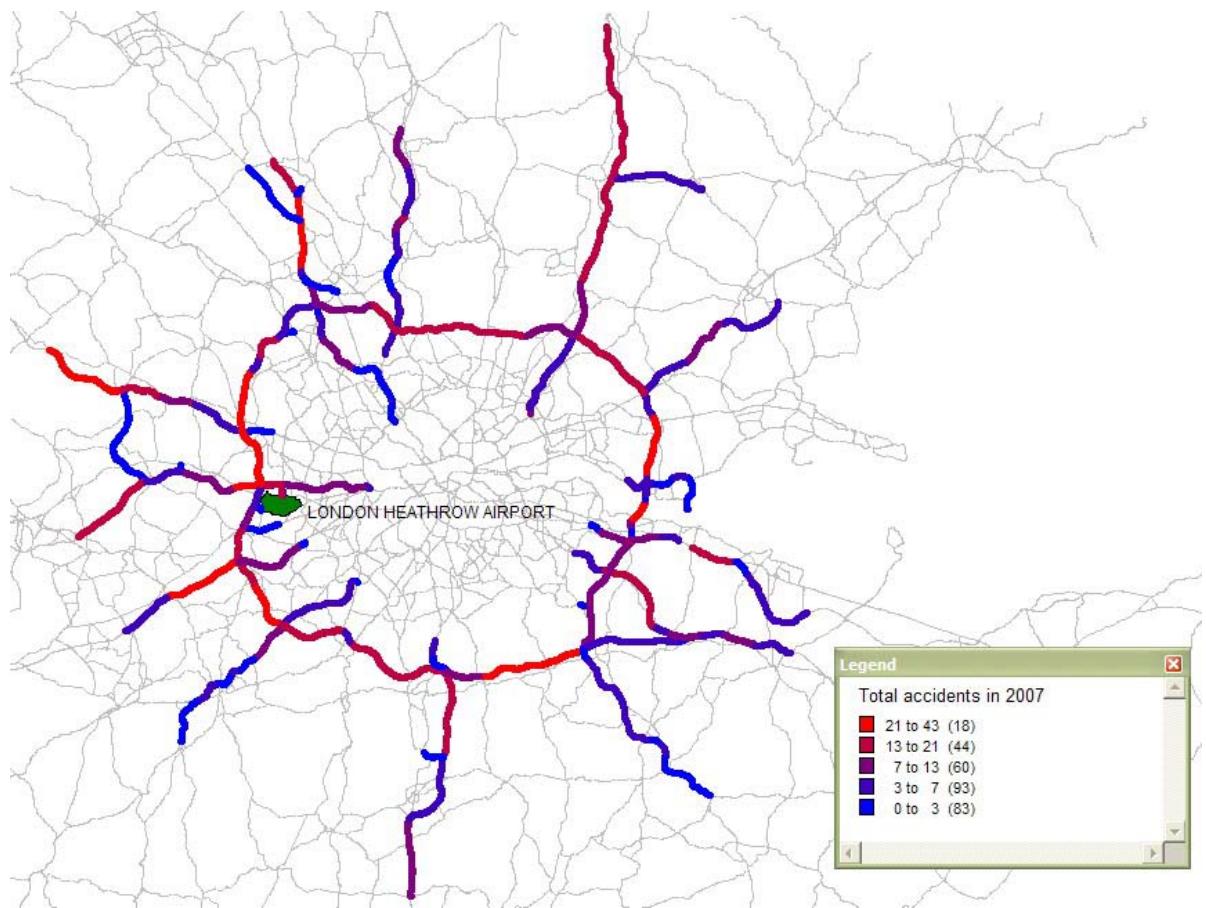


Figure 5.10 Spatial distribution of AADT on the M25 and surround in 2007



**Figure 5.11 Spatial distribution of total accidents on the M25 and surround in 2007**

An initial analysis of the data has been conducted to see whether there is any association between selected variables. This is presented in Figures 5.12-5.14.

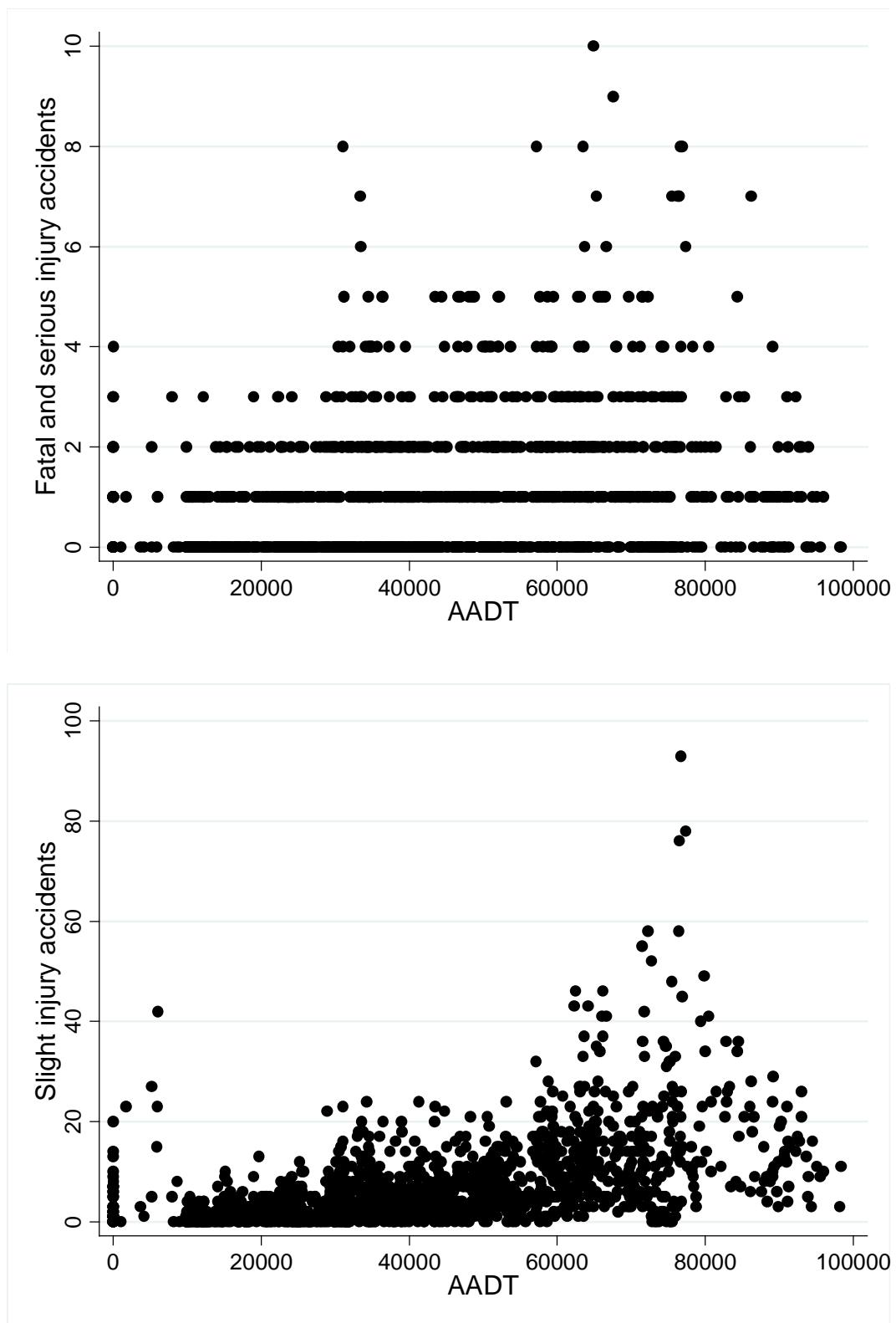


Figure 5.12 Road accidents and AADT (2003-2007)

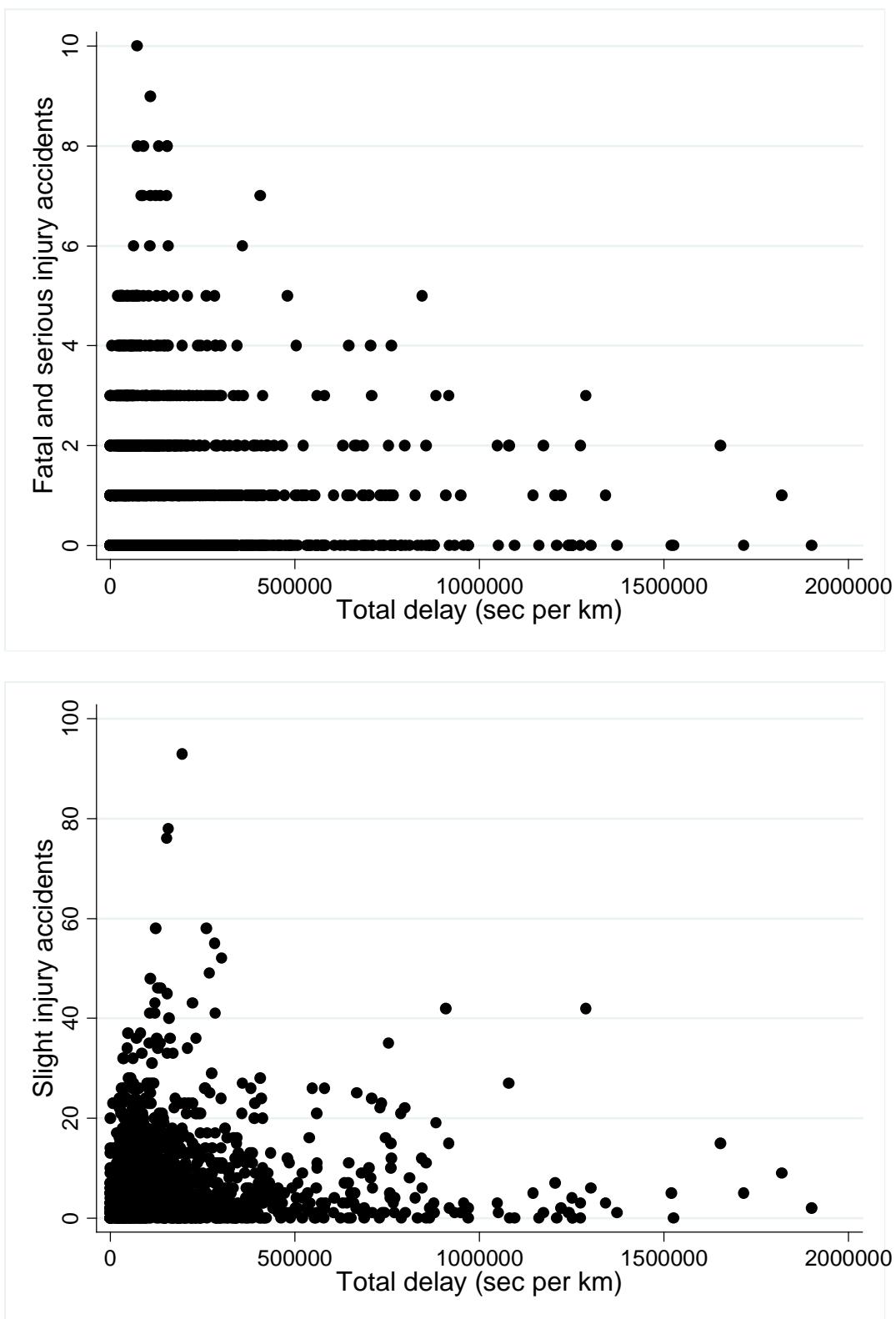
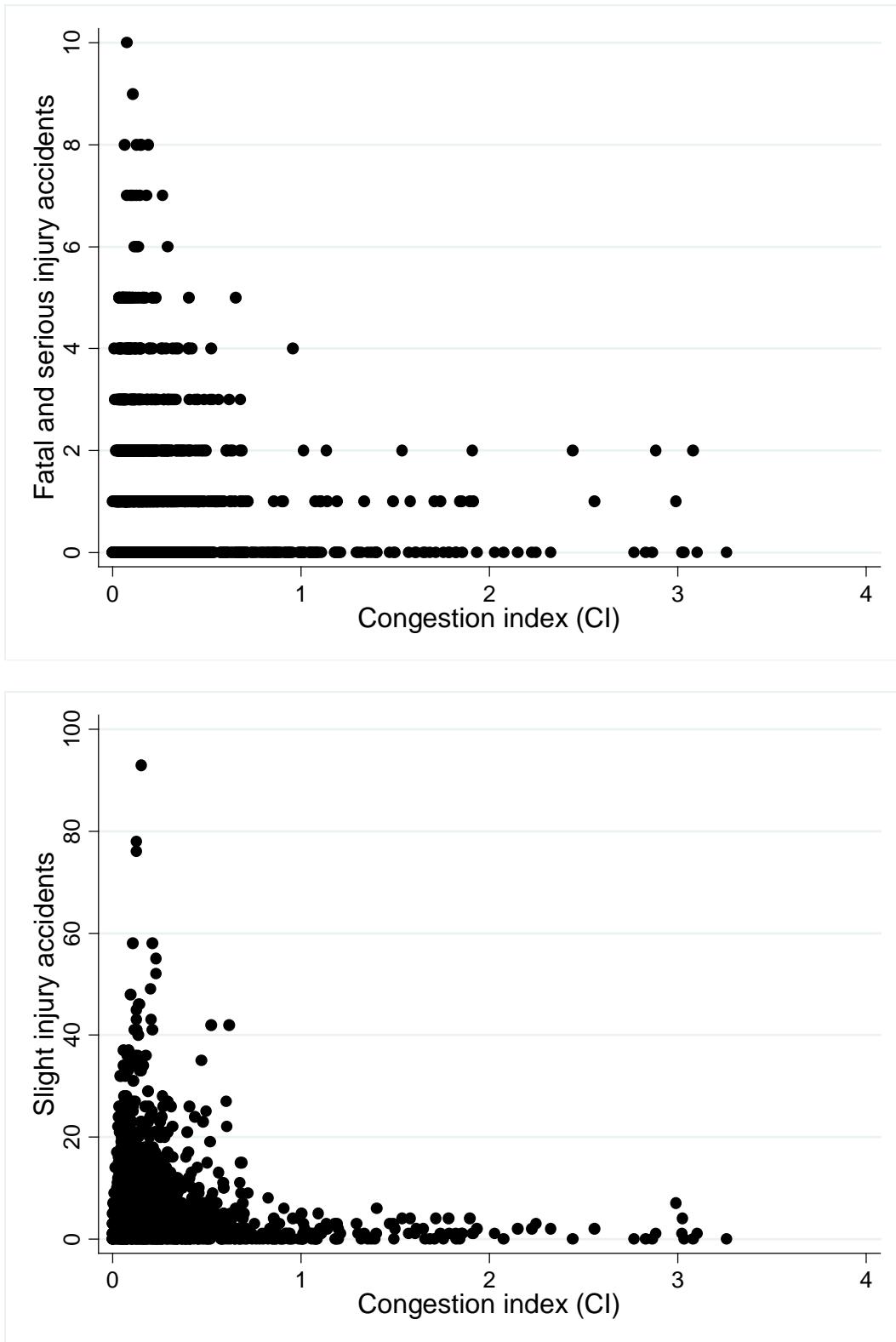


Figure 5.13 Road accidents and total delay per km (2003-2007)



**Figure 5.14 Road accidents and congestion index (CI) (2003-2007)**

As can be seen from Figures 5.12-5.14, no clear relationship can be found between fatal and serious injury accidents and AADT, total delay or congestion index. This may be due to the low count of fatal and serious injury accidents per road segment per year (see

Table 5.1). Generally a positive association can be noticed between slight injury accidents and AADT (Figure 5.12); however again no clear relationship is observed between slight injury accidents and total delay or the congestion index (Figure 5.13 and Figure 5.14). An econometric model controlling for other relevant risk factors therefore is required to fully understand the relationship between the number of accidents and the interested variables such as traffic congestion.

## 5.4 Data for analysing accident severity

In addition to accident location and severity information, other relevant data have been derived from the STATS19 database. This includes date, time, lighting, weather conditions, number of vehicles and number of causalities for each accident. The accident data have also been integrated into traffic and road geometry data from the UK Highways Agency based on the information of accident (location, time and date) and the corresponding segment-based characteristics. As a result, traffic and road geometry data for each accident record data such as level of congestion, speed, traffic flow and road curvature has been determined. In order to avoid the impact of an accident itself on traffic conditions, traffic data corresponding to a time period that is 30 minutes prior to the occurrence of an accident are used. For example, if an accident happened at 15:20 then hourly traffic data for 14:00 – 15:00 were used.

Finally, a dataset containing various traffic, road and environment information for each accident record on the M25 and surround during 2003-2007 was established. The summary statistics of the variables for the accident severity analysis are presented in Table 5.2:

**Table 5.2 Summary statistics of the variables for accident severity analysis**

| Variable                                   | Obs    | Mean      | Standard Deviation | Min  | Max     |
|--|--------|-----------|--------------------|------|---------|
| Level of accident severity*                | 12,613 | 1.140     | 0.393              | 1    | 3       |
| <i>Traffic characteristics</i>             |        |           |                    |      |         |
| Level of traffic congestion (min per 10km) | 12,284 | 8.562     | 22.436             | 0    | 751.935 |
| Traffic flow (veh/h)                       | 12,066 | 3,220.986 | 1,684.076          | 0    | 8,251   |
| Average travel speed (km/h)                | 12,613 | 84.733    | 21.140             | 3.1  | 190.3   |
| <i>Road segment infrastructure</i>         |        |           |                    |      |         |
| Minimum radius (m)                         | 12,613 | 725.540   | 295.619            | 4.94 | 2,000   |
| Maximum gradient (%)                       | 12,613 | 3.211     | 1.123              | 0.6  | 8       |
| Number of lanes ≤ 3 indicator              | 12,613 | 0.791     | 0.406              | 0    | 1       |
| Number of lanes ≥ 5 indicator              | 12,613 | 0.034     | 0.180              | 0    | 1       |
| Motorway indicator                         | 12,613 | 0.835     | 0.371              | 0    | 1       |
| Speed limit (km/h)                         | 12,613 | 109.093   | 10.395             | 32   | 112     |
| <i>Environment indicators</i>              |        |           |                    |      |         |
| Lighting condition (darkness)              | 12,613 | 0.321     | 0.467              | 0    | 1       |
| Weather (fine)                             | 12,613 | 0.820     | 0.384              | 0    | 1       |
| Weather (raining)                          | 12,613 | 0.142     | 0.349              | 0    | 1       |
| Weather (snowing)                          | 12,613 | 0.005     | 0.068              | 0    | 1       |
| Other weather conditions (e.g. fog/mist)   | 12,613 | 0.034     | 0.181              | 0    | 1       |
| <i>Other factors</i>                       |        |           |                    |      |         |
| Peak time indicator                        | 12,613 | 0.827     | 0.379              | 0    | 1       |
| Weekday indicator                          | 12,613 | 0.753     | 0.431              | 0    | 1       |
| Single vehicle accident indicator          | 12,613 | 0.192     | 0.394              | 0    | 1       |
| Number of casualties per accident          | 12,613 | 1.605     | 1.189              | 1    | 42      |

\* 1=slight injury accident, 2=serious injury accident, 3=fatal accident

As can be seen from Table 5.2 there were a total number of 12,613 accidents on the M25 and surround, over the period 2003-2007 with approximately 2,500 accident records each year. The mean value of the accident severity variable is 1.14, meaning that the majority of accidents are slight injury accidents. To be more precise, 87.75% (11,068) of total accidents were slight injury accidents; 10.54% (1,329) were serious injury accidents; and only 1.71% (216) were fatal accidents. The mean values of some interested variables, such as the level of traffic congestion, average travel speed and traffic flow at each accident severity level is presented in Table 5.3:

**Table 5.3 Mean values of some interested variables at each accident severity level**

| Accident severity | Congestion (min per 10km) | Average speed (km/h) | Traffic flow (veh/h) |
|-------------------|---------------------------|----------------------|----------------------|
| Slight            | 8.772                     | 84.371               | 3309.122             |
| Serious           | 7.372                     | 86.781               | 2697.431             |
| Fatal             | 5.036                     | 90.684               | 1941.438             |

As shown in Table 5.3, the average level of traffic congestion (min per 10km) for the case of slight injury accidents is 8.772min. This decreases to 7.372min for the case of serious injury accidents and further decreases to 5.036min for the case of fatal accidents. This suggests that there may be an inverse relationship between the level of congestion and accident severity. A similar association can be found for traffic flow. Average speed on the other hand shows a different but expected result: namely increased average speed is associated with a higher accident severity level.

It is also worth noting that although the maximum value of the level of congestion is 751.9 (min per 10km), the mean value of this variable is only 8.562, meaning that the congestion level is relatively low (compared to the maximum value) for most accidents that occurred on the M25 and surround. To be more precise, congestion levels for more than 95% of accidents are below 50 (min per 10km). The histogram of the levels of traffic congestion is shown in Figure 5.15.

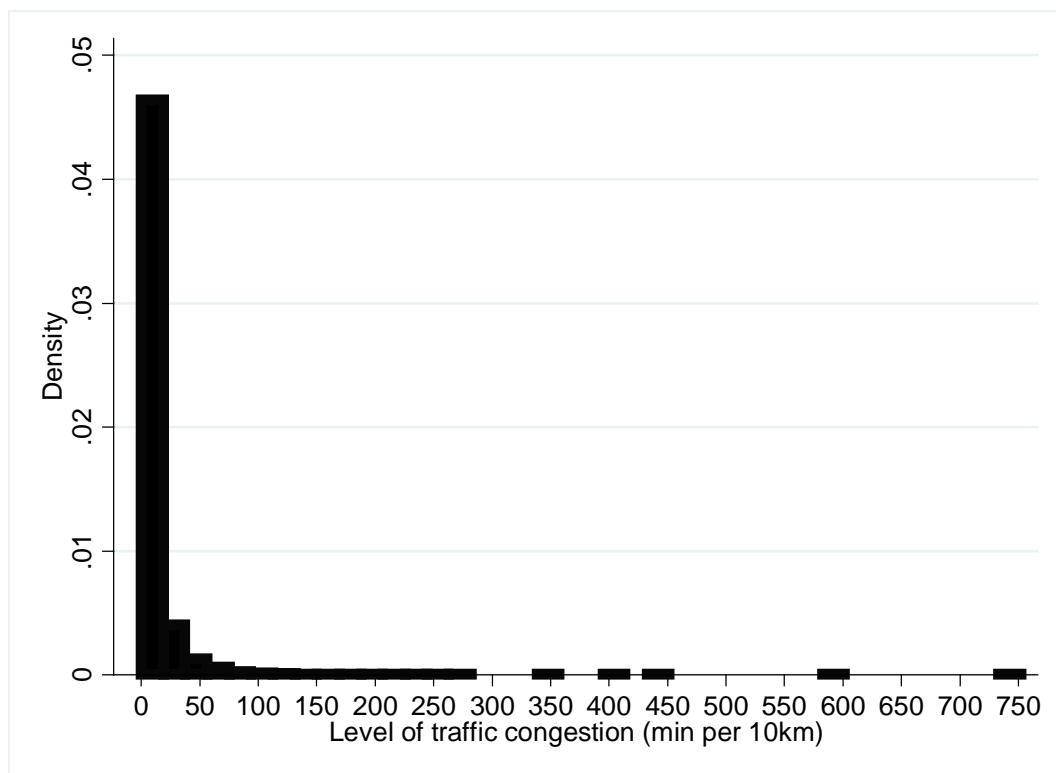


Figure 5.15 Histogram of the levels of traffic congestion for individual accidents

## 5.5 Data validation

As mentioned above, the data used in this thesis come from two sources: STATS19 database for accident data; and the UK Highways Agency for traffic and road characteristics data. It is important to validate the data to ensure accuracy and quality. Otherwise if the data were inaccurate or in poor quality, the modelling results would also be biased.

The accident data, i.e. the STATS19 data are collected by the police in the UK and therefore, are considered the “most detailed, complete and reliable single source” of accident data in the UK (DfT, 2009a). In addition to the police data (i.e. the STATS19 data), there are several other sources of data relating to road accidents in the UK, such as death registrations data, hospital data, compensation claims data and National Travel Survey (NTS) data on road accidents. DfT (2009a) compares the STATS19 data with the external data sources, concluding that the STATS19 data are the most “useful” and “best” source of accident data. Data on road fatalities may be the most reliable. This can be illustrated in Figure 5.16 which shows the comparison between the STATS19 data and the death registration data. However the STATS19 data are not perfect, for example, there are some differences in serious injury accidents between STATS19 data

and hospital data; and the NTS data suggested that a considerable number of non-fatal accidents were not reported to the police (DfT, 2009a). As to the under-reporting problem, accidents were classified into different categories by their severity levels and were modelled separately in the accident frequency analysis. In addition, as discussed in Chapters 3 and 4, the unordered nominal response models employed in this thesis were able to handle the under-reporting problem in the accident severity analysis.

As for road characteristics data (from the Highways Agency), it can be compared with the data from digital maps in MapInfo (a GIS software package) and images from Google Maps. For example, the length of each road segment was calculated from the digital maps in MapInfo, which was then compared with the road length data obtained from the Highways Agency. It has been found that for road segment length the average (absolute) difference between the two sources is 0.13 (km). A t-test has been performed showing that the differences between the two data sources on road segment length are statistically insignificant at the 95% confidence level. The images from Google Maps have also been used to validate the road characteristics data. For instance, “number of lanes” per road segment were examined by the images from Google Maps which shows the data from the Highways Agency is accurate.

As for traffic characteristics data, a probe vehicle was driven around the M25 (on 26 November 2009, in the anticlockwise direction) so as to investigate the reliability of the travel time data provided by the Highways Agency. Figure 5.17 compares travel time on the M25 road segments collected by the probe vehicle with the data provided by the Highways Agency (5 years’ average). It can be seen that the two sources of data are reasonably consistent with each other for most road segments. A t-test has also been performed and the result has indicated that the differences between the two data sources are statistically insignificant at the 95% confidence level. Therefore it is believed that the traffic characteristics data (e.g., travel time, delay and traffic flow) from the Highways Agency are reliable and of sound quality.

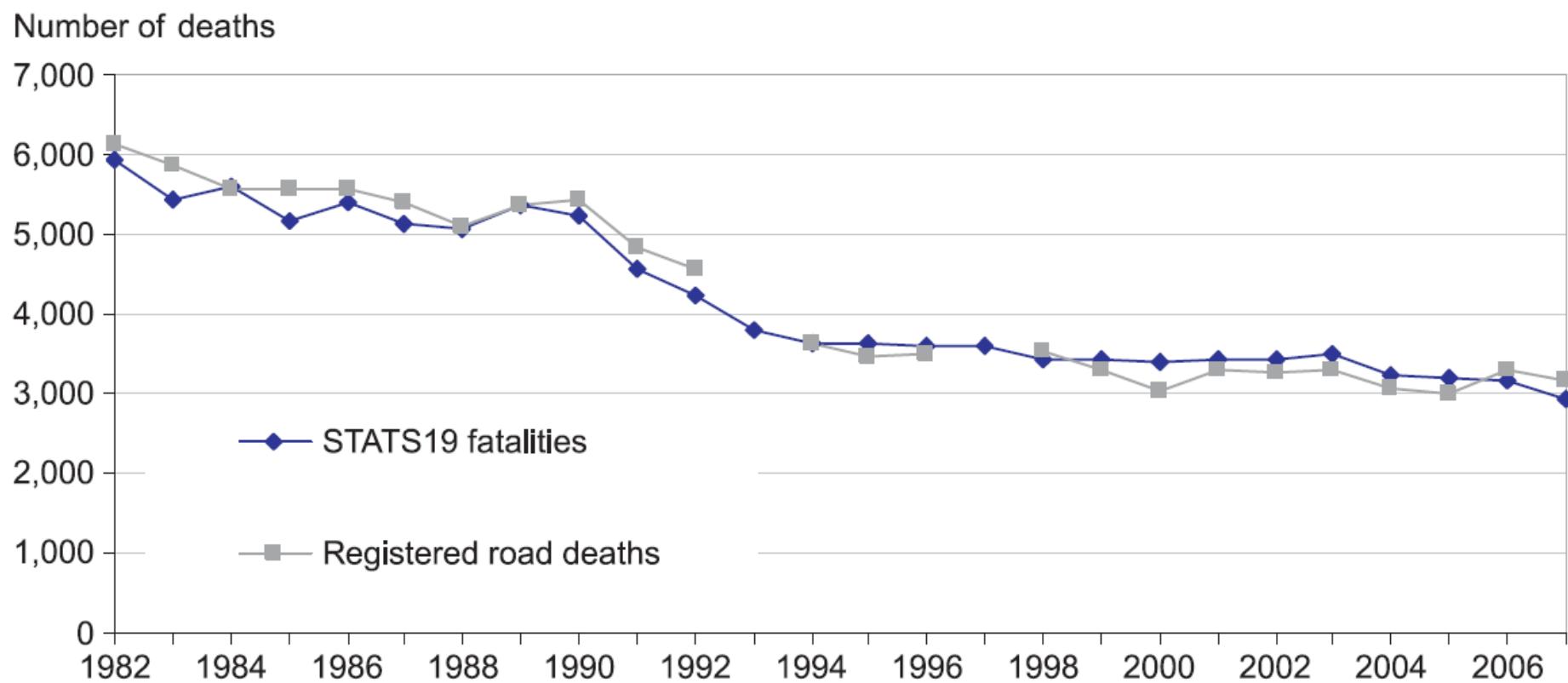


Figure 5.16 Comparison between STATS19 fatalities and registered road deaths in Great Britain (source: DfT, 2009a)

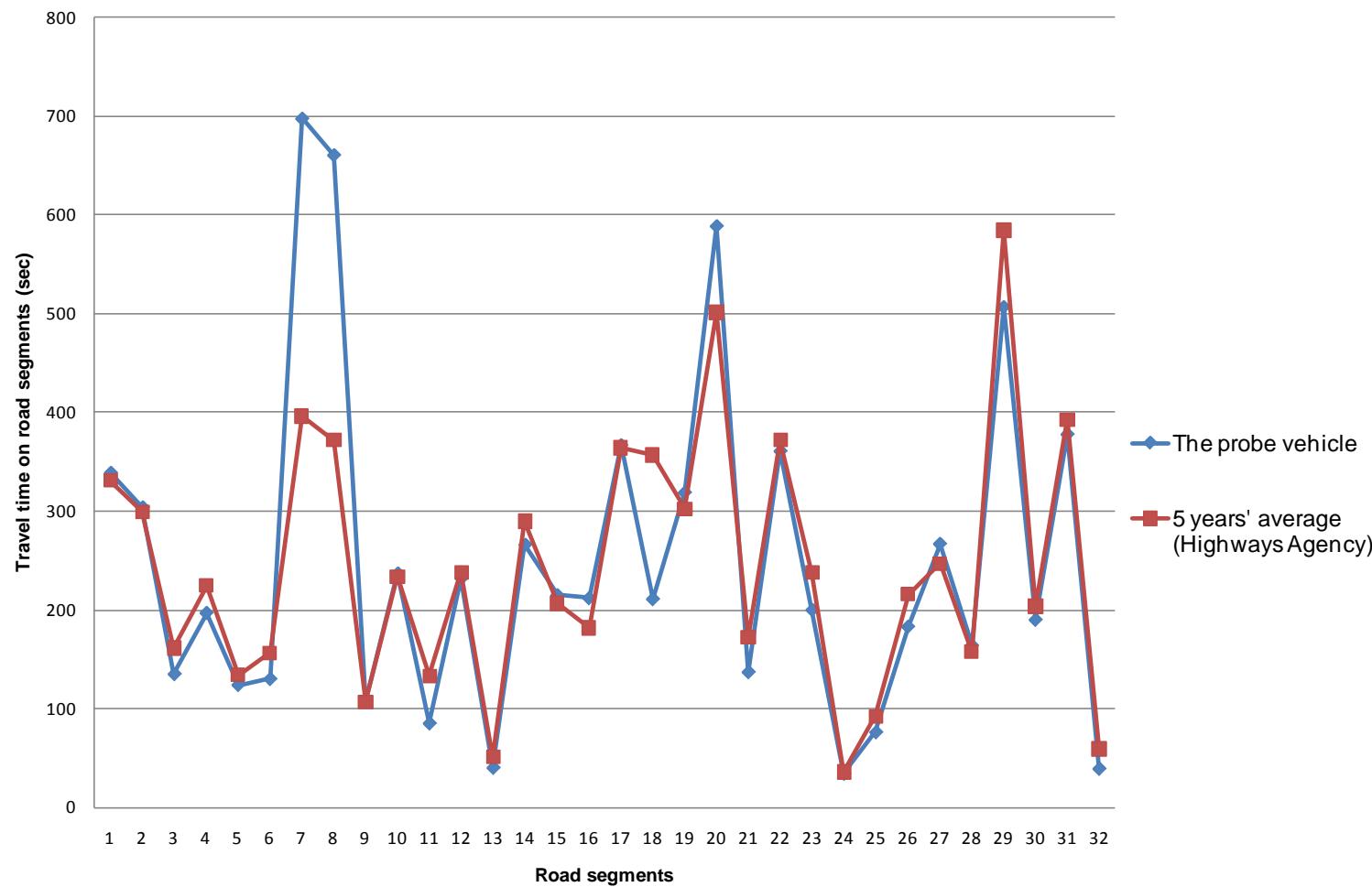


Figure 5.17 Comparison between the travel time data collected by the probe vehicle and the Highways Agency data (5 years' average)

## 5.6 Summary

This chapter has presented the data to be employed in the following chapters. This includes the two congestion measurements – i.e. the congestion index and total delay per length of road. Both the congestion measurements produced similar spatial patterns on the M25 and surround, and therefore they are consistent to each other in terms of spatial variations at an aggregate road segment level. Total delay per length was found to be appropriate at a disaggregate individual accident level as it produced expected temporal variations over a day.

The descriptive statistics of the variables (e.g., number of accidents, traffic flow and radius of road curvature) to be employed in both accident frequency and accident severity models were also presented. Data were validated externally to ensure its accuracy and quality. The accident data (i.e. STATS19 data) were compared with other sources of data such as the death registration data. The road characteristics data (obtained from the Highways Agency) were compared with the data from MapInfo and images from Google Maps. The traffic characteristics data (also from the Highways Agency) were compared with the data collected by a probe vehicle. It was concluded that generally the data used in this thesis are reliable and of sound quality.

The model estimation results using the data are presented in the subsequent chapters.

# CHAPTER 6 RESULTS FROM ACCIDENT FREQUENCY MODELS

## **6.1 Introduction**

The relationship between traffic congestion and road accidents has been investigated in two aspects: the effect of traffic congestion on accident *frequency* and the effect of traffic congestion on accident *severity*. The effect of traffic congestion on road accident frequency has been examined using the accident frequency models described in Chapter 4 (see section 4.5). The model estimation results and findings are presented in this chapter. The results on the effect of traffic congestion on accident severity are presented in the next chapter.

This chapter is organised as follows: first, the results from a spatial analysis of the M25 as a case study are presented. This is followed by a more comprehensive spatio-temporal analysis of a wider road network (the M25 and surround) consisting of data for multiple years (2003-2007). Finally a summary of the results and findings is provided.

## **6.2 A spatial analysis of the M25**

A preliminary spatial analysis in a cross-sectional setting has been conducted, based on the M25 motorway as a case study, to explore the relationship between traffic congestion and the frequency of road accidents. A total of 70 road segments (excluding road segments with missing values) have been identified on the M25. Hourly segment-based traffic characteristics data (such as average travel time, average travel speed, traffic flow and total vehicle delay) for the year 2006 have been used. As discussed in Chapter 5, fatal and serious injury accidents were combined due to the low frequency of fatal accidents. Accident data (at all severity levels) for 2004-2006 have been aggregated so as to avoid many segments with a zero accident count, especially for the case of fatal and serious injury accidents. This can also ease the variability of accident frequency from year to year and this is also a common practice in existing studies (e.g., Abdel-Aty and Radwan, 2000; Graham and Glaister, 2003; Haynes et al., 2007). In this case study of the M25, the direction of the road segments is also considered and

included in the models as a dummy variable with 0 representing anticlockwise and 1 representing clockwise direction. Four different model specifications that are suitable for cross-sectional count data were estimated using a full Bayesian approach: a Poisson-lognormal, a Poisson-gamma and a Poisson-lognormal with conditional autoregressive (CAR) priors (first and second order neighbouring structure) as described in Chapter 4 (see section 4.5.2).

A congestion index measured as the ratio of delay over free flow travel time has been employed in the models as a measurement of traffic congestion (see section 4.3.2 in Chapter 4). To reduce the large variation among the explanatory variables, annual average daily traffic (AADT) and radius of road curvature have been transformed into a logarithmic scale. Other forms of explanatory variables have also been tested, for example, radius of curvature and gradient have been transformed into indicator (dummy) variables and such dummy variables have provided similar results. Average vehicle speed has been excluded from the models as this is highly correlated with the congestion index (correlation coefficient: -0.71). The correlation coefficients between other independent variables have also been examined and the maximum value has been found to be 0.59 suggesting that multicollinearity is not a problem for the rest of the explanatory variables. The correlation coefficients of the variables considered are presented in Table 6.1.

**Table 6.1 Correlation coefficients between variables employed in the model**

|                     | Congestion index | Road segment length | Average speed | log(minimum radius) | Maximum gradient | Number of lanes | Direction |
|---------------------|------------------|---------------------|---------------|---------------------|------------------|-----------------|-----------|
|                     | log(AADT)        |                     |               |                     |                  |                 |           |
| Congestion index    | 1.00             |                     |               |                     |                  |                 |           |
| log(AADT)           | -0.54            | 1.00                |               |                     |                  |                 |           |
| Road segment length | -0.34            | 0.30                | 1.00          |                     |                  |                 |           |
| Average speed       | <b>-0.71</b>     | 0.22                | 0.47          | 1.00                |                  |                 |           |
| log(minimum radius) | -0.06            | 0.59                | 0.15          | -0.04               | 1.00             |                 |           |
| Maximum gradient    | -0.08            | -0.31               | 0.32          | 0.14                | -0.42            | 1.00            |           |
| Number of lanes     | -0.22            | 0.59                | 0.10          | 0.21                | 0.21             | -0.38           | 1.00      |
| Direction           | -0.17            | 0.02                | 0.00          | 0.16                | -0.10            | 0.00            | -0.06     |
|                     |                  |                     |               |                     |                  |                 | 1.00      |

The posterior means and standard deviations (S.D.) of the coefficients for the explanatory variables, the standard deviations of heterogeneity<sup>20</sup> and spatial correlation have been estimated using the Markov Chain Monte Carlo (MCMC) method. Two chains were simulated with different initial values and the initial 20,000 iterations (for

<sup>20</sup> For Poisson-gamma models the standard deviations of  $\exp(v)$  have been estimated.

the case of the fatal and serious injury accident model) and 75,000 iterations (for the case of the slight injury accident model) were discarded as burn-ins to achieve the convergence of the two chains. Further, 70,000 – 75,000 iterations for each chain were performed and kept to calculate the summary statistics of interested parameters such as posterior means and standard deviations. The estimation results for both categories of accidents (i.e. fatal and serious injury accidents and slight injury accidents) are presented in Tables 6.2 and 6.3.

**Table 6.2 Models for fatal and serious injury accidents on the M25**

| Variables            | Poisson-lognormal |        | Poisson-gamma   |        | Poisson-lognormal<br>CAR<br>(1st order neighbour) |         | Poisson-lognormal<br>CAR<br>(2nd order neighbour) |         |
|----------------------|-------------------|--------|-----------------|--------|---|---------|---|---------|
|                      | Mean              | S.D.   | Mean            | S.D.   | Mean  | S.D.    | Mean  | S.D.    |
| Congestion index     | -0.5877           | 0.6958 | -0.4225         | 0.7935 | -0.6934   | 0.7256  | -0.7836   | 0.7485  |
| log(AADT)            | <b>1.212**</b>    | 0.4942 | <b>1.856**</b>  | 0.5465 | <b>1.435**</b>                                    | 0.4316  | <b>1.227**</b>                                    | 0.5195  |
| Segment length (km)  | <b>0.1351**</b>   | 0.0260 | <b>0.1475**</b> | 0.0337 | <b>0.1362**</b>                                   | 0.0241  | <b>0.1362**</b>                                   | 0.0247  |
| log(minimum radius)  | 0.234             | 0.2121 | 0.2916          | 0.2289 | 0.2525  | 0.1955  | 0.2966  | 0.3380  |
| Maximum gradient (%) | <b>0.1868*</b>    | 0.0993 | <b>0.2103*</b>  | 0.1130 | <b>0.2026**</b>                                   | 0.0912  | <b>0.2099**</b>                                   | 0.1290  |
| Number of lanes      | -0.0961           | 0.1601 | -0.2023         | 0.1869 | -0.0416   | 0.1544  | 0.0023  | 0.1892  |
| Direction            | 0.0543            | 0.1585 | 0.0855          | 0.1957 | -0.1469   | 0.3115  | -0.1596   | 0.3178  |
| Intercept            | <b>-14.77**</b>   | 5.0330 | <b>-22.08**</b> | 5.28   | <b>-17.49**</b>                                   | 4.511   | <b>-15.64**</b>                                   | 6.009   |
| S.D. ( $\mu$ )       |                   |        |                 |        | <b>0.1244**</b>                                   | 0.07992 | <b>0.2376**</b>                                   | 0.1429  |
| S.D. ( $\nu$ )       |                   |        |                 |        | <b>0.5285**</b>                                   | 0.0790  | <b>0.1759**</b>                                   | 0.1427  |
| DIC                  |                   |        |                 |        |   | 282.358 |   | 284.038 |
| <i>N</i>             |                   | 70     |                 | 70     |   | 70      |   | 70      |

\* Statistically significantly different from zero (90% credible sets show the same sign)

\*\* Statistically significantly different from zero (95% credible sets show the same sign)

**Table 6.3 Models for slight injury accidents on the M25**

| Variables            | Poisson-lognormal |        | Poisson-gamma   |        | Poisson-lognormal<br>CAR<br>(1st order neighbour) |        | Poisson-lognormal<br>CAR<br>(2nd order neighbour) |        |
|----------------------|-------------------|--------|-----------------|--------|---|--------|---|--------|
|                      | Mean              | S.D.   | Mean            | S.D.   | Mean  | S.D.   | Mean  | S.D.   |
| Congestion index     | 0.1513            | 0.4382 | -0.1181         | 0.4199 | 0.3731  | 0.5493 | 0.2966  | 0.4477 |
| log(AADT)            | <b>1.492**</b>    | 0.2919 | <b>1.026**</b>  | 0.2346 | <b>1.525**</b>                                    | 0.6250 | <b>1.376**</b>                                    | 0.3756 |
| Segment length (km)  | <b>0.1505**</b>   | 0.0231 | <b>0.1582**</b> | 0.0269 | <b>0.1587**</b>                                   | 0.0225 | <b>0.1584**</b>                                   | 0.0206 |
| log(minimum radius)  | 0.0244            | 0.1754 | 0.0526          | 0.1399 | 0.0220  | 0.1858 | 0.0647  | 0.1473 |
| Maximum gradient (%) | <b>0.2287**</b>   | 0.0871 | <b>0.1896**</b> | 0.0804 | <b>0.2285**</b>                                   | 0.0780 | <b>0.2291**</b>                                   | 0.0663 |
| Number of lanes      | <b>0.1912*</b>    | 0.1074 | <b>0.262**</b>  | 0.1159 | 0.1893  | 0.1461 | <b>0.2237*</b>                                    | 0.1204 |
| Direction            | 0.0046            | 0.1328 | 0.0049          | 0.1421 | -0.0788   | 0.2459 | -0.0664   | 0.2250 |
| Intercept            | <b>-15.53**</b>   | 3.0960 | <b>-10.55**</b> | 2.3570 | <b>-15.93**</b>                                   | 6.0140 | <b>-14.66**</b>                                   | 3.4880 |
| S.D. ( $u$ )         |                   |        |                 |        | <b>0.0964**</b>                                   | 0.0882 | <b>0.1341**</b>                                   | 0.1303 |
| S.D. ( $v$ )         | <b>0.4777**</b>   | 0.0600 | <b>0.5291**</b> | 0.0571 | <b>0.4294**</b>                                   | 0.0957 | <b>0.4184**</b>                                   | 0.0790 |
| DIC                  | 490.053           |        | 482.197         |        | 490.286   |        | 489.130   |        |
| N                    | 70                |        | 70              |        | 70  |        | 70  |        |

\* Statistically significantly different from zero (90% credible sets show the same sign)

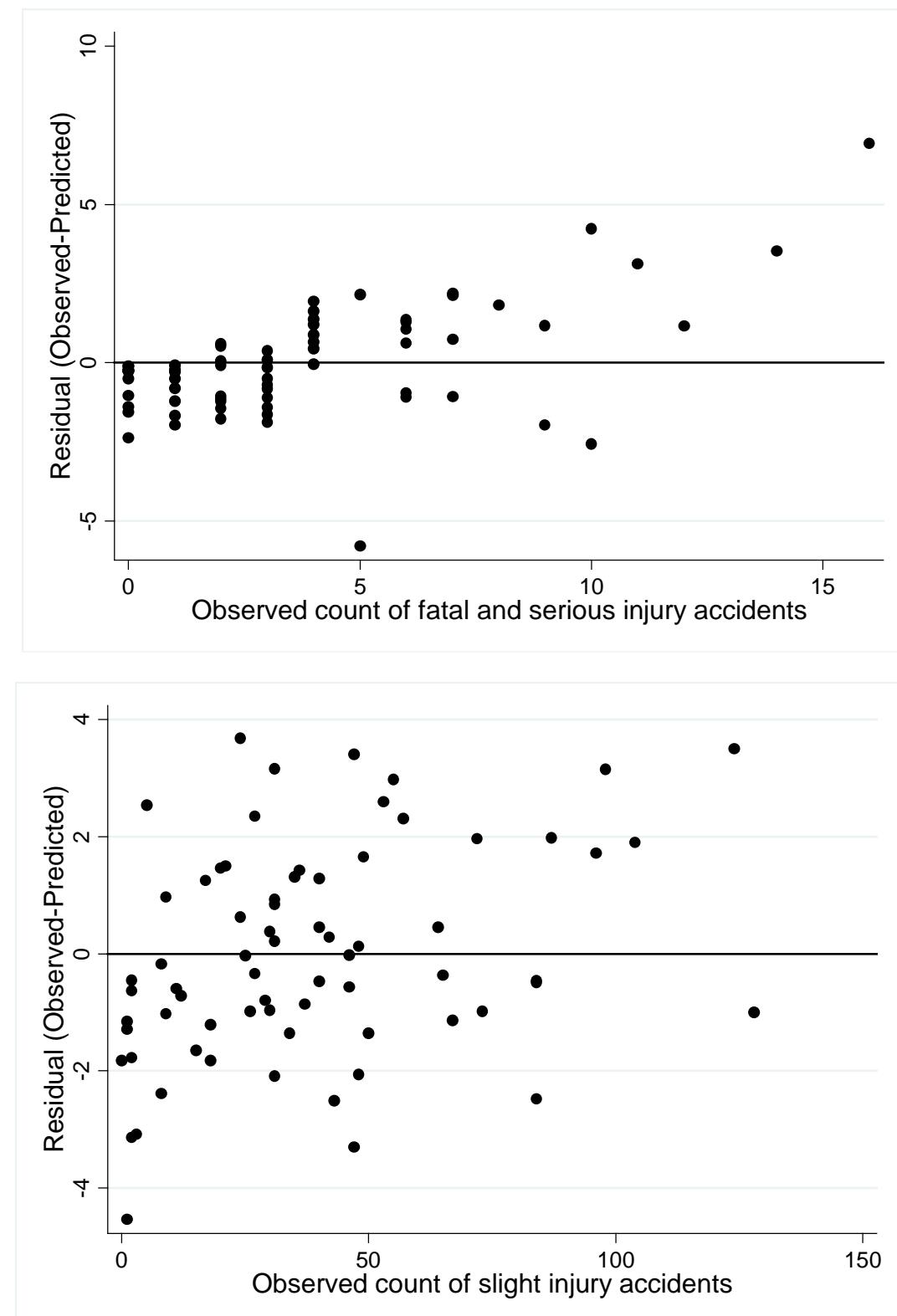
\*\* Statistically significantly different from zero (95% credible sets show the same sign)

As can be seen in Table 6.2, all specifications of Poisson models produce similar results in terms of the set of statistically significant variables and the values of their coefficients. It is also interesting to note that, as expected the mean values of the coefficients from the Poisson-gamma models under the Bayesian framework are very similar to the coefficients estimated from the classical Poisson-gamma models (i.e. Negative Binomial models) using the maximum likelihood estimation (MLE) method. In all specifications for the case of fatal and serious injury accidents, the statistically significant variables are *log of AADT*, *length of the segment* and *maximum vertical grade (%)*. These variables are also found to be statistically significant across all specifications in explaining the variation in the frequency of slight injury accidents on the segments of the M25 motorway (see Table 6.3). The variable *number of lanes* however becomes significant in all specifications except one (see Table 6.3). The posterior mean of the standard deviation of uncorrelated heterogeneity ( $v$ ) is found to be statistically significant across all models suggesting that the effect of heterogeneity does exist in the accident data. Note for Poisson-gamma models, the standard deviations of  $\exp(v)$  have been estimated, the values of which are equal to the square root of the overdispersion parameter (see Chapter 4 section 4.5.1 for the formulations). The fact that the values are significant (Tables 6.2 and 6.3) suggests that the accident data are overdispersed, so the use of a simple Poisson model is insufficient. Similarly, the posterior mean of the standard deviation of spatial correlation ( $u$ ) for both types of road accidents is also statistically significant suggesting that road accidents are spatially correlated among neighbouring road segments. The mean values for the effects of spatial correlation among neighbouring segments range from 0.09 to 0.27 and are statistically significant suggesting that one should consider such effects when developing a relationship between accident frequency and their contributing factors. The effect of spatial correlation for the case of fatal and serious injury accidents is generally found to be slightly higher than the case for slight injury accidents (with the exception for the case of off-peak accidents as shown in Tables 6.6 and 6.7).

The DIC values for different specifications are found to be similar for both categories of accidents, suggesting that there is no significant difference among different specifications tested in terms of model fit and complexity. The CAR model with the second-order neighbour does not provide a significant improvement in terms of model fit compared to the CAR model with the first-order neighbour. Generally, the Poisson-

gamma model fitted the data slightly better, especially for the case of slight injury accidents (with the exception of the case of off-peak fatal and serious injury accidents shown in Table 6.6). The better statistical fit however does not necessarily mean that the model could better reflect the theory of accidents and the actual effects of relevant factors (Lord et al., 2005b).

The predicted count of accidents from the Bayesian models can be obtained from monitoring the posterior means of the expected accident counts on road segments. Figure 6.1 shows the relationship between the observed and the residual (=observed-predicted) values of accident frequency on the M25 for the Poisson-lognormal CAR model. As can be seen, the model was specified appropriately and well fitted the data. The effects of various explanatory variables in the models are discussed below.



**Figure 6.1** The relationship between the observed and the residual values of accidents for the Poisson-lognormal CAR model

### 6.2.1 Congestion

The congestion index was calculated for each of the M25 motorway segments to appropriately represent the level of congestion. In the case of fatal and serious injury accidents, this variable revealed the negative sign suggesting that the increased level of congestion is associated with the decreased level of fatal and serious injury accident occurrences. This variable however has been found to be statistically insignificant in all forms of Poisson models for both categories of accidents (Tables 6.2 and 6.3). This means that the level of traffic congestion has no impact on the frequency of road accidents according to the data on the M25. Other measures of traffic congestion such as total vehicle delay per km length of road have also been tested and this variable has also been found to be statistically insignificant. Therefore, spatial differences of traffic congestion among road segments of the M25 cannot explain the variation in road accidents.

This result is in line with the findings of Noland and Quddus (2005) who investigated the association between traffic congestion and road accidents in London based on area-wide data, and did not find conclusive evidence showing that there is any effect of traffic congestion on road accidents.

There may be a number of reasons for the insignificance of traffic congestion in the models. Firstly, this result has been based on a congestion measurement calculated from hourly data averaged over a year so as to match with the dependent variable of the models that have been taken as the annual accident frequency per road segment. In reality, the level of congestion varies over time (such as over a day and throughout a year) and this generalisation may have an impact on the effect of congestion on accidents. As stated below, however, the data have been disaggregated into peak and off-peak periods in order to take into account the different levels of congestion. Secondly, the effects of congestion might be captured by other factors such as *speed variance* and *traffic flow*. Literature suggests that *speed variance* is an important factor in explaining the occurrence of traffic accidents (Lave, 1985; Aljanahi et al., 1999; Ossiander and Cummings, 2002). This may also be true in this case since the aggregated data used does not explicitly represent how traffic speed on a specific segment varies at different times. *Speed variance* therefore was intended to be included in the model. The variation of speed in the literature, however, is measured by

*Acceleration Noise* (AN) which is also regarded as a congestion measurement (Taylor et al., 2000b). Moreover, AN requires a considerable amount of data and due to the fact that speed variance is affected not just by traffic conditions (e.g., congestion) but also by driving behaviour AN is not considered in this thesis.

With regards to the effect of traffic flow, it can be speculated that congestion has different effects under different traffic flow conditions. For example, the effect of traffic congestion on the frequency of road accidents may be positive under low traffic flow conditions and negative under high traffic flow conditions. To investigate this, data has been disaggregated into two parts: the peak time period when the traffic flow is high; and the off-peak time period when the traffic flow is low. The peak and off-peak time periods were determined by the average hourly traffic volume.

The average hourly traffic volume on the M25 has been investigated and found to follow similar variations throughout a day as shown in Figure 5.2 (see Chapter 5). It is noticeable from Figure 5.2 that traffic flow is higher during the period 6:00am–8:00pm on weekdays and 9:00am–8:00pm on weekends. As such, these time periods are considered as peak while the rest of the time periods are considered as off-peak. All four specifications of the model have been estimated for both peak and off-peak periods. The model estimation results are presented in Tables 6.4-6.7.

**Table 6.4 Models for fatal and serious injury accidents on the M25 during the peak time period**

| Variables            | Poisson-lognormal |                 | Poisson-gamma   |                 | Poisson-lognormal<br>CAR<br>(1st order neighbour) |                 | Poisson-lognormal<br>CAR<br>(2nd order neighbour) |                 |       |
|----------------------|-------------------|-----------------|-----------------|-----------------|---|-----------------|---|-----------------|-------|
|                      | Mean              | S.D.            | Mean            | S.D.            | Mean  | S.D.            | Mean  | S.D.            |       |
| Congestion index     | -0.3544           | 0.8559          | -0.512          | 0.9461          | -0.3163   | 0.8901          | -0.3822   | 0.8938          |       |
| log(Traffic volume)  | <b>1.407**</b>    | 0.4534          | <b>1.268*</b>   | 0.7372          | <b>1.628**</b>                                    | 0.5193          | <b>1.443**</b>                                    | 0.6951          |       |
| Segment length (km)  | <b>0.1262**</b>   | 0.0306          | <b>0.1393**</b> | 0.0395          | <b>0.1336**</b>                                   | 0.0294          | <b>0.1337**</b>                                   | 0.0294          |       |
| log(minimum radius)  | 0.244             | 0.2478          | 0.3319          | 0.2878          | 0.2987  | 0.2970          | 0.3043  | 0.243           |       |
| Maximum gradient (%) | <b>0.2007*</b>    | 0.1167          | 0.2097          | 0.1396          | <b>0.2406**</b>                                   | 0.1217          | <b>0.2356**</b>                                   | 0.1174          |       |
| Number of lanes      | -0.0518           | 0.1710          | -0.01717        | 0.2302          | 0.0483  | 0.1865          | 0.0647  | 0.2045          |       |
| Direction            | 0.1469            | 0.1944          | 0.1808          | 0.2278          | -0.0044   | 0.4006          | 0.0089  | 0.3833          |       |
| Intercept            | <b>-25.65**</b>   | 7.3800          | <b>-24.02**</b> | 11.5            | <b>-30.21**</b>                                   | 8.676           | <b>-27.17**</b>                                   | 11.23           |       |
| S.D. ( $u$ )         |                   |                 |                 |                 | <b>0.1644**</b>                                   | 0.1138          | <b>0.2748**</b>                                   | 0.1946          |       |
| S.D. ( $v$ )         |                   | <b>0.3862**</b> | 0.1555          | <b>0.6015**</b> | 0.0972  | <b>0.2099**</b> | 0.1818  | <b>0.1985**</b> | 0.182 |
| DIC                  |                   | 256.244         |                 | 253.674         |   | 256.564         |   | 277.084         |       |
| N                    |                   | 70              |                 | 70              |   | 70              |   | 70              |       |

\* Statistically significantly different from zero (90% credible sets show the same sign)

\*\* Statistically significantly different from zero (95% credible sets show the same sign)

**Table 6.5** Models for slight injury accidents on the M25 during the peak time period

|                      | Poisson-lognormal |        | Poisson-gamma   |        | Poisson-lognormal<br>CAR<br>(1st order neighbour) |        | Poisson-lognormal<br>CAR<br>(2nd order neighbour) |        |
|----------------------|-------------------|--------|-----------------|--------|---|--------|---|--------|
| Variables            | Mean              | S.D.   | Mean            | S.D.   | Mean  | S.D.   | Mean  | S.D.   |
| Congestion index     | -0.0856           | 0.4662 | -0.0375         | 0.5058 | 0.1664  | 0.4660 | 0.4248  | 0.4534 |
| log(Traffic volume)  | <b>1.245**</b>    | 0.2708 | <b>1.325**</b>  | 0.3669 | <b>1.343**</b>                                    | 0.3283 | <b>1.767**</b>                                    | 0.2057 |
| Segment length (km)  | <b>0.1474**</b>   | 0.0225 | <b>0.1491**</b> | 0.0273 | <b>0.1503**</b>                                   | 0.0214 | <b>0.1466**</b>                                   | 0.0220 |
| log(minimum radius)  | 0.1053            | 0.1432 | 0.0535          | 0.1299 | 0.1622  | 0.1690 | 0.0619  | 0.1482 |
| Maximum gradient (%) | <b>0.2314**</b>   | 0.0758 | <b>0.2049**</b> | 0.0850 | <b>0.244**</b>                                    | 0.0751 | <b>0.2499**</b>                                   | 0.0752 |
| Number of lanes      | <b>0.2496**</b>   | 0.1098 | <b>0.2032*</b>  | 0.1187 | <b>0.2423**</b>                                   | 0.1205 | 0.1637  | 0.1075 |
| Direction            | 0.0080            | 0.1330 | 0.0045          | 0.1445 | -0.0894   | 0.2529 | -0.0114   | 0.2057 |
| Intercept            | <b>-20.74**</b>   | 3.9560 | <b>-21.42**</b> | 5.9060 | <b>-22.79**</b>                                   | 4.8460 | <b>-29.07**</b>                                   | 3.0760 |
| S.D. ( $u$ )         |                   |        |                 |        | <b>0.0965**</b>                                   | 0.0888 | <b>0.0903**</b>                                   | 0.1073 |
| S.D. ( $v$ )         |                   |        |                 |        | <b>0.4754**</b>                                   | 0.0617 | <b>0.5281**</b>                                   | 0.0580 |
| DIC                  |                   |        |                 |        |   |        | <b>0.413**</b>                                    | 0.0801 |
| $N$                  |                   | 70     |                 | 70     |   | 70     |   | 70     |

\* Statistically significantly different from zero (90% credible sets show the same sign)

\*\* Statistically significantly different from zero (95% credible sets show the same sign)

**Table 6.6 Models for fatal and serious injury accidents on the M25 during the off-peak time period**

| Variables            | Poisson-lognormal |         | Poisson-gamma   |        | Poisson-lognormal<br>CAR<br>(1st order neighbour) |        | Poisson-lognormal<br>CAR<br>(2nd order neighbour) |        |
|----------------------|-------------------|---------|-----------------|--------|---|--------|---|--------|
|                      | Mean              | S.D.    | Mean            | S.D.   | Mean  | S.D.   | Mean  | S.D.   |
| Congestion index     | -0.1946           | 0.6714  | -0.0583         | 0.7412 | -0.1708   | 0.7381 | -0.1681   | 0.7240 |
| log(Traffic volume)  | <b>1.24**</b>     | 0.4693  | <b>1.762**</b>  | 0.7319 | <b>1.365**</b>                                    | 0.6978 | <b>1.369*</b>                                     | 0.6625 |
| Segment length (km)  | <b>0.1438**</b>   | 0.0323  | <b>0.1699**</b> | 0.0467 | <b>0.1448**</b>                                   | 0.0339 | <b>0.1437**</b>                                   | 0.0338 |
| log(minimum radius)  | 0.1556            | 0.3083  | 0.0975          | 0.3478 | 0.161   | 0.3038 | 0.1553  | 0.3029 |
| Maximum gradient (%) | 0.1723            | 0.1396  | 0.1573          | 0.1667 | 0.17  | 0.1407 | 0.1713  | 0.1405 |
| Number of lanes      | -0.2636           | 0.2186  | -0.3739         | 0.2709 | -0.2869   | 0.2429 | -0.2970   | 0.2392 |
| Direction            | -0.1331           | 0.2212  | -0.1152         | 0.2788 | -0.2605   | 0.2975 | -0.2226   | 0.2728 |
| Intercept            | <b>-20.34**</b>   | 6.8320  | <b>-27.73</b>   | 10.97  | <b>-22.18**</b>                                   | 10.09  | <b>-22.17**</b>                                   | 9.61   |
| S.D. ( $u$ )         |                   |         |                 |        | <b>0.0522**</b>                                   | 0.0424 | <b>0.0628**</b>                                   | 0.0610 |
| S.D. ( $v$ )         | <b>0.0607**</b>   | 0.05778 | <b>0.5454**</b> | 0.1029 | <b>0.0641**</b>                                   | 0.0608 | <b>0.0586**</b>                                   | 0.0553 |
| DIC                  | 175.083           |         | 185.187         |        | 179.572   |        | 178.668   |        |
| N                    | 70                |         | 70              |        | 70  |        | 70  |        |

\* Statistically significantly different from zero (90% credible sets show the same sign)

\*\* Statistically significantly different from zero (95% credible sets show the same sign)

**Table 6.7 Models for slight injury accidents on the M25 during the off-peak time period**

| Variables            | Poisson-lognormal |        | Poisson-gamma   |        | Poisson-lognormal<br>CAR<br>(1st order neighbour) |        | Poisson-lognormal<br>CAR<br>(2nd order neighbour) |        |
|----------------------|-------------------|--------|-----------------|--------|---|--------|---|--------|
|                      | Mean              | S.D.   | Mean            | S.D.   | Mean  | S.D.   | Mean  | S.D.   |
| Congestion index     | -0.2619           | 0.4068 | -0.2558         | 0.4335 | 0.0927  | 0.4122 | 0.0998  | 0.4214 |
| log(Traffic volume)  | <b>0.8131**</b>   | 0.2149 | <b>0.8331**</b> | 0.2739 | <b>0.6662**</b>                                   | 0.2775 | <b>0.776**</b>                                    | 0.3342 |
| Segment length (km)  | <b>0.1442**</b>   | 0.0262 | <b>0.1492**</b> | 0.0315 | <b>0.1555**</b>                                   | 0.0239 | <b>0.155**</b>                                    | 0.0243 |
| log(minimum radius)  | -0.0435           | 0.1668 | -0.0390         | 0.1956 | 0.0991  | 0.1723 | 0.0634  | 0.1933 |
| Maximum gradient (%) | <b>0.246**</b>    | 0.0873 | <b>0.2483**</b> | 0.1030 | <b>0.2918**</b>                                   | 0.0868 | <b>0.2782**</b>                                   | 0.0896 |
| Number of lanes      | <b>0.2952**</b>   | 0.1230 | <b>0.2808**</b> | 0.1382 | <b>0.3631**</b>                                   | 0.1332 | <b>0.3285**</b>                                   | 0.1417 |
| Direction            | 0.0192            | 0.1523 | 0.0109          | 0.1723 | -0.1550   | 0.3325 | -0.1290   | 0.3048 |
| Intercept            | <b>-13.07**</b>   | 2.9520 | <b>-13.3**</b>  | 3.6920 | <b>-12.19**</b>                                   | 3.8340 | <b>-13.49**</b>                                   | 4.5260 |
| S.D. ( $u$ )         |                   |        |                 |        | <b>0.1706**</b>                                   | 0.1303 | <b>0.2633**</b>                                   | 0.2171 |
| S.D. ( $v$ )         |                   |        |                 |        | <b>0.2473**</b>                                   | 0.1608 | <b>0.2462**</b>                                   | 0.1684 |
| DIC                  | 334.021           |        | 332.995         |        | 334.559   |        | 335.156   |        |
| $N$                  | 70                |        | 70              |        | 70  |        | 70  |        |

\* Statistically significantly different from zero (90% credible sets show the same sign)

\*\* Statistically significantly different from zero (95% credible sets show the same sign)

As can be seen, the results in Tables 6.4-6.7 are consistent with the results presented in Tables 6.2 and 6.3 in terms of the set of statistically significant variables. The congestion index continues to be statistically insignificant across all models, both in the peak and off-peak time periods. This further confirms that congestion has no impact on the frequency of traffic accidents according to the data on the M25.

### **6.2.2 Other contributing factors**

*AADT* and *road segment length* are the two most important factors explaining road accident frequency in the models. *AADT* and *road segment length* are both statistically significant and positively associated with accidents in all models. This is to be expected, as *AADT* and *segment length* are considered to be the main exposure to accident risks.

The coefficient of  $\log(AADT)$  indicates the elasticity of accidents with respect to *AADT*, suggesting that a 1% increase in *AADT* would increase fatal and serious injury accidents by 1.21-1.86%. The coefficient of  $\log(AADT)$  for the case of slight injury accidents is found to be close to that for the case of fatal and serious injury accidents ranging from 1.03 to 1.53. The elasticity of *AADT* appears higher than some of the previous studies which reported that the elasticity ranges from 0.3 to 0.9 (e.g., Abdel-Aty and Radwan, 2000; Bird and Hashim, 2006; Aguero-Valverde and Jovanis, 2008). This may be because these studies were undertaken under different road conditions. For example, the study conducted by Abdel-Aty and Radwan (2000) was based on a “principal arterial” passing through the centre of Orlando in Florida in which *AADT* was normalised by the number of lanes. Bird and Hashim (2006) used a sample of rural two-lane single carriageways in the UK, and the coefficient of  $\log(AADT)$  ranges from 0.3 to 0.9 in different models estimated. A similar study undertaken by Aguero-Valverde and Jovanis (2008) was also based on rural two-lane roads. Mitra et al. (2007) further showed that the effects of *AADT* on different roads are different while looking at junction accidents, and it was found that generally the coefficient of *AADT* for “major” roads is higher than “minor” roads. The M25 motorway is one of the busiest in Europe and therefore, the higher value of the coefficient of *AADT* can be seen as reasonable. In addition, as a recent study by Geedipally et al. (2010) reported, depending on different accident types (e.g., head-on accidents and rear-end accidents), the elasticity of *AADT* can be significantly different, ranging from 0.6-1.8. It can be speculated that some type

of road accidents (e.g., rear-end accidents) on the M25 are over presented, and as such the elasticity of AADT may be high.

The estimates of coefficients for *segment length* are generally similar among different model specifications, which is around 0.13 for fatal and serious injury accidents (Table 6.2) and 0.15 for slight injury accidents (Table 6.3). The corresponding mean elasticity<sup>21</sup> of *segment length* is 0.68 for fatal and serious injury accidents and 0.79 for slight injury accidents. These values are found to be lower than some existing studies (e.g., Bird and Hashim, 2006) and higher than other studies (e.g., Abdel-Aty and Radwan, 2000). It can be speculated that the relationship between accident frequency and road segment length is non-linear, and as such the elasticity of accidents with respect to segment length can be different in different scenarios.

The *radius of road curvature* that reflects the degree of horizontal curvature of a road segment is included as the literature suggests that this may have an impact on accidents (Milton and Mannering, 1998). This variable has however been found to be statistically insignificant in all models. This may be due to the fact that there is a mixed effect of road curvature (Milton and Mannering, 1998; Haynes et al., 2007), especially on long road segments. This may also be due to the fact that there is not enough variation in horizontal curvature among the M25 road segments. An indicator variable representing the high road curvature (i.e. the radius of curvature is less than 500m) was also tested but found to be statistically insignificant. *Gradient (%)* which represents the vertical grade of the segment was also included in the models and found to be statistically significant and positively associated with accidents (Tables 6.2 and 6.3). This is consistent with the study by Milton and Mannering (1998) who used an indicator variable to represent vertical grade. This variable was found to be more significant (at a 95% confidence level) in the Poisson-lognormal CAR models for the case of fatal and serious injury accidents.

The variable representing the *number of lanes* has been found to be statistically insignificant in all fatal and serious injury accident models, but has become significant and positively related to the frequency of slight injury accidents in all specifications except one which is the Poisson-lognormal with CAR priors (for the case of first-order

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<sup>21</sup> Mean elasticity is defined as  $E = \frac{\partial \mu}{\partial x} \cdot \frac{\bar{x}}{\mu} = \beta \mu \cdot \frac{\bar{x}}{\mu} = \beta \bar{x}$ .

neighbour) (Tables 6.2 and 6.3). *Direction* has been included in the models as a dummy variable (clockwise and anticlockwise) to investigate whether there is an association between the frequency of accidents on the M25 and its directions. Li et al. (2007) suggested that the roadway directions need to be differentiated to better evaluate roadway risks. *Direction* has however been found to be statistically insignificant in all models suggesting that this variable does not have any effect on accidents.

While in this case study on the M25 no significant relationship has been found between traffic congestion and road accidents, the case study has the limitation in terms of the data used: accident and traffic data were considered for only one major road (i.e., M25) and for only one year (i.e., 2006). There are many other major motorways and A roads connected to the M25. As such, there is a need to consider a road network (rather than a single road) as more spatio-temporal variations are expected on a wider road network. Moreover, data for multiple years should be considered to control for the unobserved effects that change over time. As such, the next section extends the study area to a larger road network over multiple years, so as to further examine the impact of traffic congestion on road accidents.

### 6.3 A spatio-temporal analysis of the M25 and surround

The primary objective of this section is to further investigate the effect of traffic congestion on road accidents by extending the previous case study in three ways:

- (1) extending the study area to include 13 different motorways and 17 different A roads, leading to a total of 298 road segments (the segments are within approximately 50km to the central London);
- (2) considering traffic and accident data for 5 years (2003-2007); and
- (3) employing a spatio-temporal Bayesian hierarchical count model that controls for spatial correlation among neighbouring segments and time effects over the years in question.

It is expected that by extending the previous case study both spatially and temporally, more spatio-temporal variations of the level of congestion and accidents will be observed, which would make the results more general and provide a better understanding of the relationship between traffic congestion and road accidents.

Details of the data used in this spatio-temporal analysis have been documented in Chapter 5 section 5.3. The count of annual accidents per road segment is viewed as a function of various factors, and as such several econometric models that are suitable for panel count data are used (see panel count data models in Chapter 4 section 4.5). The relationship between traffic congestion and the number of road accidents has been examined using two types of econometric models namely: the classical count outcome model and the spatial model using a full Bayesian approach. Two categories of accidents were modelled: (1) fatal and serious injury accidents; and (2) slight injury accidents. The level of segment-based traffic congestion has been measured by the total delay (in sec) per kilometre of roadway. Other congestion measurements, such as the congestion index (CI) have also been tested. Some of the explanatory variables have been transformed into a logarithmic scale in order to reduce the variance among the variables, including total delay, annual average daily traffic (AADT), road segment length and radius of road curvature. Average speed has been excluded from the model so as to avoid multicollinearity with the variable of interest – total delay per km (correlation coefficient: -0.86). Correlation coefficients between other variables have also been checked and no significant correlations have been found. The correlation coefficients between various variables are presented in Table 6.8.

**Table 6.8 Correlation coefficients between variables using the data on the M25 and surround**

|                     | log(delay)   | log(AADT) | Average speed | log(segment length) | log(minimum radius) | Maximum gradient | Number of lanes | Speed limit | Motorway indicator |
|---------------------|--------------|-----------|---------------|---------------------|---------------------|------------------|-----------------|-------------|--------------------|
| log(delay)          | 1.00         |           |               |                     |                     |                  |                 |             |                    |
| log(AADT)           | -0.06        | 1.00      |               |                     |                     |                  |                 |             |                    |
| Average speed       | <b>-0.86</b> | 0.21      | 1.00          |                     |                     |                  |                 |             |                    |
| log(segment length) | -0.26        | 0.10      | 0.25          | 1.00                |                     |                  |                 |             |                    |
| log(minimum radius) | -0.15        | 0.44      | 0.27          | 0.11                | 1.00                |                  |                 |             |                    |
| Maximum gradient    | -0.05        | -0.28     | -0.05         | 0.25                | -0.34               | 1.00             |                 |             |                    |
| Number of lanes     | 0.02         | 0.52      | 0.13          | 0.08                | 0.39                | -0.26            | 1.00            |             |                    |
| Speed limit         | -0.11        | 0.11      | 0.38          | 0.15                | 0.29                | -0.17            | 0.16            | 1.00        |                    |
| Motorway indicator  | -0.03        | 0.32      | 0.11          | 0.22                | 0.22                | -0.10            | 0.29            | 0.19        | 1.00               |

Since the spatial models capture the spatially correlated effects among neighbouring road segments, it is expected that the spatial models can better fit the data and produce more coherent results. The model estimation results and findings from both the classical count outcome model and spatial model using a full Bayesian approach are presented below.

### 6.3.1 Classical count outcome models

A series of fixed- and random-effects Negative Binomial (NB) models have been tested for both fatal and serious injury accidents and slight injury accidents. A Hausman test was performed and it was found that the random-effects NB model is more suitable for the data used in this thesis. For each type of accident, models for both balanced and unbalanced panel data have been considered. As such, a total number of four classical count outcome models have been estimated. Year dummies have been included in the models to control for the fixed time effects where the year 2003 has been considered as the reference case. The model estimation results are presented in Table 6.9 (for fatal and serious injury accidents) and Table 6.10 (for slight injury accidents).

**Table 6.9 Random-effects NB models for fatal and serious injury accidents**

| Variables                    | Model for balanced panel data |         | Model for unbalanced panel data |         |
|------------------------------|-------------------------------|---------|---------------------------------|---------|
|                              | Coefficient                   | z value | Coefficient                     | z value |
| log(delay in sec per km)     | <b>0.115**</b>                | 2.93    | <b>0.120**</b>                  | 3.17    |
| log(AADT)                    | <b>0.568**</b>                | 5.01    | <b>0.560**</b>                  | 5.14    |
| log(segment length in metre) | <b>0.941**</b>                | 13.99   | <b>0.945**</b>                  | 14.39   |
| log(minimum radius)          | <b>0.216**</b>                | 3.07    | <b>0.203**</b>                  | 2.97    |
| Maximum gradient (%)         | <b>0.061*</b>                 | 1.67    | 0.052                           | 1.47    |
| Number of lanes              | 0.018                         | 0.24    | 0.036                           | 0.5     |
| Speed limit                  | 0.009                         | 1.22    | 0.009                           | 1.32    |
| Motorway                     | -0.149                        | -1.38   | <b>-0.173*</b>                  | -1.7    |
| Year 2004                    | <b>-0.195**</b>               | -2.34   | <b>-0.210**</b>                 | -2.57   |
| Year 2005                    | <b>-0.221**</b>               | -2.64   | <b>-0.219**</b>                 | -2.66   |
| Year 2006                    | <b>-0.390**</b>               | -4.46   | <b>-0.383**</b>                 | -4.46   |
| Year 2007                    | <b>-0.280**</b>               | -3.25   | <b>-0.285**</b>                 | -3.36   |
| Intercept                    | <b>-15.152**</b>              | -9.29   | <b>-15.168**</b>                | -9.64   |
| Parameter <i>a</i>           | 75.662                        |         | 77.716                          |         |
| Parameter <i>b</i>           | 6.444                         |         | 6.799                           |         |
| Log likelihood               | -1624.98                      |         | -1701.9                         |         |
| AIC                          | 3279.954                      |         | 3433.801                        |         |
| <i>N</i>                     | 1330                          |         | 1391                            |         |

\* p<0.1, \*\* p<0.05

**Table 6.10 Random effects NB models for slight injury accidents**

| Variables                    | Model for balanced panel data |         | Model for unbalanced panel data |         |
|------------------------------|-------------------------------|---------|---------------------------------|---------|
|                              | Coefficient                   | z value | Coefficient                     | z value |
| log(delay in sec per km)     | <b>0.048**</b>                | 2.02    | <b>0.050**</b>                  | 2.15    |
| log(AADT)                    | <b>0.144**</b>                | 3.44    | <b>0.149**</b>                  | 3.57    |
| log(segment length in metre) | <b>0.852**</b>                | 13.84   | <b>0.870**</b>                  | 14.23   |
| log(minimum radius)          | <b>0.094*</b>                 | 1.77    | <b>0.096*</b>                   | 1.84    |
| Maximum gradient (%)         | -0.002                        | -0.05   | -0.014                          | -0.4    |
| Number of lanes              | <b>0.424**</b>                | 6.37    | <b>0.419**</b>                  | 6.41    |
| Speed limit                  | -0.003                        | -0.6    | -0.004                          | -0.76   |
| Motorway                     | <b>0.260**</b>                | 2.75    | <b>0.230**</b>                  | 2.51    |
| Year 2004                    | <b>0.118**</b>                | 3.32    | <b>0.121**</b>                  | 3.4     |
| Year 2005                    | <b>0.081**</b>                | 2.25    | <b>0.086**</b>                  | 2.39    |
| Year 2006                    | 0.024                         | 0.64    | 0.029                           | 0.78    |
| Year 2007                    | <b>-0.066*</b>                | -1.73   | -0.056                          | -1.5    |
| Intercept                    | <b>-7.765**</b>               | -8.3    | <b>-7.889**</b>                 | -8.53   |
| Parameter a                  | 13.964                        |         | 13.288                          |         |
| Parameter b                  | 3.620                         |         | 3.549                           |         |
| Log likelihood               | -3281.42                      |         | -3437.06                        |         |
| AIC                          | 6592.842                      |         | 6904.122                        |         |
| N                            | 1330                          |         | 1391                            |         |

\* p<0.1, \*\* p<0.05

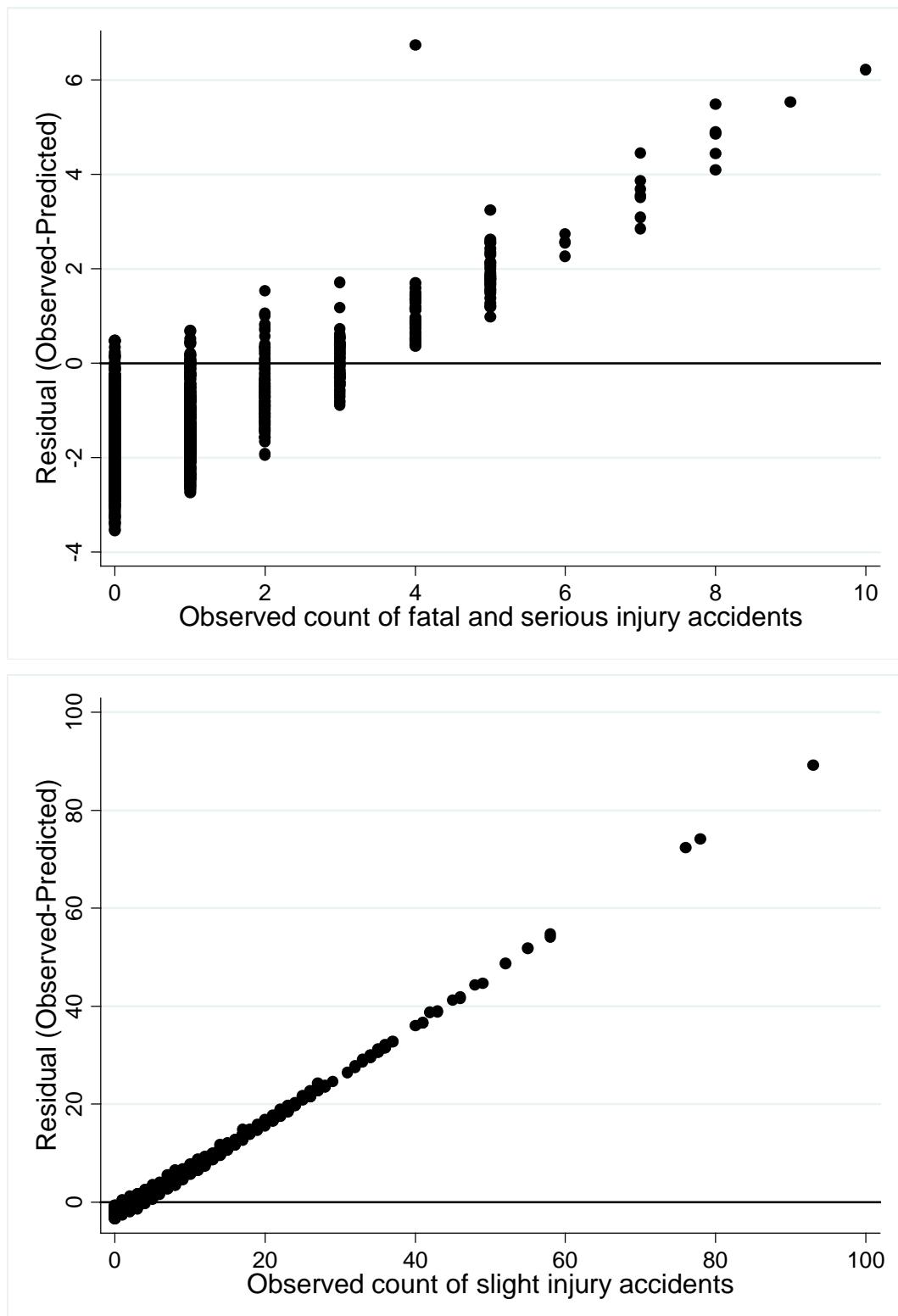
As shown in Tables 6.9 and 6.10, model estimation results for balanced and unbalanced panel data are consistent with each other in terms of both the set of statistically significant variables and the magnitude of their coefficients. *Traffic delay* (sec per km) was found to be statistically significant and positively related to the frequency of both fatal and serious injury accidents and slight injury accidents. This means that the number of accidents increases with an increase in the level of traffic congestion. The coefficient of log(delay in sec per km) indicates the elasticity of accidents with respect to *traffic delay*, suggesting that a 1% increase in *traffic delay* per km would increase fatal and serious injury accidents by around 0.1% and slight injury accidents by 0.05%. This result is consistent with the study by Kononov et al. (2008) who found that fatal and injury accidents increase with traffic congestion. The other congestion measurement, i.e. the congestion index (CI) has also been tested and found statistically significant and positive in the fatal and serious injury accident model (statistically insignificant in the slight injury accident model) for the case of unbalanced panel data. This further confirms that there is a positive association between traffic congestion and the number of accidents. The impact of this finding will be fully presented in Chapter 9.

*AADT* and *road segment length* are both statistically significant and positively associated with accidents in all models. This is expected as *AADT* is considered to be the main risk exposure to accidents. The elasticity of *AADT* for the case of fatal and serious injury accidents was found to be around 0.56 which is in line with the previous UK study conducted by Bird and Hashim (2006). The elasticity of *AADT* for slight injury accidents appears a little low at around 0.15. The coefficient of log(segment length in metre) is approximately 1 in all models suggesting that the elasticity of *road segment length* with respect to accidents is about 1. This means a 1% increase in *road segment length* would increase accident frequency by 1%.

As for the road segment characteristics, the minimum *radius* of horizontal curvature has been found to be statistically significant (at a 90% confidence level for slight injury accidents) and positively related to accidents. This implies there are more accidents on straighter road segments, which is counter-intuitive at first glance but is actually consistent with previous studies (e.g., Haynes et al., 2007) which found road curvature is protective, especially at highly aggregate spatial units. *Gradient* which represents the vertical grade of the road segment has been found to be statistically insignificant except in the balanced panel data model for fatal and serious injury accidents (at a 90% confidence level). *Number of lanes* is statistically significant and positively associated with slight injury accidents, suggesting more slight injury accidents would occur on roads with more lanes. This is consistent with the previous study by Kononov et al. (2008). *Speed limit* has been found statistically insignificant in all models. This may be because there are not enough variations of this variable across the M25 and surround: 268 out of 298 road segments have the speed limit of 112 km/h. *Motorway* was included as a dummy variable to investigate whether accident frequency would be different on motorways. It has been found that compared to A roads, motorways tend to have more slight injury accidents but less fatal and serious injury accidents (at a 90% confidence level in the unbalanced panel data model).

Fixed time effects are significant and negative in fatal and serious injury models, suggesting that fatal and serious injury accidents tend to decrease in the years 2004-2007 compared to 2003. The expected number of slight injury accidents, on the other hand, increases in the years 2004-2005 compared to 2003, and then decreases in the years 2006-2007.

Figure 6.2 shows the relationship between the observed and the residual (=observed-predicted) values of accident frequency on the M25 and surround using the classical count outcome models (balanced panel data).



**Figure 6.2** The relationship between the observed and the residual values of accidents for classical count outcome models

As can be seen from Figure 6.2, the classical count models do not fit the data very well, especially for the slight injury accidents. There is a clear pattern of the residuals: the residuals increase with respect to the increase in observed values. This is the case for both categories of accidents. The predictions are less reliable when the observed number of accidents is large. The maximum value of the residual is nearly 90 for slight injury accidents. As discussed in Chapter 3, classical count outcome models largely ignore the effect of spatial correlation, which may lead to biased model estimation results. To control for the spatial correlation, a spatial model can be used, which is presented in the following section.

### **6.3.2 Spatial models using a full Bayesian hierarchical approach**

Four spatial models have been estimated using the full Bayesian hierarchical approach to take into account both spatial correlation and unobserved heterogeneity. The model specifications follow the descriptions in Chapter 4 section 4.5.2, where models suitable for panel count data were used. The heterogeneity effects ( $v_i$ ) has been assumed to be normally distributed and only the first order neighbouring structure was employed since results from section 6.2 indicate that first or second order neighbouring structures give very similar results. For each category of accidents (i.e. fatal/serious injury accidents and slight injury accidents), a spatial model with fixed time effects and random time effects using a first-order random walk (RW (1)) prior have been estimated. The posterior means and standard deviations (S.D.) of the coefficients for the explanatory variables ( $\beta$ 's), time effects ( $\delta_t$ ), and the standard deviations of other random terms ( $v_i$ ,  $u_i$ ,  $e_{it}$ ) have been estimated using the MCMC method. Two chains were simulated with different initial values. The convergence of the two chains was examined by visual inspection of the MCMC trace plots. Generally the initial 30,000 – 180,000 iterations were discarded as burn-ins to achieve convergence and a further 30,000 iterations for each chain were performed and kept to calculate the posterior estimates of interested parameters. The Monte Carlo (MC) errors (i.e. the Monte Carlo standard error of the mean) were also monitored, and they were less than 0.005 for most parameters. Using the guide from the WinBUGS user manual (Spiegelhalter et al., 2003), MC errors less than 0.05 indicate that convergence may have been achieved. All spatial models have been estimated using the balanced panel data. The results are presented in Table 6.11 (for fatal and serious injury accidents) and Table 6.12 (for slight injury accidents).

**Table 6.11 Spatial models for fatal and serious injury accidents**

| Variables                    | Model with fixed time effects |       | Model with RW(1) time effects |       |
|------------------------------|-------------------------------|-------|-------------------------------|-------|
|                              | Mean                          | S.D.  | Mean                          | S.D.  |
| log(delay in sec per km)     | <b>0.081*</b>                 | 0.044 | <b>0.088**</b>                | 0.044 |
| log(AADT)                    | <b>0.232**</b>                | 0.079 | <b>0.244**</b>                | 0.095 |
| log(segment length in metre) | <b>0.974**</b>                | 0.073 | <b>0.991**</b>                | 0.061 |
| log(minimum radius)          | <b>0.252**</b>                | 0.069 | <b>0.255**</b>                | 0.069 |
| Maximum gradient (%)         | <b>0.077*</b>                 | 0.041 | <b>0.079*</b>                 | 0.042 |
| Number of lanes              | <b>0.207**</b>                | 0.079 | <b>0.206**</b>                | 0.079 |
| Speed limit (km/h)           | 0.010                         | 0.010 | 0.013                         | 0.009 |
| Motorway                     | -0.089                        | 0.176 | -0.111                        | 0.175 |
| Year 2003                    | 0                             | -     | <b>0.189**</b>                | 0.050 |
| Year 2004                    | <b>-0.187**</b>               | 0.081 | 0.038                         | 0.046 |
| Year 2005                    | <b>-0.211**</b>               | 0.080 | -0.011                        | 0.045 |
| Year 2006                    | <b>-0.375**</b>               | 0.085 | <b>-0.134**</b>               | 0.050 |
| Year 2007                    | <b>-0.284**</b>               | 0.083 | -0.082                        | 0.051 |
| Intercept                    | <b>-15.071**</b>              | 1.504 | <b>-15.995**</b>              | 1.536 |
| S.D. ( <i>u</i> )            | <b>0.164**</b>                | 0.079 | <b>0.170**</b>                | 0.075 |
| S.D. ( <i>e</i> )            | <b>0.067**</b>                | 0.058 | <b>0.062**</b>                | 0.053 |
| S.D. ( <i>v</i> )            | <b>0.344**</b>                | 0.104 | <b>0.342**</b>                | 0.096 |
| S.D. ( <i>t</i> )            | -                             | -     | <b>0.177**</b>                | 0.098 |
| DIC                          | 3225.6                        |       | 3224.31                       |       |

\* Statistically significant from zero (90% credible sets show the same sign)

\*\* Statistically significant from zero (95% credible sets show the same sign)

**Table 6.12 Spatial models for slight injury accidents**

| Variables                    | Model with fixed time effects |       | Model with RW(1) time effects† |       |
|------------------------------|-------------------------------|-------|--------------------------------|-------|
|                              | Mean                          | S.D.  | Mean                           | S.D.  |
| log(delay in sec per km)     | 0.044                         | 0.032 | 0.020                          | 0.034 |
| log(AADT)                    | <b>0.129**</b>                | 0.036 | <b>0.148**</b>                 | 0.052 |
| log(segment length in metre) | <b>0.925**</b>                | 0.067 | <b>0.726**</b>                 | 0.207 |
| log(minimum radius)          | <b>0.138**</b>                | 0.070 | -0.019                         | 0.213 |
| Maximum gradient (%)         | <b>0.068*</b>                 | 0.040 | <b>0.115*</b>                  | 0.099 |
| Number of lanes              | <b>0.455**</b>                | 0.071 | <b>0.421*</b>                  | 0.176 |
| Speed limit (km/h)           | -0.0002                       | 0.004 | 0.050                          | 0.075 |
| Motorway                     | <b>0.278**</b>                | 0.143 | <b>0.348**</b>                 | 0.222 |
| Year 2003                    | 0                             | -     | -0.031                         | 0.026 |
| Year 2004                    | <b>0.115**</b>                | 0.037 | <b>0.068**</b>                 | 0.023 |
| Year 2005                    | <b>0.079**</b>                | 0.038 | 0.042                          | 0.022 |
| Year 2006                    | 0.028                         | 0.039 | -0.006                         | 0.023 |
| Year 2007                    | -0.048                        | 0.040 | <b>-0.073**</b>                | 0.026 |
| Intercept                    | <b>-10.61**</b>               | 0.857 | <b>-13.473**</b>               | 6.137 |
| S.D. ( <i>u</i> )            | <b>0.230**</b>                | 0.061 | <b>0.276**</b>                 | 0.169 |
| S.D. ( <i>e</i> )            | <b>0.179**</b>                | 0.018 | <b>0.182**</b>                 | 0.018 |
| S.D. ( <i>v</i> )            | <b>0.499**</b>                | 0.048 | <b>0.716**</b>                 | 0.357 |
| S.D. ( <i>t</i> )            | -                             | -     | <b>0.128**</b>                 | 0.069 |
| DIC                          | 6133.92                       |       | 6154.35                        |       |

\* Statistically significant from zero (90% credible sets show the same sign)

\*\* Statistically significant from zero (95% credible sets show the same sign)

† Model not fully converged

As indicated in Table 6.11, model estimation results from the two model specifications (i.e. the models with fixed time effects and RW (1) random time effects) are very similar to each other for the case of fatal and serious injury accidents. Both model specifications produce similar posterior estimates in terms of coefficients of explanatory variables and standard deviations of random terms (i.e. *u*, *e*, and *v*). The DIC values of the two model specifications are very close to each other meaning that there is no significant difference between these models in terms of statistical fit and model complexity.

For the case of slight injury accidents (Table 6.12), since the model with RW (1) prior does not fully converge for a long period of simulation, the results from this model are considered unstable. Considering that the RW (1) model does not show any significant difference compared to the fixed time effect model (Tables 6.11 and 6.12), the results from the fixed time effect models for both categories of accidents will be used for further interpretation and discussion below.

In addition to the models for different categories of accidents, a Bayesian spatial model for the total number of accidents (regardless of severities) has also been estimated. This model, as discussed in Chapter 4 will be used for estimating posterior means of total accident counts in a two-stage site ranking process. The results of this model are presented in Table 6.13, in which fixed time effects are used. For comparison, a random-effects NB model has also been estimated and presented in Table 6.13. Not surprisingly, the model estimation results are very similar to the slight injury accident models (Tables 6.10 and 6.12), since the majority of accidents are slight injury accidents (87.75%).

**Table 6.13 Models for total number of accidents**

| Variables                | Random-effects NB model |         | Bayesian spatial model |       |
|--------------------------|-------------------------|---------|------------------------|-------|
|                          | Coefficient             | z value | Mean                   | S.D.  |
| log(delay in sec per km) | <b>0.051**</b>          | 2.26    | 0.043                  | 0.024 |
| log(AADT)                | <b>0.137**</b>          | 3.36    | <b>0.110**</b>         | 0.036 |
| log(segment length in m) | <b>0.864**</b>          | 14.54   | <b>0.944**</b>         | 0.054 |
| log(minimum radius)      | <b>0.120**</b>          | 2.34    | <b>0.169**</b>         | 0.059 |
| Maximum gradient (%)     | 0.005                   | 0.16    | <b>0.066*</b>          | 0.038 |
| Number of lanes          | <b>0.395**</b>          | 6.12    | <b>0.428**</b>         | 0.077 |
| Speed limit (km/h)       | -0.002                  | -0.35   | 0.001                  | 0.005 |
| Motorway                 | <b>0.199**</b>          | 2.16    | 0.218                  | 0.149 |
| Year 2003                |                         |         | 0                      | -     |
| Year 2004                | <b>0.079**</b>          | 2.35    | <b>0.079**</b>         | 0.035 |
| Year 2005                | 0.043                   | 1.27    | 0.044                  | 0.036 |
| Year 2006                | -0.026                  | -0.75   | -0.018                 | 0.036 |
| Year 2007                | <b>-0.096**</b>         | -2.71   | <b>-0.078**</b>        | 0.037 |
| Intercept                | <b>-7.957**</b>         | -8.8    | <b>-10.543**</b>       | 0.62  |
| S.D. ( $u$ )             | -                       |         | <b>0.220**</b>         | 0.059 |
| S.D. ( $e$ )             | -                       |         | <b>0.178**</b>         | 0.016 |
| S.D. ( $v$ )             | -                       |         | <b>0.498**</b>         | 0.045 |
| Parameter $a$            | 13.818                  |         | -                      |       |
| Parameter $b$            | 3.874                   |         | -                      |       |
| Log likelihood           | -3402.441               |         | -                      |       |
| AIC / DIC                | 6834.882                |         | 6350.15                |       |
| N                        | 1330                    |         | 1330                   |       |

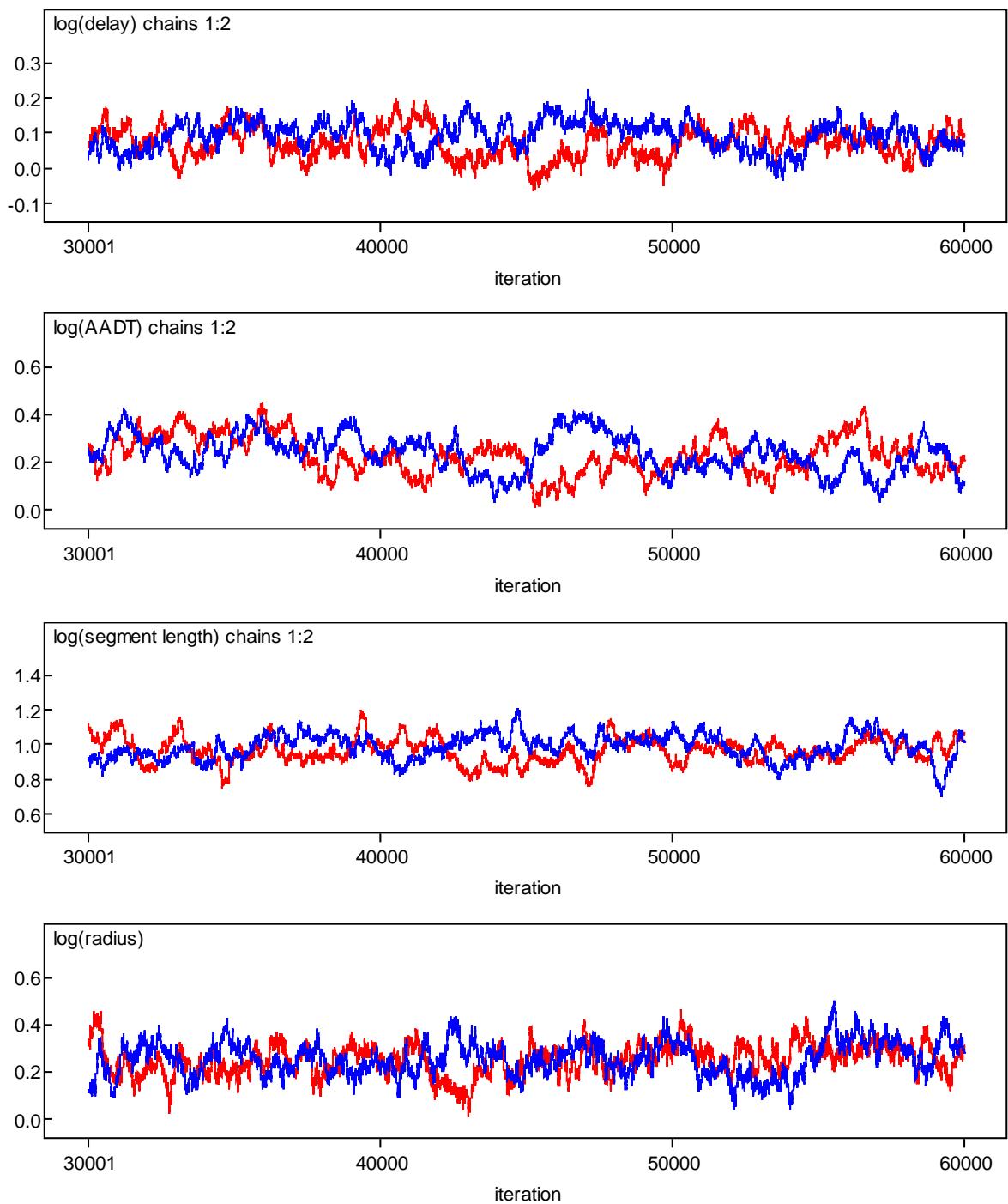
\* Statistically significant from zero (90% credible sets show the same sign in the Bayesian model;  $p<0.1$  in the random-effects NB model)

\*\* Statistically significant from zero (95% credible sets show the same sign in the Bayesian model;  $p<0.05$  in the random-effects NB model)

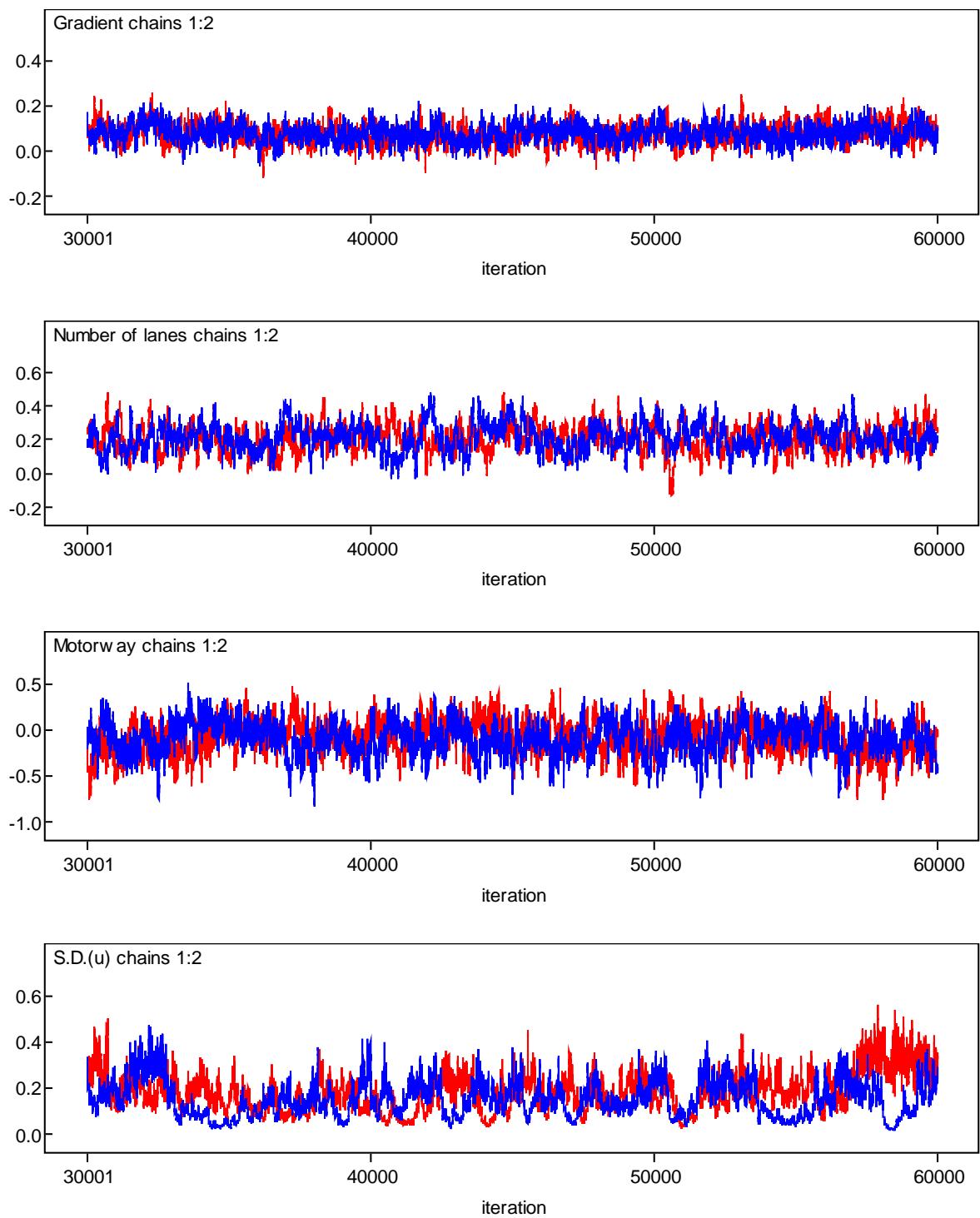
As for models for different categories of accidents, as can be seen in Tables 6.11 and 6.12, the posterior estimates of standard deviation of  $u$  ranges from 0.16-0.23 and they

are statistically significant, suggesting that the spatially correlated effects ( $u$ ) exist for both types of accidents. The spatial correlation is higher for the case of slight injury accidents relative to fatal and serious injury accidents, which is consistent with previous studies (Aguero-Valverde and Jovanis, 2006). Similarly, uncorrelated heterogeneity ( $v$ ) and space-time interaction effects ( $e$ ) are also found to be statistically significant.

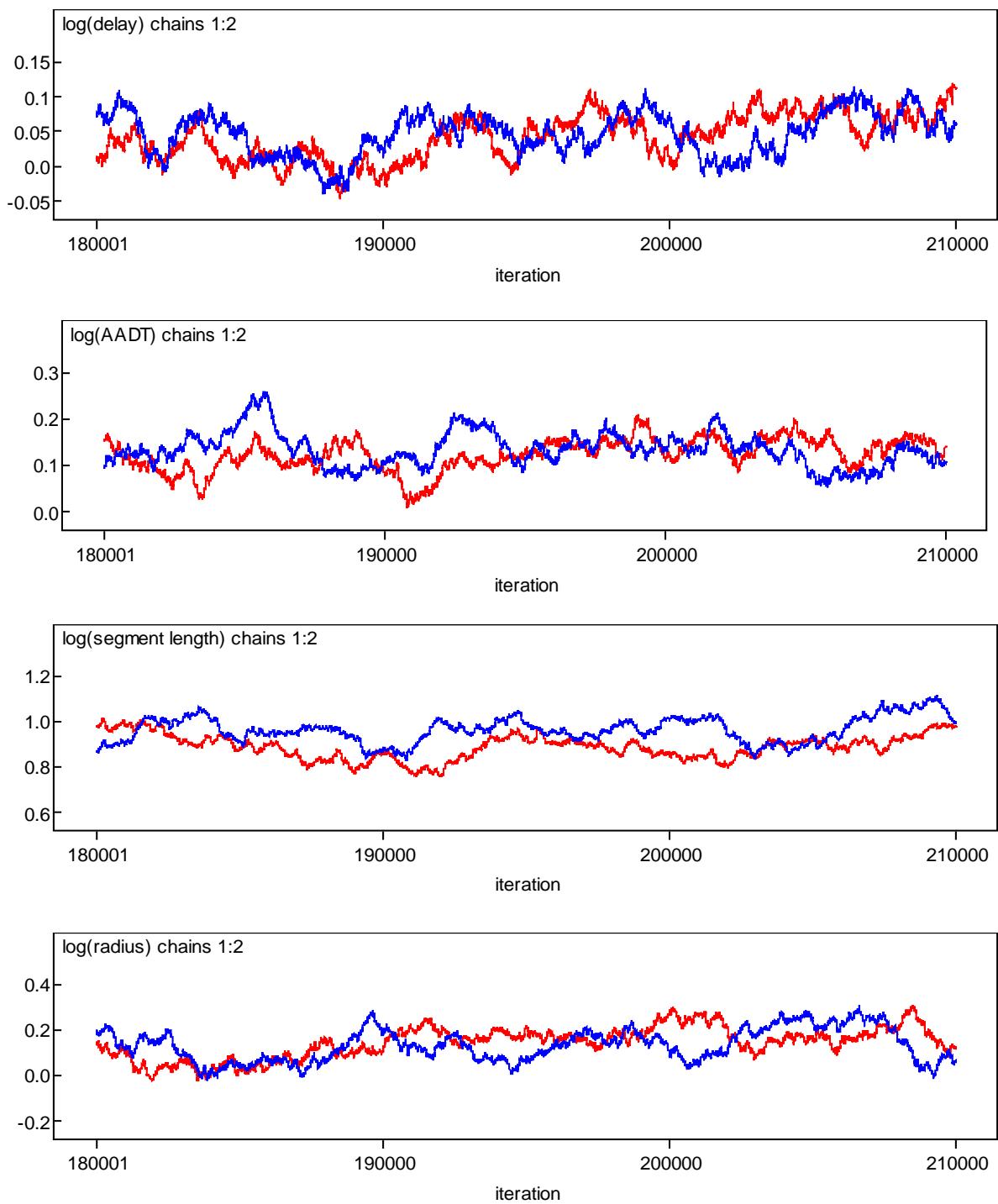
The MCMC output for selected parameters of interest in the fixed time effect models are presented in Figure 6.3 (fatal and serious injury accidents) and Figure 6.4 (slight injury accidents). As can be seen, after running 30,000 iterations in the fatal and serious injury accident model and 180,000 iterations in the slight injury accident model, the MCMC simulation becomes reasonably stable. Figure 6.5 and Figure 6.6 demonstrate the estimates of posterior distributions of the parameters in the fixed time effect models. Generally normal curves are found for the parameters, which is consistent with the prior assumptions of the distributions for these parameters.



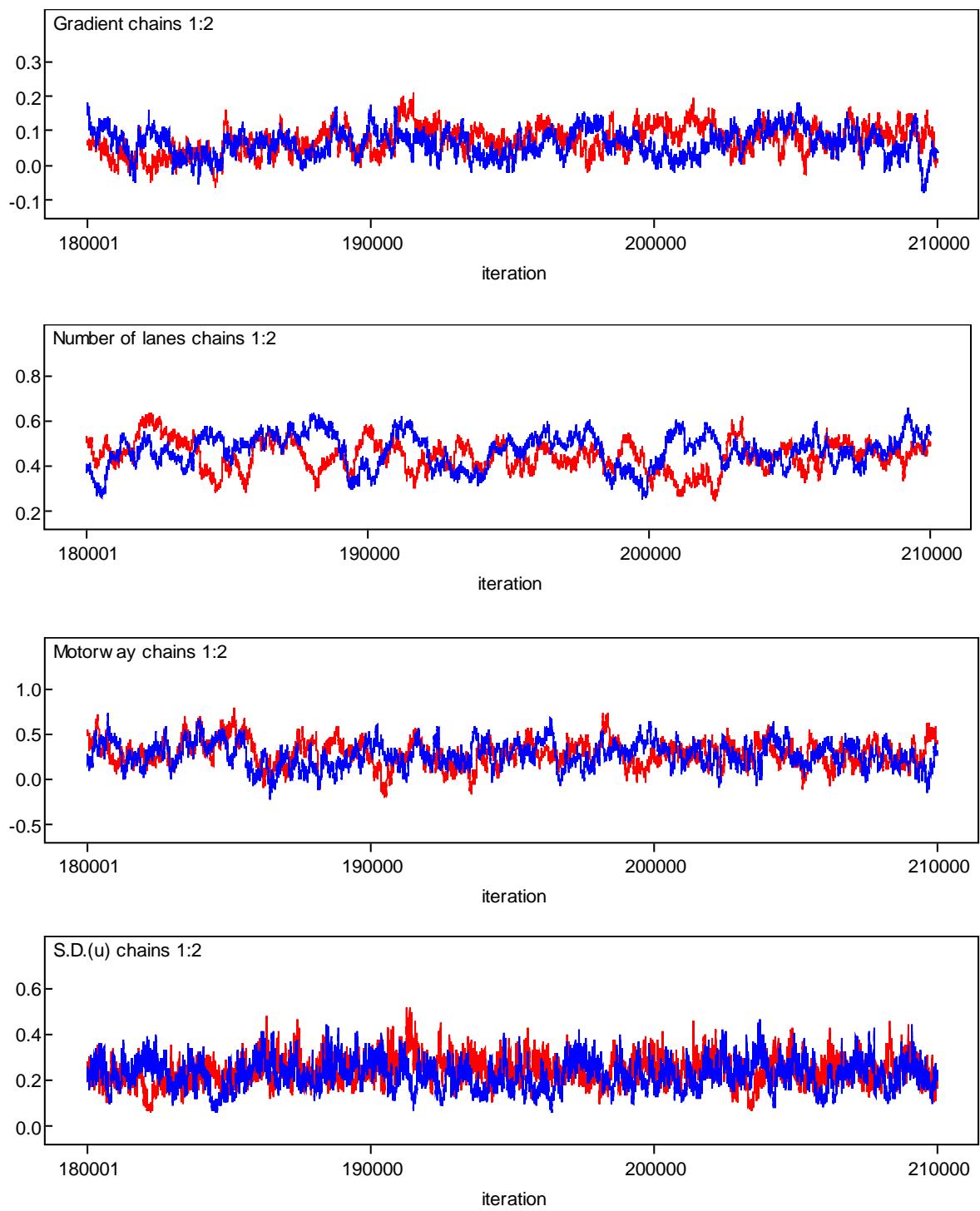
**Figure 6.3 MCMC output for fixed time effect models (fatal and serious injury accidents)**



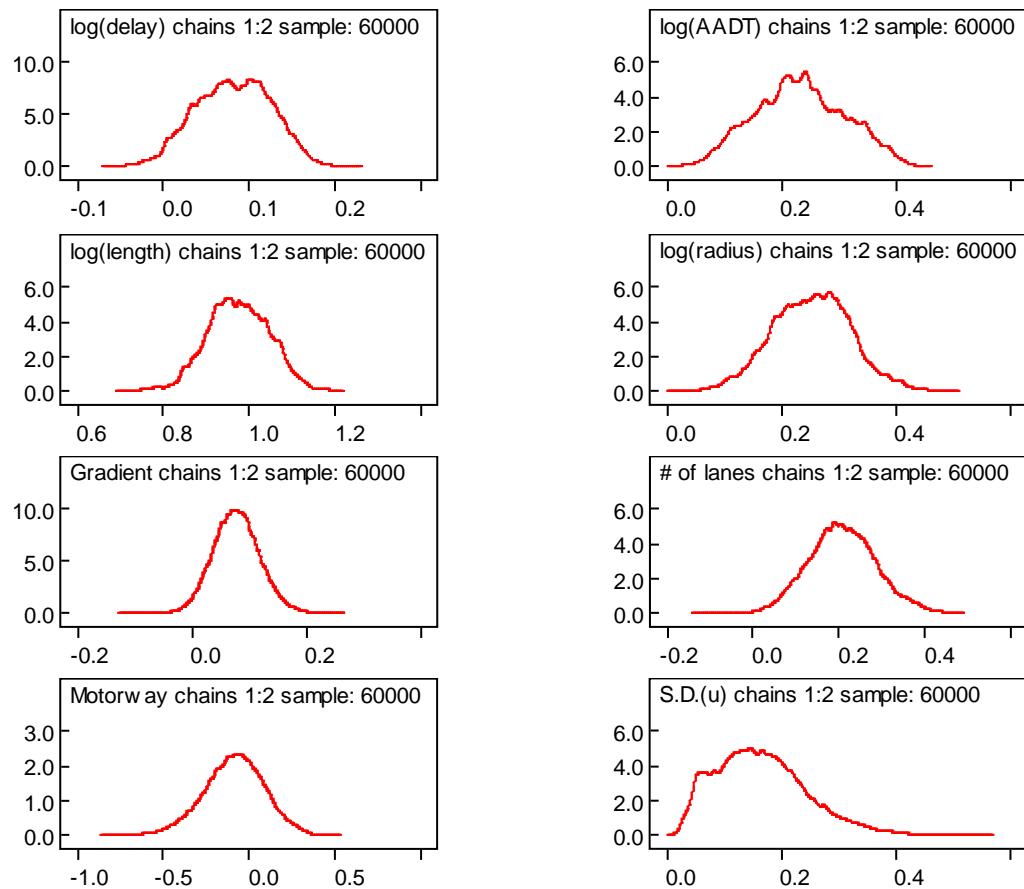
**Figure 6.3 (Continued)**



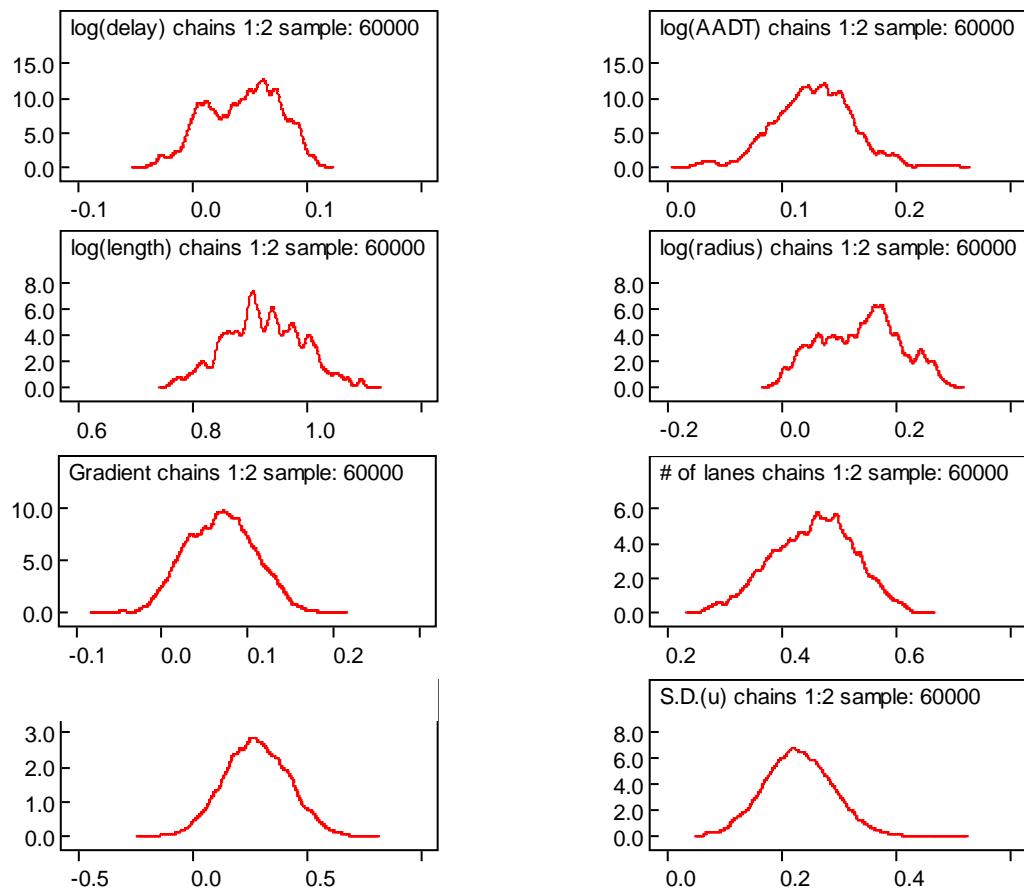
**Figure 6.4** MCMC output for fixed time effect models (slight injury accidents)



**Figure 6.4 (Continued)**



**Figure 6.5 Posterior density curves of variables of interest (fatal and serious injury accidents)**



**Figure 6.6 Posterior density curves of variables of interest (slight injury accidents)**

Compared to the results from the classical count outcome models (i.e. random-effects NB models) for the same balanced panel dataset, most of the explanatory variables that are statistically significant in the classical models (Tables 6.9 and 6.10) are also significant in the spatial models (Tables 6.11 and 6.12). The values of the coefficients are also fairly close to the estimates from the classical models. The notable exceptions are the effects of *AADT* and *number of lanes* in fatal and serious injury accident models, and *traffic delay*, *radius* and *gradient* in the slight injury accident models. The coefficient of  $\log(AADT)$  decreases from 0.57 in the classical model (Table 6.9) to 0.23 in the spatial model (Table 6.11) for the case of fatal and serious injury accidents. This may be because the effects of *AADT* have been captured by other unobserved spatially correlated effects in the spatial models, such as weather and roadway conditions. The effect of the *number of lanes* is statistically insignificant in the classical model (Table 6.9) but becomes significant in the spatial model (Table 6.11).

For the case of slight injury accidents, *traffic delay* shows different results between the classical and spatial models. This variable is statistically significant and positively associated with the slight injury accidents in the classical model (Table 6.10), but becomes statistically insignificant in the spatial model (Table 6.12). This means that *traffic delay* has no impact on the frequency of slight injury accidents according to the results from the spatial model. In addition, *radius* becomes significant at a greater confidence level (95% in the spatial model compared to 90% in the classical model). *Gradient* has now become positive and significant at a 90% confidence level in the spatial model while this variable was negative and statistically insignificant in the classical model. This result (positive and statistically significant) for *gradient* in the spatial model is in line with previous research findings (e.g. Shankar et al., 1995; Milton and Mannering, 1998). This suggests that the spatial model can produce more coherent results (i.e. better inference) compared to the classical count outcome model.

The difference in the model estimation results between the classical models and Bayesian spatial models may partially be due to the fact that the latter controls for spatial correlation. To examine whether the spatially correlated effects have been captured by the Bayesian spatial models, Moran's *I* statistics (Anselin, 1988) have been calculated to test the spatial correlation in the residuals (=observed-predicted values) across road segments. The residuals from the Bayesian spatial models have been checked and found to be approximately normally distributed for the case of slight injury

accidents, so only residuals from the slight injury accident models were tested. The Moran's *I* tests whether the data is spatially correlated (i.e. requires cross-sectional data), however the data used is panel data, so Moran's *I* statistics were calculated for each of the years separately. The results of Moran's *I* tests using first-order neighbouring structure for the 266 road segments during 2003-2007 are presented in Table 6.14:

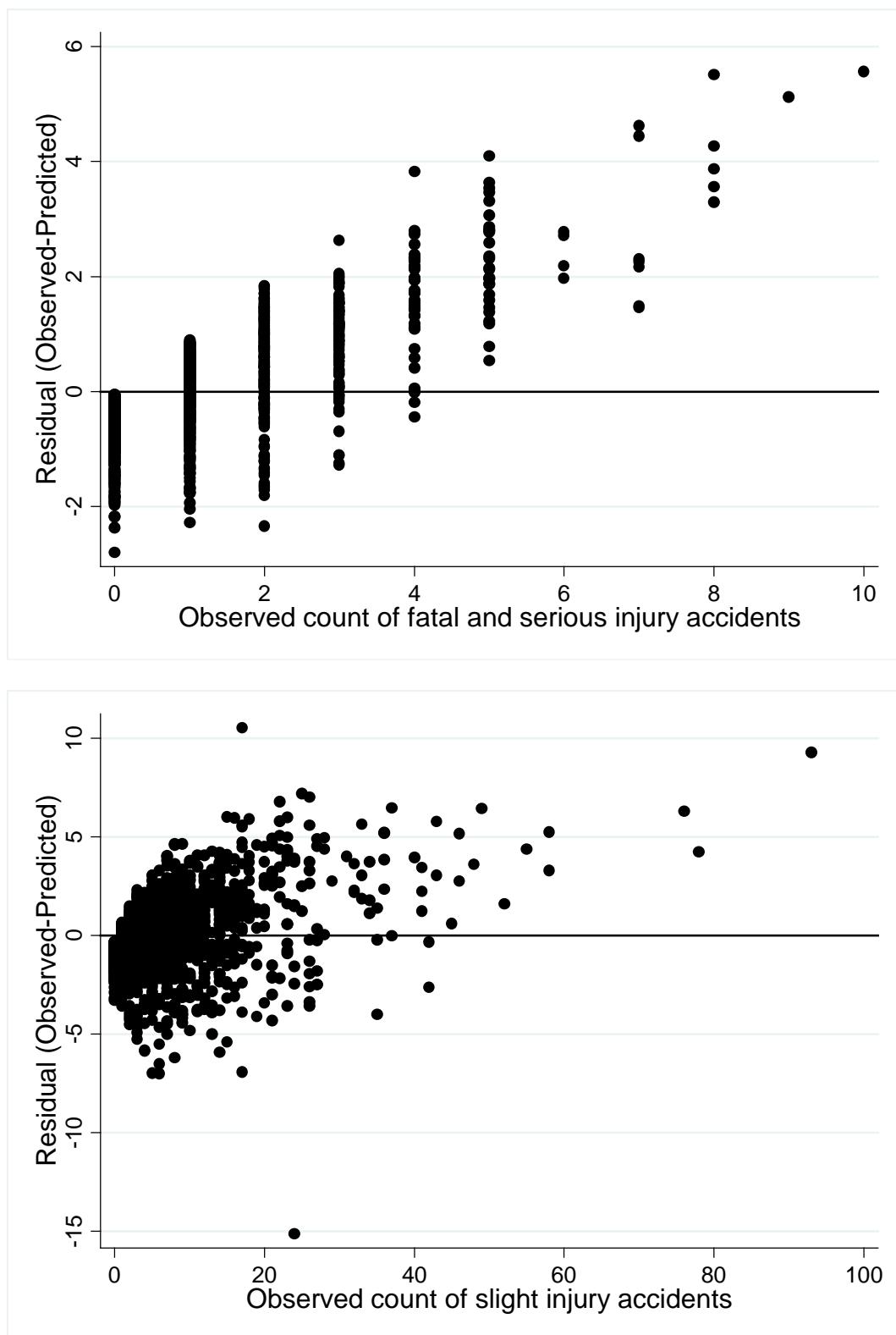
**Table 6.14 Moran's *I* statistics for residuals from the Bayesian spatial models**

|      | <i>I</i> | z value |
|------|----------|---------|
| 2003 | -0.017   | -0.218  |
| 2004 | 0.085*   | 1.439   |
| 2005 | 0.086*   | 1.446   |
| 2006 | 0.069    | 1.204   |
| 2007 | 0.073    | 1.238   |

\* p<0.1, \*\* p<0.05, 1-tail test

From Table 6.14 it can be seen that all the Moran's *I* statistics are statistically insignificant (at a 95% confidence level) for slight injury accidents, which suggests that there is no or little effect of spatial correlation in the residuals. This means that spatially correlated effects have been successfully captured and removed by the Bayesian spatial models.

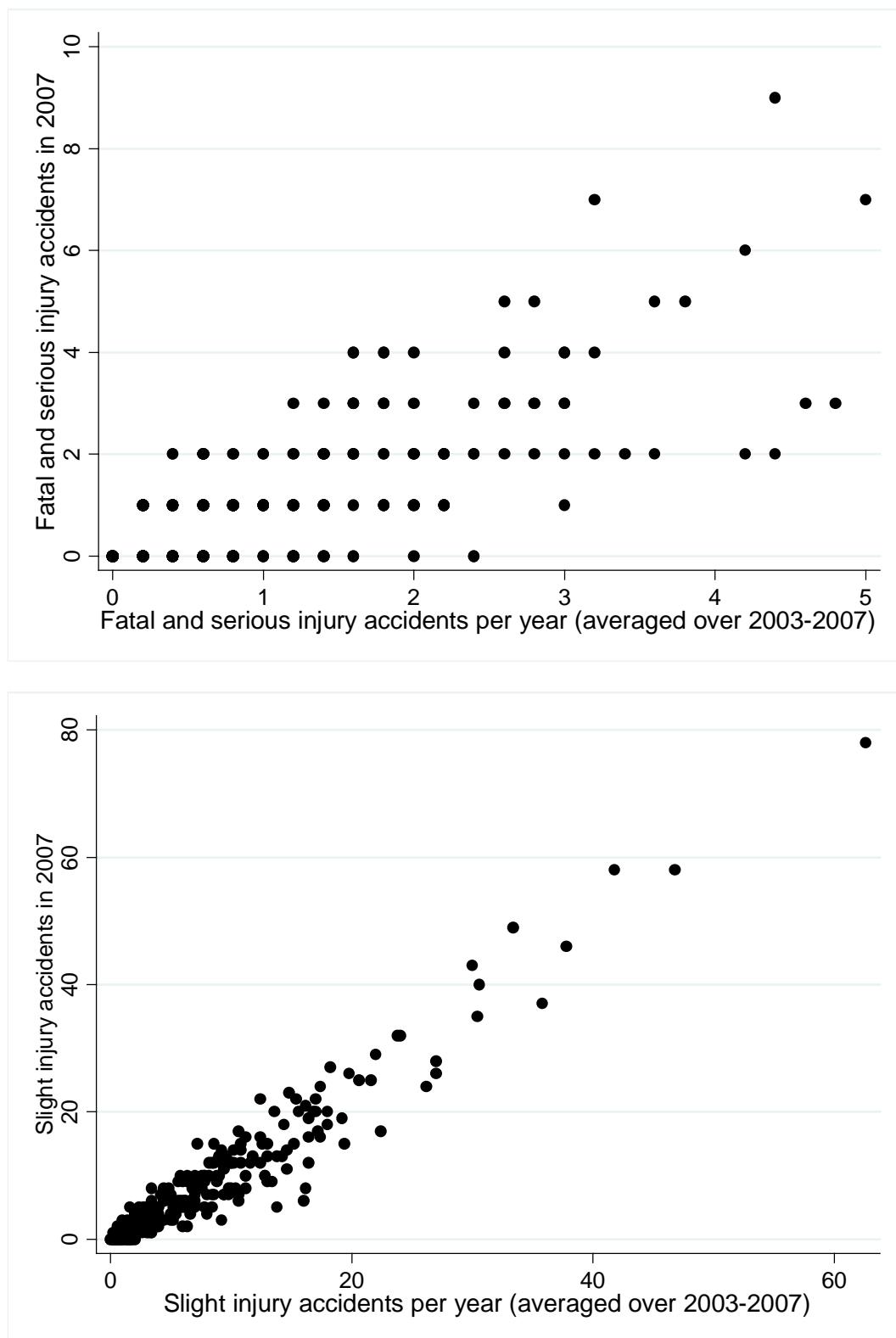
The predicted count of accidents from the Bayesian spatial models can be obtained from monitoring the posterior means of the expected accident counts on road segments. Figure 6.7 shows the relationship between the observed and the residual (=observed-predicted) values of accident frequency on the M25 and surround.



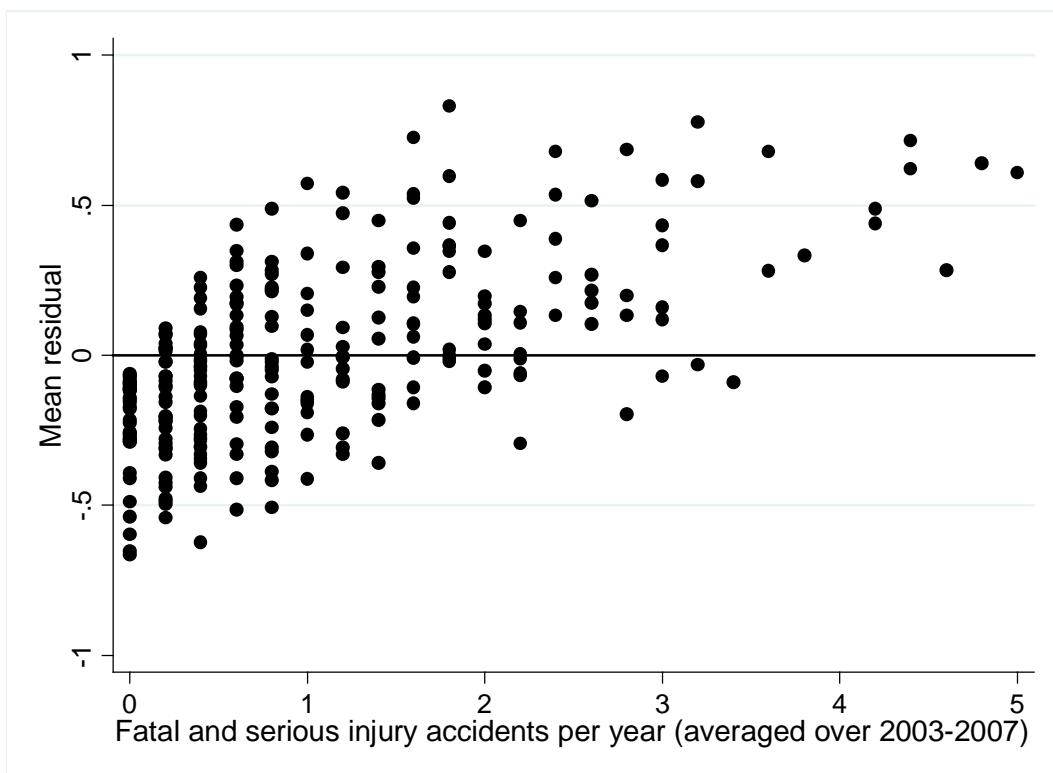
**Figure 6.7** The relationship between the observed and the residual values of accidents for Bayesian spatial models

As can be seen in Figure 6.7 for the case of fatal and serious injury accidents, the pattern of the residuals from the Bayesian spatial model is similar to that of the residuals from the classical count models (Figure 6.2). There is still a clear pattern of the residuals (i.e. increasing with respect to observed values) even when spatially correlated effects have been controlled for in the Bayesian spatial models. The reason for this may be due to the higher regression-to-the-mean effect in fatal and serious injury accidents compared to slight injury accidents. Fatal and serious injury accidents are very rare events – around 47% of the observations (accident counts per segment per year) are zeros. Also as shown in the next chapter, the probability of a fatal/serious injury accident occurring is very low. Due to the regression-to-the-mean effect, segments with low accident counts in one year may actually have a high level of risk and could result in high accident counts in the following year, and *vice versa*.

To illustrate the regression-to-the-mean effect, observed accident count per road segment has been averaged over the five years' period (2003-2007), which provides the estimate of a segment's long-term expected accident frequency. The annual average accident count per segment is then compared with the actual (observed) accident count in 2007. This is presented in Figure 6.8. As can be seen, it is clear that the observed number of fatal and serious injury accidents in 2007 is quite inconsistent with the long-term (2003-2007) annual average compared to slight injury accidents. This implies that there is higher regression-to-the-mean effect in the fatal and serious injury accidents. Figure 6.9 presents the comparison between the annual average accident count per segment and the mean residual estimated from the spatial model for fatal and serious injury accidents. It can be seen that the residual plot in Figure 6.9 has been much improved compared to the residual plot in Figure 6.7. The mean residual is within  $\pm 1$  (see Figure 6.9) which is much lower than the previous residuals (see Figure 6.7). Also the increasing trend in the residuals has been eliminated to a great extent. This suggests that the regression-to-the-mean effect has been successfully captured by the model which correctly predicted the expected number of fatal and serious injury accidents.

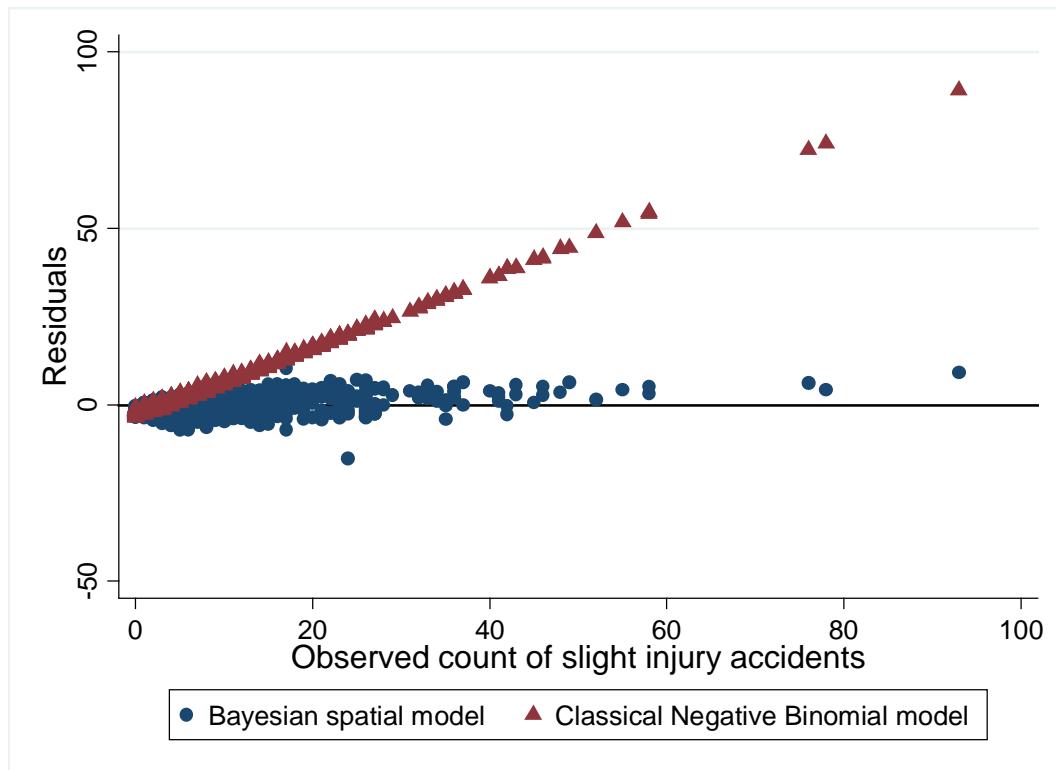


**Figure 6.8** The relationship between the annual average accident count per segment and the observed accidents in 2007



**Figure 6.9 The relationship between the annual average accident count per segment and the mean residual**

While the pattern of residuals is very similar between classical count models and spatial models for the case of fatal and serious injury accidents, there is significant difference for slight injury accident: it can be seen that the predictions from the Bayesian spatial models (Figure 6.7) are much more accurate than classical count outcome models (Figure 6.2). The maximum (absolute) value of residual is around 15 for slight injury accidents using the Bayesian spatial model, which is much smaller compared to the classical count model (the maximum residual is around 90; see Figure 6.2). The difference in residuals between classical and Bayesian spatial models for slight injury accidents is presented in Figure 6.10, which clearly shows that the Bayesian spatial model is much better in terms of model fit for slight injury accidents.



**Figure 6.10 Comparison of residuals: Bayesian spatial model vs. classical NB model**

Given that the Bayesian spatial model is superior in terms of its underlying theory (e.g., taking account of spatial correlation), goodness-of-fit and model inference, it is believed that the Bayesian spatial models more accurately estimated the effects of covariates. Therefore, the results from the Bayesian spatial models are preferred, and for the effects of traffic congestion on the frequency of road accidents, it can be summarised that: traffic congestion is positively associated with fatal and serious injury accidents, namely a 1% increase in the level of traffic congestion will increase fatal and serious injury accidents by 0.08%. Traffic congestion has little or no impact on slight injury accidents. Considering that the majority (86%) of fatal and serious injury accidents are serious injury accidents, it can be speculated that traffic congestion would mainly affect the frequency of serious injury accidents. This has been confirmed by the serious injury accident models that are presented in Table 6.15. Not surprisingly, the results from the serious injury accident models (Table 6.15) are very similar to the fatal and serious injury accident models (Tables 6.9 and 6.11).

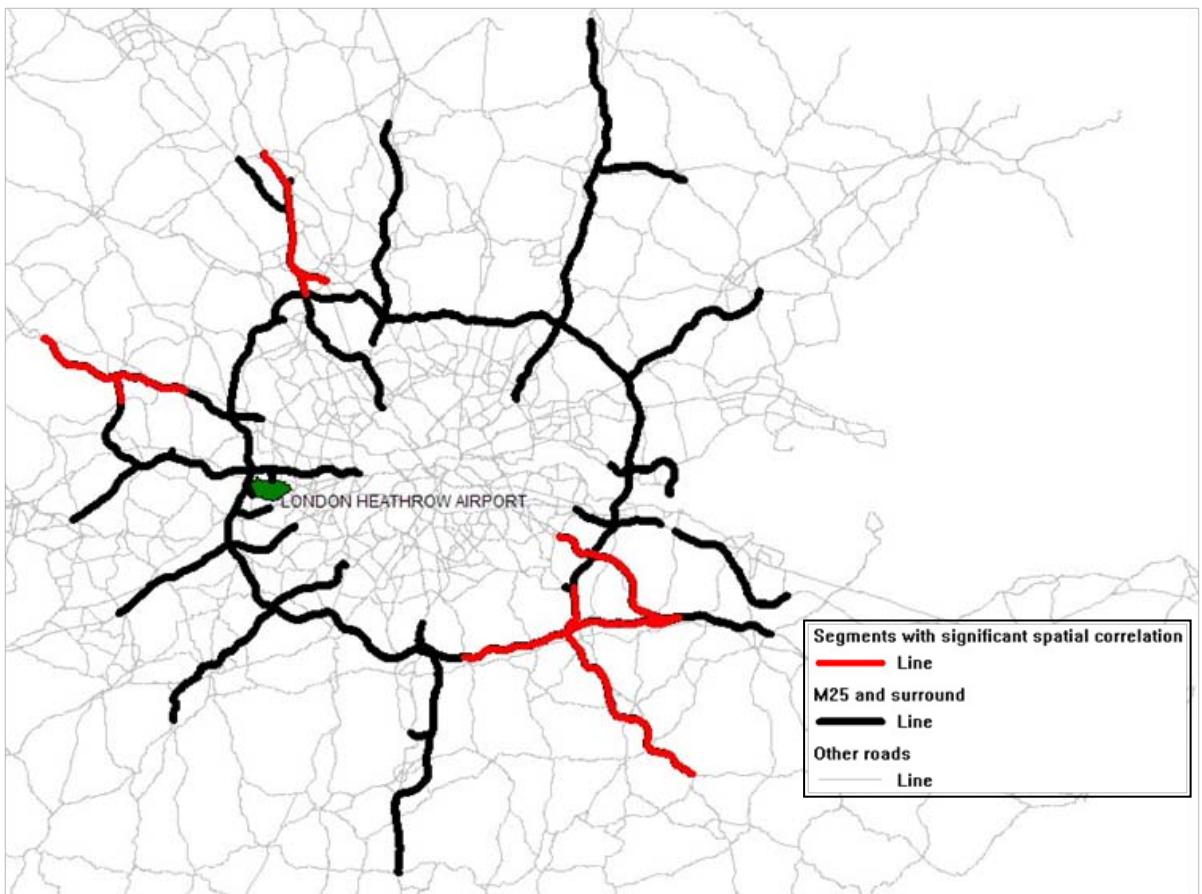
**Table 6.15 Models for serious injury accidents**

| Variables                | Random-effects NB model |         | Bayesian spatial model |       |
|--------------------------|-------------------------|---------|------------------------|-------|
|                          | Coefficient             | z value | Mean                   | S.D.  |
| log(delay in sec per km) | <b>0.146**</b>          | 3.56    | <b>0.119**</b>         | 0.046 |
| log(AADT)                | <b>0.568**</b>          | 4.87    | <b>0.266**</b>         | 0.098 |
| log(segment length in m) | <b>0.936**</b>          | 13.52   | <b>0.998**</b>         | 0.079 |
| log(minimum radius)      | <b>0.230**</b>          | 3.15    | <b>0.267**</b>         | 0.083 |
| Maximum gradient (%)     | <b>0.079**</b>          | 2.12    | <b>0.097**</b>         | 0.043 |
| Number of lanes          | 0.031                   | 0.42    | <b>0.207**</b>         | 0.082 |
| Speed limit (km/h)       | 0.006                   | 0.84    | 0.009                  | 0.009 |
| Motorway                 | -0.125                  | -1.13   | -0.118                 | 0.174 |
| Year 2003                |                         |         | 0                      | -     |
| Year 2004                | <b>-0.181**</b>         | -2.03   | <b>-0.169*</b>         | 0.086 |
| Year 2005                | <b>-0.240**</b>         | -2.66   | <b>-0.234**</b>        | 0.088 |
| Year 2006                | <b>-0.428**</b>         | -4.53   | <b>-0.415**</b>        | 0.092 |
| Year 2007                | <b>-0.312**</b>         | -3.36   | <b>-0.316**</b>        | 0.091 |
| Intercept                | <b>-15.528**</b>        | -9.3    | <b>-16.3**</b>         | 1.671 |
| S.D. ( $u$ )             | -                       |         | <b>0.198**</b>         | 0.081 |
| S.D. ( $e$ )             | -                       |         | <b>0.070**</b>         | 0.061 |
| S.D. ( $v$ )             | -                       |         | <b>0.232**</b>         | 0.135 |
| Parameter $a$            | 84.119                  |         | -                      |       |
| Parameter $b$            | 7.161                   |         | -                      |       |
| Log likelihood           | -1523.631               |         | -                      |       |
| AIC / DIC                | 3077.261                |         | 3040.68                |       |
| <i>N</i>                 | 1330                    |         | 1330                   |       |

\* Statistically significant from zero (90% credible sets show the same sign in the Bayesian model;  $p<0.1$  in the random-effects NB model)

\*\* Statistically significant from zero (95% credible sets show the same sign in the Bayesian model;  $p<0.05$  in the random-effects NB model)

Figure 6.11 presents road segments on the M25 and surround, where segments with significant (at a 95% confidence level) spatially correlated effects ( $u_i$ ) in the fatal and serious injury accident model are highlighted (i.e. those road segments with significant posterior estimates of  $u_i$ ). A total number of 32 road segments are identified to have significant spatially correlated effects, and clearly these segments are clustered in the northwest and southeast parts of the road network. Given the fact that road segments with spatial correlation are clustered, the clustered segments can be treated as groups in road safety programmes.



**Figure 6.11 Road segments with significant spatially correlated effects on the M25 and surround**

## 6.4 Summary

This chapter has presented the estimation results and findings from the accident frequency models which examined the impact of traffic congestion on the frequency of road accidents while controlling for other contributing factors.

A preliminary case study based on the M25 motorway was conducted. While controlling for other contributing factors such as annual average daily traffic (AADT) and road geometry, it was found that traffic congestion has no impact on the frequency of accidents on the M25. Several non-spatial models (such as Poisson-lognormal and Poisson-gamma) and spatial models (Poisson-lognormal with conditional autoregressive priors) were employed in order to investigate the effect of traffic congestion on road accidents. Congestion was measured using the congestion index and this variable was found to be statistically insignificant in all models, meaning that traffic congestion has little or no impact on the frequency of accidents according to the

data on the M25. Other congestion measurements such as total delay per kilometre length of road was also tested and subsequently found to be statistically insignificant.

While no statistically significant association was observed in the case study on the M25 motorway, a more comprehensive spatio-temporal analysis on the M25 motorway and its surrounding major motorways and A roads (the M25 and surround) was conducted. This analysis significantly extended the data used in the M25 case study to 13 different motorways and 17 different A roads for a 5 year period. Several classical count outcome models and spatial models using a full Bayesian approach were developed to investigate the effect of traffic congestion (measured by delay per kilometre) on road accidents. While the results from the classical and spatial models were generally similar to each other, there were some inconsistencies between them for some variables, for example, the effect of traffic delay (congestion) for slight injury accidents. The results from the spatial models were argued to be preferable as they accommodate spatial correlation and better fit the data. From the model estimation results, it was found that traffic congestion is positively associated with the frequency of fatal and serious injury accidents: a 1% increase in the level of traffic congestion would increase fatal and serious injury accidents by around 0.1%. A separate serious injury accident model also confirmed that traffic congestion would increase the frequency of serious injury accidents. On the other hand, traffic congestion was found to have little impact on slight injury accidents. Similar results were obtained while the congestion index was employed in place of the total delay per km length of roadway for the case of unbalanced panel data (i.e. including all observations). The effects of other contributing factors were found to be generally consistent with previous studies. Considering that the spatio-temporal analysis on the M25 and surround significantly extended the M25 case study both spatially and temporally, the spatio-temporal analysis was therefore believed to provide more coherent results which more accurately described the relationship between traffic congestion and the frequency of road accidents.

The next chapter presents the results of the impact of traffic congestion on the severity of road accidents.

# CHAPTER 7 RESULTS FROM ACCIDENT SEVERITY MODELS

## 7.1 Introduction

This chapter presents the results of accident severity models aimed at investigating the effect of traffic congestion on the severity of accidents. As discussed in Chapter 4 (section 4.6), two types of model are suitable for categorical data (i.e. accident severity levels), namely ordered response models and unordered nominal response models, and these have been considered and tested.

This chapter is organised as follows: first of all, the results and findings from the ordered response models are presented; this is followed by the results and findings from the nominal response models as an alternative modelling approach. Finally, the model estimation results and findings are summarised at the end of the chapter.

## 7.2 Ordered response models

A series of ordered response models (ORM) have been developed so as to examine the effect of traffic congestion on accident severity as severity outcomes are ordinal in nature. Accident severity is coded as follows: 1 for a slight injury accident, 2 for a serious injury accident and 3 for a fatal accident. Traffic congestion is measured as total traffic delay (in min) per 10 kilometres length of roadway per hour, as this measurement of congestion seems to be appropriate while estimating the impact of congestion on accident severity at a disaggregate individual accident level. This was discussed in Chapter 5 (section 5.2). Summary statistics of the data used in the ORM are presented in Table 5.2 in Chapter 5. Some of the explanatory variables have been transformed into a logarithmic scale so as to reduce the variance among the variables, including traffic flow and radius of road curvature. Year dummies have also been included in the models with 2003 being assumed as the reference case.

The correlation coefficients of the explanatory variables have been examined and presented in Table 7.1. It has been found that *average speed* is correlated with *traffic congestion* (correlation coefficient -0.69); and the *peak time indicator* has been found to be correlated with *traffic flow* (correlation coefficient 0.71). An initial test showed that

the inclusion of *average speed* in the models would reduce the confidence level of *traffic congestion*. Since the effect of *traffic congestion* is the focus of this thesis, *average speed* has been excluded from the models. The *peak time indicator* was kept in the models as the initial test of the models showed that the inclusion of this variable did not significantly change the model estimation results.

A total of four models have been estimated: an ordered logit (OLOGIT) model, a heterogeneous choice model (HCM), a generalised ordered logit (GOLOGIT) model and a partial proportional odds (PPO) model. The model estimation results are presented in Table 7.2.

**Table 7.1 Correlation coefficients between variables in the accident severity analysis**

|  | Level of traffic congestion | log(traffic flow) | Average speed | log(minimum radius) | Maximum gradient | Number of lanes ≤ 3 indicator | Number of lanes ≥ 5 indicator | Motorway indicator | Speed limit |
|--|-----------------------------|-------------------|---------------|---------------------|------------------|-------------------------------|-------------------------------|--------------------|-------------|
| Level of traffic congestion              | 1.00                        |                   |               |                     |                  |                               |                               |                    |             |
| log(traffic flow)                        | 0.11                        | 1.00              |               |                     |                  |                               |                               |                    |             |
| Average speed                            | <b>-0.69</b>                | -0.20             | 1.00          |                     |                  |                               |                               |                    |             |
| log(minimum radius)                      | -0.05                       | 0.14              | 0.09          | 1.00                |                  |                               |                               |                    |             |
| Maximum gradient                         | -0.04                       | -0.11             | 0.02          | -0.27               | 1.00             |                               |                               |                    |             |
| Number of lanes ≤ 3 indicator            | -0.07                       | -0.23             | -0.02         | 0.01                | 0.08             | 1.00                          |                               |                    |             |
| Number of lanes ≥ 5 indicator            | 0.07                        | 0.13              | -0.07         | 0.07                | -0.24            | -0.36                         | 1.00                          |                    |             |
| Motorway indicator                       | -0.04                       | 0.22              | 0.04          | 0.22                | -0.07            | -0.07                         | 0.08                          | 1.00               |             |
| Speed limit                              | -0.08                       | 0.02              | 0.14          | 0.22                | 0.00             | 0.11                          | -0.20                         | 0.21               | 1.00        |
| Lighting condition (darkness)            | -0.04                       | -0.40             | 0.07          | 0.00                | 0.02             | 0.04                          | -0.02                         | -0.02              | 0.01        |
| Weather (raining)                        | 0.03                        | -0.05             | -0.04         | 0.00                | 0.04             | 0.01                          | -0.02                         | -0.03              | 0.01        |
| Weather (snowing)                        | -0.01                       | -0.04             | 0.01          | 0.01                | 0.01             | 0.00                          | -0.01                         | 0.00               | 0.01        |
| Other weather conditions (e.g. fog/mist) | 0.01                        | -0.01             | -0.02         | -0.01               | 0.00             | -0.02                         | 0.03                          | -0.02              | -0.02       |
| Peak time indicator                      | 0.12                        | 0.71              | -0.20         | 0.02                | -0.02            | -0.06                         | 0.03                          | 0.03               | 0.00        |
| Weekday indicator                        | 0.07                        | 0.15              | -0.13         | -0.01               | 0.03             | -0.05                         | 0.01                          | 0.00               | -0.02       |
| Single vehicle accident indicator        | -0.12                       | -0.32             | 0.20          | -0.05               | 0.05             | 0.08                          | -0.06                         | -0.10              | 0.03        |
| Number of casualties per accident        | 0.02                        | 0.01              | -0.02         | 0.03                | 0.01             | 0.02                          | -0.02                         | 0.03               | 0.02        |

**Table 7.1 (continued)**

|  | Lighting condition (darkness) | Weather (raining) | Weather (snowing) | Other weather conditions (e.g. fog/mist) | Peak time indicator | Weekday indicator | Single vehicle accident indicator | Number of casualties per accident |
|--|-------------------------------|-------------------|-------------------|--|---------------------|-------------------|-----------------------------------|-----------------------------------|
| Lighting condition (darkness)            | 1.00                          |                   |                   |  |                     |                   |                                   |                                   |
| Weather (raining)                        | 0.10                          | 1.00              |                   |  |                     |                   |                                   |                                   |
| Weather (snowing)                        | 0.04                          | -0.03             | 1.00              |  |                     |                   |                                   |                                   |
| Other weather conditions (e.g. fog/mist) | 0.06                          | -0.08             | -0.01             | 1.00                                     |                     |                   |                                   |                                   |
| Peak time indicator                      | -0.50                         | -0.03             | -0.01             | -0.02                                    | 1.00                |                   |                                   |                                   |
| Weekday indicator                        | -0.04                         | 0.00              | 0.02              | 0.01                                     | 0.16                | 1.00              |                                   |                                   |
| Single vehicle accident indicator        | 0.08                          | 0.04              | 0.02              | -0.02                                    | -0.22               | -0.11             | 1.00                              |                                   |
| Number of casualties per accident        | 0.01                          | 0.00              | -0.02             | -0.01                                    | 0.00                | -0.10             | -0.11                             | 1.00                              |

**Table 7.2 Estimation results for ordered response models**

| Variables                                       | OLOGIT      |         | HCM         |          | GOLOGIT              |         | PPO                  |         |
|---|-------------|---------|-------------|----------|----------------------|---------|----------------------|---------|
|   | Coefficient | z value | Coefficient | z value  | Coefficient<br>(y>1) | z value | Coefficient<br>(y>1) | z value |
| Level of traffic congestion (min per 10km)      | -0.0003     | -0.21   | 0.0001      | 0.42     | -0.0002              | -0.18   | -0.0003              | -0.19   |
| log(Traffic flow in veh/h)                      | -0.313**    | -6.32   | -0.011      | -0.56    | -0.295**             | -5.98   | -0.295**             | -5.98   |
| log(minimum radius)                             | 0.132**     | 2.43    | 0.033**     | 2.12     | 0.130**              | 2.37    | 0.130**              | 2.37    |
| Maximum gradient (%)                            | 0.027       | 1.00    | 0.007       | 1.06     | 0.032                | 1.16    | 0.032                | 1.16    |
| Number of lanes ≤ 3 indicator                   | 0.150*      | 1.78    | 0.023       | 1.15     | 0.158*               | 1.87    | 0.152*               | 1.81    |
| Number of lanes ≥ 5 indicator                   | 0.003       | 0.01    | 0.019       | 0.43     | 0.009                | 0.04    | 0.003                | 0.01    |
| Motorway indicator                              | -0.215**    | -2.71   | -0.049**    | -2.17    | -0.214**             | -2.70   | -0.212**             | -2.68   |
| Speed limit (km/h)                              | 0.002       | 0.70    | 0.000       | 0.23     | 0.002                | 0.62    | 0.002                | 0.69    |
| Lighting condition (darkness)                   | -0.101      | -1.36   | -0.033*     | -1.78    | -0.110               | -1.49   | -0.102               | -1.38   |
| Weather (raining)                               | -0.358**    | -3.99   | -0.095**    | -3.09    | -0.354**             | -3.93   | -0.358**             | -3.98   |
| Weather (snowing)                               | -0.527      | -1.10   | -0.14       | -1.06    | -0.482               | -1.00   | -0.516               | -1.08   |
| Other weather conditions (e.g. fog/mist)        | -0.402**    | -2.16   | 0.131*      | 1.75     | -0.384**             | -2.06   | -0.397**             | -2.14   |
| Peak time indicator                             | -0.268**    | -2.48   | -0.051*     | -1.66    | -0.273**             | -2.51   | -0.270**             | -2.49   |
| Weekday indicator                               | 0.015       | 0.22    | 0.009       | 0.55     | 0.005                | 0.08    | 0.015                | 0.22    |
| Single vehicle accident indicator               | 0.503**     | 7.13    | 0.135**     | 3.88     | 0.498**              | 7.03    | 0.507**              | 7.20    |
| Number of casualties per accident               | 0.324**     | 15.06   | 0.063**     | 3.58     | 0.318**              | 14.5    | 0.324**              | 15.00   |
| Year 2004                                       | -0.290**    | -3.33   | 0.014       | 0.39     | -0.288**             | -3.31   | -0.290**             | -3.34   |
| Year 2005                                       | -0.276**    | -3.16   | -0.070**    | -2.60    | -0.282**             | -3.24   | -0.277**             | -3.19   |
| Year 2006                                       | -0.339**    | -3.76   | -0.077**    | -2.64    | -0.346**             | -3.83   | -0.337**             | -3.74   |
| Year 2007                                       | -0.173*     | -1.89   | -0.038      | -1.57    | -0.182**             | -1.98   | -0.173*              | -1.89   |
| Cut-point 1                                     | 0.854       | 1.51    | 0.654**     | 4.09     | 0.937*               | 1.66    | 0.985*               | 1.75    |
| Cut-point 2                                     | 3.003**     | 5.29    | 1.200**     | 4.91     | 1.749                | 1.16    | 0.031                | 0.04    |
| <i>Variables with different error variances</i> |             |         |             |          |                      |         |                      |         |
| log(Traffic flow in veh/h)                      |             |         |             | -0.191** | -6.20                |         |                      |         |
| Other weather conditions (e.g. fog/mist)        |             |         |             | -0.520** | -2.44                |         |                      |         |
| Number of casualties per accident               |             |         |             | 0.049**  | 3.69                 |         |                      |         |
| Year 2004                                       |             |         |             | -0.187** | -2.50                |         |                      |         |

\* p&lt;0.1, \*\* p&lt;0.05

**Table 7.2 (continued)**

| Variables                                  | OLOGIT                 | HCM                    | GOLOGIT                         | PPO                             |
|--|------------------------|------------------------|---------------------------------|---------------------------------|
|  | Coefficient<br>z value | Coefficient<br>z value | Coefficient<br>(y>2)<br>z value | Coefficient<br>(y>2)<br>z value |
| Level of traffic congestion (min per 10km) |                        |                        | -0.001 -0.23                    | - -                             |
| log(Traffic flow in veh/h)                 |                        |                        | -0.616** -6.53                  | -0.649** -9.11                  |
| log(minimum radius)                        |                        |                        | 0.122 0.88                      | - -                             |
| Maximum gradient (%)                       |                        |                        | -0.138** -2.05                  | -0.121* -1.94                   |
| Number of lanes ≤ 3 indicator              |                        |                        | -0.081 -0.38                    | - -                             |
| Number of lanes ≥ 5 indicator              |                        |                        | -0.610 -0.81                    | - -                             |
| Motorway indicator                         |                        |                        | -0.205 -1.12                    | - -                             |
| Speed limit (km/h)                         |                        |                        | 0.013 1.37                      | - -                             |
| Lighting condition (darkness)              |                        |                        | 0.210 1.12                      | - -                             |
| Weather (raining)                          |                        |                        | -0.460** -2.05                  | - -                             |
| Weather (snowing)                          |                        |                        | -13.601 -0.02                   | - -                             |
| Other weather conditions (e.g. fog/mist)   |                        |                        | -1.210* -1.69                   | - -                             |
| Peak time indicator                        |                        |                        | -0.160 -0.67                    | - -                             |
| Weekday indicator                          |                        |                        | 0.222 1.38                      | - -                             |
| Single vehicle accident indicator          |                        |                        | 0.702** 4.47                    | - -                             |
| Number of casualties per accident          |                        |                        | 0.368** 9.00                    | - -                             |
| Year 2004                                  |                        |                        | -0.428* -1.84                   | - -                             |
| Year 2005                                  |                        |                        | -0.167 -0.78                    | - -                             |
| Year 2006                                  |                        |                        | -0.059 -0.26                    | - -                             |
| Year 2007                                  |                        |                        | 0.012 0.05                      | - -                             |
| <i>Statistics</i>                          |                        |                        |                                 |                                 |
| Log likelihood                             | -4693.478              | -4657.376              | -4666.036                       | -4676.007                       |
| Likelihood-ratio index                     | 0.053                  | 0.060                  | 0.059                           | 0.057                           |
| AIC  | 9430.957               | 9366.752               | 9416.072                        | 9400.014                        |
| N  | 11830                  | 11830                  | 11830                           | 11830                           |

\* p<0.1, \*\* p<0.05

In Table 7.2, the second column under OLOGIT shows the estimation results of the basic ordered logit model. For HCM, those explanatory variables with different error variances were identified using a stepwise selection method, indicating that *log(Traffic flow)*, *other weather conditions* (e.g., *fog/mist*), *number of causalities per accident* and *year 2004* are the variables affecting error variance. This is also confirmed by the model estimation results where these variables have all been found to be statistically significant in the error variance equation, which suggests that these variables are the potential source of heteroscedasticity.

As discussed in Chapter 3, the proportional odds assumption in the OLOGIT model is often violated, which may lead to misleading results. To test if the assumption is violated, an approximate likelihood-ratio test has been performed so as to compare the log likelihood from the OLOGIT with that estimated from pooling binary logit models (Wolfe and Gould, 1998). The results showed that the proportional odds assumption was rejected at the 95% confidence level for the OLOGIT model, which implies that the

results from the OLOGIT model may be inappropriate. In order to address the problem related to the proportional odds assumption in the OLOGIT model, two additional ORM have been estimated: GOLOGIT and PPO models (Table 7.2). In the OLOGIT model, coefficients for equations  $y>1$  and  $y>2$  (see equation (4.18) in Chapter 4 section 4.6.1) are constrained to be the same, while the coefficients in GOLOGIT and PPO models are allowed to vary across different equations. For PPO models, a series of Wald tests were performed on each explanatory variable to identify which variable varies across equations and thus violates the proportional odds assumption. It has been found that two variables, namely the  $\log(Traffic\ flow)$  and *maximum gradient* did not meet the proportional odds assumption, suggesting that the OLOGIT model may be mis-specified.

To compare different models, the Akaike information criterion (AIC) is used to compare model goodness-of-fit and complexity. The lower the AIC value the better the model. It can be seen from Table 7.2 that the OLOGIT model has produced a much higher AIC value compared with other models, suggesting that the OLOGIT model is the worst fitted model. This further implies that it is important to control heteroscedasticity and proportional odds assumption in an ordered response model. Both the GOLOGIT and PPO models fit the data better compared to the OLOGIT model and the PPO model is slightly better than the GOLOGIT model in terms of the AIC value. The HCM has produced the lowest AIC value among all models, making it the best model estimated in terms of goodness-of-fit and complexity. This is also confirmed by the likelihood-ratio index, for which the HCM obtained the highest value. The coefficients estimated by the HCM however are slightly inconsistent with other model (OLOGIT, GOLOGIT and PPO) estimations: for most of the variables, especially for those statistically significant variables, the absolute values of the coefficients are much smaller than estimates from other models. To further compare different models, marginal effects of statistically significant explanatory variables on the probabilities of each severity outcome for OLOGIT, HCM and PPO models have been calculated and presented in Table 7.3. The marginal effect for a continuous variable is defined as:

$$\text{marginal effect} = \frac{\partial \Pr(y=j)}{\partial x}, \quad j=1,2,3$$

where  $y$  is the severity outcome and  $x$  is the explanatory variable of interest while all explanatory variables are held at their mean values. For dummy variables, the marginal effect is defined as the discrete change of dummy variables from 0 to 1. As can be seen in Table 7.3, the marginal effects for OLOGIT, HCM and PPO models are very similar to each other, while the effects are slightly greater for HCM (i.e. the marginal changes are greater). Since all models have produced similar results and the HCM better fit the data than other models, the HCM will be used for further interpretation of the effects of various explanatory variables on accident severity. This is presented below.

**Table 7.3 Marginal effects for ordered response models**

|  |  | OLOGIT            | HCM               | PPO               |
|--|--|-------------------|-------------------|-------------------|
| Slight<br>injury<br>accident<br>(y=1)  | log(Traffic flow in veh/h)               | 0.030** (6.32)    | 0.044** (6.96)    | 0.029** (6.00)    |
|  | log(minimum radius)                      | -0.013** (-2.43)  | -0.015** (-2.50)  | -0.013** (-2.38)  |
|  | Maximum gradient (%)                     | -0.003 (-1.00)    | -0.003 (-1.10)    | -0.003 (-1.16)    |
|  | Number of lanes ≤ 3 indicator            | -0.014* (-1.85)   | -0.01 (-1.25)     | -0.014* (-1.88)   |
|  | Motorway indicator                       | 0.022** (2.56)    | 0.023** (2.41)    | 0.022** (2.54)    |
|  | Lighting condition (darkness)            | 0.01 (1.38)       | 0.014* (1.95)     | 0.01 (1.40)       |
|  | Weather (raining)                        | 0.031** (4.44)    | 0.037** (4.89)    | 0.031** (4.43)    |
|  | Other weather conditions (e.g. fog/mist) | 0.034** (2.54)    | 0.038** (2.60)    | 0.033** (2.50)    |
|  | Peak time indicator                      | 0.028** (2.32)    | 0.024* (1.74)     | 0.028** (2.33)    |
|  | Single vehicle accident indicator        | -0.055** (-6.40)  | -0.068** (-7.08)  | -0.056** (-6.45)  |
|  | Number of casualties per accident        | -0.031** (-15.15) | -0.038** (-13.41) | -0.031** (-15.08) |
|  | Year 2004                                | 0.026** (3.55)    | 0.031** (3.83)    | 0.026** (3.57)    |
|  | Year 2005                                | 0.025** (3.37)    | 0.029** (3.55)    | 0.025** (3.40)    |
|  | Year 2006                                | 0.030** (4.09)    | 0.031** (3.86)    | 0.030** (4.06)    |
|  | Year 2007                                | 0.016** (1.98)    | 0.016* (1.78)     | 0.016** (1.98)    |
| Serious<br>injury<br>accident<br>(y=2) | log(Traffic flow in veh/h)               | -0.026** (-6.29)  | -0.034** (-6.13)  | -0.021** (-4.92)  |
|  | log(minimum radius)                      | 0.011** (2.43)    | 0.013** (2.49)    | 0.011** (2.38)    |
|  | Maximum gradient (%)                     | 0.002 (1.00)      | 0.003 (1.10)      | 0.004* (1.82)     |
|  | Number of lanes ≤ 3 indicator            | 0.012* (1.85)     | 0.009 (1.25)      | 0.013* (1.87)     |
|  | Motorway indicator                       | -0.019** (-2.57)  | -0.020** (-2.42)  | -0.019** (-2.54)  |
|  | Lighting condition (darkness)            | -0.008 (-1.38)    | -0.013* (-1.95)   | -0.009 (-1.40)    |
|  | Weather (raining)                        | -0.027** (-4.41)  | -0.033** (-4.87)  | -0.028** (-4.41)  |
|  | Other weather conditions (e.g. fog/mist) | -0.029** (-2.52)  | -0.027** (-1.96)  | -0.029** (-2.49)  |
|  | Peak time indicator                      | -0.024** (-2.32)  | -0.021* (-1.74)   | -0.025** (-2.34)  |
|  | Single vehicle accident indicator        | 0.047** (6.42)    | 0.060** (7.07)    | 0.049** (6.46)    |
|  | Number of casualties per accident        | 0.027** (14.81)   | 0.032** (13.33)   | 0.028** (14.77)   |
|  | Year 2004                                | -0.023** (-3.54)  | -0.024** (-3.26)  | -0.023** (-3.56)  |
|  | Year 2005                                | -0.022** (-3.36)  | -0.025** (-3.54)  | -0.022** (-3.39)  |
|  | Year 2006                                | -0.026** (-4.07)  | -0.028** (-3.85)  | -0.027** (-4.05)  |
|  | Year 2007                                | -0.014** (-1.98)  | -0.014* (-1.78)   | -0.014** (-1.98)  |
| Fatal<br>accident<br>(y=3)             | log(Traffic flow in veh/h)               | -0.004** (-5.95)  | -0.010** (-8.30)  | -0.008** (-9.30)  |
|  | log(minimum radius)                      | 0.002** (2.39)    | 0.002** (2.45)    | 0.002** (2.34)    |
|  | Maximum gradient (%)                     | 0.000 (1.00)      | 0.000 (1.09)      | -0.001* (-1.95)   |
|  | Number of lanes ≤ 3 indicator            | 0.002* (1.85)     | 0.001 (1.25)      | 0.002* (1.87)     |
|  | Motorway indicator                       | -0.003** (-2.49)  | -0.003** (-2.33)  | -0.003** (-2.46)  |
|  | Lighting condition (darkness)            | -0.001 (-1.37)    | -0.002* (-1.94)   | -0.001 (-1.39)    |
|  | Weather (raining)                        | -0.004** (-4.34)  | -0.004** (-4.68)  | -0.004** (-4.27)  |
|  | Other weather conditions (e.g. fog/mist) | -0.005** (-2.58)  | -0.010** (-6.27)  | -0.004** (-2.52)  |
|  | Peak time indicator                      | -0.004** (-2.25)  | -0.003* (-1.69)   | -0.003** (-2.26)  |
|  | Single vehicle accident indicator        | 0.008** (5.74)    | 0.008** (6.04)    | 0.007** (5.63)    |
|  | Number of casualties per accident        | 0.004** (11.02)   | 0.005** (8.53)    | 0.004** (10.03)   |
|  | Year 2004                                | -0.004** (-3.51)  | -0.007** (-4.19)  | -0.003** (-3.48)  |
|  | Year 2005                                | -0.004** (-3.33)  | -0.003** (-3.46)  | -0.003** (-3.33)  |
|  | Year 2006                                | -0.004** (-4.01)  | -0.003** (-3.72)  | -0.004** (-3.93)  |
|  | Year 2007                                | -0.002** (-1.99)  | -0.002* (-1.78)   | -0.002** (-1.98)  |

\* p&lt;0.1, \*\* p&lt;0.05; z values in parentheses

### 7.2.1 Findings for traffic congestion

The *level of traffic congestion* (measured by traffic delay in min per 10km length of roadway per hour) has been included in the model to explore whether there is a relationship between congestion and accident severity. It was expected that increased traffic congestion would decrease the accident severity as the traffic speed may be relatively low in congested conditions, and *vice versa*. The variable for congestion has however been found to be statistically insignificant in all models, meaning that there is no association between congestion and accident severity. This is in line with the study by Quddus et al. (2010) who found that traffic congestion does not affect the severity of traffic accidents on major roads.

One may suspect that traffic congestion is highly correlated with *traffic flow* or time of the day (*peak time indicator*) and thus the model estimation results would be incorrect. This is however not the case as the correlation coefficient is around 0.1. Various combinations of explanatory variables have been tested, for example, dropping the *peak time indicator*, the level of congestion has still been statistically insignificant. Other congestion measurements, such as the congestion index (CI) have also been tested and been found to be statistically insignificant. This further confirms that the level of congestion has little or no impact on the severity outcome of an accident according to the ordered response model estimation results.

### 7.2.2 Findings for other contributing factors

#### Traffic flow

The variable  $\log(\text{Traffic flow})$  has been found to be statistically significant and negatively associated with accident severity, suggesting that increased *traffic flow* would decrease the accident severity outcome. The marginal effects of slight injury, serious injury and fatal accidents with respect to  $\log(\text{Traffic flow})$  have been found to be 0.044, -0.034 and -0.010, meaning that one unit increase in average  $\log(\text{Traffic flow})$  would increase the probability of slight injury accidents by 0.044, decrease the probability of serious injury accidents by 0.034 and fatal accidents by 0.01. From this it is also possible to calculate the mean elasticity which is defined as follows:

$$E = \frac{\partial \Pr(y=j)}{\partial x} \cdot \frac{\bar{x}}{\Pr(y=j)}, \quad j=1,2,3$$

For the case of *traffic flow*,

$$E = \frac{\partial \Pr(y=j)}{\partial(\text{traffic flow})} \cdot \frac{\text{traffic flow}}{\Pr(y=j)} = \frac{\frac{\partial \Pr(y=j)}{\partial \log(\text{traffic flow})}}{\frac{\partial \log(\text{traffic flow})}{\text{traffic flow}}} \cdot \frac{\text{traffic flow}}{\Pr(y=j)} = \frac{\partial \Pr(y=j)}{\Pr(y=j)}.$$

Therefore, a 1% increase in *traffic flow* would increase the probability of slight injury accidents by 0.05%, decrease the probability of serious injury accidents by 0.34% and fatal accidents by 0.90%.

The predicted probabilities calculated at the mean values of explanatory variables have been found to be:  $\Pr(y=\text{slight})=0.89$ ,  $\Pr(y=\text{serious})=0.10$  and  $\Pr(y=\text{fatal})=0.01$ . Figure 7.1 illustrates the change in predicted probabilities of different severity outcomes with the change in traffic flow. These probabilities have been estimated for single vehicle accidents, under fine weather and non-dark lighting conditions, during peak time in weekdays, on motorways with three lanes or less in 2007 while other variables (e.g., radius) are held at their mean values.

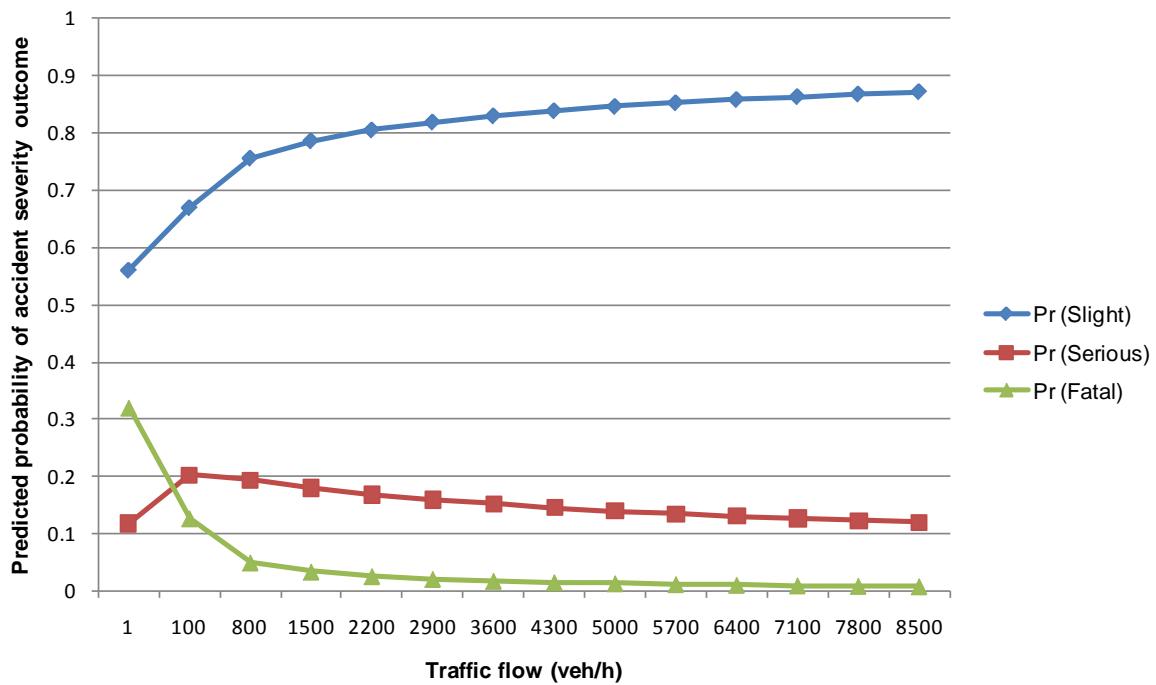


Figure 7.1 The predicted probabilities of different accident severity outcomes (using HCM)

As can be seen from Figure 7.1, if traffic flow increases, the probability of a slight injury accident occurring increases and the probability of a serious or a fatal accident (when traffic flow  $\geq 100$  veh/h) occurring decreases.

### Road segment infrastructure

Two variables *radius* and *gradient* were considered in the model to control for degrees of road curvature. The variable  $\log(\text{minimum radius})$  has been found to be statistically significant and positive, meaning that accidents on straighter road segments tend to be more severe. This is counter-intuitive at first sight but is consistent with previous studies (e.g. Shankar et al., 1996; Savolainen and Mannerling, 2007; Kim et al., 2007; Milton et al., 2008); and this is also in line with the results from the frequency models detailed in Chapter 6 (section 6.3). *Maximum gradient* has however been found to be statistically insignificant in all models, except in the GOLOGIT and PPO models for the  $y>2$  equation (i.e. slight and serious injury accidents vs. fatal accidents. See Chapter 4 section 4.6.1) where the coefficient is negative, meaning that an increased vertical curve would decrease the accident severity level from fatality to serious injury.

The number of lanes was considered in the model by using a series of dummy variables: *three lanes or less*; and *five lanes or more*. *Four lanes* was used as a reference case. The results show that the variable for *three lanes or less* is insignificant in the HCM but becomes significant at the 90% confidence level for other models (OLOGIT, GOLOGIT and PPO). This implies that accidents on a three (or less) lane road segment tend to be more severe compared to those on four lane roads. There is no difference in terms of accident severity between four-lane and five (or more)-lane roads.

The *motorway indicator* variable has also been included in the models so as to control for the difference in road configuration between motorways and A roads. It has been found that motorways tend to decrease the accident severity compared to A roads, which may be due to the higher engineering standard and better road designs on motorways. This finding is consistent with the previous study by Chang and Mannerling (1999) who found that interstate highways are more likely to result in property damage only accidents instead of possible injury or injury/fatal accidents. *Speed limit* has been found to be statistically insignificant in all models, which may be because there is not enough variation in this variable: more than 90% road segments have 112 km/h speed limits.

## Environmental factors

*Lighting condition (darkness)* has been found to be statistically significant (at the 90% confidence level in the HCM) and negatively related to accident severity, suggesting that darkness condition would decrease accident severity. This is a surprising result as one would normally expect the opposite. This finding is inconsistent with some previous studies (e.g., Kim et al., 2007; Eluru et al., 2008). This may be due to the use of ordered response models as this variable shows dissimilar signs in different equations in the GOLOGIT model. Therefore, a more flexible model structure may be required such as an unordered nominal response model. It is also likely that in darkness drivers are more vigilant and possibly would lower their speed, which would decrease the severity outcome. By using a multinomial logit (MNL) model, Ulfarsson and Mannering (2004) reported that darkness would increase the probability of “evident injury” and “no injury” and decrease the probability of “fatal/disabling injury” and “possible injury” for male drivers; and for female drivers darkness would only increase the probability of “no injury” meaning that darkness decreases accident severity for the female. This implies that the impact of the lighting condition is not uniform on different categories of severity outcomes.

Several variables for different *weather conditions* have been tested in the model, such as *raining*, *snowing* and *others (fog/mist)*. “*Fine*” weather has been used as the reference case. *Raining* weather has been found to be statistically significant and negatively associated with severity outcomes, suggesting that *raining* weather decreases the severity of a road accident, which may be due to lower driving speed in rainy weather. This finding is consistent with the study by Savolainen and Mannering (2007) who found that accidents on wet pavement are more likely to be “no injury” accidents (i.e. less severe). Similar results were found by Khorashadi et al. (2005). Chang and Mannering (1999) also reported that a dry road surface increases the probability of injury/fatality outcome. *Snowing* has been found to be statistically insignificant in all models. *Other weather conditions (fog/mist)* has been found to decrease the severity level (see Table 7.3 for marginal effects).

## Other contributing factors

The variable *peak time indicator* shows a statistically significant and negative sign (Table 7.2), suggesting that accidents during peak time are less severe. No difference in

terms of the level of severity has been found between weekdays and weekends. A *single vehicle accident* has been found to be more severe than a multiple vehicle accident. The *number of casualties per accident* has been found to be statistically significant and positive as expected, meaning that an accident would be more severe if more people are injured, if all other factors remain the same.

A series of year dummy variables have been included in the models to capture some unobserved effects that change over time (e.g., improvements of medical service over time). 2003 was used as a reference case. Generally significant and negative signs can be observed<sup>22</sup> for year 2004-2006, which suggests that accidents during the period 2004-2006 tend to be less severe compared to 2003 if all other factors are held constant.

The results from the ordered response models have been found generally to be coherent and consistent with previous studies. The effect of traffic congestion on accident severity has been found to be statistically insignificant in all models. As discussed in Chapter 3 (section 3.4.2), ordered response models have two limitations which are related to the constraint on variable influences and under-reporting in accident data. Therefore, alternative and more flexible unordered nominal response models can be employed. The model estimation results from the nominal response models are presented in the next section.

### 7.3 Nominal response models

The unordered nominal response models have been developed to investigate the effect of traffic congestion on road accident severity using the same data that was used in the ORM. As discussed in Chapter 3, compared to the ORM, nominal response models have the advantages due to their flexible functional forms and consistent coefficient estimates when under-reporting occurred in the data. As a result, nominal response models may be appropriate for the data and have the ability to provide more robust estimation results. Two nominal response models have been estimated, namely a standard multinomial logit model (MNL) and a mixed logit model. Compared to the

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<sup>22</sup> 2004 is insignificant and positive when error variance is assumed to be the same in HCM; 2004 however becomes significant and negative when error variance is assumed to be different in HCM (Table 7.2). The marginal effect for HCM (Table 7.3) shows that 2004 decreases accident severity outcome, which confirms that accidents in 2004 tend to be less severe compared to 2003.

MNL model, the mixed logit model can take into account the unobserved correlated effects and additional unobserved heterogeneity between different accident severity categories (Milton et al., 2008), thus the mixed logit model is expected to provide more coherent estimation results.

The MNL model has been estimated using the standard maximum likelihood method. The mixed logit model has been estimated using the maximum simulated likelihood (MSL) method in which Halton draws have been employed. In the mixed logit model, the model specification has followed the technique outlined by Milton et al. (2008). More specifically, coefficients are considered to be random parameters if they produce statistically significant standard deviations for their assumed normal distributions. In this study, the results have been obtained from 150 Halton draws. Model estimation results for the MNL and mixed logit model are presented in Table 7.4:

**Table 7.4 Estimation results for MNL and mixed logit models**

| Variables                                  | MNL         |         | Mixed logit †     |              |
|--|-------------|---------|-------------------|--------------|
|  | Coefficient | z value | Coefficient       | z value      |
| <i>Serious injury accident</i>             |             |         |                   |              |
| Level of traffic congestion (min per 10km) | 0.000       | -0.02   | -0.020 (0.039**)  | -1.50 (2.00) |
| log(Traffic flow in veh/h)                 | -0.237**    | -4.34   | -0.318**          | -2.46        |
| log(minimum radius)                        | 0.126**     | 2.17    | 0.194*            | 1.88         |
| Maximum gradient (%)                       | 0.054*      | 1.85    | 0.079             | 1.61         |
| Number of lanes $\leq$ 3 indicator         | 0.185**     | 2.05    | 0.282*            | 1.85         |
| Number of lanes $\geq$ 5 indicator         | 0.069       | 0.31    | 0.053             | 0.17         |
| Motorway indicator                         | -0.218**    | -2.57   | -0.309**          | -2.00        |
| Speed limit (km/h)                         | 0.000       | 0.14    | -0.001            | -0.26        |
| Lighting condition (darkness)              | -0.157**    | -1.98   | -0.243*           | -1.72        |
| Weather (raining)                          | -0.346**    | -3.62   | -0.445**          | -2.41        |
| Weather (snowing)                          | -0.277      | -0.58   | -0.361            | -0.54        |
| Other weather conditions (e.g. fog/mist)   | -0.285      | -1.49   | -0.382            | -1.32        |
| Peak time indicator                        | -0.268**    | -2.28   | -0.381*           | -1.87        |
| Weekday indicator                          | -0.028      | -0.40   | -0.005            | -0.05        |
| Single vehicle accident indicator          | 0.473**     | 6.25    | 0.658**           | 2.79         |
| Number of casualties per accident          | 0.305**     | 13.31   | 0.378** (0.333**) | 2.99 (2.37)  |
| Year 2004                                  | -0.274**    | -3.00   | -0.376**          | -2.18        |
| Year 2005                                  | -0.305**    | -3.30   | -0.435**          | -2.31        |
| Year 2006                                  | -0.378**    | -3.93   | -0.531**          | -2.50        |
| Year 2007                                  | -0.210**    | -2.16   | -0.297*           | -1.77        |
| Intercept                                  | -1.358**    | -2.26   | -2.042* (1.773)   | -1.83 (1.47) |

Slight injury accident is the base outcome; \* p<0.1, \*\* p<0.05

† Standard deviations and their associated z values of random parameters in parentheses

**Table 7.4 (continued)**

| Variables                                  | MNL         |         | Mixed logit †     |               |
|--|-------------|---------|-------------------|---------------|
|  | Coefficient | z value | Coefficient       | z value       |
| <i>Fatal accident</i>                      |             |         |                   |               |
| Level of traffic congestion (min per 10km) | -0.003      | -0.65   | -0.004 (0.007)    | -0.40 (0.45)  |
| log(Traffic flow in veh/h)                 | -0.566**    | -6.08   | -1.309**          | -2.27         |
| log(minimum radius)                        | 0.141       | 1.01    | 0.254             | 0.88          |
| Maximum gradient (%)                       | -0.106      | -1.59   | -0.229            | -1.36         |
| Number of lanes $\leq$ 3 indicator         | 0.010       | 0.05    | 0.035             | 0.08          |
| Number of lanes $\geq$ 5 indicator         | -0.647      | -0.87   | -1.005            | -0.78         |
| Motorway indicator                         | -0.266      | -1.42   | -0.413            | -1.03         |
| Speed limit (km/h)                         | 0.015       | 1.54    | 0.024             | 1.30          |
| Lighting condition (darkness)              | 0.223       | 1.20    | 0.497             | 1.21          |
| Weather (raining)                          | -0.467**    | -2.04   | -1.021*           | -1.74         |
| Weather (snowing)                          | -13.315     | -0.02   | -32.821           | 0.00          |
| Other weather conditions (e.g. fog/mist)   | -1.263*     | -1.86   | -2.326            | -1.57         |
| Peak time indicator                        | -0.302      | -1.26   | -0.384            | -0.73         |
| Weekday indicator                          | 0.186       | 1.14    | 0.369             | 1.09          |
| Single vehicle accident indicator          | 0.686**     | 4.15    | 1.421**           | 2.29          |
| Number of casualties per accident          | 0.412**     | 11.44   | 0.791** (0.436*)  | 2.50 (1.94)   |
| Year 2004                                  | -0.419*     | -1.77   | -0.943            | -1.46         |
| Year 2005                                  | -0.090      | -0.41   | -0.137            | -0.30         |
| Year 2006                                  | -0.133      | -0.59   | -0.302            | -0.63         |
| Year 2007                                  | -0.015      | -0.07   | -0.079            | -0.17         |
| Intercept                                  | -2.404      | -1.60   | -4.968 (-4.448**) | -1.53 (-2.01) |
| <i>Statistics</i>                          |             |         |                   |               |
| Log likelihood                             | -4670.132   |         | -4655.158         |               |
| AIC  | 9424.264    |         | 9406.316          |               |
| N  | 11830       |         | 11830             |               |

Slight injury accident is the base outcome; \* p<0.1, \*\* p<0.05

† Standard deviations and their associated z values of random parameters in parentheses

In Table 7.4, the estimation results for the categories of serious injury accidents and fatal accidents are presented, with the category of slight injury accidents being used as the base outcome. As can be seen, the estimation results from the MNL and mixed logit models are similar in terms of the set of statistically significant variables and the signs of their coefficients. The values of the coefficients, however are different: for some variables the difference is small such as log(*traffic flow*) in the serious injury accident category; for some variables the difference is quite noticeable such as log(*traffic flow*) in the fatal accident category. Considering that the mixed logit model provided low AIC value (i.e. better model performance) and the fact that the mixed logit model can control for the unobserved correlated effects and heterogeneity, it is believed that the mixed

logit model is more accurate and fits the data better than the MNL model. Therefore, the results from the mixed logit model are preferred.

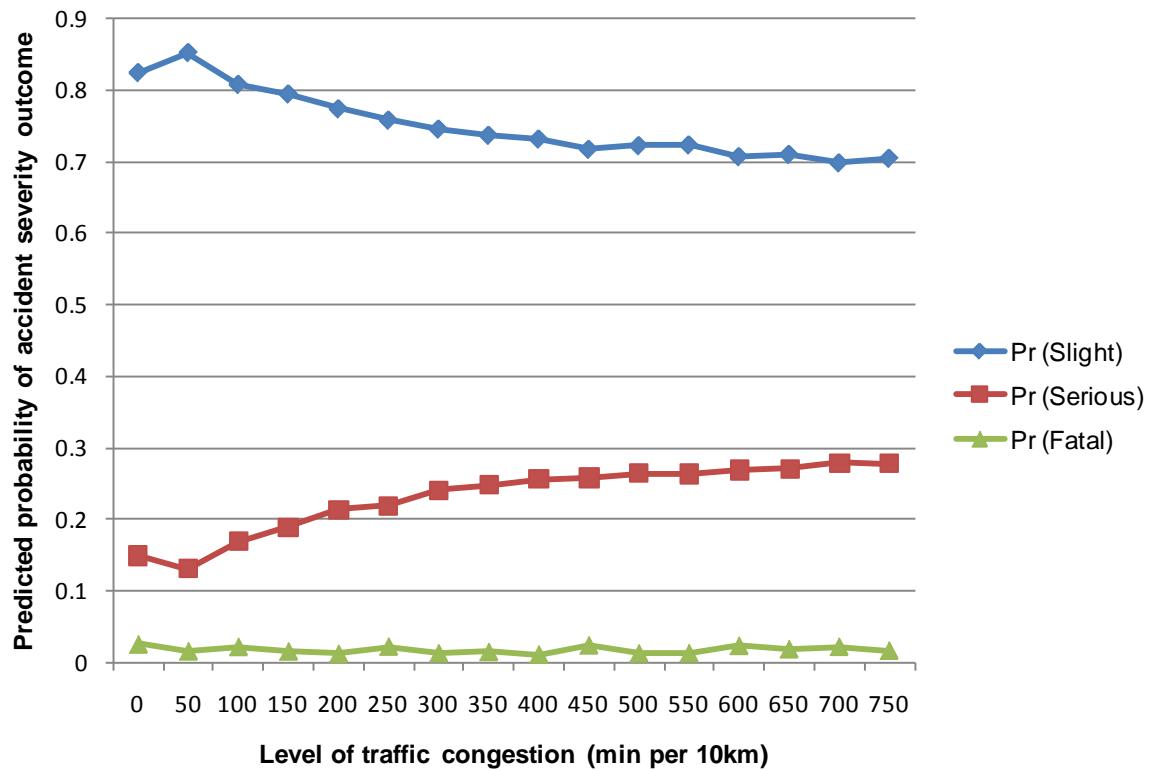
When comparing the results of the HCM (see Table 7.2) with the results of the mixed logit model, it can be seen that most statistically significant variables in the HCM are also significant in nominal response models (MNL and mixed logit) for serious injury accidents (Table 7.4). For the category of fatal accidents, many variables however become insignificant such as  $\log(\text{minimum radius})$ , *number of lanes* ( $\leq 3$ ), *motorway indicator*, *lighting conditions (darkness)*, *peak time indicator* and *year dummies*. This result is quite similar to the GOLOGIT model in which many variables become insignificant for the  $y>2$  equation (i.e. slight and serious injury accidents vs. fatal accidents). This further confirms that the effects of various variables are different across different categories of accident severity outcomes. In terms of the model goodness-of-fit and complexity, using the same data, the mixed logit model has produced the AIC value of 9,406 which is very close to the AIC value provided by the PPO model but higher than the HCM. This means that the mixed logit model is the second best model estimated in terms of model performance. It should however be noted that the log likelihood of the mixed logit model and the HCM are very close to each other (the mixed logit model is slightly higher than the HCM). The reason that the mixed logit model has a higher AIC value than the HCM is that the mixed logit model estimated far more parameters: it estimated two models, one for serious injury accidents and one for fatal accidents. This may be worthwhile because, as explained, the effects of various variables are different across different categories of accident severity outcomes. The GOLOGIT model works in a similar fashion but has a higher AIC value than the mixed logit model (the difference is nearly 10). Therefore, considering both model flexibility and performance, and the fact that an unordered model is better in handling missing data, the mixed logit model is an attractive alternative to the HCM or GOLOGIT model. The results and findings from the mixed logit model are interpreted below.

### 7.3.1 Findings for traffic congestion

The coefficient of the *level of traffic congestion* has been taken as a random parameter (assuming a normal distribution) in the mixed logit model. As Table 7.4 shows, the estimated mean value of the coefficient for the category of the serious injury accidents is negative and statistically significant only at the 85% confidence level in the mixed

logit model (the coefficient is insignificant in the MNL model). The standard deviation of the coefficient for the case of serious injury accidents is statistically significant at the 95% confidence level, which means that the effect of congestion varies across different accidents. From the estimated parameters (mean -0.02 and standard deviation 0.039), it can be seen that 70% of the (normal) distribution is less than 0 and 30% of the distribution is greater than 0. Therefore, for 70% of the accidents, an increased level of congestion decreases the probability of a serious injury accident occurring (compared to the probability of a slight injury accident occurring); and for 30% of the accidents, an increased level of congestion increases the likelihood of a serious injury accident occurring. Overall the increased level of congestion decreases the probability of an accident being serious (as the mean of the coefficient is negative), which is expected as the traffic speed is relatively low in the congested situation (compared to uncongested situation). Congestion has little impact on the probability of a fatal accident occurring, as the mean of the coefficient for fatal accidents is statistically insignificant in the mixed logit model.

Therefore, it can be concluded that overall, increases in congestion would result in accidents to be less severe, although the effect is only significant at the 85% confidence level. Figure 7.2 shows how the predicted probabilities of different severity outcomes change with respect to a change in the level of congestion. Similar to Figure 7.1, the predicted probabilities were calculated based on different levels of traffic congestion for single vehicle accidents, under fine weather and non-dark lighting conditions, during the peak time in weekdays, on motorways with three lanes or less in 2007 while other variables (e.g., radius) are held at their mean values.



**Figure 7.2 The predicted probabilities of different accident severity outcomes (mixed logit model)**

As can be seen from Figure 7.2, increases in the level of congestion have little impact on the probability of a fatal accident occurring. As for slight and serious injury accidents, it can be seen that when congestion is lower than 50 (min per 10km), increased congestion would increase the probability of a slight injury accident and decrease the probability of a serious injury accident. When congestion is higher than 50 (min per 10km), generally the opposite result can be observed, i.e. increased congestion decreases the probability of a slight injury accident and increases the probability of a serious injury accident. This confirms that the effect of congestion on accident severity is not uniform across accidents. For the accident severity data used in this thesis, the majority (more than 95%) of the traffic congestion are below 50 (min per 10km) (see Chapter 5 section 5.4 for more details), therefore an overall negative association between traffic congestion and accident severity (i.e. decreases the probability of a serious injury accident and increases the probability of a slight injury accident) is expected.

This finding suggests that under low traffic congestion conditions (e.g., total delay below 50 min per 10km per hour), traffic congestion tends to decrease accident severity. Under this condition (traffic delay from 0 to 50 min per 10km), the discrete

change<sup>23</sup> is 0.00056 for slight injury accidents and -0.00036 for serious injury accidents. This means a unit change in the level of congestion would change the predicted probability of a slight injury accident by 0.00056 and a serious injury accident by -0.00036, holding all other variables constant. The corresponding pseudo-elasticity<sup>24</sup> (at 50 min per 10km) is 0.0328 and -0.1363 for slight and serious injury accidents respectively. This means that a 1% change in traffic congestion would change the predicted probability of slight injury accidents by about 0.03% and serious injury accidents by about -0.14%.

### 7.3.2 Findings for other contributing factors

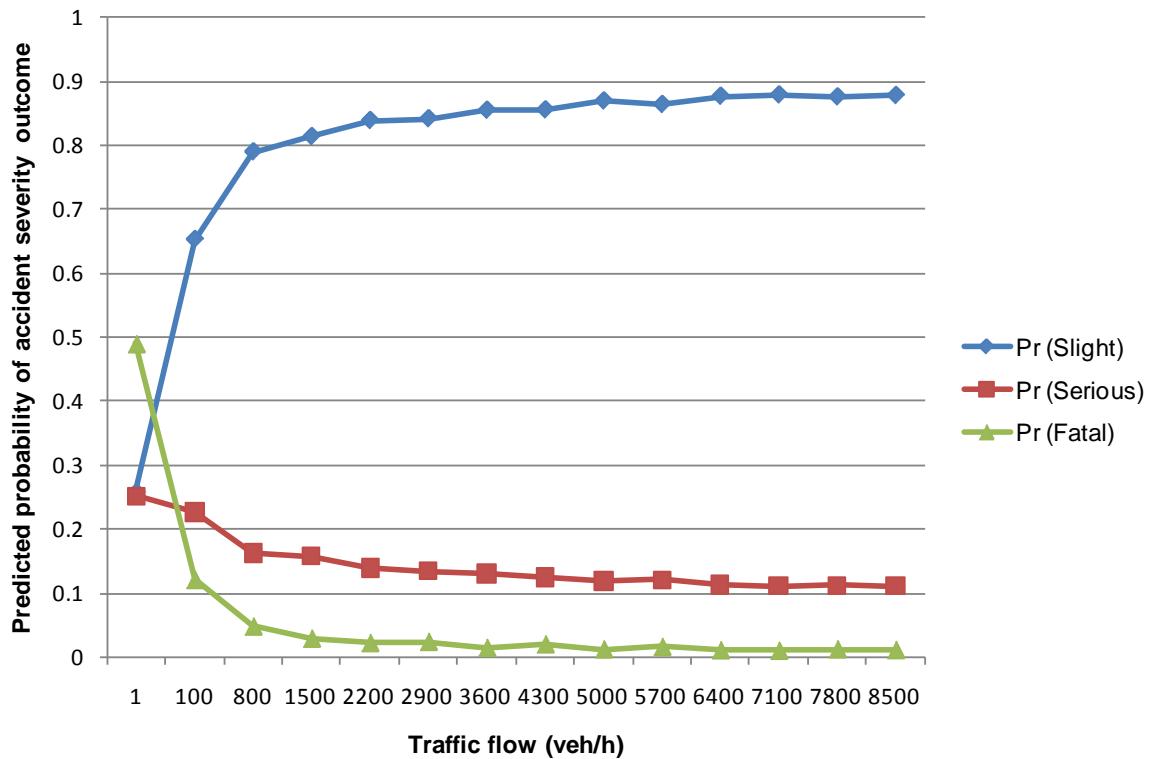
The coefficient of  $\log(\text{Traffic flow})$  has been modelled as a fixed parameter, and it has been found to be negative and statistically significant for both serious injury accidents and fatal accidents. This indicates that increases in traffic flow would decrease the probability of serious injury and fatal accidents. This finding is in line with the ordered response models presented in the previous section. As with Figure 7.1, the predicted probabilities of different severity outcomes were plotted against different values of *traffic flow* in Figure 7.3 for the same values of other explanatory variables.

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<sup>23</sup> Discrete change is similar (though not equivalent) to marginal effect (change). The discrete change is

defined as  $\frac{\Delta \Pr(y=j)}{\Delta x}$ .

<sup>24</sup> The pseudo-elasticity is defined as  $\frac{\Delta \Pr(y=j)}{\Delta x} \cdot \frac{x}{y}$ .



**Figure 7.3 The predicted probabilities of different accident severity outcomes (mixed logit model)**

As can be seen, the changes in probabilities of different accident severity outcomes in Figure 7.3 are very similar to those of in Figure 7.1. The result from the mixed logit model confirms that increased *traffic flow* decreases the accident severity level. For *traffic flow* changing from 2900 to 3600 (veh/h), the discrete changes of the probability of a slight injury occurring is  $1.89 \times 10^{-5}$ , a serious injury accident occurring is  $-5.4 \times 10^{-6}$  and a fatal accident occurring is  $-1.3 \times 10^{-5}$ . This means that, for example, a unit increase in traffic flow would increase the probability of a slight injury accident occurring by  $1.89 \times 10^{-5}$ . The pseudo-elasticity of severity outcomes with respect to *traffic flow* at 2900 (veh/h) is 0.065, -0.117 and -1.619 for slight injury accidents, serious injury accidents and fatal accidents respectively. This means that, for example, a 1% increase in *traffic flow* from 2900 (veh/h) would increase the probability of a slight injury accident occurring by 0.065%.

With regard to the results of road infrastructure factors,  $\log(\text{minimum radius})$  has been found to be positive and statistically significant at the 90% confidence level for serious injury accidents, suggesting that straighter road segments tend to have accidents that are serious injury as opposed to slight injury. This finding is consistent with ordered response models. As for *maximum gradient*, similar to the HCM estimation results, this

variable has also been statistically insignificant in the mixed logit model. Other variables have also been found to have similar effects compared to ordered response models, e.g. *number of lanes*, *motorway indicator* and *speed limit*.

As for environmental factors, *lighting condition (darkness)* has been found to be negative and statistically significant at the 90% confidence level in the mixed logit model. This is consistent with the HCM, although not in line with other ordered models as this variable is not significant in other ordered models. For *weather conditions*, the results for *raining* and *snowing* are similar to the HCM. For example, *raining* weather has been found to decrease the probability of serious injury and fatal accidents and increase the probability of slight injury accidents. *Other weather conditions (fog/mist)* has been found to be statistically significant in ordered models but it has become statistically insignificant in the mixed logit model.

*Peak time indicator* and *weekday indicator* have both been found to have similar effects on accident severity outcomes compared to the HCM. The variable – *single vehicle accident* has been found to be statistically significant and positively associated with both serious injury and fatal accidents, suggesting that a *single vehicle accident* is more likely to be serious or fatal. This finding is also consistent with the HCM. The *number of casualties per accident* has been found to be a normally distributed random parameter with a mean of 0.378 and a standard deviation of 0.333 for serious injury accidents; and with a mean of 0.791 and a standard deviation of 0.436 for fatal accidents. Both the means and standard deviations are statistically significant, meaning that the effect of the *number of casualties per accident* varies across different accidents. In other words, for some accidents the *number of casualties per accident* has a positive effect on accident severity and for others this variable has a negative effect. Given the mean and standard deviation of a normal distribution, it can be calculated that 87.2% of the distribution is greater than 0 for the case of serious injury accidents; and 96.5% of the distribution is greater than 0 for the case of fatal accidents. This implies that, for 87.2% of accidents the increased *number of casualties per accident* increases the probability of a serious injury accident occurring; and for 96.5% of accidents the increased *number of casualties per accident* increases the probability of a fatal accident occurring. Only for a small proportion of accidents does the increased *number of casualties per accident* decrease the probability of serious injury accidents (12.8%) or fatal accidents (3.5%). This strongly supports and confirms the findings from the

ordered models that an accident would be more severe when more people were injured, if all other factors are held constant.

Finally, year dummies have been found to have similar effects to the ordered models, i.e. accidents during 2004-2007 tend to be less severe compared to 2003.

## 7.4 Summary

This chapter has presented the estimation results and findings from the accident severity models which examined the impact of traffic congestion on the severity of road accidents given that the accidents occurred, while controlling for other contributing factors.

Based on the M25 and surround data, two types of models were developed: the ordered response models (such as an ordered logit and a heterogeneous choice model) and the nominal response models (such as a multinomial logit model and a mixed logit model). Traffic congestion at the time of an accident was measured as the total delay (min) per 10km (per hour) at the time of 30min prior to the accident. Traffic congestion was found statistically insignificant in all models estimated except in the mixed logit model, in which the variable was negative and statistically significant at the 85% level. The mixed logit model was arguably the best model estimated for its model flexibility and performance.

From the estimation results from the mixed logit model, it was found that the coefficient of traffic congestion for serious injury accidents was a normally distributed random parameter. This means that the effect of traffic congestion on accident severity varies over different accidents: for almost 70% of the accidents, an increased level of congestion decreases the probability of a serious injury accident; and for about 30% of accidents, an increased level of congestion increases the likelihood of a serious injury accident. Further analysis revealed that the effect of traffic congestion on accident severity was different under different congestion conditions. When traffic congestion is low (e.g., traffic delay below 50 min per 10km per hour), increases in congestion tend to decrease the accident severity level: a 1% increase in traffic congestion would increase the probability of a slight injury accident by 0.03% and decrease the probability of a serious injury accident by 0.14%. Under high congestion level conditions (less than 5% of the cases in the data), increases in congestion would

however increase accident severity. Traffic congestion appears to have little impact on the probability of a fatal accident occurring. All other contributing factors were controlled for and found to be generally consistent with previous studies.

The next chapter presents the results of site ranking.

# CHAPTER 8 SITE RANKING

## **8.1 Introduction**

This chapter presents an important application of the accident prediction models used in this thesis, namely the site ranking which aims to identify hazardous road segments (i.e. accident hotspots) for further engineering investigation and safety treatment. This chapter will firstly present the results from the two-stage mixed multivariate model, which combines both accident frequency and severity models and is an alternative to traditional accident frequency analysis for site ranking. This chapter will then present the ranking results on the M25 and surround, followed by a summary of results and findings at the end of this chapter.

## **8.2 Results from the two-stage model**

As discussed in Chapter 4, a two-stage mixed multivariate model is used in site ranking, aimed at identifying accident hotspots for further safety examination and remedial treatment. This modelling approach, as discussed in Chapters 3 and 4 has several advantages compared to traditional accident frequency based models, in that more detailed data can be utilised at a disaggregate individual accident level and it is able to predict low frequency accidents in certain categories (such as fatal accidents).

The two-stage model combines both accident frequency and severity models, the estimation results of which have been presented in Chapters 6 and 7 respectively. Therefore, it is relatively straightforward to combine the results of accident frequency and severity models so as to obtain the expected number of accidents at different severity levels. In the two-stage process, two types of data are computed: (1) total expected number of accidents, which are the posterior estimates of count of accidents using the full Bayesian accident frequency models; and (2) the expected proportions of accidents for different severity levels (i.e. fatal, serious and slight), which are obtained from the accident severity models. The Bayesian spatial model and mixed logit model are used in the two-stage process to estimate accident frequency and severity respectively, since these model specifications are considered the most appropriate in terms of model inference as demonstrated in Chapters 6 and 7.

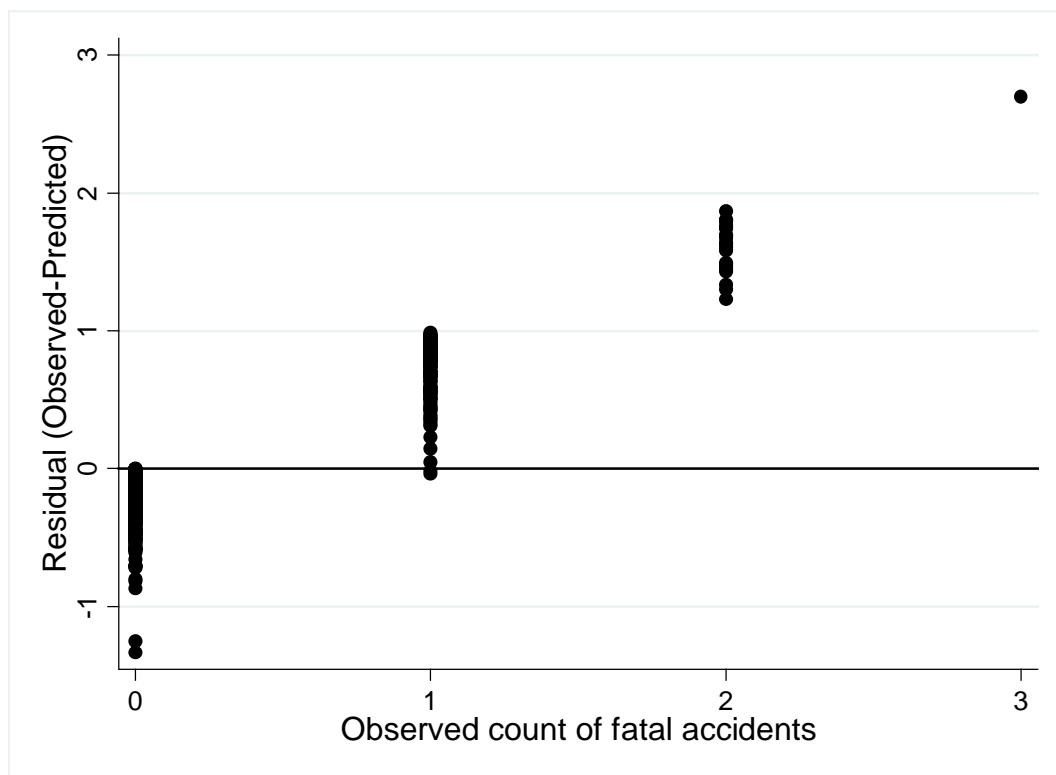
Summary statistics of the predicted number of total accidents and proportions of accidents for different severity levels on the M25 and surround during 2003-2007 are presented in Table 8.1:

**Table 8.1 Summary statistics of the predicted number and proportions of accidents**

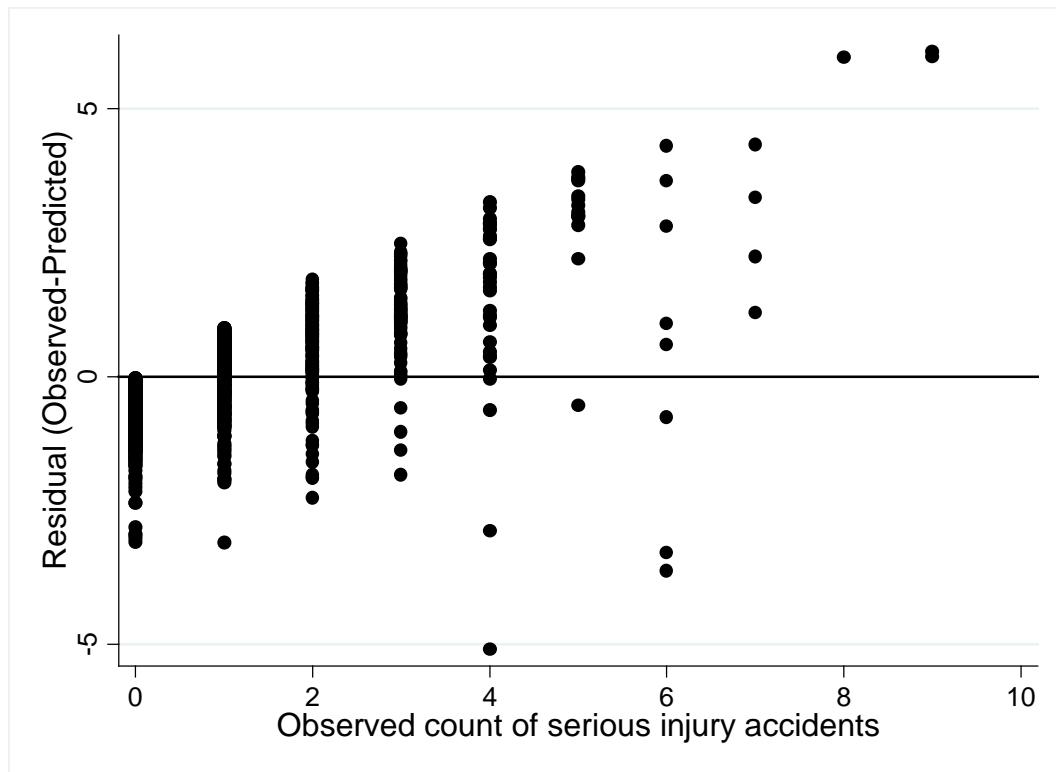
| Variable                               | N    | Mean  | Standard Deviation |       |        |
|--|------|-------|--------------------|-------|--------|
|  |      |       | Min                | Max   |        |
| Total number of accidents              | 1330 | 8.952 | 9.306              | 0.364 | 87.850 |
| Proportion of fatal accidents          | 1201 | 0.021 | 0.016              | 0.000 | 0.155  |
| Proportion of serious injury accidents | 1201 | 0.113 | 0.040              | 0.042 | 0.349  |
| Proportion of slight injury accidents  | 1201 | 0.866 | 0.053              | 0.548 | 0.954  |

It can be seen from Table 8.1 that, as expected most of predicted accidents are slight injury accidents and there are small proportions of fatal accidents. The mean values of the predicted proportions of fatal, serious and slight injury accidents on the M25 and surround are also consistent with the data reported from the DfT for accidents on all motorways and A roads in Great Britain in 2007 (the proportions of observed fatal, serious and slight injury accidents are 0.018, 0.133 and 0.849 respectively. See the DfT, 2008). Note that since some road segments during certain years have zero accidents observed, no predicted proportions of accidents can be obtained in this situation. This is because to let an accident severity model work (i.e. the mixed logit model in this case), at least one accident, no matter at which severity level, should be observed on a given road segment, and so the predicted probabilities for this accident of being fatal, serious or slight can be obtained. This means that the accident severity model still works if a road segment has no fatal accident but has serious or slight injury accidents. However, if a road segment has no accident at all then no predicted proportions of accidents for different severity levels can be obtained.

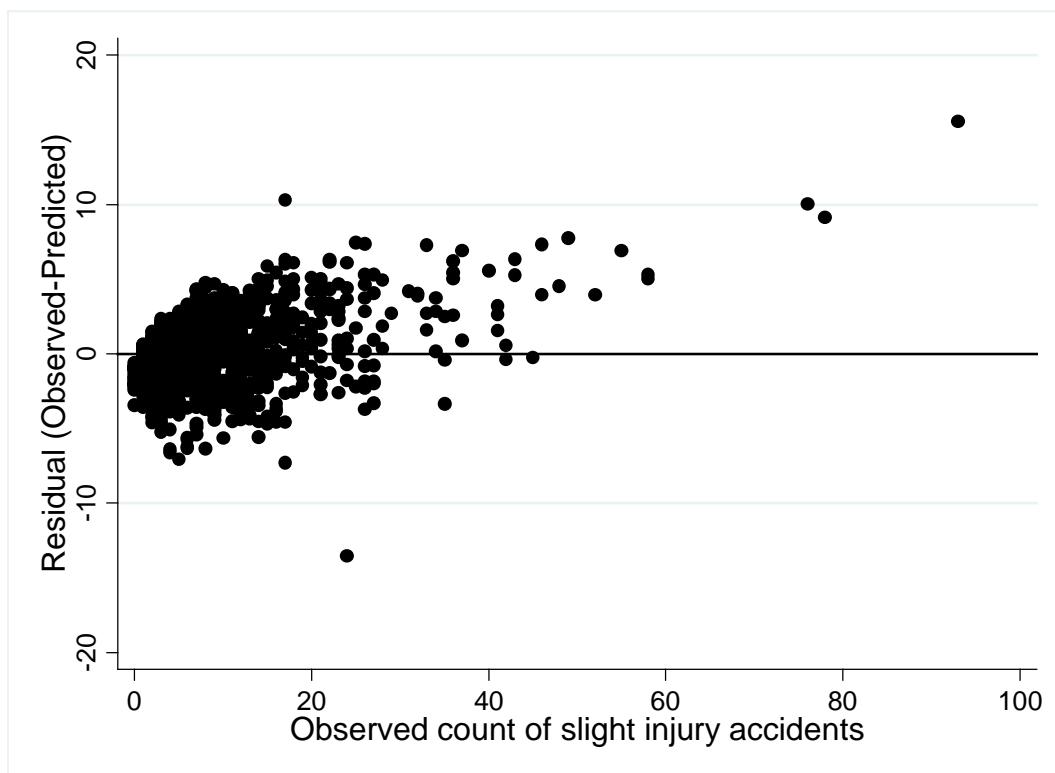
Based on the total number of accidents and the proportions for each severity level, it is straightforward to calculate the predicted number of accidents at different severity levels. The observed and the residual values (using the two-stage models) of accident frequency at different severity levels are presented in Figure 8.1:



8.1 (a) Fatal accidents



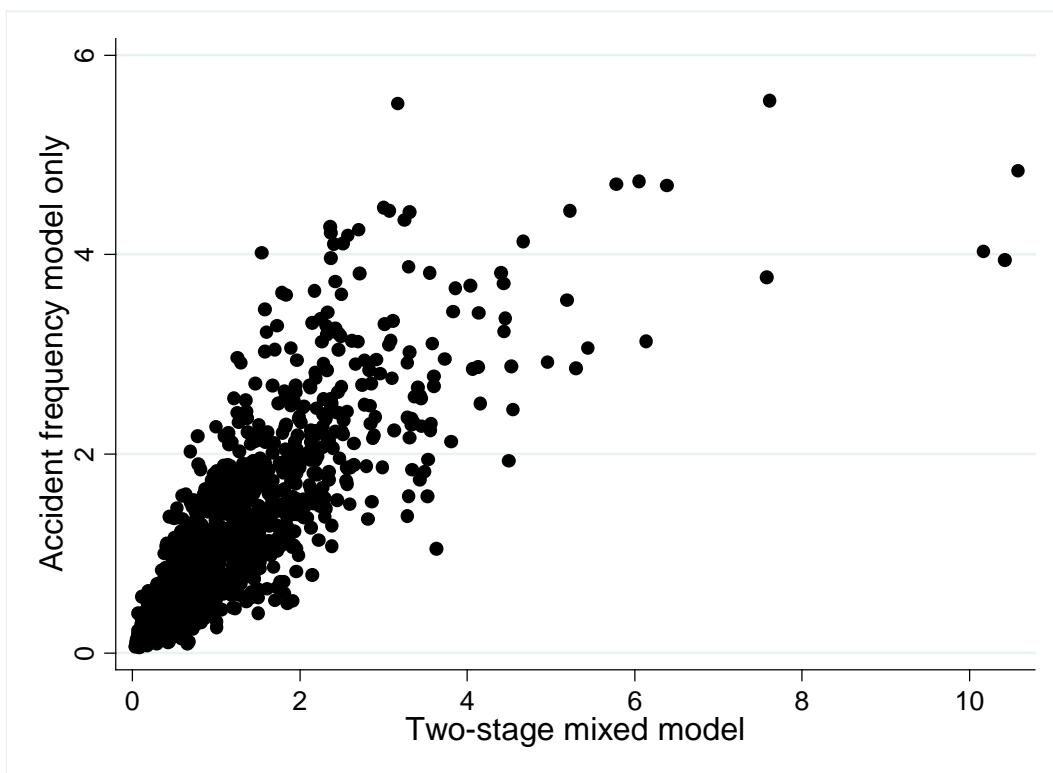
8.1 (b) Serious injury accidents



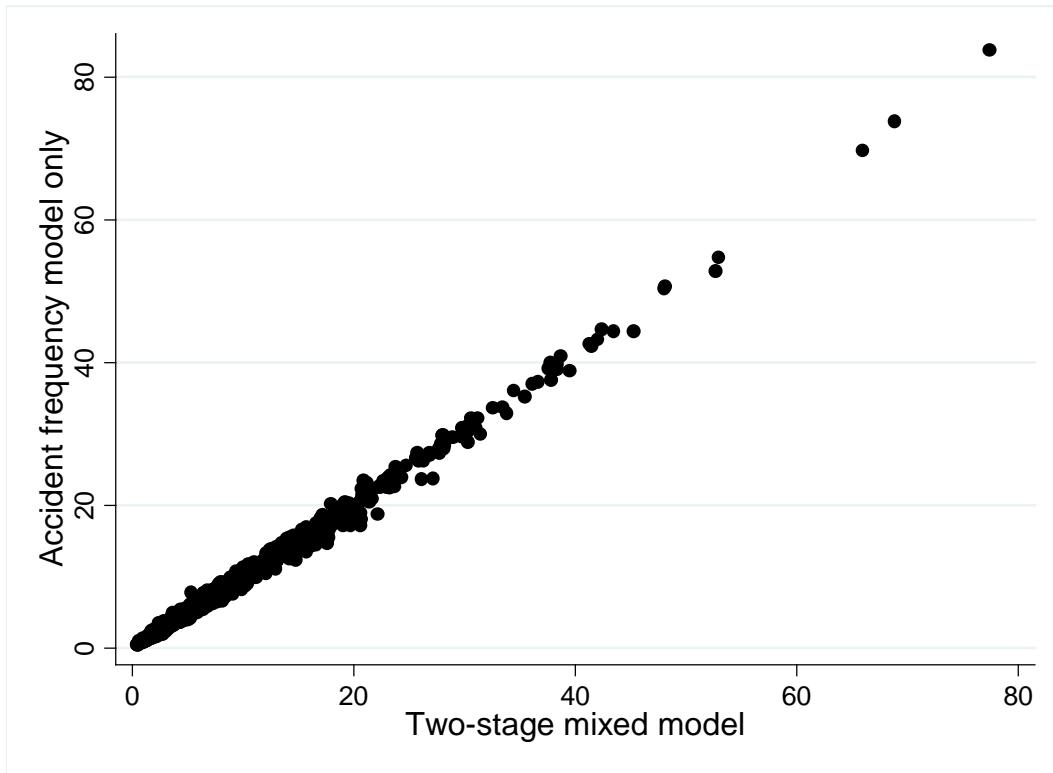
### 8.1 (c) Slight injury accidents

**Figure 8.1 The observed and the residual values (using two-stage models) of accidents**

It is noticeable that the pattern of observed and residual values for slight injury accidents in Figure 8.1 (c) is very similar to the results using only accident frequency models (i.e. Bayesian spatial models with fixed time effects; see Chapter 6 Figure 6.7). This implies that the results from the two-stage models are very similar to the accident frequency models for the case of slight injury accidents. There is also an increasing trend in the residuals for fatal/serious injury accidents. As discussed in Chapter 6 section 6.3.2, this increasing trend may be caused by the regression-to-the-mean effect. To further examine the differences between the two types of models, the predicted counts of accidents at different severity levels are compared to each other. This is presented in Figure 8.2:



8.2 (a) Fatal and serious injury accidents



8.2 (b) Slight injury accidents

Figure 8.2 Two-stage model vs. accident frequency model only

Figure 8.2 compares the predicted number of accidents at different severity levels between using the two-stage model and accident frequency model only. Predicted numbers of fatal and serious injury accidents from the two-stage models are combined so that it can be compared with accident frequency models only. Figure 8.2 (b) shows that the predicted numbers of slight injury accident from the two models are very close to each other. This is however not the case for fatal and serious injury accidents: as can be seen in Figure 8.2 (a), the prediction from the two-stage model is slightly different from the frequency model. The mean absolute deviation (MAD) may be used to compare fitted performance of the two models (Xie et al., 2007). The MAD can be written as:

$$\text{MAD} = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (8.1)$$

where  $n$  is sample size;  $\hat{y}_i$  and  $y_i$  are predicted and observed values respectively. A lower MAD value indicates better model fit. The MAD values for both the two-stage model and accident frequency model are presented in Table 8.2:

**Table 8.2 Mean absolute deviation (MAD) for two-stage mixed and accident frequency models**

|                                    | Two-stage mixed model | Accident frequency model |
|------------------------------------|-----------------------|--------------------------|
| Fatal and serious injury accidents | 0.73                  | 0.70                     |
| Slight injury accidents            | 1.58                  | 1.56                     |

As can be seen in Table 8.2, the MAD values from the two types of models are very close to each other, suggesting that the two types of models have similar fitted performance. The accident frequency model is slightly better in terms of MAD values. It should however be noted that, as discussed in Chapter 4, due to the low frequency of fatal accidents, it is not statistically feasible to predict fatal accidents using accident frequency models directly. The two-stage model resolves this issue and is able to predict the number of fatal and serious injury accidents separately, which is therefore considered superior to the traditional accident frequency modelling approach.

### 8.3 Site ranking results

After obtaining the expected number of accidents per segment at each severity level using the two-stage model, monetary costs can then be applied to the accidents to calculate the total costs of accidents on road segments for the purpose of site ranking.

Monetary costs of accidents are different for different severity levels, which reflects different levels of importance for these accidents. The monetary costs of accidents at each severity level for a given year are obtained from the UK Department for Transport (DfT, 2004, 2005b, 2006, 2007b and 2008), which are presented in Table 8.3.

**Table 8.3 Average values of prevention of road accidents (£ per accident)**

|      | Fatal     | Serious | Slight |
|------|-----------|---------|--------|
| 2003 | 1,492,910 | 174,520 | 17,540 |
| 2004 | 1,573,220 | 184,270 | 18,500 |
| 2005 | 1,645,110 | 188,960 | 19,250 |
| 2006 | 1,690,370 | 196,020 | 20,120 |
| 2007 | 1,876,830 | 215,170 | 22,230 |

It is interesting to note from Table 8.3 that the costs of accidents increase gradually from 2003 to 2007, for all severity levels. This may reflect inflation over the years.

Sites (road segments) can then be ranked by the total accident cost rate for the period of 2003-2007. The higher accident cost rate of a road segment, the more hazardous it is considered to be. The top 20 most hazardous road segments ranked by the accident cost rate are listed in Table 8.4. For comparison, naïve ranking using observed accident count data has also been produced and presented.

**Table 8.4 Ranking of segments**

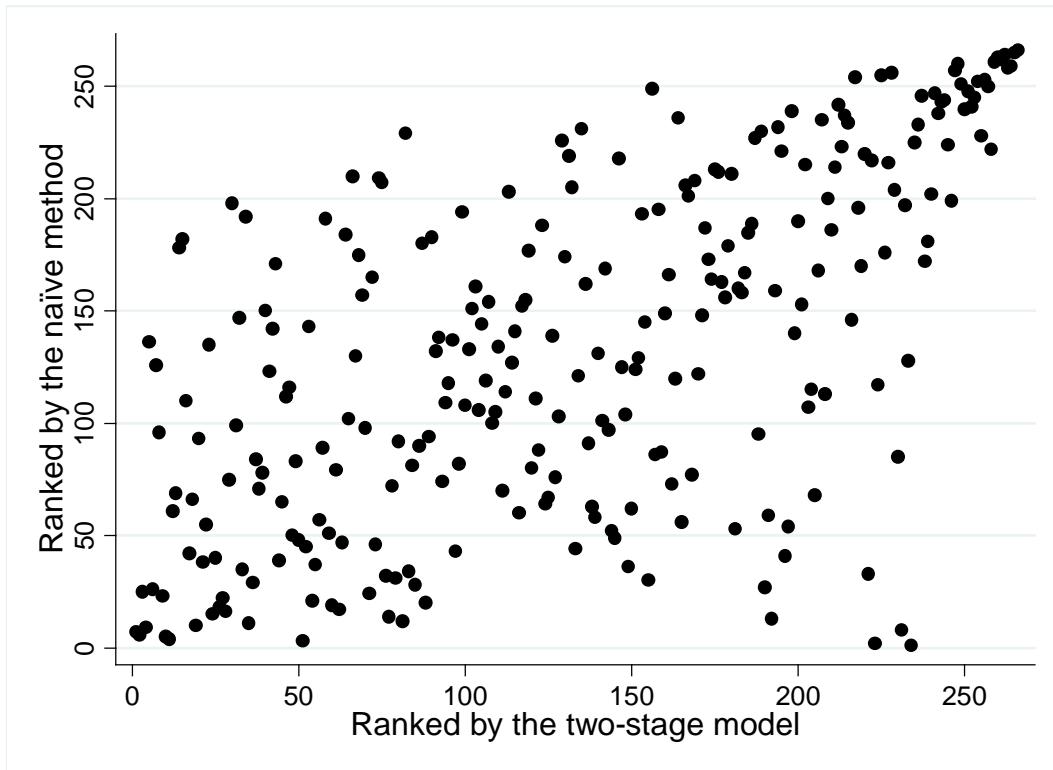
| Road number | Segment description  | Model base ranking |            | Naïve ranking |            |
|-------------|----------------------|--------------------|------------|---------------|------------|
|             |                      | Rank               | Cost rate* | Rank          | Cost rate* |
| M1          | M1 J10 to M1 J9      | 1                  | 3.57       | 7             | 2.48       |
| A3          | A3100 to A3100       | 2                  | 2.50       | 6             | 2.49       |
| M1          | M1 J8 to M1 J9       | 3                  | 2.46       | 25            | 1.48       |
| A1          | A5135 to M25 J23     | 4                  | 2.37       | 9             | 2.27       |
| M25         | M25 J19 to A41       | 5                  | 2.17       | 136           | 0.53       |
| M25         | M25 J21 to M25 J21A  | 6                  | 1.95       | 26            | 1.46       |
| M25         | A41 to M25 J19       | 7                  | 1.69       | 126           | 0.58       |
| A3          | A320 to A322         | 8                  | 1.65       | 96            | 0.73       |
| M1          | M1 J9 to M1 J8       | 9                  | 1.60       | 23            | 1.51       |
| A23         | M23 J7 to A23        | 10                 | 1.58       | 5             | 2.66       |
| A1M         | A1(M) J8 to A1(M) J7 | 11                 | 1.57       | 4             | 2.66       |
| A2          | A2018 to A2          | 12                 | 1.57       | 61            | 0.94       |
| M23         | M23 J8 to M23 J7     | 13                 | 1.56       | 69            | 0.89       |
| A20         | A20 to M25 J3        | 14                 | 1.56       | 178           | 0.37       |
| M23         | M23 J7 to M23 J8     | 15                 | 1.51       | 182           | 0.37       |
| A3          | A31 to A322          | 16                 | 1.48       | 110           | 0.65       |
| M25         | M25 J26 to M25 J25   | 17                 | 1.46       | 42            | 1.15       |
| A13         | M25 J30 to A1306     | 18                 | 1.44       | 66            | 0.90       |
| A3          | A247 to A3100        | 19                 | 1.43       | 10            | 2.25       |
| M10         | M10 J1 to M1 J7      | 20                 | 1.41       | 93            | 0.75       |

\* Cost rate is in £ per 100 vehicle kilometres in 2003 – 2007

As can be seen from Table 8.4, the two-stage model is producing significantly different rankings than the naïve ranking method. 14 out of the top 20 road segments in the model based ranking are not in the top 20 in the naïve ranking. The differences between model based ranking and naïve ranking are significant. Accident cost rates for the majority of the top 20 road segments ranked by the two-stage models are higher than the naïve estimates. This implies that the naïve ranking method underestimated the accident costs for road segments.

The differences between the model based ranking and naïve ranking are presented in Figure 8.3. It is clear that there are significant differences between the two ranking methods. This result is consistent with previous studies (e.g., see Miaou and Song, 2005; Huang et al., 2009 for the comparison between model based ranking and naïve ranking). The differences between the two ranking methods are mainly due to the high stochastic and sporadic nature of accidents, and the fact that considerably higher costs are given to fatal accidents than the other two types of accidents (Miaou and Song, 2005). As discussed in Chapter 3 (section 3.4.3), due to the regression-to-the-mean

problem, the ranking results using the naïve method may be biased and inaccurate, and as such the model based ranking method is preferred.



**Figure 8.3 Comparison of ranking results: two-stage model vs. naïve method**

Based on the ranking results using the two-stage model, the spatial distribution of accident cost rates on the M25 and surround are shown in Figure 8.4. It is noticeable that the most hazardous road segments are randomly located throughout the road network. The locations of the top 20 most hazardous road segments listed in Table 8.4 are highlighted in Figure 8.5. For each of these road segments, the rank, road number and direction information is shown in Figure 8.5 (a); and accident cost rate calculated from the two-stage model is shown in Figure 8.5 (b). Again, the top ranked segments are found randomly located throughout the road network.

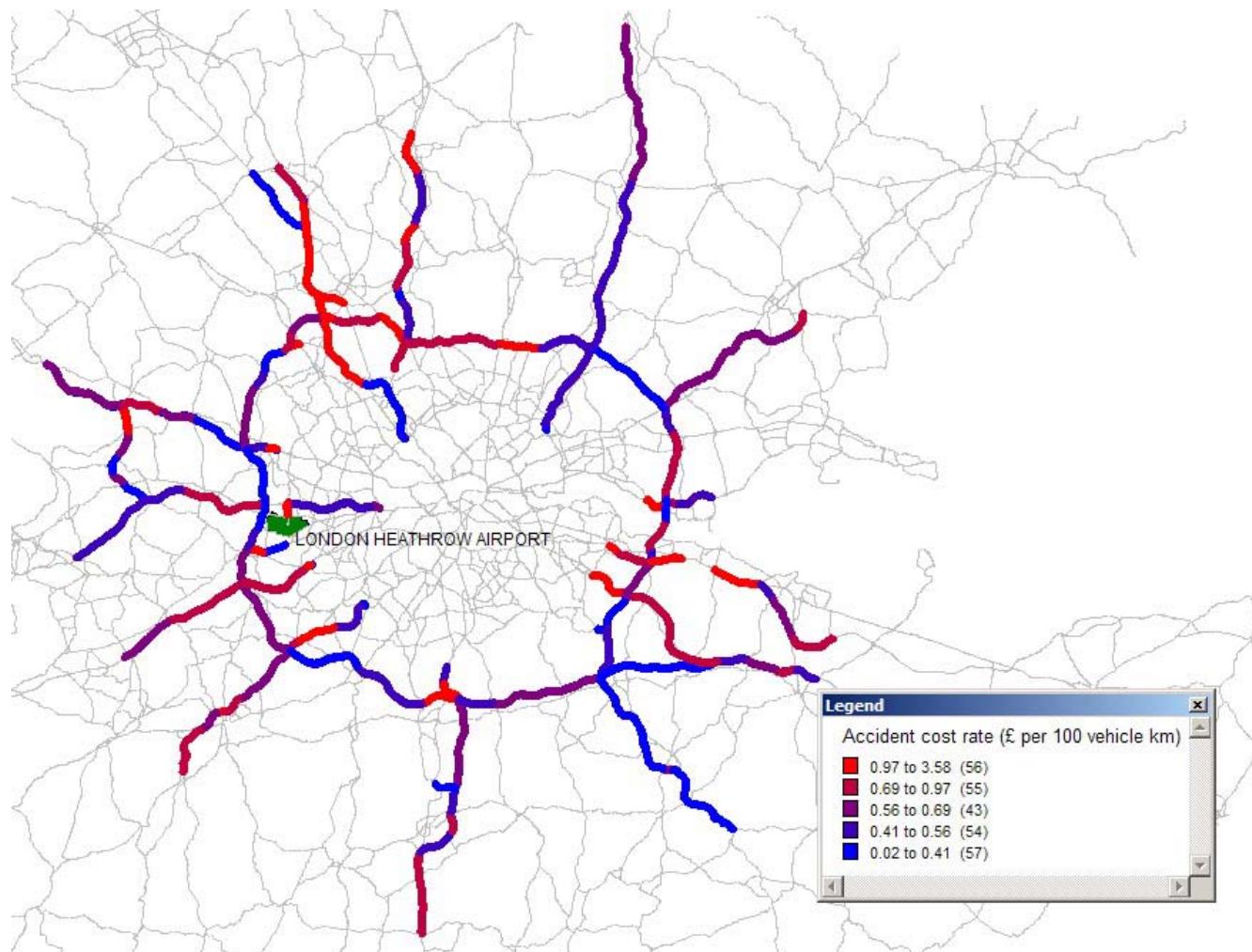
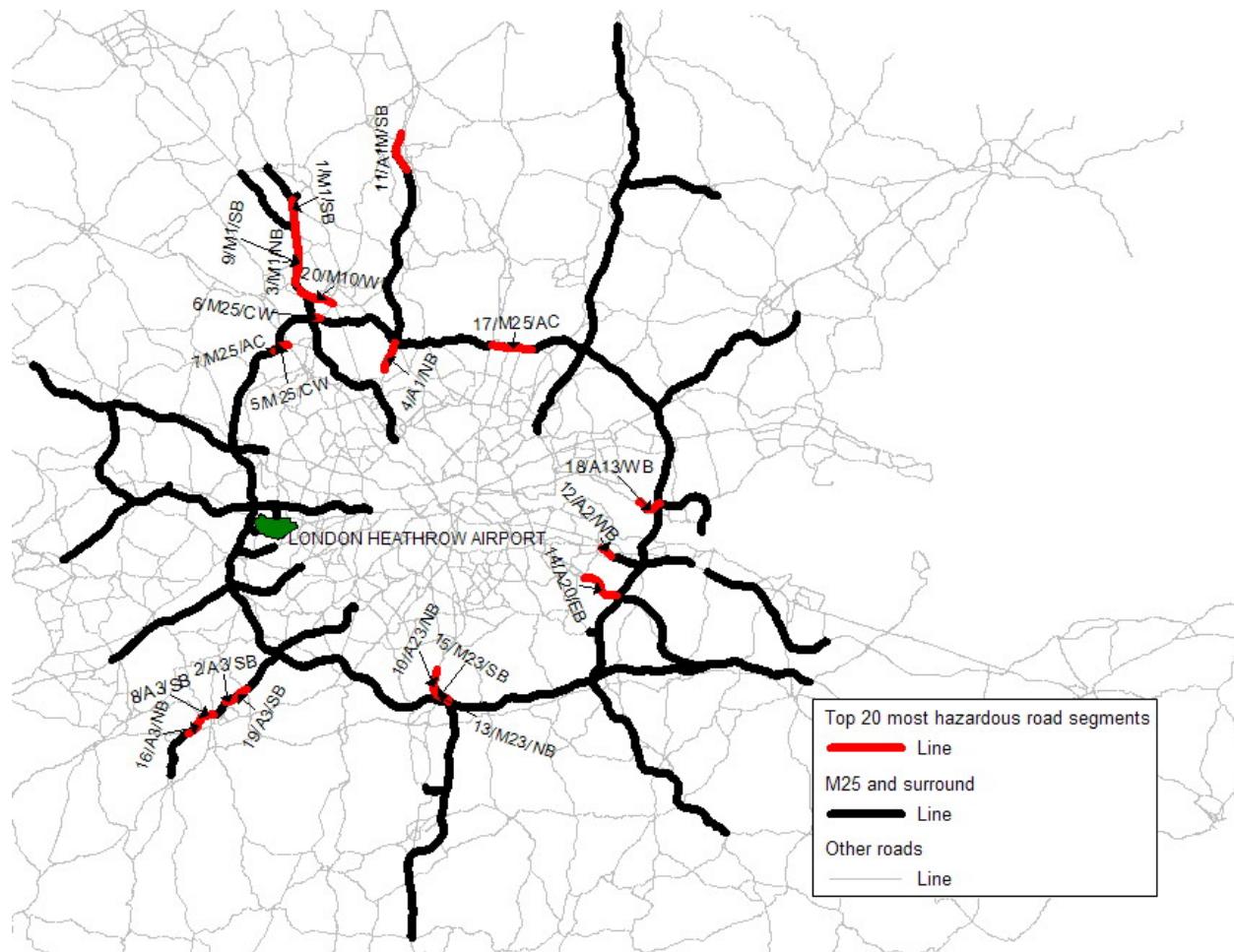
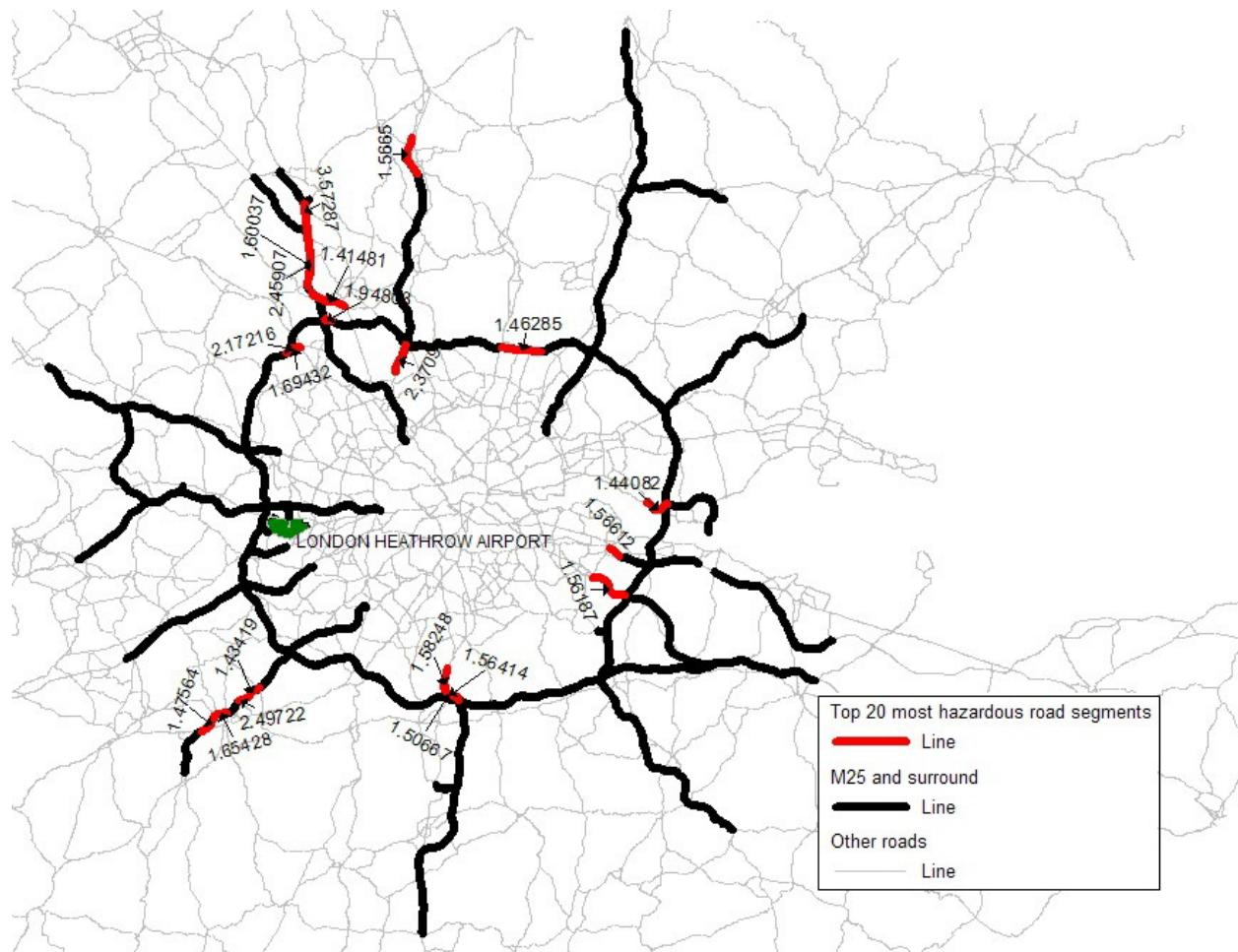


Figure 8.4 Spatial distribution of accident cost rates using the two-stage model on the M25 and surround during 2003 – 2007



8.5 (a) Rank/Road number/Direction of the top ranked 20 road segments

Figure 8.5 Top ranked 20 most hazardous road segments using the two-stage model



8.5 (b) Accident cost rates (£ per 100 vehicle kilometres) on the top ranked 20 road segments

Figure 8.5 (continued)

After identifying the hazardous road segments, further safety examination and treatment can be applied on these road segments. The higher ranked segments can be given higher priorities for safety treatment with a limited budget. A cost-benefit analysis of potential safety treatment can also be performed by policy makers based on the predicted accident costs on the road segments (Miaou and Song, 2005).

## 8.4 Summary

This chapter presented the results of site ranking which aims to identify hazardous road segments (i.e. accident hotspots) on the M25 and surround.

To control for the regression-to-the-mean effects, a model based ranking method was employed. The model used for site ranking was a two-stage mixed multivariate model which combines both accident frequency and severity models as detailed in Chapter 4. The prediction of the expected number of accidents using the two-stage model was produced and compared with the prediction using an accident frequency model only. It was found that the results from the two-stage model were consistent with the accident frequency model for the case of slight injury accidents, but differed slightly for the case of fatal and serious injury accidents. The two-stage model was preferred as more detailed data can be utilised at a disaggregate individual accident level and it was able to predict the number of fatal and serious injury accidents separately. As such the two-stage model is a promising alternative to accident frequency models in predicting counts of accidents for site ranking.

Based on the results from the two-stage model, road segments on the M25 and surround were ranked by their monetary cost rate (£ per 100 vehicle km) of accidents. The model based rankings were also compared with the naïve rankings using observed accident data. It was found that there were significant differences in terms of ranking results between the two ranking methods. Naïve ranking method tends to underestimate the cost of accidents on road segments. Top ranked hazardous road segments were also identified and located based on the results from the two-stage model.

# CHAPTER 9 DISCUSSION AND POLICY IMPLICATIONS

## **9.1 Introduction**

This thesis explores the relationship between traffic congestion and road accidents. This has been achieved by examining the effects of traffic congestion on accident *frequency* and accident *severity*. Appropriate econometric models were employed for both accident *frequency* and *severity* analyses (Chapter 4). Model estimation results and findings for accident *frequency* analysis were presented in Chapter 6; and model estimation results and findings for accident *severity* analysis were presented in Chapter 7. An important application of the accident prediction models, i.e. site ranking was also explored and presented in Chapter 8. This chapter aims to further discuss the results and findings from Chapters 6-8, and based on these discussions to provide a deeper understanding of the relationship between traffic congestion and road accidents. Policy implications of this research will also be discussed. The following sections of this chapter will firstly discuss the effects of traffic congestion on accident frequency and severity respectively, followed by an overall discussion of the relationship between traffic congestion and road safety. Policy implications based on the findings from Chapters 6-8 will then be discussed. Finally, a summary of this chapter will be provided.

## **9.2 Traffic congestion and road accident frequency**

Chapter 6 presented the model estimation results from the accident frequency analysis. Based on the analysis of data from the M25 and surround, it was found that traffic congestion is positively associated with the frequency of fatal and serious injury accidents: a 1% increase in the level of traffic congestion (measured by traffic delay per length of roadway) would increase fatal and serious injury accidents by around 0.1%. A separate model also showed that traffic congestion would increase the number of serious injury accidents. Traffic congestion is found to have little impact on slight injury accidents. The effects of other contributing factors such as AADT, radius and gradient were found to be consistent with previous research.

This result suggests that roadways with a high level of traffic congestion tend to have more fatal and serious injury accidents. This result is consistent with the previous study by Kononov et al. (2008) who found that fatal and injury accidents increase as traffic congestion increases. Other previous studies providing empirical evidence either found an inverse relationship between congestion and accidents (Baruya, 1998) or an insignificant relationship (Noland and Quddus, 2005). Their studies however as discussed in Chapter 2, often lack a direct measurement for congestion or an appropriate econometric method. In order to evaluate the effect of congestion on road accidents, it is of importance to measure traffic congestion correctly. Instead of using a proxy for traffic congestion as used in some of the previous studies (Baruya, 1998; Noland and Quddus, 2005; Kononov et al., 2008), this thesis employed a direct measurement of traffic congestion. It is therefore believed that the congestion measurement used in this thesis is more appropriate, as it reflects the nature of the congestion – traffic delay. Similar congestion measurements are used and recommended by the UK Department for Transport (DfT), for instance the “driving time lost per mile” (DfT, 2005a).

The reasons for the positive association between the level of traffic congestion and the frequency of road accidents on major roads may be due, at least partially, to the high speed variance among vehicles within and between lanes and erratic driving behaviour. Although increased traffic congestion is expected to decrease road fatalities because of the lower average speed under traffic congestion as proposed by Shefer and Rietveld (1997), the speed variance among vehicles within and between lanes may not be necessarily low. In contrast, speed variance may be large in congested situations because drivers need to adjust speed frequently (e.g., “stop-go-stop” actions)<sup>25</sup>, which significantly increases the complexity of driving. In this scenario drivers may not have enough time to react (i.e. short time between “go-stop” actions), so more conflict is expected. As stated by the law of complexity (Elvik, 2006), the increased complexity of traffic situations like this can increase the probability that accidents would happen (see Chapter 2 section 2.2 for details of the accident risk laws). Though the data on speed variance among vehicles is not available, the speed variance was calculated based on

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<sup>25</sup> This (“stop-go-stop” actions) also depends on the level of traffic congestion. If traffic is extremely congested (gridlock), there would be fewer “stop-go-stop” actions. Such extreme congestion may be less common on motorways and major A roads.

the hourly average speed on the M25 and surround, and it was found to be highly correlated with traffic congestion (correlation coefficient: 0.70). This implies that in congested situations though average traffic speed is low, speed variance is likely to be high. It has been argued that it is the speed variance that causes safety problems instead of speed itself (Lave, 1985), thus the increased speed variance in congested situations may result in more serious injury accidents, especially on major roads such as motorways and A roads. There is also empirical evidence that the go-stop actions in congestion would increase the chances of collisions (Hanbali and Fornal, 1997). In addition, traffic speeds may be lowered in congested situations, but the resulting speed may still be relatively high on major roads because of high speed limits. Therefore although this reduced speed may reduce accident severity, the speed may still be high enough to result in many serious or even fatal accidents. This may explain the result that traffic congestion has greater effects on fatal and serious injury accidents than on slight injury accidents on the M25 and surround.

Driving behaviour also plays an important role in increased accidents under congestion conditions. Driving under congested conditions is different from driving under free-flow conditions. It is well established that driving behaviour becomes worse in the presence of congestion. For example, it was found that congestion would result in higher driver stress leading to increased aggressive driving behaviour such as purposeful tailgating and yelling at others (Hennessy and Wiesenthal, 1997). Shinar (1998) showed that congestion is associated with aggressive behaviour such as honking of horns. A study by Shinar and Compton (2004) found that there was a strong positive linear association between congestion and the frequency of aggressive behaviour and drivers are more likely to behave aggressively during weekday rush hour when the value of time is high, such as cutting across one or more lanes in front of another driver and passing on the hard shoulder. The results found in this thesis would not be surprising, since increased congestion would cause more aggressive driving, and considering that aggressive driving is a major road safety concern (Shinar and Compton, 2004), this increased aggressive driving would subsequently result in more accidents.

### 9.3 Traffic congestion and road accident severity

Chapter 7 presented the model estimation results from accident severity analysis. Based on the analysis on the M25 and surround, it was found that the relationship between traffic congestion and accident severity is complex. The effect of traffic congestion (measured by traffic delay per length of roadway) on accident severity varies across different road accidents. For approximately 70% of accidents, traffic congestion is negatively associated with the probability of a serious injury accident (relative to the probability of a slight injury accident); and for about 30% of accidents, traffic congestion is positively associated with the probability of a serious injury accident. The confidence level for this relationship is only at the 85% level. Traffic congestion appears to have little impact on the probability of a fatal accident. Overall it can be seen that increased traffic congestion decreases the severity of an accident, which is especially the case for low congested situations (e.g., when total traffic delay is less than 50 min per 10km length of roadway per hour). All other contributing factors were controlled for and found to be consistent with previous studies.

Generally the results suggest that for most cases, traffic congestion reduces accident severity. This is not surprising as the average speed is reduced because of traffic congestion, and lower speed tends to reduce accident severity (see the discussions in Chapter 2 section 2.3.1). For other cases (around 30%) of accidents, traffic congestion appears to increase the severity of an accident, which may be related to the higher speed variance prior to an accident in congested situations. As discussed in the previous section, driving behaviour in highly congested situations may be erratic, thus under this condition accidents may be more severe. This is confirmed by the results showing that traffic congestion is more likely to increase accident severity in highly congested situations (traffic delay greater than 50 min per 10km per hour). This however may not hold if traffic is in *extreme* congested conditions (standstill) as the traffic speed would be extremely low thus unlikely to result in a fatal or a serious injury accident.

The effect of traffic congestion on accident severity presented in Chapter 7 is however at a weak confidence level (85%), hence the impact of traffic congestion is limited. The fact that the standard deviation of the variable representing congestion (which is a random parameter) is significant further confirms that the effect of traffic congestion on road accident severity is complex and not uniform over all accidents. In addition, in the

accident severity analysis the level of congestion used for each accident was 30min prior to an accident, therefore a shorter period of time (e.g., 1min prior to an accident) may be used to more accurately measure the traffic congestion prior to an accident and thus better understand the effect of traffic congestion on accident severity. This requires traffic characteristics data for a shorter period (the data employed in this thesis is hourly data).

## 9.4 Traffic congestion and road safety

Combining the results from both accident frequency and severity models, it can be concluded that traffic congestion increases the occurrences of road accidents (mainly fatal and serious injury accidents), and decreases the severity outcome of the accidents occurred on major roads.

Therefore, traffic congestion has a *mixed* effect on road safety: increased traffic congestion has a negative impact on road safety in terms of increased accident frequency; it however has a positive impact on road safety in terms of decreased accident severity.

This mixed effect on road accidents (safety) is not unique to traffic congestion. For example, traffic flow is also found to have a mixed effect on road accidents: increased traffic flow (or AADT) increases the frequency of traffic accidents (see Chapter 6 Tables 6.11 and 6.12), meanwhile it decreases accident severity (i.e. decreases the probability of a fatal or serious injury accident; see Chapter 7 Tables 7.2 and 7.4). As discussed, the reason for the positive association between traffic flow and accident frequency is that traffic flow increases the risk exposure; and the reason for the negative association between traffic flow and accident severity may be due to lower average speed in high traffic flow conditions. Considering the similarity between traffic flow and congestion, the similar mixed effect can be expected. It is worth noting that one may speculate that traffic flow and congestion are highly correlated; however it is not the case according to the data analysed in this thesis. High traffic flow does not necessarily cause traffic congestion (delay) if the vehicles are moving smoothly with high speed. Besides traffic flow, the other two variables showing a mixed effect on road safety (in terms of frequency and severity) in the analyses are: the number of lanes and the motorway indicator. As shown in Chapter 6 (Tables 6.11 and 6.12), the increased

number of lanes increases accident frequency at all severity levels; however as shown in Chapter 7 (Tables 7.2 and 7.4), compared to 4-lane roads, accidents on roads with 3 lanes or less are more severe, meaning that the increased number of lanes decreases accident severity. Similarly, motorways were found to have more accidents (i.e. higher accident frequency) compared to A roads on the M25 and surround (Tables 6.11 and 6.12), whilst accidents on motorways tend to be less severe (Tables 7.2 and 7.4). There is evidence in the literature that such mixed effects of a factor affecting road safety exists, for instance, as discussed in Chapter 2 section 2.3.1, increased speed is believed to increase accident severity, but some studies have reported that increased speed decreases accident frequency (Baruya, 1998; Taylor et al., 2000a).

Since there is a mixed effect of traffic congestion on road accidents, i.e. increased traffic congestion increases accident frequency (mainly fatal and serious injury accidents) but reduces accident severity, it poses a dilemma for transport policy makers who aim to improve road safety: one wants to reduce traffic congestion in order to reduce accident frequency, but it may increase accident severity. It should however be noted that as the model estimation results suggested (see Chapter 7), the effect of traffic congestion on accident severity is complex and not uniform over all accidents. While overall traffic congestion reduces accident severity, for some cases (30%) traffic congestion could also increase accident severity. In addition, the effect of traffic congestion on accident severity is limited as the effect is statistically significant only at the 85% confidence level. Therefore considering the aspects of both accident frequency and severity, it can be argued that the effect of traffic congestion on accident frequency is more significant and important than accident severity, and as such overall traffic congestion has a negative impact on road safety. In other words, increased traffic congestion reduces road safety on major roads, and thus it is desirable to reduce traffic congestion so as to improve road safety.

## 9.5 Policy implications

Since traffic congestion decreases road safety, it is desirable for transport policy makers to reduce traffic congestion, which will benefit society both in terms of improving road safety and reducing the social costs incurred by traffic congestion. The findings from this thesis have added to the debate about the relationship between mobility and safety, i.e. whether mobility and safety can be achieved simultaneously. It has been shown that

mobility and safety can be improved simultaneously since there is a positive relationship between traffic congestion and number of road accidents. Therefore, there is significant *additional* benefit of reducing traffic congestion, in the sense that it not only reduces the costs relating to increased travel time (i.e. traffic delay) but also the costs associated with accidents.

The impact of traffic congestion on road safety is large. As shown in Chapter 6, a 1% reduction in the level of traffic congestion would decrease fatal and serious injury accidents by around 0.1%. According to the DfT (2008), there were a total number of 1,641 fatal accidents and 11,898 serious injury accidents on major roads (including motorways and A roads) in Great Britain in 2007. Therefore, if the level of traffic congestion could be decreased by 10% on major roads in Great Britain, a reduction of 135 fatal and serious injury accidents would be achieved (based on 2007 data) in a year, which is equivalent to about £64 million of reduced cost in preventing accidents<sup>26</sup>. Therefore it can be seen that the impact of traffic congestion on road safety is significant, and thus it is important to reduce traffic congestion so as to improve road safety.

Since there is additional benefit of reducing traffic congestion in terms of road safety, some measures could be reinforced to optimise and smooth the traffic flow. For example, electronic warning signs can be displayed in real-time at some sites when congestion occurs, making drivers more prepared for the congestion ahead and the associated risk of accidents. Information on congestion is already displayed on many motorways throughout the UK. For example, Figure 9.1 shows an electronic warning sign displayed on the M25 warning drivers “QUEUE CAUTION”. The findings from this thesis re-confirm the benefit of the electronic warning signs, as in addition to smoothing the traffic flow, they also improve road safety. Therefore more warning signs could be introduced on major roads in the UK.

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<sup>26</sup> Using the estimated proportion of fatal/serious injury accidents (see Table 8.1 in Chapter 8), among the 135 fatal and serious injury accidents, there would be 21 fatal accidents and 114 serious injury accidents. The average value of the benefits of prevention of accidents was £1,876,830 per fatal accident and £215,170 per serious injury accident in 2007 (DfT, 2008). Hence the total cost of the 135 fatal and serious injury accidents was 63,942,810 (£).



**Figure 9.1 An electronic sign warning the queue ahead displayed on the M25**

In addition to the electronic warning signs, some advanced traffic management systems could be introduced to smooth the traffic for reducing traffic congestion and road accidents. Empirical evidence from Hanbali and Fornal (1997) found that adaptive traffic signal systems were very effective in reducing both traffic congestion and road accidents at intersections, especially the “stop-and-go” driving related collisions. The adaptive traffic signal systems involve the installation of a closed-loop, traffic-responsive signal systems at intersections, changing the green-to-cycle (g/c) ratio for the congested roadways to reduce traffic congestion.

Another promising advanced traffic management system is the Active Traffic Management (ATM)<sup>27</sup> which is currently in operation on the M42 motorway in the UK. The ATM monitors the traffic flows on the roads using sensor loops and automatically calculates the best speed limit for the current traffic. The optimised speed limits are displayed on electronic overhead gantries. Other information can also be displayed, for example, drivers can be directed to use the hard shoulder during congested periods. Figure 9.2 illustrates the ATM in operation on the M42, where drivers were directed to

<sup>27</sup> See Highways Agency website (<http://www.highways.gov.uk/knowledge/1361.aspx>) for more details.

use the hard shoulder. The ATM system was originally introduced to reduce traffic congestion; the preliminary monitoring results however showed that the ATM also reduced accidents from 5.1 to 1.8 a month (monthly average based on 6 years' data) despite initial safety concerns (Highways Agency, 2008). This indicates that smoothed traffic flow (i.e. decreased traffic congestion) does reduce risks of accidents. Therefore, similar schemes could also be introduced on other major roads in the UK.



**Figure 9.2 Active Traffic Management (ATM) on the M42**

(Source: Highways Agency <http://www.highways.gov.uk/knowledge/1361.aspx>)

The implementation of these measures (e.g., ATM) is traditionally justified in terms of congestion reduction. Since the results from this thesis show that reduced traffic congestion is associated with less road accidents, it suggests that the measures such as the ATM may be beneficial to road safety, adding the additional benefits of implementing these measures. Therefore, the findings from this thesis are helpful to transport policy makers in devising safety programmes and allocating highway funds.

As discussed in section 9.2, it was argued that the positive association between traffic congestion and the number of fatal and serious injury accidents on major roads is partially due to the increased speed variance and erratic driving behaviour in congested situations. Therefore some measures could be introduced to reduce speed variance and improve driving behaviour in congested situations. As for reducing speed variance, “average speed check cameras” could be installed on a stretch of a roadway that has been identified as an accident hotspot (see Chapter 8 for accident hotspot identification) to enforce a suitable “average speed” on the roadway. This ensures that all vehicles

travel at a similar and consistent speed on the stretch of the roadway, which reduces speed variance and improves road safety. Transport Scotland (2009) recently reported that the enforcement of a consistent speed of 40mph (64km/h) on the M80 had successfully enhanced road safety during M80 road works. In addition to the enforcement of average speed, inappropriate speed should be avoided. The inappropriate speed includes excessive speed and very low speed. Slow drivers are as much a hazard as fast ones since they increase speed variance (Lave, 1985), which is especially a concern for major roads with high posted speed limits. Therefore, *minimum* speed limits could be introduced to enforce the minimum speed that drivers are required to drive on major roads. Minimum speed limits are operated in many countries outside the UK. For example, freeways in Michigan in the US usually have 55mph (89km/h) for minimum speed limits (Michigan Legislature, 2009). Similar policies for minimum speed limits could be introduced to the UK to ban inappropriate low speed on major roads for safety.

Erratic driving behaviour in congested situations may be more difficult to tackle. As suggested by Shinar and Compton (2004), some measures could be implemented to reduce aggressive driving behaviour in congested situations, such as encouraging car sharing and flexitime, enhancing law enforcement and promoting driver education and public campaigns. There have been a number of road safety campaigns in the UK since 1960 (DfT, 2008), and a campaign highlighting the dangers of aggressive driving in congested situations may be useful for improving road safety on busy major roads.

In addition to the relationship between traffic congestion and road accidents, this thesis has also demonstrated how the accident prediction models employed can be helpful for transport policy makers. Chapter 3 discussed several practical applications of the accident prediction models, including identifying factors affecting road accidents, evaluating the effectiveness of safety treatment implemented to roadway sites and site ranking. Site ranking aims to identify accident hotspots with underlying safety problems for further engineering examination and remedial treatment. This is useful for transport policy makers in allocating highway funds and ensures cost-effectiveness in resource allocation. The application of accident prediction models in site ranking on the M25 and surround was illustrated in Chapter 8. This method is transferable and can be applied on other road networks.

The spatial econometrics (i.e. the Bayesian spatial models used in Chapter 6) employed in this thesis are also useful for identifying road segments (sites) with similar spatial characteristics (e.g., in terms of infrastructure and environment). Since these road segments share similar conditions they are likely to be correlated to each other. As shown in Figure 6.11 (see Chapter 6), the spatially correlated road segments are well clustered in different parts of the road network. Therefore, along with other factors, the clustered road segments can be treated in groups for further safety investigation. For example, road segments in the southeast section of the M25 and surround could probably be treated as a group in safety programming as they have significant spatially correlated effects. Therefore, the spatial econometrics used in this thesis can aid transport policy makers in planning safety programmes and highway funds.

## 9.6 Summary

This chapter has firstly discussed the effects of traffic congestion on road accident *frequency* and *severity* respectively. Traffic congestion is found to increase accident frequency (mainly fatal and serious injury accidents), and the reasons for this result may be due to higher speed variance among vehicles within and between lanes and erratic driving behaviour in congested situations. Although average speed is reduced in congestion, speed variance can be higher as drivers need to adjust speed frequently (e.g., “stop-go-stop” actions), which considerably increases the chances of conflict. In addition, as previous studies suggest, aggressive driving is more frequent in congested situations, which significantly increases the risks of being involved in an accident. Therefore, considering all these factors, increased traffic congestion is ultimately associated with more accidents. Traffic congestion, on the other hand, has been found overall to decrease accident severity. This is expected as average speed in congestion is relatively low, and thus the accidents occurred are likely to be less severe.

Since traffic congestion increases accident frequency but decreases accident severity, it can be concluded that traffic congestion has a mixed effect on road safety. Considering that the effect of traffic congestion on accident severity is limited and not uniform over accidents, the effect of traffic congestion on accident frequency is argued to be more significant and important than accident severity, and thus overall traffic congestion has a negative impact on road safety. This finding added to the debate about the relationship

between mobility and safety, showing that mobility and safety can be improved simultaneously.

Based on this argument, several policy measures can be introduced or considered to smooth the traffic in order to reduce traffic congestion and road accidents. This includes extending the use of the electronic warning signs for traffic congestion, introducing advanced traffic management systems such as the Active Traffic Management (ATM) on other major roads. In addition to reducing traffic congestion, these measures have additional benefits in terms of improved road safety. Since higher speed variance and erratic driving behaviour in congested situations are argued to be responsible for the effect of traffic congestion on road safety, some measures can be implemented to reduce speed variance and aggressive driving for improving road safety on major roads. These measures include enforcing “average speed” on a stretch of a roadway that has been identified as an accident hotspot by installing “average speed check cameras”; introducing minimum speed limits in the UK; encouraging car sharing and flextime; enhancing law enforcement and campaigning of the dangers of aggressive driving in congested situations on major roads.

Finally, this chapter has discussed the practical applications of the accident prediction models employed in this thesis, such as the site ranking which aims to identify accident hotspots. These applications are useful for transport policy makers in devising safety programmes and allocating highway funds.

# CHAPTER 10 CONCLUSIONS AND FURTHER RESEARCH

## 10.1 Summary and conclusions

Both traffic congestion and road accidents impose a burden to society, and therefore it is important to reduce the impact of them. This however may not be possible as it was hypothesised that there is an inverse relationship between traffic congestion and road fatalities (Shefer and Rietveld, 1997), which poses a potential dilemma for transport policy makers between mobility and safety. Previous studies often lack quantitative evidence based on real-world data, a direct congestion measurement or an appropriate econometric model. This thesis therefore aimed to **explore the relationship between traffic congestion and road accidents**. This has been achieved by examining the effect of traffic congestion on both accident frequency and accident severity, using a suitable congestion measurement and an appropriate econometric model based on real-world data. Other contributing factors affecting road accidents such as traffic flow and road geometry were also controlled for. Practical applications of accident prediction models developed in this thesis and their associated policy implications were also discussed.

This thesis firstly examined various factors affecting road accidents by conducting an in-depth literature review. The factors affecting road accidents were related to traffic characteristics (e.g., traffic flow, density, speed and congestion), road geometry and infrastructure, demographic characteristics, driving behaviour, land use and environment. Some of these factors that were considered in the econometric models in this thesis include: traffic congestion, traffic flow, road geometry (e.g., radius of curvature, gradient, length of the segment and number of lanes), speed limit, roadway classification (comparison between motorway and A roads), lighting and weather conditions. Other factors were not included in the econometric models because of data unavailability, model requirements (e.g., to exclude a factor to avoid collinearity), or the fact that some factors are not applicable to road segment level analysis (e.g., population and employment).

In terms of econometric models, popular models employed by road safety modellers were considered and reviewed. For the case of accident frequency analysis, classical

count outcome models (e.g., Negative Binomial models) and spatial models using a full Bayesian hierarchical approach were considered appropriate and therefore used in this thesis. For the case of accident severity analysis, several categorical outcome models were considered, including ordered response models (e.g., ordered logit and generalised ordered logit) and nominal response models such as multinomial logit and mixed logit.

Real-world data were collected to conduct this research. This thesis was based on road segment level analysis, and the study area chosen was the M25 motorway and its surrounding major motorways and A roads. The data were obtained primarily from two sources: STATS19 database for accident data; and the UK Highways Agency for road and traffic characteristics data. The Highways Agency provided traffic delay data, which were used to measure traffic congestion. Two congestion measurements based on traffic delay data were considered: (1) congestion index, and (2) total delay per length of roadway. Data were investigated and refined to improve the quality of the analysis. Due to the error in both accident data and motorway segment data, there was a mismatch between them when the accidents are overlaid onto spatial road segments (centre-line data). An appropriate method was therefore developed to match the accidents to the correct road segments. Data were also validated externally to ensure its accuracy and quality.

A preliminary spatial analysis was conducted on the M25 for the year 2006, and no statistically significant association was found between traffic congestion and road accident frequency. A further spatio-temporal analysis was then carried out on the larger road network (the M25 and surround) during the period 2003-2007. The model estimation results from the spatio-temporal analysis showed that traffic congestion was positively associated with the frequency of fatal and serious injury accidents according to the data on the M25 and surround: a 1% increase in the level of traffic congestion would increase fatal and serious injury accidents by about 0.1%. A separate model also showed that increased traffic congestion would increase serious injury accidents. On the other hand, traffic congestion was found to have little impact on slight injury accidents. In terms of econometric models, it was found that the Bayesian spatial models outperform classical count models in terms of model inference, statistical fit and the fact that spatially correlated effects can be controlled for by the spatial models. The reasons for the positive association between the level of traffic congestion and the frequency of road accidents (mainly fatal and serious injury accidents) on major roads

were argued to be the high speed variance among vehicles within and between lanes and erratic driving behaviour. It was argued that speed variance in congested situations is high, and thus may cause more serious injury accidents, especially on major roads such as motorways and A roads. Also more aggressive driving in congested situations also contributes to the occurrence of accidents.

As for the case of accident severity analysis, a series of ordered and nominal response models were tested. Traffic congestion was found to be statistically insignificant in all models estimated except in the mixed logit model. The mixed logit model was arguably the best model estimated for its flexibility and model performance. According to the results from the mixed logit model, the effect of traffic congestion on accident severity is random (assumed a normal distribution) and not uniform: for about 70% of the accidents occurred, traffic congestion decreases the probability of a serious injury accident occurring; and for about 30% of the accidents occurred, traffic congestion increases the probability of a serious injury accident occurring (relative to the probability of a slight injury accident). Traffic congestion appears to have little impact on the probability of a fatal accident occurring. Overall it can be concluded that traffic congestion decreases accident severity. This is not a surprising result as the average speed of traffic in congestion is relatively low, and lower speed tends to reduce accident severity. However, such an effect of traffic congestion on accident severity is marginal as the level of confidence is only at 85%.

Based on the results from the accident frequency and severity models, it can be concluded that traffic congestion has a *mixed* effect on road safety: increased traffic congestion has a negative impact on road safety in terms of increased accident frequency; it however has a positive impact on road safety in terms of decreased accident severity. Since the effect of traffic congestion on accident severity is marginal, it was argued that overall traffic congestion has a negative impact on road safety. As such it is desirable for transport policy makers to reduce traffic congestion so as to improve road safety. This thesis has shown that mobility and safety can be improved simultaneously, therefore there is a significant *additional* benefit of reducing traffic congestion in terms of road safety. This justifies and further confirms the benefit of the use of electronic warning signs for congestion and advanced traffic management systems such as the Active Traffic Management (ATM) which allows road users to use hard shoulders during rush hours. Some policy implementations were proposed aimed

at reducing speed variance in congested situations in order to improve road safety, including enforcing “average speed” on a stretch of a roadway that has been identified as an accident hotspot by installing “average speed check cameras”; and introducing minimum speed limits in the UK. Some other potential policy implications for reducing erratic driving behaviour were also discussed, such as encouraging car sharing and flextime, campaigning of the dangers of aggressive driving in congested situations on major roads.

This thesis also demonstrated a useful application of accident prediction models, namely the site ranking aiming at identifying accident hotspots for further safety examination and remedial treatment. This was done by using a two-stage mixed multivariate model which combines both the accident frequency and severity models. The two-stage model offered several advantages compared to traditional methods that used only accident frequency models. This includes: more detailed data can be utilised at a disaggregate individual accident level and it is able to predict low frequency accidents in certain categories (such as fatal accidents). This method is also transferable and can be applied to other road networks. Site ranking is useful for transport policy makers in devising safety programmes and effectively allocating highway funds.

## 10.2 Contribution to knowledge

This thesis has made a number of contributions to knowledge. These comprise the following areas:

- (1) The effect of traffic congestion on road accidents
- (2) The use of a two-stage mixed multivariate model in accident predictions and site ranking
- (3) Mapping accidents to correct road segments on major roads

Regarding the first, this thesis has explored the relationship between traffic congestion and road accidents, shedding light on the debate with respect to the relationship between mobility and safety. This thesis has revealed that mobility and safety can be improved simultaneously.

More specifically, in the case of accident *frequency* analysis, this thesis has found that traffic congestion increases the frequency of fatal and serious injury accidents, and that traffic congestion has little impact on slight injury accidents. Due to the low frequency

of fatal accidents on the M25 and surround, this thesis has not however investigated the effect of traffic congestion on the frequency of fatal accidents as this was not statistically feasible. Therefore, the hypothesis proposed by Shefer and Rietveld (1997) (i.e. an inverse relationship between traffic congestion and road fatalities) cannot be tested<sup>28</sup>. However, as shown in Table 6.15 (Chapter 6 section 6.3.2), traffic congestion is statistically significant and positively associated with serious injury accidents. *Therefore, this thesis proposes a new alternative hypothesis that traffic congestion on major roads may increase the occurrence of serious injury accidents.* Based on the results, it can be seen that there is a significant additional benefit of reducing traffic congestion in the sense that it not only reduces the costs relating to increased travel time (i.e. traffic delay) but also the costs relating to preventing accidents. As for the econometric models used in the accident frequency analysis, this thesis presented and compared several models, including classical count outcome models and Bayesian spatial models. The results confirmed the superiority of Bayesian spatial models.

In addition to the effect of traffic congestion on accident frequency, this thesis also examines the impact of traffic congestion on road accident *severity*, which appears to have been rarely investigated in the previous research literature. The thesis showed that, as expected traffic congestion generally reduces accident severity, though this impact is marginal and for some cases increased traffic congestion also increases accident severity. In terms of econometric models, the mixed logit model has rarely been used in accident severity analysis in previous studies, especially at an individual accident level. This thesis has demonstrated how a mixed logit model can be used in examining accident severity at an individual accident level. It has been shown that the mixed logit model is a promising model for accident severity analysis as an alternative to regular ordered or nominal response (e.g., ordered/multinomial logit) models.

Second, this thesis has also demonstrated how accident frequency and severity models can be combined to form a mixed multivariate model in accident predictions. This is particularly useful in site ranking in which prediction is of major interest. Traditional site ranking methods tend to use only accident frequency models to predict the expected

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<sup>28</sup> It should also be noted that the number of fatal accidents are not equal to the number of fatalities. In order to investigate the effect of a risk factor on road fatalities, it is required to know the total number of people (drivers and passengers) on the roadway as an exposure factor. However, the data on the total number of people on the M25 and surround is not available.

number of accidents at different severity levels. This can be enhanced by the use of accident severity models jointly. The advantages of using the two-stage model is that it utilises more detailed data at a disaggregate individual accident level and it is able to predict low frequency accidents. Individual accident level data can be conveniently obtained from the STATS19 database, which enables researchers to develop an insight into the severity distribution of accidents. To achieve this, this thesis has shown how results from an accident severity model at a disaggregate individual accident level can be aggregated to predict the proportions of types of accidents on a road segment in the two-stage modelling process. In addition, although the analysis in this thesis is based on a road segment level, this two-stage modelling method is applicable to area-wide based analysis, therefore this modelling method is also useful for other researchers seeking to predict the number of accidents at different severity levels in an area.

Third, another important contribution of this research is its development of an appropriate method to match the accidents to correct road segments. This improves the quality of the data and is transferable to other major roads. Therefore, this method is useful for safety researchers in order to reduce the errors in the data caused by the mismatch between locations of accidents and the digital road map.

Finally, since it was found that traffic congestion imposes safety problems, several policy implications have been proposed, such as reinforcing Active Traffic Management, enforcing “average speed” on the roadway and introducing minimum speed limits in the UK. These measures would be useful for transport policy makers in improving road safety.

## 10.3 Limitations and further research

There are several limitations in this research. They are mainly related to data and econometric models, which are discussed below. Recommendations for further research are also offered.

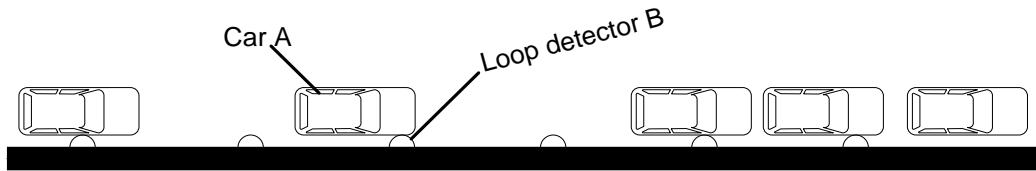
### 10.3.1 Data

In the case of the accident frequency analysis, the number of severe accidents on the road segments is rather low, especially for the fatal accidents, and as such the effect of traffic congestion on the frequency of fatal accidents cannot be examined. Slight injury accidents, on the other hand, as discussed in Chapter 5 (section 5.5) suffer from the

problem of under-reporting, which may affect the modelling results. For modelling fatal accidents, an area-wide analysis may be useful as a sufficient number of fatal accidents may be obtained at a certain spatial level (e.g., at district level), so a statistical association can be established. However, an area-wide analysis needs to address problems such as assigning accidents to correct areas and developing an area level congestion measurement. The technique proposed in this thesis for mapping accidents to correct road segments (Chapter 4 section 4.4) is not applicable to area-wide analysis, so clearly further research is required to resolve this issue.

In addition, the data used in the accident frequency analysis was highly aggregated (annual) data. The aggregation was necessary so that sufficient number of accidents (i.e. accident frequency) can be observed and analysed using accident frequency models. However, as congestion can be highly localised and time specific, this aggregation may affect the model estimation results on the relationship between congestion and accident frequency. Therefore further research is needed to investigate whether this aggregation significantly affects the results.

In the accident severity analysis, the level of traffic congestion used for each accident record was 30min prior to an accident. Traffic flow and congestion conditions may change during this time interval so ideally a shorter period of time (e.g., 1min prior to an accident) would be preferred, subject to data availability. In addition, the level of traffic congestion was assumed to be homogeneous over a road segment (average length is 5km. See Table 5.1 in Chapter 5), which may however not always be the case (i.e. a part of a road segment may be more congested than other parts of the road segment). In other words, it could be the case that the congestion level for a whole segment is high, but the level of congestion may be low at the location where accidents occurred. Therefore, a road segment based congestion measurement may be inadequate, and a congestion measurement for a specific location on a road segment is required for the accident severity analysis. This may be achieved by using dense loop detectors (such as those on the M42) to obtain traffic data for a more specific location. This is illustrated in Figure 10.1: as can be seen, the right section of the road segment is more congested compared to other parts the segment. If “Car A” had an accident, ideally the traffic data for “Loop detector B” (e.g., traffic flow or congestion level around this detector) should be used instead of road segment based traffic data.



**Figure 10.1 Loop detectors and cars on a road segment**

The traffic congestion in this thesis is measured by traffic delay normalised by road length or free flow travel time. This measurement is straightforward as it is directly measuring traffic congestion (i.e. more delay means more congestion). It would be interesting to compare this measurement with other traffic characteristics data, such as traffic density to see how traffic congestion evolves with respect to traffic density and whether a similar relationship can be found between traffic density and road accidents.

### **10.3.2      *Econometric models***

In terms of econometric methods, there are a number of areas that could be extended. For example, as discussed in Chapter 2, this research is based on an observational analysis, and therefore further research is required to examine whether there is a causal relationship between traffic congestion and road accidents. This may be achieved by using a more disaggregate analysis, for example using individual driver's data.

As for accident frequency models, this thesis employed the conditional autoregressive (CAR) models under Bayesian framework for modelling spatial correlation. As discussed in Chapter 3 section 3.4.1, there are a number of other spatial modelling techniques, such as the spatial filter models. Future research can be conducted to compare the spatial filter and CAR models in accident frequency analysis. Another concern regarding the accident frequency models is the functional form used for the relationship between traffic congestion and road accidents. As indicated in Figure 2.2 in Chapter 2, the hypothetical relationship between road fatalities and traffic congestion (measured by traffic density as a proxy) follows an inverse U-shaped pattern. Therefore, it is natural to consider a quadratic term for traffic congestion in the model specification. This means that, for instance, if  $x$  is the variable for traffic congestion, instead of a functional form of  $\log(\mu_i) = \alpha + \beta_1 x$ ,  $\log(\mu_i) = \alpha + \beta_1 x + \beta_2 x^2$  should be used as suggested by some studies (e.g., Graham et al., 2005). This thesis did not include the quadratic term in the model specification, which may not appropriately

represent the true relationship between traffic congestion and road accidents. It should however be noted that, in the functional form of  $\log(\mu_i) = \alpha + \beta_1 x + \beta_2 x^2$ ,  $x$  and  $x^2$  are usually highly correlated (for the data used in this thesis, correlation coefficient is 0.9 if  $x$  is the congestion variable). This causes the problem of multicollinearity and thus the coefficients estimated (i.e.  $\beta_1$  and  $\beta_2$ ) may be biased. Nevertheless, future studies are required to explore different functional forms to better represent the relationship between traffic congestion and road accidents.

The accident frequency models may also suffer from the problem of endogeneity, as the level of traffic congestion may also depend on the frequency of accidents (i.e. reverse causality). The frequency of road accidents is a function of traffic congestion, as suggested by the models developed in this thesis. In reality, the level of traffic congestion on a road segment may also depend on the frequency of accidents occurred on the road segment, as road accidents result in increased traffic congestion. Therefore, this is a problem of endogeneity. If this endogeneity is ignored it may lead to erroneous conclusions (Carson and Mannerling, 2001). To investigate whether this is the case for the models developed in this thesis, a Durbin-Wu-Hausman test (Verbeek, 2008) has been performed with the results showing that the traffic congestion variable is not endogenous. Future studies should examine the problem of endogeneity (for instance using an instrumental variables approach as suggested by Carson and Mannerling, 2001).

The accident severity models employed in this thesis were estimated using the maximum (simulated) likelihood method, and according to Train (2003) the estimation results are asymptotically equivalent to the Bayesian method given the large sample size used (there were 12,613 observations in the accident severity analysis, see Chapter 5 section 5.4). It would be interesting to see how the Bayesian method performs compared to the maximum (simulated) likelihood method for accident severity models with a small sample size.

Both accident frequency and severity models may suffer from the problem of omitted variable bias, since accident risk factors such as lighting and weather conditions were not considered in the accident frequency models; and factors that may affect accident severity (such as vehicle design and seat belt usage) were also not included in the accident severity models. Resolving the problem of omitted variable bias requires much

more data collection. As discussed in Chapter 2, it may be impossible or impractical to collect data for all accident risk factors and there may also be risk factors that were not previously known (i.e. imperfect information), which is the main motivation of developing and using a sophisticated model. The econometric models used in this thesis should be able to take account of some unobserved heterogeneity. For example, the spatial econometrics can control for unobserved similar roadway characteristics (e.g., pavement conditions) among neighbouring road segments. In addition, as can be seen in Chapter 4, various random terms were used to control for a range of unobserved spatial and temporal effects; and as discussed in Chapter 3, the mixed logit model is also able to take into account unobserved heterogeneity. Therefore the sophisticated modelling techniques used in this thesis may reduce the impact of omitted variable bias to a great extent. The models however cannot resolve the issue of omitted variable bias completely; and indeed, as Train (2003) pointed out, “there is a natural limit on how much one can learn about things that are not seen.”

### ***10.3.3 Extensions of the study area***

This thesis is focusing on the M25 and its surrounding major roads (motorways or A roads). Therefore, further research is required to investigate the effect of traffic congestion on road accidents on other major roads in the UK and other countries. Road infrastructure and traffic characteristics in other parts of the UK or in other countries may be different than the M25 and surround, for instance roads in rural or urban settings; and the effect of traffic congestion on different road users (e.g., motorised and non-motorised transport) may also be different. This thesis proposed the hypothesis that traffic congestion may increase the serious injury accidents on major roads. Further studies for other major roads can test this hypothesis and offer further empirical evidence, which may eventually provide a conclusive statement on the relationship between traffic congestion and road accidents. This would widen the potential use of the findings from this thesis. In addition to major roads, the impact of traffic congestion on other types of roads or junctions also needs to be examined.

### ***10.3.4 Policy formulation and testing***

This thesis proposes a number of policy implications, such as enforcing “average speed” on a stretch of a roadway that has been identified as an accident hotspot by installing “average speed check cameras”; introducing minimum speed limits in the

UK; and campaigning of the dangers of aggressive driving in congested situations on major roads. Therefore further research is required to formulate and test the effectiveness of these policies on road safety improvement.

Since it was proposed that the increased speed variance in congested situations causes safety problems (Chapter 9 section 9.2), it is yet to examine the factors affecting speed variance, such as traffic composition (e.g., percentage of heavy goods vehicles) and variable speed limits, so effective policies can be developed to reduce the speed variance. Similarly, driving behaviour in congestion should be investigated so as to control and reduce aggressive driving in congested situations.

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## APPENDIX

A number of papers have been published in journals or presented at conferences by the author as a result of this research. The following lists the papers that have been published or accepted in peer-reviewed international journals during this research:

- Wang, C., Quddus, M.A. and Ison, S.G., 2009. The effects of area-wide road speed and curvature on traffic casualties in England. *Journal of Transport Geography*, **17**(5), pp. 385-395. [doi:10.1016/j.jtrangeo.2008.06.003](https://doi.org/10.1016/j.jtrangeo.2008.06.003).
- Wang, C., Quddus, M.A. and Ison, S.G., 2009. Impact of traffic congestion on road accidents: a spatial analysis of the M25 motorway in England. *Accident Analysis & Prevention*, **41**(4), pp. 798-808. [doi:10.1016/j.aap.2009.04.002](https://doi.org/10.1016/j.aap.2009.04.002).
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In addition to the papers mentioned above, another academic paper has recently been produced and submitted to a journal and it is currently under review.