SAFETY OF PROFESSIONAL DRIVERS IN HONG KONG

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Safety of Professional Drivers in Hong Kong

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CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

_______________________________ (Signed)

CHEN Tiantian_____________________ (Name of student)

Dedicated with love and gratitude to the memory of my grandfathers,

Zhenxiong Chen and Winglam Chong.

Abstract

Safety of professional drivers is of great concern around the world, especially in the public transit-oriented cities like Hong Kong. The higher rates of traffic violation rates, fatigue driving, aggressive driving, as well as the increasing proportion of older drivers are the main contributory factors to the crashes involving commercial vehicles. In this study, safety of professional drivers in Hong Kong is assessed from the behavioural, psychological, and empirical perspectives. Therefore, effective traffic control and driver management measures can be implemented to improve the safety of professional drivers.

First, effects of driving time, age, traffic condition and road environment on the driving performance of professional drivers are evaluated using the driving simulator approach, with which the difference in the driving performance between professional and non-professional drivers are considered. Results indicate that age-related impairments on driving performance could be reduced by the driving experience and task familiarity of professional drivers. Furthermore, two modified traffic conflict measures were used to investigate the compensatory strategy and strategic adaptation of professional drivers. It is found that, despite the longer brake reaction time of older drivers, the likelihood of more severe traffic conflict of older drivers was lower, especially for professional drivers.

Second, attitudes of professional drivers towards the enforcement and penalties against speeding violations are evaluated using a perception survey. A stated preference survey approach is adopted to gauge the trade-off between enforcement strategies, penalty levels and speed choice of the professional drivers. A panel mixed logit regression model is adopted to account for the effects of unobserved heterogeneity. Results indicated that the professional drivers are more sensitive to the increase in driving-offence points as compared to monetary fines. Also, presence of a warning sign is effective in enhancing speed compliance. Several demographic and employment characteristics, driving history and perception variables also influence drivers’ choices of speed compliance.

Third, safety effects of the composition of commercial vehicles including taxis, public buses, light goods vehicles, and heavy goods vehicles are assessed based on the integrated traffic and crash data. A Bayesian random-parameter Tobit approach is adopted to measure the relationship between explanatory factors and the overall crash rates by injury severity. Results reveal significant increasing effects of the proportions of taxi, buses, light goods vehicles on the overall crash risk. Additionally, a Bayesian multivariate Tobit model is applied to identify possible risk factors to the crash rates across different vehicle types. Results indicate that crash rates of private car and light commercial vehicle would increase with the increase in average lane width and presence of on-street parking, while such finding is not valid for heavy commercial vehicle. Moreover, intersection density has significant increasing effect only for the crash rate of light commercial vehicle.

Overall, findings of driving simulator study, stated preference survey and crash risk analysis of professional drivers should be indicative to the driver licensing, training and education, enforcement, and driver management strategies of the authorities and transport operators that can enhance the safety performance of professional drivers in the long run.

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Tiantian Chen
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Chapter 1 Introduction

1.1 Background of this study

Economic losses attributed to road injuries cost the society around 3% of the national income. The share of these losses contributed by road crashes involving commercial vehicles are considerable (Health and Safety Commission, 2001; WHO, 2018). It is because the crashes involving passengers (e.g. light bus, bus and taxi) and goods vehicles do not only result in severe injury and death of the convicted drivers, but also those of other innocent road users including passengers on the vehicles and pedestrians on roads (Barua and Tay, 2010; Mooren et al., 2014; Meng et al., 2019). In Hong Kong, although commercial vehicles merely constitute about 20% of total vehicle fleets, they are involved in over 70% of road crashes. One possible reason may be the high mileages of commercial vehicles (Transport Department, 2018a; Pei et al., 2012). However, safety of professional drivers is also of great concern since the rates of professional drivers involved in crashes and traffic violation are higher, compared to non-professional drivers (Chen et al., 2020; Öz et al., 2010a; Wong et al., 2008).

The road-based public transportation modes in Hong Kong primarily include a regular bus mode (operated either publicly or privately), a light bus mode (or mini-bus mode that typically carries up to 19 passengers, again operated publicly or privately), and taxis (while the taxi mode may not be traditionally viewed as a public transportation mode, it is not uncommon in Hong Kong for the use of taxis to access bus stations and rail stations, making it an integral component of public transportation use in the country). The substantial dependence on the road-based public transportation modes contribute to, on a per capita basis, a low vehicle miles of travel (VMT) in Hong Kong. This low exposure, along with low speeds (due to high vehicle densities) and the protective cushion offered by large buses, has resulted in a relatively low number of crashes in Hong Kong, especially those resulting in serious injuries/death. In particular, there were 108 fatalities and 2,214 individuals seriously injured in road traffic crashes in 2017 (Transport Department, 2017). Based on a population estimate of about 7.4 million in Hong Kong in 2017, this translates to a per capita fatality rate of 14.6 deaths per million population (relative to, for example, 28 road traffic fatalities per million population in the UK and 107 deaths per million population in the US).

Clearly, Hong Kong's traffic safety record, at least on a per capita basis, is superior relative to many other western nations. However, an issue of concern in Hong Kong is that, unlike many western countries, a vast majority of the vehicles being driven on the roads are by professional drivers (interestingly, ride-hailing services have yet to be legalized in Hong Kong, and, as indicated earlier, taxi rides are a common way to access the road-based public transportation modes, in addition to walking; and taxi drivers are carefully regulated in terms of licensing requirements). Thus, it is of concern in Hong Kong that the crash involvement rate of public transport vehicles is seven times higher than that of the private car (Transport Department, 2017). It certainly brings into spotlight the safety performance of professional drivers and the licensing regulations in place for such drivers. While professional driver-related crashes and the organization/travel culture has been examined at some length in the west and the middle-east (for example, see Mallia et al., 2015; Newnam et al., 2018; Öz et al., 2010a, 2010b; Rosenbloom and Shahar, 2007), there has been relatively little research into the causes and considerations associated with professional driver-related crashes in the far-east. This is particularly surprising, given that professional drivers make up more of the pool of overall drivers in Hong Kong relative to the west and the middle east. Therefore, such an obvious research gap existing for the professional drivers motivates us to assess their safety performance from the perspectives of driving performance, attitudes, and crash risks.

1.1.1 Driving performance of professional drivers

The proportion of older drivers in the transport sector has been increasing because of the ageing population, shortage of labor and economic incentives (Duke et al., 2010). In Hong Kong, the percentage of the population aged 60 or above increased from 16.8% in 2008 to 23.6% in 2017 (Census and Statistics Department of HKSAR, 2017). Accordingly, the percentage of the full driving license holders aged above 60 in Hong Kong increased from 8% in 2008 to 16% in 2017 (Transport Department of HKSAR, 2017). The effect of age on driving performance is thus of increasing concern. Driving performance is recognized to be deteriorated with age (Islam and Mannering, 2006; Shanmugaratnam et al., 2010).

It in turn increases the associated crash and injury risks (Hole, 2007). Increase in crash risk of older driver is found to be associated with the degradation in physical, mental and cognitive conditions of human being (Lundberg et al., 1998). These associations have been examined using the driving simulator experiments. For example, older drivers generally show a degraded neuropsychological performance, which is in turn associated with the degraded lateral control performance (Andrews and Westerman, 2012; Shanmugaratnam et al., 2010). Also, older drivers perceive greater mental workload from driving (Cantin et al., 2009), and perform worse at controlling the vehicle simultaneously than younger drivers (Bélanger et al., 2010). Despite that there is negative correlation between age and driving performance, professional drivers tend to have better driving skills since they have more on-road experience. It is controversial that whether the age-related impairments on driving performance could be offset by the driving experience and task familiarity of professional drivers (Andrews and Westerman, 2012). On the other hand, older (non-professional) drivers tend to drive less and the reduction in exposure could be a more significant factor to crash risk, compared to driving experience and task familiarity (Tay, 2006, 2008). To our knowledge, the interaction between driver type (i.e. professional driver or not) and age on the driving performance is still unclear, and therefore it is of our great interest.

1.1.2 Attitudes and behaviours of professional drivers

Driver aggressiveness and prevalence of traffic offences are identified to be the factors contributing to crashes involving professional drivers (Rosenbloom et al., 2007; Öz et al., 2010a). It could be attributed to the fact that professional drivers have to withstand high work and time pressure due to their job nature (Öz et al., 2013). More importantly, professional drivers deliberate over the trade-off between traffic offence-penalties and potential income (Rosenbloom et al., 2007). Yet, the attitude of professional driver could be controversial. Studies also suggest that professional drivers show a high intention to avoid risky behaviours due to the perceived social responsibility (Rohani et al., 2013; Shams et al., 2011). In this case, research is urgently needed to better understand the perceptions and attitudes of professional drivers towards traffic offences and therefore to tackle the problem of their impaired safety performance.

1.1.3 Crash risk of commercial vehicles

Commercial vehicles in Hong Kong presented higher crash involvement rates over the years, as compared with private cars (Transport Department, 2018a). Previous studies reveal that increase in the overall proportion of commercial vehicle is associated with the increases in severe crashes on motorways and at signalized intersections (Wong et al., 2007; Xu et al., 2014). Despite that the significance of mixed traffic situation on road safety performance has been established by earlier research (Dinu and Veeraragavan, 2011; Srinivas et al., 2007), study limitation comes from the availability of elaborated traffic data for the proportions of various commercial vehicle types. Nevertheless, a recent study found that increases in the proportion of private cars, as well as that of the medium trucks, are associated with the increase in injury crashes on highway segments (Wen et al., 2018). As such, taking the advantage of more detailed breakdown of the proportions of various commercial vehicle types, this study aims to shed light on the safety effects of the composition of commercial vehicles. On the other hand, numerous studies have proposed a need to model crashes by type (e.g. injury severity, collision type, transportation mode, road users), as the effects of risk factors vary across crash types (Guo et al., 2019; Ulak et al., 2018; Wang et al., 2017; Lee et al., 2015). However, studies considering the crashes by vehicle type have been so far scanty. The only study simultaneously estimating crashes by vehicle type (larger trucks and passenger cars) was by Dong et al. (2014), suggesting that understanding the effects of geometric factors on crash frequencies by vehicle type is of significance. In order to develop effective safety measures for different commercial vehicles, identifying possible risk factors to crashes of different vehicle types is therefore a must.

This study attempts to assess safety of professional drivers from the behavioural, psychological, and empirical perspectives. Five research questions are therefore proposed here: 1) whether age-related impairments on driving performance can be reduced by the driving experience and task familiarity of professional drivers, 2) whether the compensatory strategies of older drivers are different between professional and non-professional drivers, 3) how the penalty and enforcement strategies deter professional drivers from traffic violations, 4) whether the relationship between commercial vehicle proportions and crashes can be moderated by roadway attributes, and 5) whether the effects of risk factors vary across crashes categorized by vehicle type.

1.2 Research aims and objectives

This study aims to assess safety of professional drivers in Hong Kong from the behavioural, psychological, and empirical perspectives. It is of great importance to assess the driving performance of professional drivers, to evaluate their attitudes towards legislation and law enforcement, to investigate the safety effects of commercial vehicle mix, and to identify risk factors across crashes by vehicle type. Driving simulator experiments, perception survey, and crash risk analysis are employed to achieve the aim. The specific objectives of this study are as follows:

1) Driving performance

- To examine the effects of driving time, age, traffic condition and road environment on the driving performance of professional drivers, with which the difference in the driving performance between professional and non-professional drivers is considered.
- To evaluate effects of driving time, age and traffic condition on driver's conflict risk using surrogate safety measures, with the concern of difference between professional and non-professional drivers.
- To explore the relationship between traffic conflict risk and compensatory behaviour of professional drivers

2) Perception evaluation

- To investigate the perceptions and attitudes of professional drivers towards the enforcement and penalties using a stated preference survey approach.

3) Crash risk analysis

- To measure the association between the commercial vehicle proportion and crash rate and to examine the mediating (moderating or magnifying) effects of roadway attributes on this association.

- To measure the relationships between possible risk factors and the crash rates of different vehicle types using multivariate approach, with which correlations between crash rates across vehicle types are considered.

It is expected that findings from this study would support the decision making of transport operators regarding the driver recruitment and management, enhance the current understanding and effectiveness of penalties and speed-enforcement strategies, and provide useful insights into relevant countermeasures (that can enhance the safety culture and awareness of professional drivers and crashworthiness of commercial vehicles). Therefore, safety performance of professional drivers can be improved in the long run.

1.3 Thesis organization

Chapter 2 reviews the literature on various aspects of driver safety studies, including driving performance and behaviours, driver perception and attitudes, as well as the crash risk of commercial vehicles.

Chapter 3 assesses the driving performance of professional drivers using a driving simulator study. Effects of driving time, age, traffic condition and road environment on the driver's speed, lateral and steering control performances are revealed. Difference in contributory factors to driving performance between professional and non-professional drivers is discussed. Interaction between age-related impairments on driving performance and task familiarity of professional drivers is also explored.

Chapter 4 focuses on the professional drivers' traffic conflict risk. Two surrogate safety measures: time exposed time-to-collision (TET) and time integrated time-to-collision (TIT) are adopted to indicate the risk of more severe rear-end traffic conflict in the car-following tasks. Other performance indicators include the brake reaction time (BRT), lateral control, average driving speed, and time headway. A driving simulator study is used to evaluate the effects of driving time, age, and traffic condition on the risk of rear-end conflict. Furthermore, relationship between traffic conflict risk and compensatory behaviour of professional drivers is discussed.

Chapter 5 investigates the perceptions and attitudes of professional drivers towards the enforcement and penalties in Hong Kong to deter speeding. A stated preference survey is used to gauge the trade-offs among enforcement strategies, penalty levels and speed choice of the professional drivers. Also, effects of factors including driver demographic, socioeconomics, driving experience and crash record are considered.

Chapter 6 measures the relationship between the proportions of different commercial vehicle types and the overall crash rates by injury severity, with which the confounding factors including road geometry, traffic control and time period are considered. Also, risk factors affecting the crash risks of different vehicle types are identified using multivariate analysis, which accommodates possible correlations between crash rates across vehicle types.

Chapter 7 concludes the study with a summary of the findings, implications, limitations, and future research directions.

Chapter 2 Literature review

This chapter reviews the literature on driver safety from the behavioural, psychological, and empirical perspectives. Section 2.1 discusses the driving performance of professional drivers, contributory factors to driving performance, compensatory driving, and the indicators that commonly used to measure the performance. Section 2.2 reviews the literature with respect to drivers' perceptions, attitudes, and behaviours. Previous findings regarding the attitudes and behaviours of professional drivers and elderly drivers are presented first. Then, drivers' perceptions towards traffic legislation including penalty and enforcement are discussed. Lastly, Section 2.3 reviews the crash risks of commercial vehicles, safety effects of the percentages of various commercial vehicle types, and crashes modelled by types.

2.1 Driving performance

2.1.1 Driving performance of professional drivers

Hong Kong is a city with high population density and limited road space. The ability of public transport to serve high density cities well, as well as the relatively high costs of private vehicle ownership and high operational costs (especially parking costs) resulting from the limited road space, has resulted, in Hong Kong, in the dominance of public transport as the primary mode for work-related as well as non-work travel. Of particular note is the relatively seamless integration of road-based and rail-based metro public transportation services in Hong Kong, with transfers between the two broad modes of public transportation commonplace. Overall, over 90% of commute trips as well as over 46 % of non-commute trips in the territory are undertaken by road-based and/or rail-based public transport (Transport and Housing Bureau, 2017; Transport Department, 2014). However, crash involvement rates (per million vehicle-km) of commercial vehicles, particularly taxi, light bus and bus, are higher than that of the private car in Hong Kong (Transport Department of HKSAR, 2017). It certainly brings into spotlight the safety performance of professional drivers.

Indeed, driving under the influence of fatigue has been a significant safety issue (Bunn et al., 2005; Duke et al., 2010; Rosenbloom and Shahar, 2007). Professional drivers are more vulnerable to the fatigue as they have to drive for longer time, as compared to the general drivers. Also, aggressive driving behavior (attributed to desire for higher revenue and expectation from the customers/employers) can contribute to higher crash rates (Matthews et al., 1999; Sullman et al., 2002; Kontogiannis, 2006, Öz et al., 2010a). In addition, increase in the exposure of professional drivers is also associated with the increase in crash involvement rate. Regarding the difference in the behaviors between professional and non-professional drivers, one possible factor is the vehicle ownership. Professional driver who does not own the vehicle may have a higher propensity of committing convicted driving behavior. Hence, moral hazard may occur since the driver (who is not the owner) has less incentive to avoid any risky event (Tay and Choi, 2016). However, professional drivers are believed to have better driving skills (Andrews and Westerman, 2012; Borowsky and Oron-Gilad, 2013). It is therefore crucial to assess the driving performance of professional drivers (i.e. whether it is better than that of non-professional drivers), and the possible contributory factors.

Moreover, ageing population is now a common problem faced by many countries or regions because of the reduction in fertility rates and increased life expectancy. By 2035, proportion of population of age above 65 in Hong Kong would reach 25% (Sze and Christensen, 2017). In recent years, of the peoples who hold the valid driving licenses, percentage of elderly has been increasingly rapidly in other ageing societies (Newman et al., 2018, 2019). In Hong Kong, proportion of drivers who held valid public transport vehicle (e.g. taxi, light bus and bus) driving license of age above 60 was 37-46% in 2017 (Lee, 2018). Prevalence of older drivers in the transport industry can be attributed to the issues including labour shortage, lack of social welfare and seeking of social engagement (Duke et al., 2010; Navarro et al., 2007). However, it was recognized that cognitive performance could be deteriorated when driver age increased, and the potential crash risk of elderly driver could be higher than that of the younger counterpart (Hole, 2007; Islam et al, 2006; Shanmugaratnam et al., 2010). Performance deterioration of older drivers can be the results of audio and visual loss and extended perception-reaction time (Yan et al., 2005; Yan and Radwan, 2006). However, the impacts on road safety because of the ageing population and prevalence of older drivers in the transport sector have not been thoroughly investigated.

2.1.2 Risk compensation and driving performance

Despite of the age-related deterioration, some older drivers, especially the professional drivers who spend more time on roads, can still demonstrate satisfactory driving performance. Then, no evidence can be established for the elevated crash risk of older drivers in some studies (Braitman et al., 2007; Langford et al., 2006). Additionally, satisfactory driving performance of older drivers could be attributed to self-regulation. Older drivers might drive more cautiously and avoid driving under the adverse conditions, such as traffic congestion, peak hours, high speed roads, bad weather and poor visibility conditions. Modification of driving behavior that offsets the perceived risk attributed to deteriorated physiological, cognitive and driving performances is known as compensatory strategy (Lyman et al., 2001). Compensatory strategies are prevalent for older drivers who had known cognitive impairment, traffic violations and crash involvement records (Charlton et al., 2006; Molnar et al., 2008). For instances, older drivers may drive at a lower speed, maintain a longer headway with leading vehicle, and avoid complicated roads and maneuvers (Andrews and Westerman, 2012; Merat et al., 2005). Hence, the potential crash risk of older drivers could be reduced by the compensatory strategies (De Raedt et al., 2000; Molnar et al., 2008).

Moreover, professional drivers have higher capability to identify road hazards, and a brief perception training intervention can improve the hazard perception skills of such experienced drivers (Borowsky and Oron-Gilad, 2013; Li et al., 2015). Also, professional drivers can have better risk anticipation and quicker response to potential road hazards (Damm et al., 2011; De Craen et al., 2008). Consider the above, it is necessary to evaluate the difference in the compensatory strategies between older professional and non-professional drivers.

On the other hand, fatigue is one of the leading causes of crashes involving professional drivers (Duke et al., 2010; Meng et al., 2015). Professional drivers often need to drive for long distance and extended period per trip and/or per day (Öz et al., 2010a; Williamson and Boufous, 2007). Additionally, fatigue can also increase the risk of fatality and severe injury of professional drivers (Bunn et al., 2005). However, some researchers argued that drivers could self-detect the occurrence of fatigue, and accommodate the impairment while driving (Filtness et al., 2012; Williamson et al., 2014; Meng et al., 2015). For example, drivers would slow down when they feel tired to mitigate the potential crash risk attributed to driving under the influence of fatigue (Williamson et al., 2002). Strategic adaptation refers to the intentional modification of driving behavior to adapt for the impairment or driving under the influence of distraction, therefore driving and safety performance can be optimized. Considered the experience in prolonged driving and high-demand situations, it is expected that strategic adaptation of professional drivers is more prevalent, and the elevated crash risk of professional drivers after prolonged driving can be marginal.

2.1.3 Driving performance indicators

Driving simulator experiment is a safe and cost-effective approach to evaluate the driving performance. In particular, the effects of road design and traffic condition on the driving performance could be assessed in a controlled manner (Boyle et al., 2010; Lee et al., 2003). Using a driving simulator, Otmani et al. (2005) found that sleepiness of male professional drivers increases over time during the 90-min simulated driving task. Consistently, Oron and Ronen (2007) indicated that fatigue of truck drivers was detected through their degraded steering performance over time. Indeed, fatigue impaired driver’s capability in terms of vehicle control and collision avoidance through withdrawing driver's attention to the road and traffic condition progressively (Brown, 1994).

Measures of driving performance are commonly used to detect driver’s fatigue or alertness (Brookhuis and De Waard, 1993; Brown, 1997). For example, the impaired lateral control of the vehicle was revealed strongly associated with the driver fatigue resulted from prolonged driving (Van der Hulst et al., 2001; Boyle et al., 2008). Standard deviation of vehicle speed (SD-SPEED), standard deviation of the lateral position (SDLP), standard deviation of steering wheel angle (SDSWA) reflect driver’s longitudinal, lateral and steering control of the vehicle, which have been frequently adopted in simulator studies (Boyle et al., 2008; Cantin et al., 2009; Shanmugaratnam et al., 2010; Li et al., 2016).

In addition to conventional driving performance indicators, traffic conflict, as a road safety surrogate measure, provides rich information for road safety assessment. A traffic conflict was defined as "… an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remain unchanged" (Hydén, 1987). It has been revealed that driving simulator could be an efficient alternative for traffic conflict analysis (Chang et al., 2019; Yan et al., 2008). Using a driving simulator, near-departure events of drivers could be identified based on the corresponding thresholds of the selected indicators (e.g. lateral distance to departure, time to departure). Then, the expected number of lane departures could be estimated (Tarko, 2012). On the other hand, critical events (e.g. pedestrian crossing; car incursion; sudden brake by the leading vehicle) can be incorporated into the driving simulator experiment to assess the driver performance (Andrews Westerman, 2012; Bélanger et al., 2010). Meanwhile, the effects of driver characteristics on the driving performance during the critical situations can be evaluated. For example, elderly drivers tend to show impairments on driving performance when facing a challenging event that required synchronous reactions (Bélanger et al., 2010).

Time to collision (TTC) is one of the most widely used conflict indicators. It is defined as the time left before two vehicles collide when there is no evasive maneuver to avoid a collision (Hayward, 1972). The minimum TTC (TTC_{min}) value is the shortest time span required for a driver's perception and reaction to prevent a collision from happening. TTC_{min} can be used to distinguish the conflict events once it is less than the predetermined threshold (i.e. 1.0 s to 5.0 s) (Autey et al., 2012; Sayed et al., 2013; Zheng et al., 2014). Time exposed time-to-collision (TET) and time integrated time-to-collision (TIT) are two modified indicators based on TTC. When using TET and TIT for safety analysis, a TTC threshold should be selected to differentiate the critical conditions from the safe conditions. TET is defined as "… a summation of all moments (over the considered time period) that a driver approaches a front vehicle with a TTC value below the threshold value TTC" (Minderhoud and Bovy, 2001). In other words, TET reflects the duration of safety-critical situation, given that the TTC values are lower than the threshold. TIT is defined as "… uses the integral of the TTC profile of drivers to express the level of safety (in s^2)" (Minderhoud and Bovy, 2001). TIT considers both the duration of safety-critical situation and the absolute difference between TTC value and the threshold. Other common conflict indicators include post encroachment time (Cooper 1984), time to accident (Hydén 1987), headway (Vogel 2003), braking time (Lu et al. 2012), etc.

2.2 Perceptions, attitudes, and behaviours

2.2.1 Attitudes and behaviours of professional drivers

A driver's crash risk was revealed to be correlated with his/her perceived stress caused by the road traffic (Matthews et al., 1999). Professional drivers are more likely to experience driver stress, which contributes to the prevalence of driving aggression and traffic violation (Öz et al., 2010a; Kontogiannis, 2006; Westerman and Haigney, 2000). Wong et al. (2008) revealed that minibus drivers in Hong Kong tend to drive aggressively and violate traffic rules due to the keen market competition. Machin and De Souza (2004) also found that taxi drivers with aggressive personality reported more frequent risky behaviors. Sullman et al (2002) examined the relationship between aberrant driving behaviors (including three categories, i.e. error, lapse and violation) and crash involvement of truck drivers in New Zealand. Results suggest that violation behavior of truck drivers was the only significant predictor to their crash involvements.

Indeed, compared with non-professional drivers, risky driving behaviors are more prevalent among professional drivers. One possible reason is the difference in risk perception between professional and non-professional drivers. Due to the higher exposure on roads, professional drivers are more familiar with the traffic hazards and therefore perceive certain situations less risky (Öz et al., 2010a). Rosenbloom and Shahar (2007) reported that professional drivers may sometimes regard committing minor offences as a possible way to increase their income. For example, professional drivers may earn more money by driving faster or stopping in restricted area to pick up more passengers. As a result, professional drivers are often caught by minor traffic offences. However, professional drivers are less likely to commit egregious risky behaviors (e.g. drink driving, drug driving) than the non-professional drivers (Knipling et al., 2004), which could be attributed to their greater sense of social responsibility (Paleti et al., 2010).

Referring to the theory of planned behavior (TPB) (Ajzen, 1991), attitude, subjective norms, and perceived control are the three factors that determine the behavioral intentions. While the behavioral intention is the best predictor of a person's behavior. TPB has been widely used to explain and predict human behaviors including driver and pedestrian behaviors (Poulter et al., 2008). Applying the TPB model, Newnam et al. (2004) found that drivers show lower speeding intention when driving a work vehicle compared with his/her personal vehicle. This could be explained by the difference in subjective norms (that is, attitudes of important others towards his/her behavior) between driving the work vehicle and personal vehicle. It is suggested that subjective norms could have significant effects on driver behavior particularly in a work environment. In addition, factor of perceived control is revealed to affect the law-abiding behaviors of drivers. For example, truck drivers are found more likely to comply with traffic regulations when they perceive greater controllability over the work.

Moreover, professional drivers are usually regular employees of an organization, such as logistic firms or bus companies. It is found that safety culture of the organization significantly affects the attitudes of professional drivers towards risky driving (Öz et al., 2010b, 2014). This could be attributed to the company's driver management system. For example, penalties would be issued to the drivers in accordance with the safety driving policy because of their risky behaviors. In Hong Kong, the public bus companies encourage the bus drivers to meet the driving safety requirements with monetary bonus. While others who have the record of risky driving may need to attend additional training and counseling courses. As a result, the organizational safety climate would help lower the drivers' intention to commit risky driving (Newnam et al., 2004).

2.2.2 Effect of driver age on attitudes and behaviours

Driving behavior can be predicted by attitudes (Ajzen, 1991), while risk perception directly affect road safety attitude (Ram and Chand, 2016). Rosenbloom et al. (2008)

indicated that older drivers perceive higher risk while driving, which contributes to their cautious and careful behaviors (Ram and Chand, 2016). Consistently, Tseng (2013) found that elderly drivers tend to drive in a cautious and law-abiding manner. For example, they are less likely to commit speeding violations compared with younger drivers. In addition, involvements of aggressive driving were reported to decrease as the driver age increases (Sullman et al., 2002).

Moreover, avoidance behaviour is found prevalent among elderly drivers (De Raedt and Ponjaert-Kristoffersen, 2000; Molnar et al., 2008). For example, previous studies revealed that elderly drivers tend to avoid driving under heavy-traffic condition, in peak hours, on expressways, under the adverse weather and at night (Abdel-aty et al., 1998; Ball et al., 1998; Charlton et al., 2006; Molnar et al., 2008). This is because they try to adjust their exposure for a satisfactory driving performance or a lower crash risk (Langford et al., 2006; Lyman et al., 2001). Besides, elderly drivers who are aware of their functional and cognitive impairments often accommodate the driving task by modifying driving behaviour (Lyman et al., 2001). For example, they tend to drive at a lower speed or keep a longer headway with the vehicle in front to ameliorate their crash risk (Ni et al., 2010; Shinar et al., 2005).

2.2.3 Driver's perception towards traffic legislation

Earlier studies in other regions of the world, such as those referenced earlier, suggest that driver aggressiveness, caused by high work and time pressure and resulting in a trade-off deliberation between traffic offence-penalties and potential income gains from saved time in the face of congested travel conditions, contribute to the high crash risk of professional drivers (Öz et al., 2010a; Rosenbloom and Shahar, 2007). In particular, speeding has been identified as a common aggressive driving behavior exhibited by professional drivers, and speeding has also been identified in many earlier studies as being the single most important factor impacting the occurrence and severity of roadway traffic crashes (Fitzpatrick et al., 2017; Watson et al., 2015; WHO, 2018). In this context, in some OECD countries, the proportion of drivers who self-report being guilty of excessive speeding is as high as 80% (WHO, 2018). The same situation manifests itself in Hong Kong, with speeding being one of the most common recorded traffic offences among professional drivers and drivers at large. According to the number of prosecutions against traffic offences in 2017, speeding accounted for over 42%, while red light running and drunk driving accounted for 13% and 0.17% of the total number of prosecutions in Hong Kong, respectively (Hong Kong Police Force, 2018). Admittedly, these statistics from Hong Kong do not necessarily reflect the relative prevalence of speeding compared to other illegal driving behaviors, because the statistics may simply be an indication of the type and intensity of resources dedicated to enforcing speed limits relative to other illegal driving behaviors. Even so, the very fact that more investment is made in preventing speeding relative to other behaviors is in and of itself an acknowledgment that countermeasures aimed at speed reduction are considered one of the most cost-effective ways to enhance traffic safety.

Monetary fine, driving disqualification and imprisonment are the common penalties to address and reduce speeding offence occurrences (as well as other driving offences; see Hössinger and Berger, 2012; Li et al., 2014). In Hong Kong, the Driving-offence Points (DOPs) system was introduced in 1984. Over 50 items of traffic offences carry DOPs in addition to a monetary penalty. As would be logical, more DOPs and higher monetary fines are issued as the level of speeding increases. Thus, a severe speeding offence (excess of speed limit by more than 30 km/h but less than or equal to 45 km/h) incurs five DOPs and HK$ 600 penalty (Transport Department, 2018b). Under this DOP system, persons who have incurred 15 points or more within two years are disqualified from driving.

Some previous studies have revealed a significant negative correlation between the monetary fine level imposed and penalty points, and the occurrence of traffic offences (Hössinger and Berger, 2012; Li et al., 2014; Wong et al., 2008). For example, an increase of fine by 10 Euros is associated with the reduction in speeding frequency by 5% among Austrian drivers (Hössinger and Berger, 2012). However, there are studies suggesting that monetary fine levels and penalty points alone have only a relatively minor deterrent effect on the speeding offence (Elvik and Christensen, 2007; Fleiter et al., 2010; Langlais, 2008; Ritchey and Nicholson-Crotty, 2011; Sagberg and Ingebrigtsen, 2018). Specifically, these studies raise the issue of not only the level of the penalty on speeding deterrence, but the risk of being subjected to that penalty (Kergoat et al., 2017; Li et al., 2014; Tay, 2009).

That is, the propensity for speeding depends on both the level of penalty as well as the prevalence of speed enforcement operations, with some studies finding that the latter is much more effective in curbing speeding offences than the former (see, for example, Gargoum and El-Basyouny, 2018; Lawpoolsri et al., 2007; Ryeng, 2012; Truelove et al., 2017). In other words, fines and DOPs penalty, according to these earlier studies, do not function very well when the level of speed enforcement is not adequate (and thus the risk of being subjected to the penalties is low). This finding also has backing in criminal justice-based deterrence theory (Gibbs, 1985), which stems from the notion that individuals effectively undertake a cost-benefit analysis of pursuing a "crime", and the effectiveness of a dissuasive mechanism originates from the costs being perceived as higher than the benefits. The cost-benefit analysis itself is conducted within a frame of three criteria: the certainty, celerity (swiftness or rapidity of imposition), and the severity of a sanction. While the relative contributions of these three criteria may vary based on the crime under question, lower "crime" activities (at least as viewed traditionally by society, such as illegal driving behaviors) are typically dominated by the "certainty of being apprehended" criterion in the cost-benefit evaluation of individuals (Høye, 2014; Watson et al., 2015). In the context of speeding, this "certainty" criterion is directly related to the level of enforcement of speed limits.

The automated speed enforcement camera (ASEC) system is generally considered as a promising and cost-effective enforcement technique that increases the certainty of being apprehended if speeding (Carnis and Blais, 2013; De Pauw et al., 2014a; Tay, 2009). Once the cameras are installed, such systems obviate the need for more costly human police patrols along roadways. Of course, some studies suggest that human police patrols are still effective, when combined with ASEC systems, because many drivers feel embarrassed when confronted by a fellow human (that is, a police person) who is perceived as passing a judgment on one's societal conduct. In addition, the fear of a verbal reprimand by the police also can add to the embarrassment factor, elevating the cumulative cost of being detained by a human police to be even higher than the fear of risking one's life or that of others through speeding (Kergoat et al., 2017; Silcock et al., 2000). But drivers also understand that human agents, even if equipped with hand-held radar/laser speed guns that provide accurate and reliable readings, can get fatigued over long periods of time in terms of holding and directing the speed guns in appropriate directions, and cannot have a consistent level of vigilance over extended periods of time, leading to speeding event "misses" (see Kergoat et al., 2017). On the other hand, properly functioning ASEC systems are more reliable in detecting speeding violations over extended stretches of time. Even so, there is the issue of driver ability to dodge the dangers posed by spatially fixed ASEC systems (that is, an ASEC with overtly announced camera locations, as opposed to covert or unpublicized camera locations). In particular, according to the integrative social-cognitive protection-motivation theory (PMT) (see Rogers, 1983), the effectiveness of a "threat" (that is, a speed enforcement mechanism in the context of roadway speeding) is based both on threat appraisal (by way of the certainty, celerity, and severity, as proposed by deterrence theory) as well as coping appraisal (that is, the ability to cope with and dodge the danger). As an individual's self-efficacy (the ability to perform an action needed to dodge a threat) and the response efficacy (the efficacy of the response to actually dodge the danger) increase, there will be less incentive to not commit an offence based on a positive coping appraisal.

In the context of a spatially fixed ASEC systems, drivers typically perceive more controllability and a positive coping appraisal (that is, a higher belief that they have the capability to effectively dodge the speeding enforcement threat) by simply reducing speeds in the immediate vicinity of the camera locations. This so-called "kangaroo effect" (abrupt reductions close to camera locations and abrupt speed jumps upstream and downstream of locations relatively removed from the camera range) has been well-identified in earlier studies (De Pauw et al., 2014a, 2014b; Elvik, 1997; Marciano et al., 2015). On the other hand, previous studies (see, for example, Cameron et al., 2003; Dowling and Holloman, 2008) have shown the higher effectiveness of covert (or unmarked and unpublicized) ASEC systems relative to fixed ASEC systems because of a lower coping appraisal and higher uncontrollability to dodge a threat on the part of drivers. However, such covert ASEC systems are not legally allowed in Hong Kong and many other countries, both due to privacy regulations as well as the notion that ASEC systems should be fundamentally aimed at preventing speeding rather than apprehending offenders (Høye, 2014).

2.3 Crash risk analysis

2.3.1 Effects of road environment on crash risk

Environmental factors including road type and traffic flow condition are revealed to affect the association between crash and possible risk factors. For examples, sleep-related road crashes are more prevalent on the motorways, as compared to the urban roads (Horne and Reyner, 1999; Maycock, 1996). Crash risks on the rural roads are also higher than that on the urban roads because of the monotonous road environments and limited stimuli on roads (Blower et al., 1993). For the traffic flow condition, increase in traffic volume and presence of moderate traffic congestion are associated with the reduction in crash risk and crash severity (Martin, 2002; Yau, 2004). The association between road environment, traffic flow condition and crash risk could be attributed to the variation in driving performance across different environments. For instances, variation in the steering and lateral stability are associated with the complexity of driving task (e.g. reduced horizontal and vertical curvatures, traffic interactions and roadside stimuli) (Thiffault and Bergeron, 2003; Jamson and Merat, 2005; Arnedt et al., 2005; Boyle et al. 2008; Teh et al., 2014).

Several studies have discussed the relationships between road lane width and crash frequency and severity (Chen et al., 2017a; Wu et al., 2015; Pei et al., 2012; Gross and Jovanis, 2007). Park et al. (2012) and Chen et al. (2017b) determined the extent to which the traffic lane width, within a certain standard range, correlates negatively with the frequency of different crash patterns or severity levels. An increase in the lane width by 1 ft could result in a 2% decrease in crash frequency (Abdel-Rahim and Sonnen, 2012). Therefore, wider lanes generally promote vehicle safety. A few studies suggested that beyond a certain limit, an increase in total traffic road width could possibly increase the crash risk (Mohamed et al., 2013). Tulu et al. (2015, 2013) explained that this could be due to the effects of lane width on drivers' perception and driving speed.

With regard to the effect of road alignment, an increase in horizontal curve density is revealed to be correlated to fewer casualties in previous research (Lamptey, 2004; Labi, 2011). A few past studies for major roads in Hong Kong had found little or no evidence of relationships between road curvature and crash frequency (Zeng et al., 2016; Pei et al., 2016, 2012), while Elvik (2019) indicated that increased number of curves for the road segment could lower the crash rate.

2.3.2 Crash risks of commercial vehicles

In Hong Kong, over 46 % of non-commute trips and 90% of commute trips are made by public transport. In particular, over 60% of public transport are road-based. They include buses, light buses, and taxis (Transport and Housing Bureau, 2017; Transport Department, 2014). This can be attributed to limited parking infrastructure, high density development, high burden of private car ownership, and more importantly, availability of economical, efficient and reliable public transport services (Chen et al., 2020). On the other hand, as an important entrepot in Asia, freight logistics industry constituted to 3.2% of Hong Kong's GDP, provided more than 180,000 job opportunities, and accounted for 29% of service export in 2017 (Hong Kong Trade Development Council, 2019). The long-term economic development, to a certain extent, depends upon the efficient and safety movements of passengers and goods on Hong Kong roads.

Commercial vehicles in Hong Kong (including buses, light buses, taxis, goods vehicles) merely constitute about 20% of total vehicle fleets. However, they are involved in more than 70% of road crashes. This could be attributed to the higher exposure of commercial vehicles on roads (Pei et al., 2012). On the other hand, safety of professional drivers should be of great concern. Previous studies indicate that professional drivers tend to involve in more road crashes and traffic violations compared with non-professional drivers (Chen et al., 2020; Öz et al., 2010; Wong et al., 2008). In particular, crash involvement of taxi drivers was positively associated with the increase in driver workload, driving hours, and more aggressive driving behavior (Wang et al., 2019a, 2019b). Additionally, elevated crash risk of taxi was associated with the ageing of taxi drivers, which their performances were more likely impaired by the deteriorating health, fatigue and distraction (Chen et al., 2019a; Meng et al., 2017).

In Hong Kong, franchised bus and public light bus constituted to 49% and 24% of overall road-based public transport patronage (Transport Department, 2014). Bus drivers are usually more risk averse since they usually have stronger sense of social responsibility.

Also, they have lower tendency to commit traffic offense because of the better safety management of operators (Paleti et al., 2010; Chen et al., 2020; Öz et al., 2010, 2013). For example, all franchised bus companies in Hong Kong have comprehensive driver surveillance, reward and penalty system to deter against speeding and other driving offences and increase the safety awareness of bus drivers. However, safety of public light bus has been of major concern in Hong Kong. Public light bus drivers are usually self-employed, and their salaries are trip-based. They are more aggressive and are likely to commit various driving offenses to compete for the business (Wong et al., 2008). Hence, fatal and severe crash risk of public light bus-related crash is higher than that of franchised bus (Transport Department, 2017a).

Goods vehicles in Hong Kong are classified into three categories - light, medium and heavy, depending on the weight and dimensions. Light goods vehicle (also known as 'light van') drivers are self-employed and their salaries are trip-based, and medium and heavy goods vehicle drivers are usually employed by the logistic firms and their salaries are monthly or daily-based. Indeed, employment type can also affect the drivers' attitudes and behaviors. Light van drivers are usually more aggressive (Chen et al., 2020). Studies also indicated that number of light trucks is positively associated with overall fatal crash and pedestrian fatalities and severe injuries (Ballesteros et al. 2004; Desapriya et al., 2010). Moreover, road environments and working conditions also affect the driving performance of goods vehicle drivers. Driving under the influence of fatigue is prevalent when a light goods vehicle driver is exposed to congested urban traffic environment for extended period. In contrast, driving fatigue is prevalent when a heavy goods vehicle driver is driving on monotonous rural highway (Friswell and Williamson, 2013). It is necessary to estimate the effects of driver characteristics, road environment, traffic condition and time period on the commercial vehicle crash risk. Therefore, effective driver education and training programs can be introduced to enhance the safety awareness and thus reduce the crash risk of commercial vehicle drivers.

2.3.3 Effect of commercial vehicle mix

The commercial vehicle proportion (CVP) refers to the ratio of commercial vehicles to all vehicles in the traffic stream. Previous studies indicate that the relationship between commercial vehicle proportion and crashes is influenced by the class of commercial vehicle in question (Tay, 2003; Ballesteros et al., 2004; Desapriya et al., 2010). Furthermore, even for a given class of commercial vehicles, it has been determined that the direction of the effect of vehicle proportion on crash rate can vary with the roadway feature type and crash severity level. For example, with regard to buses, Dinu and Veeraragavan (2011) found that an increase in their proportion is associated with an increase in night-time highway crashes, while Xu et al. (2014) determined that an increase in the bus proportion is associated with a decrease in slight-injury crashes at intersections. With regard to trucks, Wen et al. (2018) indicated that an increase in truck proportion is associated with an increase in injury crashes at road segments, while Dinu and Veeraragavan (2011) found that an increase in truck proportion is associated with a decrease in night-time crashes. Dong et al. (2014) revealed that an increase in the percentage of heavy trucks in traffic stream is associated with the increase in intersection crashes.

It is interesting to note in the literature that a number of studies have used commercial vehicle data to develop indicators of potential crash risk, and have discussed the policy implications of doing this (Bao et al., 2019; Zhou and Zhang, 2019). Bao et al. (2019) found that the spatial distribution of taxi trips exhibits a similar pattern with that of crashes, and that locations with higher density of taxi trips are positively correlated with those with high daytime crashes. However, the authors emphasized that the relationship between taxi trips and crashes is non-monotonic, meaning that it can be moderated by other environmental factors such as weather and land-use variables.

Indeed, the argument for the need to investigate the moderating effects of road attributes on the CVP-crash relationship is rooted in the longstanding realization that the roadway environment (physical and operational) profoundly influences the crash experience (Zegeer at al., 1988; Hauer, 1988; Dumbaugh, 2006; Gross and Jovanis, 2007). Recently, there has been research efforts that have thrown more light on the safety effects of road environment features including geometric characteristics, ambient natural factors, the nature of traffic flow, and types of traffic control facilities (Chen S. et al., 2019a; Zeng et al., 2016, 2017b; Sze et al., 2019; Álvarez et al., 2020).

Interaction is present where two or more objects have an effect upon one another. In a statistical model, an interaction is a term in which the effect of two (or more) variables is not additive. In other words, the effect of factor A plus the effect of factor B is different than the effect of factors A and B combined. Therefore, interaction effects refer to the modification of the effect of one independent variable on the dependent variable due to the presence of a second independent variable. Such modification may be a diminished or mitigating effect (moderation) or an exacerbated effect (magnified). Failure to account for such interaction effects could lead to poor model performance.

A large number of past research studies have addressed interactions between various road crash factors without explicitly identifying or explaining any moderating or magnifying effects of the interacting variables. Ahmed et al. (2012) indicated that the positive association between steep grades and mountainous freeway crashes is magnified significantly in the snow season, suggesting that the interaction of road geometry and weather condition has a significant effect on crashes. Wen et al. (2019) found that an increase in roadway vertical gradient generally contributes to reduced highway crashes; however, the interactions between vertical gradient and weather variables (such as wind speed and visibility) was found to have positive coefficients, suggesting that increase in crash propensity with increased interaction (of vertical gradient, wind speed, and poor visibility) which is intuitive. It seems clear that introducing interaction terms in a crash prediction model indeed has several benefits including improvement of the model's goodness-of-fit and intuitiveness, identification of potential sources of heterogeneity (Azimi et al., 2020), and quantification of the moderating effects of the roadway environment on the relationships between crash frequency and any specific crash factor. The conclusions of the Bao (2019) and similar studies lend credence to the notion that the interaction effect (which can be considered as a third variable) potentially influences the relationship between commercial vehicle proportion and crash risk.

However, there is relatively limited research on the safety effects of the interaction of roadway attributes and commercial vehicle proportion. This can be considered a research gap in the literature because (a) commercial vehicles are a critical aspect of urban transportation and therefore, urban social and economic development, (b) commercial vehicles have been found to contribute significantly to crashes, (c) roadway design and operations attributes significantly influence crashes (d) unlike most crash factors, roadway design and operations attributes are within the control of the city authorities. Therefore, we feel that the stated research gap is very significant, from a practical perspective.

Table 2. 1 Summary of past related work

Study scope	Reference	Study region/ period	Independent variables	Outcome variable
Only examined main effects	Tay, 2003	Queensland/ 1997-2001	Commercial vehicle factors: Proportion of truck (+), Proportion of bus (-), Proportion of van (+) Other factors: season	Nr. of fatal crashes
	Wong et al., 2007	Hong Kong/ 2002-2003	Commercial vehicle factors: Proportion of overall commercial vehicles (+) Geometric factors: Curvature (+), Average lane width (-), Presence of tram stops (+) Traffic flow & traffic control factors: AADT (IS), pedestrian flow (+)	Nr. of fatal & severe intersection crashes
	Dinu and Veeraragavan, 2011	Chennai, India/ 2001-2003	Commercial vehicle factors: Proportion of bus (+), Proportion of trucks (-) Geometric factors: Curvature (+), Segment length (+), Driveway density (+) Traffic flow & traffic control factors: Hourly traffic volume (+)	Nr. of night-time highway crashes
	Xu et al., 2014	Hong Kong/ 2002-2003	Commercial vehicle factors: Proportion of commercial vehicles (-) Geometric factors: Curvature (+), Four or more approaches (+), Presence of a turning pocket (+), Nr of pedestrian crossings (+) Traffic flow & traffic control factors: AADT (+)	Nr. of slight intersection crashes
	Dong et al., 2014	Tennessee/ 2001-2005	Commercial vehicle factors: Proportion of trucks (+) Geometric factors: Angle of intersection (-), Shoulder width (+), Nr. of left-turn lanes (+), Roughness index (+), Rutting depth (+) Traffic flow & traffic control factors: AADT (+), Speed limit (+)	Nr. of intersection crashes
	Zeng et al., 2017a	Hong Kong/ 2002-2006	Geometric factors: Curvature (-), Average lane width (+), Nr. of lanes (+), Nr. of merging ramps (-), Presence of median barrier (-), Presence of bus stop (+) Traffic flow & traffic control factors: AADT (-), speed limit (-), Nr. of intersections (-) Other factors: Rainfall (IS)	Crash rates of road segments
	Wen et al., 2018	Guangdong, China/ 2014	Commercial vehicle factors: Proportion of medium bus & medium truck (+), Proportion of large bus & large truck (IS) Geometric factors: Curvature (IS), Vertical gradient (IS), Part of a bridge (IS), presence of ramps (IS) Traffic flow & traffic control factors: daily vehicle-km traveled (+)	Highway injury crash frequency
Considered interaction effects	Wen et al., 2019	Guangdong, China/ 2014	Commercial vehicle factors : proportion of medium bus & medium truck (IS), proportion of large bus & large truck (-) Geometric factors: Vertical gradient (-), Curved road (IS) Traffic flow & traffic control factors: Monthly vehicle-km travelled (+) Interaction terms: Gradient × wind speed (+), Gradient × precipitation (-), Gradient × visibility (+), Curve × precipitation (+)	Highway injury crash frequency
	Zhao et al., 2019	State of Connecticut/ 2011-2015	Geometric factors: Nr. of through lanes (-), Rural setting (+), Outside shoulder width (+), Segment length (+), Inside shoulder width (-) Traffic flow & traffic control factors: Monthly traffic volume (+) Other factors: temperature (-), precipitation (+), wind speed (+) Interaction terms: Nr. of through lanes × rural setting (-), Nr. of through lanes × monthly traffic (+), Nr. of through lanes × outside shoulder width (-)	Highway injury crash frequency
	Zhai et al., 2019	Hong Kong/ 2015	Commercial vehicle factors: Goods vehicle (+), taxi (+), bus (+) Geometric factors: One-way road (-) Interaction terms: Raining × pedestrian jaywalking (+), Raining × Careless driving (+), Raining × footpath overcrowded (-), Above 30 ℃ × driver inattention (+), Above 30℃ × pedestrian run onto the road (+)	Severity of pedestrian crashes
	Azimi et al., 2020	State of Florida/ 2007-2016	Geometric factors: Dry and sand road surface (+), Unpaved shoulder (+), Downhill grade (+), Curve right alignment (+) Traffic flow & traffic control factors: Vehicle speed of 20 to 49 (mph) (+), Vehicle speed of 50 to 75 (mph) (+)	Severity of truck rollover crashes

			Interaction terms: Vehicle speed of 20 to 49 (mph) × clear vision (-), Vehicle speed of 20 to 49 (mph) × Driver careless driving (+), Dark condition × driver speeding (+), Dark condition × fog weather (+)	

Note: (direction of the parameter: (+)positive; (-)negative; (IS)examined but not statistically significant

2.3.4 Modelling crash counts and crash rates

To address the issue of excessive zeros in crash count observations, earlier studies applied the zero-inflated Poisson and negative binomial models (ZIP and ZINB), assuming a dual-state generating process of crash data (Shankar et al., 2003; Qin et al., 2004). Mannering and Bhat (2014) reviewed that zero-inflated models have been the most popular model to handle the excessive zeros, and they are still frequently used in recent research (Raihan et al., 2019; Gu et al., 2020). However, this approach has also been criticized by Lord et al. (2005), Lord et al. (2007) and Lord and Mannering (2010), suggesting that zero-inflated crash count models can create theoretical inconsistencies regarding the source of the predominance of zeros. For example, instead of being generated from inherently safe sites, excessive zeros can be cause by the roadway entities with low vehicle exposure and high heterogeneity, short data collection time, small spatial scale, underreported crashes, etc. Though many studies tried to avoid excessive zeros using the aggregated analysis, it creates another problem of ignoring the time-varying factors (Behnood and Mannering, 2019; Mannering, 2018). In this context, Pei et al. (2016) developed a highly disaggregated model that incorporated the variables of year, day of the week, and time of day. To accommodate the predominance of zero-crash observations, the authors adopted a bootstrap resampling approach while still applying a traditional negative binomial model. Nonetheless, the computation time would increase remarkably when generating large bootstrap samples to reduce the effects of random sampling errors (Efron and Tibshirani, 1994; Efron, 2014).

On the other hand, modelling the crash rate (e.g. crash count per million vehicle kilometres travelled) is now advocated as an alternative to conventional crash count modelling. Crash rate analysis has its advantages such as providing a standardized measure of the safety performance of roadway entities (Xu et al., 2014; Zeng et al., 2017a, 2017b). Tobit regression approach is commonly applied to address the left-censoring problem at zero of crash rates since many roadway entities can have zero crash record. Using a multivariate random parameter Tobit model, Ulak et al. (2018) estimated the crashes involving elderly (aged above 65) drivers, passengers, bicyclists, and pedestrians. This study adopted the same set of explanatory variables for different crash types to gain comparable results. It is revealed that there are positive correlations between crashes by types of elderly road users, except between pedestrians and bicyclists. Results also indicate that the effects of risk factors on crashes vary by road user type. For examples, increase in density for aging population would increase the crash rates of elderly drivers and passengers, but decrease the crash rates of elderly bicyclists and pedestrians. Additionally, increase in traffic flow would decrease the crash rates of elderly drivers, passengers, and bicyclists, while it has no significant effect on elderly pedestrians. Similarly, Guo et al. (2019) looked into crash rates by collision types such as rear-end, sideswipe, and angle crashes at freeway diverge areas. Results show that effects of contributing factors on crash rates vary across collision types.

In the context of substantial differences in vehicle feature and driver behaviour across vehicle types, the effects of explanatory variables on crashes can vary across vehicle types. Indeed, rather than simply predicting the overall crash counts or crash rates in either a microscopic (roadway entities, e.g. road segments, intersections) or a macroscopic level (spatial units, e.g. traffic analysis zones), recent studies have investigated the crash counts/rates by crash types using multivariate analysis (Lee et al., 2015; Li et al., 2015; Wang et al., 2017; Ulak et al., 2018; Alarifi et al., 2018; Guo et al., 2019). It has been proven by previous research that there could be strong correlations between crashes by types within each study unit. Lee et. al (2015) applied a multivariate Poisson log-normal regression approach to simultaneously investigate the motor vehicle, bicycle, and pedestrian crashes. Shared unobserved factors across crashes by different transportation modes were captured by the multivariate model, in which positive correlations were found. Moreover, significant explanatory factors to motor vehicle, bicycle, and pedestrian crashes are different. For examples, 'proportion of household without vehicles' is significant only for pedestrian crashes, while 'proportion of roadway with speed limit less than or equal to 20 mph' is significant only for bicycle crashes. Similarly, Wang et al. (2017) investigated crash counts by severity level (i.e. property damage only, non-incapacitating injury, and fatal and incapacitating injury) and collision type (i.e. same-direction, intersecting-direction, opposite-direction, and single-vehicle crashes).

Multivariate Poisson log-normal model was used to accommodate the unobserved shared effects across severity levels and collision types. More importantly, results of the parameter estimates indicate that the coefficient for a risk factor can have different signs (positive or negative) across crash types. As such, looking into crashes by type would provide more useful insights since it identifies different contributory factors across crash types.

To summarize, these studies justify a need to consider variations in crash counts or crash rates by crash type (e.g., severity, transportation mode, collision type). It is suggested that modelling crashes by type could be more favourable when identifying crash contributing factors. However, estimating crashes by type using separated prediction models has its limitation due to the assumption of independence in crash counts/rate across crash types. Univariate models ignoring possible correlation resulted from common unobserved factors across crash types within each site would have degraded modelling performance and biased parameter estimation, compared with multivariate models. As such, due to the differences in driver behaviour and crashworthiness among vehicle types, there is a need to simultaneously model the crashes by vehicle type to identify risk factors while accommodating possible correlation between crash types. In this way, effective countermeasures can be tailored to enhance the safety performance of a specific vehicle type.

2.4 Concluding remarks

This chapter demonstrates the results of the literature survey on driver safety assessment studies. In particular, previous findings in terms of the professional drivers' driving performance, perception, attitude, behaviour and the corresponding crash risk are presented. Conventional driving performance indicators and surrogate safety measures are introduced. The phenomenon of increasing elderly drivers in the transport sector and its possible negative effect on the safety performance of professional drivers are also discussed. For the perceptions and attitudes of professional drivers, contributory factors revealed in previous studies and their corresponding effects are explored. Deterrence theory to measure driver's perception towards traffic legislation, protection-motivation theory, as well as the theory of planned behaviour are reviewed. This chapter also discussed crash risks of professional drivers by commercial vehicle types and safety effects of commercial vehicle mix.

There are several research gaps identified in the literature because (a) interaction between better driving skill of professional driver and impaired driving performance of elderly drivers is still unclear; (b) for the effectiveness of penalty and enforcement strategies, there has been relatively little research focusing on the perception and attitude of professional drivers; (c) while the compensatory strategy adopted by older general drivers has been studied in some depth, there is little work that researches into the compensatory behavior and its safety implications of older professional drivers; (d) interactions between road safety factors, including road user behaviour, weather, and road geometric factors, have been investigated in past research. However, this has rarely been done for the proportion of commercial vehicles and roadway features. While consideration of the interactions between these two specific factors may be a contribution that seems to be only incremental, it is important to address this gap in the literature because both roadway features and commercial vehicle proportion have been found to be significant factors of urban road crash propensity; (e) last but not least, research is urgently needed to estimate crashes by vehicle type simultaneously to better understand different effects of contributing factors. Therefore, effective countermeasures can be tailored to tackle the higher crash risk of commercial vehicles. These deficiencies are of great concern, given that professional drivers make up more of the pool of overall drivers in Hong Kong. It provides us with the motivation to fill the research gap.

Chapter 3 Evaluation of driving performance using driving simulator

3.1 Introduction

Professional drivers, due to their work nature, spend much longer time on roads than the non-professional drivers, which may contribute to their better driving skill. However, fatigue and risk-taking behaviours are also prevalent among professional drivers, which could increase the associated crash injury risk (Bunn et al., 2005; Duke et al., 2010; Rosenbloom and Shahar, 2007). On the other hand, the proportion of elderly drivers in transport sector has been increasing because of the ageing population, shortage of labor and economic incentives (Duke et al., 2010). In Hong Kong, the percentage of the population aged 60 or above has increased from 16.8% in 2008 to in 23.6% 2017 (Census and Statistics Department, 2017). Accordingly, the percentage of the full driving license holders who aged above 60 in Hong Kong increased from 8% in 2008 to 16% in 2017 (Transport Department, 2017a). The effect of age on driving performance is of increasing concern since driving performance was recognized to be deteriorated with age (Islam and Mannering, 2006; Shanmugaratnam et al., 2010).

This chapter aims to explore the interaction between age-related impairments on driving performance and task familiarity of professional drivers using a driving simulator approach. Two hypotheses are thus proposed, (1) age-related impairments on driving performance can be reduced by the driving experience and task familiarity of professional drivers; and (2) contributory factors to driving performance of professional drivers are different from that of non-professional drivers. Section 3.2 provides the details of experimental design and procedures of driving simulator test. Section 3.3 and 3.4 describe the driving performance indicators and method of analysis used in this study. The results and implications will be discussed in Section 3.5 Eventually, Section 3.6 provides the concluding remarks. It is anticipated that the results will be indicative to the dispatch policies and driver management strategies of the transport operators. This is particularly important to a compact and ageing society like Hong Kong, where the public transport usage is very high.

3.2 Simulator experiment design

3.2.1 Participants

A total of 50 male drivers were recruited for the driving simulator study. The selection criteria were: (1) holding a valid full driving license; (2) driving for at least 5 hours a week; and (3) having good health condition. Of the 50 participants, 26 were professional drivers and 24 were non-professional drivers respectively. For the professional drivers, one must be a full-time driver of taxi, public light bus, bus, or goods vehicle. In the subsequent analysis, the professional drivers will be stratified into two groups: (i) passenger vehicle (i.e. taxi, light bus and bus) drivers and (ii) goods vehicle drivers. It is because the difference in the experience and driving skills between vehicle types may moderate the association between driving performance and possible factors. Age of the participants ranged from 40 to 69 years. The participants were classified into two categories by age: (i) “mid-aged” referred to the drivers of age from 40 to 55 years; and (ii) “older” referred to the drivers of age from 56 to 69 years. Such classification was consistent to that of previous study (Li et al., 2016). Informed consent of the participation was obtained, and monetary reward was provided. US$50 and US$25 were paid to the professional drivers and non-professional drivers respectively for the participation. All participants were required to have a good rest and abstain from the consumption of alcohol and caffeinated beverages on the day before the experiment. **Table 3.1** provides the summary of the participants. Overall, the mean age was 53.2 years and the mean driving experience (year holding driving license) was 29.0 years respectively.

A number of driving simulator studies have been carried out to examine the effects of fatigue induced by prolonged driving time on driver performance. The duration of driving tests varied from 30 minutes to 2 hours (Thiffault and Bergeron, 2003; Filtness et al., 2012; Ahlström et al., 2018). In this study, duration of 60 minutes is adopted for each simulated driving test. This is consistent to the time duration of a typical bus or goods vehicle trip in Hong Kong. Also, according to the results of pilot tests, 60-minute driving is long enough to reveal the driving performance under the influence of fatigue, while avoiding the simulator sickness.

Table 3. 2 Summary of the participants of driving simulator study

Driver Group	Number of participants	Age	Year holding full driving license	Annual driving distance (10^3 km)
		Mean (s.d.)		
Older professional	12	63.7 (2.9)	41.3 (4.3)	35.4 (10.1)
Mid-aged professional	14	43.9 (2.8)	22.1 (4.7)	51.6 (13.2)
Older non-professional	12	59.4 (3.3)	31.9 (6.7)	7.3 (2.1)
Mid-aged non-professional	12	47.2 (4.8)	21.7 (8.5)	10.7 (4.5)
Overall	**50**	**53.2**	**29.0**	**27.3**

3.2.2 Apparatus, driving scenario and test procedures

The apparatus is a fix-based driving simulator - OKTAL CDS-650. The apparatus is depicted in **Figure 3.1**. As shown in Figure 3.1, three 32’’ full HD LED displays were set up to provide 100^{o} horizontal field of view. The simulator is equipped with clutch, brake and throttle pedals, steering wheel (real Peugeot wheel with OKTAL force-feedback system), signaler, dashboard, and a sound system. They are expected to provide realistic feedback to the participants.

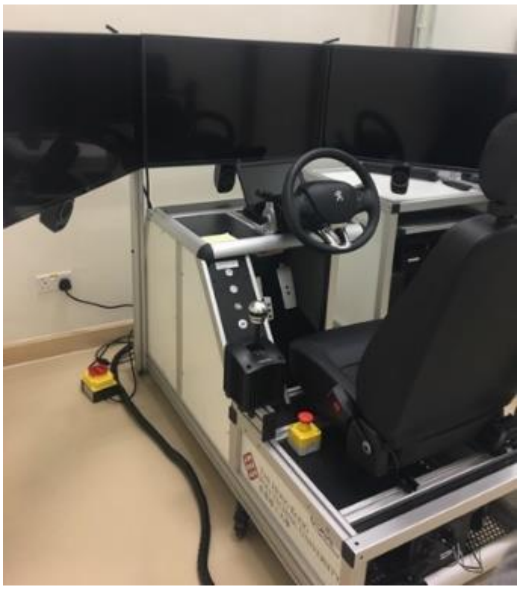
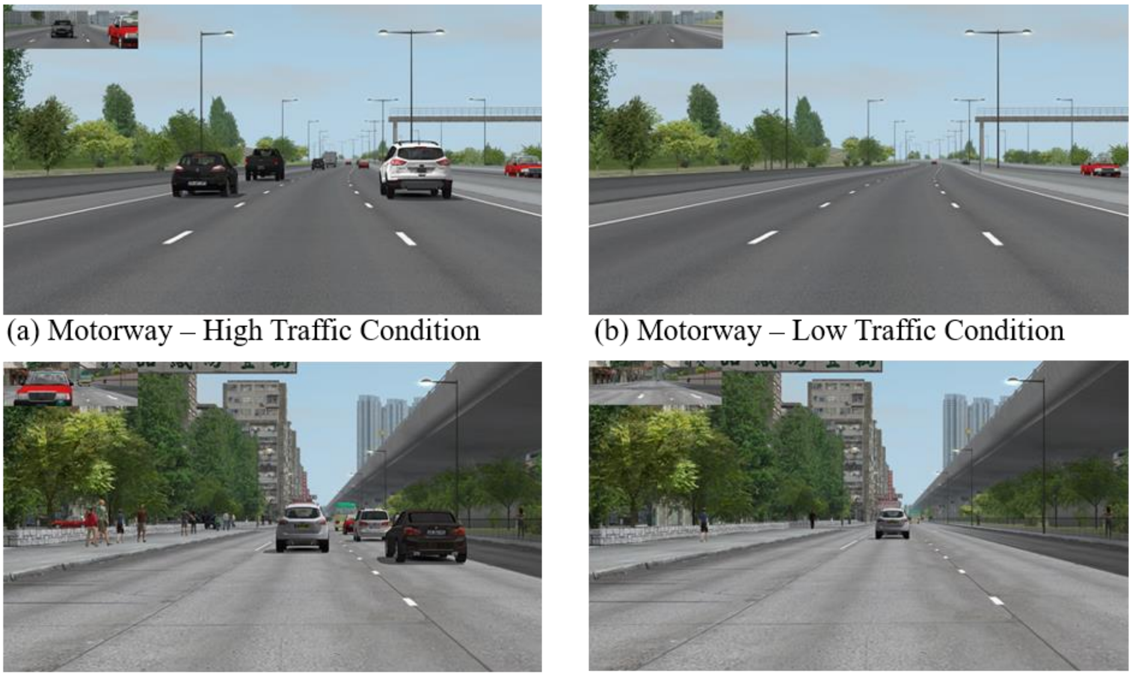


Figure 3. 1 OKTAL CDS-650 driving simulator

The simulated driving scenario is generated by the SCANeR^{TM} studio software. The scenarios are depicted in **Figure 3.2**. The typical road environments in Hong Kong are simulated. In particular, two distinct road environments are set out: (1) Inner city road with numerous roadside activities including but not limited to off-street parking, cyclists, and pedestrians (walking or standing); and (2) Dual carriageway three-lane motorway with no roadside activity. Speed limits of inner city road and motorway are 50km/h and 80km/h respectively, which are consistent to the actual driving environment in Hong Kong.



(a) Motorway – High Traffic Condition

(b) Motorway – Low Traffic Condition

(c) Inner City Road – High Traffic Condition

(d) Inner City Road – Low Traffic Condition

Figure 3. 2 Typical scenarios for the simulated driving experiment

There are four types of simulated driving scenarios, with respect to road environment and traffic flow condition, namely (i) Motorway – high traffic flow condition (**Figure 3.2a**); (ii) Motorway – low traffic flow condition (**Figure 3.2b**); (iii) Inner city road – high traffic flow condition (**Figure 3.2c**); and (iv) Inner city road – low traffic flow condition (**Figure 3.2d**). Each participant was asked to complete two driving simulator tests. In the experiment, a private car was simulated. Drivers were asked to drive on the middle lane and were not allowed to make any overtake. In the low traffic flow condition, two vehicles travelling around the subject vehicle were simulated. In the high traffic flow condition, ten vehicles travelling around the subject vehicle were simulated. Also, a car would be following the subject vehicle, while a safe following distance should be maintained. For the geometric design, average lane width of the motorway is 3.5 m, and that of the inner city road is 3.3 m respectively. To simulate the environment of urban area, a grid street network in Shum Shui Po district, with traffic signals, buildings and shops, were presented in the inner-city scenario. Also, walking and standing pedestrians (number of pedestrians varied with traffic volume) on the footpaths would be simulated. To simulate the environment of motorway, a highway section with bridges, interchanges, and roadside features like plantation and slopes were presented. Also, the horizontal curvature and vertical grade could vary. It is expected that the road environment (motorway versus inner-city road) and traffic condition (low versus high traffic conditions) could moderate the association between driver type, age and driving performance.

Table 3.2 provides the distribution of the simulated driving tests by driver group, road environment and traffic flow condition. Because of the simulator sickness and unavailability, some participants only completed one simulated driving test. Hence, a total of 94 tests (instead of 100) were completed. Also, the distribution of the tests by road environment, traffic flow condition and driver group, were not perfectly balanced (as shown in Table 3.2).

Table 3. 3 Distribution of the completed driving simulator tests

Driver Group	**Inner city road**		**Motorway**		**Total**
	High traffic flow	**Low traffic flow**	**High traffic flow**	**Low traffic flow**	
	Number of tests				
Older professional	5	6	6	6	23
Mid-aged professional	7	7	7	7	28
Older non-professional	5	5	6	6	22
Mid-aged non-professional	5	5	6	5	21
Overall	22	23	25	24	94

Prior to the experiment, a 15-minute practice was provided to help the participants familiarize with the control of simulator and detect the possible syndromes of simulator sickness. After the practice, each participant was asked to complete the two 60-minute driving simulator tests: one was on the motorway and the other was on the inner city road respectively. The driving tasks were similar for the two tests. Between the tests, a 30-

minute break was given. In addition, the orders of the tests were randomized and counterbalanced. Furthermore, the experiment would be stopped immediately when a participant felt unwell.

3.3 Driving performance indicators

Four indicators are used to assess the driving performance. They are standard deviation of lateral position (***SDLP***), standard deviation of heading error (***SDHE***), mean heading error (***MeanHE***), and standard deviation of speed (***SDspeed***). In particular, lateral position is defined as the perpendicular distance between the centerlines of a traffic lane and the vehicle. On the other hand, as shown in **Figure 3.3**, the heading error is defined as the angular deviation of the vehicle centerline from the tangent to the (curved) road centerline (Mollenhauer et al., 1994; Comte et al., 2000). Increases in *SDLP*, *SDHE*, *MeanHE* and *SDspeed* imply the prevalence of lateral instability, steering control instability, steering error and inability of speed control respectively (Shanmugaratnam et al., 2010; Li et al., 2016; Meng et al., 2019). Additionally, these indicators also imply the existence of driver fatigue and sleepiness, especially after the prolonged driving (Boyle et al., 2008; Meng et al., 2019). Furthermore, they are sensitive to the interactions between road environment, driver fatigue and driving performance (Thiffault and Bergeron, 2003; Ahlström et al., 2018). In this study, all the driving performance indicators were recorded at a very high frequency (100Hz) throughout the test. In addition, the data was aggregated into twelve time periods, i.e. [0-5) minute, [5-10) minute, [10-15) minute, [15-20) minute, [20-25) minute, [25-30) minute, [30-35) minute, [35-40) minute, [40-45) minute, [45-50) minute, [50-55) minute, [50-60) minute respectively. Therefore, there were 1128 observations (94 tests x 12 time periods) in total for each driving performance indicator.

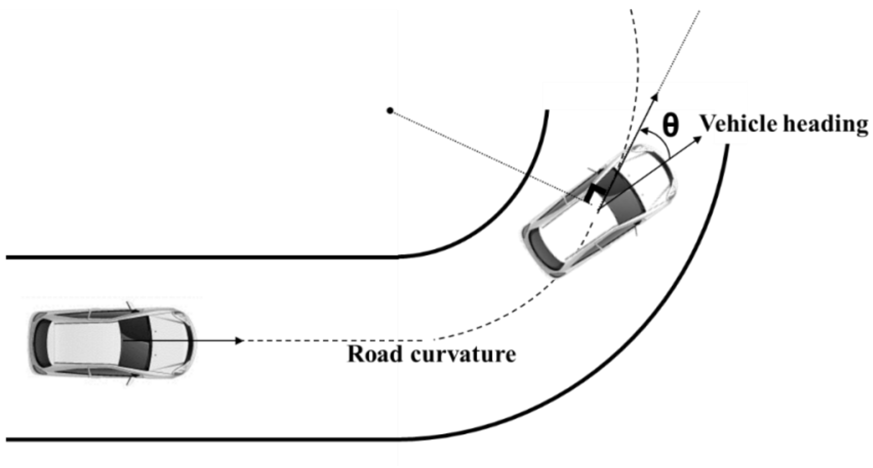


Figure 3. 3 Illustration of the heading error θ

Table 3.3 summarizes the data collected in the simulated driving tests. As shown in Table 3.3, the professional drivers may have better driving performance than the non-professional drivers, as the average *SDLP, MeanHE* and *SDspeed* of professional drivers are lower than that of the counterpart. On the other hand, performances of the mid-aged drivers are better than that of the older drivers. For the road environment, driving performances on inner city road are better than that on motorway, given that the average *SDLP*, *SDHE, MeanHE* and *SDspeed* are lower on inner city road, as compared to that on motorway. Furthermore, the driving performance tends to degrade over time in general, as the average *SDLP*, *SDHE, MeanHE* and *SDspeed* in the last two time periods are all higher than that in the first two time periods, and so on and so forth.

Table 3. 4 Summary statistics for the simulated driving tests (N=1128)

Variable	**Number of observations**	**SDLP**	**SDHE**	**MeanHE**	**SDspeed**
			Mean (s.d.)		
Professional driver	612	0.20 (0.08)	0.33 (0.21)	0.33 (0.14)	3.49 (1.59)
Passenger vehicle driver	408	0.21 (0.07)	0.32 (0.20)	0.34 (0.13)	3.59 (1.45)
Goods vehicle driver	204	0.19 (0.08)	0.33 (0.22)	0.33 (0.15)	3.29 (1.61)
Non-professional driver	516	0.21 (0.07)	0.32 (0.21)	0.36 (0.13)	3.52 (1.49)
Older driver	540	0.22 (0.08)	0.34 (0.21)	0.36 (0.14)	3.76 (1.69)
Mid-aged driver	588	0.20 (0.06)	0.32 (0.20)	0.33 (0.13)	3.26 (1.34)
High traffic flow	564	0.21 (0.08)	0.32 (0.20)	0.35 (0.11)	3.56 (1.54)
Low traffic flow	564	0.21 (0.08)	0.34 (0.21)	0.34 (0.16)	3.44 (1.56)
Motorway	588	0.26 (0.05)	0.51 (0.12)	0.44 (0.11)	4.43 (1.38)
Inner city road	540	0.15 (0.05)	0.13 (0.02)	0.24 (0.05)	2.49 (0.95)
Time period 1 (0-5 min)	94	0.20 (0.07)	0.28 (0.16)	0.31 (0.10)	3.13 (1.19)
Time period 2 (6-10 min)	94	0.20 (0.07)	0.28 (0.17)	0.32 (0.11)	3.26 (1.37)
Time period 3 (11-15 min)	94	0.18 (0.06)	0.29 (0.16)	0.32 (0.11)	3.36 (1.45)
Time period 4 (16-20 min)	94	0.19 (0.07)	0.28 (0.16)	0.32 (0.11)	3.63 (1.60)
Time period 5 (21-25 min)	94	0.21 (0.08)	0.35 (0.23)	0.35 (0.14)	3.35 (1.49)
Time period 6 (26-30 min)	94	0.22 (0.08)	0.34 (0.22)	0.35 (0.14)	3.54 (1.48)
Time period 7 (31-35 min)	94	0.20 (0.07)	0.33 (0.20)	0.35 (0.12)	3.52 (1.57)
Time period 8 (36-40 min)	94	0.20 (0.06)	0.31 (0.19)	0.33 (0.12)	3.62 (1.68)
Time period 9 (41-45 min)	94	0.21 (0.08)	0.36 (0.23)	0.36 (0.14)	3.55 (1.53)
Time period 10 (46-50 min)	94	0.22 (0.08)	0.35 (0.23)	0.37 (0.17)	3.50 (1.55)
Time period 11 (51-55 min)	94	0.22 (0.08)	0.38 (0.24)	0.38 (0.15)	3.65 (1.57)
Time period 12 (56-60 min)	94	0.23 (0.08)	0.37 (0.24)	0.38 (0.15)	3.88 (1.76)

3.4 Statistical method

Multiple regression approach is applied to measure the effects of driver type, age, road environment, traffic flow condition and driving time on driving performance. Also, the interaction effect between driver type and age is considered. Then, disaggregated models by driver type (i.e. professional and non-professional drivers) are developed based on the results of market segmentation analysis (Wong et al., 2008; Szeto et al., 2013).

In this study, each participant was asked to complete two simulated driving tests (each for 60 minutes). On the other hand, there were twelve observations (by twelve time periods) for each test. The observations within the same test and of the same participant would be correlated because they shared the common (unobserved) random effect. To allow for the correlation between observations, the panel random intercept regression approach was applied to measure the association between driving performance and possible factors, including road environment, traffic flow condition, driver occupation, age and driving time. The random intercept models (θ_1 for *SDLP*, θ_2 for *SDHE*, θ_3 for *MeanHE* and θ_4 for *SDspeed* respectively) are specified as follows,

$$\theta_{1it} = \beta_{10} + \mu_{1i} + \sum x_{itj}\beta_{1j} + \varepsilon_{1it} \tag{1}$$

$$\theta_{2it} = \beta_{20} + \mu_{2i} + \sum x_{itj}\beta_{2j} + \varepsilon_{2it} \tag{2}$$

$$\theta_{3it} = \beta_{30} + \mu_{3i} + \sum x_{itj}\beta_{3j} + \varepsilon_{3it} \tag{3}$$

$$\theta_{4it} = \beta_{40} + \mu_{4i} + \sum x_{itj}\beta_{4j} + \varepsilon_{4it} \tag{4}$$

where i refers to the test (i = 1, 2, 3, …, and 94); t refers to the time period (t = 1, 2, 3 … 12); μ refers the independent residual (between tests); ε_{it} refers to the independent residual (between observations); x is the value of explanatory variable (including road environment, traffic flow condition, driver type, age, and time period) and β is the corresponding coefficient respectively.

The coefficients were estimated using the maximum likelihood approach. To assess the goodness-of-fit of the proposed model, the likelihood ratio test statistics are given by,

$$LR = -2\,[LL(\beta_{H0}) - LL(\beta_{ML})] \tag{5}$$

where $LL(\beta_{H0})$ is the restricted log likelihood function and $LL(\beta_{ML})$ is the unrestricted log likelihood function respectively. Under the null hypothesis, LR is χ^2 distributed with q degree of freedom (q is the difference in the number of parameters between the restricted and unrestricted models). A good fit was indicated by a statistically significant LR. In this study, the statistical package *NLOGIT 5.0* was used to establish the proposed random intercept models.

3.5 Results

In this study, the random intercept approach was used to measure the effects of factors including driving time, age, driver type, road type and traffic flow condition on the driving performance, with which the unobserved effect of correlation between observations of the same participant and in the same test was controlled for. There were 1128 observations for each model (*SDLP*, *SDHE, MeanHE* and *SDspeed*). **Table 3.4** presents the results of parameter estimation of the overall models. Since driver type, age, traffic flow condition and driving time are the variables of interest in this study, they are all considered in the proposed models, even no evidence can be established for significant correlation with the driving performance indicators. Additionally, two types of professional drivers (i.e. passenger vehicle and goods vehicle drivers) are considered. This is to control for the effects of differences in experience and skills between vehicle types. For the interaction effect, focus was paid on the two interested variables (i.e. older and professional driver). However, no significant evidence related to the driving performance of older professional drivers could be established.

Table 3. 5 Results of parameter estimates of the (overall) random intercept models

Variable	SDLP		SDHE		MeanHE		SDspeed	
	Coeff.	**(z-stat.)**	**Coeff.**	**(z-stat.)**	**Coeff.**	**(z-stat.)**	**Coeff.**	**(z-stat.)**
Constant	0.140	(14.26)**	0.098	(7.16)**	0.206	(12.61)**	1.875	(8.00)**
High traffic flow	-0.0005	(-0.06)	-0.031	(-3.00)**	0.004	(0.32)	0.115	(0.59)
Motorway	0.109	(13.24)**	0.370	(35.70)**	0.204	(14.98)**	1.946	(9.95)**
Goods vehicle driver	-0.027	(-2.37)*	-0.011	(-0.79)	-0.031	(-1.63)	-0.264	(-0.97)
Passenger vehicle driver	-0.005	(-0.58)	-0.010	(-0.90)	-0.023	(-1.52)	0.085	(0.39)
Older driver	0.023	(2.70)**	0.017	(1.66)	0.021	(1.52)	0.472	(2.40)*
Time period 2 (5-10 min)	0.001	(0.14)	0.006	(0.65)	0.005	(0.71)	0.105	(1.07)
Time period 3 (10-15 min)	-0.020	(-4.92)**	0.016	(1.66)	0.006	(0.86)	0.201	(2.04)*
Time period 4 (15-20 min)	-0.007	(-1.65)	0.002	(0.21)	0.010	(1.40)	0.471	(4.79)**
Time period 5 (20-25 min)	0.015	(3.59)**	0.076	(7.67)**	0.041	(5.84)**	0.194	(1.97)*
Time period 6 (25-30 min)	0.015	(3.75)**	0.062	(6.31)**	0.040	(5.72)**	0.384	(3.91)**
Time period 7 (30-35 min)	0.004	(0.92)	0.054	(5.47) **	0.039	(5.47)**	0.362	(3.68)**
Time period 8 (35-40 min)	-0.0002	(-0.04)	0.037	(3.76)**	0.019	(2.74)**	0.469	(4.77)**
Time period 9 (40-45 min)	0.015	(3.60)**	0.079	(7.96)**	0.050	(6.95)**	0.399	(4.05)**
Time period 10 (45-50 min)	0.015	(3.73)**	0.077	(7.84)**	0.065	(9.19)**	0.344	(3.50)**
Time period 11 (50-55 min)	0.022	(5.33)**	0.098	(9.95) **	0.066	(9.41)**	0.491	(4.99)**
Time period 12 (55-60 min)	0.028	(6.85)**	0.097	(9.87)**	0.070	(9.98)**	0.761	(7.72)**

		Goodness-of-fit		
Unrestricted loglikelihood	2281.89	1348.18	1671.35	-1299.14
Restricted loglikelihood	1320.83	178.47	671.08	-2084.54
Likelihood ratio test	1922.12**	2339.42**	2000.54**	1570.80**

*** Statistical significance at the 1% level*

** Statistical significance at the 5% level*

In addition, the market segmentation analysis using the Watson and Westin pooling approach (Wong et al., 2008; Szeto et al., 2013) was conducted to examine the possible intervention effect by driver type (i.e. professional versus non-professional drivers) on the relationship between driving performance and possible factors. Disaggregated models for professional and non-professional drivers were then established based on the results of market segmentation analysis (shown in **Table 3.5)**. Therefore, differences in possible factors between professional and non-professional drivers could be assessed. **Table 3.6** presents the results of the disaggregated analyses. Overall, the proposed models fit well with the observations, all at the 1% level of significance. Results of parameter estimation for each of the four driving performance indicators (i.e. *SDLP*, *SDHE*, *MeanHE and SDspeed*) are described one by one in the following Section 3.5.1, 3.5.2, 3.5.3 and 3.5.4.

Table 3. 6 Results of market segmentation analysis

Indicator	$LL(\beta_{H0})$	$LL(\beta_{ML})$	**Degrees of freedom**	**Likelihood Ratio**
SDLP	2280.24	2294.37	16	28.26*
SDHE	1348.18	1379.61	16	62.86**
MeanHE	1671.27	1684.44	16	26.34*
SDspeed	-1299.90	-1280.12	16	41.38**

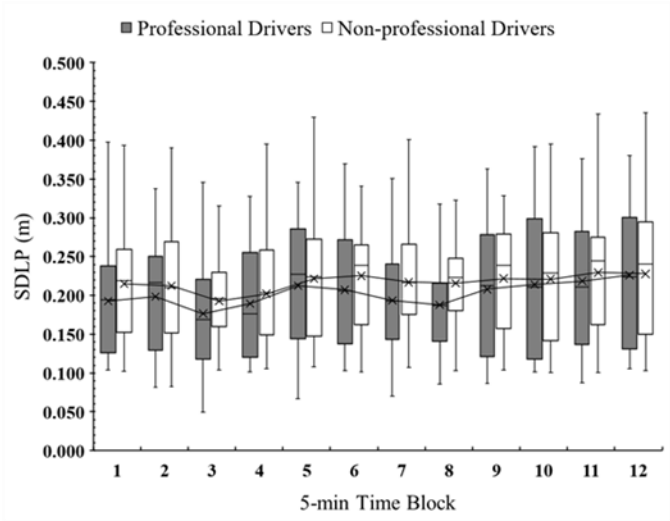
*** Significant at the 1% level*
** Significant at the 5% level*

Table 3. 7 Results of parameter estimates for professional and non-professional drivers

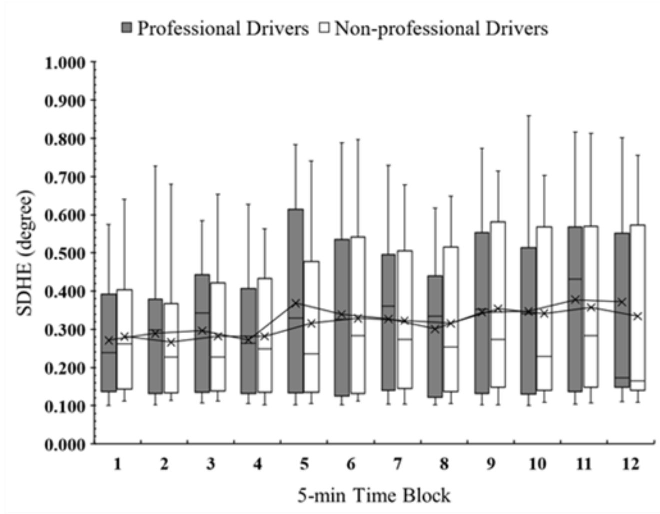
Variable	**SDLP**		**SDHE**		**MeanHE**		**SDspeed**	
	Pro	**Non-Pro**	**Pro**	**Non-Pro**	**Pro**	**Non-Pro**	**Pro**	**Non-Pro**
Constant	0.121**	0.148**	0.095**	0.101**	0.180**	0.226**	2.026**	1.668**
High traffic flow	0.001	0.000	-0.040*	-0.051**	-0.002	-0.026	-0.142	0.443
Motorway	0.117**	0.098**	0.365**	0.379**	0.205**	0.206**	1.803**	2.094**
Older driver	0.021*	0.021	0.006	0.001	0.023	-0.021	0.690**	0.212
Older x High traffic flow	--	--	--	0.060*	--	0.076*	--	--
Time period 2	0.006	-0.005	0.018	-0.008	0.017	-0.009	0.032	0.193
Time period 3	-0.016**	-0.025**	0.026	0.005	0.011	-0.001	0.143	0.271*
Time period 4	-0.003	-0.011	0.001	0.003	0.012	0.008	0.391**	0.567**
Time period 5	0.020**	0.009	0.097**	0.050**	0.043**	0.038**	0.071	0.342**
Time period 6	0.015*	0.016**	0.068**	0.055**	0.039**	0.042**	0.326*	0.455**
Time period 7	0.001	0.007	0.056**	0.051**	0.042**	0.035**	0.345*	0.385**
Time period 8	-0.005	0.005	0.030*	0.046**	0.019	0.019*	0.425**	0.523**
Time period 9	0.015**	0.014*	0.074**	0.084**	0.043**	0.056**	0.214	0.619**
Time period 10	0.021**	0.008	0.076**	0.079**	0.071**	0.057**	0.253	0.454**
Time period 11	0.026**	0.017**	0.106**	0.088**	0.072**	0.060**	0.314*	0.671**
Time period 12	0.031**	0.024**	0.104**	0.090**	0.070**	0.070**	0.689**	0.849**

Variable	SDLP		SDHE		MeanHE		SDspeed	
	Pro	**Non-Pro**	**Pro**	**Non-Pro**	**Pro**	**Non-Pro**	**Pro**	**Non-Pro**
<u>Goodness-of-fit</u>								
Unrestricted Loglikelihood	1228.76	1065.61	670.85	711.28	868.62	818.49	-752.79	-527.33
Restricted Loglikelihood	711.38	613.19	93.37	85.22	341.32	336.59	-1121.04	-963.07
Likelihood ratio test	1034.58**	904.84**	1154.96**	1252.12**	1054.60**	963.80**	736.50**	871.48**

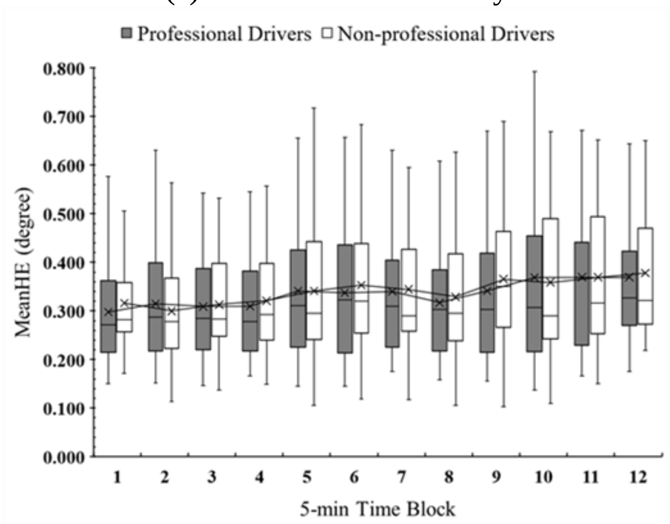
Notes:
*** Statistical significance at the 1% level*
** Statistical significance at the 5% level*
"Pro" refers to professional driver and "non-Pro" refers to non-professional driver respectively



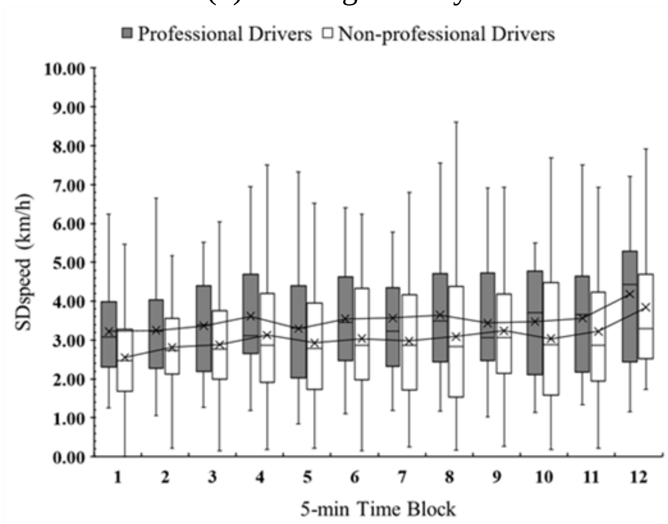
(a) Lateral control stability



(b) Steering stability



(c) Steering control



(d) Speed Control

Figure 3. 4 Driving performance of professional and non-professional drivers over time

Note:

1. The box plots indicate the minimum, 1st quartile, median, 3rd quartile and maximum of the performance indicators (i.e. SDLP, SDHE, MeanHE, SDspeed)

2. "X"s indicate the average value

3.5.1 Lateral stability

Standard deviation of lateral position is widely used to reflect the driver's ability to maintain the lateral stability (Boyle et al., 2008). Increase in *SDLP* implies the degradation in lateral control performance. As shown in **Table 3.4**, for the main effect, driver type, driver age, road type and driving time are found associated with *SDLP*. In particular, *SDLP* of older driver is higher than that of the mid-aged driver. *SDLP* of goods vehicle driver is lower than that of the non-professional driver. Also, *SDLP* tends to increase when driving on the motorway. In addition, *SDLP* increases remarkably when the driving time is greater than 25 minutes (Time period 5).

As shown in **Table 3.6**, driver age, road type and driving time significantly affected the lateral stability of professional driver. SDLP of older professional driver tends to be higher than that of the mid-aged professional driver. Also, remarkable increase in SDLP could be observed after driving for 25 minutes (Time period 5). On the other hand, no evidence could be established for the association between driver age and SDLP of non-professional driver. Yet, obvious increase in SDLP of non-professional driver could be observed after 30 minutes (Time period 6).

3.5.2 Stability of steering control

Standard deviation of heading error reflects the driver's stability of steering wheel control. Increase in *SDHE* indicates the degradation in steering performance. As shown in Table 3.4, for the main effects, traffic flow condition, road type and driving time are found associated with *SDHE,* all at the 1% level of significance. In particular, *SDHE* increases when driving on the motorway and decreases when driving under the high traffic flow condition. In addition, *SDHE* increases remarkably when the driving time is greater than 25 minutes (Time period 5).

For the disaggregated analyses, as shown in Table 3.6, traffic flow condition, road type and driving time significantly affected the *SDHE*, both of professional and non-professional drivers. However, the interaction effect between driver age and traffic flow condition was significant only among non-professional drivers. In particular, steering stability of older non-professional driver tends to be worse than that of the mid-aged non-professional drivers, when driving under the high traffic flow condition.

3.5.3 Steering error

Mean heading error refers to the mean angular deviation of the vehicle trajectory from that of the road centerline. Increase in *MeanHE* indicates the degradation in steering accuracy. As shown in Table 3.4, for the main effects, road type and driving time are found associated with *MeanHE* at the 1% level of significance. In particular, *MeanHE* increases when driving on the motorway. Also, *MeanHE* increases remarkably when the driving time is greater than 25 minutes (Time period 5).

For the disaggregated analyses, as shown in Table 3.6, main effects of road type and driving time on *MeanHE* were found significant both for the professional and non-professional drivers. However, the interaction effect between driver age and traffic flow condition on *MeanHE* is significant only among the non-professional drivers. In particular, steering error of older non-professional driver was greater than that of the mid-aged non-professional driver, when driving under the high traffic flow condition.

3.5.4 Speed stability

Standard deviation of speed is widely used to reflect the driver’s ability to maintain the stability of driving speed. Increase in *SDspeed* implies the degradation in speed control performance. As shown in Table 3.4, for the main effect, driver age, road type and driving time are found associated with *SDspeed*. In particular, *SDspeed* of older driver is higher than that of the mid-aged driver. Also, *SDspeed* tends to increase when driving on the motorway. In addition, *SDspeed* increases remarkably when the driving time is greater than 15 minutes (Time period 3).

For the disaggregated analyses, as shown in Table 3.6, driver age, road type and driving time all affect the speed control performance of professional drivers. *SDspeed* of older professional driver tends to be higher than that of the mid-aged professional driver. Also, significant increase in the *SDspeed* of professional driver could be observed after 20 minutes (Time period 4). On the other hand, no evidence could be established for the association between driver age and *SDspeed* of non-professional driver. Yet, remarkable increase in the *SDspeed* could be observed for non-professional driver after 15 minutes (Time period 3).

3.6 Discussion

In this study, we hypothesized that (1) the age-related impairments on driving performance could be reduced by the driving experience and task familiarity of professional drivers; and (2) contributory factors to the driving performance of professional drivers were different from that of non-professional drivers. Results of overall model indicate that increase in age and driving on the motorway are associated with the degradation of lateral and speed control stability. In addition, road type and traffic flow condition are associated with the steering performance. Furthermore, results of disaggregated models indicate that effects of possible environmental factors on the driving performances of professional drivers are similar to that of non-professional drivers. Nevertheless, interaction effect by driver age on the association between traffic flow condition and driving performance is remarkable exclusively for the steering performance of non-professional drivers. In particular, the older non-professional drivers tend to have higher *MeanHE* and *SDHE* when driving under the high traffic flow condition. On the other hand, effect of age is exclusive for the lateral and speed control performances of professional drivers.

3.6.1 Effect of age on driving performance

Overall, older drivers show poorer lateral and speed control performance than the mid-aged drivers in this study. It is consistent to the findings of previous studies that driving performance deteriorates with age (Islam and Mannering, 2006; Shanmugaratnam et al., 2010). This could be attributed to the degraded physical, mental and cognitive capabilities (Lundberg et al., 1998; Andrews and Westerman, 2012). In addition, older people have higher perceptual sensitivity to the mental workload induced by driving, as compared to the younger counterpart (Cantin et al., 2009).

Estimation results for non-professional driver indicate that interaction between age and traffic condition is statistically significant. For non-professional driver, degradation in steering performance by age is found remarkable under the high traffic flow condition. Such findings in line with that of previous studies (Cantin et al., 2009; Trick et al., 2010). In particular, older drivers often consider driving under the high traffic flow condition as a challenging task (with higher mental workload). Since older drivers tend to be risk averse, they would avoid driving under the unfavorable road environment and traffic condition (Molnar and Eby, 2008; Cantin et al., 2009; Trick et al., 2010; Teh et al., 2014). In contrast, no evidence could be established for the degraded driving performance of older professional drivers under the high traffic flow condition. This could be attributed to the task familiarity of older professional drivers (Andrews and Westerman, 2012). Yet, it is recommended that more rigorous medical assessment should be implemented for the renewal of driving license of older drivers, considering their high crash involvement rates. Also, the moderating effects by other environmental conditions, such as lighting and weather, on the association between age and driving performance must be explored in the extended study.

3.6.2 Performance of professional drivers

Results of overall model indicate that goods vehicle drivers have better lateral control performance than the non-professional drivers. This can be attributed to the higher driving experience and better driving skill of goods vehicle drivers (Borowsky and Oron-Gilad, 2013). Seemingly, goods vehicle drivers in Hong Kong demonstrate better driving skills and attitudes. Indeed, the crash involvement rate (per million vehicle-km) of goods vehicle was lower than that of other commercial vehicles (i.e. taxi, light bus and bus) in Hong Kong (Transport Department of HKSAR, 2017). Yet, no evidence can be established for significant difference in driving performance between passenger vehicle drivers and non-professional drivers. Seemingly, superior driving skill of passenger vehicle drivers related to driving experience on different types of the roads, vehicle size relative to road width, and work-related trips could be offset by the aggressive driving behaviors (Kontogiannis, 2006; Öz et al., 2010a; Li et al., 2019). Examples of aggressive driving behaviors include but are not limited to speeding, red light running, and improper lane changing. They are indeed more prevalent for passenger vehicle drivers because of the desire for higher revenues and expectations of the employers/customers (Wong et al., 2008). In this study, effects of operation characteristics and attitudes of the drivers on the driving performance are however not considered. It is worth exploring the effects of driver perceptions and characteristics (e.g. perceived or observed aggressive behaviours, risk-taking traits, traffic offenses, and crash involvement) on the driving performance in the extended study. Furthermore, it is of essence to measure the association between the road geometry, driving performance (especially on steering performance) and crash risk, when comprehensive vehicle trajectory and crash data of professional drivers are available (Ahlström et al., 2018).

For the difference in effects of possible factors between professional and non-professional drivers, age effect is found significant only among the professional drivers. In particular, lateral and speed control performances of mid-aged professional drivers are better than that of the older professional drivers. Seemingly, the reduction in exposure by age could be a significant contributory factor to the degraded performance of professional drivers. Older professional drivers have lower annual driving distance that their mid-aged counterparts. It could be because the working and/or driving hours of older professional drivers tend to be lower. It is likely that the older professional drivers proactively reduce their exposure on road to mitigate the elevated crash risk due to age-related impairments. On the other hand, the driving hours of older professional drivers can be limited by the safety management policy of the transport operators. To this end, it is proposed that additional driver training, particularly on lateral stability and speed control, could be provided to the older professional drivers to mitigate the age-related impairments.

3.6.3 Effect of other factors on driving performance

As revealed in this study, the lateral performance of driver degrades over the 60-minute drive in general. It is consistent to the findings of previous studies (Oron-Gilad and Ronen, 2007; Ting et al., 2008; Farahmand and Boroujerdian, 2018). This could reflect the increase in fatigue level resulted from the prolonged driving (Du et al., 2015; Ahlström et al., 2018). Degradation of speed control, lateral stability and steering performance are associated with the increase in driver sleepiness and fatigue, particularly after prolonged driving (Boyle et al., 2008; Meng et al., 2019). In addition, the results of overall and disaggregated models show that degraded lateral, steering and speed control performances tend to occur when driving on the motorways. This could be attributed to the drowsiness due to the monotonous driving environment, and limited roadside activities and interactions with other road users (Oron-Gilad and Ronen, 2007; Williamson et al., 2014; Du et al., 2015; Ahlström et al., 2018). Yet, such findings could be verified when information on both subjective and physiological indicators are available in the extended study (Oron-Gilad et al., 2008). On the other hand, the degraded driving performance on the motorways could also be attributed to the geometric and operational characteristics of the roadway. Indeed, degradation of lateral and speed stabilities could be profound when speed limit and road width increase (Ahlström et al., 2018; Meng et al., 2019). It would be worth exploring the effect of road curvature (in term of the number of curves, interval between curves and radius of curvature), road width and speed limit on the association between driving performance and driving time in the extended study.

It was expected that the effect of driving time on driving performance should be different between professional and non-professional drivers, since the professional drivers are more skillful in general. Results of disaggregated model indicated that onset of the significant degradations in lateral and speed control performance are different between professional and non-professional drivers. Moreover, the lateral and steering performance of professional drivers started to degrade after driving for 25 minutes. This should be indicative to the safety management strategies of the transport operators, especially the design and development of in-vehicle driver monitoring and assistance system on the commercial vehicle fleets (Davidse et al., 2009). For example, eye tracking unit for the detection of driver fatigue, and electronic stability control system could be installed on the passenger vehicles (for franchised buses in Hong Kong, a subsidization scheme has been introduced to retrofit smart safety devices including electronic stability control on the existing bus fleets).

3.7 Concluding remarks

Professional drivers are considered more skillful and experienced. However, the overall crash involvement rate of professional drivers is higher than their counterparts in Hong

Kong. Also, the population of older professional driver is increasing because of the ageing population. In this chapter, we examined two hypotheses 1) the impairment of driving performance by age could be reduced by the driving experience and task familiarity of professional drivers; 2) the contributory factors to the driving performance of professional drivers should be different from that of non-professional drivers. The driving performance indicators considered are standard deviation of lateral position, standard deviation of heading error, mean heading error and standard deviation of driving speed.

Results of overall model indicate that goods vehicle drivers tend to have better lateral stability than the non-professional drivers. Driving performances of mid-aged drivers tend to be better than that of the older drivers. Based on the results of disaggregated analysis, the impairments on driving performance by age (i.e. older) are more prevalent when driving under the high traffic flow condition among non-professional drivers. No evidence could be established for the degraded driving performance of older professional drivers under the high traffic flow condition. Although older drivers are often risk averse and would avoid driving under the high traffic flow condition, age-related impairments could be reduced by the driving experience and task familiarity of professional drivers. Therefore, for the driver recruitment and management, decision making of transport operators should not be solely based on driver age. Instead, rigorous assessment of driving skills and enhanced training could be provided for the older drivers. Furthermore, results of the disaggregated models indicate that the effect of age is found prevalent only among the professional drivers. Lateral and speed control performance of mid-aged professional drivers were superior than that of older professional drivers. Seemingly, reduction in exposure could be a contributory factor to the impaired driving performance of older professional drivers. It is recommended that driver training could be provided to the older drivers, particular on vehicle control. This is to mitigate the increase in collision risk attributed to reduced exposure. As for the second hypothesis, results of disaggregated analyses indicate that effects of possible environmental factors (i.e. motorway and high traffic flow condition) of professional drivers are similar to that of non-professional drivers. However, the interaction between age and traffic flow condition are exclusive to the non-professional drivers only.

In this study, the interaction effects by the driver perception and attitude on the association between driving performance and driver characteristics are not considered. Additionally, the driving performances of male drivers only are assessed in the driving simulator experiment, given the relatively small sample size. Effect of gender on driving performance is therefore not attempted. It is worth exploring the effects of driver characteristics (in term of crash involvement, traffic offense and risk perception) on the driving performance when the comprehensive information is available from the attitudinal survey (Wong et al., 2008; Li et al., 2014). Furthermore, effects of road design and environmental condition (e.g. lighting and weather) on the crash risk of professional driver can be revealed based on comprehensive vehicle trajectory and crash data in extended study.

Chapter 4 Evaluation of conflict risk using driving simulator

4.1 Introduction

The percentage of elderly who hold a valid driving license has been increasing rapidly in those ageing societies (Newnam et al., 2020, 2018). Indeed, Hong Kong is facing the problem of ageing population because of the reduction in fertility rates and increased life expectancy. By 2035, proportion of population of age above 65 in Hong Kong would reach 25% (Sze and Christensen, 2017). The proportion of drivers aged above 60 with a valid public transport vehicle (e.g. taxi, light bus, and bus, etc.) driving license was 37-46% in 2017 (Lee, 2018).

Safety of professional drivers is of great concern since they have much higher exposure on roads. In Hong Kong, 50% of work trips are made by taxi, public light bus, and bus (Hong Kong Transport Department, 2014). More importantly, the proportion of older drivers in the transport sector increases dramatically because of the shortage of labour. Given the age-related declines in driving performance, the strategy adopted by older drivers to compensate for their elevated crash risk has drawn increasing attention in recent years. This issue is of importance to employers given their multiple responsibilities to keep the drivers, passengers, and cargo safe, as well as to support their older employees who want to stay in the industry. This information can be used to review and revise control measures, as well as develop new intervention, designed to promote the safety, health and wellbeing of older professional drivers.

While the compensatory strategy adopted by older general drivers has been studied in some depth, there is little work that researches into the compensatory behavior and its safety implications of older professional drivers. This is surprising given that the proportion of older drivers in the transport sector has been increasing dramatically because of the shortage of labor. Therefore, we are motivated to study the driving performance of professional drivers from the behavioral perspective. The aim of this study is to address the research question that whether the older professional drivers reduce the crash risk more effectively by capitalizing on their rich experience, and to provide suggestions on driver training and management policy for transport authority and operators.

In this chapter, two hypotheses are proposed, (i) older professional drivers have lower likelihood and severity of rear-end conflict, as compared with older non-professional drivers; and (ii) likelihood and severity of rear-end conflict after prolonged driving would be higher for older non-professional drivers. The hypotheses are proposed considering the possible differences in driving skill, exposure, and experience (especially driving long hours) between professional and non-professional drivers. A car-following scenario with sudden brakes of the leading vehicle is used to test the hypotheses. Time exposed time-to-collision (TET) and time integrated time-to-collision (TIT) are adopted as performance measure indicating the severity of traffic conflict. Also, drivers' brake reaction times for the sudden events are recorded. A random-parameter Tobit regression approach is applied to investigate the associations between performance measures and possible factors including driver occupation, driver age and traffic flow condition.

The remainder of this chapter is structured as follows. Section 4.2 describes the experimental design and data collection. Section 4.3 and 4.4 illustrate the surrogate safety measures and analysis method, respectively. Results of the hypotheses are presented in Section 4.5 and implications of the results are discussed in Section 4.6. Finally, Section 4.7 provides the concluding remarks.

4.2 Simulator experiment design

4.2.1 Participants

Forty-four male drivers were recruited for the driving simulator experiment. The inclusion criteria are having a full driving license, minimum driving time of 5 hours per week and (self-declared) good health condition. The exclusion criteria are feeling unwell and having any syndrome of simulator sickness (e.g. headache, nausea, blurred vision and dizziness, etc.). Participants were asked to have enough rest and abstain from alcohol and caffeinated beverages 24 hours prior the simulator test. Prior to the experiment, a 15-minute training session was provided to each participant to help familiarize the participants with the driving simulator controls. Informed consent in accordance with the requirements of university research ethics committee was obtained, and monetary compensation (US$25-50) was provided for the participation.

Table 4. 1 Summary of participants of driving simulator study

	Professional driver		**Non-professional driver**		**Overall**
	Mid-aged	**Older**	**Mid-aged**	**Older**	
Number of participants	10	9	11	11	41
			Mean (S.D.)		
Age	43.5 (2.5)	63.4 (3.1)	46.5 (4.5)	60.1 (3.2)	53.3 (9.1)
Year holding full driving license	21.5 (4.5)	41.4 (4.7)	21.4 (8.9)	32.1 (7.0)	29.1 (10.4)
Annual driving distance (10^3 km)	51.6 (13.8)	34.4 (9.8)	10.8 (4.7)	7.0 (2.0)	26.0 (2.1)

All participants need to complete a short questionnaire survey to provide information on driver age, annual driving distance, occupation, record of traffic convictions and accident involvement. **Table 4.1** presents the summary of participants of driving simulator study. Of the 44 participants, three (i.e. 1 mid-aged professional and 2 older professional drivers) were excluded since they had driving simulator sickness. Data collected from 19 professional drivers and 22 non-professional drivers were used for the analysis. In this study, professional drivers refer to the full-time taxi, public light bus, public bus and goods vehicle drivers. Furthermore, the participants were classified into two categories: (i) mid-aged and (ii) older drivers, in accordance with the classification in some recent studies in Hong Kong (Li et al., 2016; Chen et al., 2019). Specifically, “mid-aged” drivers refer to those who are aged from 40 to 55 years, and “older” drivers refer to those who are aged from 56 to 69 years.

4.2.2 Driving scenario and test procedures

In this study, the experiments were carried out using the OKTAL CDS-650 compact fix-based simulator and the simulated driving scenarios were developed using the SCANeRTM studio package. For instance, there are three 32’’ full HD LED monitors providing a 100o horizontal field of view. Particularly, the simulator is equipped with force-feedback pedals, steering wheel and indicator of real vehicle (e.g. Peugeot). It is to provide the participants realistic control experience, especially the road texture and kerb side. Driving and vehicle movement attributes including acceleration, speed, lateral position, pedal force and steering angle are recorded at a frequency of 100 Hz.

As depicted in **Figure 4.1**, typical Hong Kong road environment is simulated in the driving experiment. In particular, buildings, roads, intersections and road furniture in Sham Shui Po District (a densely populated urban district in Hong Kong) are simulated. The roads simulated are of three lanes (with on-street parking space on the left hand side) and single direction. They form a grid network and the speed limit is 50km/h. Also, two traffic conditions: (i) high traffic flow, more pedestrians on the footpaths and more surrounding vehicles; and (ii) low traffic flow, less pedestrians and less surrounding vehicles, are simulated. In high traffic flow condition, there are 10 vehicles moving around the subject vehicle and 10 pedestrians per 100 meter long footpath. In low traffic flow condition, there are 2 vehicles moving around the subject vehicle and 0.5 pedestrians per 100 meter long footpath.

(a) High traffic flow **(b) Low traffic flow**

Figure 4. 1 Typical simulated driving scenarios

Each participant was asked to complete one simulated driving session, either under the low or high traffic condition. Duration of every session was 60 minutes. The scenarios (high versus low traffic conditions) presented were randomized and counterbalanced across the participants. In the experiment, participants were asked to drive as if driving a small passenger car. They were instructed to drive on the middle lane and follow a leading vehicle, with a comfortable and constant following distance. They were also required not to overtake during the simulated driving. To assess the drivers' response, 'events' (sudden brake of leading vehicle as indicated by the 'brake light') were induced after 5 minutes and 55 minutes of driving respectively. In particular, the leading vehicle would decelerate from 50 km/h to complete stop within 3 seconds, stop for 2 seconds, and then accelerate gradually to 50 km/h again.

4.3 Surrogate safety measures

In 1970s, researcher first attempted to evaluate safety using traffic conflict technique as defined by the shortest time-to-collision (TTC) (Hayward, 1972). TTC refers to the remaining time before two vehicles would collide, if there was no evasive maneuver to avoid a collision. For car-following scenario, there is always a definite TTC when the speed of leading vehicle is lower than that of following vehicle. When the separation reduces or the speed difference increases, value of TTC decline. Value of TTC should be sufficiently small to define a conflict. Threshold of minimum TTC can be defined based on the driver perception-reaction time plus the time required for evasive maneuver to avoid collision. In conventional studies, threshold of minimum TTC ranges from 1 to 5 second (Autey et al., 2012; Sayed et al., 2013; Zheng et al., 2014). To indicate the severity of traffic conflict, two modified TTC-based measures - time exposed time-to-collision (TET) and time integrated time-to-collision (TIT) were developed (Minderhoud and Bovy, 2001). Values of *TET* and *TIT* are sensitive to the threshold of minimum TTC as which a traffic conflict is defined. Threshold of 3 second is adopted for this study (Sayed et al., 2013)[1].

In this study, surrogate safety measures – TET and TIT are depicted in **Figure 4.2**. In particular, TET refers to the duration when a safety-critical situation (i.e. TTC is lower than the threshold) persists, and TIT refers to the integral that gives the area bounded by the TTC curve and TTC threshold (during which TTC is lower than the threshold) respectively. Increases in TET and TIT both indicate the increase in the severity level of traffic conflict. It should be noted that the TET and TIT could become zero when the minimum TTC is higher than the threshold (i.e. 3 second). It implies the absence of traffic

[1] Different thresholds of minimum TTC (from 1 second to 5 second) were considered in preliminary analysis. However, influences on the TET and TIT estimates and modeling results were marginal when reducing the threshold further below 3 second. Hence, threshold of 3 second is considered appropriate.

conflict. Additionally, as shown in Figure 2, brake reaction time refers to time lag for the onset of evasive action (i.e. when the driver of following vehicle presses the brake pedal, tbr) in response to an event (i.e. sudden deceleration of a leading vehicle, tse). Also, standard deviation of lateral position (SDLP) and standard deviation of driving speed (SD_Speed) are employed to assess driver's lateral and longitudinal controls (Chen et al., 2019; Li et al., 2016; Shanmugaratnam et al., 2010). Moreover, average speed and time headway are measured to examine the possible compensatory behaviors (Andrews and Westerman, 2012; Martchouk et al., 2011; Ni et al., 2010).

To sum up, the performance indicators can be classified into three categories: (1) driving capability, i.e. SDLP, SD_Speed, and brake reaction time (BRT), etc.; (2) compensatory behavior, i.e. average speed and time headway, etc.; and (3) safety risk , i.e. TET and TIT, etc. In particular, SDLP, SD_Speed, average speed, and time headway during the five-minute period prior to the onsets of sudden brake, i.e. [0-5) minute and [50-55) minute were measured.

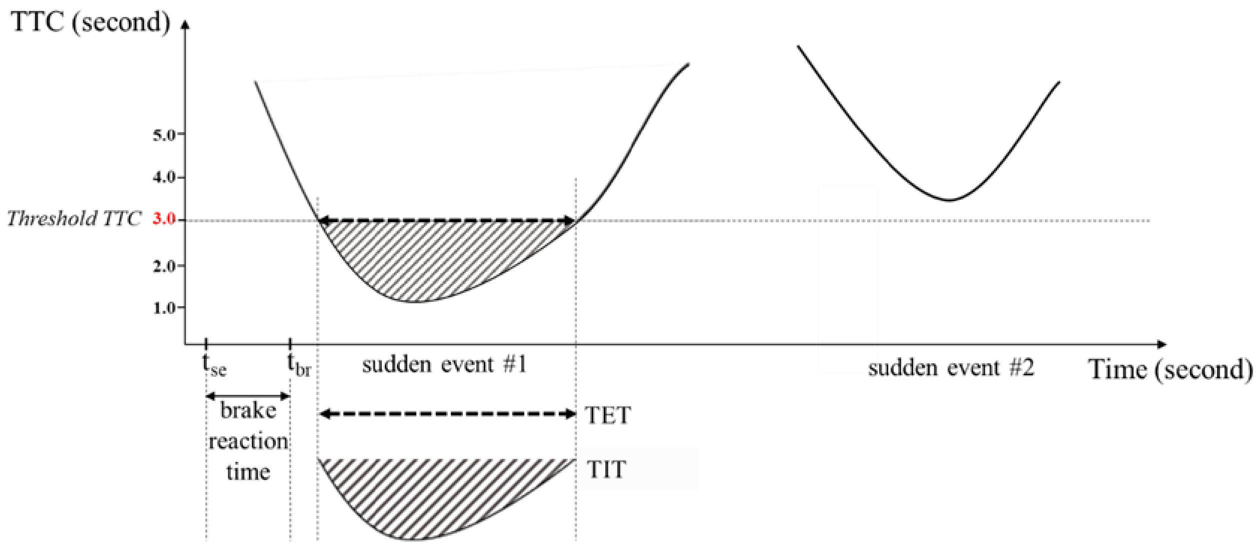


Figure 4. 2 Illustration of proposed driving performance indicators

4.4 Statistical method

To accommodate the censoring nature (either left-censored or right-censored) of dependent variable, Tobit regression was proposed (Tobin, 1958). In road safety research, Tobit regression approach is commonly used to model the crash rate, which is left-censored (Zeng et al., 2017, 2018; Anastasopoulos et al., 2008, 2012). In this study, the surrogate safety measures - TET and TIT, are non-negative, continuous, and left censored at zero. To address the problem of unobserved heterogeneity attributed to repeated observations (at different driving time), random parameter Tobit regression should be applied to measure the association between conflict risk and possible factors including driver age, driving time, and traffic flow condition (Anastasopoulos et al., 2012). Separated prediction models were established for professional and non-professional drivers since the effects of possible factors could be different. For instance, the proposed Tobit model can be specified as,

$$\theta_{it}^{*} = \beta_0 + \sum_{j} \beta_j x_{itj} + \varepsilon_{it} \tag{1}$$

$$\begin{cases} \theta_{it}^{*} = \theta_{it} & if\ \theta_{it} > 0 \\ \theta_{it}^{*} = 0 & if\ \theta_{it} \leq 0 \end{cases}$$

where θ_{it} denotes the performance indicator (i.e. TET and TIT), x denotes the explanatory variable, β denotes the corresponding coefficient, and ε_{it} denotes the independent residual ($\varepsilon_{it} \sim N(0, \sigma^2)$), of ith participant (i = 1, 2, 3, …, 41) and tth event (t = 1, 2) respectively.

The parameters are estimated using maximum likelihood approach. To evaluate the effect of possible factor on the likelihood of traffic conflict, zero sensitivity is estimated using the formulation specified as (Anastasopoulos et al., 2008),

$$\frac{\partial E(\theta')}{\partial x_j} = \beta_j * [1 - z\, \frac{\varphi\ (z)}{\Phi(z)} - \frac{\varphi\ (z)^2}{\Phi(z)^2}] \tag{2}$$

where $E(\theta')$ denotes the expectation of occurrence of traffic conflict (i.e. TET and TIT being greater than zero), z denotes the normalized variable, $\Phi(z)$ denotes the probability distribution function, and $\varphi\ (z)$ denotes the probability density function respectively.

To model the brake reaction time, the random parameter linear model can be specified as,

$$Y_{it} = \beta_0 + \sum_j \beta_j x_{itj} + \varepsilon_{it} \tag{3}$$

where Y_{it} denotes the brake reaction time, *x* denotes the explanatory variable, β denotes the corresponding coefficient, and ε_{it} denotes the independent residual ($\varepsilon_{it} \sim N(0, \sigma^2)$), of *i*th participant (*i* = 1, 2, 3, …, 41) and *t*th event (*t* = 1, 2) respectively.

To access the goodness-of-fit of proposed models, Maddala R^2 and likelihood ratio test statistics would be estimated (Maddala, 1986; Anastasopoulos et al., 2008). In this study, parameter estimations of proposed models are carried out using the software package *NLOGIT 5.0*.

4.5 Results

Table 4.2 summarizes the performances (i.e. driving capability, compensatory behavior, and safety risk) of simulated driving tests, with respect to driver type and age group. As shown in Table 4.2, TIT and TET of older drivers are lower than that of the counterpart. Also, average BRT of mid-aged drivers is lower than that of older drivers.

Table 4. 2 Summary statistics for the simulated driving tests

Scope of work	**Driving performance indicator**	**Professional driver**				**Non-professional driver**			
		Mid-aged		**Older**		**Mid-aged**		**Older**	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Driving capability	SDLP (m)	0.14	0.03	0.15	0.05	0.16	0.04	0.17	0.07
	SD_Speed (km/h)	2.64	1.13	2.61	1.01	2.64	0.84	2.32	0.62
	BRT (s)	1.18	0.32	1.35	0.42	1.26	0.32	1.46	0.47
Compensatory behavior	Average speed (km/h)	51.20	1.25	51.38	1.60	51.91	2.16	50.61	1.26
	Time headway (s)	2.25	0.56	2.50	0.59	2.20	0.44	2.42	0.59
Collision risk	TET (s)	1.32	0.43	0.70	0.63	1.17	0.53	0.78	0.60
	TIT (s^2)	1.10	0.71	0.51	0.68	1.01	0.79	0.63	0.70

4.5.1 Driving capability

In this study, driving capability measures considered are SDLP, SD_Speed, and BRT. SDLP reflects the ability of a driver to maintain lateral stability. Increase in SDLP indicates the degradation of lateral control performance. As shown in **Table 4.3**, traffic flow condition, event time, driver type, and driver age are found significantly associated with the lateral stability all at the 5% level. For instance, SDLP of professional drivers are lower than that of the non-professional drivers. Also, SDLP of older drivers are higher than that of the younger drivers. In addition, SDLP after prolonged driving and under the high traffic flow condition are found to be higher.

On the other hand, SD_Speed reflects the driver's capability of longitudinal control. Increase in SD_Speed implies the incapability to maintain good longitudinal control. As also shown in Table 4.3, SD_Speed when driving under the high traffic flow condition are higher than that when driving under the low traffic flow condition. However, no evidence can be established for the association between longitudinal control, driver type, and driving time. Lastly, BRT of older drivers are significantly longer than that of mid-aged drivers. Also, BRT increase when driving under the high traffic flow condition and after driving for 55-minute, all at the 1% significant level.

4.5.2 Compensatory behaviour

In this study, compensatory behaviour is indicated by the average driving speed and time headway in the car-following task. As shown in **Table 4.4**, separated prediction models are established for professional drivers and non-professional drivers. As shown in Table 4.4(a), there exists difference in the contributing factors to average driving speed between professional and non-professional drivers. For non-professional drivers, driver age and event time significantly affect the average speed, at the 1% level. Results indicate that older non-professional drivers tend to drive at a lower speed in the car-following task, as compared with the mid-aged non-professional drivers. In addition, non-professional drivers would reduce the driving speed after prolonged driving. In contrast, no evidence can be established for the association between the average driving speed of professional drivers and the factors including driver age, driving time, and traffic flow condition. As shown in Table 4.4(b), driver age and traffic flow condition are found associated with the time headway of professional drivers. Older professional and older non-professional drivers tend to keep a longer time headway when following a leading vehicle. In addition, professional drivers tend to keep a longer time headway when driving under the high traffic flow condition.

4.5.3 Safety effectiveness of the compensatory strategy

To indicate the effectiveness of compensatory driving behavior in enhancing driving safety, two safety surrogate measures - TET and TIT are used. **Table 4.5** illustrates the results of random parameter models for the association between safety risk and possible contributory factors. Zero sensitivity indicates to the changes in the likelihood of the prevalence of traffic conflict (i.e. TET and TIT being greater than zero) given the per unit change of possible attribute. As shown in Table 4.5(a), TET of older drivers is significantly lower than that of mid-aged drivers, both for the professional drivers (at the 1% level) and non-professional (at the 5% level) drivers. This implies the lower likelihood of severe traffic conflict of older drivers. In particular, the zero sensitivity of older driver is -3.8% for professional drivers and -2.6% for non-professional drivers respectively. In other words, the compensatory driving behaviors of older drivers are effective in reducing the likelihood of traffic conflict, especially for the professional drivers. Similar findings could be revealed for TIT. Again, as shown in Table 4.5(b), TIT of older drivers is significantly lower than that of mid-aged drivers, both for the professional (at the 1% level) and non-professional (at the 5% level) drivers. Also, reduction in the likelihood of traffic conflict of older professional drivers (-4.0%) is more remarkable than that of older non-professional drivers (-2.8%).

For the effect of time, as shown in Table 4.5(a), TET after driving for 55 minutes is significantly lower than that after driving for 5 minutes among the professional drivers. This implies the reduction in possible collision risk after prolonged driving. Specifically, the zero sensitivity of event time for TET of professional driver is -2.1%. In contrast, no evidence can be established for the relationship between TET and event time among the non-professional drivers. Similar findings are revealed for TIT. Again, as shown in Table 4.5(b), TIT after driving for 55 minutes is significantly lower than that after driving for 5 minutes among the professional drivers, at the 1% level. In particular, the zero sensitivity of event time for TIT of professional driver is -3.3%.

For the effect of traffic flow condition, as shown in Table 4.5(a) and Table 4.5(b), except for the TET of professional driver, the likelihood of severe traffic conflict under the high traffic flow condition is higher than that under the low traffic flow condition, both for the professional and non-professional drivers. In particular, increase in the likelihood of traffic conflict among non-professional drivers (4.2%) is apparently higher than that among professional drivers (2.5%).

Table 4. 3 Estimation results of random intercept models for driving capability

Factor	**Attribute**		**SDLP**		**SD_Speed**		**BRT**	
			Coefficient	**z-statistic**	**Coefficient**	**z-statistic**	**Coefficient**	**z-statistic**
Constant		Mean	0.145**	24.08	2.321**	19.00	0.933**	13.67
		S.D.	0.046**	19.29	0.731**	12.96	0.154**	4.65
Traffic flow condition	High traffic flow *(Control: Low traffic)*		0.011*	2.08	0.305**	2.85	0.269**	4.41
Event time	55 minutes *(Control: 5 minutes)*		0.016**	3.11	0.192	1.76	0.360**	5.69
Driver type	Professional *(Control: Non-professional)*		-0.023**	-4.50	0.146	1.36	-0.075	-1.20
Driver age	Older *(Control: Mid-aged)*		0.014**	2.63	-0.192	-1.80	0.199**	3.20
Unrestricted loglikelihood			147.29		-88.93		-18.90	
Restricted loglikelihood			126.21		-104.99		-40.66	
Likelihood ratio test statistics			42.16**		32.12**		43.52**	

** Statistical significance at the 5% level*

*** Statistical significance at the 1% level*

Table 4. 4 Estimation results of random intercept models for compensatory behavior

(a) Average speed

Factor	Attribute		Professional driver Coefficient	Professional driver z-statistic	Non-professional driver Coefficient	Non-professional driver z-statistic
Constant		Mean	51.338**	143.74	52.134**	129.03
		S.D.	0.792**	3.37	1.165**	6.65
Traffic flow condition	High traffic *(Control: Low traffic)*		-0.011	-0.03	0.582	1.50
Event time	55 min *(Control: 5 min)*		-0.261	-0.69	-1.084**	-2.63
Driver age	Older *(Control: Mid-aged)*		0.178	0.46	-1.299**	-3.41
Unrestricted loglikelihood			-65.09		-81.27	
Restricted loglikelihood			-66.45		-90.08	
Likelihood ratio test statistics			2.72		17.62**	

** Statistical significance at the 5% level*
*** Statistical significance at the 1% level*

(b) Time headway

Factor	Attribute		Professional driver Coefficient	Professional driver z-statistic	Non-professional driver Coefficient	Non-professional driver z-statistic
Constant		Mean	2.038**	14.79	2.264**	22.15
		S.D.	0.371**	5.75	0.376**	6.96
Traffic flow condition	High traffic *(Control: Low traffic)*		0.302*	2.42	-0.129	-1.25
Event time	55 minutes *(Control: 5 minutes)*		0.099	0.78	0.010	0.09
Driver age	Older *(Control: Mid-aged)*		0.276*	2.18	0.216*	2.05
Unrestricted loglikelihood			-25.38		-28.36	
Restricted loglikelihood			-32.76		-34.33	
Likelihood ratio test statistics			14.76*		11.94*	

** Statistical significance at the 5% level*
*** Statistical significance at the 1% level*

Table 4. 5 Estimation results of random parameter Tobit models for safety risk

(a) TET

Factor	**Attribute**		**Professional driver**		**Non-professional driver**	
			Coefficient	**Zero sensitivity**	**Coefficient**	**Zero sensitivity**
Constant			1.38**	--	1.05**	--
Traffic flow condition	High traffic *(Control; Low traffic)*		0.29	--	0.44*	2.31%
Event time	55 minutes *(Control: 5 minutes)*		-0.40**	-2.14%	-0.28	--
Driver age	Older *(Control: Mid-aged)*	Mean	-0.72**	-3.84%	-0.50*	-2.63%
		S.D.	0.58**		0.52**	
Unrestricted loglikelihood			-30.53		-39.64	
Restricted loglikelihood			-41.42		-47.71	
Likelihood ratio test statistics			21.78**		16.14**	
Maddala R^2			0.44		0.31	

** Statistical significance at the 5% level*
*** Statistical significance at the 1% level*

(b) TIT

Factor	**Attribute**		**Professional driver**		**Non-professional driver**	
			Coefficient	**Zero sensitivity**	**Coefficient**	**Zero sensitivity**
Constant			1.18**	--	0.75*	
Traffic flow condition	High traffic *(Control: Low traffic)*		0.47**	2.48%	0.78**	4.15%
Event time	55 minutes *(Control:5 minutes)*		-0.63**	-3.34%	-0.40	--
Driver age	Older *(Control: Mid-aged)*	Mean	-0.76**	-4.00%	-0.53*	-2.79%
		S.D.	0.64**		0.52**	
Unrestricted loglikelihood			-36.84		-46.57	
Restricted loglikelihood			-42.26		-54.74	
Likelihood ratio test statistics			10.84**		16.34**	
Maddala R^2			0.25		0.31	

** Statistical significance at the 5% level*
*** Statistical significance at the 1% level*

4.6 Discussion

This study attempts to investigate the compensatory behavior of professional drivers, coping with the elevated safety risk attributed to ageing, using the driving simulator study. Many modern societies are facing the problem of ageing population. The proportion of older peoples who hold driving licensing has been increasing rapidly. There is great concern for the prevalence of older drivers in the transport sector, since the drivers' physiological and cognitive performances may deteriorate with the increase in age. However, as evidenced in this study, older drivers could reduce the anticipated risk by compensatory behaviors, such as intentionally reducing the speed and increasing the time headway when following a car. Furthermore, professional drivers usually have better driving skills, such as detecting the road hazards and adapting for the demanding driving task. This research provides a significant contribution to furthering our understanding of the safety of older professional drivers by filling the knowledge gap on the difference in compensatory driving behavior between professional and non-professional drivers.

This study found that degraded lateral control performance and longer brake reaction time among older drivers, as compared with mid-aged drivers. This aligns with the previous findings that driving performance deteriorates with age because of the impairments on physical and cognitive performance (Biernacki and Lewkowicz, 2020; Chen et al., 2019; Andrews and Westerman, 2012; Shanmugaratnam et al., 2010). Indeed, older drivers tend to have longer perception-reaction time. It could then result in the delay and even absence of evasive maneuver (Islam and Mannering, 2006; Yan et al., 2005).

However, this study also found that older drivers tend keep a longer time headway and lower driving speed in the car-following tasks. Such findings justify that compensatory behavior is prevalent among the older drivers (Dykstra et al., 2020; Molnar et al., 2008). Indeed, previous studies revealed that older drivers tend to compensate for the elevated crash risk resulted from cognitive impairment by reducing the driving speed and increasing the time headway in car-following process (Bao et al., 2020; Martchouk et al., 2011; Ni et al., 2010; Shinar et al., 2005). Furthermore, it is revealed that compensatory behaviors (e.g. to keep a longer time headway) are more effective in reducing the safety risk of older professional drivers, as compared to the non-professional drivers.

Above finding indicates that age should not be the only consideration for human resource management of transport operators. For example, some bus drivers in Hong Kong are compelled to work part-time or retire when they reach their 60s, without undergoing any health and driving capability assessment. This study also provides useful insights into the driver licensing policy for the transport authority. Licensing requirements for older drivers vary among jurisdictions. Policy strategies including shortened time intervals between license renewals, mandatory health assessments, visual acuity checks and driving tests, and defensive driving courses for older drivers are implemented (Transport Department of HKSAR, 2020; Transport for New South Wales, 2015; Thomas et al., 2013). It would be of essence to assess the capability of compensatory strategy of older drivers in the driving tests for license renewals. In addition, older professional drivers can shed some light on the driving skills for the younger cohorts.

4.6.1 Effective compensatory strategy of professional drivers

The findings of this study showed that older professional drivers showed a greater reduction in the likelihood of traffic conflict. In other words, the compensatory strategy adopted by the older professional drivers is more effective as compared with the older non-professional drivers. This is consistent to the findings of previous studies that existence of compensatory strategy is closely related to driving experience (Farrow and Reynolds, 2012; Andrews and Westerman, 2012). Professional drivers are good at identifying hazards since they have higher exposure on roads. Therefore, their driving performances are better than that of non-professional drivers (Borowsky and Oron-Gilad, 2013). As experience accumulated over times, older professional drivers can maintain the satisfactory driving performance (Newnam et al., 2018; Chen et al., 2019). While a recent study reported that the driving experience of older professional drivers can not compensate for their reaction slowed down by aging (Medic-Pericevic et al., 2020), our results provide evidence of effective compensatory strategy reducing their safety risk. Findings of this research contribute further to the literature on the safety of older professional drivers from the behavioral perspectives. Transport operators can develop tailored management strategies for older drivers to keep the drivers in the workforce for as long as safely possible (Newnam et al., 2020; Newnam and Watson, 2011). For example, regular assessments of cognitive performance and driving skills (including effective compensatory behaviors) for the older drivers can be implemented. In addition, training courses and driver enhancement programs on hazard identification and defensive driving skills can be provided. Yet, it is worth exploring the relationship between driver performance, safety perception and hazard identification skills based on cognitive assessment and perception survey in the extended study (Chen et al., 2020).

4.6.2 Strategic adaptation of professional driver

Strategic adaptation refers to the intentional modification of driving behavior to adapt for the prolonged driving or hazardous conditions. It is expected that strategic adaptation of professional drivers is more prevalent than the non-professional drivers, and the elevated crash risk of professional drivers after prolonged driving can be marginal. For the effect of driving time, our results showed the impaired lateral control and longer brake reaction time after driving for 55 minutes, as compared with those after 5 minutes. This could be attributed to the existence of possible psychological fatigue. As also indicated in previous driving simulator studies, greater variations in lateral position, longitudinal speed and steering angle were observed after driving for 30 to 60 minutes (Chen et al., 2019; Ting et al., 2008; Otmani et al., 2005). Interestingly, despite the degraded driving performance and slower response over time, results indicate that the likelihood of traffic conflict of professional drivers remarkably reduced after driving for 55 minutes, while there was no such finding for the non-professional drivers. One possible explanation is that professional drivers adopted strategic adaptation – that is, adjusting their behaviors to accommodate the driving task. For example, professional drivers may adapt to the situation by reducing the driving speed where appropriate (Smiley and Rudin-Brown, 2020; Williamson et al., 2002; Cnossen et al., 2004). In particular, detection of possible fatigue and potential road hazards could trigger the strategic adaptation of professional drivers (Filtness et al., 2012; Williamson et al., 2014). Meng et al.'s (2015) study suggests that professional drivers are usually more confident in coping with fatigue given the rich experience in long driving and working time. Moreover, Iseland et al.'s (2018) study affirms that long-haul truck drivers usually engage in various secondary tasks intentionally to get rid of the tedious driving task and maintain the level of alertness. Just, no evidence could be established for the association between prolonged driving time and presence of adaptation behaviors (e.g. reduction in driving speed or increase in time headway) among the professional drivers in this study. As such, it is worth exploring the adaption behavior of professional driver using alternate behavioral and psychological metrics in the extended study.

Moreover, current study also considers the effects of traffic flow condition on the driving capability, compensatory behavior, and safety risk. Results indicate the increase in brake reaction time, and the degradations in lateral and longitudinal controls when driving under high traffic condition. It could be attributed to the increase in visual stimuli and mental workload, given the increase in surrounding vehicular traffic and pedestrian (Cantin et al., 2009). However, though professional drivers tend to adopt the longer time headway under the high traffic condition, current results indicate that their safety risk still increases. It is worth exploring the relationship between traffic volume, strategic adaptation and potential crash risk based on empirical observation survey in the extended study.

4.6.3 Study limitations

The findings from this research should be interpreted in the context of the limitations. First, the ability of simulator studies to reflect realistic driving is often questioned. However, many previous studies have demonstrated the absolute and relative validity of the simulator experiment (Wynne et al., 2020; Meuleners and Fraser, 2015). Moreover, the real-world driving data have been successfully explained by the findings from the simulator research (Saifuzzaman et al., 2015). In this study, a high-fidelity driving simulator was used. The driving scenario replicating the local environment in Hong Kong was created with high-resolution images trying to simulate the real-life scenery as much as possible. Nevertheless, naturalistic driving studies could aid in understanding the interaction between the compensatory strategy of older drivers and the increased driving experience of professional drivers.

Second, as compared with the random parameters linear model, hazard-based duration models can be applied to analyse drivers' reaction times to improve the estimation accuracy in future study (Ali et al., 2019; Choudhary and Velaga, 2017). For example, Haque and Washington (2014, 2015) used a parametric accelerated failure time (AFT) duration model with a Weibull distribution to identify the factors affecting drivers' reaction times. Results confirmed that the Weibull-AFT model with gamma heterogeneity showed the best statistical fit.

Third, the cognitive ability of older drivers is not examined in current study. As compensatory strategy is prevalent for the drivers who have known cognitive impairment, traffic violation and crash involvement records (Wong et al., 2012; Molnar et al., 2008; Charlton et al., 2006), it is worth collecting the data of safety perception, hazard identification skills, and cognitive ability. Therefore, the association between these human factors and compensatory strategy of older professional drivers can be measured.

Forth, the driving simulator experiment in this study involves the car-following task for one hour. Presence of strategic adaptation is examined based on the changes in driving performances between two time points (i.e. 5 minute and 55 minute). Despite that possible driving simulator sickness can be avoided, one-hour drive may not be sufficient to induce driver fatigue. In the extended study, it is possible to investigate the strategic adaptation behaviors of long-haul drivers using naturalistic driving study (Mahajan et al., 2019). Moreover, car following behavior of professional drivers at work could be influenced by time pressure and market competition. However, it is not possible to incorporate the effect of work pressure in the driving simulator study. In the extended study, it is worth exploring the effect of work pressure when comprehensive information is available using naturalistic driving study. Also, robustness of the results can be improved when the sample size of each experimental group increases.

4.7 Concluding remarks

This simulator study investigated the effectiveness of the compensatory strategy adopted by older professional drivers as compared with older non-professional drivers. Specifically, the safety effects of compensatory behaviors on the rear-end conflict risk were examined. Two modified traffic conflict measures: time exposed time-to-collision (TET) and time integrated time-to-collision (TIT) were adopted to indicate the risk of severe rear-end traffic conflict in the car-following tasks. Possible changes in the conflict risk could indicate the effectiveness of compensatory strategy. Results reveal the longer brake reaction time and greater variability in lateral position of older drivers as compared with the mid-aged drivers, while the time headway of older drivers is longer. This demonstrates the degradation in driving capability and the presence of compensatory behavior among older drivers. More importantly, the effectiveness of compensatory strategy is more profound among the older professional drivers, as compared to the older non-professional drivers, given that the reduction in conflict risk among professional drivers is more remarkable. The focus of existing research has tended to be on the compensation mechanism of older drivers while few have considered that of the older professional drivers. As anticipated, older professional drivers are able to adopt more effective compensatory strategy to reduce the rear-end crash risk by capitalizing on their rich experience. In the near future, the proportion of older drivers in the transportation industry would continue to increase and older drivers would become a major cohort. Findings of this research provide useful insights into the driver management strategies tailored for older drivers. For example, not only the regular health checks, but also the comprehensive assessments of cognitive performance and driving skills for older drivers should be introduced. Furthermore, special training program that can improve the hazard identification and defensive driving skills of professional drivers will be of essence. Yet, it is worth investigating the effectiveness of driver education and training in improving the safety of older professional drivers in the long run.

Chapter 5 Perceptions and attitudes of professional drivers

5.1 Introduction

In this study, we examine the effectiveness of a fixed ASEC system in Hong Kong to deter speeding. While Hong Kong employs a combination of human agent-based mobile speed enforcement mechanisms as well as a fixed ASEC system, the focus will be on a fixed ASEC system in this paper. In Hong Kong, the shares of speed enforcement prosecutions based on human agent-based mobile speed enforcement and a fixed ASEC system are about the same (Hong Kong Police Force, 2018). From time to time, strong public sentiment has been expressed to expand the ASEC system as a means not only to enhance the deterrent effect, but also to reduce the costs associated with police human resources. In this context, it become particularly imperative to evaluate the impacts of alternative designs for such an expanded ASEC system. While there may be benefits to supplementing an expanded automation-based ASEC speed enforcement mechanism with a much smaller base (relative to today) of human-based enforcement mechanisms, examining the possible optimal combination of investments in such fused mechanisms is not considered here. In any case, society has consistently moved closer to automation in traffic operations, and it is not inconceivable at all that there will be a time in the near future when no human-based resources (police personnel) will be invested on the task of field monitoring of speed for enforcement purposes.

Four main attributes associated with threat and coping appraisals related to an ASEC system are evaluated in the paper: DOP penalty, fine levels, camera-to-housing ratio (explained in detail later), and the placement of the warning sign. Among these four attributes, the first three may be considered to be associated with threat appraisal, while the last may be considered to be associated with coping appraisal (for instance, if a warning sign is placed farther away from the camera location, it may provide individuals with more time to absorb the information and act to adjust their speed to comply with the speed limit before arriving within the range of the camera detection zone). A stated preference experiment is conducted by developing scenarios that combine the attribute levels of the four attributes just identified. The scenarios are presented to professional drivers, who are asked to respond by choosing a speed level at which they would travel on a 50 km/h road at each of three sections of a roadway (corresponding to a standard section with no enforcement and no warning, a warning section that starts from 23 meters ahead of the placement of a warning sign, and the camera housing section itself in which a camera detects speeding violations).

Driver perceptions regarding speeding consequences and driving history (current level of DOP points, whether received a speeding ticket in the past 12 months, and exposure to ASEC systems when driving), as well as driver demographic characteristics and employment characteristics, are also collected in the survey. These variables are considered as direct influencers of travel speed as well as moderating the impact of the four main attributes of the SP experiment (to capture inter-individual differences in perceptions of threat appraisal and coping appraisal of speed enforcement, as well as overall intentions to speed or not and general attitudes toward the risks travel speeding poses to society). In doing so, we attempt to recognize the direct and moderating effects of driver characteristics on travel speed levels, and contribute further to the literature on the effectiveness of speeding enforcement mechanisms. Many earlier studies of enforcement mechanisms, on the other hand, have considered drivers as a single monolithic group or considered variations across drivers in a relatively limited manner. In addition, unlike many other earlier studies on professional driver speed decisions, we consider unobserved individual-specific heterogeneity to accommodate unobserved individual factors that are likely to influence speed choices. Such heterogeneity is important to consider in travel choice and safety studies to ensure consistent estimation of model parameters (see, for example, Mannering et al., 2016).

In this chapter, Section 5.2 and 5.3 discusses the stated preference survey used for data collection as well as the methodology for our analysis, respectively. Section 5.4 provides a description of the sample used in the analysis. Section 5.5 presents the results. Section 5.6 concludes the paper with a summary of the findings and policy implications.

5.2 Stated preference survey design

The data used in the current analysis is drawn from a face-to-face survey conducted during the period from October 2018 to February 2019 (months inclusive). Our emphasis on a face-to-face survey is to avoid respondent biases that may accrue from less expensive web-based and other social media-based surveys. The professional driver participants were approached either at on-road parking areas (e.g. public bus, taxi, and public light bus stations) or outside the licensing offices of the Hong Kong Transport Department. The inclusion criteria were (1) having valid licences of bus, minibus, taxi or goods (cargo) vehicles, and (2) driving for income, either full-time or part-time. Prior to the survey, the ethical approval from the Human Subjects Ethics Sub-committee (HSESC) of the Hong Kong Polytechnic University was obtained.

The questionnaire had three sections: (1) SP questions regarding speed choices, (2) Driving history and safety perceptions, and (3) Demographics and employment characteristics of professional drivers. The SP part is discussed in the next section. The second section collected information on the involvement with traffic offences and crashes, attitudes towards different speed enforcement measures, and actual experience with speed enforcement. The third section collected information on driver demographics (gender, age, education, marital status, and income) and employment characteristics (salary system, driving hours per day etc.)

In this study, drivers' perceptions and attitudes towards the deterrent effect of enforcement and penalty against speeding was gauged using their stated speed choices in an SP survey design. SP surveys have been widely applied to evaluate the effects of enforcement strategies and speeding penalties on the propensity for traffic offences by measuring the driver's response under hypothetically constructed conditions (Hössinger and Berger 2012; Li et al., 2016; Ryeng, 2012; Wong et al., 2008). The SP questions in the current paper are based on the scenario of driving on an urban road with a speed limit of 50km/h. For each question, three speed choices are presented to drivers for each of three location sections. The location sections are defined as follows: (1) a standard section, defined as one with neither ASEC-based speed enforcement and nor warning signs of such enforcement, (2) a warning section, defined as the road section indicating the presence of speed camera housing unit ahead (this section starts 23 meters ahead of the warning sign and ends at the location of warning sign; the design of the section length is based on the vision standard for the driver licensing requirement in Hong Kong), and (3) a camera section, defined as being within the range of speed violation detection by the camera (this section starts 23 meters ahead of a camera housing unit and ends at the location of the housing; see **Figure 5.1**). The three speed choices (one to be selected) are: (1) comply with the prescribed speed limit; (2) exceed the prescribed speed limit by 15 km/h or less (traveling at 51-65 kms./hour, corresponding to <u>speeding range 1</u>); and (3) exceed the prescribed speed limit by more than 15 km/h but less than or equal to 30 km/h (traveling at 66-80 kms./hour, corresponding to <u>speeding range 2</u>). Thus, for each SP question presented, the respondent makes a speed choice at each of the three location sections, providing three choices.

In each of the SP questions presented to respondents, four attributes are used to characterize the choice context: (1) Driving Offence Points (DOP) for different ranges of speeding infractions, (2) Monetary fines for different ranges of speeding infractions, (3) Camera-to-housing ratio, and (4) placement of the warning sign that determines the distance of the warning section. A screenshot of the content and format of a sample SP question is provided in **Figure 5.1**.

The levels of the first attribute - DOP – were set by pivoting off the current DOP for each of the two speed infraction ranges (of course, there are no DOPs for being within the speed limit). The current DOPs are zero for speeding range 1 and three for speeding range 2. We used these base DOPs and also introduced a higher DOP level of two for speeding range 1 and a DOP level of five for speeding range 2. Thus, for each speeding range, there are two possible DOP levels, and across the two speeding ranges, there are a total of four possible DOP levels.

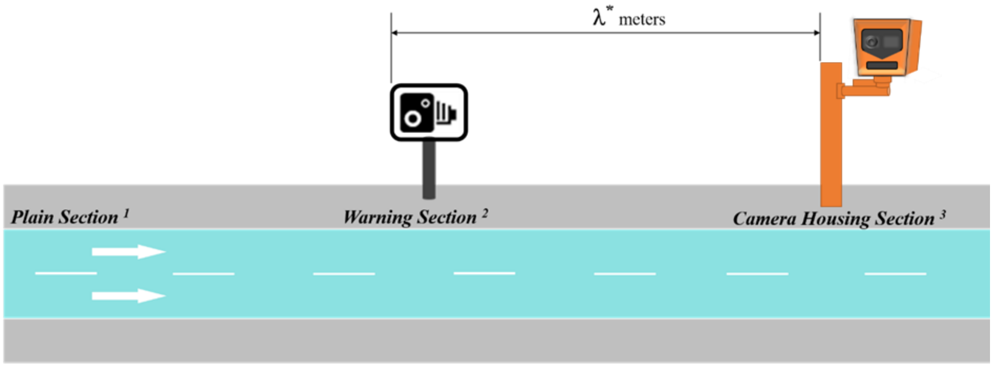
The levels of the second attribute – monetary fine – were also set based on the current fine levels of 320 HKD (about US $40) for speeding range 1 and 450 HKD (about US $57) for speeding range 2. Again, we used these base fine levels, and also introduced increased levels of 420 HKD (about US $54) for speeding range 1 and 550 HKD (about

US $ 70) for speeding range 2. Across the two speeding ranges, there are a total of four possible fine levels.

In Hong Kong, not all the camera housings necessarily contain a speed camera, to save on costs (both installation and operating costs). Thus, while Hong Kong laws require that citizens be informed of any camera locations, it is not required that all the announced camera locations necessarily have an actual functional camera. Dummy camera housing boxes are allowed to be installed. However, the ratio of actual speed cameras to camera housings must be publicized. The current ratio of speed camera-to-housing is 1:6. In particular, there are 20 speed cameras and 120 housings across the entire territory of Hong Kong (Audit Commission of HKSAR, 2013). Four levels of the third attribute -- camera-to-housing ratio -- are set out by either increasing the number of housings or increasing the number of cameras: 20:240, 20:120 (status quo), 40:120, and 60:120. An analysis of how Hong Kong professional drivers respond to different camera-to-housing levels can inform speed enforcement strategies considering the economic constraints of the transport authority.

Finally, four levels of the fourth attribute associated with the placement of the warning sign are considered: 50 meters, 100 meters, 150 meters, and 200 meters upstream of the speed camera housing (see **Figure 5.1**). According to the Transport Department, to remind drivers of the presence of a speed enforcement camera ahead, the distance between the camera housing unit and the warning sign is about 100m for most of the enforcement sites. Exploring the effect of the placement of the warning sign helps better understand alternative coping mechanisms, and can provide insights regarding the optimal placement of the warning sign that can minimize the “Kangaroo effect” associated with speed cameras.

Scenario 1:



1 No enforcement and no warning signs in roadway section
2 Warning sign indicating the presence of speed camera housing unit ahead
3 Camera housing unit present in roadway section

* Warning sign is placed λ meters ahead of the housing unit

Background information		**Speed（km/h）**		
		< **50**	**51 - 65**	**66 - 80**
Penalty for speed violation	➢ DOPs ➢ Fine	0 0	0 HK$ 320	3 HK$ 450
Camera-to-Housing ratio		20 cameras in 240 housing units		
Location of the warning sign		Warning sign placed 50 meters ahead of housing unit		

If you are at the **Standard section**, at which speed range would you travel? (choose one option from below)

□ **≤ 50 km/h** □ **51-65 km/h** □ **66-80 km/h**

If you are at the **Warning Section**, at which speed range would you travel? (choose one option from below)

□ **≤ 50 km/h** □ **51-65 km/h** □ **66-80 km/h**

If you are at the **Camera Housing Section**, at which speed range would you travel? (choose one option from below)

□ **≤ 50 km/h** □ **51-65 km/h** □ **66-80 km/h**

Figure 5. 1 Illustration of the location type and a hypothetical scenario for the stated preference game

All the levels for each of the attributes were tested extensively for reasonability in pilot surveys, and several changes were made before arriving at the final levels. In all, the SP experiments have four factors, each with four levels. If the full factorial design were considered, there would be 256 (4 × 4 × 4 × 4) combinations of factor attributes in total for the SP question. It is however not efficient and feasible to gauge the drivers' perceptions and attitudes if all the 256 combinations of scenarios are used. Therefore, an orthogonal fractional factorial design (Bhat and Sardesai, 2006; Hössinger and Berger, 2012; Lavieri and Bhat, 2019; Li et al., 2014) was adopted to reduce the number of combinations from 256 to 16. Further, our design enabled us to estimate models that are more general than the multinomial logit model by maintaining factor orthogonality within and between alternatives. Our design allowed for the estimation of main effects of attributes, as well as two-way interaction effects between attributes and respondent characteristics. Next, we developed a block design of four sets of four SP scenarios, because it would be too much burden to ask each respondent to answer 16 SP questions. Each participant was then presented with one of the four blocks of four SP scenarios in the survey. The entire survey instrument is available at http://www.baige.me/v?i=RxE.

5.3 Data collection and sample used

A total of 401 professional drivers completed the questionnaire survey. Therefore, the dataset has a total of 401×12=4,812 SP choice occasions, with 1,604 choice occasions at each of the three location sections (standard, warning, and camera). The distribution of the dependent variable was as follows within the 1,604 choice occasions, as also shown in **Table 5.1**: (1) Standard section – Not speeding (14.1%), Speeding Range 1 (71.2%), and Speeding Range 2 (14.7%), (2) Warning section – Not speeding (57.2%), Speeding Range 1 (40.0%), and Speeding Range 2 (2.8%), (3) Camera housing section – Not speeding (99.8%), Speeding Range 1 (0.2%), and Speeding Range 2 (0%). As can be observed from these descriptive statistics, drivers combine their threat and coping appraisals due to which a large proportion of them are generally willing to speed at the standard section (at least at speed range 1), but are more likely to adhere to the speed limit at the camera housing section. Indeed, there is literally no variation in adherence at the camera housing section regardless of the levels of DOP, monetary fine, camera-to-housing ratio, warning sign placement, as well as driver characteristics. Thus, we drop the 1,604 choice occasion observations corresponding to the camera housing section in our analysis, because they do not contribute to understanding the effects of independent variables on speeding ranges. The final sample for analysis includes the 3208 choice occasions at the standard and warning sections.

Table 5. 1 Distribution of speed choices by location type

Section	**Speed choice**					
	Speed compliance (≤50 km/h)		Speeding range 1 (51-65 km/h)		Speeding range 2 (66-80 km/h)	
	Count	*%*	*Count*	*%*	*Count*	*%*
Standard	226	14.1	1142	71.2	236	14.7
Warning	918	57.2	641	40.0	45	2.8
Camera Housing	1600	99.8	4	0.2	0	0

Table 5.2 shows cross-tabulations of the four SP attributes with speed choice percentages at each of the standard and warning sections. As expected, increasing the DOP penalty by two points decreased the percentage of drivers choosing for speeding range 1 and speeding range 2 in the standard section. Further, increasing the DOP penalty by two points for both speeding levels led to a greater percentage of drivers complying with speed limit. The descriptive statistics do not show a clear trend of the speed choices with respect to increasing monetary fines. Interestingly, in the standard section, it seems that a greater proportion of drivers choose to speed when the fine is increased. More discussion on this will follow in the model results section. In the context of camera-to-housing ratio values, an increase in the ratio from status quo (20:120) to 40:120 shows a greater decrease in the percentage of drivers choosing speed ranges 1 or 2 than that from increasing the ratio further to 60:120. It appears that the bang per buck is greater for increasing the ratio from 20:120 to 40:120 than that to 60:120. As for the placement of warning sign, there is a monotonous trend of increasing percentage of speed compliance choice with decreasing distance between the warning sign and the camera housing location.

Of course, the discussion above does not consider differential effects of the SP attributes based on observed and unobserved driver characteristics, which is the focus of the multivariate model results in Section 5.4.

Table 5. 2 Crosstabulation of SP attributes with speed choices at plain and warning sections

Factor	**SP attribute level for different speeds (<50kmph, 51-65kmph, 66-80kmph)**			**Speed choice %**					
				Standard section			**Warning section**		
				Speed compliance	Speeding range 1	Speeding range 2	Speed compliance	Speeding range 1	Speeding range 2
	≤50	51-65	66-80 km/h						
DOPs	0	0	3 (status quo)	13.2%	69.6%	17.2%	54.6%	2.6%	2.8%
	0	0	5	12.0%	73.6%	14.4%	52.5%	3.8%	3.7%
	0	2	3	13.2%	68.6%	18.2%	53.7%	4.3%	2.0%
	0	2	5	15.5%	73.1%	11.4%	68.1%	9.2%	2.7%
Monetary fine (HK$)	0	320	450 (status quo)	11.8%	73.3%	14.9%	54.8%	1.3%	3.9%
	0	320	550	15.2%	64.6%	20.2%	57.4%	9.9%	2.7%
	0	420	450	14.5%	78.6%	6.9%	59.9%	8.7%	1.4%
	0	420	550	15.0%	67.3%	17.7%	56.9%	0.1%	3.0%
Camera-to-Housing ratio	20:240			12.7%	71.8%	15.5%	57.9%	8.7%	3.4%
	20: 120 (status quo)			13.5%	67.3%	19.2%	55.6%	0.1%	4.3%
	40:120			13.7%	72.6%	13.7%	58.4%	8.7%	2.9%
	60:120			16.2%	72.1%	11.7%	56.1%	2.4%	1.5%
Placement of warning sign	50m upstream			--	--	--	77.8%	2.2%	0%
	100m upstream (status quo)			--	--	--	65.3%	1.2%	3.5%
	150 m upstream			--	--	--	43.1%	3.9%	3%
	200m upstream			--	--	--	42.6%	1.6%	5.8%

5.3.1 Driver demographics and employment characteristics

Table 5.3 presents the demographic and other characteristics of the 401 participants, beginning with the demographic characteristics in the first set of rows. All participants of this study are male. This is consistent with the distribution of employed persons by occupation and gender in the population census dataset, which indicates that 97% of workers in the machine operation sector are male (Census and Statistic Department, 2018a). Although the information on the official registry of professional drivers in Hong Kong is not available, male drivers are believed to dominate the transport sector. The age distribution of our sample is close to that of the driving licensing record of general drivers in Hong Kong (Transport Department, 2017a). In terms of educational background, 79% of the drivers in our sample have attained at least secondary education (the closest possible comparison at the Hong Kong-wide level is that 89% of male workers in Hong Kong have attained secondary education (Census and Statistic Department, 2018b). In our sample, 73% of the drivers were married (the closest possible comparison is the most updated marital status statistics in Hong Kong, which indicates that 62% of the males are married (Census and Statistic Department, 2018c). Interestingly, almost all (395 of the 401) drivers provided their monthly income values. For the remaining six drivers who did not provide this information, we imputed the income values based on the procedure discussed in Bhat (1997). A little over 31% of the drivers have a monthly income below HK$ 15,000 and a little over 21% of the sample earn over HK$ 20,000.

Table 5. 3 Distribution of the sample

Variable	**Count**	**%**
Demographics		
Gender (Male)	401	100%
Age		
Older (>55 years old)	98	24.4
Younger (<45 years old)	151	37.7
Mid-aged (46-55 years old)	152	37.9
Education		
Primary or below	84	20.9
Secondary or above	317	79.1
Marital status		
Married	293	73.1
Unmarried	108	26.9
Monthly income		

less than 15K	127	31.7
Between 15K and 20K	183	45.6
More than 20K	85	21.2
Operational characteristics		
Salary system		
Trip-based	136	33.9
Monthly-based	126	31.4
Others (hourly or shift based)	139	34.7
Daily driving hours		
More than 9 hours	168	41.9
Less than 8 hours	39	9.7
8 to 9 hours (normal working hours)	194	48.4
Work time per week		
less than or equal to 48 hours	184	45.9
more than or equal to 63 hours	37	9.2
Others	179	44.9
Vehicle type		
Bus	67	16.7
Taxi and Red Minibus	157	39.2
Green minibus	56	14.0
Goods vehicle	121	30.2
Driver history and safety perceptions		
Received speeding ticket(s)		
Yes	99	24.7
No	302	75.3
Perceive speeding as a cause of injury		
High	281	70.1
Low	6	1.5
Neutral	114	28.4
Perceive speeding cameras are effective		
High	270	67.3
Low	24	6.0
Neutral	107	26.7
Frequency of sighting cameras		
High (7-10 times in 10 trips)	250	62.3
Medium (4-6 times in 10 trips)	98	24.4
Low (0-3 times in 10 trips)	53	13.3

Drivers' employment characteristics are presented in the next set of rows in the table. The salary system of professional drivers is stratified into three categories: (i) trip-based (34% of the sample), (ii) monthly-based (31%), and (iii) others (hourly or shift based, 35%). The trip-based drivers are self-employed, and their incomes vary greatly with the number and distance of trips made (e.g. taxi, red minibus and light van drivers). The drivers who are paid on a monthly basis are usually regular employees of a large corporation or transport operator, such as the franchised bus companies and logistic firms. The hourly or shift based drivers are usually (full-time or part-time) employees of small transport operators, such as the green minibus. Their salaries vary greatly with the daily working time. As for the daily driving hours, 8% of our sample drive for less than or equal to 7 hours per day while 42% of them drive for more than 9 hours daily. The corresponding statistic from official reports is not accessible. The closest possible comparison is that 51% of bus drivers in Hong Kong drive for more than 9 hours daily (Legislative Council of HKSAR, 2018). In terms of weekly working hours, 46% of drivers in our sample work for 48 hours or less per week, which is comparable to the 50% of employees in the transport sector who work for less than or equal to 48 hours a week. However, only 9% of our sample work for more than or equal to 63 hours per week, while the corresponding percentage in the transport sector is close to 25% (Census and Statistic Department, 2018b). The commercial vehicles driven by our sample are categorized into four types – bus, green minibus, taxi and red minibus, and goods vehicles (accounting for 17%, 14%, 39%, and 30% of the sample respectively). The official distribution for the vehicle types of the commercial vehicle fleet in Hong Kong is not accessible.

Overall, the characteristics of drivers in the sample are reasonably close to general expectations for Hong Kong professional drivers, at least based on the latest statistics gleaned from the Census. Of course, one cannot be conclusive of the true representativeness of our sample because there is no official registry of professional drivers in Hong Kong, and the closest comparison we are able to make is with the population census demographics for people employed in the transport sector.

5.3.2 Driver history and safety perceptions

The last set of rows in Table 5.3 report the descriptive statistics for driving history and safety perceptions of the 401 participants, which might influence how they would respond to the SP choice questions. As can be observed from these rows, 25% of the interviewed professional drivers have received at least one speeding ticket in the recent past. 70% of the drivers perceived speeding as a cause of injury while only 1.5% perceived a small effect of speeding on traffic injuries. As for the perception on effectiveness of cameras, 67% of drivers believed that speeding cameras are effective in catching offenders, while a smaller percentage (6%) perceived low effectiveness of this enforcement technique. The frequency of drivers sighting camera housings was also collected in terms of the number of times a driver would sight camera housings in 10 trips. It appears that a majority (62%) of the drivers do usually visually locate camera housings at a frequency of at least 7 times in 10 trips.

All the above driver history and perception variables are likely to influence drivers' responses to the SP choice questions. Also, while we make no claim of our sample being representative of the population of professional drivers, there is no reason to believe that the individual-level relationship we develop between speed range choices and SP attributes/driver characteristics would not be applicable for the general population of professional drivers.

5.4 Statistical method

In this study, we formulate a panel mixed multinomial logit (or MMNL) model for the speed choice of professional drivers. The panel MMNL model formulation accommodates heterogeneity across individuals due to both observed and unobserved individual attributes, while also recognizing correlations among the different observations of a same individual. In the following discussion of the model structure, we will use the index q ($q = 1, 2, \ldots, Q$) for the decision-makers, i for the speed alternative ($i = 1, 2, \ldots, I$) and k for the choice occasion, *i.e.* SP choice occasions for a particular decision-maker, ($k = 1, 2, \ldots, K$). In the current study $I = 3$ (as indicated earlier, the choice alternatives are speed compliance, or speeding range 1, or speeding range 2) and $K = 4\times3 = 12$ for all q. Within each of the four SP attribute scenarios presented, the respondents were asked to state their speed range choice in three different sections – standard, warning, and camera housing sections.

In the usual tradition of utility maximizing models of choice, we write the utility or valuation U_{qik} that an individual *q* associates with the alternative *i* (speed range) on choice occasion *k* as follows:

$$U_{qik} = (\beta' + v'_q) \; x_{qik} + \varepsilon_{qik} \, , \tag{1}$$

where x_{qik} is a $(M \times 1)$-column vector affecting the valuation of individual *q* for alternative *i* at the k^{th} choice occasion, and that includes the following: (1) choice-occasion specific attributes (that is, the four attributes varied in the SP experiments), (2) alternative-specific constants for speeding ranges 1 and 2 (with no speeding being the base category), (3) individual-specific attributes (driving history and perception, driver demographics and employment characteristics), and (4) interactions within each of the choice-specific and individual-specific variables, as well as across the two sets of variables. β is a corresponding $(M \times 1)$-column vector of the mean effects of the coefficients of x_{qik} on speeding range valuations, and v_q is another $(M \times 1)$-column vector with its m^{th} element representing unobserved factors specific to individual *q* that moderate the influence of the corresponding m^{th} element of the vector x_{qik}. A natural assumption is to consider the elements of the v_q vector to be independent realizations from a normal population distribution; $v_{qm} \sim N(0, \sigma_m^2)$. ε_{qik} represents a choice-occasion specific idiosyncratic random error term assumed to be identically and independently standard Gumbel distributed. ε_{qik} is assumed to be independent of x_{qk}.

For a given value of the vector v_q, the probability that individual *q* will choose speed range *i* at the k^{th} choice occasion can be written in the usual multinomial logit form (McFadden, 1978):

$$P_{qik} \mid v_q = \frac{e^{\beta' x_{qik} + v'_q x_{qik}}}{\sum_{j=1}^{I} e^{\beta' x_{qjk} + v'_q x_{qjk}}} \tag{2}$$

The unconditional probability can then be computed as:

$$P_{qik} = \int_{v_q} (P_{qik} \mid v_q) d\boldsymbol{F}(v_q \mid \sigma) \tag{3}$$

where $\boldsymbol{F}$ is the multivariate cumulative normal distribution and σ is a vector that stacks up the σ_m elements across all m. The reader will note that the dimensionality in the integration above is dependent on the number of elements in the v_q vector.

In the MMNL model, marginal effects are calculated for variables x_{qik}. For the marginal effects of dummy variables, they are calculated as the differences in the estimated probabilities when the variables change from 0 to 1, while the means of other variables are used for the computation. The marginal self and cross effects are computed as (Shaheed and Gkritza, 2014; Xie et al., 2012; Washington et al., 2020):

$$\frac{\partial \mathrm{P}_{qik}}{\partial x_{qik}^{m}} = \beta_i^m \mathrm{P}_{qik}(1 - \mathrm{P}_{qik}) \tag{4}$$

$$\frac{\partial \mathrm{P}_{qjk}}{\partial x_{qik}^{m}} = -\beta_i^m \mathrm{P}_{qik} \mathrm{P}_{qjk} \tag{5}$$

where Eq. (4) represents the effect that one unit change in x_{qik} has on the probability for the decision-maker q to choose the speed alternative i on the choice occasion k (denoted by P_{qik}). Eq. (5) shows the effect of one unit change in the variable m of speed alternative i ($i \neq j$) on the probability (P_{qjk}) for the decision-maker q to choose the speed alternative j on the choice occasion k.

The parameters to be estimated in the model of Equation (3) are the β and σ vectors. To develop the likelihood function for parameter estimation, we need the probability of each individual's sequence of observed SP choices. Conditional on v_q, the likelihood function for individual q's observed sequence of choices is:

$$L_q(\beta \mid v_q) = \prod_{k=1}^{K} \left[\prod_{i=1}^{I} \{P_{qik} \mid v_q\}^{\delta_{qik}} \right] \tag{6}$$

where δ_{qik} is a dummy variable taking the value of 1 if the q^{th} individual chooses the i^{th} speed range in the k^{th} occasion, and 0 otherwise. The unconditional likelihood function for individual q's observed set of choices is:

$$L_q(\beta, \sigma) = \int_{v_q} L_q(\beta \mid v_q) dF(v_q \mid \sigma) \tag{7}$$

The log-likelihood function is $L(\beta, \sigma) = \Sigma_q \ln L_q(\beta, \sigma)$. We apply quasi-Monte Carlo simulation techniques to approximate the integrals in the likelihood function and maximize the logarithm of the resulting simulated likelihood function across all individuals with respect to the parameters β and σ. Under rather weak regularity conditions, the maximum (log) simulated likelihood (MSL) estimator is consistent, asymptotically efficient, and asymptotically normal (see Hajivassiliou and Ruud, 1994; Lee and Carter, 1992; McFadden and Train, 2000).

In the current study, we use Halton sequences to draw realizations for v_q from its assumed normal distribution. Details of the Halton sequence and the procedure to generate this sequence are available in Bhat (2001, 2003).

5.5 Results and discussion

Table 5.4 presents the results of a panel mixed multinomial logit model estimated on the afore-mentioned 3,208 observations – 1604 for the standard section and 1604 for the warning section[2] – with normal distributed random coefficients[3]. The dependent variable is speed choice (i.e. speed compliance, speeding range 1, or speeding range 2; with speed compliance considered as the base alternative). For each independent variable, a common coefficient was estimated for both standard and warning sections as well as a difference coefficient was introduced to account for the differential effect of that variable on the warning section compared to the standard section. In Table 5.4, the parameter estimates reported under the "Standard section" column are that of the common coefficients, which may also be interpreted as coefficients for the standard section. The parameter estimates under the "Difference between Warning and Standard section" column are the difference coefficients. For a given variable, a sum of its common coefficient and the difference coefficient would give its coefficient for the warning section. The parameter estimates are interpreted and discussed next in Sections 5.4.1-5.4.4. The coefficients on the constants indicate a general aversion to speeding, especially at level 2, at both the standard and warning sections. This aversion is typically higher in the warning section than in the standard section, though there is unobserved heterogeneity (captured by the significant standard deviation estimates on the constants) in these general trends (the panel nature of the data allows us to estimate the standard deviations on the constants in the table).

An important note is in order here. All results in this paper pertain to the influence of variables on the reported speed choices in our stated experiments, not actual speed choices in the real world. But, for presentation ease and tightness, we do not belabour over this distinction in the rest of this paper and use the general word "speeding". However, all our statements should be viewed in the context of stated speed choices, not actual speed choices.

[2] Recall from the descriptive analysis of the SP choice data for the camera housing section that only a single alternative (speed compliance) was chosen 99.8% of the times. So, these data were not included in the model as the speed choice is deterministic in the camera housing section. This observation is consistent with the findings of previous studies that drivers would slow down when they notice or are warned of cameras (De Pauw et al., 2014a; De Pauw et al., 2014b; Elvik, 1997; Marciano and Norman, 2015).

[3] We also explored alternative distributional assumptions such as log-normal for the random coefficients, but the model with normal distribution provided the best fit. Besides, other distributions did not offer substantive interpretations that were very different from the model with normal distributions.

Table 5. 4 Parameter estimates of a panel MMNL model for the speed choice of professional drivers*

Explanatory variables			Standard section			Difference between warning and standard sections	
			Speed compliance	Speed range 1	Speed range 2	Speed range 1	Speed range 2
Constants		Mean	0 (Fixed)	-1.35 (-2.52)	-10.14 (-1.77)	-5.59 (-3.71)	-13.16 (-4.64)
		SD	3.82 (10.73)	1.24 (2.46)	7.55 (6.5)	1.41 (1.67)	1.91 (2.18)
Stated Preference (SP) attributes							
DOP		Mean		-0.17 (-1.96)	-0.17 (-1.96)	-0.48 (-1.80)	-0.48 (-1.80)
		SD		0.15 (1.82)	0.15 (1.82)	1.19 (5.20)	1.19 (5.20)
DOP x drivers with recent speeding ticket				IS	IS	-0.17 (-2.17)	-0.17 (-2.17)
Fines (in HK$ 100)		Mean		Dropped	Dropped	-0.11 (-1.76)	-0.11 (-1.76)
		SD		-	-	0.14 (2.13)	0.14 (2.13)
Fine (in HK$ 100) x drivers with trip-based salary				IS	IS	-0.13 (-2.43)	-0.13 (-2.43)
Fine (in HK$ 100) x drivers with recent speeding ticket				IS	IS	-0.23 (2.05)	-0.23 (2.05)
Camera-to-Housing ratio *(Base case: status quo (20/120) and (20/240)*	Minor increase (40/120)	Mean		IS	-1.92 (-2.7)	IS	IS
		SD		-	1.33 (2.8)	IS	IS
	Major Increase (60/120)	Mean		IS	-2.03 (-3.6)	IS	IS
		SD		-	IS	IS	IS
Distance of warning sign from the camera section *(Base case: 100m)*	50 m			-	-	-2.09 (-6.44)	-3.91 (-1.72)
	150 m			-	-	2.42 (6.64)	4 (1.96)
	200 m			-	-	2.31 (6.5)	9.2 (4.6)
Drivers' operational and perception characteristics							

Age *(Base case: Mid-age 46-55 years*)	Older drivers (> 55 years)			IS	IS	-0.70 (-2.13)	IS
	Young drivers (<45 years)			IS	IS	IS	3.75 (2.1)
Education status *(Base case: secondary and tertiary education)*	Up to primary level			1.81 (2.99)	IS	IS	IS
Marital status *(Base case: unmarried*)	Married			-0.45 (-2.56)	-2.59 (-2.68)	IS	IS
Monthly income (in HK$) *(Base case: less than 15K)*	Between 15K and 20K			IS	IS	IS	IS
	More than 20K			IS	IS	1.78 (2.49)	7.86 (1.94)
Salary system *(Base case: others)*	Trip-based			1.37 (2.07)	10.32 (5.90)	IS	IS
	Monthly			IS	IS	IS	IS
Daily driving hours	More than 9 hours			IS	-2.41 (-1.91)	-1.16 (-1.98)	-11.36 (-2.4)
	Less than 8 hours			IS	IS	0.57 (2.71)	2.45 (2.32)
Vehicle Type *(Base case: Bus)*	Green minibus			5.19 (5.77)	IS	-2.71 (-2.6)	IS
	Goods vehicle			7.30 (7.87)	5.02 (2.35)	-3.06 (-3.4)	-3.31 (-2.58)
	Red minibus and Taxi			5.77 (4.41)	IS	-2.23 (-1.95)	IS
Dummy if the driver recently received speeding ticket				7.16 (2.93)	10.74 (3.35)	IS	-5.02 (2.16)
Perception on speeding as a cause of injury *(Base case: Neutral and high*)	Low			IS	6.00 (2.84)	IS	IS

Perception on effectiveness of cameras (*Base case: Low and neutral*)	High			IS	IS	IS	-2.30 (-1.79)
Frequency of sighting cameras *(Base case: Medium (4-6/10) and low (0-3/10)*	High (>7 times per 10 trips)			IS	-3.61 (-3.25)	IS	-7.15 (-1.95)
Goodness of fit measures:							
Number of cases			3208				
Number of parameters			56				
Log-likelihood of constants only model			-2911.09				
Log-likelihood at convergence			-1279.21				
Bayesian Information Criterion			3010.53				

Base alternative: Speed compliance; IS: Statistically Insignificant at 90% confidence level.

5.5.1 Effects of penalty level and enforcement strategy

Among the SP attributes for penalty and enforcement, the DOP variable shows a statistically significant deterrence on speeding in both standard and warning sections, with higher deterrence in the warning section than in the standard section. Professional drivers are indeed, generically speaking, sensitive to the increase in DOPs since incurring DOPs may lead to disqualification of driving license, which is the source of their livelihood (Wong et al., 2008). However, there is significant heterogeneity in the influence of the DOP variable both due to observed and unobserved factors. Specifically, drivers who were recently issued a ticket are more likely than their peers to be deterred by DOPs when traveling in the warning section. Considerable unobserved heterogeneity also exists in the influence of DOPs on drivers' speeding choices in both standard and warning sections. Interestingly, the standard deviation of the DOP coefficient in the warning section is higher than in the standard section, implying that the deterrent effect of an increased DOP penalty tends to be more diverse in the warning section despite its greater deterrent effect on average. This finding could be attributed to the heterogeneity in driver's threat and coping appraisals of the warning messages (Kergoat et al., 2017), as well as the effects of drivers' characteristics on the comprehension of traffic signs (Ng and Chan, 2008). For example, different drivers may perceive the self-efficacy of avoiding the speeding penalty differently when forewarned about camera enforcement. Thus, some drivers may actually initially increase their speeds as soon as they encounter the warning section (to compensate for the fact that they have to reduce speeds at the downstream camera section) because they feel confident in their ability (self-efficacy) to estimate where the camera section will begin and in their ability to decelerate at the right time to avoid speeding penalties in the camera section. Other drivers may immediately reduce their speed upon encountering the warning section because they feel less confident in their ability to take evasive speed reduction actions later downstream to avoid penalties in the camera section. Such variations in self-efficacy are likely to get magnified as the DOP penalty increases in the camera section, leading to the higher speed variance in the warning section as the DOP penalty increases.

Unlike the deterrent effect of DOPs, the monetary fines variable turned out to have a marginally positive coefficient in the standard section suggesting an increase in the propensity for speeding with an increase in fines. While this may be a coping mechanism to “make up” time in the standard section in anticipation of lost time due to adherence to speed limits in the warning section, we noted that this effect had a strong interaction with the length of the warning section. Thus, we chose to drop this variable and include the length of the warning section as the primary determinant variable in our model (more on this warning section length effect later). In the warning section itself, monetary fines are associated with a negative coefficient for a majority of the sample (obtained from the mean and standard deviation of the corresponding random coefficient), suggesting a deterrent effect of monetary fine when it is combined with a warning of speed enforcement ahead for a majority of the drivers. Furthermore, there is heterogeneity in response to fines in the warning section based on driver characteristics. Specifically, in warning sections, monetary fines have a larger deterrent effect (in the context of speeding) for drivers who are paid on a per-trip basis and those with a recent speeding ticket relative to other drivers. These results are again an illustration of the interplay between drivers' threat and coping appraisal mechanisms, where drivers respond to the threat of a monetary fine when they are made aware of the cameras that will increase the likelihood of them being fined. And such interplay appears to vary across drivers based on both observed and unobserved factors.

In the context of camera-based enforcement strategy, reducing the camera-to-housing ratio from the status quo (i.e., from 20:120 to 20:240 camera-to-housing ratio) did not show a statistically significant effect on the drivers' stated speeding choices. However, drivers were less likely to opt for severe speeding (range 2) in both the standard and warning sections when the camera to housing ratio was increased from the status quo. This is presumably because an increase in the number of camera installations would result in an increased “threat” of being apprehended for speed limit violations. Interestingly, the standard deviation associated with the coefficient of a minor increase in camera-to-housing variable suggests that a small fraction (9%) of the drivers tend to choose speeding with an increase in camera-to-housing. This result may be attributed to the risk-taking behaviors of such individuals as well as heterogeneity in perceiving a threat of apprehension due to a minor increase in the number of cameras. However, with a major increase in the camera-to-housing ratio, this risk-taking behavior reduces, perhaps due to a greater perception of the threat of apprehension.

The placement of the warning sign – that is, the distance of the warning sign from the camera housing location – exhibits an influence on speeding in the warning section. Specifically, reducing the distance between the warning sign and the housing unit leads to lower speeding tendencies (for both speeding ranges). This is intuitive as individuals may want to start slowing down (or at least not speed) to avoid sudden decelerations just before arriving at the camera housing. In fact, the presence of a warning sign (upstream of a fixed speed camera) has been found to be associated with reductions in mean driving speed and proportion of more severe speeding (Retting et al., 2008; Høye, 2014). Kergoat et al. (2017) postulated that the distance between warning sign and speed camera should be increased to weaken the "Kangaroo effect". However, the parameter estimates for speeding range 2 suggest a heightened increase in the propensity to choose that speeding range when the warning sign is installed 150m or 200m upstream of a camera housing. That is, our results suggest that the deterrent effect of a warning sign could in fact be diminished when the distance between the warning sign and the housing unit increases excessively. That is, as drivers learn that the warning signs are placed farther away from the housing, they speed up because they know they have a larger cushion to decelerate and they also want to make up some time in anticipation of slowing down closer to the actual camera housing location. Basically, as warning signs are placed farther away from the camera housing, professional drivers start to view the early part of the warning section as a "standard" section. This indicates a need for optimal placement of warning sign that can tradeoff between the "Kangaroo effect" and effectiveness of the warning sign in deterring speeding behavior.

5.5.2 Effects of demographic characteristics of professional drivers

Driver age does not have a strong association with speeding behavior in the standard section. This could be because all professional drivers, regardless of age, tend to be more aggressive when there is no speed enforcement and no warning (Öz et al., 2010a, Wong et al., 2008). In contrast, in the warning section, older drivers are less likely to speed up to range 1 and younger drivers are more likely to speed up to range 2. These results suggest that the likelihood of speeding offences decreases with driver age, perhaps because older drivers tend to be more cautious (Ram and Chand, 2016; Rosenbloom and

Shahar, 2007) but younger people are more likely to be sensation- and thrill-seeking (Delhomme et al., 2012; Fernandes et al., 2010; Tseng, 2013). In the context of education background, individuals with up to primary level education are more likely to speed up to range 1 in both standard and warning sections. Previous studies also suggest that professional drivers with higher education attainment are less likely to commit traffic offences (Mallia et al., 2015; Mehdizadeh et al., 2018; Tronsmoen, 2010). Married drivers (relative to those who are single) are less likely to speed in both the standard and warning sections (see Mehdizadeh et al., 2018 and Wong et al., 2008 for similar findings), perhaps because married individuals, due to their familial responsibilities, tend to be more responsible in driving than single individuals.

Individuals with high monthly income (>20K), *ceteris paribus*, are more likely than others to choose to violate speed limits in warning sections. This is perhaps because they can afford to pay the fines. Also, recall from earlier discussion that the maximum fine of HK$550 for speeding range 2 is a rather small percentage of HK$ 20K per month. In contrast, the maximum monetary fine for speeding can reach 50% of average monthly incomes of taxi drivers in the United States (United States Department of labor, 2018) and 35% in the United Kingdom (Sentencing Council, 2017), respectively. In road safety research, deterrence theory is widely used to investigate driver's perception of the sanctions (in terms of severity, certainty and celerity) for traffic offences (Kergoat et al., 2017; Li et al., 2014; Tay, 2005a, 2005b, 2005c, 2009). It is based on the idea that people avoid committing a crime due to the threat and fear of being legally punished, which also involves an evaluation of the costs and benefits of the crime (Gibbs, 1985). In this sense, the ratio of the cost (monetary fine) to the benefits (possible income) of speeding offence is indeed quite low in Hong Kong.

5.5.3 Effects of operational characteristics of professional drivers

As discussed earlier, drivers who earn on a per-trip basis (i.e., trip-based salary) are more likely to be deterred by monetary fines in the context of speeding in warning sections. Regardless of the level of monetary fines, the coefficients of the trip-based salary dummy variable suggest that such drivers are more likely than others to commit speeding offences in both the standard and warning sections. Since their earnings depend on the number and distance of the trips made, trip-based salaried drivers have a higher incentive to speed up to arrive at the destination quickly. In Hong Kong, trip-based drivers (these are typically drivers of taxis, light vans, red minibuses etc.) are generally self-employed and are not well-regulated (Meng et al., 2017; Wong et al., 2008). In contrast, the monthly-salaried drivers are typically regular employees of large transport operators and logistics firms with good safety culture and driver management systems (Newnam et al., 2004; Öz et al., 2010b, 2013) including GPS-based tracking of vehicle speeds. These factors also have a bearing on the salary system-based differences in speeding choices.

Individuals who drive for more than nine hours per day have a lower inclination than others to violate speed limits. This could be attributed to the possible driver fatigue caused by a prolonged driving time. Drivers may adopt a compensation strategy by reducing their speed to lower their risk of fatigue-related crashes (Williamson et al., 2002). In contrast, individuals who drive for less than eight hours per day are associated with a greater likelihood (than others) of violating speed limits in the warning section. This finding will need further investigation to assess its robustness.

In the context of vehicle type, drivers of all types of vehicles other than buses have a higher tendency of speeding up in both standard and warning sections, albeit they are relatively less likely to speed up in warning sections than in standard sections. Indeed, minibus drivers and taxi drivers in Hong Kong have been recognized as problematic and risk-taking groups (Meng et al., 2017; Wong et al., 2008). On the other hand, goods vehicle drivers are paid to drive for the transport of goods while bus drivers are to drive for the transport of passengers. A greater sense of social responsibility on bus drivers might make them less aggressive (at least in a stated preference setting) than the drivers of other types of vehicles (Paleti et al., 2010).

5.5.4 Driver history and safety perceptions

Driving history and safety perceptions have a substantial influence on the participants' stated speed choices. For instance, drivers who recently received a traffic ticket are associated with a greater likelihood of speeding in both standard and warning sections (albeit the tendency for speeding range 2 is lower in warning sections than that in standard sections). Further, as discussed earlier in the context of interaction between this variable with the SP attributes, increasing fines or DOP appears to reduce the speeding tendency of these drivers in warning sections. However, even at the highest level of fine and DOP values presented in the SP experiment, these drivers show a higher tendency (than others without recent tickets) to violate speed limits. These results suggest that risk-taking behavior and aggressive driving styles of these drivers overshadow any deterrent effect from receiving a speeding ticket (Sagberg and Ingebrigtsen, 2018). It appears that simply imposing fines or DOPs might not suffice to reduce the aggressive driving traits of such drivers. This result suggests a need for additional investigations to assess the effectiveness of combining DOPs and fines with driver training programs aimed to reduce risk-taking and aggressive driving traits.

Individuals who perceive that speeding does not cause injuries have a higher tendency of opting for speed range 2 in both standard and warning sections. This aligns with the previous findings that drivers with lower risk perception tend to be associated with aggressive driving behaviors (Cestac et al., 2011; Rosenbloom, 2003). In addition, drivers who perceive that cameras are highly effective in catching offenders are associated with a lower tendency of speeding in speed range 2 in the warning section, while their disposition for speed range 1 is not statistically different from compliance. Individuals who sight speed enforcement camera housings more frequently (in at least 7 out of 10 trips) have a lower tendency of speeding in range 2 (in both standard and warning sections). This could be attributed to the perceived higher level of enforcement, which may contribute to the decrease in driver's speeding intention (Blincoe et al., 2006; Hössinger and Berger, 2012) at least in the high-speed range.

5.5.5 Marginal effects due to changes in SP attributes

The model was applied to estimate marginal effects on market shares (of speed choice) in response to changes in the SP attributes. As shown in **Table 5.5**, the marginal effects were computed for both the standard and warning sections. According to these results, an increase in the DOP by 1 point resulted in greater than 4% increase in compliance in both the sections. In the context of monetary fines, a 10% increase resulted in only a 1.73% increase in compliance. Such a low marginal effect is consistent with the discussion of model estimation results that monetary fines alone might not significantly deter professional drivers from speed violations. Note that the percentage reduction in the share of drivers who would opt for speeding range 2 is high (13.02%). However, such a high percentage reduction is an artifact of a rather small proportion of drivers choosing this option in the base case.

Increasing camera-to-housing ratio from the status quo (20:120) to 40:120 shows a considerable (at least 29%) decrease in the share of drivers choosing speed range 2. However, the decrease is not substantial when the ratio is increased to 60:120. This suggests that the marginal benefit from increasing the camera-to-housing ratio beyond 40:120 might not be substantial. Furthermore, since the proportion of drivers choosing speed range 2 is itself very small (1%), even a 32% decrease in this share due to increasing the ratio to 60:120 does not appear to hold practical effectiveness.

In the context of the placement of warning sign, increase in the distance between the warning sign from 100m is associated with a substantial increase in the proportion of drivers choosing to speed in the warning section. Even if we neglect these increases for speed range 2 (due to a rather small base market share for this alternative), the increases in the proportion of people choosing speed range 1 is substantial when the distance is increased. These results suggest the need for an optimal placement of warning sign that can trade-off between the “Kangaroo effect” and effectiveness of the warning sign in deterring speeding behavior.

Table 5. 5 Marginal effects due to changes in the SP attributes

Variables		Percentage change in market shares					
		Standard section			Warning section		
		Speed Compliance	Speed range 1	Speed range 2	Speed Compliance	Speed range 1	Speed range 2
DOP	Market share in base case	16.96%	78.64%	4.40%	66.27%	32.88%	0.85%
	Change in market share upon increment by 1 point	4.22%	-0.64%	-4.85%	4.63%	-9.01%	-12.74%
Fines	Market share in base case	16.96%	78.64%	4.40%	66.27%	32.88%	0.85%
	Change in market share upon increment by 10 percent	0.00%	0.00%	0.00%	1.73%	-3.16%	-13.02%
Camera-to-Housing ratio (Base case: 20/120)	Market share in base case	16.89%	77.78%	5.34%	66.20%	32.80%	1.00%
	Change in market share upon change from base case to minor increase (40/120)	0.83%	2.11%	-33.39%	0.20%	0.50%	-29.52%
	Change in market share upon change from base case to major increase (60/120)	0.96%	2.40%	-38.06%	0.22%	0.55%	-32.80%
Distance of warning sign from camera housing unit (base case: 100m)	Market share in base case	18.01%	80.91%	1.08%	73.50%	26.41%	0.09%
	Change in market share upon change from base case to 50m	0.00%	0.00%	0.00%	14.18%	-34.37%	-50.09%
	Change in market share upon change from base case to 150m	0.00%	0.00%	0.00%	-23.02%	63.56%	143.85%
	Change in market share upon change from base case to 200m	0.00%	0.00%	0.00%	-22.81%	59.00%	1277.90%

5.6 Concluding remarks

This study applied a stated preference survey and a panel mixed logit model to evaluate the deterrent effects of penalty and enforcement strategies – DOP penalty, monetary fines, and speed enforcement cameras along with a warning of such enforcement – on the propensity and severity of speeding among professional drivers. In doing so, the study controlled for the effects of driver demographics and operational characteristics as well as driver history and safety perceptions. As importantly, observed and unobserved heterogeneity were incorporated in drivers' responses to penalty and enforcement strategies. A panel mixed logit model is estimated and applied to understand the effectiveness of penalties and enforcement strategies on driver's speeding behaviors.

The results indicate that an increase in DOP penalty is more effective as a deterrent against speeding than increasing monetary fines. This could be attributed to the higher sensitivity of professional drivers to the increase in DOPs since incurring more DOPs may lead to disqualification of the driving licence. Monetary fines were not found to be very effective, perhaps because the monetary fine levels were very low relative to the income levels of the drivers. It remains to be explored if increasing the quantity of fines combined with appropriate warning messages (such as "Check speed—fines up to $1000") can help increase the effectiveness of monetary fines. Significant heterogeneity was found in the influence of the DOP variable both due to observed and unobserved factors. Specifically, while increasing DOP deters all drivers from speeding, doing so when combined with a warning (i.e., in the warning sections) appears to more strongly deter those who recently received a speeding ticket than others. However, the unobserved variation in the warning section is greater than that in the standard section, perhaps because of differences in drivers' threat and coping appraisals of the warning messages, as discussed in section 5.4.1.

In the context of camera-based enforcement strategy, increasing the ratio from status quo (20:120) to 40:120 showed a considerable effect (29%) on reducing the percentage of drivers opting for severe speeding, albeit it should be noted that the base percentage of drivers in this category is only 1%. Increasing it further to 60:120 did not show a substantial effect in the policy simulations we conducted. Further, reducing the ratio from the status quo (20:120) to 20:240 did not show a significant effect on the drivers' stated speeding choices.

The placement of the warning sign – that is, the distance of the warning sign from the camera housing location – exhibits an influence on speeding behaviors in the warning section. Placing it close to the camera housing location decreases the likelihood of speeding but can potentially increase the "kangaroo" effect. And placing it too far from the camera location would substantially increase the percentage of speeding behaviors. These findings suggest a need for the optimal location of warning signs. Alternatively, information on the penalty level can be added to the warning signs to increase the threat appraisal of the driver for reducing speeding behaviors in warning sections.

The demographic characteristics of drivers such as age, education, income have an influence on how drivers respond to strategies aimed at increasing speed compliance. Similarly, the drivers' operational characteristics, driving history and perceptions have a substantial bearing on the efficacy of speed compliance strategies. Therefore, targeted driver educational and training campaigns might help increase the speed compliance rates in the population. For example, drivers with a recent history of traffic tickets continue to demonstrate a greater tendency for speeding even for high levels of DOP and monetary fines. It appears that simply imposing fines or DOPs might not suffice to reduce the aggressive driving traits of such drivers. A combination of DOPs and fines with driver training programs aimed at addressing risk-taking and aggressive driving traits may be needed to increase safe driving tendencies among these drivers. Further, higher penalties may be considered for repeat offenders to enhance the deterrent effect of the penalties (Watson et al., 2015). Similar penalty strategies have been applied for repeat offenders of drink driving in Hong Kong (Li et al., 2014).

Speeding and other traffic offences may be attributed to drivers' goals of travel time saving and revenue maximization (Cestac et al., 2011; Peer, 2010; Tarko, 2009), while safe driving performance and social responsibility may be lower in the hierarchy of professional drivers' goals (Hatakka et al., 2002). Therefore, inclusion of positive motives and goals in the education/training and licensing of professional drivers may be beneficial.

In addition, technology-based interventions, such as GPS-based automated speed surveillance and related automated speed enforcement mechanisms, may aid in reducing speeding behaviors.

The results from this study help enhance the current understanding and effectiveness of penalties and speed-enforcement strategies (i.e. penalties, warning signs, camera housings, etc.). Yet, this study is limited to the assessment of a few demographics and operational characteristics of professional drivers. It would be worth exploring the possible effects of latent characteristics on speeding propensity and severity, when more comprehensive information on the physiological and psychological metrics of the participants is available. Moreover, results of this questionnaire survey are derived from a scenario of a typical city road with a speed limit of 50km/h. It would be interesting to explore the effect of other road environments, such as an expressway with a speed limit of 70 km/h or higher, on the speeding behavior of professional drivers. Further, it would be helpful to undertake a study that evaluates the effectiveness of combining speeding penalties with driver education/training campaigns in reducing risk-taking and aggressive driving. Also, the separation between the placement of a warning sign and the camera housing unit was expressed as a distance in the current study. Perhaps a time separation rather than a space separation would be a better approach to capture how individuals respond to warning signs before entering monitored roadway section. Yet another line of research would be to investigate whether fixed ASEC systems, when complemented with a small human police force, would have a higher impact in reducing speeding than a fixed ASEC system alone. And, if so, what may be the optimal combination of investment in human-based and machine-based enforcement mechanisms. Perhaps most importantly, all the results and recommendations in this study are based on self-reported speed indications within stated experiments, which clearly can influence the reliability and accuracy of the relationships estimated. A study based on an actual field experimental design and field observations of speed at different sections would be more credible.

Chapter 6 Effects of commercial vehicle mix and multivariate analysis of crash rates by vehicle type

6.1 Introduction

In Hong Kong, commercial vehicles (buses, taxis, light-goods vehicles, and medium- and heavy-goods vehicles) constitute only 20% of total vehicle fleet but are involved in over 70% of road crashes. A plausible reason for such disproportionate crash share of commercial vehicles could be their relatively higher travel amounts (per-vehicle distance) (Pei et al., 2012; Transport Department, 2019). For example, recently-published statistics indicate that the annual per-vehicle distances travelled (million km) by commercial vehicles (licensed taxi (0.14), bus (0.06), light goods vehicle (0.03), medium and heavy goods vehicle (0.03)) are all significantly higher compared to the private car (0.01) (Transport Department, 2019). In addition, it has been determined that traffic violation rates and crash involvement are higher for commercial vehicle drivers compared to private car drivers (Chen et al., 2020a; Öz et al., 2010; Tang et al., 2018; Wong et al., 2008).

In this chapter, the commercial vehicle proportion (CVP) refers to the ratio of commercial vehicles to all vehicles in the traffic stream. Interactions between road safety factors, including road user behaviour, weather, and road geometric factors, have been examined in previous studies. However, this has rarely been done for the CVPs and roadway features. While consideration of the interactions between these two specific factors may be a contribution that seems to be only incremental, it is important to address this gap in the literature because both roadway features and commercial vehicle proportion have been found to be significant factors of urban road crash propensity. Therefore, in this study, we hypothesize that these two factors have some interaction effects on road safety. If this is affirmed, then one of the two factors (the prevailing roadway features) potentially mediates the safety effect of the second factor (CVP). In that case, the urban road design and operations policies related to commercial vehicle operations that fail to consider such mediating effects, could lead to increased urban crashes involving commercial vehicles

(Bao et al., 2019). This is a critical issue, given the realization that in several urban areas including the city used in the methodology demonstration (Hong Kong), commercial vehicles account for a significant fraction of all trips.

Against the background presented in the previous section, the goal of this paper is to measure the association between the commercial vehicle proportion and crash rate; more importantly, to examine the mediating (moderating or magnifying) effects of roadway attributes on this association; and ascertain how this association and the moderating effects vary by the commercial vehicle type, considering the crash severity level and road attribute type. It is anticipated that the results will help guide policy development by the road authorities and transport operators regarding the management and regulation of commercial vehicles and their drivers.

The scope of this study is such that it addresses commercial vehicles at urban areas. The reason for this is the higher travel amounts (per-vehicle mileages) and crash propensities of this vehicle class compared to other vehicle classes in urban areas, as evidenced in past research. The role of commercial vehicle operations in urban road safety has come under increasing scrutiny in recent years, and the resolution of the problem of high crash rates for commercial vehicles at such areas, continues to be an important roadway safety issue and public relations concern for urban road agencies. Therefore, city road authorities and transport operators seek to regularly review crash propensities and to revise safety countermeasures, including operations policies and physical roadway interventions, to enhance commercial vehicle safety. The commercial vehicle classes are: (i) public buses, including single- and double-decker buses, and light buses, (ii) taxi, (iii) light van or light-goods vehicle (5.5 tonnes maximum gross vehicle weight, and (iv) medium- and heavy-goods vehicles (24 and 38 tonnes, respectively). This study analyses the safety effects of the interaction between commercial vehicle percentage and roadway attributes.

This chapter is organized as follows. Section 6.2 describes the method of analysis. Section 6.3 presents the method of data collection. The analysis results and interpretations for the overall crash rates at different severity levels are given in Section 6.4. Section 6.5 provides the results and discussion on the multivariate analysis of crash rates by vehicle type. Finally, findings and recommendations are summarized in Section 6.6.

6.2 Data collection

6.2.1 Overall crash rates by injury severity

This study used comprehensive crash and traffic data from eighty-eight (88) road segments in the study area (the City of Hong Kong) spanning a four-year period (2014–2017) (**Figure 6.1**). The road segments under investigation are widely distributed spatially over the study area. The traffic count data were collected from the Annual Traffic Census (ATC) database which was established by the road agency primarily for transport planning purposes. The ATC database provided road geometry data (e.g., the number of lanes, lane width, and road type), and the traffic data. This included the annual average daily traffic by vehicle type, hourly variation, and weekday/weekend distribution), and the proportions of vehicle classes including public bus, taxi, light-, medium-, and heavy-goods vehicles. The source of the crash data is the Hong Kong Transport Department's Transport Information System (TIS) which includes accident data (e.g., injury severity, date and time, and location), vehicle attribute data (e.g., vehicle type and year of manufacture), and casualty characteristics (e.g., injury severity, casualty role, age, and gender). The crash severity levels are: killed (fatal), severe injury, and slight injury. Due to the paucity of fatal and severe injuries, these two levels were combined to form a single level: killed and severe injury (KSI).

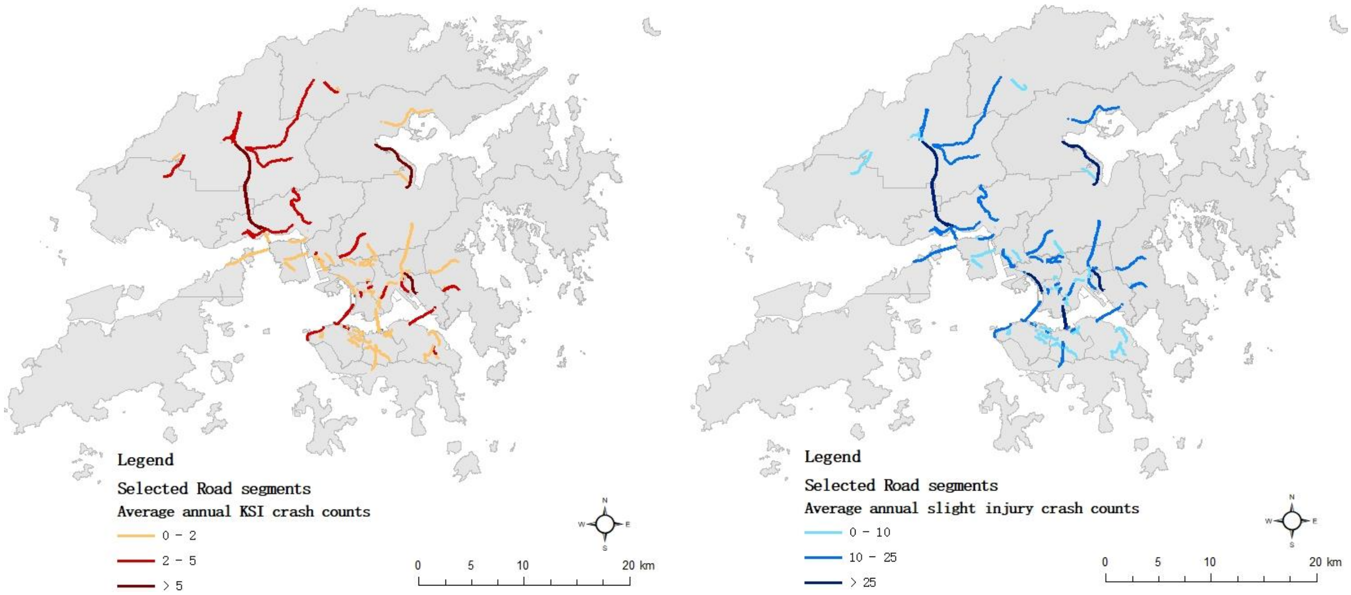
The Hong Kong Road Network Dataset provided data on the length, number of intersections, presence of on-street parking, and speed limits of the road segments. The data on hourly variations and percentage distribution across the commercial vehicle classes, were available for a 16-hour period (7AM to 11PM) during weekdays; therefore, crashes that occurred within 11PM-7AM and on weekends are not included in the data. The traffic and crash data were aggregated into eight 2-hour periods: 7AM–9AM, 9AM–11AM, 11AM–1PM, 1PM–3PM, 3PM–5PM, 5PM–7PM, 7PM–9PM, and 9PM–11PM. The traffic, crash and road network characteristics data were mapped to the corresponding road segments using a geographical information system (GIS) platform.

In the study, the overall weekday crash rate (crash count per million vehicle-kilometers travelled) of crash severity level *k* at road segment *i* in period *p* of year *t*, is specified as:

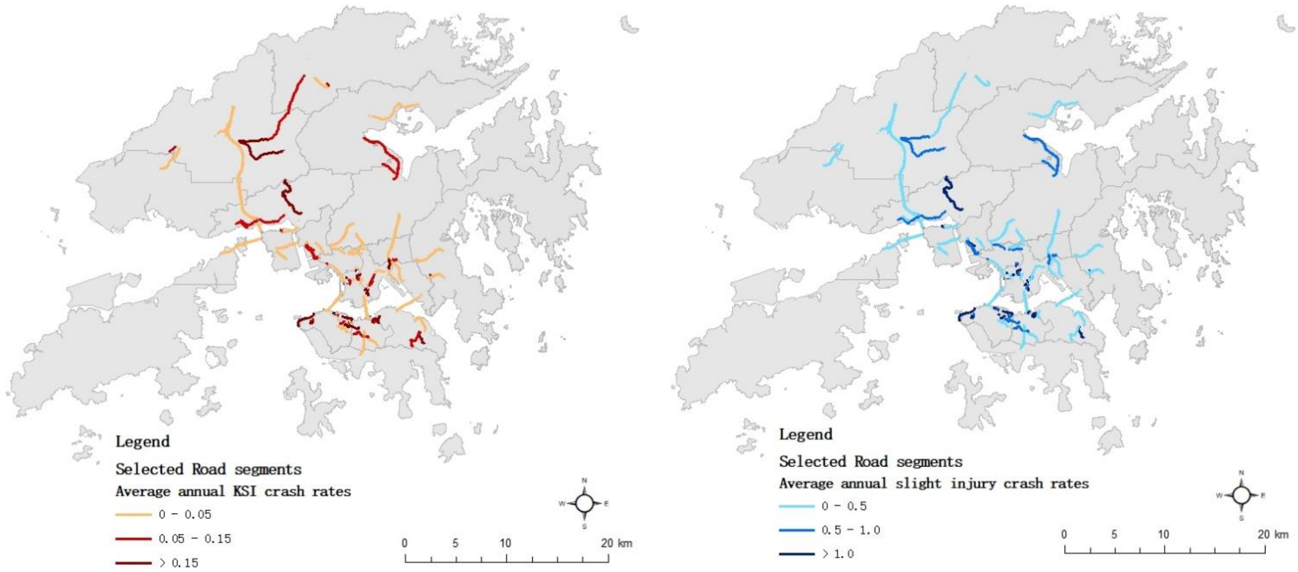
$$Crash\ rate_{itp}^{k} = \frac{Crash\ Count_{itp}^{k}}{Traffic\ Flow_{ip}^{t} \times Length_{i} \times 365/1{,}000{,}000} \quad (1)$$

Where: i = 1,2,…88; k = 1,2; p = 1,2,…,8; t = 2014, 2015, 2016, 2017; $Crash\ Count_{itp}^{k}$ is the number of weekday crashes at severity level k at road segment i in period p of year t; $Traffic\ Flow_{ip}^{t}$ is the two-hour traffic flow of road segment i in period p of year t (calculated by hourly variation of the weekday AADT on road segment i in year t); $Length_i$ is the length of road segment i.

The crash data are aggregated into eight 2-hour periods to mitigate the problem of excessive zero (crash) observations. Of the 2,816 observations, 1,018 observations had zero slight-injury crashes and the remaining 1,798 had at least one slight-injury crash; 2,322 observations had no KSI crashes and the remaining 494 had at least one KSI crash. **Figure 6.2** presents the temporal distribution of the various vehicle classes at the road segments under study, and **Table 6.1** defines and presents the descriptive statistics of the variables considered in this study.



(a) Average annual KSI and slight-injury crash counts of the selected road segments, 2014-2017



(b) Average annual KSI and slight-injury crash rates of the selected road segments, 2014-2017

Figure 6. 1 Study area (Hong Kong) showing the road segments studied and safety trends

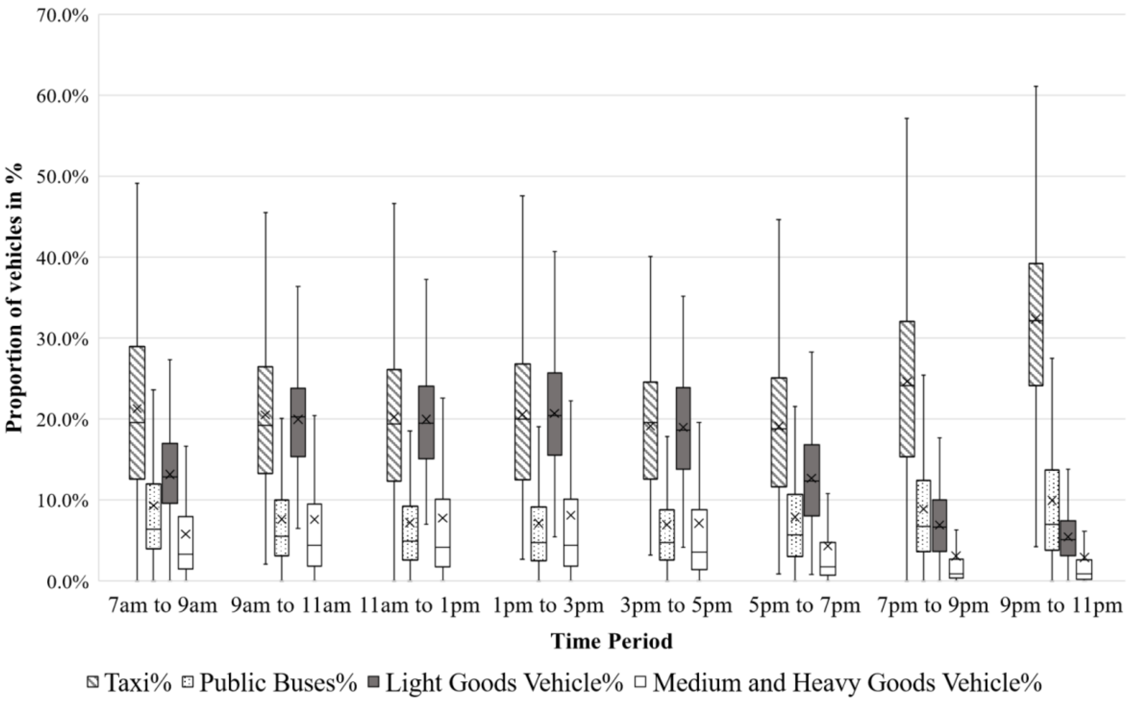


Figure 6. 2 Variation of commercial vehicle percentage by time of day

Table 6. 1 Descriptive statistics of the variables

Variable	**Mean**	**S.D.**	**Min.**	**Max.**
KSI crash rate	0.17	1.12	0.00	30.72
Slight-injury crash rate	1.16	4.14	0.00	151.43
Length (km)	3.00	3.48	0.18	19.08
Logarithm of 2-hour traffic flow	8.11	1.01	4.42	9.94
Average lane width (m)	3.59	0.45	2.70	5.25
Wide roadway (more than four traffic lanes: yes = 1, no = 0)	0.48	0.50	0	1
High intersection density (≥ 3 intersections per km, yes = 1, no = 0)	0.21	0.41	0	1
Speed limit (km/h)	64.79	13.07	30	100
Presence of on-street parking (yes = 1, no = 0)	0.06	0.23	0	1
Proportion of taxi (%)	22.20	11.18	0.00	69.75
Proportion of public buses (%)	8.08	7.34	0.00	60.15
Proportion of light-goods vehicles (%)	14.69	8.09	0.20	40.70
Proportion of medium and heavy (M&H) goods vehicles (%)	5.80	8.07	0.00	57.95

Figure 6.3 attempts to better demonstrate possible relationship between commercial vehicle mix and crash rates by injury severity. The z-axis of Figure 6.3 is the normalized crash rates using the equation (2) below (see Ulak et al., 2018), in order to get the same scale for KSI and slight injury crash rates. However, it should be noted that the crash rates used in statistical modeling are $Crash\, rate_{itp}^{k}$ from equation (1).

$$Normalized\, Crash\, rate_{itp}^{k} = \frac{Crash\, rate_{itp}^{k}}{\max\,(Crash\, rate_{tp}^{k})} \tag{2}$$

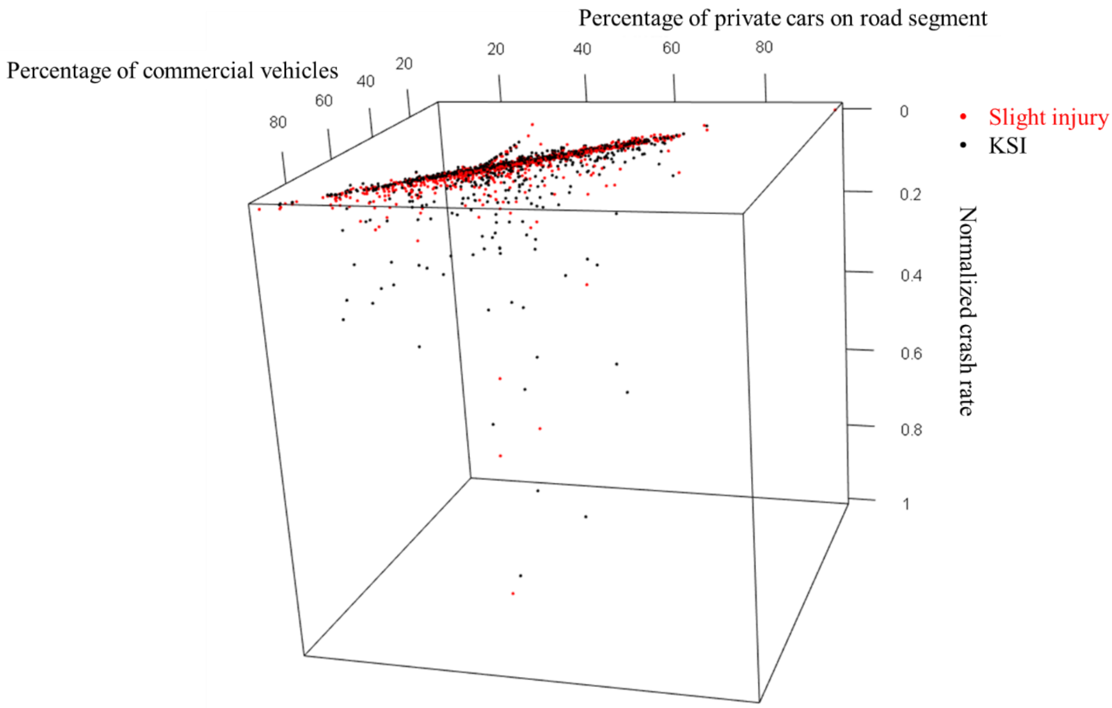


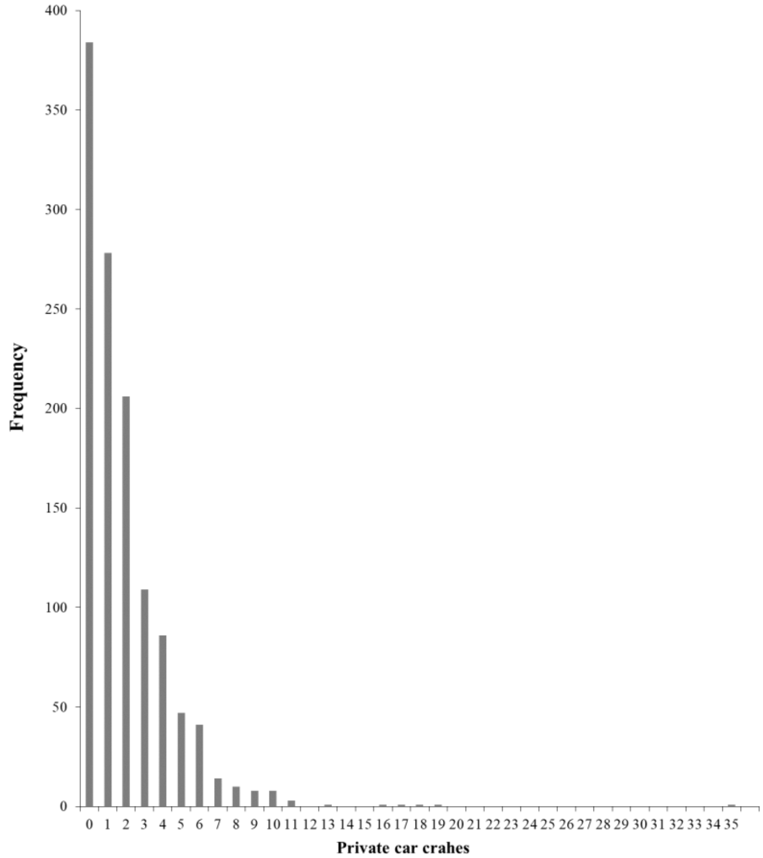
Figure 6. 3 Normalized overall crash rates by injury severity under different commercial vehicle mix

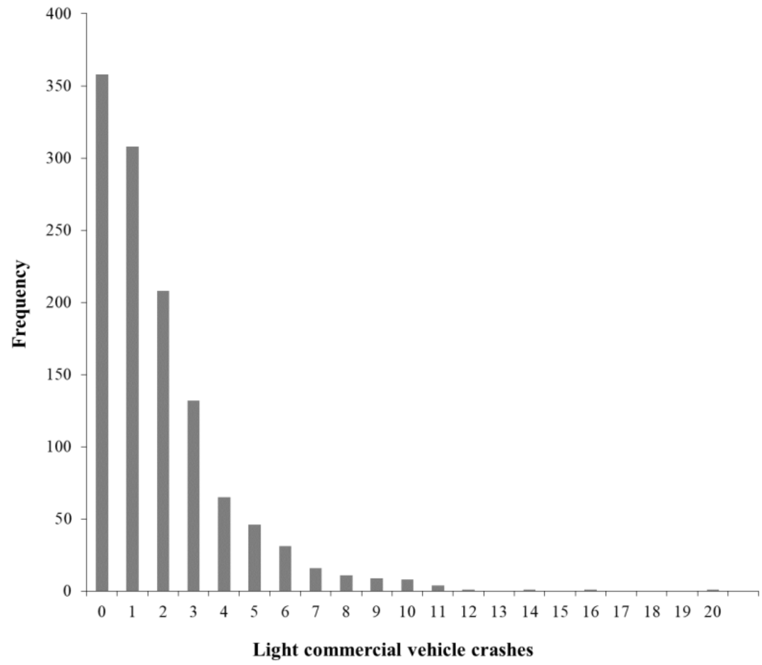
6.2.2 Crash rates by vehicle type

In this study, comprehensive crash and traffic data of 100 road segments in Hong Kong in the 3-year period from 2015 to 2017 are used. For instances, crash data are obtained from the Transport Information System (TIS) of Hong Kong Transport Department during the period from 2015 to 2017. TIS database consists of three profiles: accident profile (e.g. injury severity, date and time, location, speed limit, road type, etc.); vehicle attributes (e.g. vehicle type, year of manufacture, driver age, etc.), and casualty characteristics (e.g. injury severity, casualty role, age, gender, etc.). Crashes are stratified into three categories in accordance to injury severity: killed, severely injured and slightly injured. Since the numbers of killed crash and severely injured crash are too small for efficient analysis, they are combined into 'killed and severely injured' crash (known as 'KSI').

On the other hand, traffic count (e.g. annual average daily traffic by vehicle type and hourly variation) and road geometry data (e.g. number of lanes, lane width, road type, etc.) are obtained from the Annual Traffic Census (ATC) database. Vehicle classes considered are private car, bus, light bus, taxi, light goods vehicle, and medium and heavy goods vehicles. Furthermore, information on road segment length and number of intersections are obtained from the Hong Kong Road Network Dataset. Since the information on hourly variation and percentages of different vehicle classes is available only for 16-hour period from 7 am to 11 pm. Crashes occurred in the period from 11 pm to 7 am are not considered in the subsequent analysis. Also, the sample would be too small if the crashes are disaggregated at hourly level. Then, the traffic and crash data are aggregated to four-hour period as: 7 am – 11 am (morning), 11 am – 3 pm (noon), 3 pm – 7 pm (afternoon) and 7 pm – 11 pm (evening). The abovementioned traffic, crash and road network characteristics data are mapped to the corresponding road segments using the geographical information system (GIS) technique.

Furthermore, crashes are classified into three categories by vehicle type -private car, light commercial vehicle, and heavy commercial vehicle. In Hong Kong, road traffic regulations (see chapter 374A, construction and maintenance of vehicles) has specified the maximum gross vehicle weights of private car (3.0 tonnes), taxi (3.0 tonnes), light bus (5.5 tonnes), light goods vehicle (5.5 tonnes), bus (24 tonnes), medium goods vehicle (24 tonnes), and heavy goods vehicle (38 tonnes). In this study, light commercial vehicles include taxis, light goods vehicles, and light buses, while heavy commercial vehicles include medium and heavy goods vehicles, and buses. A total of 2323, 2655, and 1024 crashes were identified to involve private cars, light commercial vehicle crashes, and heavy commercial vehicle crashes, respectively. Among these 6002 crashes, 1233 only involved private cars, 2114 only involved light commercial vehicle, and 458 only involved heavy commercial vehicle. The remaining crashes could be multiple-vehicle crashes involving different vehicle types. It is likely that private car often collides with other vehicle types, so does the heavy commercial vehicle. It should be noted that the multiple-vehicle crashes involving a motorcycle (that is, a private car/light commercial vehicle/heavy commercial vehicle collides with a motorcycle) were not excluded in this study. **Figure 6.4** presents the histograms of crashes involving private cars, light commercial vehicles, and heavy commercial vehicles across observations.


400
350
300
250
200
150
100
50
0
Frequency
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35
Private car crahes


400
350
300
250
200
150
100
50
0
Frequency
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Light commercial vehicle crashes

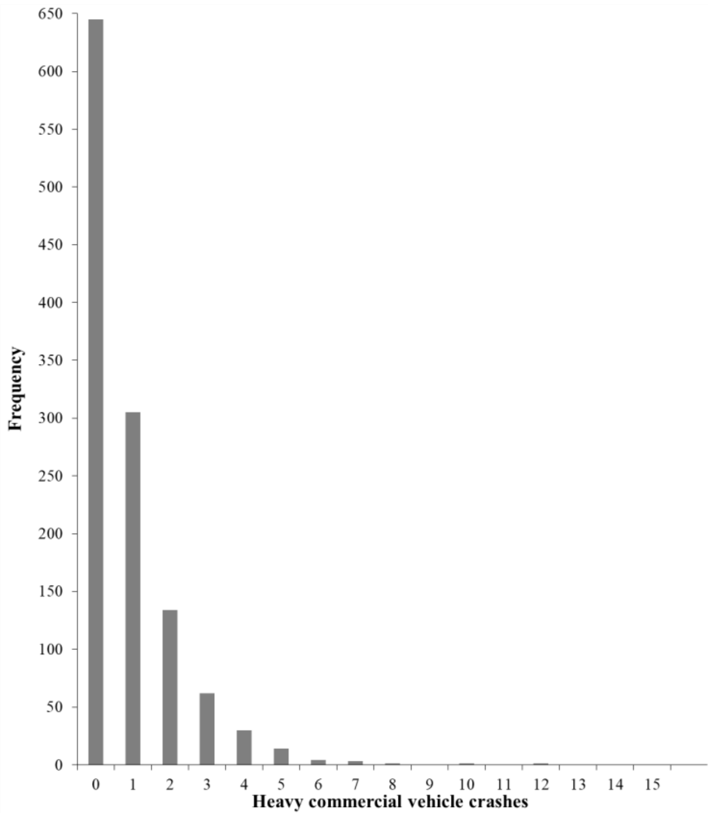


Figure 6. 4 Histograms of private car, light commercial vehicle, and heavy commercial vehicle crashes

In this study, crash rate (per million vehicle-kilometre travelled) of vehicle type *v* at road segment *i* in period *p* of year *t* is specified as,

$$Crash\ rate_{itp}^{v} = \frac{Crash\ Count_{itp}^{v}}{Traffic\ Flow_{ip}^{t} \times Length_{i} \times 365/1{,}000{,}000} \tag{3}$$

i = 1,2,…100; v = 1,2,3; t = 1, 2, 3; p = 1,2,3,4

Table 6.2 summarizes the statistics of considered variables. Prior to parameter estimation, multicollinearity test is conducted to assess the correlation between independent variables. Results indicate that VIF (variance inflation factor) of independent variables are all less than 3, hence, there is no multicollinearity between independent variables.

Table 6. 2 Descriptive statistics of the variables

Variable	Mean	SD	Min.	Max.
Private car crash count	1.94	2.48	0	35
Light vehicle crash count	1.89	2.21	0	20
Heavy vehicle crash count	0.85	1.28	0	12
Private car crash rate	1.69	11.58	0	274.85
Light vehicle crash rate	1.62	7.47	0	195.28
Heavy vehicle crash rate	0.75	7.75	0	262.86
Length (km)	2.71	3.35	0.08	19.08
Average lane width (m)	3.75	0.89	2.70	10.00
Number of lanes	4.58	2.35	1	12
Intersection density (number per km)	2.08	3.24	0.00	14.36
Speed limit (km/h)	64	13	30	100
Logarithm of four-hour traffic flow	1.74	1.11	-3.30	3.66
Presence of on-street parking (yes = 1, no = 0)	0.12	0.33	0	1

6.3 Model specification and goodness-of-fit

In this section, the formulations of univariate random parameter Tobit model for overall crash rates by injury severity (KSI and slight injury), and multivariate Tobit model for crash rates by vehicle types (private car, light commercial vehicle and heavy commercial vehicle) are specified under the Bayesian framework.

6.3.1 Random parameter Tobit model

In conventional safety literature, crash frequencies are typically modeled using count-data approaches. In this paper, however, we examine the crash experience using an alternative outcome – the crash rate, that is, the number of crashes per million vehicle-kilometer travelled (Anastasopoulos et al., 2008). The advantages of crash-rate analysis have been discussed by several recent studies (Zeng et al., 2017b, 2019; Guo et al., 2019). For example, crash rate represents a standardized measure of the relative safety performance of road entities as it neutralizes the crash exposure. Crash rates have always been a common feature of government agency safety reports, and cash rate analysis currently has several common applications including the identification of hotspots. The crash rate variable is continuous in nature and left-censored at zero, as some road segments in the study dataset have zero crashes; therefore, as recommended by previous studies (Anastasopoulos et al., 2008; Guo et al., 2019; Zeng et al., 2017a, 2017b, 2018), this study uses a Tobit regression approach.

The dependent variable is the crash rate, and the analysis is carried out for each level of crash severity. The crash rate is a non-negative and continuous variable that is censored at zero (meaning that there could exist road segments where no crash is observed during a specific period). As such, in the analysis, we used a Tobit model (an econometric technique originally proposed by Tobin (1958)) to resolve the problem of left- or right-censoring of the dependent variable. Anastasopoulos et al. (2008) first applied the Tobit approach in road safety research. It is often recommended to develop crash prediction models separately for each level of crash severity because underreporting is often more prevalent for less severe crashes (Anastasopoulos et al., 2012b; Pei et al., 2016). Additionally, separate development of models by crash severity level helps eliminate estimation bias that may arise from any shared but unobserved heterogeneity across observations. To address this issue, previous researchers including Guo et al. (2019), Chen et al. (2017a), Zeng et al. (2018, 2017a, 2017b), Anastasopoulos et al. (2012a, 2012b), and Anastasopoulos (2016) have used advanced modelling approaches including random parameter Tobit model, multivariate Tobit model and multivariate random-parameter Tobit model.

In this study, a random-parameter Tobit model[4] was developed to account for unobserved shared effect among crashes and any heterogeneity in the effects of certain crash factors across the observations. This was done for different levels of crash severity. The analysis helped examine the associations between the crash rate and the commercial vehicle mix (i.e., the respective proportions of the five commercial vehicle classes), and other prospective explanatory factors including year, time of the day, road geometry, traffic control, traffic flow were examined. The model proposed for the analysis has the form (Equation (2) and Equation (3)):

[4] To account for the possible unobserved shared effect among crashes at different crash severity levels, multivariate Tobit model was also considered. However, results of goodness-of-fit assessment suggest that multivariate Tobit model did not outperform the univariate one. Besides, our preliminary results suggest that there is no evidence for significant correlation between KSI and slight crash rates.

$$Y_{ip}^{k*} = \beta_{ip}^{k0} + \sum_j \beta_{ip}^{kj} x_{ip}^{j} + \varepsilon_{ip} \tag{2}$$

$$\begin{cases} Y_{ip}^{k} = Y_{ip}^{k*} & if\ Y_{ip}^{k*} > 0 \\ Y_{ip}^{k} = 0 & if\ Y_{ip}^{k*} \leq 0 \end{cases}$$

$$\beta_{ip}^{kj} = \beta^{kj} + \omega_{ip} \tag{3}$$

Where: i = 1, 2, …, N; p = 1, 2, …, P; k = 1, 2, …, K; Y_{ip}^{k*} denotes the latent variable linking the expected crash rate of severity level k at segment i during period p; Y_{ip}^{k} denotes the observed crash rate; N, P and K refer to the total number of road segments, time periods and crash severity levels, respectively; x_{ip}^{j} denotes the value of j^{th} explanatory variable at segment i during period p; ε_{ip} refers to a normally and independently distributed random error term with zero mean and variance σ^2; β_{ip}^{k0} is a constant; β_{ip}^{kj} is the normal distributed random parameter[5] with a mean vector of β^{kj} (that is, the coefficient of the j^{th} explanatory variable corresponding to crash severity level k). ω_{ip} refers to a normally and independently distributed random error term with zero mean and variance σ_w^2. It should be noted that β_{ip}^{kj} is set to be random only when its variance is statistically significant at 5% level, otherwise the parameter is set to be fixed.

With regard to the non-zero crash case, the marginal effect (i.e., effect of per unit increase in an independent variable on the expected crash rate) can be determined using methodologies established in the literature (Anastasopoulos et al., 2008, 2016; Roncek, 1992):

$$\frac{\partial E[Y^{\wedge}]}{\partial x_j} = \beta_j \times \left[1 - z \times \frac{f(z)}{F(z)} - \frac{f(z)^2}{F(z)^2} \right]$$

For the zero-crash case, the marginal effect can be specified as,

[5] Alternative distributional assumptions such as log-normal for the random parameters were also explored. Nevertheless, the model with normal distribution provided the best fit. For the considerations about the random-parameter density functions, detailed discussions can refer to Anastasopoulos and Mannering (2009). Moreover, the model with normal distribution can provide substantive interpretations that were very different from models with other distributions.

$$\frac{\partial F(z)}{\partial x_j} = \beta_j \times \frac{f(z)}{\sigma}$$

Where: $\partial E[Y^{\wedge}]/\partial x_j$ denotes the change in the expected crash rate for non-zero crash case; $\partial F(z)/\partial x_j$ denotes the change in the cumulative probability of having a crash for the cases with no crashes; $\boldsymbol{\beta_j}$ denotes the coefficient of the jth explanatory variable; F(z) is the area bounded by the normal curve (i.e., the normal distribution function) for the propensity of the crash occurrence; z denotes the normalized score; f(z) denotes the standard normal density function; σ is the standard deviation of the error term ε_{ip}.

6.3.2 Multivariate Tobit model

To capture common unobserved factors across different crash types, multivariate analysis is commonly adopted in previous research for a better modelling performance. For examples, Lee et al., (2015) presented a significant unobserved shared effect between the numbers of motor vehicle, bicycle, and pedestrian crashes, using multivariate Poisson log-normal model. Zeng et al. (2017b) and Anastasopoulos et al. (2012b) accommodated the significant correlation between crash rates at different severity levels, using multivariate Tobit model. Guo et al. (2019) investigated the rear-end, sideswipe, and angle crashes at freeway diverge areas and revealed the presence of unobserved risk factors that jointly affect different crash rates by collision type. As the dependent variables of the proposed analysis are crash rates by different vehicle type (private car, light commercial vehicle, and heavy commercial vehicle), a multivariate Tobit model is specified as follows:

$$Y_{ip}^{v*} = \beta_{v0} + \sum_j \beta_{vj} x_{ip}^j + \varepsilon_{ip}^v \tag{6}$$

$$\begin{cases} Y_{ip}^v = Y_{ip}^{v*} & if\ Y_{ip}^{v*} > 0 \\ Y_{ip}^v = 0 & if\ Y_{ip}^{v*} \leq 0 \end{cases}$$

i = 1,2,…,N; p = 1,2,…,P; v = 1,2,3

where Y_{ip}^{v*} denotes the latent variable linking the expected crash rate of vehicle type *v*

(1,2,3 represents for private car, light commercial vehicle, and heavy commercial vehicle crashes per million vehicle-kilometer traveled in road segment i, respectively) at segment i during period p, while Y_{ip}^{v} denotes the observed crash rate. β_{v0} is the constant, β_{vj} is the estimated parameter for j^{th} explanatory variable corresponding to vehicle type v. ε_{ip}^{v} refers to a multivariate normally and independently distributed random error term with zero mean, variance Σ, and correlation ρ, which can be expressed as ε_{ip}^{v} ~ N (0, Σ). The covariance matrix is,

$$\varepsilon_{ip}^{v} = \begin{pmatrix} \varepsilon_{ip}^{1} \\ \varepsilon_{ip}^{2} \\ \varepsilon_{ip}^{3} \end{pmatrix}, \ \Sigma_{\varepsilon_v} = \begin{pmatrix} \sigma_1^2 & \rho_{21}\sigma_2\sigma_1 & \rho_{31}\sigma_3\sigma_1 \\ \rho_{12}\sigma_1\sigma_2 & \sigma_2^2 & \rho_{32}\sigma_3\sigma_2 \\ \rho_{13}\sigma_1\sigma_3 & \rho_{23}\sigma_2\sigma_3 & \sigma_3^2 \end{pmatrix} \tag{7}$$

where σ_1^2, σ_2^2, σ_3^2 represents the variance of error term ε_{ip}^{1}, ε_{ip}^{2}, ε_{ip}^{3}, respectively.

6.3.3 Goodness-of-fit

To assess the goodness-of-fit of the proposed model using Bayesian approach, deviance information criteria (DIC) and Bayesian R^2 are commonly used (Huang et al., 2016; Zeng and Huang, 2014; Zeng et al., 2017a, 2017b, 2018; Wen et al., 2018). DIC is essentially a generalization of Akaike's Information Criterion (AIC) and is given by (Spiegelhalter et al., 2002),

$$\mathrm{DIC} = \overline{D} + \mathrm{pD} \tag{8}$$

$\overline{D}$ denotes the posterior mean of deviance, pD is the complexity term for the effective number of parameters in the model. Model with the lowest DIC value, among the candidate models, is considered to have the best prediction performance. Yet, difference in DICs between models should also be considered. Specifically, difference should be preferably greater than ten (Spiegelhalter et al., 2005).

For the multivariate analysis of crash rates by vehicle type, another goodness-of-fit measure – Bayesian R^2 is also considered (Ahmed et al., 2011). Bayesian R^2 refers to the ratio of explained sum of squares to total sum of squares. Bayesian R_k^2 for model of crash severity k is specified as:

$$R_k^2 = 1 - \frac{\sum_{i=1}^{N}\sum_{p=1}^{P}(Y_{ip}^k - \lambda_{ip}^k)^2}{\sum_{i=1}^{N}\sum_{p=1}^{P}(Y_{ip}^k - \overline{Y^k})^2} \quad , \mathrm{k} = 1, 2 \tag{9}$$

$$\overline{Y^k} = \frac{1}{N \times P}\sum_{i=1}^{N}\sum_{p=1}^{P} Y_{ip}^k \tag{10}$$

$$\begin{cases} \lambda_{ip}^k = \beta_{ip}^{k0} + \sum_j \beta_{ip}^{kj} x_{ip}^j, & if\ \beta_{ip}^{k0} + \sum_j \beta_{ip}^{kj} x_{ip}^j > 0 \\ \lambda_{ip}^k = 0, & if\ \beta_{ip}^{k0} + \sum_j \beta_{ip}^{kj} x_{ip}^j \le 0 \end{cases} \tag{11}$$

where λ_{ip}^k denotes the estimated crash rate of severity level k at segment i during period p, and $\overline{Y^k}$ represents the mean observed crash rate of severity level k.

In addition, for the multivariate Tobit model, R_v^2 and R_{total}^2 represent the Bayesian R^2 values of crash rates by vehicle type v and all observations. They are specified as:

$$R_v^2 = 1 - \frac{\sum_{i=1}^{N}\sum_{p=1}^{P}(Y_{ip}^v - \lambda_{ip}^v)^2}{\sum_{i=1}^{N}\sum_{p=1}^{P}(Y_{ip}^v - \overline{Y^v})^2} \quad , v = 1, 2, 3 \tag{12}$$

$$R_{total}^2 = 1 - \frac{\sum_{v=1}^{V}\sum_{p=1}^{P}\sum_{i=1}^{N}(Y_{ip}^v - \lambda_{ip}^v)^2}{\sum_{v=1}^{V}\sum_{p=1}^{P}\sum_{i=1}^{N}(Y_{ip}^v - \bar{Y})^2} \tag{13}$$

$$\begin{cases} \lambda_{ip}^v = \beta_{v0} + \sum_j \beta_{vj} x_{ip}^j, & if\ \beta_{v0} + \sum_j \beta_{vj} x_{ip}^j > 0 \\ \lambda_{ip}^v = 0, & if\ \beta_{v0} + \sum_j \beta_{vj} x_{ip}^j \le 0 \end{cases} \tag{14}$$

$$\overline{Y^v} = \frac{1}{P \times N}\sum_{p=1}^{P}\sum_{i=1}^{N} Y_{ip}^v \tag{15}$$

$$\bar{Y} = \frac{1}{V \times P \times N}\sum_{v=1}^{V}\sum_{p=1}^{P}\sum_{i=1}^{N} Y_{ip}^v \tag{16}$$

where λ_{ip}^{v} denotes the estimated crash rate of vehicle type v at segment i during period p, $\overline{Y^v}$ and $\bar{Y}$ represent the mean observed crash rate of vehicle type v and all observations, respectively.

In this study, WinBUGS software was used to specify the formulations of the random-parameter Tobit models under the Bayesian framework. Markov chain Monte Carlo (MCMC) simulations were used to sample the posterior distribution of the model parameters. Prior distributions of β_{ip}^{kj} were specified as being diffusely and normally distributed $N(0, 10^4)$ (Guo et al., 2019; Lee et al., 2015; Zeng et al., 2017b, 2019).

For each model, a chain of 200,000 iterations of Markov chain Monte Carlo (MCMC) simulation were established. In particular, the first 5,000 iterations served as burn-ins and therefore were discarded. MCMC convergence was assessed by visually inspecting the time-series plots of the estimated parameters, and the ratios of MC error to the corresponding standard deviation of the estimates –specifically, the ratios should be less than 0.05 (Ahmed et al., 2011; Guo et al., 2019; Wen et al., 2018; Zeng et al., 2017a, 2017b).

6.4 Results and discussion on the effects of commercial vehicle mix

Prior to parameter estimation, a multicollinearity test was conducted to assess the correlations between the independent variables. The results indicated that the VIFs (variance inflation factor) of the pairs of independent variables are all less than 5, hence, there is no multicollinearity between the independent variables. The random parameter Tobit models were used to identify the crash factors associated with crash rates by severity level. Two broad categories of analysis were carried out: 1) basic models to reaffirm the main effects of commercial vehicle proportions (CVP) on crashes, and 2) refined models to closely examine the mediating effect of road environment crash factors on the CVP-crash rate relationship. In the basic models, variables that were found not statistically significant at the 5% level were eliminated using a backward stepwise regression technique (Abdel-Aty et al., 2004; Bose et al., 2013; Huo et al., 2020). However, variables including speed limit, public buses%, taxi%, and segment with wide roadways were retained in the model. This is to allow for the possible confounding effects on the crash rates. Then, refined models were developed to consider any interactions between the significant variables representing the CVP and the other crash factors related to the roadway environment, particularly, road geometry and traffic control facilities. In the refined models, only the variables significant at the 5% level were included. **Table 6.3** presents the goodness-of-fit results for the models developed. The refined models were generally superior to the basic models in terms of DIC value, and the interactions between the variables were manifest to a greater degree.

Table 6. 3 Results of the goodness-of-fit tests

	Slight-injury crash rate		**KSI crash rate**	
	Basic model	Refined model	Basic model	Refined model
D bar	–4,185	–3,925	–9,254	–9,417
pD	6,353	6,071	3,865	3,784
DIC	2,167	2,145	–5,389	–5,633
DIC_{basic}-$DIC_{refined}$	22		244	

Note: Model with lower DIC (difference in DICs exceeding 10) has superior prediction performance.

Tables 6.4 and **6.5** present the estimation results of random-parameter Tobit models for slight-injury crash rate and KSI crash rate, respectively. The basic model (Table 6.4) confirmed that the factors representing traffic flow, road geometry, traffic control, commercial vehicle proportion, and time of day all influenced the slight-injury crash rate. In particular, the [log of 2-hour] traffic flow (coefficient = –1.009) and the proportion of medium and heavy goods vehicle (–0.026) were associated with lower slight-injury crash rate. On the contrary, a wide roadway or 5 or more traffic lanes (0.926), high intersection density (1.120), presence of on-street parking (1.818), proportions of taxi (0.029) and light goods vehicle (0.061), and the time of day from 5PM to 9PM (0.630), were found positively associated with slight-injury crash rate, at 5% significance level. Also, the heterogenous effect of the average lane width (mean of 0.479 and standard deviation of 1.151) on slight-injury crash rate was found to be statistically significant. With regard to the basic model in Table 6.4, also, log of 2-hour traffic flow (–0.092) and the proportion of medium- and heavy-goods vehicle (–0.006) were associated with lower KSI crash rate. In contrast, presence of on-street parking (0.392), proportions of public buses (0.009) and light-goods vehicle (0.005) were found to be positively associated with the KSI crash rate.

Also, it was shown that the effects of average lane width (mean of 0.124 and standard deviation of 0.035) and high intersection density (mean of 0.168 and standard deviation of 2.920) on KSI crash rate varied across the observations.

The refined models for slight-injury and KSI crash rates (Table 6.5) present the interaction effects of the commercial vehicle proportion which were found to be statistically significant in the basic model and the other potential crash factors. The interaction terms that were significant at the 5% level were included in the final set of the refined models. A comparison of the estimation results of the basic and refined models showed that most of the contributory factors showed consistent safety effects across these two groups of models. The exception is that the insignificant variable (wide roadways) becomes statistically significant when the interaction terms are considered for the KSI crash rate (see Table 6.5). Thus, only the interaction effects in the refined models are discussed here. As shown in Table 6.5, the interactions between (i) the proportion of taxi and high intersection density, and (ii) the proportion of light goods vehicle and presence of on-street parking, were significantly associated with slight-injury crash rate at the 5% level. On the other hand, interactions between (iii) the proportion of medium- and heavy-goods vehicle and high intersection density, and (iv) the proportion of medium and heavy goods vehicle and a wide roadway (5 or more lanes) were significantly associated with KSI crash rate at the 5% level (see Table 6.5).

Table 6.6 presents the marginal effects of the refined models. For example, for the cases above the limit (with crashes), a 10% increase in the proportion of taxi is expected to contribute to an increase in the slight-injury crash rate by 0.07, while it contributes to an increase in the slight-injury crash rate of road segments with high intersection density by 0.14. Also, it is expected that a 10% increase in the proportion of light-goods vehicle generally increases the slight-injury crash rate by 0.21, while it increases the slight-injury crash rate of road segments with on-street parking areas by 0.53. Moreover, a 10% increase in the proportion of medium- and heavy-goods vehicle is expected to increase the KSI crash rate of road segments with high intersection density by 0.16, while it decreases the KSI crash rate of road segments with more traffic lanes by 0.02.

On the other hand, for the cases at the limit (no crashes), the probability of having a slight-injury crash is expected to be increased by 2.9%, due to a 10% increase in the proportion of taxi on the road segments with high intersection density. The probability of having a slight-injury crash is expected to increase by 10.5% for the road segments with on-street parking areas, due to 10% increase in the proportion of light-goods vehicle. For the road segments with high intersection density and zero-crash observation, the probability of having a KSI crash is expected to increase by 6.8%, due to a 10% increase in the proportion of medium- and heavy-goods vehicle.

Table 6. 4 Results of random-parameter Tobit model

Variable	Basic model				Refined model			
	Mean	S.D.	BCI		Mean	S.D.	BCI	
			2.5%	97.5%			2.5%	97.5%
Constant	5.844	1.050	**4.018**	**7.948**	5.736	0.873	**4.145**	**7.646**
Ln (2-hour traffic flow)	**–1.009**	0.088	**–1.183**	**–0.841**	**–1.030**	0.097	**–1.214**	**–0.857**
Average lane width	**0.479**	0.177	**0.105**	**0.728**	**0.531**	0.121	**0.238**	**0.725**
S.D. of Average lane width	**1.151**	0.035	**1.089**	**1.215**	**1.149**	0.031	**1.089**	**1.212**
Wide roadway (nr. of traffic lanes >4)	**0.926**	0.199	**0.559**	**1.328**	**0.925**	0.158	**0.624**	**1.248**
Speed limit	–0.008	0.007	–0.022	0.006	-	-	-	-
High intersection density (≥3 per km)	**1.120**	0.219	**0.717**	**1.545**	-	-	-	-
Presence of on-street parking	**1.818**	0.352	**1.169**	**2.501**	-	-	-	-
Variables for commercial vehicle proportions								
Public buses %	0.000	0.012	–0.022	0.024	-	-	-	-
Taxi %	**0.029**	0.008	**0.013**	**0.046**	**0.019**	0.010	**0.001**	**0.038**
Light-goods vehicle %	**0.061**	0.013	**0.037**	**0.089**	**0.055**	0.013	**0.028**	**0.079**
M&H-goods vehicle %	**–0.026**	0.013	**–0.050**	**–0.001**	**–0.045**	0.013	**–0.073**	**–0.023**
Time effect variables								
5PM-9PM	**0.630**	0.177	**0.302**	**0.987**	**0.554**	0.211	**0.134**	**0.905**
Interaction effect variables								
Taxi % × High intersection density	-	-	-	-	**0.038**	0.006	**0.025**	**0.048**
Light goods vehicle % × Presence of on-street parking	-	-	-	-	**0.138**	0.023	**0.091**	**0.190**

BCI refers to Bayesian credible interval
***Boldface** indicates statistical significance at the 5% level*
Insignificant variables are retained in the basic model to account for the possible confounding effects on crash rates
In the refined model, only significant variables are retained

Table 6. 5 Random parameter Tobit model for KSI crash rate

Variable	Basic model				Refined model			
	Mean	S.D.	BCI		Mean	S.D.	BCI	
			2.5%	97.5%			2.5%	97.5%
Constant	**0.435**	0.201	**0.055**	**0.844**	0.425	0.258	**–0.068**	**0.952**
Ln (2-hour traffic flow)	**–0.092**	0.019	**–0.130**	**–0.055**	**–0.108**	0.024	**–0.156**	**–0.062**
Average lane width	**0.124**	0.036	**0.040**	**0.189**	**0.121**	0.057	**0.022**	**0.232**
S.D. of Average lane width	**0.035**	0.001	**0.033**	**0.038**	**0.071**	0.002	**0.067**	**0.075**
Wide roadway (nr. of traffic lanes >4)	0.041	0.037	–0.032	0.113	**0.121**	0.052	**0.023**	**0.226**
Presence of on-street parking	**0.392**	0.065	**0.267**	**0.522**	**0.487**	0.087	**0.320**	**0.662**
High intersection density (≥3 per km)	**0.168**	0.079	**0.012**	**0.323**	-	-	-	-
S.D. of High intersection density	**2.920**	0.214	**2.525**	**3.365**	-	-	-	-
Speed limit	–0.001	0.001	–0.004	0.001	-	-	-	-
Variables for commercial vehicle proportions								
Taxi %	–0.003	0.002	–0.006	4.13E-04	-	-	-	-
Public buses %	**0.009**	0.002	**0.004**	**0.014**	**0.006**	0.003	**8.62E-05**	**0.011**
Light-goods vehicle %	**0.005**	0.002	**4.03E-04**	**0.009**	**0.005**	0.002	**1.26E-04**	**0.010**
M&H-goods vehicle %	**–0.006**	0.002	**–0.011**	**–0.002**	-	-	-	-
Interaction effect variables								
M&H-goods vehicle % × High intersection density	-	-	-	-	**0.084**	0.020	**0.045**	**0.123**
M&H-goods vehicle % × Wide roadway	-	-	-	-	**–0.010**	0.003	**–0.016**	**–0.005**

***Boldface** indicates statistical significance at the 5% level*
Insignificant variables are retained in the basic model to account for the possible confounding effects on crash rates
In the refined model, only significant variables are retained.

Table 6. 6 Marginal effects results for the refined models

	Slight-injury crash rate		KSI crash rate	
	$\partial E[Y^{\wedge}]/\partial x_j$	Zero-crash sensitivity	$\partial E[Y^{\wedge}]/\partial x_j$	Zero-crash sensitivity
Ln (2-hour Traffic flow)	-0.392	-7.83%	-0.020	-0.87%
Average lane width	0.202	4.04%	0.023	0.98%
More traffic lanes (>4)	0.352	7.03%	0.023	0.98%
Presence of on-street parking	--	--	0.091	3.94%
Public buses %	--	--	0.001	0.05%
Taxi %	0.007	0.14%	--	--
Light goods vehicle %	0.021	0.42%	0.001	0.04%
M&H goods vehicle %	-0.017	-0.34%	--	--
5pm-9pm	0.211	4.21%	--	--
Taxi % * High intersection density	0.014	0.29%	--	--
Light goods vehicle % * Presence of on-street parking	0.053	1.05%	--	--
M&H goods vehicle % * High intersection density	--	--	0.016	0.68%
M&H goods vehicle % * More traffic lanes	--	--	-0.002	-0.08%

Note: Zero crash sensitivity is determined as multiplying $\partial F(z)/\partial x_j$ *by 100%*

6.4.1 Effects of geometric factors

The model results suggest that the average lane width is positively associated with slight-injury crash rate and KSI crash rate. Specifically, when the average lane width increases, the rate of slight-injury crashes increases at 66.1% of the road segments and the rate of KSI crashes increases at 100% of the road segments. This finding is generally consistent with that of recent studies (Zeng et al., 2017b). This could be because drivers tend to be less cautious and speed up when the traffic lane is wider. Therefore, potential crash and injury risks both increase (Gross and Jovanis, 2007). Furthermore, heterogeneity for the effect of lane width can be attributed to the variation in pavement surface condition and driver response. In other words, the relationship between lane width and crash propensity is not necessarily monotonic. As our results also suggest that 33.9% of the road segments would experience reduction in slight-injury crash rate with an increase in average lane width. Indeed, it has been reported that crash propensity increases when the lane width first increases (known as ‘driver extreme cautious zone’), then decreases when the lane width further increases (‘driver normal zone’), and eventually bounce back again (‘reckless driving zone’) (Labi et al., 2017; Chen S., 2019b; Chen S. et al., 2019c; Chen et al., 2020b). As such, it is worth exploring the non-linear relationship between lane width and crash propensity when comprehensive information on driving behavior is available in a future extended study. The analysis results also suggest that a wider roadway (with more traffic lanes) is generally positively associated with slight-injury crash rate, and this results could be attributed to increased lane-changing opportunities when the number of lanes increases (Pei et al., 2012, 2016; Zeng et al., 2017b; Chen S. et al., 2019c).

6.4.2 Effects of Traffic flow and traffic control

With regard to the effect of traffic flow, the two-hour overall traffic flow (logarithmic form) is negatively associated with slight-injury and KSI crash rates. This result, which suggests that the increased traffic volume would reduce the average travel speed of the road segment and thereby decrease the likelihood of crash occurrence and severity, is consistent with the findings of previous studies (Anastasopoulos et al., 2012a, 2012b; Huang et al., 2016; Zeng et al., 2017a, 2017b, 2018). With regard to the effect of traffic control, the results suggest that the presence of on-street parking increases slight-injury and KSI crash rates. This aligns with the previous findings that higher crash propensity is associated with more frequent roadside activities near the on-street parking areas (Pei et al., 2016).

In addition, high intersection density was found to be positively associated with slight-injury and KSI crash rates, which could be attributed to the effect of prevalent traffic conflicts typically experienced at intersections (Wong et al., 2007; Sze and Wong, 2007). However, our results also suggest that for 47.7% of the road segments, high intersection density is associated with lower KSI crash rates. Such heterogeneous effect of intersection density on KSI crash rate can be explained by the risk compensation theory (Mannering and Bhat, 2014; Chen et al., 2017) where drivers adopt more cautious driving behavior to compensate for the increased crash propensity arising from a complex driving environment such as frequent intersections In particular, since pedestrian crashes at intersections are more likely to be fatal or have serious injury (Zhai et al., 2019; Sze et al., 2019), drivers generally may pay more attention to the pedestrian's location and behavior when driving through an intersection. As such, the lower KSI crash rate found in some road segments with high intersection density could be attributed to the risk compensation by drivers at these locations (Zeng et al., 2017b).

6.4.3 Temporal effect

The study did not find any temporal variations in the slight-injury and KSI crash rates over the years of study. With respect to the time of day, it was determined that in the period 5PM –9PM, the slight-injury crash rate is significantly higher than that of other time periods at 5% level of significance. This is not surprising since such period covers the evening peak hours that the city residents are off work and are engaging various activities including homebound trip, shopping, and gathering with friends. In particular, drivers tend to drive less cautiously during their off-work hours; therefore, at this period, violation behaviours are relatively more prevalent, thus are characterized by higher crash risk (Chin and Huang, 2009). Moreover, driving under the influence of fatigue (particularly among commercial vehicle drivers) is more likely to occur during this period (Boufous and Williamson, 2006). In contrast, no significant evidence was found for the effect of time on KSI crash rate, suggesting that the temporal variation in crash rates are different across the different levels of crash severity.

6.4.4 Main effects of commercial vehicle proportions (CVPs)

There exist anecdotal reports that the drivers of Hong Kong taxis and light-goods vehicles tend to be risk-prone and aggressive because they are self-employed and their income levels depend on the number and distance of their trips (Chen et al., 2020a; Meng et al., 2017). It has also been found that taxi drivers in general, in several countries including China, are more likely to involved in texting while driving, speeding, dangerous overtaking and red light running (Wang et al., 2019a, 2019b; Nguyen-Phuoc et al., 2020). The situation is exacerbated further by the taxi driver demographics: the aging taxi driver population contributes to elevated crash propensity, as their driving performance is more likely to be impaired plausibly due to deteriorating health, fatigue and slow response time (Chen et al., 2019a, 2019b; Meng et al., 2017). Hence, it is not surprising that increases in the proportions of taxi and light goods vehicle both are associated with higher rates of slight-injury crashes.

Moreover, an increase in the proportion of light-goods vehicle is associated with an increase in the KSI crash rate. Indeed, it could also be attributed to the difference in sense of social responsibility across various types of professional drivers (Paleti et al., 2010).

For example, light-goods vehicle drivers who transport goods, presented a higher tendency to commit traffic offenses and a higher injury risk, i.e., fatal and severe injury (see Zhang et al., 2013, 2014), whereas a higher proportion of medium- and heavy-goods vehicles is associated with lower rates of slight-injury and KSI crash rates. This result could be due to the stricter regulation of the driving speed of medium- and heavy-goods vehicles (Transport Department, 2020a). Besides the cognizance of the regulations, heavy-goods vehicle drivers themselves tend to drive at a lower speed to compensate for the elevated injury risk resulted from their higher vehicle weights (Saifizul et al., 2011).

On the other hand, it was expected that bus is a relatively safe transportation mode (Feng et al., 2016). Bus drivers tend to be more risk averse because they typically possess a stronger sense of social responsibility and lower preference to commit traffic offense (possibly due to greater enforcement of regulations for heavy-vehicles operators) (Paleti et al., 2010; Chen et al., 2020a; Öz et al., 2010, 2013). Surprisingly, our results showed that the higher proportion of public buses is generally associated with a higher KSI crash rate. This could be attributed to the exposure of commuters, the passenger capacity, the size and weight of public buses, as well as the determination of crash severity levels (Chimba et al., 2010; Feng et al., 2016; Tsui et al., 2009). In Hong Kong, crash severity is determined based on the observations by police at scene and the follow-up hospital records for up to 30 days. A severe injury crash refers to a traffic accident in which one or more persons injured and detained in hospital for more than twelve hours. In this context, larger capacity of passengers on the bus and higher exposure of commuters on the road segments would contribute to the increase in KSI crash rate, as the severity level is mainly determined by the people involved in the crash. Specifically, the passenger capacity of public buses is much higher than that of other passenger vehicles (e.g., the maximum capacity of a double-decker bus can reach 150 passengers, while that of a taxi is 5 in Hong Kong). In addition, public buses in Hong Kong (including franchised bus and public light bus) constitute 73% of overall road-based public transport patronage (Transport Department, 2014). They are operated on fixed routes and schedules by sizeable operators, which are regulated by the Hong Kong Transport Department. Road segments with higher proportion of public buses tend to be located in Central Business District, where the exposure of commuters tend to be very high on weekdays.

6.4.5 Interaction effects of CVPs and roadway attributes

Tables 6.4 and 6.5, which present the interaction effects, suggest that traffic control and road geometry influence the relationship between commercial vehicle mix and slight-injury crash rate. In particular, the increasing effect of taxi proportion on slight-injury crash rate is magnified at road segments with high intersection density. This could be attributed to the prevalence of traffic violations and reckless driving among taxi drivers at intersections as evidenced in the literature. For example, Wu et al. (2016) revealed that non-professional drivers generally tend to be more careful when driving through intersections while taxi drivers are prone to committing red-light running and other violations. Also, Xu et al. (2014) found that taxis are more likely to be involved in traffic conflicts at intersections compared with other vehicle types. As such, greater emphasis could be placed on enforcement strategies to combat the traffic violation behaviours by taxi drivers at intersections. For example, Hong Kong presently has very few (195) intersections with digital red-light cameras in operation (out of a total of 1,916 signalized intersections) (Transport Department, 2017b, 2020b) and these could be significantly increased. Based on our current finding, it is suggested that for expanding the red-light camera network, priority could be given to road segments with relatively high proportions of taxis. Besides, it is recommended that taxi drivers should be carefully regulated in accordance with the licensing requirements. For example, the licensing office may invite the taxi drivers (particularly those with a record of red-light running) to attend educational program aimed at addressing risk-taking behaviour at intersections.

Similarly, the increasing effect of light-goods vehicle percentage on slight-injury crash rate is magnified at road segments with on-street parking. In Hong Kong, on-street parking is typically provided at the urban roads to facilitate direct access to the buildings. Hence, it is likely that the road segments with on-street parking would have more frequent roadside pick-ups, drop-offs, and loading/unloading activities involving light goods vehicles (Sze and Wong, 2007). To address the higher crash propensity at on-street parking areas, police patrols could be enforced at these areas, particularly at those urban road segments that tend to have a higher proportion of light-goods vehicles. With regard to medium- and heavy-goods vehicles on the other hand, the association between the CVP percentage and the KSI crash rate seems to be moderated by the roadway width (number of traffic lanes). Specifically, the decreasing effect of medium- and heavy-goods vehicle percentage on KSI crash rate would be magnified by the increase in the roadway width. A previous study revealed a dichotomous effect of heavy truck percentage on lane-changing frequency across different traffic phases (e.g., free flow, synchronized flow and congestion); however, the frequency of lane-changing events was found to decrease remarkably with effective lane control measures for heavy trucks (Li et al., 2016). Hong Kong road traffic regulations specify that medium- and heavy-goods vehicles are not allowed to use the rightmost lane of expressway with three or more lanes in each direction, and lane control measures implemented at such roadways are effective in separating traffic flows by vehicle class. Thereby, such, possible conflicts between heavy truck and other light vehicles, as well as the likelihood of fatal or serious-injury crashes, are generally reduced (Mooren et al., 2014).

Finally, the association between medium- and heavy-goods vehicle percentage and KSI crash rate was found to be moderated by intersection density (number of intersections within a given unit length of road). In particular, an increase in medium- and heavy-goods vehicle percentage would contribute to the increase in KSI crash rate of the road segments with high intersection density. A possible explanation is the design of intersections. Over the past decades, the dimension and weight of heavy vehicles have increased substantially. Therefore, Dong et al. (2014) aptly questioned whether intersections designed using earlier standards is capable of serving vehicles with various dimensions and weights. The authors developed count models for intersection crashes and found that an increase in the percentage of heavy trucks in the traffic stream contributes to the increase in truck-involved crashes. Another possible explanation is the dilemma zone driver behaviour. It was revealed that heavy truck drivers are less likely to decelerate in response to a yellow stage of the traffic signal, thus contributing to a higher rate of red-light running (Gates et al., 2007, 2010). Therefore, it is not surprising that in this study, the KSI crash rate was found to be sensitive particularly to the interaction between high intersection density and medium- and heavy-goods vehicle percentage. This result suggests that the existence of a need for government road agencies to review the service capability of the intersections at roads that serve a significant fraction of medium- and heavy-goods vehicles; that way, it may be possible to reduce crashes caused by or related to such vehicle classes at road intersections. On the other hand, to eliminate the risk-prone behaviours of heavy-truck drivers in dilemma zones, trucking employers and freight carriers could provide tailored training programs for their drivers to ensure enhanced driving decisions and responsible driving behaviour.

6.5 Results and discussion on crash rates by vehicle type

Two models were considered to analyse the crash rates of three vehicle types: (i) univariate Tobit model, and (ii) multivariate Tobit model. Results of DIC shown in **Table 6.7** suggest that multivariate Tobit model outperforms the univariate one (difference in DIC more than 10). **Table 6. 8** presents the error parameters and goodness-of-fit of the multivariate Tobit model. Significant correlation between crash rates across vehicle types are found. The positive correlation between private car and light commercial vehicle, as well as the negative correlation between private car and heavy commercial vehicle could be attributed to the unobserved common risk factors affecting the crash rates across vehicle types simultaneously. Moreover, it is likely that the significant correlations come from the multiple-vehicle crashes. For example, the crash count used for calculating the crash rate of private car includes private car only, private car-light commercial vehicle, private car-heavy commercial vehicle, and private car-motorcycle crashes. Therefore, when the number of private car-light commercial vehicle crashes increases, both the crash rates of private car and light commercial vehicle increase. In either explanation, multivariate analysis should be employed to accommodate the correlations between crash rates.

Table 6. 7 Comparison of model performance

	Multivariate Tobit	Univariate Tobit		
		Private car	Light commercial vehicle	Heavy commercial vehicle
D bar	25351	9168	8084	8286
pD	42	13	13	13
DIC	25393	9181	8097	8299

Table 6. 8 Multivariate Tobit model error parameters and goodness-of-fit

	Mean	SD	95% BCI*
$\sigma_{\text{private car}}$	**121.80**	5.00	**(113.8, 130.2)**
$\sigma_{\text{light commercial vehicle}}$	**49.35**	2.03	**(46.12, 52.77)**
$\sigma_{\text{heavy commercial vehicle}}$	**58.38**	2.39	**(54.56, 62.43)**
$\rho_{\text{(private car vs. light commercial vehicle)}}$	**0.379**	0.025	**(0.338, 0.420)**
$\rho_{\text{(private car vs. heavy commercial vehicle)}}$	**-0.053**	0.029	**(-0.101, -0.005)**
$\rho_{\text{(light commercial vehicle vs. heavy commercial vehicle)}}$	-0.017	0.029	(-0.065, 0.031)
R^2_{total}	0.104	0.005	(0.095, 0.112)
$R^2_{private\ car}$	0.126	0.005	(0.117, 0.133)
$R^2_{light\ commercial\ vehicle}$	0.036	0.005	(0.027, 0.043)
$R^2_{heavy\ commercial\ vehicle}$	0.084	0.002	(0.079, 0.087)

**BCI refers to Bayesian credible interval*

***Boldface** indicates statistical significance at the 5% level*

The estimation results of multivariate Tobit model are presented in **Table 6.9**. It is found that number of lanes, average lane width, traffic flow, presence of on-street parking, and year are associated with the crash rates of private car and light commercial vehicle, all at the 95% credibility level. However, effect of intersection density is significant only for light commercial vehicle. Time period is revealed to be associated with the crash rates of private car and heavy commercial vehicle. For heavy commercial vehicle, two more risk factors - number of lanes and traffic flow are found significantly affect its crash rate. Difference in the risk factors to crash rates by vehicle type is discussed in the following paragraphs.

Table 6. 9 Results of multivariate Tobit model

Variable	Private car			Light commercial Vehicle			Heavy commercial Vehicle		
	Mean	SD	95% BCI*	Mean	SD	95% BCI*	Mean	SD	95% BCI*
Constant	-1.339	2.284	(-5.075, 2.431)	0.928	1.455	(-1.438, 3.332)	0.669	1.568	(-1.934, 3.211)
Number of lanes	**0.540**	0.207	**(0.202, 0.881)**	**0.359**	0.132	**(0.143, 0.576)**	**0.289**	0.143	**(0.054, 0.524)**
Average lane width	**1.533**	0.434	**(0.819, 2.246)**	**0.572**	0.279	**(0.112, 1.025)**	0.245	0.300	(-0.249, 0.738)
Density of intersection	-0.023	0.082	(-0.157, 0.111)	**0.252**	0.052	**(0.167, 0.338)**	-0.025	0.056	(-0.118, 0.067)
Presence of on-street parking	**3.053**	1.274	**(0.955, 5.148)**	**2.719**	0.811	**(1.384, 4.052)**	1.100	0.883	(-0.356, 2.553)
Ln(4-hour traffic flow)	**-2.501**	0.521	**(-3.363, -1.644)**	**-1.466**	0.333	**(-2.015, -0.923)**	**-1.317**	0.362	**(-1.909, -0.719)**
Speed limit	-0.020	0.028	(-0.067, 0.026)	-0.017	0.018	(-0.046, 0.012)	-0.010	0.020	(-0.043, 0.021)
Temporal effect (reference: 7pm-11pm)									
Time period 1 (7am-11am)	0.395	0.929	(-1.133, 1.926)	0.152	0.594	(-0.823, 1.130)	0.478	0.645	(-0.584, 1.538)
Time period 2 (11am-3pm)	**1.938**	0.925	**(0.414, 3.455)**	0.721	0.593	(-0.254, 1.695)	0.511	0.645	(-0.553, 1.569)
Time period 3 (3pm-7pm)	**1.857**	0.928	**(0.332, 3.381)**	0.440	0.595	(-0.537, 1.421)	**1.549**	0.648	**(0.482, 2.614)**
Year (reference: year 2015)									
Year 2016	-1.108	0.778	(-2.386, 0.171)	-0.730	0.496	(-1.548, 0.086)	-0.193	0.538	(-1.078, 0.694)
Year 2017	**-1.525**	0.777	**(-2.805, -0.250)**	**-1.422**	0.495	**(-2.236, -0.608)**	0.494	0.537	(-0.389, 1.378)

**BCI refers to Bayesian credible interval*
***Boldface** indicates statistical significance at the 5% level*
Insignificant variables are retained to account for the possible confounding effects on crash rates

6.5.1 Effects of geometric factors

For the effect of road geometry, average lane width is positively associated with private car and light commercial vehicle crash rates. However, such finding is not applicable to the crash rate of heavy commercial vehicle. This could be attributed to the differences in gross vehicle weight and dimensions (mainly the vehicle width) across vehicle types. In particular, the weight of heavy commercial vehicle (e.g. 24 tonnes) is much higher than that of private car (e.g. 3.0 tonnes) or light commercial vehicle (e.g. 5.5 tonnes). Indeed, the consequences of crashes involving professional drivers, especially drivers of buses and heavy goods vehicles, are often mortality and severe injury of other innocent road users (Alvarez and Fierro, 2008). Therefore, to control vehicle trajectories and avoid lane departure events, various systems have been developed and installed to stabilize the lateral position of heavy vehicles (Imine et al., 2011; Netto et al., 2004; Hingwe et al., 2002). On the other hand, crash rates of private car and light commercial vehicle would increase with the increase in average lane width of road segments. This could be attributed to driver's reckless driving on the wider lane (Labi et al., 2017). The increase in average lane width appears to provide relatively more space for light vehicles, which may imbue a false sense of security to drivers, thus leading to degraded driving performance. Moreover, wider lane in general leads to more overtaking events, in which private car, taxi, and light goods vehicle drivers tend to overtake aggressively (Shackel and Parkin, 2014).

Number of lanes is associated with a positive coefficient for the crash rates of private car, light commercial vehicle, and heavy commercial vehicle. This finding suggests that crash risk would increase with the increase in lane-changing opportunities (Pei et al., 2012, 2016; Zeng et al., 2017b). Furthermore, effect of intersection density is found significant only for the light commercial vehicles. This could be attributed to the prevalence of traffic violations among light commercial vehicle drivers (Chen et al., 2020; Meng et al., 2017). For example, light bus drivers have a higher tendency of red light running, speeding, and/or stopping at intersections (Wong et al., 2008), while bus drivers tend to drive in a cautious manner with a greater sense of social responsibility (Chen et al., 2020; Paleti et al., 2010). Consistently, Wu et al. (2016) revealed that non-professional drivers are more careful when driving through the intersection while taxi drivers are inclined to commit red-light running. Moreover, taxis are more likely to be involved in traffic conflicts at intersections compared with private cars (Xu et al., 2014). Hence, crash rate of light commercial vehicle increases when intersection density of the road segment increases.

Presence of on-street parking increases the crash rates of private car and light commercial vehicle. This aligns with the previous findings that higher crash risk is associated with more frequent roadside activities near the on-street parking areas (Pei et al., 2016). In Hong Kong, on-street parking areas are normally provided for the urban roads giving direct access to the buildings. Hence, it is likely that the road segments with on-street parking would have more frequent roadside pick-ups, drop-offs, and loading/unloading activities involving private cars and light commercial vehicles (Sze and Wong, 2007). Moreover, these roadside activities could translate into more frequent incidences of errant pedestrian behavior (such as reckless crossing), thus increasing pedestrian-vehicle crash frequency (Kim et al., 2017; Granié et al., 2014; Ukkusuri et al., 2012).

6.5.2 Effects of traffic condition and time

Regardless of the crash types, crash rates are generally lower when the overall traffic flow increases. This could be because the mean travel speed of the road segment reduces when the traffic volume increases (Huang et al., 2016; Zeng et al., 2017a, 2017b). However, previous study also revealed that increase in exposure would lead to higher crash risk (Pei et al., 2012, 2016). In this study, the four-hour traffic flow (in a logarithmical form) is also considered as one of the exposure measures to the risk involved. As such, it would be worth introducing other exposure measures such as the flows of different vehicle types in the proposed crash prediction models. In addition, although it is expected that speed limit would present different effects on crash rates by vehicle type, no significant evidence could be established based on the current results.

As for the temporal variation, the crash rates of private car and light commercial vehicle are found to be statistically lower in year 2017 compared with 2015 (see Table 6.9). Such reductions in crash risk appear to be a favourable consequence of implementing various road safety measures (e.g. penalty and enforcement strategies against traffic offences, driver educational and training programs, and road remedial works, etc.). Moreover, as discussed in Pei et al. (2016), the relationship between year and crash risk could possibly resulted from the effects of other confounding factors over time. As such, it would be more appropriate to say, effect of the crash year is used as a proxy to the effects of unobserved risk factors.

With respect to the time of day, crash rate of private car is higher during noon (11am-3pm) and afternoon (3pm-7pm), as compared to the evening period (7pm-11pm). This is not surprising since such periods cover the afternoon peak hours that private car drivers are off work for various activities (e.g. back home, shopping, gathering with friends, etc.). Higher exposure of private cars on road during afternoon peak hours would contribute to their higher crash risk. Moreover, private car drivers tend to drive less cautiously during their off-work hours, when violation behaviours are prevalent, thus increasing the crash risk (Huang and Chin, 2009). Also, it is revealed that heavy commercial vehicle would have higher crash risk during the afternoon period (3pm-7pm). In contrast, no significant evidence was found for temporal variation in the crash rate of light commercial vehicle. Nevertheless, effects of time on crash rates are revealed to be different across vehicle type, suggesting different temporal patterns for crash risks across vehicle types.

6.6 Concluding remarks

This chapter proposes two research objectives, 1) to throw more light on the moderating (mitigating) or magnifying (exacerbating) safety effects of the interaction between commercial vehicle proportion and road features, and to provide some indication of the variation of these mediating effects across the commercial vehicle classes, 2) to simultaneously estimate the crash rates of private car, light commercial vehicle, and heavy commercial vehicle using the same set of possible risk factors. Effects of road geometry, traffic control and time period are also considered. Such knowledge could help urban road authorities develop more context-sensitive and effective roadway design and commercial traffic operations policies for overall urban road safety enhancement. The Bayesian random parameter Tobit model and multivariate Tobit model are adopted respectively for the two objectives, to account for unobserved heterogeneity across observations and unobserved shared effects across crashes of different vehicle types.

For the first objective, the influence of the proportions of each class of commercial vehicles (bus, taxi, light-goods vehicle, and medium- and heavy-goods vehicles) on crash rates, for different levels of crash injury severity, were examined. The effects of road geometry, traffic control and time of day were also investigated. The study also investigated whether the association between the commercial vehicle percentage and crashes is moderated by prevailing roadway attributes. The study used random parameters techniques within a Bayesian Tobit modelling framework, to accommodate possible heterogeneous effects of the crash factors across the observations. Results suggest that increases in the proportions of taxi and light-goods vehicle contribute to higher rates of slight-injury crashes, while the proportion of medium- and heavy-goods vehicles showed the opposite effect. Also, KSI crash rate decreases with the increase in the proportion of medium and heavy goods vehicle, while the proportions of public buses and light-goods vehicle impose an increasing effect. More importantly, significant interaction effects of commercial vehicle proportions and roadway attributes were revealed in this study. First, the increasing effect of taxi proportion on slight-injury crash rate is magnified at road segments that have high intersection density, second, the increasing effect of light-goods vehicle proportion on slight-injury crash rate is magnified at road segments with on-street parking, and third, the association between the medium- and heavy- goods vehicle proportion and KSI crash rate is moderated by the roadway width (number of traffic lanes). Fourth, an increase in the proportion of medium- and heavy-goods vehicles contributes to the increase in KSI crash rate of the road segments with high intersection density.

This study bridges the gap in the literature on the interaction between roadway attributes and commercial vehicle percentages on crash rates, for different levels of crash severity. The findings of this research provide the transport authority some policy implications in terms of the further expansion of the red-light camera system, licensing requirements, arrangement of human police patrols, lane control measures, and review of roadway design. As there exist limited options to reduce the crash exposure of commercial vehicles, it is necessary to mitigate their crash risk by improving the safety climate associated with the operations of trucking companies and regulating the behaviour of their professional drivers. Therefore, the results of this study can help enhance driver education and training programs that can enhance the social responsibility and safe driving behaviours of professional drivers.

For the second objective, results show that significant correlations exist between crash rates across vehicle types. In particular, positive coefficient is found for the correlation between private car and light commercial vehicle, while negative coefficient is found for the correlation between private car and heavy commercial vehicle. Effects of average lane width and presence of on-street parking are significant only for the crash rates of private car and light commercial vehicle. This could be attributed to the difference in vehicle characteristics (e.g. gross weight and dimensions), as well as more frequent roadside activities involving private cars and light commercial vehicles. On the other hand, previous studies reveal that drivers of light commercial vehicle show higher probability of traffic violations at intersections, compared with private car and heavy vehicle drivers. Consistently, our results show that intersection density has statistically significant increasing effect only for the crash rate of light commercial vehicle. In addition, significant associations between risk factors including number of lanes, traffic flow, and temporal variation, and crash rates across three vehicle types are revealed.

To summarize, contribution of this study is twofold. First, it enhances the understanding on the interaction between commercial vehicle percentages and roadway attributes on crash rates. Second, risk factors associated with the crash rates across different vehicle types are identified using the multivariate Tobit regression approach. As it is not viable to reduce the crash exposure of commercial vehicles, it is necessary to mitigate their crash risk by moderating the behaviour of professional drivers and crashworthiness of commercial vehicle fleets. Yet, this study is limited to the major roads that have continuous and detailed traffic count data. In the extended study, it is worth exploring the effects of other road environment factors like road class and traffic control when comprehensive vehicle trajectory data from the transport agency or operators is available.

Chapter 7 Conclusions and recommendations

7.1 General conclusions

In this study, attempts have been made to assess safety of professional drivers in Hong Kong from the behavioural, psychological, and empirical perspectives. First, we conducted simulators studies to evaluate the interaction between better driving skills of professional drivers and age-related impairments on driving performance of elderly drivers, using both conventional performance indicators and surrogate safety measures. Second, we applied deterrence theory and stated preference survey to investigate the perceptions and attitudes of professional drivers towards the traffic legislation, in terms of the penalty and enforcement strategies. Lastly, we developed prediction models for crash rates by injury severity and vehicle type, incorporating the factors of commercial vehicle mix, road geometry, traffic control, and time period. Overall, findings of the driving simulator studies, the perception survey of professional drivers, and the crash risk analysis of commercial vehicles would provide useful insights into the training and education, driver management strategies of the transport operators, as well as the driver licensing policy and enforcement effectiveness of the authorities. Therefore, safety performance of professional drivers would be enhanced in the long run.

Chapter 2 reviews the literature on the safety of professional drivers, with respect to driving performance, perception and attitude, and crash risks. Driving under the influence of fatigue, compensatory and adaptive driving of professional drivers can be measured using driving simulator approach. Conventional driving performance indicators such as lateral, steering and speed controls over the vehicle, as well as surrogate safety measures such as time-to-collision, headway and braking time, are commonly used to assess the safety of drivers from the behavioural perspective. From the psychological perspective, questionnaire survey is widely used to measure drivers' perceptions, attitudes, and self-reported behaviours. More importantly, emphasis was given to the drivers' perceptions towards traffic legislation in terms of penalty and enforcement. Also, findings of the empirical studies indicating the crash risks of various commercial vehicle types are presented. An obvious research gap existed for the effects of increasing elderly drivers in the transport sector on road safety. Effects of age, road environment and traffic condition on the driving performance have been attempted in previous research. However, the moderating effects by better driving skill and task familiarity of professional drivers have yet to be explored. Another research gap lays in the evaluation of professional drivers' perceptions and attitudes towards traffic legislation. As revealed by previous studies, professional drivers show higher traffic violation rates and propensity to aggressive driving. It is necessary to apply perception survey to enhance the understanding and effectiveness of penalty and enforcement strategies. Last but not least, driver behaviour and crashworthiness of different vehicle types are different. A study examining the safety effects of the commercial vehicle proportions is thus urgently needed. Overall, the aforementioned deficiencies motivated us to bridge the gap in the safety assessment of professional drivers.

Of the road crashes involving personal injury in Hong Kong, over 70% involved at least one commercial vehicle. Besides, the proportion of older drivers in the transport sector has been increasing due to the shortage of labor and aging population. It is believed that increase in age can have adverse impact on driving performance, even that professional drivers may possess better driving skill than non-professional drivers and the age-related impairment can be reduced by task familiarity of professional drivers. In Chapter 3, a driving simulator experiment was conducted to address this question. Additionally, possible factors that affect the driving performance of professional drivers and that of non-professional drivers were examined. A total of 50 participants were recruited and 94 tests were completed. Driving performance was assessed in terms of standard deviation of lateral position (SDLP), standard deviation of heading error (SDHE), mean heading error (MeanHE) and standard deviation of speed (SDspeed). Results of random intercept models indicate that lateral and speed control performances of mid-aged drivers were better than those of older drivers. Then, disaggregated models were established for professional and non-professional drivers respectively based on the results of market segmentation analysis. It is found that lateral and speed control performance of mid-aged professional drivers were better than that of older professional drivers. In contrast, older non-professional drivers were more likely to have degraded steering performance under high traffic conditions. Results of this study are indicative to the driver management strategies of the transport operators for sustained safety improvement of commercial vehicle fleet.

In Chapter 4, we attempt to examine the compensatory behavior and its safety effect amongst older professional drivers, as compared to those of older non-professional drivers, using the driving simulator approach. It has been a controversial issue for the effect of ageing population on driving safety. Apparently, drivers' physiological and cognitive performances deteriorate with age. However, older drivers may compensate for the elevated risk by adjusting their behaviors, known as compensatory strategy. Despite the extensive research on this topic, the compensatory strategy of older professional drivers is not well understood since many studies focused on the differences in compensatory behavior between older and young drivers. Professional drivers tend to be more skillful and able to cope with the unfavorable driving environments, thus presenting a higher capability to mitigate the risk. In the driving simulator experiment, participants were asked to follow a leading vehicle for one hour, and two sudden brake events were presented. 41 (mid-aged and older) drivers completed the driving tests. Each participant was required to complete a car-following test, either under high or low traffic flow conditions. Performance indicators include driving capability (i.e. lateral control, longitudinal control, and brake reaction time) and compensatory behavior (i.e. average speed, and time headway). Additionally, two modified traffic conflict measures: time exposed time-to-collision (TET) and time integrated time-to-collision (TIT) are applied to indicate the traffic conflict risk. The random parameter Tobit models were estimated to measure the association between conflict risk and driver attributes, and random intercept models were used to assess other driving performance indicators. Results show that despite the impaired lateral control performance and longer brake reaction time of older drivers, the likelihood of severe traffic conflict of older drivers is lower than that of mid-aged drivers. Furthermore, though both older professional and older non-professional drivers adopted longer time headway, the reduction in the risk of severe traffic conflict is more profound among the older professional drivers. Such findings suggest that older professional drivers are more capable of mitigating the possible collision risk by adopting the compensatory strategy, as compared to older non-professional drivers. This justifies the existence of compound effect by the compensatory strategy of older driver and better driving skills of professional driver. This research provides useful insights into driver training and management strategies for employers, as older drivers would become a major cohort in the transportation industry.

Next, for the drivers' perceptions and attitudes, Chapter 5 presents an evaluation of the effectiveness of different penalty and camera-based enforcement strategies in curbing speeding offences by professional drivers in Hong Kong. A stated preference survey approach is employed to measure the association between penalty and enforcement strategies and drivers' speed choices. Data suggest that almost all drivers comply with speed limits when they reach a camera housing section of the road. For other road sections, a panel mixed logit model is estimated and applied to understand the effectiveness of penalties and enforcement strategies on driver's speeding behaviors. Driving-offence points (DOPs) are found to be more effective than monetary fines in deterring speeding offences, albeit there is significant heterogeneity in how drivers respond to these strategies. Warning drivers of an upcoming camera-based enforcement section increased speed compliance. Several demographic and employment characteristics, driving history and perception variables also influence drivers' choices of speed compliance. Finally, besides penalty and enforcement strategies, driver education and training programs aimed at addressing aggressiveness/risk-taking traits might help reduce repeated speeding offences among drivers.

Finally, in Chapter 6, we aim to examine the main and interaction effects of commercial vehicle proportion (CVP) and roadway attributes on the overall crash rates, and to conduct a multivariate analysis of crash rates by vehicle type. First, a random-parameter Tobit model was used to measure the relationships between the CVP and crash rates by severity level. Second, a multivariate Tobit model is applied to identify the risk factors affecting the crash rates across different vehicle types (including private car, light commercial vehicle, and heavy commercial vehicle). A comprehensive database integrating the crash, traffic and road inventory data of the target road segments in Hong Kong was used. The results suggest that the CVP of each class significantly and directly affect the crash rates, for the various crash severity levels. The results also suggest that the interaction between CVP and roadway attributes is significant enough to mediate the effect of CVP on crash rates, and the magnitude and direction of such mediation varies across the vehicle classes, crash severity levels, and roadway attribute type in four ways. First, the increasing effect of taxi proportion on slight-injury crash rate is magnified at road segments with high intersection density. Second, the increasing effect of light-goods vehicle proportion on slight-injury crash rate is magnified at road segments with on-street parking. Third, the association between the medium- and heavy-goods vehicle proportion and killed/severe injury (KSI) crash rate, is moderated by the roadway width (number of traffic lanes). Finally, a higher proportion of medium- and heavy-goods vehicles generally contributes to increased KSI crash rate at road segments with high intersection density. Furthermore, the results of crash rates across three vehicle types show that correlations exist between crash rates across vehicle types. Crash risks of private car and light commercial vehicle are affected by number of lanes, average lane width, traffic flow, presence of on-street parking, and year. While effect of intersection density is significant only for the light commercial vehicle. For the crash risk of heavy commercial vehicle, three risk factors - number of lanes, traffic flow, and time period are significant. Overall, the findings of this research are expected not only to help guide commercial vehicle enforcement strategy, licensing policy, and lane control measures, but also to review existing urban roadway designs to enhance safety.

7.2 Main findings and contributions

This thesis has assessed the safety of professional drivers in Hong Kong by addressing five research questions from the behavioural, psychological, and empirical perspectives: 1) whether age-related impairments on driving performance can be reduced by the driving experience and task familiarity of professional drivers, 2) whether the compensatory strategies of older drivers are different between professional and non-professional drivers, 3) how the penalty and enforcement strategies deter professional drivers from traffic violations, 4) whether the relationship between commercial vehicle proportions and crashes can be moderated by roadway attributes, and 5) whether the effects of risk factors vary across crashes categorized by vehicle type. The main findings are concluded below.

1) Driving performance of professional drivers

- Results of the driving simulator experiment evidence the better driving skill of professional drivers and impaired driving performance of older drivers. It is revealed that age-related impairments on driving performance (i.e. steering control) could be reduced by the driving experience and task familiarity of professional drivers.

2) Conflict risk of professional drivers

- Two modified traffic conflict measures: time exposed time-to-collision (TET) and time integrated time-to-collision (TIT) are applied to indicate the traffic conflict risk.
- Though both older professional and older non-professional drivers adopted longer time headway for risk compensation, a more profound reduction in conflict risk is found for the older professional drivers.
- Older professional drivers are more capable of mitigating the possible collision risk by adopting the compensatory strategy, as compared to older non-professional drivers.

3) Perceptions and attitudes of professional drivers

- A stated preference approach was employed to evaluate the deterrent effects of penalty and enforcement strategies on the speeding behaviours of professional drivers.
- Driving-offence points are found to be more effective than monetary fines in deterring speeding offences among professional drivers. Also, warning drivers of an upcoming camera enforcement section increased speed compliance.

4) Safety effect of commercial vehicle mix

- This study examines the moderating effects of roadway attributes on the association between commercial vehicle proportion and crash rate.
- Small commercial passenger vehicle (taxi) proportion: effect on slight-injury crash rate is moderated by intersection density.
- Light-goods commercial vehicle proportion: effect on slight-injury crash rate is magnified by the presence of on-street parking.
- Medium- and heavy-goods vehicle proportion: association with KSI crash rate is moderated by the number of traffic lanes and intersection density.

5) Risk factors to crash rates of different vehicle types

- Vehicles are categorized into three types — private car, light commercial vehicle, and heavy commercial vehicle.
- A Bayesian multivariate Tobit model was used to estimate the crash rates of private car, light commercial vehicle, and heavy commercial vehicle simultaneously. Significant correlations exist between crash rates across vehicle types.
- Effects of geometric factors and traffic control on crash rates vary among different vehicle types.

Based on the results from the proposed research questions, this thesis is able to make contributions to driver recruitment and management strategies, effective penalties and enforcement strategies against traffic violations, as well as safety countermeasures tailored for professional drivers. Here suggest some potential implications derived from the above findings. For examples, (i) in the context of the driver recruitment and management in an aging society like Hong Kong, transport operators should not make decisions solely based on driver age. Instead, rigorous assessment of driving skills and training programs should be provided for the older drivers. (ii) For the effectiveness of penalties, combining the quantity of fines with appropriate warning messages could probably increase the deterrent effect of monetary fines. Further, higher penalties could be considered for repeat offenders. Moreover, equipping all dummy camera housing boxes with actual speed cameras may not necessarily enhance the effectiveness of camera-base enforcement. (iii) Increases in the proportions of taxi, light bus, light goods vehicle is associated with increase in the crash rates of the studied road segments. Transport authorities or operators should provide taxi, light bus and light goods vehicle drivers with additional training programs aimed to reduce risk-taking and aggressive driving traits. (iv) Effects of geometric factors and traffic control vary across the crash rates of private car, light commercial vehicle, and heavy commercial vehicle. This would provide useful insights for the roadway safety design. For instance, engineers would consider whether a particular design (e.g. lane width, intersection) is capable of serving heavy vehicles and private cars simultaneously.

7.3 Limitations

Despite the contributions to the literature described in the above paragraphs, this research should be interpreted in the context of the limitations. Firstly, with respect to the simulator studies, effect of gender on driving performance is not attempted. The driving performances of male drivers only are assessed in the driving simulator experiment, given the relatively small sample size. In addition, although many previous studies have demonstrated the absolute and relative validity of the simulator experiment, the ability of simulator studies to reflect realistic driving is often questioned. Naturalistic driving studies could aid in verifying the findings of our simulator studies. In particular, car following behaviour of professional drivers at work could be influenced by time pressure and market competition. However, it is not possible to incorporate the effect of work pressure in the driving simulator study. Moreover, compensatory strategy could be prevalent for the drivers who have known cognitive impairment and crash involvement records. However, the cognitive ability of older drivers is not examined in current study.

Secondly, for the stated preference survey, the study merely investigates a few demographics and operational characteristics of professional drivers, while the information on the psychological metrics of the participants is not collected. In addition, our scenarios are limited to a typical city road with a speed limit of 50km/h. Moreover, for the attribute associated with the placement of the warning sign, distance of 50 meters, 100 meters, 150 meters, and 200 meters upstream of the speed camera housing are considered in the survey setting. Perhaps a time separation rather than a space separation (between the placement of a warning sign and the camera housing unit) would be better capture how individuals respond to warning signs before entering monitored roadway section. It is also important to note, findings of this study are based on self-reported speed choices within stated experiments, which could influence the reliability and accuracy of the relationships estimated. A study based on an actual field experimental design and field observations of speed at different sections would be more credible. Finally, for sensitive questions related to social desirability, a self-administered or internet survey could improve the reliability of the survey, despite that face-to-face interviews help receive more serious responses from the participants.

There were limitations for the crash rate analysis as well. First, its scope is limited to the major roads that have continuous and detailed traffic count data. Also, due to the data availability, this study only considered weekday crashes. Moreover, the effects of other road attributes such as road functional class, horizontal alignment and the mean speed of traffic are not attempted. Last but not least, consistent with the positions of Zhai et al. (2019), Xing et al. (2019), and Gao et al. (2020), it will be worth exploring, when comprehensive weather information is available, the moderating effects of weather conditions on the association between commercial vehicle percentage and crash rates.

7.4 Recommendations for future research

Section 7.1 and 7.2 has outlined the contributions of this thesis to the safety assessment of professional drivers through the behavioural, psychological, and empirical studies. Yet, the current work can be further extended in the future. The recommendations for future research in four aspects are listed.

7.4.1 Conventional driving performance measured by simulator

Further studies could explore the possible effect of personal characteristics on the level of aggressiveness, and thus the driving behaviour, when more comprehensive information on the psychological metrics of participants is available. Similarly, the effects of driving history (e.g. crash involvement, traffic offense) and risk perception of professional drivers on the driving performance should be attempted. The effect of gender on the temporal change in driving performance of professional drivers could be explored. Moreover, cognitive measures for the elderly drivers could be adopted, as well as the subjective or physiological measures for mental workload and fatigue. Furthermore, effects of environmental factors such as road design, lighting condition and weather on the driving performance of professional drivers can be revealed in extended study.

7.4.2 Traffic conflict analysis using driving simulator

Driving simulator can capture the driving behaviour and vehicle trajectory data in a controlled driving environment. Thus, it could be a promising approach for traffic conflict analysis in the future. In addition, other surrogate measures such as headway, post encroachment time, lateral distance to departure, etc., can be adopted in driving simulator experiments to explore their applicability. Moreover, other critical events (e.g. pedestrian crossing; car incursion from roadside) can be incorporated into experimental design to assess the driver's conflict risk in different situations. Furthermore, effects of other driver characteristics (e.g. income, vehicle type, salary system), driving history, and safety perception on drivers' conflict risks certainly constitute important avenues for future research as the findings from these studies could be indicative to the safety management of professional drivers.

7.4.3 Perception survey

In addition to a few demographics and operational characteristics of professional drivers, it would be worth exploring the possible effects of latent characteristics on the propensity and severity of traffic offense, when more comprehensive information on the physiological and psychological metrics of the participants is available. Moreover, other driving environments could be incorporated in the stated preference design. It would be interesting to explore the effects of different road environments on the violation behaviour of professional drivers. On the other hand, the perceptions and attitudes of private car drivers towards the penalty and enforcement strategies could be revealed in the extended study for a comparable result. Also, similar approach can be applied to examine the deterrent effect of police surveillance, as drivers would perceive differently when encountering automated enforcement systems and manual enforcement.

7.4.4 Crash risk analysis for commercial vehicles

In future studies, it will be worthwhile to explore the safety effects of other road attributes such as road class, horizontal alignment and average vehicle speed of traffic when more comprehensive data are available. Furthermore, the study did not include the crash pattern, and therefore, in a future study of this kind, it will be illuminating to consider that factor using a multivariate approach. For the multivariate analysis, possible heterogeneous effects of risk factors across observations should be carefully considered by introducing random parameters. Also, defining an exposure measure is critical in crash risk assessment. As such, it would be worth introducing other exposure measures such as the flow of vehicles by different modes in crash prediction models.

Moreover, the safety effects of behavioural attributes of commercial vehicle drivers could be insightful to the practical effectiveness of traffic control and management strategies geared towards commercial vehicle safety enhancement and could be considered in future studies. Last but not least, it may be worthwhile collecting comprehensive weather information and including such data in similar future analysis. That way, the moderating effects of weather conditions on the association between commercial vehicle percentage and crash rates. Prospectively, the information to be earned from all such future research could help the road agency refine existing driver regulations and streamline urban traffic control and management strategies related to commercial vehicle operations and safety.

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Appendix

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING
土木及環境工程學系

Questionnaire survey for speeding violation

Section 1 State Preference

Comprehensive strategy has been adopted by the Hong Kong Government to tackle the speeding problem and to improve road safety. The application of camera systems is one of the major approaches for the speed enforcement since 1999. As of 2012, the transport department has installed 120 camera housing units for speed enforcement, of which only 20 have actual cameras within these units (that is, the camera-to-housing ratio today is 20:120). However, in the future, this ratio may be changed to enhance the effectiveness by increasing the number of cameras or the housings. Meanwhile, adequate advance warning signs will be erected to alert drivers of the presence of this speed enforcement camera systems. Also, the current penalties for speeding are as given below.

Table 1 Current penalties for speeding in Hong Kong

Level	Speeding Offences in Excess of Speed Limit by	Monetary Fine	DOP
1	15 km/h or less	320	0
2	15 + km/h ~ 30 km/h	450	3
3	30 + km/h ~ 45 km/h	600	5

Attention：There are **<u>three types of locations</u>** on the roadway, as identified below.

Table 2 three types of locations

Location Type		Characterization
A	Plain Section	No enforcement and no warning signs in roadway section
B	Warning Section	Warning sign indicating the presence of speed camera housing unit <u>X</u> meters ahead
C	Camera housing Section	Camera housing unit present in roadway section

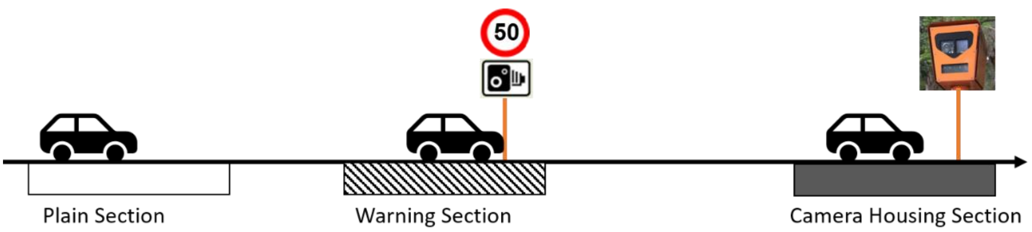

Figure 1 Illustration of the road sections

With the above as background, we will present you with four scenarios, reflecting:

(a) different levels of penalty for speed violations;
(b) different camera-to-housing ratios;
(c) different placement of the warning sign.

Consider a roadway with a speed limit of **50** km/h.

Please consider each scenario carefully, and make a choice of the speed at which you would travel for each of the three location types on the roadway.

Scenario ①

Background information		**Speed（km/h）**		
		< 50	**51 - 65**	**66 - 80**
Penalty for speed violation	➢ DOP ➢ Fine	0 0	0 320 HKD	3 450 HKD
Camera-to-Housing ratio		20 cameras in 240 housing units		
Location of the warning sign in **section B**		Warning Sign placed 50 meters ahead of housing unit		

If you are in location Type A (Plain section), at which speed range would you travel ? (choose one option from below)
☐ **≤ 50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**
If you are in location Type B (Warning section), at which speed range would you travel ?
☐ **≤ 50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**
If you are in location Type C (Camera housing section), at which speed range would you travel ?
☐ **≤ 50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**

Scenario ②

Background information		**Speed（km/h）**		
		< 50	**51 - 65**	**66 - 80**
Penalty for speed violation	➢ DOP ➢ Fine	0 0	2 320 HKD	3 450 HKD
Camera-to-Housing ratio		40 cameras in 120 housing units		
Location of the warning sign in **section B**		Warning Sign placed 200 meters ahead of housing unit		

If you are in location Type A (Plain section), at which speed range would you travel ? (choose one option from below)
☐ **≤ 50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**
If you are in location Type B (Warning section), at which speed range would you travel ?
☐ **≤ 50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**

If you are in location Type C (Camera housing section), at which speed range would you travel ?

☐ ≤ **50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**

Scenario ③

Background information		**Speed（km/h）**		
		< 50	**51 - 65**	**66 - 80**
Penalty for speed violation	➢ DOP ➢ Fine	0 0	0 320 HKD	5 450 HKD
Camera-to-Housing ratio		20 cameras in 120 housing units		
Location of the warning sign in **section B**		Warning Sign placed 150 meters ahead of housing unit		

If you are in location Type A (Plain section), at which speed range would you travel ? (choose one option from below)

☐ ≤ **50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**

If you are in location Type B (Warning section), at which speed range would you travel ?

☐ ≤ **50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**

If you are in location Type C (Camera housing section), at which speed range would you travel ?

☐ ≤ **50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**

Scenario ④

Background information		**Speed（km/h）**		
		< 50	**51 - 65**	**66 - 80**
Penalty for speed violation	➢ DOP ➢ Fine	0 0	0 420 HKD	5 550 HKD
Camera-to-Housing ratio		40 cameras in 120 housing units		
Location of the warning sign in **section B**		Warning Sign placed 100 meters ahead of housing unit		

If you are in location Type A (Plain section), at which speed range would you travel ? (choose one option from below)

☐ ≤ **50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**

If you are in location Type B (Warning section), at which speed range would you travel ?

☐ ≤ **50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**

If you are in location Type C (Camera housing section), at which speed range would you travel ?

☐ ≤ **50 km/h** ☐ **51-65 km/h** ☐ **66-80 km/h**

Section 2 Driving history and perception

1. Have you been involved in any traffic accidents in the past 12 months?
   □ No
   □ Yes〔involved in _____ time(s)〕
2. Have you received tickets for violating the speed limit in past 12 months?
   □ No 〔please turn to question 3〕
   □ Yes〔How many tickets have you received in past 12 months?〕
   ◯ 1~3 ◯ 4~6 ◯ 7~9 ◯ ≥ 10
3. In how many out of 10 trips have you noticed the orange housings?
   ◯ 0 ◯ 1~3 time(s) ◯ 4~6 times ◯ 7~9 times
4. I think speeding cameras are effective to catch offenders.
   ◯1(Strongly disagree) ◯2 ◯3 ◯4 ◯5
5. If you are speeding now, how likely will you decelerate when you see a:
   i. Warning sign for alerting motorists of the presence of speed camera system
   ◯1(Not at all) ◯2 ◯3 ◯4 ◯5(Very muc
   ii. Orange housing for speeding camera
   ◯1(Not at all) ◯2 ◯3 ◯4 ◯5(Very muc
6. Speeding violation is a very risky behavior that leads to property damage only.
   ◯1(Strongly disagree) ◯2 ◯3 ◯4 ◯5
7. Speeding violation is a very risky behavior that leads to injuries.
   ◯1(Strongly disagree) ◯2 ◯3 ◯4 ◯5

Section 3 Personal information

1. Gender: □ Male □ Female
2. Age: □18-25 □26-35 □36-45 □46-55 □56-65 □≥ 66
3. Education: □Primary □Secondary □Tertiary or above
4. Marital status:
   □ Single □Married/Cohabiting □Divorced/Separated □Widowed
5. Personal monthly income:
   □ < 10,000 HKD □ 10,000-14,999 HKD □ 15,000-19,999 HKD
   □ 20,000-24,999 HKD □ 25,000-29,999 HKD □ ≥ 30,000 HKD
6. How many years have you obtained your driving license? _______ year(s)
7. What is your current driving-offence points on driving license? _______ (0-15 point(s))
8. How many hours do you usually drive per day? _____hour(s)
9. How many days do you usually drive per week？ _______day(s)
10. What is the type of your vehicle?
    □Taxi □Private Bus □Franchised Bus □Public Light Bus
    □Light Van □Medium/heavy Goods vehicle □Others ________
11. What is your current employment status?
    □ Self-employed □ Permanent □ Contract
12. What is your current salary system?
    □Trip based □ Hourly □ Shift based □ Monthly